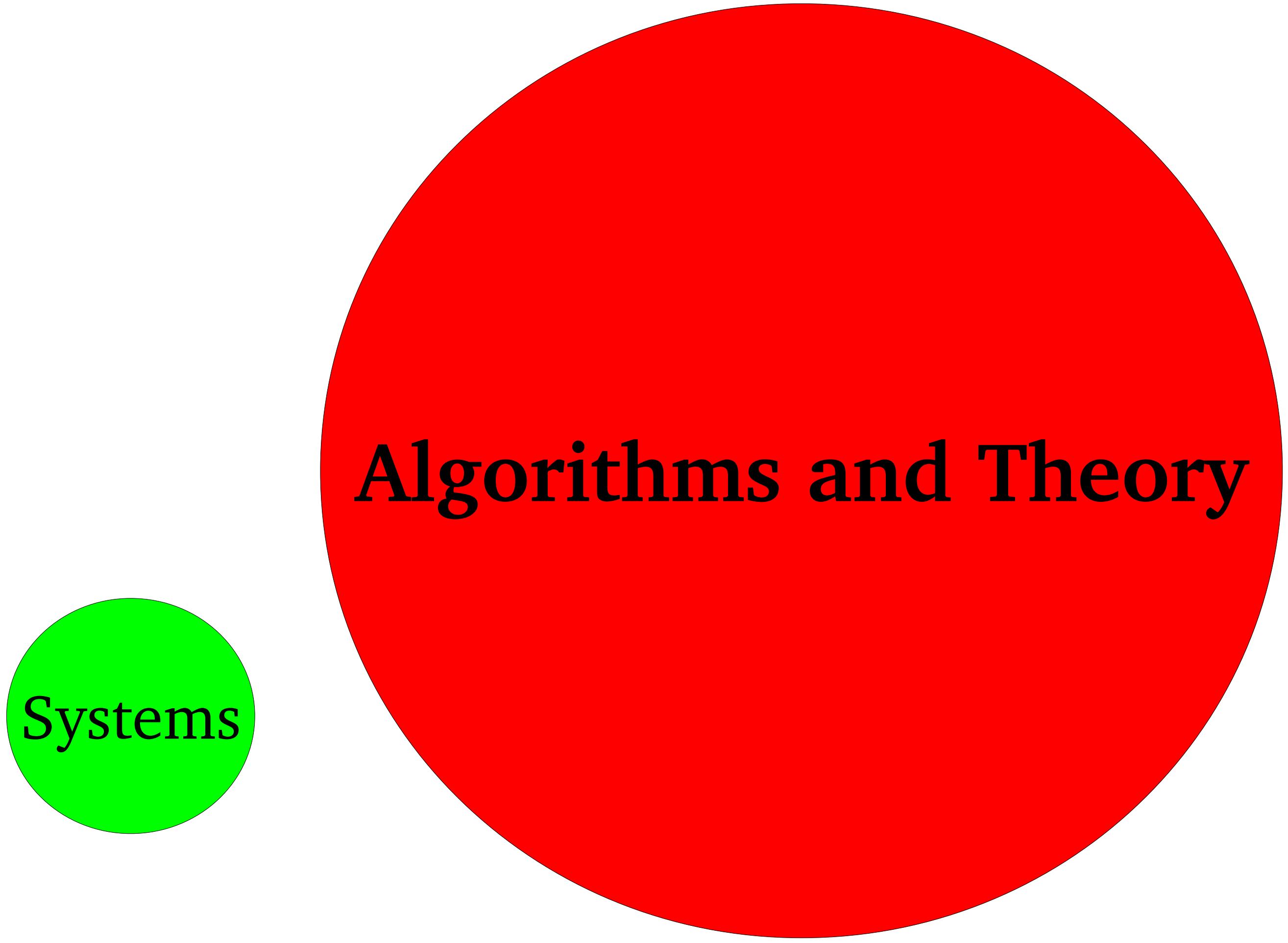
Data Warehousing
and Data Mining

Lecture dates (subject to change):

- November 13, 14, 27, 28
- December 4, 5, 11, 12, 18, 19
- January 8, 9

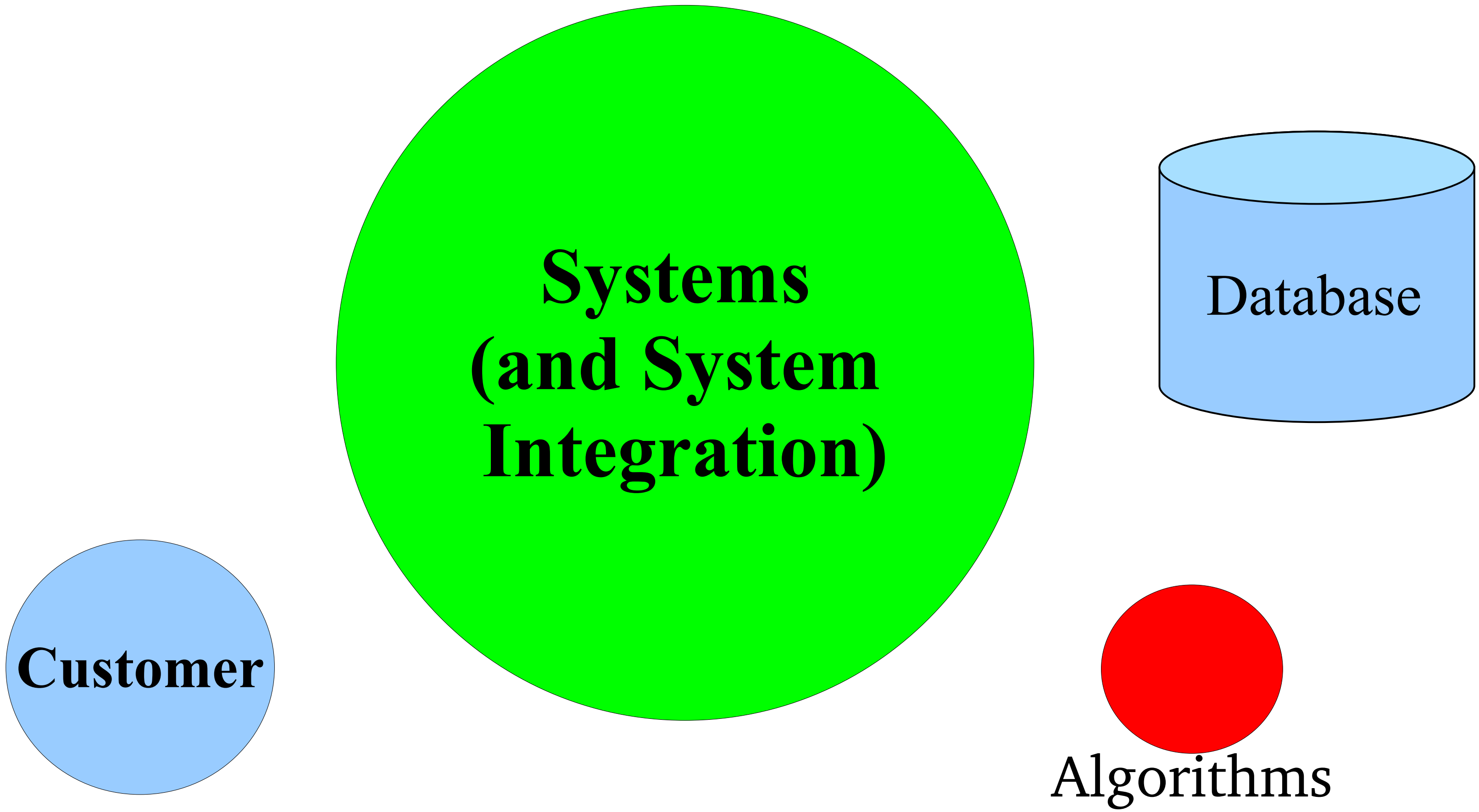
The Big Picture of DWDM/1

- What's important for researchers:



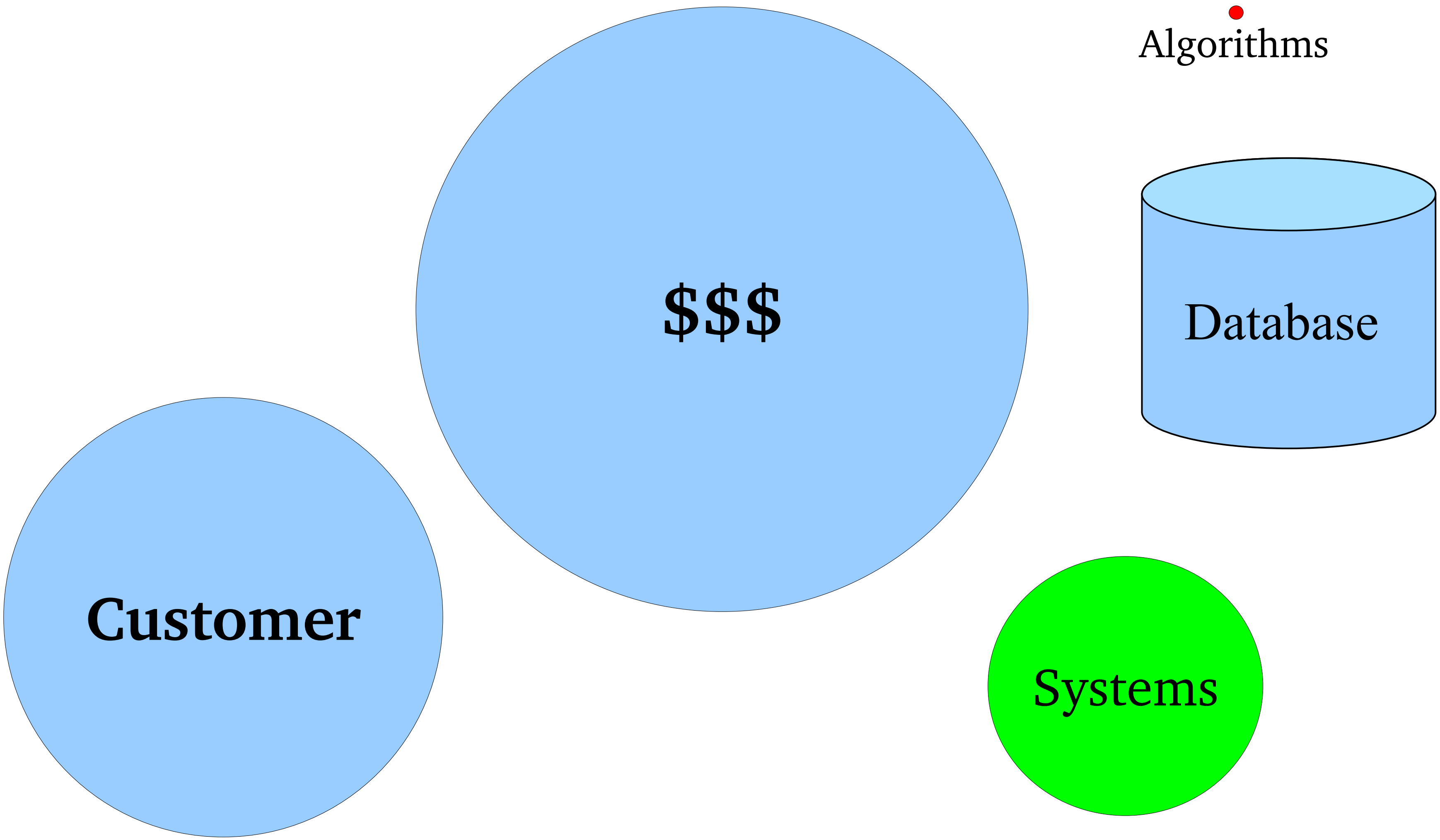
The Big Picture of DWDM/2

- What's important for real world applications:



The Big Picture of DWDM/3

- What's important for businesses:



Remarks about the DW part

- We learn how to design, build, and use a data warehouse.
- Relevance to the real world is an important guideline.

- Not only/mainly crisp algorithms, theorems, etc.
- We will look at a number of concrete and important case studies.
- A good way to prepare and learn the subject is to participate to lectures.
- We solve case studies and examples on the board.
- At the exam this part turns out to be difficult.

Content of the DW Part

1) **Data warehousing**: business intelligence, data integration, data warehouse, facts, dimensions, DW design
2) **SQL OLAP extensions**: analytical functions, crosstab, group by extensions, hierarchical cube, moving windows
3) **Generalized multi-dimensional join**: GMDJ, evaluation, subqueries, optimization rules, distributed evaluation
4) **DW performance**: pre-aggregation, lattice framework, view selection, view maintenance, bitmap indexing

Remember...

- At the end of the course (aka exam) you have to **present** your knowledge in terms of an **example**.
- The **exact plan** for a presentation must be prepared in advance.
- Choose the example wisely (talking a lot decreases your score; get to the **key points**).
- **Prepare** summaries and presentation plans throughout the course; at the end there will not be enough time.
- It often happens that people know the material but fail to present it.
- The **details** are important.

Data Warehousing

1. Business intelligence
    - Data integration
    - Data warehouse introduction
    - Data analysis

2. Multidimensional modeling
    - Dimensions, facts
    - Data warehouse design process
    - Data warehouse implementation

Goals

- Be able to design a data warehouse for a given real world problem description.
- Understand the key issues of multidimensional models.
- Know state of the art solutions for key problems of multidimensional modeling.

What is Business Intelligence?

- BI is a combination of technologies
  - Data Warehousing (DW)
  - On-Line Analytical Processing (OLAP)
  - Data Mining (DM)
  - Data Visualization (VIS)
  - Decision Analysis (what-if)
  - Customer Relationship Management (CRM)
- BI is buzzword compliant
  - Many new trends are extensions or integrations of the technologies above
- The “opposite” of Artificial Intelligence (AI)
  - AI systems **make** decisions **for** the users
  - BI systems **help** users make the **right** decisions, based on the available data
  - Many BI techniques have roots in AI, though.

Example BI Queries

- **Q1**: On October 11, 2000, find the 5 top-selling products for each product subcategory that contributes more than 20% of the sales within its product category.
- **Q2**: As of March 15, 1995, determine shipping priority and potential gross revenue of the orders that have the 10 largest gross revenues among the orders that had not yet been shipped. Consider orders from the book market segment only.

- Regular database models and systems are not suitable for this type of queries.

BI is Crucial and Growing

- Meta Group: DW alone = $15 bio. in 2000
- Palo Alto Management Group: BI = $113 bio. in 2002
- The Web made BI more necessary:
  - Customers do not appear ”physically” in the store
  - Customers can change to other stores more easily
- Thus:
  - You have to know your customers using data and BI.
  - Web logs makes is possible to analyze customer behavior in a more detailed than before (what was **not** bought?)
  - Combine web data with traditional customer data
- Wireless Internet adds further to this:
  - Customers are always ”online”
  - Customer’s position is known
  - Combine position and customer knowledge => very valuable

BI: Key Problems

1) **Complex and unusable models**
   - Many DB models are difficult to understand
   - DB models do not focus on a single clear business purpose
2) **Same data found in many different systems**
   - Example: customer data in 14 systems
   - The same concept is defined differently
3) **Data is suited for operational systems**
   - Accounting, billing, etc.
   - Do not support analysis across business functions
4) **Data quality is bad**
   - Missing data, imprecise data, different use of systems
5) **Data are ”volatile”**
   - Data deleted in operational systems (6 months)
   - Data change over time – no historical information

BI: Solution

- Problems
  - Same data found in many different systems
  - Data is suited for operational systems
  - Data quality is bad
  - Data are ”volatile”
- Solution: a **new analysis environment** (a data warehouse) where data is
  - Integrated (logically and physically)
  - Subject oriented (versus function oriented)
  - Supporting management decisions (different organization)
  - Stable (data not deleted, several versions)
  - Time variant (data can always be related to time)

Data Integration

Problem:

- Different interfaces
- Different data representations
- Duplicated information
- Inconsistent information

Integrated System

Goal:

- Collect and combine information
- Provide an integrated view
- Provide a uniform user interface
- Support sharing of data

Query-Driven Data Integration

- Data is integrated on demand (lazy)
- PROS
  - Access to most up-to-date data (all source data directly available)
  - No duplication of data
- CONS
  - Delay in query processing
    - Slow or unavailable information sources
    - Complex filtering and integration
  - Inefficient and expensive for frequent queries
  - Competes with local processing at sources
  - Data loss at the sources (e.g., historical data) cannot be recovered
- Has not caught on in industry

Warehouse-Driven Data Integration

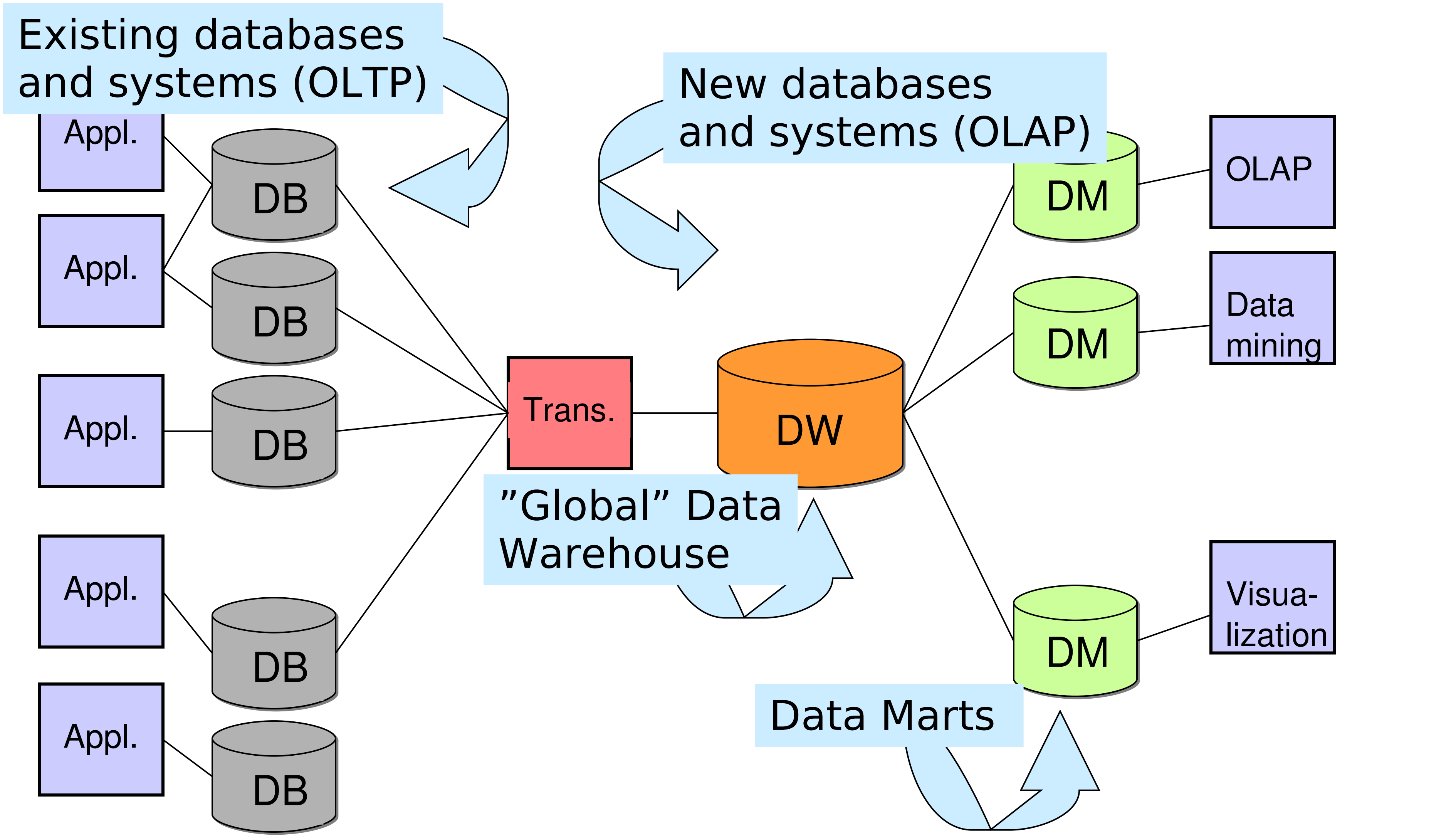
- Data is integrated in advance (eager)
- Data is stored in DW for querying and analysis
- PROS
  - High query performance
  - Does not interfere with local processing at sources
    - Assumes that data warehouse update is possible during downtime of local processing
    - Complex queries are run at the data warehouse
    - OLTP queries are run at the source systems
- CONS
  - Duplication of data
  - The most current source data is not available
- Has caught on in industry

OLTP versus OLAP/1

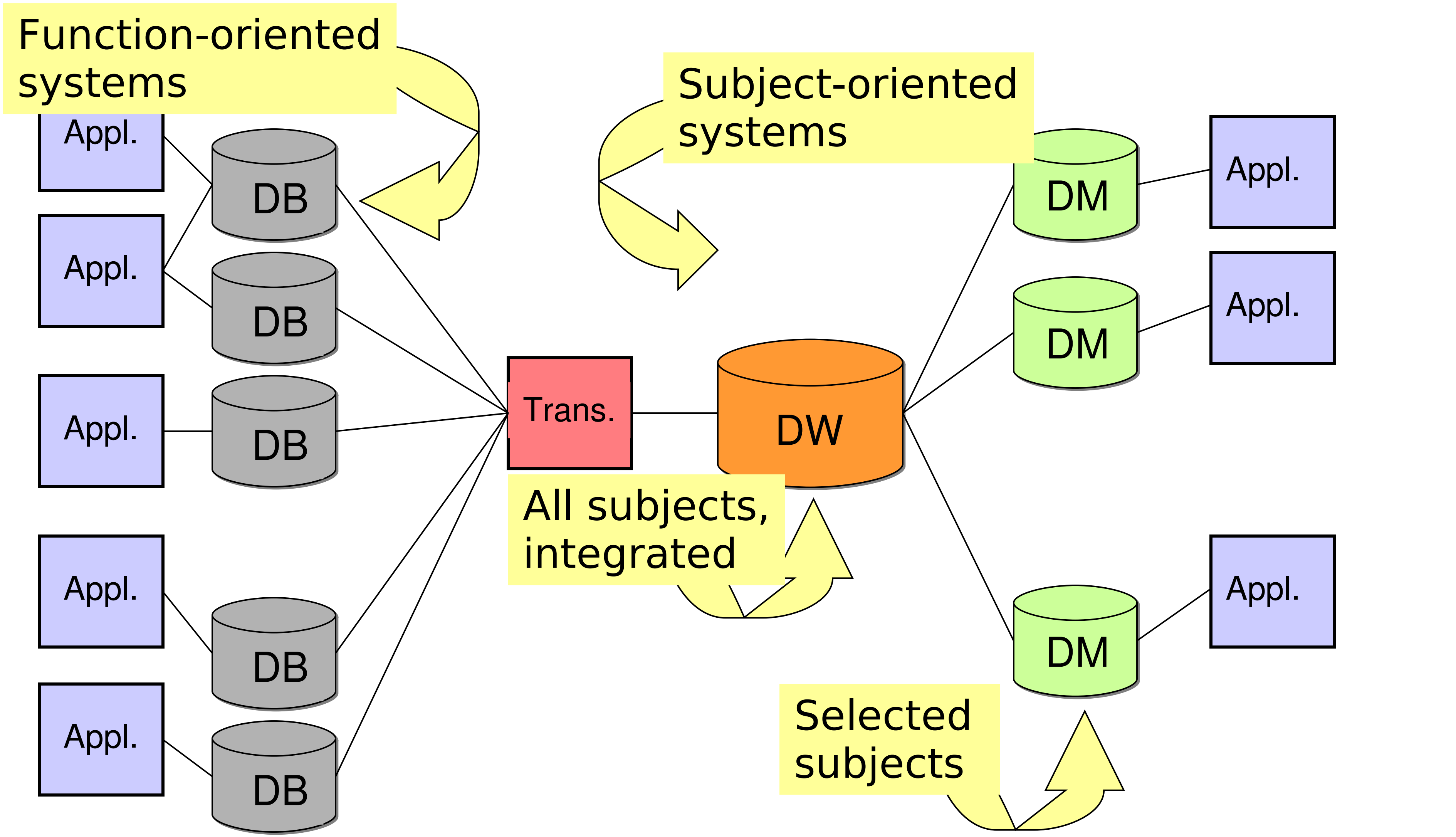
- On-Line Transaction Processing (OLTP)
  - Many, ”small” queries
  - Frequent updates
  - The system is always available for both updates and reads
  - Smaller data volume (few historical data)
  - Complex data model (normalized)

- On-Line Analytical Processing (OLAP)
  - Fewer, but ”bigger” queries
  - Frequent reads, in-frequent updates (daily)
  - 2-phase operation: either reading or updating
  - Larger data volumes (collection of historical data)
  - Simple data model (multidimensional/de-normalized)

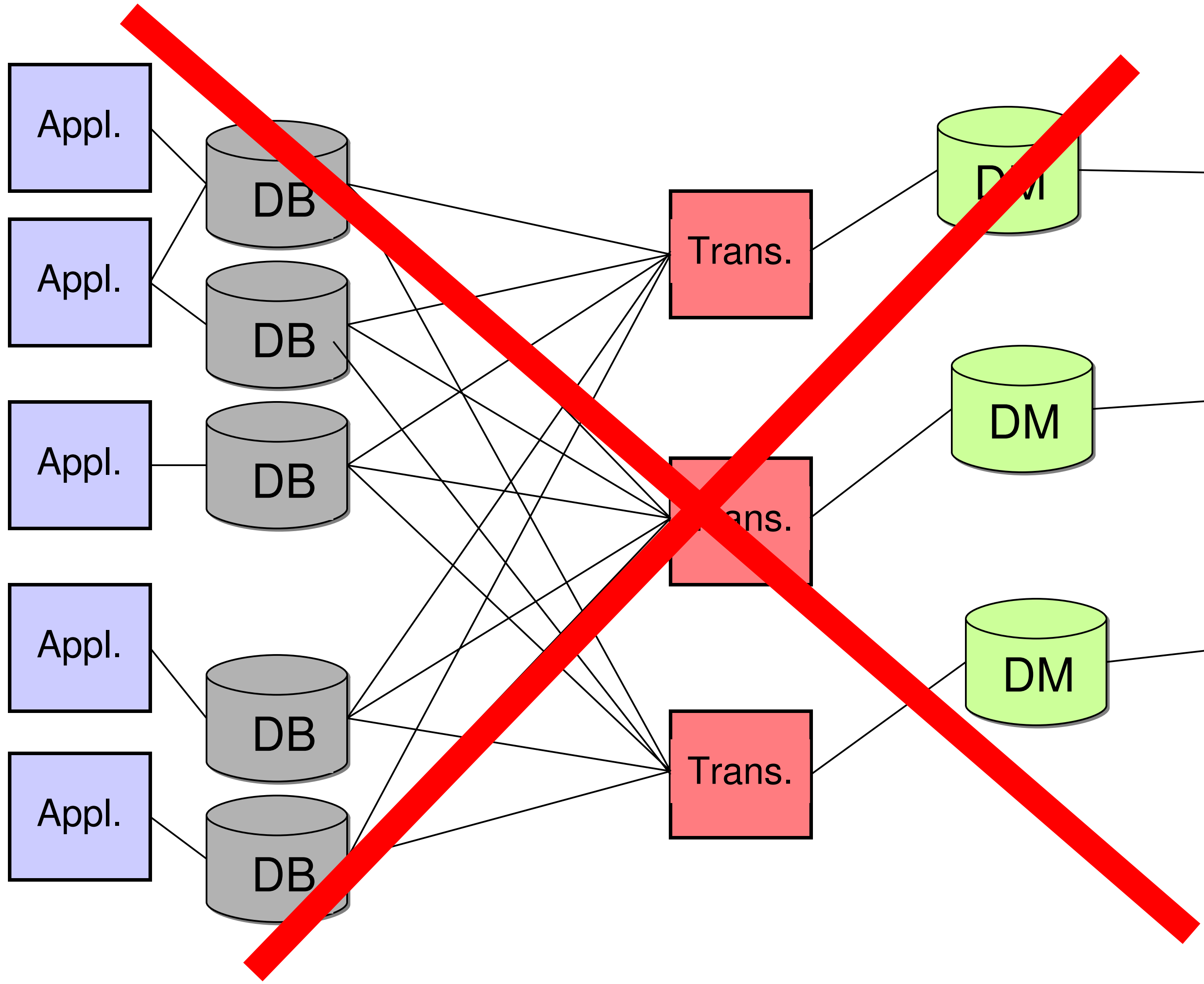
OLTP versus OLAP/2



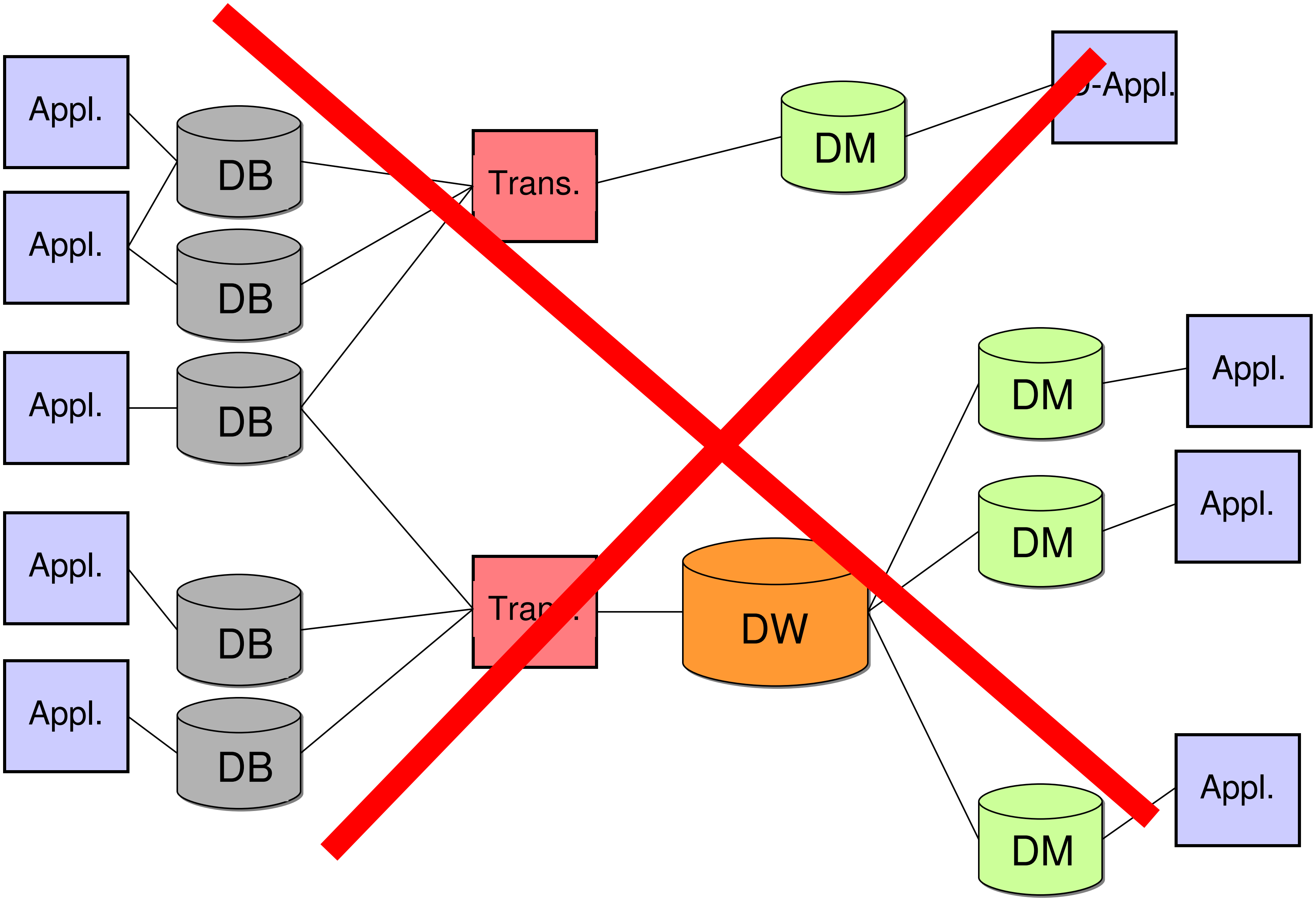
Function- versus Subject Orientation



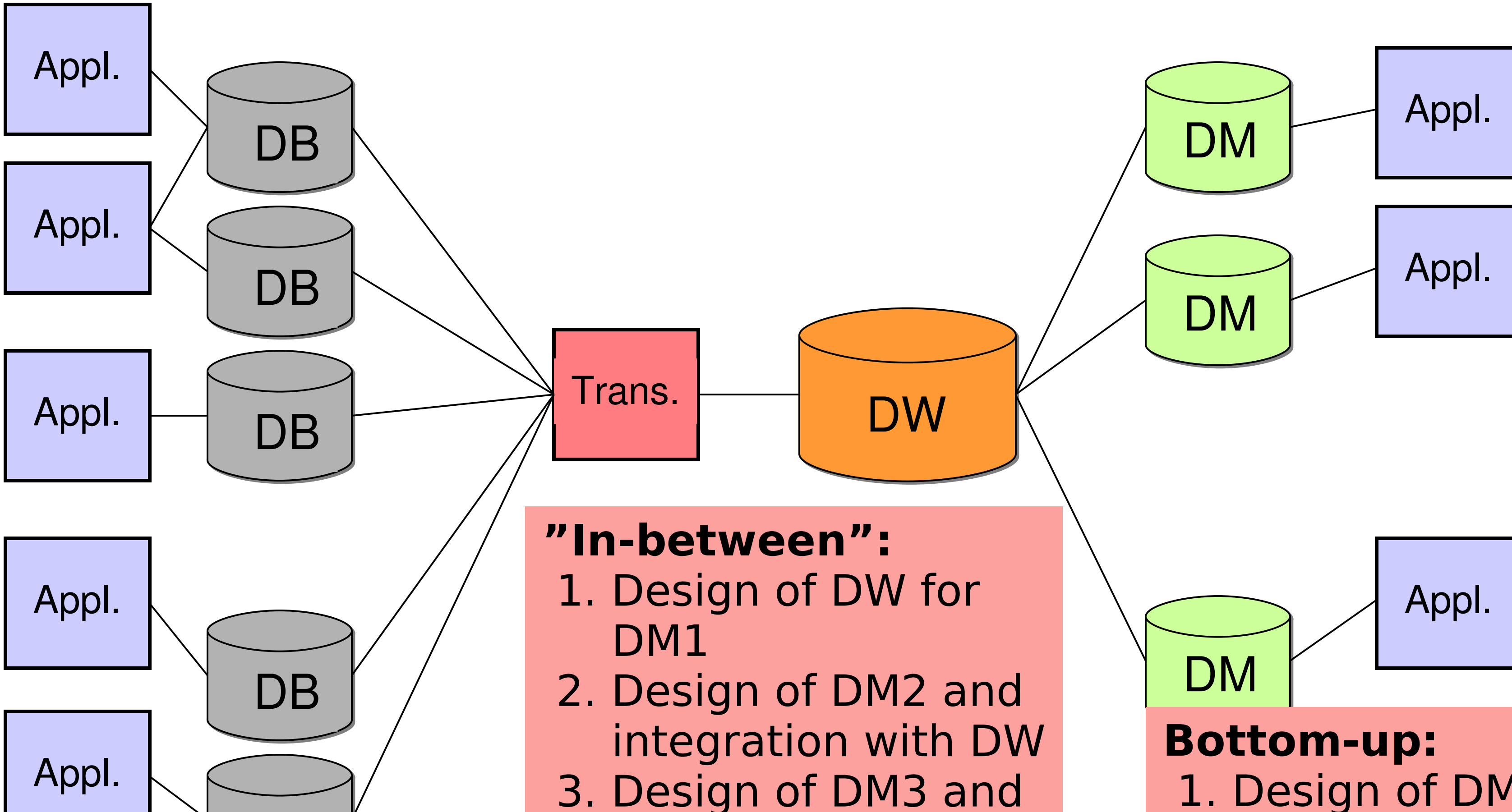
Risk: Many Ways to Not Integrate/1



Risk: Many Ways to Not Integrate/2



Approach: Top-down vs. Bottom-up



"In-between":

1. Design of DW for DM1
2. Design of DM2 and integration with DW
3. Design of DM3 and integration with DW
4. ...

Top-down:

1. Design of DW
2. Design of DMs

Bottom-up:

1. Design of DMs
2. Integration of DMs in DW
3. Maybe no physical DW

Definition of a Data Warehouse/1

- Barry Devlin, IBM Consultant

A data warehouse is simply a **single**, **complete**, and **consistent** store of data obtained from a **variety** of sources and made available to end users in a way they can **understand** and **use** it in a **business context**.

Definition of a Data Warehouse/2

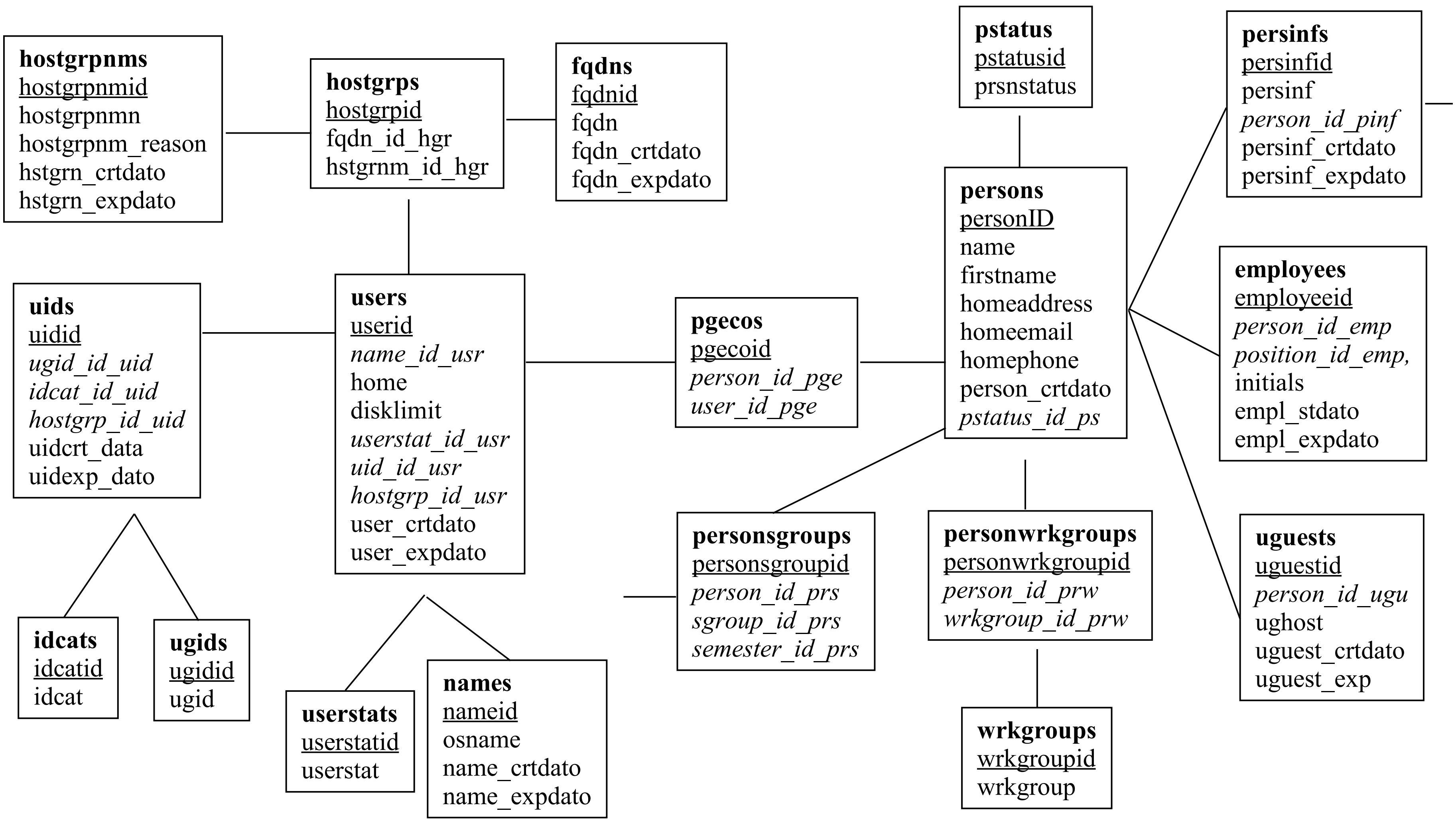
- W. H. Inmon, Building the Data Warehouse

A data warehouse is a
- **subject-oriented**,
- **integrated**,
- **time-varying**,
- **non-volatile**

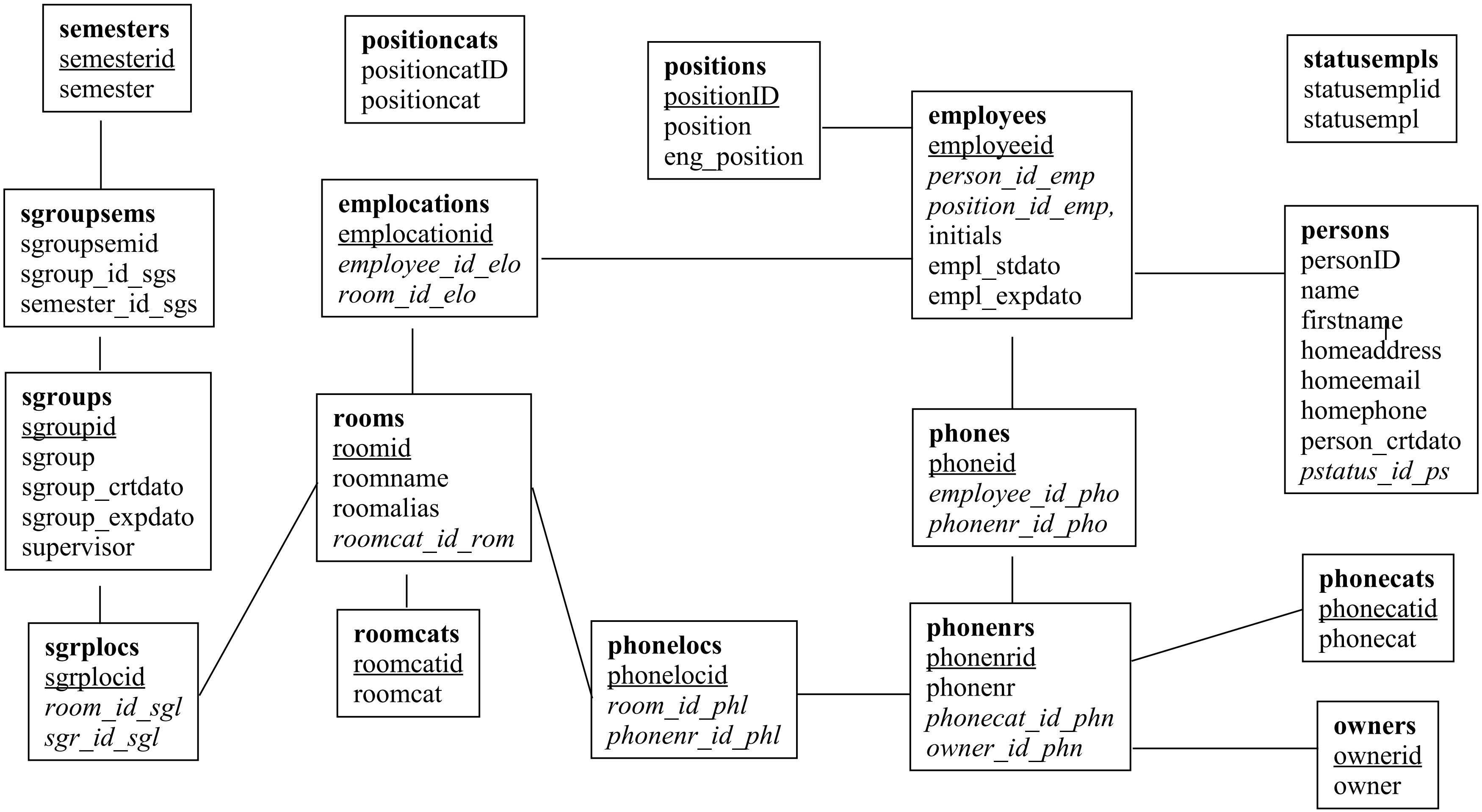
collection of data that is used primarily in
- **organizational decision making**.

OLTP Example: CS Dept/1

1, 2, 3, 4



OLTP Example: CS Dept/2



Summary

- Business intelligence is well-recognized and is a combination of a number of techniques.
- Real data analysis problems are good drivers.
- The data warehouse (DW) stores the data.
- Applications that **use** the DW
  - OLAP
  - Data mining
  - Visualization

- BI can provide many advantages to your organization
  - A good DW is a prerequisite for BI
  - But, a DW is a **means** rather than a **goal**...it is only a success if it is heavily used

Multidimensional Modeling

- Motivation
- Cubes
- Dimensions
- Facts
- Measures
- Data warehouse queries
- Relational design
- Redundancy
- Strengths and weaknesses of the multidimensional model

Why a New Model?

- We know E/R and OO modeling
- All types of data are “equal”
- E/R and OO models: many purposes
  - ***Flexible***
  - ***General***
- No difference between:
  - What **is** important
  - What just **describes** the important
- ER/OO models are **large**
  - 50-1000 entities/relations/classes
  - Hard to get an overview
- ER/OO models implemented in RDBMSes
  - Normalized databases **spread** information
  - When analyzing data, the information must be **integrated** again

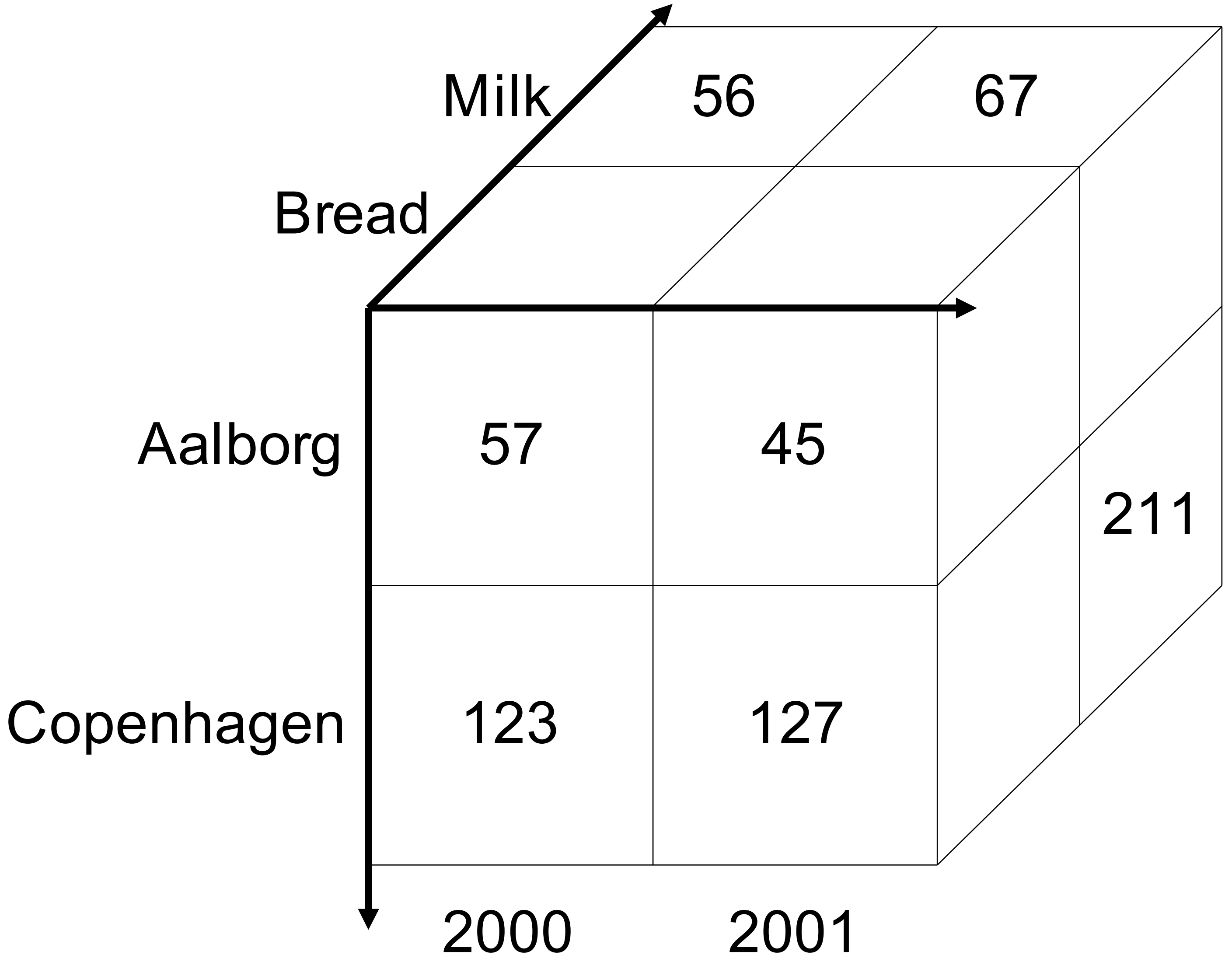
The Multidimensional Model/1

- One purpose
  - **Data analysis**
- Better at **that** purpose
  - Less flexible
  - Not suited for OLTP systems
- More **built in** “meaning”
  - What **is** important
  - What **describes** the important
  - What we want to **optimize**
  - Automatic aggregations means easy querying
- Recognized by OLAP/BI tools
  - Tools offer powerful query facilities based on MD design

The Multidimensional Model/2

- Data is divided into:
  - **Facts**
  - **Dimensions**
- Facts are the **important** entity: a sale
- Facts have **measures** that can be aggregated: sales price
- Dimensions **describe** facts
  - A sale has the dimensions Product, Store and Time
- Facts “live” in a multidimensional **cube**
  - Think of an array from programming languages
- Goal for dimensional modeling:
  - Surround facts with as much context (dimensions) as possible
  - Hint: redundancy may be ok (in well-chosen places)
  - But you should **not** try to model **all** relationships in the data (unlike E/R and OO modeling!)

Cube Example: Sales

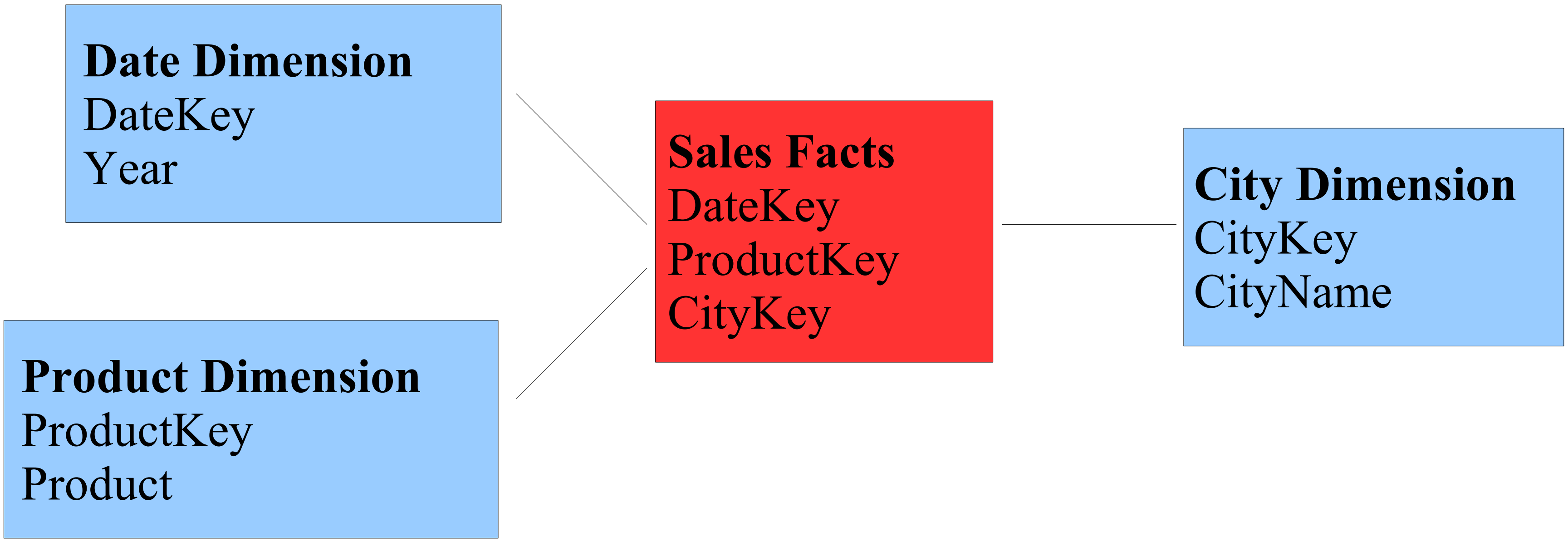


Cubes

- A “cube” may have **many** dimensions.
  - More than 3 - the term ”hypercube” is sometimes used
  - Theoretically no limit for the number of dimensions
  - Typical cubes have 4-12 dimensions
- But only 2-3 dimensions can be viewed at a time
  - Dimensionality reduced by queries via projection/aggregation
- 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 few non-empty cells
  - A **dense** cube has many non-empty cells
  - Cubes become sparser for many/large dimensions

Star Schema

- A common approach to draw a dimensional model is the star schema.
- The star schema shows a fact table and dimension tables.
- For each table we specify the attributes.



Dimension Schema and Instance

Date
DateKey
Date
DateFull
DayOfWeek
CalMonth
CalYear
Holiday

schema of dimension Date

instance of dimension Date

Date

DateKey	Date	DateFull	DayOfWeek	CalMonth	CalYear	Weekday
1	01/01/02	Januar 1, 2002	Tuesday	January	2002	Weekday
2	01/02/02	Januar 2, 2002	Wednesday	January	2002	Weekday
3	01/03/02	Januar 3, 2002	Thursday	January	2002	Weekday
4	01/04/02	Januar 4, 2002	Friday	January	2002	Weekend
5	01/05/02	Januar 5, 2002	Saturday	January	2002	Weekend

Dimensions/1

- Dimensions are the core of multidimensional databases
  - Other types of databases do not support dimensions
- Dimensions are used for
  - **Selection** of data
  - **Grouping** of data at the right level of detail
- Dimensions consist of **dimension values**
  - Product dimension has values ”milk”, ”cream”, …
  - Time dimension has values ”1/1/2001”, ”2/1/2001”,…
- Dimension values may have an **ordering**
  - Used for comparing cube data across values
  - Example: ”percent sales increase compared with last month”
  - Especially used for Time dimension

Dimensions/2

- Dimensions have **hierarchies** with **levels**
  - Typically 3-5 levels (of detail)
  - Dimension values are organized in a **tree structure**
  - **Product**: Product->Type->Category
  - **Store**: Store->Area->City->County
  - **Time**: Day->Month->Quarter->Year
  - Dimensions have a **bottom level** and a **top level** (ALL)
- Levels may have **attributes**
  - Simple, non-hierarchical information
  - Day has Workday as attribute

- Dimensions should contain much information
  - Time dimensions may contain holiday, season, events,...
  - Good dimensions have 50-100 or more attributes/levels

Facts

- Facts represent the **subject** of the desired analysis
  - The ”important” in the business that should be analyzed
- A fact is most often 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** dimension value in each dimension
  - Only be attached to dimension values in the bottom levels
  - Some models do not require this

Granularity

- **Granularity** of facts is important
  - What does a single fact mean?
  - **Level of detail**
  - Given by combination of bottom levels
  - Example: ”total sales per store per day per product”
- Important for number of facts
  - Scalability
- Often the granularity is a single business transaction
  - Example: sale
  - Sometimes the data is aggregated (**total** sales per store per day per product)
  - Aggregation might be necessary due to scalability
- Generally, transaction detail can be handled
  - Except perhaps huge clickstreams etc.

Measures

- Measures represent the fact property that the users want to **study and optimize**
  - Example: total sales price
- A measure has two components
  - **Numerical value**: (sales price)
  - **Aggregation formula** (SUM): used for aggregating/combining a number of measure values into one
  - Measure value determined by dimension value combination
  - Measure value is meaningful for all aggregation levels
- Most multidimensional models have measures
  - A few do not

DW Design Steps

1. Choose the **business process(es)** to model
   - Sales
2. Choose the **grain** of the business process
   - Items by Store by Promotion by Day
   - Low granularity is needed
   - Are individual transactions necessary/feasible ?
3. Choose the **dimensions**
   - Time, Store, …
4. Choose the **measures**
   - Dollar_sales, unit_sales, dollar_cost, customer_count

The Grocery Store Example/1

- A grocery chain. 500 stores spread over a five-state area. Each of the stores is a typical modern supermarket with a full complement of departments including grocery, frozen foods, dairy, meat, bakery, hard goods, liquor, and drugs. Each store has roughly 60’000 individual products on its shelves.
- The individual products are called stock keeping units (SKUs). About 40’000 of the SKU come from outside manufacturers and have bar codes imprinted on the product package. These bar codes are called universal product codes (UPCs). UPCs are at the same grain as individual SKUs. Each different package variation of a product has a separate UPC and hence is a separate SKU.

The Grocery Store Example/2

6

- The remaining 20’000 SKUs come from departments like meat or bakery departments and do not have nationally recognized UPC codes. The grocery store assigns SKU numbers to these products by sticking scanner labels on the items. Although the bar codes are not UPCs they are certainly SKU numbers.
- Data is collected at several places in a grocery store. Some of the most useful data is collected at the cash registers as customers purchase products. Our modern grocery store scans the bar codes directly into the point-of-sale (POS) system. The POS system is at the front door of the grocery store where customer takeaway is measured. The back door, where vendors make deliveries, is another interesting data-collection point.

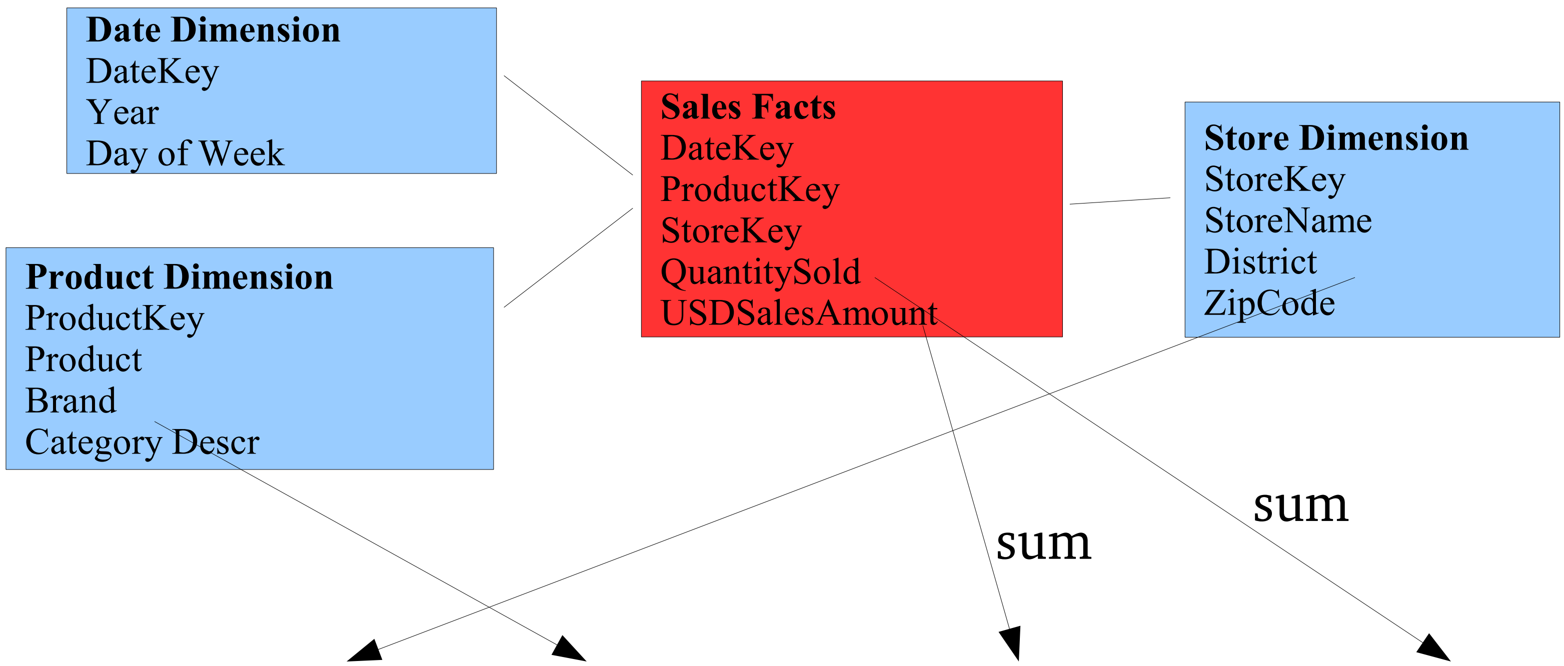
The Grocery Store Example/3

7, 8

- At the grocery store, management is concerned with the logistics of ordering, stocking the shelves, and selling the products while maximizing the profit at each store. The profit ultimately comes from charging as much as possible for each product, lowering costs for product acquisition and overhead, and at the same time attracting as many customers as possible.
- The most significant decisions have to do with pricing and promotions. Both store management and headquarters marketing spend a great deal of time tinkering with pricing and running promotions. Promotions in a grocery store include temporary price reductions, ads in newspapers and newspaper inserts, displays in the grocery store, and coupons.

Working with a Dimensional Model

- A common activity is to drag and drop dimensional attributes and measures into a simple report.



report

District	Brand	USDSalesAmount	QuantitySold
Gries	Kellogs	3198	1023
Haslach	Danone	1099	671
Oswald	Kellogs	2876	800

The Grocery Store

- Stock Keeping Units (SKUs)
- Universal Product Codes (UPCs)
- Point Of Sale (POS) system
- Stores
- Promotions

- Grain: sales of SKUs

The Grocery Store Dimensions

- The Date dimension
  - Explicit date dimension is needed (events, holidays,..)
- The Product dimension
  - Six-level hierarchy allows drill-down/roll-up
  - Many descriptive attributes (often more than 50)
- The Store dimension
  - Many descriptive attributes
  - First_open_date is a key to an outrigger table (new Date dim table that is a subset of the main Date dim table)
- The Promotion dimension
  - Used to see if promotions work/are profitable
  - Ads, price reductions, end-of-aisle displays, coupons
    - Highly correlated (only 5000 combinations)
    - Separate dimensions? (size&efficiency versus simplicity&understanding)

Types Of Facts

- **Event** fact (transaction)
  - A fact for every **business event** (sale)
- ”**Fact-less**” facts
  - A fact per event (customer contact)
  - **No** numerical measures
  - An event happened for a dimension value combination
- **Snapshot** fact
  - A fact for every dimension combination at given time intervals
  - Captures **current** status (inventory)
- **Cumulative snapshot** facts
  - A fact for every dimension combination at given time intervals
  - Captures **cumulative** status up to now (sales to date)
- Every type of facts answers **different** questions
  - Often event facts and snapshot facts exist

Types Of Measures

- Three types of measures

- Additive
  - Can be aggregated over **all** dimensions
  - Example: **sales price**
  - Often occur in event facts
- Semi-additive
  - **Cannot** be aggregated over **some** dimensions - typically time
  - Example: **inventory**
  - Often occur in snapshot facts
- Non-additive
  - **Cannot** be aggregated over **any** dimensions
  - Example: **gross margin**
  - Occur in all types of facts

The Grocery Store Measures

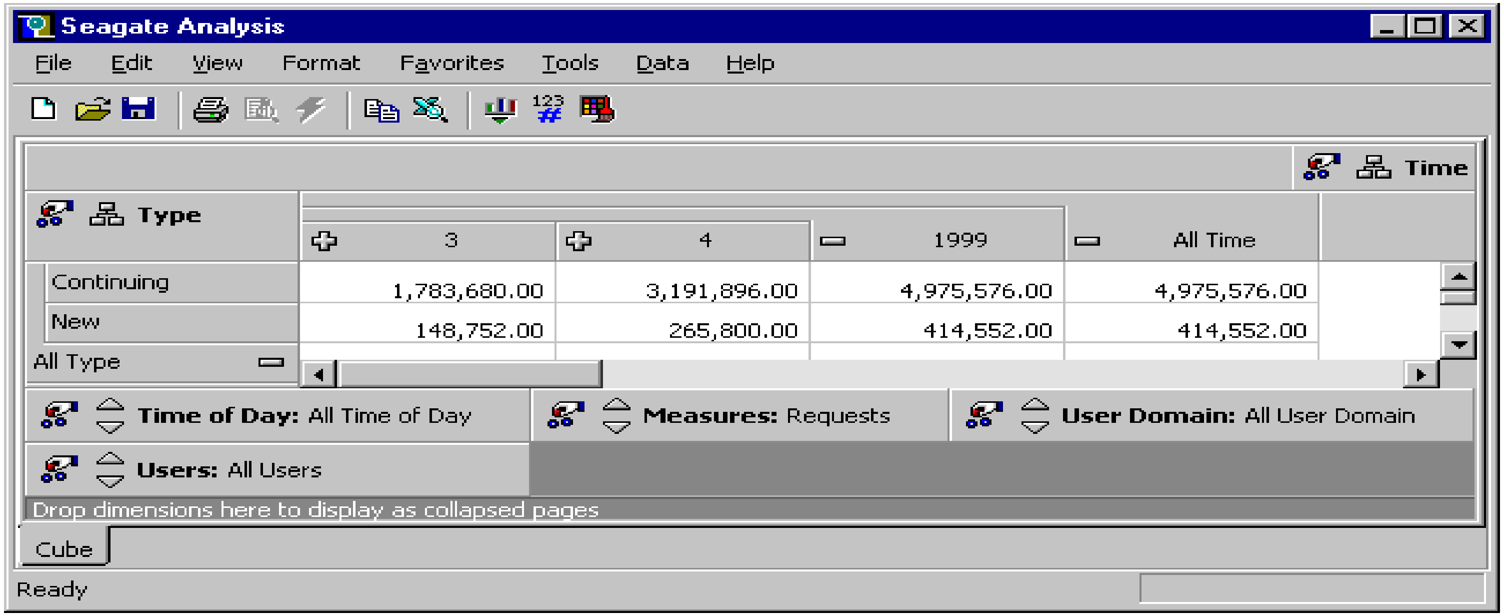
- Sales_Dollar_Amount
- Sales_Quantity
- Cost_Dollar_Amount
- Gross_Profit_Dollar_Amount
- All **additive** across all dimensions
- Gross profit
  - Computed from sales and cost
  - Additive
- Unit cost
  - **Non-additive** across all dimensions
- Customer_count
  - Additive across time, promotion, and store
  - **Non-additive** across product
  - **Semi-additive**

Database Sizing

- Time dimension: 2 years = 730 days
- Store dimension: 300 stores reporting each day
- Product dimension: 30,000 products, only 3000 sell per day
- Promotion dimension: 5000 combinations, but a product only appears in one combination per day
- Number of fact records: 730*300*3000*1 = 657,000,000
- Number of fields: 4 key + 4 fact = 8 fields
- Total DB size: 657,000,000 * 8 fields * 4 bytes = 21 GB
- **Small** database by today's standards?
- Transaction level detail is feasible today

DW Applications: OLAP

- Reporting and querying
- Problem and opportunity analysis
- Planning applications
- Example: Click analysis
  - Still fast query response for million clicks due to specialized DBMS technology

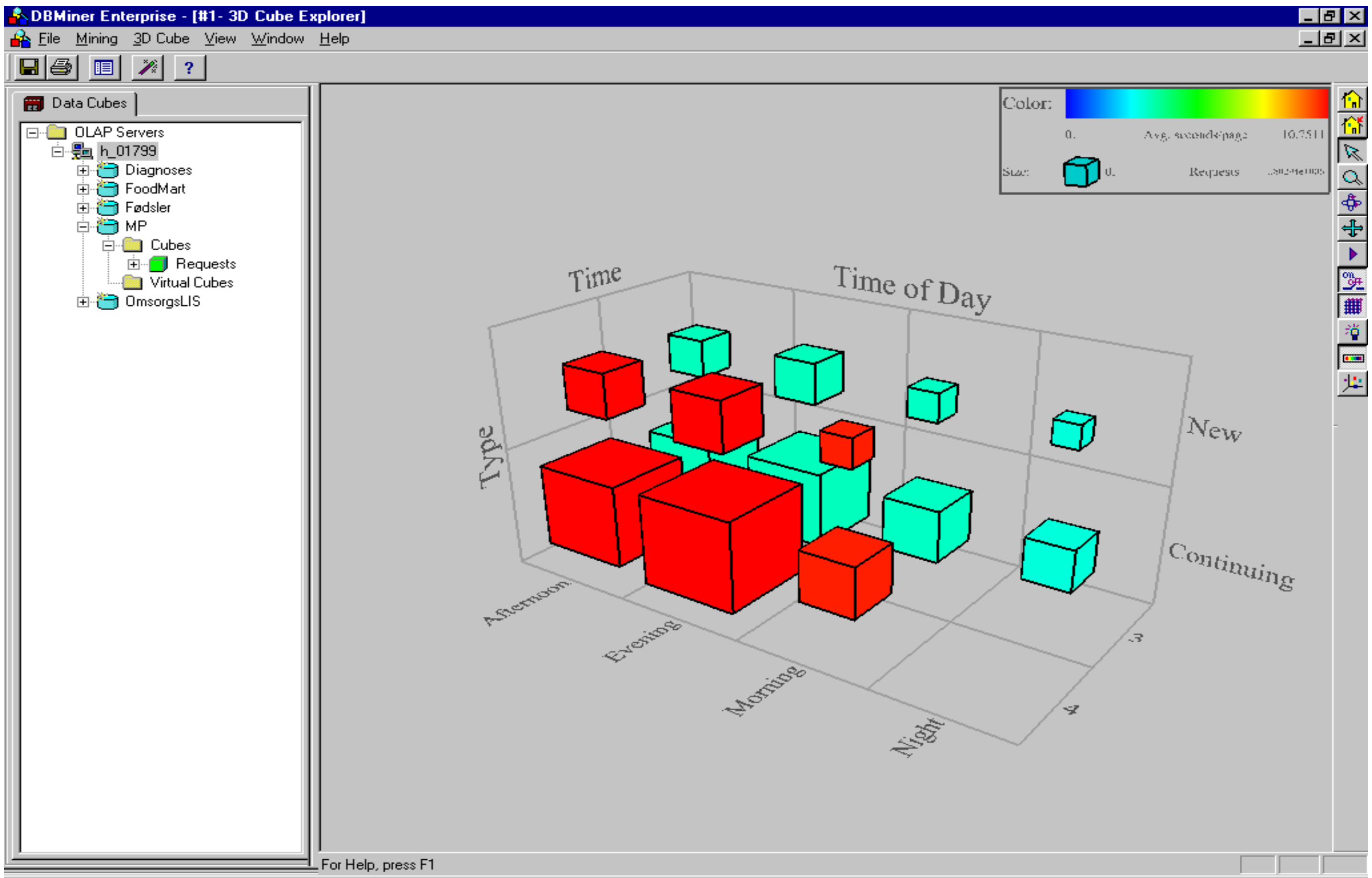


(Relational) OLAP Queries

- **Aggregating** data, e.g., with SUM
- **Starting level**: (Quarter, Product)
- **Roll Up**: less detail, Quarter->Year
- **Drill Down**: more detail, Quarter->Month
- **Slice/Dice**: selection, Year=1999
- **Drill Across**: “join” on common dimensions
- **Visualization** and **exceptions**
- Note: only **two** kinds of queries
  - **Navigation queries** examine one dimension
    - SELECT DISTINCT l FROM d [WHERE p]
  - **Aggregation queries** summarize fact data
    - SELECT d1.l1,d2.l2,SUM(f.m)
      FROM d1,d2,f
      WHERE f.dk1=d1.dk1 AND f.dk2=d2.dk2 [AND p]
      GROUP BY d1.l1,d2.l2

DW Applications: Visualization

- Graphical presentation of complex result
- Color, size, and form help to give a better overview



DW Applications: Data Mining/1

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

DW Applications: Data Mining/2

- Wal-Mart: USA’s largest supermarket chain
  - Has DW with all ticket item sales for the last 2 years (big!)
  - Use DW and mining heavily to gain business advantages
  - Analysis of association within sales tickets
    - Discovery: Beer and diapers on the same ticket
    - Men buy diapers, and must ”just have a beer”
    - Put the expensive beers next to the diapers
    - Put beer at some distance from diapers with chips, videos in-between!
  - Wal-Mart's suppliers use the DW to optimize delivery
    - The supplier puts the product on the shelf
    - The supplier only get paid when the product **is sold**
- Web log mining
  - What is the association between time of day and requests?
  - What user groups use my site?
  - How many requests does my site get in a month? (Yahoo)

ROLAP

- Relational OLAP
- Data stored in relational tables
  - Star (or snowflake) schemas used for modeling
  - SQL used for querying
- Pros
  - Leverages investments in relational technology
  - Scalable (billions of facts)
  - Flexible, designs easier to change
  - New, performance enhancing techniques adapted from MOLAP
    - Indices, materialized views, special treatment of star schemas
- Cons
  - Storage use (often 3-4 times MOLAP)
  - Response times

MOLAP

- Multidimensional OLAP
- Special multidimensional data structures used
- Pros
  - Less storage use (“foreign keys” not stored)
  - 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 as open technology

HOLAP

- Hybrid OLAP
- Aggregates stored in multidimensional structures (MOLAP)
- Detail data stored in relational tables (ROLAP)
- Pros
  - Scalable
  - Fast
- Cons
  - Complexity

Relational Implementation

- The cube is often implemented in an RDBMS
- Fact table stores facts
  - One column for each measure
  - One column for each dimension (foreign key to dimension table)
- Dimension table stores dimension
  - Integer key column (surrogate keys)
  - Don’t use production keys in DW!
- Goal for dimensional modeling: ”surround the facts with as much context (dimensions) as we can”
- **Granularity** of the fact table is important
  - What does one fact table row represent ?
  - Important for the size of the fact table
  - Often corresponding to a single business transaction (sale)
  - But it can be aggregated (sales per product per day per store)

Relational Design

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

Star Schema Example

Product Dimension

ProductId	Product	Type	Category
1	Bud	Beer	Beverage

Date Dimension

DateId	Day	Month	Year
1	25	May	1997

Sales Facts

ProductId	StoreId	DateId	Quantity
1	1	1	575

Store Dimension

StoreId	Store	City	Country
1	Bilka	Aalborg	Denmark
2	Spar	Bolzano	Italy

Snowflake Schema Example

Product Category

TypeId	Type	CategoryId
1	Beer	1

MonthYear Description

MonthId	Month	YearId
1	May	1997

Product Dimension

ProductId	Product	TypeId
1	Bud	1

Date Dimension

DateId	Day	MonthId
1	25	1

Sales Facts

ProductId	StoreId	DateId	Sale
1	1	1	5.75

Store Dimension

StoreId	Store	City	Country
1	Bilka	Aalborg	Denmark
2	Spar	Bolzano	Italy

Star Schemas

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

Snow-flake Schemas

- \+ Hierarchies are made explicit/visible
- \+ Very flexible
- \+ Dimension tables use less space
- \- Harder to use due to many joins
- \- Worse performance

Inventory Example

- Advanced retail business requires inventory information. Making sure the right product is in the right store at the right time minimizes out-of-stocks and reduces overall inventory costs. The retailer needs the ability to analyze daily quantity-on-hand inventory levels by product and store.
- Design dimensional models that support the analysis of inventories for retail businesses (grocery stores).

Redundancy In The DW

- Only very little redundancy in fact tables
  - Order head data copied to order line facts
  - 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

Limits And 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 wrong”
- Hierarchies have a fixed height
- Hierarchies don’t change?

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Summary

- OLAP, Multidimensional cubes
- Dimensions, Facts, Measures
- Case study
  - Grocery store
- Relational design
- Redundancy, strengths and weaknesses