

## **Business Intelligence**

04 Data Warehouse Modeling II

& First Short Introduction to Data Mining

Prof. Dr. Bastian Amberg (summer term 2024) 10.5.2024

### Schedule



		Wed., 10:00-12:00				Fr., 14:00-16:00 (Start at 14:30)	Self-study	
	W1	17.4.	17.4. (Meta-)Introduction		19.4.		Python-Basics	Chap. 1
	W2	24.4.	Data Warehouse – Overview & O	DLAP :	26.4.	[Blockveranstaltung SE Prof. Gersch]		Chap. 2
Basics	W3	1.5.			3.5.	Data Warehouse Modeling I		Chap. 3
	W4	8.5.	Data Warehouse Modeling I & II		10.5.	Data Mining Introduction		
	W5	15.5.	CRISP-DM, Project understandi	ing	17.5.	Python-Basics-Online Exercise	Python-Analytics	Chap. 1
	W6	22.5.	Data Understanding, Data Visualiz	zation	24.5.	No lectures, but bonus tasks 1.) Co-Create your exam		Chap. 2
	W7	29.5.	Data Preparation		31.5.	2.) Earn bonus points for the exam		
lain art	W8	5.6.	Predictive Modeling I		7.6.	Predictive Modeling II (10:00 -12:00)	BI-Project	Start
art	W9	12.6.	Fitting a Model I		14.6.	Python-Analytics-Online Exercise		1
	W10	19.6.	Guest Lecture	:	21.6.	Fitting a Model II		1
	W11	26.6.	How to avoid overfitting		28.6.	What is a good Model?		1
eep-	W12	3.7.	Project status update Evidence and Probabilities		5.7.	Similarity (and Clusters) From Machine to Deep Learning I		
ning	W13	10.7.			12.7.	From Machine to Deep Learning II		1
	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.	Projektberi	cht

2

#### Last lesson

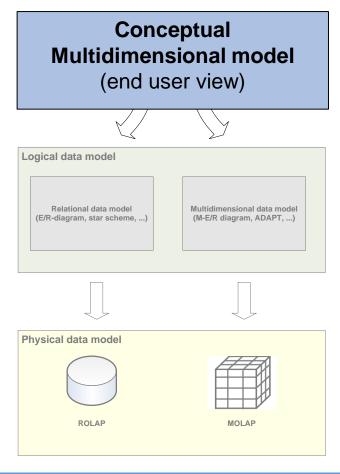


US. OLTP

- ✓ Online Analytical Processing (OLAP)
- ✓ How can multidimensional data models be developed and stored?
  - 1. Identify facts and dimensions
  - 2. Create a conceptual data model

3. Derive a **logical** data model from the semantic model

4. Derive a **physical** data model from the logical model



Dimension = finite set of categories which are semantically related to each other with respect to business matters

Categories of one dimension represent a different levels of aggregation of the associated business measures (facts)

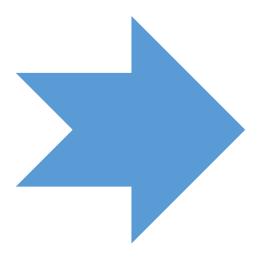
For example, dimension "date"
Four categories: day ⇒ month ⇒ quarter ⇒ year



Ref.

### Agenda





## **Continuation Data Warehouse Modeling**

Basic Elements of multidimensional modeling

#### **Conceptual modeling**

Logical modeling

Physical modeling

### **Conceptual Modeling**

Dimensional fact model (or fact scheme)

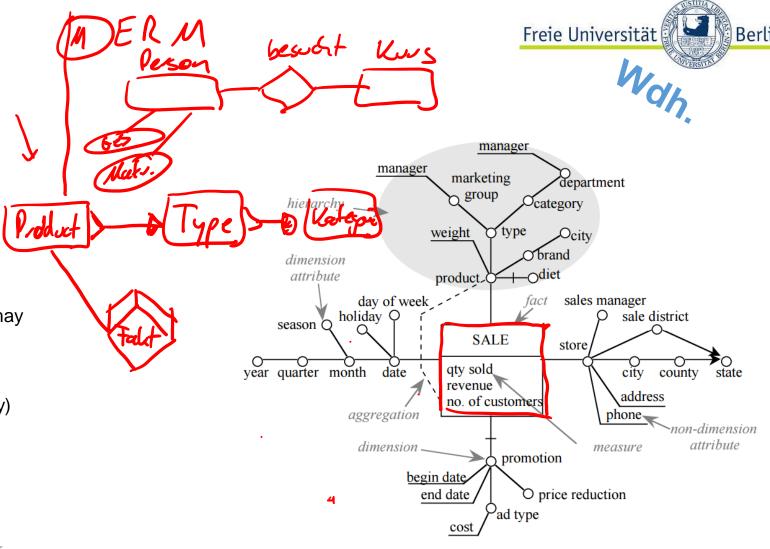
Categories of a dimension arranged in a non-cyclic graph, directed between allcategory and log-categories

Categories can have an arbitrary number of (non recursive) relations between each other

Several aggregation paths (e.g., sum/count/mean) may be included in the graph

Hierarchies are discrete attributes and define the granularities of facts (i.e., product -> type -> category)





Ref. Golfarelli et al. (1998), helpful reading (with exercises) by A. Prosser & M.-L. Ossimitz, Hahne (2006)

Image: see ref. (link), Matteo.golfarelli (2010) | Wikimedia

#### Non-& Cross-dimensional attributes

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#### Dimensional fact model

There may be various types of relations between individual categories of one (or more) dimension(s)

Categories having 1:1 relations can be summarized into a single category

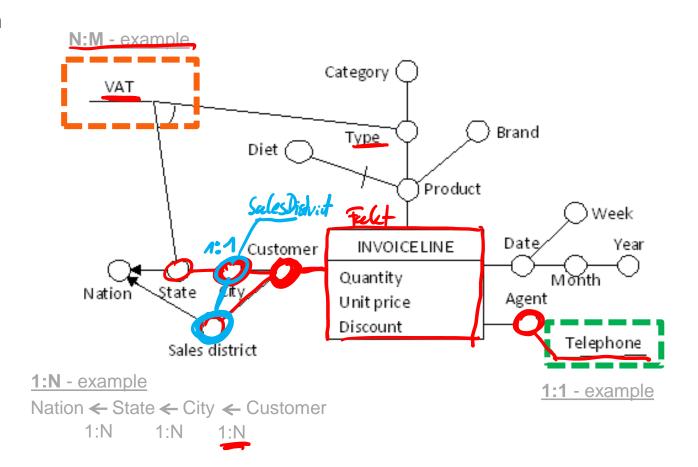
When previous categories become non-dimensional, descriptive attributes

Non-dimensional attributes provide additional information and have 1:1 relations with the corresponding categories (phone-No. cannot be aggregated)

OLAP-compliant queries encompassing non dimensional attributes are generally not supported

#### Categories having **1:N** or N:M relations

When value is defined by multiple categories (e.g., product type and state. For instance, VAT for water or books in Germany's. USA) they become cross-dimensional attributes.



#### **Exercise**

Conceptual Modeling (Dimensional fact model)

Design a **conceptual model** for the local Food Company:

### Conny's Corner Shop

Your managers need to keep themselves up to date on the number of items in the company's inventory. They especially want to keep an eye on their products with regards to location, and time.

Conny's Corner Shop sells a range of snacks and beverages. Both categories have different types of products, such as juices and water, as well as prezels and crackers.

- The products are sold under different brands.
- Products have different package types sizes, and weights.
- They store products in different stores across Europa

Dany:

Devolution of year

Month

Jon,

Jay Inventory

Store city skile (on December)

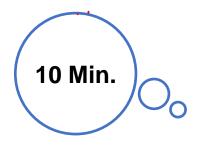
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Freie Universität

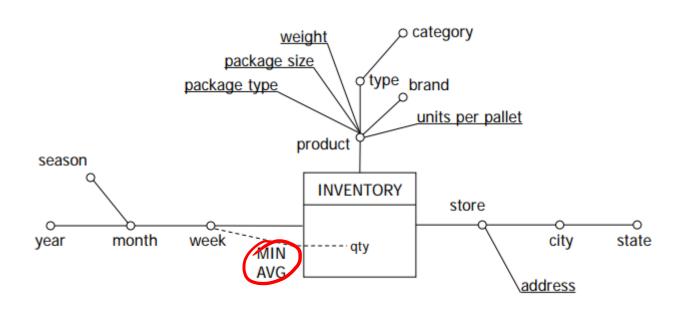
Show your conceptual model as a dimensional fact model. Make reasonable assumptions if necessary.

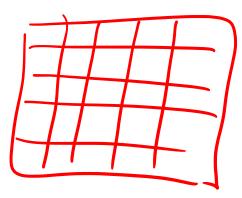


#### **Exercise**

#### One solution for the exercise







### **Identifying fact groups**

Single Star Scheme



A graphical overview should be created for each fact group

single star scheme

Distinction between materialized facts and derived facts should be drawn

High level of abstraction: aggregation formulas are commonly not modeled

cash date geography **TURNOVER** quantity pre-tax value (VAT) sales discounts sales value product range promotion revenues

Remember: **Fact group = set of facts** featuring *a common set* of dimensions

Ref.

### **Combining fact groups**

Multiple Star Scheme



A data warehouse data model encompasses a number of fact groups (multiple star scheme)
The sets of associated dimensions of different fact groups may overlap.

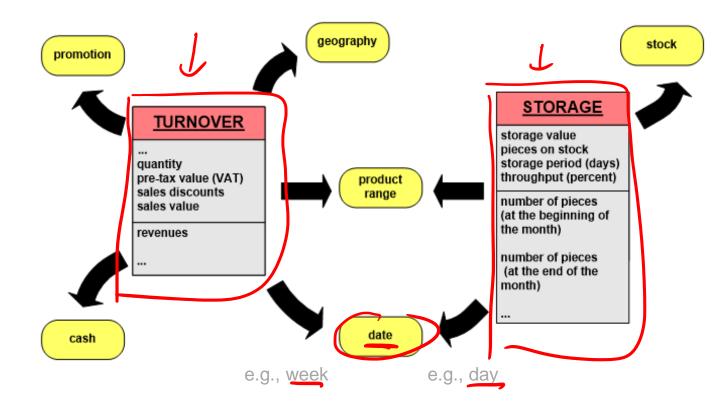
Different fact groups may use different logcategories with respect to one common dimension

e.g., actual / debit values:

Actual facts: log-category of dimension date: day

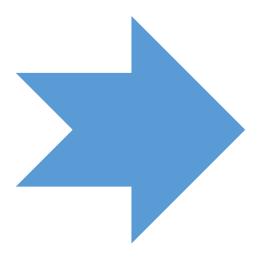
Target facts: log-category of dimension date: month

Category used as log-category should be specified in the model (at least if standard log-category is not used)



### Agenda





## **Continuation Data Warehouse Modeling**

Basic Elements of multidimensional modeling

Conceptual modeling

Logical modeling

Physical modeling

Ref.

### Basic tasks with logical modeling



**Logical modeling** is about adapting the general conceptual schema to the applied database technology

#### Relational database technology

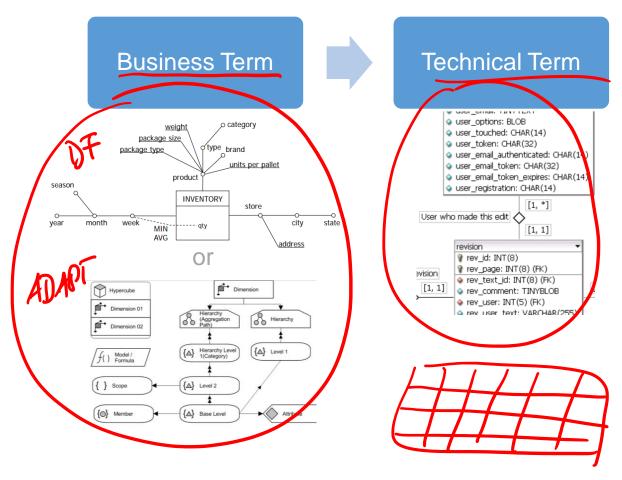
⇒ ER diagrams, ...

#### Multidimensional database technology

⇒ M-ER diagrams, ADAPT diagrams, ...

M-ER: Multidimensional Entity-Relationship
ADAPT: Application Design for Analytical Processing Technologies
(Both also usable as starting point for relational DB design)

Star Scheme is the standard way of logical modeling concerning relational DBMS









Properties of star scheme models

A number of fact tables are associated with a set of dimension tables each (via unique keys)

One dimension is mapped to exactly one relation

Primary key of a fact table consists of the keys of the associated dimensions

Keys of the dimension tables are usually "artificially" created (e.g. serial numbers)

1:m type relations between dimensions and facts

Typical "multi-join" query for star schemes:

```
D1.State_Province, D2.Month,

SUM (F1.Units_Sold)

FROM Dim_Store D1, Dim_Date D2, Fact_Sales F1

WHERE

D1.Id = F1.Store_Id AND

D2.Id = F1.Date_Id

GROUP BY D1.State_Province, D2.Month

Result?
```

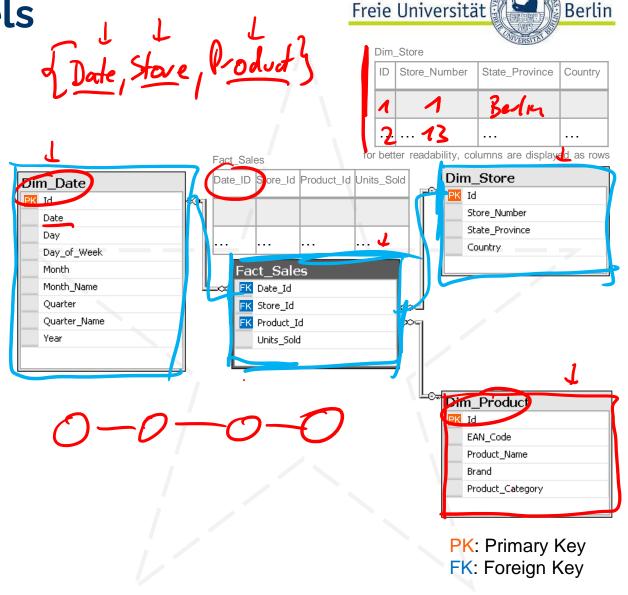
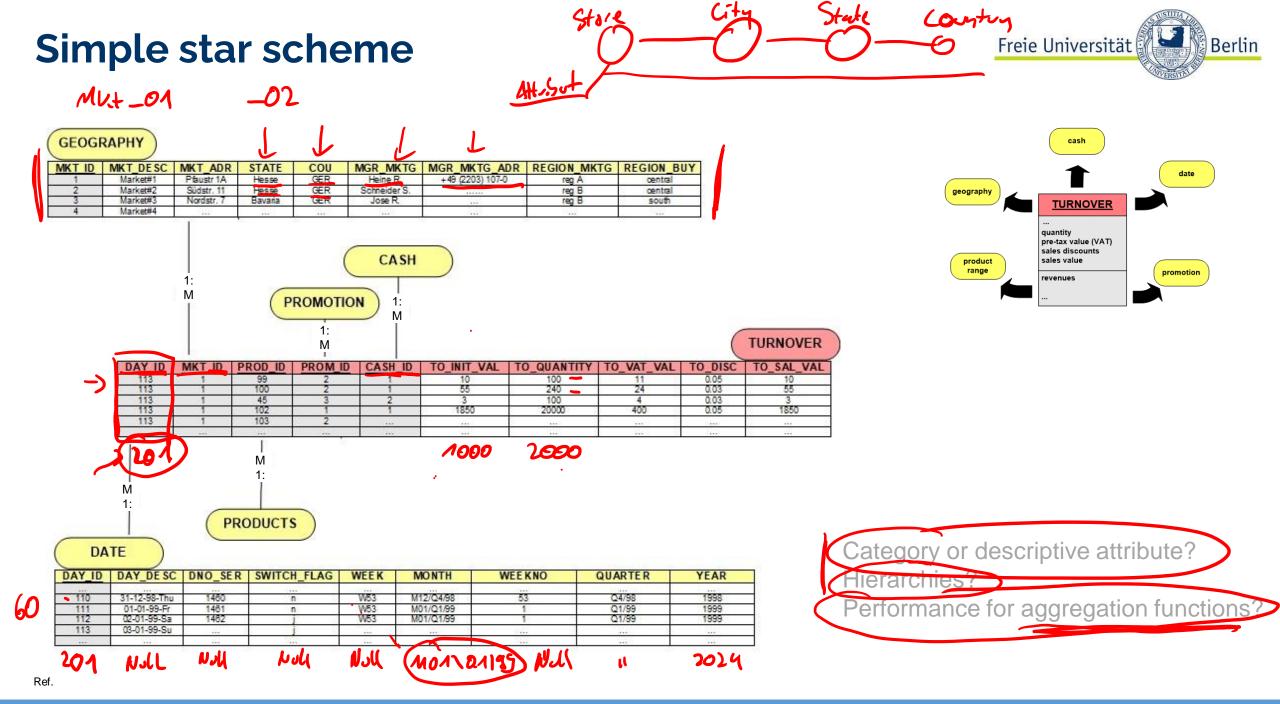


Image: SqlPac (2008) | Wikipedia (cc by-sa)



### Simple star schemes

**Pros and Cons** 



#### **PRO**

Simple, intuitive model

Not many physical join-operations needed

### Not many physical tables needed

- $\Rightarrow$  maintenance easy
- ⇒ Extract, Transform, Load (ETL) easy

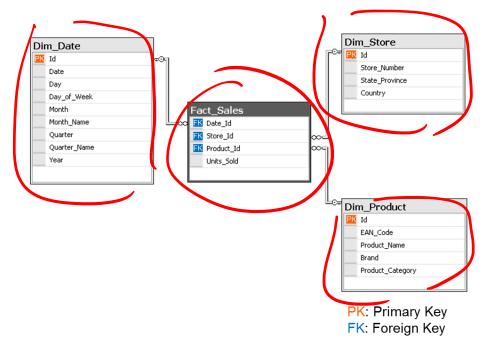
#### CON

Large dimension tables may cause bad response times

Creation of materialized views (aggregated summary tables) difficult ⇒ wrong aggregate values may be calculated due to multiple counting of entries

Changes of the conceptual model cause extensive reorganization efforts on the tables ⇒ versioning of meta data required

Redundancy



#### Variants of the star scheme



#### **Snowflake scheme:**

**Normalization** of the dimensional tables of a star scheme (see also example on next slide)

Dimensional tables are broken down into several small lookup-tables ⇒ no double entries

#### Consolidated star scheme:

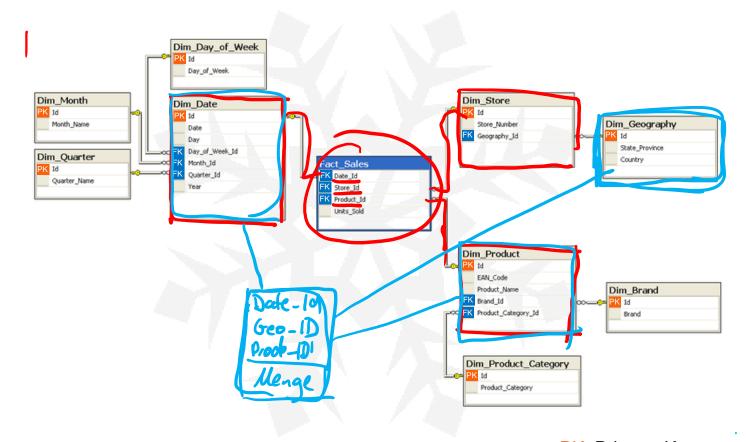
Basic idea: storage of aggregate values within the fact tables ("in-table aggregation")

Requires level attributes within the dimensional tables

Provides good response times ⇒ calculations displaced to ETL-procedure (extract, transform, load)

#### Fact constellation scheme:

Variant of consolidated star schemes (avoids level-attributes, uses additional fact tables for storage of aggregated values)

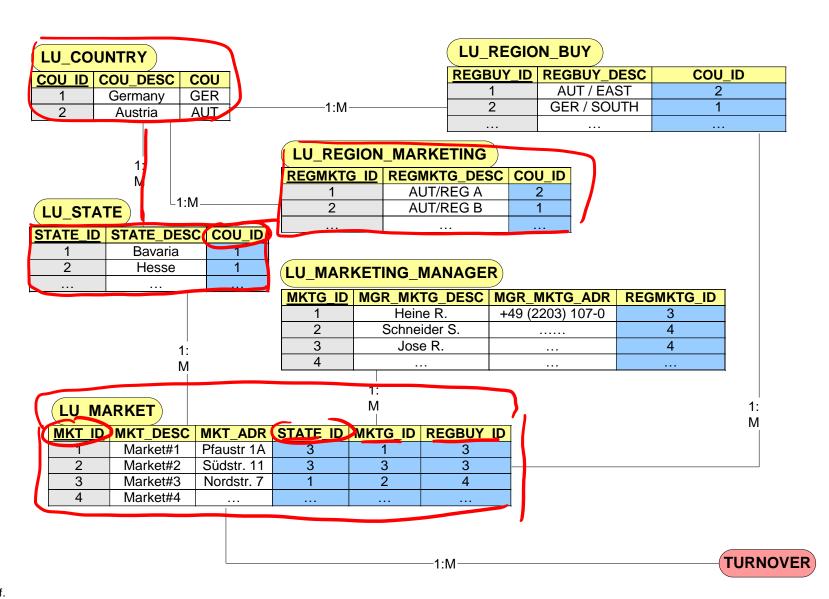


PK: Primary Key FK: Foreign Key

Image: Alan ffm (2012) | Wikimedia (cc by-sa 3.0)

#### Snowflake scheme





GEOGRAPHY

Hierarchies?

Storage of aggregated values?

#### Snowflake scheme

#### **Pros and Cons**



#### **PRO**

Good support of materialized views
Browsing can be easily
implemented based on snowflake
schemes

No redundancy within the dimension tables

#### CON

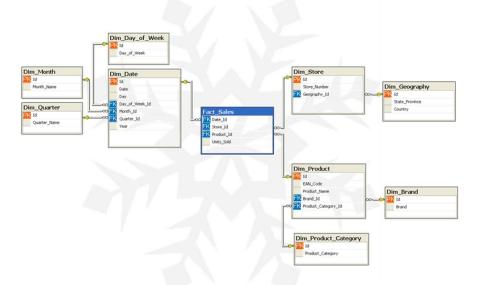
More physical join operations required

More physical tables required Higher level of complexity

ETL-process

Maintenance

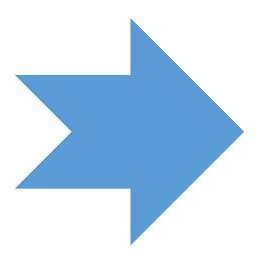
**SQL-queries** 



PK: Primary Key FK: Foreign Key

### Agenda





## **Continuation Data Warehouse Modeling**

Basic Elements of multidimensional modeling

Conceptual modeling

Logical modeling

**Physical modeling** 

### Physical modeling

Database architectures

Physical implementation of logical schemata in a database system.

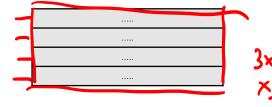


#### Relational database

usually denormalized structure for storage (star scheme)

..virtual cube"

Examples: MS Access, see Genealogy of RDBMS for more



Z.B. Absatz. Dimensionen:

#### **Multidimensional database**

(precalculated) data stored in multidimensional data structures on OLAP server

#### cube on server

K2

Artikel 1

КЗ

K1

K2

Artikel 2

Monat 1

Examples: IBM Cognos TM1, Oracle Hyperion/Essbase, Jedox

K1

КЗ

K2 K3

Artikel 3

K1

K2

Artikel 1

КЗ

K1

K2

Artikel 2

Monat 2

#### Client-based files

small extracts of data are held on clients

cube on client



2-9+1.3+1

•											
	17	18	19	20	21	22	23	24	25	26	27
					'						_
	K2	КЗ	K1	K2	КЗ	K1	K2	КЗ	K1	K2	K
/	Artikel	3	A	Artikel	1	,	Artikel .	2	1	Artikel	3
						- 1	Monat	3			

#### Select and fine tune the used DBMS technology

Building the database using the specific data definition language (e.g.: SQL-DDL-commands)

Decide on how to index, partition, denormalize and partly pre-aggregate the data.

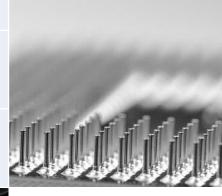
```
CREATE TABLE employees
id INT(6) AUTO INCREMENT PRIMARY KEY,
first name VARCHAR (50) not null,
last name VARCHAR (75) not null,
age INT(3) not null,
dateofbirth DATE not null )
```

Images: Vornberger/Müller (2001), Teller/McMillan (1998)

# Physical modeling OLAP architectures



	OLAP	- architectures	RDBMS	STORAGE MDBMS	client-based
		SQL	ROLAP (thin client)	-	-
100	PROCESSING	multidimensional server engine	(thin client)	MOLAP (thin client)	-
		client multidimensional engine	ROLAP (fat client)	MOLAP (fat client)	DOLAP (fat client)
MOLAP – multid	imensional OI AP	HOLAP			



MOLAP = multidimensional OLAP (data in cubes)

ROLAP = relational OLAP

DOLAP = desktop OLAP

Recent developments in data warehousing,

see article "Paradigmenwechsel: Data Warehouses für die Cloud" Kursmaterial > Readings/Übungen

Ref. e.g., Jukic et al. (2008)



### Fragen?

✓ Data Warehouse Modeling

#### **Exercise**

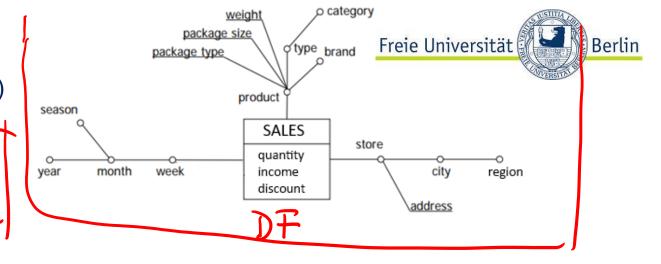
Conceptual Modeling and Logical Model (Star Scheme)

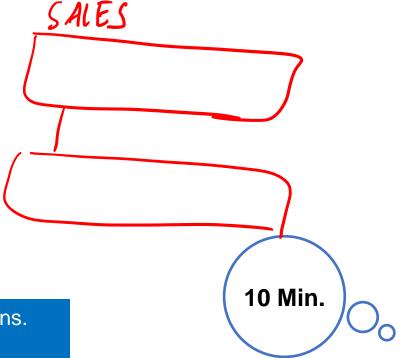
Design a logical model for the local Food Company:

### Conny's Corner Shop

Your managers need to keep themselves up to date on the company's situation. They especially want to keep an eye on their products with regards to location, and time.

- Conny's Corner Shop sells beverages and snacks. Both categories have different types of products, such as juices and water, as well as prezels and crackers. The products are either branded as strictly vegan or organic (bio).
- Products are sold in different cities, regions and EU-countries
- Most managers are interested in quantities, income and discounts of sales.





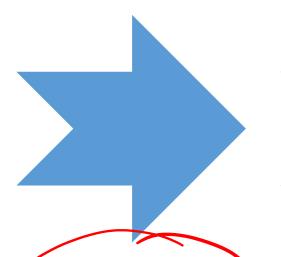
Create a simplified Star Scheme (logical model) with tables/relations. Use your conceptual model as input.

#### Outlook next lesson

**Data Mining Introduction** 

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





(1) The need for data

IF THAT'S THE SAME THING AS SPAM, WE'RE HAVING A GOOD MEETING HERE.

(2) From business problems to data mining tasks

(3) Supervised vs. unsupervised methods

WE HAVE A GIGANTIC DATABASE FULL OF CUSTOMER BEHAVIOR INFORMATION.

EXCELLENT. WE CAN USE NON-LINEAR MATH AND DATA MINING TECHNOLOGY TO OPTIMIZE OUR RETAIL CHANNELS!

mining

"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."

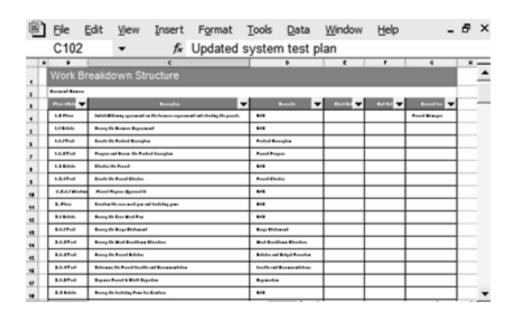
(Hand, Mannila, Smyth (2001), Principles of Data Mining

### The need for data mining



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

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



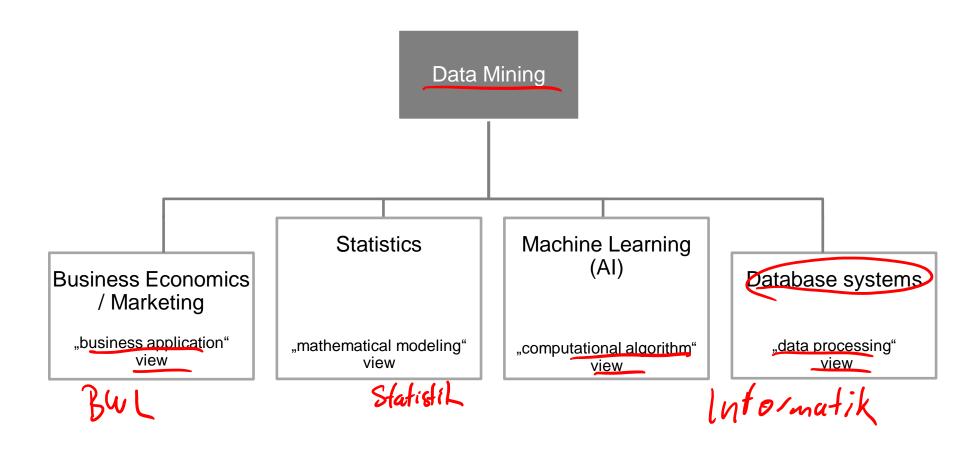
#### Disadvantages of conventional tools:

- 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

Ref. Images: WBS excel (2009) | Flickr (cc by 2.0)

### **Major roots of data mining**

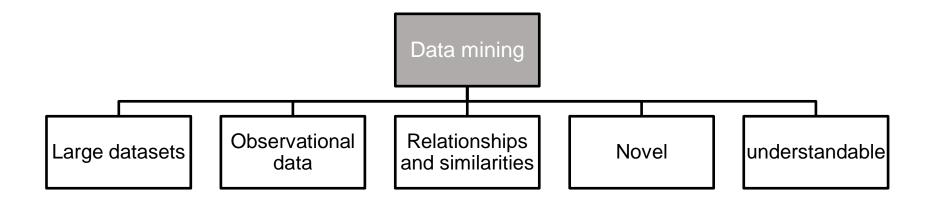




Ref.

### Data mining: definition (1/3)



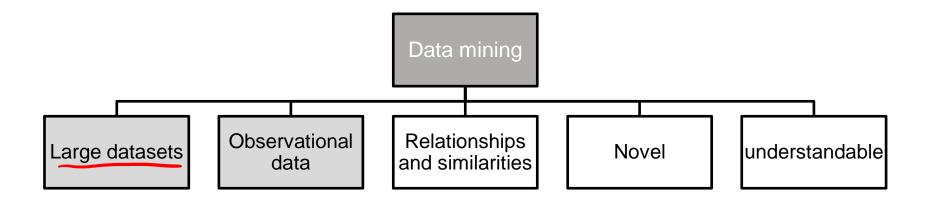


"Data mining is the analysis of (often large) observational data sets to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data owner."

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

### Data mining: definition (2/3)





#### Often large datasets:

Small datasets ⇒ 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

Operationale DB

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)

Ref.

### Data mining: definition (3/3)



 $\int \rho \left( y > 2,05 \right) \times \left( \frac{\text{Freie Un}}{80} \right)$ 

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Data mining

Large datasets

Observational data

Relationships and similarities

Novel

understandable

### 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

### **Exercise: Data Mining vs. OLAP**



Typical questions

Fragestellung	Data Mining	X	OLAP	
Kundenwert	Welche Kunden bieten uns das größte Deckungsbeitragspotenzial?	\ /	Wer waren letztes Jahr unsere 10 be Kunden?	sten

Kahoot-Fragen

www.kahoot.it

(über Smartphone oder Laptop)
PIN folgt

(Diese Folie ist nach der Vorlesung mit Lösungen verfügbar



#### Fragen?

Data Mining Introduction
 (will be continued in the next lesson)

#### **Todo for next Week**



Support Conny's Corner Shop by creating a (or finishing the) simplified Star Scheme (logical model) with tables/relations.

See exercise on slide 23

### **Bibliography**



- Hand, David J., Heikki Mannila, and Padhraic Smyth. *Principles of data mining*. MIT press, 2001.
- Vaisman, A., & Zimányi, E. (2014). *Data Warehouse Systems*. Springer, Heidelber

### Recommended reading (for next lessons)



#### **Data Mining**

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)