FRIEDRICH-ALEXANDER
UNIVERSITÄT
ERLANGEN-NÜRNBERG

Chapter IV: OLAP

Knowledge Discovery in Databases

Luciano Melodia M.A.
Evolutionary Data Management, Friedrich-Alexander University Erlangen-Nürnberg
Summer semester 2021

Chapter IV: Data warehousing and online analytical processing

Data warehouse: basic concepts.

Data-warehouse modeling: data cube and OLAP.

Data-warehouse design and usage.

Data-warehouse Implementation.

Data generalization by attribute-oriented induction.

Summary.

FAU FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG

What is a data warehouse?

Defined in many different ways, but not rigorously:

A **decision-support** database that is **maintained separately** from the organization's operational database.

Supports information processing by providing a solid platform of **consolidated, historical data** for analysis.

Famous:

A data warehouse is a subject-oriented, integrated, time-variant, and nonvolatile collection of data in support of management's decision-making process.
– W. H. Inmon.

Data warehousing: The process of constructing and using data warehouses.

Data warehouse – subject-oriented

Organized around major subjects.

Such as customer, product, sales.

Focusing on the modeling and analysis of data for decision makers.

Not on daily operations or transaction processing.

Provide a simple and concise view around particular subject issues.

By excluding data that are not useful in the decision-support process.

Data warehouse – integrated

Constructed by integrating multiple heterogeneous data sources.

Relational databases, flat files, online transaction records, . . .

Data-cleaning and data-integration techniques are applied.

Ensure consistency in naming conventions, encoding structures, attribute measures, etc. among different data sources.

E.g., hotel price: currency, tax, breakfast covered, etc.

When data is moved to the warehouse, it is converted.

ETL – Extraction, Transformation, Loading, see below.

Data warehouse – time variant

The time horizon for a data warehouse is significantly longer than that of operational systems.

Operational database: current-value data.

Data warehouse: provide information from a historical perspective, e.g. past $5 - 10$ years.

Every key structure in the data warehouse contains an element of time, explicitly or implicitly.

The key of operational data may or may not contain a "time element."

Data warehouse – nonvolatile

A physically separate store of data.

Transformed from the operational environment.

By copying.

No operational update of data:

Hence, does not require transaction processing,

i.e. no logging, recovery, concurrency control, etc.

Requires only three operations:

Initial loading of data.

Refresh (update, often periodically, e.g. over night).

Access of data.

OLTP vs. OLAP

	OLTP	OLAP
users	clerk, IT professional	knowledge worker
function	day-to-day operations	decision support
DB design	application-oriented	decision support
data	current, up-to-date; detailed, flat relational; isolated	historical; summarized, multidimensional, integrated, consolidated
usage	repetitive	ad-hoc
access	read/write; index/hash on primary key	lots of scans
unit of work	short, simple transaction	complex query
#-records accessed	10	10^6
#-users	1000	100
DB size	100 MB to GB	100 GB to TB
quantification	transaction throughput	query throughput, response

Why a separate data warehouse?

High performance for both systems:

DBMS: tuned for OLTP; Access methods, indexing concurreny control, recovery.

Warehouse: tuned for OLAP; Complex OLAP queries, multidimensional view, consolidation.

Different functions and different data:

Missing data:

Decision support (DS) requires **historical data**
which operational DBs do not typically maintain.

Data consolidation:

DS requires **consolidation** (aggregation, summarization)
of data from heterogeneous sources.

Data quality:

Different sources typically use inconsistent data representations,
codes and formats which have to be reconciled.

**Note: There are more and more systems which perform OLAP
analysis directly on relational databases.**

Three data-warehouse models

Enterprise Warehouse:

Collects all of the information about subjects spanning the entire organization.

Data mart:

A **subset** of corporate-wide data that is of value to a **specific group of users.**
Its scope is confined to specific, selected groups, such as marketing data mart.
Independent vs. dependent (directly from warehouse) data mart.

Virtual warehouse:

A set of **views** over operational databases.
Only some of the possible summary views may be materialized.

Extraction, transformation, and loading (ETL)

Extraction:

Get data from multiple, heterogeneous, and external sources.

Cleaning:

Detect errors in the data and rectify them if possible.

Transformation:

Convert data from legacy or host format to warehouse format.

Loading:

Sort, summarize, consolidate, compute views, check integrity, and build indexes and partitions.

Refresh:

Propagate only the updates from the data sources to the warehouse.

Metadata repository

Metadata: the data defining data-warehouse objects.

Description of the structure of the data warehouse:

Schema, view, dimensions, hierarchies, derived-data definition, data-mart locations and contents.

Operational metadata:

Data lineage (history of migrated data and transformation path).

Currency of data (active, archived, or purged).

Monitoring information (warehouse-usage statistics, error reports, audit trails).

Algorithms used for summarization.

Mapping from operational environment to data warehouse.

Data related to system performance:

Warehouse schema, view and derived-data definitions.

Business data:

Business terms and definitions, ownership of data, charging policies.

Chapter IV: Data warehousing and online analytical processing

Data warehouse: basic concepts.

Data-warehouse modeling: data cube and OLAP.

Data-warehouse design and usage.

Data-warehouse Implementation.

Data generalization by attribute-oriented induction.

Summary.

From tables and spreadsheets to data cubes

Data warehouse: basic concepts.

Based on a **multidimensional data model** which views data in the form of a **data cube**.

Data cube.

Allows data (here: sales) to be modeled and viewed in multiple dimensions.

Dimension tables: such as: item (item_name, brand, type),

or: time (day, week, month, quarter, year).

Fact table: Contains **measures** (such as dollars_sold) and references (foreign keys) to each of the related dimension tables.

n-**dimensional base cube.**

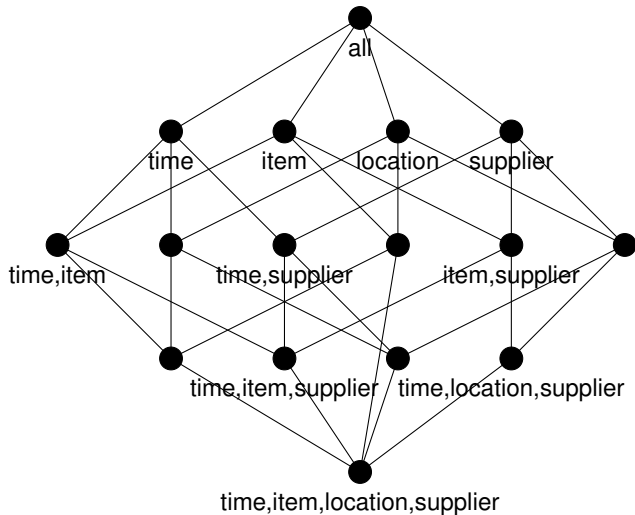Called a base cuboid in data-warehousing literature.

Top most 0-**dimensional cuboid.**

Holds the highest-level of summarization.

Called the apex cuboid.

Lattice of cuboids. (Forms a data cube)

Cube: a lattice of cuboids

all	0-dimensional (apex) cuboid
time, item, location, supplier	1-dimensional cuboid
time,item, time,supplier, item,supplier	2-dimensional cuboid
time,item,supplier, time,location,supplier	3-dimensional cuboid
time,item,location,supplier	4-dimensional (base) cuboid

Conceptual modeling of data warehouses

Star schema:.

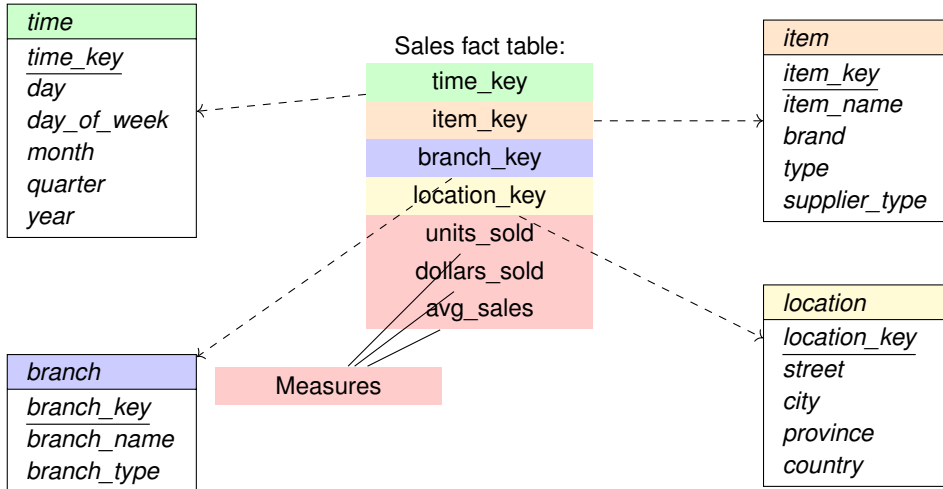A fact table in the middle connected to a set of dimension tables.

Snowflake schema:.

A refinement of the star schema where some dimensional hierarchy
is **normalized** into a set of smaller dimension tables,
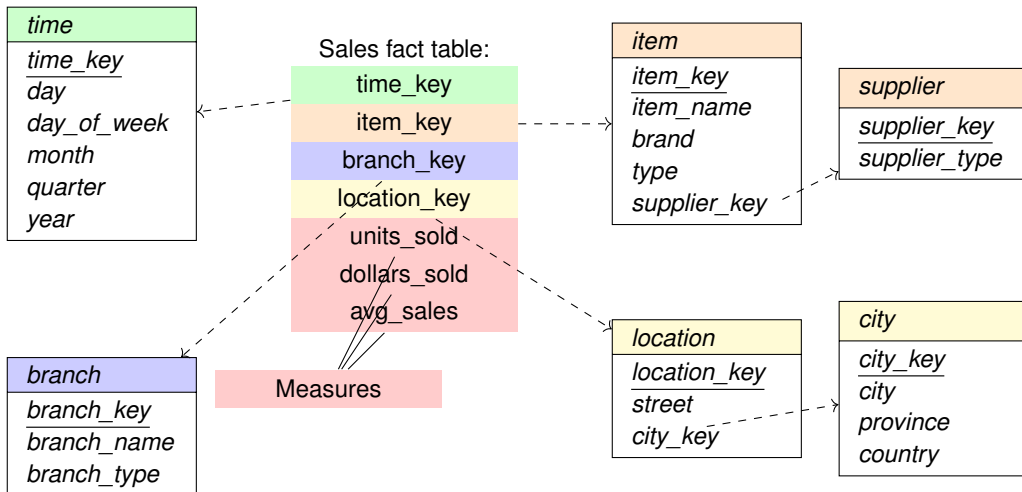forming a shape similar to a snowflake.

Fact constellations:.

Multiple fact tables sharing dimension tables,
viewed as a collection of stars, therefore called
galaxy schema or fact constellation.

Example of star schema

time
- *time_key*
- *day*
- *day_of_week*
- *month*
- *quarter*
- *year*

Sales fact table:

| time_key |
| item_key |
| branch_key |
| location_key |
| units_sold |
| dollars_sold |
| avg_sales |

Measures

item
- *item_key*
- *item_name*
- *brand*
- *type*
- *supplier_type*

branch
- *branch_key*
- *branch_name*
- *branch_type*

location
- *location_key*
- *street*
- *city*
- *province*
- *country*

Example of snowflake schema

time
- *time_key*
- *day*
- *day_of_week*
- *month*
- *quarter*
- *year*

Sales fact table:

| time_key |
| item_key |
| branch_key |
| location_key |
| units_sold |
| dollars_sold |
| avg_sales |

Measures

item
- *item_key*
- *item_name*
- *brand*
- *type*
- *supplier_key*

supplier
- *supplier_key*
- *supplier_type*

branch
- *branch_key*
- *branch_name*
- *branch_type*

location
- *location_key*
- *street*
- *city_key*

city
- *city_key*
- *city*
- *province*
- *country*

Example of fact constellation

time
- *time_key*
- *day*
- *day_of_week*
- *month*
- *quarter*
- *year*

Sales fact table:
- time_key
- item_key
- branch_key
- location_key
- units_sold
- dollars_sold
- avg_sales

Measures

item
- *item_key*
- *item_name*
- *brand*
- *type*
- *supplier_type*

Shipping fact table:
- time_key
- item_key
- shipper_key
- from_location
- to_location
- dollars_cost
- units_shipped

branch
- *branch_key*
- *branch_name*
- *branch_type*

location
- *location_key*
- *street*
- *city*
- *province*
- *country*

shipper
- *shipper_key*
- *shipper_name*
- *location_key*
- *shipper_type*

A concept hierarchy: dimension (location)
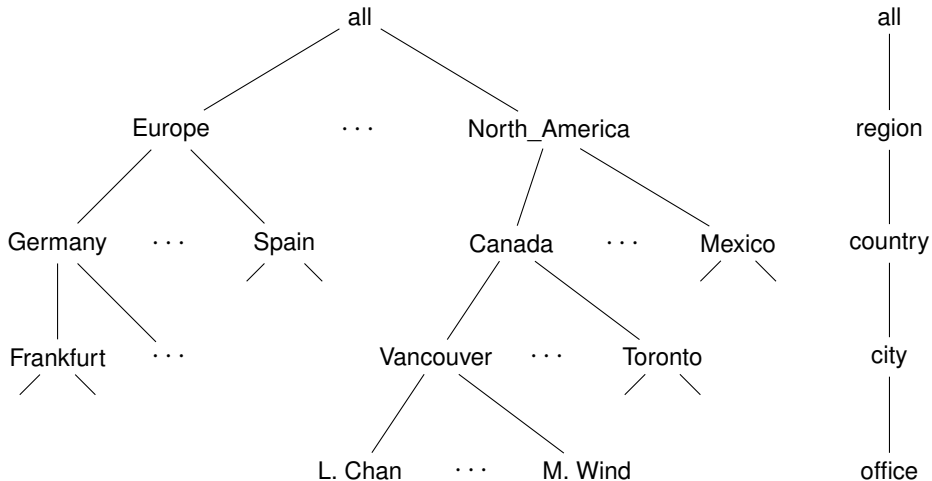
Data-cube measures: three categories

Distributive:

If the result derived by applying the function to the n aggregate values obtained for n partitions of the dataset is the same as that derived by applying the function on all the data without partitioning.

E.g. COUNT, SUM, MIN, MAX.

Functional:

If it can be computed by an algebraic function with M arguments, each of which is obtained by applying a distributive aggregate function.

E.g. AVG, MIN_N, STD.

Holistic:

If there is no constant bound on the storage size needed to describe a subaggregate.

E.g. MEDIAN, MODE, RANK.

Aggregation type

Non-trivial property.

Next to name and value range.

Defines the set of aggregation operations that can be executed on a measure (a fact).

FLOW:

Any aggregation.

E.g. sales turnover.

STOCK:

No temporal aggregation.

E.g. stock, inventory.

VPU (Value per Unit:

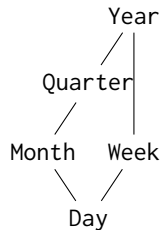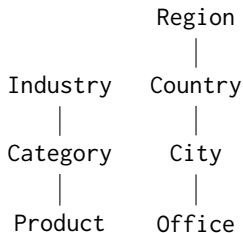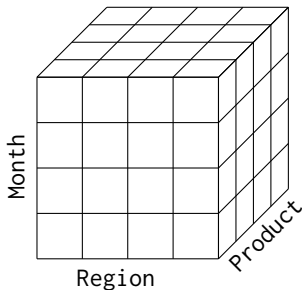No summarization.

E.g. price, tax, in general factors.

(Always applicable: MIN, MAX and AVG).

Aggregation type

Sales volume as a function of product, month, and region.

Dimensions: Product, Location, Time.
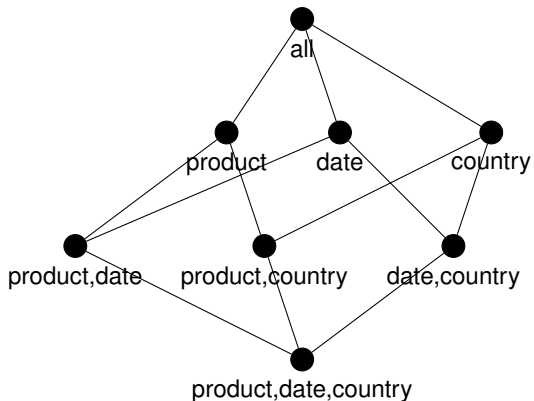Hierarchical summarization paths.

Data cube sample

		rail			
Route	ground	road			
	non-ground	sea			
		air			

Africa	190	215	160	240
	Feb-17-99	Apr-22-99	Sep-07-99	Dec-01-99
Asia	5294	2858	6362	8477
	Jan-24-46	Feb-20-65	Mar-30-1	Dec-21-92
Australia	7460	8413	6615	3610
	Mar-19-72	Aug-28-51	Jul-14-80	Dec-19-44
Europe	654	6963	322	7805
	Dec-30-42	Apr-25-60	Jun-21-77	Dec-23-100
North America	8441	476	3773	8769
	Jul-11-9	Sep-19-29	Mar-12-53	Apr-1-94
South America	8180	3996	5288	9666
	Dec-29-28	Apr-7-31	Jul-21-40	Feb-18-71

Eastern Hemisphere: Africa, Asia, Australia, Europe
Western Hemisphere: North America, South America

Cuboids corresponding to the cube

0-dimensional (apex) cuboid

1-dimensional cuboid

2-dimensional cuboid

3-dimensional (base) cuboid

Chapter IV: Data warehousing and online analytical processing

Data warehouse: basic concepts.

Data-warehouse modeling: data cube and OLAP.

Data-warehouse design and usage.

Data-warehouse Implementation.

Data generalization by attribute-oriented induction.

Summary.

Data generalization

Summarize data:

By replacing relatively low-level values
e.g. numerical values for the attribute `age`
with higher-level concepts
e.g. `young`, `middle-aged` and `senior`.
By reducing the number of dimensions
e.g. removing `birth_date` and `telephone_number`
when summarizing the behavior of a group of students.
Describe concepts in concise and succinct terms at generalized (rather than low) levels of abstractions:

Facilitates users in examining the general behavior of the data.
Makes dimensions of a data cube easier to grasp.

Attribute-oriented induction

Proposed in 1989 (KDD'89 workshop).

Not confined to categorical data nor to particular measures.

How is it done?

Collect the **task-relevant data** (initial relation) using a relational database query.

Perform **generalization** by attribute removal or attribute generalization.

Apply **aggregation** by merging identical, generalized tuples and accumulating their respective counts.

Interaction with users for knowledge presentation.

Attribute-oriented induction: an example

Example: Describe general characteristics of graduate students in a University database.

Step 1: Fetch relevant set of data using an SQL statement, e.g.

```
SELECT name, gender, major, birth_place, birth_date, residence, phone#, gpa)
FROM student
WHERE student_status IN "Msc", "MBA", "PhD";
```

Step 2: Perform attribute-oriented induction.

Step 3: Present results in generalized-relation, cross-tab, or rule forms.

Class characterization: an initial relation (I)

Name	Gender	Major	Birth place	Birth date	Residence	Phone number	GPA
Jim	M	CS	Vancouver, BC, Canada	08-21-76	3511 Main St., Richmond	687-4598	3.67
Scott Lachance	M	CS	Montreal, Que, Canada	28-07-75	345 1st Ave., Richmond	253-9106	3.70
Laura Lee	F	Physics	Seattle, WA, USA	25-08-70	125 Austin Ave., Burnaby	420-5232	3.83
Removed	Retained	Sci, Eng, Bus	Country	Age range	City	Removed	Excl, Vg,...

Class characterization: prime generalized relation (II)

Gender	Major	Birth region	Age range	Residence	GPA	Count
M	Science	Canada	20-35	Richmond	Very good	16
F	Science	Foreign	25-30	Burnaby	Excellent	22
…	…	…	…	…	…	…

Class characterization: an example (III)

Cross-table of birth region and gender:

	Canada	Foreign	Total
M	16	14	30
F	10	22	32
Total	26	36	62

Basic principles of attribute-oriented induction

Data focusing:

Task-relevant data, including dimensions

The result is the **initial relation**.

Attribute removal:

Remove attribute A, if there is a large set of distinct values for A,

but (1) there is no generalization operator on A,

or (2) A's higher-level concepts are expressed in terms of other attributes.

Attribute generalization:

If there is a large set of distinct values for A,

and there exists a **set of generalization operators** on A,

then select an operator and generalize A.

Attribute-threshold control:

Typical 2-8, specified/default.

Generalized-relation-threshold control:

Control the final relation/rule size.

Attribute-oriented induction: basic algorithm

InitialRel:

Query processing of task-relevant data, deriving the initial relation.

PreGen:

Based on the analysis of the number of distinct values in each attribute, determine generalization plan for each attribute: removal? Or how high to generalize?

PrimeGen:

Based on the PreGen plan, perform generalization to the right level to derive a "prime generalized relation", accumulating the counts.

Presentation:

User interaction:

1. Adjust levels by drilling.
2. Pivoting.
3. Mapping into rules, cross tabs, visualization presentations.

Presentation of generalized results

Generalized relation:

Relations where some or all attributes are generalized, with counts or other aggregation values accumulated.

Cross tabulation:

Mapping results into cross-tabulation form (similar to contingency tables).

Visualization techniques: pie charts, bar charts, curves, cubes, and other visual forms.

Quantitative characteristic rules:

Mapping generalized result into characteristic rules with quantitative information associated with it, e.g.

$$\text{grad}(x) \wedge \text{male}(x) \implies \text{birth\_region}(x) \tag{1}$$

$$= \text{"Canada"}[t : 53\%] \vee \text{birth\_region}(x) \tag{2}$$

$$= \text{"foreign"}[t : 47\%]. \tag{3}$$

Mining-class comparisons

Comparison: Comparing two or more classes.

Method:

Partition the set of relevant data into the **target class** and the **contrasting class(es)**.

Generalize both classes to the same high-level concepts (i.e. AOI).

Including aggregation.

Compare tuples with the same high-level concepts.

Present for each tuple its description and two measures.

Support – distribution within single class (counts, percentage).

Comparison – distribution between classes.

Highlight the tuples with strong discriminant features.

Relevance Analysis:

Find attributes (features) which best distinguish different classes.

Concept description vs. cube-based OLAP

Similarity:

Data generalization.

Presentation of data summarization at multiple levels of abstraction.

Interactive drilling, pivoting, slicing and dicing.

Differences:

OLAP has systematic preprocessing, query independent, and can drill down to rather low level.

AOI has automated desired-level allocation and may perform dimension-relevance analysis/ranking when there are many relevant dimensions.

AOI works on data which are not in relational forms.

Chapter IV: Data warehousing and online analytical processing

Data warehouse: basic concepts.

Data-warehouse modeling: data cube and OLAP.

Data-warehouse design and usage.

Data-warehouse Implementation.

Data generalization by attribute-oriented induction.

Summary.

Summary

Data warehousing: multi-dimensional model of data.

A data cube consists of dimensions and measures.

Star schema, snowflake schema, fact constellations.

OLAP operations: drilling, rolling, slicing, dicing and pivoting.

Data-warehouse architecture, design, and usage.

Multi-tiered architecture.

Business-analysis design framework.

Information processing, analytical processing, data mining, OLAM (Online Analytical Mining).

Implementation: efficient computation of data cubes.

Partial vs. full vs. no materialization.

Indexing OALP data: Bitmap index and join index.

OLAP query processing.

OLAP servers: ROLAP, MOLAP, HOLAP.

Data generalization: attribute-oriented induction.

References (I)

S. Agarwal, R. Agrawal, P. M. Deshpande, A. Gupta, J. F. Naughton, R. Ramakrishnan, and S. Sarawagi: On the computation of multidimensional aggregates. VLDB'96.

D. Agrawal, A. E. Abbadi, A. Singh, and T. Yurek: Efficient view maintenance in data warehouses. SIGMOD'97.

R. Agrawal, A. Gupta, and S. Sarawagi: Modeling multidimensional databases. ICDE'97.

S. Chaudhuri and U. Dayal: An overview of data warehousing and OLAP technology. ACM SIGMOD Record, 26:65-74, 1997-

E. F. Codd, S. B. Codd, and C. T. Salley: Beyond decision support. Computer World, 27, July 1993.

J. Gray, et al. Data cube: A relational aggregation operator generalizing group-by, cross-tab and sub-totals. Data Mining and Knowledge Discovery, 1:29-54, 1997.

A. Gupta and I. S. Mumick. Materialized Views: Techniques, Implementations, and Applications. MIT Press, 1999.

References (II)

J. Han: Towards on-line analytical mining in large databases. ACM SIGMOD Record, 27:97-107, 1998.

V. Harinarayan, A. Rajaraman, and J. D. Ullman: Implementing data cubes efficiently. SIGMOD'96.

J. Hellerstein, P. Haas, and H. Wang: Online aggregation. SIGMOD'97.

C. Imhoff, N. Galemmo, and J. G. Geiger: Mastering Data Warehouse Design: Relational and Dimensional Techniques. John Wiley, 2003.

W. H. Inmon: Building the Data Warehouse. John Wiley, 1996.

R. Kimball and M. Ross: The Data Warehouse Toolkit: The Complete Guide to Dimensional Modeling. 2ed. John Wiley, 2002.

P. O'Neil and G. Graefe: Multi-table joins through bitmapped join indices. ACM SIGMOD Record, 24:8–11, Sept. 1995.

P. O'Neil and D. Quass: Improved query performance with variant indexes. SIGMOD'97.

Microsoft. OLEDB for OLAP programmer's reference version 1.0. In http://www.microsoft.com/data/oledb/olap, 1998.

Thank you for your attention.
Any questions about the fourth chapter?

Ask them now, or again, drop me a line:
✈ luciano.melodia@fau.de.