Dimensional Modeling

Krzysztof Dembczyński

Intelligent Decision Support Systems Laboratory (IDSS)
Poznań University of Technology, Poland

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Review of the Previous Lecture

- Processing of massive datasets.
- Evolution of database systems:
  - Operational (OLTP) vs. analytical (OLAP) systems.
  - Analytical database systems.
  - Design of data warehouses.
  - Relational model vs. multidimensional model.
  - NoSQL.
  - Processing of massive datasets.

Outline

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  - What is the distribution of students over faculties, semesters, etc.?

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  - What is the number of students over academic years?
  - What is the average score by faculties, instructors, etc.?
  - What is the distribution of students over faculties, semesters, etc.?
  - ...

Example

- An exemplary query could be the following:

```
SELECT Instructor, Academic_year, AVG(Grade)
FROM Data_Warehouse
GROUP BY Instructor, Academic_year
```

- And the result:

Academic_year	Name	AVG(Grade)
2010/11	Stefanowski	4.2
2011/12	Stefanowski	4.5
2010/12	Słowiński	4.3
2011/12	Słowiński	4.1
2011/12	Dembczyński	:)

Motivation

- **Problem to solve**: How to design a database for analytical queries?

Outline

Conceptual schemes of data warehouses

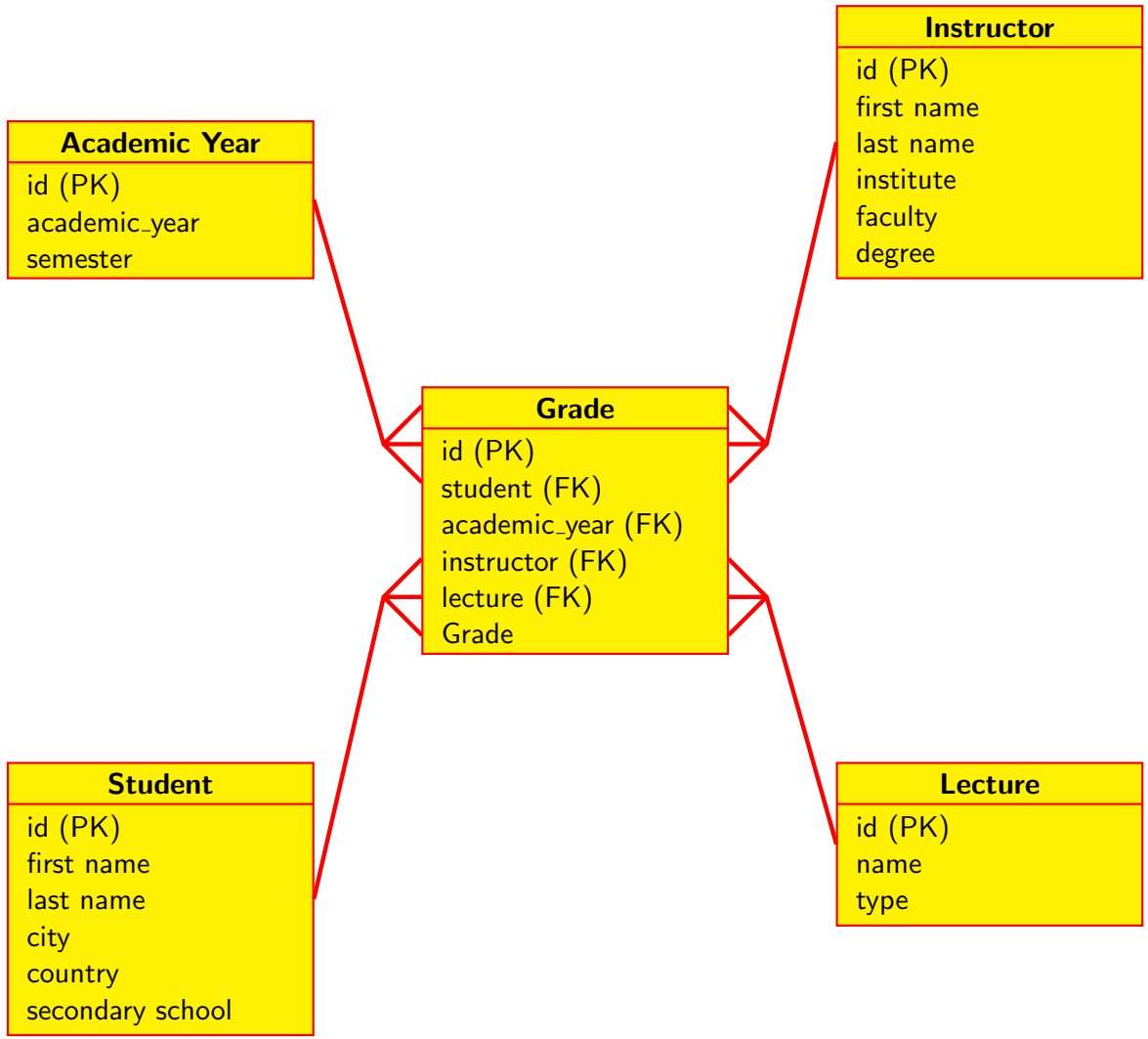
- Three main goals for logical design:
  - Simplicity:
    - Users should understand the design,
    - Data model should match users' conceptual model,
    - Queries should be easy and intuitive to write.
  - Expressiveness:
    - Include enough information to answer all important queries,
    - Include all relevant data (without irrelevant data).
  - Performance:
    - An efficient physical design should be possible to apply.

Three basic conceptual schemes

- Star schema,
- Snowflake schema,
- Fact constellations.

Star schema

- A single table in the middle connected to a number of dimension tables.



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  - Represent information about dimensions (student, academic year, etc.).
  - Each dimension has a set of descriptive attributes.

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- The aggregated fact columns are the matter of the analysis.

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- Dimension tables describe facts stored in the fact table.

Fact table vs. Dimension tables

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Facts contain numbers, dimensions contain labels

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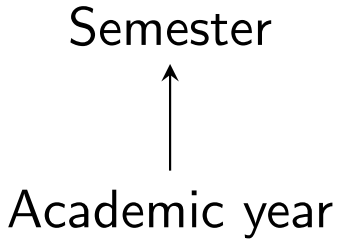
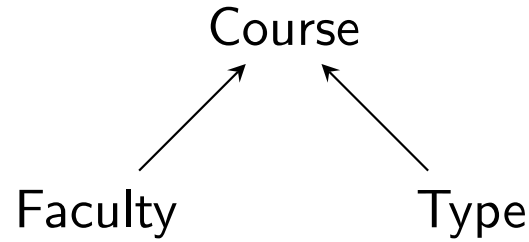
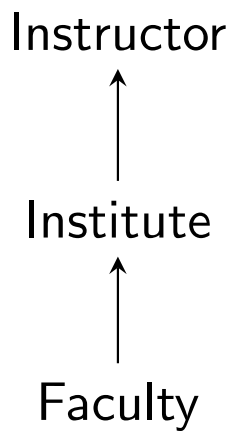
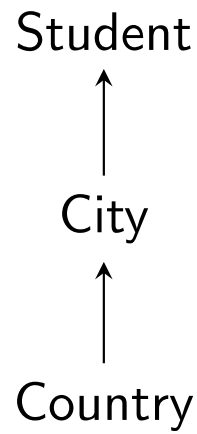
Dimension hierarchies

- For each dimension, one can define several hierarchies of attributes.



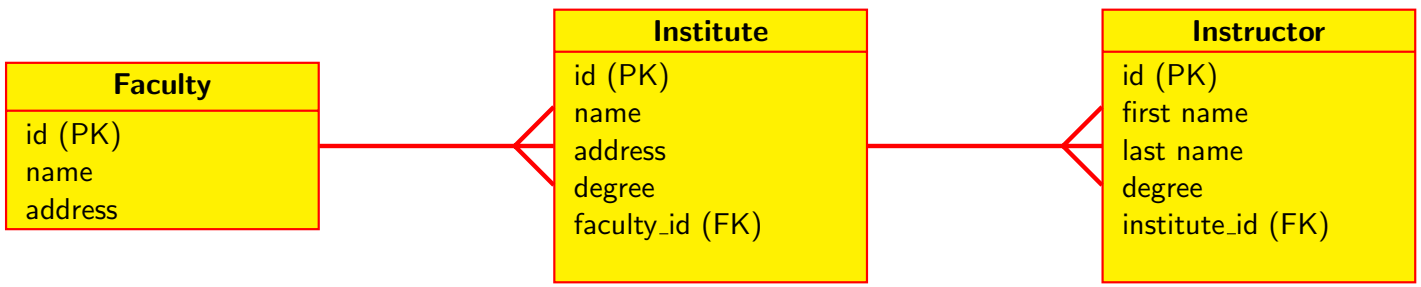






Snowflake schema

- Snowflake schema is a refinement of star schema where the dimensional hierarchy is represented explicitly by normalizing the dimension tables.



Normalization

- **Normal forms** provide criteria for determining a table's degree of vulnerability to inconsistencies, redundancy and update anomalies.
  - First normal form (1NF),
  - Second normal form (2NF),
  - Third normal from (3NF),
  - Boyce-Codd normal form (BCNF),
  - Fourth normal form (4NF),
  - ...

Denormalization

- Denormalization is the process of attempting to optimize the performance of a database by adding redundant data or by grouping data.
- Denormalization helps cover up the inefficiencies inherent in relational database software.
- **Normalize until it hurts, denormalize until it works** :)

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- Such schema appears in a design of a data warehouse for a huge and complex problem.
- One should start with a simple model, and then try to define a more complex one (project success).

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  - Identify the numeric measures for the facts (e.g. price, quantity).

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- **Examples**: sales, orders, teaching.
- Business process should not be referred to an organizational business department or function.
- Selection of the business process should be dependent on its complexity, and also on time and budget of the project.

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- **Examples**: line item from a cash register receipt, daily snapshot of inventory level for a product in a warehouse, monthly snapshot for each bank account.
- Finer-grained fact tables are more expressive, but have more rows and grow faster.

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- **Examples**: localization, product, date, promotion, etc.

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  - non-additive: are completely non-additive, such as ratios (store the fully additive components of the non-additive measure and sum these components into the final answer before calculating the final non-additive fact)

Dimensional modeling techniques

- Derived measures vs. calculated measures,
- Describing dimensions,
- Date and time dimension,
- Surrogate keys,
- Degenerate dimensions,
- Role-playing dimensions,
- Junk dimension,
- Slowly changing dimensions,
- Mini dimension,
- Factless fact tables,
- Data warehouse bus architecture.

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- Data warehouse is huge from the definition, so storing additional values does not change a lot.
- Computing additional measures (like profit from incomes and outcomes) decreases performance of data warehouse.

Describing dimension

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- Use as many as possible, but useful, dimension attributes

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- Date dimension allows analysis of time trends.
- Should we treat date as a separate dimension or use timestamps to compute all needed information?
  - A separate dimension is more reasonable ...

Date dimension

- Typical attributes in date dimension:
  - date and time (candidate key),
  - day (number) of year,
  - day (number) of month,
  - day (number) of week,
  - day number in epoch,
  - weekday,
  - weekend,
  - 24-hour work day
  - holiday
  - week of year,
  - month,
  - name of month,
  - quarter,
  - year,
  - fiscal year,
  - selling season,
  - back-to-school
  - Christmas

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- For finer-grained time measurements, use separate date and time-of-day

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  - Resistant to reuse of old value of natural key.

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  - Use a **degenerate dimension** ...

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- Such a dimension serves to group together products that were bought in the same market basket (market basket analysis).

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- **Example**: a fact is associated with several dates (e.g. order, payment, or delivery date), each of which is represented by a foreign key.

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  - **Example**: consider such attributes as payment method (cash and credit card) and packing type (box, paper, or none).
- A possible solution is to create a single **junk dimension** combining these columns together.
- This dimension does not need to be the Cartesian product of all the attributes' possible values, but should only contain the combination of values that actually occur in the source data.

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  - Change of product categorization.

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- **Examples**
  - Wrong name of the street (correct approach),
  - Change of customer address:
    Nowak moves from Poznań to Warsaw $\rightarrow$ all products purchased in Poznań move to Warsaw too!!!

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- **Examples**:
  - Nowak moves to Warsaw:

id	local_id	name	city	row effective date	row expiration date	current row indicator
23401	234	Nowak	Poznań	2012-01-01	2014-01-05	Expired
23402	234	Nowak	Warsaw	2014-01-06	9999-12-31	Current

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  - Old fact table rows point to the old row, and new fact table rows point to the new row,
  - To report on Nowak's activity over time one can use:

```
WHERE local_id = "234"
```

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- **Examples**:
  - Administrative reform in Poland:

id	previous name	current name
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23402	pilskie	wielkopolskie

  - All the fact table rows point to both values.

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- For such attributes it may be reasonable to create a separate dimension table called **mini dimension**.
- It relies on removing of frequently-changing or frequently-queried attributes from an original dimension and adding them to a new mini-dimension table.
- The link between the original dimension and the mini dimension is through the fact table, but additional foreign key can be added to the original dimension.

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  - Dummy measure is included that always has value 1.
  - Describe relationships between dimensions.
  - **Example**: Which products were on promotion in which stores for which days?

Data warehouse bus architecture

- In order to create an data warehouse for entire organization, which takes into account several processes, one can use a **data warehouse bus matrix**.

Business process	Common dimensions	Date	Product	Store	Promotion	Warehouse	Vendor	Contract	Shipper
Retail sales		*	*	*	*				
Retail inventory		*	*	*					
Retail deliveries		*	*	*					
Warehouse inventory		*	*			*	*		
Warehouse deliveries		*	*			*	*		
Purchase orders		*	*			*	*	*	*
...									

Some other problems

- Querying fact tables or dimensions?

  It is generally reckoned that some 80 percent of data warehouse queries are dimension-browsing queries. This means that they do not access any fact table.

  Ch. Todman (2001)

- **Example**:
  - How many customers do we have?

Outline

Summary

- Three goals of the logical design of data warehouse: **simplicity**, **expressiveness** and **performance**.
- The most popular conceptual schema: **star schema**.
- Designing data warehouses is not an easy task ...

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