Technische Universität Berlin

Quantitative Decision Making: Introduction to Business Analytics

Fakultät Wirtschaft & Management, Institut für Technologie und Management

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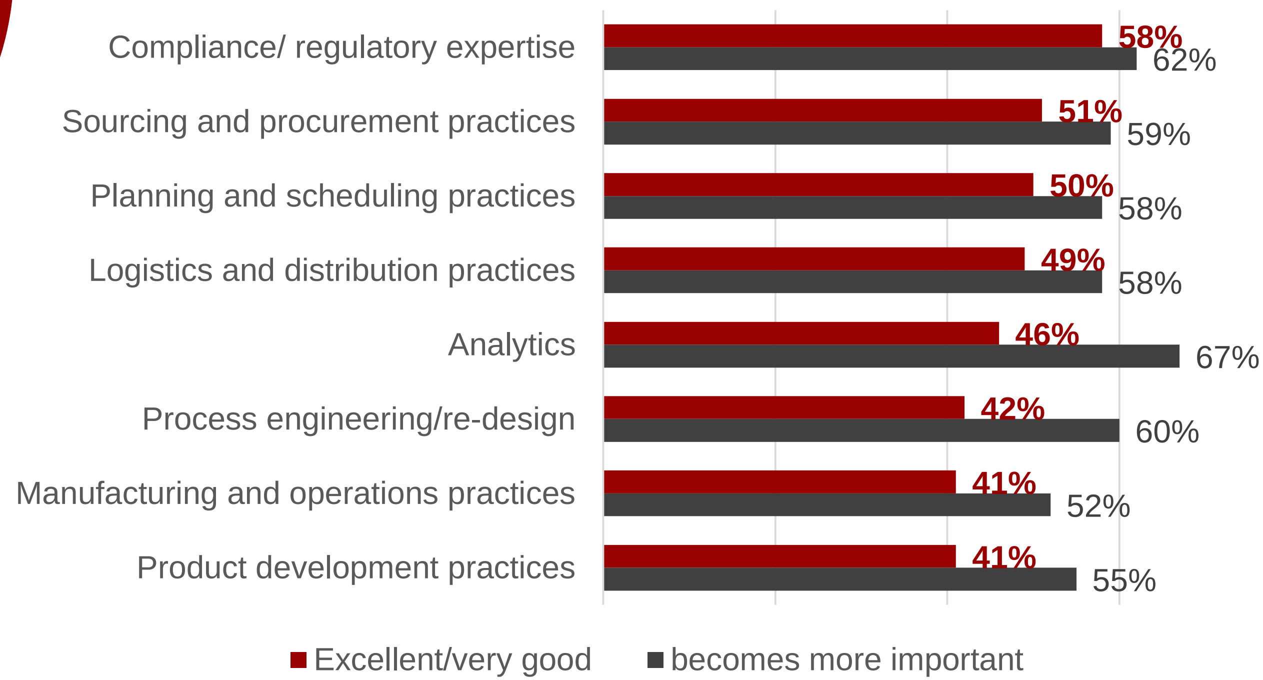
Discussion

67

...percent of executives stated in Deloitte's 2015 Supply Chain Talent of the future survey that analytics is becoming more important to employees as a technical competence (highest rating). Only 46% said that they performed excellent/very well in the company.

Technical competencies of company‘s employees



Agenda

(Business) Analytics

> *Analytics are the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions*.

Business Intelligence

a set of technologies and processes that use data to understand and analyze business performance

- Analytics
  - Optimization
  - Predictive Modeling
  - Forecasting/exploration
  - Statistical Analysis
- Access and reporting
  - Alerts
  - Query/drill down
  - Ad hoc reports
  - Standard Reports

Competitive Advantage

Source: Davenport and Harris (2007)

Business Analytics - verschiedene Definitionen

- Es existiert eine Vielzahl an Definitionen mit verschiedenen Perspektiven auf das Thema

Perspective	Definitions
A Movement	▪ *"management philosophy" through which "insights can be gained and decision making improved" based on a "rich set of data"* ▪ *movement […] driven by technically literate executives who make fact-based decisions, the availability of good data, a process orientation to running an enterprise, and improved software for data capture, processing, and analysis"*
A collection of Practices & Technologies	▪ *"a group of tools that are used in combination with one another to gain information, analyze that information, and predict outcomes of the problem solutions* ▪ *a wide range of techniques and technologies" that "make it easier to get value, meaning, from data*
A Transformation Process	▪ *more than just analytical methodologies or techniques used in logical analysis. It is a process of transforming data into actions through analysis and insights in the context of organizational* ▪ *decision making and problem solving* ▪ *process of transforming data into actions through analysis and insights in the context of organizational decision making and problem solving*
A Capability Set	▪ *extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions* (<- **see previous slide**) ▪ *discipline of applying advanced analytical methods ranging from descriptive to predictive to prescriptive modeling*
Specific Activities	▪ *accessing, aggregating, and analyzing large amounts of data from diverse sources to understand historical performance or behavior, or to predict— or manage—outcomes* ▪ *examine and manipulate data to drive positive business actions*
A Decisional Paradigm	▪ *the "part of decision management" that involves "logical analysis based on data to make better decisions* ▪ *data-driven decision making" rather than "ignore the evidence and make our strategic decisions based on anecdotes and guesses… simply because harvesting the right data to inform our decisions is more complex than it might first appear*

Quelle: Holsapple (2014)

Why using Analytics? – The business environment

In many industries Companies…

- offer similar Products and services
- Use comparable technology and business processes
- Don‘t have geographical advantages and are not protected by regulations
- …

In operational business processes remains profitable potential in…

- Choosing the best locations
- Preventing stock-outs
- Using high volumes of transactional data
- …

Motivation for using Business Analytics

- Execute business with maximum efficiency and effectiveness
- Make the smartest business decisions possible
- Extract the biggest possible value from business processes and key decisions.

Source: Davenport and Harris (2007)

Why using Analytics? – Rationale for Analytics

Businesses pursue Business Analytics to…

- Achieve a competitive advantage
- Support of an organization's strategic and tactical goals
- Obtaining value from data
- Better organizational performance
- Knowledge production
- Better decision outcomes
- Better or more informed decision processes

Source: Holsapple (2014)

Data

> *Data are defined as symbols that represent properties of objects, events and their environment. They are the products of observation. But are of no use until they are in a useable (i.e. relevant) form. The difference between data and information is functional, not structural*

- In the Data-Information-Knowledge-Wisdom (DIKW) hierachy / pyramid, data builds the bottom level…
  - From which Information is inferred (Information systems generate, store, retrieve and process data.)
  - While Knowledge is information transferred into instruction
  - While wisdom is the integration of knowledge
- Data has the least meaning and thus, the least value

Source: Rowley (2007)

Data – Data Structures

Structured Data

Data containing a defined data type, format, and structure (that is, transaction data, online analytical processing [OLAP] data cubes, traditional RDBMS, CSV files, and even simple spreadsheets).

Semi-Structured Data

Textual data files with a discernible pattern that enables parsing (such as Extensible Markup Language [XML] data files that are self-describing and defined by an XML schema).

Quasi-Structured Data

Textual data with erratic data formats that can be formatted with effort, tools, and time (for instance, web clickstream data that may contain inconsistencies in data values and formats)

Unstructured Data

Data that has no inherent structure, which may include text documents, PDFs, images, and video.

Source: Dietrich et. al (2015)

Statistical and quantitative analysis, explanatory and predictive models – Statistics

Statistics is the study and analysis of empirical observations on variables known as populations. From a given population, we compute what we call “statistics” to be used to compute or estimate population parameters.

Statistics is intimately related to Probability Theory.

- **Probabilities**: likely outcomes of random experiments.
- **Random experiment**: a repetitive process, observation, or operation that determines the results of any one of a number of possible outcomes.
- **Event**: The outcome of a random experiment. The set of all possible outcomes of an experiment is called the sample space or event space.

***Descriptive statistics** concisely summarizes the information content of collected observational data via distributions, measures of central tendency, and measures of dispersion.*

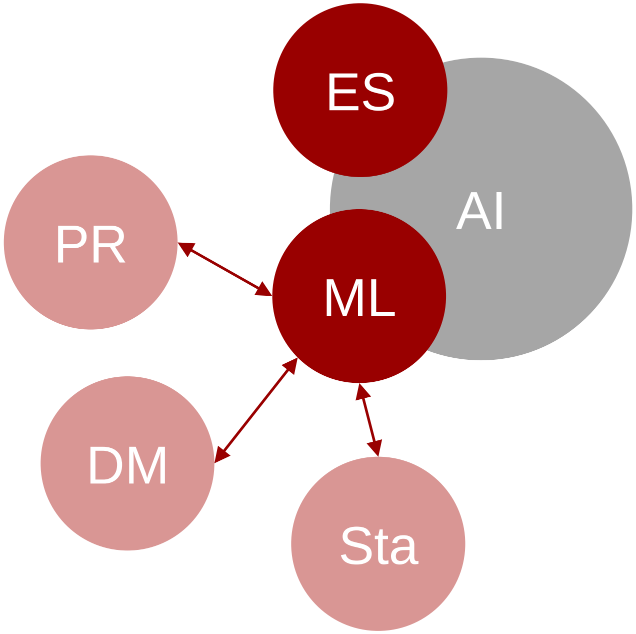
***Inferential statistics** draws valid inferences about a population based on an analysis of a representative sample of that population. The results of such an analysis are generalized to the larger population from which the sample originates, in order to make assumptions or predictions about the population*

Source: Das et al (2013)

Statistical and quantitative analysis, explanatory and predictive models – Machine Learning

Machine learning methods are a collection of methods for extracting (predictive) models from data. It arose as a subfield of Artificial Intelligence, which was concerned with methods for improving the knowledge or performance of an intelligent agent over time, in response to the agent's experience in the world. Such improvement often involves analyzing data from the environment and making predictions about unknown quantities.

- Machine learning methods are widely used across various disciplines including data mining, pattern recognition and applied statistics, while these disciplines are closely related.
- Result: The distinction between these areas has become blurred



- **Artificial intelligence:** for independent action of machines
- **Expert Systems:** experts provide knowledge about the system behavior from which the models are developed
- **Machine Learning:** System input-output behavior is observed and the ML method extracts model about system behavior

Quelle: Provost and Fawcett (2013); Das et al. (2013)

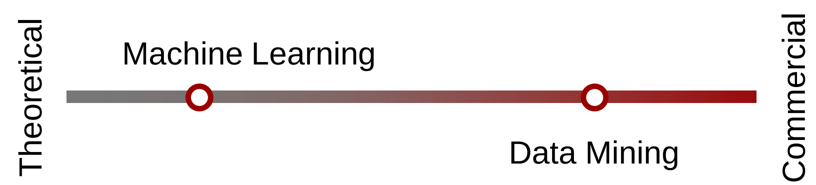
Statistical and quantitative analysis, explanatory and predictive models – Data Mining

Data mining is the extraction of knowledge from data, via technologies that incorporate fundamental principles to guide the extraction. *(Provost and Fawcett 2013)*

Data mining is the application of specific algorithms for extracting patterns from data. *(Fayyad 1996)*

- Data Mining (either seen as Part of the field of “Knowledge Discovery in Databases [KDD] or as synonym) is more concerned with the overall process of data analytics

- As spin-off from Machine Learning, Data Mining is more concerned with real-word applications focusing on business issues applicable is commercial use.



Source: Provost and Fawcett (2013), Fayyad (1996)

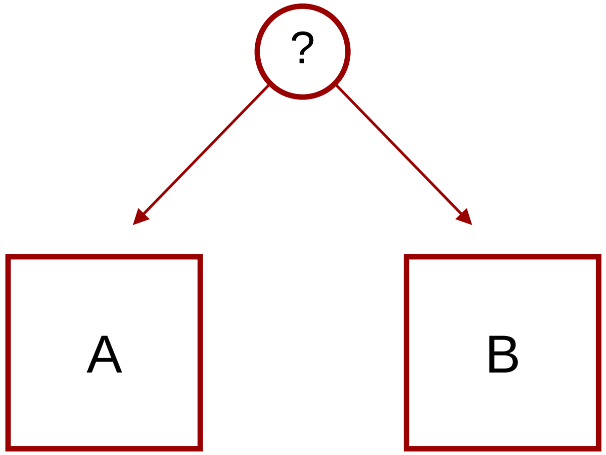
Statistical and quantitative analysis, explanatory and predictive models – Examples: Classification

Classification

Examples:
Will a customer respond to an add or not?

attempt to predict, for each individual in a population, which of a (small) set of classes this individual belongs to. Usually the classes are mutually exclusive.

Supervised



Quelle: Provost and Fawcett (2013)

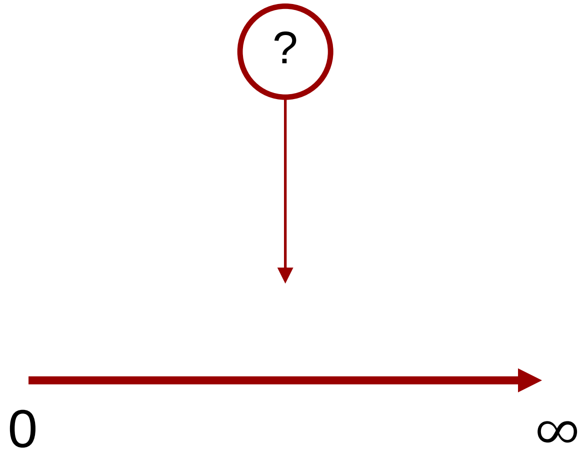
Statistical and quantitative analysis, explanatory and predictive models – Examples: Regression

Regression

Examples:
How much service
will a customer use?

attempts to estimate or predict, for each individual, the numerical value of some variable for that individual.

Supervised



Quelle: Provost and Fawcett (2013)

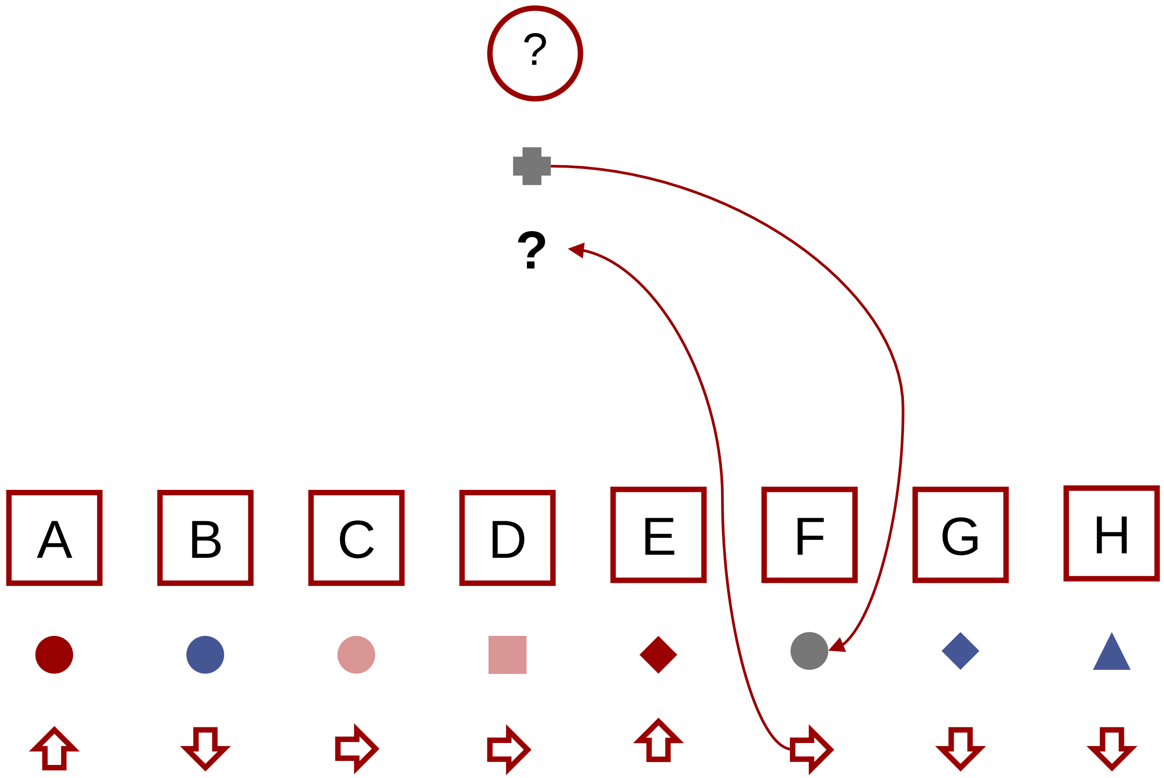
Statistical and quantitative analysis, explanatory and predictive models – Examples: Similarity Matching

Similarity Matching

Examples:
If the customer liked this product, who else will like it?

attempts to identify similar individuals based on data known about them.

Supervised or unsupervised



Quelle: Provost and Fawcett (2013)

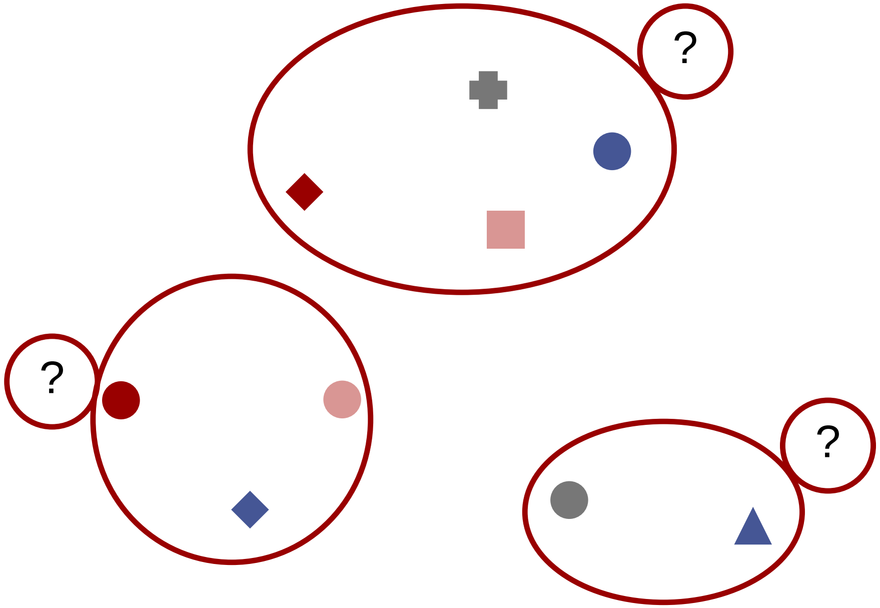
Statistical and quantitative analysis, explanatory and predictive models – Examples: Clustering

Clustering

Examples:
Are there natural groups among our customers?

attempts to group individuals in a population together by their similarity, but not driven by any specific purpose.

Unsupervised



Quelle: Provost and Fawcett (2013)

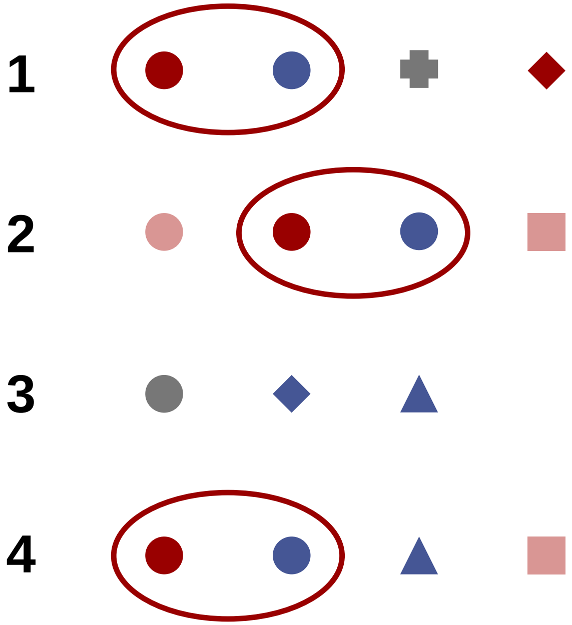
Statistical and quantitative analysis, explanatory and predictive models – Examples: Co-occurrence Grouping

Co-occurrence Grouping

Examples:
Which products or services are commonly used together?

attempts to find associations between entities based on transactions involving them.

Unsupervised



Quelle: Provost and Fawcett (2013)

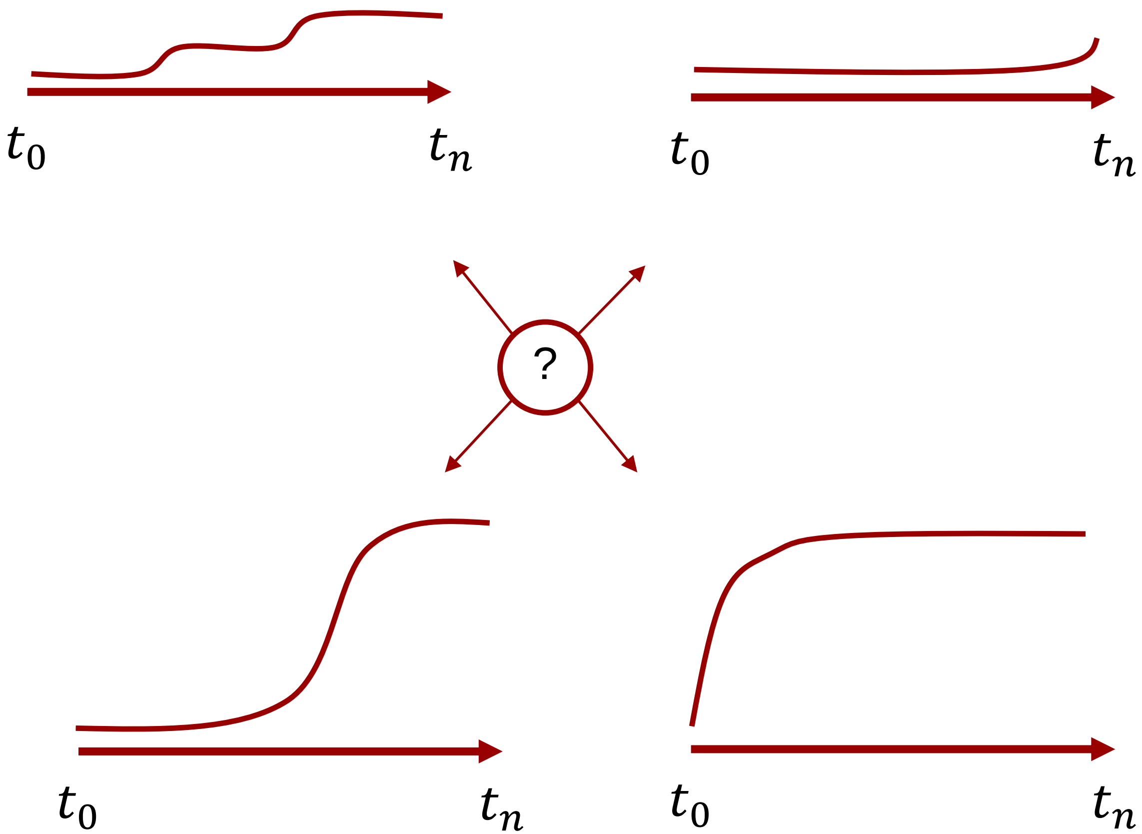
Statistical and quantitative analysis, explanatory and predictive models – Examples: Profiling

Profiling

Examples:
What is the typical demand behaviour of the product group?

attempts to characterize the typical behavior of an individual, group, or population.

Unsupervised



Quelle: Provost and Fawcett (2013)

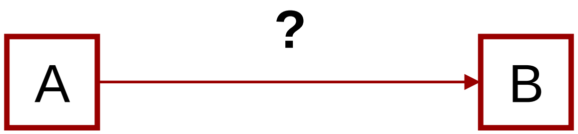
Statistical and quantitative analysis, explanatory and predictive models – Examples: Link Prediction

Link Prediction

Examples:
Since those two parts share the same breakdown behaviour, could they be connected?

attempts to predict connections between data items, usually by suggesting that a link should exist, and possibly also estimating the strength of the link.

Supervised or unsupervised



Quelle: Provost and Fawcett (2013)

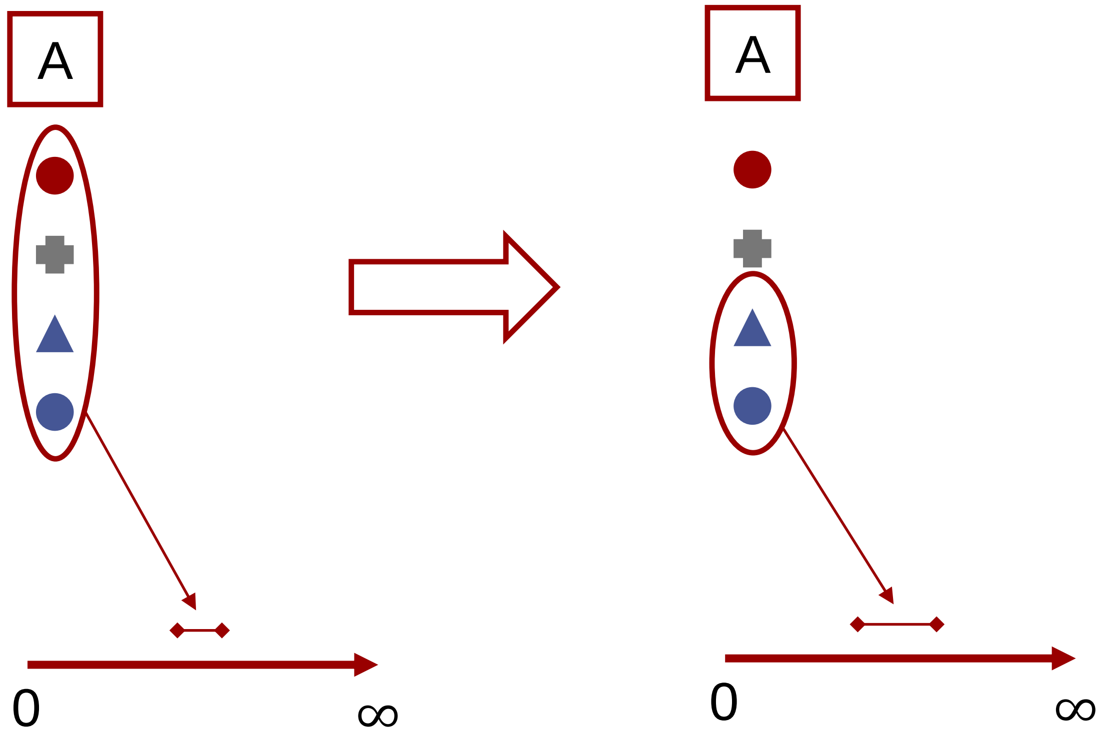
Statistical and quantitative analysis, explanatory and predictive models – Examples: Data Reduction

Data Reduction

Examples:
Reduce to a few sensor signals, best predicting machine failure

attempts to take a large set of data and replace it with a smaller set of data that contains much of the important information in the larger set. The smaller dataset may be easier to deal with or to process.

Supervised or unsupervised



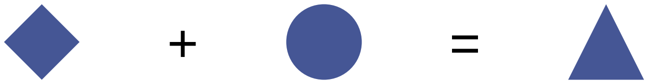
Statistical and quantitative analysis, explanatory and predictive models – Examples: Causal Modeling

Causal Modeling

Examples:
Does this factor influence on-time delivery

attempts to help us understand what events or actions actually influence others.

Supervised



Fact-based management

- Fact-based refers to the use of data in the decision-making process

The concept is evolving to…

- **Evidence-based (management)**
  - refers to using hard facts, reliable measurements, justified estimates, well-reasoned approximations, unbiased observations, credible explanations, authoritative advice, and the like in decision-making.
  - Does not include arbitrary or unfounded beliefs, guesses, opinions, speculations, conjectures, suspicions, or hearsay / Not driven by desires, emotions, politics, or ideology; nor is it a captive of preconceptions.
- However, it accepts unavailability of facts, confinement of bounded rationality, limited completeness and precision, costliness, lateness or infeasibility of fact gathering
  - Decision input with non-absolute certitude is included (e.g. with what-if analysis, simulation modeling, using sales-force estimates, or drawing on expert opinions)

Source: Holsapple (2014)

Decisions and Actions

> *In order for analytics to be of any use, a decision maker has to make a decision and take action.*

Decisions

Fact-based decisions employ objective data and analysis as the primary guides to decision making through
- a rational and fair-minded process
- Not biased by conventional wisdom or personal biases.

Executive decisions should not be a “black box”
- decision “engineers” could improve decision making
- Analysts could improve decision processes instead of providing an answer
- Process and information of key decisions could be assessed

Actions

The outcome of an analytics process should trigger an action
- it is the part that counts!

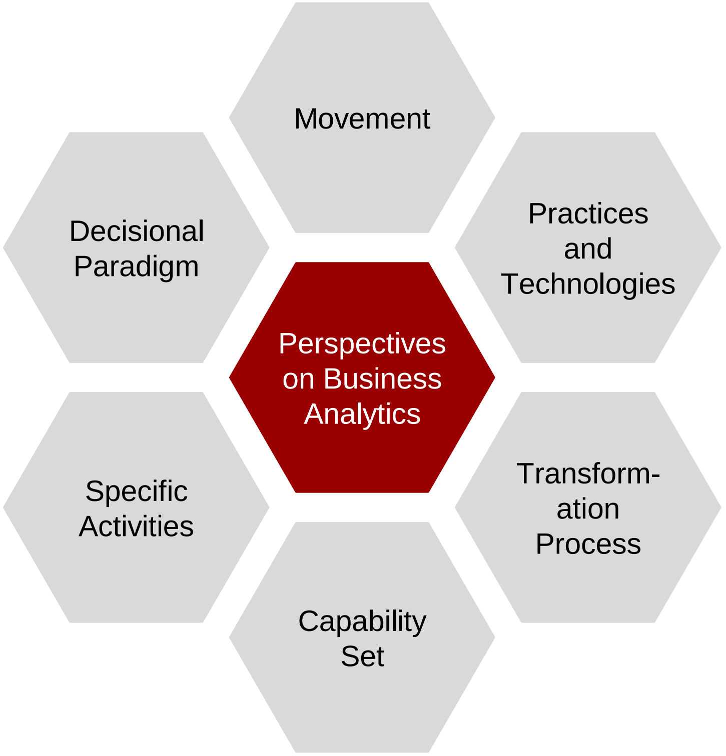
However, many companies do not act on the information provided or are reluctant, because it may contradicts previous behavior

Source: Davenport and Harris (2007), Davenport et al. (2010)

Business Analytics – A (somewhat more) sophisticated definition

> *Analytics is concerned with evidence-based problem recognition and solving that happen within the context of business situations.*

- There are several perspectives on Business Analytics, which do not enable the success of BA individually
- The perspectives (and means and actions behind them) interact and guide the successful use of Analytics

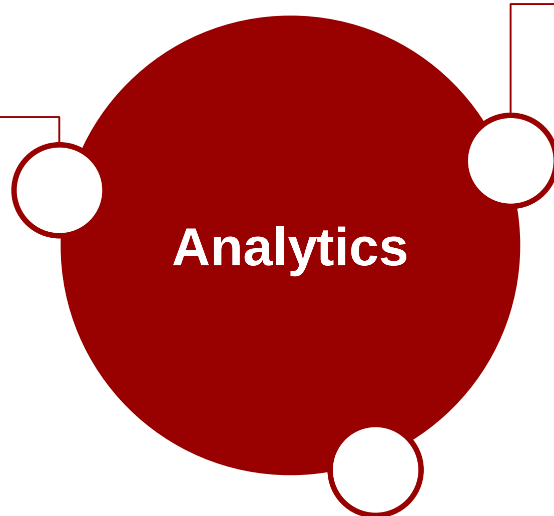


Source: Holsapple (2014)

Capabilities differentiating competitors using Analytics

Organization

- Insight into performance drivers
- Choosing a distinctive capability
- Performance management and strategy execution
- Process redesign and integration



People

- Leadership and senior executive commitment
- Establishing a fact-based culture
- Securing and building skills
- Managing analytical people

Technology

- Quality data
- Analytic technologies

Source: Davenport and Harris (2007)

Capabilities – An Analytical Competitor

An Analytics Competitor uses Analytics extensively and systematically to outthink and outexecute the competition

Analytics supports as strategic, distinctive capability

- Analytics is valued in the firm as means to set the business apart from its competitors and makes it successful in the marketplace.

The approach to and management of analytics is enterprise-wide

- The data and analyses are made available broadly throughout the organization and proper care is take to manage data and analyses efficiently and effectively

Senior management is committed to the use of analytics

- The use of Analytics and fact-based decision making requires change in organizational culture, process, behavior and skills. This change has to be led top down.

Large-Scale Ambition

- Organizations aspire scale and scope of results which are large enough to affect organizational fortunes instead of minor tactical improvements

Source: Davenport and Harris (2007)

Capabilities – Organization

Early maturity of Capabilities

- **Analytical objective**
  - Sporadic gain of insight
  - Autonomous activities to build experience
- **Analytical process**
  - Doesn’t exist or is very disconnected

High level maturity of Capabilities

- **Analytical objective**
  - Strategic insight
  - Continuous renewal and improvement
- **Analytical process**
  - The use of Analytics is embedded into business processes

Source: Davenport and Harris (2007)

Capabilities – Technology

Early maturity of Capabilities

- **Technology**
  - Poor data quality
  - Unitegrated systems
  - Missing data and information

High level maturity of Capabilities

- **Technology**
  - High-quality data
  - IT processes and governance principles in place
  - Enterprise-wide Business Analytics architecture largely implemented

Source: Davenport and Harris (2007)

Capabilities – People

Early maturity of Capabilities

- **Skills**
  - Isolated analysts
- **Sponsorship**
  - At a tactical level at most
- **Culture**
  - Pride in unerring intuition
  - Designs for more objective data

High level maturity of Capabilities

- **Skills**
  - Highly skilled, leveraged, centralized skill base
- **Sponsorship**
  - C-Level and Board-based commitment
- **Culture**
  - Broadly supported fact-based culture

Source: Davenport and Harris (2007)

Barriers – Technology

Need to upgrade Systems

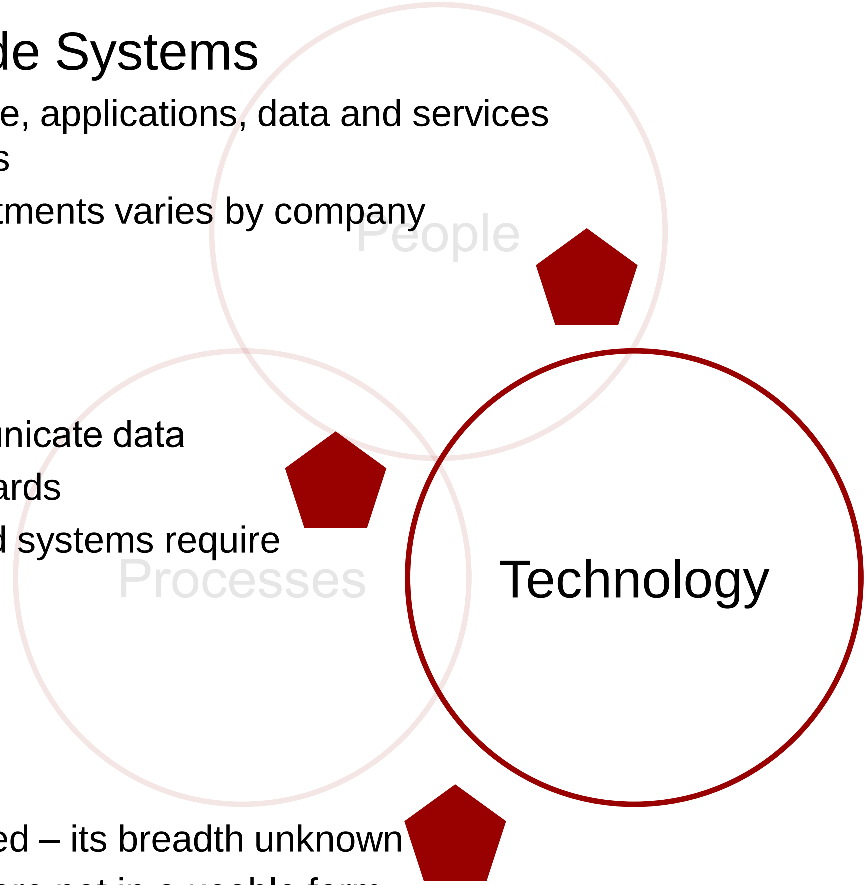
- hardware, software, applications, data and services may need updates
- The level of investments varies by company

Legacy Systems

- Several systems already don‘t communicate data
- Incompatable data formats and standards
- Either new systems or upgrades of old systems require significant investments

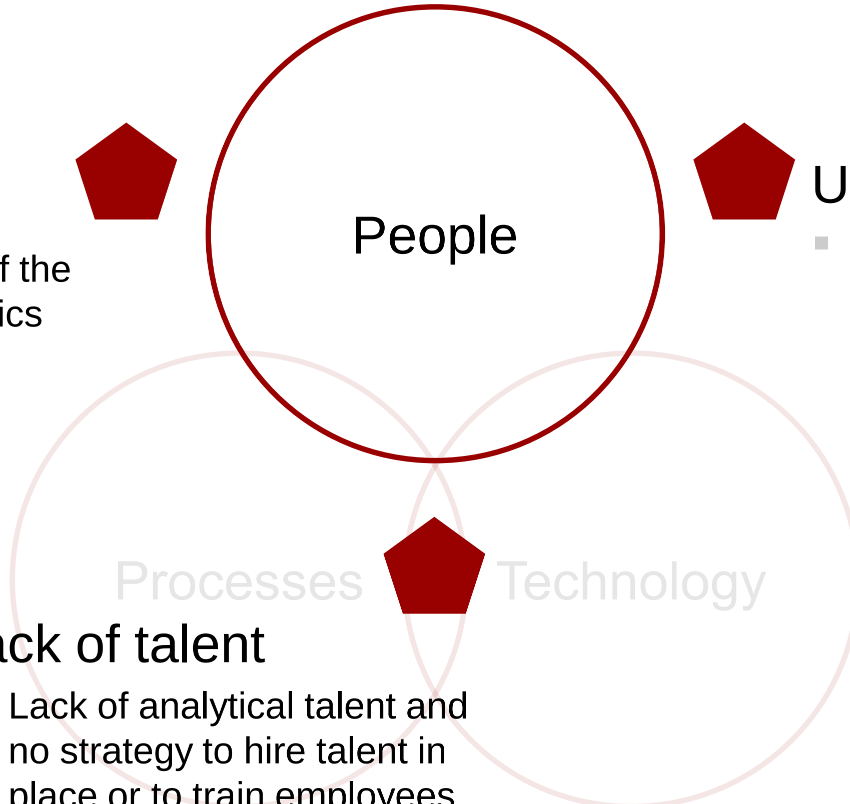
Access to data

- Existing data is not catalogued – its breadth unknown
- Some existing data sources are not in a usable form
- Partners may not see incentives in sharing data



Source: Sanders (2014)

Barriers – People I/IV



Lack of leadership

- Lack of understanding of the value of data and analytics

Unsupportive culture

- Shared values, beliefs and assumptions of organizational member must change from intuition to evidence-driven

Lack of talent

- Lack of analytical talent and no strategy to hire talent in place or to train employees

Source: Sanders (2014)

Barriers – Processes

People

Processes

Technology

IT is not integrated into workflow

- The analytics capability is often limited to a support role, not integrated in decision-making processes

IT is not included in initiatives

- If excluded form initiating discussion of strategic initiatives or new opportunities, potential analytics capabilities may remain unused

Siloed decision-making

- Analytics needs to be a cross-enterprise effort

Lack of incentive

- To transform into organization, driven by data and analytics, employees need to see advantages and not feel threatened.

Source: Sanders (2014)

Barriers – Additional Management

Intuition

- It is not to goal of Business Analytics to replace managerial intuition nor has it the capability
- Managerial intuition is needed for interpretation of results as well as basis for decision-making when no data is available
- However, there is evidence that analytics based decisions are more likely to be correct…
- …even if intuition based decision-making is easier, faster and „feels“ better

Willingness

- If decision-makers don‘t trust the results of the Analytics and the fact-based decision-making process or don‘t pay attention…
- …the recommended actions will not be translated into action
- Senior level support enhances the use of Business Analytics in a firm, unwillingness will stop it
- Considering the growth of data, managerial guidance and discipline is important to select the right data and analysis

Quelle: Davenport and Harris (2007), DiFilippo et al. (2014)

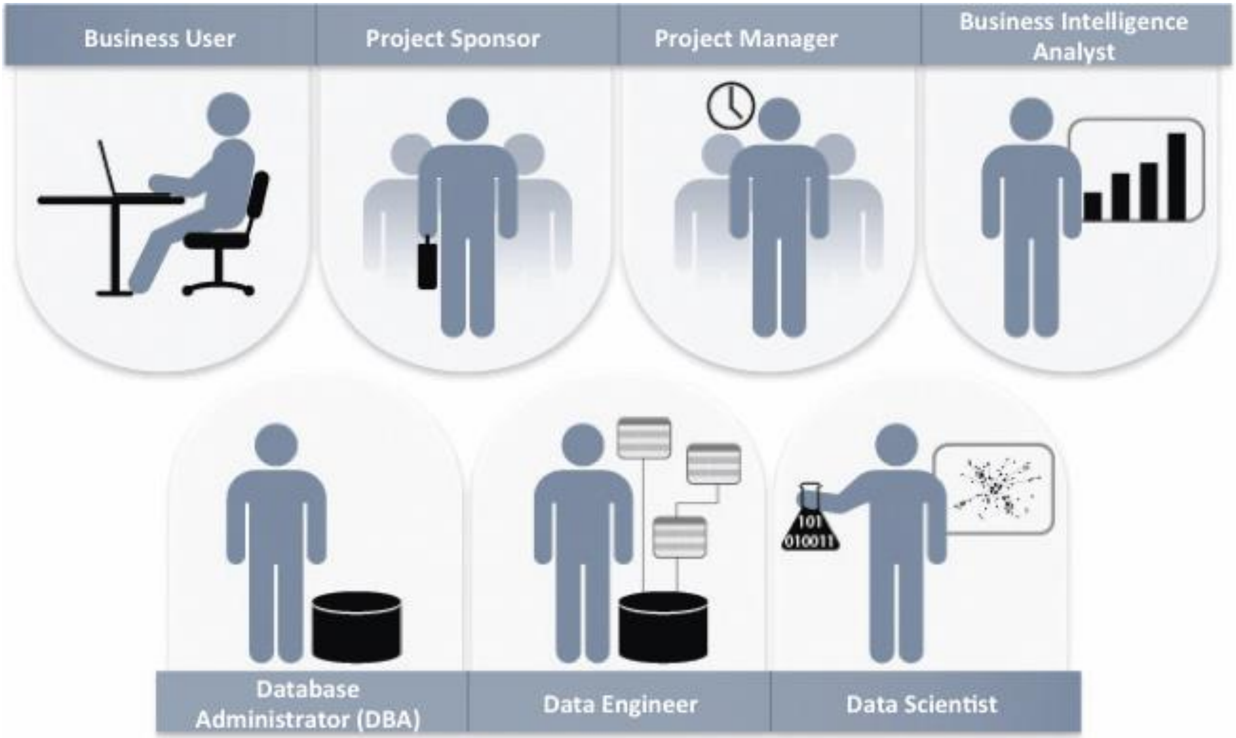
Barriers – Additional
Unrealistic Expectations

- unrealistic expectations are common in the marketplace
  - see trends like Cloud Computing, Big Data or Data Science,
- Results are expected faster, easier and bigger as realistically possible
  - with disregard for the process or resources needed
  - newness of the concepts likely increases time for the first value to be realized
- Visible failures due to unrealistic expectations will be the result and might “burst bubbles” or reverse trends
  - and puts the concepts under criticism

Source: Franks (2014), Harris (2013)

Barriers – Additional Skill Base diversity

- It is not enough to have analytical and technical skills – it is essentially nessecary to incorporate **Domain Knowledge** to
  - Understand the problem
  - Guide the process
  - Interpret the results
  - Create actions



Key roles in an Analytics Project

Source: Dietrich et. al (2015)

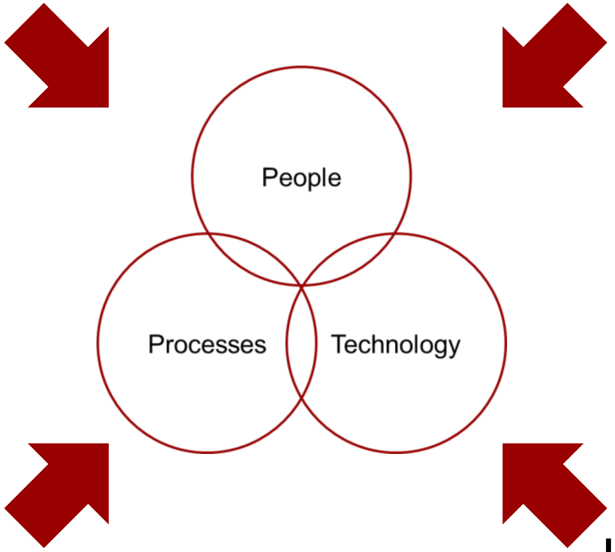
Further Barriers

Analysis Paralysis

- Organizations are overwhelmed with the speed of technological capability, they don't know what to do first and thus do nothing - like paralyzed

Measurement minutiae

- Organizations try to measure everything such that they loose focus on what measurement is relevant



A needle in a haystack

- Randomly searching for causation to find something with luck

Island of excellence

- Analytics is used to optimize sub processes but not the whole system

Source: Sanders (2014)

Agenda

1. Business Analytics
    1. Definition
    2. Key capabilities
    3. Barriers
2. Types of Analytics
3. Analytics Projekt cylce

Types of Analytics

Descriptive Analytics

Summarize and describe what happened in the past such that you gain insight in the underlying phenomenon or process

Predictive Analytics

Predict an unknown value [esp. what will happen in the future]

Prescriptive Analytics

Determine actions to take to make the future happen

Source: Franks (2014), Provost and Fawcett (2013)

Predictive Analytics

In some states in the USA, judges are provided with predictions of repeated offenders' criminal offences if the level of punishment is to be determined. The final decision is subject to the judge.

Objective: To predict whether a criminal will commit another offence after detention, based on his or her history, education, marital status, social class or even physical characteristics, such as gender and ethnic origin.

Causes: based on correlations

Prediction: of the expected behavior of an individual

Actions: remain open!

Types of Analytics
Prescriptive Analytics

In some states in the USA, judges are provided with predictions of repeated offenders' criminal offences if the level of punishment is to be determined. The final decision is subject to the judge.

Objective (fictitious): Determine the best course of action for a number of offenders, a limited capacity of cells, likelihood of rehabilitation of the offenders, severity of the crime, minimum sentences of imprisonment, probation or social hours to maximize the common good.

Causes: assumed interrelationships/rules

Prediction: can be entered as input, but are not hit

Actions: optimal actions are determined

Typen der Analytics (beispielhaft)

Descriptive Analytics

In some states in the USA, judges are provided with predictions of repeated offenders' criminal offences if the level of punishment is to be determined. The final decision is subject to the judge.

Objective (fictitious): Determine causal reasons of delinquency and the influence of access to education, income from the parents' home or residential area on delinquency.

Causes: Causalities are determined

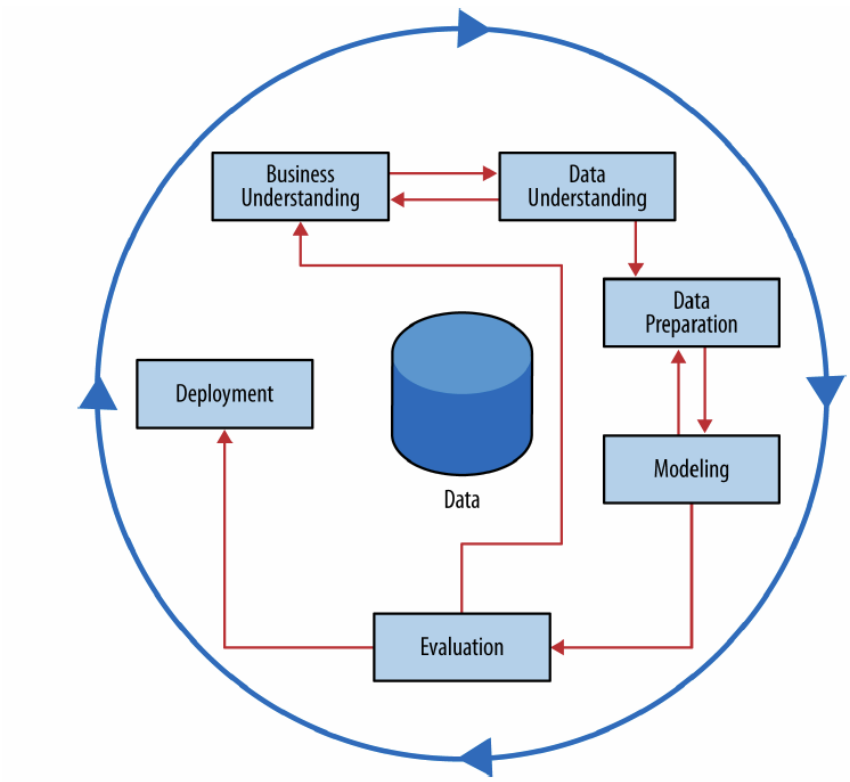
Prediction: Causalities are not necessarily useful for predictions (lack of educational facilities in a district may lead to higher crime, but not everyone with poor education becomes a criminal)

Actions: in order to combat the causes, the following must be designed

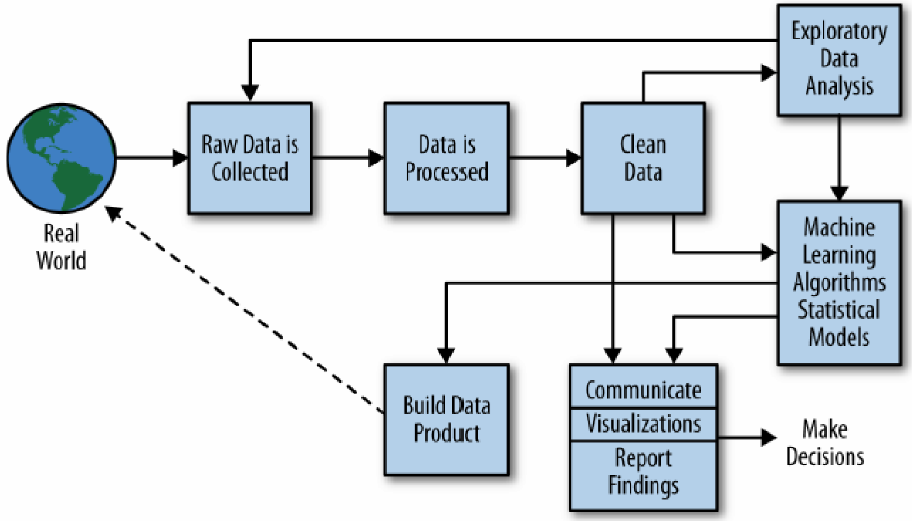
Agenda

Data Analysis Project Cycles
Example I

The "CRISP-DM"* process



"The Data Science Process"

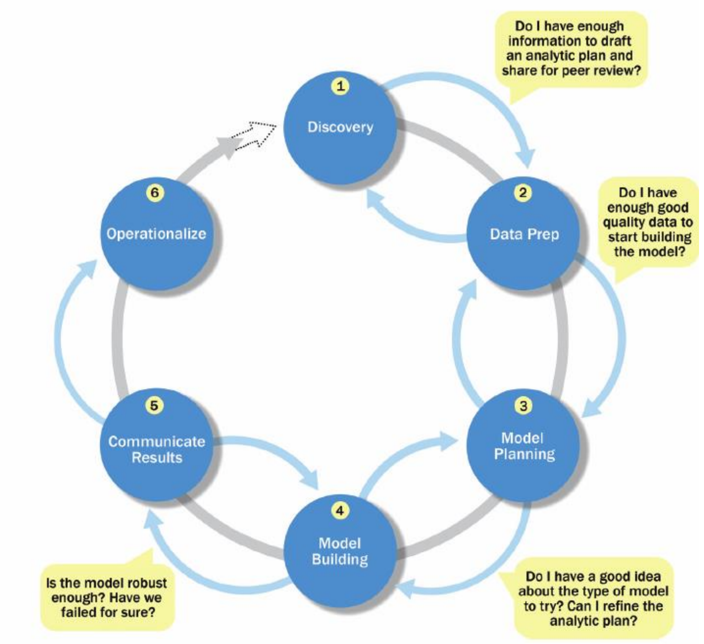


*Cross Industry Standard Process for Data Mining

Quelle: Provost and Fawcett (2013); Schutt and O'Neil (2013)

Data Analysis Project Cycles
Example II

"Data Analytics Lifecycle"



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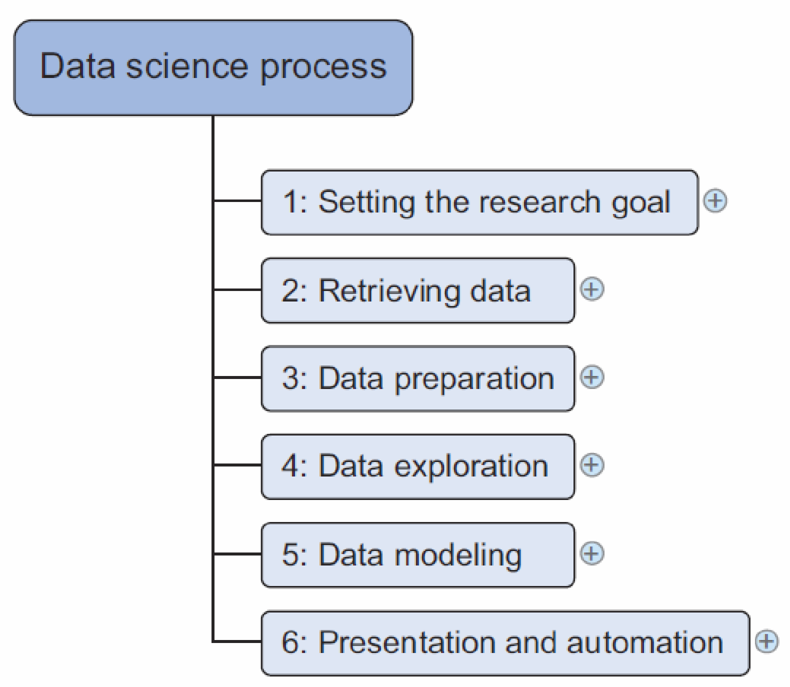
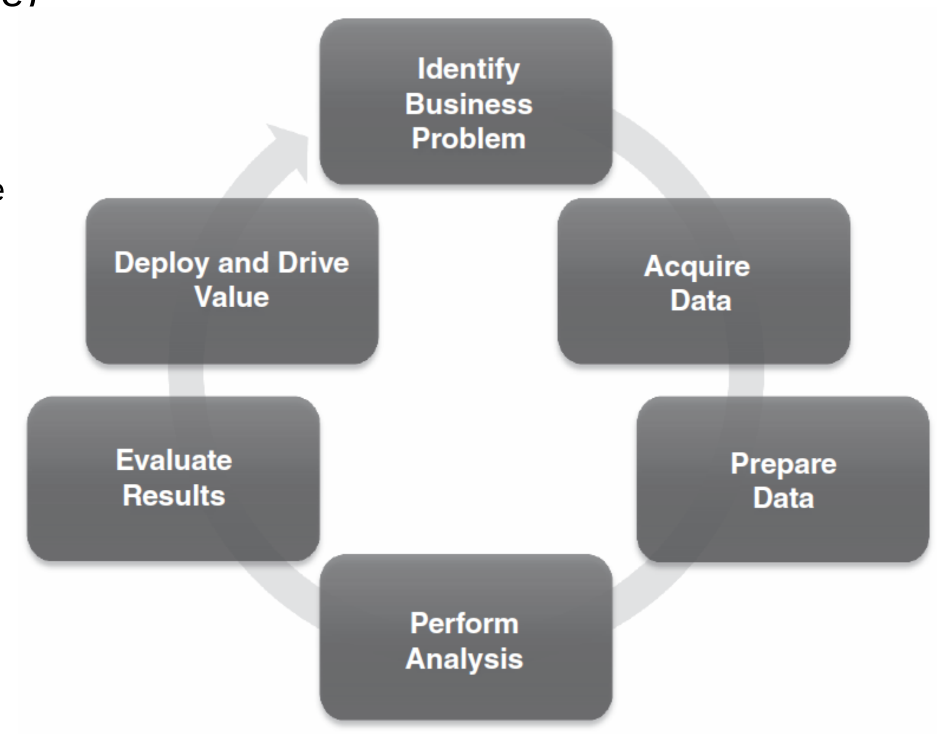


Quelle: Dietrich et al. (2015); Cielen et al. (2016)

Data Analysis Project Cycles
A generic Process

- Due to some individual streams of developments (e.g. Big Data or Data Science) several processes have developed
  - The processes are very consistent
  - All are very similar to the CRISP-DM developed in the 1990s.
- Recurring process steps:
  - problem identification
  - data gathering
  - data preparation
  - Executing the analysis
  - Evaluation of results
  - Deployment and benefit generation



Quelle: Franks (2014)

Data Analysis Project Cycles
Steps I

Phase 1:
Problem identification

- Building understanding of the business problem or research goal and the business context in which the problem occurs or the goal is to be achieved
- Analytical-competent persons fail especially at this step, because the brilliant analyses do not solve the actual problem.
- The business problem usually has to be converted into several subproblems for data analysis

Phase 2:
Data gathering

- Types of data collection:
  - Data has already been collected by the company and is available in databases, data marts, data warehouses or data lakes
  - Data is procured by third parties
  - Data must be collected again
- For internal data, procurement can also be problematic if:
  - relevant data is stored on local computers, e.g. in an Excel file
  - Relevant data is protected by physical and digital barriers (so-called "Chinese walls")

Quelle: Provost and Fawcett (2013); Dietrich et al. (2015); Cielen et al. (2016)

Data Analysis Project Cycles
Steps II

Phase 3:
Data preparation

- For modeling, data must be loaded into a sandbox and prepared ("extract-load-transform" (ELT))
  - Formatting: transferred to a format that promises better results for modeling
- Exemplary errors:
  - Incorrect manual entry; Redundant entries; Missing values; Impossible values

Phase 3a:
Exploratiry Data analysis

- An intermediate step at this point is the explorative data analysis to gain understanding of the data.
  - Primarily visual techniques

Phase 4:
Modelling

- The primary level in which statistical and quantitative methods are applied
- Several different models are set up and evaluated (against each other)
- **Descriptive, Predictive and Prescriptve Analytics can be chained**

Quelle: Provost and Fawcett (2013); Dietrich et al. (2015); Cielen et al. (2016)

Data Analysis Project Cycles
Steps III

Phase 5: Evaluation of results

- assessment of whether the patterns and results found are truly regular, or anomalies in the samples
- Test of the model in a laboratory setting
- Verify that the model meets business objectives
- Accordingly, qualitative and quantitative assessments are made

Phase 5a: results communication

- The results are communicated to the main interested parties (decision makers)
  - The most important results are summarized, the added value of model provision in the company is estimated and a "narrative" for communicating the results is developed ("storytelling with data").

Phase 6: Deployment

- In deployment, the model, including code and technical documentation, is transferred and put into production (it is used in the process / implemented in information systems). It is usually adapted to the systems to ensure speed and compatibility.
  - A pilot phase is usual

Quelle: Provost and Fawcett (2013); Dietrich et al. (2015); Cielen et al. (2016)

Zusammenfassung: Business Analytics

- Analytics deals with evidence-based problem identification and problem solving in the context of business situations.
- Key capabilities for the application of analytics to differentiate oneself from competitors lie in the areas of technologies, organization and people.
- Barriers can occur due to a wide variety of internal and external factors, and can also inhibit successful application even with existing competence.
- There are 3 types of analytics: descriptive, predictive and prescriptive

Diskussion/ „Significant Digit“

142.729

...$ Average salary for a data scientist for San Francisco, United States of America (according to Glassdoor)

- Calculated based on 607 salaries recorded in San Francisco

The average (US) is $120,931 and $141,257 ($165,123 in San Francisco) for Senior Data Scientists. Further collected values are e.g.

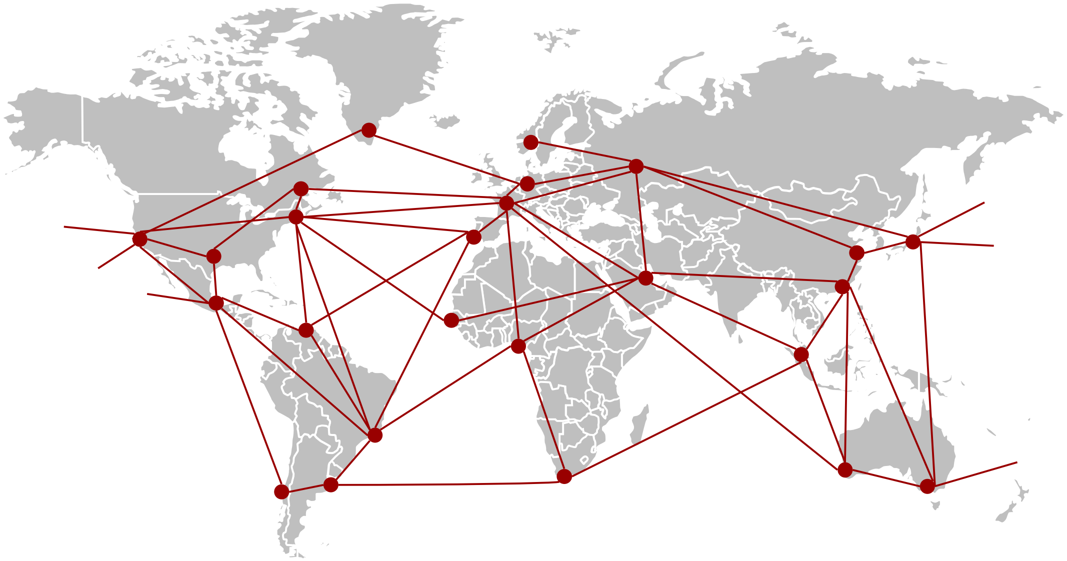
- 118,225 (New York, 316 observations)
- $120,774 (Los Angeles, 98 observations)
- 103,685 (Chicago, 161 views)

In Germany, on the other hand, payment is more conservative

- 52,000 (nationwide, 75 observations)

...in comparison a consultant earns €55.495 (Berlin, 226 observations)

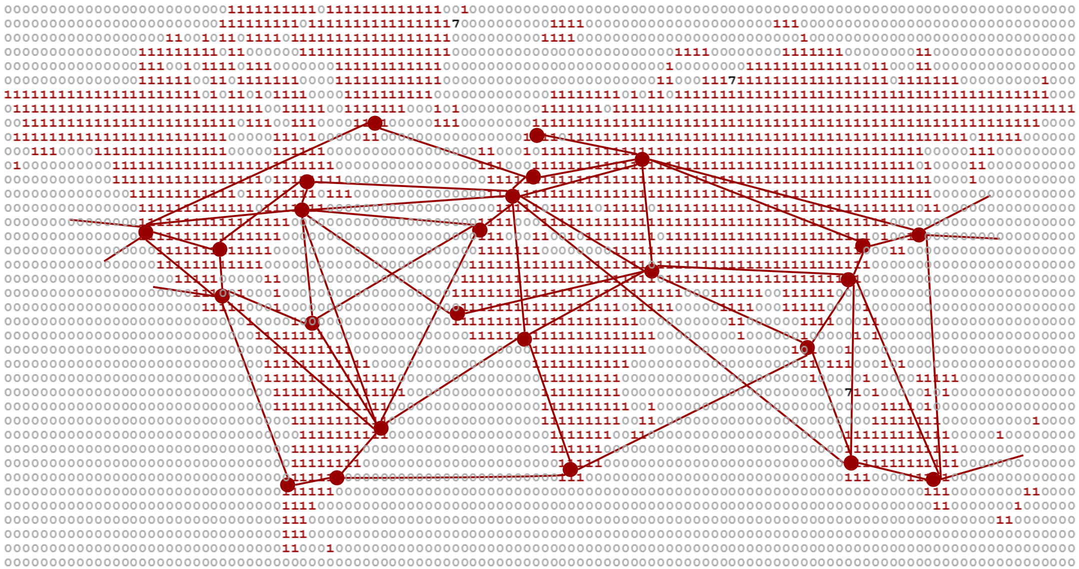
Supply Chain Management



- Supply chain management is a set of approaches used to efficiently integrate suppliers, producers, warehouses and points of sale so that goods are produced and distributed in the right quantity, at the right place, and at the right time, while minimizing system-wide costs and satisfying service level requirements.

Quelle: Simchi-Levi et. al (2003)

Supply Chain Analytics



Supply chain analytics is the use of business analytics to support and improve Supply Chain Management.

- Supply Chain Analytics "*is concerned with evidence-based problem recognition and solving that happen within the context of supply chain and logistics related business situations*"
- Supply chain analytics "*is the application of quantitative and qualitative methods from a variety of disciplines in combination with SCM theory to solve relevant SCM problems and predict outcomes, taking into account data quality and availability issues*".*

*Form Waller and Fawcett (2013), the term originally defined is "SCM Data Science"

Theoretical Motivation

- **Eligibility**
- Accessibility
- Performance Increase
- Competitive Advantage
- Barriers

Early user

- Logistics is one of the first areas that uses analytics (or quantitative models) for decision making
- E.g. with EOQ model for inventory optimization or operations research for routing, allocation or localization problems

Applicable on different levels

- The methods can be used at different organizational levels and periods...
- ... on the strategic level, e.g. for long-term demand forecasts
- ... at the operative level, e.g. for daily demand program planning

Complexity of decisions

- Alignment of supply and demand / capacity quickly achieves a complexity that is difficult to control and requires analytical decision support
- For example, due to several available suppliers, partners, locations, product families, cost components...

Quelle: Herden (2018)

Theoretical Motivation

- Eligibility
- **Accessibility**
- Performance Increase
- Competitive Advantage
- Barriers

Development of data collection technologies

- More and more diverse data are available than ever before...
- ...e.g. from position by RFID and GPS; IoT sensors with detection of temperature, vibration, light; motion profiles, images, sound from mobile devices such as smart phones; text messages from social media

Development of data transmission technologies

- The Internet and its expansion are constantly increasing the speed of data transmission.

Development of data storage technologies and related methods of evaluation

- In recent years there has been extensive progress in...
- ...Development of (Big Data) technologies for the evaluation of large amounts of data (e.g. Hadoop)
- ...methods of machine learning (e.g. neural networks)
- ...application software that makes it easier for data-related non-statisticians to use the procedures (e.g. Rapidminer, Tensorflow)

Quelle: Herden (2018)

Theoretical Motivation

- Eligibility
- Accessibility
- **Performance Increase**
- Competitive Advantage
- Barriers

Research has shown and argued for increased logistics performance through better coordination of

Supply/capacity on demand (e.g. by better forecasting) or...

from demand to supply/capacity (e.g. through pricing),

connected with...

Often improvement is already achieved by the creation of **Visibilty**.
This is often technologically complex (integration of data), but methodically simple.

Reduction of costs	(e.g. by overview of actual donations)
Reduction of times	(e.g. real-time tracking of transports for faster response)
Increased efficiency	(e.g. uncovering empty runs)
Increase of effectiveness	(e.g. shorter planning cycles due to better information from partners)
Increased customer orientation	(e.g. detection/avoidance of stock-outs)

Quelle: Herden (2018)

Theoretical Motivation

Eligibility

Accessibility

Performance Increase

Competitive Advantage

Barriers

Researchers regularly discuss the potential of new technologies and concepts to achieve competitive advantages...

... also for analytics in the field of logistics

Competitive advantages were argued by...

- ...the dynamic interaction of knowledge sources, through which valuable, rare and unimitable skills are created, with which customer satisfaction is achieved that is better than that of the competition.
- ...the ability to broaden the use of analytics in the company's process, which depends on the resources available for connectivity and information exchange. This capability increases the performance of logistics and therefore creates competitive advantages.

Quelle: Herden (2018)

Theoretical Motivation

- Eligibility
- Accessibility
- Performance Increase
- Competitive Advantage
- **Barriers**

The logistics market is highly fragmented (many smaller companies, few large ones)

- Analytics costs are difficult for small businesses to bear
- Coordination effort between data-exchanging partners is high
- Unwillingness to exchange data makes this even more difficult

As a cross-functional cross-functional function, analytics activities in the company would have to be coordinated, but...

- ...fragmented analytics activities lead to singular optimality in favor of sub-optimality in the overall process

Furthermore, companies are inhibited by common barriers

- Lack of experience in personnel and management
- Data security must be created and ensured
- Fragmented systems also in the companies themselves
- Adaptation difficulties to new technology
- Lack of data for the intended applications
- Too much data for which there is no use case

Quelle: Herden (2018)

Practical Motivation

Users achieve costs and efficiency advantages

- According to industry studies, users in logistics achieve advantages through analytics
- e.g. inventory reduction, risk reduction, faster reactivity

Opportunities from the company's point of view

- Logistics is one of the preferred areas for analytics investments in companies, alongside finance and marketing, due to promising ROIs
- Improvements in logistics also lead to an improvement in overall corporate performance in some companies.

Opportunities for logistics companies

- Companies are improving existing business models and...
- create new business models, among other things by passing on data to interested users

Organisational advantages

Opprtunities

Customer orientation

Reluctance

Quelle: Herden (2018)

Practical Motivation

A highlighted advantage of analytics is the possibility of **personalization** (e.g. advertising in marketing, treatments in medicine). Logistics describes this as **customer orientation**

- Analytics helps logistics to increase customer satisfaction through a better understanding of needs and requirements
- Provision of information on the customer (e.g. expected time of arrival forecasts)
- Improved possibilities to check suppliers / supplier products for compliance with customer requirements

However, industry studies also show that logistics is behaving cautiously with regard to analytics

- Few companies achieve excellence
- There is a lack of ideas and knowledge on the application of analytics
- The desired benefit is not achieved
- Compared to the industry, logistics is only in the midfield in terms of operating range and experience with analytics.

Organisational advantages

Opprtunities

Customer orientation

Reluctance

Quelle: Herden (2018)

Case: Brueckner

- General information about Brueckner
  - Brueckner is building mechanical engineering company from Siegsdorf, Germany with estimated 2,000 employees
  - Among others, Brueckner is building machines for companies producing foliage and high quality wrapping material
- Sensors in the build machines monitor up to 10,000 Parameters, captured by about 100,000 measuring points with an updated rate of 1,000 measures per second. Sensor points are collected together with videos, pictures and quality reports
- To enable the use of the Data and make them available as well as to *explain the relationship of the quality of the product and the machine setting*, a system to monitor, store and analyze the data was developed

Case: Otto

- General information about Otto
  - Otto is a multi-channel fashion retailer based in Hamburg, Germany with operating in more than 20 countries
  - Otto is selling fashion products of several brands, with items often only offered for 1 single season making forecasting especially difficult
- Based on the prediction algorithm of blueyonder (an algorthim based in particle physics called “neural network”), otto and blueyonder individualized a software to predict demand to reduce stockouts and overproduction at the same time
- The algorithm predicted demand based on more than 200 input varables including item related data like style, colour, brand, price, sales as well as external data like weather and cultural events

- The new algorithm resulted in a reduction of the percentage of products having a forecast deviation of more than 20% from an initial of 63% to 11%.
- Estimated savings are about 10 million € per year.
- Further benefits are the reduction secondary orders resulting in better prices from suppliers as well as the reduction of transports and with it CO2 emission.

Case: UPS

- General information about United Parcel Service
  - UPS is the worldwide largest package delivery service with its headquarter in Atlanta, USA
  - More than 55,000 daily routes are driven by UPS delivery drivers in the US
- UPS developed and implemented its own real-time routing optimization system, called On-Road Integrated Optimization and Navigation (ORION). The system is optimizing the route of delivery drivers while they are already on their delivery run
- UPS estimated a US$ 50 million cost saving a year per reduced daily average mile per driver

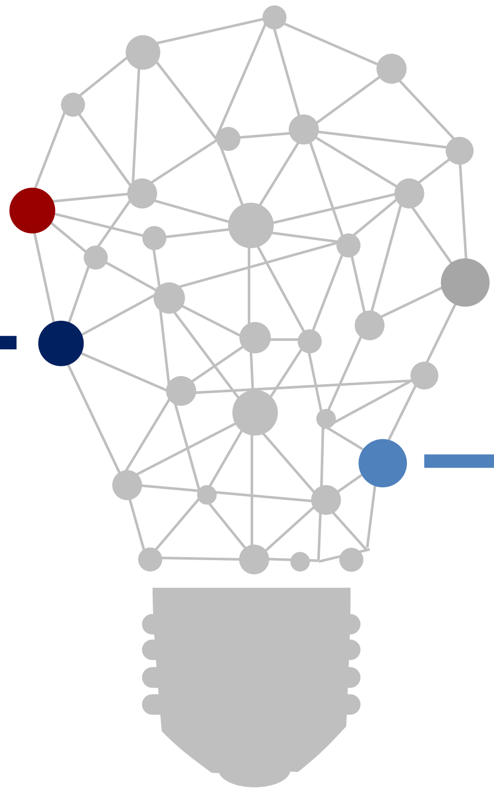
- Implementing ORION resulted in an average reduction of six to eight miles per day per driver resulting in estimates of US$ 400 million cost savings per year (in about 10 million gallons of fuel)
- The fuel and route length reduction is further estimated to reduces 100,000 metric tons of greenhouse gas emission per year

Summary: Supply Chain Analytics

- Supply Chain Analytics can be defined as "*is the application of quantitative and qualitative methods from a variety of disciplines in combination with SCM theory to solve relevant SCM problems and predict outcomes, taking into account data quality and availability issues*"
- It has impactions for all stages of the supply chain – from the suppliers to the customer
- Thus, it is in line with the systems theory of supply chain management and logistcs

Thank you
For your attention

Questions
Are welcome



Comments and directions
Will be greatly appreciated

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Tino Herden

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