Chapter IV: OLAP

Knowledge Discovery in Databases

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

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.

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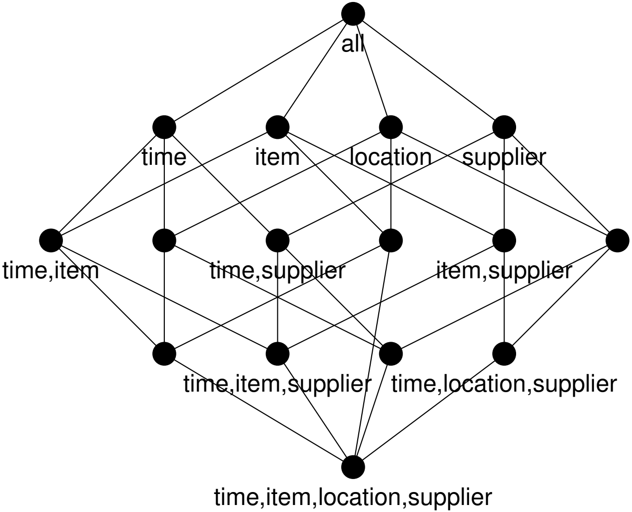
From tables and spreadsheets to data cubes

- 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



0-dimensional (apex) cuboid

1-dimensional cuboid

2-dimensional cuboid

3-dimensional cuboid

4-dimensional (base) cuboid

Conceptual modeling of data warehouses

Star schema:.

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

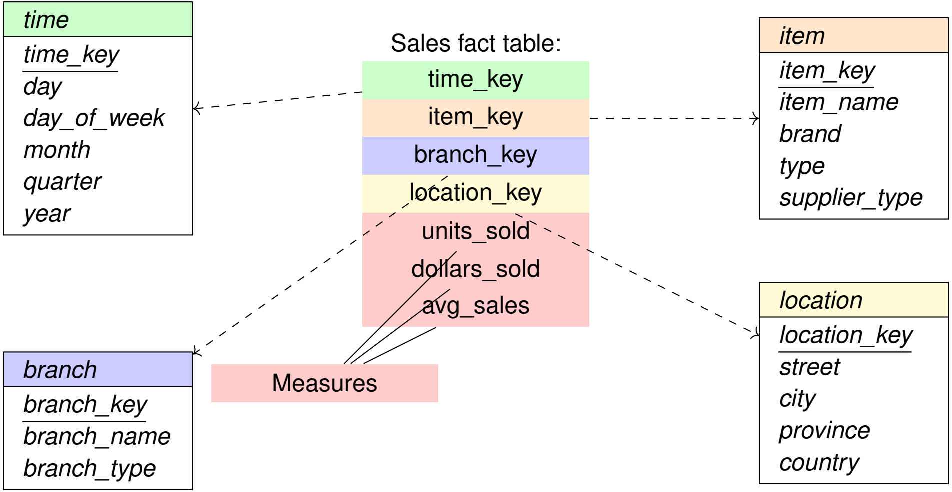
Snowflake schema:.

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.

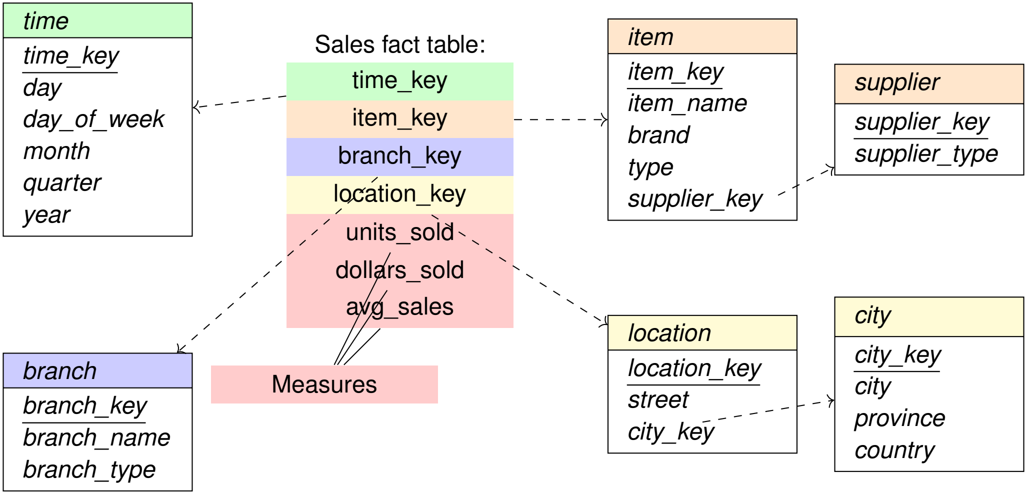
Fact constellations:.

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

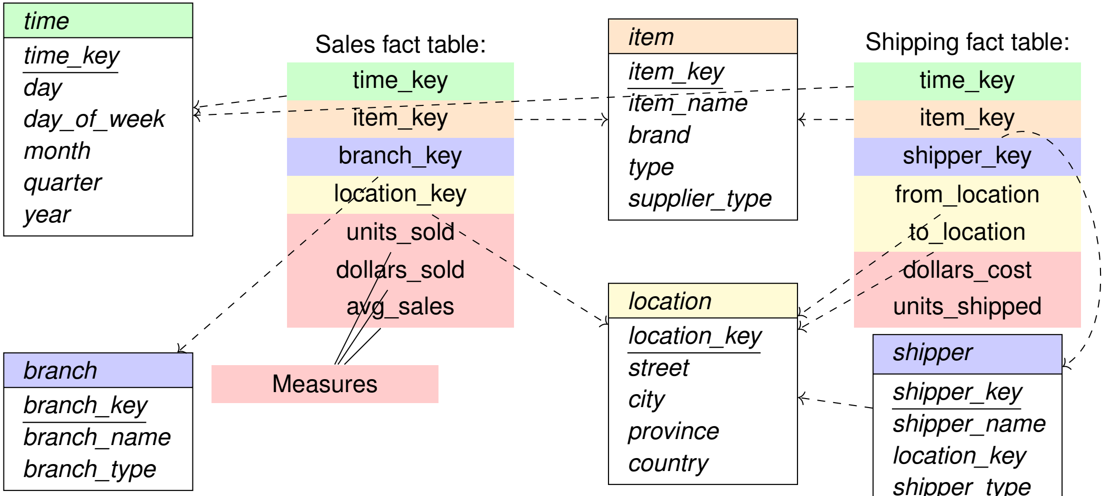
Example of star schema



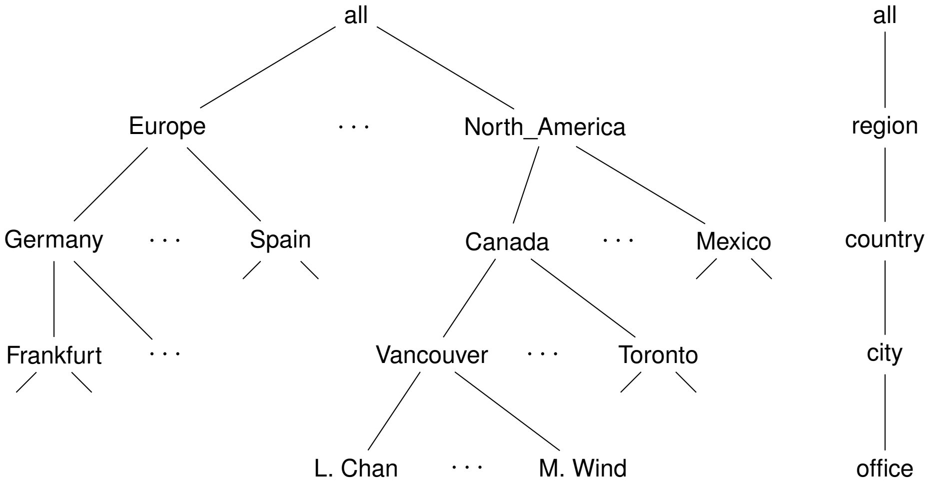
Example of snowflake schema



Example of fact constellation



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`, $\mathtt{MIN}_N$, `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.

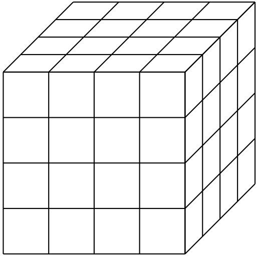
(Always applicable: `MIN`, `MAX` and `AVG`).

Aggregation type

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

Dimensions: `Product`, `Location`, `Time`.

Hierarchical summarization paths.



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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.

$$\begin{aligned} \text{grad}(x) \wedge \text{male}(x) &\implies \text{birth\_region}(x) && (1)\\ &= \text{"Canada"}[t : 53\%] \vee \text{birth\_region}(x) && (2)\\ &= \text{"foreign"}[t : 47\%]. && (3) \end{aligned}$$

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.

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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`.