Data Analytics in Organisations and Business

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Chapter 1

Introduction

1.1 What is (Data) Analytics?

Starting with a self-experiment and starting a Google search for "Analytics" gives approximately 619'000'000 results in 0.52 seconds. The top 10 results are from "Google Analytics", "Twitter Analytics", "Free Web Analytics", an Analytics Blog to "iTunes Connect - App Analytics" (see Figure 1.1). Thus, at a first sight, it seems that Analytics is primarily something related to Online, Web-based and social media.

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]

There are many similar terms used, and often the users of such expressions have similar but not the same understanding of their meanings. Similar terms used are:

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

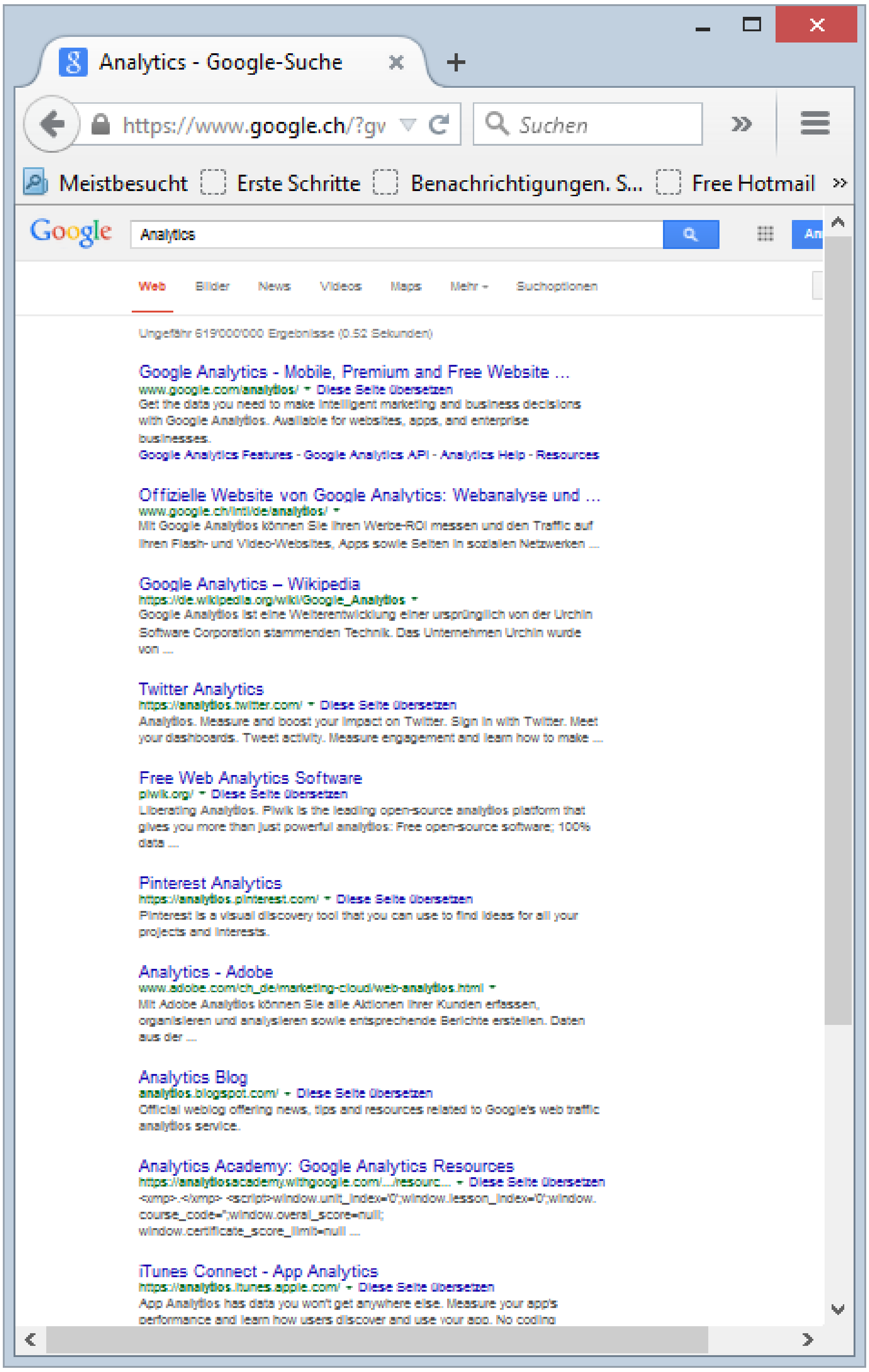

Figure 1.1: Google search for Analytics 2015-08-02

- and few more...

All have in common that they mean "analysis of data for decision making and adding value" but want to emphasise different aspects of analytics.

"Predictive" emphasises the prediction of future, whereas "Data Mining" focuses more on the process of analysing the data from various perspectives, "Advanced" means just "with advanced methods and algorithms", and "Business" accents the business use. Web or Online Analytics is focused on Web data analysis, often interchangeably used with "Big Data".

"Big Data" is becoming more a buzz word but finally means nothing else than data which are too voluminous for storing and proceeding them on a notebook or even one single server, are too unstructured to be stored in the usual structure of a relational database and are produced on a continuous basis such that they do not fit anymore in a static data warehouse.

And "Data Analysis" finally, focuses on the whole data analysis process.

But why Data Analytics becomes increasingly more and more important?

In 2015 there will be data generated of

$$8500 \text{ exabytes}$$

and 1 exabyte is 1 billion gigabytes, i.e. 10^{18} bytes.

And in 2040 there will be data generated of

$$40'000 \text{ exabytes.}$$

This amount of data cannot anymore be grasped with the human brain nor proceeded for extracting the relevant information. Thus, today's business world is changing from making decisions based on knowledge and intuition to so-called *fact-based decisions*.

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.

To link these different perspectives requires utilities for transforming all these "hidden" or unreadable information to into human-understandable facts.

The **attempt of 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].

Data Analytics is typically classified into

- Descriptive
- Predictive
- Prescriptive

according to their methods and purpose (see Figure 1.2).

Descriptive Analytics describes what happened in the past. It contains of gathering and organising data, plotting the data and giving characteristics of the data sample. It is used for classifying groups of data e.g. customer groups. Historically, it is used for *Reporting* and to show how and organisation was performing. But it say 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. First, the associations among the variables are identified and after the dependent variable is forecasted e.g. how many customer would buy a product due to a product campaign or to rebates of products. Also, in predictive analytics we do not necessarily assume causal-effects. In fact, causal effects are not always necessary to predict accurately certain behaviour. E.g. a grocery store found out that women who stopped buying cookies will be lost as a customer within the next three month. There is no causal relationship but one can predict the future behaviour with such an information.

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. Examples are in determining 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

analyses based on the process and data employed.

Qualitative Analysis has the purpose gaining an understanding of the underlying (qualitative) reasons or motivations for a behaviour. The goal is to gain insight in causal effects from a behavioural perspective. Often, one collects unstructured data of some "small" and "non-representative" samples which are "analysed" non-statistically. It is typically used as part of exploratory research in the earliest stage of an analytics process.

Classification	Questions	Examples from Business
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

Figure 1.2: Types of Analytics

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.

The different types of analytical methods for conducting quantitative analyses depend on the purpose of the research and might contain [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.

The traditional environment of analytics are "small data" i.e. up to few terabytes today (1 terabyte = 1 TB = 10^{12} bytes = 1000 gigabytes). But today companies are using "big data" for fact-based decision making. "Big data" are any collection of large volume, structured and unstructured and complex data where data processing becomes challenging.

Examples of “big data” are:

- Twitter produces 15 terabytes data per day
- Google can proceed 1 petabyte of data each hour (1 petabyte = 1 PB = 10^{15} bytes = 1000 teraabytes)

With every electronic device one leave a trail that describes the performance, the location, or the status. Sensors and microprocessors are installed everywhere for collecting data even in industrial companies (Industry 4.0 or smart manufacturing) Devices and the people who are using such devices are communicating typically through internet and are leaving another vast data source.

To make use of all these data and the information contained in all different industries there is a extensive need of people who can do detailed analyses and know about how to conduct data analytics projects.

And these analyses are used for fact-based decision making.

1.2 What is this Lecture about? - ...and what it is not

First: If you are looking for a lecture where you can learn ”fancy” techniques for proceeding data, then you are wrong here!

Why? You have already learnt or you will still learn a lot of these ”fancy” techniques in all the other lectures about Regression, Time Series Analysis, Machine Learning, and so on. But how are these methods applied in companies and organisations?

What you will learn is this lecture is 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.

Everything costs money. Thus, a data analytics project or analysis is only conducted in a company if the return out of the results of such an analysis is higher than the costs for this analysis. Further, the buyers or sponsors of such analyses i.e. the people in a company who have a budget that is the money for such projects are typically on a management level and are not experts in that area. Also, often the ”real” problem which has to be solved is not known. People often have a feeling that something goes not so well but they cannot express what it could be. Then, data are somewhere and somehow available.

But of course never in a structured and cleansed manner nor the data one would really need for the analysis.

In a statistical or data mining project the rule of thumb is that 20% is data analysis and 80% is data cleansing. In a data analytics project the rule of thumb is that 20% data analysis and the other 80% is something else whereas this 80% consists of project management, finding out the underlying problem which has to be analysed, stakeholder management, explaining to non-experts what and why one is doing certain things, explaining differences between causal relationships and patterns, searching for data and if found cleansing them and finally, present the results.

Thus, besides the technical skills a lot more of skills are required for successfully conduct a data analytics project:

- The ability to manage a project in a structured way
- The ability to see the "big picture"
- The ability to structure a problem
- The ability to communicate with non-experts and management
- The ability to use the already existing and often suboptimal data
- The ability to see the business use and benefit
- The ability to cope with all the uncertainties and non-precision in the real world
- The ability to present results to non-experts

To address these skills, the lecture contains the following topics:

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 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

Further, one should become familiar with all the business terms used.

And last but not least one should understand that data analytics is a process and one have to go through cycles and refining previous results and information to gain most out of it.

Chapter 2

Framing the Business Problem

A Business Situation. Your are sitting in the office and your phone is ringing. On the line there is a CFO of FinInnova Ltd., a financial institution that is selling financial products to wealthy people. "We would like to hear more about the possibilities in applying data analytics to improve our business" says the voice. "And we would like to have a presentation about what are others doing and how this could help us."

"Do you have any view what or in which direction do you want to see applications?" I am asking back. "And who is the target audience for this presentation?".

"Well, our CEO, head sales and myself will take part" the voice is kindly answering the questions. "And if you could just present different examples, but in my opinion we have too high costs and I am wondering if there is a possibility to improve them based on data analytics results."

Several days later when reaching out each of the three prospective participants of the presentation and asking about their expectations towards the presentation and information needed, the CFO is explaining that they have a growth rate below the market's average and thus again, that they have to improve the cost basis.

The CEO on the other side then tells you that they have already a lean organisation but their biggest issue is that they would not have the right strategy. He would be interested how to assess the strategy and to optimise it compared to the market expectations, the competitors and under certain scenarios.

And last the head sales is telling you, that he has just the wrong products, too few information about their customer such that he is not able to properly respond to the needs of their customer. The head sales would like to know more about the possibilities in customer analytics and how products and product bundles could be improved.

What is the problem of this organisation?

2.1 Content of this Chapter

In this chapter the first and one of the most important steps of a data analytics project is introduced: How to frame the business problem.

The framing of the business problem is broken down again in several steps.

The so-called sponsor or buyer of an data analytics project is typically a decision-maker in an organisation who has a problem to solve and who want to make decisions about improvements related to the business of the company. Such decisions can contain customer or product strategies i.e. which customer one have to contact with which media at what time point and with what product. Other examples ar how can one improve the maintenance of production machines or what is the optimal price of a product.

Besides the sponsor or buyer there are many other stakeholder in this process involved or interested in the results. Some of these stakeholder are happy with such a projects and others are of course not as it is against their interested e.g. if it would result in a reorganisation or if the analysis would cause more work for them e.g. collecting data.

Thus, all of these stakeholders can be supportive to a project or not.

As the stakeholders are such an important element which are determining if a project will finally be successful or not, the business problem framing cycle starts and ends with stakeholder-related actions and analyses:

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

2.2 Obtain or work out the description of the business problem and what should be the usability

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.

As in the example above the starting point could be 'our growth rate is below the market growth rate' or 'we are experiencing production problems and cannot deliver in time' or 'we are loosing customers'.

In most cases people are coming to an analytics professional if they are facing and experiencing problems. And they are telling that in their terms and expressions and in the terms and expressions of their organisation and industry.

Further, each stakeholder has its own interest and its own advantage and disadvantage out of the outcomes of such an analysis. Thus, everybody is giving the information through their own lenses and in the context of their own interest and are often biased. And often the real underlying problem is hidden by this biased information. A variety of perspectives are often more useful as this gives a more granular picture of the business problem.

Thus, one have first to collect structure this information in an understandable context. One technique to do that are 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 1. Problem: A bank suffers the movement of customers.

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

Possible answers:

- 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

Why does the problem occur? Why this problem should be solved?

Possible answers:

- 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 more thus, more revenues. The bank is loosing profit.

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

Besides the five W's there are other sources of information. E.g. there have been done analyses or even data analytics work in past addressing part of the problem.

For guiding the stakeholder to a problem definition and for characterising the problem, the following problem definition checklists can additionally be used:

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

2. What would be the perfect solution?	
Why this question is important?	Asking directly about expectations Avoidance of "hidden" expectations
What is this question seeking?	Unspoken expectations
Likely responses and meaning	Vague descriptions Press for more detailed answers
Follow-up Questions	What is the business case behind this project? What are the expected returns out of this project?
Special considerations	Often there is some other unsolved problem There are some must-have features that drive the decision

3. How would you characterise the desired solution?	
Why this question is important?	Lack of understanding of the different solution possibilities 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 Look for indications that additional explanations are needed

4. What makes that problem hard?	
Why this question is important?	Often there have been unsuccessful trials for solving the issue Find out what have been the methods that failed Find out why the methods failed in solving the problem
What is this question seeking?	Knowing what have failed gives a lot information about the problem
Likely responses and meaning	Vague answers and past failure not fully understood
Follow-up Questions	Asking the people who have worked before on that problem
Special considerations	Questions about past unsuccessful work can be problematic Be sensitive about the organisations politics

5. What is the current level of performance?	
Why this question is important?	Current level of performance is the lower bound of the result Results only as good as the existing is regarded as waste of effort
What is this question seeking?	Determination of the level of performance that is regarded as success
Likely responses and meaning	Unrealistic goals
Follow-up Questions	Asking for quantitative performance measures Vague responses and room for interpretation leads to failure
Special considerations	Maybe the problem cannot be solved by data analytics

6. What is good performance and what is bad performance?	
Why this question is important?	Just improving the performance does not mean success 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 Vague responses and room for interpretation leads to failure
Special considerations	Maybe the problem cannot be solved by data analytics

Often the same problem has already been analysed - qualitatively or quantitatively. Thus, all previous findings connected to this problem should be investigated. Investigating the previous findings is helping to think about how the problem has been structured so far and how it might be conceptualised in different ways.

Often something is discovered in the review of the previous findings which is leading to a substantial revision of the problem definition.

A complete review of any of the previous findings is a must in any given quantitative analysis. You cannot make something out of nothing in analytics.

Important: often your problem is not as unique as you think, and it is likely that many people have already done something similar just what you are trying to do.

2.3 Identifying all stakeholders i.e. all direct or indirect stakeholders

Besides the in-depth and thorough understanding of the business problem, the stakeholders and stakeholder expectations and management are most crucial during an data analytics project. Stakeholders are anyone affected by the project, not just those in the initial meetings, and they may have different levels of input or involvement during the project. A stakeholder analysis helps identify the following:

- The interests of all stakeholders, who may affect or be affected by the project, along with their constraints.
- Potential issues that could disrupt the project.
- Key people for information distribution during execution phase.
- Groups that should be encouraged to participate in different stages of the project.
- Communication planning and stakeholder management strategies during the project planing phase.
- Ways to reduce potential negative impacts and manage negative stakeholders.

The most obvious stakeholders in this first step are the "owners" of the business problem, primarily managers and decision makers and then the sponsor or buyer. But there are a lot of other stakeholders. Some questions to ask:

- Which stakeholders are interested in the planned analysis?
- What is their feeling about the problem?
- Can these stakeholders take actions on the results of the analysis?
- Are they feeling sceptical that the problem even exists?
- How likely can they be persuaded in doing something even if the analysis is bulletproof?

For the identification if all questions have been answered in appropriate the following worksheet can help:

Stakeholder Analysis Worksheet (see [Davenport and Harris, 2007]) *All these questions should be answered with "yes"if the project should be successful*:

Identifying all stakeholders Is it clear what executives have a stake in the success of your quantitative analysis project?

Documenting stakeholders needs Have they been briefed on the problem and the outline of the solution?

Assessing and analysing stakeholder interest/influence Do they have the ability to provide the necessary resources and to bring about the business changes needed to make the project successful?

Managing stakeholders' expectations Do they generally support the use of analytics and data for decision making?

Take actions Does the proposed analytical story and method of communicating it coincide with their typical way of thinking and deciding?

Reviewing status and repeating Do you have a plan for providing regular feedback and interim results to them?

Important note out of the experience: Even the most sound and bulletproof data analysis approach will not be successful if it the decision makers are not supportive.

It is helpful to focus on decisions. Because the decision focus makes all participants realise that that is the reason for the quantitative analysis and that it is not just an "nice to have" exercise. Further, the focus on the decision is helping identifying the key stakeholders, the decision makers. And finally, if there are no decisions planned, it may maybe not be worth doing the analysis.

Ask the stakeholders

What is the decision they want to make as a result of the analysis?

It helps the stakeholder to frame their needs and expectations.

2.4 Analyse whether the business problem is amenable to an analytics solution

After having a good picture about the problem and the stakeholder a first time out should be taken and a first assessment whether or not the problem could have a data analytics solution should be done.

Solving the problem are costs for the organisation. Thus, cost - benefit analysis if a data analytics solution is appropriate should be undertaken. The questions to be asked are:

- Is the answer out of the analytics process and the implementation within the organisation's control?
- Would be data available to perform an analysis?
- How likely it is that the problem can be modelled and solved?
- Will the organisation accept the solution and deploy it?

Example 2. Result of an analysis: A life insurance company looses policy holders because the investment return participation for the policyholder is too low compared to banking products.

Due to low interest rates in the market and regulatory restrictions the insurance company cannot change that as the company cannot control them.

Example 3. A hotel wants to introduce dynamic pricing i.e. prices for the rooms are depending on demand and trigger events but have no detailed past data recorded about the utilised capacity in the past.

Example 4. A government wants to analyse the potential change of the strategy of location but cannot provide economic interactions nor expert judgement about influences.

Example 5. Result of the analysis: It would be more cost effective to close down a manufacturing plant and to by these items from a third party. The manufacturing plant was build few years ago out of a strategic decision of the board of directors and the management. 90% of these people are still in the same position.

If there isnt a feasible way forward, the ethical analyst will say so to the key stakeholders.

2.5 Refinement of the problem statement and if necessary depict known or possible constraints

After an initial analysis, it may be necessary to refine or even redefine the problem statement to make it more accurate and more appropriate to the stakeholders. Further, it has to make more amenable to available analytic tools and methods as well as to the available data.

Hence, this part of the process contains the necessity to define what constraints the project will operate under. These constraints could be analytical, financial, or political in nature.

Example 6. In an optimisation problem with a large number of contraints no solution can be found with available tools or software. Weakening the constraints would lead in inappropriate results.

Example 7. The required data analytics effort including data cleansing would be several weeks and thus, the project too expensive for an organisation.

Example 8. If the results could show explicitly or implicitly a past failure in decision making of some key stakeholder, there is no interest in doing an analysis.

All these is narrowing the problem. Nevertheless, one should stay open for alternative directions and variety of causes of the problem. As already stated above, if there is e.g. a performance issue in one business unit the cause can range from customer dissatisfaction to wrong products to operational issues.

Thus, having completed this refinement step, the following question should be answered:

Worksheet for framing the business problem (see [Davenport and Harris, 2007]) If the problem is framed well the following questions can be answered in a positive way:

1. Have you defined a clear problem or opportunity to address what is important to your business or organisation?
2. Have you considered multiple alternative ways to solve the problem?
3. Have you identified the stakeholders and that the willuse the results to make a decision?
4. Are you confident that the way you plan to solve the problem will resonate with the stakeholders and that they will use the results to make a decision?
5. Are you clear on what decision is to be made - and who will make it - on the basis of the results from your analysis once the problem is solved?
6. Have you started with a broad definition of the problem but then narrowed it down to a very specific problem with a clear phrasing on the question to be addressed, the data to be applied to it and the possible outcomes?
7. Are you able to describe the type of analytical story that you want to tell in solving this particular question?
8. Do you have someone who can help you in solving that particular type of analytical story?
9. Have you looked systematically to see whether there are previous findings or experiences related to this problem either within or outside your organisation?
10. Have you revised your problem definition based on what you have learned from your review of previous findings?

Examples of refinements of an analytics problem are:

Example 9. Direct marketing

In direct marketing potential customer are contacted - by e-mail or phone - making them buying our products.

Typical approach is test a sample of customers and based on the results back from the customers developing a response model. This model is then used to score the customer about their likelihood to buy the product.

The model itself is quite simple.

But what is wrong with that approach?

This approach and model suggest the response" of the customer in buying the product is caused by the marketing contact.

But there are customers who went anyway to a shop / on-line store and buy the article. Or there are customers who never will buy this product and it does not matter if they are contacted or not. And contacting both of them is waste of money and time.

Thus, you have to re-frame the problem to the customer who will buy the product based on the fact that they are contacted. And this is a much more complex problem with much more complex models used to solve this.

Example 10. Cross-boarder activities of client advisors

For compliance reasons client advisors of banks have restrictions to certain countries where they are permitted to acquire new customers or assets (money). To monitor compliance the travelling, expenses and cash transactions associated to a certain client advisor is monitored.

One question is if a client advisor was travelling abroad, follow then transactions from the geographical area where the advisor has been which are related to his or her visit?

It can be relatively simply tested if there are cash transactions from this region after a certain period after the visit. And thus, all these transactions can be reviewed be a compliance officer.

But are these really the transaction we want to review?

There are transactions made on a regular basis if there a certain obligations like rent, pension fund plan or just other regular spendings. All these transactions happen anyway and do not relate to the client advisor's trip.

Thus, one have to identify the transactions which happen directly linked to this travel abroad. And this needs then another approach of analysis then the first one.

Although you cannot spend all your time in re-thinking, re-examining and re-framing each and every step it is worth to invest some time into reviewing each step with the new information and findings out of the previous findings review.

2.6 Determine the business benefits

The determination of business benefits goes hand in hand with the determination of the costs of conducting a data analytics project as well as implementing the results and deploy them.

Benefits can be determined quantitatively or qualitatively. If quantitative, it may be financial or contractual (e.g., service level agreements). This is also known as the business case.

The usual measures in financial analyses are:

- Return on Investment (ROI)
- Net Present Value (NPV) calculation
- Internal rate of return (IRR)
- Cost of Capital (CoC)
- Payback Period

But: it is often very difficult to quantify the return or cash flows out of data analytics results.

Example 11. How to estimate and allocate the following costs and benefits:

- Costs of the IT infrastructure used and the support of the IT experts?
- Costs of the people involved in the projects for providing support when question arises?
- How to quantify the benefit of better compliance with regulations in the cross-boarder activities of client advisors example?

2.7 Obtain stakeholder agreement on the business problem statement

When the problem is finally clearly defined and a cost - benefit analyses has been conducted and shows a positive result, it is necessary to obtain stakeholder agreement before proceeding further with the project.

It may be necessary to repeat this cycle several times until stakeholder concurrence with the particulars of the project are achieved and permission to proceed is granted.

At the end of this process, you will have agreement in writing on the projects objectives, the definition of the problem, the resources, the time frame, the performance measures and the budget to get there.

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