# Data Analytics in Organisations and Business

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## Data Analytics in Organisations and Business

#### Some organisational information:

Tutorship:

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Beginning of lecture: Wednesday, 16th of September.

Beginning of exercises: 23rd of September (bi-weekly)

Room: HG D7.1

Lecture notes: https://stat.ethz.ch/education/semesters/as2015/analytics

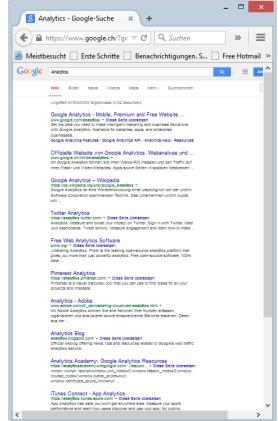
## Data Analytics in Organisations and Business

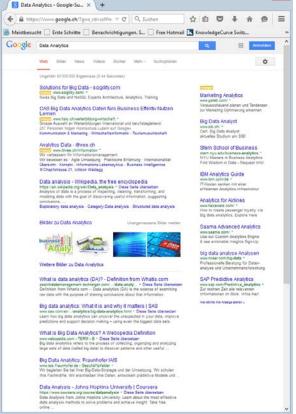
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# Chapter 1 Introduction

Google search: «Analytics» & «Data Analytics» (619'000'000 results in 0.52 seconds):





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Data Analytics in Organisations and Business - Dr. Isabelle Flückiger

Wikipedia says about Analytics: "Analytics is the discovery and communication of meaningful patterns in data. Especially valuable in areas rich with recorded information, analytics relies on the simultaneous application of statistics, computer programming and operations research to quantify performance. Analytics often favours data visualization to communicate insight." [Wikipedia, 2015]

Many similar terms used, and often the users of such expressions have similar but not the same understanding of their meanings:

- Predictive Analytics
- Data Mining
- Advanced Analytics
- Business Analytics
- Web or Online Analytics
- Big Data Analytics
- Data Analysis

But why Data Analytics becomes increasingly more and more important?

In 2015 there will be data generated of 8500 exabytes and 1 exabyte is 1 billion gigabytes, i.e.  $10^{18}$  bytes.

And in 2040 there will be data generated of 40'000 exabytes.

Three facts about data and analytics.

- 1. The amount of data cannot anymore be grasped with the human brain nor proceeded for extracting the relevant information.
- 2. And today's business world is changing from making decisions based on knowledge and intuition to so-called fact-based decisions.
- 3. The reason is that on one side the world becomes more global and more complex networked but on the other side there is an ongoing decentralisation of information and data storage.

A definition of (Data) Analytics:

Definition 1. Analytics is the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and add value [Davenport and Harris, 2007].

#### Classes of analytics:

- Descriptive
- Predictive
- Prescriptive

Classification	Questions	<b>Examples from Business</b>
Prescriptive	What is the best outcome? What if?	Optimisations Scenario testing Randomised tests
Predictive	What could happen? What is happening next? Why is this happening?	Statistical modelling Forecasting
Descriptive	What happened? How many, how often? What action is needed?	Standard and ad hoc reports Queries Alerts

#### **Descriptive Analytics**

- Describes what happened in the past
- Contains of gathering and organising data, plotting the data and giving characteristics
- Used for classifying groups of data e.g. customer groups
- Historically used for reporting and to show how and organisation were performing
- Says nothing about the cause why something happened nor what could happen in the future

#### **Predictive Analytics**

- Uses models and data from the past to forecast the future
- Associations among the variables are identified and then the dependent variable is forecasted e.g. how many customer would buy
- In predictive analytics we do not necessarily assume causal effects
- In fact, causal effects are not always necessary to predict accurately certain behaviour

Example: A grocery store found out that women who stopped buying cookies will be lost as a customer within the next three month

#### **Prescriptive Analytics**

- Gives actions to perform
- It includes experimental design and optimisation.
  - Experimental Design makes causal inference by conducting experiments for answering questions of WHY something happened.
  - Optimisation wants to achieve the optimised level of a particular variable in its relationship to another variables

Example: Determination of the price of a product which leads to the highest profitability, highest margin or highest market share

Analytics can typically be further classified in

- Qualitative and
- Quantitative

Data Analytics.

#### **Qualitative Analysis**

- Has the purpose gaining an understanding of the underlying (qualitative) reasons or motivations for a behavior
- Has the goal to gain insight in causal effects from a behavioural perspective
- Includes collection of unstructured data of some "small" and "non-representative" samples which are "analysed" non-statistically
- Typically used as part of exploratory research in the earliest stage of an analytics process

#### **Quantitative Analysis**

- Is the systematic empirical investigation of a phenomena by statistical, mathematical or computational methods
- Contrary to a qualitative analysis, data are collected in structured manner out of a large representative sample and analysed

#### **Different types of analytical methods** [Davenport and Harris, 2007]

- *Statistics*: The science of collection, organisation, analysis, interpretation and presentation of data.
- *Forecasting*: The estimation of some variable of interest at some specified future point in time as a function of past data.
- *Data Mining*: The automatic and semiautomatic extraction of previously unknown, interesting patterns in large quantities of data through the use of computational and statistical techniques.
- *Text Mining*: The process of deriving patterns and trends from the text in manner similar to data mining.
- *Optimisation*: The use of mathematical techniques to find optimal solutions with regard to some criteria while satisfying constraints.
- Experimental Design: The use of test and control groups, with random assignment of subject or cases to each group, to elicit the cause and effect relationship in a particular outcome.

#### Small Data vs Big Data

#### Examples:

- Twitter produces 15 terabytes data per day ((1 terabyte = 1 TB =  $10^{12}$  bytes = 1000 gigabytes)
- Google can proceed 1 petabyte of data each hour (1 petabyte =  $1 \text{ PB} = 10^{15} \text{ bytes} = 1000 \text{ terabytes}$ )

If you are looking for a lecture where you can learn "fancy" techniques for process data, then you are in the wrong place!

What you will learn is this lecture

- How to conduct data analytics projects in the real world with many people who are not experts in that area but who are the buyer of such services
- That in data analytics projects the rule of thumb is that 20% is data analysis and the other 80% is something else whereas
  - this consists of project management,
  - finding out the underlying problem which has to be analysed,
  - stakeholder management,
  - explaining to non-experts what and why
  - search for, discover and cleansing data
- Often the "real" problem which has to be solved is originally not known but has to be defined
- How to deal with data which are somewhere and somehow available

...and a lot of Case Studys

...and become familiar with all the business terms and phrases used

#### Thus, the lecture will contain:

- 1. How to frame the business problem
- 2. How to transfer it to a problem which can be solved with analytics methods
- 3. Data identification and prioritisation, data collection and data harmonisation
- 4. Identification of problem solving approaches and appropriate tools (not only R even though this is important)
- 5. How to set up and validate models
- 6. The deployment of a model
- 7. Model lifecycle
- 8. Some words about soft skills needed by statistical and mathematical professionals

# Chapter 2 Framing the Business Problem

### 2.1 Content of this Chapter

#### How to frame the business problem:

- 1. Obtain or work out the description of the business problem and what should be the usability
- 2. Identifying all stakeholders i.e. all direct or indirect stakeholders
- 3. Analyse whether the business problem is amenable to an analytics solution
- 4. Refinement of the problem statement and if necessary depict known or possible constraints
- 5. Determine the business benefits
- 6. Obtain stakeholder agreement on the business problem statement

Definition: A description of a business problem is a *business problem* statement.

This business problem statement contains a description about the business opportunity or threat, or an issue.

Example: "We are experiencing production problems and cannot deliver in time"

But this information is still insufficient to identify the full detailed problem.

To collect and structure this information in an understandable context: The five W's: who, what, where, when, and why.

- **Who** are the stakeholders who are sponsoring the project, who are using the results, who are making decisions based on the outcome and who are affected by the results?
- What problem has to be solved? What would be the perfect solution of that problem? What happen if the problem is not solved?
- Where does the problem occur? Where does the function requires to perform?
- When does the issue occur, or the function requires to be performed? When does the project need to be completed?
- **Why** does the problem occur, or function need to perform? Why this problem should be solved?

Example: A bank suffers the movement of customers.

Who are the stakeholder? Who is interested in this issue? Who is affected by solving this Problem?

- The management (CEO, CFO, and so on): sponsor or buyer of the analytics and decision makers
- Division managers: affected by project support and by client segment and product decisions, is interested in solving the issue
- Product managers: affected by project involvement and product decisions
- Client advisors: affected by project e.g. information gathering and by client segment and product decisions, is interested in solving the problem
- IT department: affected by project support e.g. data, affected by decisions which would affect the IT landscape
- Compliance officer: affected by the project e.g. sensitive information or if decisions are compliant with regulations, affected by implementation of solutions
- Risk management: affected by decisions and affected by setting up possible new risk management processes

Example cont'd: A bank suffers the movement of customers. Why does the problem occur? Why this problem should be solved?

- Wrong products?
- Insufficient customer service?
- Too less diversified customer basis?
- Not an attractive brand?

If it will not be solved the bank is loosing more clients and thus, more revenues. The bank is losing profit.

#### Important:

The full understanding of the problem is the most important aspect and is guiding the whole analytics process.

How to guide the stakeholder to a problem definition and for characterising the problem?

<ol> <li>What problem are we addressing?</li> </ol>		
	Having a clear understanding is key for success	
Why this question is important?	Users might not clearly understand what data anyalytics is	
	There are unspoken and maybe unreasonable expectations	
	Definition of success for the project	
What is this question seeking?	List of project deliverables	
	State and quantify elements of performance	
	Vague descriptions	
Likely responses and meaning	Widely divergent answers	
	They probably do not know what they want	
	What are the requirements?	
	What are desired results	
Follow-up Questions	What are measures of performance?	
	What are the project deliverables	
	How is success and failure determined?	
Special considerations	Questions from people who are evaluating the project	
Special considerations	Expectations of the sponsor or buyer	

How to guide the stakeholder to a problem definition and for characterising the problem? (cont'd)

3. How would you characterise the desired solution?			
	Lack of understanding of the different solution possibilities		
Why this question is important?	Working together through this decision		
	Avoidance to solve the wrong problem		
What is this question seeking?	This answer drives the analytics process and methods used		
Likely responses and meaning	Vague and confusing answers		
Follow-up Questions	What are special features needed as outcome?		
Special considerations	Most users have little knowledge about this aspect		
special considerations	Look for indications that additional explanations are needed		

How to guide the stakeholder to a problem definition and for characterising the problem? (cont'd)

6. What is good performance and what is bad performance?		
Why this question is important?	Just improving the performance does not mean success	
why this question is important:	The cost - benefit ratio have to be considered	
What is this question seeking?	To find the benefit of an organisation	
Likely responses and meaning	Business answers vs technical answers	
Follow-up Questions	Asking for quantitative performance measures	
Follow-up Questions	Vague responses and room for interpretation leads to failure	
Special considerations	Maybe the problem cannot be solved by data analytics	

Review of previous analyses of the problem:

- All previous findings connected to this problem should be investigated
- Is helping to think about how the problem has been structured so far and how it should be newly structured

Important: Often your problem is not as unique as you think, and it is likely that many people have already done something similar