The Concept of Information

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THE CONCEPT OF INFORMATION

Bo Sundgren

Acknowledgement. Many of the definitions and basic descriptions used in this report are based on Wikipedia articles, which are referred to in my article by links. However, for the purposes of this report, for improved readability, and in order to keep this report within a reasonable length, I have had to select and transform the material from Wikipedia. Furthermore, it should be noted that the Wikipedia articles are not only useful sources by themselves; they also serve the important purpose of giving an overview of a lot of relevant articles and books, and guidance to how to read them and put them into a context.

Introduction

The concept of information is an interdisciplinary concept in the sense that it appears in many different academic disciplines. The concept is also frequently referred to in daily talk in our society, which is sometimes called an information society, producing, consuming, and trading with information products and information services – rather than with traditional physical products and services.

On the other hand, the concept of information is not really one and the same concept across disciplines, although the same term “information” is used. One striking example is the concept of information used by Shannon in his mathematical “information theory”, which is certainly very different from information concepts used in social sciences and in the context of media.

There have been attempts to form a true interdisciplinary and holistic academic discipline, based on a true interdisciplinary and common information concept with one definition. See for example:


In my opinion, no such attempt has yet been successful, and probably never will be, but discussions involved in such attempts may still be quite useful in order to obtain sharper, information-related concepts and theories, suitable for the different purposes and universes of discourse of different academic disciplines, and in order for researchers to better understand each other across disciplines, and to discover possibilities of enriching one’s own discipline by borrowing from others.

There is a tendency among academics to view related disciplines as subfields or special cases of one’s own discipline. A researcher in discipline A may tend to see (parts of) discipline B as a subfield of A, whereas a researcher in discipline B may tend to see (parts of) discipline A as a subfield of B. A more constructive and less provocative approach is to see a number of related disciplines as partially overlapping as regards topics, concepts, and theories.

I will now discuss “information” and related concepts that play important roles in different disciplines. The topics covered by the different chapters are:

- Chapter 1. The nature of information and related concepts.
- Chapter 2. The instrumental role of information.
- Chapter 3. The information society and the information economy.
- Chapter 4. Information for good governance in e-society.
- Chapter 5. Information for welfare, happiness, and prosperity.
- Chapter 6. The concept of information in different academic disciplines.
- Chapter 7. Strategies and methods for research in information systems and computing.
CHAPTER 1. The nature of information and related concepts

Information and related concepts, like knowledge, meaning, concepts (themselves), symbols, and reality, have been analysed, discussed, and written about through the human history since the time of the Greek philosophers Plato and Aristotle and long before them. The discussions concern the concepts as such and their relations to each other, but also how human beings may acquire and communicate knowledge, and how they may process the knowledge, for example by means of induction and deduction, and thereby obtain new knowledge.


The origin of the word “information” can be traced back to Latin and old Greek. The Latin noun “informatio” means “concept” or “idea”, and the verb “informare” means “to give form”, or “to form an idea”.

The real world, the mental world, and the world of symbols

Intuitively, and, as we shall see, a bit naively, many of us feel that the universe in which we live our lives as human beings can be divided into three different “worlds”: the real world, the mental world, and the world of symbols.

The real world is first of all the physical world around us, which we can perceive with our senses, consisting of concrete physical objects, animals, plants, and the physical bodies of ourselves and our fellow human beings. But does the real world contain anything more? What about abstract entities, for example? Does the real world exist in an objective way, independently of subjects like human minds? We shall return to these questions.

The mental world is associated with the human mind, including concepts, thoughts, knowledge, emotions, attitudes, etc. Information, as we treat it in this report, belongs to this world.

The world of symbols contains physical data, created, communicated, and interpreted by human beings, representing entities and phenomena in human minds and (indirectly) entities and phenomena in the real world. The symbols may be, for example, letters in an alphabet, combined into words and sentences in a written or spoken language, graphic icons like signs in Chinese and other languages. The symbols exist in the physical world. Some symbols may have similarities with the entities that they (indirectly) represent, for example images, gestures, and onomatopoetic words.

Throughout history, philosophers and scientists have analysed, written about, and debated these worlds of entities and phenomena – and, not least, the relations and interactions between them.

The meaning of meaning

In his seminal book “The meaning of meaning”, Chapter I: “Thoughts, Words, and Things”, the English linguist, philosopher, and writer Charles Kay Ogden illustrated his analysis of issues associated with these three worlds and the relations between them by means of a triangle; see Figure 1.

Ogden himself explains the triangle as follows:

“Between a thought and a symbol causal relations hold. When we speak, the symbolism we employ is caused partly by the reference we are making and partly by social and psychological factors — the purpose for which we are making the reference, the proposed effect of our symbols on other persons, and our own attitude. When we hear what is said, the symbols both cause us to perform an act of
reference and to assume an attitude which will, according to circumstances, be more or less similar to the act and the attitude of the speaker.

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**Figure 1.** Ogden’s triangle, as originally presented by Ogden in Ogden et al (1923).

Between the Thought and the Referent there is also a relation; more or less direct (as when we think about or attend to a coloured surface we see), or indirect (as when we ‘think of’ or ‘refer to’ Napoleon), in which case there may be a very long chain of sign-situations intervening between the act and its referent: word—historian—contemporary record—eye-witness—referent (Napoleon).

Between the symbol and the referent there is no relevant relation other than the indirect one, which consists in its being used by someone to stand for a referent. Symbol and Referent, that is to say, are not connected directly (and when, for grammatical reasons, we imply such a relation, it will merely be an imputed, as opposed to a real, relation) but only indirectly round the two sides of the triangle."

The triangle has been reused and sometimes more or less radically rearranged and reinterpreted by others until today. Figure 2 below shows a more recent version illustrating the relationships between reality, information about reality, and data representing information about reality.

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**Figure 2.** A more recent version of Ogden’s triangle, illustrating the relationships between reality, information about reality, and data representing information about reality.
Where is the place of “language” in Ogden’s triangle? A language consists of words (symbols) combined into expressions and sentences according to some syntax, and the words, expressions, and sentences represent concepts, thoughts, ideas, and information.

Linguistic structures are pairings between meaning and form, that is, they seem to connect to both the top corner and the bottom-left corner in Ogden’s triangle.

According to Ogden there is no direct connection between symbols in languages and objects and phenomena in the real world (the “referents” in Ogden’s triangle). The connection is only indirect, via thoughts or references in human minds. However, according to Ogden:

“An exceptional case occurs when the symbol used is more or less directly like the referent for which it is used, as for instance, it may be when it is an onomatopoeic word, or an image, or a gesture, or a drawing. In this case the triangle is completed; its base is supplied, and a great simplification of the problem involved appears to result. For this reason many attempts have been made to reduce the normal language situation to this possibly more primitive form. Its greater completeness does no doubt account for the immense superiority in efficiency of gesture languages, within their appropriate field, to other languages not supportable by gesture within their fields.”

The distinction between the real world and the mental world

As was stated earlier, many of us intuitively feel that there is a clear distinction between on the one hand, our own mental world, associated with our mind, our world of concepts and thought, and on the other hand the mind-external real world, which we at least at first may believe has a more objective existence, independent of the concepts and thoughts of human minds. For example, physical entities like mountains, lakes, animals, and plants, may very well continue to exist, even if all human beings would suddenly be swept away from the earth.

But how clear is the distinction between the real world and the mental world if we think about it more carefully? For example, to which world does a company belong? Of course a company is associated with many physical objects, clearly belonging to the real, mind-external world: buildings, raw materials used by the company, products produces, machines, instruments, and vehicles, etc. But certainly the company as such is something more than these physical objects. The company has owners, managers, and employees, who act together as an organisation in order to fulfil certain goals. The organisation is an abstract entity. Does it belong to the real world or only to the mental worlds of some human beings – or does it possibly belong to both, thus being part of an overlap between the real world and the mental world? Certainly abstractions belong to mental worlds, but on the other hand probably most of us in practice treat an abstract entity like a company as a part of the real world.

Philosophers have taken different positions vis-à-vis this question. On one extreme, there are those who think that there is no objectively existing real world at all: all entities and phenomena that we perceive with our senses are personal or possibly social constructions, invented by our minds. Probably no one advocates the other extreme, which would claim that all contents of human minds belong to an objectively existing real world, but certainly many of us would maintain that there are certain entities and phenomena belonging to a real, extra-mental world, which all human beings may observe with our senses, even though we may not completely agree upon what it is that we observe. And we may certainly not be sure that we actually interpret our observations in the same way, using the same categories or implicit definitions.

Reality as a social construction

In their seminal book “The social construction of reality – a treatise in the sociology of knowledge” (Berger & Luckmann, 1966), the sociologists Peter L. Berger and Thomas Luckmann launched the concept of “the social construction of reality”, or reality as a social construction.
What does “the social construction of reality” mean? A short definition provided by Hiebert (2014), “the social construction of reality” is

- “the process whereby people continuously create, through their actions and interactions, a shared reality that is experienced as objectively factual and subjectively meaningful”

According to Hiebert, this process consists of three phases:

1. **Externalization**: the process whereby individuals, by their own human activities, create their social worlds:
   - a. physical environment: nature, given to humans
   - b. social environment: culture, created by humans
      - i. material culture: tools and technologies, e.g. axes, microchips
      - ii. non-material culture: abstract order, e.g. beliefs, values, norms

2. **Objectivation**: the process whereby individuals apprehend everyday life as an ordered, prearranged reality that imposes itself upon, but is seemingly independent of human beings

3. **Internalization**: the process whereby individuals learn the legitimation of the institutional order

Rivers are nature, roads are culture, but rivers can be enculturated, transformed by humans into culture, for example rivers may be enculturated into playgrounds, transportation roads, political boundaries, sources of hydropower, sacred spaces, etc.

Hiebert (2014) concludes:

### Conclusions:

1. Practical embodied activity in the material world is part of human knowing and being.
2. Humans do not socially construct all reality, but rather primarily their beliefs about reality.
3. It comes down to the physical nature given by God compared to the social culture constructed by humans.
4. The best conclusion is “the social construction of social reality.”

Hiebert, D. (2014). *What does “the social construction of reality” mean?* YouTube video. [https://www.youtube.com/watch?v=SqFhd-lgs6w](https://www.youtube.com/watch?v=SqFhd-lgs6w)

**The role of language for social constructions**

According to Berger & Luckmann (1966):

“Language, which may be defined here as a system of vocal signs, is the most important sign system of human society. Its foundation is, of course, in the intrinsic capacity of the human organism for vocal expressivity, but we can begin to speak of language only when vocal expressions have become capable of detachment from the immediate ‘here and now’ of subjective states. It is not yet language if I snarl, grunt, howl or hiss, although these vocal expressions are capable of becoming linguistic in so far as they
are integrated into an objectively available sign system. The common objectivations of everyday life are maintained primarily by linguistic signification. Everyday life is, above all, life with and by means of the language I share with my fellowmen. An understanding of language is thus essential for any understanding of the reality of everyday life.”

Information and data

Linguistic note. “Data” is the plural form of “datum”, which is originally a Latin noun meaning “something given”. In some languages (like English and Swedish) there is today a tendency to treat “data” as a collective noun in singular (like information), whereas in other languages the plural form prevails, for example French “données and German “Daten”. “Medium” – “media” is another example of the same phenomenon.

Data are physical symbols of mental entities (for example concepts and pieces of information) in the real, mind-external world.

Information exists only in the minds of human beings, and is used by a human being for understanding and coping with the world around her, e.g. decision-making and problem-solving. Information may be represented by data on different media outside the human brain, and information is communicated to other human beings by means of data, e.g. digital data transmitted through cables or in wireless mode.

- Data may be the result of a measurement or a direct observation performed by a human being, or by a measurement instrument designed by a human being.
- Data may also be the result of a mental and physical process, where a human being tries to represent and communicate information by means of data.
- Data may be transformed into other data by means of processes, designed by human beings and executed by human beings, machines (e.g. computers), and/or human beings and machines in cooperation.

The conceptual distinction between “information” and “data” should now be clear, at least in principle. However, it is not always easy to maintain the distinction consistently in everyday language. For example, when we say that “this book contains a lot of information”, we probably mean that a reader of the book will get a lot of information by interpreting the text, the data, which the book actually contains.

Furthermore, especially in social sciences, the term “data” often means both “data” and “information” at the same time. If a social scientist says that she has collected a lot of data about elderly women, she does not only mean that a lot of data representations, data values, have been collected and stored, but she also implies that these data represent a lot of (factual) information.

The infological equation

Information and knowledge cannot be stored and processed outside human minds. However, like human beings have learnt to design and construct tools and machines to help us perform physical tasks, like moving heavy physical objects, thereby amplifying our physical abilities and strength, we have also invented tools and other artefacts to amplify our mental abilities, like capturing, storing, processing, and communicating information – for our own purposes and for the purposes of groups, societies, and organisations to which we belong. Data, physical representations of information outside the human mind, are the basic artefacts used for amplifying our mental capabilities in this sense.

Human beings have used different forms of data representations of information for a very long time, maybe from the very beginning when human beings became human beings: signs and gestures, spoken language, written language, paintings, pictures, etc. Sometimes symbols are used, which are very easy to
understand because of their resemblance with the object or phenomenon, which they symbolize. Sometimes the representation is not so straightforward, but may rather be seen as the result of a coding process, where you need some kind of explanation or coding key, in order to be able to interpret the representation, for example a thesaurus and a grammar, formalizing a language.

Today computers and other artefacts based on computer technology (like mobile phones) are the most advanced and most important amplifiers of the mental capabilities of human beings. But it should be remembered that tools for capturing, storing, processing, and communicating data representations of information have been invented and used long before computers came around.

Data are not perfect representations of information. Data and data processing tools are not perfect counterparts of the corresponding mental entities and processes. They are just proxies of their mental counterparts. Different persons may interpret the same data in different ways, depending on their cultural backgrounds other differences between them, for example different life experiences resulting in different frames of reference in their minds. Similarly different people will form different concepts, based on different observations and experiences, and sometimes different people will use the same name, or language label, for different concepts, which will lead to misunderstandings in the communication between people. An example is the concept of “unemployment”, which is often used with different meanings by different people. These differences in meaning may be unconscious and inadvertent, but even when the differences are analysed and formalized by means of definitions, they may cause a lot of difficulties in the communication between people and in political debates.

The distinction between information and data may be formalized and illustrated in different ways. For example, Langefors (1995) describes the mental process of interpreting data into information by means of the infological equation:

\[ I = i(D, S, t) \]

where

- \( I \) is the information contents obtained by a human being
- \( i \) is the process of interpretation and creation of meaning
- \( D \) is the received data
- \( S \) is the frame of reference, or accumulated knowledge, used by the interpreter
- \( t \) is the time used for interpretation

**Relationships between information, data, and reality: a graphical illustration**

Figure 3 illustrates the relationships between information, data, and reality. A human being perceives reality through her senses and interprets these perceptions, using the concepts that she has already formed in her mind. This results in an update of the information that the person has in her mind. In order to be sure to remember information, the person may use data representations, e.g. on a piece of paper, or in computer storage. Similarly the person may use spoken, written, or computer-supported data communication in order to communicate information to other human beings.

When data are used to store and communicate information outside the mind of a human being, these data become themselves part of the mind-external reality and have to be perceived and (re)interpreted in order to become meaningful information in a human being’s mind again.

**Mind-external metadata as amplifiers of mind-internal frames of reference**

Like people use mind-externally stored data in order to strengthen her memory and communication capabilities, they use metadata, data about other data, as mind-external amplifiers of mind-internal
frames of reference, helping people to remember concepts and definitions and to increase the likelihood that other people receiving the data will interpret them as intended by the sender. See also Figure 4.

Figure 3. Basic “reality-information-data” relationships.

Figure 4. The roles of metadata (mind-external) and frames of reference (mind-internal). - Obtaining information about reality by (i) direct observation; and by (ii) interpretation of data, accompanied by metadata, “data about data”, facilitating for human being to interpret the data “correctly”.

Different types of information and different forms of data

As human beings we use different types of information for different purposes, and we represent information by different forms of data, depending on our needs, for example, whether the data are to be used by and between human beings, or whether they are to be used by artefacts like computers.

Some different types of information
- specific information about individual object instances, cases, events, relationships, etc.
- general information: laws (laws of nature, mathematics, logic, judicial laws in a society)

- descriptive information: (alleged) facts
- explanatory information – provides explanations: cause → effect
- predictive information: prognoses for the future
- prescriptive information: how to perform a task; instructions, algorithms, heuristics
- normative information: information about goals and values
- evaluative information: performance indicators (quality, efficiency, goal fulfilment)

- quantitative information: measurable on a scale, mathematical operations applicable
- qualitative information: classifications may be used, frequencies may be counted

- operative information: information needed for business operations and operative decisions
- analytical (directive) information: information for improving operations and decision-making
- statistical information: information for statistical and analytical purposes
- administrative information: information for administrative purposes

- geographical information, epidemiological information, business information, environment information, economic information, etc., depending on purposes and application areas

General information, which is the result of induction from a wide range of empirical observations and/or logical deductions from other general information may be called knowledge or, in certain contexts, wisdom. But it should always be remembered that even (alleged) knowledge and wisdom may sometimes turn out to be false, and even seemingly solid theories may sometimes have to be replaced as the result of a so-called scientific revolution, sometimes involving modifications or radical changes of established scientific paradigms. Note also that “experience may actually be another term for “prejudice”...

**Data representations**

Some different forms of data:

- data to be used by people, artefacts (like computers), or both
- digital vs analogue data
- textual vs graphical data
- symbolic data
- free-text data vs more or less formalized and structured data
- “big data” (to be explained later in this report)

If we assume that information, strictly speaking, can only be stored and processed inside human minds, and if we also assume that information cannot be communicated directly between human minds, we need some kind of mind-external representations in order to be able to store, process, and communicate information. Such representations are called “data”.

Examples of data representations: voice and video recordings and transmissions, printed texts and graphs, digital data stored in computers and secondary storage media like hard disks and USB memories, etc.

In disciplines like computer science and physics the main focus, as far as data are concerned, are on the data representations as such: how to store, process, and transmit data in an efficient and safe way. The link to the information represented by the data is not neglected, but it is often regarded as
unproblematic or a topic that is the concern of other disciplines. However, there are disciplines and subdisciplines where a lot of attention is given to both information, data, and the links between them, for example database design, where both conceptual models and physical data models and the mappings between them are carefully considered, software design, and artificial intelligence.

Disciplines focusing on data and data processing (by means of algorithms and computer programs) are sometimes referred to as (branches of) data science or datalogy. Some pioneers within these disciplines are Peter Naur and Donald Knuth. Structured programming.

**Statistical data: microdata, macrodata, and metadata**

Statistical data are data used and/or produced for statistical and analytical purposes. There are three major categories of statistical data: microdata, macrodata, and metadata.

- **Microdata** – data about individual objects
- **Macrodata** – summarized (aggregated) data about collectives of objects, estimated values of statistical characteristics, "statistics"
- **Metadata** – "data about data":
  - exploratory metadata, e.g. metadata to be used by search engines
  - explanatory metadata, e.g. definitions, quality declarations
  - technical metadata, e.g. formats and data types

Note that we use the term “statistical data” in a rather broad sense, including all kinds of data that are used and/or produced for statistical purposes. Microdata are the results of measurements of properties of individual objects and are used as inputs to aggregation processes, and these processes in turn result in estimates of statistical characteristics, or, what people usually call “statistics”, or “statistical figures”, typically presented in statistical tables and graphs. Thus “statistics” is a more narrow term than “statistical data”. Note that “statistical data” also include “statistical metadata”, data about statistical data.

**The history of the term “metadata”**

The term “metadata” has created some controversy as regards its history. The most recent version of this history has been thoroughly researched and documented by Jane Greenberg, Director of the Metadata Research Center, University of North Carolina in her publication *Metadata and Digital Information (2009)*. Her version of the history may be summarized as follows:

- The first known reference to “metadata” appears in Bo Sundgren (1973), *An Infological Approach to Data Bases*, pp 104-105
- Claims in the 1990’s by Jack E Myers to be the originator and owner of the term “metadata” were refuted by the U. S. legal system, with reference to Sundgren (1973) and “the longstanding use of the term in the statistical community”.
- In 1986 Myers had registered “Metadata Inc.” as a company, and “Metadata” as trade mark of that company. He later started to threaten people and agencies in the U.S. with legal actions, if they did not stop using the term “metadata” as a generic term.
- The Solicitor of the U.S. Department of the Interior decided that "metadata" has entered the public domain by becoming a general term.

Jack Myers has not been able to provide any documentation supporting his claim to have coined the term “metadata” in the 1960’s.

**The use of data in human communication and information processing**
The extensive use of computers and computer-supported information systems in contemporary societies implies advanced and very integrated and interactive use of data in all phases of human intellectual activities, both in businesses and in our private lives: from the capturing of perception data through our senses and raw data from other sources via different forms of refinements and analyses, derivations by means of inductive and deductive methods, to final conclusions and actions based on information.

There are different kinds of data. The term “perception data” is used for the data perceived through our senses, and which are stored and transmitted through the nervous system, including the brain. Mental processes interpret the perception data and transform them into concepts and information.

Human perception may sometimes be replaced by different kinds of instruments, which register data, for example thermometers, cameras, video recorders, etc. These measurement processes are designed and created by human beings, and human beings interpret the data emanating from these instruments and processes, so as to transform them into information.

As human beings we may not only perceive, register, and interpret data. We may also create data ourselves in order to store information on mind-external media, and in order to communicate data to other people, possibly through more or less complex intermediary data processing and transmission processes.

Figure 5. Data and data processing has a highly integrated role in most mental processes and usages of information in contemporary societies.

Information and knowledge

Knowledge may be understood as more highly developed information, more refined, more scientific.

Information may be categorized in different ways, e.g.:
specific information: facts about specific objects
- general information: rules, laws, theories

Information may also be referred to as knowledge, especially larger sets of well integrated specific and general information.

**Information as increments**

Especially in the context of media and communication, it is often the incremental aspects of information that are in focus – information as messages, which inform and add to the available information. If the same message is received twice, the second instance of the message will not add anything to the accumulated information contents. However, this does not necessarily mean that the second instance of the message has no value. Especially if the two instances of the messages come from different, independent sources, the credibility of the information will increase.

**Langefors' concept of elementary message, or e-message**

In his early papers, Börje Langefors developed a theory of e-messages as the smallest meaningful pieces of factual information, a kind of information atoms. An e-message \(<o, p, t>\) consists of three parts:

- an object part (o), identifying an object instance
- a property part (p), identifying a property
- a time part (t), referring to a point of time or a time interval

An e-message \(<o, p, t>\) asserts that the object instance o has/had the property p at the time t.

An object instance typically belongs to an object type O, for example “person”, and it also belongs to a population, for example the set of persons who lived in Sweden on the 31st of December 2014. Object instances are identified by identifiers, which must be unique within the population of interest in a certain context, and it should preferably be informationless, since it should be stable and never change.

A property is often referred to as “a value of a variable” or “a value of an attribute”, for example, “age = 15 years”. A variable, V, will take values belonging to a certain value set. The variable and the value set may be quantitative or qualitative.

There is another type of e-messages, asserting that an n-tuple or set of object instances are/were related to each other in a relation R at the time (or during the time interval) t:

\(<<o_1, \ldots, o_n>, R, t>\>

For example, an e-message may assert that two persons, A and B, were married to each other at a certain time or during a certain time interval. Another e-message may assert that a person P was employed by a company C at a certain time or during a certain time interval.

**Elementary concepts, or e-concepts**

Langefors also defined so-called elementary concepts, or e-concepts. An e-concept may be defined as a type of e-messages “of the same kind”. Examples of e-concepts:

- \(<\text{Object type Person, Variable Age}>\>
- \(<<\text{Object type Person, Object type Company}>, \text{Employment}>\>

**Ontology – What is? What exists?**
Sources: Corazzon (2015), University of Idaho (2015).

Many of the issues that we have discussed so far in this report are associated with ontology, the branch of philosophy that deals with existential problems. “Ontology” concerns the overall nature of what things are, trying to identify, in the most general terms, the kinds of things that actually exist, in other words addressing the question: What is existence? and What is the nature of existence? When we ask deep questions about “what is the nature of the universe?” or “Is there a God?” or “What happens to us when we die?” or “What principles govern the properties of matter?” we are asking inherently ontological questions.

In comparison, epistemology is concerned with the nature of knowledge itself, its possibility, scope, and general basis. More broadly: How do we go about knowing things? or How do we separate true ideas from false ideas? or How do we know what is true? or How can we be confident when we have located ‘truth’? What are the systematic ways we can determine when something is good or bad?

So ontology is about what is true, and epistemology then is about methods of figuring out those truths.

Researchers in the academic discipline of artificial intelligence (AI) have borrowed the term “ontology” from philosophy but filled it with a rather different meaning and contents, which has more kinship with “conceptual model” and “data model” as used by researchers and practitioners within the field of information systems. We shall return to this issue later in the report.

Concept formation and knowledge acquisition (epistemology)

From the moment when we are born as human beings, we are hit by impressions, which are perceived through our senses (sight, hearing, taste, smell, touch, …), digested and processed by our mental functions, and stored in our minds. Despite intelligent efforts and lively debates during centuries among philosophers, linguists, psychologists, biologists, medical scientists, and other categories of researchers, we do not know exactly how these processes work, but we know enough in order to draw important conclusions for the design and operation of computer-enabled information systems used by human beings and organisations.

What is a concept?

Before we start of our analysis, it is appropriate to give a few examples of what a concept could be, and how concepts could be formed in practice. A new-born child will soon learn to recognize her mother and her father, and then other persons, phenomena, and things around her, and properties associated with them, for example colours, and to form mental concepts corresponding to these entities. In interaction with her parents and other people she will learn names for these concepts in the language used. When the child observes something that she has not observed before, she may nevertheless, based on similarities, sometimes guess that this new entity belongs to the same category as something that she already knows, for example “a dog”. Sometimes these guesses may be wrong, at least according to the opinion of the people around her, and then she will be corrected, and this helps her to adjust her concepts to the concepts of other people, integrating their so-called frames of reference.

Perceptions through senses

Our mental functions help us to form concepts from the perceptions that we receive through our senses, and these concepts help us to make sense of the world around us and to interact and communicate with other human beings. Concepts are the building-blocks of information, and they help us organize the information and knowledge that we acquire throughout our lives.

Mental processes and the frame of reference
Thus the perceptions are transformed into concepts, information, and knowledge by means of mental processes, such as

- conceptualisation, categorisation
- interpretation, reflection, thinking

Figure 6. Human perception and concept formation.

Like perception, these processes have their roots in the human brain. The results of the processes are stored, accumulated, and digested in the human mind, and constitute the frame of reference for the ever ongoing mental processes, which again update the frame of reference.

Figure 7. Mental processes.

The perception processes include impressions gained from interactions with other human beings and living creatures.

Even without new impressions and perceptions from the physical world, the intellectual processes of the mind will continue and process concepts, information, and knowledge into new, and possibly more complex concepts, information, and knowledge, and thus further update the contents of the frame of reference, the memory function of the human mind.

Concept formation and information processes are iterative and interactive. The concepts that we have already formed in our minds at a certain point of time, and the information and knowledge that we have accumulated on the basis of these concepts, help us to interpret new perceptions, and to add new concepts and new information to our existing frame of reference, the framework of concepts and knowledge that we have already accumulated. Sometimes new impressions may lead us to revise or delete parts of our frame of reference.
Information and knowledge is organised around concepts in the minds of people. It is debated whether some basic concepts are actually inherited, or whether they are all the result of observation and communication processes after you are born. Anyhow, concepts and their definitions are very important for our understanding of the world and society around us, and concepts may vary considerably between different societies and cultures.

As human beings we form and modify concepts from the time we are born until we die. We do this by perceiving the world around us through our senses, and by trying to make sense of all these perceptions and observations. We also adjust and standardise our concepts in on-going communication with people around us, within the family, within the place where we live, the place where we work, and places we travel to and visit.

Concepts are the basic components, or atoms, of information and knowledge. The mental processes by which a human being forms and modifies concepts are not clear, but concept formation is an ongoing process throughout the life of a person, and it is fed by the person’s own observations and through personal and social interactions with other people. Thus the environment of a person will be important for the mental conceptual framework that a person develops over time. The environment will consist of the physical and social world, where the person is living, including family, acquaintances, and workplaces. A person will typically be a member of more than one culture, for example the family culture and the culture of a workplace, and this means that the person has to be able to manage several conceptual frameworks, understanding and speaking several “languages”.

**Intuitive understanding of fuzzy concepts**

Most people may not be able to define what they mean by, say, a dog, but they may still be very good and consistent about recognising something as a dog, when they see it. Why? Dogs have many things in common: head with nose, two ears, two eyes, mouth, body with four legs, tail; a dog barks now and then ...

But what if a dog has only three legs? We realize that it could be an exception because of accident or a disease ...

As human beings we are quite good at accepting, reconciling, and adjusting the concepts we use to such exceptions, without knowing exactly how we do it. Formal systems like computerized information systems are not always equally flexible.

Similarly, we learn in interaction with our fellow human beings, what a colour is, and how to distinguish different colours from each other. We also combine simple concepts into more complex ones: for example, we combine “car” and “colour” into “the colour of a car”.

**Definition, identity, and gene identity (Heraclitus)**

Some concepts are very easy to agree upon, e.g. the concept of a person. A person is well defined by means of a lot of properties, and in a modern society a person may even be uniquely identified by means of an identification number, a registration card, etc. Persons are also well separated from each other, except possibly in the case of Siamese twins, and at least up to recently, it was not a great problem to determine when a person was born, and when a person died.

However, many concepts used in a modern society are much more complex, abstract, and constructed than “natural” concepts like “persons”. Consider two simple examples: households (families) and enterprises (organisations).

Intuitively, a household consists of a number of people who live together and share their daily lives to some extent, e.g. by having meals together. But what if one person in a household moves away for some time? Do the remaining persons still constitute the same household as before, only slightly changed as to its members, or is it a new household? And does the person who moved away constitute a new household, possibly consisting of the person together with some other person(s), to whom the first person moves? And if all or some members of a household moves to another place – under which
conditions is it still the same household? If a household splits into two parts – are both parts new households, and what happened to the old household that existed before the split? How many successive, small changes can a household undergo, and still remain the same household? And if a household at a later time \( t_2 \) is obviously quite a different household from the household that existed at an earlier time \( t_1 \), for example because all the members are different, and they live in a different place, when exactly did the first household \( H_1 \) cease to exist, and when did the second household \( H_2 \) come into existence, assuming that the transformation from \( H_1 \) to \( H_2 \) took place in small, incremental steps, no single one of which seems to be fatal for the originally existing household?

Similar problems as those pointed to above were discussed already by the old Greek philosopher Heraclitus. The philosophical problem is referred to as the problem of **gene identity**.

Heraclitus of Ephesus (c. 535 – c. 475 BC) was a pre-Socratic Greek philosopher. Heraclitus was famous for his insistence on ever-present change as being the fundamental essence of the universe, as stated in the famous saying, "No man ever steps in the same river twice" (see panta rhei, below). This position was complemented by his stark commitment to a unity of opposites in the world, stating that "the path up and down are one and the same".

Now let us consider the concept of an enterprise or an organisation. How is an enterprise defined, and how do we separate one enterprise from another one? Since many types of enterprises and organisations (but not all) have to be registered, an operational definition is to say that the enterprise is exactly that entity that is registered, the so-called legal unit. However, statisticians are often more interested in enterprises and organisations in their role as the “home” of a set of more or less homogenous activities, with some kind of common goal, and being executed by some kind of staff, a number of persons working together. Statisticians are often interested to observe such enterprise objects, which are reasonably homogeneous as regards their kind of activities, location, etc., and to summarise the production, use of resources, number of employees, etc., over classification variables such as “kind of activity”, “kind of input resource”, “kind of output result”, “location of enterprise”, etc. Whether an enterprise consists of several legal units, or whether it is a part of a bigger legal unit, is often not so important from a statistical point of view.

In practice it is often very difficult to identify those ideal, homogenous enterprises, or parts of enterprises, that statisticians are interested in, and even more difficult to collect data from them, since those ideally defined enterprises do not exist as real-world entities, but only as abstractions. The activities performed in a certain location, by a certain legal unity, may be a mixture of different kinds of activities, and on the other hand, the same kind of activity may be performed by the same legal unit in different places. The book-keeping systems and reporting structures of an enterprise may not at all coincide with the ideal structure looked for by the statisticians. As a result, pragmatic compromises often have to be made when collecting data for business statistics and national accounts.

**Two epistemological paradigms: rationalism and empiricism**

Knowledge acquisition, **epistemology**, is a topic which has a long tradition in philosophy. There are two main, competing paradigms: empiricism and rationalism.

According to **empiricism** all knowledge must be based on observations and experiences, whereas according to **rationalism** logical thinking is the way to knowledge. There are strong arguments in favour of, and against, both paradigms, which have been thoroughly presented and argued about in numerous philosophical books and articles through the centuries, and the debate is still going on. A pragmatic conclusion seems to be that the paradigms have to be combined and synthesized, and that different approaches may be more or less relevant for different research problems concerning physical, social, and other topics of human interest.
**Induction, deduction, and abduction**

Mental processes – “thinking” – may themselves lead to updates of our frames of reference. There is an eternal controversy among philosophers and scientists as to which extent we are able to acquire knowledge from rational thinking and deduction, and to which extent we are dependent on empirical perceptions and observations through our senses, followed by induction – inference of general knowledge from specific information.

When using **induction** you go from specific observations to general conclusions. For example, if you see one raven after the other, and for each raven you observe that it is black, at some point you may conclude that all ravens are black, a general rule.

When using **deduction**, on the other hand, you go from the general to the specific. For example, if you have learnt at school that all ravens are black, and you hear that somebody has seen a raven, you may conclude that the bird that the other person saw was black. If the other person then tells you that the bird was in fact white, you may conclude either that the bird was not a raven after all, or that the rule that you learnt at school was wrong, or at least has exceptions.

**Abductive reasoning** (also called **abduction, abductive inference, or retroduction**) is a form of logical inference which goes from an observation to a theory which accounts for the observation, ideally seeking to find the simplest and most likely explanation. In abductive reasoning, unlike in deductive reasoning, the premises do not guarantee the conclusion. One can understand abductive reasoning as "inference to the best explanation".

The American philosopher Charles Sanders Peirce (1839–1914) first introduced the term as "guessing". Peirce said that to abduce a hypothetical explanation \( a \) from an observed circumstance \( b \) is to surmise that \( a \) may be true because then \( b \) would be a matter of course. Thus, to abduce \( a \) from \( b \) involves determining that \( a \) is sufficient, but not necessary, for \( b \).

For example, suppose we observe that the lawn is wet. If it rained last night, then it would be unsurprising that the lawn is wet. Therefore, by abductive reasoning, the possibility that it rained last night is reasonable. However, some other process may have also resulted in a wet lawn, e.g. dew or lawn sprinklers. Moreover, abducting that it rained last night from the observation of a wet lawn can lead to false conclusions.

Peirce argues that good abductive reasoning from \( P \) to \( Q \) involves not simply a determination that \( Q \) is sufficient for \( P \), but also that \( Q \) is among the most economical explanations for \( P \). Simplification and economy both call for that “leap” of abduction.

The fields of law, social sciences, computer science, and artificial intelligence have renewed the interest in the subject of abduction. Diagnostic expert systems frequently employ abduction.

For more information about abduction and relevant references, see Wikipedia (Abductive reasoning), [https://en.wikipedia.org/wiki/Abductive_reasoning](https://en.wikipedia.org/wiki/Abductive_reasoning).

**Metainformation and metadata**

**Bibliographic note.** “Metainformation”, “metadata”, and related concepts were first introduced and defined in Sundgren (1973). See also the history of metadata in Greenberg (2009).

Data are not perfect representations of information. Data and data processing tools are not perfect counterparts of the corresponding mental entities and processes. They are just proxies of their mental counterparts. Different persons may interpret the same data in different ways, depending on their cultural backgrounds and other differences between them, for example different life experiences.
resulting in different frames of reference in their minds. Similarly different people will form different
concepts, based on different observations and experiences, and sometimes different people will use the
same name, or language label, for different concepts, which will lead to misunderstandings in the
communication between people. Metainformation informs about other information and entities, both
mental and physical, associated with information, for example concepts and data representations of
concepts and information.

Metadata are physical, symbolic representations of metainformation, intended to help people interpret
and understand other data in the same way, the way intended by the original sender of data.

We can never be sure that

- different people interpret the same data in the same way
- a receiver of data interprets the data as intended by the sender

By extensive use of metadata, and by expressing the same message redundantly in many different ways,
we may increase the likelihood that different people understand a message in the same way, and in the
way intended by the sender.

For practical reasons, daily human communication by means of natural languages must be allowed to be
a bit fuzzy. We cannot include definitions of concepts and other metadata all the time. However, in some
contexts, for example professional discussions and political debates, it is often important to be more
careful, so that the vagueness of natural languages does not lead to accidental or intentional
misunderstandings. For example, statistical concepts like “unemployment” and crime rates (rapes,
suicides) may often be defined and measured in different ways, and such conceptual differences may
sometimes be misused by politicians and others in order to create false impressions about controversial
phenomena in society. Even when the differences in meaning are unconscious and inadvertent, they
may cause a lot of difficulties in the communication between people and in political debates.

In addition to help clarifying the intended meaning of concepts and information, metadata can be used
for more practical purposes, such as

- helping us to find and retrieve relevant information for a certain purpose, a process which may be
  supported by modern search engines using metadata
- driving software and computerized processes

Paradata


Paradata, or process data, are metadata which inform about processes and thus indirectly about the
data used and produced by processes. The term paradata is attributed to Couper (1998), a survey
statistician, who, like other survey statisticians use the term in the context of statistical surveys. See for
example Kreuter et. al. (2010) and Scheuren (2000).

The paradata of a survey are data about the process by which the survey data were collected; Groves &

Paradata are usually "administrative data about the survey; Safir et. al. (2001).

For example, paradata about a survey include the times of day interviews were conducted, how long the
interviews took, how many times there were contacts with each interviewee or attempts to contact the
interviewee, the reluctance of the interviewee, and the mode of communication (such as phone, Web,
email, or in person); Taylor (2008). Thus there are paradata about each observation in the survey. These
attributes affect the costs and management of a survey, the findings of a survey, evaluations of interviewers, and inferences one might make about non-respondents.

Models and conceptual models

“Conceptual model” is a term often used in the context of analysis and design of databases and information systems. Here we shall discuss the meaning of this term and the concept behind it. We shall start by discussing the concept of a model.

Models and modelling

In contemporary thinking, both in academic disciplines and in practice, the term “model” is often used. A model is basically a conceptual entity, belonging to a human mind, but the main purpose of a model is often to explain ideas and constructs to other people. In order to fulfil such purposes, models have to be represented by real-world constructions like graphs, mathematical formulas, or by some kind of analogous physical constructs, for example a model in the scale 1:100.

Thus a simple definition of a model could be that it is a man-created construct intended to represent something else for some purpose.

Models are often used as tools in design and construction processes, for example the design and construction of a building or an information system. The process of creating and testing the model will then be an integrated part of the design and construction of “the real thing”. An advantage of using models and modelling processes is that models are easier and less expensive to test and change than “the real things”, which means that more iterations can be afforded, hopefully resulting in better outcomes from the real design and creation processes.

Patterns of thinking

Sometimes the term “model” is used to denote a “pattern of thinking”. As human beings we use patterns of thinking in order to organize and systematize the contents of our minds. By doing so, we may analyse and solve new problems more efficiently, since we may regards them as new instances of more generic problems that we have encountered before. Furthermore we may gain new insights, more general knowledge, when we see the patterns on a higher and more abstract level. See also Lundeberg (1992), Lundeberg (1993), and Sundgren et al. (2003).

Descriptive and normative models

As has already been stated, the basic purpose of a model is to represent something else. Such models may be called “descriptive models”. However, models, and especially models in the sense of “patterns of thinking”, may also have more normative purposes, prescribing how a certain task should be performed, and which tools should be used. Consider for example the task of designing a database. The normative model may prescribe that this task should be performed as follows:

1. Develop a so-called conceptual model in cooperation with the future users of the database.
2. Transform the conceptual model into a physical data model, for example a relational data model, by following certain rules.
3. Optimize the data model, if necessary.

Note that the normative model above contains two descriptive models – the conceptual model and the physical data model – as tools.

To which world does a model belong?
Does a model belong to the mental world or to the world of symbols, or possibly to both? A model belongs first of all to the mental world, the world of thinking, since it is a conceptual representation of something in the real world. But in order to fulfil its communicative role, the model must also be represented by symbols, which can be understood by other people, for example verbal, mathematical, or graphical symbols.

We may compare with an artist, who creates a mental picture of a landscape in his mind, and then represents this mental conception by a physical painting; see Figure 1.

![Figure 1. A physical representation of a mental model conceptualizing a part of the real world in the mind of a human being. From Sundgren&Tolis&Steneskog (2005).](image)

Similarly, when we use models in a design and creation process, for example the design and creation of a business model or an information system, we represent the models we use by means of some kind of documentation; see Figure 9.

![Figure 9. From Sundgren&Steneskog (2003) and Sundgren&Tolis&Steneskog (2005).](image)

Representing mental concepts – and indirectly the real world entities that they may refer to – by real world symbols like drawings and verbal descriptions and documentations – may strengthen the impression that mental concepts and abstract constructions like organisations, events, etc., are really objectively existing entities in the real world. The symbolic representations also help us agree upon socially constructed concepts, so that we understand, interpret, and define them in more or less the same way, and do not misunderstand each other when we communicate with each other.

A mental model organizes parts of the contents of a human being’s frame of reference according to some patterns and principles. When a human being creates a mental model, this process may itself result in new concepts and abstractions that help to form the patterns needed.

To repeat: All kinds of models typically first occur in the minds of people – as mental models. However, people are not able to communicate with each other “mind-to-mind”. We are dependent on spoken and written languages and other kinds of expressions that we may exchange via our senses: sight, hearing, etc. We also need some kind of tangible and permanent representations in order to document and
preserve our models for the future. Furthermore, we may need other types of model representations in order to make them suitable for computers in computer-supported information systems.

The role of the documented models with regard to the mental processes should not be underestimated. For example, it is interesting to look at Newton’s original, verbal presentation of his theory of mechanics, and compare it with the same theory expressed in modern mathematical notation. The latter is much easier to understand, even for people who are not advanced mathematicians. On the other hand there is also a lot of exaggerated (mis)use of mathematical formulae in modern science. One may sometimes suspect that mathematical models are used only to make rather simple ideas look more “scientific”.

Nevertheless, good models used in the right contexts may be very helpful to organize concepts and knowledge so as to become easier to understand and apply in practice. Like physical tools may help people to perform physical tasks in more convenient and efficient ways, models may help people to perform intellectual tasks.

**All models are conceptual but different forms of physical representations are needed**

All models are conceptual in the sense that they are created by human minds. They always exist in the mind of a person or a group of cooperating persons before they are represented by material constructions or artefacts. Physical representations of models are necessary in order for human beings to be able to communicate and discuss them. Different forms of graphs, more or less formalized, are common representations of models, but a verbal documentation, again more or less formalized, may also be a representation of a model. For example, a computer program written in a programming language may be a representation of a process model or an abstract algorithm.

Some model representations are really very concrete and physical, for example a wooden model of a new building or a whole city, but even such models have first existed as conceptual models in the mind of some person or a group of communicating persons.

**Mental constructions**

Thus models are always first mental constructions, conceptual models, which may sometimes be represented by physical constructions in order to facilitate communication in time and space, between different people, or between different “time versions” of the same person.

Mental models and constructions may also have slightly different purposes. The intellectual processes in the mind of a person have the function to organize and systematize the contents of the frame of reference of the person. Here is where mental models and patterns of thinking may also come in.

A mental model organizes parts of the contents of a human being’s frame of reference according to some patterns and principles. When a human being creates a mental model, this process may itself result in new concepts and abstractions that help to form the patterns needed.

**Models of information contents**

In the context of databases and information systems, conceptual models are created and used in a more narrow sense, as models of information contents.

**Data models**

Conceptual models are sometimes called “data models”. However, a data model is, strictly speaking, a model of data representations of information contents. Thus a data model of a database is a model of the data and data structures representing the information contents of the database. Information contents is something mental in the mind of a person, whereas data representations are physical
symbols, for example in the form of natural language texts, graphs on paper or a computer screen, or digital data stored in a computer or on a server.

**The OPR framework for creating conceptual models**

The OPR framework (OPR = Object-Property-Relation) is a typical framework for creating conceptual models in the sense of models of information contents. This framework, and other similar frameworks, are often used in the context of analysis, design, and construction of databases and information systems. Conceptual models created by such frameworks may also be transformed into data models in the sense of models of the data and data structures representing information contents.

All information systems contain information about something. This “something” is sometimes called the **Universe of Discourse (UoD)**, or “**the object system**”. The UoD covers certain parts or aspects of some kind of “reality”, and it is in this sense a (simplifying) model of reality.

Thus:

- **Reality of interest = Universe of Discourse = Object system**

**Basic concepts in the OPR framework: objects, properties, and relations**

The OPR framework is a framework for modelling and visualizing a universe of discourse in terms of objects (O), properties (P) of objects, and relations (R) between objects. Model instances following the rules of the OPR framework are called **OPR models**. An OPR model is a conceptual model in the sense of a model of information contents, the information contents of interest concerning the object system. At the same time as being a model of information contents, an OPR model is also a model of the object system, the piece of reality which is of interest in a particular context, also called the Universe of Discourse. Thus OPR models may be used for conceptualizing both the object system as such – some kind of reality – and information about this reality, for example the information contents of a database or an information system.

As just said, object systems as well as OPR models of object systems are by necessity simplifications of reality, and like all simplifications and models they may not be valid outside the intended context.

The OPR framework has its roots in the seminal theory of information and information systems created by Börje Langefors in the 1960’s; see Langefors (1966), Langefors (1995). The first version of the OPR framework as such – then referred to as “the infological model” – was developed by Bo Sundgren and presented in Sundgren (1973, 1974, 1975) and in Langefors & Sundgren (1975). The framework was further refined and elaborated in a series of papers; refer to the Bibliography at the end of this document, and to [https://sites.google.com/site/bosundgren/](https://sites.google.com/site/bosundgren/).

The objects in an object system may be active, passive, or complex:

- **Active objects**, also called **actors or subjects**, are active in the sense that they are capable of making decisions and act – they are typically people, groups of people, or organisations (consisting of people).

- **Passive objects** are more like “**things**”, material or abstract entities that may be owned, acted upon, or related in some other ways to subjects.

- **Complex objects** are based on **relations between other objects**, for example events, transactions, or other relationships like marriage, employment, and ownership.
Object graphs: visualisations of object systems and information about object systems

OPR models are visualized by means of object graphs illustrating object types, properties associated with the object types, and relations between object types. Figure 10 is an example, illustrating an object system and information of interest concerning a fictive video renting business.

An object graph is easy to understand for most people and may therefore be useful for discussions in project teams, reference groups, and steering committees engaged in the analysis or development of an information system.

In order to get object graphs well organized, and to some extent standardized and easier to interpret, it may be practical – like in the example in Figure 10 – to place active object types to the left in the graph, passive objects to the right, and complex objects, connecting active objects and passive objects, in the middle.

Furthermore it may be noted that an object graph is a model which conceptualizes

- both the Universe of Discourse, the so-called object system, comprising the parts and aspects of reality which are of interest in a particular context;
- and the information of interest, for example the actual or planned information contents of a database

Figure 10. An OPR model for a video renting business, visualized by a so-called object graph. The graph represents parts and aspects of a piece of reality, which is of interest in a particular context, as well as information of interest about this piece of reality.

Looking at Figure 10, we may note the following things:

- The object graph contains
  - rectangular boxes, representing object types;
  - dots linked to the object type boxes, representing property types (also called variables or attributes) associated with the respective object types; and
  - lines between the object type boxes, representing relations between the respective object types

- The object types are
  - Customer, an active object type
  - FilmCopy and FilmTitle, passive object types, “things”
o Rental, a complex object type, based on the Rental relation between Customer and FilmCopy; the Rental object type is also called a relational object type

- The property types (variables, attributes) associated with the respective object types are:
  - Customer:
    - CustomerId, underlined, the values of which identifies Customer instances
    - Name
    - Address
    - Discount, the discount in % that a customer is entitled to get
  - FilmCopy:
    - FilmId, underlined, part of the identifier for FilmCopy instances
    - CopyNr, underlined, part of the identifier for FilmCopy instances
    - Rented? Is this FilmCopy instance rented
    - NumberOfRents: How many times has this FilmCopy instance been rented?
  - FilmTitle:
    - FilmId, identifier for FilmTitle instances
    - Title
    - Price
    - Actor*; * means “multivalued variable”, a FilmTitle may have several actors
    - Story, free-text variable
    - NumberOfCopies: How many copies exist of this FilmTitle?
    - NumberOfRents: How many times have copies of this FilmType been rented?
  - Rental (combines one Customer with one FilmCopy):
    - CustomerId, underlined, part of the Identifier for Rental instances
    - FilmTitleId, underlined, part of the Identifier for Rental instances
    - CopyNr, underlined, part of the Identifier for Rental instances
    - RentalNr, underlined, part of the Identifier for Rental instances
    - RentalDate
    - AgreedReturnDate
    - Returned?
    - ActualReturnDate

- The relations are:
  o Rents/IsRentedBy between Customer and FilmCopy; functionality “many-to-one”
  o Represents/IsRepresentedBy between FilmCopy and FilmTitle; “many-to-one”

The functionality “many-to-one” for the relation Represents/IsRepresentedBy means that one FilmCopy may only Represent one FilmTitle, whereas one FilmTitle may be represented by several instances of FilmCopy. Similarly, one Customer may only rent one FilmCopy (as part of one and the same Rental transaction), whereas one and the same FilmCopy may be rented by different Customers at different times. The functionalities of relations are indicated by symbols at the end of the relation lines (forks and arrows in this example)

Other frameworks for conceptual modelling

The OPR framework is not the only framework of its kind. Several researchers have more or less independently of Langefors and Sundgren developed similar frameworks; see for example Durchholz & Richter (1974), Lindgreen (1974), Falkenberg et. al. (1983), Leung & Nijssen (1988), Halpin (2007) and several authors of papers in Klimbie & Koffeman (1974). The work by Michael Senko (1973) should also be mentioned.

Frameworks similar to the OPR framework are often called Entity-Relationship (ER) or Entity-Attribute-Relationship (EAR) models, and many papers have been written on such frameworks. For some strange reason the paper of this kind which has probably most often been referred to in the literature is Chen
(1976), although it is certainly not the first, the best, or the most original paper belonging to this category; for a critical review of Chen’s ER model, see Nijssen et.al. (1990).

Some people find it insulting to “objectify” people by treating them as only one of many different types of objects, including passive objects. But it should be remembered that being information objects in an object system model is only one of the roles that people have in the context of an information system. In addition, people naturally have to be given “special treatment” in the development and operation of information systems because of issues of ethics, privacy, etc. On the other hand, if an information system is going to serve the interests of people in a good way, for example in health information systems, it is necessary to have high quality information, well integrated and easily accessible, in such systems.

More reading: Sundgren (2014), Sundgren et al. (2005)

Transforming an OPR model into a relational data model

For several decades now, the relational data model, originally defined by Codd (1971), has been the de facto standing for representing factual information in databases, relational databases. A relational data model consists of relational tables, where each table consists of rows and columns. The tables represent object types, the rows represent object type instances, and the columns represent variables (attributes) associated with the object type.

The relational data model is a model – or rather a framework – for organizing the data in a database in a structured and standardized way. The terms “relational database” and “relational data model” were first proposed and defined by E. F. Codd in his paper Codd (1971), but similar ideas had been presented and used earlier, for example by Senko, as documented in Senko (1973).

One may even trace some important features of the relational model back to the days when the records of a data file were stored on 80-column punched cards in a standardised way. Each record in such a file would correspond to an object of the same type, e.g. a person or a product, each object having a fixed number of variables, and each variable having a certain value for each object instance represented by a record in the file. The value of a certain variable of a certain object instance would be represented by a certain field (sequence of positions) on the card. For example the variable “person number” could be represented by a field consisting of the first 10 positions of the card – the standardised cards contained 80 positions all in all.

Before computers came around, card decks could be processed in standardised ways by special machines performing operations like sorting, collating (merging and matching), etc. See http://en.wikipedia.org/wiki/Unit_record_equipment. These card operations (or unit-record operations as they were also called) have their counterparts in the relational algebra associated with the relational data model as defined by Codd. “Flat files” is another term that was used for this type of standardised files before the terminology of the relational data model became popular.

Short definition of a relational data model

The essential characteristics of a relational database and a relational data model, as defined by Codd, will be listed below. The following example of a relational table called EMPLOYEES will be used for illustrating the different features in the list:

**EMPLOYEES**

<table>
<thead>
<tr>
<th>EmployeeNumber</th>
<th>Name</th>
<th>Sex</th>
<th>Phone</th>
<th>Salary</th>
<th>Boss*</th>
</tr>
</thead>
<tbody>
<tr>
<td>35133</td>
<td>Peter</td>
<td>Male</td>
<td>897</td>
<td>25</td>
<td>89144</td>
</tr>
</tbody>
</table>
A relational database organized in accordance with the relational data model should conform to the following rules:

1. The database is regarded as collection of named tables (called relations, since the tables may be regarded as relations in the mathematical sense: sets of n-tuples).

2. A relation (or relational table) consists of rows and named columns. The names of the columns are sometimes called role names. From a mathematical point of view, the rows may be regarded as n-tuples, and the relational table as a whole may be regarded as a matrix.

3. The intersection between a row and a column in a relational table is called a cell. Every cell in a relational table should contain exactly one value, possibly a null value (missing value). The value should be atomic, that is, it must not consist of a set of other values.

   In the example above, Penelope has no boss, because she is the highest boss in the company herself, and this is indicated by a null value (Φ) in the cell in the “Boss” column of Penelope’s row in the relational table EMPLOYEES.

4. The value set, from which a column takes its values, is called the domain of the column.

5. No particular order must be assumed between the rows or the named columns in the relational model.

6. A relational table must not contain duplicate rows, that is, no two rows in a relational table must contain exactly the same values in all cells.

7. A candidate key is a column, or combination of columns, the values of which uniquely identifies rows in a relational table. (Note that according to rule 6 above, the combination of all named columns will always be a valid candidate key.)

   In the EMPLOYEES example above, the columns “EmployeeNumber”, “Name”, and “Phone” seem to be possible candidate keys, since each one of these columns contain different values in all rows. However, if two different employees could actually have the same name or the same phone, these columns would not be qualified to be candidate keys.

8. A primary key is a selected candidate key, that is, a candidate key which is “appointed” by the designer of the relational model as the primary key or “official identifier” of rows in the table.
In the EMPLOYEES example above, we may appoint “EmployeeNumber” as the primary key, if we know that different employees in the company will always have different employee numbers.

Like in the example above, primary keys may be indicated by underlining the column name: “EmployeeNumber”.

9. A foreign key is a column, or combination of columns, which takes it values (or value combinations) from the same value set or domain (or domain combination) as the primary key of another (or possibly the same) relational table.

In the EMPLOYEES example above, the column “Boss” takes its values from the same value set (domain) as the primary key “EmployeeNumber” of the same relational table, EMPLOYEES. Thus the column “Boss” is a foreign key. This is indicated by an asterisk after the column name. One may also indicate foreign keys by drawing an arrow from the foreign key column to the primary key column to which it refers. See Figure 11.

![Figure 11. A simple relational data model.](image)

Correspondences between conceptual models and relational models

The formal rules stated in the previous section do not tell anything about how to interpret the data contents of relational tables. The contents in the cells of a relational table are just physical data representations, but they do not tell what they refer to in terms of entities in the real world, the universe of discourse (UoD), or information about the real world. The names of the columns of a relational table and the name of the relational table as such, may give some clues to the meaning of the data in a relational table, but this is all, and there are no rules to ensure that the names really give such clues.

However, a good database design, based on a good design of a relational data model, should ensure that the relational data model is based on a suitable conceptual model, for example an OPR model. Such a design would ensure clear and meaningful correspondences between the concepts in the conceptual model on the one hand (objects, properties/variables, relations, etc.) and concepts in the relational data model on the other (relational tables, rows, columns, cells, etc.). These correspondences could be visualised by an object graph illustrating a conceptual OPR model, on the one hand, combined with a set of relational tables illustrating the relational data model, on the other.

**The EMPLOYEE example**

Let us illustrate some such correspondences by means of the very simple EMPLOYEES example that we have used above for illustrating the definition of a relational data model; see Figure 12.
In this simple example we may note the following simple correspondences between the conceptual model and the relational data model:

- The relational table EMPLOYEES (as a whole) corresponds to the object type EMPLOYEE.
- The following columns in the relational table EMPLOYEES correspond to the following variables of the object type EMPLOYEE:
  - the column “Id” corresponds to the variable “EmployeeNumber”
  - the column “Name” corresponds to the variable “Name”
  - the column “Sex” corresponds to the variable “Sex”
  - the column “Phone” corresponds to the variable “Phone”
  - the column “Salary” corresponds to the variable “Salary”
- The foreign key column “Boss” corresponds to the object relation “Boss” between employees and their bosses, indicated by an arrow from the EMPLOYEE object type to itself. The object relation is of the type “zero-one-or-more” to “zero-or-one”, since an employee may have zero, one, or more subordinates, and one or zero bosses (where the latter holds for the highest boss in the company).
- Every row in the EMPLOYEES relational table corresponds to an instance of the object type EMPLOYEE.
- The values in the cells of an EMPLOYEES table row correspond to the values of the variables corresponding to the columns.
- The values in the cells of the “Boss” column correspond to instances of the object relation “Boss”. The column combination [Boss*, Id] corresponds to the object relation “Boss”.

The video rental business example

This simple EMPLOYEE example contains only one relational table in the relational model of the database and correspondingly only one object type in the conceptual OPR model. The next example that we will use for illustration purposes is based on the OPR model in Figure 10, the video rental business example, and is a little more complex. The relational data model corresponding to the OPR model in Figure 10 is shown in Figure 13.

Many more examples of correspondences between OPR models and relational data models can be found in Sundgren (2014).
Figure 13. The conceptual model of a video renting business transformed into a data model.

Transformation rules

An OPR model may very easily be transformed into a relational data model by applying a number of transformation rules. The most important transformation rules are:

Transformation rule 1: Object types

Object types in an OPR model are normally transformed to relational tables in a relational data model according to the following transformation rule.

Transformation rule 1: object type → relational table
• The object type as such is transformed to a relational table.
• The object instances are transformed to rows in the relational table.
• The variables of the object types are transformed to columns in the relational table.
• The identifier of the object type is transformed into the primary key of the relational table.

Transformation rule 2: Object relations

Transformation rule 2a (main rule): object relation → relational table

• An object relation of degree n in an OPR model is normally transformed to a relational table.
• A relational table, representing an n-ary object relation, will have a primary key consisting of n foreign keys: \( f_1, \ldots, f_n \), where the foreign key \( f_i \) takes its values from the same value set (domain) as the primary key of the relational table representing the \( i \)th object type component in the n-ary object relation. Thus the foreign keys link together the relational table representing the object relation with each one of the relational tables, which – according to Transformation rule 1 – represent the related object types.

Transformation rule 2b (alternative rule for hierarchical relations): object relation → foreign key

• A binary, hierarchical, “one-to-many” relation in an OPR model may (as an alternative to following Transformation rule 2a) be represented by a foreign key in the relational table which (according to Transformation rule 1) corresponds to the object type in the “many”-end of the “one-to-many”-relation.

A more complete set of transformation rules can be found in Sundgren (2014).

Extending the OPR framework with statistical concepts and time → OPR(t) and the \( \alpha\beta\gamma\tau \)-model


Statistical information – or “statistics” for short – is built up from structured sets of estimates of statistical characteristics. The concept of a statistical characteristic is very central to statistics and statistics production.

In this section it will be explained how the OPR framework can be extended with statistical concepts. In particular we will introduce the so-called \( \alpha\beta\gamma\tau \)-model, which is based upon the OPR framework, but which also manages and takes advantage of the typical multidimensional structures that are common in statistics, especially in official statistics about social and economic conditions in society.

Furthermore, as indicated by the letter tau (\( \tau \)) in “\( \alpha\beta\gamma\tau \)”, the extended framework, sometimes called the OPR(t) framework, makes explicit use of the concept of time. In principle, all concepts used in a conceptual OPR model should be qualified by time, explicitly or implicitly, when the model is instantiated:

• When object types are instantiated into sets (populations) of object instances, these sets are typically defined as the sets of object instances that existed at a certain point of time, or during a certain time interval.
• Similarly properties, or the values of variables, are typically specified as the properties associated with object instances at certain times, and relations are typically specified as relations prevailing at certain times.
The use of time in OPR(t) models will be illustrated by several examples below.

Statistical information lends itself naturally to multidimensional structuring. Many statistical tables on paper or on a computer screen can be seen as two-dimensional projections of multidimensional structures. From a logical point of view, a statistical table often consists of more than two dimensions, but if one wants to present the table on paper, or on a computer monitor, one has to project the table onto the two dimensions that are available on those media.

The $\alpha\beta\gamma\tau$-model makes use of the concept of statistical characteristics and some other basic statistical concepts. The model was first introduced in Sundgren (1973) and Sundgren (1975). It was further developed in several papers, e.g. in Sundgren (1990). It was also presented in Sundgren (1999) and Sundgren (2001).

**Statistical characteristics**

A statistical characteristic $S$ can be defined as a statistical measure, $f$, applied to the values of a variable, $V$, of the object instances in a set of objects, $O$, in order to summarise some those values in some way:

$$S = O.V.f$$

From a statistical point of view, the object set is often a population, or a subset of a population, e.g. a so-called domain of interest.

The value of a statistical characteristic, $S$, is on an aggregated level, or macro level, relative to the values of the object characteristic

$$C = O.V$$

that it summarises. The object characteristic $C$ has a value of the variable $V$ for each object instance in the object set $O$.

**Example 1:** “Average income during the year 1999 for those persons who were registered in Stockholm at the end of the year 2000.”

Here the set of objects, $O$, the population of interest, is “the persons who were registered in Stockholm at the end of the year 2000”, the variable, $V$, is “income during the year 1999”, and the statistical measure, $f$, is “(arithmetical) average”.

The object characteristic in the example is “income during the year 1999 of a person registered in Stockholm at the end of the year 2000.”

**Example 2:** “Number of persons registered in Stockholm at the end of the year 2000.”

This example can be viewed in two ways. According to both interpretations the population of interest is “the persons who were registered at the end of the year 2000”. One view is that the statistical measure is a function, “count”, that summarises “the frequency aspect” of the objects directly, not via any particular variable. The other view is that the statistical measure summarises the values of a variable that takes the value “1” for all objects in the population.

**Example 3:** “The correlation between age at the end of the year 2000 and income during the year 1999 for persons registered in Stockholm at the end of the year 2000.”

In this example, it is not the values of a single variable that are summarised, but the values of a vector of variables,
<age at the end of the year 2000, income during the year 1999>,

and the statistical measure $f$, summarising the values of the vector variable is “correlation”.

Thus we have to generalise the concept of a statistical characteristic by allowing the “$V$” in “$S = O.V.f$” to be interpreted as a vector of variables.

**Estimated statistical characteristics: statistics**

If it were possible to make perfectly correct observations of exactly those objects that are in the population aimed for, the target population or population of interest, then it would be possible to obtain perfectly correct values of statistical characteristics for this population; the complete and true values of the object characteristics would lead to the true values of the statistical characteristics; one would just have to apply the appropriate statistical measures correctly. In practice this “ideal procedure” for computing statistical characteristics is hardly ever possible to implement. Some important reasons for this are:

1. One cannot identify and localise exactly those objects that are in the target population. Typically one uses some kind of list or register, called the frame, in order to find the objects concerned. The set of objects that the frame leads to is called the frame population. The frame population may differ from the target population by containing objects that are not part of the target population, over-coverage, and by not containing objects that are part of the target population, under-coverage.

2. One cannot afford to investigate/observe all objects in the target population. This can lead to a sample survey instead of a complete or total survey, a so-called census.

3. Regardless of whether one goes for a sample survey or a total survey, one usually will not succeed in observing all objects and all variables aimed for – so-called total or partial non-response; total non-response occurs when no observations at all are obtained for a certain object instance, whereas partial non-response is the case when observed values have been obtained for some, but not all, intended variables of a certain object instance.

4. The observations that are actually made will be subject to errors and uncertainties of different kinds, measurement errors, processing errors, etc., that is, one will not always be able to obtain the true values of the variables, the values of which are to be summarised by the statistical measures.

5. Sometimes it is not even possible to observe the target population and/or the target variables directly. Then one may sometimes be able to observe them indirectly, either by using other sources, like other surveys or administrative registers, or by observing related objects and/or related variables and deriving the object and variables aimed for. This procedure may also lead to over-coverage, under-coverage, non-response, and measurement errors.

Thus instead of the target population $O$ and the target variables $V$, aimed at, one will in practice obtain an actually observed set of objects $O'$, differing from $O$ because of over-coverage, under-coverage, sampling, and total non-response, and an actually observed variable $V'$, differing from $V$ because of total and partial non-response, measuring errors, and processing errors.

Hence one has to be satisfied with approximations, estimates, of the true values of the statistical characteristics aimed for, the target characteristics. These estimations have to be based on the incomplete, erroneous, and uncertain observations that one has been able to make, directly or indirectly.
When estimating the true value of a statistical characteristic $S = O \cdot V \cdot f$ on the basis of an actually observed set of objects, $O'$, and actually obtained, processed, and finally registered values of a variable, or variable vector, $V'$, one has to apply a function $f'$, the estimator, which is somehow related to, but usually not identical with, the statistical measure $f$. The difference between $f'$ and $f$ is the result of an attempt to compensate for the deviations of $O'$ and $V'$ from the ideal $O$ and $V$.

In summary, the basic idea of a statistical survey, in a broad sense (including surveys based on administrative registers), implemented by means of a statistical production system, is to

- estimate the true values of statistical characteristics, $O \cdot V \cdot f$,
- on the basis of observed values of object characteristics, $O' \cdot V'$,
- by applying an estimator, $f'$, on the observed values,
- thus computing $O' \cdot V' \cdot f'$.

**Estimates of the uncertainties of estimates**

It follows from what has been said, that estimates of statistical characteristics, and hence statistics as such, are subject to uncertainties of different kinds. One can try to decrease these uncertainties by improving the statistical production processes, including the estimation procedures, but some uncertainties will always remain. At best the uncertainties can themselves be estimated, once again with some uncertainty, of course. These estimates should try to quantify the uncertainties of obtained estimates of statistical characteristics, and they may form the basis for quality declarations of the produced statistics. Sometimes it may be very difficult to obtain quantified estimates of uncertainties of good quality, but then one should at least discuss the uncertainties in a more qualitative way, by means of verbal descriptions and arguments, trying to estimate at least the order of size of the uncertainties, as well as the sensitivity of different analyses for uncertainties in the obtained estimates.

We have thus identified the three main tasks of the science of statistics production:

- how to design a statistical survey, in a broad sense, in order to be able to make optimal estimations of statistical target characteristics within certain restrictions (time, costs, etc)
- designing an optimal process for estimating given statistical target characteristics on the basis of a given statistical production system
- designing an optimal process for estimating the uncertainties of given estimation procedures in a given statistical production system, thereby providing the basis for a quality declaration of the produced statistics

Naturally there has to be a lot of interaction and feed-back between the tree main tasks.

**Summary of the basic statistical concepts**

Figure 14 summarises the discussion so far.
Figure 14. Some basic concepts of statistics production: statistical characteristics, estimates of statistical characteristics, and estimates of the uncertainties of estimates of statistical characteristics. Source: Rosén & Sundgren (1991).

Multidimensional structures of statistics - statistical hypercubes

Statistics are typically presented by means of tables and graphs. Traditionally paper was the medium, but nowadays computer-supported media, like displays and CDs, provide powerful and attractive alternatives. Among other things, the computer-support makes it possible for the user to make the final decisions as to how the statistics should actually be presented. For example, pivot functions enable the
user to rearrange the dimensions of a statistical table, moving variables between the stub and the heading, switching the order of variables, etc.

Statistical tables can be perceived in two different ways, depending on whether you focus on how they look when presented on a piece of paper, or on a computer-supported display, or whether you focus on the logics behind these presentations. When looked upon in the first way, statistical tables often seem to be very complex. When looked upon in the second way, many statistical tables become quite simple.

The $\alpha\beta\gamma\tau$-model focuses on the fundamental logic and information structure behind statistical tables and other forms of presentation of statistics.

**Structuring statistics by means of population cross-classification**

A typical statistical table contains statistics concerning a family of statistical characteristics, where the family members are related in a certain way.

*Example 4.* Consider the following statistics: “Average income during the year 1999 for those persons who were registered in Stockholm at the end of the year 2000: by sex and age group.”

Suppose that there are two sexes, male and female, and three age groups, young, middle-aged, old. Then Example 4 specifies at least six statistics in addition to the statistic in Example 1 earlier in this paper. The six statistics are represented by the six cells in the following cross-classification:

<table>
<thead>
<tr>
<th>O = Persons registered in Stockholm at the end of the year 2000</th>
<th>Young</th>
<th>Middle-aged</th>
<th>Old</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Thus the original target population $O$, has been subdivided into six subpopulations, or domains of interest, and the subpopulations have been formed by cross-classifying the original population by means of the variables “sex” and “age group”.

When statistics are presented in statistical tables, some marginal sums are usually computed as well. In the example above we could get:

<table>
<thead>
<tr>
<th>O = Persons registered in Stockholm at the end of the year 2000</th>
<th>Young</th>
<th>Middle-aged</th>
<th>Old</th>
<th>All age-groups</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All sexes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Major dimensions of the AlfaBetaGammaTau-model: the AlfaBetaGammaTau-matrix**

The table below illustrates the following discussion of the four major dimensions in the $\alpha\beta\gamma\tau$-model. The table represents a matrix, a so-called $\alpha\beta\gamma\tau$-matrix, with different columns for the major dimensions, as well as for the major components of the concept of a statistical characteristic.
The alfa dimension

The $\alpha$-dimension contains the populations of the statistical characteristics. In the table below there are the following populations:

$\alpha_1$: “Persons registered in Sweden at the end of t” in S1, S2, and S3.
$\alpha_2$: “Domestic migrations during t” in S4 and S6.
$\alpha_3$: “Domestic migrations during t, where the target commune of the migration has a lower tax rate during t than the home commune of the migrating person” in S5

“Domestic migrations” are defined as “migrations inside Sweden”.

Note that “O” in “O.V.f” denotes alternatively

- the whole $\alpha$-population, $O^\alpha$, or
- each one of the subdomains of interest, $O^\alpha$ by $V'$, or $O^\alpha \setminus V'$, defined by the classification $O^\gamma \setminus V''$, where $V'$ is a cross-classification of n variables, the $\gamma$-variables: $V'' = V''_1 \times V''_2 \times ... \times V''_n$.

The beta dimension

The $\beta$-dimension contains the summarising functions of the statistical characteristics, that is, statistical measures that are applied to zero, one, or more variables, the $\beta$-variables. A statistical measure may have zero, one, or more arguments. Some examples:

count  counts the number of object instances in O, a function with zero arguments
sum   summarises the values of a variable $V$, a function with one argument
average averages the values of a variable $V$, a function with one argument
 correlation computes the correlation between two variables, $V_1$ and $V_2$, thus two arguments
percentage computes the percentage of object instances in O satisfying a Boolean variable $V$, a function with one variable

The average function can alternatively be expressed as a sum divided by a count, and a count can alternatively be expressed as a sum of a variable that takes the value 1 for all objects in O. Correlations and percentages can also be expressed in terms of other functions.

The following $\beta$-variables appear in the table below:

$\beta_1$: “income(t-1): the person’s income during t-1 according to taxation performed during t” in S1 and S3
$\beta_2$: “age(t): the person’s age in whole years at the end of t” in S3
$\beta_3$: “to_lower_tax(t): migration to commune with lower tax during t than the migrator’s home commune”, a Boolean variable in S6.

The following summarising functions are formed by applying statistical measures to the $\beta$-variables:

S1: average($\beta_1$) or, with dot notation, $\beta_1$.average
S2, S4, S5: count
S3: correlation($\beta_1$, $\beta_2$) or ($\beta_1$, $\beta_2$).correlation
S6: percentage($\beta_3$) or $\beta_3$.percentage
<table>
<thead>
<tr>
<th>STATISTICAL CHARACTERISTICS</th>
<th>REFERENCE TIME t</th>
<th>SETS OF OBJECTS O</th>
<th>CLASSIFICATION</th>
<th>SUMMARIZING FUNCTION</th>
<th>STATISTICAL MEASURES f</th>
</tr>
</thead>
<tbody>
<tr>
<td>( S = O.V.f: ) by variables ( G )</td>
<td>( \tau )-dimension</td>
<td>POPULATION ( \alpha )-dimension</td>
<td>( \gamma )-dimension</td>
<td>VARIABLES ( V )</td>
<td>( \beta )-dimension</td>
</tr>
<tr>
<td>S1: “Average income during the year ( t-1 ) for those persons who were registered in Sweden at the end of the year ( t ): by commune, sex, and age.”</td>
<td>Year ( t = 1995, 1996, \ldots )</td>
<td>Persons registered in Sweden at the end of ( t )</td>
<td></td>
<td></td>
<td>average</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) commune( (t) ): the commune where the person was registered at the end of ( t )</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) sex( (t) ): the person’s sex at the end of ( t )</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) age( (t) ): the person’s age in whole years at the end of ( t )</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) income( (t-1) ): the person’s income during ( t-1 ) according to taxation performed ( t )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S2: “Number of persons registered in Sweden at the end of the year ( t ): by sex, age, and income bracket.”</td>
<td>Year ( t = 1995, 1996, \ldots )</td>
<td>Persons registered in Sweden at the end of ( t )</td>
<td></td>
<td></td>
<td>count</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) sex( (t) ): see above</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) age( (t) ): see above</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) income bracket: the person’s income bracket according to classification xxx, based on the person’s income during ( t-1 )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S3: “The correlation between age at the end of the year ( t ) and income during the year ( t-1 ) for persons registered in Sweden at the end of the year ( t ): by commune and sex.”</td>
<td>Year ( t = 1995, 1996, \ldots )</td>
<td>Persons registered in Sweden at the end of ( t )</td>
<td></td>
<td></td>
<td>correlation</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) commune( (t) ): see above</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) sex( (t) ): see above</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) age( (t) ): the person’s age in whole years at the end of ( t )</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) income( (t) ): the person’s income during the year ( t-1 )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S4: “Domestic migrations during the year ( t ): by sex and income bracket.”</td>
<td>Year ( t = 1995, 1996, \ldots )</td>
<td>Domestic migrations during ( t )</td>
<td></td>
<td></td>
<td>count</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) sex( (t) ): the migrating person’s sex at the time of migration</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) income bracket( (t-1) ): the migrating person’s income bracket during ( t-1 ) according to classification xxx based upon the person’s income during ( t-1 )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S5: “Domestic migrations during the year ( t ) from a commune with higher tax to a commune with lower tax: by sex and income bracket.”</td>
<td>Year ( t = 1995, 1996, \ldots )</td>
<td>Domestic migrations during ( t ) where the target commune of the migration has a lower tax rate during ( t ) than the home commune of the migrating person</td>
<td></td>
<td></td>
<td>count</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) sex( (t) ): see above</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) income bracket( (t) ): see above</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S6: “Percentage of the domestic migrations during the year ( t ) that took place from a commune with higher tax to a commune with lower tax: by sex and income bracket.”</td>
<td>Year ( t = 1995, 1996, \ldots )</td>
<td>Domestic migrations during ( t )</td>
<td></td>
<td></td>
<td>percentage</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) sex( (t) ): see above</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) income bracket: see above</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>( \bullet ) to_lower_tax: migration from commune with higher tax during ( t ) to commune with lower tax during ( t )</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Alternatively: ( S6 = 100% \times S5/S4 )</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The gamma dimension

The $\gamma$-dimension contains variables that cross-classify the population into domains of interest, to which the statistical measures are applied in the same way as they are applied to the crossclassified population itself. In the table above the following cross-classifications occur:

S1: The population $\alpha_1$ is cross-classified by
   $\gamma_1$: “commune(t): commune where the person was registered at the end of $t$”
   $\gamma_2$: “sex(t): the person’s sex at the end of $t$”
   $\gamma_3$: “age(t): the person’s age in whole years at the end of $t$”, that is, $\beta_2$

S2: The population $\alpha_1$ is cross-classified by $\gamma_2$, $\gamma_3$, and $\gamma_4$: “income_bracket(t-1): the person’s income bracket according to the classification xxx, based upon the person’s income during $t-1$”

S3: The population $\alpha_1$ is cross-classified by $\gamma_1$ and $\gamma_2$.

S4: The population is cross-classified by $\gamma_5$: “sex(t): the migrating person’s sex at the time of migration”
   $\gamma_6$: “income_bracket(t-1): the migrating person’s income bracket according to the classification xxx based upon the person’s income during $t-1$”

Note that $\gamma_5$ and $\gamma_6$ are different from $\gamma_2$ and $\gamma_4$, since the former are (derived) variables of migrations, whereas the latter are variables of persons.

S5: The population is cross-classified by $\gamma_5$ and $\gamma_6$.

S6: The population is cross-classified by $\gamma_5$ and $\gamma_6$.

Note that the $\gamma$-variables form sub-dimensions of the $\gamma$-dimension.

The tau dimension

The $\tau$-dimension specifies reference times for the statistical characteristics. Time can be explicitly specified for all populations, variables, etc, but this is often unpractical. Instead a time parameter $t$ is used, and all times are expressed as functions of $t$. The $\tau$-dimension also states the value set of $t$.

In the table above the $\tau$-dimension specifies the parameter $t$ with a value set consisting of the years 1995, 1996, and onwards.

Visualizing multidimensional structures of statistics

Figure 15 visualizes a universe of interest that covers the concepts needed to express, among other things, the statistical characteristics specified in the $\alpha\beta\gamma\tau$-matrix in the previous section. The graph used for visualising the objects, variables, and relationships in the universe of discourse is called an object graph or an ObjectVariableRelation (OVR) graph.

Figure 16 visualises a hypothetical final observation register, accommodating a set of observations concerning the universe of discourse in the figure above. The observation register consists of a number of ObjectVariable (OV) matrixes, in principle one matrix per object type in the universe of
discourse. This model of the final observation register could also be seen as a specification of a relational database implementation.

Figure 15. Object graph for the examples in this section.

Figure 16. OV-matrixes corresponding to the OVR-graph in Figure 15.
Figure 17 visualises a two-dimensional and a three-dimensional structure, often called “box” or “cube”, corresponding to some statistical characteristics expressible in terms of the concepts of the universe of discourse presented above.

![Figure 17. A two-dimensional and a three-dimensional cube accommodating estimated values of some statistical characteristics concerning the universe of discourse in Figure 15.](image)

**Figure 17. A two-dimensional and a three-dimensional cube accommodating estimated values of some statistical characteristics concerning the universe of discourse in Figure 15.**

**Representing time in the relational data model**

The concept of time may be represented by relational tables in at least three different ways:

**Time representation method 1: One table for each time instance**

<table>
<thead>
<tr>
<th>SALES 2011</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ProductId</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>SALES 2012</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ProductId</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>SALES 2013</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ProductId</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>
**Ontologies and conceptual models**

The discipline of artificial intelligence (AI) has a special liking for fanciful terms borrowed from other disciplines. Unfortunately, the use of such terms within AI is often far from their meaning in the disciplines they have been borrowed from. “Ontology” is such a term.

**The meaning of “ontohgy” in philosophy**

We have already discussed the meaning of “ontology” in philosophy in an earlier section of this report. Very briefly “ontology” in the philosophical sense may be defined as “the study of what exists and why”.

**AI definition of “ontology”**

In AI there is no universally accepted definition of “ontology”, but the most quoted definition seems to be a definition given by Tom Gruber in Gruber (1995).

In the early 1990s, the widely cited Web page and paper "Toward Principles for the Design of Ontologies Used for Knowledge Sharing" by Tom Gruber is credited with a deliberate definition of *ontology* as a technical term in computer science. Gruber introduced the term to mean a specification of a conceptualization:

“An ontology is a description (like a formal specification of a program) of the concepts and relationships that can formally exist for an agent or a community of agents. This definition is consistent with the usage of ontology as set of concept definitions, but more general. And it is a different sense of the word than its use in philosophy,” Gruber (2001).

According to Gruber (1993):

“Ontologies are often equated with taxonomic hierarchies of classes, class definitions, and the subsumption relation, but ontologies need not be limited to these forms. Ontologies are also not limited to conservative definitions — that is, definitions in the traditional logic sense that only introduce terminology and do not add any knowledge about the world. To specify a conceptualization, one needs to state axioms that do constrain the possible interpretations for the defined terms.”
More sources


See also: Shirky (2005, 2015), “Ontology is overrated”.

Ontology components


Contemporary ontologies share many structural similarities, regardless of the language in which they are expressed. Most ontologies describe individuals (instances), classes (concepts), attributes, and relations. In this section each of these components is discussed in turn.

Common components of ontologies include:

- **Individuals**: instances or objects (the basic or "ground level" objects)
- **Classes**: sets, collections, concepts, classes in programming, types of objects, or kinds of things
- **Attributes**: aspects, properties, features, characteristics, or parameters that objects (and classes) can have
- **Relations**: ways in which classes and individuals can be related to one another
- **Function terms**: complex structures formed from certain relations that can be used in place of an individual term in a statement
- **Restrictions**: formally stated descriptions of what must be true in order for some assertion to be accepted as input
- **Rules**: statements in the form of an if-then (antecedent-consequent) sentence that describe the logical inferences that can be drawn from an assertion in a particular form
- **Axioms**: assertions (including rules) in a logical form that together comprise the overall theory that the ontology describes in its domain of application. This definition differs from that of "axioms" in generative grammar and formal logic. In those disciplines, axioms include only statements asserted as a priori knowledge. As used here, "axioms" also include the theory derived from axiomatic statements
- **Events**: the changing of attributes or relations

Ontologies are commonly encoded using **ontology languages**.

Types

*Domain ontology*

A domain ontology (or domain-specific ontology) represents concepts which belong to part of the world. Particular meanings of terms applied to that domain are provided by domain ontology. For example, the word *card* has many different meanings. An ontology about the domain of poker would model the "playing card" meaning of the word, while an ontology about the domain of computer hardware would model the "punched card" and "video card" meanings.

Since domain ontologies represent concepts in very specific and often eclectic ways, they are often incompatible. As systems that rely on domain ontologies expand, they often need to merge domain
ontologies into a more general representation. This presents a challenge to the ontology designer. Different ontologies in the same domain arise due to different languages, different intended usage of the ontologies, and different perceptions of the domain (based on cultural background, education, ideology, etc.).

At present, merging ontologies that are not developed from a common foundation ontology is a largely manual process and therefore time-consuming and expensive. Domain ontologies that use the same foundation ontology to provide a set of basic elements with which to specify the meanings of the domain ontology elements can be merged automatically. There are studies on generalized techniques for merging ontologies, but this area of research is still largely theoretical.

**Upper ontology**

An upper ontology (or foundation ontology) is a model of the common objects that are generally applicable across a wide range of domain ontologies. It usually employs a core glossary that contains the terms and associated object descriptions as they are used in various relevant domain sets.

There are several standardized upper ontologies available for use, including BFO, BORO method, Dublin Core, GFO, OpenCyc/ResearchCyc, SUMO, the Unified Foundational Ontology (UFO), and DOLCE. WordNet, while considered an upper ontology by some, is not strictly an ontology. However, it has been employed as a linguistic tool for learning domain ontologies.

**Ontologies vs conceptual models**

Theoretically there does not seem to be a big difference between ontologies, as defined in the AI literature that we have just referred to above, and conceptual models as we have discussed them earlier in this Chapter. In particular the OPR framework for conceptual models seems to be based on similar concepts and ideas as AI ontologies. For example, objects, attributes, relations, and application domains (universes of discourse) seem to be important concepts in both AI and information systems related disciplines.

However, if we move to practice, it seems that AI is more focused on how ontologies are integrated in software, whereas conceptual models, as used in information systems development are more focused on developing a common understanding of real world concepts among a community of people, not least the users of the information systems, concepts which are essential for information systems applications being developed.

There also seems to be a difference between the natures of the typical domains concerned. That has to do with differences between what are typical AI applications, and what are typical information systems applications in businesses and organisations.

**Conceptual standardisation and integration**

Conceptual standardisation and integration is a necessary precondition for integration and coherence of the information contents of information systems. We will now briefly discuss what this could mean in practice. We will start these discussions for public information systems and applications on a national and international level, as reflected in official statistics, but we will then also discuss how similar principles and methods may be applied in other contexts, for example information systems and applications inside a business or some other type of organisation, where conceptual standardisation and integration will be particularly relevant on the corporate level, so that different information systems and people within different parts of the organisation can communicate and cooperate with each other without a lot of misunderstandings and difficulties to compare and
combine information from different parts and systems in the organisation. This will be particularly important for statistical and analytical usages of corporate information.

**Standard classifications**

National statistical agencies and international organisations have a long and reasonably successful history of creating and maintaining standard classifications on national and international levels. Standard classifications are extremely important for the coherence and comparability (in time and space) of official statistics, and together with registers and standard concept definitions, standard classifications will be the backbone of any information system for statistical and analytical purposes.

**Standardised time and space coordinates**

Almost all official statistics are associated with time and space coordinates, and standardisation of these coordinate systems are (like standard classifications) of utmost importance for ensuring coherence and comparability.

**Time: frequencies, delays, current data and historical data**

Most official statistics have a typical frequency – yearly, quarterly, monthly – but there are other frequencies as well, including no frequency at all – ad hoc surveys.

A register may be very flexible with regard to time. Primarily, a register should be up-to-date, that is, it should reflect the current status of the objects in the register with as little delay as possible. However, a statistical register should not be limited to reflecting the current status; ideally it should also contain (or be associated with) a complete history of all objects, including those that have ceased to exist. Such historical registers (or systems of registers) will make it possible to reconstruct the status of all objects at an arbitrary point in time, and to reconstruct statistics for the population associated with the register, as it was at an arbitrary point in time.

**Space: coordinates, maps, regional classifications, and geodata**

Thanks to modern technology it is nowadays relatively easy and inexpensive to associate any objects with their current locations in space, and to create high-quality maps, possibly animated, of all locations and objects and data associated with these locations (over time).

Before the technological development made it easy to associated data with “real” space coordinates, regional classifications were used as proxies for space coordinates. Regional classifications are still very useful – but now also as aggregation levels for microdata associated with “real” space coordinates, obtained by GPS devices etc.

**Other concepts that need to be defined and standardized**

A wide range of concepts that need to be standardized have been covered above: objects as defined by registers, qualitative variables as defined by classifications, time and space coordinates. However, there are even more concepts and variables that need to be properly defined and harmonized, e.g. important quantitative concepts and variables like “income”.

**A coherent conceptual model**

Traditionally, the official statistics of a country consist of a hundred or more statistical surveys. According to the stovepipe approach to official statistics, each one of these surveys is designed without very much coordination with other surveys. Each survey has its own main purposes, its own
main users, and its own design. This approach easily leads to higher costs, and higher response burdens, than necessary. It also makes the data from one survey less comparable and less coherent with data from other surveys than desirable, especially when socio-economic developments become more complex, and when more analysts and politicians and other main users of official statistics become interested in the effects of decisions and actions on society as a whole. A more holistic approach is needed, where different statistics are more coherent and comparable and support an integrated view of society as a whole.

How can official statistics become more holistic? The main problems and opportunities are in the conceptual models that are applied – explicitly or implicitly – in the design of the individual surveys that together form the system of official statistics. Today, at best, the designers and main users of a statistical survey discuss and decide upon a conceptual model for the particular survey under consideration. They analyse which objects and variables need to be observed, according to which ideal and operational definitions, in order to be suitable for producing the statistical estimates required and asked for. They may even visualize the conceptual model graphically by means of some framework like OPR, which we discuss and illustrate elsewhere in this report.

These individual conceptual models for individual surveys may be the starting-point for an integration process of the surveys that together comprise the statistical system of a country. Here are some methods for making the individual conceptual models of stovepipe-designed surveys become more integrated, compatible, comparable, and coherent with each other:

- Use object types, identifiers, populations, subpopulations, links to other object types, etc., as defined in standard base registers
- Use standard definitions of variables and standard classifications
- Use standard time scales, space coordinates, and regional classifications

**Conceptual standardisation and integration within companies and other organisations**

Figure 18 illustrates how one can start analysing the existing or planned information systems of a company. The company in the example is assumed to sell different products, some of which are at least partly manufactured by the company itself. Certain types of components are purchased from other companies and assembled into final products by our company.

The figure indicates, by means of conceptual models, some important concepts in a number of basic business functions: Purchase, Store, Personnel, Sales, Accounting, and Delivery. Some or all of these functions could be supported by an Enterprise System (cf. Davenport, 2000). However, this would require co-ordination of concepts.

A practical consequence of such integration of concepts and systems is that we would have to find answers to questions like:

- Is the **Customer** concept the same in Sales, Accounting, and Delivery? If so, are they identified in the same way, e.g. by the same number?
- How are the concepts of **Order**, **Invoice**, and **Delivery** related to each other? For example, can there be several, separate deliveries (and invoices) for one and the same order?
- Is the **Item** concept the same in Purchase, Sales, and Delivery?
- How are the concepts of **Item** (in Purchase), **Component** (in Store), and **InputResource** and **OutputResult** (in Production) related to each other?
- How are the **Supplier** concept in Purchase and the **Provider** concept in Store related to each other?
- Could a **Customer** be (a) a company; (b) a private person?
Could the same company be (a) a Supplier; (b) a Customer? If so, are they identified in the same way?

**Figure 18. Enterprise system applications and a corporate data warehouse as illustrated by means of conceptual models.**

The information system applications indicated in the upper part of the figure support basic, operative business functions. They may also feed a data warehouse with input data – the lower part of the figure. Whereas the different applications in the upper part of the figure are by and large dedicated to different business functions, the data warehouse will be a corporate asset, available to all parts of the business.
The considerations above concerning the need for conceptual standardisation and integration apply to non-profit organisations and government administrations on all levels as well, although the typical concepts, functions, and applications may be somewhat different. The principles are the same as we discussed and illustrated earlier for conceptual standardisation, integration, and coherence in statistical and analytical information systems in the public sector, for example national statistical offices and international organisations.

References: Davenport (2000), Sundgren et al. (2005)

Quality of information and data

When we receive data messages representing information in the sense of assertions about reality, we have to judge the trustworthiness and quality of the data. Are the assertions true or false? Where do they come from? Are they the result of some kind of measurements? What is the quality of these measurements and the resulting data?

ISO 8402 (1994) defines quality as fitness for purpose: “the totality of features and characteristics of a product or service that bear on its ability to satisfy stated or implied needs”. What does this mean in an information context?

Statisticians have been occupied for decades with the issue of quality of statistical information and statistical data, and how it can possibly be defined and measured, and have been so for several decades. In 2003 Eurostat, the statistical office of the European Union, defined a quality concept and how quality of statistical data should be documented; see Eurostat (2003a, b) and later revisions of these documents.

A basic requirement on statistical data is that they should be objective. That is, concepts and measurements should be designed and implemented by statistical professionals and not be unduly influenced by politicians and other stakeholders so as to favour their interests. One may compare with the task of public service journalists, which is to inform society in an objective and impartial way. Perfect objectivity may be difficult to achieve for a journalist, who cannot be an expert in all fields, but at least the journalist can strive for impartiality by letting different experts and stakeholders involved in a controversial issue present and argue for their respective views.

Eurostat (2003a) defines quality of statistics with reference to the following six criteria:

- relevance
- accuracy
- timeliness and punctuality
- accessibility and clarity
- comparability
- coherence

The six quality components are defined as follows:

Relevance

Relevance is the degree to which statistics meet current and potential users’ needs: whether all statistics that are needed are produced, and the extent to which concepts used (definitions, classifications etc.) reflects user needs.
Accuracy (precision)

Accuracy in the general statistical sense denotes the closeness of computations or estimates to the exact or true values. Deviations from the true values are usually described in terms of different kinds of errors, or uncertainties:

- **sampling errors**, affecting sample surveys, are simply due to the fact that only a subset of the population, usually randomly selected, is observed;
- **non-sampling errors** comprise coverage errors, measurement errors, processing errors, non-response errors, and model assumption errors.

Timeliness and punctuality

Timeliness of information reflects the length of time between its availability and the event or phenomenon it describes. Punctuality refers to the time lag between the release date of data and the target date when it should have been delivered.

Accessibility and clarity

Accessibility refers to the physical conditions in which users can obtain data: where to go, how to order, delivery time, pricing policy, marketing conditions (copyright, etc.), availability of micro and/or macro data, various formats (paper, files, CD-ROM, Internet...), etc.

Clarity depends on, *inter alia*, the availability of appropriate metadata accompanying the data, illustrations such as graphs and maps, availability of quality information, including limitations in possible uses.

Comparability

Comparability aims at measuring the impact of differences in applied statistical concepts and measurement tools/procedures when statistics are compared between geographic areas, nongeographic domains, or over time.

Coherence

Coherence of statistical data is their adequacy to be combined and integrated in a meaningful and reliable way for different purposes. When originating from a single source, statistical data are normally coherent in the sense that elementary results derived from the concerned survey can be reliably combined in numerous ways to produce more complex results. When originating from different sources, and in particular from statistical surveys of different nature and/or frequencies, statistics may not be completely coherent in the sense that they may be based on different approaches, classifications and methodological standards.

Fitness for purpose

All quality components listed above have to do with “fitness for purpose” as stated in the general ISO definition of quality:

Relevance: relevant for certain users and usages, but not necessarily for others
Accuracy: precise enough in a certain context, for certain purposes
... and so on
Validity and reliability

In social sciences it is common to talk about two aspects of the quality of data, validity and reliability, sometimes illustrated like in the figure below by William M. K. Trochim (2006) in his “Research Methods Knowledge Base” (2006), http://www.socialresearchmethods.net/kb/relandval.php

![Figure 19. Illustrating the concepts of validity and reliability. Source: Trochim (2006).](image)

“Validity” has certain aspects in common with the concept of relevance, as defined above, and “reliability” has kinship with “accuracy” and “precision”.

**Literature**

CHAPTER 2. The instrumental role of information

In most of our activities, both as private persons and in our professional roles, we need and use information. This is nothing new for the age of computers, but computers and computer-based tools, and in particular the Internet, have given us new opportunities to use information as a relatively simple, inexpensive, and efficient instrument to help us in our activities.

We may roughly distinguish between the following three major subcategories of the instrumental role of information:

1. **Operational use of information**: using information in concrete, daily activities, privately, as a member of an organisation, or at work

2. **Directive/strategic/analytical use of information**: using information when planning major decisions or trying to solve major problems, privately or in our professional roles, for example as business managers, researchers, or politicians

3. **Educational use of information**, for example when studying for a degree, when training for a certain task, or just for curiosity or a wish to learn and understand

**Operational use of information**

In all private activities and all business activities we need information in order to be able to perform the activities. For example, if we are going to travel from A to B, we need to find out which travelling alternatives there are: by car, by taxi, by public transport, etc.

In a business activity between a customer and a provider of goods and/or services, both the customer and the provider need information, and they also need to exchange information between themselves and possibly also with other actors involved in the business, like suppliers, entrepreneurs, etc.

Figure 20 shows an example of a business engaged in e-commerce, and which needs different types of information for its activities.

E-commerce is based on communication via the Internet between the customer, which may be a private person or a company, and the provider, which is typically a company or some other type of organisation, for example a government agency.

The business in this example is built according to a so-called service-oriented architecture. This means that the service as a whole is felt by the customer to be provided via one single customer interface, provided via the Internet. This is a so-called one-stop solution. Behind this interface, the business may be broken down into a number of sub-services, provided by different functions in the company, or even in interaction with other companies. All interactions take place via request/response-messages. A request message requests something from another service, and this service performs what it is told to do and sends a response message back. Some request messages may result in something more material in addition to the response message, for example the manufacturing or the retrieval of a certain physical product.

The request from the customer results in an order, for example an order of a book from a virtual book-shop. This order is then processed, and the requested book is delivered to the customer from a physical warehouse. An invoice is produced and sent to the customer as well, physically or electronically, and the customer finally makes a payment, possibly via an e-bank.
Note that the different sub-tasks involved in this business transaction may very well be performed by different companies, which are independent businesses, cooperating as equals within a network, a so-called network-organized business. Nevertheless, from the customer’s point of view, the network as a whole acts as one business, via one customer interface, a one-stop solution. If there are any problems with the business transaction, the customer will communicate via this single interface, and the service-provider interacting with the customer will take the full responsibility vis-à-vis the customer, even if the problem is caused by some other actor, which is not visible to the customer.

The label “information resources” in Figure 20 covers data and metadata which are necessary for the processing of the order in the example. Some of these data are obtained from the customer, for example the name and address of the customer, which may alternatively already be in a customer database. The identifier and quantity of the product ordered must also be provided. Other data may be stored in the data warehouse of the service provider, or obtained from some other actor in the business network, for example quantity-in-stock, expected time of delivery.

The label “other resources” may cover material and products needed by the business, as well as instruments and methods used (which may alternatively belong to the information resources). Human resources may also be included.

Even in a very operational business, like the business in this example, information may also be systematically collected and analysed for more strategic use. For example, the customers may be encouraged to provide feedback information about their satisfaction or dissatisfaction with the different steps in the business process:
Was it easy to find information about available products and services via the website?
Was it easy to provide the order?
Was the customer service function helpful when problems occurred?
Was the delivery of the product satisfactory?
Did the purchased product or service itself meet the expectations of the customer?

So-called paradata resulting from a continuous monitoring of the business processes may also be useful feedback for dynamic adaption and optimization of the business processes, resulting in faster response times in different steps of the business process.

**Information-based analysis and decision-making**

It is a deeply rooted habit and ideal in modern western societies that decision-making and problem-solving should be rational and based on information (often called “facts” or “data” in this context). Roughly speaking, the process goes as follows:

1. A decision to be made, or a problem to be solved, is specified. The context will typically be a business (in a broad sense, including non-profit organisations), or a society on some level: central, regional, local.

2. Information/facts/data are collected from different sources, in order to illuminate the decision to be made, or the problem to be solved.

3. The data are organized, processed, aggregated, and analysed by more or less sophisticated methods (tabulations, visualisations, animations, simulations, statistical analyses, etc.).

4. The results from the analyses are presented for decision-makers, who may ask questions requiring further data collection and/or analyses.

5. A decision is taken and implemented in terms of actions.

6. The effects of the decision and actions are observed and analysed in a feedback loop (which is often neglected, unfortunately, by the decision-makers, e.g. politicians).

Figure 21 illustrates the major steps in analytical use of information for problem-solving or decision-making. Figure 22 provides a more elaborated view of the same process, focusing on the information resources used, processed, and produced.

Figure 23 illustrates analytical information processes applied to political decision-making in a society. The political decisions are assumed to be, at least partly, based on high-quality official statistics, and the effects of the decisions are assumed to be analysed and evaluated in a serious way.
Figure 22. More elaborated model of analytical information processes.

Figure 23. Decision-making based on official statistics – including a feedback loop.
We shall now go through the different parts and processes of Figure 22 in more detail – with focus on the collection, storage, processing, and analysis of information resources: data, metadata, including paradata. The model is based on a service-oriented architecture (SOA), with exchange of information and control taking place via request/response-messages.

We shall often talk in terms of statistical data and statistical processes, but most of the contents in the following sections are equally relevant for other types of analytical use of data, such as the use of data in businesses and other organisations for analysis and decision-making. However, the statistical community, especially national statistical agencies and international organisations, have conducted a lot of research in this area and applied it to nationwide and international statistical information systems, and this is why the concepts and terminology used here will often have a statistical flavour.

Collecting and combining data from different data sources

Data for problem solving and decision-making may be obtained from many different data sources, often in combination. Data used for analytical purposes of ten have to be accepted as they are – there is usually not time for designing new data collection procedures, but one has to use what is available without time-consuming new observations or preparatory operations.

The following list gives a number of examples of typical data sources:

- Data which have been collected by means of traditional surveys: sample surveys or total enumerations (censuses). Ideally the sample surveys are based on random samples with known selection probabilities > 0. The original data may emanate from mailed pen-and-pencil questionnaires, face-to-face interviews, telephone interviews, web-based surveys (mailed or online) – or a combination of these data collection modes, so-called mixed-mode surveys.

- Data which have been collected by means of subjective sampling methods or self-selection. The data collection procedures are often web-based.

- Data from available administrative registers or databases.

- Data generated as side-effects from processes in society or businesses. The processes may be “real-world” processes, or Internet-based processes, often reflecting “real-world” processes.

- Data generated by “things”, possibly via the so-called “Internet of Things” (IoT).

Data generated as side-effects of on-going processes and data generated via the Internet of Things are often so-called **streaming data**; they are generated – and can be analysed – online, “in real time”.

Administrative data sources

In countries like Sweden, up to 99% of the data used for official statistics emanate from administrative data sources, and only 1% from traditional surveys. According to a Dutch study, referenced in Wallgren & Wallgren (2007), it is roughly 100 times more expensive to collect data by a traditional census than by using administrative data.

If we generalize the Dutch findings to all statistics produced by Statistics Sweden, the 1% of the data that emanate from traditional surveys would still account for about 50% of the costs. If Statistics Sweden would, for some reason, no longer have the option of using administrative data, the Swedish government would have to increase the budget of Statistics Sweden by a factor 100 in order to secure
the same amount of official statistics with the same quality. This would never happen. The government would more likely leave the budget as it is, demanding Statistics Sweden to decrease the number of topics covered, and decrease the quality of the estimates in terms of bias and precision, by decreasing sample sizes and introducing less costly procedures for non-response management.

From another point of view, we may argue that the use of administrative data for statistics production will not only drastically reduce costs. It may also contribute positively to several quality dimensions, e.g. the richness and coherence of the statistical data, as well as reduced bias and increased precision of the estimates. This is particularly true, if administrative data and survey data are systematically used to strengthen each other and reduce each other’s weaknesses.

In the future the concept of “administrative data” as a source for official statistics is likely to become generalized to many different kinds of “operational data” generated as side effects of different kinds of processes: public processes, business processes, and private processes (e.g. social media). This development has already started. For example, proxies of the official consumer price indexes have been produced with good results from price available on the Internet. The proxies are very close to the official indexes, and they can be produced and published much faster. See AAPOR (2015):

“The MIT Billion Prices Projects, PriceStats, [http://bpp.mit.edu/](http://bpp.mit.edu/), is an academic initiative using prices collected daily from hundreds of online retailers around the world to conduct economic research. One statistical product is the estimation of inflation in the US. Changes in inflation trends can be observed sooner in PriceStats than in the monthly Consumer Price Index (CPI). Figure 1 shows aggregated inflation series on a monthly basis for the U.S. from 2008 to 2014 where the statistics derived from the PriceStats Index are displayed in orange, overlaid with the CPI estimates in blue.

![Figure 1. US Aggregated Inflation Series, Monthly Rate, PriceStats Index vs. Official CPI. Accessed January 18, 2015 from the PriceStats website.](http://bpp.mit.edu/)
Some National Statistical Institutes in Europe are now using internet robots to collect prices from the web or scanner data from retailers as part of their data collection for the CPI.”

**Combining surveys and administrative data**

We will now briefly discuss how traditional surveys and administrative data sources could best be integrated within a common framework and a common system, and how they could complement each other.

Traditional statistical surveys and statistics production based upon administrative data have their relative advantages and disadvantages. The strongest merits of administrative data have to do with costs, response rates, response burden, coherence, timeliness, and flexibility.

The strongest merits of traditional surveys, on the other hand, are within the area of relevance, the possibilities to tailor the design of a survey to specific statistical needs.

**Costs**

The merits of using existing administrative data sources as regards costs have already been mentioned and exemplified above. On the other hand, the costs of collecting data by means of traditional surveys are typically increasing all the time, mainly because of growing difficulties to find and establish contacts with respondents, and to motivate them to participate in surveys.

**Relevance**

It is virtually impossible for designers of official statistics to have any influence over the definitions used by administrative registers and administrative processes generating administrative data. The administrative processes are governed by laws, and these laws may become changed now and then, as the result of political decisions. Those responsible for official statistics will have to adapt to these definitions, and changes of definitions, as intelligently as possible, in order to make the administrative data useful for statistical purposes, and in order to maintain continuity in official statistics despite the changes in definitions resulting from political decisions.

In contrast, designers of traditional surveys, at least theoretically, have the freedom to tailor the definitions used in those surveys to the needs of official statistics. However, in practice the tailoring may not be as simple as it seems. Using definitions that are different from definitions used in administrative processes may create great difficulties for many respondents, not least in companies, whose information systems have to be adapted to laws and administrative processes – but not necessarily to the needs of official statistics.

**Non-response**

Non-response has been a steadily growing problem for statistical surveys over several decades. Administrative data sources, on the other hand, have relatively little difficulties with non-response. The persons and enterprises concerned by the administrative systems usually have a strong motivation to provide data to these systems; they may even be forced to do so by laws, or the data may even be generated automatically by actions and events that take place anyhow.

Actually, data from administrative systems may also be one of the best tools for coming to grips with the growing non-response problems in traditional surveys, and to reduce the bias of the estimates in such surveys. Administrative data may be used as supplementary information to intelligently designed estimation processes. A lot of literature on this topic already exists, and it is a very promising research area among statistical methodologists.
Bias

As was just mentioned, administrative data may be used for reducing bias in data resulting from traditional statistical surveys. On the other hand, administrative data have their own problems with bias. It was mentioned above that an advantage of using administrative data is that respondents are often strongly motivated to provide data to administrative processes. Unfortunately, the motivation may not necessarily be to provide correct data. For example, if a citizen or a company has to provide income data to the tax authorities, there is an obvious risk of bias in the data provided.

Coverage

Administrative registers are not free from problems of overcoverage and undercoverage. For example, a population register may contain persons who have immigrated or emigrated without reporting this properly to the administrative authority responsible for population registration. Here traditional statistical surveys may have a role to detect such errors in the administrative systems.

Timeliness

If reasonably relevant data are available from an administrative source, the lead time for producing official statistics from these data will be very short – much shorter than if a traditional statistical survey had to be designed and executed. Moreover, statistics production based on administrative data could be repeated as often as you like, at a very low cost. “We can make a census every day”, is a proud (and almost true) statement from a statistical agency that has replaced traditional population censuses, carried out every 5 or 10 years, with statistics based on administrative registers.

Time series and comparability over time

Provided that events and life histories are maintained in historical versions of registers, registers are excellent, inexpensive, and flexible sources of time series data, both on micro and macro level.

Coherence

Official statistics based on a core of well-designed registers may become much coherent, at a much lower price, than official statistics based upon traditional, stovepipe-organized statistical surveys.

Information potential and flexibility

The needs for official statistics and other analytical data will continue to grow. Because of growing complexity of the decision problems of a modern society, official statistics will be required to be more coherent than is possible in the present stovepipe model. Finally, ad hoc requirements for new statistics will occur more frequently because of the appearance of new and complex problems that require immediate attention by analysts and politicians, e.g. financial crises, environment problems, natural disasters, and migration caused by wars.

Is there a need for a new statistical methodology?

When producers of official statistics started to use administrative registers as a source of data, as an alternative or complement to traditional surveys and censuses, this created a debate among statisticians whether established statistical theories and methodologies would be able to cope with this new breed of official statistics. One standpoint on this issue is that many established statistical theories and methods are indeed highly relevant also when data are collected from administrative registers, but certain adaptations and new interpretations of the problems have to be made. Certainly some new theories and methods have to be developed as well.
For example, when administrative data are used for statistical purposes, the first steps of the data collection process is designed and executed by administrative staff, often with limited statistical background, and statistical agencies reusing these data for statistical purposes usually have very limited possibilities to influence the design and execution of these process steps. Statisticians could possibly convince the administrative professionals to make use of sound knowledge from behavioural sciences concerning how to design measurement processes and measurement instruments, e.g. questionnaires, but when it comes to the definitions of object types, populations, and variables to be observed, it will be very difficult for the statisticians to convince the administrative authorities to use any other definitions than those which are optimal from an administrative point of view.

Statisticians will have to develop methods for transforming data obtained through non-ideal definitions (from a statistical point of view) to data that are better suited for the purpose of producing statistics. For example, it may be possible to develop automatic or at least computer-supported procedures for transforming, or recoding, data collected according to one administrative classification to another classification used for statistical purposes. Interesting experiments along these lines have been made in the Netherlands by Statistics Netherlands in cooperation with researchers.

The role of registers

Registers have always had an important role as so-called frames for statistical surveys. A frame is a list of the objects belonging to a particular statistical population, which can be used for drawing samples to be investigated in a sample survey, and for identifying and locating the objects in the sample.

Nowadays registers are also important for combining and integrating data from different sources, for example in the context of statistical/analytical information systems, databases, and data warehouses.

Definition

A basic, orthodox definition of a register is the following one:

- A register is an authorized, up-to-date list of all objects belonging to a certain population
- The objects listed in the register are uniquely identified by an authorized identifier, such as person number for persons, organisation number for organisations, etc.
- In addition to the identifier, a register may contain additional basic and up-to-date information about the objects, such as name (not necessarily unique) and location and other contact information, e.g. address and telephone number

Example: A person register is an authorized list of persons belonging to a certain population, e.g. all persons living in a certain country at a certain point of time.

A core set of registers for official statistics of a country may contain (at least)

- a register of persons
- a register of organisations
- a register of real estate objects: houses, dwellings, localities

Such registers are sometimes called base registers. They define basic object types and populations of fundamental importance for the administration of a modern society, as well as for official statistics.
Links between registers

The base registers should also be linked to each other, thus materializing important relations between the basic object types, e.g. “the dwelling where a person lives”, “the organisation where a person works”, “the locality where an organisation is located”.

Unique and informationless identifiers

The identifiers of the objects in a register must be unique and stable over time. The safest way of ensuring stability of identifiers over time is to make them informationless. If an identifier contains information, there is always the risk that this information changes, either because the information turns out to be wrong, or because the status of the object really changes.

For example, person identifiers sometimes contain information about the birth date of the person. This information is believed to be stable, but sometimes it is discovered that the information is wrong and has to be corrected. However, if the information about the birth date is corrected, it will also cause the information-bearing identifier of the person to change, which will inevitably cause a lot of problems, both for the person concerned and for others.

The identifiers of the objects in a register must be unique (over time) within the population covered by the register, e.g. a country.

Standard definitions of registered objects

The definition of a person is relatively straightforward, but many other object types are not so easy to define. For example, there are many possible definitions of an organisation or an enterprise. Different definitions may be suitable for different purposes.

Administrative registers and statistical registers

One may distinguish between administrative registers and statistical registers:

- An **administrative register** is a register used for administrative purposes
- A **statistical register** is a register used for statistical purposes

A statistical register may be created from one or more administrative registers, possibly in combination with data from other sources, such as traditional statistical surveys. See Wallgren & Wallgren (2007) for more details.

In order to be useful for statistical surveys, a register should contain contact information for all objects in the register: name, postal address, physical address, email address, phone number, etc., for the object itself and/or a human respondent representing the object.

It is also useful if a statistical register contains classification variables that make it easy to create strata and subgroups to be used in the design, production, presentation, and analysis of survey data.

Extended registers and satellite registers

A register may also be extended with other data concerning the objects in the register, which can be used in combination with, or instead of, data collected by surveys. Such register data may reduce the response burden and improve the quality and efficiency of official statistics.
Links to other registers and data sources; satellite registers

As has been mentioned already, a register should contain links to other registers, thus representing relations between object types and between populations of objects. Such links between registers effectively multiplies the amount of information contained in a system of registers. For example, by linking persons with their dwellings, we indirectly associate persons with variables and properties of their dwellings, e.g. “persons living in one-family houses”, “persons living in the same dwelling” (possibly forming a household), etc.

Furthermore, a register may be linked to other databases or files containing data about special subgroups of the population of objects contained in the register. Such data sets are sometimes regarded as satellite registers to the registers that they are linked to; they may or may not fulfil the strict definition of a register stated above. For example, a person register may have satellite registers like “student registers” and “patient registers”. Satellite registers are sometimes named after some important (type of) variable in the registers, e.g. “income registers” and “education registers”.

Event registers

Some registers contain event type objects, e.g. road accidents and crimes. Such registers are cumulative in the sense that they contain all events of a certain kind that have occurred since the time when the registration of such events started.

Base registers containing all basic objects of a certain kind, e.g. all persons living in a country, are often closely associated with one or more event registers, containing information about certain types of events that the basic objects are involved in, e.g. birth and death events, migration events, marriages and divorces, etc.

Life history registers

Base registers in combination with event registers may be used for forming life histories of the basic objects in a base register (or objects belonging to a certain subpopulation, registered in a satellite register), e.g. the life histories of patients or criminals. Life history registers, or life history databases, may be used for longitudinal studies.

Coordinating and integrating data from different sources

Registers are an important tool in a platform for coordinating data from different and conceptually disparate source, and for forming the backbone of the information contents of a corporate data warehouse supporting both operational and analytical usages of an organisation’s data capital.

We have discussed other methods and tools for conceptual coordination and integration elsewhere in this report. We have also discussed the OPR framework, which can be used for the same purpose. We will continue the discussion here by showing how the OPR framework can be used for conceptual integration of statistical and analytical information in particular.

A conceptual model of a statistical survey or a domain of statistics

Figure 24 gives a graphical illustration, a so-called object graph, of a concrete domain of statistics. More exactly it illustrates the conceptual model of UNESCO’s education statistics. See also Bruneforth & Sundgren (2007).

A concrete, domain-specific conceptual model of a piece of reality, looked at through the glasses of the designers of a statistical survey or a statistical information system, may be based on a generic
conceptual model, or conceptual framework, like the OPR framework introduced earlier in this report, which may be described as follows; see also Sundgren (1973, 2004a, 2004b, 2005, 2006):

- There are objects (e.g. persons or enterprises) belonging to object types (e.g. PERSON or ENTERPRISE) and populations (e.g. persons living in a certain country at a certain time), visualised by rectangular boxes in the graphical version of the conceptual model.

- The individual objects (also called object instances) are uniquely identified by means of an identifying variable (also called identifier). Ideally an identifier should have no other function than identifying objects uniquely within a certain domain; thus it should be something like a random number or some other informationless variable, which is guaranteed to be stable over the lifetime of the object. Unfortunately, in practice designers often choose identifiers, which are not informationless, and which cannot be guaranteed to be stable over time.

- Objects have properties, which may be qualitative or quantitative. Properties used in statistics are often formalised as \(<\text{variable}, \text{value}>\) pairs. For example, the property “female” of a person may be formalized as “sex=female”.

- Like in Figure 24, the variables associated with an object type or a population may be represented by a list of variable names in the box representing the object type or population in the object graph.

- Objects may be related to each other by means of object relations (of degree 2, 3, or sometimes even higher). For example, a trade relation may relate three objects: a seller, a buyer, and a commodity. Both the seller and the buyer may be a person or an enterprise.

- Object relations may themselves be “objectified” into relation objects, which have their own properties and variables. For example, the trade relation just mentioned may be objectified into a trade transaction object with the variables “quantity in tons” and “amount in Euro”.

Figure 24. A conceptual model of education statistics collected and produced by UNESCO.

Figure 25 illustrates the generic model, or conceptual framework, described above. This graphical version is actually on an even higher level of abstraction, where specific object types are seen as specialisation of three major categories of object types: active object types (actors), visualized to the left in the graph, passive objects (things or utilities), visualized to the right in the graph, and complex object types (relationships, activities, events, transactions), visualized in the middle of the graph.
As you can see, the specific object types in Figure 24 are arranged in accordance with the scheme just described: actors to the left, “things” to the right, and complex object types in the middle.

![Diagram](image)

**Figure 25. Generic model of the contents of a system of official statistics.**

Actually the contents of all branches of official statistics, and all domains or sectors of society can be expressed as specialisations of this generic model. This thesis has been verified in a large number of practical examples, and no counter-examples have been found. Schematic examples of this kind of object graphs have been presented in Sundgren (2005, 2006, 2007) for a number of domains that are typical for official statistics on both national and international level.

**Organizing data and metadata in a data warehouse**

Streaming data may be used “on the fly” without storing them first in a database. This may speed up the analyses, so that they can be used “in real time” as well, for example with the purpose of controlling and optimizing an on-going process by means of feedback from the analyses; see Figure 26.

![Diagram](image)

**Figure 26. Streaming data vs stored data.**

However, in most cases data obtained from different sources are stored in a well-organized database or data warehouse, containing both the data themselves and metadata describing the data. The metadata may originate from both design processes and operational processes, for example measurement and observation processes. The design processes will generate definitions of concepts and measurement procedures. Measurement and observation processes may generate metadata about non-response and other errors, which may cause uncertainties and quality problems. When the data used for analytical purposes by one organisation emanate from databases and data collection
procedures in other organisations, it is important to acquire not only the data from the other organisations, but also documentations and metadata.

The metadata may also include so-called paradata, data about the processes which may be used for monitoring on-going processes and possibly adjusting them dynamically, “on the fly”, for achieving better process performance in terms of quality and efficiency.

The data and the databases may be more or less structured. So-called relational databases, or SQL databases, have been a dominating standard for several decades now, and data in such databases are typically highly formatted and well structured. However, with increasing use of free-text data and other less structured and more heterogeneous data, often captured from the Internet, it has become necessary to develop new types of databases, sometimes called “NoSQL databases”, where “NoSQL” stands for “Not Only SQL”. As indicated by this term, a data warehouse built for analysis and decision-making may make use of both traditional, well-structured SQL databases, and other types of databases, suitable for the analysis of less structured data.

A data warehouse architecture for a statistical system

One of the main reasons for having a special statistical function in a country or within some other kind of organisation (e.g. an international organisation or even a business company) is that both specialized statistical systems and administrative systems in society or in individual businesses and other organisations generate a lot of data over time. These data have a considerable information potential, and they can be used over and over again, for many different purposes, often purposes that are quite different from the purposes for which the data were originally collected and used.

By taking care of all these data and by storing them, well documented, in an organized way, a statistical function may accumulate a data capital, the future yields of which may go far beyond the value of the first usages of the data. The advantage of having a specialized function for this task arises even if the statistical organisation does not do very much more than we have just described: storing the data together, well documented, and making them available as a collective national or corporate resource. However, using its statistical competence, the statistical function may also add new value to the data, e.g. by integrating the data not only in a physical way, but also from a contents-oriented point of view, by making the data more comparable and coherent, by using standardized concepts and classifications, etc. Some improvements in these directions may be done a posteriori, when the data have already been collected, but it is even better, of course, if these aspects are considered already when the data collection processes are planned – data co-ordination a priori.

In Figure 23 earlier in this report we visualized a statistical system as a reasonably complete and coherent reflection of important aspects of a society. Such a system could be the basis for advanced analysis, decision-making, and evaluations of decisions already taken and implemented by politicians and others. Similar systems could be designed and implemented in individual businesses and other organisations for supporting analyses and decision-making there. Now we shall study what the architecture of such a system could be. We will start with a brief historical background of the data warehouse approach to statistical data, and then proceed to a modern version of the same concept.

Historical background

The roots of the modern data warehouse approach to official statistics are to be found in the works from the 1960’s of Svein Nordbotten on what he called a statistical file system, or an archive-statistical system. This approach was further developed and put into practice in some statistical agencies, notably Statistics Sweden, where particular emphasis was put on the emerging database technology, development and use of standardized software for the typical processes of statistics
production, and – last but not least – the development and use of advanced metadata systems; the availability of high-quality documentation and metadata are of particular importance when statistical data are to be reused and combined for other purposes than those for which they were originally collected, so that the “fitness for purpose” of the existing data for new purposes can be responsibly judged.

**Nordbotten’s statistical file system or the archive-statistical approach**

Probability-based sample surveys and use of administrative data for statistical purposes are two important ways of obtaining statistical data in an economical way. Another way of economizing with resources, and also speeding up the production of official statistics, is to reuse survey data that have already been collected earlier, possibly for other purposes than those at hand. This approach (in combination with use of administrative data) was advocated by professor Svein Nordbotten in some seminal papers published as early as the 1960’s. See Nordbotten (1966, 1967a, b, c).

Nordbotten’s vision included standardized microdata files, systematically documented in a data catalogue¹, and managed by standardised processes supported by generalized software. The top management of Statistics Sweden became interested in Nordbotten’s ideas, and started a number of development projects at the end of the 1960’s with the intention to reengineer the production processes of Statistics Sweden from both a technical and an organisational point of view. The data warehouse would include both microdata and macrodata in standardized form, and the data would be described in a catalogue of variables, both from a technical and from a contents-oriented perspective. Microdata and macrodata processes would be driven by standardized software. The vision is presented in Fastbom (1974).

The privacy debate triggered by the 1970 population census in Sweden made it impossible for Statistics Sweden to continue the development of a data warehouse including microdata. The contents of the data warehouse had to be limited to aggregated statistics on a relatively high level. In 1976 Statistics Sweden launched its first online database, available to external users, and including a wide range of statistics, e.g. socio-demographic statistics, economic time series, and regional statistics. All data were managed by the AXIS database management system, developed by Statistics Sweden. The system was metadata-driven, and the metadata model used for that system is still used, in modified form by the current Internet-based output databases, Sweden’s Statistical Databases, which were launched by Statistics Sweden in 1996.

The development work at Statistics Sweden in the early 1970’s also resulted in a generalized, metadata-driven software product for tabulations, TAB68, which could be used by non-programmers. Later developments resulted in a whole family of generalized software products, based on the TAB68 program code, for statistical processes like data editing, file matching, data transformations, and variance computations. A more recent development in the same tradition is the PC-AXIS software for user-friendly retrieval and manipulation of statistical data.

The theoretical basis for these developments is elaborated in Sundgren (1973). It is based on the already mentioned work by Nordbotten, and on the work by Langefors (1966), where the distinction between information and data is made clear, and where a comprehensive theory of information systems is presented. Sundgren (1973) formulates an infological theory of databases and introduces conceptual modelling as a systematic way of describing the contents of databases and information systems; see also Sundgren (1974) and Sundgren (1975). This framework is further developed for statistical purposes in Rosén & Sundgren (1991).

¹ The term “metadata” was introduced by Sundgren (1973). Nordbotten’s data catalogues were in fact holdings of metadata.
In summary, Nordbotten’s approach as further developed and practiced by Statistics Sweden, and later used also by many other statistical agencies in the world, contained a number of features, which are still very relevant:

- a standardized data model for all data in the data archive
- standardized files stored in a standardized way in the data archive
- good documentation of the data in the data archive
- standardized processes and standardized software for processing of the data in the data archive: both pre-planned and ad hoc statistics production

The database concept

One important step in the historical development of the concept of a statistical data warehouse was the growing interest for databases among researchers and practitioners in information systems and software engineering. The first international conference on database management was held in the small village of Cargese, Corsica, in 1974; Klimbie & Koffeman (1974). Very much of the focus of that conference was on the emerging data models that were proposed as foundations for standards for the design of databases so-called database management systems, generalized software products for managing databases. The major contenders at the Corsica conference were the network model and the relational data model. The network model was being developed by the ANSI/CODASYL standardisation organisation, and was supported by all major computer manufacturers with the exception of IBM. The relational data model was being developed by researchers associated with IBM, such as Mike Senko, Ted Codd, and Chris Date.

Data models and conceptual models

Both the network model and the relational data model were data models in the literal sense – models of physical data representations. At the Corsica conference some researchers also presented more abstract, conceptual data models, aiming at modelling the conceptual information contents and the real world represented by the data. Thus, for example, Sundgren presented his infological approach; Abrial presented a model called Data Semantics, etc. The ideas of these more conceptually oriented researchers were that a user should not have to know anything about how the data were stored on different media – instead they should be able to communicate with computerized systems in terms of concepts and models that were relevant for them, and these concepts and models would then be mapped into more computer-oriented data models by the database management software.

Conceptual models, like the infological approach, were received respectfully at the time when they were launched, but they were regarded as far too abstract for being feasible for software implementation, a criticism that also hit the relational data model. However, a few years later the ideas were picked up again by many researchers. These models had names like the Entity Relationship (ER) model, or the Entity Attribute Relationship (EAR) model, and they were very similar to the infological model, or Object Property Relation (OPR) model, suggested by Sundgren (1973). These conceptual models have since then become mainstream models used by most practitioners in the field when designing databases. Some software developers have also taken up the ideas of using more conceptual data models under the umbrella of object-orientation and object-oriented databases.

Data independence and data/metadata-driven systems

The introduction of the database concept also meant the breakthrough for so-called data independence. Until then, computer programs had usually contained within themselves, not the actual data that they were processing, but the descriptions of the data, the metadata or data
declarations. If the organisation or the storage of the data was changed, ever so little, modifications of the software source code had to be carried out, and the programs had to be recompiled. This was a rigid, time-consuming, and error-prone process. By placing the metadata outside the computer programs, as part of the database containing the data to be processed by the programs, the processing became much more streamlined and flexible. The computer programs were designed to access the database whenever they needed data, first for the data descriptions, and then for the data themselves. If the data and metadata had changed since last time the program had been executed, the program would automatically adapt to the changes, since it would automatically get the new, updated data descriptions, when it accessed the database for metadata and data.

A more appropriate and exact term for data independence would be software/data/metadata independence. Software applications built on the principles of software/data/metadata independence are sometimes called data/metadata-driven systems.

As a practical example of metadata-driven systems in a statistical environment, we could consider the use of classifications stored in a classification database. Classifications are usually subject to modifications and even more drastic structural changes from time to time, and new versions of the classifications will occur as results of these changes. It is certainly essential that an application program, when processing certain statistical data, will use the right version of classifications with regard to these statistical data (which may be the most current data or historical data). If the software applications are forced to “consult” the classification database, when accessing the data, this could automatically ensure that the right classification version will be selected.

Database management systems (DBMS)

A database management system (DBMS) is a generalized software product for managing databases. The breakthrough of the database concept among information system practitioners created a huge market for such software, and the need for standardisation was imminent. This intensified the struggles between advocates of different data models. Although many of the researchers developing the relational data model were financed by IBM, IBM was not ready to give up its investments in old-fashioned hierarchical database management software. Thus small garage companies, like ORACLE, got a chance to establish themselves within the relational database niche, before it was obvious that relational database management systems would become the de facto industry standard for a long time. At this time IBM was ready to give full support for its relational database management system DB2, and later another small garage company called Microsoft was born and (much later) jumped on the bandwagon to compete with ORACLE and IBM for the database management software market with its SQL Server; SQL, pronounced “Sequel” was originally a research prototype, which was presented along with other similar products at the above-mentioned Corsica conference.

Statistical databases and statistical database management

Most databases in commercial environments were, and still are, so-called transaction databases, that is, the objects about which data are stored and processed are most of the time business transactions, e.g. a bank customer making a deposit or a withdrawal. Naturally “status-holding” objects, like customers and accounts, are also important objects in business applications, but it is the capacity to manage large volumes of transaction data concerning individual objects (customers, accounts) that determines the performance of a database management system for business purposes.

The requirements of statistical systems are quite different. Individual transactions are certainly important during the data collection and data preparation stages, but even then, the transactions typically occur in relatively well organized batches, and furthermore the batches of transactions associated with a typical sample survey are relatively small, and the batches of transactions
associated with big censuses or administrative registers are well known in advance and can be planned for by the statistics producer; there is no customer waiting for money at a cash machine.

On the other hand, statistical systems require database management software that is able to react in a flexible and efficient way to requests for statistical outputs (e.g. tables and graphs), which may require dynamic processing of millions of database records, stored in different files that need to be linked together (“joined” as the term is in the relational data model) on the fly, unless the requests have been foreseen in advanced, and the requested aggregated data have been stored in multi-dimensional structures typical for statistics.

The special requirements on database management systems implied by statistical systems have been analysed and discussed among statistical and scientific organisations for a long time, and a conference series on Statistical and Scientific Data Base Management Systems (SSDBMS) has been running for many years. However, since statistical systems and statistical applications show a requirement profile that is quite different from the typical requirement profiles of traditional business applications, no commercial market for statistical database management systems has existed for a long time. With the growing interest for data warehouses in business companies, this has finally changed.

*The αβγτ-model for multi-dimensional statistical data (hypercubes)*

A standard model for managing multi-dimensional statistical data was presented in Sundgren (1973). For a more recent presentation of this model, see Sundgren (2001), *The AlfaBetaGammaTau-model: A theory of multidimensional structures of statistics*.

The multidimensional structures typical for statistical databases have also become known as “cubes” or “hypercubes” (since they may certainly have more than three dimensions).

For more detailed presentations of the AlfaBetaGammaTau-model, with many examples, see Sundgren (2004) and Sundgren (2005).

*Statistical data warehouses*

Two key concepts in business-oriented information management are “enterprise system” and “data warehouse”. Software firms are developing and marketing standard software products supporting information systems based on these concepts.

When the ideas of statistical data warehouses were launched by Nordbotten, and long after that, there was no interest among commercial software developers to support such ideas, at least not to their full potential. The introduction of data warehouses in business environments has changed the situation, since applications based upon data warehouses have many similarities with production and usage of statistics: input data to data warehouses often come from many different sources, e.g. different operational applications; data warehouses again are used for more analytical purposes, like strategic decision-making. All these circumstances, input from multiple, possibly incompatible sources, output for multiple, possibly incompatible purposes, quite different from the purposes of the applications feeding the data warehouses with input data, call for elaborated metadata of similar kinds as are needed by statistical systems – for very much the same reasons.

*Enterprise systems and data warehouses in business environments*

An enterprise system typically supports a number of common business operations, such as the management of customers, orders, inventory, personnel, accounting, etc. In order to be able to support the business operations in a standardised way, the software products must be based on
standardised business models, and the enterprises adopting the software products in their information systems have to adapt to these models.

An enterprise system uses and produces a lot of data. In order to exploit the full potential of an enterprise system, these data (and the concepts behind the data) have to be co-ordinated, so that the different components of the system, corresponding to different business operations, can communicate and share data between themselves, wherever applicable. For example, an order, a product, an employee, and a customer should be defined in the same way in all components of an enterprise system. This may lead to an integrated, corporate data model, based upon standardised concepts and an integrated, corporate business model.

Thus a successful implementation of an enterprise system may lead to a set of well integrated databases supporting the operations of the business. The next step may be to make these data available also for non-operational purposes, notably so-called directive or analytical purposes, such as planning, decision-making, evaluations, etc. This requires the data to be organised in a different way than they are organised in the databases supporting the operations of the business. The business processes typically require information systems that are very efficient in handling individual transactions, e.g. an order from a customer. The data used by operational systems must be correct and up-to-date. Analytical systems, on the other hand, will have characteristics which are very similar to those of statistical systems. Analytical applications are typically based on large sets of data, often current data in combination with historical data in the form of time series. Data warehouses are basically databases based on operational data but adapted to the needs of analytical applications.

A data warehouse may be seen as a part of an enterprise system, but it is more common to see it as a counterpart in the sense that it is a system in its own right, co-operating with an enterprise system. The enterprise system will feed the data warehouse with input, which may be used for many different estimation processes and statistical analyses.

A data warehouse, as it is implemented and supported by commercial software firms, will typically be based on a combination of microdata and macrodata. The microdata, e.g. data about individual business transaction, customers, employees, products, etc., are tapped from the operational systems at certain time intervals, e.g. once a day. Data coming from different components in the enterprise system, and from different points in time, may be inconsistent because of errors and less than perfect integration in the enterprise system. The inconsistencies may require some “cleaning” of the microdata before they are allowed to enter the data warehouse. (Note the parallel between this so-called data cleaning and what we call data editing in connection with statistical systems.)

Once the data have entered the data warehouse, they are redistributed into another kind of database structure than is typically used in the enterprise system. The data structures of a data warehouse are adapted to the analytical needs. A data warehouse should be efficient in responding to requests for aggregated data, macrodata, based upon large sets of microdata. The requests are often ad hoc, that is, they cannot be exactly foreseen in advance, neither as regards contents or time. On the other hand the data in a data warehouse is usually archival in the sense that it is never, or at least very seldom, changed after it has entered the data warehouse (after the cleaning process). The data warehouse is only updated when new generations of microdata are added to the data warehouse, typically at certain time intervals, as was just mentioned.

One important consequence of the differences in requirements between data warehouses, on the one hand, and databases supporting operational systems, on the other, is that the data in a data warehouse do not necessarily have to adhere to the non-redundancy requirements that are usually essential in operational systems. On the contrary, it may be very efficient to replicate data in a data
warehouse in much different way, so as to be able to respond to many different ad hoc requests, which may require data to be structured in many different ways.

In particular, a data warehouse will often contain the original microdata, as they were received (after cleaning) from the operational systems, together with some macrodata, aggregated from the microdata. The macrodata are chosen so as to correspond to frequent output requests, and especially to those requests which would otherwise require very complex and time-consuming ad hoc processing of microdata.

So what does the growing popularity of data warehouses in business environments mean for statistical systems? Obviously there are a lot of similarities between enterprise systems and data warehouses on the one hand, and statistical systems on the other. One important implication is that there will be a much bigger market for a kind of software products that were previously regarded as “niche products” for the statistical market. We have already seen a rapid development of so-called OLAP products, where “OLAP” stands for On Line Analytical Processing. We may also hope for a growing interest among software firms in developing products supporting more sophisticated metadata management than non-statistical organisations have felt a need for up to now. When statistics production and statistical analysis becomes a more common and routine part of business information systems, the businesses are likely to discover similar kinds needs for metadata and metadata management that we have since long been aware of in the statistical world, but for which we have by and large lacked adequate software support; commercial software firms have not been interested in developing such software, and for statistical agencies such software development has often turned out to be too complex and resource-consuming.

The roles of data warehouses in statistical systems

As was mentioned earlier, Svein Nordbotten launched the data warehouse concept to the statistical community already in the early 1960’s, and he actually lined out in quite some detail, how a technical system based on those ideas could be implemented already with the computer technology that was available at that time. For various reasons, mainly organisational reasons and a general conservatism among statisticians, Nordbotten’s ideas have not started to get implemented on full scale until recently – and probably most people now implementing the data warehouse concept in statistical offices have forgotten who invented it, or they have never even heard about it.

The most obvious role for a data warehouse in a statistical system is as a well organised repository for final observation registers and statistical output databases. From an external user’s point of view, it should be possible to see the whole clearinghouse, or data warehouse, as one common resource, with one common interface, through which the user could put his or her requests for statistical data and receive relevant replies in return to the requests. If a user is only interested in statistical end-products in the form of aggregated statistics presented in tables or graphs, he or she should not even have to know from which internal statistical system the end-products come, or if the statistics are already available in preaggregated form or have to be aggregated from microdata on demand.

Up to now the development in most statistical organisations have focused on this first role of a data warehouse. In particular, the focus has been on making the final statistics (macrodata) produced by a statistical organisation available to external users via the Internet. Such data warehouses are also called statistical output databases.

Figure 27 illustrates the architecture of an integrated, data- and metadata-driven integrated system for production of official statistics.
However, in addition to this, a statistical data warehouse may also serve other functions and have other roles in statistical organisations. Figure 28 *Fell Hittar inte referenskälla,* gives an overview of how an advanced statistical warehouse, consisting of an input data warehouse and an output data warehouse, both including metadata, could be the navel of virtually all activities in a statistical organisation.

For the internal users, the producers of statistics, a data warehouse could be seen as a common clearinghouse for data and metadata, a shared resource, from which both raw data/metadata, semi-processed data/metadata, final products, and other sharable data/metadata resources (e.g. registers and classifications) can be retrieved and combined for further processing, resulting in new and/or updated data/metadata, belonging to the categories just mentioned, which are then returned to the data warehouse to be used by other processes and producers/users.

The statistical output databases have not included microdata. At best there have been equipped with certain pre-defined routines, supported by standard software, for tapping off the inputs to the output warehouse from the regular statistical production processes. In some advanced cases this has even been done in such a way that the statistical output database is updated first, and after this the regular outputs, e.g. the statistical reports, are produced by standard software from the statistical output database. This latter solution is of course much more efficient, and is finally becoming more common. However, since it requires some co-ordination and subordination to standards, it has been difficult to achieve in stovepipe-organised statistical agencies.
There are several good reasons why microdata should also play a role in connection with statistical output databases. One is that it may sometimes be more efficient, and provide more flexibility, to derive macrodata from microdata on demand rather than storing them permanently.

Another reason is that certain categories of users of statistical data, e.g. researchers and advanced analysts, are at least equally interested in microdata as in macrodata. Certainly a lot of precautions have to be taken by the statistics producers, if and when microdata are made available to such users, but assuming that these problems have a solution, there is no reason why a user of statistical data should not have all the data available from the statistical office presented in a uniform way, through one gateway, regardless of whether the data are microdata or macrodata.

Some interesting models for making microdata available to researchers in an attractive way have been launched by several statistical offices during the last few years.

If we return to the internal usages of statistical data warehouses, there is a recent trend in statistical offices to develop input data warehouses. One purpose of an input data warehouse is to support the more flexible exchange of input data between statistical surveys necessitated by the efforts to coordinate data collection processes in a better way from the point of view of respondents. Ideally data providers should be able to provide their inputs to the statistical processes as by-products of the operational work that they are doing anyhow as part of their own business. This will create a need for an input data warehouse functioning as a clearing-house between the input data collection processes and the statistical production processes aiming at different statistical outputs.

Figure 29 and Figure 30 elaborate further on the subsystems of a statistical system, and on the interactions between them, including both data flow interactions and control interactions. Figure 29
illustrates a statistical system as seen from a design/evaluation, monitoring, and control point of view. **Metadata** (data about data) and **process data** (data about processes, also called *paradata*) are important components in the control of a statistical system. Figure 30 focuses on the main operations of a statistical system.

**Figure 29. Control and execution of a statistical production system.**

**Figure 30. Basic operations in a database-oriented statistical production system.**
Standardisation of data: canonical forms and normalisation

The growing interest in databases, both among researchers and practitioners, also led to standardisation efforts as regards the representation and structuring of data.

Microdata

One of the strengths of the relational data model was that it introduced a rigorous standard for data structures in a database. From a practical point of view the standard had great similarities with so-called flat files, which had been in use since the childhood of computers in the form of 80-column card decks.

The relational data model can be seen as a theory of flat files based upon the concept of a relation in the sense of the mathematical set theory. A relation in this sense is defined as a set of n-tuples, and such a relation could be viewed as a matrix or table, where the rows correspond to the n-tuples, and the i:th column corresponds to the i:th component of the n-tuples. From a conceptual point of view the rows correspond to objects, and the columns correspond to variables of the objects.

The relational data model puts a number of restrictions on the contents of the rows and the columns and the cells of a relational table. For example, the value in a cell must always be regarded as atomic; no substructure can be assumed or modelled. Furthermore, each relational table should have a column, or combination of columns—the so-called primary key—the values of which uniquely identify rows in the table; there must not be two identical rows in a table.

The theory of relational data models formulates a number of normal forms (first, second, third, etc.) which stipulate stricter rules for the contents of a relational table. The purpose of these rules are to ensure that the database will not contain any redundant data in the sense that one and the same “fact” is stored in more than one place. In addition to wasting space (which is not so serious if space is cheap), redundancies in stored data may be a threat to data consistency.

Provided that a database is designed on the basis of a sound conceptual model, like the kind of models suggested by Sundgren (1973) and others, the set-theoretical normalisation exercises recommended by the literature on the relational data model become rather superfluous. Basically a conceptual model transformed into a relational model according to certain simple rules suggested by Sundgren in several papers, will automatically become normalised.

Macrodata

Flat files and relational data tables lend themselves in a very natural way to standardised storing of statistical microdata. Actually the same standard formats can also be used for storing macrodata, and this is done in many statistical database management systems, at least on a basic level. However, another type of standard format, so-called multidimensional cubes, or hypercubes, are often used in software for managing statistical macrodata, typically as a user-oriented layer on top of either a relational database or some proprietary non-standard format.

One hypercube format for storing aggregated statistical data is described in Sundgren (1973). This so-called multidimensional box format or alfa-beta-gamma-tau format is further developed by Sundgren in later papers, e.g. Sundgren (2001).

Metadata

Templates and formats for storing and communicating statistical metadata (including documentation and quality declarations) in a standardised way have been discussed for many years, but so far there
are no widely accepted standards. However, there is maybe what one could call an emerging consensus about some major concepts and contents components of such standards. See for example Rosén & Sundgren (1991) and Eurostat (2003 a, b).

**The data/metadata lifecycle**

Figure 31 illustrates what is sometimes called the statistical data/metadata life cycle or value chain; cf Porter (1985), Sundgren (2003a), Sundgren & Lindblom (2004), ECB & Eurostat (2003).

During the life cycle statistical data and accompanying metadata pass through four relatively well-defined stages, corresponding to forms and interfaces:

Stage 1: The input data stage: the input data/metadata as registered on some kind of input form, e.g. a completed (paper or electronic) questionnaire.

Stage 2: The final microdata stage: the input data/metadata as finally stored in some kind of final observation register, e.g. a relational database, after data preparation operations such as coding, editing, and other transformations (e.g. computation of derived variables).

Stage 3: The final macrodata stage: the output statistics (estimated values of statistical characteristics) and accompanying metadata as finally computed and stored in some kind of output database.

Stage 4: The output product stage: the statistical data/metadata as published and disseminated via printed and electronic media.

As indicated by the “fork arrows” ( ) between the four boxes in Figure 31, there are “many-to-many”-relationships between the four stages, i.e. the same input observations used in several observation registers, each one of which may be used in the production of several output data sets, which again may be combined into several statistical end-products; and vice versa: a certain statistical end-product may be based upon several output data sets, each one of which may be derived from several observation registers, which again may be the result of combining input data from several sources.

It should be noted that these complex relationships between inputs, throughputs, and outputs already exist to a high degree in modern statistics production, although most statistical offices are still organized according to the traditional stovepipe model; the production system logic is not necessarily isomorphic with the organisational structure. This is something that has to be carefully considered when designing statistical production systems.

**More about the technical aspects of a statistical system**

When designing information systems, one may use standardized structuring methods and architectures, such as database orientation, process orientation, client/server architecture, and service orientation.

Today’s applications are often database-oriented, that is, different functions of the system interact with each other via a common database, including both data and metadata.
Figure 31. The data/metadata lifecycle in a statistical production system.
Until recently, database-orientation has often been combined with a structuring of the information system according to the client/server principle. In its original form, the client/server architecture consists of two types of subsystems: (a) user-oriented client systems, which are served by (b) server systems, handling common resources like printers and databases. There are developments of the client/server architecture, using three or more types of subsystems, called tiers. In a three-tier client/server architecture there is a distinction between

- subsystems for user interactions
- subsystems for business logic
- subsystems for data management

With the rapidly growing importance of the Internet and web-based information systems, the client/server architecture is becoming replaced by service-oriented architectures (SOA), based on well-defined, standardized services, which can be used in a standardized way, via standardized messages and communication protocols, by other services.

Service-oriented architectures are based on the following design principles; Erl (2005):

- **Loose coupling** – Services maintain a relationship that minimizes dependencies and only requires that they retain an awareness of each other.
- **Service contract** – Services adhere to a communications agreement, as defined collectively by one or more service descriptions and related documents.
- **Autonomy** – Services have control over the logic they encapsulate.
- **Abstraction** – Beyond what is described in the service contract, services hide logic from the outside world.
- **Reusability** – Logic is divided into services with the intention of promoting reuse.
- **Composability** – Collections of services can be coordinated and assembled to form composite services.
- **Statelessness** – Services minimize retaining information specific to an activity.
- **Discoverability** – Services are designed to be outwardly descriptive so that they can be found and assessed via available mechanisms.

More briefly and concretely expressed, a service is a piece of reusable software, smaller or bigger, which performs a well-defined function, described in a standardized way. The service can be requested by other pieces of software, which may themselves be services, through standardized messages. The service requestor should not have to know anything about the internal functioning of the activated service, and the latter should not have to know anything about its external environment, but only perform its function and (possibly) provide a standardized response message in return. During its execution a service may itself request the execution of other services in the same way.

Service-orientation can be seen as a further development of earlier software design methodologies like modular programming and object-orientation. It is obviously well in line with the general systems approach and systems thinking; cf the description of services above with our earlier discussions of the systems concept and about how to manage complexity and unperceivable systems.

Service-orientation, as defined above, has the great advantage that it can be introduced step by step in an organisation, e.g. a statistical agency. Any large organisation today has an enormous burden of legacy systems that cannot quickly and easily be redesigned and redeveloped. A legacy system that has not been developed in accordance with modern design principles can be encapsulated into a large black box component, which is not internally consistent with service-oriented principles, but which interacts with its environment according to such principles. Of course it requires some work to
develop the “sarcophagus” surrounding the black box, making it look and behave like a true service to the other services in the system, with which it interacts, but this is a small effort in comparison with a total make-over or redevelopment of the whole legacy system.

Service-orientation often goes hand in hand with process-orientation. On the business level – for example the business of statistics production – the employees interact with customers, suppliers (respondents and data providers in the case of statistics production), colleagues, and external and internal service systems (typically computerized), in order to provide services, demanded by the customers, to the customers. This work may be organized into processes, preferably standardized processes, so as to ensure that the work is done according to best methods and best practices and will give the same good quality results to the customer, regardless of which individual persons are executing the processes.

Another recent trend is to replace in-house software developments, and even in-house licensing and installation of commercial software packages, with software components that are provided as services, for free or for a fee, via the Internet. This is called “cloud computing” or “Software as a Service”, SaaS, and is also consistent with service-oriented architectures and process orientation.

**Summary of a modern data warehouse approach to official statistics**

Some important characteristics of a modern version of the data warehouse approach to official statistics would be:

- **standardized and coherent conceptual models** for all statistical data – as discussed earlier in this document
- **a standardized input data warehouse**, storing all microdata obtained from different data sources through standardized data collection procedures: traditional statistical surveys, administrative registers, and other administrative data sources
- **a standardized output data warehouse**, storing all macrodata produced through pre-planned and ad hoc aggregation and estimation processes
- **standardized input, throughput, and output processes** for the collection, transformation, aggregation, and communication of statistical data
- **standardized documentation and metadata/paradata** for supporting users’ needs, and for monitoring and evaluating the quality and efficiency of the statistical production processes
- **standardized software** developed and maintained according to best practices at any point in time (service-oriented architecture, cloud computing etc.)
- **communication interfaces corresponding to the needs of all important stakeholders**: respondents and data providers, production statisticians and system operators, designers and evaluators, managers, different categories of users of statistical outputs, developers and providers of additional services
- **standardized storage formats and communication procedures** for microdata, macrodata, and metadata (including process data, or paradata)

**Sources:** For references and more literature, see the bibliography at the end of this report.
Data preparation

Data preparation involves different types of operations, for example

- **data editing** (checking for suspected errors + taking actions on such data);
- **coding** (categorizing free-text data);
- **deriving new concepts and values** from other data, possibly from different sources, etc.

Data editing – checking and correcting data

Data will almost always contain errors. The errors are of different types and will be more or less serious for different types of usages. When data are used for operational purposes, for example in e-commerce applications, it is important that certain data are exactly correct, for example the identity and address of a customer, and the identity and the quantity and price of a product ordered – errors will lead to big problems for both the customer and the service provider. It is necessary to maintain so-called “book-keeping quality” in such applications.

However, when it comes to analytical use of data for problem-solving and decision-making purposes, the quality requirements become different. Book-keeping quality will not be necessary. Small random errors can be accepted, as long as they do not affect the results of the analyses to be made. Since checking and correcting data (called “data editing” or “data cleaning” by statisticians) is an expensive and time-consuming operation, one should focus on errors in the data that will affect the results of the analyses to be made. Is it possible to find those errors quickly, without having to check all data with the same priority and intensity? Yes, there are statistical methods for data editing, which may help us with this, so-called “selective editing” or “significance editing” or “macro-editing”. Among other things these methods will identify so-called “outliers”, observations which are far away from other observations from a statistical point of view, often illustrated by means of graphs; see Figure 32.

![Figure 32. Outliers.](image-url)
Selective editing means, expressed in a simple way, that the editing process is focused on those suspected errors in the data, which can be estimated to have (the most) significant effects on the estimates to be produced. This editing method assumes that the estimates to be produced are known. However, the data collected may also be made available for other purposes than those at hand, for example within the framework of a statistical system. Then many of the estimates to be produced in the future on basis of the data at hand, possibly in combination with data from other sources, are unknown during the design and execution of the editing process at hand. How should such situations be treated? As a minimum the statisticians responsible for the data at hand must provide good information about how the editing of the data at hand has been done, which assumptions have been made, which usages of the data could be particularly uncertain or dangerous, etc. Probably, as a routine, the original, unedited data should also be archived, so as to make it possible for future reusers of the data to design and execute alternative editing procedures on the same data.

When suspected errors are discovered in data, the next question is what to do with them. If there is good reason to believe that the errors are not important for the purposes of the planned analyses of the data, nothing should be done, if the actions needed are expensive and time-consuming – for example since they involve investigations undertaken by experts, or even going back to the original data providers, asking them for clarifications. Sometimes advanced methods, like neural networks, may be used for replacing human expertise, thus enabling automatic data editing with good results.

Coding – categorizing free-text data

Another part of the data preparation is so-called “coding”, which means categorizing (classifying) free-text answers to open questions. Like editing, coding may also be supported by computerized procedures, in order to make the coding operations faster, less expensive, and even better than manual methods.

Derivation of new concepts and values

Finally, data preparation may also involve derivation of new concepts and values from the concepts and values which are directly represented in the data collected from different sources. Some of the derivations may involve the combination of data from different sources.

When complex statistical systems are designed, combining different surveys, administrative data, archival data, etc., similar problems will occur, as when administrative registers were introduced in statistics production, but on a much larger scale and in more advanced forms. Complex statistical systems will certainly offer a wide range of major challenges for future statisticians.

More about data editing in statistical systems

In parallel with his early engagement in the development of statistical data warehouses, at the time (the 1960's) called archive-statistical systems, Svein Nordbotten from the Norwegian statistical office and later head of the UN statistical office, and professor in information science at the University of Bergen, was very active in developing methods for automating the statistical data editing and imputation process, which has traditionally been very labour-intensive and costly, and still is. Nordbotten published the seminal papers Nordbotten (1963) and Nordbotten (1965) more than 10 years before Fellegi & Holt published their famous paper within the same field; Fellegi & Holt (1976).

Several studies have shown that data editing accounts for about 40% of the total costs of the production of official statistics, and this fact alone motivates focus on standardized, rationalized, and more “intelligent” data editing methods.
If the estimates to be made are known in advance, selective editing is relatively straightforward, and may easily save 30-50% of the resources needed for data editing.

In an archive-statistical system, where many of the estimates to be made in the future are not known at the time of data collection, selective editing is associated with more difficult methodological problems, some of which still remain to be approached and solved.

In addition to his contributions to the methodology of selective editing, Nordbotten has made innovative use of neural networks to manage editing and imputation problems.


Literature

For references and more literature, see the bibliography at the end of this report.

Aggregation and estimation

Aggregation of microdata into macrodata may be used for producing estimates of statistical parameters, like sums, averages, medians, variances, and correlations. Processing of microdata may also be used as integrated parts of more or less advanced statistical analysis, for example regression analysis and different statistical tests. Standard errors may be computed for estimating uncertainties and confidence intervals of estimated statistical characteristics.

Analysis

There are many different types of more or less advanced statistical analysis, for example:

- Statistical tabulations and cross-tabulations
- Graphical presentations, visualisations
- Animations
- Correlation and regression analyses
- Statistical tests of hypotheses
- Time series analysis

One may also distinguish between different purposes of different types of analyses:

- Descriptive purposes
- Explanatory purposes
- Prognosticative purposes
- Normative purposes

Qualitative vs quantitative methods

For discussions of the use of qualitative and quantitative methods in the context of information systems and computing, see Oates (2005), Sundgren (2013), and Sundgren (2014).
Especially among social scientists it is common to distinguish between qualitative and quantitative analyses, depending on the nature of the data used. Text data are typical qualitative data, but they may be categorized (coded) into a number of classes, and then the number of texts belonging to the different classes may be counted and tabulated, a very simple form of quantitative analysis.

Quantitative data are data upon which more or less advanced mathematical operations can be performed in a meaningful way. Different types of scales are used for measuring different kinds of quantitative variables:

- Nominal scales: classifications as just described in the context of qualitative data
- Ordinal scales: the values may be ordered by less/more
- Interval scales: the interval between two values is well defined, addition and subtractions are meaningful mathematical operations
- Ratio scales: multiplication and division are meaningful operations as well

Quantitative analysis

Source: Oates (2015), Chapter 17

Quantitative data are data, or evidence, based on numbers. It is the main type of data generated by experiments and surveys, but it can be generated by other research strategies too. It is primarily used and analysed by positivist researchers, but is sometimes generated by interpretive and critical researchers.

Examples of numeric data include:

- number of people expressing satisfaction with ...
- a company’s annual turnover for each of the last 5 years
- time in seconds to process a data file
- number of characters in a computer animation
- number of people using the Internet for more than 20 hours per week
- number of hot links on a website

The idea of data analysis: look for patterns in the data and draw conclusions.

Established techniques for analysing quantitative data

- simple table, charts, or graphs
- simple descriptive statistical measures: averages, variation measures, correlations
- more complex statistical techniques, visualisations, and animations

Types of quantitative data

- **Nominal data – categorical data**
  - Nominal data indicate categories or classes in a classification.
  - Numerical values are often used to represent the classes, but they are not really quantitative data; it is not meaningful to carry out arithmetical operations on them.
  - The only quantitative analysis possible is to count frequencies.

- **Ordinal data – ranked data**
  - Numbers are allocated to a quantitative scale, providing an order or rank.
We know the order between the points on the scale, but not the distance. Example: student marks.

- **Interval data**
  - Interval data are like ordinal data, but now we know that the distances between the points on the scale are the same, e.g. years.
  - For such data subtractions are meaningful, but not multiplication or division.

- **Ratio data**
  - There is a true zero on the measurement scale, e.g. people’s age, height, weight.
  - Addition, subtraction, multiplication, division are meaningful.

**Further categories: discrete data (whole numbers) vs continuous data.**

**Data preparation operations**

Before collected data can be used for data analysis, they must be prepared by so-called data coding and data editing operations. “Coding” means transforming the data into pre-defined classes (categories). “Editing” means checking the data for suspected errors, and correcting (or at least changing) the data, when motivated.

**Data editing:**

- The data obtained from measurements, observations, questionnaires, etc., will contain different kinds of errors.
- **Checks should be made to discover suspected errors, focusing on errors that would seriously distort analyses and results. Checks could look for:**
  - missing data
  - invalid data, values which are not in the code-book
  - inconsistent data
  - unusual data, outliers
- Suspected errors could lead to further checks (e.g. contacts with the respondents, although this will usually be very costly), and possibly – but not necessarily – to changes of the data, possibly imputations: automatic generation of replacements for missing data or suspected errors.
- Data editing can be done by manual or computer-supported processes.
- Data editing will not necessarily improve the quality of the data, but it may make the data easier to analyse, e.g. by removing or changing suspicious data that “disturb” analytical patterns or computerised processes.

**Qualitative analysis**

Source: Oates (2015), Chapter 16

**The concept of qualitative data includes all non-numeric data** – words, images, sounds, and so on – found in such things as interview tapes, researchers’ diaries, company documents, websites, and developers’ models. It is the main type of data, or evidence, generated by case studies, action research, and ethnography. It is also the main type of data used and analysed by interpretive and critical researchers, but can be generated by positivist researchers too.

You can use quantitative (numerical) analysis on qualitative data. For example, you could:
• Count the number of times a particular word or phrase occurs in some text.
• Count the number of words or pages allocated to different topics on a website.

However, most qualitative data analysis involves abstracting from the research data the verbal, visual, or aural themes and patterns that you think are important to your research topic.

*Analysing textual data*

*Data preparation*

• Get all your data into standard formats.
• Plan an efficient filing system for your data.
• Make backup copies of your data, and always work with a backup copy.

*Data analysis*

• Start off by reading through all data to get a general impression. Start to identify key themes in the data. Initially three themes could be enough:
  o Segments that have no relation to your overall research purpose and so are not needed.
  o Segments that provide general descriptive information that you will need in order to describe the research context for your readers; e.g. history of a company, background data about respondents.
  o Segments that appear to be relevant to your research question(s).

• Focus on the third category above. Categorise each segment or unit of data by writing in the margin a heading, subheading, or other label.

• To start with, the choice of categories is not crucial. They may come from:
  o Existing theories – the deductive approach.
  o The data themselves, e.g. categories used by respondents – the inductive approach.

• Refine your categories, e.g. by breaking them down, or grouping together.

• Look for themes and inter-connections between segments and categories.

• Use visual aids, e.g. tables or diagrams, to analyse the data.

• Go beyond the patterns you see, and try to explain them. Document the analysis.

*Data coding*

• For closed questions: Each predefined answer option is transformed into a unique code.

• For open questions: There has to be a well-defined classification scheme corresponding to each open question. Each class (category) is indicated by a code. Each free-text answer given by a respondent to the open question is transformed into a code in the classification scheme.

• The coding scheme must contain codes (classes) that are mutually exclusive and exhaustive.

• All coders must apply the coding scheme in the same way.
• There should be a code book, where each code is noted and defined.

• There should be special codes for different types of missing data, e.g.:
  o data missing because the respondent did not respond at all, object non-response
  o data missing because the respondent ignored the particular question, item non-response
  o data missing because the question is not relevant for the particular respondent

• Data coding could be a manual process or computer-supported in different ways.

Simple descriptive methods

In traditional statistics production the analysis phase often starts with well-established methods and techniques for describing, visualizing, and – more recently – animating statistical data: statistical tables, diagrams and graphs, etc. This first step of data analysis may lead to more advanced methods, such as pattern recognition and predictive analytics.

More advanced descriptive methods

Correlations and more or less advanced forms of regression play important roles in the analysis of big data. As always, it must be stressed that patterns discovered by such analyses do not alone prove causal relationships between different factors. The patterns and covariations need to be supported and explained by means of theories from the application domains as well. At least this has been “common wisdom” until big data came around. Some of the most remarkable applications of big data seem to be working quite well, without much domain theory to support them, and have sometimes produced strikingly better results than traditional theory- and knowledge-based approaches. Automatic language translation, with Google Translate representing the new big data based approach, is but one example.

However, this is an area of big debate and controversy at present. We shall return to this later.

Predictive analytics

Some more advanced methods of data analysis are associated with so-called predictive analytics. Predictive analytics deals with extracting information from data and using it to predict trends and behaviour patterns. Often the unknown of interest is in the future, but predictive analytics can be applied to any type of unknown whether it be in the past, present or future, for example, identifying suspects after a crime has been committed, or credit card fraud as it occurs.

Predictive analytics encompasses a variety of statistical techniques from modelling, machine learning, and data mining that analyse current and historical facts to make predictions about future, or otherwise unknown, events.

In business, predictive models exploit patterns found in historical and transactional data to identify risks and opportunities. Models capture relationships among many factors to allow assessment of risk or potential associated with a particular set of conditions.

Predictive analytics will be treated more in-depth in a later section of this chapter.

Problem-solving, decision-making, and actions

Analyses of available data may result in problem solutions, decisions, and actions. This is sometimes referred to as fact-based or even “rational” decision-making as opposed to decisions taken by other methods or no methods at all: political gut feelings, throwing dices, asking an oracle.
Evaluating decisions and actions

In many types of decision-making, not least political decision-making, it is important to at least try to evaluate the effects of decision-making and actions taken to implement the decisions, in order to find out to what extent the decisions and actions led to the expected results, and in order to learn for the future.

The evaluation may be described in terms of a feedback loop. The effects of implemented decisions are studied by means of observations and measurements, which are then collected and processed in the next iteration of the process described by Figure 21, Figure 22, and Figure 23 earlier in this report.

Big Data, Business Intelligence, and related concepts

Starting with “Decision Support Systems” (DSS), which were launched several decades ago, a large number of seemingly similar and related concepts with more or less fanciful names have been invented and marketed over the years, for example:

- Decision Support Systems (DSS)
- Knowledge-Based Systems (KBS) and expert systems
- Simulation and gamification
- Machine learning and neural networks
- Data mining and knowledge discovery
- Business Intelligence (BI)
- Big Data

These concepts are highly overlapping, having similar goals (supporting strategic planning, decision-making, and problem-solving) and using similar methods and techniques. It is sometimes amusing to see how some software vendors, as soon as there is a hype around a new concept, very seriously claim that they have the right tools for implementing the emerging new concept, but if one looks more closely at those, they are to a large extent the same tools, maybe slightly modernized, as those which were marketed in connection with previous hypes around preceding concepts.

Decision support systems (DSS)

For more information and references to relevant literature, see Wikipedia (Decision support system), http://en.wikipedia.org/wiki/Decision_support_system

A decision support system (DSS) supports business or organisational decision-making activities. It serves the management, operations, and planning levels of an organisation (usually mid and higher management) and help people make decisions about problems that may be rapidly changing and not easily specified in advance, that is, unstructured and semi-structured decision problems. Decision support systems can be either fully computerized, human-powered or a combination of both.

Sprague (1980) specifies some important DSS characteristics:

- DSS tends to be aimed at the less well structured, underspecified problem that upper level managers typically face;
- DSS attempts to combine the use of models or analytic techniques with traditional data access and retrieval functions;
• DSS specifically focuses on features which make them easy to use by noncomputer people in an interactive mode; and
• DSS emphasizes flexibility and adaptability to accommodate changes in the environment and the decision making approach of the user.

A properly designed DSS is an interactive software-based system intended to help decision makers compile useful information from a combination of raw data, documents, and personal knowledge, or business models to identify and solve problems and make decisions.

One common type of software tools used in the first generation of Decision Support Systems were so-called OLAP tools (OLAP = On Line Analytical Processing as opposed to OLTP = On Line Transaction Processing).

Knowledge-based systems (KBS) and expert systems

A knowledge-based system (KBS) is software that reasons and uses a knowledge base to solve complex problems. The term is broad and is used to refer to many different kinds of systems. The one common theme that unites all knowledge based systems is an attempt to represent knowledge explicitly via tools such as ontologies and rules rather than implicitly via code the way a conventional computer program does.

A knowledge based system has two types of sub-systems: a knowledge base and an inference engine. The knowledge base represents facts about the world, often in some form of subsumption (is-a) ontology. The inference engine represents logical assertions and conditions about the world, usually represented via if-then rules.

The first knowledge-based systems, developed by AI researchers, were so-called expert systems. The difference between the terms used was is in the view taken to describe the system. The term “expert system” refers to the type of task the system is trying to solve, to replace or aid a human expert in a complex task. Knowledge-based system refers to the architecture of the system, that it represents knowledge explicitly rather than as procedural code.

While almost all early knowledge-based systems were expert systems, the same tools and architectures have since been used for many other types of systems. One of the most famous rule-based expert systems was Mycin, a program for medical diagnosis. The early expert systems represented facts about the world as simple assertions in a flat database and used rules to reason about and add results to these assertions. Representing knowledge explicitly via rules had several advantages:

1. **Acquisition & Maintenance.** Using rules meant that domain experts could often define and maintain the rules themselves rather than via a programmer.

2. **Explanation.** Representing knowledge explicitly allowed systems to reason about how they came to a conclusion and use this information to explain results to users. For example, to follow the chain of inferences that led to a diagnosis and use these facts to explain the diagnosis.

3. **Reasoning.** Decoupling the knowledge from the processing of that knowledge enabled general purpose inference engines to be developed. These systems could develop conclusions that followed from a data set that the initial developers may not have even been aware of.

As knowledge-based systems became more complex the techniques used to represent the knowledge base became more sophisticated. Rather than representing facts as assertions about
data, the knowledge-base became more structured, representing information using similar techniques to object-oriented programming such as hierarchies of classes and subclasses, relations between classes, and behaviour of objects.

Another advancement was the development of special purpose automated reasoning systems called classifiers. They allow developers to simply declare facts about the world and let the classifier deduce the relations. In this way a classifier also can play the role of an inference engine.

For sources and other references to relevant literature: https://en.wikipedia.org/wiki/Knowledge-based_systems

Simulation and gamification

**Simulation** is the imitation of a real-world process or system over time. The act of simulating something first requires that a model be developed; this model represents the key characteristics or behaviours/functions of the selected physical or abstract system or process. The model represents the system itself, whereas the simulation represents the operation of the system over time.

Simulation is used in many contexts, such as simulation of technology for performance optimisation, safety engineering, testing, training, education, and video games. Simulation is often used with scientific modelling of natural systems or human systems to gain insight into their functioning. Simulation can be used to show the eventual real effects of alternative conditions and courses of action. Simulation is also used when the real system cannot be engaged, because it may not be accessible, or it may be dangerous or unacceptable to engage, or it is being designed but not yet built, or it may simply not exist.

Key issues in simulation include acquisition of valid source information about the relevant selection of key characteristics and behaviours, the use of simplifying approximations and assumptions within the simulation, and fidelity and validity of the simulation outcomes.

Traditionally, the formal modelling of systems has been via a mathematical model, which attempts to find analytical solutions enabling the prediction of the behaviour of the system from a set of parameters and initial conditions. Computer simulation is often used as an adjunct to, or substitution for, modelling systems for which simple closed form analytic solutions are not possible.

For more on simulation and relevant literature references: https://en.wikipedia.org/wiki/Simulation

**Gamification** is the application of game-design elements and game principles in non-game contexts. Gamification is often used in attempts to improve user engagement, focused motivation or flow (in the sense of positive psychology), organisational productivity, learning, employee recruitment and evaluation, ease of use and usefulness of systems, physical exercise, traffic violations, and voter apathy, among others.

For more on gamification and references to relevant literature: https://en.wikipedia.org/wiki/Gamification

Machine learning

For sources and references to relevant literature: https://en.wikipedia.org/wiki/Machine_learning#Artificial_neural_networks
Machine learning explores the study and construction of algorithms that can learn from and make predictions on data. Such algorithms operate by building a model from example inputs in order to make data-driven predictions or decisions, rather than following strictly static program instructions.

Machine learning has strong ties to mathematical optimization, which delivers methods, theory and application domains to the field. Machine learning is employed in a range of computing tasks where designing and programming explicit algorithms is infeasible. Example applications include spam filtering, optical character recognition (OCR), search engines, and computer vision.

In 1959, Arthur Samuel defined machine learning as a "field of study that gives computers the ability to learn without being explicitly programmed".

Tom M. Mitchell provided a widely quoted, more formal definition:

"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E"

This definition is notable for its defining machine learning in fundamentally operational rather than cognitive terms, thus following Alan Turing's proposal in his paper "Computing Machinery and Intelligence" that the question "Can machines think?" be replaced with the question "Can machines do what we (as thinking entities) can do?"

Machine learning is typically classified into three broad categories:

1. **Supervised learning**: The computer is presented with example inputs and their desired outputs, given by a "teacher", and the goal is to learn a general rule that maps inputs to outputs.

2. **Unsupervised learning**: No labels are given to the learning algorithm, leaving it on its own to find structure in its input. Unsupervised learning can be a goal in itself (discovering hidden patterns in data) or a means towards an end.

3. **Reinforcement learning**: A computer program interacts with a dynamic environment in which it must perform a certain goal (such as driving a vehicle), without a teacher explicitly telling it whether it has come close to its goal or not. Another example is learning to play a game by playing against an opponent.

**Supervised learning** aims at inferring a function from labelled training data. The training data consist of a set of training examples. In supervised learning, each example is a pair consisting of an input object (typically a vector) and a desired output value (also called the supervisory signal). A supervised learning algorithm analyses the training data and produces an inferred function, which can be used for mapping new examples. An optimal scenario will allow for the algorithm to correctly determine the class labels for unseen instances. This requires the learning algorithm to generalize from the training data to unseen situations in a "reasonable" way.

The parallel task in human and animal psychology is often referred to as **concept learning**.

**Unsupervised learning** tries to find hidden structure in unlabelled data. Since the examples given to the learner are unlabelled, there is no error or reward signal to evaluate a potential solution. This distinguishes unsupervised learning from supervised learning and reinforcement learning.
Reinforcement learning is inspired by behaviourist psychology, concerned with how software agents ought to take actions in an environment so as to maximize some notion of cumulative reward. The problem, due to its generality, is studied in many other disciplines, such as game theory, control theory, operations research, information theory, simulation-based optimization, multi-agent systems, swarm intelligence, statistics, and genetic algorithms.

Reinforcement learning differs from standard supervised learning in that correct input/output pairs are never presented, nor sub-optimal actions explicitly corrected. Further, there is a focus on on-line performance, which involves finding a balance between exploration (of uncharted territory) and exploitation (of current knowledge).

Machine learning and data mining often employ the same methods and overlap significantly. They can be roughly distinguished as follows:

- Machine learning focuses on prediction, based on known properties learned from training data.
- Data mining focuses on the discovery of (previously) unknown properties in the data.

The two areas overlap in many ways: data mining uses many machine learning methods, but often with a slightly different goal in mind. On the other hand, machine learning also employs data mining methods as "unsupervised learning" or as a pre-processing step to improve learner accuracy. Much of the confusion between these two research communities comes from the basic assumptions they work with: in machine learning, performance is usually evaluated with respect to the ability to reproduce known knowledge, while in knowledge discovery and data mining the key task is the discovery of previously unknown knowledge. Evaluated with respect to known knowledge, an uninformed (unsupervised) method will easily be outperformed by supervised methods, while in a typical knowledge discovery task; supervised methods cannot be used since there is no training data.

Machine learning also has intimate ties to optimization: many learning problems are formulated as minimization of some loss function on a training set of examples. Loss functions express the discrepancy between the predictions of the model being trained and the actual problem instances (for example, in classification, one wants to assign a label to instances, and models are trained to correctly predict the pre-assigned labels of a set examples). The difference between the two fields arises from the goal of generalization: while optimization algorithms can minimize the loss on a training set, machine learning is concerned with minimizing the loss on unseen samples.

History

As a scientific endeavour, machine learning grew out of the quest for artificial intelligence (AI). Already in the early days of AI, some researchers were interested in having machines learn from data. They attempted to approach the problem with various symbolic methods, as well as what were then termed "neural networks"; these were mostly perceptrons and other models that were later found to be reinventions of the generalized linear models of statistics. Probabilistic reasoning was also employed, especially in automated medical diagnosis.

However, an increasing emphasis on the logical, knowledge-based approach caused a rift between AI and machine learning. Probabilistic systems were plagued by theoretical and practical problems of data acquisition and representation. By 1980, expert systems had come to dominate AI, and statistics was out of favour. Work on symbolic/knowledge-based learning did continue within AI, leading to inductive logic programming, but the more statistical line of research was now outside the field of AI proper, in pattern recognition and information retrieval. Neural networks research had been
abandoned by AI and computer science around the same time. This line, too, was continued outside the AI/CS field, as "connectionism", by researchers from other disciplines.

Machine learning, reorganized as a separate field, started to flourish in the 1990s. The field changed its goal from achieving artificial intelligence to tackling solvable problems of a practical nature. It shifted focus away from the symbolic approaches it had inherited from AI, and toward methods and models borrowed from statistics and probability theory. It also benefitted from the increasing availability of digitized information, and the possibility to distribute that via the Internet.

**Relation to statistics**

Machine learning and statistics are closely related fields. According to Michael I. Jordan, the ideas of machine learning, from methodological principles to theoretical tools, have had a long pre-history in statistics. He also suggested the term data science as a placeholder to call the overall field.

**Clustering**

Cluster analysis is the assignment of a set of observations into subsets (called clusters) so that observations within the same cluster are similar according to some predesignated criterion or criteria, while observations drawn from different clusters are dissimilar. Different clustering techniques make different assumptions on the structure of the data, often defined by some similarity metric and evaluated for example by internal compactness (similarity between members of the same cluster) and separation between different clusters. Other methods are based on estimated density and graph connectivity. Clustering is a method of unsupervised learning, and a common technique for statistical data analysis.

**Bayesian networks**

A Bayesian network, belief network or directed acyclic graphical model is a probabilistic graphical model that represents a set of random variables and their conditional independencies via a directed acyclic graph (DAG). For example, a Bayesian network could represent the probabilistic relationships between diseases and symptoms. Given symptoms, the network can be used to compute the probabilities of the presence of various diseases. Efficient algorithms exist that perform inference and learning.

**Neural networks**

For sources and references to relevant literature: https://en.wikipedia.org/wiki/Artificial_neural_network

An artificial neural network (ANN) learning algorithm, usually called "neural network" (NN), is a learning algorithm that is inspired by the structure and functional aspects of biological neural networks. It is used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. Artificial neural networks are generally presented as systems of interconnected "neurons" which exchange messages between each other. The connections have numeric weights that can be tuned based on experience, making neural nets adaptive to inputs and capable of learning.

For example, a neural network for handwriting recognition is defined by a set of input neurons which may be activated by the pixels of an input image. After being weighted and transformed by a function (determined by the network's designer), the activation of these neurons are then passed on to other neurons. This process is repeated until finally, an output neuron is activated. This determines which character was read.
Like other machine learning methods - systems that learn from data - neural networks have been used to solve a wide variety of tasks that are hard to solve using ordinary rule-based programming, including computer vision and speech recognition.

Modern neural networks are non-linear statistical data modelling tools. They are usually used to model complex relationships between inputs and outputs, to find patterns in data, or to capture the statistical structure in an unknown joint probability distribution between observed variables.

There is no single formal definition of what an artificial neural network is. However, a class of statistical models may commonly be called neural if it possesses the following characteristics:

- contains sets of adaptive weights, i.e. numerical parameters that are tuned by a learning algorithm
- capability of approximating non-linear functions of their inputs
- the adaptive weights can be thought of as connection strengths between neurons, which are activated during training and prediction

Neural networks are similar to biological neural networks in the performing of functions collectively and in parallel by the units, rather than there being a clear delineation of subtasks to which individual units are assigned. The term neural network usually refers to models employed in statistics, cognitive psychology and artificial intelligence.

In modern software implementations of artificial neural networks, the approach inspired by biology has been largely abandoned for a more practical approach based on statistics and signal processing. In some of these systems, neural networks or parts of neural networks (like artificial neurons) form components in larger systems that combine both adaptive and non-adaptive elements. While the more general approach of such systems is more suitable for real-world problem solving, it has little to do with the traditional, artificial intelligence connectionist models. What they do have in common, however, is the principle of non-linear, distributed, parallel and local processing and adaptation. Historically, the use of neural network models marked a directional shift in the late eighties from high-level (symbolic) AI, characterized by expert systems with knowledge embodied in if-then rules, to low-level (sub-symbolic) machine learning, characterized by knowledge embodied in the parameters of a dynamical system.

**Data mining and knowledge discovery**

For sources and references to relevant literature:  

Data mining (the analysis step of the "Knowledge Discovery in Databases" process, or KDD), is the process of discovering patterns in large data sets involving methods at the intersection of artificial intelligence, machine learning, statistics, and database systems. The overall goal of the data mining process is to extract information from a data set and transform it into an understandable structure for further use. Aside from the raw analysis step, it involves database and data management aspects, data pre-processing, model and inference considerations, interestingness metrics, complexity considerations, post-processing of discovered structures, visualization, and online updating.

The actual data mining task is the automatic or semi-automatic analysis of large quantities of data to extract previously unknown, interesting patterns such as groups of data records (cluster analysis), unusual records (anomaly detection), and dependencies (association rule mining). This usually involves using database techniques such as spatial indices. These patterns can then be seen as a kind...
of summary of the input data, and may be used in further analysis or, for example, in machine learning and predictive analytics. For example, the data mining step might identify multiple groups in the data, which can then be used to obtain more accurate prediction results by a decision support system. Neither the data collection, data preparation, nor result interpretation and reporting are part of the data mining step, but do belong to the overall KDD process as additional steps.

The related terms data dredging, data fishing, and data snooping refer to the use of data mining methods to sample parts of a larger population data set that are (or may be) too small for reliable statistical inferences to be made about the validity of any patterns discovered. These methods can, however, be used in creating new hypotheses to test against the larger data populations.

In the 1960s, statisticians used terms like "data fishing" or "data dredging" to refer to what they considered the bad practice of analysing data without an a-priori hypothesis. The term "data mining" appeared around 1990 in the database community.

The manual extraction of patterns from data has occurred for centuries. Early methods of identifying patterns in data include Bayes' theorem (1700s) and regression analysis (1800s). Computer technology has dramatically increased data collection, storage, and manipulation ability. As data sets have grown in size and complexity, direct "hands-on" data analysis has increasingly been augmented with indirect, automated data processing, aided by other discoveries in computer science, such as neural networks, cluster analysis, genetic algorithms (1950s), decision trees and decision rules (1960s), and support vector machines (1990s). Data mining is the process of applying these methods with the intention of uncovering hidden patterns in large data sets. It bridges the gap from applied statistics and artificial intelligence to database management by exploiting the way data is stored and indexed in databases to execute the actual learning and discovery algorithms more efficiently, allowing such methods to be applied to ever larger data sets.

**Business intelligence (BI)**


**Business intelligence (BI)** is the set of techniques and tools for the transformation of raw data into meaningful and useful information for business analysis purposes. BI technologies are capable of handling large amounts of unstructured data to help identify, develop and otherwise create new strategic business opportunities. The goal of BI is to allow for the easy interpretation of these large volumes of data. Identifying new opportunities and implementing an effective strategy based on insights can provide businesses with a competitive market advantage and long-term stability.

BI technologies provide historical, current and predictive views of business operations. Common functions of business intelligence technologies are reporting, online analytical processing, analytics, data mining, process mining, complex event processing, business performance management, benchmarking, text mining, predictive analytics, and prescriptive analytics.

BI can be used to support a wide range of business decisions ranging from operational to strategic. Basic operating decisions include product positioning or pricing. Strategic business decisions include priorities, goals and directions at the broadest level. In all cases, BI is most effective when it combines data derived from the market in which a company operates (external data) with data from company sources internal to the business such as financial and operations data (internal data). When combined, external and internal data can provide a more complete picture which, in effect, creates an "intelligence" that cannot be derived by any singular set of data.

In their review of Business Intelligence technology, Chaudhury et al. offer the following description:
“Business intelligence (BI) software is a collection of decision support technologies for the enterprise aimed at enabling knowledge workers such as executives, managers, and analysts to make better and faster decisions. The past two decades have seen explosive growth, both in the number of products and services offered and in the adoption of these technologies by industry. This growth has been fuelled by the declining cost of acquiring and storing very large amounts of data arising from sources such as customer transactions in banking, retail as well as in e-businesses, RFID tags for inventory tracking, email, query logs for Web sites, blogs, and product reviews. Enterprises today collect data at a finer granularity, which is therefore of much larger volume. Businesses are leveraging their data asset aggressively by deploying and experimenting with more sophisticated data analysis techniques to drive business decisions and deliver new functionality such as personalized offers and services to customers. Today, it is difficult to find a successful enterprise that has not leveraged BI technology for its business. For example, BI technology is used in manufacturing for order shipment and customer support, in retail for user profiling to target grocery coupons during checkout, in financial services for claims analysis and fraud detection, in transportation for fleet management, in telecommunications for identifying reasons for customer churn, in utilities for power usage analysis, and health care for outcomes analysis.”

Everything in this description seems to be as applicable to Big Data as to Business Intelligence. The authors summarize:

- The cost of data acquisition and data storage has declined significantly. This has increased the appetite of businesses to acquire very large volumes in order to extract as much competitive advantage from it as possible.
- New massively parallel data architectures and analytic tools go beyond traditional parallel SQL data warehouses and OLAP engines.
- The need to shorten the time lag between data acquisition and decision making is spurring innovations in business intelligence technologies.

**Big data**

When was the term “Big Data” first coined, and by whom, and when did someone first try to define the concept of “Big Data”, and who was that person? These two questions do not necessarily have the same answer. It seems to be very difficult to establish when and by whom the term was first used, as well as when and by whom the concept a first definition of the concept was formulated and published, by a scientist or by a practitioner.

Today it is common to associate the concept of “Big Data” with the so-called 3Vs: volume, velocity, and variety. Doug Laney of the META Group (now a part of Gartner) is often recognized as the originator of the 3Vs, based on his research note Laney (2001). However, it should be noted that Doug Laney never mentions the term “Big Data” in this research note. He rather uses the 3Vs as labels for three data management trends that he expects to become important, and he describes these development trends in a way that has clear resemblances with what we call today “Big Data”.

On the other hand, if one makes a literature search for the word combination “big data”, one will get hits from the 1960’s and 1970’s in phrases like “big data files”, “big databases”, etc., although similar terms like “large files”, “large databases”, and “very large databases” were probably more common in documents from that time. However, the concepts corresponding to those terms were rather different from what we think of as “big data” today – even if all these concepts, including “big data” of course, are still rather fuzzy. But fuzzy concepts are not necessarily bad – they often stimulate critical and innovative thinking among academics and serious practitioners, although sales people often misuse them for their own purposes and thereby devaluate their value and usefulness.
Diebold (2012) mentions a few early usages of the term “big data”, which are in the spirit of modern versions of the concept, as suggested by the following quotations from Diebold’s paper:

- “There is, however, some pre-2000 (non-academic, unpublished) activity that is spot-on. In particular, Big Data the term, coupled with awareness of Big Data the phenomenon, was clearly percolating at Silicon Graphics (SGI) in the mid-1990s. John Mashey, retired former Chief Scientist at SGI, produced a 1998 SGI slide deck entitled ‘Big Data and the Next Wave of InfraStress,’” which demonstrates clear awareness of Big Data the phenomenon, http://static.usenix.org/event/usenix99/invited_talks/mashey.pdf.”

- “Related, SGI ran an ad that featured the term Big Data in Black Enterprise (March 1996, p. 60), several times in Info World (starting November 17, 1997, p. 30), and several times in CIO (starting February 15, 1998, p. 5). Clearly then, Mashey and the SGI community were on to Big Data early, using it both as an advertising hook and as a unifying theme for technical seminars.”

- “There is also at least one more relevant pre-2000 Big Data reference in computer science. It is subsequent to Mashey et al., but interestingly, it comes from the academic as opposed to industry part of the computer science community. Weiss and Indurkhya (1998) note that “...very large collections of data...are now being compiled into centralized data warehouses, allowing analysts to make use of powerful methods to examine data more comprehensively. In theory, ‘big data’ can lead to much stronger conclusions for data-mining applications, but in practice many difficulties arise.”

The conclusion in Diebold (2012) is also worth quoting:


Are “big data” different from other data?

Are “big data” different from other data? Is the concept of “Big Data” different from concepts like “Business Intelligence” (BI), “data mining”, and “Decision Support Systems” (DSS)? Yes and no.

Evelson (2015) compares a definition of “Business Intelligence” with a definition of “Big Data”. Both definitions originate from the company he is working for, Forrester Research, www.forrester.com, a marketing research company.

Forrester’s definition of “Business Intelligence” reads:

- Business Intelligence: A set of methodologies, processes, architectures, and technologies that transform raw data into meaningful and useful information used to enable more effective strategic, tactical, and operational insights and decision-making.
Forrester’s definition of “Big Data” reads:

- **Big Data:** The practices and technologies that close the gap between the data available and the ability to turn that data into business insight.

As Evelson says; while BI has been a thriving market for decades and will continue to flourish for the foreseeable future, the world doesn't stand still and:

- Recognizes a need for more innovation. Some of the approaches in earlier generation BI applications and platforms started to hit a ceiling a few years ago. For example, SQL and SQL-based database management systems (DBMS), while mature, scalable, and robust, are not agile and flexible enough in the modern world where change is the only constant.

- Needs to address some of the limitations of earlier generation BI. In order to address some of the limitations of more traditional and established BI technologies, big data offers more agile and flexible alternatives to democratize all data, such as NoSQL, among many others.

It is hard to see that the two definitions would correspond to different concepts. One would rather conclude that the terms “Business Intelligence” and “Big Data” are synonyms, referring to the same concept. However, it should be noted that both definitions are purpose-oriented. They imply that “Business Intelligence” and “Big Data” have the same intention, the same purpose, that of exploiting whatever data you have, by whatever methods you can think of, into useful insights and decisions.

But this common objective of “Business Intelligence” and “Big Data” does not exclude the possibility that the two concepts are associated with different roads towards the objective: different data sources, different kinds of data, different analytical methods, different computing methods, etc. And indeed, such differences between the two concepts – and other concepts within the same family – do exist, both in theory and in practice.

While new terms are important to emphasize the need to evolve, change, and innovate, what’s infinitely more imperative is that both strive to achieve the same goal: transform data into information and insight.

Contrary to some of the market hype, data democratization and big data do not eliminate the need for certain basics, such as data governance, data quality, master data management, data modelling, well thought out data architecture, etc. All of the typical end-to-end steps necessary to transform raw data into insights still have to happen; now they may just happen in different places and at different times in the process.

**The 3Vs and other core characteristics of Big Data**

While the objectives and purposes of Big Data should be an important part of a definition of the concept, a purpose-oriented definition is not enough to distinguish it from phenomena with similar objectives. We need to characterize Big Data in other ways as well. Most definitions of Big Data, which are in use today, seem to have a core of characteristics in common – the core of characteristics that were first formulated by Doug Laney in 2001 and which are known as the 3Vs.

In a 2001 research report and related lectures, META Group (now Gartner) analyst Doug Laney defined data growth challenges and opportunities as being three-dimensional, i.e.

- **volume** (amount of data)
- **velocity** (speed of data in and out)
variety (range of data types and sources)

Already in this early research report Doug Laney gave a quite extensive elaboration of the meaning and implications of the 3Vs. Nevertheless, the report never mentions the term "Big Data". It rather sees the 3Vs as part of ongoing and future trends in Data Management Solutions, summarized in the figure below:

Here is a verbal summary of Doug Laney’s vision from 2001:

“3D Data Management: Controlling Data Volume, Velocity and Variety. Current business conditions and mediums are pushing traditional data management principles to their limits, giving rise to novel and more formalized approaches.

META Trend: During 2001/02, leading enterprises will increasingly use a centralized data warehouse to define a common business vocabulary that improves internal and external collaboration. Through 2003/04, data quality and integration woes will be tempered by data profiling technologies (for generating metadata, consolidated schemas, and integration logic) and information logistics agents. By 2005/06, data, document, and knowledge management will coalesce, driven by schema-agnostic indexing strategies and portal maturity.

The effect of the ecommerce surge, a rise in merger & acquisition activity, increased collaboration, and the drive for harnessing information as a competitive catalyst is driving enterprises to higher levels of consciousness about how data is managed at its most basic level. In 2001/02, historical, integrated databases (e.g. data warehouses, operational data stores, data marts), will be leveraged not only for intended analytical purposes, but increasingly for intraenterprise consistency and coordination. By 2003/04, these structures (including their associated metadata) will be on par with application portfolios, organization charts and procedure manuals for defining a business to its employees and affiliates.
Data records, data structures, and definitions commonly accepted throughout an enterprise reduce fiefdoms pulling against each other due to differences in the way each perceives where the enterprise has been, is presently, and is headed. Readily accessible current and historical records of transactions, affiliates (partners, employees, customers, suppliers), business processes (or rules), along with definitional and navigational metadata (see ADS Delta 896, 21st Century Metadata: Mapping the Enterprise Genome, 7 Aug 2000) enable employees to paddle in the same direction. Conversely, application-specific data stores (e.g. accounts receivable versus order status), geographic-specific data stores (e.g. North American sales vs. International sales), offer conflicting, or insular views of the enterprise, that while important for feeding transactional systems, provide no “single version of the truth,” giving rise to inconsistency in the way enterprise factions function.

While enterprises struggle to consolidate systems and collapse redundant databases to enable greater operational, analytical, and collaborative consistencies, changing economic conditions have made this job more difficult. Ecommerce, in particular, has exploded data management challenges along three dimensions: volumes, velocity and variety. In 2001/02, IT organizations must compile a variety of approaches to have at their disposal for dealing with each.”

Gartner, and now much of the industry, continue to use this "3Vs" model for describing big data. In 2012, Gartner updated its definition as follows:

- "Big data are high volume, high velocity, and/or high variety information assets that require new forms of processing to enable enhanced decision making, insight discovery and process optimization."

If Gartner’s definition (the 3Vs) is still widely used, the growing maturity of the concept fosters a more sound difference between Big Data and Business Intelligence, regarding data and their use:

- Business Intelligence uses descriptive statistics with data with high information density to measure things, detect trends, etc.

- Big Data uses inductive statistics with data with low information density, whose huge volume allow to infer laws (regressions…) and thus giving (with the limits of inference reasoning) to Big Data some predictive capabilities.

AAPOR (2015) provides a brief, and yet relatively precise, informative, and comprehensive summary of how the 3Vs could be interpreted in a contemporary e-society:

- **Volume**: This refers to the sheer amount of data available for analysis. This volume of data is driven by the increasing number of data collection instruments (e.g., social media tools, mobile applications, sensors) as well as the increased ability to store and transfer those data with recent improvements in data storage and networking.

- **Velocity**: This refers to both the speed at which these data collection events can occur, and the pressure of managing large streams of real-time data. Across the means of collecting social information, new information is being added to the database at rates ranging from as slow as every hour or so, to as fast as thousands of events per second.

- **Variety**: This refers to the complexity of formats in which Big Data can exist. Besides structured databases, there are large streams of unstructured documents, images, email messages, video, links between devices and other forms that create a heterogeneous set of data points. One
effect of this complexity is that structuring and tying data together becomes a major effort, and therefore a central concern of Big Data analysis.

Volume

Since the childhood of computers, we have become so spoilt by the rapid developments in hardware technology that we have learnt not to regard the capacity of hardware as a bottleneck. Even if it should be a bottleneck for the moment, we only have to wait a couple of years for new technological developments that will solve the capacity problems for us. However, this “truth” may not be quite indisputable when it comes to Big Data. When we speak about Big Data, it will typically not be questions of megabytes or terabytes – it will be petabytes or more – and then the capacity of technology may be a problem for the foreseeable future.

Many actors, and in particular Google have taken this problem seriously, and new hardware and software solutions have been developed, which have already made it possible to cope with the problems of volumes in constructive ways.

The hardware solutions include features such as parallel processing, computer networks, grid technology, cluster computing.

Velocity

The concept of velocity is particularly relevant and challenging when it comes to capturing and analysing real-time streaming data. Real-time streaming is the process of delivering data about processes and events as they occur. In this context, “real-time” means “very short latency or delay”. The total latency may be structured into data latency, analysis latency, and action latency, where:

- **data latency** is the time taken to collect and store the data
- **analysis latency** is the time taken to analyse the data and turn it into actionable information
- **action latency** is the time taken to react to the information and take action

All real-time systems have some latency, but the goal in real-time big data analysis is to minimize the time from an event happening in a real-world process to a corrective action or notification being initiated, that is, to reduce all three latencies to as close to zero as possible, whereas traditional business intelligence only seeks to reduce data latency and does not address analysis latency or action latency since both are governed by manual processes.

A more relevant formulation of the goal may be to say that information should be delivered just before it is required, and not necessarily in real-time.

With today’s technology, transaction data generated by business events may be directly fed into a data warehouse, which instantly updates and maintains the current state of the business. Such a data warehouse may not only support the classic strategic functions of data warehousing for deriving information and knowledge from passed business activities; it may also provide real-time tactical support to drive business actions that react to events as they occur. This use of modern technology is called real-time business intelligence.

While traditional business intelligence presents historical data for manual analysis, real-time business intelligence compares current business events with historical patterns to detect problems or opportunities automatically. This automated analysis capability enables corrective actions to be initiated and/or business rules to be adjusted to optimize business processes.
Real-time business intelligence makes sense for some applications but not for others – a fact that organisations need to take into account as they consider investments in tools for capturing, storing, and analysis of real-time data streams.

In today’s competitive environment with high consumer expectation, decisions that are based on the most current data available may be essential for improving customer relationships, maximizing operational efficiencies, and increasing revenues. In some times of operations, for example traffic control, real-time decision-support based on streaming data may even save lives.

Software supporting real-time streaming analytics is emerging. Microsoft Azure is an example.

Sources:


**Variety**

The variety of big data is often a question of variety in several dimensions, and this multidimensional variety may cause considerable complexity, which is difficult to cope with in practice.

Some examples of variety dimensions:

**Data sources**, for example business operations generating real-time data streams, administrative registers and information systems in businesses and governmental agencies, social media, internet-connected sensors and “things” – cf the Internet of Things (IoT), traditional statistical surveys

**Data types**, for example structured vs unstructured, quantitative vs qualitative

**Data quality**, for example relevance, accuracy, timeliness, comparability, coherence, availability ...; cf Eurostat (2003 and later)

Variety in data sources

A major advantage of many of the new data sources exemplified above is that the data are readily available and cheap to acquire.

Variety in data types

For example, a researcher will likely not have any control of data from different social media platforms and it could be difficult to decipher a text from social media. For administrative data on the other hand, a statistical agency can form partnership with owners of the data and influence the design of the data. Administrative data are more structured, well defined and more is known about the data than perhaps other Big Data sources.

Data quality

The sources used for obtaining big data are typically less controllable by the users than the traditional sources for statistical and analytical data, such as statistical surveys and scientific
experiments. The researchers and practitioners trying to make use of big data from most of the sources mentioned above have to accept what is available and make the best of it.

Administrative and operational information systems will typically be well suited, well structured, and of good quality for the administrative and operational purposes that they have been designed for, although, as just mentioned, they may not be as well suited for statistical and analytical purposes. Maybe even more importantly, the kind of qualities which are important for statistical and analytical purposes may not be known or well described.

For administrative and operational purposes, it is important that registered information about individual objects is correct, so that individual cases concerning individual persons and enterprises are handled correctly. For statistical and analytical purposes data errors on the individual level may not be serious, but it may be serious if the data are biased, since this may affect conclusions and decisions on the aggregated level.

“Found data” vs “made data”

See AAPOR (2015).

In the context of public opinion studies, a survey researcher could measure opinion by prompt responses about a topic that may never naturally appear in a Big Data source. On the other hand, the “found” data of social media are “nonreactive,” or “naturally occurring,” so that a data point, devoid of researcher-manipulation, may be a more accurate representation of a true opinion or behaviour.

While the scale of data often used is what receives prominence, hence the name Big Data, it is actually this “found” nature of the data that is of concern to survey researchers. For example, since the data were not created for research there often are no informed consent policies surrounding their creation, leading to ethical concerns. Additionally, there are statistical concerns with respect to the representative nature of the data. While these are serious concerns, they are not necessarily fatal to the proposition Big Data can be used to construct social insights.

Data created through administering the tax systems, social programs, and regulation, are also a form of “found” data. They are not created with a specific scientific research question in mind, but rather are the by-product for the respective administrative processes. Just like (certain types of) paradata are created as a by-product of survey data collections. In many instances these administrative data are large in volume, and share the unstructured nature of many other Big Data sources.

**Predictive analytics**

For more information on this topic and many useful references to relevant literature, see Wikipedia (Predictive analytics), [https://en.wikipedia.org/wiki/Predictive_analytics](https://en.wikipedia.org/wiki/Predictive_analytics)

More advanced analysis of big data is often associated with so-called predictive analytics. It is easy for statisticians to see, how traditional, well established statistical methods “reoccur” in the new contexts of “machine learning”, “neural networks”, “data mining”, “business intelligence”, and “big data”. However, both statisticians and non-statisticians must observe that new conditions, assumptions, and models may often apply, when the old methods are used in new contexts. Some of the methods, especially those based on machine learning and artificial neural networks, may not be familiar to traditional statisticians, even though these methods too are based on statistical methods – actually in opposition to what used to be mainstream knowledge- and rule-based artificial intelligence methods.
Definition

Predictive analytics uses data to predict trends and behaviour patterns. Often an unknown event of interest is in the future, but predictive analytics can be applied to any type of unknown whether it be in the past, present, or future, for example, identifying suspects after a crime has been committed, or credit card fraud as it occurs.

The core of predictive analytics relies on capturing relationships between explanatory variables and predicted variables from past occurrences, and exploiting these relationships to predict the unknown outcome. It is important to note, however, that the accuracy and usability of results will depend greatly on the level of data analysis and the quality of assumptions.

Predictive analytics is often defined as predicting at a rather detailed level of granularity. This distinguishes it from forecasting. Predictive analytic learns from experience (data) to predict the future behaviour of individuals in order to drive better decisions.

Predictive analytics encompasses a variety of statistical techniques from modelling, machine learning, and data mining that analyse current and historical facts to make predictions about future, or otherwise unknown, events.

In business, predictive models exploit patterns found in historical and transactional data to identify risks and opportunities. Models capture relationships among many factors to allow assessment of risk or potential associated with a particular set of conditions, guiding decision making for candidate transactions.

Predictive analytics may provide a predictive score (probability) for each individual (customer, employee, healthcare patient, product, vehicle, component, machine, or other organisational unit) in order to determine, inform, or influence organisational processes that pertain across large numbers of individuals, such as in marketing, credit risk assessment, fraud detection, manufacturing, healthcare, and government operations including law enforcement.

Predictive analytics is used in actuarial science, marketing, financial services, insurance, telecommunications, retail, travel, healthcare, pharmaceuticals and other fields. One of the most well-known applications is credit scoring, which is used throughout financial services. Scoring models process a customer’s credit history, loan application, customer data, etc., in order to rank-order individuals by their likelihood of making future credit payments on time.

Different types of models

Predictive models

Predictive models are models of the relation between the specific performance of a unit in a sample and one or more known attributes or features of the unit. The objective of the model is to assess the likelihood that a similar unit in a different sample will exhibit the specific performance. This category encompasses models in many areas, such as marketing or fraud detection. Predictive models often perform calculations during live transactions, for example, to evaluate the risk or opportunity of a given customer or transaction, in order to guide a decision.

The available sample units with known attributes and known performances is referred to as the “training sample.” The units in other samples, with known attributes but unknown performances, are referred to as “out of training sample” units. For example, the training sample may consist of literary attributes of writings by Victorian authors, and the out of training sample unit may be newly found.
writing with unknown authorship; a predictive model may aid in attributing a work to a known author. Another example is given by analysis of blood splatter in simulated crime scenes in which the out of sample unit is the actual blood splatter pattern from a crime scene.

**Descriptive models**

Descriptive models quantify relationships in data in a way that is often used to classify customers or prospects into groups. Unlike predictive models that focus on predicting a single customer behaviour (such as credit risk), descriptive models identify many different relationships between customers or products. Descriptive models do not rank-order customers by their likelihood of taking a particular action the way predictive models do. Instead, descriptive models can be used, for example, to categorize customers by their product preferences and life stage. Descriptive modelling tools can be utilized to develop further models that can simulate large number of individualized agents and make predictions.

**Decision models**

Decision models describe the relationship between all the elements of a decision — the known data (including results of predictive models), the decision, and the forecast results of the decision — in order to predict the results of decisions involving many variables. These models can be used in optimization. Decision models are generally used to develop decision logic or a set of business rules that will produce the desired action for every customer or circumstance.

**Applications**

We list below a few examples where predictive analytics has shown positive impact in recent years:

**Analytical customer relationship management (CRM)**

Methods of predictive analysis are applied to customer data to pursue CRM objectives, which involve constructing a holistic view of the customer no matter where their information resides in the company or the department involved. Analytical CRM can be applied throughout the customer’s lifecycle (acquisition, relationship growth, retention, and win-back).

**Clinical decision support systems**

Experts use predictive analysis in health care to determine which patients are at risk of developing certain conditions, like diabetes, asthma, heart disease, etc. Sophisticated clinical decision support systems incorporate predictive analytics to support medical decision making at the point of care.

**Collection analytics**

Many portfolios have a set of delinquent customers who do not make their payments on time. The financial institution has to undertake collection activities on these customers to recover the amounts due. A lot of collection resources are wasted on customers who are difficult or impossible to recover. Predictive analytics can help optimize the allocation of collection resources by identifying the most effective collection agencies, contact strategies, legal actions, and other strategies to each customer, thus significantly increasing recovery and reducing collection costs.

**Fraud detection**

Fraud is a big problem for many businesses and can be of various types: inaccurate credit applications, fraudulent transactions (both offline and online), identity thefts, and false insurance claims. A predictive model can help to identify high-risk fraud candidates in business or the public sector.
example, the Internal Revenue Service (IRS) of the United States uses predictive analytics to identify tax fraud.

Predictive behaviour analysis is also used for web fraud detection. Heuristics are used in order to study normal web user behaviour and detect anomalies indicating fraud attempts.

**Portfolio, product or economy-level prediction**

Often the focus of analysis is not the consumer but the product, portfolio, firm, industry, or the economy. A retailer may be interested in predicting store-level demand. Or the Federal Reserve Board might be interested in predicting the unemployment rate. These types of problems can be addressed by predictive analytics using time series techniques. They can also be addressed via machine learning approaches which transform the original time series into a feature vector space, where the learning algorithm finds patterns that have predictive power.

**Risk management**

When employing risk management techniques, the purpose is to predict and benefit from a future scenario. Many businesses have to account for risk exposure due to their different services and determine the cost needed to cover the risk. For example, auto insurance providers need to determine the amount of premium to cover each automobile and driver. A financial company needs to assess a borrower’s potential and ability to pay before granting a loan. Predictive analytics can help estimate the chances of illness, default, bankruptcy, etc.

Predictive analytics in the form of credit scores have reduced the amount of time it takes for loan approvals, especially in the mortgage market where lending decisions are now made in a matter of hours rather than days or even weeks. Proper predictive analytics can lead to proper pricing decisions, which can help mitigate future risk of default.

**Analytical Techniques**

The approaches and techniques used to conduct predictive analytics can broadly be grouped into regression techniques and machine learning techniques.

**Regression techniques**

Regression models are the mainstay of predictive analytics. The focus lies on establishing a mathematical equation as a model to represent the interactions between the different variables in consideration. Depending on the situation, there are a wide variety of models that can be applied while performing predictive analytics. Some examples:

- Linear regression model
- Discrete choice models
- Logistic regression
- Multinomial logistic regression
- Probit regression
- Time series models
- Survival or duration analysis
- Classification and regression trees
- Multivariate adaptive regression splines
Machine learning techniques

Machine learning, a branch of artificial intelligence, was originally employed to develop techniques to enable computers to learn. Today, since it includes a number of advanced statistical methods for regression and classification, it finds application in a wide variety of fields including medical diagnostics, credit card fraud detection, face and speech recognition and analysis of the stock market. In certain applications it is sufficient to directly predict the dependent variable without focusing on the underlying relationships between variables. In other cases, the underlying relationships can be very complex and the mathematical form of the dependencies unknown. For such cases, machine learning techniques learn from training examples to predict future events.

Here are some of the methods used for predictive analytics:

- Neural networks
- Multilayer Perceptron (MLP)
- Radial basis functions
- Naïve Bayes for performing classifications tasks
- Pattern recognition methods, k-nearest neighbours
- Geospatial predictive modelling

A detailed study of machine learning can be found in


Tools

Historically, using predictive analytics tools—as well as understanding the results they delivered—required advanced skills. However, modern predictive analytics tools are no longer restricted to IT specialists. As more organisations adopt predictive analytics into decision-making processes and integrate it into their operations, they are creating a shift in the market toward business users as the primary consumers of the information. Business users want tools they can use on their own. Vendors are responding by creating new software that removes the mathematical complexity, provides user-friendly graphic interfaces and/or builds in short cuts that can, for example, recognize the kind of data available and suggest an appropriate predictive model.

Predictive analytics tools have become sophisticated enough to adequately present and dissect data problems, so that any data-savvy information worker can utilize them to analyse data and retrieve meaningful, useful results. For example, modern tools present findings using simple charts, graphs, and scores that indicate the likelihood of possible outcomes.

Criticism

There are plenty of sceptics when it comes to computers and algorithms abilities to predict the future, including Gary King, a professor from Harvard University and the director of the Institute for Quantitative Social Science. People are influenced by their environment in innumerable ways. Trying to understand what people will do next assumes that all the influential variables can be known and measured accurately:

"People's environments change even more quickly than they themselves do. Everything from the weather to their relationship with their mother can change the way people think and act. All of those variables are unpredictable. How they will impact a person is even less predictable. If put in the same situation tomorrow, they may make a completely different decision. This means that a statistical
prediction is only valid in sterile laboratory conditions, which suddenly isn't as useful as it seemed before."

**Disruptive changes causing paradigm shifts**

Like never before in human history, the easy and instantaneous availability via the Internet of huge amounts of potentially relevant and useful data for virtually all kinds of data-supported research and decision-making has led to disruptive changes and a questioning of traditional scientific paradigms based on knowledge-building, understanding, and logical reasoning.

We have come to a point, where we really need to consider and draw further consequences from Alan Turing’s proposal in his paper "Computing Machinery and Intelligence" that the question "Can machines think?" be replaced with the question "Can machines do what we (as thinking entities) can do?" Maybe data-empowered and computer-supported systems, although still human-designed and human-constructed, can help us to achieve even more impressive information-based results than we can ourselves, by using methods which are fundamentally different from our human ways of thinking, modelling, analysing, reasoning, and deriving new knowledge?

Some pragmatic researchers and engineers associated with information disciplines and information-based systems, tools, and activities have gone so far as to declare established scientific methods obsolete, thereby provoking a lot of people. Peter Norvig, Google's Director of Research and co-author of the most popular artificial intelligence textbook in the world, is one of the provokers; Chris Anderson, Chief Editor of Wired Magazine, is another one.

**Peter Norvig** presents some of his arguments for the new paradigm in his article “Colorless green ideas learn furiously: Chomsky and the two cultures of statistical learning” in Significance (2012), pages 30–33. [http://onlinelibrary.wiley.com/doi/10.1111/j.1740-9713.2012.00590.x/epdf](http://onlinelibrary.wiley.com/doi/10.1111/j.1740-9713.2012.00590.x/epdf). The article deals with the topic of language translation, where Google Translate is the result of using the new paradigm. The language philosopher Noam Chomsky is critical, and Peter Norvig examines Chomsky's arguments in this article, which starts as follows:

“Language recognition programs use massive databases of words, and statistical correlations between those words, to translate or to recognise speech. But correlation is not causation. Do these statistical data-dredgings give any insight into how language works? Or are they a mere big-number trick, useful but adding nothing to understanding? One who holds the latter view is the theorist of language Noam Chomsky. Peter Norvig disagrees.”

**Chris Anderson** presents his provocations in his article “The End of Theory: The Data Deluge Makes the Scientific Method Obsolete” in Wired Magazine (2008), [http://archive.wired.com/science/discoveries/magazine/16-07/pb_theory](http://archive.wired.com/science/discoveries/magazine/16-07/pb_theory). Here are some statements from his article:

- "All models are wrong, but some are useful." So proclaimed statistician George Box 30 years ago, and he was right. But what choice did we have? Only models, from cosmological equations to theories of human behaviour, seemed to be able to consistently, if imperfectly, explain the world around us. Until now. Today companies like Google, which have grown up in an era of massively abundant data, don't have to settle for wrong models. Indeed, they don't have to settle for models at all. Sixty years ago, digital computers made information readable. Twenty years ago, the Internet made it reachable. Ten years ago, the first search engine crawlers made it a single database. Now Google and like-minded companies are sifting through the most measured age in history, treating this massive corpus as a laboratory of the human condition. They are the children of the Petabyte Age.
At the petabyte scale, information is not a matter of simple three- and four-dimensional taxonomy and order but of dimensionally agnostic statistics. It calls for an entirely different approach, one that requires us to lose the tether of data as something that can be visualized in its totality. It forces us to view data mathematically first and establish a context for it later. For instance, Google conquered the advertising world with nothing more than applied mathematics. It didn't pretend to know anything about the culture and conventions of advertising — it just assumed that better data, with better analytical tools, would win the day. And Google was right.

This is a world where massive amounts of data and applied mathematics replace every other tool that might be brought to bear. Out with every theory of human behaviour, from linguistics to sociology. Forget taxonomy, ontology, and psychology. Who knows why people do what they do? The point is they do it, and we can track and measure it with unprecedented fidelity. With enough data, the numbers speak for themselves.

The big target here isn't advertising, though. It's science. The scientific method is built around testable hypotheses. These models, for the most part, are systems visualized in the minds of scientists. The models are then tested, and experiments confirm or falsify theoretical models of how the world works. This is the way science has worked for hundreds of years.

Scientists are trained to recognize that correlation is not causation, that no conclusions should be drawn simply on the basis of correlation between X and Y (it could just be a coincidence). Instead, you must understand the underlying mechanisms that connect the two. Once you have a model, you can connect the data sets with confidence. Data without a model is just noise.

But faced with massive data, this approach to science — hypothesize, model, test — is becoming obsolete. Consider physics: Newtonian models were crude approximations of the truth (wrong at the atomic level, but still useful). A hundred years ago, statistically based quantum mechanics offered a better picture — but quantum mechanics is yet another model, and as such it, too, is flawed, no doubt a caricature of a more complex underlying reality.

Now biology is heading in the same direction. The models we were taught in school about “dominant” and “recessive” genes steering a strictly Mendelian process have turned out to be an even greater simplification of reality than Newton's laws. The discovery of gene-protein interactions and other aspects of epigenetics has challenged the view of DNA as destiny and even introduced evidence that environment can influence inheritable traits, something once considered a genetic impossibility.

In short, the more we learn about biology, the further we find ourselves from a model that can explain it.

There is now a better way. We can stop looking for models. We can analyse the data without hypotheses about what it might show. We can throw the numbers into the biggest computing clusters the world has ever seen and let statistical algorithms find patterns where science cannot.

The new availability of huge amounts of data, along with the statistical tools to crunch these numbers, offers a whole new way of understanding the world. Correlation supersedes
causation, and science can advance even without coherent models, unified theories, or really any mechanistic explanation at all.

- There's no reason to cling to our old ways. It's time to ask: What can science learn from Google?

For references, see the bibliography at the end of this report.

**Contrasting views**

Provocations like those by Norvig and Anderson have not been left without counter-arguments. Maybe a dialectical thesis-antithesis-synthesis debate will finally lead to a better understanding of different roads to new insights and new ways of knowledge formation supported by human beings, data, and computers in unprecedented cooperation.

At the present stage of this debate the following counter-arguments to the provocations by people like Norvig and Anderson have been presented.

**Jeff Leek:** “Why big data is in trouble: they forgot about applied statistics”,
http://simplystatistics.org/2014/05/07/why-big-data-is-in-trouble-they-forgot-about-applied-statistics/:

The idea that statistics is important for big data has exploded into the popular media. Here are a few examples, starting with the Lazer et. al paper in *Science* that got the ball rolling on this idea:

- The parable of Google Flu: traps in big data analysis
- Big data are we making a big mistake?
- Google Flu Trends: the limits of big data
- Eight (No, Nine!) Problems with Big Data

These articles warn about issues that statisticians have been thinking about for a very long time.

**Kevin Gold:** “Norvig vs. Chomsky and the Fight for the Future of AI”,

For references, see the bibliography at the end of this report.

**A paradigm shift based on disruptive changes?**

The concept of Big Data implies a revolution in information society for many stakeholders: domain scientists and researchers as well as statistical methodologists and business practitioners. The revolution is associated with a paradigm shift, and it is caused and enabled by a number of so-called disruptive changes in technologies and methodologies, such as:

- new data sources and new data generation methods providing an unprecedented volume and richness of data available
- new storage and processing capabilities
- new database management software capable of efficient management and combination of different kinds of data structures and different kinds of data
- new methods for visualisation, animation, analysis, and conclusions
• “made data” replaced by “found data”

• computer-aided systems operated, monitored, evaluated, and improved by humans, replaced by human-aided self-controlling and self-learning systems

• realtime analysis of and responses to online streaming data enabled by capable and efficient hardware and software

Each one of these developments and changes are by themselves disruptive or at least dramatic, and together they may imply a change of paradigm, a scientific revolution.
CHAPTER 3. The information society and the information economy

The society, which we are now living in has developed from an agricultural society to an industrial society to the present information society, or e-society as it is sometimes called. One of the debated issues is whether the fundamental economic conditions in e-society are so different from the conditions in “the old economy” that we must talk about “a new economy” with new economic theories and rules.

Historical perspective

The information economy is the latest phase in the advancement of a society’s economy. In the information economy, the development and use of tools based on information technology has become extremely important and contributes more and more to socio-economic wellbeing and progress.

Tools based on information technology, such as computers and computer software, typically amplify the power of the human mind by facilitating intellectual processes. During the preceding industrial era, the development and use of another category of tools facilitated rationalisation and automation of manual manufacturing processes, producing material goods. Before that, in an economy based on agriculture and natural resources (mining, forestry, etc.), manpower was the dominating production factor.

Manpower is still an important production factor, but now more so in the service industry. Human brainpower has of course always been important, not least in the transitions from one type of economy to another. However, with the rapidly increasing availability of powerful information technology based products and services, the impact and productivity of human brainpower has increased drastically, and will continue to do so for the foreseeable future.

In summary, a society’s socio-economic development may be structured into four phases:

- **Phase 1.** This phase is dominated by agriculture and exploration and exploitation of natural resources. The goods produced are food, raw materials, handmade tools, and energy.

- **Phase 2.** During this phase, manufacturing of goods, as well as tools and machines to assist in the production of food, goods, and energy, becomes more and more important, and more and more efficiently done, first by specialized craftsmen, later on a larger scale by specialized factories, using tools and machines, which are themselves manufactured with the help of other tools and machines in other factories. Manual labour is replaced or supported by machines, thus increasing the productivity of each worker. Also the farmers are empowered by machines, produced by the manufacturing industry, and thus the productivity increases in the agricultural sector, too.

- **Phase 3.** During this phase, the production of food and physical products and tools have become so automated and rationalized that a relatively larger share of the economy can be devoted to the production of services. Services were needed also during earlier phases of the socio-economic development, but during those phases many services could only be demanded by relatively few rich people, and by businesses. Since farmers and workers have now become more productive and therefore earn more money, they are able to demand and pay for more services.
Phase 4. During this phase modern information technology, in the shape of computers, computer software, and communication networks (like the Internet), is introduced and used on a large scale in all sectors of society. While the traditional, mechanical technology amplifies the physical capabilities of man, information technology amplifies mental and intellectual capabilities. The information technology has enabled large-volume production and consumption of non-expensive products and services, based on information. Computers are typically much faster and less error-prone than human beings in performing mental operations. The human being is still superior in tasks requiring imagination, innovation, and unplanned and sometimes unexpected initiatives, but even in performing such tasks, people may increase their efficiency by using advanced tools based on information and information technology.

Through the history, the relative importance of different sectors in the economy has changed dramatically. For example, agriculture accounts for only a few percent of the gross national product of an advanced society, and the manufacturing industry is going the same way as agriculture. There is an increasing demand for social services in modern societies. A major problem here is how to finance this demand for labour-intensive and often publicly financed services without increasing taxes to unacceptable levels. Inexpensive information technology and information services could play an important role to improve the productivity and efficiency in service production – as we have already seen in white-collar work both in the industry and in governments on different levels.

Information as products and services

A modern information society (e-society) is associated with computers and computerized systems. But it is also associated with information and information-based products and services. Computers and computerized systems and networks, like the Internet, have made it so much simpler and cheaper to create, reproduce, and communicate information represented by digitalized data. This has in turn created the basis for a new important sector in the economy of modern societies, an economy based on information products and information services. Of course such a sector existed even before computers and digitalized data, but the importance of the information sector and the e-based economy is growing rapidly.

The information economy is based on information products and services, whereas the traditional economy is based on farming, manufacturing and industrial production of material goods, and labour-intensive services.

The information economy – a new economy?

Around the year 2000 there was a hype around “the new economy”, an economy based on information technology and information products and services.

Is the information economy a new economy? During the IT hype in the beginning of this century, it became common to talk about a “new economy”, where the traditional laws of economics did not apply any longer. Entrepreneurs and venture capitalists used the term to defend huge investments in companies which had yet everything to prove. Year after year these companies produced only losses, and for many of them that was virtually the only thing they had produced, when the bubble became apparent and exploded. Only those who sold their shares in time became rich.

During the “IT hype” just described, it was suggested that the information economy is a completely new economy, governed by other economic laws than the traditional economy. This is not true. However, there are some cost parameters that have changed drastically in the information economy.
For example, the Internet has lowered the marginal cost for reproduction and distribution of information products to almost zero.

Why was the situation in the information economy in the beginning of this century so dramatic, so that even some economists and investors started to believe that the use of information technology would lead to a new economy, with new economic laws?

**What does classic economic theory say?**

Now let us look more carefully about what classic economic theory says about this situation:

1. According to traditional economic laws, which are still valid, companies competing on free markets will continue to produce and sell their products, as long as they get their marginal costs covered, that is, as long as the market price of the product is higher than the marginal cost of producing and selling it, it will add to the producer’s revenue and profit to produce and sell an extra instance of it.

2. On the other hand, in a well functioning market economy with perfect competition, the market price of a product cannot be much higher then the marginal cost of producing an extra instance of the product, because if one of the competing companies will try to charge a higher price, another company will outcompete that company by setting a price closer to the marginal cost of producing it.

3. Thus under perfect market conditions (perfect competition, profit-maximizing sellers, buyers with full information, etc), the price of a good will be equal to the marginal cost of producing another instance (unit) of the good. See, for example, Samuelson (1948), Clifton (1977), Lee (1998), and Mas-Colell, Whinston, and Green (1995).

There are several important assumptions, which must be fulfilled for a market to function well, and for competition to be “perfect”. For example, the competing companies must have equal access to equivalent production methods and tools, the competing products must be more or less identical as regards functionalities and qualities, and both producers and consumers of the product must have access to full information about the products and prices offered by all competing producers. Easily accessible and good quality information plays an important role for the functioning of a market economy – and this information must itself not be timely and inexpensive.

So what was new at the time of the “IT hype”? Products and services based on information was nothing new. But earlier the information contents of a product or a service had been tied to physical products and/or services performed by relatively well paid human beings, for example books, newspapers, music on LPs and CDs, advice given by consultants, etc.

The marginal cost of producing an information product (for example music), bundled with a physical product (for example a vinyl or CD record) and some manual service (for example in a record shop) would certainly be higher than 0. Hence there would be no problem for the seller of an information product to set a price a bit higher than the marginal price of producing a copy of the information contents of the product (for example a piece of music). The limit on a market with perfect competition would be a price a price equal to, or maybe even slightly higher than the total marginal costs of producing the physical product and manual service accompanying the sales of an additonal copy of the contents (for example a piece of music, or the contents of a newspaper).

Why “slightly higher”? Yes, because the competition will never be perfect, and the “overcharge” would anyhow only be “slight” as a percent of the total marginal cost.
However, when using modern information technology, the electronic product (for example a digital copy of a piece of music) would need no “physical package” (for example an album cover or a CD case), and the customer could download the music from the Internet by self-service; any accompanying information about the music could also be copied and downloaded from a website by the customer, without any costly sales-person interventions.

Thus when using modern information technology, the information products and services could become more “pure” and independent of physical products and human beings, for example electronic sound and video files, expert systems, comptuerized help functions, etc.

Recovering investments and development costs

As long as the total marginal cost is significantly higher than 0, it will not be so difficult to include a modest surcharge for development costs in the price. After all the competition is never perfect, and the economic laws do not apply to the last decimal.

However, in the case of digital products, produced and marketed by means of Internet-based methods, the marginal cost for producing and distributing an extra copy will be only slightly higher than 0. This makes it difficult for producers of information products to combine an attractive price for the products, while recovering high development costs. Even a surcharge which is small in absolute figures will be very high as a percentage of a figure close to 0.

A general dilemma for the producers of products in a well functioning market economy is how they could recover the costs for the investments and development activities that they have to make, before they can start producing and selling instances of the product. These costs as well as costs associated with risks of failures and unforeseen complications may be considerable, and if the producers cannot see good chances of recovering them one way or the other, there is no incentive for them to develop the product – unless they have other motives than economic profit to do this.

The marginal cost of producing another instance of an electronic good

In the examples above, from the information economy, the marginal cost of producing another instance of the good (the information product together with web-based self-service) is very close to zero. Thus, even if the producer is profit-maximising, the price must be very close to zero, too. This situation is very common in the information economy, but very unusual in the traditional economy based on traditional production of goods and services.

Obviously the conditions just described create certain problems for companies that want to be profitable in the information economy. Probably the most important problem arises from the fact that even if the marginal cost of producing another instance of a good is very close to zero, the cost of producing the first instance, or rather the original or prototype, the generator of all instances, is often quite high, as high as it would be for a prototype, or generator, of a traditional physical product or service. In the traditional economy, these costs may be treated as investments, which are distributed over a large number of produced instances, in such a way that the effect on the price of each unit of the product or service becomes almost negligible, relatively speaking. But when the marginal cost is close to zero, even a small share of the total investment cost will have a considerable percentage effect on the price per unit, and the producer will not be able to maximize profits by applying a traditional scheme for distributing the investment costs over the instances expected to be produced and sold. The traditional investment cost allocation scheme will lead to (a) less than optimal sales, and less than optimal profits for the producer, and (b) higher than optimal prices, fewer buys, and lower than optimal total satisfaction among the potential consumers of the good.
A similar situation in the traditional economy: infrastructure investments

The dilemma just described is not completely unknown in the traditional economy. A similar situation often occurs for infrastructural goods like roads, railroads, bridges, networks for telecommunication, electricity distribution, etc. Here again the dilemma is that charging the customers more than the marginal cost of using the infrastructure will lead to underutilisation of the infrastructure, and a loss for the collective of customers (and producers), and for society as a whole. When the infrastructure is already in place, the cost of using it is often relatively low, and charging the customers extra every time they are using the infrastructure, in order to recover the investment, will inevitably decrease the usage of the infrastructure, and may actually even decrease the total revenues for the owner of the infrastructure, thus giving a negative rather than a positive contribution to the coverage of the investment costs.

Different solutions have been tried to solve this dilemma for traditional infrastructures. A common solution is to finance investments in infrastructure over the government budget. The users of the infrastructure will then pay for the infrastructure collectively, in their role as taxpayers; at the same time this financing regime will not deter any individual from using the infrastructure, once it is in place. This will lead to close-to-optimal usage of the infrastructure, assuming that the marginal cost of using it is zero or very low. If this is not the case, the infrastructure users should pay the marginal cost of using the infrastructure every time they use it.

Another method of financing infrastructures is to form so-called Public-Private Partnerships (PPP). This method may reduce needs for the government to borrow money, and it may have advantages from the point of view of risk management, but it does not seem to solve the basic problem of preventing underutilisation of infrastructures because of too high prices for using them once they have been created. For example, the Arlanda Express railway to Arlanda Airport outside Stockholm is the result of a PPP-project, but the price of the train tickets is so high that most private persons prefer to take a bus, their own cars, or even a taxi to the airport, which creates more air pollution than necessary, a so-called external diseconomy.

Information (and knowledge) exhibits the characteristics of a public good or a collective utility: non-rivalry and non-excludability. See Samuelson (1954). Non-rivalry means that consumption of the good by one individual does not reduce availability of the good for consumption by others. Non-excludability means that nobody can be effectively excluded from using the good.

From a holistic point of view (and as pointed out above) some ways of financing the production of a public good may lead to under-consumption of the good, once it has been produced and is available for everyone. More generally, production and consumption of public goods are associated with so-called externalities. An externality occurs when an economic activity causes costs or benefits to parties who are not directly involved in the activity. See Pigou (1920) and Baumol (1972).

Imperfections in the market economy

Even in a relatively well functioning market economy, there are several conditions that will enable producers to recover investment costs and compensate themselves for risks, for example:

- It will take time for competitors to develop and produce an equivalent product, and in the meantime the pioneering company may charge a higher price than the marginal cost of producing and selling an extra instance of the product.
• Even if competitors occur on the market, their products may not have exactly the same functionality and quality as that of the first company, and their production methods and tools may not be as efficient as those of the first producer.

• If competing companies produce products which are to some extent exchangeable, but still have slightly different functionalities and qualities, different consumers may value these differences in different ways, and different producers may experience weaker competition in different market segments, so as to be able to set higher prices than marginal costs.

• Producers may limit competition by using patents, authors’ rights, or other legal instruments.

Needs for new business models

Some companies, e.g. Google, have successfully introduced new business models adapted to the new situation. Many other companies in the information economy, e.g. media companies and publishers, still need to innovate and improve their business models. So far they have mainly tried to limit the free competition by relying on existing and reinforced copyright legislation and repressive actions against their own customers, especially those who use modern technology to produce almost perfect digital copies by themselves. In contrast, it was legal and accepted in the “old” economy for private persons to borrow and even produce (admittedly less perfect) copies of information products for their own use, for example tape-recorded copies of borrowed vinyl records carrying popular music, or tape recordings of streaming music from radio stations.

In reality companies belonging to the information economy, whichever they are, are governed by the same economic laws as other companies in a market economy. There is nothing mysterious about information technology from an economic point of view. Nevertheless, use of information technology will make it possible to create production processes and produce products and services that have certain characteristics, values of certain parameters, if you like, which are different from those of more traditional production processes, products, and services. Here are some examples:

• A traditional industrial process produces physical objects, e.g. cars. The individual objects produced may be very similar indeed – they may be seen as instances of one and the same type – but even so, each instance will require a non-negligible amount of resources to be produced: raw material, labour, machine capacity, etc, and these resources are associated with non-negligible costs per produced instance, or unit. In contrast, information products produced, disseminated, and consumed by means of information technology may be instantiated, or reproduced/copied, at almost no cost at all. Moreover, information may be consumed (used) without being at all consumed (worn out), that is, an information product may be used over and over again, while remaining completely intact.

• A traditional service process is heavily dependent on human labour. Unlike physical products, a traditional service cannot be stored; it must be produced and consumed at the same time; example: a receptionist answering a question from a client. In contrast, a web-based self-service system can be used by many users simultaneously, without the presence of a human producer of every instance of the service – other than the self-serving consumer of the service herself.

Alexander Osterwalder and Chris Anderson have provided innovative and concrete methods and tools for generating new business models, which are adapted to the new situation in the information economy. Actually some of these methods and tools, for example Osterwalder’s Canvas model, are not limited to the information economy, but applicable also to traditional businesses.
New frameworks and guidelines for developing business models adapted to the specific needs of an information economy may certainly be very helpful both for researchers and practitioners. At the same time, such new frameworks and guidelines do not necessarily have to contradict classic economic theories that have evolved over a long time, and which have survived many changes in society, technological and others. Thus theories and models like those presented in Samuelson (1948), Samuelson (2009), Dupuit (1844), Prest and Turvey (1965), and Kotler (1967), are still valid, by and large.

**Disruptive changes**

It is true that information technology has caused disruptive changes in many branches of the economy. This started already with the introduction of electronics replacing mechanics in some industries, which required industrialists to rethink their products and production processes. But in some branches, for example the media industry, the disruptive changes were even more drastic, and required a complete rethinking of not only products and processes, but also the business models used. This adaptation is still ongoing, and many old companies will not survive.

The dramatic changes that have occurred in the modern information society have been caused by information technology, and in particular the Internet. They are examples of so-called disruptive changes. They change the business conditions for companies in a radical and dramatic way.

Disruptive changes in an economy may occur for different reasons:
- new technology or radical changes in existing technology
- new production methods
- new skills and new knowledge needed, old skills and old knowledge becoming obsolet
- new levels of costs and relationships (production factors, processes)
- new business models required and/or occur thanks to innovative entrepreneurs

Existing companies, even big ones, often have great difficulties to adapt to disruptive changes. It is often easier for completely new companies to enter the market and outcompete those who are already established.

Disruptive changes may be met by defensive or offensive actions. Innovative offensive actions by new companies are typically those which have a chance to succeed, and often it does not take very long for them to succeed either, for example Google.

Defensive actions may try to stop or delay the more or less inevitable effects of disruptive changes by means of legislation, patents, author’s rights, taxes and tariffs, etc.

Information technology has caused disruptive changes earlier in history, for example the invention of paper for writing books on, Gutenberg’s printer, etc. But what is new now is that new disruptive changes occur very frequently, for example the development from mainframe computers to minicomputers to personal computers caused by rapidly developing information technologies.

Disruptive changes in information technology have similarities with disruptive changes in other technologies, for example the fall of “the ice business” when refrigerators came along.

Industries which have been particularly affected by disruptive changes in information technology and associated production methods, cost relationships, etc., are the media industry (publishing and distribution of newspapers, journals, books, recorded music and films, etc.) the travelling industry (travel agencies, flight operators, etc.)

If a company is going to survive a disruptive change, it will often have to change its business model in a more or less innovative and radical way – it is not enough to adapt to new production methods and new skills and competences needed. On the other hand, a company which finds a new and innovative business model, which works better than old models, may create a disruptive change in a branch of industry or a market just by introducing the new business models, without necessarily having to introduce new production methods or new technology at the same time. Examples: Nestlé (giving away coffee-machines while charging more for the coffee), printers and copying machines (dumping the printers while charging more for ink and toner). Some of these disruptive changes of business models have nothing or little to do with information technology.

**Business modelling in theory and practice**

Over the last decades there has been a growing interest in systematic studies of business models, both among practitioners, management consultants, and researchers in business economics and information systems.

There are different interpretations of the term “business model” corresponding to different needs and purposes. Maybe the most popular interpretation, at least among practitioners, is that a business model is a strategy and model for making a business profitable, especially in situations where disruptive changes have made it difficult to earn money in traditional ways. This type of business model may also be a tool for actively causing disruptive changes in a branch of industry.
Creative new business models may actually be a strong instrument for gaining decisive competitive advantages – not only in the information sector of the economy.

Note that many different kinds of business models, including business models for earning money, are relevant for all kinds of businesses and organisations, even those who do not have as a goal to make profits. Even a non-profit organisation or a government agency, for example, must secure financing of its activities and economize with available resources.

As we have already discussed, the issue of finding a business model which allows a company to make money and survive has become even more complex in the modern information society, where many businesses are based on information products, for example music and publications. The digital technology has reduced the marginal cost for producing an additional copy of such a product to almost zero – to be compared with the marginal cost of producing an additional copy of a traditional physical product, like a car, which is relatively high, even if the big cost in such production, too, is in the development and production of the first copy. According to economic theory, in a perfect market economy the price of a product tends to approach the marginal cost for producing an additional copy of the product. This creates problems for businesses, where this marginal cost is close to zero.

There are business models that are able to cope with this problem. For good examples, look at the business models of Google, Spotify, and the artist Lady Gaga for example. However, the development of such business models require innovative thinking and an ability to break away from more traditional business models.

For an elaboration on this topic, see:


Other interpretations of the term “business model” are not limited to models for earning money. Such business models may focus on a wide range of aspects of a business: goals and strategies, organisation and processes, concepts and information systems, etc.

Business models of all kinds are often supported by graphical representations of mental models and patterns of thinking. This makes them useful for practical use in the analysis and design of different aspects of a business, and make it easier for different stakeholders to participate in these activities.

Today it is widely realized and accepted, both among researchers and practitioners, that the analysis and design of information systems must combine several perspectives and views of the business to be served by the information systems; perspectives and views including people, goals, organisation, concepts, processes, and technology. This insight has led to many important consequences, for example in the ongoing development and standardisation efforts concerning enterprise architectures.

For an overview and summary of enterprise architectures, see Sundgren (2012).

Figure 34 illustrates a combination of three perspectives of business models, which can be used in a unified approach to information systems in a business context. See Sundgren et al. (2005).
Graphical illustrations of the models used in the three perspective will follow.

**Goals, values, and strategies**

![Diagram of a factor model (value graph) for a video renting business.](image)

*Figure 35. A factor model (value graph) for a video renting business.*

**Concepts and information**

We have already treated OPR models, relational models, and the correspondences between them earlier in this report. The graphs for the video rental business example used there are repeated in Figure 36 and Figure 37.
Figure 36. A conceptual model (object graph) for a video renting business.

Figure 37. The conceptual model of a video renting business transformed into a relational data model.
Processes

Figure 38. Process graph for a video renting business.

For references and more reading on business models and business modelling, see the bibliography at the end of this report.
CHAPTER 4. Information for good governance in e-society

Information is of utmost importance for the development and on-going improvements of a good society. A good society is characterized by good governance, a concept which will be further discussed in this chapter, and by good living-conditions for its citizens, including a good economy in the general sense of good economizing with scarce resources, which will be discussed in the next chapter.

Information has a fundamental role for all kinds of operations, problem-solving, and decision-making in society, on all levels and including both public and private activities. Furthermore, information is itself, in a modern information society, or e-society, a major component of products and services that are used and produced.

Information is a prerequisite for the functioning of any society, and in particular for the functioning of a society based on well-functioning markets. Theories about market economies are based on the assumption that different kinds of more or less perfect information are available for all actors in society, including both buyers and sellers of goods and services.

Last but not least, information of good quality is necessary for evaluation the performance of a society, so that its citizens and rulers can determine if, and to what extent, the society is functioning well, and which improvements are most urgent. Different stakeholders may have different opinions and preferences about these issues, but it is important that all of them have access to a common frame of reference in the shape of objective information of good quality.

In all countries in the world, one of the very first public institutions to be created has been a national statistical office with the task to create such a frame of reference of objective information of good quality. Such an institution is necessary in a democracy, but even dictators need and request objective information of good quality, although they may not want to share it with others.

The statistics produced by a national statistical office are often called official statistics. There are national and international agreements about which official statistics are particularly important, which definitions should govern them, which qualities they should possess, and how they should be designed and produced. This core of official statistics should give a coherent picture of the socio-economic situation and development in a country. The statistics should be of adequate and known quality, and they should be comparable between countries.

Governance and good governance

The meaning of good governance is elaborated in Sundgren (2013a, b, c, d, e).

Government and governance has to do with how we, as human beings, choose to organize ourselves, our lives, our organisations and institutions, and our societies. Today an e-prefix (like in e-government, e-governance, and e-society) is often used to indicate extensive use of digital technology, including the Internet, supporting government and governance in societies. At some time in the future, the e-prefix will become superfluous, since the use of information technology will be so natural in all contexts that it need not be mentioned.

Until recently (the 1980’s at least) the term “governance” was understood more or less as a synonym for “governing” and “government”. For example, according to Webster’s Third New International Dictionary from 1986, governance is a synonym for government, or:

- "the act or process of governing, specifically authoritative direction and control"
This interpretation specifically focuses on the effectiveness of the executive branch of government.

The traditional understanding of the concept of governance may be contrasted with more modern views. For example, a definition provided by the British Council emphasises that "governance" is a broader notion than government, and goes on to state:

- "Governance involves interaction between the formal institutions and those in civil society. Governance refers to a process whereby elements in society wield power, authority and influence and enact policies and decisions concerning public life and social upliftment."

This definition suggests that “governance” is a broad and complex concept, including different kinds of interactions between both formal and informal stakeholders in public decision making and control processes.

The ABC model of major actors, actions, and interactions involved in governance

One way of illustrating the concept of governance is the ABC model; it was first introduced in Sundgren (2005) and elaborated further in the publications from 2013 just referred to above.

Figure 39 gives a simple graphical overview of the ABC model, where

- A stands for “Administration”
- B stands for “Business”
- C stands for “Citizen”

The ABC model indicates some important actions and interactions between three major categories of actors in a well-functioning society.

![Figure 39. The ABC model for analysing e-governance.](image-url)
“Administrations” (A) include all kinds of government organs on all levels:

- **political organs**, such as parliaments, cabinets of ministers (also called “governments” in a narrow sense) and political committees and boards
- **administrative organs**, such as ministries, governmental agencies and offices, departments in regional and local governments, the European Commission, courts

Both political and administrative organs exist on all regional and administrative levels: central (federal, state), regional, local, international (for example the European Union).

The heads and some top executives of administrative organs are typically appointed by political organs, directly or indirectly, whereas most of the staff members are not politically appointed.

“Businesses” (B) should be interpreted in a broad sense, including all kinds of organisations, such as

- profit-seeking businesses
- non-profit organisations, defending certain values, the interests of their members, or other worthy causes
- so-called non-government organisations (NGOs)

“Citizens” (C) should be interpreted in a broad sense, too, including all human beings living in a certain administrative entity, for example a country or a municipality. “Citizens” include

- people with a formal citizenship
- other residents

The “C” in “Citizen” could also be interpreted as “Customer” or “Client”. However, the customer/client role is only one of the roles of a citizen, or human being, in society. Moreover, businesses and administrations will also occur in customer/client roles vis-à-vis other actors in society, for example in connection with e-commerce or in contacts with administrative organs.

Unlike businesses and administrations, the citizens of a society are ends in themselves. Human needs and human rights should be ensured by a good society. This puts demands and requirements on the other actors in society, including the citizens themselves.

The actions and interactions, which the actors in the ABC model perform and are responsible for, are dependent on different kinds of information and information processes, and the better this information is, and the more efficient the information processes are, the better the society will function.

For example, the reader may consider which kinds of information and information processes are necessary or desirable for the following tasks and processes, and how modern information technologies and tools could support these tasks and processes:

- Demands and requests by one actor for services and/or products from another actor
  - Citizens requesting services from administrations
  - Citizens requesting services and/or products from businesses
  - Businesses requesting products and/or services from other businesses
  - Businesses requesting services from administrations
  - Administrations requesting services from other administrations
  - Administrations requesting services from citizens (employments)
o Administrations requesting products and/or services from businesses

- Demands and requests for influence and power – “voice”
  o Citizens demanding democracy and participation in political decision-making
  o Citizens/employees demanding good salaries and working-conditions, individually or collectively (via unions)
  o Citizens/employees demanding participation in organisational decision-making
  o Businesses demanding participation in administrative decision-making, for example by means of lobbying and consultations

- Demands and requests for legal frameworks, including laws, rules, and regulations
  o Demands and requests from citizens
  o Demands and requests from businesses
  o Demands and requests from administrations

- Demands and requests for hard and soft infrastructure
  o Demands and requests from citizens
  o Demands and requests from businesses
  o Demands and requests from administrations

- Political and administrative organs responding to demands and requests by citizens and businesses for
  o influence, power, and participation – “voice”
  o services

- Businesses responding to demands and requests by (other) businesses, citizens, and administrations for products and services

- Citizens responding to demands and requests by administrations and businesses as regards
  o plans, proposals, and decisions
  o marketing of products and/or services
  o employment conditions

It is the government that has the overall responsibility for good governance in a society. But citizens and businesses do not only have rights, ensured by good governance, but they also have duties. As citizens we have duties, primarily to our fellow human beings, but also to governments and administrations in their roles as protectors of the well-being and rights of all human beings living in the society. The latter duties include:

- Respect laws and decisions taken in democratic processes
- Paying taxes for the financing of collective services and insurances
- Contributing to other collective undertakings, like police and defence

Businesses do not only have rights either. They also have duties towards their business counterparts (customers, suppliers, and other stakeholders) and towards society as a whole, represented by government authorities and administrative agencies.

**Important tasks included in good governance and supported by information**

There are some tasks of particular importance in an e-society, and there are task that have to be done in different ways than before, taking the availability of the new technology into account.
Some important tasks for political and administrative organs are:

- **To establish, operationalise, interpret, and manage legal frameworks and procedures**
  - Freedom of speech, information, and knowledge
  - Non-corrupt public procurements
  - Needs for new and adapted legislation in e-society

- **To enable citizens and organisations to make their voices heard in constructive ways**
  - Providing methods, tools, and procedures for e-democracy and e-participation

- **To provide well-functioning infrastructures**
  - Hard and soft infrastructures
  - Organising and managing registers, databases, and information systems
  - Developing and managing strategic tools and procedures, e.g. e-identification

- **To provide relevant and useful e-services to citizens, businesses, and administrations**

- **To enable and encourage innovative development**
  - Education and research
  - Entrepreneurship, e.g. development of innovative e-services

- **To organise and manage a non-corrupt and efficient public sector**
  - Objectivity, quality, coordination, and efficiency

Many of the tasks listed above have a long tradition even before computer technology and computer-based methods and tools, like the Internet, were introduced. But there are two issues where the new technology has revolutionized the possibilities to improve society in disruptive ways:

- freedom of knowledge, opening for massive inexpensive, high-quality education and training
- democracy and participation

Since knowledge is an important prerequisite for constructive democracy and participation, the two issues are linked together. Moreover, both have the potential to improve and enrich the lives of individual human beings, as well as improving the functionality and prosperity of society as a whole.

**Corporate governance: governance of companies and organisations**


Corporate governance involves regulatory and market mechanisms, and the roles and relationships between a company’s management, its board, its shareholders and other stakeholders, and the goals for which the corporation is governed. Lately, corporate governance has been comprehensively defined as "a system of law and sound approaches by which corporations are directed and controlled focusing on the internal and external corporate structures with the intention of monitoring the actions of management and directors and thereby mitigating agency risks which may stem from the misdeeds of corporate officers." See Sifuna, Anazett (2012).

In contemporary business corporations, the main external stakeholder groups are shareholders, debt holders, trade creditors, suppliers, customers and communities affected by the corporation’s activities. Internal stakeholders are the board of directors, executives, and other employees.
Much of the contemporary interest in corporate governance is concerned with mitigation of the conflicts of interests between stakeholders. Ways of mitigating or preventing these conflicts of interests include the processes, customs, policies, laws, and institutions which have an impact on the way a company is controlled. An important theme of corporate governance is the nature and extent of accountability of people in the business.

A related but separate thread of discussions focuses on the impact of a corporate governance system on economic efficiency, with a strong emphasis on shareholders' welfare. In large firms where there is a separation of ownership and management and no controlling shareholder, the principal-agent issue arises between upper-management (the "agent") which may have very different interests, and by definition considerably more information, than shareholders (the "principals"). The danger arises that rather than overseeing management on behalf of shareholders, the board of directors may become insulated from shareholders and beholden to management. This aspect is particularly present in contemporary public debates and developments in regulatory policy.


There has been renewed interest in the corporate governance practices of modern corporations, particularly in relation to accountability, since the high-profile collapses of a number of large corporations during 2001-2002, most of which involved accounting fraud. Corporate scandals of various forms have maintained public and political interest in the regulation of corporate governance. In the U.S., these include Enron Corporation and MCI Inc. (formerly WorldCom). Their demise is associated with the U.S. federal government passing the Sarbanes-Oxley Act in 2002, intending to restore public confidence in corporate governance.

**Freedom of speech, freedom of information, and freedom of knowledge**

**Sources and references:**


Good governance is closely associated with respect for basic human rights. Freedom of speech is necessary for empowering all actors in society to make their voices heard through democratic processes and participative decision-making.

**Freedom of information** is an extension of freedom of speech. Freedom of speech is not enough for having real influence in arguments, discussions, and debates in society. Ideally those activities should be based on facts and avoid prejudice and myths. This requires freedom of information, so that all participants in public discussions have access to access to relevant facts, even facts which may be uncomfortable for those in power. It is also important that journalists and others are able to investigate and criticize actions and decisions by political organs and administrations, having full access to information created and used by such institutions in their planning and decision-making. Openness is vital for a well-functioning democracy.

**Freedom of speech, or freedom of expression**, is the right to communicate one's opinions and ideas. It includes any act of communicating information or ideas, regardless of the medium used. It includes any act of communicating information or ideas, regardless of the medium used, be it orally, in written, in print, through the Internet, or through art forms.
Freedom of knowledge – in the sense of open and free access to scientific knowledge, research results, and education materials – is just about to add a new dimension to freedom of speech and freedom of information. Everyone, poor or rich, living in a poor or rich country, will soon have the possibility to get access to the best education materials, the best courses, and the best teachers without having to spend a fortune. And the students may carry out their studies almost independently of time and space by means of self-studies and net-based education/learning activities, led by live or recorded teachers, using social communities for interaction with teachers and fellow students, synchronously or asynchronously.

The new technologies introduced in e-societies have a potential to revolutionize the meaning and impact of freedom of information and freedom of knowledge. This has already happened to a great extent, not least to the new, Internet-based communication methods and tools, which enable the exchange of all kinds of information almost instantaneously between almost all people all over the world. This development will no doubt continue – with effects and implications that we can only speculate about at this stage.

Freedom of speech is understood as a multi-faceted right that includes not only the right to express, or disseminate, information and ideas, but three further distinct aspects:

- the right to seek information and ideas
- the right to receive information and ideas
- the right to forward information and ideas

Freedom of information may include opposition to patents, opposition to copyrights, or opposition to intellectual property rights. Pirate Parties International (PPI), as well as Pirate Parties in individual countries, have established political platforms based largely on freedom of information issues.

Relation to the concept of democracy

The notion of freedom of expression is intimately linked to political debate and the concept of democracy. Public debate may not be completely suppressed even in times of emergency. Alexander Meiklejohn argues that the concept of democracy is that of self-government by the people. For such a system to work an informed electorate is necessary. In order to be appropriately knowledgeable, there must be no constraints on the free flow of information and ideas. According to Meiklejohn, democracy will not be true to its essential ideal if those in power are able to manipulate the electorate by withholding information and stifling criticism. Meiklejohn acknowledges that the desire to manipulate opinion can stem from the motive of seeking to benefit society. However, he argues, choosing manipulation negates, in its means, the democratic ideal.

Thomas I. Emerson argued that freedom of speech helps to provide a balance between stability and change. Freedom of speech acts as a "safety valve" to let off steam when people might otherwise be bent on revolution. He argues that "The principle of open discussion is a method of achieving a more adaptable and at the same time more stable community, of maintaining the precarious balance between healthy cleavage and necessary consensus." Emerson furthermore maintains that "Opposition serves a vital social function in offsetting or ameliorating (the) normal process of bureaucratic decay."

Research undertaken by the Worldwide Governance Indicators project at the World Bank, indicates that freedom of speech, and the process of accountability that follows it, have a significant impact in the quality of governance of a country. "Voice and Accountability" within a country, defined as "the extent to which a country's citizens are able to participate in selecting their government, as well as
freedom of expression, freedom of association, and free media” is one of the six dimensions of
governance that the Worldwide Governance Indicators measure for more than 200 countries.

Freedom of information as an instrument for protecting other important interests

We have already emphasised the importance of freedom of speech and freedom of information as
an instrument for getting a well-functioning democracy. Freedom of information is also an important
instrument for protecting other important interests in a modern society, e.g. the interests of
consumers and investors.

Freedom of information for protecting the interests of consumers

In 1983 the United Nations Commission on Transnational Corporations adopted the United Nations
Guidelines for Consumer Protection stipulating eight consumer rights, including "consumer access to
adequate information to enable making informed choices according to individual wishes and needs".
Access to information became to be regarded as basic consumer right and preventative disclosure,
i.e. the disclosure of information on threats to human lives, health and safety began to be
emphasized.

Freedom of information for protecting the interests of investors

Secretive decision making by company directors and corporate scandals led to freedom of informa-
tion legislation for protecting the interests of investors. Such legislation was first adopted in Britain in
the early 20th century, and later in North America and other countries. Disclosure regimes regained
attention at the beginning of the 21st century as a number of corporate scandals were linked to
accountancy fraud and company director secrecy. Starting with Enron, the subsequent scandals
involving several companies prompted the US Congress to impose new information disclosure
obligations on companies with the Sarbanes-Oxley Act 2002.

Limitations to the freedom of speech and freedom of information

The right to freedom of speech and expression is closely related to other rights, and may be limited
when conflicting with other rights.

In practice, the right to freedom of speech is not absolute in any country and the right is commonly
subject to limitations, as with libel, slander, obscenity, sedition (including, for example inciting ethnic
hatred), copyright violation, or revelation of information that is classified.

As with the right to freedom of expression, there are limitations to the freedom of information. For
example, the right to privacy is also recognized as a human right, and this right sometimes comes
into conflict with the freedom of speech and the freedom of information.

Today there are also many laws concerning so-called intellectual properties which limit and restrict
the freedom of information. Laws concerning patents, copyright, and author’s rights are example of
such laws. These laws create artificial monopolies which sacrifice the freedom of information by
protecting the interests of patent holders, publishers, censors, and others.

Limitations motivated by the “harm principle” and the “offence principle”

Legal systems, and society at large, recognize restrictions on the freedom of speech, particularly
when freedom of speech conflicts with other values or rights of high dignity. Limitations to freedom
of speech may follow the "harm principle" or the "offence principle", for example in the case
of pornography, or hate speech.
In his work "On Liberty" (1859) John Stuart Mill argued that

- "... there ought to exist the fullest liberty of professing and discussing, as a matter of ethical conviction, any doctrine, however immoral it may be considered."

However, Mill also introduced what is known as the harm principle, in placing the following limitation on free expression:

- "the only purpose for which power can be rightfully exercised over any member of a civilized community, against his will, is to prevent harm to others."

In 1985 Joel Feinberg introduced what is known as the offence principle, arguing that Mill's harm principle sets the bar too high and that some forms of expression can be legitimately prohibited by law because they are very offensive. But, as offending someone is less serious than harming someone, the penalties imposed should be higher for causing harm.

Censorship and the origin of copyright laws

References

Milton (1644, 1886) and Hall (1910).


Before the invention of the printing press, a writing, once created, could only be physically multiplied by the highly laborious and error-prone process of manual copying out. No elaborate system of censorship and control over scribes existed; until the 14th century the scribes were restricted to religious institutions, and their works rarely caused wider controversy.

In response to Gutenberg's printing press, and the heresies it allowed to spread, the Roman Catholic Church moved to impose censorship. Printing allowed for multiple exact copies of a work, leading to a more rapid and widespread circulation of ideas and information. The origins of copyright law in most European countries lie in efforts by the Roman Catholic Church and governments to regulate and control the output of printers.

While governments and church encouraged printing in many ways because it allowed for the dissemination of Bibles and government information, works of dissent and criticism could also circulate rapidly. As a consequence, governments established controls over printers across Europe, requiring them to have official licenses to trade and produce books.

The notion that the expression of dissent or subversive views should be tolerated, not censured or punished by law, developed alongside the rise of printing and the press. In Areopagitica, published in 1644 without a license John Milton made an impassioned plea for freedom of expression and toleration of falsehood, stating:

- "Give me the liberty to know, to utter, and to argue freely according to conscience, above all liberties."

John Stuart Mill (1806–1873) argued that without human freedom there can be no progress in science, law or politics, which according to Mill required free discussion of opinion. In On Liberty
Mill argued that truth drives out falsity, therefore the free expression of ideas, true or false, should not be feared. Truth is not stable or fixed, but evolves with time. Mill argued that much of what we once considered true has turned out false. Therefore views should not be prohibited for their apparent falsity. For Mill, the only instance in which speech can justifiably be suppressed is in order to prevent harm from a clear and direct threat. Neither economic or moral implications, nor the speaker’s own well-being would justify suppression of speech.

In Evelyn Beatrice Hall’s biography of Voltaire, she coined the following phrase to illustrate Voltaire’s beliefs: “I disapprove of what you say, but I will defend to the death your right to say it.” Noam Chomsky states that: “If you believe in freedom of speech, you believe in freedom of speech for views you don’t like. If you’re in favour of freedom of speech, that means you’re in favour of freedom of speech precisely for views you despise.”

The problematic role of media: freedom of the press may constrain freedom of speech

The right to freedom of expression is particularly important for media, which play a special role as the bearer of the general right to freedom of expression for all. However, freedom of the press is not necessarily enabling freedom of speech. Judith Lichtenberg (1987) outlined conditions in which freedom of the press may constrain freedom of speech, for example where the media suppresses information or stifles the diversity of voices inherent in freedom of speech. Lichtenberg argues that freedom of the press is simply a form of property right summed up by the principle "no money, no voice". Or as put by A. J. Liebling: “Freedom of the press is guaranteed only to those who own one.”

http://www.jstor.org/stable/2265278?seq=1#page_scan_tab_contents

Privacy and confidentiality vs the need to know


As a general principle freedom of expression may not limit the right to privacy, as well as the honour and reputation of others. However greater latitude is given when criticism of public figures is involved.

During the 1970 population census, the first privacy debate exploded in Swedish media. The management of Statistics Sweden, the central statistical office of Sweden, was taken by complete surprise and shock. The integrity and immunity of Statistics Sweden to political and administrative pressure to release data for other purposes than statistical analysis and research had never been questioned before, and now Statistics Sweden was suddenly associated with the concept of a Big Brother society.

The privacy debate had the unfortunate effect that the management of Statistics Sweden became overly cautious about microdata, and in particular the flexible use of statistical microdata implied by the so-called archive-statistical approach, benefitting justified interests of researchers and analysts.

A positive side-effect of the privacy debate was that Statistics Sweden was given generous appropriations for studying privacy and confidentiality problems of statistics production. Advanced research projects were carried out about how to protect the confidentiality of both person data and business data. The two problem areas turned out to be quite different, although they were both essential for regaining the confidence of people and enterprises.

Major challenges as regards the issue of privacy and statistical confidentiality are to strike the right balances between
• the right to privacy vs the need to know
• legal, methodological, and technical measures for protecting privacy and confidentiality

A major methodological problem is how to avoid inadvertent disclosures in statistical databases and publications, especially how to protect against reidentifications of persons and enterprises behind the figures in statistical tables and anonymized files of microdata. Depending on the background information in the possession of an intruder, as well as the availability of public information about people and businesses, e.g. in registers, it may be relatively easy to reidentify anonymized microdata and data behind the cells in statistical tables.

Methodological projects were started to cope with the legal, administrative, methodological, and technical issues. New technology and software helped in these endeavours, and both Denmark and Sweden developed secure systems for facilitating remote access to anonymous microdata. A new law was introduced in Sweden, criminalizing all attempts to reidentify anonymized microdata.


For references and more reading, see the bibliography at the end of this report.

Intellectual property rights


Intellectual property rights imply constraints for the freedom of information and freedom of knowledge. There are different areas where property right legislations apply, for example patents and author’s rights.

What is intellectual property, and does it need protection?

According to Wikipedia, intellectual property (IP) is a term referring to creations of the intellect for which a monopoly is assigned to designated owners by law. Some common types of intellectual property rights (IPR) are copyright, patents, and industrial design rights; and the rights that protect trademarks, trade dress, and in some jurisdictions trade secrets: all these cover music, literature, and other artistic works; discoveries and inventions; and words, phrases, symbols, and designs.

While intellectual property law has evolved over centuries, it was not until the 19th century that the term intellectual property began to be used, and not until the late 20th century that it became commonplace world-wide.

Arguments in favour of intellectual property rights

There are basically two kinds of motives for legal protection of intellectual property:

• economic motives (material interests)
• author recognition (immaterial)

Author recognition means that the author or authors behind an idea, an invention, a piece of art, or some other intellectual accomplishment should be recognized and honoured. Such recognition is
immaterial and not necessarily associated with any material compensation. Pretending to be the author of somebody else’s work, e.g. plagiarism, is first of all immoral, not fair, but may also be illegal depending on prevailing legislation.

One of the economic motives behind intellectual property protection by means of legislation is that it should not be possible for a stronger part (e.g. a publisher) should not be able to exploit a weaker part (e.g. an individual author).

Another economic motive, which is nowadays maybe more often referred to, is the need for economic incentives in order to stimulate persons and companies to carry out the necessary and maybe risky work that is often necessary before the results of this work can be seen and possibly be marketed and sold. Examples: composing a piece of music, writing a book, doing research and development necessary for the creation of a new medicine, etc. Patents and copyrights will give the authors a monopoly for some time, during which the holder of the intellectual property right may sell the product at a relatively high price without competition from others.

Recognizing authorship does not seem to have any negative consequences for anyone, as long as it is not associated with any economic consequence, and most of us would see it as right and proper. Granting economic monopolies or other material advantages to owners of intellectual properties seems more questionable, since such restrictions on free competition and the freedom to use available knowledge will in most cases have negative effects on society as a whole and its citizens from both social and economic points of view. Moreover, there are realistic alternatives to ensure expensive and risky investments and developments, for example collective financing of such undertakings, like for example when research projects are financed by governments or private or public research foundations.

**Criticism of intellectual property rights – and of the concept of “intellectual property”**

Criticism of the term *intellectual property* ranges from discussing its vagueness and abstract overreach to direct contention to the semantic validity of using words like *property* and *rights* in fashions that contradict practice and law. Many detractors think this term specially serves the doctrinal agenda of parties opposing reform in the public interest or otherwise abusing related legislations; and that it disallows intelligent discussion about specific and often unrelated aspects of copyright, patents, trademarks, etc.

Richard Stallman, the founder of Free Software Foundation, argues that, although the term *intellectual property* is in wide use, it should be rejected altogether, because it “systematically distorts and confuses”, and its use was and is promoted by those who gain from this confusion. He claims that the term lumps together disparate laws, which originated separately, evolved differently, cover different activities, have different rules, and raise different public policy issues" and that it causes confusion to compare these monopolies with ownership of limited physical things. Stallman warns against abstracting disparate laws into a collective term.

Similarly, economists Boldrin and Levine prefer to use the term “intellectual monopoly” as a more appropriate and clear definition of the concept, which they argue, is very dissimilar from property rights.

Intellectual properties are abstract and fundamentally different from “real” properties like houses and vehicles. Real properties may not be used by different persons for different purposes at the same time, and real properties are often consumed and become worn out over time. In contrast, the same intellectual property, for example a piece of music, may be used (downloaded, streamed) by many persons at the same time, and it will not be worn out.

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On the assumption that intellectual property rights are actual rights, Stallman argues that this claim does not live up to the historical intentions behind these laws, which in the case of copyright served as a censorship system, and later on, a regulatory model for the printing press that may have benefitted authors incidentally, but never interfered with the freedom of average readers. Still referring to copyright, he cites legal literature such as the United States Constitution and case law to demonstrate that it is meant to be an optional and experimental bargain that temporarily trades property rights and free speech for public, not private, benefit in the form of increased artistic production and knowledge.

Law professor, writer, and political activist Lawrence Lessig has criticized the implied analogy with physical property (like land or an automobile). They argue such an analogy fails because physical property is generally rivalrous while intellectual works are non-rivalrous (that is, if one makes a copy of a work, the enjoyment of the copy does not prevent enjoyment of the original). Other arguments along these lines claim that unlike the situation with tangible property, there is no natural scarcity of a particular idea or information: once it exists at all, it can be re-used and duplicated indefinitely without such re-use diminishing the original. Stephan Kinsella has objected to intellectual property on the grounds that the word “property” implies scarcity, which may not be applicable to ideas.

Website (Lawrence Lessig TED talks), https://www.ted.com/speakers/larry_lessig

Entrepreneur and politician Rickard Falkvinge and hacker Alexandre Oliva have independently compared George Orwell’s fictional dialect Newspeak to the terminology used by intellectual property supporters as a linguistic weapon to shape public opinion regarding copyright debate and DRM.

For references and more reading, see the bibliography at the end of this report.


**Figure 40.** To the left: Demonstration in Sweden in support of file sharing, 2006. To the right: “Copying is not theft” badge. Source: Wikipedia (Intellectual property).

**Patents**

The main argument in favour of patent rights is that they are needed in order to create economic incentives for the resource-consuming and risky creative work that may have to precede a useful innovation. The assumption is that few people and businesses would invest in such work, unless there were a possibility to get an economic reward for it, for example through a patent that would
give the inventor a monopoly to use the innovation, at least for some time. (Another possibility would be to finance innovations in a similar way as infrastructure investments are often financed, that is via tax money from governments, or other collective financing.)

Another argument is that patents actually ensure that detailed information concerning innovations become well documented, as required by patent laws. Thus valuable knowledge becomes available for all citizens and business actors in society. However, no one would be able to use this knowledge by creating new products as long as the patent is valid, unless the patent holder is willing to approve of this, for example by licensing the patent against a fee.

*Author’s rights (copyright)*


Today “copyright” and “author’s rights” are often treated as synonyms, and a country may use one term or the other in its legislation. However, the two terms have very different historical backgrounds. We have already noted that “copyright” was a tool for censorship that was introduced by governments, and demanded by the Roman Catholic Church, in order to meet the threats imposed by Gutenberg’s printers. Legal protection of author’s rights, on the other hand, began to appear in the 18th century as a means to tackle the inequality in relations between authors and publishers, and the need to secure an income for authors. The solution was to give the author of a creative, intellectual work a monopoly right, initially the right to copy or otherwise reproduce the work, for a limited term.

The concept of author’s rights has two distinct components: economic rights and moral rights. The economic rights are limited in time and may be transferred by the author to others, usually by means of a written contract. The economic rights are intended to allow the author to profit financially from the work. The moral rights are intended to ensure that the author is recognized and identified as the author of the work, and to give the author the right to object to any distortion of the work that would damage the author’s reputation. The moral rights are personal and cannot be transferred except by testament.

It is interesting to note that both the economic rights and the moral rights focus on the right of the author as an individual person. The original purpose was to protect creative authors against profit-seeking businessmen and companies (e.g. publishers), who wanted to exploit the economic value of creative intellectual works. This contrasts very much to the situation in today’s information society, where it seems to be the businessmen and companies, who are the most outspoken and most militant advocates of authors’ rights and, not least, the monopolies associated with such rights, whereas the authors themselves, as well as their organisations, are often more open to new business models to secure their own incomes from their works – rather than the incomes of businesses, which reproduce, market, and disseminate their works. Maybe this will lead to a development, where the authors regain more of the economic power over their own works, and where the authors contract out more specified tasks to publishers, promoters, agents, and other businesses, on conditions that are more similar to those in other parts of the economy.

Many steps in this direction can already be seen. Music creators and artists use new distribution channels that have become available free of charge on the Internet, and from which their customers can download their works free of charge. Incomes for the authors may be generated by advertisements, live concerts, or inexpensive flat rate subscriptions to websites with very large coverage and superior availability.
Freedom of speech and freedom of information on the Internet

It is obvious that the Internet has done a lot in support of freedom speech and freedom of information. One of the more recent examples is the so-called Arab Spring, which started in 2010. However, many politicians, even in western democracies like the United States, have been frightened by the power of the Internet, and the risks of its being misused by “dark forces”, and they have tried to introduce new forms of censorship to cope with potential threats of the new technology.

Internet censorship

See Wikipedia: Internet censorship and Internet censorship by country

Jo Glanville, editor of the Index on Censorship, states that

- "the Internet has been a revolution for censorship as much as for free speech".

International, national and regional standards recognize that freedom of speech, as one form of freedom of expression, applies to any medium, including the Internet.

The Communications Decency Act (CDA) of 1996 was the first major attempt by the United States Congress to regulate pornographic material on the Internet. In 1997 the U.S. Supreme Court partially overturned the law. Judge Stewart R. Dalzell, one of the three federal judges who in June 1996 declared parts of the CDA unconstitutional, in his opinion stated the following:

- "The Internet is a far more speech-enhancing medium than print, the village green, or the mails. Because it would necessarily affect the Internet itself, the CDA would necessarily reduce the speech available for adults on the medium. This is a constitutionally intolerable result. Some of the dialogue on the Internet surely tests the limits of conventional discourse. Speech on the Internet can be unfiltered, unpolished, and unconventional, even emotionally charged, sexually explicit, and vulgar – in a word, "indecent" in many communities. But we should expect such speech to occur in a medium in which citizens from all walks of life have a voice. We should also protect the autonomy that such a medium confers to ordinary people as well as media magnates. [...] My analysis does not deprive the Government of all means of protecting children from the dangers of Internet communication. The Government can continue to protect children from pornography on the Internet through vigorous enforcement of existing laws criminalizing obscenity and child pornography. [...] As we learned at the hearing, there is also a compelling need for public educations about the benefits and dangers of this new medium, and the Government can fill that role as well. In my view, our action today should only mean that Government’s permissible supervision of Internet contents stops at the traditional line of unprotected speech. [...] The absence of governmental regulation of Internet content has unquestionably produced a kind of chaos, but as one of the plaintiff’s experts put it with such resonance at the hearing: "What achieved success was the very chaos that the Internet is. The strength of the Internet is chaos." Just as the strength of the Internet is chaos, so that strength of our liberty depends upon the chaos and cacophony of the unfettered speech the First Amendment protects."

According to Bernt Hugenholtz and Lucie Guibault the public domain is under pressure from the "commodification of information" as item of information that previously had little or no economic value, have acquired independent economic value in the information age, such as factual data, personal data, genetic information and pure ideas. The commodification of information is taking place through intellectual property law, contract law, as well as broadcasting and telecommunications law.
The concept of freedom of information has emerged in response to state sponsored censorship, monitoring and surveillance of the internet. Internet censorship includes the control or suppression of the publishing or accessing of information on the Internet.

The Global Internet Freedom Consortium claims to remove blocks to the "free flow of information" for what they term "closed societies". According to the Reporters without Borders (RWB) "Internet enemy list" the following states engage in pervasive internet censorship: China, Cuba, Iran, Myanmar/Burma, North Korea, Saudi Arabia, Syria, Turkmenistan, Uzbekistan, and Vietnam.

In 2010 Hillary Clinton, speaking on behalf of the United States, declared 'we stand for a single internet where all of humanity has equal access to knowledge and ideas'. In her 'Remarks on Internet Freedom' she also draws attention to how 'even in authoritarian countries, information networks are helping people discover new facts and making governments more accountable', while reporting President Barack Obama's pronouncement 'the more freely information flows, the stronger societies become'.

Openness in society

In this section we shall focus on open data and related concepts. We shall return to the broader concept of open knowledge – with focus on openness in education, research, and innovation – in Chapter 5.

Open data

Open data is a broader concept than Public Sector Information as defined by the PSI directive.

In December 2011, the European Commission presented an Open Data Package consisting of:


The proposal for a revision of the PSI directive proposes to further open up the market for services based on public-sector information, by

- including new bodies in the scope of application of the PSI directive such as libraries (including university libraries), museums and archives;
- limiting the fees that can be charged by the public authorities at the marginal costs as a rule;
- introducing independent oversight over re-use rules in the Member States;
- making machine-readable formats for information held by public authorities the norm.


An overview of the concept of open data

Open data is the idea that certain data should be freely available to everyone to use and republish as they wish, without restrictions from copyright, patents or other mechanisms of control. The goals of the open data movement are similar to those of other "Open" movements such as open source, open hardware, open content, and open access.

The concept of open data is not new; but a formalized definition is relatively new – the primary such formalisation being that in the Open Definition which can be summarized in the statement that

- a piece of data is open if anyone is free to use, reuse, and redistribute it

Open data is often focused not only on text data and numerical data, but also on more complex data such as maps, genomes, connectomes, chemical compounds, mathematical and scientific formulae, medical data and practice, bioscience and biodiversity. Problems often arise because these are commercially valuable or can be aggregated into works of value. Access to, or re-use of, the data may be controlled by organisations, both public and private. Control may be through access restrictions, licenses, copyright, patents and charges for access or re-use. Advocates of open data argue that these restrictions are against the communal good and that these data should be made available without restriction or fee. In addition, it is important that the data are re-usable without requiring further permission, though the types of re-use (such as the creation of derivative works) may be controlled by license.

A typical depiction of the need for open data (by John Wilbanks, VP Science, Creative Commons):

- “Numerous scientists have pointed out the irony that right at the historical moment when we have the technologies to permit worldwide availability and distributed process of scientific data, broadening collaboration and accelerating the pace and depth of discovery…..we are busy locking up that data and preventing the use of correspondingly advanced technologies on knowledge.”

Creators of data often do not consider the need to state the conditions of ownership, licensing and re-use. For example, many scientists do not regard the published data arising from their work to be theirs to control and the act of publication in a journal is an implicit release of the data into the commons. However the lack of a license makes it difficult to determine the status of a data set and may restrict the use of data offered in an Open spirit. Because of this uncertainty it is also possible for public or private organisations to aggregate said data, protect it with copyright and then resell it.

Open data in government

Several national governments have created websites to distribute a portion of the data they collect. The United Nations has an open data website that publishes statistical data from Member States and UN Agencies.

The EU Public Sector Information (PSI) directive


The main purpose of the EU Public Sector Information (PSI) directive is to stimulate the reuse of raw data that have already been collected or generated by public agencies, and which have been paid for by the tax-payers. The data should be made available to anyone interested, but in particular to
entrepreneurs who see possibilities to process and use the data for new information products and services providing value both to customers and to the entrepreneurs themselves and their companies. To make it simple to reuse the data, they should be in raw, standardised form, made available in standard data exchange formats, for example through standard Application Program Interfaces (API:s) interfacing the databases of the government agencies storing them.

Ideally the government agencies should make the data available free of charge, and in any case not at a higher cost than the marginal cost of making the already existing data accessible.

Another important part of the PSI concept is that the government agencies themselves should not compete with the entrepreneurs in developing new products and services. There are several reasons for this:

- Government agencies are, in general, not particularly good entrepreneurs
- Entrepreneurship is risky, and government agencies should not risk taxpayers’ money
- Government agencies should, in general, not compete on free, well-functioning markets; since the government agencies are financed by the government, they cannot go bankrupt, and there are considerable risks of unfair competition (including more or less visible subsidies)

The PSI directive was inspired by similar laws and policies in the United States, where the market of innovative information products and services, as a result, has grown impressively during recent years; the figure 17% per year has been mentioned, whereas the corresponding European figure is said to be only 2-3% per year.

Public sector information (PSI) is the single largest source of information in Europe. It is produced and collected by public bodies and includes digital maps, meteorological, legal, traffic, financial, economic and other data. Most of this raw data could be re-used or integrated into new products and services, which we use on a daily basis, such as car navigation systems, weather forecasts, financial and insurance services.

Re-use of public sector information means using it in new ways by adding value to it, combining information from different sources, making mash-ups and new applications, both for commercial and non-commercial purposes. Public sector information has great economic potential. According to a survey on existing findings on the economic impact of public sector information conducted by the European Commission in 2011 (Vickery study) the overall direct and indirect economic gains are estimated at €140bn throughout the EU. Increase in the re-use of PSI generates new businesses and jobs, and provides consumers with more choice and more value for money.

The PSI directive was adopted by the EU in 2003. It has introduced a common legislative framework regulating how public sector bodies should make their information available for re-use in order to remove barriers such as discriminatory practices, monopoly markets and a lack of transparency.

Arguments for and against open data

The debate on Open Data is still evolving. The best open government applications seek to empower consumers, to help small businesses, or to create value in some other positive, constructive way. Open government data is only a way-point on the road to improving education, improving government, and building tools to solve other real world problems. While many arguments have been made categorically, the following discussion of arguments for and against open data highlights that these arguments often depend highly on the type of data and its potential uses.

Arguments made on behalf of Open Data include the following:
"Data belong to the human race". Typical examples are genomes, data on organisms, medical science, environmental data following the Aarhus Convention.

- Public money was used to fund the work and so it should be universally available.
- It was created by or at a government institution.
- Facts cannot legally be copyrighted.
- Sponsors of research do not get full value unless the resulting data are freely available.
- Restrictions on data re-use create an anticommons.
- Data are required for the smooth process of running communal human activities and are an important enabler of socio-economic development (health care, education, economic productivity, etc.).
- In scientific research, the rate of discovery is accelerated by better access to data.

It is generally held that factual data cannot be copyrighted. However, publishers frequently add copyright statements (often forbidding re-use) to scientific data accompanying publications. It may be unclear whether the factual data embedded in full text are part of the copyright.

While the human abstraction of facts from paper publications is normally accepted as legal there is often an implied restriction on the machine extraction by robots.

Unlike Open Access, where groups of publishers have stated their concerns, Open Data is normally challenged by individual institutions. Their arguments have been discussed less in public discourse and there are fewer quotes to rely on at this time.

Arguments against making all data available as Open Data include the following:

- Government funding may not be used to duplicate or challenge the activities of the private sector (e.g. PubChem).
- Governments have to be accountable for the efficient use of taxpayer’s money: If public funds are used to aggregate the data and if the data will bring commercial (private) benefits to only a small number of users, the users should reimburse governments for the cost of providing the data.
- The revenue earned by publishing data permits non-profit organisations to fund other activities (e.g. learned society publishing supports the society).
- The government gives specific legitimacy for certain organisations to recover costs (NIST in US, Ordnance Survey in UK).
- Privacy concerns may require that access to data is limited to specific users or to sub-sets of the data.
Collecting, 'cleaning', managing and disseminating data are typically labour- and/or cost-intensive processes - whoever provides these services should receive fair remuneration for providing those services.

Sponsors do not get full value unless their data is used appropriately - sometimes this requires quality management, dissemination and branding efforts that can best be achieved by charging fees to users.

Often, targeted end-users cannot use the data without additional processing (analysis, apps etc.) - if anyone has access to the data, none may have an incentive to invest in the processing required to make data useful. Typical examples include biological, medical, and environmental data.

Relation to other open activities

The goals of the Open Data movement are similar to those of other "Open" movements:

- **Open access** was already discussed above. It is concerned with making scholarly publications freely available on the internet. In some cases, these articles include open datasets as well.

- **Open content** is concerned with making resources aimed at a human audience (such as prose, photos, or videos) freely available.

- **Open notebook science** refers to the application of the Open Data concept to as much of the scientific process as possible, including failed experiments and raw experimental data.

- **Open research/Open science/Open science data**.

- **Open knowledge**. The Open Knowledge Foundation argues for Openness in a range of issues including, but not limited to, those of Open Data. It covers (a) scientific, historical, geographic or otherwise (b) Content such as music, films, books (c) Government and other administrative information. Open data is included within the scope of the Open Knowledge Definition, which is alluded to in Science Commons’ Protocol for Implementing Open Access Data.

- **Open source** (software) is concerned with the licenses under which computer programs can be distributed and is not normally concerned primarily with data.

Funders' mandates

Several funding bodies which mandate Open Access also mandate Open Data. A good expression of requirements is given by the Canadian Institutes of Health Research (CIHR):

- to deposit bioinformatics, atomic and molecular coordinate data, experimental data into the appropriate public database immediately upon publication of research results

- to retain original data sets for a minimum of five years after the grant; this applies to all data, whether published or not

Closed data

Several mechanisms restrict access to or reuse of data. They include:

- making data available for a charge
• compilation in databases or websites to which only registered members or customers can have access

• use of a proprietary or closed technology or encryption which creates a barrier for access

• copyright forbidding (or obfuscating) re-use of the data

• license forbidding (or obfuscating) re-use of the data (such as share-alike or non-commercial)

• patent forbidding re-use of the data (for example the 3-dimensional coordinates of some experimental protein structures have been patented)

• restriction of robots to websites, with preference to certain search engines

• aggregating factual data into "databases" which may be covered by "database rights" or "database directives" (e.g. Directive on the legal protection of databases)

• time-limited access to resources such as e-journals (which on traditional print were available to the purchaser indefinitely)

• webstacles, or the provision of single data points as opposed to tabular queries or bulk downloads of data sets

• political, commercial or legal pressure on the activity of organisations providing Open Data (for example the American Chemical Society lobbied the US Congress to limit funding to the National Institutes of Health for its Open PubChem data

Conclusion: trends of openness and transparency in e-society

Transparency and openness seems to be an ever more often prescribed recipe for good governance, improved participation and democracy, and – not least – increased efficiency and economic and social progress in many areas and dimensions of the modern e-society.

For references and more reading, see the bibliography at the end of this report.

Participative decision-making and e-democracy

Participative decision-making and e-democracy are more or less formalised and computer-supported ways of channelling informal voices into formal decision-making processes. They are sometimes used, particularly on the local level, as an attempt to reach pareto-optimal solutions and possibly consensus on controversial issues, such as where to place a waste station or a nuclear power plant.

The citizens should have possibilities to participate constructively in important decision processes in society. The decision processes could be on all levels of society, e.g. national, regional, local, and they will typically involve other categories of stakeholders as well, such as politicians, civil servants, experts, businesses, and non-profit voice organisations engaged in the environment or other thematic issues.

E-democracy and e-participation are two concepts which are often referred to in this context. There is no sharp distinction between these two concepts. Maybe one can say that
• **e-democracy** focuses on **analysis and formation of collective opinions and policies**, either on broad topics, such as education, labour market, or housing, or on more specific issues, such as arms control or death penalty

• **e-participation** focuses on **collective decision-making on specific issues**, such as the location of a waste collection plant, measures to be taken to improve the environment in a specific area, or how to organise public transport

Both e-democracy and e-participation include **formal procedures**, regulated by laws, and **informal procedures** based on voluntary engagement by those concerned. General elections, referendums, and formalised consultation procedures (for example in connection with the planning of a new city centre) are examples that belong to the former category. Informal procedures may be the result of spontaneous initiatives from citizens and citizen groups, often in reaction to proposals and decisions by civil servants or politicians. But authorities and political bodies may also proactively invite the citizens to participate in earlier stages of decision processes, even before issues and decision alternatives have been formulated.

It is assumed that both e-democracy and e-participation can benefit a lot from exploiting the new possibilities offered by modern information technology, both as regards availability of information, and as regards methods and tools for processing information. This applies to both formal and informal procedures. For example, e-voting is a way of bringing new qualities into traditional, formalised election procedure, and new methods and tool-boxes have been developed to support participative decision-making, e-participation.

**Participative decision-making**

Participative decision-making and e-democracy are more or less formalised and computer-supported ways of channelling informal voices into formal decision-making processes. They are sometimes used, particularly on the local level, as an attempt to reach Pareto-optimal solutions and possibly consensus on controversial issues, such as where to place a waste station or a nuclear power plant.

As described in Sundgren & Larsson (2009), participative decision-making may enhance traditional decision models in a representative democracy by enabling citizens concerned by a decision to provide input in a constructive way in all steps of the decision-making process. This is in contrast to decision-making processes, where politicians and civil servants have already by and large made up their minds, before the citizens are possibly involved – if they are involved at all – and where the citizens concerned can then do little except trying to stop the decision.

Participative decision-making may also enhance traditional decision models used by governmental bodies and public agencies by enabling the people involved in the decision-making process to get a multi-faceted and nuanced understanding of all factors affecting and being affected by the decision, both more or less objective, fact-oriented factors, and more subjective and value-oriented factors. Stakeholders and decision-makers could vary the assumptions concerning different factors, and relationships between factor, thus increasing the transparency of the decision-making process, and getting a good feeling for the sensitivity or robustness of the optimal outcome of the decision to variations of different assumptions in the decision model.

*The DSV-DECIDE model for participative decision analysis and decision support*

An example. See Sundgren & Larsson (2009).
The DSV-DECIDE model enhances traditional decision models in a representative democracy by enabling citizens concerned by a decision to provide input in a constructive way in all steps of the decision-making process. This is in contrast to decision-making processes, where politicians and civil servants have already by and large made up their minds, before the citizens are possibly involved – if they are involved at all – and where the citizens concerned can then do little except trying to stop the decision.

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The DSV-DECIDE model is not the only model of its kind. There are similar models proposed or investigated in, e.g., Hämäläinen et al. (2001), Bollinger and Pictet (2003) and others. An excellent overview of models and various tools in this area is given by Rios Insua et al. (2007) in their paper “Towards decision support for participatory democracy”.

Typical characteristics of the DSV-DECIDE model are:

- The decision process model is closely associated with a tool, or rather a tool box, the DECIDE tool box.

- The decision process model is structured into three layers:

  - The **stakeholder layer**, containing the political process and the interaction with the citizens.
  - The **investigation layer**, consisting of the local government’s internal administrative process, where decision makers and civil servants are stimulated in order to arrive at reasonable sets of alternatives and civil servants make investigations and assessments necessary for taking the process further. External consultancy firms may also be utilised.
  - The **analysis layer**, or inner decision layer, into which the data from the other two layers are entered and modelled by using techniques and tools from the area of multi-criteria decision analysis; the values and views of the decision makers (and possibly stakeholders) are incorporated as weights or rankings of the criteria together with assessments of the different decision alternatives score (or fulfilment) with respect of each criterion.

- Great emphasis is put on sensitivity analysis, that is, the sensitivity of the outcome of the decision to changes in preferences, priority weights or rankings of criteria, taking into account that different stakeholders may very well differ in their values and views. Among other things, the sensitivity analysis may help to find solutions that will be more satisfactory to some stakeholders than other alternatives, without really “hurting” the interests of other stakeholders. Thus, it can be viewed as a tool for search of a perceived Pareto optimality.

So far, most of the development and practical use of the DSV-DECIDE model has been internal part of the decision process (the investigation layer and the analysis layer), involving politicians (decision...
makers) and civil servants (experts). A natural next step is to expand the involvement of external stakeholders in a structured way, that is, citizens, businesses, and others, affected one way or the other by the decision under consideration. This step will involve development and deployment of tools as well as new and adequate decision process models, including testing and theoretical development of decision process models, methods, and tools in practical applications. Naturally, this step requires access to ‘real’ decision makers and decision problems or opportunities.

**More about e-participation**

For a more extensive treatment of the subject of e-participation and participative decision-making, the reader is referred to the education module “Participative decision analysis”, developed by Aron Larsson and belonging to the course “E-society – evolution or revolution”.

The course is available via the DSV learning platform iLearn2 or via the course website [https://sites.google.com/site/esocietycourse2013/](https://sites.google.com/site/esocietycourse2013/); here is the link directly to the course module on “Participative decision analysis”: [https://sites.google.com/site/esocietycourse2013/module-3](https://sites.google.com/site/esocietycourse2013/module-3).

**E-democracy**

According to Ohlin (2011a), e-democracy is a collective name for computer-supported methods that aim to shorten the distance between the citizen and the political decision making system - it aims at a more active citizenship. E-democracy can so far hardly be looked on as a mature science; more normal would be to look upon it as a collection of methods, with an aim.

**The e-democracy concept and its relation to e-government**

E-democracy differs from e-government. E-government concerns the use of electronically supported means for provision of public services to citizens. This is often mainly a one-way activity: the government and its agencies offer services of different kinds to citizens, services that may be of educational type, of medical type, of economical type etc. These services may even be of political type, they may contain provision of political education or public insight. In this case, they approach the e-democracy situation.

E-democracy is a concept that uses two-way communication. It concerns different types of dialogues that take place between the citizen and the political decision making system.

With a slight exaggeration, you might say that e-democracy is a citizen-driven activity, while e-government is an authority-driven activity. E-democracy concerns bottom-up activities, while e-government concerns top-down activities. However, this is a matter for debate. Certain e-government services may certainly be at least partly citizen-driven, or demand-driven, for example when a citizen asks for a specific public service, a service of a specific kind. Then the service providing authority may consider this service citizen-driven. So – the difference between bottom-up and top-down in this case is not sharp.

**E-democracy: democratic content**

Ohlin (2011a) brings up a number of topics under this heading, for example:

- e-democracy: global or local
- e-society has no borders
- the role of technology
- representative democracy or direct democracy online
- the digital divide
- citizen interest
**E-democracy: democratic form**

Ohlin (2011b) brings up a number of topics under this heading, for example:

- the participation ladder
- tools
- citizen panels
- deliberation
- social media
- security and leaks
- political simulation
- e-voting

**The participation ladder**

Citizens can act democratically in many ways; they can:

- inform themselves
- show interest to be consulted
- give proposals
- participate in petitions
- suggest agendas
- participate physically in meetings offline or online, more or less close to political decision-making

This is a scale of increasing decision-making contact. This is often looked on as a ladder, where each step shows an increased degree of participation and nearness to the decisions. Several countries use this concept. One may compare with a sequence of actions for general policy-making used by the OECD:

1. Agenda setting: establishing the need for a policy or a change in policy and defining what the problem to be addressed is.

2. Analysis: defining the challenges and opportunities associated with an agenda item more clearly in order to produce a draft policy document. This can include: gathering evidence and knowledge from a range of sources; understanding the context, including the political context for the agenda item; developing a range of options (including doing nothing).

3. Creating the policy: ensuring a good workable policy document. This involves a variety of mechanisms which can include: formal consultation, risk analysis, undertaking pilot studies, and designing the implementation plan.

4. Implementing the policy: this can involve the development of legislation, regulation, guidance, and a delivery plan.

5. Monitoring the policy: this can involve evaluation and review of the policy in action, research evidence and views of users.

Turning back to the ladder, some of the ladder steps invite to be related to technology; they are close to use of ICT support. Such activities that are related to e-democracy contain:

- **ePetitioning**, systems that allow citizens to lobby decision makers
- **eChecking**, information and monitoring systems, that makes it easy for citizens to observe the behaviour of elected politicians
- **blogs and other social media**, more or less locally published citizen generated debate with comments on online discussion forums, plus activities to extract common blog opinions
- **eConsultation**, systems that allow public bodies to approach and consult citizen groups in order to find their opinions on matters of interest to them
- **ePanels, or eJuries**, groups of citizens who are defined to represent the public opinion for a limited time
- **eAgenda setting**, systems that makes it possible for citizens to take part in setting of political decision making agendas
- **participatory budgeting**, projects that makes it possible for citizens to take part in making political resource choices, systems that are more or less online
- **political simulations**, citizen systems that show consequences of different political choices
- **eVoting**, more or less online systems that make voting more efficient than today
- **eReferenda**, where groups of citizens are participating in equally based eVoting

**Tools**
IBM has presented the following list of online tools for specific engagement tools:

1. Tools for developing documents collaboratively
2. Tools for creating shared work space for teams and committees
3. Tools for surveying citizens
4. Tools for gathering and ranking ideas and solutions
5. Tools for helping citizens identify and prioritize problems that government can fix
6. Tools for facilitating large-scale deliberation online
7. Tools for helping citizens visualize land use options
8. Tools for helping citizens balance budget and revenue options
9. Tools for using “serious games” to generate interest, understanding, and input
10. Tools for aggregating the opinions expressed on social media networks

**Citizen panels**
A citizen panel is a group of citizens, whose opinions mirror the opinions of a larger population of citizens. This panel usually has access to experts who provide complementary facts about the matter to be decided on.

**Deliberation**
A deliberative process can be seen as a process where the participants with the help of cooperation and adjustment of personal opinions search a common opinion, and thereby search common influence on a process. Analysis of such processes is a central topic in political science. Here, in e-democracy, we ask if ICT, or technologically influenced methods, in some way may contribute and make such processes more accessible and efficient.

An example of a deliberative process can be the following. A selected group of citizens get together to find relevant background knowledge on a matter, and then after discussion in several “waves” formulate a common opinion – that usually differs from what was thought in the beginning.

Deliberation is relevant for public decision making, for democracy at large. In deliberation, citizens can share values and get together on common thoughts.

**Social media**
From around 2010 and onwards, as we know well, an increasing amount of activity is noted on social media. Blogging, Facebook, Myspace, Twitter etc. have become media of today. The availability of
these media makes them well suited for discussion that often turns out to be spontaneous. Social media expand very fast, and therefore also generate in size expanding political platforms. Sorted e-mail lists can do the same, but social media are especially rich, easy to handle, tempting and flourishing. What is especially tempting in social media is the triggering of emotions in present time, what we do at the moment, what thoughts we had last night etc. Social media show what is happening at this very moment. Many users spend a long time daily on this.

This is relevant for news. These media report on what is happening now, but surely also the “now” seen in perspective. It is also relevant for local everyday life of course. How about political participation?

President Obama used social media for collecting support when he ran for president. However, this was to some extent one-way activities, with the blogging that was used he wanted to get the word out. Obama used large mobile phone networks, he used the Internet as support database for campaigns and for fresh information, and sent many millions of personal emails. Often, these emails used the word “we” instead of “I”. These activities were successful, but did, technically seen, not use the interactivity of the Internet to its full capacity.

Social media no doubt invite citizens to participate in political discussion. Not seldom, however, the result of this finds itself at a certain distance from taking part in pure decision making. However, there are increasing numbers of tools available out there that make it possible to “combine blog and Facebook comments”. As this expands, which can be expected, these media will likely become even more important than today. Structured deliberations using social media for online participation may show to be especially successful.

Social media comments are often of a personal nature. They often can be looked on as an enhanced form of organized e-mail. Like lists of e-mails, lists of social media participants and comments are becoming important also for participation that moves closer and closer to decision making. This will make citizen participation even more tempting. Citizens often want to take part!

Social media from the beginning concerned discussions in small groups. When these discussions came to attract larger groups of participants, content quality was added. This is expanding fast after 2011.

As a medium for freedom of speech, social media are becoming more and more important. Examples exist from the situation 2011 in Egypt. Blogs there did create platforms for political opposition, platforms that formerly did not exist. Democratic contact has found an important place via social media.

Mathew Hindman wrote in 2008, in his award-winning, blog analysing book: “It is easy to start a blog, but who is listening?” A relevant question. Well, as the years go by, increasing numbers of citizens will likely do that - listen. But it remains to be seen to what extent blog lists will come close to decision making. Decision making needs a certain amount of organisation, and social media are – seen from the platform of their first years - often more immediate than organized. But – this may change. They may become organized. And when looking at user content, given time, the word “social” in “social media” may perhaps change to – “political”?

Security and leaks
Activities by WikiLeaks and its followers have caused much concern. Apparently, it shows to be difficult to keep secrets in information society, more difficult than was thought earlier.
This has been foreseen. As information available via the Internet spreads increasingly fast, it is natural that it becomes more and more difficult to hide knowledge behind shelters. It may be looked on as an effect of the blurring of borders, discussed earlier.

Activities that rely on secure information apparently as a consequence will meet obstacles. This includes, for instance, shelters for anonym information providers, often called whistle blowers. It becomes more and more difficult to be anonym.

Apparently there is a conflict between the diminishing of borders on one side, and the building up of leak-safe shelters on the other. How should new types of shelters around sensitive information be organized, information that could be essential for society?

These problems are to some extent of a social nature. For their solution, we can look at other similar social situations in life. We want to move freely in the streets, but we accept policemen who regulate the traffic and observe pavements for pedestrians. In most countries in Europe we have right hand traffic. This is accepted. But regulated traffic on the Internet?

It is the same kind of conflict as the conflict between efficiency and personal integrity. For an efficient public society – with rapid public service - we accept large-scale storing of certain personal citizen information that in short time can be read, compiled and acted on. On the other hand, misuse of such information can occur. Therefore, we want to restrict such compiling of certain citizen information to a minimum. On one hand, we want to eat the cake, on the other, we want to keep it. Here, often we need to look for the least harmful, and well balanced, a compromise. An open society permits insight, but apparent leaks relate to shelters. Democracy demands openness, and e-democracy most certainly does this, but efficiency asks for certain strict rules.

During the birth of information society we have seen this balance change over time. In the beginning, protection of personal data was well guarded, threats about “Big Brother”, “1984”, with access to the citizen’s “data shadow” were frequent, and central storing of personal data was looked on with suspicion. As technology has made storing of personal data so much simpler and cheaper, this carefulness has decreased. A decade after the change of century, threats from terrorists and professional hackers often are considered to motivate heavy storing not only of personal data, but also about personal traffic. This is a change. Efficiency and strict access to data is on the way to take over. This balance is to some extent political. Likely we have not seen the final and sensitive balance point.

Political simulation
There are computer applications available that provide possibility for citizens to participate in “virtual” decision making. It is sometimes called “citizen budgeting”, although it certainly concerns also other types of virtual participation than simply that which relates to economy. There are cultural and social budgets. This may be compared to SimCity and other computerised simulation games.

Citizens in this case are provided with an imaginative budget, open for spending according to personal political choices in a virtual society. To compare with reality, each citizen will have last year’s real budget. It is possible to “over-spend”, use too much, in which case the actual virtual community will have to take loans, with interest to pay. In all, this is meant to mirror reality, every citizen can here potentially become a politician. The resulting citizen priorities can be put together, to form a “peoples will”.

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eVoting
It may seem uncomplicated to perform voting via the Internet. We meet it more or less every day in
the newspapers. However, there are a number of problems to analyse before implementing
politically accepted online voting in real life and in large scale.

In many countries there is hesitation towards introduction of eVoting. In Finland, in 2008, 232 votes
were not treated correctly by an eVoting system, and a part of the whole vote had to be repeated,
creating much irritation. Also in the Netherlands and in UK, there is political hesitation, like in several
other countries. However, there is also optimism internationally. By March 2011, Estonia has carried
out five eVoting projects. In Switzerland, the city of Genève has taken a general decision to do local
voting online. Belgium is also positive. And many experiments are going on in several places, in the
US, in India, as well as in Nigeria, Africa. Norway is planning online local elections in Sept. 2011. Still,
in 2011, no similar decisions are taken in Sweden.

So, what lies behind the hesitation?

Often this refers to technical and organizational security. Politicians are afraid of hacking and threats
against voter system integrity and robustness. On the other hand, more secure technology is
currently being developed. An example, where this author took place, is the online technical system
that was tried in the CyberVote project already in 2003, where hundreds of elderly voters
participated successfully in online voting in Kista, Stockholm, and where thousands of online voters
participated in Bremen and in Paris. Here, the technological software was built on parting and
distributing of compatible system parts. A possible hacker could only get hold of a part of the
complete system, and could not do much harm.

Over the years, more and more secure online voting pieces of technology are being developed.

It often is considered important that each vote is secret, known only to the voter herself. It is said to
be difficult to guarantee that another family member does not follow what one family member does
on her online computer. Such “family voting” is analysed seriously by many.

We may list a few of the eVoting problem areas:

• Technical security, barriers against hackers and online network intruders
• Voter integrity, the voting secrecy
• Verifiability (who voted?) is not simple – not many countries have secure ID cards
• Voter participation unbalances, digital divides – often primarily the young and highly educated
  vote

On the other hand, there are advantages:

• Easier voting access may raise election participation levels
• Better voting access for citizens abroad
• Better voting access for the handicapped
• Locally connected voting machines may be used
• Secure technical online voting methods are being developed
• Fast calculation of voting results is possible
• Online voting seems natural for the young generation
The latest of these arguments seems to be getting stronger over time. At eVoting conferences after 2010, the average age of participators is usually low; lower that elsewhere at information society conferences. A usual comment given is that time is behind much deliberation and eVoting hesitation. In Estonia, the general election 2011 had eVoting as one of several methods to vote. A descriptive summary says:

“The Estonian national elections took place on 6th March 2011. As in previous elections, citizens were also able to cast their vote over the internet — this time from 24th February to 2nd March. The overall election turnout increased only marginally (by less than two percentage points over the last general election) but there was a massive rise in voters who cast their vote on the internet, from 5.5% to 24.3%. This may be partly due to the longer time during which voters could go to the online polls, which increased from three days to seven; but it also suggests an increasing awareness and acceptance of the technology. As well as voting online, Estonians made use of other online tools to help them decide whom to vote for: the website http://valijakompass.err.ee/, which is a tool that helps voters pick a party according to the policies they agree with, reports over 100,000 hits.”

This ends this Estonian comment.

It is worth to remember that no voting system is 100% fool proof. Problems are of large or small magnitude. Even today’s almost completely manual political voting system in Sweden has shown to contain technical problems, some, but not all, related to the “human factor”.

More about e-democracy

For a more extensive treatment of the subject of e-democracy, the reader is referred to the education module “E-democracy”, developed by Tomas Ohlin and belonging to the course “E-society – evolution or revolution”. The course is available via the DSV learning platform iLearn2 or via the course website https://sites.google.com/site/esocietycourse2013/; here is the link directly to the course module on E-democracy: https://sites.google.com/site/esocietycourse2013/module-2.
CHAPTER 5. Information for welfare, happiness and prosperity

Information of higher quality, made available in more efficient ways, has the potential to improve living-conditions (sometimes called happiness by sociologists) for the citizens, and to improve the functioning of the markets in a market-economy. In this chapter, we shall discuss these and related matters.

Information for monitoring and driving socio-economic progress

Objective information of good quality is a necessity for anyone who wants to monitor the socio-economic and other conditions and developments in a society, and to compare this with the situation and developments in other societies, and propose decisions and actions for improvements and progress.

This is known by the leaders of all societies in the world, even dictators, and it has been known and understood for thousands of years. As expressed by Nordbotten (2010):

“...It is difficult to state when official statistics were first produced and used, but it was probably when rulers of communities wanted to compare their power with that of their enemies. Males have most likely been enumerated and records summarized to provide the rulers with needed information on which strategic decisions could be based. According to a Canadian source, enumeration of different resources was already being regularly carried out in Babylon (Statistics Canada 2009). About 4–5 thousand years ago, Egyptian pharaohs also carried out censuses for tax gathering and to determine fitness for military and labour services as well as for surveying construction progress. It became early quite common in many countries to enumerate the male population within certain age brackets in order to provide the rulers with statistics about their potential power, and records for recruiting soldiers to their legions. These statistics have in more recent times been utilized retrospectively to estimate the total populations and their age distributions. Recording land properties was a usual means for rulers to determine taxation of their populations. Based on statistics from these records, heads of countries could evaluate their potential income and wealth as well as keep control by means of the collection process. Trade in commodities passing frontiers was another early source for collecting taxes, and the first international trade statistics appeared. The first formal offices for official statistics were established in the 18th century. They were frequently named Table offices, reflecting the fact that their purpose was to summarize administrative micro data into tables of macro data, not to collect the data themselves (Koren 1914). At this time, demographic records, tax data, public accounting data, health data, social data, medical data and school data were aggregated to separate types of statistics to describe the prosperity of the country. In the middle of the 19th century, international cooperation on official statistics was initiated. Some countries established National Statistical Bureaus, responsible for all official statistics, while other countries chose to organize statistical departments within several ministries. In both cases, the statistics prepared were mainly based on administrative data, later to be supplemented by data collected solely for statistical purposes such as population censuses and statistical sample surveys. Typical for the official statistics up to the Second World War was that the collection of data and production of statistics on different matters was to a large extent carried out independently (Sundgren 2004, Sundgren 2010). This made integration of the statistical results rather difficult. After the Second World War, the need for creating comprehensive and consistent descriptions of the economic, demographic and social aspects of countries increased, and particularly the National Accounts System became an important vehicle for organizing economic statistics into a conceptually consistent system (Vanoli 2005). However, because of the diversified nature of the data on which the different parts of the national accounts were prepared, the compilation of national accounts became a very complex operation. The intention of developing a similar System of Social and Demographic Accounts was never realized.”
In modern democratically ruled societies, official statistics have become a common, socially constructed, frame of reference for all actors in society: politicians, ordinary citizens, business people, non-government organisations, and others. The quality of these statistics is not perfect, and the strivings for comparability and coherence have still a way to go, but most actors accept this common frame of reference, even if they draw different conclusions from the factual information as regards how good or bad the situation is, and what needs to be done – depending on political and other preferences. Information from the integrated and reasonably consistent System of National Accounts (SNA), mentioned by Nordbotten in the citation above, by and large determine the views of the economy by all actors, and progress has also been made as regards a common information basis for judging the living conditions – sometimes called “happiness” by sociologists – in a country, even if many of the indicators used cannot be expressed in one common measurement unit like in the national accounts, where “money” is the common denominator. A development of a common framework of indicators of the environment has also started and will no doubt help politicians to cope with the climate change and other environmental challenges.

As pointed out above, even dictators usually want to have a true picture of the situation in their societies. They, too, try to get objective information of good quality. However, unlike democratically elected leaders in democracies, they will often keep the true facts for themselves, and order their statisticians to “massage” the figures before they are published and sent to international organisations. This is what happened in the former German Democratic Republic (GDR), for example.

### The role of information for efficient markets

As elaborated by economists, a well-functioning market economy is based on a number of assumptions that have to do with the availability (at a low cost) of information, for example:

- consumers are well informed about the qualities and prices of competing products and services from competing suppliers
- producers have knowledge about best production methods and the ability and rights to use them
- consumers and suppliers have information about experiences and satisfaction gained by other consumers, who have bought a certain product or service, or competing products and services
- producers get ideas about how products and services can be improved, and which new products and services could be developed, in order to meet the expectations of consumers

Modern, computer- and Internet-based methods and tools have drastically improved the possibilities for both consumers and suppliers to get the information they need for filling their respective roles in a market economy in a more optimal way. For example:

- consumers may find independent websites where they can compare products and prices
- consumers may make call for tenders to a number of potential suppliers, before they buy a more or less complex and costly service
- suppliers may use feedback information from consumers, for example via targeted and well-designed questionnaires, or via spontaneous information in social media, expressing problems, complaints, or praise

In market economies it is believed that free competition on free markets is the best way to ensure efficient development, production, and delivery of goods and services needed in a society. However, it is also recognised that there have to be legal frameworks and procedures in order to ensure that the competition is really free, and that diseconomies (e.g. negative effects on environment) and...
other negative side-effects of free competition (like financial crises) do not occur. The nature and extent of legal frameworks and regulations is of course a political issue.

The role of social media

The use of social media, by all kinds of actors in society, has exploded during the last decade. It is still too early to evaluate all effects of this, and to what extent different effects are good or bad. Moreover, the situation is very dynamic, and tools and usage patterns of different actors may change dramatically from one year to another.

Social media are now used by all kinds of actors in society: citizens, businesses and other organisations, as well as government administrations.

Citizen perspectives

Social media obviously play an important social role for many citizens today, citizens of all ages and backgrounds. It is easy to see how many people use social media to reinforce their self-images and the images they want to give of themselves to others. Social media may also be very useful for sharing experiences and opinions and information received from other sources.

On the other hand, being active on social media takes a lot of time. Sometimes the communication tends to be one-way only. Social media may help to spread false rumours. Even worse they may lead to mobbing and hatred. Social media may reinforce subcultures among people with the same views, and they may not stimulate people to broaden their views by taking part of the opinions and arguments by people who think differently.

Business perspectives

Business has discovered that they can use social media as yet another channel for communicating with their customers and potential customers. Direct influence on people may also be achieved indirectly through cooperation with famous bloggers, who themselves may develop these kinds of cooperation to profitable businesses. The famous bloggers, and sometimes less famous friends of individual persons, may influence people in very efficient ways, especially if they are not aware of the commercial motives behind the experiences shared with them via blogs and other social media.

If businesses take the time to listen to what is said about them and their competitors on social media, they may get very valuable feedback from these sources. In fact limiting themselves to one-way communication, like they have always done when they use traditional advertising in old media, may be very dangerous for businesses when using social media. They may not discover, until it is too late, that a lot of customers share complaints and negative opinions about their business. Thus a business which chooses to appear on social media must devote competent resources to follow what is said about them on social media and respond quickly when this is urgent and important for their reputation and future success.

Another aspect for businesses to consider is their internal policies and rules towards their own employees: should they be forbidden or encouraged to use social media when they are at work? Banning such activities may come in conflict with constitutional laws about freedom of speech, although spending work time on social media may also be regarded as stealing resources from the employer. On the other hand, some businesses actually encourage their employees to use social media at work: for obtaining valuable information, or for sharing positive images of the company, for example. This may also have certain legal effects as regards who is responsible for what the views
expressed and shared by an employee, and who will have to pay for damages caused by the employee’s activities, if such damages are established by a court decision.

**Government perspectives**

In principle, the considerations concerning the use of social media by a government administration will be similar to the considerations that have to be made by a business. However, some of the considerations may become more delicate, since a government administration and its employees have special legal obligations to the citizens and their democratically elected principals.

**The digital divide: digital exclusion and inclusion**

The **digital divide** refers to the gap between those who have access to and use information technology, in particular the Internet, and those who have not. Which factors may cause the gap, and which factors may help to close it?

Technical factors are of course fundamental: if you don’t have a computer or some other suitable device, and if you don’t have a connection to the Internet, preferably via broadband, you will not be able participate in the Internet-based information society and reap the benefits of such participation.

Thus certain technical conditions are necessary, but they are not sufficient. Your ability and tendency to actually use technical devices and communication facilities may depend on a number of demographic and socio-economic factors such as income, education, unemployment, age, sex, etc. The impact of such factors, as well as factors reflecting available technology, has been investigated by many surveys. One result is that these factors are not sufficient to provide a complete explanation of the digital divide that actually exists in a society. The motivation to use the technology may sometimes be more important than demographic and socio-economic factors. For example, a senior citizen with low income and low education, having children and grandchildren living abroad, may be highly motivated to use an Internet-based tool like Skype in order to get the chance to have virtual meetings with her loved ones, and this motivation may help her overcome any difficulties that she may have because of age, low income, and low education.

The digital divide threatens to split a society into those who are digitally included and those who are digitally excluded, and such a split may become more and more harmful for both the individual citizens and households concerned, and for society as a whole, the more dependent we become of Internet-based information and tools. It is a challenge for governments on all levels to counter-act the digital divide by making decisions and taking actions that will include citizens and households that are digitally excluded for the time being.

An example of what can be done is provided by the Government of Wales, which developed a Digital Inclusion Delivery Plan in 2010, which has then been yearly evaluated for progress, and updated. Here are some quotations from “The Digital Inclusion Delivery Plan: Annual Progress 2015”,


“...”

**Background**

In 2010, the Welsh Government developed a strategic response to the high number of adults who were digitally excluded. The Digital Inclusion Framework, published in December 2010, identified those people who were most likely to be digitally excluded, including older and disabled people; those who live in social housing; those on lower incomes; the unemployed and economically inactive. There was a recognition that achieving the digital inclusion of people, both as citizens and
consumers, is essential to ensure that they can benefit from the rapid pace of technological change. The Framework assumed a duration of five years.

In order to maximise the impact and reduce the numbers of citizens who are digitally excluded, the Framework recognised the need to:

a) Align policies;
b) Obtain ‘buy-in’ from a wide range of stakeholders; and,
c) Undertake activities which include:
   • on the ground digital inclusion delivery through community based approaches;
   • engagement through libraries;
   • learning through education and lifelong learning, and skills development;
   • increased involvement of the private, public and third sectors
   • the use of volunteers;
   • extending the range of geographical coverage where support is available.

To complement the Framework, the Digital Inclusion Delivery Plan was published in March 2011. The Delivery Plan set out the key targets, objectives, tasks to be undertaken and expected outputs and outcomes in order to reduce digital exclusion levels in Wales. ...

Rapid Pace of Technological change

Since 2011, the profile and importance of digital inclusion has evolved rapidly. Technology, and the benefits of using it, continues to develop apace. This threatens to widen the digital divide between the active users who can increasingly exploit ever improving technologies, and those who continue to struggle to overcome the barriers to getting online. These digitally excluded people are in danger of being left behind in society, as more and more services, including vital public services, go online.

Good progress

Good progress is being made in getting more people to take advantage of the opportunities of being online, with the percentage of adults in Wales not regularly using the internet falling from 34% at the end of 2010 to 19% in June 2015. Many more organisations across the public, private and third sectors now recognise the importance of getting more people to enhance their lives through the use of digital technologies, but much more still needs to be done.

In June 2015, it was estimated that 473,959 (19%) adults did not use the internet. This included 35% of those aged 50 and over, 31% of social housing tenants and 38% of Disabled People (those with a limiting long-standing illness, disability or infirmity). ...

Still about improving peoples’ lives through technologies

Digital inclusion is still about ensuring that people, both as citizens and consumers, benefit from the rapid pace of technological change that is taking place in our society. This especially applies with people being able to use the internet in ways that enhance their lives and contribute to helping them overcome other disadvantages which they might face. However, the need is now greater than ever as ‘digital’ increasingly becomes the preferred way of conducting transactions for both providers and users alike.

Whilst market forces continue to be responsible for getting many people to use the latest digital technologies, helped by cheaper equipment and faster broadband speeds, barriers still exist for
significant numbers of people that have prevented them from participating with digital technologies. Market forces have not been able to overcome the three main barriers of motivation, skills and access, which includes affordability and accessibility. Research suggests motivation is still the main reason people do not go online, but the need for people to go online will increase as more services are delivered through online channels.

Poor basic literacy skills are often the underlying reason why people struggle to take advantage of the opportunities of being online. Digital inclusion activities should therefore be tackled alongside activities that improve basic literacy skills.

**Doing more**

Digital inclusion has previously been associated with helping people acquire the most basic internet skills to help them get online, see the benefits of doing so, and leading them on the path to becoming more active users. Many people need ongoing support whether it is informal support from friends or families or community based provision like in public libraries and other community based learning venues. Others will prefer to undertake more formal accredited learning from adult learning providers.

To function in an increasingly digital world requires more than being able to surf the internet. To truly secure the benefits of being online, individuals need to be able to communicate effectively online, find and evaluate what they are looking for and safely share personal information, whether it is making a job application, undertaking a public service transaction, or buying online goods at often reduced prices. Trust and security is a concern for many, particularly the elderly. Ensuring children stay safe online is a real concern for parents and grandparents, so they will need to develop the necessary skills to do this.

**Some will never get online**

We must recognise that there will always be some people in society that will be unable or unwilling to use the latest digital technologies. For these people, there should be alternative ways to access goods and services to ensure they are not left behind. Realistically, many will continue to struggle to use the latest technologies fully independently, but with the appropriate support they can still realise the benefits of being online that most people take for granted. ...”

**Open knowledge**

Freedom of information and freedom of speech are important prerequisites for a lively and constructive debate, bringing progress to a society. In e-societies, computer-supported tools and systems, and communication networks like the Internet and social media based on the Internet, empower the citizens in a very efficient way for their participation in the development of their societies.

Freedom of knowledge takes this a step further. E-society and the Internet makes it possible to give all citizens easy access to all scientific knowledge and experiences that have been gained and accumulated over time, including the most recent findings. Moreover, all this collective knowledge of mankind can be made available to everyone in a very efficient and inexpensive way, often free of charge. Even if these possibilities are open to everyone, they are of course of special interest to researchers and students and others who want to take the chance to develop their talents and skills in order to get better jobs or just for the sake of developing themselves as human beings.

We shall take a look at the following phenomena that are important for the development of this new freedom of knowledge in e-societies:
New methods and forms of higher education, enabled by modern, web-based information technologies and new pedagogical models, are hot topics at schools and universities today. Many have a strong belief in many of these new forms of education, and the students are definitely attracted by them and often choose them when they are available.

On the other hand there are many university teachers, who are sceptical to the new methods and forms of education, and many students are also critical to some aspects of them. There are definitely needs to improve all forms of higher education in order to achieve better results in more efficient ways, both from a producer’s and from a customer/student’s perspective.

There is a lot of prejudice about e-learning. For example, many people, including some politicians and some teachers, suggest that e-learning, or distance education, is per se of lower quality than conventional, campus-based education, delivered ex cathedra. There is a tendency among these critics of e-learning to compare ideal conventional courses, given by the best teachers, with mediocre online courses produced by mediocre teachers with their main focus on low costs, rather than on high quality and other features meeting the demands of students.

On the other hand, there are also some bureaucrats who believe that net-based learning will automatically rationalize and lower the costs of producing courses, increasing the productivity drastically, since the same lectures and education material can be reused over and over again for huge masses of students. This may sometimes be true, but one should not underestimate the costs of designing and producing high-quality online courses.

So far there have been relatively few serious studies, focusing on facts, and aiming at fact-based evaluations and comparisons of different modes of teaching and learning, including so-called blended approaches, combining the best aspects of different models.

Regardless of our attitudes towards the new methods and forms of higher education, we should be able to agree that many more facts are needed as a basis for our evaluations and decisions. And we also need to know more about which aspects and criteria should be evaluated and compared.

Some visions for the future:

- The demand from students will continue to grow for new methods and forms of higher education, enabled by modern, web-based information technologies and new pedagogical models.
• The new methods and forms of higher education will continue to be improved, taking advantage of technical as well as pedagogical innovations, often in combination.

• Disruptive phenomena like Open Education Resources (OER), Massive Open Online Courses (MOOC), self-learning, and Open Access (OA) publishing will continue to grow rapidly, creating great opportunities for democratising distance education and self-learning, giving underprivileged groups of students access to advanced knowledge and skills, instrumental for a good life.

• New pedagogical methods associated with terms and phrases like “flipped classroom” and “teaching teaching & understanding understanding” will have a great impact on future teachers and future teaching and learning.

• The new methods and forms of higher education will lead to improvements of quality, cost-efficiency, and student satisfaction.

• Universities will develop and intensify cooperation and organise joint virtual educations and virtual universities, engaging the best teachers and education resources, wherever they are physically located.

• The new methods and forms of education will lead to improvements of quality, cost-efficiency, and student satisfaction.

Links to videos about “flipped classroom”:

• https://www.youtube.com/results?search_query=flipped+classroom

• https://www.google.se/search?q=youtube+%22flipped+classroom%22&oq=youtube+%22flipped+classroom%22&aqs=chrome..69i57j0l4.13963j0j7&sourceid=chrome&espv=2&es_sm=122&ie=UTF-8

Links to a series of three videos on “Teaching Teaching & Understanding Understanding”:

1. http://www.youtube.com/watch?v=iMZA80XpP6Y
3. http://www.youtube.com/watch?v=w6rx-GBBwVg

Open Educational Resources (OER)


Open educational resources (OER) are digital materials that can be re-used for teaching, learning, research and more, made available for free through open licenses,

Open educational resources (OER) are digital materials that can be re-used for teaching, learning, research and more, made available for free through open licenses, which allow uses of the materials that would otherwise not be easily permitted; Hylén (2007). OER includes different kinds of digital assets and learning contents: courses, course materials, content modules, collections, and journals. Tools include software that supports the creation, delivery, use and improvement of open learning content, searching and organisation of content, content and learning management systems, content development tools, and on-line learning communities. Implementation resources include intellectual property licenses that govern open publishing of materials, design-principles, and localization of
content. They also include materials on best practices such as stories, publication, techniques, methods, processes, incentives, and distribution.

If properly designed, certain types of open education resources, often called **learning objects**, cannot only easily be shared by many students and course providers; they can also be reused as components or services of other learning objects and courses. This idea resembles the idea of building information systems by reusing already designed and developed software services – **service-oriented architectures** (SOA).

Open Educational Resources could be seen as a generalisation of the concepts of **Open Access** (OA), **Open Archives**, and **self-archiving**, phenomena of rapidly growing importance for efficient publishing and dissemination of scientific work (articles, journals, books, etc.).

**Massive Open Online Courses (MOOC)**

Sources: [http://en.wikipedia.org/wiki/Massive_open_online_course](http://en.wikipedia.org/wiki/Massive_open_online_course) and Sundgren (2013).

A **massive open online course** (MOOC) is an online course aiming at large-scale interactive participation and open access via the web. In addition to traditional course materials such as videos, readings, and problem sets, MOOCs provide interactive user forums that help build a community for the students, professors, and teaching assistants.

Some famous **TED talks** about MOOC:

- **Shimon Schocken, The self-organizing computer course**, October 2012
- **Daphne Koller, What we're learning from online education**, June 2012
- **Peter Norvig, The 100,000-student classroom**, February 2012
- **Salman Khan, Let's use video to reinvent education**, March 2011

**Self-learning**

Possibly the most revolutionary aspect of OER and MOOC is its potential to provide free or inexpensive and efficient access to valuable knowledge and skills for **self-learning** for those who cannot afford to attend traditional university courses. This is an important possibility not only for gifted students in poor countries, but also for gifted but poor students in rich countries, like the United States, where traditional education is very expensive. According to the U.S. Bureau of Labor Statistics, quoted by Koller (2012), the prices of higher education have grown twice as fast as the prices of medical care since 1985, and four times as fast as the prices of all items. See Figure 41 below.

**Application**


E-learning is increasingly being utilized by students who may not want to go to traditional brick and mortar schools due to severe allergies or other medical issues, fear of school violence and school bullying and students whose parents would like to homeschool but do not feel qualified. Cyber schools create a safe haven for students to receive a quality education while almost completely avoiding these common problems. Cyber schools need not be limited by location, income level or class size in the way brick and mortar charter schools are.
Figure 41. Rapidly rising prices for education in the United States.

**Higher education**

In the United States and many other countries, including Sweden, e-learning has become a predominant form of post-secondary education. Enrolments for fully online learning increased by an average of 12–14 percent annually between 2004–2009, compared with an average of approximately 2 per cent increase per year in enrolments overall. In 2006, 3.5 million students participated in online learning at higher education institutions in the United States. Almost a quarter of all students in post-secondary education were taking fully online courses in 2008. In 2009, 44 percent of post-secondary students in the USA were taking some or all of their courses online; this figure is projected to rise to 81 percent by 2014. During the fall 2011 term, 6.7 million students enrolled in at least one online course. Over two-thirds of chief academic officers believe that online learning is critical for their institution. The Sloan report, based on a poll of academic leaders, indicated that students are as satisfied with online classes as with traditional ones.

Corresponding statistics for Sweden have been published by the Swedish Agency for Higher Education (Högskolverket). See Sundgren (2012).

Thus online education is rapidly increasing, and online doctoral programs have even developed at leading research universities; [https://en.wikipedia.org/wiki/Educational_technology#cite_note-60](https://en.wikipedia.org/wiki/Educational_technology#cite_note-60)

**Massively open online courses** (MOOCs) have significantly expanded: MIT, Stanford and Princeton University offer classes to a global audience, but not for college credit.

**Corporate and professional usages of net-based learning**

E-learning has now been adopted and used by various companies to inform and educate both their employees and customers. Companies with large and spread out distribution chains use it to educate their sales staff as to the latest product developments without the need of organizing physical onsite courses.
Open and net-enabled research and innovation

The trends towards openness in society are also relevant for research and education. Using the Internet for fast and free dissemination of research results, as well as Internet-based cooperation between researchers, will stimulate researchers and improve the quality and efficiency of research.

Open research and open science


**Open research** is research conducted in the spirit of free and open source software. Much like open source schemes that are built around a source code that is made public, the central theme of open research is to make clear accounts of the methodology freely available via the internet, along with any data or results extracted or derived from them. This permits a massively distributed collaboration and participation in research projects.

Open research can be applied to all kinds of sciences, for example social sciences, humanities, mathematics, engineering and medicine.

Open innovation


100open (Open innovation defined): [http://www.100open.com/2011/03/open-innovation-defined/](http://www.100open.com/2011/03/open-innovation-defined/)

**Open innovation** is a term promoted by Henry Chesbrough, a professor and executive director at the Center for Open Innovation at the University of California, Berkeley, in his book *Open Innovation: The new imperative for creating and profiting from technology*, though the idea and discussion about some consequences (especially the interfirm cooperation in R&D) date as far back as the 1960s.

According to Chesbrough (2003):

“Open innovation is a paradigm that assumes that firms can and should use external ideas as well as internal ideas, and internal and external paths to market, as the firms look to advance their technology”

Alternatively, according to [http://www.100open.com/2011/03/open-innovation-defined/](http://www.100open.com/2011/03/open-innovation-defined/), it is

"innovating with partners by sharing risk and sharing reward.”

The boundaries between a firm and its environment have become more permeable; innovations can easily transfer inward and outward.

The central idea behind open innovation is that, in a world of widely distributed knowledge, companies cannot afford to rely entirely on their own research, but should instead buy or license
processes or inventions (i.e. patents) from other companies. In addition, internal inventions not being used in a firm’s business should be taken outside the company (e.g. through licensing, joint ventures or spin-offs).

The open innovation paradigm can be interpreted to go beyond just using external sources of innovation such as customers, rival companies, and academic institutions, and can be as much a change in the use, management, and employment of intellectual property as it is in the technical and research driven generation of intellectual property. In this sense, it is understood as the systematic encouragement and exploration of a wide range of internal and external sources for innovative opportunities, the integration of this exploration with firm capabilities and resources, and the exploitation of these opportunities through multiple channels.

**Open source software**

**Sources:**

Website: Open Source Initiative, [https://opensource.org/](https://opensource.org/)

According to Wikipedia, **Open-source software (OSS)** is computer software with its source code made available and licensed with a license in which the copyright holder provides the rights to study, change, and distribute the software at no cost to anyone and for any purpose. Open-source software is very often developed in a public, collaborative manner. Open-source software is the most prominent example of open-source development and often compared to (technically defined) user-generated content or (legally defined) open-content movements.

If we define “open access” as “open access to scientific journals and scientific papers”, a short definition of “open source” could analogously be “open access to software source code”.

A more elaborate definition of “open source” is provided by the Open Source Initiative (OSI) on their website, [https://opensource.org/](https://opensource.org/). The definition is based on the assumption that the distribution of the software is associated with a license, approved in a License Review Process. According to the OSI definition of “open source”, open-source software and the associated license must comply with the following criteria:

1. **Free Redistribution.** The license shall not restrict any party from selling or giving away the software as a component of an aggregate software distribution containing programs from several different sources. The license shall not require a royalty or other fee for such sale.
2. **Source Code.** The program must include source code, and must allow distribution in source code as well as compiled form. Where some form of a product is not distributed with source code, there must be a well-publicized means of obtaining the source code for no more than a reasonable reproduction cost preferably, downloading via the Internet without charge. The source code must be the preferred form in which a programmer would modify the program. Deliberately obfuscated source code is not allowed. Intermediate forms such as the output of a preprocessor or translator are not allowed.
3. **Derived Works.** The license must allow modifications and derived works, and must allow them to be distributed under the same terms as the license of the original software.
4. **Integrity of The Author's Source Code.** The license may restrict source-code from being distributed in modified form only if the license allows the distribution of “patch files” with the source code for the purpose of modifying the program at build time. The license must explicitly permit distribution of software built from modified source code. The license may require derived works to carry a different name or version number from the original software.
5. **No Discrimination Against Persons or Groups.** The license must not discriminate against any person or group of persons.

6. **No Discrimination Against Fields of Endeavor.** The license must not restrict anyone from making use of the program in a specific field of endeavor. For example, it may not restrict the program from being used in a business, or from being used for genetic research.

7. **Distribution of License.** The rights attached to the program must apply to all to whom the program is redistributed without the need for execution of an additional license by those parties.

8. **License Must Not Be Specific to a Product.** The rights attached to the program must not depend on the program's being part of a particular software distribution. If the program is extracted from that distribution and used or distributed within the terms of the program's license, all parties to whom the program is redistributed should have the same rights as those that are granted in conjunction with the original software distribution.

9. **License Must Not Restrict Other Software.** The license must not place restrictions on other software that is distributed along with the licensed software. For example, the license must not insist that all other programs distributed on the same medium must be open-source software.

10. **License Must Be Technology-Neutral.** No provision of the license may be predicated on any individual technology or style of interface.

It is decisive for the success of business models based on concepts like “open source” and “open access” that all parties involved, especially the authors and creators of intellectual assets, feel that they gain more than they lose from providing their voluntary contributions free of charge to others. For example, an author providing open access to a scientific paper or a book, must value the following advantages higher than possible monetary revenues from royalties:

- fast publishing
- large audience
- feedback from fellow scientists
- many citations by fellow scientists

In the case of open access to scientific work it seems likely that the benefits listed above are often much more valuable to the author than any lost opportunities for incomes through royalties.

In the case of open source, the situation is not always equally clear. Some software producers, while seeing the advantages of distributing software free of charge, are still reluctant, because they fear that they will morally (if not legally) be held responsible for errors in their own code, or even in further developments of the code made by others. Businesses, on the other hand, may hesitate to use open source software for business-critical applications, because there is nobody to hold responsible for flaws in the code that may have severe consequences for the business.

**Open data in science: open access to scientific data**

**Sources:**


It is a well-established principle in science that data collected and created by scientific projects, including survey data and experiments, should be made publicly available, so that other scientists could critically examine the scientific work, and replicate surveys and experiments in order to verify or falsify scientific results published by others. This principle has turned out to be extremely successful and advantageous for the rapid developments and achievements of science over a long time.
Before e-society, the traditional way for scientists to make their data and results publicly available was through printed publications, typically managed by commercial publishers. Professional publishers were needed in order to organize printing and dissemination in a rational way. These processes were costly and the commercial publishers typically recovered the costs, and made a profit, by selling the publications, primarily to scientific libraries, usually through a subscription process. Alternatively, universities and other scientific institutions produced and disseminated scientific journals and other publications themselves, as an integrated part of their research activities. However, even such non-profit organisations have to recover at least part of the significant printing and dissemination costs by charging libraries and other recipients of the publications.

With the digital information technology available in a modern e-society, the conditions for scientific publishing have changed drastically. Printing is no longer necessary, and Internet-based dissemination is both efficient and inexpensive, and requires no commercial intermediaries. The researchers themselves, and the non-profit organisation to which they belong, can easily handle these processes themselves. Even when commercial publishers were engaged, the work of authors, scientific editors, and referees was never paid for, so these processes can be carried on like before.

The concept of open access to scientific data was institutionally established with the formation of the World Data Center system, in preparation for the International Geophysical Year of 1957-1958. The International Council of Scientific Unions (now the International Council for Science) established several World Data Centers to minimize the risk of data loss and to maximize data accessibility, further recommending in 1955 that data be made available in machine-readable form. While the open-science-data movement long predates the Internet, the availability of fast, ubiquitous networking has significantly changed the context of Open science data, since publishing or obtaining data has become much less expensive and time-consuming.

In 2004, the Science Ministers of all nations of the OECD (Organisation for Economic Co-operation and Development), signed a declaration which essentially states that all publicly funded archive data should be made publicly available. Following a request and an intense discussion with data-producing institutions in member states, the OECD published in 2007 the OECD Principles and Guidelines for Access to Research Data from Public Funding as a soft-law recommendation.

Open Access (OA), open peer reviewing, and open peer commentary

Sources:


DOAJ.org (Directory of Open Access journals), https://doaj.org/

Wikipedia (Open access), https://en.wikipedia.org/wiki/Open_access

Wikipedia (Creative Commons), https://en.wikipedia.org/wiki/Creative_Commons

Open Access is defined by Peter Suber as "free, immediate, permanent, full-text, online access, for any user, web-wide, to digital scientific and scholarly material, primarily research articles published in peer-reviewed journals. OA means that any individual user, anywhere, who has access to the Internet, may link, read, download, store, print-off, use, and data-mine the digital content of that article. An OA article usually has limited copyright and licensing restrictions."

The Directory of Open Access Journals provides a list of international open access journals.
For more information see the Wikipedia OA article. Another excellent OA overview article is provided by Peter Suber, Suber (2004).

Open Access Overview

According to Peter Suber

“Open-access (OA) literature is digital, online, free of charge, and free of most copyright and licensing restrictions. What makes it possible is the internet and the consent of the author or copyright-holder. In most fields, scholarly journals do not pay authors, who can therefore consent to OA without losing revenue. In this respect scholars and scientists are very differently situated from most musicians and movie-makers, and controversies about OA to music and movies do not carry over to research literature.

OA is entirely compatible with peer review, and all the major OA initiatives for scientific and scholarly literature insist on its importance. Just as authors of journal articles donate their labor, so do most journal editors and referees participating in peer review.

OA literature is not free to produce, even if it is less expensive to produce than conventionally published literature. The question is not whether scholarly literature can be made costless, but whether there are better ways to pay the bills than by charging readers and creating access barriers. Business models for paying the bills depend on how OA is delivered.

There are two primary vehicles for delivering OA to research articles: OA journals and OA archives or repositories.

- **OA archives or repositories** do not perform peer review, but simply make their contents freely available to the world. They may contain unrefered preprints, refereed postprints, or both. Archives may belong to institutions, such as universities and laboratories, or disciplines, such as physics and economics. Authors may archive their preprints without anyone else's permission, and a majority of journals already permit authors to archive their postprints. When archives comply with the metadata harvesting protocol of the Open Archives Initiative, then they are interoperable and users can find their contents without knowing which archives exist, where they are located, or what they contain. There is now open-source software for building and maintaining OAI-compliant archives and worldwide momentum for using it.

- **OA journals** perform peer review and then make the approved contents freely available to the world. Their expenses consist of peer review, manuscript preparation, and server space. OA journals pay their bills very much the way broadcast television and radio stations do: those with an interest in disseminating the content pay the production costs upfront so that access can be free of charge for everyone with the right equipment. Sometimes this means that journals have a subsidy from the hosting university or professional society. Sometimes it means that journals charge a processing fee on accepted articles, to be paid by the author or the author’s sponsor (employer, funding agency). OA journals that charge processing fees usually waive them in cases of economic hardship. OA journals with institutional subsidies tend to charge no processing fees. OA journals can get by on lower subsidies or fees if they have income from other publications, advertising, priced add-ons, or auxiliary services. Some institutions and consortia arrange fee discounts. Some OA publishers waive the fee for all researchers affiliated with institutions that have purchased an annual membership. There’s a lot of room for creativity in finding ways to pay the costs of a peer-reviewed OA journal, and we're far from having exhausted our cleverness and imagination.
For a longer introduction, with live links for further reading, see my Open Access Overview, http://www.earlham.edu/~peters/fos/overview.htm.


Open access (OA) is the practice of providing unrestricted access via the Internet to peer-reviewed scholarly research. It is most commonly applied to scholarly journal articles, but it is also increasingly being provided to theses, scholarly monographs and book chapters.

Open access comes in two degrees: "Gratis open access" is no-cost online access, while "libre open access" is gratis open access plus some additional usage rights; see Suber (2008). Creative Commons licenses can be used to specify usage rights.

Open access can be provided in two ways:

**Green open access self-archiving**

Authors publish in any journal and then self-archive a version of the article for free public use in their institutional repository, in a central repository, or on some other open access website. What is deposited is the peer-reviewed postprint – either the author’s refereed, revised final draft or the publisher’s version of record.

**Gold open access publishing**

Authors publish in an open access journal that provides immediate open access to all of its articles on the publisher's website. (Hybrid open access journals provide Gold open access only for those individual articles for which their authors (or their author’s institution or funder) pay an open access publishing fee).

Public access to the World Wide Web became widespread in the late 1990s and early 2000s. The low-cost distribution technology has fueled the open access movement, and prompted both the Green open access self-archiving of non-open access journal articles and the creation of Gold open access journals. Conventional non-open access journals cover publishing costs through access tolls such as subscriptions, site licenses or pay-per-view. Some non-open access journals provide open access after an embargo period of 6–12 months or longer (see delayed open access journals). Active debate over the economics and reliability of various ways of providing open access continues among researchers, academics, librarians, university administrators, funding agencies, government officials, commercial publishers, editorial staff and learned society publishers.

**Why make your research available through Open Access?**

There are many reasons as to why you should make research publications accessible in Open Access journals. Studies show that a publication with free access is read by more people, and that the published results are more often put into practical use. By giving free access to an article, authors keep the copyright and thereby can make use of their work freely. Even in cases where a work is published through a publisher, it is possible, if the contract allows it, to parallel publish the article (self-archiving). Parallel publishing can normally be done as soon as your publication has been accepted – sometimes even earlier. It has been shown that early publishing gives more citations.

The basic idea with Open Access is that there should be free online access to quality controlled scientific publications. That way it is possible even for departments lacking resources, especially in the third world, to take part of high quality research results, and thus stimulate their own research.
Since it is less expensive to publish according to the Open Access model than to traditional publishing methods, funds that today are used for subscriptions to scientific journals could instead benefit research.

**How do I give free access to my results?**

If there is a high quality journal that is freely accessible within your field of research, then this is the easiest way to make publications freely accessible. Most scientific journals allow parallel publishing. This way the publication is made freely accessible and searchable through common search engines. Most universities and research-funding organisations now have policies for scientific publishing recommending or requiring researchers to publish their work in an Open Access journal or, if that is not possible, to keep the right to self-archive the article.

**Open peer reviewing**


**Open peer review** describes a scholarly/scientific literature concept and process, central to which is the various transparency and disclosure of the identities of those reviewing scientific publications. The concept thus represents a departure from, and an alternative to, the incumbent anonymous peer review process, in which non-disclosure of these identities toward the public – and toward the authors of the work under review – is default practice. The open peer review concept appears to constitute a response to modern criticisms of the incumbent system and therefore its emergence may be partially attributed to these phenomena.

The traditional anonymous peer review has been criticized for its lack of accountability, the possibility of abuse by reviewers or by those who manage the peer review process (that is, journal editors), its possible bias, and its inconsistency, alongside other flaws. Both processes are intended to subject scholarly publications to the scrutiny of others who are experts in the same field.

The evidence of the effect of open peer review upon the quality of reviews, the tone and the time spent on reviewing is mixed, although it does seem that under open peer review, more of those who are invited to review decline to do so.

A number of reputable medical publishers have tried the Open Peer Review concept. The first open peer review trial was conducted by The Medical Journal of Australia (MJA) in cooperation with the University of Sydney Library, from March 1996 to June 1997. In that study 56 research articles accepted for publication in the MJA were published online together with the peer reviewers' comments; readers could email their comments and the authors could amend their articles further before print publication of the article.

In 1996, the Journal of Interactive Media in Education launched using open peer review. Reviewers' names are made public and they are therefore accountable for their review, but they also have their contribution acknowledged. Authors have the right of reply, and other researchers have the chance to comment prior to publication.

In 1997, the Electronic Transactions on Artificial Intelligence was launched as an open access journal by the European Coordinating Committee for Artificial Intelligence. This journal used a two-stage review process. In the first stage, papers that passed a quick screen by the editors were immediately published on the Transaction's discussion website for the purpose of on-line public discussion during a period of at least three months, where the contributors' names were made public except in exceptional cases. At the end of the discussion period, the authors were invited to submit a revised
version of the article, and anonymous referees decided whether the revised manuscript would be accepted to the journal or not, but without any option for the referees to propose further changes.

In 1999, the open access Journal of Medical Internet Research was launched, which from its inception decided to publish the names of the reviewers at the bottom of each published article. Also in 1999, the British Medical Journal moved to an open peer review system, revealing reviewers' identities to the authors (but not the readers), and in 2000, the medical journals in the open access BMC series published by BioMed Central, launched using open peer review. As with the BMJ, the reviewers' names are included on the peer review reports. In addition, if the article is published the reports are made available online as part of the 'pre-publication history'.

Atmospheric Chemistry and Physics, an open access journal launched in 2001 by the European Geosciences Union, has a two-stage publication process. In the first stage, papers that pass a quick screen by the editors are immediately published on the Atmospheric Chemistry and Physics Discussions website. They are then subject to interactive public discussion alongside formal peer review. Referees' comments (either anonymous or attributed), additional short comments by other members of the scientific community (which must be attributed) and the authors' replies are also published in ACPD. In the second stage, the peer-review process is completed and, if the article is formally accepted by the editors, the final revised papers are published in ACP. The success of this approach is shown by the ranking by Thomson Reuters of ACP as the top journal in the field of Meteorology & Atmospheric Sciences.

In 2006, a group of UK academics launched the online journal Philica, which tries to redress many of the problems of traditional peer review. Unlike in a normal journal, all articles submitted to Philica are published immediately and the review process takes place afterwards. Reviews are still anonymous, but instead of reviewers being chosen by an editor, any researcher who wishes to review an article can do so. Reviews are displayed at the end of each article, and so are used to give the reader criticism or guidance about the work, rather than to decide whether it is published or not. This means that reviewers cannot suppress ideas if they disagree with them. Readers use reviews to guide what they read, and particularly popular or unpopular work is easy to identify.

Another approach that is similar in spirit to Philica is that of a dynamical peer review site, Naboj. Unlike Philica, Naboj is not a full-fledged online journal, but rather it provides an opportunity for users to write peer reviews of preprints at ArXiv. The review system is modeled on Amazon and users have an opportunity to evaluate the reviews as well as the articles. That way, with a sufficient number of users and reviewers, there should be a convergence towards a higher quality review process.

In February 2006, the journal Biology Direct was launched by BioMed Central, providing another alternative to the traditional model of peer review. If authors can find three members of the Editorial Board who will each return a report or will themselves solicit an external review, then the article will be published. As with Philica, reviewers cannot suppress publication, but in contrast to Philica, no reviews are anonymous and no article is published without being reviewed. Authors have the opportunity to withdraw their article, to revise it in response to the reviews, or to publish it without revision. If the authors proceed with publication of their article despite critical comments, readers can clearly see any negative comments along with the names of the reviewers.

Open peer commentary

An extension of peer review beyond the date of publication is Open Peer Commentary, whereby expert commentaries are solicited on published articles, and the authors are encouraged to respond. In the summer of 2009, Kathleen Fitzpatrick explored open peer review and commentary in her
book, *Planned Obsolescence*, which was published by MediaCommons using "Commentpress", a Wordpress plugin that enables readers to comment on and annotate book-length texts. Another form of “open peer review” is community-based pre-publication peer-review, where the review process is open for everybody to join.

Note. It could be interesting to compare the experiences from open peer reviewing and open peer commentary with the experiences of the Wikipedia quality control process.

**Net-based research (e-research)**


The term **e-research** refers to the use of information technology to support existing and new forms of research. E-research extends e-science and cyberinfrastructure to other disciplines, including the humanities and social sciences.
CHAPTER 6. The concept of information in different academic disciplines

Philosophy


Philosophy as an academic discipline embraces the following main areas:

- **Aesthetics**: What is art? What is beauty? Is there a standard of taste? Is art meaningful? If so, what does it mean? What is good art? Is art for the purpose of an end, or is "art for art's sake?" What connects us to art? How does art affect us? Is some art unethical? Can art corrupt or elevate societies?

- **Epistemology**: What are the nature and limits of knowledge? What is more fundamental to human existence, knowing (epistemology) or being (ontology)? How do we come to know what we know? What are the limits and scope of knowledge? How can we know that there are other minds (if we can)? How can we know that there is an external world (if we can)? How can we prove our answers? What is a true statement?

- **Ethics**: Is there a difference between ethically right and wrong actions (or values, or institutions)? If so, what is that difference? Which actions are right, and which wrong? Do divine commands make right acts right, or is their rightness based on something else? Are there standards of rightness that are absolute, or are all such standards relative to particular cultures? How should I live? What is happiness?

- **Logic**: What makes a good argument? How can I think critically about complicated arguments? What makes for good thinking? When can I say that something just does not make sense? Where is the origin of logic?

- **Metaphysics**: What sorts of things exist? What is the nature of those things? Do some things exist independently of our perception? What is the nature of space and time? What is the relationship of the mind to the body? What is it to be a person? What is it to be conscious? Do gods exist?

Of particular interest for this report is the area of epistemology and, to some extent, logic and metaphysics (which includes ontology).

"Ontology" is a well-known term and concept in philosophy, where it concerns the overall nature of what things are, trying to identify, in the most general terms, the kinds of things that actually exist. In other words addressing the question: What is existence? and What is the nature of existence? When we ask deep questions about "what is the nature of the universe?" or "Is there a God?" or "What happens to us when we die?" or "What principles govern the properties of matter?" we are asking inherently ontological questions.

In comparison, epistemology is concerned with the nature of knowledge itself, its possibility, scope, and general basis. More broadly: How do we go about knowing things? or How do we separate true ideas from false ideas? or How do we know what is true? or How can we be confident when we have located 'truth'? What are the systematic ways we can determine when something is good or bad?

So ontology is about what is true, and epistemology then is about methods of figuring out those truths.
In Chapter 1 of this report, we discussed several important ontological issues at some length, whereas epistemological issues were treated more briefly. Here we shall therefore elaborate a bit more on some important issues belonging to epistemology, and which have occupied philosophers and scientists during a very long time. We shall focus on the topic of rationalism vs empiricism (and associated issues), which has been, and still is, a very hot topic in the academic world.

**Rationalism vs empiricism**


Epistemology is concerned with the nature and scope of knowledge, such as the relationships between truth, belief, perception and theories of justification.

**Rationalism** is the emphasis on reasoning as a source of knowledge. **Empiricism** is the emphasis on observational evidence via sensory experience over other evidence as the source of knowledge. Rationalism claims that every possible object of knowledge can be deduced from coherent premises without observation. Empiricism claims that at least some knowledge is only a matter of observation. For this, Empiricism often cites the concept of *tabula rasa*, where individuals are not born with mental content and that knowledge builds from experience or perception.

Plato (427–347 BC) combined rationalism with a form of *realism*. The philosopher's work is to consider being, and the essence of things. The characteristic of essences is that they are universal. The nature of a man, a triangle, a tree, applies to all men, all triangles, all trees. Plato argued that these essences are mind-independent "forms", that humans (but particularly philosophers) can come to know by reason, and by ignoring the distractions of sense-perception.

Modern rationalism begins with Descartes. Reflection on the nature of perceptual experience, as well as scientific discoveries in physiology and optics, led Descartes (and also Locke) to the view that we are directly aware of ideas, rather than objects. His view that reason alone could yield substantial truths about reality strongly influenced those philosophers usually considered modern rationalists (such as Baruch Spinoza, Gottfried Leibniz, and Christian Wolff), while provoking criticism from other philosophers who have retrospectively come to be grouped together as empiricists.

Empiricism states that knowledge comes only or primarily from sensory experience. Empiricism emphasizes the role of experience and evidence, especially sensory experience, in the formation of ideas, over the notion of innate ideas or traditions. Empiricists may argue however that traditions (or customs) arise due to relations of previous sense experiences.

In the philosophy of science, empiricism emphasizes evidence, especially as discovered in experiments. It is a fundamental part of the scientific method that all hypotheses and theories must be tested against observations of the natural world rather than resting solely on *a priori* reasoning, intuition, or revelation.

Empiricism, as used by natural scientists, says that "knowledge is based on experience" and that "knowledge is tentative and probabilistic, subject to continued revision and falsification. One of the basic epistemological beliefs is that sensory experience creates knowledge. The scientific method, including experiments and validated measurement tools, guides empirical research.

Both natural and social sciences use working hypotheses that are testable by observation and experiment. Philosophical empiricists hold no knowledge to be properly inferred or deduced unless it is derived from one's sense-based experience. This view is commonly contrasted with rationalism, which states that knowledge may be derived from reason independently of the senses. Robert Boyle,
a prominent advocate of the experimental method, held that we have innate ideas. The main continental rationalists (Descartes, Spinoza, and Leibniz) were also advocates of the empirical scientific method.

The notion of *tabula rasa* ("clean slate" or "blank tablet") connotes a view of mind as an originally blank or empty recorder (Locke used the words "white paper") on which experience leaves marks. This denies that humans have innate ideas. The image dates back to Aristotle:

“What the mind thinks must be in it in the same sense as letters are on a tablet which bears no actual writing; this is just what happens in the case of the mind.” (Aristotle, *On the Soul*).

Aristotle’s explanation of how this was possible was not strictly empiricist in a modern sense, but his notions contrasted with Platonic notions of the human mind as an entity that pre-existed somewhere in the heavens, before being sent down to join a body on Earth. Aristotle was considered to give a more important position to sense perception than Plato, and commentators in the middle ages summarized one of his positions as "nothing in the intellect without first being in the senses".

During the middle ages Aristotle’s theory of *tabula rasa* was developed by Islamic philosophers starting with Al Farabi, developing into an elaborate theory by Avicenna and demonstrated as a thought experiment by Ibn Tufail. For Avicenna (Ibn Sina), for example, the *tabula rasa* is a pure potentiality that is actualized through education, and knowledge is attained through "empirical familiarity with objects in this world from which one abstracts universal concepts" developed through a "syllogistic method of reasoning in which observations lead to propositional statements which when compounded lead to further abstract concepts."

In the 12th century CE the Andalusian Muslim philosopher and novelist Abu Bakr Ibn Tufail included the theory of *tabula rasa* as a thought experiment in his Arabic philosophical novel, *Hayy ibn Yaqdhan*, in which he depicted the development of the mind of a feral child "from a *tabula rasa* to that of an adult, in complete isolation from society" on a desert island, through experience alone. The Latin translation of his philosophical novel, entitled *Philosophus Autodidactus*, had an influence on John Locke’s formulation of *tabula rasa* in *An Essay Concerning Human Understanding* (1689).

A similar Islamic theological novel, *Theologus Autodidactus*, was written by the Arab theologian and physician Ibn al-Nafis in the 13th century. It also dealt with the theme of empiricism through the story of a feral child on a desert island, but departed from its predecessor by depicting the development of the protagonist’s mind through contact with society rather than in isolation from society.

The 17th century period of early modern philosophy and modern science one may spot a difference between “British” and “continental” philosophers. Two pioneers were Francis Bacon, described as empiricist, and René Descartes, described as a rationalist. Thomas Hobbes and Baruch Spinoza in the next generation are often also described as an empiricist and a rationalist respectively. John Locke, George Berkeley, and David Hume were the primary exponents of empiricism in the 18th century Enlightenment.

In response to the early-to-mid-17th century "continental rationalism" John Locke proposed in *An Essay Concerning Human Understanding* a very influential view wherein the only knowledge humans can have is *a posteriori*, i.e., based upon experience. Locke is famously attributed with holding the proposition that the human mind is a *tabula rasa*, a "blank tablet," in Locke’s words "white paper," on which the experiences derived from sense impressions as a person’s life proceeds are written. There are two sources of our ideas: sensation and reflection. In both cases, a distinction is made between simple and complex ideas. The former are unanalysable, and are broken down into primary and secondary qualities. Primary qualities are essential for the object in question to be what it is.
Without specific primary qualities, an object would not be what it is. For example, an apple is an apple because of the arrangement of its atomic structure. If an apple was structured differently, it would cease to be an apple. Secondary qualities are the sensory information we can perceive from its primary qualities. For example, an apple can be perceived in various colours, sizes, and textures but it is still identified as an apple. Therefore its primary qualities dictate what the object essentially is, while its secondary qualities define its attributes. Complex ideas combine simple ones, and divide into substances, modes, and relations. According to Locke, our knowledge of things is a perception of ideas that are in accordance or discordance with each other, which is very different from the quest for certainty of Descartes.

The Scottish philosopher David Hume (1711–1776) moved empiricism to a new level of scepticism. Skepticism is a position that questions the validity of some or all of human knowledge. Scepticism does not refer to any one specific school of philosophy, rather it is a thread that runs through many philosophical discussions of epistemology. The first well known sceptic was Socrates who claimed that his only knowledge was that he knew nothing with certainty. Descartes' most famous inquiry into mind and body also began as an exercise in scepticism. Descartes began by questioning the validity of all knowledge and looking for some fact that was irrefutable. In so doing, he came to his famous dictum: I think therefore I am.

Hume argued in keeping with the empiricist view that all knowledge derives from sense experience, but he accepted that this has implications not normally acceptable to philosophers.

Hume divided all of human knowledge into two categories: relations of ideas and matters of fact. Mathematical and logical propositions (e.g. "that the square of the hypotenuse is equal to the sum of the squares of the two sides") are examples of the first, while propositions involving some contingent observation of the world (e.g. "the sun rises in the East") are examples of the second. All of people's "ideas", in turn, are derived from their "impressions". To remember or to imagine such impressions is to have an "idea". Ideas are therefore the faint copies of sensations.

According to an extreme empiricist theory known as phenomenalism, a physical object is a kind of construction out of our experiences. Phenomenalism is the view that physical objects, properties, events (whatever is physical) are reducible to mental objects, properties, events. Ultimately, only mental objects, properties, events, exist — hence the closely related term subjective idealism. John Stuart Mill's empiricism went a significant step beyond Hume in maintaining that induction is necessary for all meaningful knowledge including mathematics. As summarized by D.W. Hamlin:

Mill claimed that mathematical truths were merely very highly confirmed generalizations from experience; mathematical inference, generally conceived as deductive and a priori in nature, Mill set down as founded on induction. Thus, in Mill’s philosophy there was no real place for knowledge based on relations of ideas. In his view logical and mathematical necessity is psychological; we are merely unable to conceive any other possibilities than those that logical and mathematical propositions assert. This is perhaps the most extreme version of empiricism known, but it has not found many defenders.

Logical empiricism (also logical positivism or neopositivism) was an early 20th-century attempt to synthesize the essential ideas of British empiricism (e.g. a strong emphasis on sensory experience as the basis for knowledge) with certain insights from mathematical logic that had been developed by Gottlob Frege and Ludwig Wittgenstein.

The neopositivists subscribed to a notion of philosophy as the conceptual clarification of the methods, insights and discoveries of the sciences. They saw in the logical symbolism elaborated by
Frege and Bertrand Russell a powerful instrument that could rationally reconstruct all scientific discourse into an ideal, logically perfect, language that would be free of the ambiguities and deformations of natural language. This gave rise to what they saw as metaphysical pseudoproblems and other conceptual confusions. By combining Frege’s thesis that all mathematical truths are logical with the early Wittgenstein’s idea that all logical truths are mere linguistic tautologies, they arrived at a twofold classification of all propositions: the analytic (a priori) and the synthetic (a posteriori). On this basis, they formulated a strong principle of demarcation between sentences that have sense and those that do not: the so-called verification principle. Any sentence that is not purely logical, or is unverifiable is devoid of meaning. As a result, most metaphysical, ethical, aesthetic and other traditional philosophical problems came to be considered pseudoproblems.

The central theses of logical positivism (verificationism, the analytic-synthetic distinction, reductionism, etc.) came under sharp attack after World War II by thinkers such as W.V. Quine and Karl Popper. By the late 1960s, it had become evident to most philosophers that the movement had pretty much run its course, though its influence is still significant among contemporary analytic philosophers such as Michael Dummett and other anti-realists.

**Pragmatism.** In the late 19th and early 20th century several forms of pragmatic philosophy arose. The ideas of pragmatism, in its various forms, developed mainly from discussions between Charles Sanders Peirce and William James when both men were at Harvard in the 1870s. Along with its pragmatic theory of truth, this perspective integrates the basic insights of empirical (experience-based) and rational (concept-based) thinking.

Charles Peirce was highly influential in laying the groundwork for today’s empirical scientific method. Although Peirce severely criticized many elements of Descartes’ peculiar brand of rationalism, he did not reject rationalism outright. Indeed, he concurred with the main ideas of rationalism, most importantly the idea that rational concepts can be meaningful and the idea that rational concepts necessarily go beyond the data given by empirical observation. In later years he even emphasized the concept-driven side of the then ongoing debate between strict empiricism and strict rationalism, in part to counterbalance the excesses to which some of his cohorts had taken pragmatism under the “data-driven” strict-empiricist view.

Among Peirce’s major contributions was to place inductive reasoning and deductive reasoning in a complementary rather than competitive mode. To this, Peirce added the concept of abductive reasoning.

**Abductive reasoning** (also called abduction, abductive inference, or retroduction) is a form of logical inference which goes from an observation to a theory which accounts for the observation, ideally seeking to find the simplest and most likely explanation. In abductive reasoning, unlike in deductive reasoning, the premises do not guarantee the conclusion. One can understand abductive reasoning as “inference to the best explanation”. The fields of law, computer science, and artificial intelligence renewed interest in abduction. Diagnostic expert systems frequently employ abduction.

The combined three forms of reasoning serve as a primary conceptual foundation for the empirically based scientific method today. Peirce’s approach "presupposes that (1) the objects of knowledge are real things, (2) the characters (properties) of real things do not depend on our perceptions of them, and (3) everyone who has sufficient experience of real things will agree on the truth about them. According to Peirce’s doctrine of fallibilism, the conclusions of science are always tentative. The rationality of the scientific method does not depend on the certainty of its conclusions, but on its self-corrective character: by continued application of the method science can detect and correct its own mistakes, and thus eventually lead to the discovery of truth".
Linguistics


Linguistics is the scientific study of language. Language is the ability to acquire and use complex systems of communication, particularly the human ability to do so, and a language is any specific example of such a system.

Questions concerning the philosophy of language, such as whether words can represent experience, have been debated since Gorgias and Plato in Ancient Greece. Thinkers such as Rousseau have argued that language originated from emotions while others like Kant have held that it originated from rational and logical thought. 20th-century philosophers such as Wittgenstein argued that philosophy is really the study of language.

Natural languages are spoken or signed, but any language can be encoded into secondary media using auditory, visual, or tactile stimuli. Depending on philosophical perspectives regarding the definition of language and meaning, "language" may refer to the cognitive ability to learn and use systems of complex communication, or to describe the set of rules that makes up these systems, or the set of utterances that can be produced from those rules. All languages rely on the process of semiosis to relate signs to particular meanings. Oral and sign languages contain a phonological system that governs how symbols are used to form sequences known as words or morphemes, and a syntactic system that governs how words and morphemes are combined to form phrases and utterances.

Human language relies entirely on social convention and learning. Its complex structure affords a much wider range of expressions than any known system of animal communication. Language is thought to have originated when early hominins started gradually changing their primate communication systems, acquiring the ability to form a theory of other minds and a shared intentionality.

Linguistics analyses human language as a system for relating sounds (or signs in signed languages) and meaning. Phonetics studies acoustic and articulatory properties of the production and perception of speech sounds and non-speech sounds. The study of language meaning, on the other hand, deals with how languages encode relations between entities, properties, and other aspects of the world to convey, process, and assign meaning, as well as to manage and resolve ambiguity. While the study of semantics typically concerns itself with truth conditions, pragmatics deals with how context influences meanings.

Grammar is a system of rules which govern the form of the utterances in a given language. It encompasses both sound and meaning, and includes phonology (how sounds and gestures function together), morphology (the formation and composition of words), and syntax (the formation and composition of phrases and sentences from words).

In the early 20th century, Ferdinand de Saussure distinguished between the notions of langue and parole in his formulation of structural linguistics. According to him, parole is the specific utterance of speech, whereas langue refers to an abstract phenomenon that theoretically defines the principles and system of rules that govern a language. This distinction resembles the one made by Noam Chomsky between competence and performance, where competence is individual’s ideal knowledge of a language, while performance is the specific way in which it is used.

The formal study of language has also led to the growth of fields like psycholinguistics, which explores the representation and function of language in the mind; neurolinguistics, which studies
language processing in the brain; and language acquisition, which investigates how children and adults acquire a particular language.

Linguistics also includes nonformal approaches to the study of other aspects of human language, such as social, cultural, historical and political factors.

Language documentation combines anthropological inquiry with linguistic inquiry to describe languages and their grammars. Lexicography covers the study and construction of dictionaries. Computational linguistics applies computer technology to address questions in theoretical linguistics, as well as to create applications for use in parsing, data retrieval, machine translation, and other areas. People can apply actual knowledge of a language in translation and interpreting, as well as in language education - the teaching of a second or foreign language.

**Linguistic structures as the pairing of meaning and form**

Linguistic structures are pairings of meaning and form. Any particular pairing of meaning and form is a Saussurean sign. For instance, the meaning "cat" is represented worldwide with a wide variety of different sound patterns (in oral languages), movements of the hands and face (in sign languages), and written symbols (in written languages).

Linguistics has many sub-fields concerned with particular aspects of linguistic structure. The theory that elucidates on these, as propounded by Noam Chomsky, is known as generative theory or universal grammar. These sub-fields range from those focused primarily on form to those focused primarily on meaning. They also run the whole spectrum of level of analysis of language, from individual sounds, to words, to phrases, up to cultural discourse.

Sub-fields that focus on a structure-focused study of language:

- **Phonetics**, the study of the physical properties of speech sound production and perception
- **Phonology**, the study of sounds as abstract elements in the speaker's mind that distinguish meaning (phonemes)
- **Morphology**, the study of morphemes, or the internal structures of words and how they can be modified
- **Syntax**, the study of how words combine to form grammatical phrases and sentences
- **Semantics**, the study of the meaning of words (lexical semantics) and fixed word combinations (phraseology), and how these combine to form the meanings of sentences
- **Pragmatics**, the study of how utterances are used in communicative acts, and the role played by context and non-linguistic knowledge in the transmission of meaning
- **Discourse analysis**, the analysis of language use in texts (spoken, written, or signed)
- **Stylistics**, the study of linguistic factors (rhetoric, diction, stress) that place a discourse in context
- **Semiotics**, the study of signs and sign processes (semiosis), indication, designation, likeness, analogy, metaphor, symbolism, signification, and communication.

Chomsky, beginning in the 1950s-60s, takes the abstract system of both phonology and grammar as necessary, but starts with the problem of syntax, language acquisition, and language productivity. His model of syntax as the internalized rules for generating expressions solves the empirical problem of "the poverty of stimulus" when seeking to explain the rapid acquisition of grammar from few experiences; that is, trying to explain how humans learn language by induction from experienced examples (i.e., how any child in any language community from around age 3-4 is capable of generating an infinite set of new grammatically formed sentences which the child has never experienced). For Chomsky, humans have an innate capacity for language and the ability to internalize a grammar from a very small set of examples, and are soon able to generate an infinite
number of new expressions in their native language. From this observation, he was able to map out a rigorous set of syntactic phrase structures capable of many transformations.


“The person who has acquired knowledge of a language has internalized a system of rules that relate sound and meaning in a particular way. The linguist constructing a grammar of a language is in effect proposing a hypothesis concerning this internalized system... the grammar proposed by the linguist is an explanatory theory; it suggests an explanation for the fact that (under the idealization mentioned) a speaker of the language in question will perceive, interpret, form, or use an utterance in certain ways and not in other ways.... Continuing with current terminology, we can thus distinguish the surface structure of the sentence, the organization into categories and phrases that is directly associated with the physical signal, from the underlying deep structure, also a system of categories and phrases, but with a more abstract character.” [pp. 23-25]


The meaning of meaning – Ogden’s triangle


Ogden’s work was discussed in Chapter 1, and this discussion will not be repeated here.

Computer-supported translation

Language translation

Wikipedia (Google Translate), https://en.wikipedia.org/wiki/Google_Translate

How useful have established language theories been in the development of translation software? For several decades, the most brilliant scientists in Artificial Intelligence (AI) used huge amounts of
research funding to solve the problem of automatic translation by means of advanced computer software. The attempts were based on domain-specific theories, that is, established language theories like those of Chomsky and others, which were used in developing software which was typically rule-based, like the early expert systems. The practical results were not impressive. After many years of research the AI experts managed to develop a computer program that was able to translate Canadian weather reports from English to French, but such limited achievements were about all of practical value that was accomplished, using the traditional paradigm.

Then came Google Translate, the result of a new paradigm, where most domain-specific knowledge was replaced by statistical methods, now known as predictive analytics. This new paradigm has caused outcries by established domain experts like Noam Chomsky.

Naturally it seems a bit unprofessional and unscientific to launch translation software like Google Translate, where neither the algorithms, nor the results, can be explained in terms of linguistic concepts and theories. But on the other hand, one must admit that the practical results from using Google Translate are useful, especially in situations where resources in terms of time and money do not permit the engagement of professional translators. The results from Google Translate are far from perfect, but they are usually understandable and useful, something that one could not say about earlier generations of translation software, based on traditional AI methods and linguistic theories.

This should not lead to the conclusion that traditional domain-specific theories are not useful, at least not from an academic point of view. Domain-specific theories and models may be able to produce a better understanding of a domain of interest, for example human languages, even if they are not as helpful in producing practical results, like automatic translation, and such understanding has a value in itself for us as human beings trying to make sense of the world we are living in. Neither should it be excluded that the statistical methods underlying Google Translate could produce even better practical translation results, if and when combined with good domain-specific theories and models from the discipline of linguistics.

See also the debate between Noam Chomsky, Peter Norvig, Chris Anderson and others referred to in the section “Disruptive changes causing paradigm shifts” in another chapter of this report.

Meaning and language


Psychology and medicine: mind and brain

Hansotia (2003)

The relation between mind and brain is one of the big scientific questions that has attracted scientists’ attention for centuries but also eluded their understanding.

The story of man's struggle to understand his mind and its relationship to his brain stretches back to ancient times. Man has long known that human beings have the unique capacity for thought. Anaximander, the early Greek philosopher of the Milesian school (610 BC), felt that “mind gives body a life force.” In the 6th century BC, Pythagoras had the notion that “the brain served as the organ of
the mind and the temple of the soul. Ancient Greek physicians, before Hippocrates (460 BC), held that life was maintained in the human body by a balance of natural forces.

A mind is the set of cognitive faculties that enables consciousness, perception, thinking, judgement, and memory—a characteristic of humans, but which also may apply to other life forms.

A lengthy tradition of inquiries in philosophy, religion, psychology and cognitive science has sought to develop an understanding of what a mind is and what its distinguishing properties are. The main question regarding the nature of mind is its relation to the physical brain and nervous system—a question which is often framed as the mind–body problem, which considers whether mind is somehow separate from physical existence (dualism and idealism), or the mind is identical with the brain or some activity of the brain, deriving from and/or reducible to physical phenomena such as neuronal activity (physicalism). Another question concerns which types of beings are capable of having minds, for example whether mind is exclusive to humans, possessed also by some or all animals, by all living things, or whether mind can also be a property of some types of man-made machines.

Whatever its relation to the physical body it is generally agreed that mind is that which enables a being to have subjective awareness and intentionality towards their environment, to perceive and respond to stimuli with some kind of agency, and to have consciousness, including thinking and feeling.

Cognition is the set of all mental abilities and processes related to knowledge, attention, memory and working memory, judgment and evaluation, reasoning and “computation, problem solving and decision making, comprehension and production of language, etc. Human cognition is conscious and unconscious, concrete or abstract, as well as intuitive (like knowledge of a language) and conceptual (like a model of a language). Cognitive processes use existing knowledge and generate new knowledge.

The usage of the term “cognition” varies across disciplines. For example, in psychology and cognitive science, “cognition” usually refers to an information processing view of an individual's psychological functions. It is also used in a branch of social psychology called social cognition to explain attitudes, attribution, and group dynamics. In cognitive psychology and cognitive engineering, cognition is typically assumed to be information processing in a participant’s or operator’s mind or brain.

Artificial Intelligence (AI)


Artificial intelligence (AI) is the intelligence exhibited by machines or software. It is also the name of the academic field of study which studies how to create computers and computer software that are capable of intelligent behavior. Major AI researchers and textbooks define this field as “the study and design of intelligent agents”, in which an intelligent agent is a system that perceives its environment and takes actions that maximize its chances of success. John McCarthy, who coined the term in 1955, defines it as “the science and engineering of making intelligent machines”.

What then is an “intelligent behaviour”, “intelligent agents”, and “intelligent machines”? Alan Turing proposed in his paper "Computing machinery and intelligence" that the question "Can machines think?" be replaced with the question "Can machines do what we (as thinking entities) can do?"
The central problems of AI research include reasoning, knowledge, planning, learning, natural language processing (communication), perception and the ability to move and manipulate objects. Currently popular approaches include statistical methods, computational intelligence and traditional symbolic AI. There are a large number of tools used in AI, including versions of search and mathematical optimization, logic, methods based on probability and economics, and many others.

The field was founded on the claim that a central property of humans, human intelligence—the sapience of Homo sapiens—“can be so precisely described that a machine can be made to simulate it.” (The Dartmouth proposal, 1956, https://en.wikipedia.org/wiki/Dartmouth_Conferences).

Research areas, methods, and tools

The general problem of simulating (or creating) intelligence has been broken down into a number of specific subproblems. These consist of particular traits or capabilities that researchers would like an intelligent system to display. The traits described below have received the most attention.

There is no established unifying theory or paradigm that guides AI research. Researchers disagree about many issues. A few of the most long standing questions that have remained unanswered are these:

- Should artificial intelligence simulate natural intelligence by studying psychology or neurology?
- Or is human biology as irrelevant to AI research as bird biology is to aeronautical engineering?
- Can intelligent behaviour be described using simple, elegant principles, such as logic or optimization?
- Or does it necessarily require solving a large number of completely unrelated problems?
- Can intelligence be reproduced using high-level symbols, similar to words and ideas?
- Or does it require "sub-symbolic" processing?

John Haugeland, who coined the term GOFAI (Good Old-Fashioned Artificial Intelligence), also proposed that AI should more properly be referred to as synthetic intelligence, a term which has since been adopted by some non-GOFAI researchers.

In the course of 50 years of research, AI has developed a large number of tools to solve the most difficult problems in computer science. A few of the most general of these methods are discussed below.

**Deduction, reasoning, problem solving**

Early AI researchers developed algorithms that imitated the step-by-step reasoning that humans use when they solve puzzles or make logical deductions. By the late 1980s and 1990s, AI research had also developed highly successful methods for dealing with uncertain or incomplete information, employing concepts from probability and economics.

For difficult problems, most of these algorithms can require enormous computational resources – most experience a "combinatorial explosion": the amount of memory or computer time required becomes astronomical when the problem goes beyond a certain size. The search for more efficient problem-solving algorithms is a high priority for AI research.
Human beings solve most of their problems using fast, intuitive judgements rather than the conscious, step-by-step deduction that early AI research was able to model. AI has made some progress at imitating this kind of "sub-symbolic" problem solving: embodied agent approaches emphasize the importance of sensorimotor skills to higher reasoning; neural net research attempts to simulate the structures inside the brain that give rise to this skill; statistical approaches to AI mimic the probabilistic nature of the human ability to guess.

**Cognitive simulation based on human problem-solving skills: Simon & Newell**

The economists Herbert Simon and Allen Newell studied human problem-solving skills and attempted to formalize them, and their work laid the foundations of the field of artificial intelligence, as well as cognitive science, operations research and management science. Their research team used the results of psychological experiments to develop programs that simulated the techniques that people used to solve problems.

**Knowledge-based methods, expert systems**

When computers with large memories became available around 1970, researchers began to build knowledge into AI applications. This "knowledge revolution" led to the development and deployment of expert systems (introduced by Edward Feigenbaum), the first truly successful form of AI software. The knowledge revolution was also driven by the realization that enormous amounts of knowledge would be required by many simple AI applications.

**Knowledge representation and knowledge engineering**

Knowledge representation and knowledge engineering are central to AI research. Many of the problems machines are expected to solve will require extensive knowledge about the world. Among the things that AI needs to represent are: objects, properties, categories and relations between objects; situations, events, states and time; causes and effects; knowledge about knowledge (what we know about what other people know); and many other, less well researched domains. A representation of "what exists" is an ontology: the set of objects, relations, concepts and so on that the machine knows about. The most general are called upper ontologies, which attempt to provide a foundation for all other knowledge.

![Figure 42. An ontology represents knowledge as a set of concepts within a domain and the relationships between those concepts. From Wikipedia (Artificial intelligence).](image)

**Symbolic approaches, symbol manipulation, sub-symbolic methods**
When access to digital computers became possible in the middle 1950s, AI research began to explore the possibility that human intelligence could be reduced to symbol manipulation. John Haugeland named these approaches to AI "good old fashioned AI" or "GOFAI". During the 1960s, symbolic approaches had achieved great success at simulating high-level thinking in small demonstration programs. Approaches based on cybernetics or neural networks were abandoned or pushed into the background. Researchers in the 1960s and the 1970s were convinced that symbolic approaches would eventually succeed in creating a machine with artificial general intelligence and considered this the goal of their field.

By the 1980s progress in symbolic AI seemed to stall and many believed that symbolic systems would never be able to imitate all the processes of human cognition, especially perception, robotics, learning, and pattern recognition. A number of researchers began to look into "sub-symbolic" approaches to specific AI problems.

**Natural language processing (communication)**

Natural language processing gives machines the ability to read and understand the languages that humans speak. A sufficiently powerful natural language processing system would enable natural language user interfaces and the acquisition of knowledge directly from human-written sources, such as newswire texts. Some straightforward applications of natural language processing include information retrieval (or text mining), question answering and machine translation.

A common method of processing and extracting meaning from natural language is through semantic indexing. Increases in processing speeds and the drop in the cost of data storage makes indexing large volumes of abstractions of the user's input much more efficient.

![Parse tree](https://via.placeholder.com/150)

*Figure 43. A parse tree represents the syntactic structure of a sentence according to some formal grammar. From Wikipedia (Artificial intelligence).*

**Machine learning**

Machine learning is the study of algorithms that improve automatically through experience.

Unsupervised learning is the ability to find patterns in a stream of input. Supervised learning includes both classification and numerical regression. Classification is used to determine what category something belongs in, after seeing a number of examples of things from several categories. Regression is the attempt to produce a function that describes the relationship between inputs and outputs and predicts how the outputs should change as the inputs change. In reinforcement learning the agent is rewarded for good responses and punished for bad ones. The agent uses this sequence of rewards and punishments to form a strategy for operating in its problem space. These three types of learning can be analysed in terms of decision theory, using concepts like utility.
Statistical methods

In the 1990s, AI researchers developed sophisticated mathematical tools to solve specific subproblems. These tools are truly scientific, in the sense that their results are both measurable and verifiable, and they have been responsible for many of AI's recent successes. The shared mathematical language has also permitted a high level of collaboration with more established fields (like mathematics, economics, or operations research). Stuart Russell and Peter Norvig describe this movement as nothing less than a "revolution" and "the victory of "the neats" over "the scruffies". Critics argue that these techniques (with few exceptions) are too focused on particular problems and have failed to address the long-term goal of general intelligence. There is an ongoing debate about the relevance and validity of statistical approaches in AI, exemplified in part by exchanges between Peter Norvig and Noam Chomsky.

Probabilistic methods for uncertain reasoning

Many problems in AI (in reasoning, planning, learning, perception and robotics) require the agent to operate with incomplete or uncertain information. AI researchers have devised a number of powerful tools to solve these problems using methods from probability theory and economics. Bayesian networks are a very general tool that can be used for a large number of problems: reasoning (using the Bayesian inference algorithm), learning (using the expectation-maximization algorithm), planning (using decision networks), and perception (using dynamic Bayesian networks). Probabilistic algorithms can also be used for filtering, prediction, smoothing and finding explanations for streams of data, helping perception systems to analyse processes that occur over time (e.g. hidden Markov models or Kalman filters).

A key concept from the science of economics is "utility": a measure of how valuable something is to an intelligent agent. Precise mathematical tools have been developed that analyse how an agent can make choices and plan, using decision theory, decision analysis, and information value theory. These tools include models such as Markov decision processes, dynamic decision networks, game theory and mechanism design.

Classifiers and statistical learning methods

The simplest AI applications can be divided into two types: classifiers ("if shiny then diamond") and controllers ("if shiny then pick up"). Controllers do, however, also classify conditions before inferring actions, and therefore classification forms a central part of many AI systems. Classifiers are functions that use pattern matching to determine a closest match. They can be tuned according to examples, making them very attractive for use in AI. These examples are known as observations or patterns. In supervised learning, each pattern belongs to a certain predefined class. A class can be seen as a decision that has to be made. All the observations combined with their class labels are known as a data set. When a new observation is received, that observation is classified based on previous experience.

A classifier can be trained in various ways; there are many statistical and machine learning approaches. The most widely used classifiers are the neural network, kernel methods such as the support vector machine, k-nearest neighbour algorithm, Gaussian mixture model, naive Bayes classifier, and decision tree. The performance of these classifiers have been compared over a wide range of tasks. Classifier performance depends greatly on the characteristics of the data to be classified. There is no single classifier that works best on all given problems; this is also referred to as the "no free lunch" theorem. Determining a suitable classifier for a given problem is still more an art than science.


**Neural networks**

The study of artificial neural networks began in the decade before the field of AI research was founded, in the work of Walter Pitts and Warren McCullough. Other important early researchers were Frank Rosenblatt, who invented the perceptron and Paul Werbos who developed the backpropagation algorithm.

The main categories of networks are acyclic or feedforward neural networks (where the signal passes in only one direction) and recurrent neural networks (which allow feedback).

![Neural network diagram](image)

*Figure 44. A neural network is an interconnected group of nodes, akin to the vast network of neurons in the human brain. From Wikipedia (Artificial intelligence).*

Hierarchical temporal memory is an approach that models some of the structural and algorithmic properties of the neocortex. The term "deep learning" gained traction in the mid-2000s after a publication by Geoffrey Hinton and Ruslan Salakhutdinov showed how a many-layered feedforward neural network could be effectively pre-trained one layer at a time, treating each layer in turn as an unsupervised restricted Boltzmann machine, then using supervised backpropagation for fine-tuning.

**Computational intelligence and soft computing**

Interest in neural networks and "connectionism" was revived by David Rumelhart and others in the middle 1980s. Neural networks are an example of soft computing; they are solutions to problems which cannot be solved with complete logical certainty, and where an approximate solution is often enough. Other soft computing approaches to AI include fuzzy systems, evolutionary computation and many statistical tools. The application of soft computing to AI is studied collectively by the emerging discipline of computational intelligence.

**Perception**

Machine perception is the ability to use input from sensors (such as cameras, microphones, tactile sensors, sonar and others more exotic) to deduce aspects of the world. Computer vision is the ability to analyse visual input. Examples of important subproblems are speech recognition, facial recognition and object recognition.

**Robotics: motion and manipulation**

The field of robotics is closely related to AI. Intelligence is required for robots to be able to handle such tasks as object manipulation and navigation, with sub-problems of localization (knowing where
you are, or finding out where other things are), mapping (learning what is around you, building a map of the environment), and motion planning (figuring out how to get there) or path planning (going from one point in space to another point, which may involve compliant motion – where the robot moves while maintaining physical contact with an object).

**Cybernetics and brain simulation, control theory**

In the 1940s and 1950s, a number of researchers explored the connection between neurology, information theory, and cybernetics. Some of them built machines that used electronic networks to exhibit rudimentary intelligence, but by 1960 this approach was largely abandoned, although elements of it would be revived in the 1980s.

Control theory, the grandchild of cybernetics, has many important applications, especially in robotics.

**Logic-based methods and "anti-logic" or "scruffy" ad-hoc solutions**

Unlike Newell and Simon, John McCarthy felt that machines did not need to simulate human thought, but should instead try to find the essence of abstract reasoning and problem solving, regardless of whether people used the same algorithms. He focused on using formal logic to solve a wide variety of problems, including knowledge representation, planning and learning. Logic was also the focus of research work in Europe and led to the development of the programming language Prolog and the science of logic programming.

Researchers such as Marvin Minsky and Seymour Papert found that solving difficult problems in vision and natural language processing required ad-hoc solutions – they argued that there was no simple and general principle (like logic) that would capture all the aspects of intelligent behaviour. Roger Schank described their "anti-logic" approaches as "scruffy". Commonsense knowledge bases (such as Doug Lenat's Cyc) are an example of "scruffy" AI.

**Bottom-up, embodied, situated, behaviour-based or nouvelle AI**

Researchers from the related field of robotics, such as Rodney Brooks, rejected symbolic AI and focused on the basic engineering problems that would allow robots to move and survive. Their work revived the non-symbolic viewpoint of the early cybernetics researchers of the 1950s and reintroduced the use of control theory in AI. This coincided with the development of the embodied mind thesis in the related field of cognitive science: the idea that aspects of the body (such as movement, perception and visualization) are required for higher intelligence.

**Search and optimization**

Many problems in AI can be solved in theory by intelligently searching through many possible solutions. Reasoning can be reduced to performing a search. For example, logical proof can be viewed as searching for a path that leads from premises to conclusions, where each step is the application of an inference rule. Planning algorithms search through trees of goals and subgoals, attempting to find a path to a target goal, a process called means-ends analysis. Robotics algorithms for moving limbs and grasping objects use local searches in configuration space. Many learning algorithms use search algorithms based on optimization.

Simple exhaustive searches are rarely sufficient for most real world problems: the search space (the number of places to search) quickly grows to astronomical numbers. The result is a search that is too slow or never completes. The solution, for many problems, is to use "heuristics" or "rules of thumb" that eliminate choices that are unlikely to lead to the goal (called "pruning the search tree").
Heuristics supply the program with a "best guess" for the path on which the solution lies. Heuristics limit the search for solutions into a smaller sample size.

A very different kind of search came to prominence in the 1990s, based on the mathematical theory of optimization. For many problems, it is possible to begin the search with some form of a guess and then refine the guess incrementally until no more refinements can be made.

**Integrating the approaches – the intelligent agent paradigm**

An intelligent agent is a system that perceives its environment and takes actions which maximize its chances of success. The simplest intelligent agents are programs that solve specific problems. More complicated agents include human beings and organizations of human beings (such as firms). The paradigm gives researchers license to study isolated problems and find solutions that are both verifiable and useful, without agreeing on one single approach. An agent that solves a specific problem can use any approach that works – some agents are symbolic and logical, some are sub-symbolic neural networks and others may use new approaches. The paradigm also gives researchers a common language to communicate with other fields—such as decision theory and economics—that also use concepts of abstract agents. The intelligent agent paradigm became widely accepted during the 1990s.

Researchers have designed systems to build intelligent systems out of interacting intelligent agents in a multi-agent system. A system with both symbolic and sub-symbolic components is a hybrid intelligent system, and the study of such systems is artificial intelligence systems integration. A hierarchical control system provides a bridge between sub-symbolic AI at its lowest, reactive levels and traditional symbolic AI at its highest levels, where relaxed time constraints permit planning and world modelling. Rodney Brooks' subsumption architecture was an early proposal for such a hierarchical system.

**Programming languages**

AI researchers have developed several specialized languages for AI research, including Lisp and Prolog.

**Philosophy and ethics**

There are three philosophical questions related to AI:

1. Is artificial general intelligence possible? Can a machine solve any problem that a human being can solve using intelligence? Or are there hard limits to what a machine can accomplish?

2. Are intelligent machines dangerous? How can we ensure that machines behave ethically and that they are used ethically?

3. Can a machine have a mind, consciousness and mental states in exactly the same sense that human beings do? Can a machine be sentient, and thus deserve certain rights? Can a machine intentionally cause harm?

**The limits of artificial general intelligence**

Can a machine be intelligent? Can it "think"?

Turing's "polite convention"
We need not decide if a machine can "think"; we need only decide if a machine can act as intelligently as a human being. This approach to the philosophical problems associated with artificial intelligence forms the basis of the Turing test:


The Dartmouth proposal

"Every aspect of learning or any other feature of intelligence can be so precisely described that a machine can be made to simulate it." This conjecture was printed in the proposal for the Dartmouth Conference of 1956, and represents the position of most working AI researchers.

Sociology: communication and interaction among people

According to the Department of Sociology at the University of North Carolina, http://sociology.unc.edu/undergraduate-program/sociology-major/what-is-sociology/:

"Sociology is the study of human social relationships and institutions. Sociology’s subject matter is diverse, ranging from crime to religion, from the family to the state, from the divisions of race and social class to the shared beliefs of a common culture, and from social stability to radical change in whole societies. Unifying the study of these diverse subjects of study is sociology’s purpose of understanding how human action and consciousness both shape and are shaped by surrounding cultural and social structures."

Information technology and especially the Internet and Internet-based tools and media, especially so-called social media, are important for sociologists in two ways:

- providing new research methods and tools
- providing new research topics, studying how human beings and organisations use the Internet

See for example Oates (2005).

Sociology of knowledge

With their seminal book “The social construction of reality – a treatise in the sociology of knowledge” (Berger & Luckmann, 1966), Peter L. Berger and Thomas Luckmann made sociology join the sciences that do serious research about concept formation, information, knowledge, and the nature of “reality”. They launched the concept of reality as a social construction.

The ideas presented by Berger and Luckman build on earlier work by

We have already discussed the theory of reality as a social construction in Chapter 1.

Netnography

“Netnography”, doing research about and with the Internet, has become established a subdiscipline of sociology and ethnography. According to Wikipedia, https://en.wikipedia.org/wiki/Netnography:

Netnography is the branch of ethnography that analyses the free behaviour of individuals on the Internet that uses online marketing research techniques to provide useful insights. The word “netnography” comes from “Internet” and “ethnography” and was a process and term coined by Robert Kozinets. As a method, “netnography” can be faster, simpler, and less expensive than ethnography, and more naturalistic and unobtrusive than focus groups or interviews (Kozinets, 2009,
Netnography ... provides information on the symbolism, meaning, and consumption patterns of online consumer groups (Kozinets, 2010) or online communities consumption unrelated but online sociability based on the exchange of information (del Fresno, 2011). Netnography is focused on cultural, symbolic information insights.

**Social media, the digital divide, digital inclusion/exclusion**

These topics are important research areas for sociologists. We have already discussed them to a certain extent in another chapter of this report.

**Pedagogics**

New methods and forms of higher education, enabled by modern, web-based information technologies and new pedagogical models, are hot topics at schools and universities today. Many have a strong belief in many of these new forms of education, and the students are definitely attracted by them and often choose them when they are available.

On the other hand there are many university teachers, who are sceptical to the new methods and forms of education, and many students are also critical to some aspects of them. There are definitely needs to improve all forms of higher education in order to achieve better results in more efficient ways, both from a producer’s and from a customer/student’s perspective.

Regardless of our attitudes towards the new methods and forms of higher education, we should be able to agree that many more facts are needed as a basis for our evaluations and decisions. And we also need to know more about which aspects and criteria should be evaluated and compared.

We have already discussed topics such as net-based learning, e-learning, distance education, and self-learning in Chapter 5 of this report. All these topics have both pedagogical and technical aspects, which need to be considered in an integrated way.

For references and more reading, see Chapter 5 and the bibliography at the end of this report.

**Law, legal informatics**

Legal informatics has become a specialization with the discipline of Law:


There are many new topics and issues of legal nature that need to be addressed in a modern information society, often caused by the digital storage and communication of data supported by computers and international networks like the Internet. There are even more topics and issues where traditional laws based on paper documents need to be updated.

An efficient, trustworthy, and well functioning e-society is dependent on certain strategic tools, standards, and procedures, in particular for securing safe identification, authentication, and authorisation. There are three important roles for the government here:

- The government needs to create trust by standing behind and guaranteeing these tools and procedures.
- The government also has to adapt the legislation, so that the new e-tools and e-procedures can replace traditional paper-and-pencil-based tools and procedures in practice.
The government should also finance this very critical part of the e-infrastructure in order to avoid unnecessary delays in the development and implementation of it, and in order to avoid suboptimal solutions.

**E-identification: identity cards, certificates, and digital signatures**

In individual countries, as well as internationally, there is a need for trustworthy e-identifications (e-legitimations): certificates and identification cards, hard and/or soft, which can be used for safe authentication and authorisation of persons and other legal entities. These tools should be provided and guaranteed by relevant government authorities. Ideally they should be widely applicable in both manual and computer-supported, digitalised processes. Estonia is a country which has been very successful in this area, and they have created an identity card, which can be used as passport, driving license, health service card, etc.; it can even be used in public transport. The card is accepted and used by all citizens in the country.

A related issue is the problem of digital signatures. Many digital documents still have to be printed, manually signed, and sent by ordinary surface mail to the recipient in order to be legally valid. For example, in Sweden companies have to send their annual accounts on paper, signed manually by the managing director, to a government agency, Bolagsverket, the Swedish Companies Registration Office, where they are archived. A former director general of Bolagsverket called the procedure for doing this “the digital-analogue idiot loop” for the following reason. Most companies nowadays have their accounts in digital form. First the company has to print the accounts on paper, transforming them from digital to analogue form, then the printed document has to be signed manually by the managing director and sent by ordinary surface mail to Bolagsverket. No-one at Bolagsverket actually has the time to check the manual signature of the alleged managing director – it could be signed by “Donald Duck” – and the paper document is then digitalised by scanning and filed in the archive of Bolagsverket.

**Internationalisation of digital resources and communication**

When a person or a company communicates and stores and uses digital resources via the Internet, “the cloud”, it is difficult to know where data are physically stored and processed. International borders will often be crossed, and the legal complications of this may be complex and not always coordinated with national legislation. Even relatively small companies and administrations are becoming dependent on practical solutions to such problems, which have to be addressed both nationally and internationally in order not to prevent people and organisation from using practical and economic data processing solutions.

**Intellectual property rights**

We have already earlier in this report discussed the legal problems associated with intellectual property rights such as copyright, author’s rights, and patents. These rights involve the creation of temporary monopolies, which involve complex conflicts of interest between the owners of these rights (often commercial companies like publishers and corporations developing and producing innovative products), the original authors and inventors, and the public at large, such as consumers of music and films and patients in need of certain advanced and expensive drugs.

For references and more reading, see Chapter 4, and the bibliography at the end of this report.

**Political science**

Wikipedia (Political science): [https://en.wikipedia.org/wiki/Political_science](https://en.wikipedia.org/wiki/Political_science)
Political science is a social science discipline that deals with systems of government and the analysis of political activity and political behaviour. (Oxford Dictionary.) It deals extensively with the theory and practice of politics which is commonly thought of as the determining of the distribution of power and resources. Political scientists "see themselves engaged in revealing the relationships underlying political events and conditions, and from these revelations they attempt to construct general principles about the way the world of politics works". (The University of North Carolina at Chapel Hill.)

Political scientists study matters concerning the allocation and transfer of power in decision making, the roles and systems of governance including governments and international organisations, political behaviour and public policies. They measure the success of governance and specific policies by examining many factors, including stability, justice, material wealth, peace and public health. Some political scientists seek to advance positive (attempt to describe how things are, as opposed to how they should be) theses by analysing politics. Others advance normative theses, by making specific policy recommendations.

Political scientists provide the frameworks from which journalists, special interest groups, politicians, and the electorate analyse issues.

Modern information technology has certainly advanced and improved the possibilities for citizens, parliaments, and governments to strive for and achieve "good governance" in a non-corrupt society with well-functioning freedoms and human rights, adequate legal infrastructures, ample possibilities for citizens to participate in and influence important decisions (for example through e-democracy and e-participation), and high-quality services within areas such as health care and education.

We have discussed these issues in Chapter 3 and Chapter 4 of this report. For references and further reading, see these chapters and the bibliography at the end of this report.

Economics – including political economy and business economics

The role of information in a modern information economy are discussed at length in several chapters of this report. For example we discussed the following issues:

- Needs for well-functioning information infrastructures in a modern information economy
- Is the information economy a new economy, with new economic laws?
- Information-based products and services
- Electronic business: e-business, e-commerce, e-advertising
- Public and private e-services in e-society
- Disruptive changes and needs for new business models, especially in media industries
- Management: business modelling, goals and strategies, decision-making
- Information-based analysis and decision-making: business intelligence and “big data”
- Business networks, virtual businesses
- Information-based innovations

For references, see earlier chapters and the bibliography at the end of this report.

Journalism, media studies, and communication

Some important topics belonging to these disciplines have been discussed in earlier chapters, for example:
For references, see earlier chapters and the bibliography at the end of this report.

**Claude Shannon’s information theory: storage and transmission of data**

Claude Shannon is a pioneer in information-related disciplines. Although his work is referred to (also by himself) as “information theory”, it explicitly excludes the semantic aspects of data and the meaning of data from consideration.


Information theory, as defined and studied by Shannon, can be seen as a branch of applied mathematics, electrical engineering, and computer science, involving the quantification of information. Shannon studied data transmission (signal processing) and how to store, communicate, and compress data in efficient and reliable ways.

A key concept in Shannon’s information theory is “entropy”, defined as the average number of bits needed to store or communicate one symbol in a message. Entropy quantifies the uncertainty involved in predicting the value of a random variable. For example, specifying the outcome of a fair coin flip (two equally likely outcomes) provides less information (lower entropy) than specifying the outcome from a roll of a die (six equally likely outcomes).

Other disciplines that have taken up and used some of the concepts and findings of Shannon’s information theory are statistical inference, natural language processing, cryptography, neurobiology, ecology, thermal physics, linguistics, pattern recognition, anomaly detection, and other forms of data analysis.

**Holistic approaches**

There have been attempts to form a true interdisciplinary and holistic academic discipline, based on a true interdisciplinary and common information concept with one definition. In my opinion, most such attempts have not been very successful, but discussions involved in such attempts may still be quite useful in order to obtain sharper, information-related concepts and theories, suitable for the different purposes and universes of discourse of different academic disciplines, and in order for researchers to better understand each other across disciplines, and to discover possibilities of enriching one’s own discipline by borrowing from others.

There is a tendency among academics to view related disciplines as subfields or special cases of one’s own discipline. A researcher in discipline A may tend to see (parts of) discipline B as a subfield of A, whereas a researcher in discipline B may tend to see (parts of) discipline A as a subfield of B. A more constructive and less provocative approach is to see a number of related disciplines as partially overlapping as regards topics, concepts, and theories.

We shall now discuss a number of disciplines with holistic ambitions.
Computer science


The term “computer science” is an old-fashioned and misleading name of an academic discipline, which focuses on algorithms and software for managing and processing information represented by digital data – rather than mathematical computations only. However, when computers were invented and first introduced, nobody had the phantasy to imagine that computers could be used for a much broader range of applications. Since computers were very expensive in the beginning – although they were much less powerful than the most modest personal computers are today – governments appointed committees, populated by the most brilliant mathematicians at the time, to prognosticate how many computers could be needed in their respective countries. The typical answer was one, two, or possibly three...

Computer science vs computer engineering

Despite its name, computer science does not focus on computers and computer technology as such. Such topics are instead dealt with in computer engineering. Here is an extract from how The University at Buffalo, School of Engineering and Applied Sciences formulates the distinction between “computer science” and “computer engineering”, http://www.eng.buffalo.edu/undergrad/academics/degrees/cs-vs-cen:

What is computer science?

Computer science is the systematic study of algorithmic methods for representing and transforming information, including their theory, design, implementation, application, and efficiency. ... The main branches of computer science are the following:

- Algorithms ...
- Theory of computation ...
- Computer architecture ...
- Software systems ...
- Artificial intelligence ...

Other important topics in computer science include computer graphics, databases, networks and protocols, numerical methods, operating systems, parallel computing, simulation and modeling, and software engineering.

What is computer engineering?

Computer engineering is the design and prototyping of computing devices and systems. ... The main branches of computer engineering are the following:

- Networks is concerned with design and implementation of distributed computing environments, from local area networks to the World Wide Web.
- Multimedia computing is the blending of data from text, speech, music, still image, video and other sources into a coherent datastream, and its effective management, coding-decoding and display.
- VLSI systems involves the tools, properties and design of micro-miniaturized electronic devices (Very Large Scale Integrated circuits).
- Reliable computing and advanced architectures considers how fault-tolerance can be built into hardware and software, methods for parallel computing, optical computing, and testing.
The term "data science" (originally used interchangeably with "datalogy") has existed for half a century and was used initially as a substitute for computer science by Peter Naur in 1960. In 1974, Naur published Concise Survey of Computer Methods, which freely used the term data science in its survey of the contemporary data processing methods that are used in a wide range of applications.

In 1997, C.F. Jeff Wu gave a lecture entitled "Statistics = Data Science?" where he characterized statistical work as a trilogy of data collection, data modeling and analysis, and decision making. In conclusion, he coined the term "data science" and advocated that statistics be renamed data science and statisticians data scientists.

In 2001, William S. Cleveland introduced data science as an independent discipline, extending the field of statistics to incorporate "advances in computing with data" in his article "Data Science: An Action Plan for Expanding the Technical Areas of the Field of Statistics", which was published in Volume 69, No. 1, of the April 2001 edition of the International Statistical Review. In his report, Cleveland establishes six technical areas which he believed to encompass the field of data science: multidisciplinary investigations, models and methods for data, computing with data, pedagogy, tool evaluation, and theory.

In 2005, The National Science Board published "Long-lived Digital Data Collections: Enabling Research and Education in the 21st Century" defining data scientists as "the information and computer scientists, database and software and programmers, disciplinary experts, curators and expert annotators, librarians, archivists, and others, who are crucial to the successful management of a digital data collection" whose primary activity is to "conduct creative inquiry and analysis."

Thus “data science” is since long something quite different from “computer science” and Peter Naur’s concept of “datalogy”. Today more appropriate descriptions of “data science” are the following extracts from Wikipedia:

- Data Science is an interdisciplinary field about processes and systems to extract knowledge or insights from large volumes of data in various forms, either structured or unstructured, which is a continuation of some of the data analysis fields such as statistics, data mining and predictive analytics, as well as Knowledge Discovery in Databases (KDD).

- Data science is the practice of deriving valuable insights from data. Data science is emerging to meet the challenges of processing very large data sets i.e. "Big Data" consisting of structured, unstructured or semi-structured data that large enterprises produce. At centre stage of data science is the explosion of new data generated from smart devices, web, mobile and social media. Many practicing data scientists commonly specialize in specific domains such as the fields of marketing, medical, security, fraud and finance. However, data scientists rely heavily upon elements of statistics, machine learning, optimization, signal processing, text retrieval and natural language processing to analyse data and interpret results.

Data scientists apply expertise in data preparation, statistics, and machine learning to investigate complex problems in many various domains, such as marketing optimization, fraud detection, setting public policy, etc. These areas represent great breadth and diversity of knowledge, and a data scientist will most likely be expert in only one or at most two of these areas and merely proficient in
the other(s). Therefore a data scientist typically works as part of a team whose other members have knowledge and skills which complement their own.

Data scientists use the ability to find and interpret rich data sources; manage large amounts of data despite hardware, software, and bandwidth constraints; merge data sources; ensure consistency of datasets; create visualizations to aid in understanding data; build mathematical models using the data; and present and communicate the data insights/findings (preferably actionable insights) to specialists and scientists in their team and if required to a non-technical audience.

Data science techniques affect research in many domains, including the biological sciences, medical informatics, health care, social sciences and the humanities. It heavily influences economics, business, and finance. From the business perspective, data science is an integral part of competitive intelligence, a newly emerging field that encompasses a number of activities, such as data mining and data analysis.

**Domain specific interests**

Data science is the practice of deriving valuable insights from data. Data science is emerging to meet the challenges of processing very large data sets, “big data” consisting of structured, unstructured or semi-structured data that large enterprises produce. A domain at centre stage of data science is the explosion of new data generated from smart devices, web, mobile and social media. Data science requires a versatile skill-set. Many practicing data scientists commonly specialize in specific domains such as the fields of marketing, medical, security, fraud and finance. However, data scientists rely heavily upon elements of statistics, machine learning, optimization, signal processing, text retrieval and natural language processing to analyse data and interpret results.

![Data Science Process](https://upload.wikimedia.org/wikipedia/commons/thumb/9/9f/Data_visualization_process_v1.png/1130px-Data_visualization_process_v1.png)

**Figure 45.** "Data visualization process v1" by Farcaster - Flowchart created from data visualization process descriptions. Licensed under CC BY-SA 3.0 via Wikipedia.

**Information science**


An early definition of Information science (going back to 1968, the year when the American Documentation Institute renamed itself as the American Society for Information Science and Technology) states:
"Information science is that discipline that investigates the properties and behavior of information, the forces governing the flow of information, and the means of processing information for optimum accessibility and usability. It is concerned with that body of knowledge relating to the origination, collection, organization, storage, retrieval, interpretation, transmission, transformation, and utilization of information. This includes the investigation of information representations in both natural and artificial systems, the use of codes for efficient message transmission, and the study of information processing devices and techniques such as computers and their programming systems. It is an interdisciplinary science derived from and related to such fields as mathematics, logic, linguistics, psychology, computer technology, operations research, the graphic arts, communications, library science, management, and other similar fields. It has both a pure science component, which inquires into the subject without regard to its application, and an applied science component, which develops services and products." (Borko, 1968).

Information science is an interdisciplinary field primarily concerned with the analysis, collection, classification, manipulation, storage, retrieval, movement, dissemination, and protection of information. Information science seems to have a lot in common with library science and archival science. Information science deals with all the processes and techniques pertaining to the information life cycle, including capture, generation, packaging, dissemination, transformation, refining, repackaging, usage, storage, communication, protection, presentation etc. in any possible manner.

Informatics, information systems, information management

In some places the discipline of “informatics” – like “information science” has its roots in library science and information retrieval.

In Sweden and some other countries, “informatics” and “information systems” are two common names of academic disciplines, which typically belong to faculties of social sciences and to management and business schools. In other countries, “informatics” often has slightly different meanings, as illustrated by the following text, based on Wikipedia, https://en.wikipedia.org/wiki/Informatics:

“Informatics is the science of computer information systems. As an academic field it involves the practice of information processing, and the engineering of information systems. The field considers the interaction between humans and information alongside the construction of interfaces organisation, technology and system. It also develops its own conceptual and theoretical foundations and utilizes foundations developed in other fields. As such, the field of informatics has great breadth and encompasses many individual specializations, including disciplines of computer science, information system, information technology and statistics. Since the advent of computers, individuals and organisations increasingly process information digitally. This has led to the study of informatics with computational, mathematical, biological, cognitive and social aspects, including study of the social impact of information technologies.”

In 1957 the German computer scientist Karl Steinbuch coined the word “Informatik” by publishing a paper called Informatik: Automatische Informationsverarbeitung (“Informatics: Automatic Information Processing”).

The French term informatique was coined in 1962 by Philippe Dreyfus together with various translations—informatics (English), and informatica (Italian, Spanish, Romanian, Portuguese, Dutch), referring to the application of computers to store and process information.
The term was coined as a combination of "information" and "automatic" to describe the science of automating information interactions. The meaning extends easily to encompass both the science of information and the practice of information processing.

Mikhailov et al. advocated the Russian term *informatika* (1966), and the English *informatics*, as names for the theory of scientific information, and argued for a broader meaning, including study of the use of information technology in various communities (for example, scientific) and of the interaction of technology and human organizational structures.

Usage has since modified this definition in three ways. First, the restriction to scientific information is removed, as in business informatics or legal informatics. Second, since most information is now digitally stored, computation is now central to informatics. Third, the representation, processing and communication of information are added as objects of investigation, since they have been recognized as fundamental to any scientific account of information. Taking information as the central focus of study distinguishes informatics from computer science. Informatics includes the study of biological and social mechanisms of information processing whereas computer science focuses on the digital computation. Similarly, in the study of representation and communication, informatics is indifferent to the substrate that carries information. For example, it encompasses the study of communication using gesture, speech and language, as well as digital communications and networking.

In the English-speaking world the term informatics was first widely used in the compound, ‘medical informatics’, taken to include ‘the cognitive, information processing, and communication tasks of medical practice, education, and research, including information science and the technology to support these tasks’; see Greenes & Shortliffe (1990). Many such compounds are now in use; they can be viewed as different areas of "applied informatics".

Informatics encompasses the study of systems that represent, process, and communicate information. However, the theory of computation in the specific discipline of theoretical computer science, which evolved from Alan Turing, studies the notion of a complex system regardless of whether or not information actually exists. Since both fields process information, there is some disagreement among scientists as to field hierarchy; for example Arizona State University attempted to adopt a broader definition of informatics to even encompass cognitive science at the launch of its School of Computing and Informatics in September 2006.

A broad interpretation of informatics, as "the study of the structure, algorithms, behaviour, and interactions of natural and artificial computational systems," was introduced by the University of Edinburgh in 1994 when it formed the grouping that is now its School of Informatics. This meaning is now (2006) increasingly used in the United Kingdom.

We shall now look a bit closer at one particular interpretation of “informatics” or “information systems” as an academic discipline, the interpretation launched by Börje Langefors in 1966 at the Stockholm University, which was based upon his theory of information and information systems; see Langefors (1966).

**Langefors’ theory of information and information systems – Infology:**

Information systems: *for people, by people, about people* – enabled by methods, models, and technology (Langefors)

Börje Langefors (1915-2009) established “Information Systems” or “Information Processing”, as it was called then, as a modern academic discipline. This took place during the 1960s, when he formed
a university department that was shared by the Royal Institute of Technology in Stockholm and The Faculty of Social Sciences at Stockholm University.

Langefors wanted to focus academic research and education not only on the technical and formal aspects of information systems (like in computer science, mathematics, and engineering sciences) but also on the role of computer-supported information systems in society. This was an internationally unique initiative by Börje Langefors. Langefors was himself an engineer, who had a leading role in the development of the first Swedish computers for practical purposes at DataSaab, a part of Saab, whose main product was military airplanes. But Langefors also took a deep interest in as different disciplines as philosophy and business management and was well-read in those areas as well.

The title of this section is an attempt to summarize the interdisciplinary approach taken by Langefors towards information systems, with the needs and different roles of people, at the same time as the potential of technology and rigorous methods is recognized and taken advantage of – for the benefit of people and organisations in a modern society.

Nevertheless, this section will not be a historical review in a literal sense. It will rather take a fresh look at some important aspects and features of the information systems as they are treated by academic researchers, and as they applied by practitioners. I will focus on aspects and features, where you can see the inheritance from Börje Langefors.

Some major contributions by Börje Langefors are within the following topics:

- Establishing “information systems” as an interdisciplinary academic field with people, organisations, and society in focus, and with methods, models, and technology as important enablers – as suggested by the title of this section.

- Making a clear distinction between information and data, and emphasizing the role of concepts and information – rather than data alone – in information systems developed for serving people and organisations.

- Applying general systems theory and systems thinking when analysing and developing information systems, recognizing that information systems are complex, so-called imperceivable systems, systems which cannot be grasped as a whole, in one go, by the human mind.

- Developing and testing theoretically well founded methods and models for analysing and developing information systems in a rational and systematic way, again recognizing that information systems are developed for human beings and by human beings in a social context.

These and other contributions – both in theory and in practice – led Langefors to the formulation of a new and comprehensive theory of information systems, which marked the foundation of the so-called Scandinavian School in the academic discipline of informatics or information systems. Before Langefors there was a theory of information, founded by Claude Shannon. This information theory is a branch of applied mathematics, electrical engineering, and computer science involving the quantification of information and deals with concepts such as entropy, (lossless and lossy) data compression, efficiency of data transmission, coding, cryptology, etc.

Information systems for people

The basic purpose of an information system is to serve people, for example by providing them with information or by supporting them in performing certain tasks. The people served may be called “users”, “customers”, “clients”, “employees”, etc, depending on which roles they have inside or outside an organisation, or as citizens in a society.

Inspired by Enid Mumford (1924-2006) and others, Börje Langefors early realized that the implementation of computer-supported information systems often resulted in failure to produce satisfactory outcomes. Such failures could arise even when the underlying technology was adequate. An inability or even neglect to recognise and deal with human factors associated with the implementation and use of computers and information systems could often be observed. Still today, despite the identification of these socio-technical factors and the development of methodologies to overcome such problems, information system implementations are often unsuccessful in practice.

Today there is hardly anyone who would deny the importance of acceptance, accessibility, usability, etc, of information system. The meaning of concepts like those just mentioned are not always clear enough, and they are complex and sometimes even contradictory. Consider, for example, an information system that has the purpose to provide people with information about the pension that they may expect to get. A group of users may be asked to try a prototype A of such a system that has been developed. The users are then asked about their opinion of the system, and they give some feedback. The developers develop another prototype B of the system on the basis of the feedback that they have got. The users turn out to be much more satisfied with the new prototype, because they felt it was easier to use. However, it also turned out that it took longer time for the users to get a result from the system about their expected system, and, even worse the result was more often wrong, because the users made more errors with prototype B than with prototype A. Thus prototype B was more user-friendly in certain ways (as experienced by the users), but at the same time it was less efficient and less useful in other ways than prototype A, since it gave more erroneous results and required the users to work with the system for a longer time.

It is often emphasized how important it is that users participate in the development of an information system. But who are the users? As long as we develop information system for a relatively small population of employees in an organisation, it is at least realistic to involve the users in the development work, but what if the users are the public at large, a huge population of potential customers of the organisation?

Moreover, there are often different types of users of an information systems, with different and sometimes even conflicting needs and competences, and some of the needs maybe future needs, which are partly unknown today.

In addition to users, customers, clients, or whatever we choose to call those for which an information system is intended, there are also other categories of stakeholders, for example the employees of an organisation serving the final users, customers, or clients, and the owners, those who finance the development, implementation, and operation of the information system. All these have a legitimate interest to have a say and be listened to.

The socio-technical view of information systems was one of the first steps in recognizing human beings as fundamental, integrated, and active parts of an information system. Börje Langefors brought this view an important step further by emphasizing the distinction between information and data. Following a long scientific tradition established by philosophers (from ancient Greece and onwards) and psychologists and linguists (in more modern times), Langefors regarded information and knowledge as something associated with the human mind, and which is organized by concepts,
formed and elaborated by the minds of human beings from the moment when we are born and onwards in our interplay with the world and other human beings around us. Without human beings there would be no information.

These and other findings – both in theory and in practice – led Langefors to the formulation of a new and comprehensive theory of information systems, which marked the foundation of the so-called Scandinavian School in the academic discipline of informatics or information systems. Before Langefors there was a theory of information, founded by Claude Shannon. This information theory is a branch of applied mathematics, electrical engineering, and computer science involving the quantification of information and deals with concepts such as entropy, (lossless and lossy) data compression, efficiency of data transmission, coding, cryptology, etc.

**Information systems by people**

Information systems embrace both people and artefacts created by people, both information and data, both processes executed by human minds and processes executed by artefacts like computers and data communication equipment. As a whole an information is an artefact, the result of a human design and creation process. Thus, as an academic discipline and a research topic, “information systems” may be seen as a so-called design and creation science, a science where the design and creation research strategy is relevant and applicable.

The design and creation research strategy is described by Oates (2005) as a research strategy that focuses on the development of artefacts. This research strategy is particularly relevant within disciplines such as information systems and computing, where the design and development of artefacts such as application systems and software have always played an important role, as has the development of auxiliary artefacts like methods and models used in the development of application systems and software.

However, it has always been questioned whether the development of an artefact could actually qualify as a piece of research, rendering the developer an academic degree. The answer given by Oates (2005) is yes and no. The development of an artefact could be a part of a research project – even a very important part, both quantitatively (in terms of time devoted to it) and qualitatively (in terms of knowledge contributions). But the artefact as such cannot be the only output from a research project, however advanced it seems to be. It must be associated with other outputs in order to qualify as a contribution to academic knowledge. For example, the project may have developed well documented methods for developing the artefact, and it may be possible to prove that these methods have been of decisive importance for the success of the design and creation project.

It may also be possible to investigate in a scientific way, whether the artefact fulfils the requirements and expectations of different stakeholders in the projects; does the artefact have the expected qualities, does it meet user needs, etc. The artefact may also be compared with earlier solutions of similar problems – in what ways are this solution better or worse than earlier solutions. Finally, even a design and creation project that has failed may actually be quite interesting to analyse from an academic point of view; why did it fail?

Information systems are developed by people for people. Thus people are involved in (at least) two different roles in information systems and information systems development. Sometimes the same people may be involved both as developers and users (customers, clients, etc) of a systems. This may be seen as ideal from many points of view and may be described as “participative information systems development”, comparable with “participative decision-making”, known from governance theories in political science.
Information systems about people

As we have just discussed, information systems are developed by people for people. Many information systems also store and process information about people, that is, people appear in these information systems as object of information, information objects. The people that are informed about may be partly the same people as the developers and/or the users (customers, clients, etc) of the information system.

All information systems contain information about something. This “something” is sometimes called the Universe of Discourse (UoD), or “the object system”. The UoD covers certain parts or aspects of some kind of “reality”, and it is in this sense a (simplifying) model of reality.

Thus:

- Reality of interest = Universe of Discourse = Object system

The OPR framework is a framework for modelling and visualizing a universe of discourse in terms of objects (O), properties (P) of objects, and relations (R) between objects. Model instances following the rules of the OPR framework are called OPR models. OPR models help to conceptualize object systems, and they are therefore called conceptual models. They may be used for conceptualizing both the object system as such – some kind of reality – and information about this reality, for example the information contents of a database or an information system.

As just said, object systems as well as OPR models of object systems are by necessity simplifications of reality, and like all simplifications and models they may not be valid outside the intended context.

The OPR framework has its roots in the seminal theory of information and information systems created by Börje Langefors in the 1960’s; see Langefors (1966), Dahlbom (1995). The first version of the OPR framework as such – then referred to as “the infological model” – was developed by Bo Sundgren and presented in Sundgren (1973, 1974, 1975) and in Langefors & Sundgren (1975). The framework was further refined and elaborated in a series of papers; refer to the Bibliography at the end of this document, and to https://sites.google.com/site/bosundgren/.

The objects in an object system may be active or passive. Active objects, also called actors or subjects, are active in the sense that they are capable of making decisions and act – they are typically people, groups of people, or organisations (consisting of people). Passive objects are more like “things”, material or abstract entities that may be owned, acted upon, or related in some other ways to subjects. A third category of objects are so-called complex objects, which are based on relations between other objects, for example events, transactions, or other relationships like marriage, employment, and ownership. See Figure 46.

The OPR framework is not the only framework of its kind. Several researchers have more or less independently of Langefors and Sundgren developed similar frameworks; see for example Lindgreen (1974), Falkenberg et. al. (1983), Leung & Nijssen (1988), Halpin (2007) and several authors of papers in Klimbie & Koffeman (1974). The work by Michael Senko (1973) should also be mentioned.

Frameworks similar to the OPR framework are often called Entity-Relationship (ER) or Entity-Attribute-Relationship (EAR) models, and many papers have been written on such frameworks. For some strange reason the paper of this kind which has probably most often been referred to in the literature is Chen (1976), although it is certainly not the first, the best, or the most original paper belonging to this category; for a critical review of Chen’s ER model, see Nijssen et.al. (1990).
Some people find it insulting to “objectify” people by treating them as only one of many different types of objects, including passive objects. But it should be remembered – as we have already discussed above – that being information objects in an object system model is only one of the roles that people have in the context of an information system. In addition, people naturally have to be given “special treatment” in the development and operation of information systems because of issues of ethics, privacy, etc. On the other hand, if an information system is going to serve the interests of people in a good way, for example in health information systems, it is necessary to have high quality information, well integrated and easily accessible, in such systems.

Enabling methods and models

It has already been mentioned that “information systems” as an academic discipline belongs to the category of so-called “design and creation” disciplines, focusing on the development of artefacts. Methods and models, which are themselves artefacts, are often important tools in such disciplines, and this is certainly the case within the discipline of information systems.

Börje Langefors and his followers within the Scandinavian School of information systems have devoted a lot of attention to methods and models, both in theoretical and applied research, not least in the context of developing information systems for businesses in a broad sense, including profit-oriented enterprises, government agencies, and non-profit organisations.

By nature models are simplifying conceptualisations and descriptions of some kind of reality, for example a business. We may use the Ogden triangle again for visualizing some important relationships; see Figure 47:

![Figure 46. A specific OPR model.](image-url)

![Figure 47. A model of models.](image-url)
**Systems theory and the systems approach**

Systems theory was an important starting-point and inspiration for Börje Langefors and his research, and systems theory is indeed the basis for many methods and models that we use in practice today, both in systems development and in programming – although we may not always be aware of that.

**General systems theory (Bertalanffy)**

The systems approach was elaborated by Bertalanffy (1968). He noted that all systems studied by physicists are closed systems: they do not interact with the outside world. When a physicist makes a model, she assumes that all masses, particles, forces that affect the system are included in the model. It is as if the rest of the universe did not exist. This makes it possible to calculate future states with perfect accuracy, since all necessary information is known.

However, as a biologist von Bertalanffy knew that most practical phenomena cannot be treated as closed systems. If a living organism is separated from its surroundings, it will die shortly because of lack of oxygen, water, and food. Organisms are open systems: they cannot survive without continuously exchanging matter and energy with their environment. Open systems interact with other systems outside of themselves through inputs and outputs. A system and its environment are in general separated by a boundary, an interface. The output of a system is in general a direct or indirect result from the input. But the system is not just a passive tube, but an active processor, a transformer. For example, the food, drink and oxygen we take in, leave our body as urine, excrements, and carbon dioxide. The transformation of input into output by the system is usually called throughput. This has given us the basic components of a system as it is understood in systems theory; see Figure 48. A system in interaction with its environment. From Heylighen (1998).

![Figure 48. A system in interaction with its environment. From Heylighen (1998).](image)

When we look more closely at the environment of a system, we see that it, too, consists of systems interacting with their environments. For example, the environment of a person is full of other persons. If we now consider a collection of such systems which interact with each other, that collection could again be seen as a system. For example, a group of interacting people may form a family, a firm, or a city. The mutual interactions of the component systems, or parts, are what makes the system as a whole something more than the sum of its parts. With respect to the whole, the parts are seen as subsystems. With respect to the parts, the whole is seen as a supersystem.

If we look at a system as a whole, we don't need to be aware of all its parts. We can just look at its total input and total output without worrying which part of the input goes to which subsystem. For example, if we consider a city, we can measure the total amount of fuel consumed in that city.
(input), and the total amount of pollution generated (output), without knowing which person was responsible for which part of the pollution. This point of view considers the system as a **black box**, something that takes in input, and produces output, without us being able to see what happens in between. In contrast, if we can see the system's internal processes, we might call it a white box, or, maybe better, a **transparent box**. The black box approach is often necessary for the human brain to be able to grasp a complex system. However, when necessary, one may make a black box transparent, in order to see the details of the inside of a system – this requires that the inside of the system is known, though, which is not always the case. See also Figure 49. A system as a transparent box, containing a collection of interacting subsystems, and as a black box, without observable components. From Heylighen (1998).

![Figure 49](image.png)

**Figure 49. A system as a transparent box, containing a collection of interacting subsystems, and as a black box, without observable components. From Heylighen (1998).**

These two complementary views of the same system, "black" and "transparent", illustrate a general principle: systems are structured hierarchically. They consist of different levels. At the higher level, you get a more abstract, encompassing view of the whole, without attention to the details of the components or parts. At the lower level, you see a multitude of interacting parts but without understanding how they are organised to form a whole.

There are different types and views of systems. We have already talked about open vs closed systems, and about black box views vs transparent views. There is also a distinction between soft systems and hard systems. **Hard systems**, e.g. technical systems, are associated with quantifiable variables, whereas **soft systems** usually involve people and both quantifiable variables, and variables that are not easy to quantify; see, for example, Checkland (1981).

We may also distinguish between **man-designed systems** and systems that are just “given” – by God, by Nature, or whatever we choose to believe. Among the man-designed systems we may distinguish between **man-independent systems** (or parts of systems) that will continue to exist, at least for some time, even if all human beings were to disappear from earth, and **man-independent systems** that are what Berger & Luckmann (1966) call **social constructions** of reality, in the sense that will cease to exist, if they lose their human components. Buildings are examples of the former category, whereas enterprises are examples of the latter.
Development of complex systems (Langefors)

“We define ‘imperceivable system’ to mean a system such that the number of its parts and their interrelations is so high that all its structure cannot be safely perceived or observed at one and the same time” Langefors (1966, 1973) p 69.

Computer-supported information systems are complex systems. One reason for this is that they are socio-technical systems with closely integrated social and technical subsystems, people and technology in cooperation. Social systems with interactions between people are of course by themselves quite complex, and it is well known that so-called social engineering is not an easy task. The involvement of technology and technical subsystems may enhance the capabilities and performance of an information system dramatically, but it does not make the information system less complex. In a way, this was very clear and visible when computers first entered the scene. They were then physically very big and really looked complex. Now, five decades later, a computer of at least the same complexity as those early giants could easily be built into a single chip of minimal size, and a small notebook computer is millions of times more powerful and complex, both in terms of hardware and software.

Complex systems, like information systems, are what Langefors (1966, 1973) called imperceivable systems, systems which cannot be completely perceived and understood by the human brain in one go. It is impossible for the human brain to overview, take in, and foresee such systems.

In order to be able to design, construct, monitor, and operate complex, imperceivable systems, human beings must adopt something like the systems approach. It is impossible for a human being to grasp such a system as a whole — and all its subsystems and components and their relations to and interactions with each other — in one mental operation at a single time. At best all people involved can share more or less the same view and understanding of the system as a whole, but the more or less detailed knowledge about different subsystems and components will have to be shared and communicated between many people, everyone being in possession of only a fraction of the total knowledge about the system at a time.

Complex systems may be controlled by human beings by breaking them down into sub-systems, sub-subsystems, etc., until one reaches a level where the components can be fully perceived and understood by a single human being at a single moment of time. The breaking down of a system into subsystems, etc., is an analytical top-down process, where one derives necessary and sufficient properties of the subsystems from the properties of the supersystems. This is not to say that there is only one way to break down a systems into subsystems — not at all.

In parallel with the analytical top-down process, there must be a synthetic, bottom-up process, verifying that the subsystems of a supersystem, once they exist, if they are possible to create, will together exhibit the desirable characteristics of the supersystem. The parallel and iterative analytical and synthetic processes will come to an end, only if and when one reaches a bottom level, where all subsystems and components are perceivable, well understood, and proven possible to create and make behave and interact in such a way that they satisfy the requirements of the systems on the next higher level, and these systems again will behave and interact in a such a way that they in their turn satisfy the needs of their supersystems, etc.

According to Nissen & Andersen (1977), a subsystem can be said to be perceivable, possible for a human being to take in as a whole, when

- its internal structure is not of any interest for the analysis at hand
- it has only a few, say less than 7, relevant properties
Creating an overview is an iterative process, where the following sequence of activities have to be performed; see Figure 50 below and refer to Langefors (1968, 1973), Langefors (1995), Lind (2001), Nissen & Andersen (1977):

a) Specify the external properties of the system
b) Find a limited number of subsystems, which the system is assumed to consist of
c) Identify the relations between the subsystems
d) Find the external properties of every subsystem and consider every subsystem as a new system
e) Derive all external properties of the system of subsystems, and check that they are consistent with the specified external properties of the original system

The check in step e) may very well fail, and then one has to reiterate the whole process or parts of it. Otherwise one may continue the process until one has reached a bottom level, where all subsystems are perceivable, and when all properties up to the top level satisfy the specified external properties of the whole system.

According to Langefors (1968, 1970), it is the first step in the process, which is the creative step. A feasible subsystem structure must in principle be found intuitively.

**Standardisation as a tool for reducing complexity and increasing flexibility**

Standardisation is a powerful tool for managing and reducing the complexity of man-designed systems. Standardisation has been a well-known design principle for technical systems since the beginning of industrialism, e.g. the standardisation of track width of railroads, but it is equally applicable to socio-technical systems like information systems. For example, most of us do not open manuals or instruction books any more, when we start using a new web-based system on our computers. We recognise intuitively “the look and feel” of such systems, and the reason for that is that the designers of the systems have followed architectural standards and standards for user interfaces. It does not matter so much if the standards are formally established or *de facto* standards.

Standards may concern system components, e.g. software modules, or interfaces between components, e.g. languages and formats for communication, exchange of messages. Both types of standards are important, but most important is the standardisation of interfaces. Standardised interfaces enable system components – and even whole systems – to remain independent of each other, while still being able to interact and co-operate smoothly. See Figure 51 from Sundgren (1996).

![Figure 51. A standardised interface reduces complexity and increases flexibility at the same time. From Sundgren (1996).](image)

Figure 51. A standardised interface reduces complexity and increases flexibility at the same time. From Sundgren (1996).

It is sometimes argued that standardisation has a disadvantage in the form of less flexibility. This is not true – at least not for the kind of standardisation that we are discussing here. In fact, standardisation on a lower level will typically increase the flexibility on a higher level. Standardised components may combined in many more ways than non-standardised components – and much more easily, if standardised interfaces are in place.

Again we may use Figure 51 as an illustration. If we want to add another system to the system on the right-hand side of Figure 51, the only thing we have to do is to ensure that the new system is able to communicate via the standardised interface – and it will automatically be able to communicate with all other systems. In contrast, if we want to add another system to the system on the left-hand side of Figure 51, we have to establish a unique communication protocol for every other system that we want the new system to be able to communicate with.
Thus, by introducing standardised interfaces in a “system of systems”, we increase the usefulness and flexibility of all component systems; at the same time we decrease times and costs for systems development.

If one makes sure that different systems can communicate with one another via standardised interfaces, a certain system need not know “the inside” of another system in order to be able to communicate with it and exploit its functionality.

As regards information systems, including statistical systems, standardisation may be applied on all levels, for example:

- global level: network of co-operating information systems
- intermediary level: individual information systems, subsystems and processes
- local level: software products or software components

**What is an information system?**

A basic definition of an information system, originating from Langefors, is that it is a system for obtaining, storing, processing, analysing, and providing information. Data processing systems are important subsystems of information systems, since, as we have already discussed, information and information processes can only exist in human minds, and all storing, processing, and communication of information outside and between human minds has to take place by means of data and data processing proxies.

Figure 52 illustrates an information system as a system including both people and technical enablers:
Data and data processing has a highly integrated role in most mental processes and usages of information in contemporary societies. 

Figure 52. Data and data processing has a highly integrated role in most mental processes and usages of information in contemporary societies.

Read more:


Information systems as subsystems of larger systems

Information systems are not ends in themselves. They serve other systems, for example a society or a business. Figure 53 illustrates a statistical system as a part of government decision-making in a society. The figure may easily be translated into information systems in other environments, with other purposes.
At an early stage in their research, Börje Langefors himself and his followers in the research group ISAC, led by Mats Lundeberg and with members like Göran Goldkuhl, Anders G Nilsson, and many others, realized that information systems cannot be considered independently of other aspects of a business. Sometimes when it is believed that an information system is the root cause of the problems that a business experiences, it may be found that the business has bigger problems, like unclear goals and strategies, and that the problems with the information system are just symptoms of these bigger problems.

Mats Lundeberg, Göran Goldkuhl, and Anders G Nilsson have also, over the years, developed, and tested in practice, many well-structured methods for focusing on and including people in information systems.


**Business modelling**


**Software development and programming**
Being in charge of the software development at DataSaab, Börje Langefors engaged himself early in the development of software development methods, and he inspired the development of programming languages like ALGOL and SIMULA, as well as methods like modular programming, object-oriented programming, and structured programming.

**Object-oriented programming**

Object-oriented software and systems development has a long history from Langefors and onwards to Dahl, Jacobson, and many others; see for example Jacobson (1992).

**Structured programming**

Structured programming is based on the proposition that all computer programs may be built up from three basic structures: sequence, selection, and iteration; see Figure 54.

![Structured Programming Diagram](image)

*Figure 54. Basic elements of computer programs according to structured programming principles.*

See Dahl & Dijkstra & Hoare (1972).

The principles and basic elements of structured programming may also be applied to systems design. See Jackson Structured Programming (JSP) and Jackson Structured Design (JSD): Jackson (1975).

**Service-oriented architecture (SOA)**

When designing information systems, one may use standardised structuring methods and architectures, such as database orientation, process orientation, client/server architecture, and service orientation.

Today’s applications are often database-oriented, that is, different functions of the system interact with each other via a common database, including both data and metadata.
Until recently, database-orientation has often been combined with a structuring of the information system according to the client/server principle. In its original form, the client/server architecture consists of two types of subsystems: user-oriented client systems, which are served by server systems, handling common resources like printers and databases. There are developments of the client/server architecture, using three or more types of subsystems, called tiers. In a three-tier client/server architecture there is a distinction between

- subsystems for user interactions
- subsystems for business logic
- subsystems for data management

With the rapidly growing importance of the Internet and web-based information systems, the client/server architecture is becoming replaced by service-oriented architectures (SOA), based on well-defined, standardised services, which can be used in a standardised way, via standardised messages and communication protocols, by other services.

Figure 55 illustrates the SOA concept.

Service-oriented architectures are based on the following design principles; Erl (2005):

- **Loose coupling** – Services maintain a relationship that minimises dependencies and only requires that they retain an awareness of each other.
- **Service contract** – Services adhere to a communications agreement, as defined collectively by one or more service descriptions and related documents.
- **Autonomy** – Services have control over the logic they encapsulate.
- **Abstraction** – Beyond what is described in the service contract, services hide logic from the outside world.
- **Reusability** – Logic is divided into services with the intention of promoting reuse.
- **Composability** – Collections of services can be coordinated and assembled to form composite services.
- **Statelessness** – Services minimise retaining information specific to an activity.
- **Discoverability** – Services are designed to be outwardly descriptive so that they can be found and assessed via available mechanisms.

More briefly and concretely expressed, a service is a piece of reusable software, which performs a well-defined function, described in a standardised way. The service can be requested by other pieces of software, which may themselves be services, through standardised messages. The service requestor should not have to know anything about the internal functioning of the activated service, and the latter should not have to know anything about its external environment, but only perform its function and (possibly) provide a standardised response message in return. During its execution a service may itself request the execution of other services in the same way.
Service-Oriented Architecture (SOA)

Service-orientation can be seen as a further development of earlier software design methodologies like modular programming and object-orientation. It is obviously well in line with the general systems approach and systems thinking; compare the description of services above with our earlier discussions of the systems concept and about how to manage complexity and imperceivable systems.

Service-orientation, as defined above, has the great advantage that it can be introduced step by step in an organisation. Any large organisation today has an enormous burden of legacy systems that cannot quickly and easily be redesigned and redeveloped. A legacy system that has not been developed in accordance with modern design principles can be encapsulated into a large black box component, which is not internally consistent with service-oriented principles, but which interacts with its environment according to such principles. Of course it requires some work to develop the “sarcophagus” surrounding the black box, making it look and behave like a true service to the other services in the system, with which it interacts, but this is a small effort in comparison with a total make-over or redevelopment of the whole legacy system.

Service-orientation often goes hand in hand with process-orientation. On the business level – for example the business of statistics production – the employees interact with customers, suppliers (respondents and data providers in the case of statistics production), colleagues, and external and internal service systems (typically computerised), in order to provide services demanded by the customers, to the customers. This work may be organised into processes, preferably standardised processes, so as to ensure that the work is done according to best methods and best practices and will give the same good quality results to the customer, regardless of which individual persons are executing the processes.

Another recent trend is to replace in-house software developments, and even in-house licensing and installation of commercial software packages, with software components that are provided as
services, for free or for a fee, via the Internet. This is called “cloud computing” or “Software as a Service”, SaaS, and is also consistent with service-oriented architectures and process orientation.

References: Erl (2005), Sundgren (2012).

Enabling technologies

Technologies and technical solutions for enabling information systems are primarily studied within departments belonging to faculties and schools of computer science, engineering, natural sciences, and mathematics. Ideally there should be a lot of cooperation and interdisciplinary research between such departments and departments of informatics, social sciences, and business management – preferably within frameworks of interdisciplinary projects with common goals, including the best researchers and specialists from different discipline, sharing engagement for the common goals of such projects.
CHAPTER 7. Strategies, and methods for research in information systems and computing

This overview of the research process is an elaboration of the research model discussed in Oates (2005) and visualised in Figure 3.1 of that book. My elaborated model is visualized in Figure 56.

Inputs → Procedure → Outputs. Like any other process, a research process transforms certain inputs to certain outputs by means of some kind of procedure, the body or throughput of the process.

The model presented here, and which is based on Oates (2005), is general and applicable to all kinds of academic research, but it pays special attention to research in disciplines, where modern information technology (IT), IT-supported solutions, and the Internet are important, either as research objects in their own right, or as means to an end, or both.

Oates discusses six different research strategies. One of them is called “Design and creation”, and this strategy is particularly relevant for research in information systems and computing. It is treated in Chapter 8 of Oates’ book.

The research strategy “Design and creation” is particularly relevant within disciplines such as information systems and computing, where the design and development of artefacts such as application systems and software have always played an important role.

Inputs to the research process created during a pre-research process

A research question triggers a research process. The input that triggers a research process is a research question. During a pre-research process, the research question emerges and is elaborated, in iterative steps, often starting from a rather vague idea in the researcher’s mind about a research area, a topic, and a number of issues and problems, which the researcher finds interesting to pursue, and where there is a potential for creating some new knowledge by means of academic research.

The elaboration of the researcher’s initial, vague idea into a well formulated research question will usually take a number of iterations in collaboration with a supervisor and research colleagues.

The researcher must also find and study relevant academic literature about the research area and research topic in order to place the research question in a natural, theoretical and practical context, and to relate the research question to earlier research by other researchers.

Formulating the research question in a rigorous and operational way. The study of the literature may also give the researcher access to one or more conceptual frameworks that may help the researcher to formulate the research question in a rigorous and operational way:

• “Rigorous” means that the research question is well defined, making it easier for the researcher to communicate with other researchers (including colleagues and supervisors) about the research question, and to understand the meaning of the research question properly.

• “Operational” means that it should be possible to see feasible ways forward in the research process, choosing an adequate research method, and executing the research process, until interesting and useful outcomes have been produced: new knowledge and possibly some artefacts, e.g. a computer-supported system, or a piece of software.
It is important for the success of the research process that the researcher feels motivated to grapple with the research question by means of academic research. A research process will always have its ups and downs, and without strong motivation it may become impossible for the researcher to complete the endeavor in a successful way.

**In summary:** During a pre-research process a research question is elaborated and refined, step by step,

- stimulated by the researcher’s own experiences and motivation, including discussions with colleagues and supervisors, and
- supported by relevant theories and concepts based on a literature review.

The pre-research process should result in a rigorously formulated research question, which is feasible to tackle within an operationally well-defined research procedure,

- based on established, respectable research methods,
- so that valuable research outputs can be produced,
- consisting of knowledge contributions and, possibly, some useful artefact, such as a computer-supported application system, a piece of software, or a piece of art.

See also Figure 56 and Oates (2005), Chapter 2.

**Choosing research method and executing a research procedure**

A research method typically consists of the following four components:

- a research paradigm
- a research strategy
- one or more data collection methods (also called data generation methods)
- one or more data analysis methods

**Research paradigms**

A research paradigm consists of a general, philosophical approach to research. The research paradigm defines and reflects how the researcher looks upon some fundamental issues, such as:

- **ontology or world view:** is the object of our research – the so-called reality or universe of discourse –
  - an objectively existing reality, which we can observe and measure objectively, and for which we can obtain true facts, and derive general laws – **positivism**; or it
  - a subjective construction, based on disputable interpretations of our human perceptions and conceptualisations of the universe of discourse – **interpretivism**

- **epistemology or how to obtain knowledge:**
  - rationalism: knowledge is obtained by thinking and deduction
  - empirism: knowledge is obtained by perception and induction
  - inductive/deductive iterations, e.g. hypothesis testing, grounded theory approaches

- **pragmatics or the purpose of research:**
  - get insights, understand
  - solve problems, facilitate decision-making (rational man)
  - empower people to improve their lives or work conditions (critical research)
Within the natural sciences – like physics, chemistry, biology – the positivistic world view has dominated for a long time, and nobody can deny that this world view and research approach has been extremely successful, both in terms of creating new knowledge, and in terms of improving at least material living conditions for people. It has become widely accepted, not only by scientists, but by people in general that the physical world exists in an objective way, independently of the existence of human beings, and that it can be explored by objective observations, measurements, and experiments.

However, when academic researchers became more actively interested in exploring social aspects of our world, our societies, the positivist research approach was not equally successful. Social researchers tried to study the socio-economic aspects of our world, first using, by analogies, the same research methods that had proved to be so successful in the natural sciences. Sometimes such studies were successful, but more often they turned out to be problematic. There were several reasons behind the problems, for example:

- objects in the social world, like organisations, are obviously highly dependent on the existence and activities of people; they do no exist in the same objective way as objects in the physical world

- many aspects of social conditions and relations are not as easy to observe and measure objectively as phenomena in the physical world; some aspects can be measured in monetary terms, but many properties and variables cannot be transformed into euros and cents in a straightforward way, neither in theory or in practice

- it is very difficult, if not impossible, to carry out experiments in an organisation in the same rigorous was as in a laboratory for physical and technical experiments

As a consequence of all these problems and difficulties, social researchers have tried to find research paradigms and research strategies that are more suitable for social research. So far no single research method has established itself with such power, acceptance, and obviousness as positivist methods have within the natural sciences. Instead there is a wide range of methods, with their respective advocates and typical application areas. Whereas a positivist researcher does not have to spend much effort to explain his positivist research philosophy, at least not when applied within traditional natural sciences, a social researcher always has to explain and defend his or her research paradigms and research strategy in great detail.

See also Oates (2005), Chapter 19 and Chapter 20.

**Research strategies**

Oates (2005) describes and analyses six different research strategies (see Figure 56):

1. **Survey** – See Oates (2005), Chapter 7

   In a survey the researcher studies the objects in a population, e.g. a population of persons, organisations, events, decisions, transactions. The researcher may study all objects in the population, a so-called total survey, or a subset of the population, typically a random sample, so that statistical methods can be used to draw conclusions about the whole population, given data about the objects in the sample. A survey is a suitable research strategy, when the researcher wants to collect a relatively small set of well-defined data (facts or opinions). The data are often collected by established statistical procedures, such as interviews and questionnaires. Administrative registers
and the Internet are becoming increasingly popular data sources in surveys, sometimes as complements to data collected in more traditional ways.

2. **Design and creation** – See Oates (2005), Chapter 8

The research strategy “Design and creation” is particularly relevant within disciplines such as information systems and computing, where the design and development of artefacts such as application systems and software have always played an important role.

However, it has always been questioned whether the development of an artefact could actually qualify as a piece of research, rendering the developer an academic degree. The answer given by Oates (2005) is yes and no:

- The development of an artefact could be a part of a research project – even a very important part, both quantitatively (in terms of time devoted to it) and qualitatively (in terms of knowledge contributions). But the artefact as such cannot be the only output from a research project, however advanced it seems to be. It must be associated with other outputs in order to qualify as a contribution to academic knowledge.

- For example, the project may have developed well documented methods for developing the artefact, and it may be possible to prove that these methods have been of decisive importance for the success of the design and creation project.

- It may also be possible to investigate in a scientific way, whether the artefact fulfils the requirements and expectations of different stakeholders in the projects; does the artefact have the expected qualities, does it meet user needs, etc.

- The artefact may also be compared with earlier solutions of similar problems – in what ways are this solution better or worse than earlier solutions.

- Finally, even a design and creation project that has failed may actually be quite interesting to analyse from an academic point of view; why did it fail?

3. **Experiment** – See Oates (2005), Chapter 9

In everyday language, we often speak of doing an experiment when we mean we will try something and find out what happens. In academic research, an experiment is a strategy that investigates **cause and effect relationships**, seeking to prove or disprove a causal link between one or more factors and an observed outcome. Experiments are often associated with research in the natural sciences and is at the heart of the scientific method and positivism.

Researchers start by developing a **theory** about their topic of interest, which leads to a statement that can be tested via an experiment. The statement to be tested is called the **hypothesis**, and is typically of the form “**Factor A causes B**”. The experiment is designed to prove or disprove a relationship between two or more factors: **causal factor(s)**, **called independent variable(s)**, and **effect factor(s)**, **called independent variable(s)**. All factors that may affect the results, without being a causal factor, are excluded from the study, or kept under control. If the researchers are confident that no other factor could have caused the observed results, their hypothesis that “A causes B” has been proven. However, even the most carefully designed and laboratory-based experiment might have been contaminated by some unrecognised other factor. Good researchers would not draw firm
conclusions from experiments until they have been repeated many times, preferably in different environments, by themselves and by other researchers.

4. **Case study** – See Oates (2005), Chapter 10

**Definition:** A case study is an empirical inquiry that makes an in depth investigation of a phenomenon, with all its complexities, and within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident.

A case study **focuses on one (or a few) instance(s) of the “thing” to be investigated:** an organisation, a department, an information system, a project, a decision, etc. This one instance, or **case,** is studied **in depth,** using a wide range of data sources and data collection methods (observation, interviews, questionnaires, documents, etc.) to obtain **multiple perceptions** of the phenomenon under study, **both quantitative and qualitative data** can be used. The aim is to obtain a rich, detailed insight into the “life” of the case and its complex relationships and processes.

**Contrasting with other research strategies:** In a **survey,** a researcher is able to take a wide but only shallow view of lots of instances of the phenomenon under investigation and is unlikely to obtain much information about the context of the phenomenon for each instance. In an **experiment,** the researcher must divorce the phenomenon from its context in order to establish that the measured outcomes can only have been caused by the researcher’s manipulation of an independent variable, and not by anything else. **Both surveys and experiments simplify the complexities of the real world.**

A case study, on the other hand, looks at the chosen case within its real-life context, and focuses on all the factors, issues, politics, processes, and relationships that constitute the messiness of the real world. By exploring all these factors, and painting a detailed picture of how they link together, a researcher will try to explain how and why certain outcomes might occur in a particular situation. A case study does not test hypotheses, as in experiments, but from studying a particular instance. Nevertheless, the aim is to gain insights and generate knowledge, which may be at least partly **generalizable** to other situations.

**A case study takes place in a natural setting, not in a laboratory or other artificial situation.** The case existed prior to the researcher arriving on the scene, and, normally, continues to exist after the researcher has moved on. The researcher tries to disturb the setting as little as possible.

**Case studies tend to be holistic:** the researcher focuses on the complexities of relationships and processes, and how they are interconnected and inter-related, rather than trying to isolate individual factors.

5. **Action research** – See Oates (2005), Chapter 11

Action research comes from a **concern** to **make social science research more directly useful** by applying research techniques directly to practical social problems, rather than doing research just to write books or papers that only other academics would read. Action research has been used particularly by **professionals who want to investigate and improve their own working practices,** for example nurses and teachers. Academics carrying out action research in a practical situation would be expected to **collaborate with the practitioners** working in that setting. Hence, action research aims to **be a participative approach,** ideally leading to a **democratisation** of research.

**Characteristics of action research:**
Concentration on practical issues: It addresses the concerns and complex problems expressed by practitioners in their daily work. It requires researchers to work in the field, in the messiness of human affairs.

An iterative cycle of plan-act-reflect: Action research is about research into action. The researchers plan to do something in a real-world situation, do it, and then reflect on what happened or was learnt, and then begin another cycle of plan-act-reflect.

An emphasis on change: The researchers do not simply observe and describe. They are concerned with doing things that make a difference, and learning about how they effected the change.

Collaboration with practitioners: People living and working in the situation under study are active participants in the research.

Multiple data generation methods: There are no restrictions on the types of data that are appropriate to action research.

Action outcomes plus research outcomes: Ideally both types of outcome should be achieved. However, sometimes projects may not lead to practical achievement, but can still be judged as successful by academic researchers, if learning is made about models, theories, processes, etc, including possible reasons for the failure to alleviate the practical problem.

6. Ethnography – See Oates (2005), Chapter 12

Ethnography means a description of peoples or cultures, for example the culture prevailing in a particular (part of an) organisation. Anyone starting a new job, or moving to a new country, has to learn about the culture and ways of acting of people already there. The people already there do not think about this, "it is just the ways things are and are done around here".

Whenever we are faced with learning about a new culture, we could be said to be acting as ethnographers. As researchers, ethnographers gather and record data about the culture being studied, reflect on this, link to earlier research, present conclusions in academic articles, etc. Initial research question for an ethnographer: "What is life like for these people?". Ethnography originated in anthropology, but an ethnographer typically lives in less exotic environments and for shorter time.

The ethnographer spends time in the field, taking part in the life of the people there, that is, carrying out participant observation rather than being a detached observer. The ethnography does not take place in an artificial experimental setting, but in the natural setting of the subjects, which, as far as possible, should be undisturbed by the presence of the ethnographer. The ethnographer becomes the research instrument, using multiple data generation methods such as interviews, observations, and documents and, especially, field notes about what they see, feel, and experience. The ethnographer tries to construct a representation of the world as perceived by the people who live in that world. The test of success of this is whether those people recognise the ethnographer’s description of familiar features of their own culture. The ethnographer tries to produce a holistic description of the culture, including social, cultural, and economic aspects of the situation, rather than just concentrating on one or two aspects of life in that world.

Data collection methods

Each research strategy (see Figure 56) is associated with one or more data collection methods, also called data generation methods. Oates (2005) describes and analyses four different data generation methods:

1. Interviews – Oates (2005), Chapter 13
A research interview is a particular kind of conversation between people:

- The interviewer wants to gain information from the interviewee(s) for a certain purpose.
- The interview is planned in some way.
- The researcher has an agenda and will steer the interview towards certain topics.
- A research interview is carried out openly; the interviewee knows and agrees.

**Interviews may be suitable when a researcher wants to:**

- obtain detailed information
- ask questions that are complex or open-ended, or whose order and logic may need to be different for different people
- explore emotions, experiences, or feelings that cannot easily be observed or described via pre-defined questionnaire responses
- investigate sensitive issues, or privileged information

**Interviews are much used in case studies and ethnographies.** They are also used when planning or following up questionnaire-based surveys. Interviews are often one-to-one, but can be used for groups as well, e.g. so-called focus groups.

2. **Observation** – Oates (2005), Chapter 14

Observing is something we do all the time: seeing, hearing, noting... Researchers use observations to find out what people actually do, rather than what they report they do when questioned. Often observation involves looking and hearing, but it may also involve other senses: smelling, touching, tasting, interpreting body language, ...

Observation as a data generation method can be used within any of the six research strategies that we have discussed. There is a wide range of approaches to observation, as discussed in Oates (2005).

One important distinction is between overt and covert observation:

- In **covert observation** the researcher is like a spy. **Advantage:** People behave naturally. **Disadvantage:** No consent. Is it ethical? Maybe in public places.

- In **overt research** the people know they are being observed. **Advantage:** Less likely to cause upset and anger. No risk for the researcher of being revealed. **Disadvantage:** The **Hawthorn Effect**: people modify their behaviour because they know they are being observed.

Another important distinction: **systematic observation vs participant observation**.

3. **Questionnaires** – Oates (2005), Chapter 15

A questionnaire is a pre-defined set of questions, assembled in a pre-determined order. Respondents are asked to answer the questions, thus providing the researcher with data that can be analysed and interpreted.

Questionnaires are often associated with the survey research strategy, but they can also be used in case studies, action research, design and creation.
Questionnaires can be self-administered or researcher-administered. The latter is a kind of structured interview – see Oates (2005), Chapter 13 – and can be face-to-face or via telephone.

Questionnaires provide an efficient way of collecting data from many people. They are best suited in situations where the researcher:

- wants to obtain data from a large number of people
- wants to obtain relatively brief and uncontroversial information from people
- needs to obtain standardised data, by posing identical questions to each respondent, and predefining the range of answers which can be given
- can expect the respondents to be able to understand the questions and possible answers
- has the money to pay for producing, distributing, and collecting questionnaires, and the time to wait between the questions and getting the responses back

A questionnaire has to be carefully designed and constructed.

4. Documents – Oates (2005), Chapter 16

Documents can be used as another source of data, an alternative to interviews, observations, and questionnaires. There are two main types of documents:

- Found documents: already exist prior to the research, such as documents found in most organisations: production schedules, profit and loss accounts, internal telephone directories, job descriptions, procedure manuals, etc.

- Researcher-generated documents: put together solely for the purpose of the research task.
  - For example, a researcher undertaking an ethnography would take photographs and make field notes. These become an important source of data for analyses.
  - Similarly, a researcher who is designing and creating an IT artefact would produce many models and diagrams. These are important in illustrating and justifying the design process.
  - A researcher can also design a document but ask someone else to complete it, for example a log for recording different kinds of requests to a help desk.

Second-hand data from earlier research may be found in books and papers.

The document concept may be extended to any symbolic representation that can be recorded and retrieved for analysis:

- computerised files, registers, and databases
- multimedia representations
- websites
- etc.

Data analysis

Oates (2005) discusses two major categories of data analysis (see Figure 56):

Quantitative data analysis – Oates (2006), Chapter 17

Quantitative data means data, or evidence, based on numbers. It is the main type of data generated by experiments and surveys, but it can be generated by other research strategies too. It is primarily
used and analysed by positivist researchers, but is sometimes generated by interpretive and critical researchers.

Examples of numeric data

- number of people expressing satisfaction with ...
- a company’s annual turnover for each of the last 5 years
- time in seconds to process a data file
- number of characters in a computer animation
- number of people using the Internet for more than 20 hours per week
- number of hot links on a website

The idea of data analysis: look for patterns in the data and draw conclusions.

Established techniques for analysing quantitative data

- simple table, charts, or graphs
- simple descriptive statistical measures: averages, variation measures, correlations
- more complex statistical techniques, visualisations, and animations

Types of quantitative data

- **Nominal data – categorical data**
  - Nominal data indicate categories or classes in a classification.
  - Numerical values are often used to represent the classes, but they are not really quantitative data; it is not meaningful to carry out arithmetical operations on them.
  - The only quantitative analysis possible is to count frequencies.

- **Ordinal data – ranked data**
  - Numbers are allocated to a quantitative scale, providing an order or rank.
  - We know the order between the points on the scale, but not the distance. Example: student marks.

- **Interval data**
  - Interval data are like ordinal data, but now we know that the distances between the points on the scale are the same, e.g. years.
  - For such data subtractions are meaningful, but not multiplication or division.

- **Ratio data**
  - There is a true zero on the measurement scale, e.g. people’s age, height, weight.
  - Addition, subtraction, multiplication, division are meaningful.

Further categories: discrete data (whole numbers) vs continuous data.

**Data preparation operations**

Before collected data can be used for data analysis, they must be prepared by so-called data coding and data editing operations. “Coding” means transforming the data into pre-defined classes (categories). “Editing” means checking the data for suspected errors, and correcting (or at least changing) the data, when motivated.

**Data coding**
For closed questions: Each predefined answer option is transformed into a unique code.

For open questions: There has to be a well-defined classification scheme corresponding to each open question. Each class (category) is indicated by a code. Each free-text answer given by a respondent to the open question is transformed into a code in the classification scheme.

The coding scheme must contain codes (classes) that are mutually exclusive and exhaustive.

All coders must apply the coding scheme in the same way.

There should be a code book, where each code is noted and defined.

There should be special codes for different types of missing data, e.g.:

- data missing because the respondent did not respond at all, object non-response
- data missing because the respondent ignored the particular question, item non-response
- data missing because the question is not relevant for the particular respondent

Data coding could be a manual process or computer-supported in different ways.

Data editing

- The data obtained from measurements, observations, questionnaires, etc, will contain different kinds of errors.

- **Checks should be made to discover suspected errors, focusing on errors that would seriously distort analyses and results. Checks could look for:**
  - missing data
  - invalid data, values which are not in the code-book
  - inconsistent data
  - unusual data, outliers

- Suspected errors could lead to further checks (e.g. contacts with the respondents, although this will usually be very costly), and possibly – but not necessarily – to changes of the data, possibly imputations: automatic generation of replacements for missing data or suspected errors.

- Data editing can be done by manual or computer-supported processes.

- **Data editing will not necessarily improve the quality of the data, but it may make the data easier to analyse**, e.g. by removing or changing suspicious data that “disturb” analytical patterns or computerised processes.

**Qualitative data analysis – Oates (2005), Chapter 18**

The concept of qualitative data includes all non-numeric data – words, images, sounds, and so on – found in such things as interview tapes, researchers’ diaries, company documents, websites, and developers’ models. It is the main type of data, or evidence, generated by case studies, action research, and ethnography. It is also the main type of data used and analysed by interpretive and critical researchers, but can be generated by positivist researchers too.

You can use quantitative (numerical) analysis on qualitative data. For example, you could:

- Count the number of times a particular word or phrase occurs in some text.
- Count the number of words or pages allocated to different topics on a website.

However, most qualitative data analysis involves abstracting from the research data the verbal, visual, or aural themes and patterns that you think are important to your research topic.

Data preparation

- Get all your data into standard formats.
• Plan an efficient filing system for your data.
• Make backup copies of your data, and always work with a backup copy.

Data analysis

• Start off by reading through all data to get a general impression. Start to identify key themes in the data. Initially three themes could be enough:
  o Segments that have no relation to your overall research purpose and so are not needed.
  o Segments that provide general descriptive information that you will need in order to describe the research context for your readers; e.g. history of a company, background data about respondents.
  o Segments that appear to be relevant to your research question(s).

• Focus on the third category above. Categorise each segment or unit of data by writing in the margin a heading, subheading, or other label.

• To start with, the choice of categories is not crucial. They may come from:
  o Existing theories – the deductive approach.
  o The data themselves, e.g. categories used by respondents – the inductive approach.

• Refine your categories, e.g. by breaking them down, or grouping together.
• Look for themes and inter-connections between segments and categories.

• Use visual aids, e.g. tables or diagrams, to analyse the data.

• Go beyond the patterns you see, and try to explain them. Document the analysis.

Outputs from the research process: outcomes and presentations

See Figure 56 and Oates (2005), Chapter 2, Chapter 8, and Chapter 21.

The outcomes of a research project

A research process should always result in some kind of knowledge outcome, sometimes associated with an artefact that is also an outcome from the research process.

Furthermore, the knowledge outcome and, if applicable, the artefact must be presented, described, and analysed, together with the research process itself, in some kind of research report, typically a text document, but other presentation forms are also possible, at least as complements, for example multimedia presentations. Thus, in addition to the knowledge outcomes, and possibly some artefact, a research process should result in a tangible presentation outcome, for example a thesis, a scientific article, or a book.

The knowledge outcome from a research project may be of many different types. In natural sciences, the knowledge outcome often consists of new, modified, or augmented theory that is verified or falsified on the basis of analyses of empirical data, generated by surveys or experiments.

In social sciences the knowledge outcome could consist of a new theory or conceptual framework that can help to analyse and interpret empirical data, generated by, for example, surveys, case studies, or action research. Rather than verifying or falsifying a theory or hypothesis, like in natural
sciences, social science research typically aims at a richer understanding of social phenomena, sometimes by means of alternative, competing or complementary interpretations of empirical data.

In disciplines like computer science, information systems, and other areas where information technology plays an important role, a research project may include the development, study, and/or application of a computer-supported artefact, for example a piece of software or an application system.

Further examples of artefacts that may be outcomes from research projects following what Oates (2005), Chapter 8, calls the design and creation research strategy:

- **Constructs**: e.g. the notions of entities, objects, or data flows

- **Models**: combinations of constructs that represent a situation and are used to aid problem understanding and solution development, e.g. a data flow diagram, a use case scenario, or a storyboard

- **Methods** (also called methodologies): guidance on the models to be produced and process stages to be followed to solve problems using IT, including
  - formal mathematical algorithms
  - commercial and published methodologies such as Soft System Methodology or Information Engineering
  - organisations’ in-house procedure manuals and informal descriptions of practice derived from experience

- **Instantiations**: a working system that demonstrates that constructs, models, methods, ideas, genres, or theories can be implemented in a computer-based system

A design and creation research project may involve the design and development of a computer-based product. Or it may explore and exhibit possibilities of digital technology. For such projects to be considered as research, rather than only an illustration of technical skills and cleverness, they should also demonstrate academic qualities such as analysis, explanation, argument, justification, and critical evaluation. The projects must also contribute to knowledge in some way. How this is done depends on the role that the IT system plays. The IT system may be:

- the main focus of research
- a vehicle for something else
- a tangible end-product of a project where the focus is on the development process

Design and creation may be combined with other research strategies, for example case studies or experiments.

Examples where the IT system is the main focus, and thus is itself a contribution to knowledge:

- An IT application that uses IT in a new domain
- An IT application that incorporates a new theory, e.g.
  - an educational theory incorporated into a computer-aided learning package
  - an economic theory on consumer behaviour applied to an e-commerce site
- An IT application that expresses or explores novel artistic ideas, for example, how feelings of fear or wonder might be induced via computer art
Examples where the IT system is a vehicle for something else:

- A project where the contribution to knowledge is based on a literature review and/or field research, but the conclusions drawn from this work are illustrated via a prototype IT application
- An IT application is developed, but the contribution to knowledge is based on what happens next, when the application is used in a real-life context
- An IT application is developed using two different software programs, so that the researcher can compare and evaluate the two different programs
- An IT application presents and explains the results of a literature and/or field study

Examples where an IT system is an end-product, but the focus is on the development process:

- An IT application is developed in order to study the use of a particular development method
- A research project analyses existing development approaches and then argues for, develops, and illustrates the use of a new, better approach for developing IT applications
- A research project investigates, compares, and evaluates two or more development methods (or constructs, or models) by following these methods to analyse, design, and implement an IT application

Some opportunities and risks associated with design and creation research projects, having an IT artefact as a major outcome:

- Opportunities:
  - You have something tangible to show for your efforts, rather than just abstract theories and other knowledge
  - It appeals to people who enjoy technical and creative development work
  - It is the normal mode of research in some computing areas such as computer science and software engineering
  - Because of the potential for IT in new domains, and because of rapid technological advances, there is plenty of scope for new IT artefacts
- Risks:
  - You must clearly demonstrate why and how your work is academic research and not just a piece of normal engineering work and craftsmanship
  - It is risky if you do not have the necessary technical skills
  - Results may be difficult to generalise
  - The success of an IT artefact may depend too much on the researchers being present
  - It may produce perishable research, rapidly becoming obsolete

Research projects aiming at the creation of an IT artefact may often be suggested by practitioners, and such projects, undertaken in cooperation between business companies and the academy may be of great mutual interest and value. However, there must be an understanding and agreement between the practitioners and university researchers involved in such a project that there are important differences between an academic research project and a consultancy. There must be enough time in the project set aside for the academic aspects of the work. The outcome of the project may be very successful from a practical point of view, but, as we have discussed, this is not
enough for the outcomes to be recognised as interesting and valuable from an academic point of view. On the other hand, a design and creation project that does not succeed in producing a useful artefact need not necessarily be a failure from an academic point of view, provided that interesting lessons can be learnt from the project, thus contributing to generizable new knowledge and insights.

Presentation of the outcomes of a research process – See Oates (2005), Chapter 21:

Whatever kind of research you have undertaken, and whatever knowledge outcomes and artefacts have been produced, it needs to be reported and presented, typically in written form. For many researchers, a written text will be the only tangible evidence of the research that others can evaluate. For design and creation researchers, there may be a computer-based system or a piece of digital art that others can assess, but such work must also be described, justified and placed in context via a written report. Oates (2005), Chapter 21, provides a checklist of aspects to be considered when writing up a research project:

- **Getting started:** Start writing from the very beginning of your research project. It helps to clarify ideas for yourself and for others. Continue writing all along the research process.

- **Structure and style:** Typical structure:
  - Beginning part: title, authors, abstract, keywords
  - Main part: introduction, literature review, research methodology, results, discussion of results, limitations to the research, conclusions, recommendations or implications, suggestions for further work
  - End part: references, appendices (e.g. questionnaire used, sample of interview transcripts, program code)

- **Making an argument:** Another term for "thesis" is "argument". When writing up a piece of research, think of it as presenting an argument. You have to assemble evidence to convince your readers that you have created some new knowledge using an appropriate academic research process. Ask yourself the following six questions:
  - What is my research question? What is my conceptual framework for understanding the question?
  - How did I set about answering the question? What is the answer to the question? What is the evidence? So what?

- **Developing a writing routine:** Develop your preferred mode of writing. Keep writing.

- **Reviews:** Review your own chapters after a few days. Don’t ask your supervisor to review your first draft, but don’t wait until you have the "perfect" draft either. Recognise that critical reviewers usually have points, although you may find it hard to admit at first.

**Reference**


**List of Chapters:**

1. Introduction
2. The purpose and products of research
3. Overview of the research process
4. Internet research
5. Participants and research ethics
6. Reviewing the literature
7. Surveys
8. Design and creation
9. Experiments
10. Case studies
11. Action research
12. Ethnography
13. Interviews
14. Observations
15. Questionnaires
16. Documents
17. Quantitative data analysis
18. Qualitative data analysis
19. Philosophical paradigms – positivism
20. Alternative philosophical paradigms
21. Presentation of the research
Figure 56. A model of the research process.
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**Chapter 6**


**Chapter 7**
