Advanced Data Management Technologies

Unit 5 — Logical Design and DW Applications

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Outline

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Logical Design

- The **logical design** transforms the conceptual schema for a DM into a logical schema.
  - Choice of the type of logical schema, e.g., snowflake vs. star schema
  - Translation of conceptual schemata
  - Optimization (view materialization, fragmentation)

$\boxed{\text{Conceptual Schema}} \Longrightarrow \boxed{\text{Logical Design}} \Longrightarrow \boxed{\text{Logical Schema}}$

- Different principles from the one used in operational databases
  - data redundancy
  - denormalization of relations
- Frequently, DM design starts with a logical model.
- The logical model is based on the so-called multidimensional model

The Multidimensional Model/1

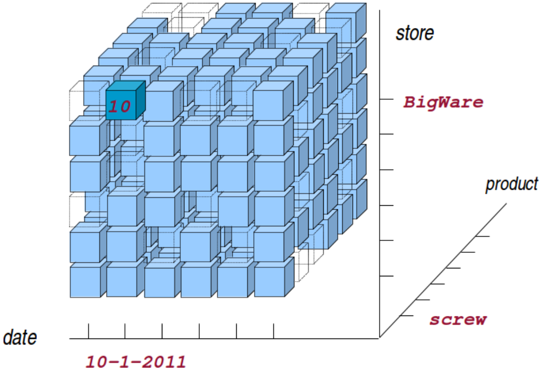
- The Multidimensional Model divides data into facts (with measures) and dimensions
- Facts
  - are the important entity, e.g.,a sale
  - have measures that can be aggregated, e.g., sales price
- Dimensions
  - describe facts
  - e.g., a sale has the dimensions Product, Store and Time

The Multidimensional Model/2

- Multidimensional model is a logical model with one purpose: data analysis
- Better at that purpose than ERM since it has more built in "meaning":
  - What **is** important
  - What **describes** the important
  - What we want to optimize
  - Automatic aggregations → easy querying
- Less flexible and not suited for OLTP systems.
- Most popular data model for DW.
- Recognized and supported by OLAP/BI tools.
- Goal for dimensional modeling
  - Surround facts with as much context (dimensions and attributes) as possible;
  - Redundancy is ok in well-chosen places.
  - But you should not try to model all relationships (unlike ER/OO modeling!)

MD Cubes/1

- Facts (data) “live” in a **multidimensional cube**.
- Example: Sales cube with 3 dimensions



MD Cubes/2

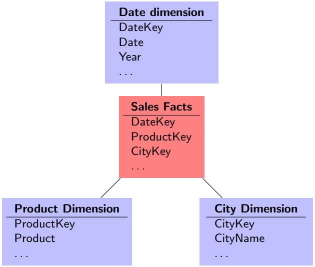
- A cube consists of cells.
  - A given combination of dimension values.
  - A cell can be empty (no data for this combination).
  - A sparse cube has many empty cells.
  - A dense cube has few empty cells.
  - Cubes become sparser for many/large dimensions.
- A cube may have many dimensions.
  - For more than 3 dimensions, the term hypercube is sometimes used.
  - Theoretically, there is no limit for the number of dimensions.
  - Typical cubes have 4-12 dimensions.
- Only 2-3 dimensions can be viewed at a time.
  - Dimensionality reduced by queries via projection/aggregation.

Outline

Star Schema

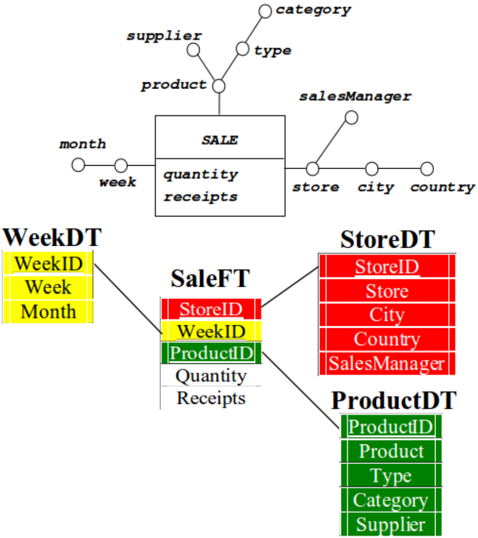
- A common approach to draw a multidimensional model (in relational systems) is the **star schema**, which consists of
  - a set of dimension tables, $DT_1, \ldots, DT_n$, with a primary key k_i and dimensional attributes;
  - a fact table including measures and foreign keys k_i to the dimensional tables.
- As we will see later, a star schema is a relational implementation of the multidimensional model.

Example: Star schema for sales facts with 3 dimensions



Translating Conceptual Schema to Star Schema

- Create a fact table including all measures
- For each dimension, create a dimension table with a primary key and one column for each dimensional attribute
- Besides this simple rule, specific solutions are required for different advanced constructs of the DFM



Instance of Star Schema

ProductDT

ProductKey	Product	Type	Category
P1	Bud	Beer	Beverage
P2	Forst	Beer	Beverage
P3	Warst	Beer	Beverage

DateDT

DateKey	Day	Month	Year
D1	25	May	2013
D2	26	May	2013

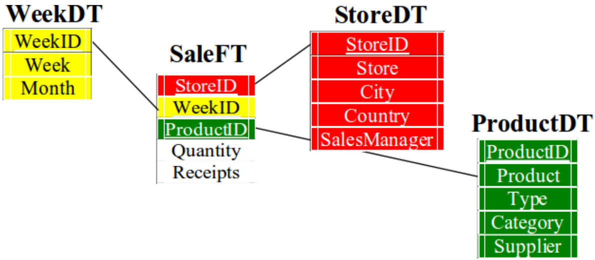
SalesFT

ProductKey	StoreKey	DateKey	Quantity
P1	S1	D1	575

StoreDT

StoreKey	Store	City	Country
S1	Bilka	Aalborg	Denmark
S2	Spar	Bolzano	Italy

OLAP Query on Star Schema



- Query: *Total quantity sold for each product type, week, and city, only for food products.*

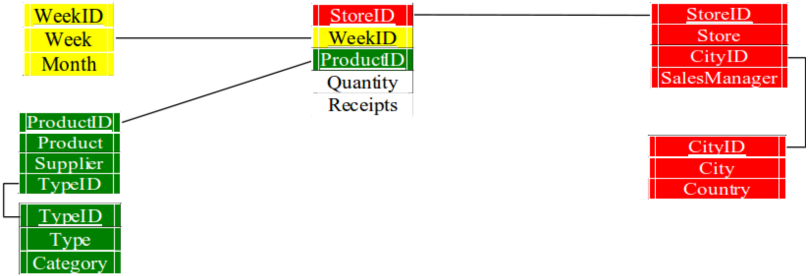
```
SELECT    City, Week, Type, SUM(Quantity)
FROM      WeekDT, StoreDT, ProductDT, SaleFT
WHERE     WeekDT.WeekID = SaleFT.WeekID AND
          StoreDT.StoreID = SaleFT.StoreID AND
          ProductDT.ProductID = SaleFT.ProductID AND
          ProductDT.Category = 'Food'
GROUP BY City, Week, Type;
```

Star Schema

- PROS
  - Simple and easy overview → ease-of-use
  - Relatively flexible
  - Fact table is normalized
  - Dimension tables often relatively small
  - "Recognized" by many RDBMSes → good performance
- CONS
  - Hierarchies are "hidden" in the columns
  - Dimension tables are de-normalized

Snowflake Schema

- The star schema can be optimized in terms of space if one or more dimensions are normalized → snowflake schema.



Instance of Snowflake Schema

ProductTypeDT

TypeKey	Type	CategoryKey
T1	Beer	Beverage
T2	Wine	Beverage

MonthYearDT

MonthKey	Month	Year
M1	May	2013

ProductDT

ProductKey	Product	TypeKey
P1	Bud	T1
P2	Forst	T1
P3	Warst	T1

DateDT

DateKey	Day	MonthKey
D1	25	M1

SalesFT

ProductKey	StoreKey	DateKey	Quantity
P1	S1	D1	575

StoreDT

StoreKey	Store	City	Country
S1	Bilka	Aalborg	Denmark
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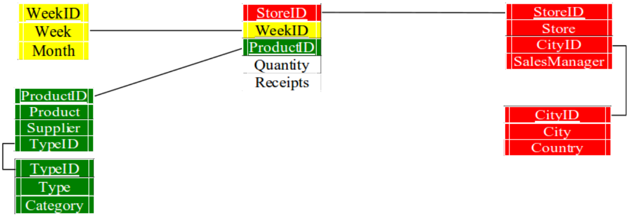
OLAP Query on Snowflake Schema



- Query: *Total quantity sold for each product type, week, and city, only for food products.*

```
SELECT   City, Week, Type, SUM(Quantity)
FROM     WeekDT, StoreDT, ProductDT, CityDT, TypeDT, SaleFT
WHERE    WeekDT.WeekID = SaleFT.WeekID AND
         StoreDT.StoreID = SaleFT.StoreID AND
         ProductDT.ProductID = SaleFT.ProductID AND
         StoreDT.CityID = CityDT.CityID AND
         ProductDT.TypeID = TypeDT.TypeID AND
         ProductDT.Category = 'Food'
GROUP BY City, Week, Type;n
```

Snow-flake Schema

- PROS
  - Hierarchies are made explicit/visible
  - Very flexible
  - Dimension tables use less space
    - However this is a minor saving
    - Disk space of dimensions is typically less than 5 percent of disk for DW
- CONS
  - Harder to use due to many joins
  - Worse performance
    - e.g., efficient bitmap indexes are not applicable

Redundancy in DW

- Only very little redundancy in fact tables.
  - The same fact data (generally) only stored in one fact table.
- Redundancy is mostly in dimension tables.
  - Star dimension tables have redundant entries for the higher levels.
  - Redundancy problems?
    - Inconsistent data: the central load process helps with this.
    - Update time: the DW is optimized for querying, not updates.
    - Space use: dimension tables typically take up less than 5% of DW.
- So: controlled redundancy is good, up to a certain limit.

Strengths

- Many-to-one relationship from fact to dimension
- Many-to-one relationships from lower to higher levels in the hierarchies
- Therefore, it is impossible to "count/sum wrong"

Outline

Dimensions/1

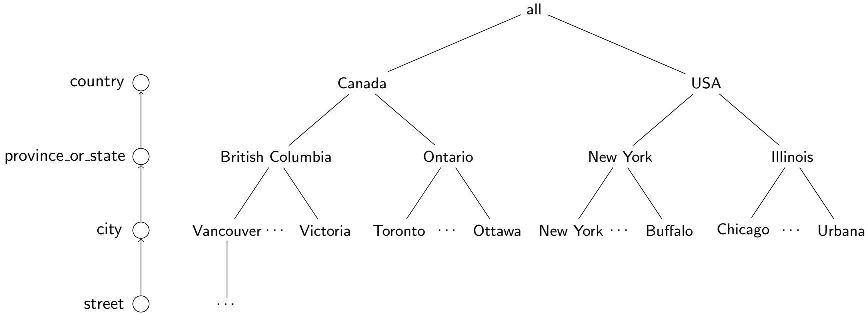
- **Dimensions** are the core of multidimensional databases.
  - Other types of data models do not explicitly support dimensions.
- Dimensions are used for the
  - selection of data;
  - grouping/aggregating data at the right level of detail.
- Dimensions consist of (discrete) dimension values
  - Product dimension has values "milk", "cream", ...
  - Time dimension has values "01/10/2013", "02/10/2013", ...
- Dimension values may have an ordering.
  - Used for comparing cube data across values,
    - e.g., percentage of sales increase compared with last month.
  - Especially used for Time dimension.

Dimensions/2

- Dimensions encode **hierarchies** with levels.
  - Typically 3-5 levels (of detail).
  - Dimension values are organized in a tree structure or lattice
    - Product: Product $\rightarrow$ Type $\rightarrow$ Category
    - Store: Store $\rightarrow$ Area $\rightarrow$ City $\rightarrow$ County
    - Time: Day $\rightarrow$ Month $\rightarrow$ Quarter $\rightarrow$ Year
  - Dimensions have a
    - bottom level: most detailed;
    - top level (ALL): most general.
  - **General rule:** dimensions should contain much information
    - Time dimensions may contain holiday, season, events, ...
    - Good dimensions have 50-100 or more attributes/levels.

Concept Hierarchy Example

- A Location dimension with attributes street, city, province_or_state, and country encodes implicitly the following hierarchy.



Facts

- **Facts** represent the subject of the desired analysis.
  - The "important" in the business that should be analyzed.
- A fact is identified via its dimension values.
  - A fact is a non-empty cell.
  - Some models give facts an explicit identity.
- Generally, a fact should
  - be attached to exactly one value in each dimension;
  - only be attached to dimension values in the bottom levels,
    - e.g., if the lowest time granularity is day, for each fact the exact day should be specified;
    - some models do not require this.

Different Types of Facts

- **Event** facts (transaction)
  - A fact for every business event, e.g., sale.
  - Event happened for a combination of dimension values and has measures.
- **"Fact-less"** facts
  - A fact per event, e.g., customer contact.
  - Has no numerical measures.
  - Event just happened for a combination of dimension values.
- **(Periodic) Snapshot** facts
  - Captures current status, e.g., inventory, sales of today.
  - A fact for every dimension combination for a given time interval.
- **Cumulative snapshot** facts
  - Captures cumulative status of a process up to now, e.g, sales order.
  - Typically several date stamps, which are updated as the process is completed, e.g., order date, shipping date, paying date.

- Every type of facts answers different questions.
- Event facts and snapshot facts are most frequent.

Granularity

- **Granularity** of facts is important.
  - What does a single fact mean?
  - Determines the level of detail.
  - Given by the combination of bottom dimension levels
    - e.g., total sales per store per day per product.
- Has an impact on the number of facts, hence the scalability!
- Often the granularity is a single business transaction, e.g., sale.
- Sometimes the data is aggregated, e.g., total sales per store per day per product.
  - Aggregation might be necessary for scalability.
- Generally, transaction detail can be handled
  - Except perhaps huge clickstreams, etc.

Measures

- **Measures** represent the fact property that users want to study and analyze,
  - e.g., total sales or average sales per day.
- A measure has two components
  - **Numerical value:** used to describe a fact/event, e.g., sales price, # of items in a transaction.
  - **Aggregation formula:** used for aggregating/combining a number of measure values into one, e.g., SUM, AVG, MAX.
- Single fact table rows/measures are (almost) never retrieved, but aggregations over millions of fact rows.

Additivity of Measures

- A measure is called **additive along a dimension** if the SUM operator can be used to aggregate it along that dimension (hierarchy); otherwise it is **non-additive** along that dimension.
- Additivity is an important property of measures
  - Provides flexibility in aggregation and navigation.
  - Most frequently the case.
- Classification of measures based on additivity.

Different Types of Measures/1

- **Additive** measures (flow measures):
  - Additive along all dimensions
  - Refer to a timeframe, at the end of which they are evaluated cumulatively
  - Typically the case for event facts,
    - e.g., the number of products sold in a day, monthly receipts, yearly number of births, gross profit per year, cost, etc.
- **Semi-additive** measures (level measures)
  - Additive only over some dimensions (typically non-temporal dimensions)
  - Are evaluated at particular times and often occur in snapshot facts
    - e.g., the number of products in inventory: non-additive across time
    - customer_count: additive across store, non-additive across product
    - the number of inhabitants in a city
- **Non-additive** measures (unit measures)
  - Additive over none of the dimensions
  - Are evaluated at particular times but are expressed in relative terms
    - e.g., product unit price, discount percentage, currency exchange: SUM makes no sense along any dimension, but AVG, MIN, MAX.

Different Types of Measures/2

Measures	Temporal hierarchies	Nontemporal hierarchies
Additive (Flow)	**SUM**, AVG, MIN, MAX	**SUM**, AVG, MIN, MAX
Semi-additive (Level)	AVG, MIN, MAX	**SUM**, AVG, MIN, MAX
Non-additive (Unit)	AVG, MIN, MAX	AVG, MIN, MAX

Non-aggregable Measures

- A measure is called **non-aggregable along a dimension** if it cannot be aggregated along that dimension using any aggregation operator.

- **Example:** A measure `numberOfCustomers` with dimensions `product`, `store`, and `day` that is estimated from the number of receipts.
- Non-aggregable along product dimension, since a receipt is likely to contain several products.
  - many-to-many relationship between receipts and products (instead of many-to-one)
- Can be aggregated over store and date dimension.

Outline

Reporting

- **Reporting** is for users who need a regular access to information in an almost static way.
  - e.g., local health authorities must send monthly reports to state offices.
- Report is defined by a query (multiple queries) and a layout (diagrams, histograms, etc.).

CdC 8090		2008	BUDGET				2009			BUDGET 2010			
VOLUMI, MIX E QUALITA' PRODUZIONE	FINO AL		PIANO	PESO	Limite inferiore	Limite superiore	PROIEZ.	SCOST.	MATURATO	BUDGET	PESO	Limite inferiore	Limite superiore
Dimessi ordinari	31.08.	293	296	0%	0	0	270	-8,8%	0%	270			
Trasferimento	31.08.	1	2				0	-100,0%	0%	0			
gg di degenza	31.08.	990	939				993	5,8%	0%	993			
n. posti letto	31.08.	5	5				5		0%				
Accessi day hospital/surgery	31.08.	887	981	0%	0	0	1.168	19,0% !	0%	1.168			
n. posti letto day hosp./surg.	31.08.	4	6				6		0%	6			
Totale attività per esterni	31.08.	45.870	46.986	0%	0	0	44.039	-6,3%	0%	44.039			
Totale attività per interni	30.09.	566	548	0%	0	0	559	1,9%	0%	559			
Totale attività ricevuta	30.06.	2.561	0	0%	0	0	2.502		0%	2.502			
- di cui di laboratorio	31.08.	2.295	2.202	0%	0	0	2.340	6,3%	0%	2.340			
- di cui di radiologie	31.08.	185	171	0%	0	0	102	-40,4%	0%	102			
n° prest. di lab. x dimessi ordinari	31.08.	7,83					6,67		0%	6,67	40%		6,67
n° prest. di rad. x dimessi ordinari	31.08.	0,63					0,38		0%	0,38	30%		0,38
COSTI ED EFFICIENZA													
Consumi beni sanitari	30.09.	486.304	411.792	50%	0	432.382	501.299	21,7% !		501.299			
PHT + H-CSP2	30.09.						0		0%	0			
Consumi beni non sanitari	30.09.	3.648	3.728	0%	0	0	3.284	-11,9%	0%	3.284			
altri costi	30.09.	4.459	3.831	0%	0	0	6.524	70,3% !	0%	6.524			
Totale consumi		494.411	419.351	0%	0	0	511.107	21,9% !	0%	511.107			
costi personale (non da pianificare)	30.06.	994.834					1.029.189						
unità personale	30.09.	5,75	7,00	0%	0.00	0.00	6,26	-10,6%	0%	6,44			
presenza media	31.08.	5,16					6,44						
Tasso utilizzo letti	31.08.	54,10%	51,31%	0%	0,00%	0,00%	54,20%		0%	54,20%			
degenza media	31.08.	3,33	3,16	0%	0.00	0.00	3,60		0%	3,60			
tasso up	30.06.	70,76%.	87,23%	0%	0,00%	0,00%	70,73%		0%	70,73%			
% ricoveri di 1 giorno	31.08.	7,64%	2,00%	50%	0,00%	3,00%	6,40%			6,40%	30%		6,40%
peso medio drg	30.06.	0,66	0,81				0,89		0%	0,89			
mobilità provinciale passiva	30.06.	151.396	0	0%	0	0	133.248		0%				
mobilità provinciale attiva	30.06.	880.010	0				954.940		0%				
mobilità Innsbruck	30.06.	30.775	0				24.448		0%				
servizio trasporti: n° pazienti	31.08.	32	0	0%	0	0	21		0%				
servizio trasporti: €	31.08.	1.566	0				999		0%				
Summe Gewichtung				100%					0%				

OLAP/1

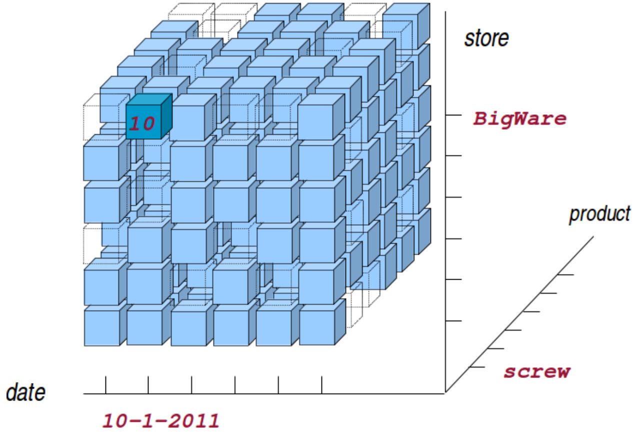
- **OLAP (Online Analytical Processing)** is the most popular way to exploit information in a DW.
- Provides more flexibility, especially when the analysis needs are not defined beforehand.
- Interactive way to explore data on the basis of the multidimensional model.
  - Each step is the result of the outcome of preceding steps.
- Each step of an analysis session applies an OLAP operator.
- OLAP tools typically use tables with multiple headers and colors to visualize multidimensional query results.

OLAP/2

- Two kinds of OLAP operators/queries:
  - Aggregation operators summarize fact data, e.g., with SUM.
  - Navigation operators allow to examine data from different viewpoints and detail levels.
- Analysis starts at some level, e.g. (Quarter, Product).
  - Roll Up: less detail, e.g., Quarter $\rightarrow$ Year
  - Drill Down: more detail, e.g., Quarter $\rightarrow$ Month
  - Slice/Dice: selection, e.g., Year=1999
  - Drill Across: "join" on common dimensions

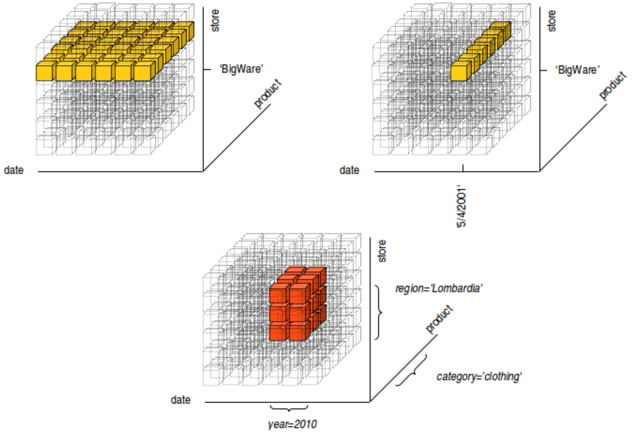
OLAP Example/1

- Sales Cube



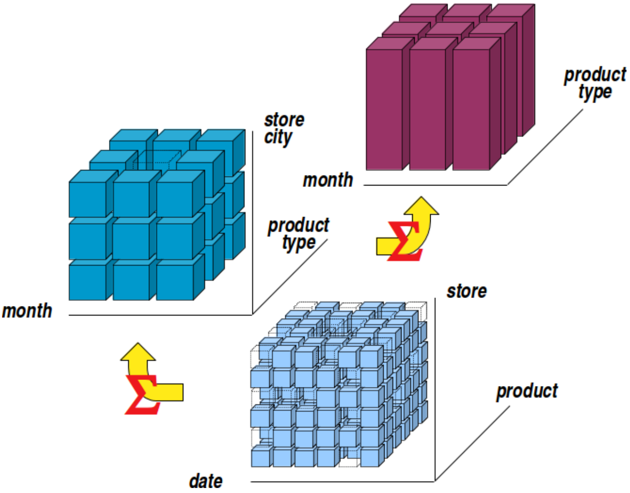
OLAP Example/2

- Slicing and Dicing: select specific (ranges of) values for dimension attributes



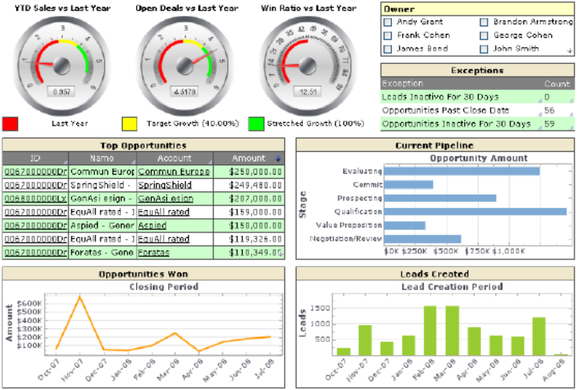
OLAP Example/3

- Aggregation



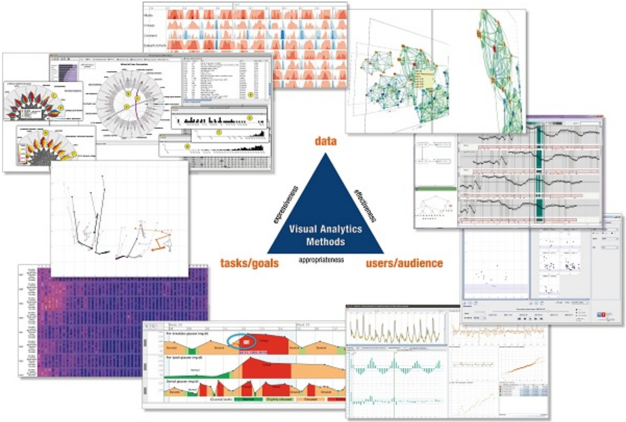
Dashboards

- **Dashboards** display a limited amount of information in a easy-to-read graphical format.
- Frequently used by senior managers who need a quick overview of the most significant changes,
  - e.g., real-time overview of trends.
- Not useful for complex and detailed analysis.



Visual Analytics

- **Visual Analytics** is about analytical reasoning supported by interactive visual interfaces.
- Graphical presentation of complex result.
- Color, size, and form help to give a better overview.



Data Mining

- **Data mining** is automatic knowledge discovery.
- Has its roots in AI and statistics.
- Different tasks:
  - Classification
    - Partition data into pre-defined classes.
  - Clustering
    - Partition data into groups such that the similarity within individual groups ist greatest and the similarity between groups is smallest.
  - Affinity grouping/associations
    - Find associations/dependencies between data.
    - Rules: $A \rightarrow B(c\%, s\%)$: if A occurs, B occurs with confidence c and support s.
  - Prediction
    - Predict/estimate unknown value based on similar cases.
- Important to choose the granularity for mining.
  - Too small granularity gives no good results (shirt brand, . . .).

Outline

Relational OLAP (ROLAP)

- Data/Cube is stored in relational tables.
  - Fact table stores facts.
    - One column for each measure and dimension.
  - Dimension tables store dimensions.
  - SQL is used for querying.
- PROS
  - Leverages investments in relational technology.
  - Huge amount of literature and broad experience with RDBMSs.
  - Scalable to billions of facts.
  - Flexible design and easier to change.
  - New techniques adapted from MOLAP.
    - Indexes (e.g., bitmap), materialized views, special handling of star schemas.
- CONS
  - Storage use often 3-4 times higher than in MOLAP.
  - Higher response times due to joins.

Relational OLAP (ROLAP) Schemas

- One completely de-normalized table
  - Bad: inflexibility, storage use, bad performance, slow update.
- Star schema
  - One fact table
  - De-normalized dimension tables
  - One column per level/attribute
- Snowflake schema
  - Dimensions are normalized
  - One dimension table per level
  - Each dimension table has integer key, level name, and one column per attribute

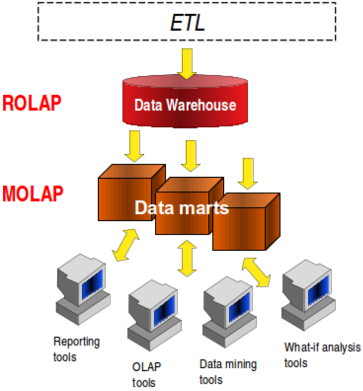
Multidimensional OLAP (MOLAP)

- Data/cube is stored in special multidimensional data structures.
  - Arrays with positional access.
- PROS
  - Less storage use ("foreign keys" are not stored).
  - Multidimensional operations can be performed without complex and costly joins.
  - Faster query response times.
- CONS
  - Up till now not so good scalability.
  - Less flexible, e.g., cube must be re-computed when design changes.
  - Does not reuse an existing investment (but often bundled with RDBMS).
  - "New technology", not an open technology.
  - No standards yet available, very specific optimizations are used.

Hybrid OLAP (HOLAP)

- ROLAP and MOLAP elements are combined into a single architecture.
  - Aggregates stored in multidimensional structures (MOLAP)
  - Detail data stored in relational tables (ROLAP)

- PROS
  - Scalable and fast.
  - Largest amount of data and sparse subcubes are stored in RDBMS.
  - Dense subcubes of aggregated data (DMs) are stored in multidimensional structures.
    - Most frequently needed by the user.
- CONS
  - Complexity



Summary

- Logical design transforms the conceptual model into a logical model
- Multidimensional model is de facto standard logical model.
  - Consists of dimensions, facts, and measures
  - Facts are the important entities, dimensions describe the important entities/facts.
  - Data lives in multidimensional cubes.
- In relational systems, the multidimensional model is materialized as star or snowflake schema: 1 fact table and several dimension tables.
- Different fact types:
  - event facts, fact-less facts, snapshot facts, cumulative snapshot facts.
- Additivity is an important property of measures.
  - Additive measures, semi-additive measures, non-additive measures.
- Different DW applications: Reporting, OLAP, dashboards, visual analytics, and data mining.
- Different DW implementations
  - ROLAP
  - MOLAP
  - HOLAP