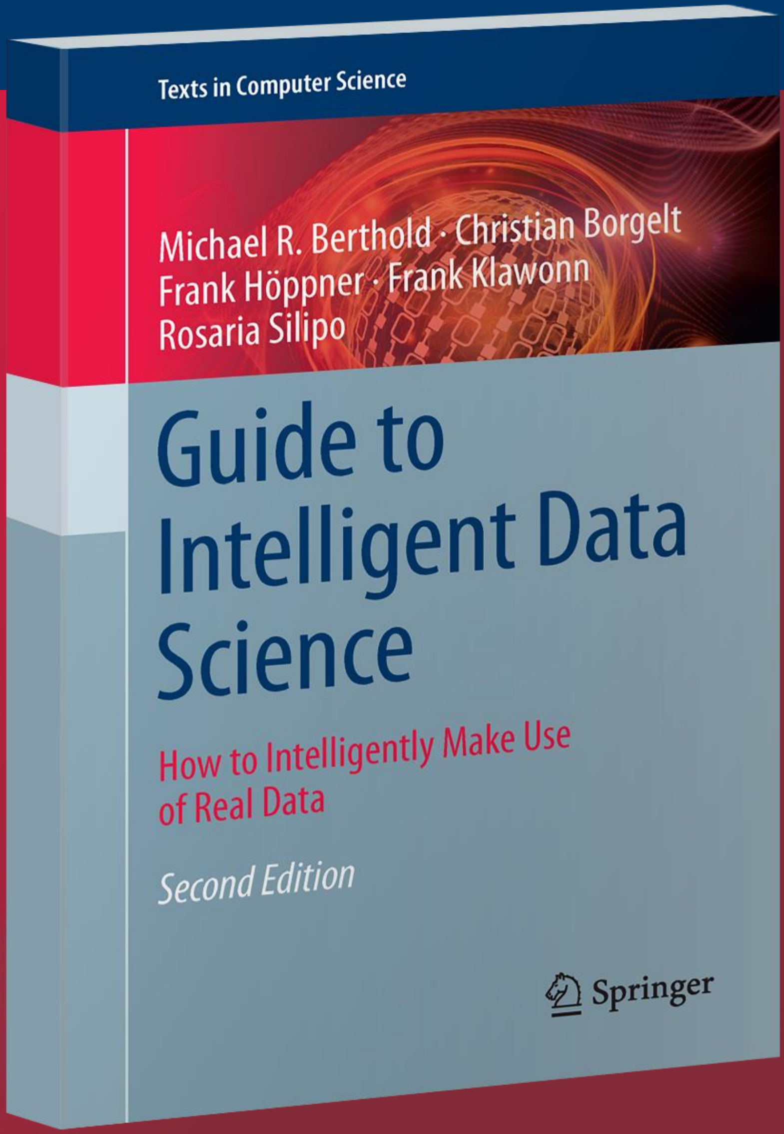
# Project& Data Understanding




Caption

# Summary of this lesson

*„... the goal of the project understanding phase is to assess the main objective, the potential benefits, as well as the constraints, assumptions, and risks"*

How do we identify the main objective of a project, and plan the approach?

**This lesson refers to chapter 3 and part of chapter 4 of the GIDS book*

# Content of this lesson

- Some Classic Use Cases
- Project Understanding
- ETL: Extraction, Transformation Loading
- Data Understanding
- Describing your Data
- Finding Patterns
- Finding Models
- Finding Predictors
- A tiny bit of History
- One final word of Warning: Correlation vs. Causality

# Some Classic Use Cases

# Churn Prediction: will a customer quit the contract?

CRM System
Data about your customer

- Demographics
- Behavior
- Revenues

Model

- Churn Prediction
- Upselling Likelihood
- Product Propensity /NBO
- Campaign Management
- Customer Segmentation
- …

# Customer Segmentation: which groups of customers am I serving?

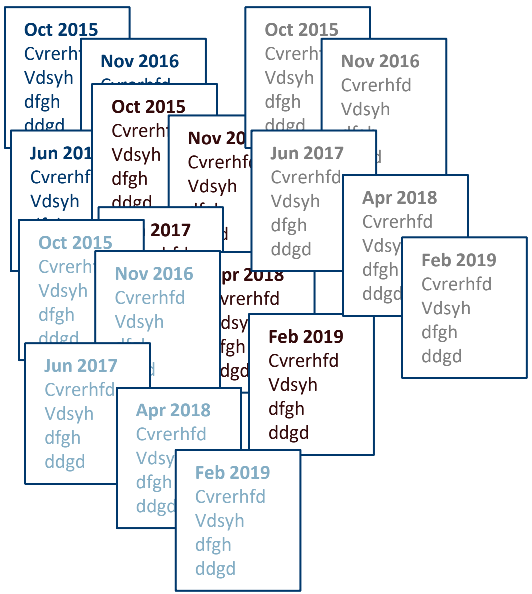
CRM System
Data about your customer
- Demographics
- Behavior
- Revenues

Model

- Churn Prediction
- Upselling Likelihood
- Product Propensity /NBO
- Campaign Management
- Customer Segmentation
- …

# Risk Assessment: is this person going to repay the loan?

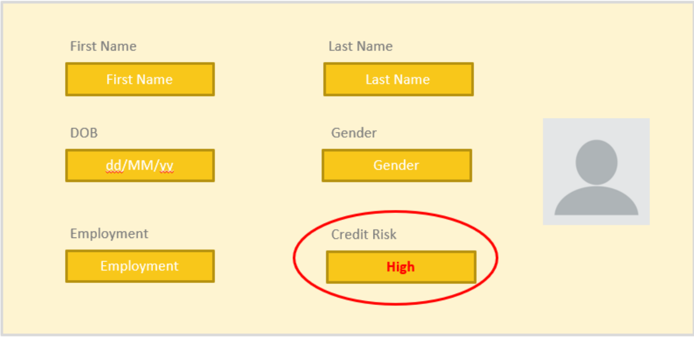
## Customer History




Model

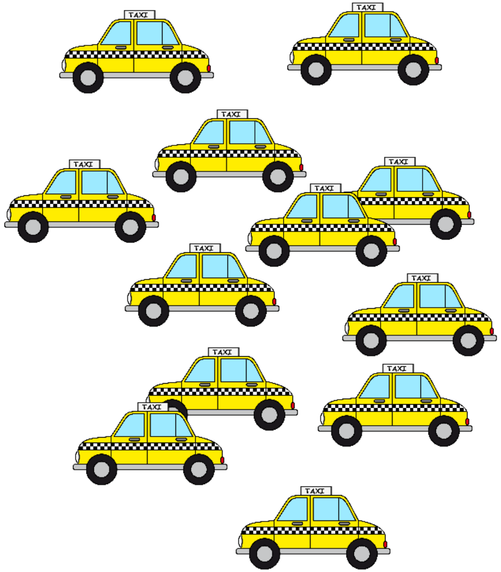
## Risk Prognosis

- High Risk
- Low Risk
- High Risk
- Very High Risk
- Very Low Risk
- Medium Risk
- …

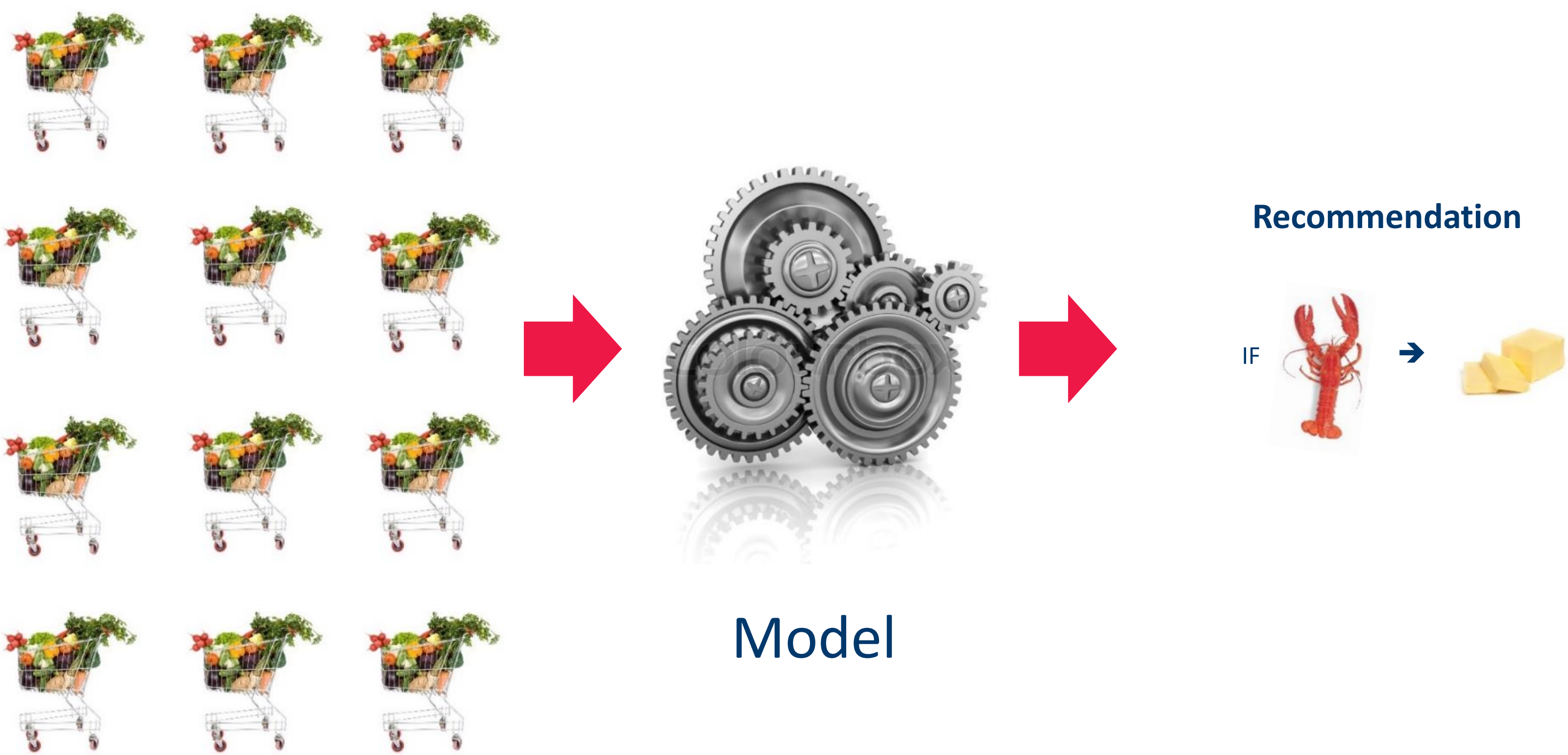


- How many taxis do I need in NYC on Wednesday at noon?
- Or how many kW will be required tomorrow at 6am in London?
- Or how many customers will come tonight to my restaurant?


Model



Recommendation Engines: People who bought this item were often interested in this other items.



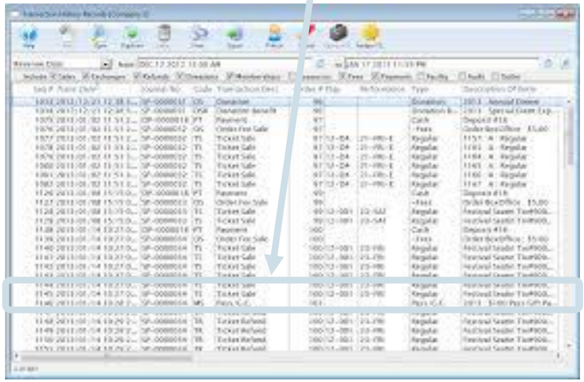
# Fraud Detection: Is this transaction legitimate or is it a fraud?

Transactions

- Trx 1
- Trx 2
- Trx 3
- Trx 4
- Trx 5
- Trx 6
- …

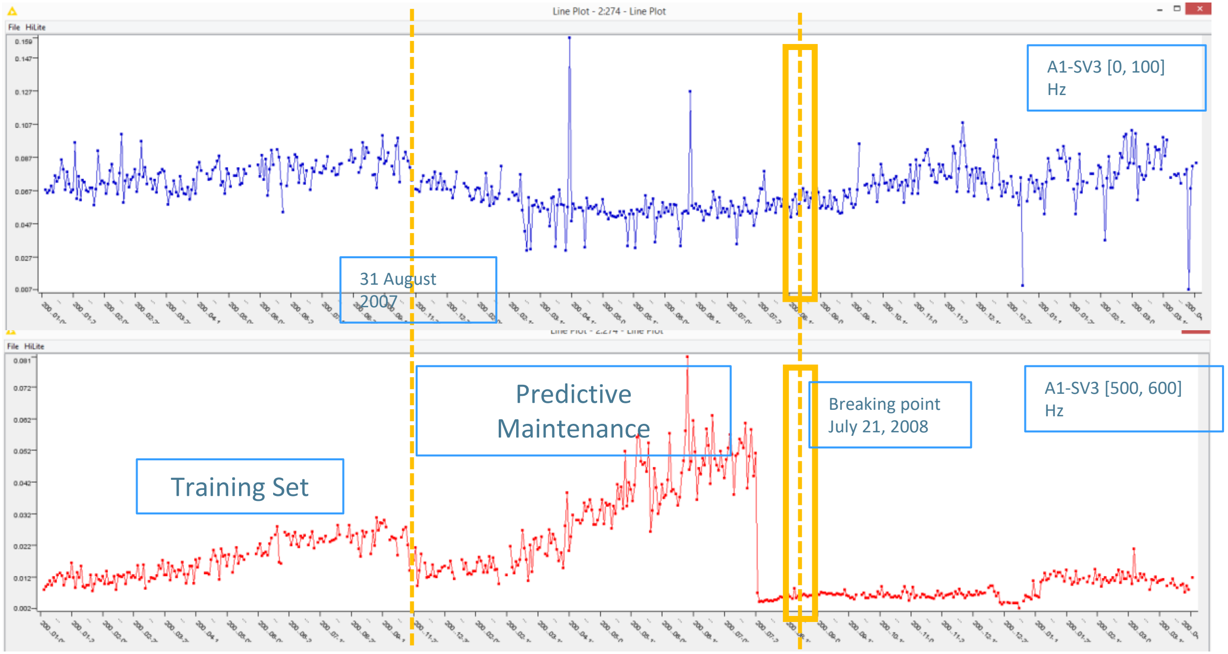
Model

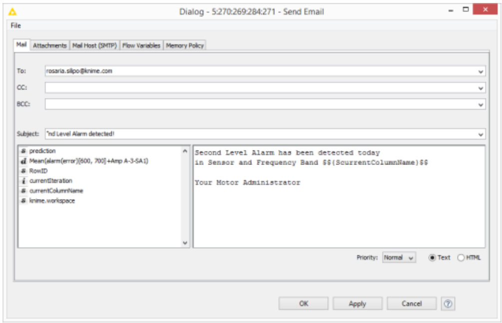
Suspicious Transaction



## Sentiment Analysis: how can I know what people are thinking?

# Predicting mechanical failure as late as possible but before it happens



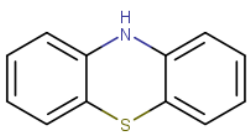


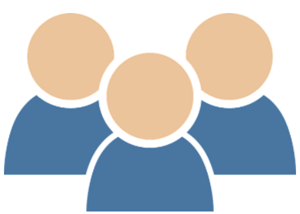
**via REST**

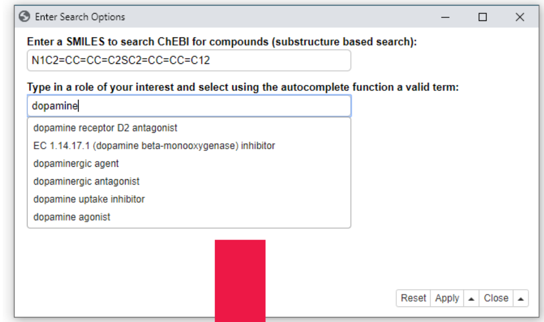
Only some Spectral Time Series shows the break down

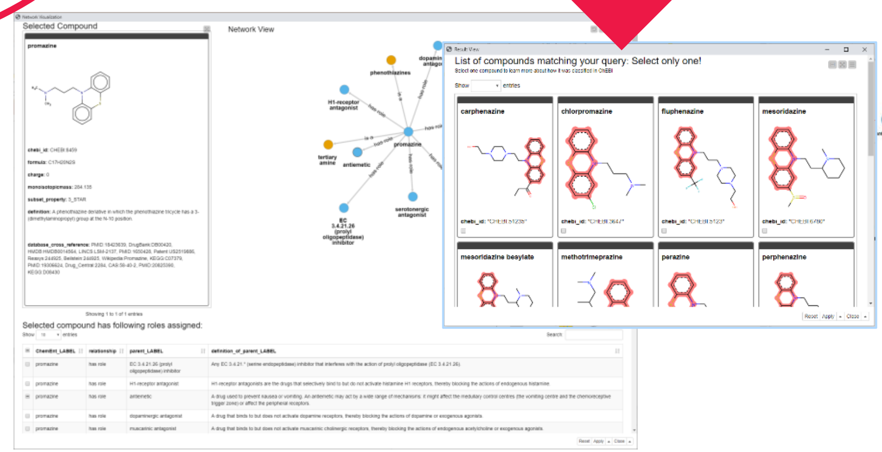
# Compound Search

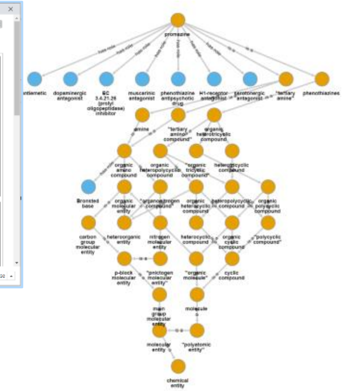
Are there other compounds having this substructure and being a dopaminergic antagonist?





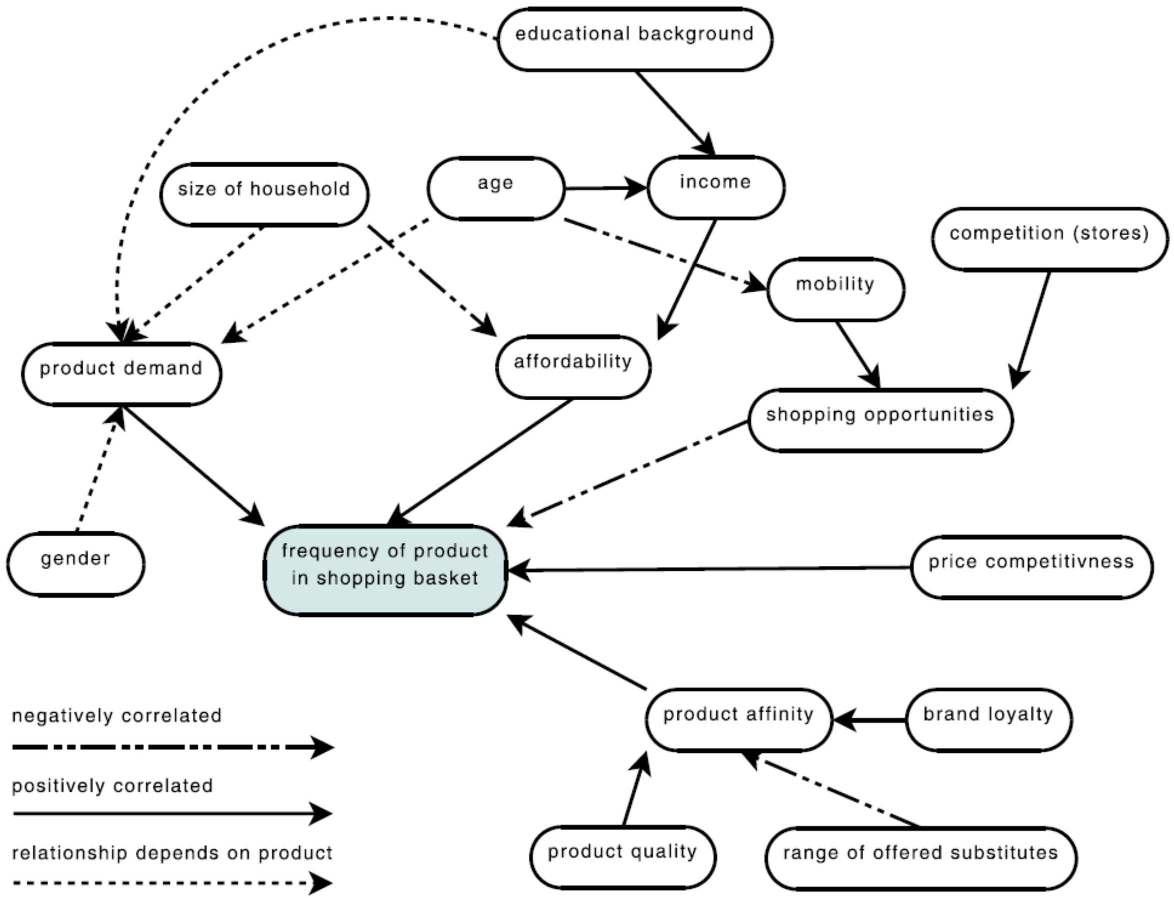
# Project Understanding

- What is the primary objective?
- What are the criteria for success?
- These are difficult to define
  - The project owner & the analysis *speak different languages*

| Problem source | Project owner perspective | Analyst perspective |
|---|---|---|
| Communication | Project owner does not understand the technical terms of the analyst | Analyst does not understand the terms of the domain of the project owner |
| Lack of understanding | Project owner was not sure what the analyst could do or achieve<br>Models of analyst were different from what the project owner envisioned | Analyst found it hard to understand how to help the project owner |
| Organization | Requirements had to be adopted in later stages as problems with the data became evident | Project owner was an unpredictable group (not so concerned with the project) |

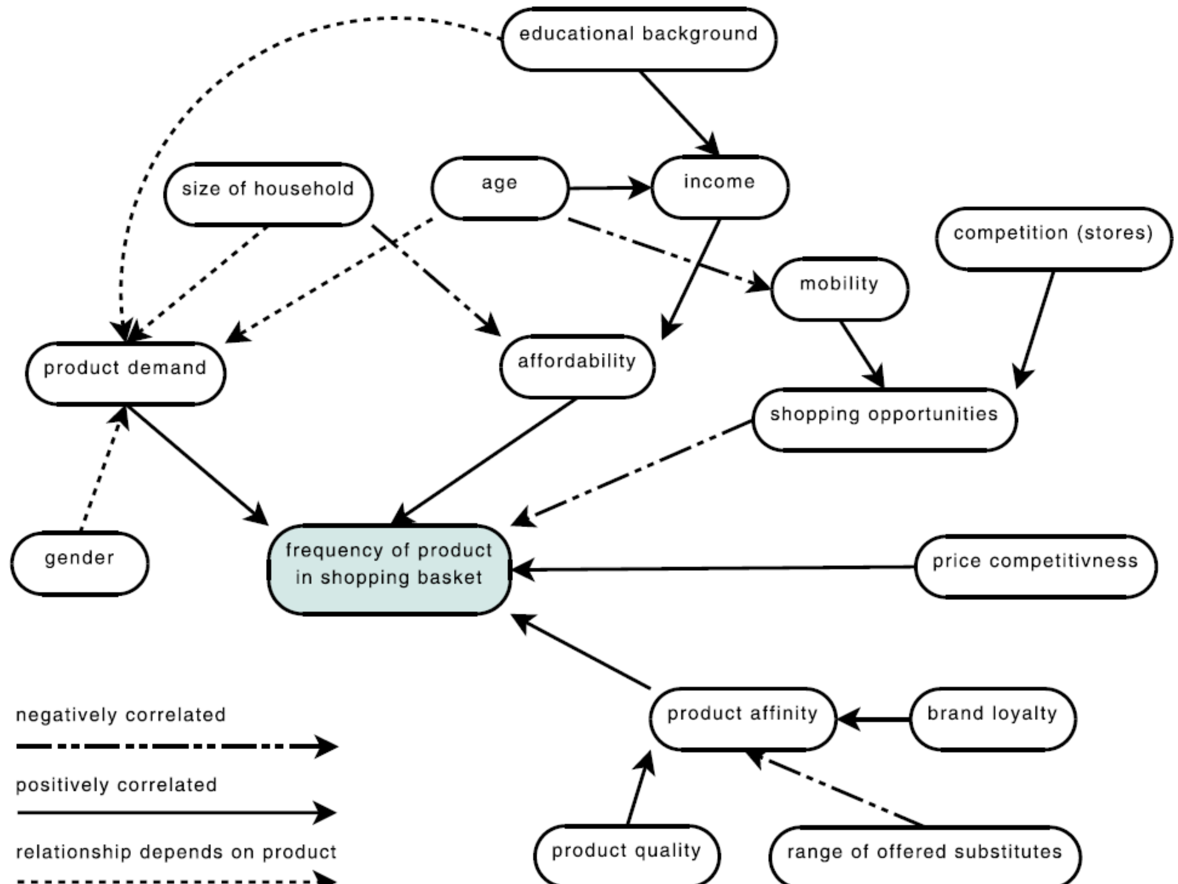
# Cognitive maps

- Tool to sketch
  - Beliefs
  - Experiences
  - Known factors
  - How they influence each other



# Cognitive maps

- How often will a certain product be found in a basket?
  - Directly influenced by factors around it
    - E.g., affordability
  - Indirectly influenced by other factors
    - E.g., size of household
  - Postive or negative correlation



- Once the solution is identified
  - Explore advantages & disadvantages
- Is the goal
  - Precise enough?
  - Actionable?

| | |
|---|---|
| **Objective** | Increase revenues (per campaign and/or per customer) in direct mailing campaigns by personalized offer and individual customer selection |
| **Deliverable** | Software that automatically selects a specified number of customers from the database to whom the mailing shall be sent, runtime max. half-day for database of current size |
| **Success criteria** | Improve order rate by 5% or total revenues by 5%, measured within 4 weeks after mailing was sent, compared to rate of last 3 mailings |

# Assess the Situation

- Will this be a successful data analysis project?
- Examine the following:

- **Requirements and constraints**
  - Model requirements (e.g., explanatory model)
  - Ethical, political, and legal issues (e.g., must exclude gender, race, and/or age)
  - Technical constrains
- **Assumptions**
  - Representativeness (the sample represents the whole population)
  - Informativeness (influencing factors should be included in the model)
  - Good data quality
  - Presence of external factors

## Select models and techniques with the following properties

- **Interpretability**
  - The model can be understood / interpreted
- **Reproducibility / stability**
  - Similar model performance every time the analysis is carried out
- **Model flexibility / adequacy**
  - The model can adapt to more complicated situations
- **Runtime**
  - Strict runtime requirements may limit computationally intensive approaches
- **Interestingness / use of expert knowledge**
  - Experts may already know the finings from the analysis

# ETL: Extraction, Transformation, Loading

Getting the data in not always easy:

- Different resources: flat files, different databases, excel spreadsheets, ...
- Integration is cumbersome: Missing/not unique IDs, wrong entries, ...
- Sometimes also privacy concerns (not all data in one location)

Data needs to be transformed:

- Type conversions
- Missing value correction/clean up/imputation
- Generation of new values (e.g. convert year of birth into age)

# ETL

- Three files:
  - customers,
  - products,
  - shopping baskets.

- Can we load these file and create a new attribute “age”?

- Can we find out:
  - how often each customer went shopping
  - how much (s)he bought together (and on average)

- Database issues

- More details regarding pre-processing later:
  - Normalization
  - Binning
  - Feature (and Data!) Reduction
  - ...

**The 80% Rule**
Over 80% of data analysts' time is spent on loading and cleaning data.

# Data Understanding

- **Goal of the Data Understanding phase**
  - Gain general insights about the data that will potentially be helpful for the further steps in the data analysis process
- **Reasons**
  - Never trust any data as long as you have not carried out some simple plausibility checks.
- **Results**
  - At the end of the data understanding phase, we know much better whether the assumptions we made during the project understanding phase concerning representativeness, informativeness, data quality, and the presence or absence of external factors are justified

# Attribute Understanding

| No | Sex | Age | Blood pr. | Height | Drug |
|---|---|---|---|---|---|
| 1 | male | 20 | normal | 175,0 | A |
| 2 | female | 73 | normal | 172,2 | B |
| 3 | female | 37 | high | 163,8 | A |
| 4 | male | 33 | low | 171,4 | B |
| 5 | female | 48 | high | 165,9 | A |
| 6 | male | 29 | normal | 182,3 | A |
| 7 | female | 52 | normal | 167,2 | B |
| 8 | male | 42 | low | 177,2 | B |
| 9 | male | 61 | normal | 168,4 | B |
| 10 | female | 30 | normal | 174,9 | A |

**Attributes**, features, variables…

**Instances**, records, data objects, entries…

- Data can usually be described in terms of table or matrices
- Sometimes data are spread among different table that need to be **joined**

# Attribute Understanding

Categorical　Ordinal　Numeric

| No | Sex | Age | Blood pr. | Height | Drug |
|---|---|---|---|---|---|
| 1 | male | 20 | normal | 175,0 | A |
| 2 | female | 73 | normal | 172,2 | B |
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| 10 | female | 30 | normal | 174,9 | A |

Numeric　Categorical

- Attributes differ for their **scale type**, according to the type of values that they can assume
- Three scale types:
  - Categorical / Nominal
  - Ordinal
  - Numeric

# Categorical Attributes

Categorical

| No | Sex | Age | Blood pr. | Height | Drug |
|---|---|---|---|---|---|
| 1 | male | 20 | normal | 175,0 | A |
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Categorical

- Categorical (or Nominal) attributes have a finite set of possible values
- Granularity must be taken into account
  - Hierarchical structure of the categories
  - e.g. shallow subdivision: *food, non-food, drinks…*
  - further subdivision for drinks: *water, beer, wine…*
  - Which level of granularity is appropriate?
- Dynamic Domain
  - Some attributes have a fixed domain (e.g. months)
  - For other attributes the domain can change over time (e.g. the products in a catalogue)
  - Those attributes must be identified and handled

# Ordinal Attributes

Ordinal

| No | Sex | Age | Blood pr. | Height | Drug |
|---|---|---|---|---|---|
| 1 | male | 20 | normal | 175,0 | A |
| 2 | female | 73 | normal | 172,2 | B |
| 3 | female | 37 | high | 163,8 | A |
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| 10 | female | 30 | normal | 174,9 | A |

- Ordinal attributes have an additional linear ordering offered by the domain
- The ordering does not provide the distance between two object
- e.g. for an attribute containing university degrees, we can state that a *Ph.D* is an higher degree than a *M.Sc.* and that this is higher than a *B.Sc.*.

# Attribute Understanding

Numeric continuous

| No | Sex | Age | Blood pr. | Height | Drug |
|---|---|---|---|---|---|
| 1 | male | 20 | normal | 175,0 | A |
| 2 | female | 73 | normal | 172,2 | B |
| 3 | female | 37 | high | 163,8 | A |
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Numeric discrete

- The domain of numerical attributes are numbers. They can be
- **Discrete**
  - e.g. age, count…
  - Represented as integer values
- **Continuous**
  - e.g. height, weight, distance…
  - Represented as real values
  - Precision (rounding) has to be handled
- The scale of numeric attributes can be:
  - Interval e.g. date
  - Ratio Scale e.g. distance, with a canonical zero value
  - Absolute Scale e.g. counting

# Data Quality


- Data quality refers to how well the data fit their intended use
- There are various data quality dimensions
  - Accuracy
  - Completeness
  - Unbalanced Data
  - Timeliness

**Accuracy** is defined as the closeness between the value in the data and the true value.

## Syntactic

- The value might not be correct but it belongs at least to the domain of the corresponding attribute
- Easy to spot: verify values lying in the domain

e.g. “fmale” for the attribute Gender and “-15” for the attribute Weight violate the syntactic accuracy

## Semantic

- The value might be in the domain of the corresponding attribute, but it is not correct
- Hard or impossible to spot: double check with other sources or check “business rules”

e.g. “*2090*” for the attribute *YearOfBirth* is (at least at the moment) surely incorrect, therefore violates the semantic accuracy

# Completeness

- Completeness with respect to **attributes**
  - All the attributes have a value associated
  - i.e. Missing Values (coming soon in next lessons)
  - Missing values might not always be explicitly marked

- Completeness with respect to **records**
  - The data set contains the necessary information required for the analysis
  - Some rows might have been lost for various reasons (e.g. during DB migration)
  - Sometimes data about a certain situation simply does not exist (e.g. data about a failure that has never –yet- occurred)
  - It is hard to obtain a reasonably wide dataset containing all the possible combinations of data

## Unbalanced Data

- Data regarding a certain situation might be underrepresented
- E.g. machine quality control: parts produced with flaws are – hopefully – lower than the correct ones, therefore the corresponding data will be way less

## Timeliness

- Available data are too old to provide up to date information
- Often a problem in dynamically changing domains, where older data might indicate trends that have vanished

# Describing your Data

# Looking at the Data

Familiarize yourself with the data

- Identify trends
- strange patterns
- outliers
- ...

Types of views

- Basic Statistics
- 1D: Histograms
- 2D: Scatterplots, Scatter Matrix, Multi Dimensional Scaling
- 3D Scatterplots
- 3D: Parallel Coordinates

# Visual Inspection: Example

- Let’s look at our data
- Can we find some connections between age and shopping cart size?
- Anything else that looks a bit odd? (...the age distribution, maybe?)
- Visualizations are a good way for first sanity checks
- Interactivity on a plot or among plots is very helpful

# Simple Descriptors

- Simple statistical descriptors, such as:
  - range
  - mean/median
  - standard deviation
  - nominal values and their frequencies
  - ...
- can help to sanity check your data (and find dependencies that otherwise might surprise you quite a bit afterwards!)

- Can we look at the range and other simple 1D descriptors?
- How about 2D correlations between attributes?

# Finding Patterns

# Finding Patterns

- Finding (significant?) patterns in data may reveal interesting connections:

- Global patterns: groups of customers or products
  - Clusters

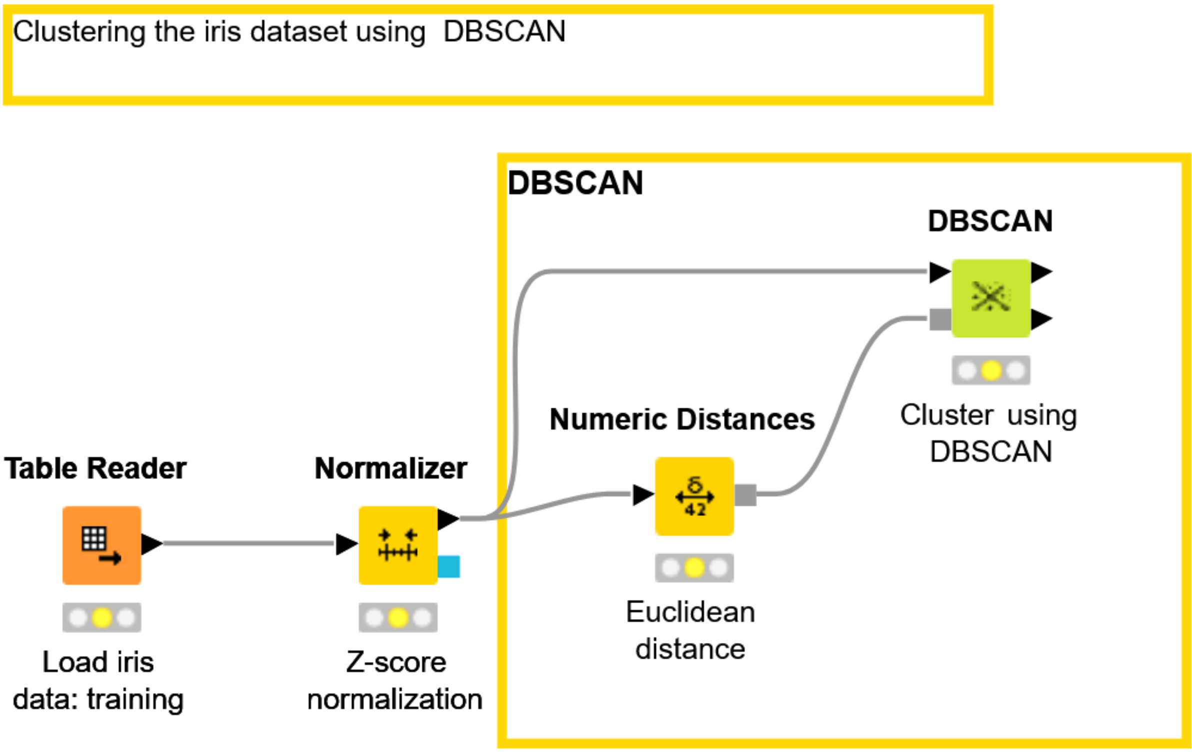
- Local patterns: connections between products, sub populations of customers (recommendation engines!)
  - Subgroups
  - Association Rules

# Example

- Can we find groups of similar customers?
- (and what does similarity mean, anyway?)

- **Similarity**
- Finding the right similarity metric is an art.
- (and what is a cluster anyway?)
- Distance based methods in high dimensions offer all sorts of interesting surprises...

– Screenshot of KNIME workflow with clustering



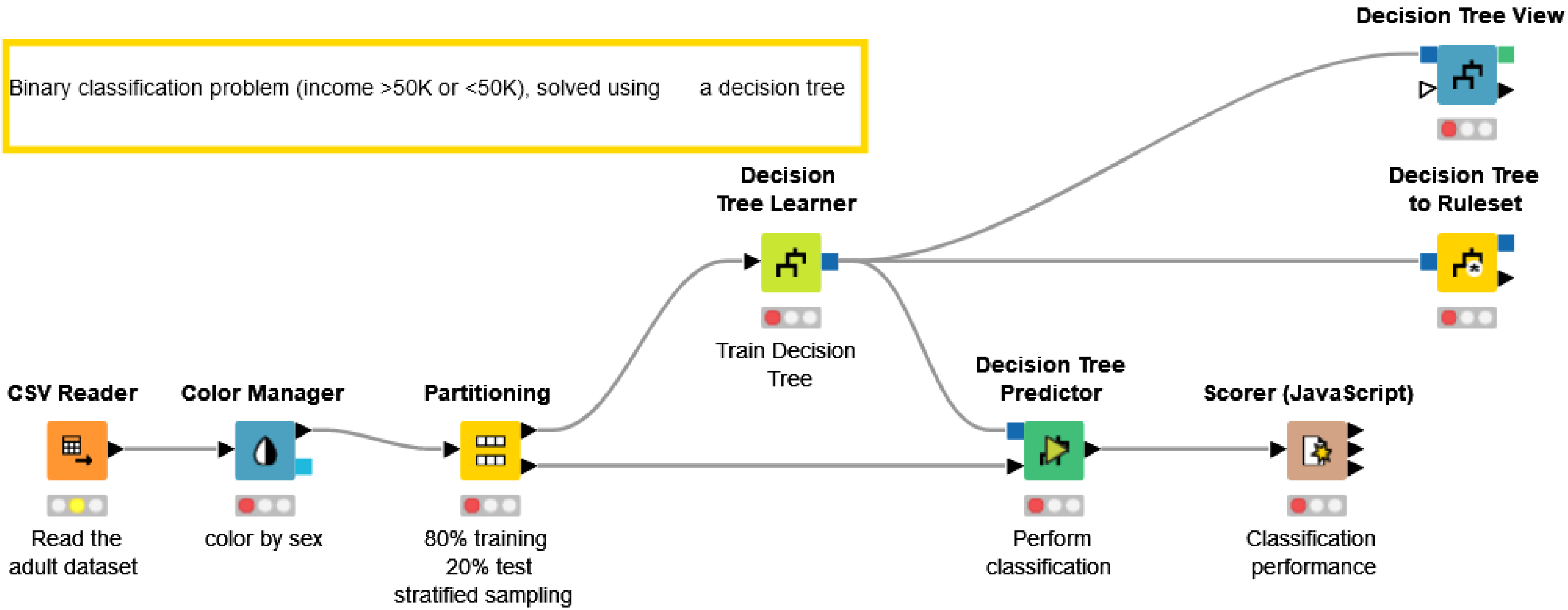
# Finding Models

## Finding Models

- Deriving models that describe (aspects of) the data:
  - Rules
  - Trees
  - Typical (or really odd!) examples
  - ...
- Models attempt to describe what is going on in the system that “generated” the data.

- Example:
  - Can we find a decision tree describing why certain customers buy so much?

– Screenshot of KNIME workflow with decision tree



# Finding Predictors

# Finding Predictors

- Sometimes we want to find a model which we can use to later predict the target variable(s):

- Predict future shopping behaviour
- Predict credit risk
- Predict activity of a chemical compound
- Predict tomorrow’s weather, stock market, ...

- And we may not care too much about actually understanding the model itself.

## Brute Force Predictors

Very simple: look at your closest neighbour

- Case based reasoning works that way
- Depends heavily on your distance function
- Does not work well with outliers/noise

Slightly better: look at a few of your neighbors

- K Nearest Neighbor
- Works pretty well
- But pretty expensive to compute...

Even better: look at all neighbors, but weight them

- Weighted K Nearest Neighbor
- Works even better
- Even more expensive...

# Other Predictors

- Decision Trees, Rules, ... (all of our models!)
- (Naïve) Bayes Classifiers
- Regression
- (Artificial) Neural Networks
- Support Vector Machines (Kernel Methods)

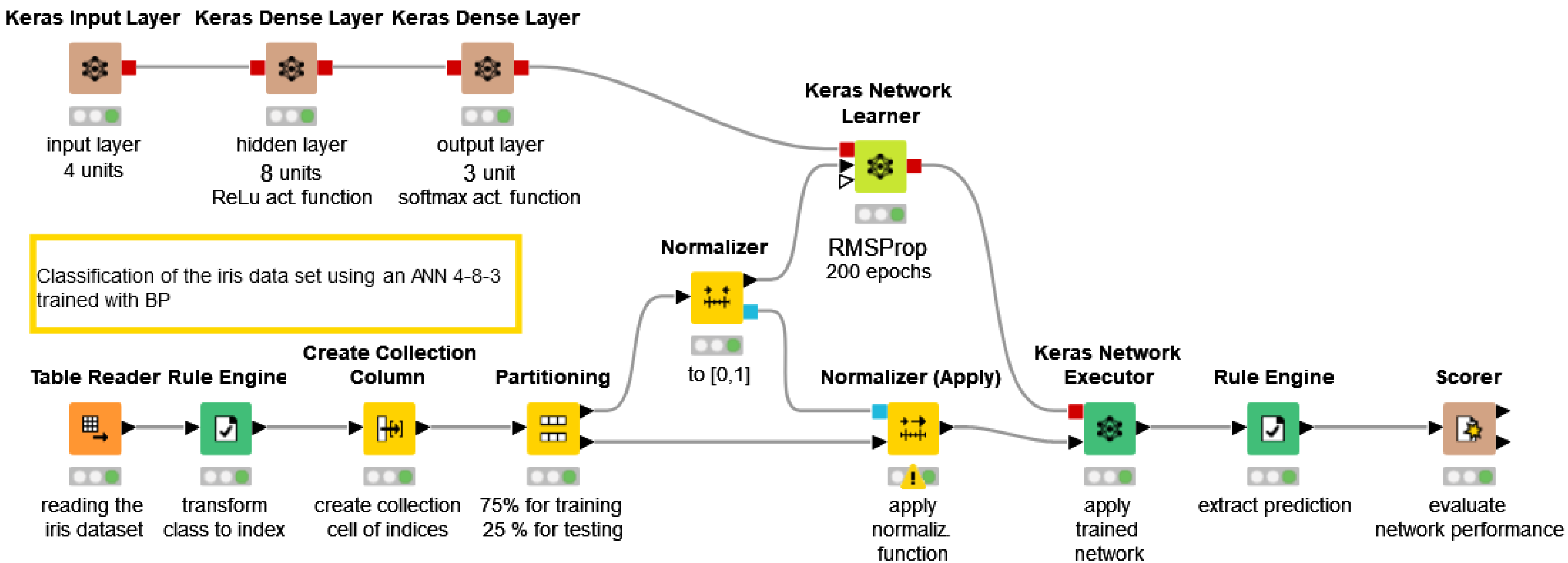
## Finding Predictors: Example

Can we predict the size of shopping-cart?

- Brute force: look at a (few) neighbor(s).
- Use our decision tree?...

What’s wrong with that approach?

– Screenshot of KNIME workflow with a neural network



## What kind of systems do we need?

- easy to use (also by non Data Mining Expert!)
- simple knowledge representation (understandable!)
- mergers of disciplines (machine learning, stats, databases, ...)
- (partial) automation of feedback ("Intelligent" Data Science!)
- quick turn-around (interactive!)

# A tiny bit of History

- **History: Classical Data Analysis**

- Small, usually manually recorded data sets
- Calculation of correlation measures and statistical significance measures.
- Calculations done with minimal to no compute support.
- Calculations later supported by basic calculation equipment

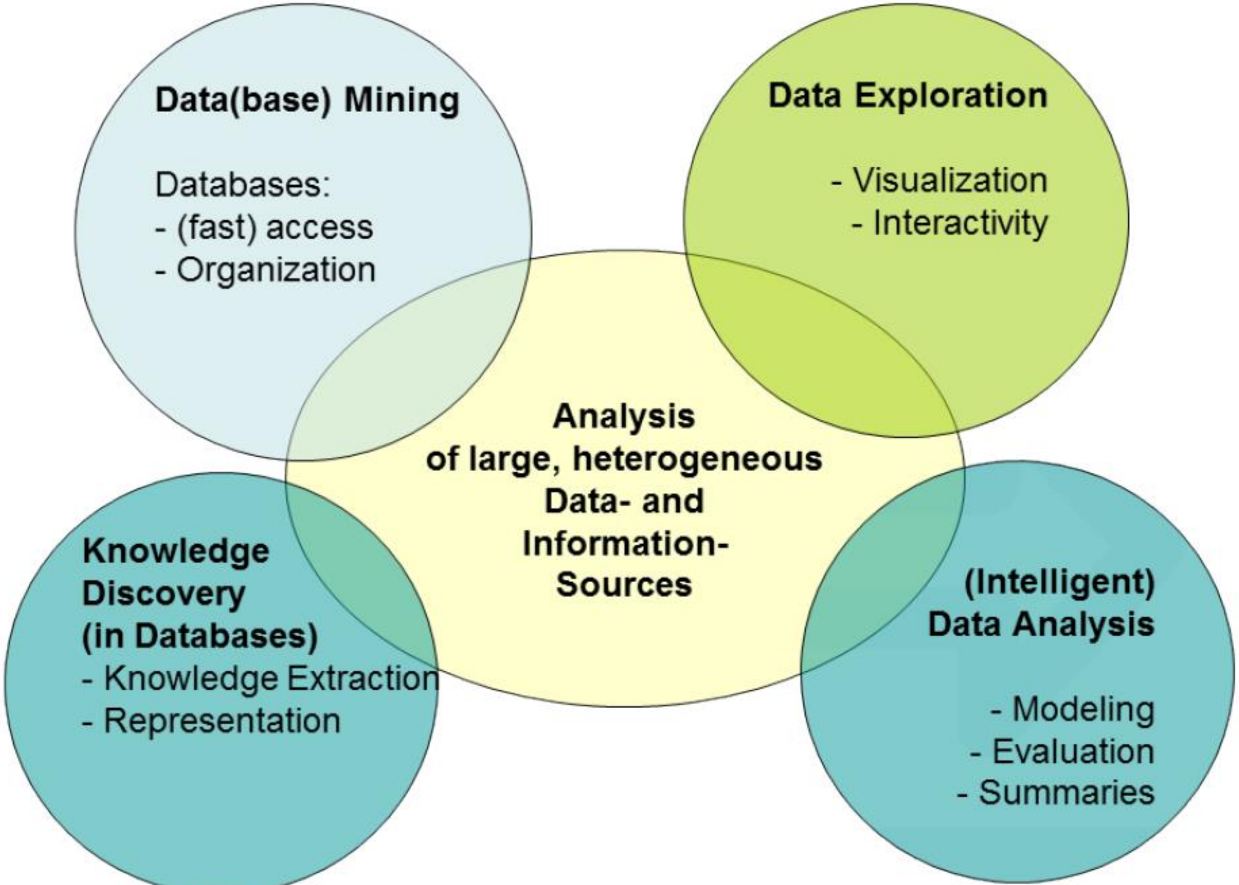
- **History: Table based Analysis**

- Data points are stored in tables, often recorded in spread sheets
- Simple analyses performed automatically on demand (calculate mean, add columns, ...)
- Visicalc, ...

- **Today: Large Scale Mining**

- Data in various formats and from various sources
- manual analysis impossible
- efficient compute support essential
- analysis still question driven:
  - find patterns of this type
  - check correlations
  - build model to predict this behaviour

# Terminology



# One final Word of Warning

# Correlation $\not\Rightarrow$ Causality

Hypothesis: Storks bring babies

And the data?

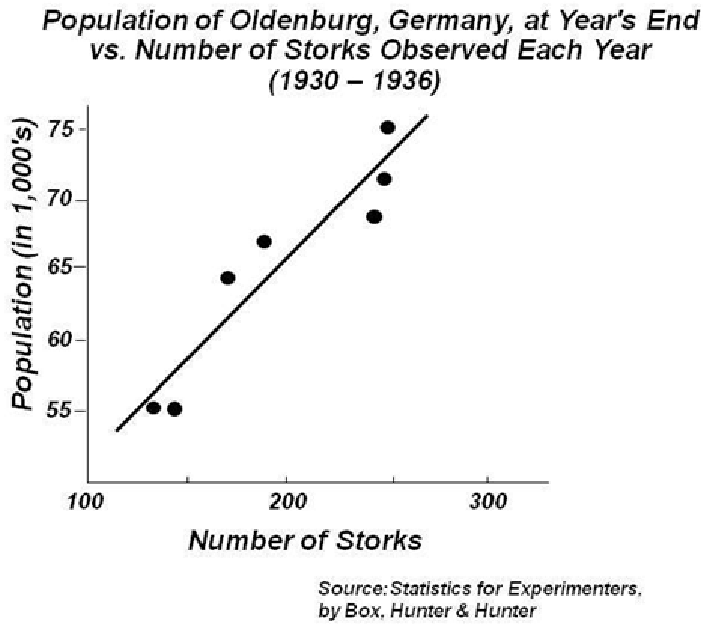
Hypothesis: Storks bring babies

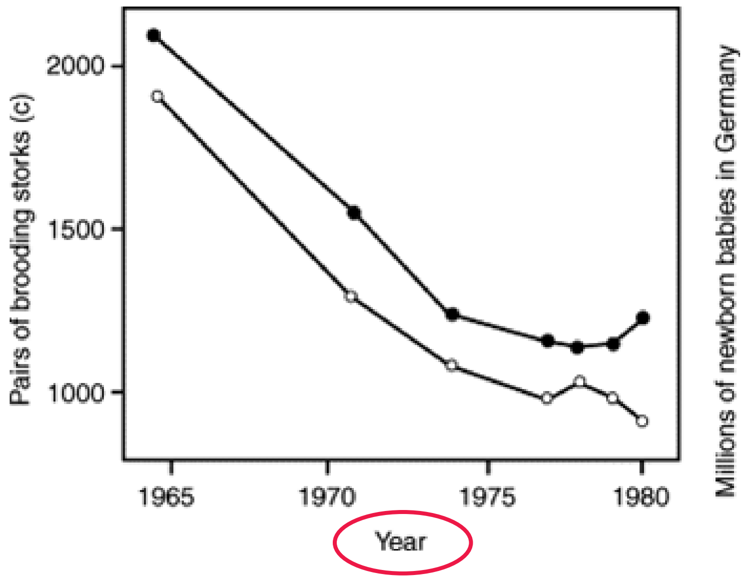
And the data?


Correlation is significant and positive!

Hypothesis: Storks bring babies

And the data?

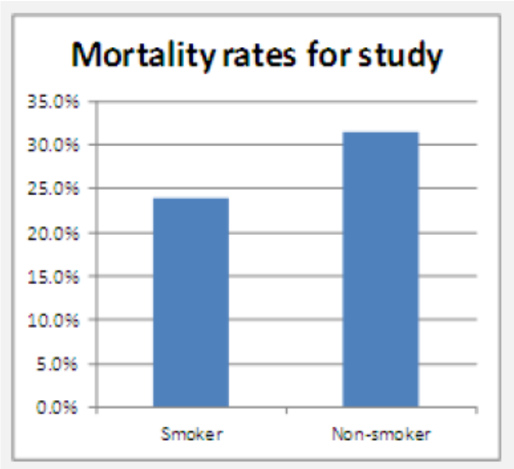



Correlation is significant and positive!

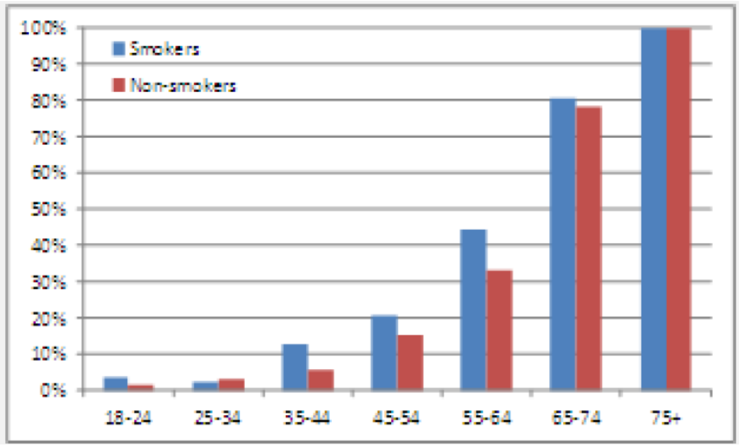
- Should I start smoking to live longer?
- **Mortality Rate Study**

| | Died | Survived | Total | Rate |
|---|---|---|---|---|
| Smokers | 139 | 443 | 582 | 23.9% |
| Non Smokers | 230 | 502 | 732 | 31.4% |
| Total | 369 | 945 | 1314 | 28.1% |

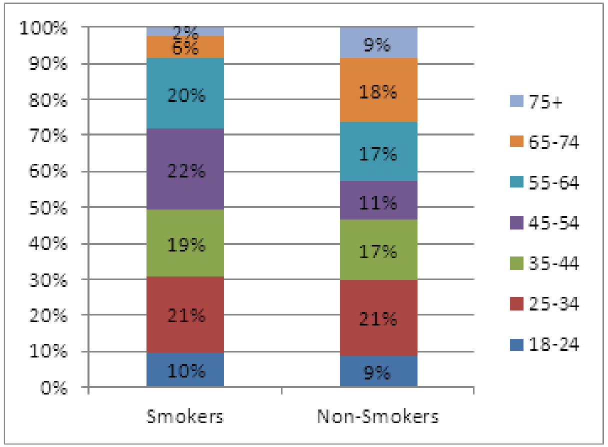



Credit: http://www.significancemagazine.org/details/webexclusive/2671151/

## Mortality Rates by Age




## Distribution of Age by Smoking Status




Credit: http://www.significancemagazine.org/details/webexclusive/2671151/

Simpsons-Paradox-A-Cautionary-Tale-in-Advanced-Analytics.html

# Simpson‘s Paradox

| | Tax Rate | | % of total income | |
|---|---|---|---|---|
| **Adjusted gross income** | **1974** | **1978** | **1974** | **1987** |
| Under $5000 | 0.054 | 0.035 | 4.73 | 1.60 |
| $5000 - $9999 | 0.093 | 0.072 | 16.63 | 9.89 |
| $10000 - $14999 | 0.111 | 0.100 | 21.89 | 13.83 |
| $15000 - $99999 | 0.160 | 0.159 | 53.40 | 69.62 |
| $100000 and more | 0.384 | 0.383 | 3.34 | 5.06 |
| **Total** | **0.141** | **0.152** | **100** | **100** |

Table Credit: Counting for Something by William S. Peters

. . . does the overall tax rate go up, while all individual rates go down?

## and what about Chocolate and Nobel prices?

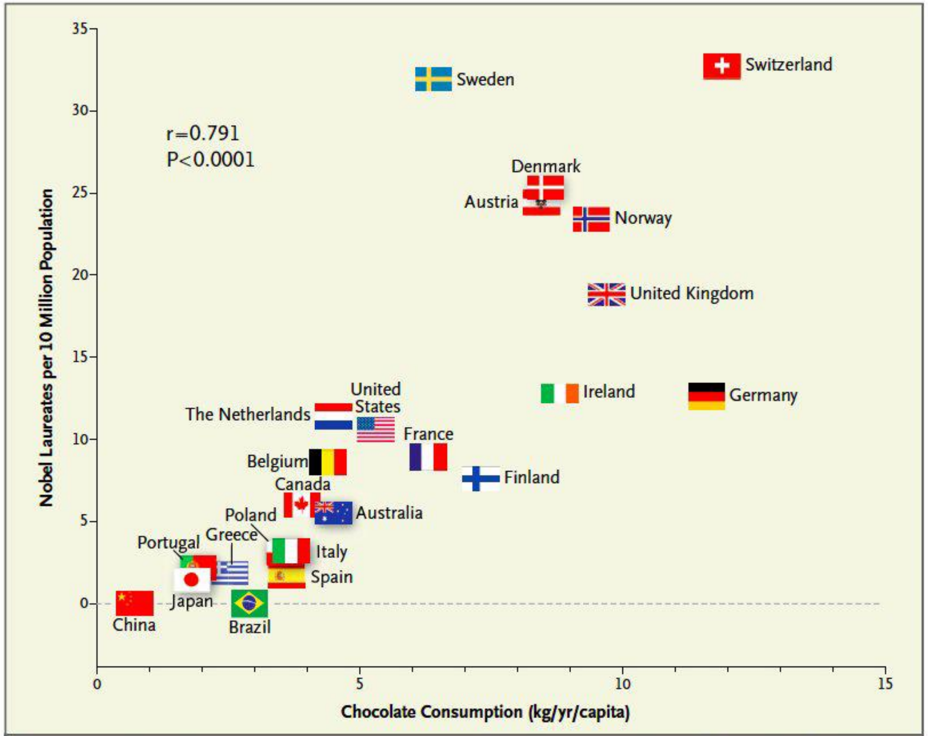



**Figure 1.** Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.

Image Credit: http://www.nejm.org/doi/full/10.1056/NEJMon1211064

# Do not trust your numbers!

**Tymans's Law**

Any statistic that appears interesting is almost certainly a mistake.

# What you have learned

- The different kind of projects
  - Common Use Cases
  - Search strategies
- The steps in project understanding
- The different kinds of datasets
- The steps in data understanding
  - ETL
  - Describing your Data
  - Finding Patterns
  - Finding Models
  - Finding Predictors
- A tiny bit of History
- Correlation vs. Causality

For any questions please contact: email@email.com