



# Business Intelligence


## 05a Data Mining Introduction (continued)

Prof. Dr. Bastian Amberg  
(summer term 2024)  
15.5.2024

# Schedule

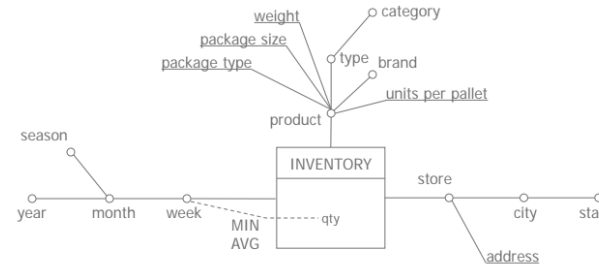
14.30 - 16<sup>00</sup>



	Wed., 10:00-12:00			Fr., 14:00-16:00 (Start at 14:30)		Self-study	
Basics	W1	17.4.	(Meta-)Introduction	19.4.		Python-Basics	Chap. 1
	W2	24.4.	Data Warehouse – Overview & OLAP	26.4.	[Blockveranstaltung SE Prof. Gersch]		Chap. 2
	W3	1.5.		3.5.	Data Warehouse Modeling I 		Chap. 3
	W4	8.5.	Data Warehouse Modeling I & II	10.5.	Data Mining Introduction		
Main Part	W5	15.5.	CRISP-DM, Project understanding	17.5.	Python-Basics-Online Exercise	Python-Analytics	Chap. 1
	W6	22.5.	Data Understanding, Data Visualization	24.5.	No lectures, but bonus tasks 1.) Co-Create your exam 2.) Earn bonus points for the exam		Chap. 2
	W7	29.5.	Data Preparation	31.5.			
	W8	5.6.	Predictive Modeling I	7.6.	Predictive Modeling II (10:00 -12:00)	BI-Project	Start
	W9	12.6.	Fitting a Model I	14.6.	Python-Analytics-Online Exercise		
	W10	19.6.	Guest Lecture	21.6.	Fitting a Model II		
	W11	26.6.	How to avoid overfitting	28.6.	What is a good Model?		
	W12	3.7.	Project status update Evidence and Probabilities	5.7.	Similarity (and Clusters) From Machine to Deep Learning I		
Deepening	W13	10.7.		12.7.	From Machine to Deep Learning II		
	W14	17.7.	Project presentation	19.7.	Project presentation		End
Ref.					Klausur 1.Termin ~ 22.7. bis 3.8. Klausur 2.Termin ~ 23.9. bis 5.10.	Projektbericht	

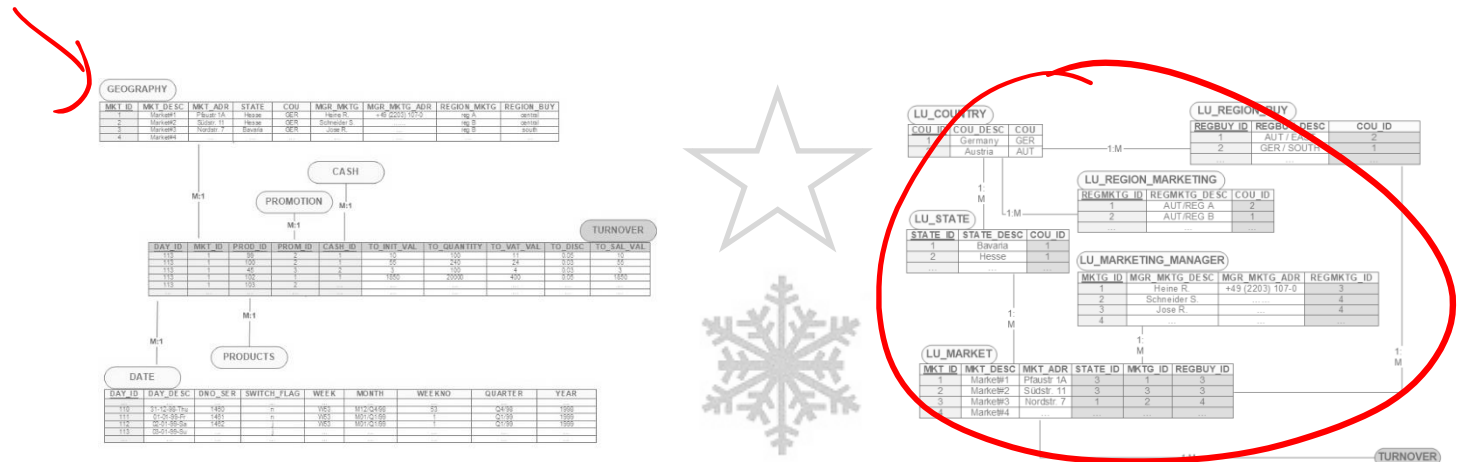
✓ How can multidimensional data models be developed and stored?

## Conceptual modeling



## Logical modeling

## Physical modeling



○ Introduction **Data Mining**

Where are the limits of the handling of data considered so far?

“Data mining is the analysis of (often large) observational data sets to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data owner.”  
(Hand, Mannila, Smyth (2001), Principles of Data Mining)



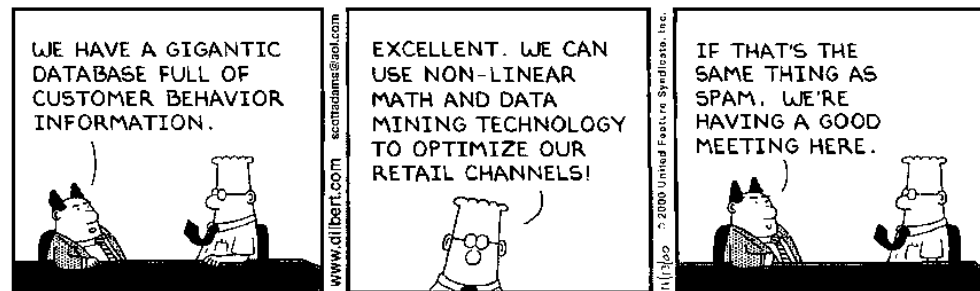
**(1) The need for data mining**



**(2) From business problems to data mining tasks**



**(3) Supervised vs. unsupervised methods**



# The need for data mining

“80% of the knowledge of interest in a business context can be extracted from data using **conventional tools**.” (Lusti)

- reporting
- query-languages (SQL, QBE, ...)
- OLAP and spreadsheets

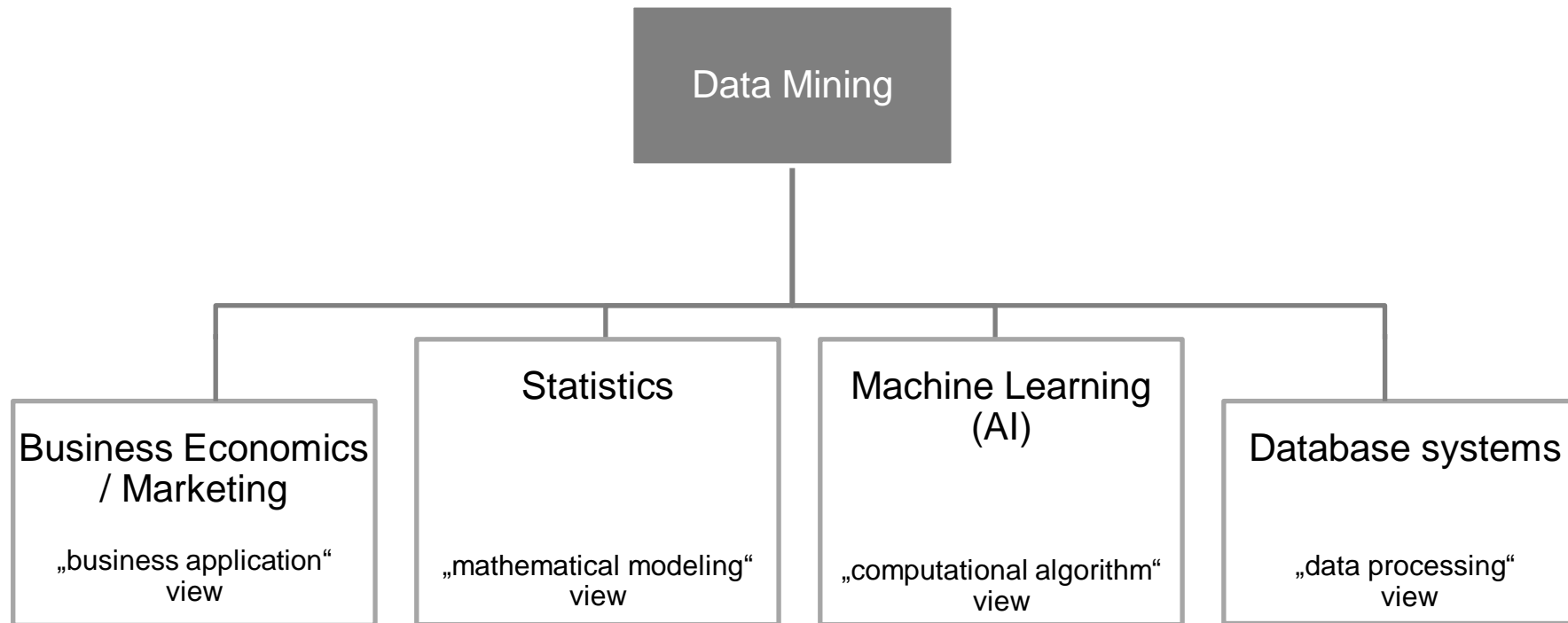


Phase ID	Description	Resource	Start Date	End Date	Resource ID
1.0 Phase	Initial planning, approval on the business requirement and defining the goals.	RFR			Project Manager
1.1 Milestone	Review the Business Requirement	RFR			
1.1.1 Task	Review the Product Requirement	Product Manager			
1.1.2 Task	Review the Business Requirement	Product Manager			
1.2 Milestone	Define the Product	RFR			
1.2.1 Task	Review the Product Definition	Product Manager			
1.2.2 Task	Review the Business Requirement	Product Manager			
1.3 Milestone	Define the Product	RFR			
1.3.1 Task	Review the Product Definition	Product Manager			
1.3.2 Task	Review the Business Requirement	Product Manager			
1.4 Milestone	Review the Business Requirement	RFR			
1.4.1 Task	Review the Business Requirement	Product Manager			
1.4.2 Task	Review the Business Requirement	Product Manager			
1.4.3 Task	Review the Business Requirement	Product Manager			
1.4.4 Task	Review the Business Requirement	Product Manager			
1.4.5 Task	Review the Business Requirement	Product Manager			
1.4.6 Task	Review the Business Requirement	Product Manager			
1.4.7 Task	Review the Business Requirement	Product Manager			
1.4.8 Task	Review the Business Requirement	Product Manager			
1.4.9 Task	Review the Business Requirement	Product Manager			
1.4.10 Task	Review the Business Requirement	Product Manager			
1.4.11 Task	Review the Business Requirement	Product Manager			
1.4.12 Task	Review the Business Requirement	Product Manager			
1.4.13 Task	Review the Business Requirement	Product Manager			
1.4.14 Task	Review the Business Requirement	Product Manager			
1.4.15 Task	Review the Business Requirement	Product Manager			
1.4.16 Task	Review the Business Requirement	Product Manager			
1.4.17 Task	Review the Business Requirement	Product Manager			
1.4.18 Task	Review the Business Requirement	Product Manager			
1.4.19 Task	Review the Business Requirement	Product Manager			
1.4.20 Task	Review the Business Requirement	Product Manager			

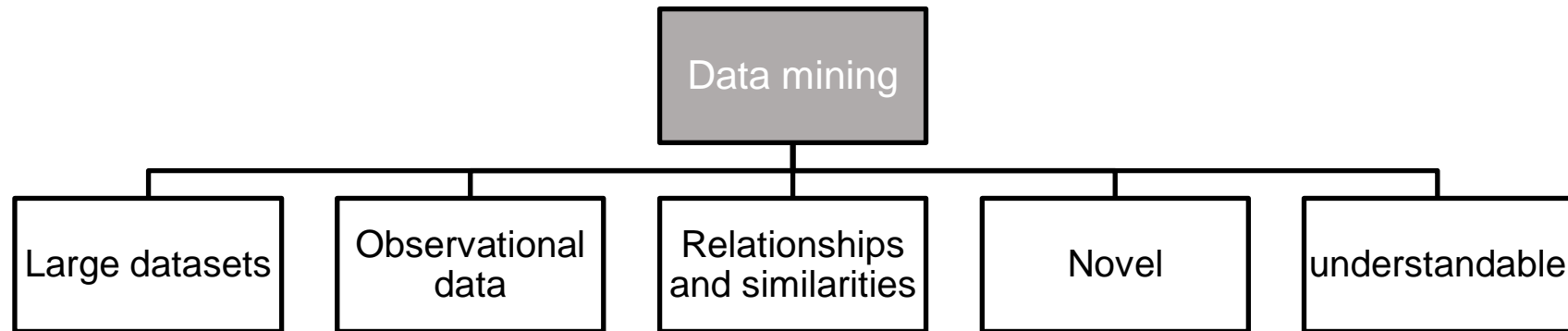
## Disadvantages of conventional tools:

- Often, merely simple questions can be answered
- OLAP: query-focused and low complexity of analysis  
*e.g., performance changes are visible, but what about the overall context/ reasons?*
- Automation of knowledge discovery is difficult  
*hypothesis needed*
- Only small amounts of data may be handled (esp. spreadsheets)  
*but exploding amount of raw data available*

# Major roots of data mining

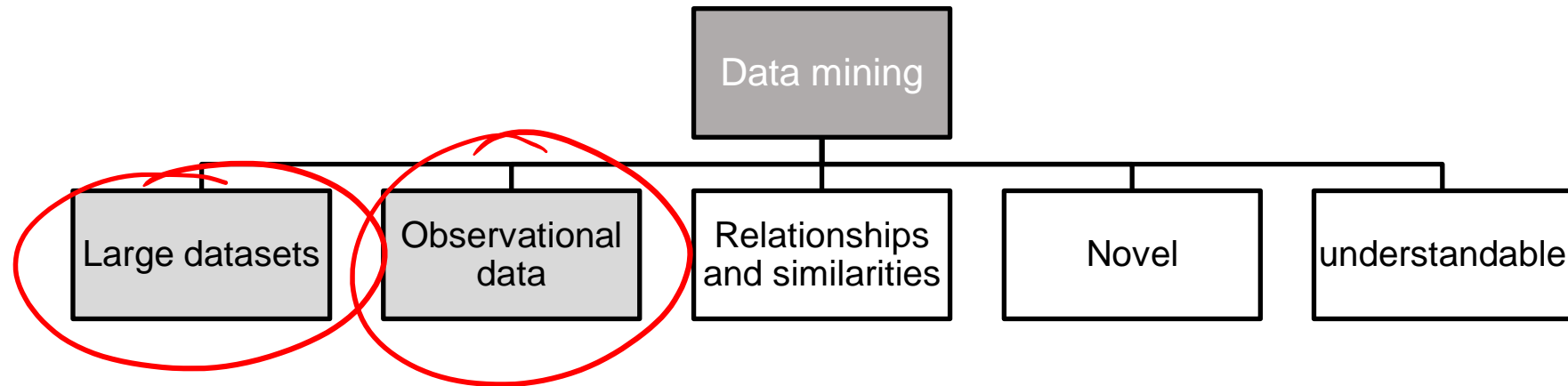


# Data mining: definition (1/3)



*“Data mining is the analysis of (often large) observational data sets to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data owner.”*

(Hand, Mannila, Smyth (2001), Principles of Data Mining)



## Often large datasets:

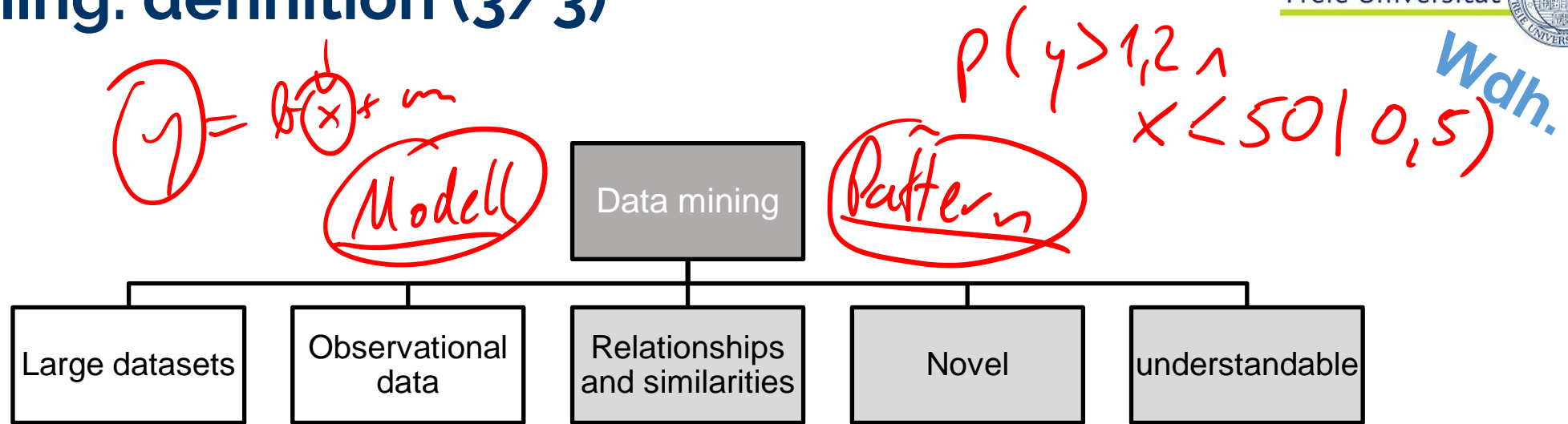
- Small datasets  $\Rightarrow$  exploratory data analysis in statistics
- Large datasets (as they exist in DWHs) provoke new problems
  - Storage and access of data
  - Runtime issues
  - Determination of representativeness of data
  - Difficulty to decide whether an apparent relationship is merely a chance occurrence or not

## Observational data:

- Data often collected for some other purpose than data mining
- Objectives of the data mining exercise play no role in data collection strategy
  - e.g., DWH data relying on an airline reservation system or a bank account administration system
- opposite: experimental data (as it is used quite often in statistics)



# Data mining: definition (3/3)



## Relationships and summaries:

often referred to as models or patterns  
e.g., linear equations, tree structures, clusters,  
patterns in time series, ...

## Understandable:

Novelty is not sufficient to qualify  
relationships worth finding  
Simple relationships may be preferred to  
complicated ones

## Novel:

Novelty should be measured relative to users prior  
knowledge

Problem understanding

# Exercise: Data Mining vs. OLAP

Typical questions

*Historie → Zukunft*

*Historie*

Fragestellung	<u>Data Mining</u>	<u>OLAP</u>
Kundenwert	Welche Kunden bieten uns das größte Deckungsbeitragspotenzial?	Wer waren letztes Jahr unsere 10 besten Kunden?

Kahoot-Fragen

[www.kahoot.it](http://www.kahoot.it)

(über Smartphone oder Laptop)  
PIN folgt

(Diese Folie ist nach der Vorlesung mit Lösungen verfügbar)

# A typical Data Mining Process

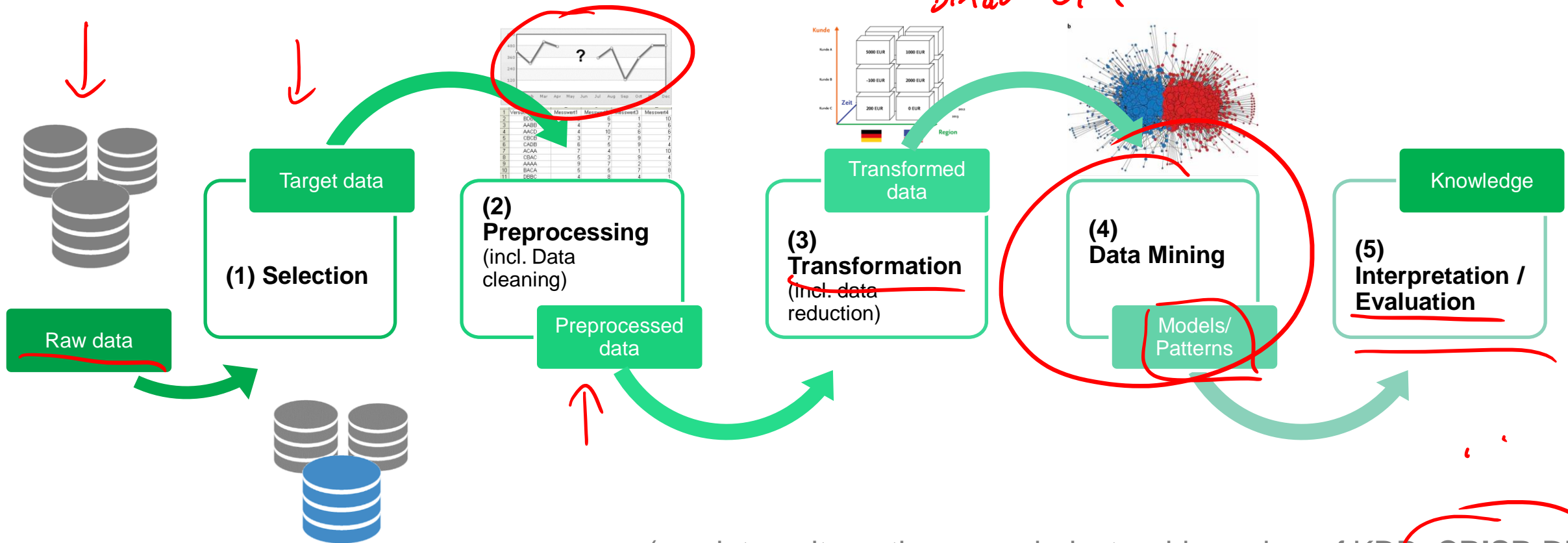
Knowledge discovery in databases (KDD)

Data mining is often set in the broader context of **knowledge discovery in databases** (KDD)

The precise boundaries of the data mining part within the KDD process are not easy to state

100 → Not < ⇒ Modell  
→ 80% Testen < 20%

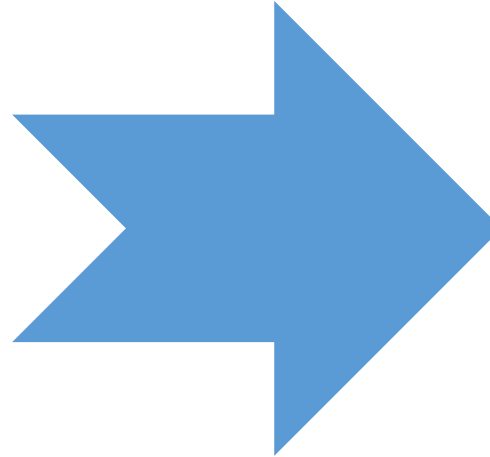
Binär 0/1



(see later: alternative, more industry-driven view of KDD: **CRISP-DM**)



(1) The need for data mining



**(2) From business problems to data mining tasks**



(3) Supervised vs. unsupervised methods

Data mining is a **process** with well-understood stages based on

- application of information technology
- analyst's creativity
- business knowledge
- common sense

Counterexample: Youtube ads, see e.g. [The Guardian, 2017](#)

*"Major brands ... pulled their ads after they were found to be appearing next to videos promoting extremist views or hate speech"*

We look at typical **tasks** and examples, then at the **process**

**Decompose** a data analytics problem into pieces such that you can solve a known task with a tool

There is a large number of data mining algorithms available, but only a limited number of data mining tasks

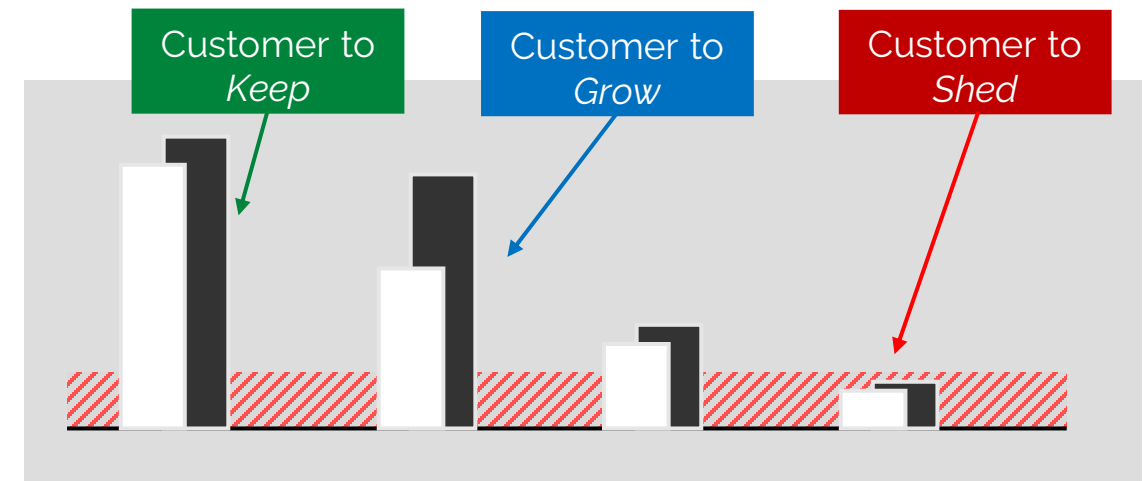
We will illustrate the **fundamental concepts** based on

- Classification
- Regression

Classification attempts to **predict**, for each individual in a population, which of a (small) *set of classes* that individual belongs to

*“Among all the customers of a cellphone company, which are likely to correspond to a given offer?”*  
~ predict whether something will happen

Classification algorithms provide models that determine which class a **new** individual belongs to (and its probability).



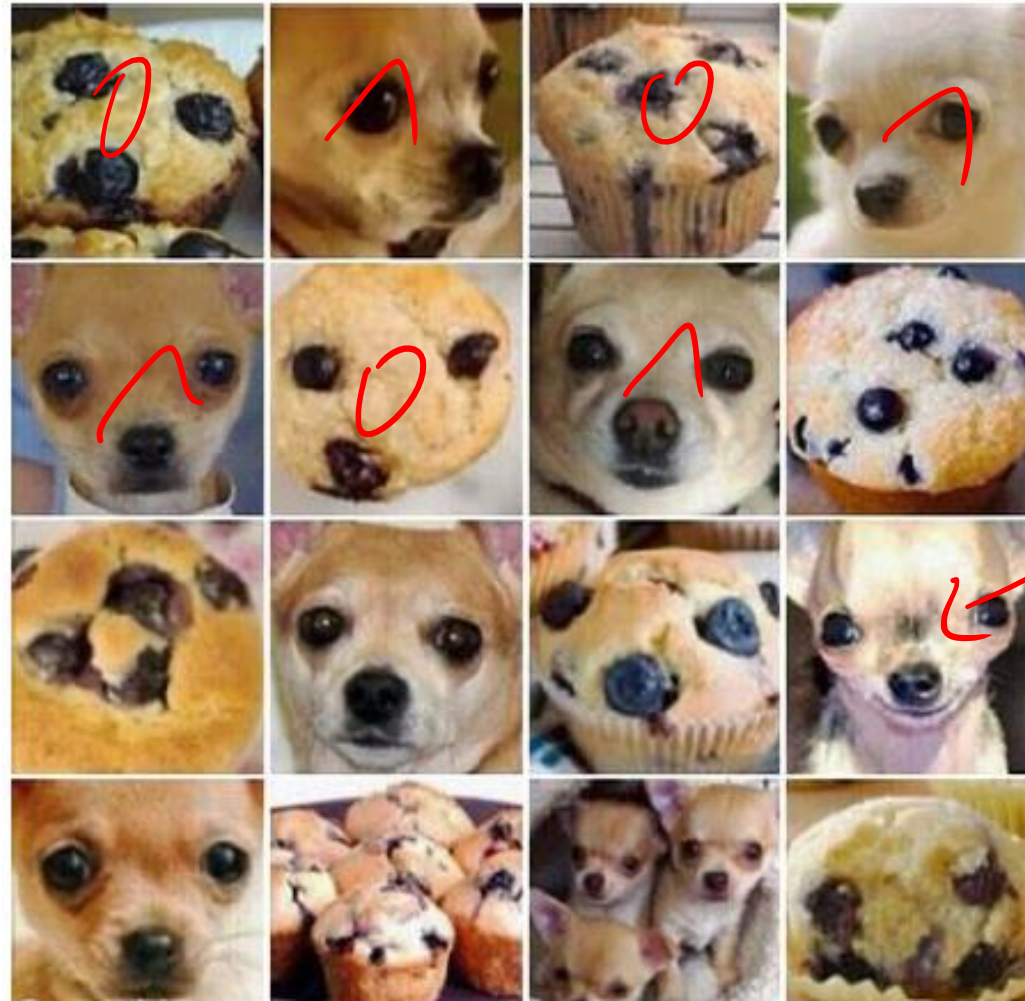
Classification is related to scoring (for instance in Customer Relationship Management) as the underlying value is categorical.

# Dog or Muffin?

1

0

Binär



Deep Learning required  
(we will talk about this in July)



# Regression

Regression (value estimation) attempts to estimate or **predict**, for each individual, the (continuous) *numerical value* for that individual

“How much will a given customer use the service?”

Predicted variable: service usage

~ predict how much something will happen

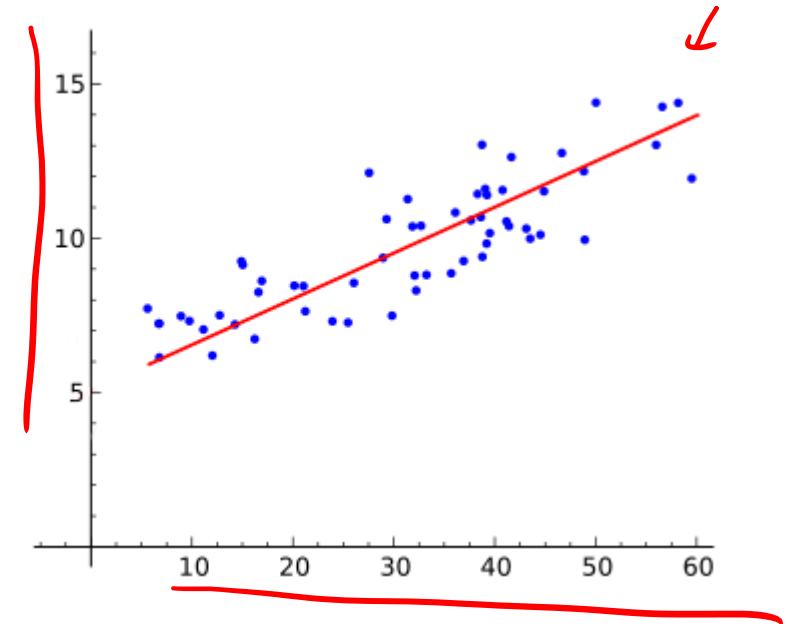
Generate regression model by looking at other, similar individuals in the population

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$$

Freie Universität



Berlin



Be careful:

linear regression vs. logistic regression



# Exercise: Classification or Regression problem?

## Examples

- a) Will this customer purchase service S1 if given incentive I?
- b) Which service package (S1, S2, or none) will a customer purchase if given incentive I?
- c) How much time will this customer spend on our web service?
- d) How long after buying a product can a repeat purchase by customer X be expected?
- e) Which potentially profitable customers are most likely to move to a competitor?

C Binär

C

R

R

C

~~Profitabilität~~  
Low Med High

Webse	Low	-	-	-
	Med	-	-	S2
	High	-	S2	S1

3 Min.

# Another fundamental data mining task: ....



Quelle: [www.welt.de](http://www.welt.de)

# .... Similarity matching

Similarity matching attempts to **identify similar individuals** based on the data known about the individuals

Find similar entities

Basis for making **product recommendations**

Find people who are similar to you in terms of the products they have liked or purchased

Distanzmaße  
Alter Einkommen  
p<sub>1</sub> 20 | 1 | 1 | 1 | 100000  
p<sub>2</sub> 21 | 1 | 1 | 1 | 80000  
 $21 - 20 = 1$   
20.000

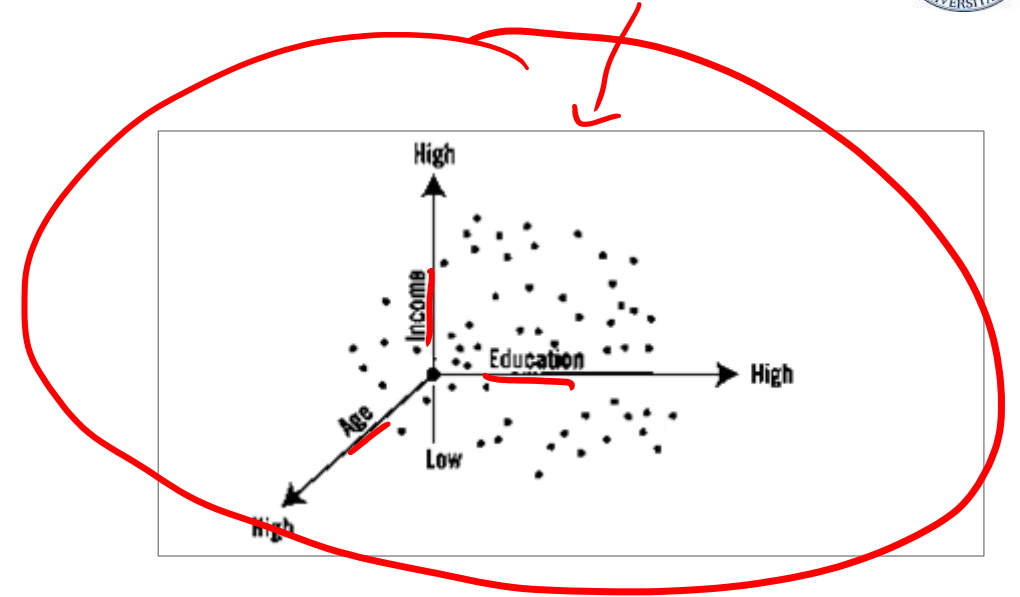


# Clustering

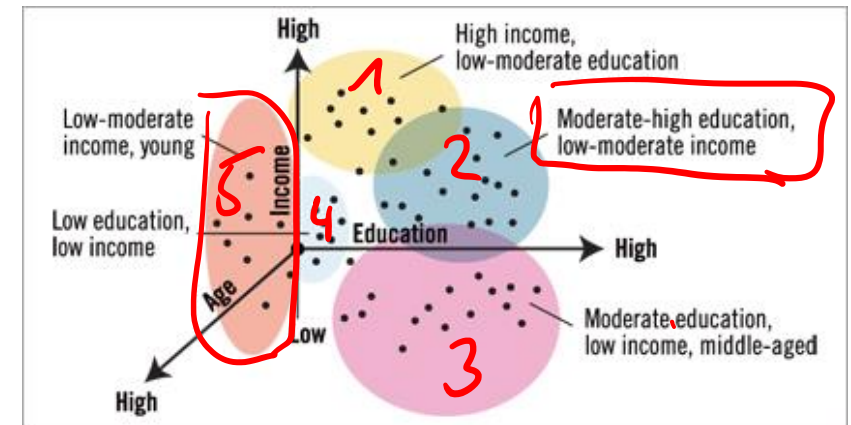
Clustering attempts to **group** individuals in a population together by their similarity, but *without regard to any specific purpose*

Do customers form natural groups or segments?

Result: groupings of the individuals of a population



Useful in preliminary domain exploration





# Co-occurrence grouping

Attempts to find associations between entities based on transactions involving them aka **association rules** or **market-basket analysis**

*“What items are commonly purchased together?”*

Considers similarity of objects based on their appearing together in transactions

Included in recommendation systems (people who bought X also bought Y)

Result: a description of items that occur together



Wird oft zusammen gekauft



Gesamtpreis: EUR 95,23

Alle drei in den Einkaufswagen

This block shows a product recommendation from Amazon. It features three books: 'Data Science for Business' by Foster Provost & Tom Fawcett, 'storytelling with data' by Cole Nussbaumer Knaflic, and 'Practical Statistics for Data Scientists' by Peter Bruce & Andrew Bruce. The books are displayed with their covers and are separated by plus signs. Above them is the text 'Wird oft zusammen gekauft' (Often bought together). To the right, the total price is listed as 'Gesamtpreis: EUR 95,23' and a button says 'Alle drei in den Einkaufswagen' (Add all three to the shopping cart).

Customers who bought this item also bought



Smeg 1.7-Liter Kettle-Pink  
★★★★☆ 56  
\$129.95 Prime

Cuisinart DLC-2A Mini-Prep Plus Food Processor, 24 Ounce, Pink  
DISCONTINUED BY...  
★★★★☆ 666  
\$39.95 Prime

KitchenAid KHM512PK 5-Speed Ultra Power Hand Mixer, Pink  
★★★★☆ 1,921  
Click for details Prime

Smeg 1.7-Liter Kettle-Pastel Green  
★★★★☆ 56  
\$129.95 Prime

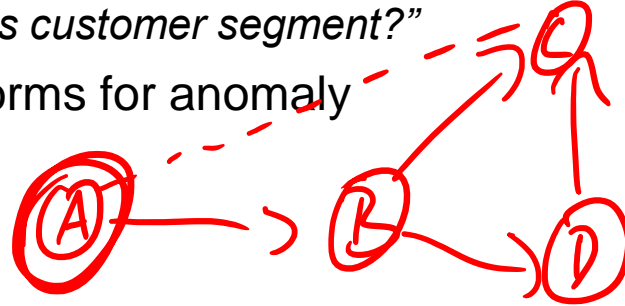
This block shows a 'Customers who bought this item also bought' section from Amazon. It displays four kitchen appliances: a pink Smeg kettle, a pink Cuisinart food processor, a pink KitchenAid hand mixer, and a pastel green Smeg kettle. Each item is shown with its image, name, star rating, number of reviews, and price. The KitchenAid mixer has a 'Click for details' link and a Prime badge.

# Some more data mining tasks

- **Profiling** attempts to characterize the typical behavior of a group or population, aka **behavior description**

*“What is the typical cellphone usage of this customer segment?”*

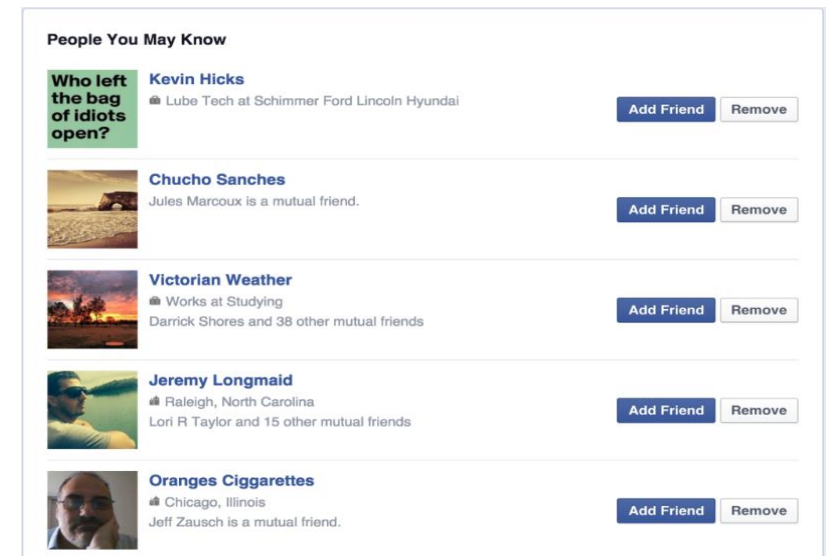
Often used to establish behavioral norms for anomaly detection (fraud detection)



- **Link prediction** attempts to predict connections between data items (→ social network systems)

*“Since you and Karen share ten friends, maybe you’d like to be Karen’s friend?”*

- **Data reduction** attempts to take a large data set of data and replace it with a smaller set of data that contains the relevant information  
(Easier processing, but often loss of information)

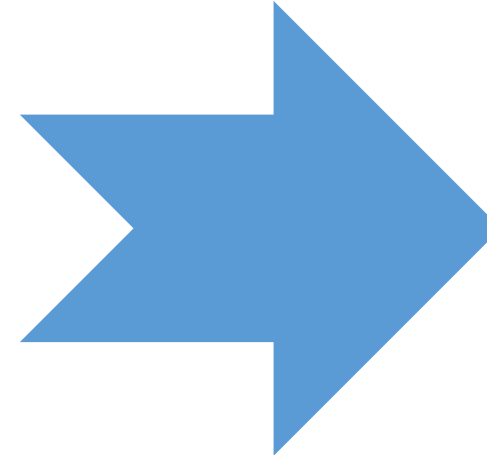




(1) The need for data mining



(2) From business problems to data mining tasks



**(3) Supervised vs. unsupervised methods**

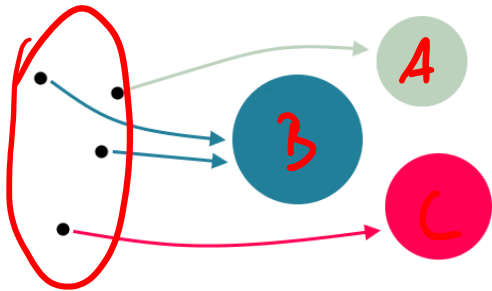
# Supervised vs. unsupervised

Überwachtes Lernen

## Supervised Learning

“Can we find groups of customers who have particularly high likelihoods of cancelling their service soon after their contracts expire?”

→ specific target ↓ *Classification*



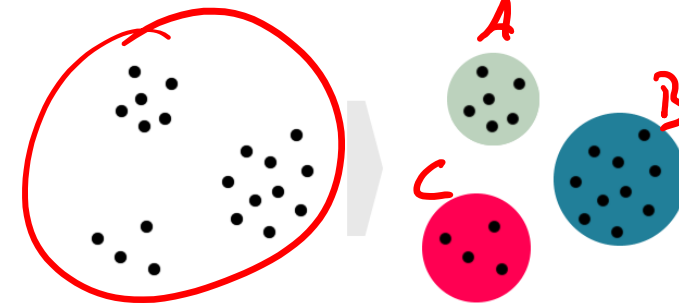
*input → output*  
Supervised and unsupervised tasks require different techniques  
*Person → gut, schlechter Anschluss*

Unüberwachtes Lernen

## Unsupervised Learning

“Do our customers naturally fall into different groups?”

↓ *Clustering*  
→ no specific target



*Person*  
There is no guarantee that unsupervised tasks provide meaningful results

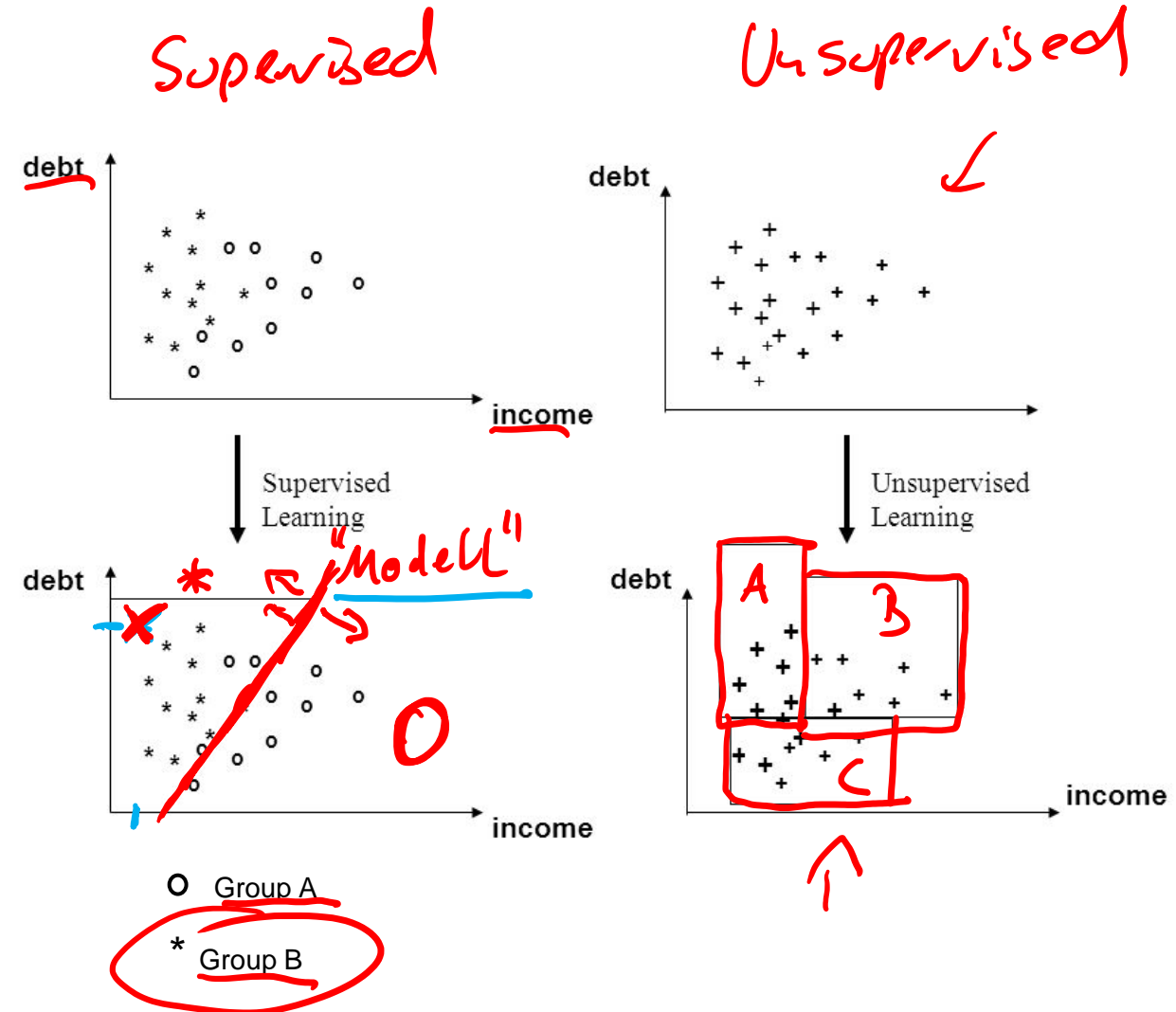


# Supervised and unsupervised techniques

Classification and regression are generally solved with **supervised** techniques

Clustering, co-occurrence grouping, and profiling are generally **unsupervised**

Similarity matching and link prediction could be either



# Supervised vs. Unsupervised vs. Reinforcement Learning

Search by yourself

e.g. <https://towardsdatascience.com/machine-learning-101-supervised-unsupervised-reinforcement-beyond-f18e722069bc> ←

Learning

Approach

Learn from.... (input? - output?)

Learn for.... (target?)

Example?

Supervised

Unsupervised

Reinforcement

e.g., Spiegel Online, 2021

“KI zockt besser als der Mensch“

Corresponding article

Ecoffet, A., Huizinga, J., Lehman, J. et al.

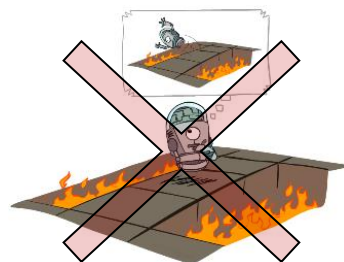
First return, then explore.

Nature 590, 580–586 (2021).

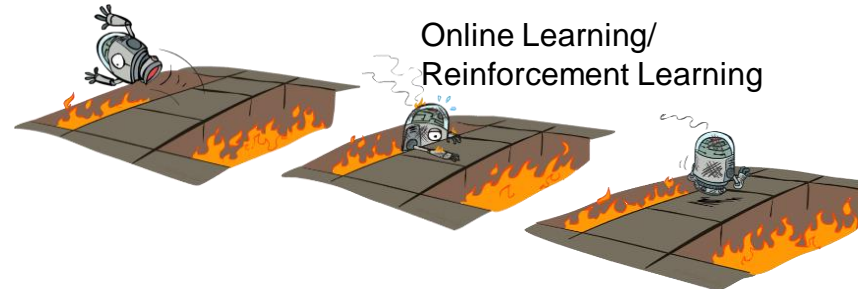
- [A.I. Learns to Drive From Scratch in Trackmania](#)  
(very well explained youtube video)

- [Demo Reinforcement Learning](#)

Ref.



Offline Solution  
(model based)



Quelle: Course188 Intro to AI at UC Berkeley

10 Min.

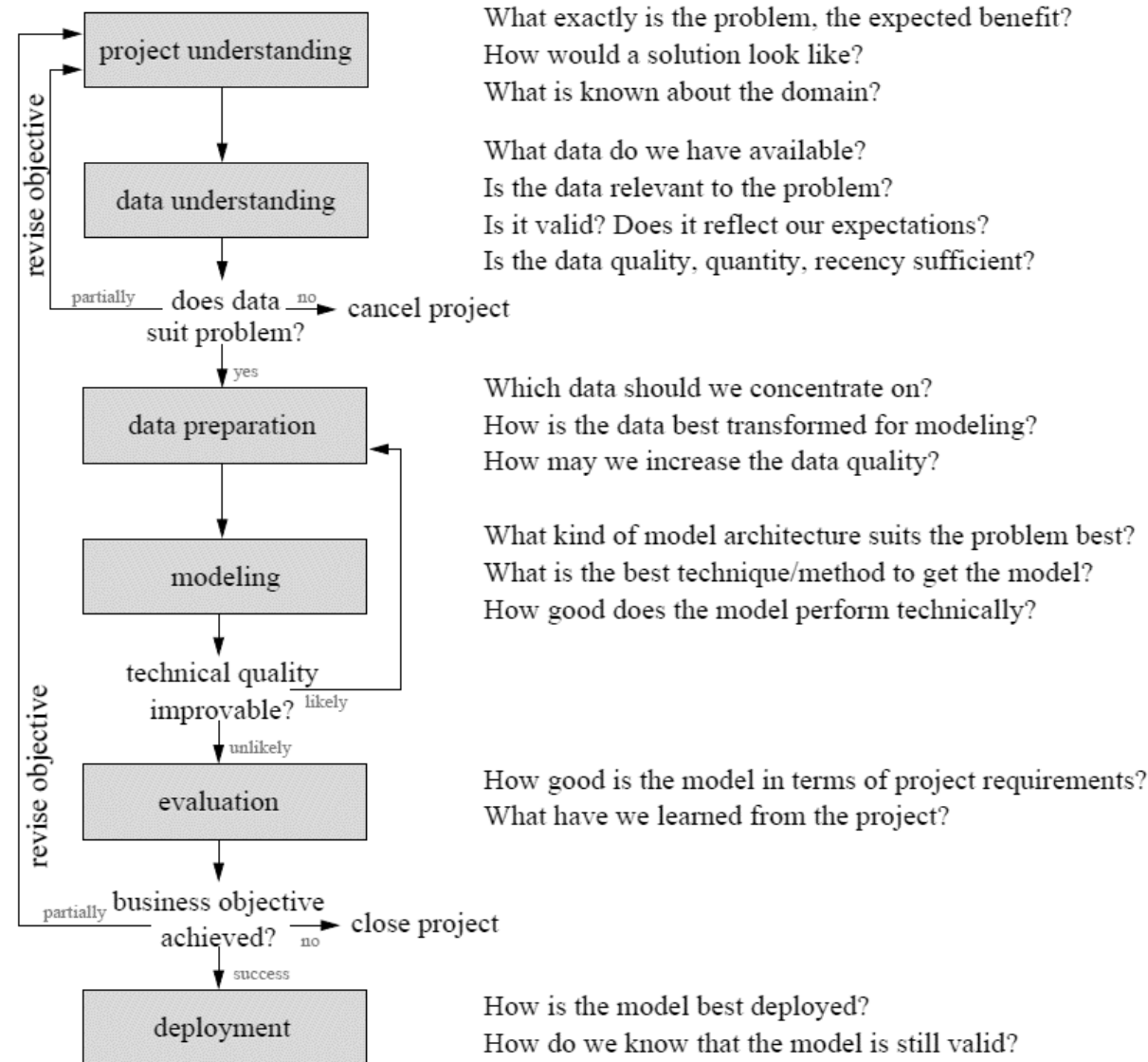
# Outlook: The data mining process - CRISP-DM

Cross  
Industry  
Standard  
Process for  
Data  
Mining

Iteration as  
a rule

Process of data  
exploration

Implementation of the  
KDD Process



## Fragen?

- ✓ The need for data mining
- ✓ From business problems to data mining tasks
- ✓ Supervised vs. unsupervised methods (vs. reinforcement learning)
- The data mining process – CRISP-DM

Provost, F.            Chapter 2  
Fawcett, T.

Berthold et al.      Chapters 1, B, C

Lusti, M.            Data Warehousing und Data Mining (Chapter 6)

Hand, D. et al.:    Principles of Data Mining (esp. Chapters 1, 5, 6 and 11)

- Azevedo, A. I. R. L. (2008). KDD, SEMMA and CRISP-DM: a parallel overview. *IADS-DM*.
- Ecoffet, A., Huizinga, J., Lehman, J. *et al.* (2021) First return, then explore. *Nature* 590, 580–586. <https://doi.org/10.1038/s41586-020-03157-9>
- Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). From data mining to knowledge discovery in databases. *AI magazine*, 17(3), 37.
- Hand, David J., Heikki Mannila, and Padhraic Smyth. *Principles of data mining*. MIT press, 2001.
- Wirth, R., & Hipp, J. (2000, April). CRISP-DM: Towards a standard process model for data mining. In *Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining* (pp. 29-39).