Data Management

A.A. 2023/2024

Data Warehousing

Domenico Lembo, Maurizio Lenzerini
Dipartimento di Ingegneria Informatica, Automatica e Gestionale A. Ruberti

Credits

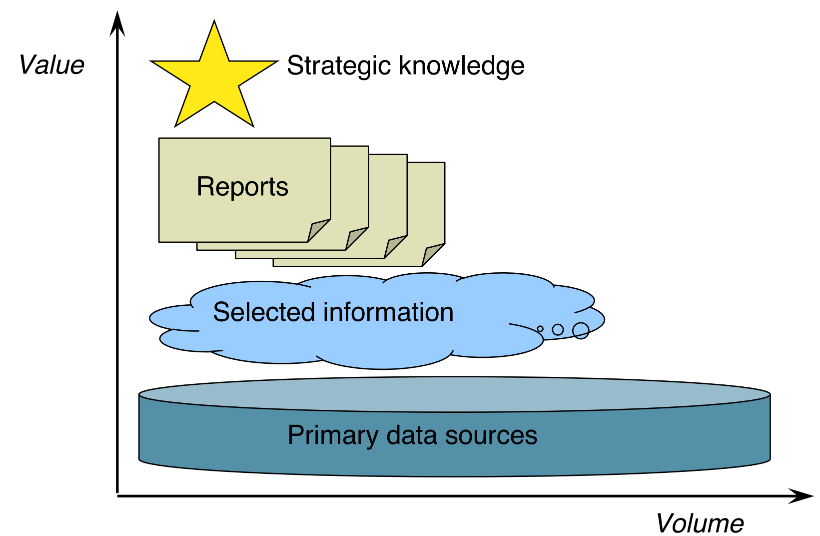
- These slides are adpated from the orginal slides of prof. Stefano Rizzi, University of Bologna

- Bibliographic reference:

  M. Golfarelli, S. Rizzi. Data Warehouse Design: Modern Principles and Methodologies. McGraw-Hill, 2009.

From data to Information

- Every organization must have **quick, comprehensive** access to the information required by decision-making processes. This strategic information is extracted mainly from the huge amount of operational data stored in databases by means of a progressive selection and aggregation process



Decision Support Systems

- Decision Support Systems (DSSs) started to become popular in the eighties:

A *DSS* is a set of expandable, interactive IT techniques and tools designed for processing and analyzing data and for supporting in decision making.

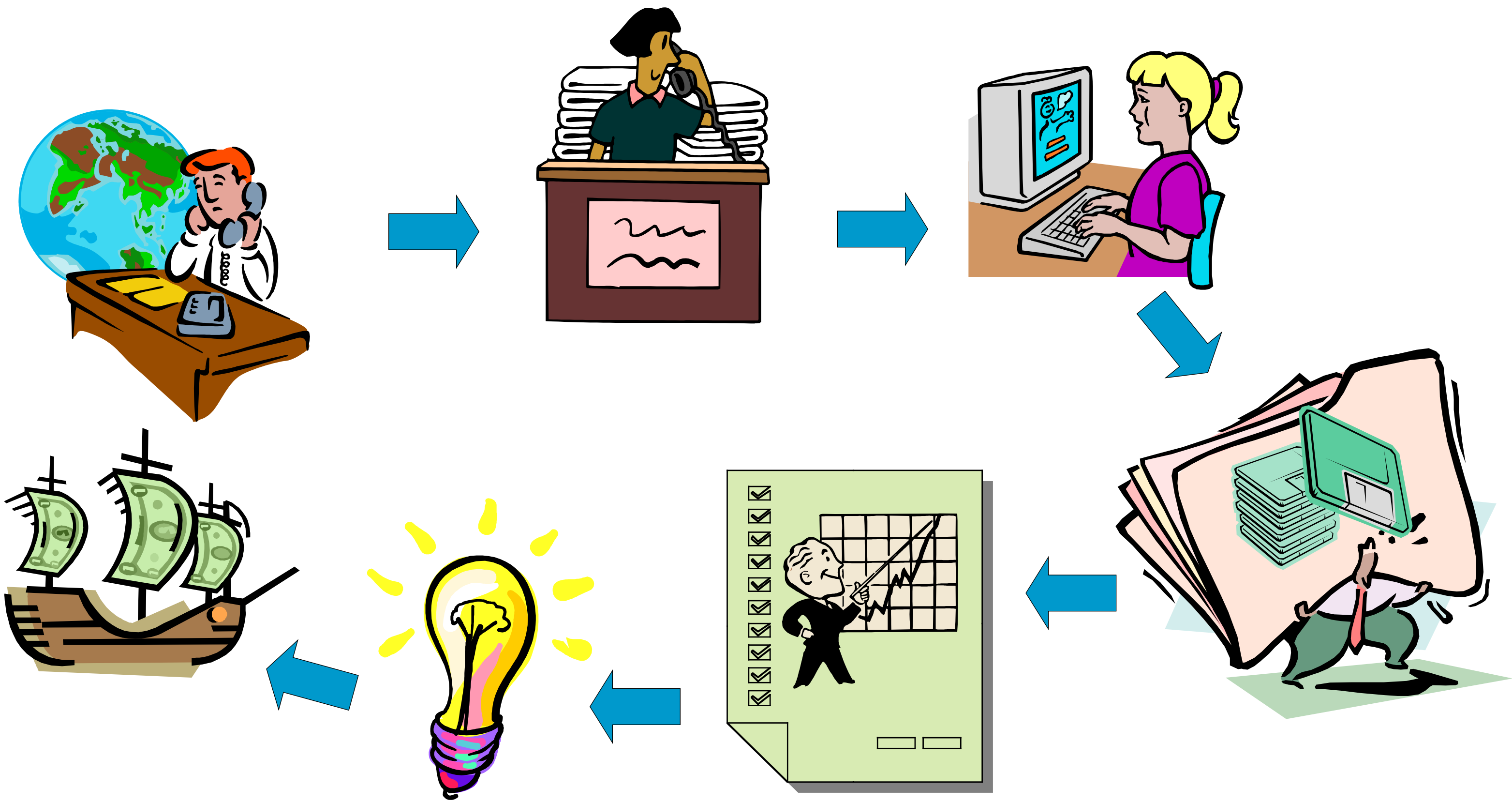
Role of DSSs

In the past	In the future
Describe the past	Anticipate future
Reduce costs	Increase Profits
Describe problems	Suggest changes

- *Data warehouse systems have been managing the data back-ends of DSSs since the 1990s*

A typical scenario....

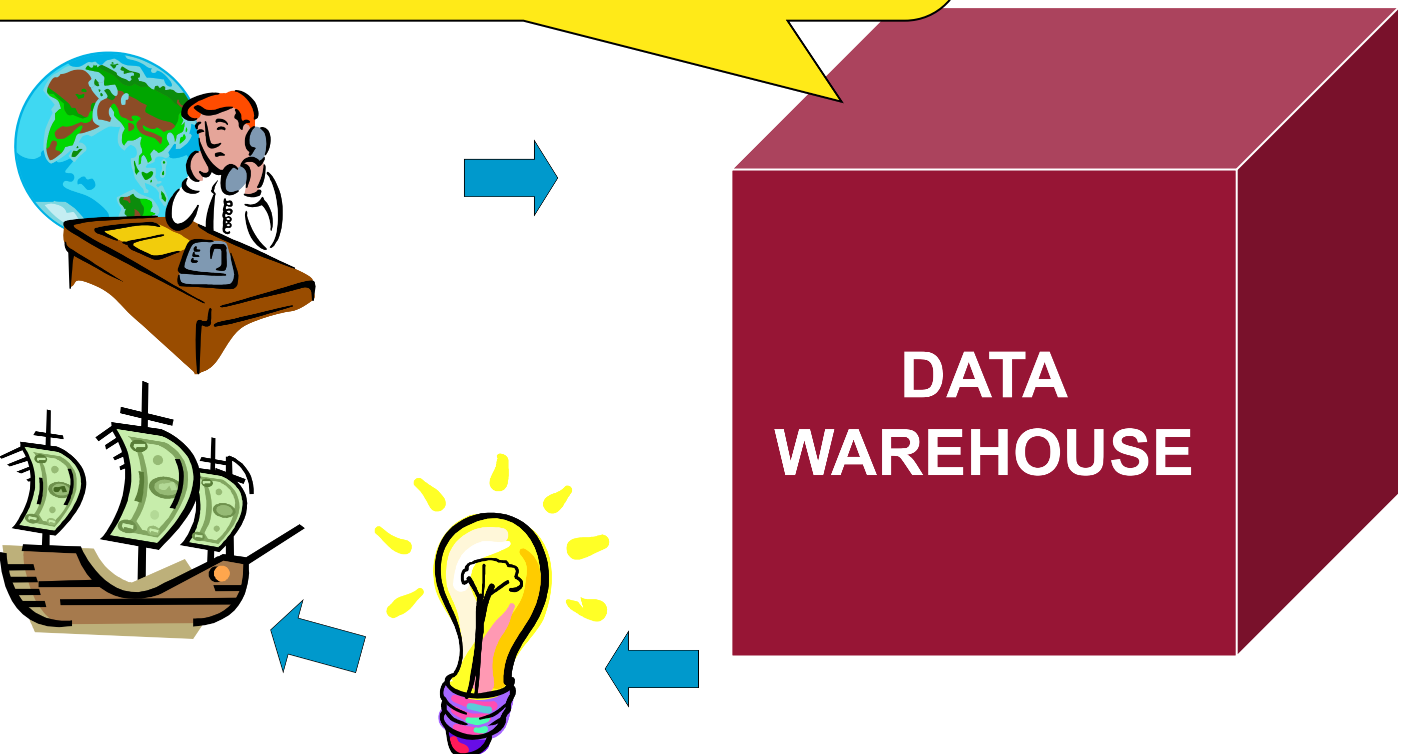
- .. is that of a large company, with numerous branches, whose managers want to evaluate the contribution of each branch to the overall business performance of the company



A typical scenario....

- . ranches, whose r f each branch to t pany

An information repository that integrates and reorganizes data collected from sources of various kind and makes them available for analysis and evaluations aimed at planning and decision-making



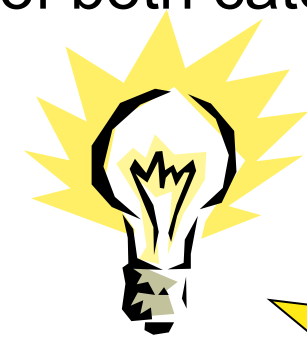
Example: Sapienza Univ. of Rome

- Day by day operations:
  - ✓ transactions dealing with data about classrooms, lectures, exams, events, student procedures, professors, etc.

- Decision support operations:
  - ✓ analysis of trends (e.g., how many enrolled students in the last decade in the various disciplines), average grades for different courses, number of graduated students, etc.

OLTP e OLAP

- Mixing together "analytical" (for Decision Support) and "transactional” (for day-by-day operations) queries leads to inevitable delays that make dissatisfied users of both categories.



One of the main aims of Data Warehousing is to **maintain separate** On-Line Analytical Processing (OLAP) from On-Line Transactional Processing (OLTP)

Some Areas where DW technologies are normally adopted

- Commerce (analysis of sales and complaints, shipping and inventory control, customer care)
- Manifacturing (control of production costs, support of suppliers and orders)
- Financial services (risk analysis, fraud detection)
- Transportation (fleet management)
- Telecommunication (analysis of call data, customer profile)
- Healthcare (analysis of admissions and discharges, accounting for cost centers)
- ....

Companies complaints

- *We have heaps of data, but we cannot access it!*
- *How can people playing the same role achieve substantially different results?*
- *We want to select, group, and manipulate data in every possible way!*
- *Show me just what matters!*
- *Everyone knows that some data is wrong!*

R. Kimball, The Data Warehouse Toolkit

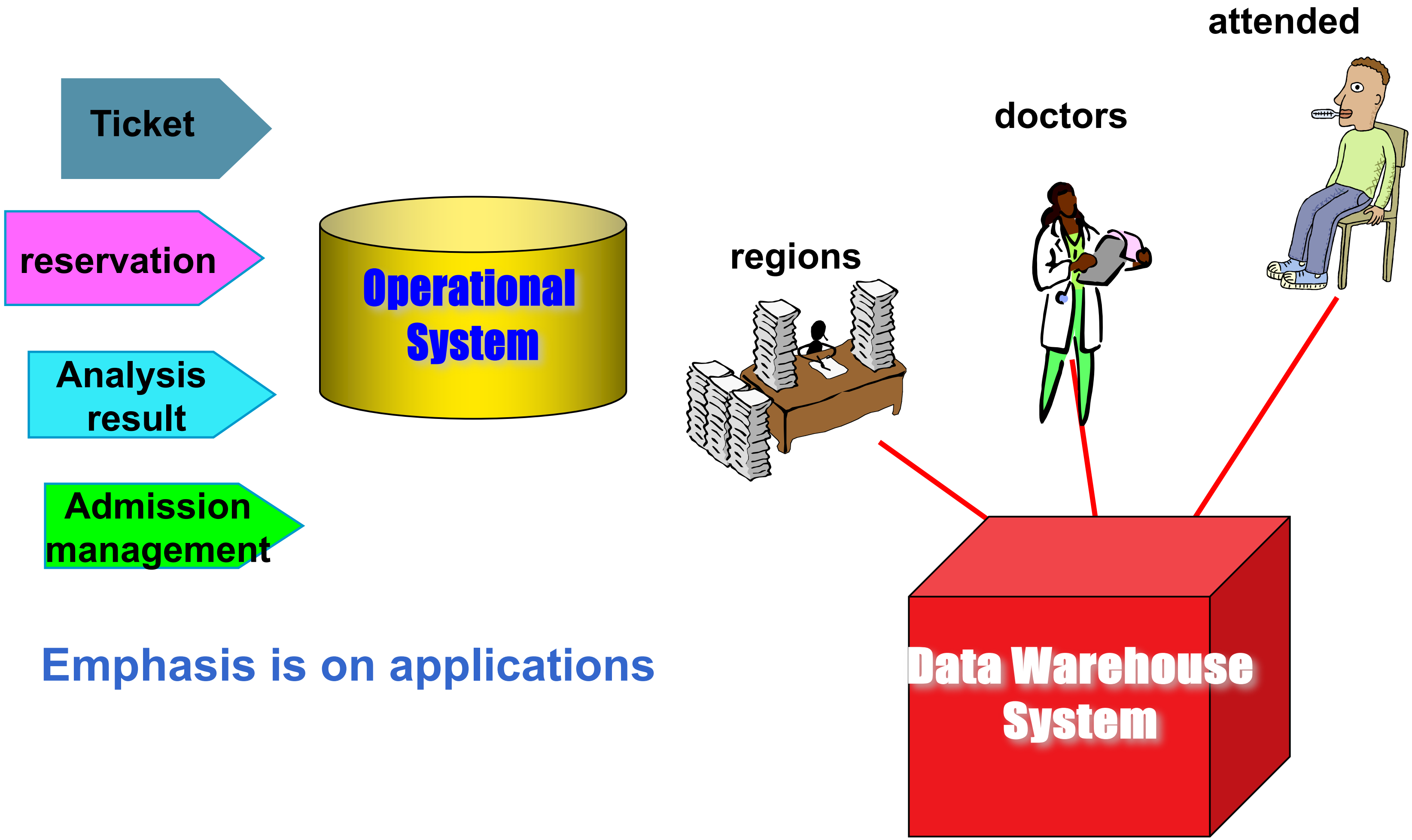
Data Warehousing Characteristics

- *accessibility* to users not very familiar with IT and data structures;
- *integration* of data on the basis of a standard enterprise model;
- *query flexibility* to maximize the advantages obtained from the existing information;
- *multidimensional representation* giving DSS users an intuitive and manageable view of information;
- *correctness and completeness* of integrated data.

Data Warehouse

- Data warehouses are placed right in the middle of this process and act as repositories for data. They make sure that the requirements set can be fulfilled.
- A *data warehouse* is a collection of data that supports decision-making processes. It provides the following features (Inmon, 2005):
  - ✓ It allows subject-oriented analysis
  - ✓ It is integrated and consistent
  - ✓ It shows evolution of data over time
  - ✓ it is not volatile (data are never deleted)

...subject oriented

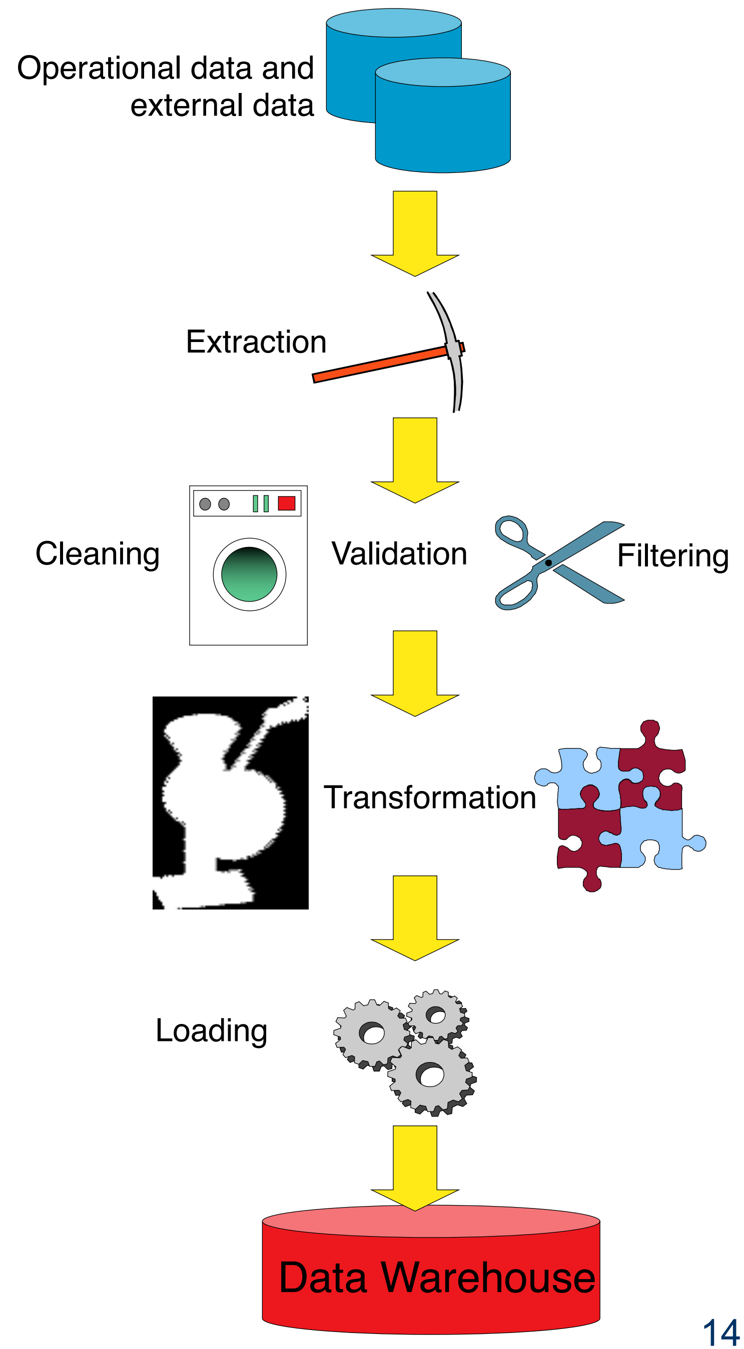


Emphasis is on applications

Emphasis is on subjects

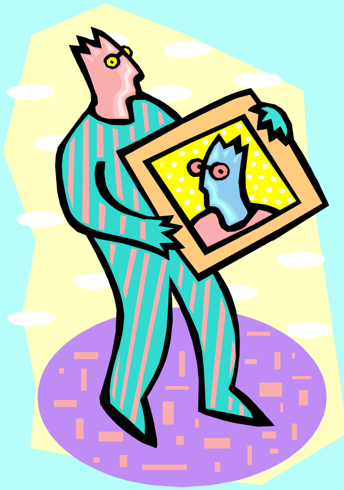
...integrated and consistent

- Data warehouses take advantage of multiple data sources, such as data extracted from production and then stored to enterprise databases, or even data from a third party's information systems.
- A data warehouse should provide a reconciled unified view of all the data. Generally speaking, we can state that creating a data warehouse system does not require that new information is added; rather, existing information needs rearranging.



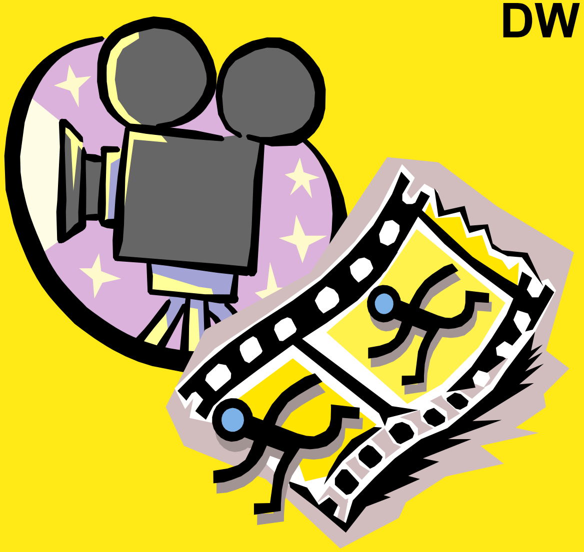
…shows data evolution over the time

Operational DBs



Operational data usually covers a short period of time, because most transactions involve the latest data. No hystorical data: data are updated and old value cancelled. Time is not in the keys.

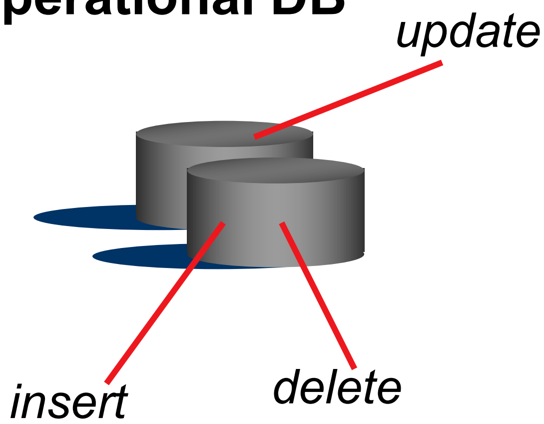
DW

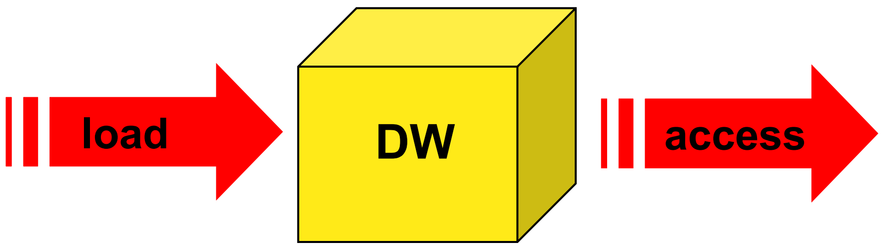


Enable analyses that cover a few years. Regularly updated and continuously growing. Time is part of the keys.

...non-volatile

Operational DB





Huge data volume:
from tens of GB to some TB
or even more

- ✓ data is never deleted from data warehouses and updates are normally carried out when data warehouses are offline.
- ✓ This means that data warehouses can be essentially viewed as read-only databases.
- ✓ in a DW there is no need for advanced transaction management techniques required by operational applications.
- ✓ Key problems are query-throughput and resilience.

Queries

- OLTP:
  - ✓ Operational queries execute transactions that generally read/write a small number of tuples from/to many tables connected by simple relations. For example, this applies if you search for the data of a customer in order to insert a new customer order.
  - ✓ The core workload is often “frozen” into applications (ad hoc data queries are occasional).

- OLAP:
  - ✓ Queries execute dynamic, multidimensional analyses that need to scan a huge amount of records to process a set of numeric data summing up the performance of an enterprise.
  - ✓ Data warehouse interactivity is an essential property for analysis sessions, so the actual workload constantly changes as time goes by.

Summarizing

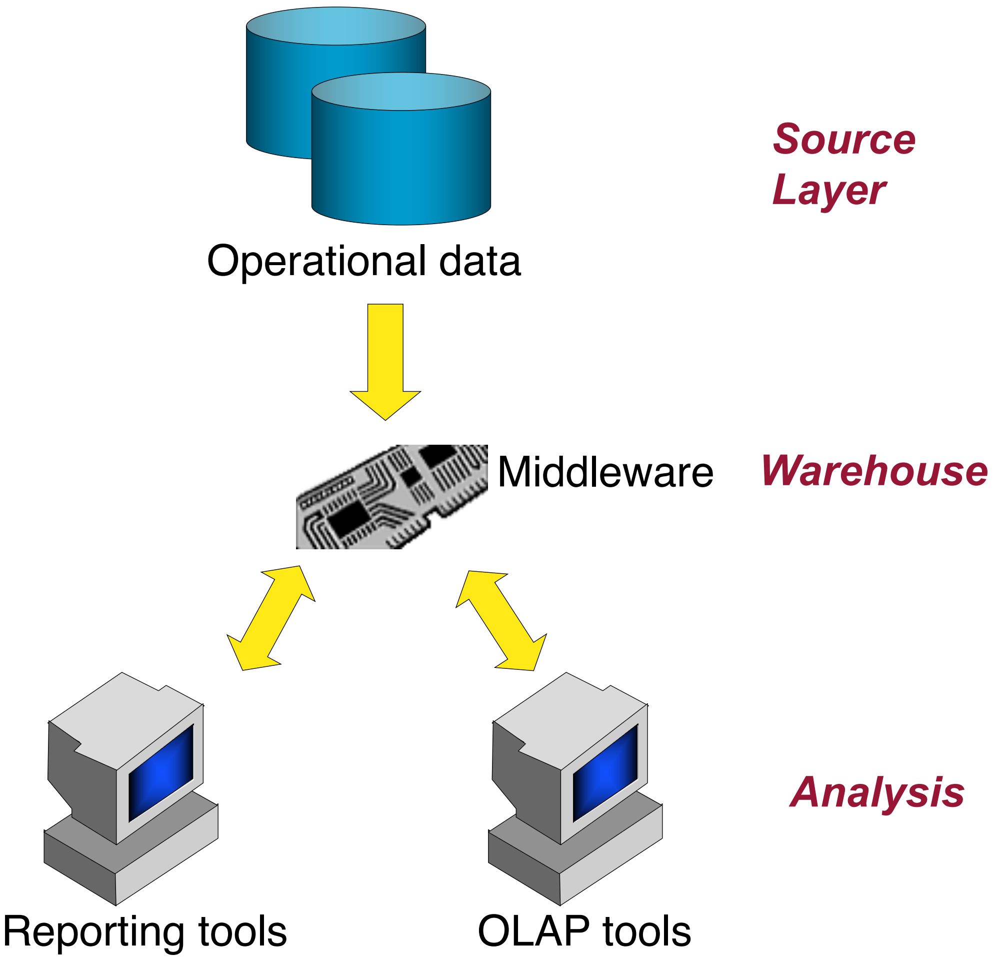
Feature	Operational Databases	Data Warehouses
Users	Thousands	Hundreds
Workload	Preset transactions	Specific analysis queries
Access	To hundreds of records, write and read mode	To millions of records, mainly read-only mode
Goal	Depends on applications	Decision-making support
Data	Detailed, both numeric and alphanumeric	Summed up, mainly numeric
Data integration	Application-based	Subject-based
Quality	In terms of integrity	In terms of consistency
Time coverage	Current data only	Current and historical data
Updates	Continuous	Periodical
Model	Normalized	Denormalized, multidimensional
Optimization	For OLTP access to a database part	For OLAP access to most of the database

Different Data Warehouse Architectures

- ✓ Single-layer architecture
- ✓ Two-layer Architecture
- ✓ Three-layer architecture

Single-Layer Architecture

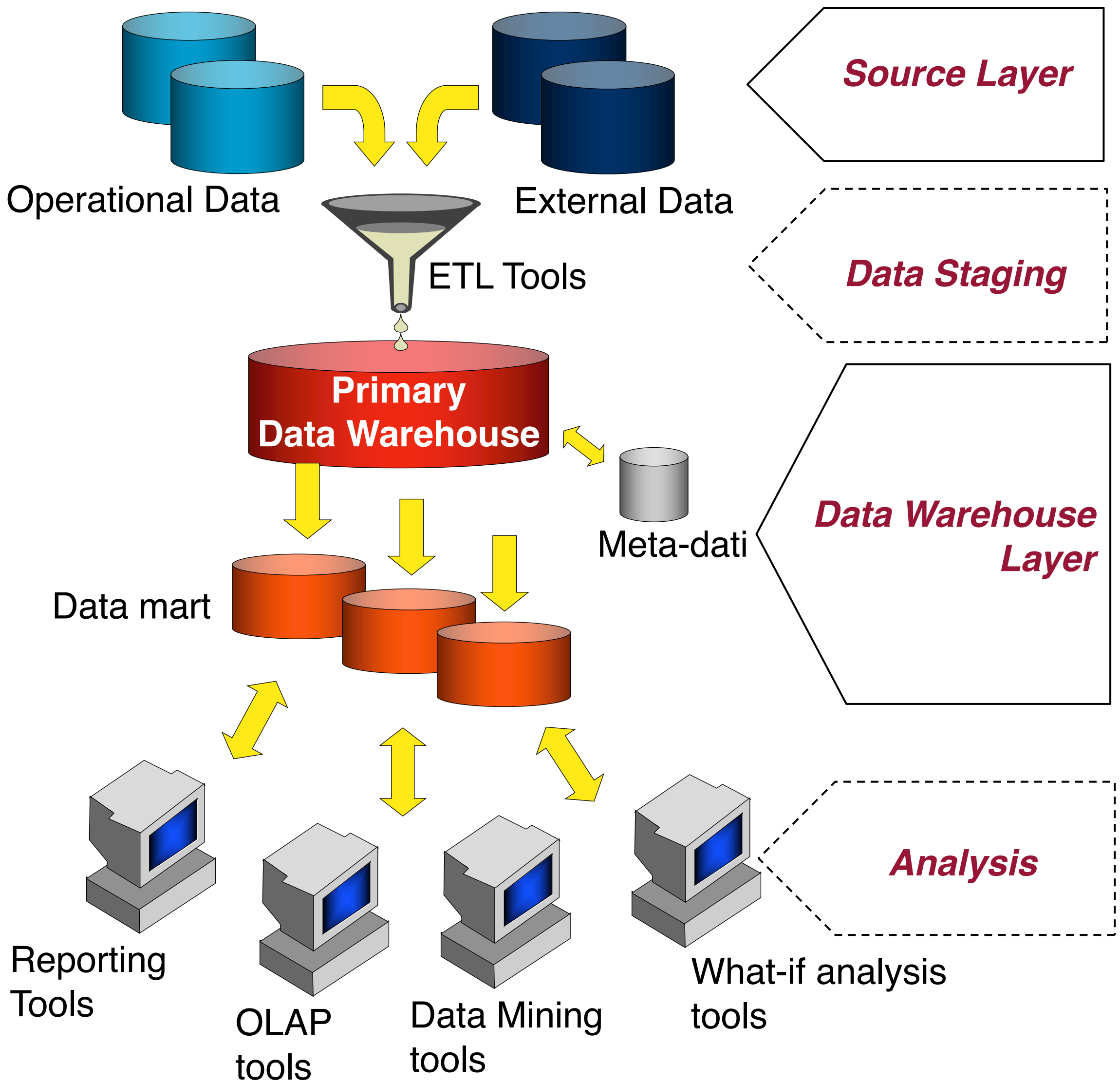
Its goal is to minimizes the amount of data stored with no attempt to integrate them with a principled approach. The only physically available layer is the source layer. In this case, data warehouse is virtual.



- ✓ Fails to meet separation between OLTP and OLAP
- ✓ Each analysis query is submitted to operational data after the middleware interprets them, thus affecting regular transactional workloads and with no guarantee of integration
- ✓ It cannot log more data than sources do

Traditionally, single-layer architecture has not been frequently used in practice: a virtual approach to data warehouses can be successful only if analysis needs are particularly restricted

Two-Layer Architecture*



DATA MART:
Subset or aggregation of the data stored in a primary data warehouse. It includes a set of information pieces, each one relevant to a specific business area, corporate department, or category of users.

* The name highlights a separation between layers, one of the physically available sources and one for primary data warehouse

Two-Layer Architecture

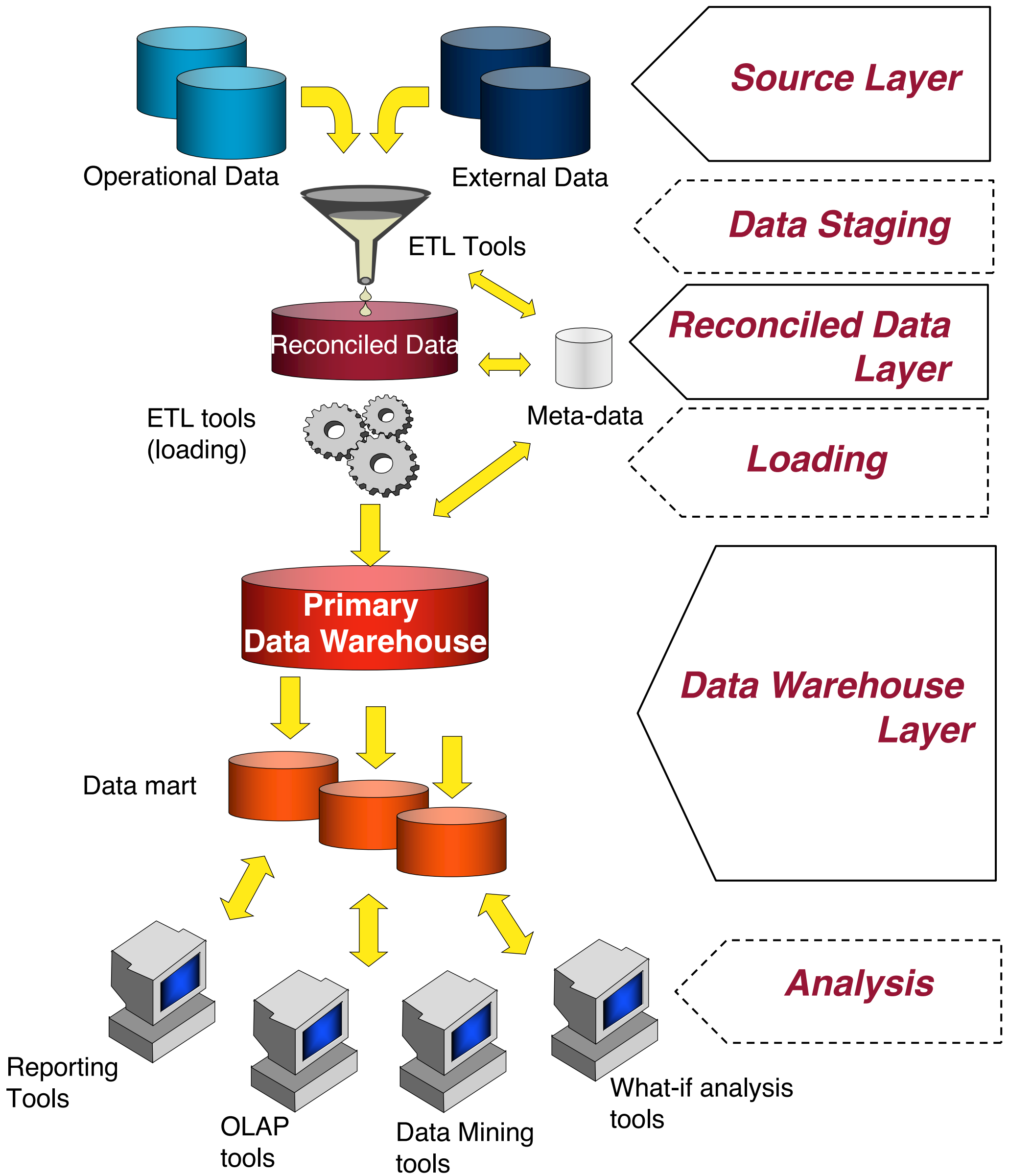
- The data marts populated from a primary data warehouse are often called *dependent*. They are very useful for data warehouse systems in midsize to large organizations because
  - ✓ they are used as building blocks while incrementally developing data warehouses;
  - ✓ each one mark out the information required by a specific group of users to solve queries;
  - ✓ they can deliver better performance because they are smaller than primary data warehouses.

- Sometimes, mainly for organization and policy purposes, a different solution is adopted in which sources are used to directly populate data marts. These data marts are called *independent*
  - ✓ In this case, there is no primary data warehouse, and this streamlines the design process, but it leads to the risk of inconsistencies between data marts.

Two-Layer Architecture

- Advantages:
  - ✓ In data warehouse systems, good quality information is always available, even when access to sources is denied temporarily for technical or organizational reasons.
  - ✓ Data warehouse analysis queries do not affect the management of transactions, the reliability of which is vital for enterprises to work properly at an operational level.
  - ✓ Data warehouses are logically structured according to the multidimensional model, while operational sources are generally based on relational or semi-structured models.
  - ✓ A mismatch in terms of time and granularity occurs between OLTP systems, which manage current data at a maximum level of detail, and OLAP systems, which manage historical and summarized data.
  - ✓ Data warehouses can use specific design solutions aimed at performance optimization of analysis and report applications.

Three-Layer Architecture



RECONCILED DATA:

This layer materializes operational data obtained after integrating and cleansing source data. As a result, those data are integrated, consistent, correct and detailed.

Three-Layer Architecture

- The main advantage of the reconciled data layer is that it creates a common reference data model for a whole enterprise. At the same time, it sharply separates the problems of source data extraction and integration from those of data warehouse population.
- However, reconciled data leads to more replication of operational source data and the design process is complicated.

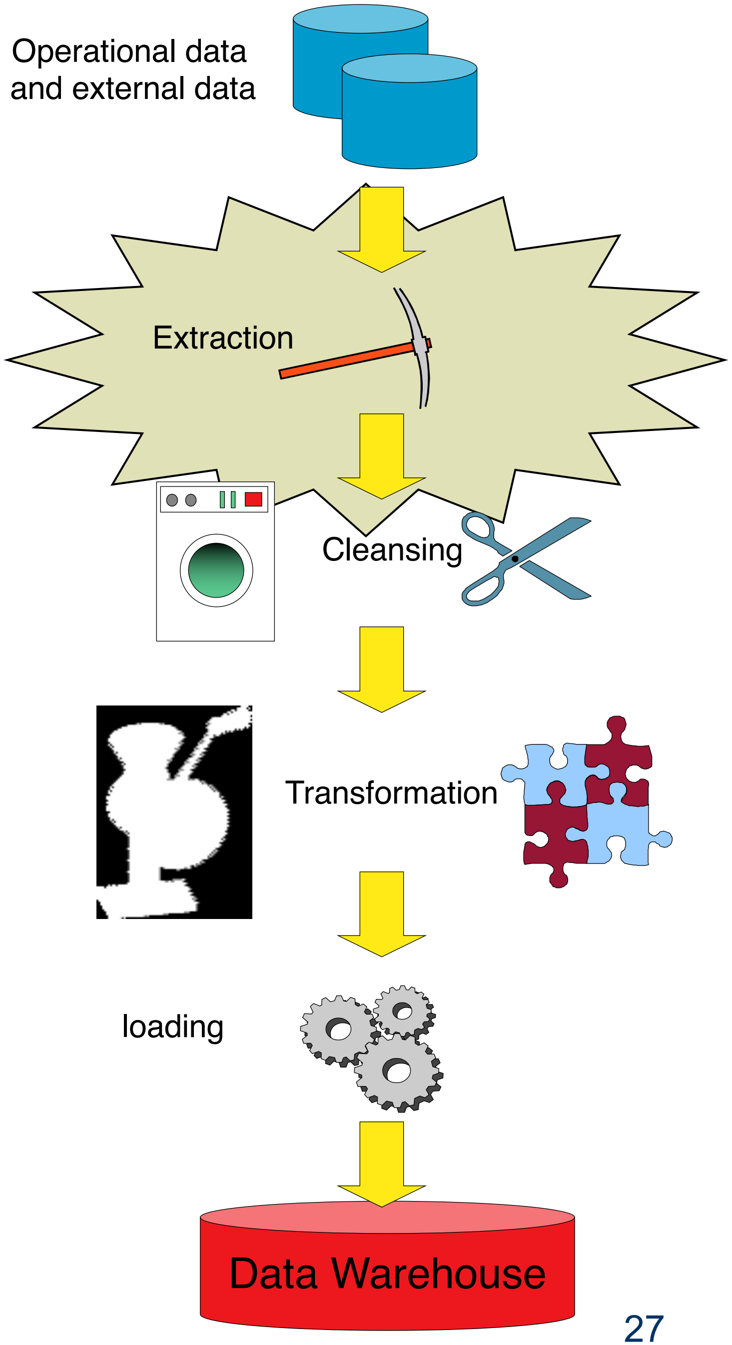
ETL

- ETL processes extract, integrate, and clean data from operational sources to eventually feed the data warehouse.
- At the abstract level, ETL processes produce a single, high-quality, detailed data source, that in turn feed the DW (*reconciliation*)
- Depending on the architecture, this data source is physical (reconciled data layer) or virtual. In the former case ETL processes are physically directly connected to the reconciled layer, in the latter to the (primary) DW or to the datamarts.
- Reconciliation takes place in two occasions: when a data warehouse is populated for the first time, and every time the data warehouse is updated.
- ETL consists in four phases:
  - ✓ extraction
  - ✓ cleansing (or cleaning)
  - ✓ transformation
  - ✓ loading

Note: Cleansing and tranformation are not always considered as separate phases in the literature. Here we say that cleansing is essentially devoted to correct *values*, whereas transformation is mainly devoted to correct *formats.*

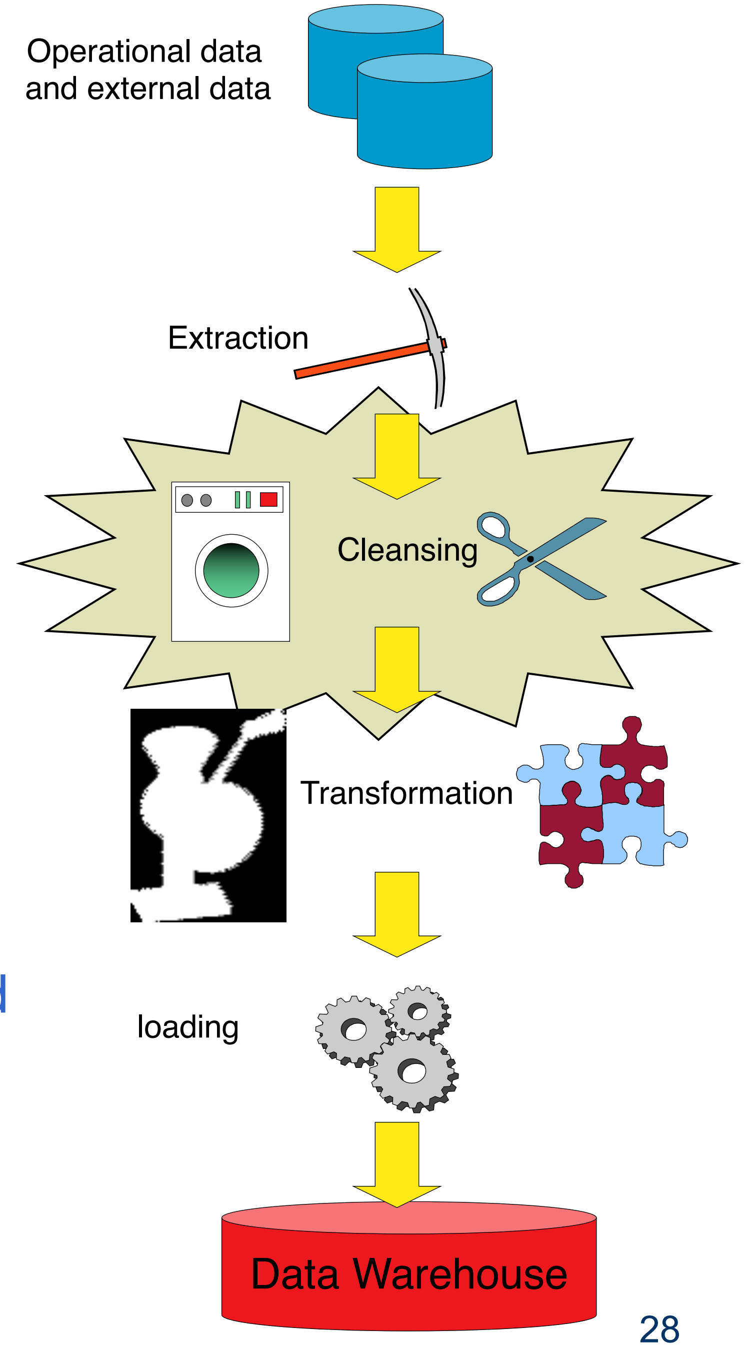
Extraction

- Relevant data is obtained from sources:
  - ✓ *Static extraction* is performed when a data warehouse needs populating for the first time. Conceptually speaking, this looks like a snapshot of operational data.
  - ✓ *Incremental extraction* is used to update data warehouses regularly, and seizes the changes applied to source data since the latest extraction.
    - often based on the log maintained by the operational DBMS
    - based on time-stamp
    - source-driven
- The data to be extracted is mainly selected on the basis of its quality.



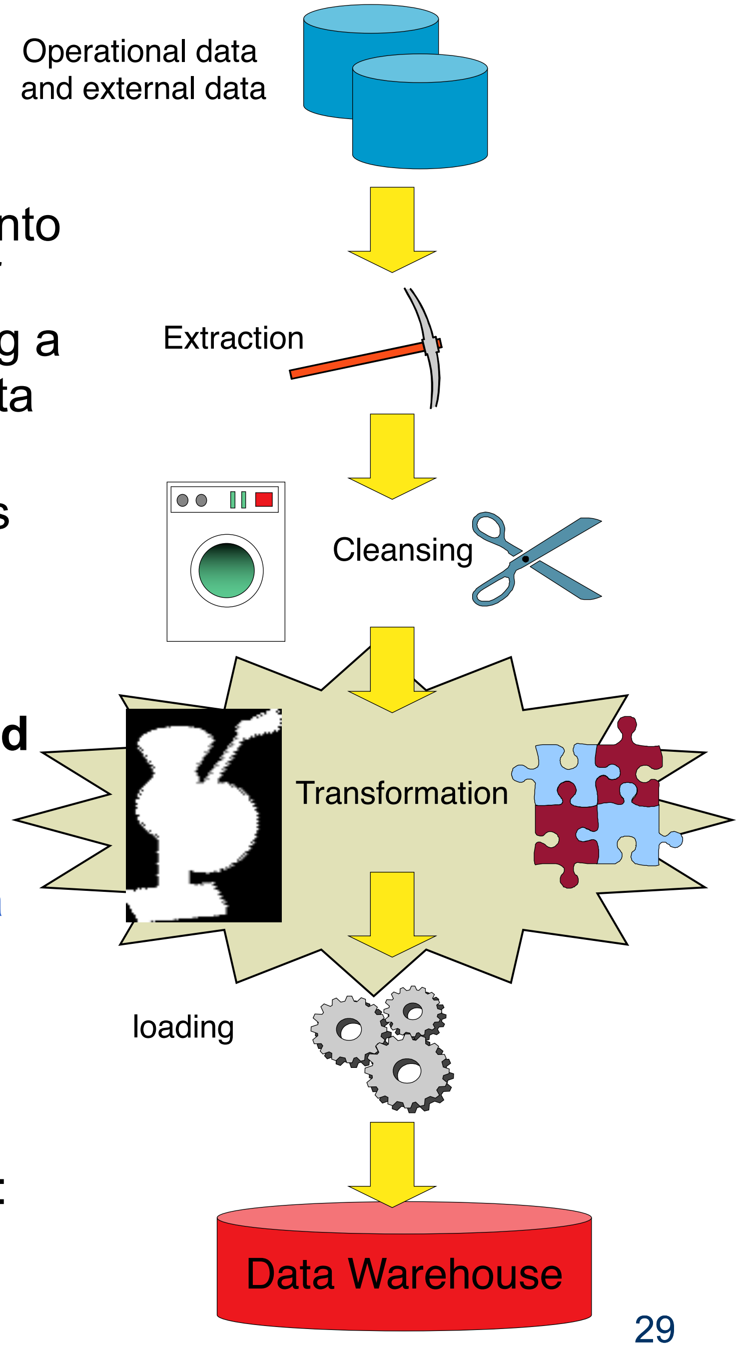
Cleansing

- It is supposed to improve data quality—sometimes quite poor in sources. The most frequent inconsistencies are due to
  - ✓ Duplicate data
  - ✓ Inconsistent values that are logically associated *(e.g.,cities and zip codes)*
  - ✓ Missing Data
  - ✓ Unexpected use of fields
  - ✓ Impossible or wrong values
  - ✓ Inconsistent values for a single entity because different practices were used *(e.g., due to use of abbreviations)*
  - ✓ Inconsistent values for a single entity because of typing mistakes



Transformation

- It converts data from its operational source format into a specific data warehouse format. Independently of the presence of a reconciled data layer, establishing a mapping between the source data layer and the data warehouse layer is generally made difficult by the presence of many different, heterogeneous sources
  - ✓ There may be loose texts that can hide valuable information
  - ✓ Different formats can be used for individual data
- main transformations for **populating the reconciled data layer**:
  - ✓ conversion and standardization that operate on both storage formats and units of measure to uniform data
  - ✓ matching that associates equivalent fields in different sources
  - ✓ selection that reduces the number of source fields and record
- main transformations for **populating the DW layer**:
  - ✓ normalization is substituted by denormalization
  - ✓ Aggregation is used to sum up data



Cleansing and Tranformation

John White
Downing St. 10
TW1A 2AA London (UK)

Formatting

firstName: John
lastName: White
address: Downing St. 10
ZIPcode: TW1A 2AA
city: London
country: UK

Standardization

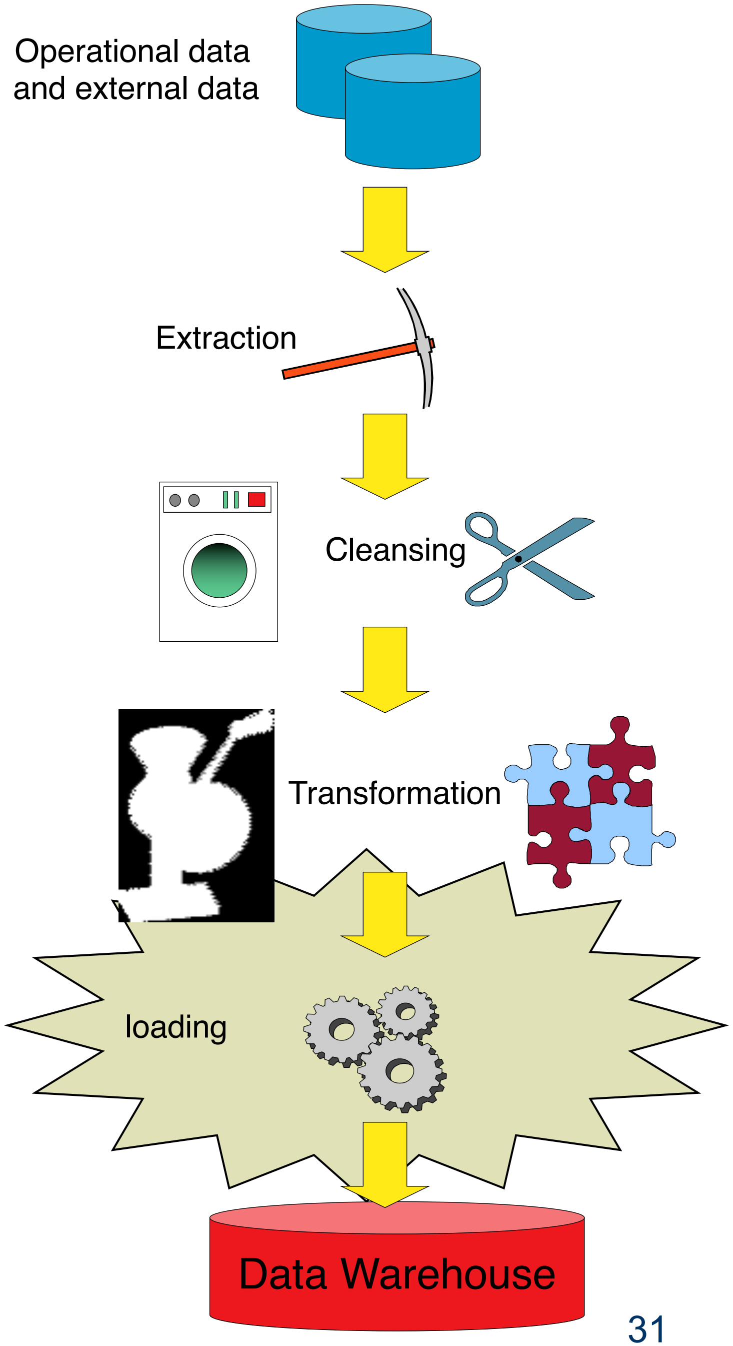
firstName: John
lastName: White
address: 10, Downing Street
ZIPcode: TWA1 2AA
city: London
country: United Kingdom

Correction

firstName: John
lastName: White
address: 10, Downing Street
ZIPcode: SWA1 2AA
city: London
nation: United Kingdom

Loading

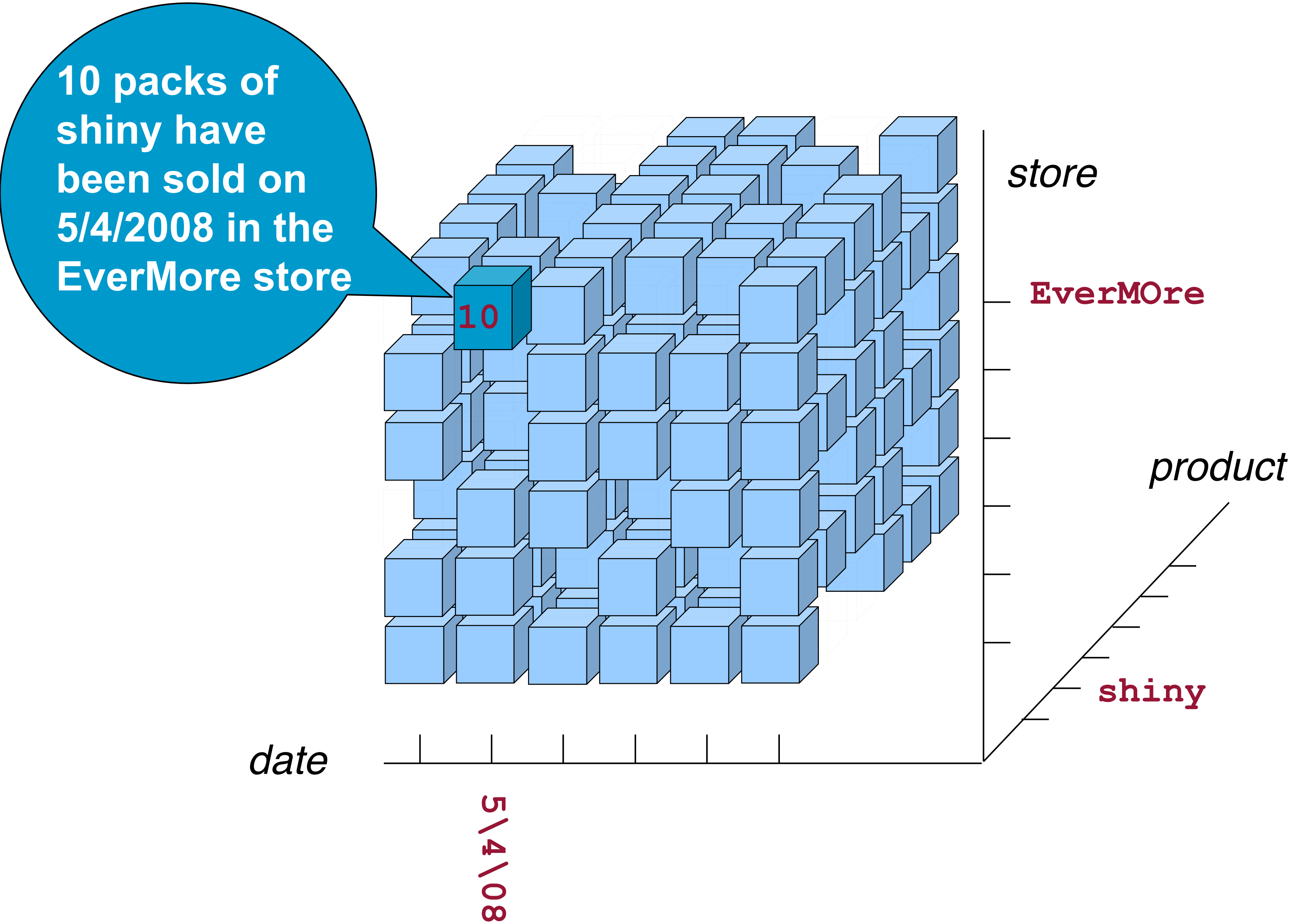
- Loading data into the DW
  - ✓ Refresh: Data warehouse data is completely rewritten. This means that older data is replaced. Refresh is normally used in combination with static extraction to initially populate a data warehouse.
  - ✓ Update: Only those changes applied to source data are added to the data warehouse. Update is typically carried out without deleting or modifying preexisting data. This technique is used in combination with incremental extraction to update data warehouses regularly.



How the users see the DW: the Multidimensional Data Model

- It is the basic principled foundation for characterizing how users see the DW, i.e., how the virtual representation of the DW is structured and queried
- Organization-specific *Facts* that are the subject of the analysis are represented as *cubes* where:
  - ✓ Each cell contains numerical *measures*, each quantifying the facts from one point of views.
  - ✓ Each axis represents a *dimension* of interest for the analysis.
  - ✓ Each dimension can be associated with a *hierarchy of dimensional attributes* used to aggregate data stored in the cubes.

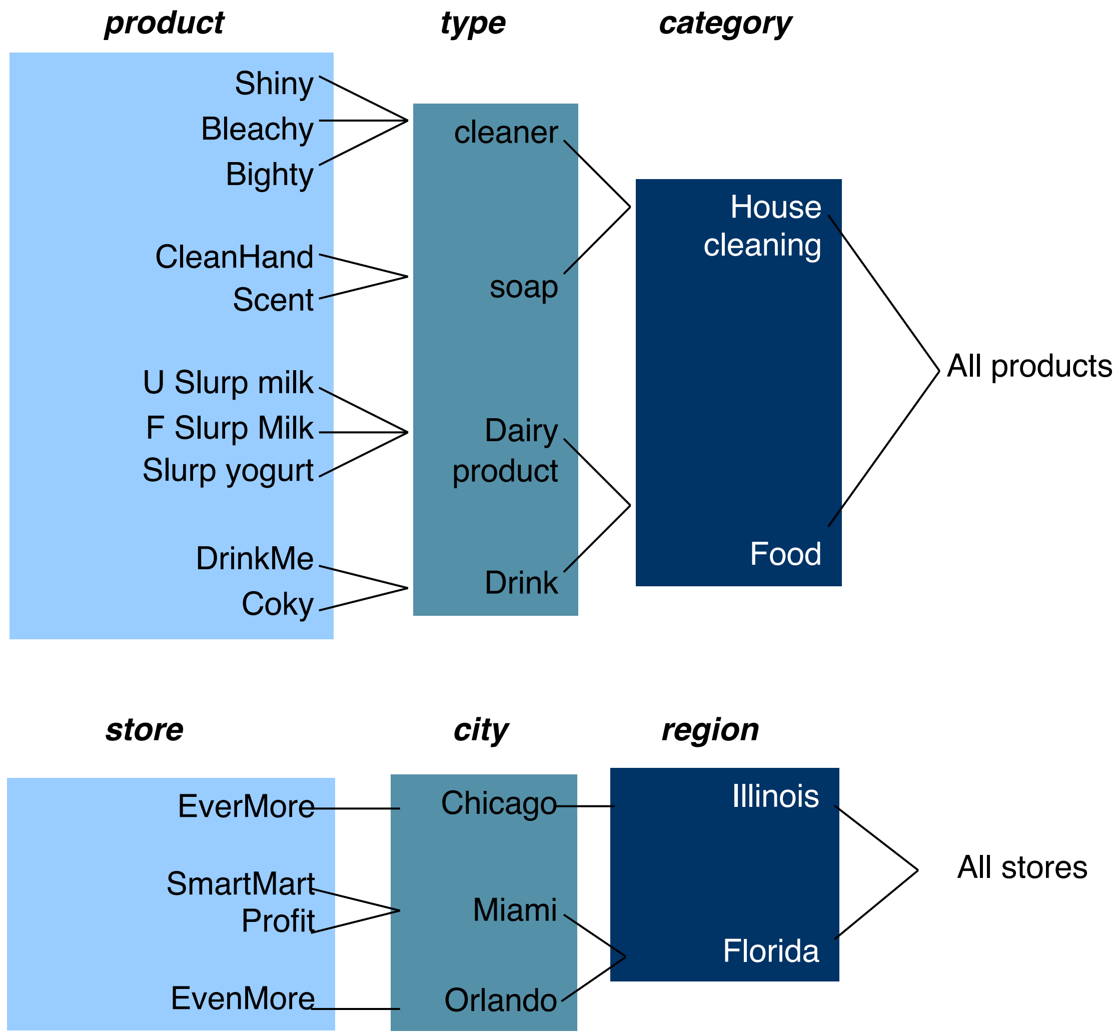
Three-dimensional cube modeling sales



Hierarchies

attribute

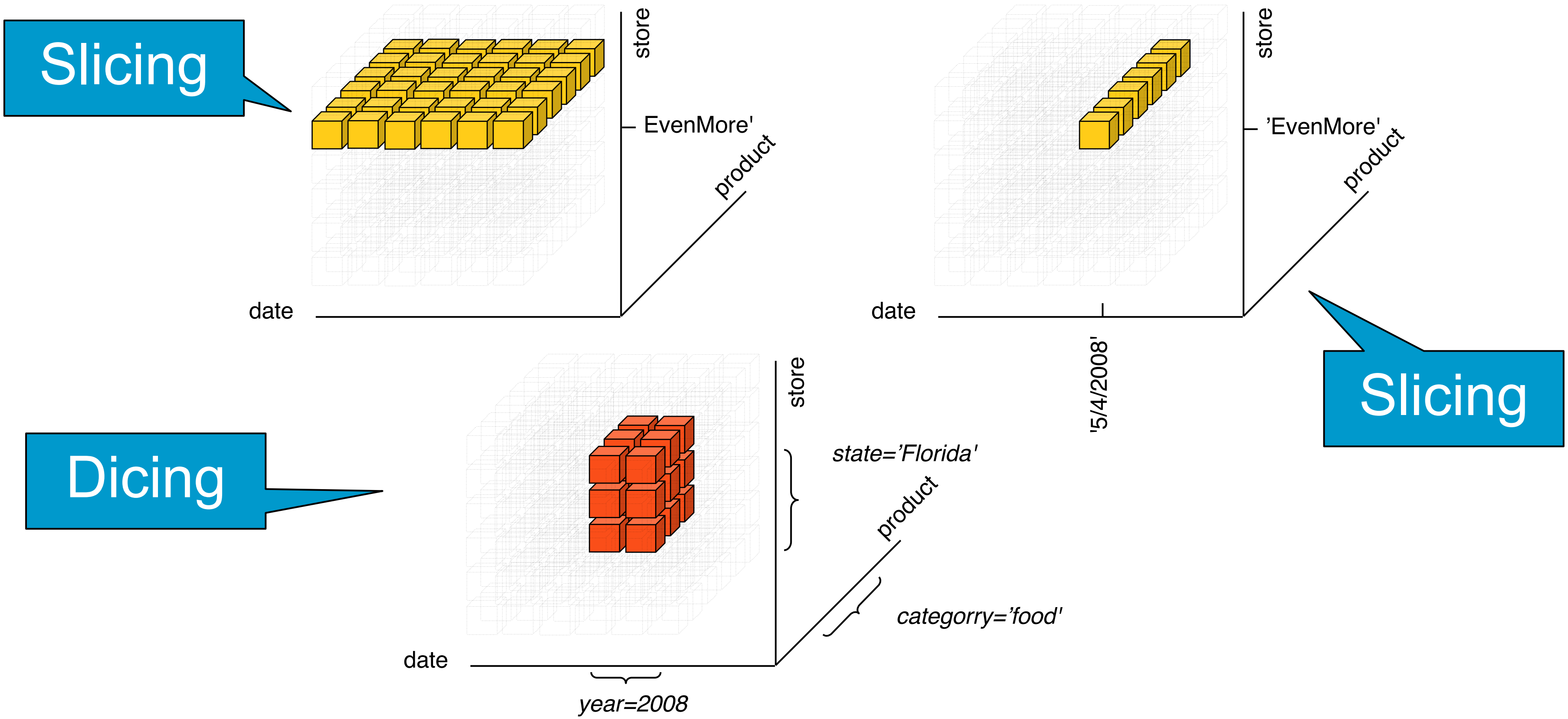
.....



- Every product has exactly on type
- Every type belongs exactly to one category
- Every store is exactly in one city
- Every city is in exactly on e region

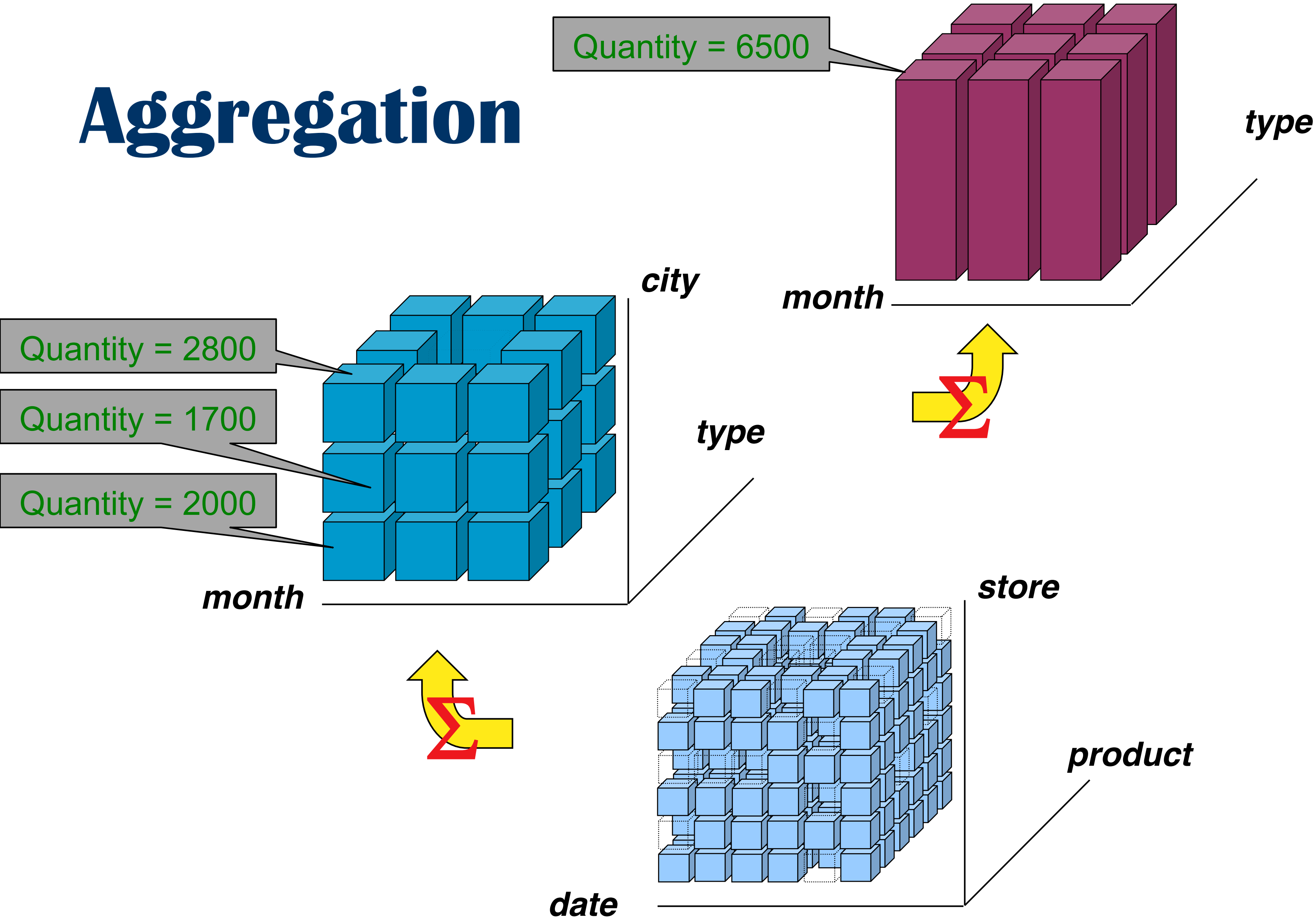
Functional dependencies: *product -> type -> category*
store->city->region

Restrictions



- When you **slice** data, you decrease cube dimensionality by setting one or more dimensions to a specific value.
- **Dicing** is a generalization of slicing. It poses some constraints on dimensional attributes (not only equalities – it acts on the hierarchy) to select only some cubes (notice that it does not aggregate).
- **Projection:** only a subset of measures are returned

Aggregation



In this case, every macro fact measure is the sum of its component fact measures

Aggregation

In these examples, cubes are represented as tables

	EvenMore	EvenMore2	SmartMart
1/1/2000	–	–	–
2/1/2000	10	15	5
3/1/2000	20	–	5
....	....	....	....
1/1/2001	–	–	–
2/1/2001	15	10	20
3/1/2001	20	20	25
....	....	....	....
1/1/2002	–	–	–
2/1/2002	20	8	25
3/1/2002	20	12	20
....	....	....	....

	EvenMore	EvenMore2	SmartMart
January 2000	200	180	150
February 2000	180	150	120
March 2000	220	180	160
....	....	....	....
January 2001	350	220	200
February 2001	300	200	250
March 2001	310	180	300
....	....	....	....
January 2002	380	200	220
February 2002	310	200	250
March 2002	300	160	280
....	....	....	....

	EvenMore	EvenMore2	SmartMart
2000	2400	2000	1600
2001	3200	2300	3000
2002	3400	2200	3200

	EvenMore	EvenMore2	SmartMart
Total:	9000	6500	7800

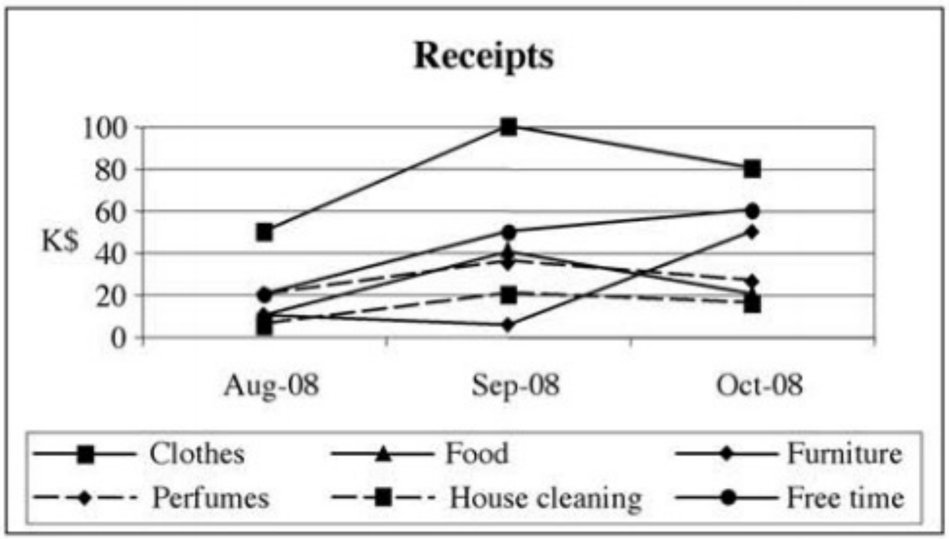
Accessing Data Warehousing

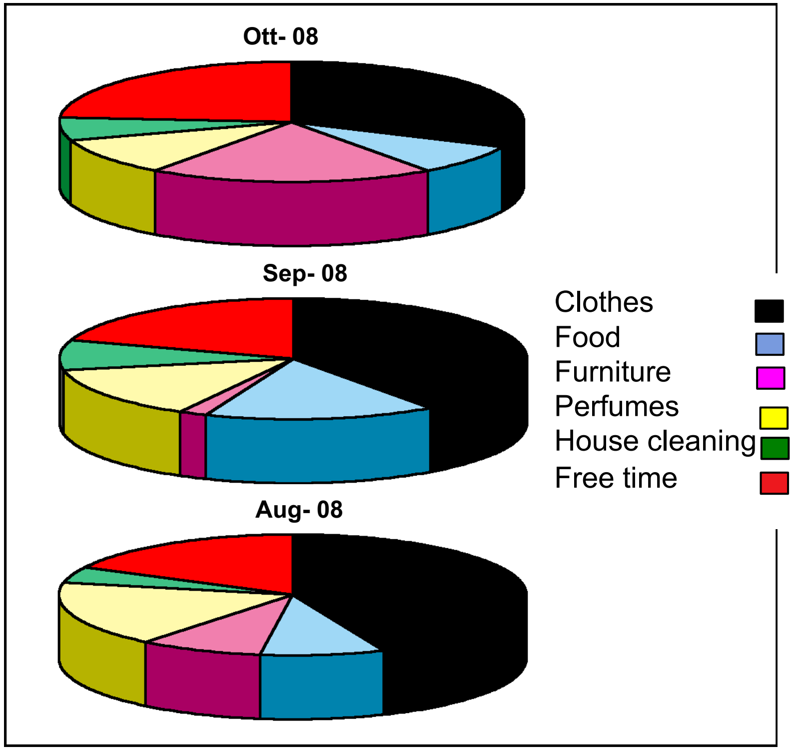
- After cleansing, integrating, and transforming data, you should determine how to get the best out of it in terms of information
- The four main approaches for end users to access the data in the data warehouses are essentially:
  - ✓ *reports:* It does not require IT knowledge
  - ✓ *dashboards:* GUIs that display a limited amount of relevant data in a brief and easy-to-read format
  - ✓ *data mining:* applies algorithms to identify hidden associations between items and make them visible to the user
  - ✓ *OLAP:* requires the user to think in a multidimensional way and to know the interface of the graphical tool used

Reports

Devoted to users that need to access information structured in an essentially static way, at predetermined time intervals

receipts (K€)	October 2008	September 2008	August 2008
clothes	80	100	50
food	20	40	10
forniture	50	5	10
Perfumes	25	35	20
House cleaning	15	20	5
Free time	60	50	20





Dashboards

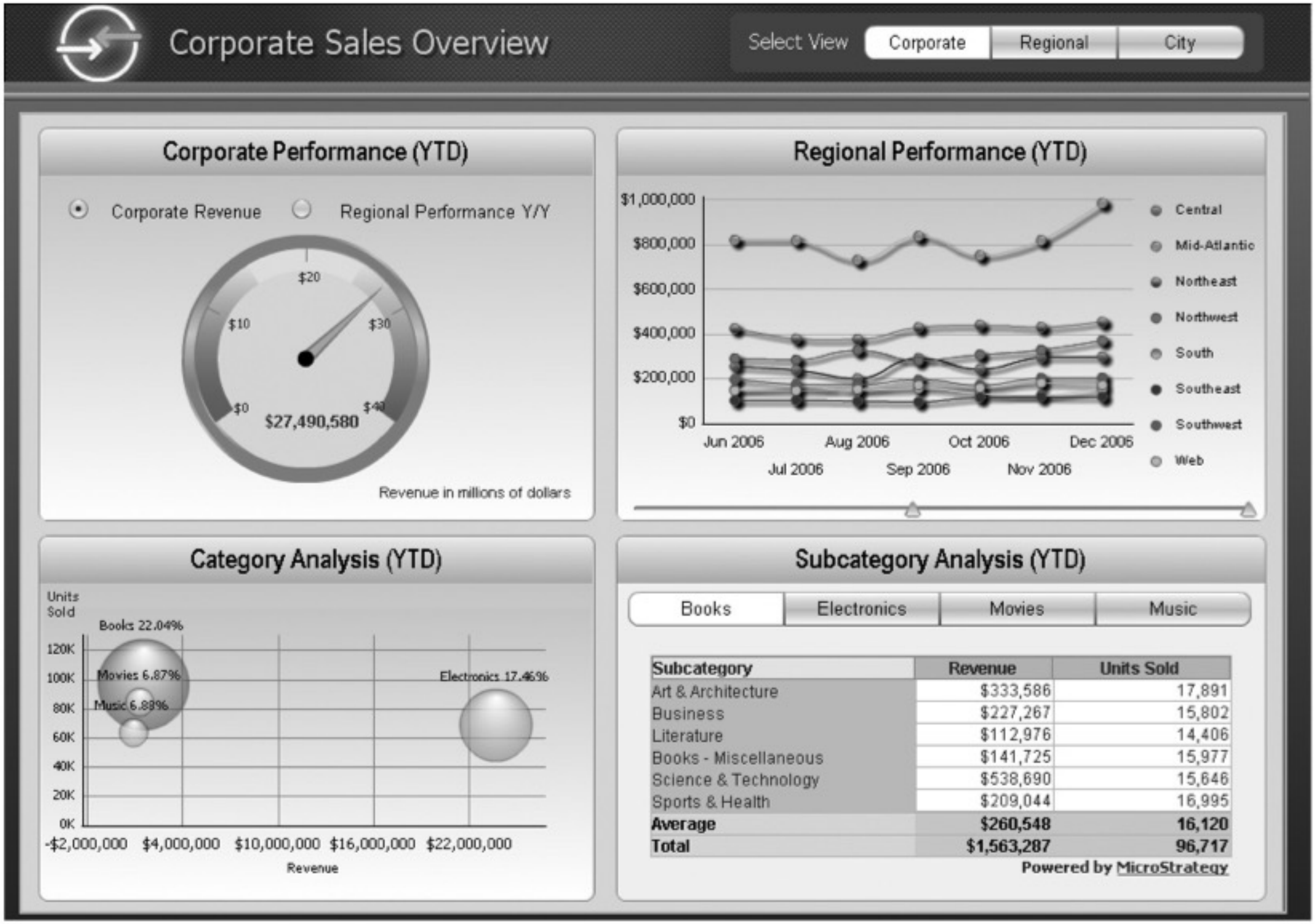
- Dashboards can provide a real-time overview of the trends for relevant phenomena and displays a limited amount of relevant data in a brief and easy-to-read format.

- The term is a visual metaphor: the group of indicators in the GUI are displayed like a car dashboard.

- Dashboards are often used by senior managers who need a quick way to view information. However, to conduct and display very complex analyses of phenomena, dashboards must be matched with analysis tools.

- Dashboards are nothing but performance indicators behind GUIs. Their effectiveness is due to a careful selection of the relevant measures, while using data warehouse information quality standard.

Dashboards



Dashboard created with MicroStrategy Dynamic Enterprise

Data mining

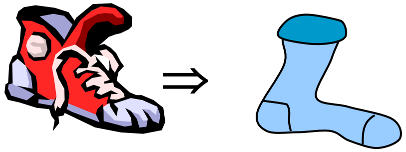
- Technique aimed at discovering information hidden in the data
  - ✓ In the presence of large-scale databases, users are not always able to find out all significative patterns (recurring schemas within data)
  - ✓ Data mining puts together a set of techniques and methodologies from **artificial intelligence and pattern recognition**, such as genetic algorithm, fuzzy logic, expert systems, neural networks, etc.
  - ✓ To discover an hidden pattern it is sufficient to indicate what and where to look for.
  - ✓ Examples of applications are:
    - Market research
    - Study of the marketing effectiveness
    - Market segmentation
    - Analysis of the buying habits
    - business Planning
    - Modeling of investments
    - Detection of fraudulent activities
    - risk category assessment
    - Recognition of similarities between sequences of events
    - Assessment of clinical cases and study of epidemiological models

Data mining: association rules

- Association rules make it possible to determine the logical implication rules that exist in databases

- Example: purchasing transactions

  {shoes} ⇒ {socks}



  The transactions containing shoes tend to contain also socks.

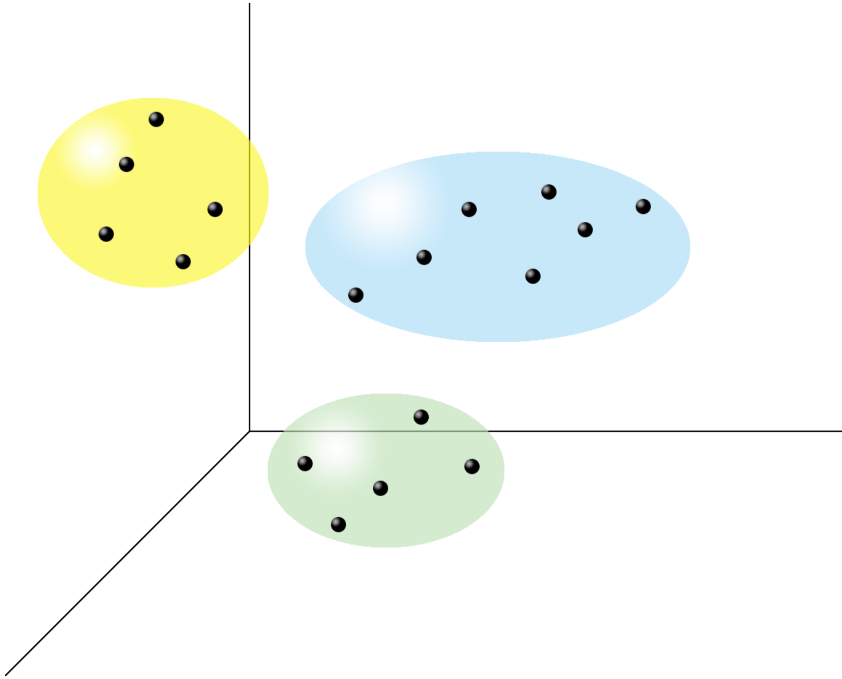
- Two measures are commonly added to evaluate how useful a rule of the form {X}⇒{Y} is:
  - ✓ **Support:** The percentage of transactions containing both X and Y
  - ✓ **Confidence:** Percentage of transactions that also contain Y among those containing X

Data mining: association rules

- Extracting association rules normally involves determining all the rules whose support and confidence figures are above a certain threshold.
- Various algorithms for this exist, e.g., the Apriori algorithm by Agrawal & Srikant
- Main applications:
  - ✓ Studies on buying habits for targeted advertising
  - ✓ Product placement on supermarket shelves (*market-basket analysis*)
  - ✓ Variations in sales in case of lacking products

Data mining: clustering

- Given a population of objects as points in a multidimensional space, in which each dimension corresponds to a particular feature, clustering refers to grouping these objects together in a reduced number of sets (clusters) better characterizing the population. Clustering identifies the similarities between items.
- Main applications:
  - ✓ Segmenting customers into categories
  - ✓ The evaluation of clinical cases on the basis of symptoms
  - ✓ Epidemiological analysis



Data mining: classifiers and decision trees

- *Training set*: a set of categories known beforehand and a set of items already labeled with the category to which they belong,

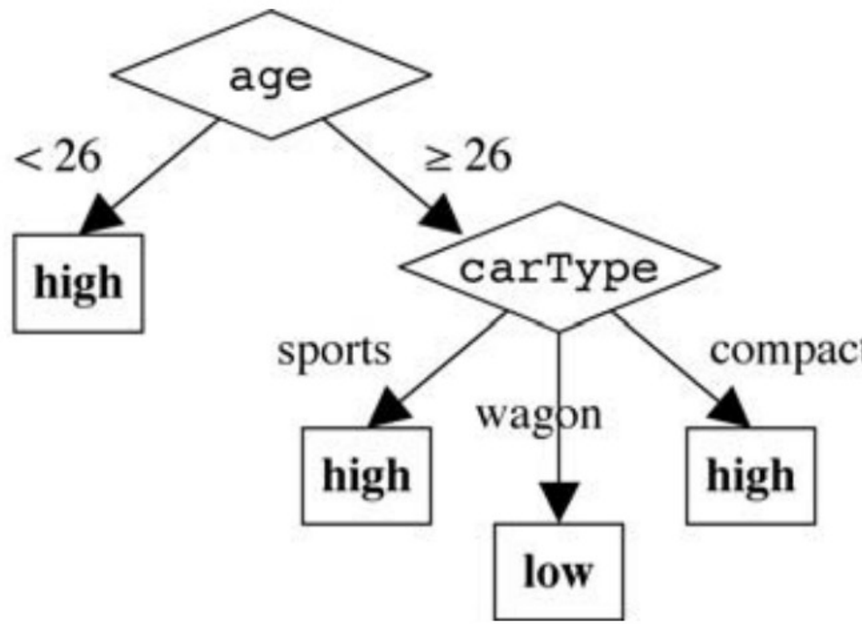
- *Classifiers* are algorithms that can create a descriptive profile for each category, based on the features of the data in the training set. They are used to assign other items not belonging to the training set to the appropriate category.

- *Decision trees* are a particular type of classifiers. They are used to understand a specific phenomenon because they can prioritize the causes leading to a specific event.

Data mining: decision trees

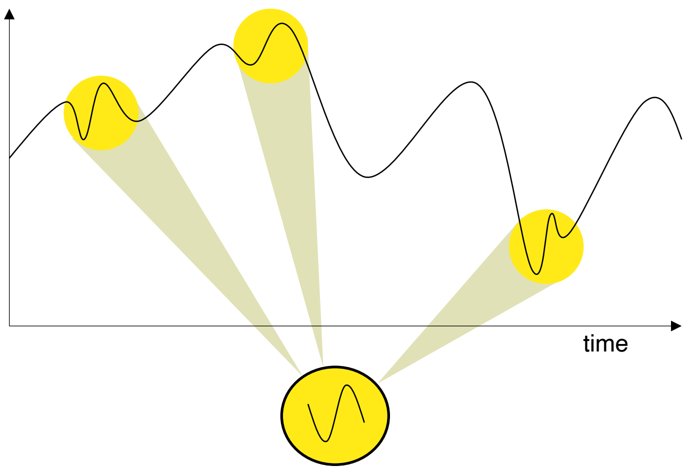
- Main Applications:
  - ✓ Assessment of customer risk categories for companies granting mortgages, loans, and insurances

age	carType	riskClass
40	wagon	low
65	sports	high
20	compact	high
25	sports	high
50	wagon	low



Data mining: time series

- The goal here is to identify recurring or atypical patterns in complex data sequences
- Applications:
  - ✓ Identifying associated growth schemata in shares on stock exchanges,
  - ✓ revealing anomalies in monitoring systems,
  - ✓ identifying companies with similar developmental models,
  - ✓ analyzing navigation routes on web sites



OLAP

- It is the most popular way to exploit information in a data warehouse.
- It gives end users, whose analysis needs are not easy to define beforehand, the opportunity to analyze and explore data interactively on the basis of the multidimensional model.
- While users of reporting tools essentially play a passive role, OLAP users are able to start a complex analysis session actively, where each step is the result of the outcome of the preceeding steps
  - ✓ in-depth knowledge of data by users is required
  - ✓ complex queries have to be allowed
  - ✓ design for users not familiar with IT has to be guaranteed

⇩

Flexible interface, easy to use and effective

OLAP: session

- An OLAP session consists of a *navigation path* that corresponds to an analysis process for facts according to different view points and different levels of detail. This path is turned into a sequence of queries, which are often not issued directly, but differentially expressed with reference to the previous query.
- At every step of the session an OLAP operator is used, which transforms the last performed query into a new one.
- The results of queries are multidimensional. OLAP tools typically use tables to display data, with multiple headers, colors, and other features to highlight data dimensions.

The notion of functional dependency

If $R(A_1,A_2,\ldots,A_n)$ is a relation schema, a functional dependency on R is a statement of the form

$$A_{i_1},A_{i_2},\ldots,A_{i_k} \rightarrow A_j$$

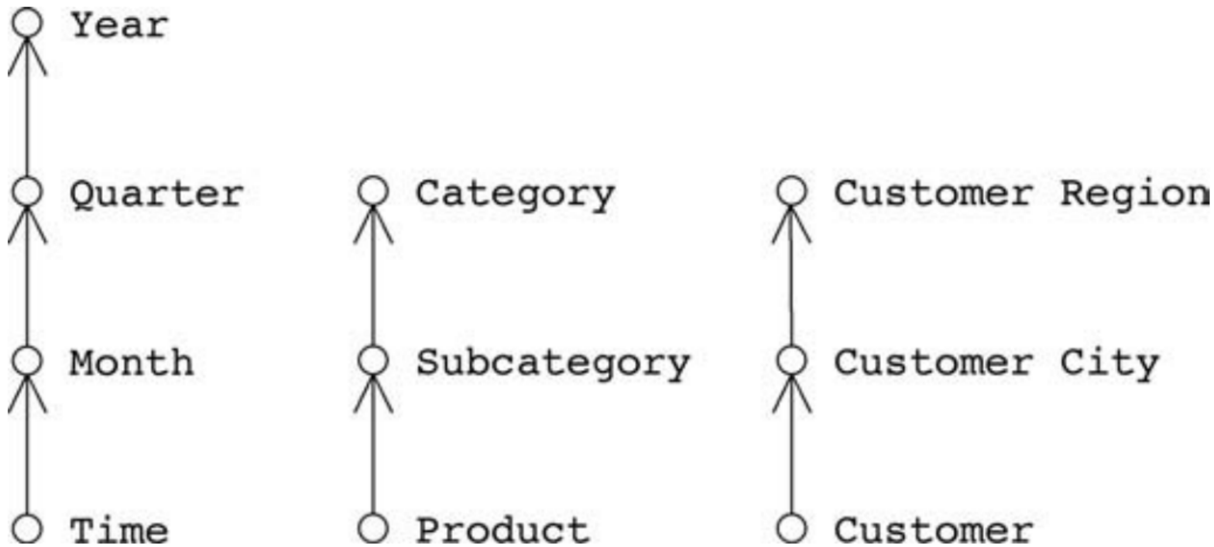
where each $A_{i_1},A_{i_2},\ldots,A_{i_k},A_j$ is in $\{A_1,A_2,\ldots,A_n\}$. Such statement is satisfied in an instance r of R if for every pair of tuples t_1,t_2 in r:

$t_1[A_{i_1},A_{i_2},\ldots,A_{i_k}] = t_2[A_{i_1},A_{i_2},\ldots,A_{i_k}]$ implies $t_1[Aj] = t_2[Aj]$

When we define a functional dependency in a relation schema R, we mean that such functional dependency must be satisfied in every instance r of R

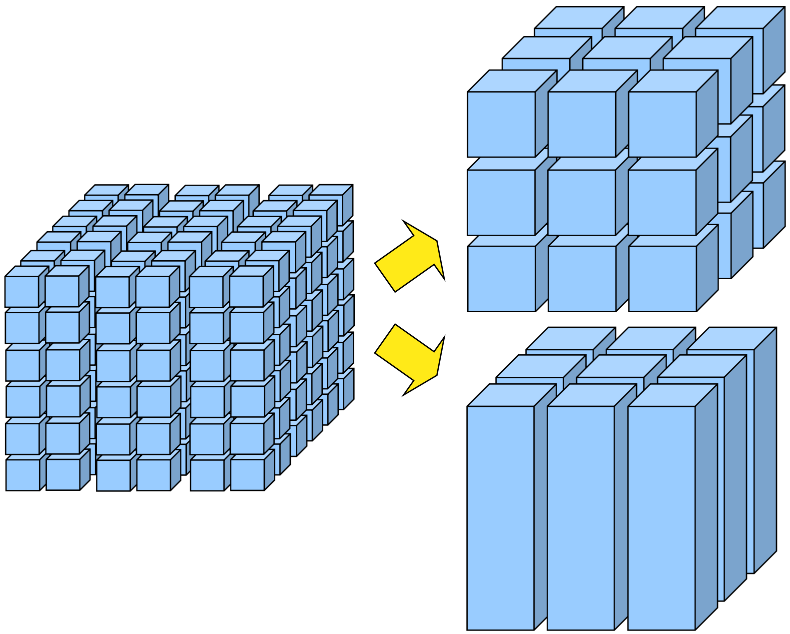
The Virtual-mall example

Attribute hierarchies in V-Mall; arrows show functional dependencies



OLAP: operators

IN SQL = GROUP BY



roll-up

The *roll-up* operator causes an increase in data aggregation and removes a detail level from an attribute hierarchy. It is based on suitable computations on measures.

OLAP: operators

Month	Metrics / Customer Region	Revenue						
		Northeast	Mid-Atlantic	Southeast	Central	South	Northwest	Southwest
Jan 2005		$160,155	$518,405	$81,381	$322,294	$98,001	$103,368	$298,730
Feb 2005		$170,777	$491,628	$80,399	$314,466	$91,222	$114,341	$373,645
Mar 2005		$200,434	$611,424	$129,102	$382,946	$123,038	$147,472	$351,602
Apr 2005		$194,811	$502,241	$93,654	$357,188	$90,663	$124,824	$304,416
May 2005		$169,998	$462,364	$117,780	$300,389	$79,999	$117,506	$311,123
Jun 2005		$202,477	$559,466	$109,979	$309,683	$115,318	$117,008	$373,526
Jul 2005		$194,490	$577,515	$105,099	$332,300	$92,730	$103,494	$369,380
Aug 2005		$203,085	$599,761	$118,805	$410,885	$119,178	$131,148	$384,555
Sep 2005		$241,992	$625,517	$122,261	$415,763	$75,655	$124,974	$364,651
Oct 2005		$217,477	$641,340	$137,925	$382,321	$89,679	$124,276	$337,489
Nov 2005		$238,004	$708,036	$156,525	$457,105	$116,478	$156,466	$386,399
Dec 2005		$273,721	$774,372	$154,139	$479,729	$119,113	$143,753	$414,983
Jan 2006		$215,786	$662,632	$125,238	$392,922	$91,791	$122,235	$343,027
Feb 2006		$253,128	$711,937	$123,725	$415,742	$97,309	$137,589	$391,277
Mar 2006		$253,564	$704,652	$135,180	$430,143	$112,459	$144,659	$406,956
Apr 2006		$255,352	$710,402	$126,717	$426,423	$113,233	$140,976	$395,924
May 2006		$231,766	$676,205	$130,981	$440,813	$107,277	$136,043	$377,349
Jun 2006		$290,534	$769,788	$123,743	$507,166	$125,631	$131,549	$439,321
Jul 2006		$247,683	$811,060	$145,955	$448,939	$113,683	$128,113	$415,251
Aug 2006		$252,313	$719,509	$125,944	$427,188	$108,987	$153,966	$421,310
Sep 2006		$288,772	$801,819	$148,023	$539,406	$112,784	$149,236	$419,878
Oct 2006		$307,610	$710,458	$163,254	$450,006	$105,218	$144,906	$440,856
Nov 2006		$284,671	$800,941	$157,117	$505,952	$118,552	$163,560	$470,591
Dec 2006		$310,775	$891,543	$170,207	$575,086	$120,228	$155,409	$534,680

Quarter	Metrics / Customer Region	Revenue						
		Northeast	Mid-Atlantic	Southeast	Central	South	Northwest	Southwest
2005 Q1		$531,366	$1,621,457	$290,882	$1,019,706	$312,261	$365,181	$1,023,977
2005 Q2		$567,286	$1,524,070	$321,413	$967,260	$285,981	$359,339	$989,065
2005 Q3		$639,567	$1,802,793	$346,165	$1,158,948	$287,563	$359,616	$1,118,587
2005 Q4		$729,202	$2,123,749	$448,589	$1,319,154	$325,269	$424,495	$1,138,871
2006 Q1		$722,478	$2,079,221	$384,143	$1,238,807	$301,559	$404,483	$1,141,260
2006 Q2		$777,651	$2,156,394	$381,441	$1,374,402	$346,141	$408,567	$1,212,593
2006 Q3		$788,768	$2,332,388	$419,923	$1,415,533	$335,455	$431,315	$1,256,439
2006 Q4		$903,056	$2,402,942	$490,578	$1,531,044	$343,998	$463,874	$1,446,127

roll-up

(on time hierarchy)

with sum

OLAP: operators

Category	Year	Metrics / Customer Region	Revenue Northeast	Mid-Atlantic	Southeast	Central	South	Northwest	Southwest
Books	2005		$416,183	$316,104	$36,517	$207,850	$137,502	$19,062	$187,368
	2006		$534,932	$401,908	$42,027	$239,806	$138,683	$22,655	$183,275
Electronics	2005		$1,860,172	$6,517,723	$1,226,825	$3,719,752	$915,633	$1,434,575	$3,625,191
	2006		$2,403,311	$8,253,620	$1,451,397	$4,631,259	$999,611	$1,615,848	$4,298,985
Movies	2005		$112,560	$138,611	$118,179	$153,556	$119,566	$27,060	$362,858
	2006		$148,785	$188,567	$147,445	$203,547	$145,434	$35,878	$463,470
Music	2005		$78,507	$99,631	$25,528	$383,911	$38,373	$27,933	$95,083
	2006		$104,925	$126,851	$35,215	$485,174	$43,424	$33,860	$110,689

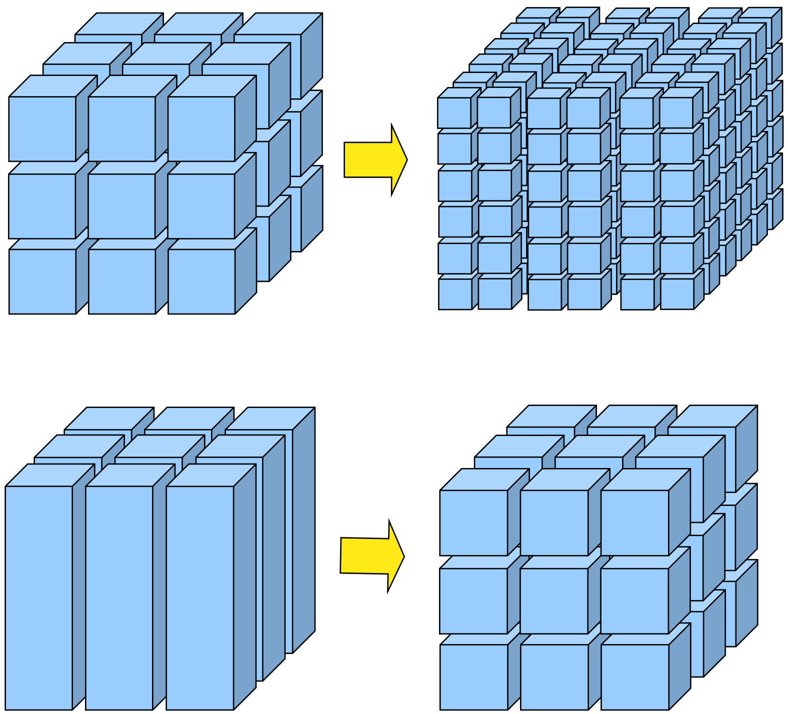
roll-up

(on customer region dimension)

with sum

Category	Year	Metrics	Revenue
Books	2005		$1,320,585
	2006		$1,563,287
Electronics	2005		$19,299,870
	2006		$23,654,030
Movies	2005		$1,032,391
	2006		$1,333,126
Music	2005		$748,966
	2006		$940,136

OLAP: operators



drill-down

It is the inverse of roll-up. We use it to reduce the level of aggregation in the data

OLAP: operators

Quarter	Metrics / Customer Region	Revenue: Northeast	Mid Atlantic	Southeast	Central	South	Northwest	Southwest
2005 Q1		$531,366	$1,621,457	$290,882	$1,019,706	$312,261	$365,181	$1,023,977
2005 Q2		$567,286	$1,524,070	$321,413	$967,260	$285,981	$359,339	$989,065
2005 Q3		$639,567	$1,002,793	$346,165	$1,150,940	$207,563	$359,616	$1,110,507
2005 Q4		$729,202	$2,123,749	$440,509	$1,319,154	$325,269	$424,495	$1,130,071
2006 Q1		$722,478	$2,079,221	$384,143	$1,238,807	$301,559	$404,483	$1,141,260
2006 Q2		$777,651	$2,156,394	$381,441	$1,374,402	$346,141	$408,567	$1,212,593
2006 Q3		$788,768	$2,332,388	$419,923	$1,415,533	$335,455	$431,315	$1,256,439
2006 Q4		$903,056	$2,402,942	$490,578	$1,531,044	$343,998	$463,874	$1,446,127

drill-down (on customer region)

Quarter	Metrics / Customer City	Revenue: Addison	Akron	Albany	Albert City	Alexandria	Allentown	Anderson	Annapolis	Arden	Arlington Heights	Arlington	Artesia	A.
2005 Q1		$7,713	$30,140	$4,626	$6,686	$29,042	$4,579	$1,948	$40,066	$23,341	$10,481		$10,922	$1
2005 Q2		$15,903	$48,029	$8,959	$2,088	$17,590	$7,268	$2,416	$42,764	$21,026	$7,514	$1,695	$2,984	$
2005 Q3		$10,091	$30,510	$5,763	$11,380	$26,389	$10,195	$568	$51,650	$25,132	$10,784	$3,796	$8,701	$
2005 Q4		$12,425	$48,588	$10,939	$10,463	$28,016	$10,426	$3,412	$67,515	$28,398	$14,692		$9,975	$1
2006 Q1		$7,256	$26,183	$7,998	$5,603	$35,959	$10,273	$2,732	$50,121	$26,351	$7,276	$1,593	$6,208	$1
2006 Q2		$10,411	$49,540	$6,065	$5,670	$25,166	$6,992	$1,377	$68,198	$27,556	$16,755	$3,420	$6,656	$1
2006 Q3		$10,325	$30,414	$9,100	$7,760	$33,170	$16,970	$021	$69,050	$33,579	$10,235	$4,319	$7,636	$1
2006 Q4		$16,613	$49,133	$13,137	$10,637	$30,344	$13,075	$747	$40,305	$32,042	$13,311	$6,176	$9,191	$1

OLAP: operators

	Metrics	Dollar Sales	
	Year	1997	1998
Category			
Electronics		$ 10.616	$ 29.299
Food		$ 5.300	$ 5.638
Gifts		$ 16.315	$ 20.047
Health & Beauty		$ 6.042	$ 5.665
Household		$ 38.383	$ 50.391
Kid's Korner		$ 2.559	$ 2.943
Travel		$ 4.497	$ 4.792

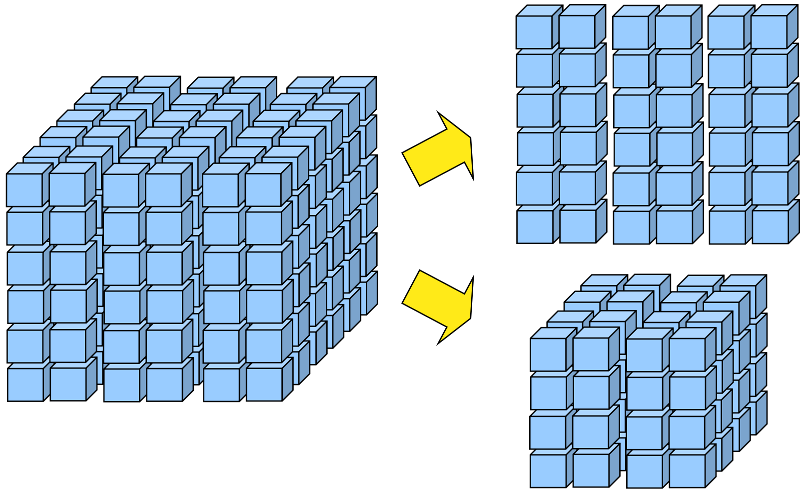
drill-down

(on customer region dimension, for year = 1998)

Filter Details:
Year = 1998

	Metrics	Dollar Sales										
	Customer Region	North-East	Mid-Atlantic	South-East	Central	South	North-West	South-West	England	France	Germany	Ca
Category												
Electronics		$ 1.184	$ 4.529	$ 1.892	$ 7.232	$ 651	$ 9.488	$ 476	$ 2.683	$ 462	$ 702	
Food		$ 538	$ 925	$ 959	$ 677	$ 213	$ 1.503	$ 261	$ 165	$ 175	$ 100	$
Gifts		$ 1.955	$ 2.785	$ 2.800	$ 2.695	$ 1.813	$ 2.844	$ 1.778	$ 1.158	$ 717	$ 686	$
Health & Beauty		$ 611	$ 887	$ 566	$ 382	$ 499	$ 1.162	$ 1.044	$ 273	$ 72		$
Household		$ 5.787	$ 5.320	$ 5.416	$ 6.812	$ 4.334	$ 5.008	$ 7.588	$ 2.139	$ 3.649	$ 2.791	$
Kid's Korner		$ 247	$ 422	$ 441	$ 380	$ 221	$ 592	$ 290	$ 198	$ 19	$ 69	
Travel		$ 608	$ 559	$ 1.096	$ 611	$ 464	$ 316	$ 573	$ 257	$ 198	$ 55	

OLAP: operators



slice-and-dice

It produces “sub-cubes” starting from cubes. Typically, this is realized through simple or complex selection conditions.

- **Slicing**: reduces the number of cube dimensions after setting one of the dimension to a specific value
- **Dicing:** reduces the set of data being analyzed by a selection criterion

OLAP: operators

		Metrics	Revenue						
Category	Year	Customer Region	Northeast	Mid-Atlantic	Southeast	Central	South	Northwest	Southwest
Books	2005		$416,183	$316,104	$36,517	$207,850	$137,502	$19,062	$187,368
	2006		$534,932	$401,908	$42,027	$239,806	$138,683	$22,655	$183,275
Electronics	2005		$1,860,172	$6,517,723	$1,226,825	$3,719,752	$915,633	$1,434,575	$3,625,191
	2006		$2,403,311	$8,253,620	$1,451,397	$4,631,259	$999,611	$1,615,848	$4,298,985
Movies	2005		$112,560	$138,611	$118,179	$153,556	$119,566	$27,060	$362,858
	2006		$148,785	$188,567	$147,445	$203,547	$145,434	$35,878	$463,470
Music	2005		$78,507	$99,631	$25,528	$383,911	$38,373	$27,933	$95,083
	2006		$104,925	$126,851	$35,215	$485,174	$43,424	$33,860	$110,689

slice-and-dice

Slicing based on the condition Year='2006'

Report Filter (Local Filter):
Year = 2006

	Metrics	Revenue						
Category	Customer Region	Northeast	Mid-Atlantic	Southeast	Central	South	Northwest	Sout
Books		$534,932	$401,908	$42,027	$239,806	$138,683	$22,655	$1
Electronics		$2,403,311	$8,253,620	$1,451,397	$4,631,259	$999,611	$1,615,848	$4,2
Movies		$148,785	$188,567	$147,445	$203,547	$145,434	$35,878	$4
Music		$104,925	$126,851	$35,215	$485,174	$43,424	$33,860	$1

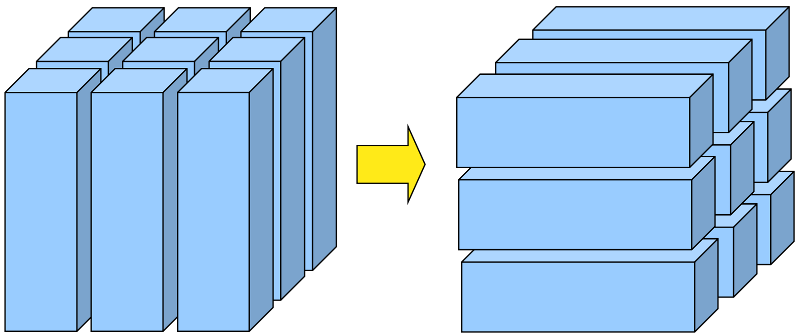
Subcategory \ Metrics: Revenue, Customer City	Addison	Akron	Albany	Albert City	Alexandria	Allentown	Anderson	Annapolis	Arden	Arlin Heig
Art & Architecture	$253	$365	$1,506	$279	$268	$1,960		$407	$282	
Business	$198	$357	$719	$75	$134	$1,225	$8	$304	$184	
Literature	$92	$116	$277	$54	$66	$503		$137	$128	
Books - Miscellaneous	$216	$95	$830	$120	$73	$605	$4	$233	$71	
Science & Technology	$363	$943	$3,271	$578	$491	$2,547		$834	$366	
Sports & Health	$220	$153	$416	$165	$128	$1,476		$409	$204	
Audio Equipment	$1,782	$32,102	$2,082	$1,318	$36,158	$7,303	$1,130	$77,501	$17,307	$
Cameras	$7,671	$39,381	$5,810	$3,898	$12,045	$8,124	$405	$33,744	$11,840	$
Computers	$1,531	$14,810	$1,935	$3,022	$7,967	$3,354		$5,097	$7,087	$
Electronics - Miscellaneous	$4,667	$25,861	$5,289	$5,979	$25,484	$4,821	$130	$9,533	$11,923	$
TV's	$9,027	$34,635	$5,013	$3,500	$33,432	$4,930		$46,933	$32,527	$
Video Equipment	$7,422	$10,078	$5,540	$2,479	$5,500	$7,470	$540	$55,552	$35,723	$
Action	$108	$302	$204	$134	$256	$259	$25	$859	$117	
Comedy	$308	$520	$355	$195	$204	$261		$361	$216	
Drama	$424	$548	$225	$243	$313	$399		$511	$415	
Horror	$339	$196	$141	$195	$188	$372		$261	$184	
Kids / Family	$361	$277	$236	$213	$235	$460	$11	$744	$323	
Special Interests	$700	$670	$353	$289	$179	$695		$816	$288	
Alternative	$1,077	$236	$114	$484	$234	$139		$365	$173	$
Country	$1,169	$336	$310	$576	$206	$123	$43	$283	$288	
Music - Miscellaneous	$1,193	$364	$167	$494	$254	$281	$18	$410	$132	$
Pop	$541	$286	$231	$302	$130	$178	$26	$350	$173	
Rock	$1,184	$324	$202	$490	$161	$341	$14	$285	$127	
Soul / R&B	$760	$225	$182	$1,496	$223	$293	$23	$463	$159	$

slice-and-dice

Subcategory \ Metrics: Revenue, Customer City	Bellevue	Bothell	Caldwell	Cheyenne	Coulee City	E
Audio Equipment	$9,945	$23,211	$2,531	$2,347	$30,857	$
Cameras	$31,245	$5,613	$5,592	$1,240	$11,250	$
Computers	$12,751	$4,771	$1,443	$713	$8,181	
Electronics - Miscellaneous	$13,940	$29,072	$3,722	$2,444	$16,254	$
TV's	$40,652	$9,788	$3,990	$1,871	$10,846	$
Video Equipment	$36,423	$26,363	$3,543	$3,947	$5,480	$

Year ='2006' AND
Category ='Electronics' AND
Revenue>80 AND
CustomerRegion ='Northwest'

OLAP: operators



pivoting

It is used to change the structure of the visualization of the cube, that is, when a different view of the data in the cube is needed.

OLAP: operators

Category	Year	Metrics Revenue
Books	2005	$1,320,585
	2006	$1,563,287
Electronics	2005	$19,299,870
	2006	$23,654,030
Movies	2005	$1,032,391
	2006	$1,333,126
Music	2005	$748,966
	2006	$940,136

Metrics	Revenue	
Year	2005	2006
Category		
Books	$1,320,585	$1,563,287
Electronics	$19,299,870	$23,654,030
Movies	$1,032,391	$1,333,126
Music	$748,966	$940,136

pivoting

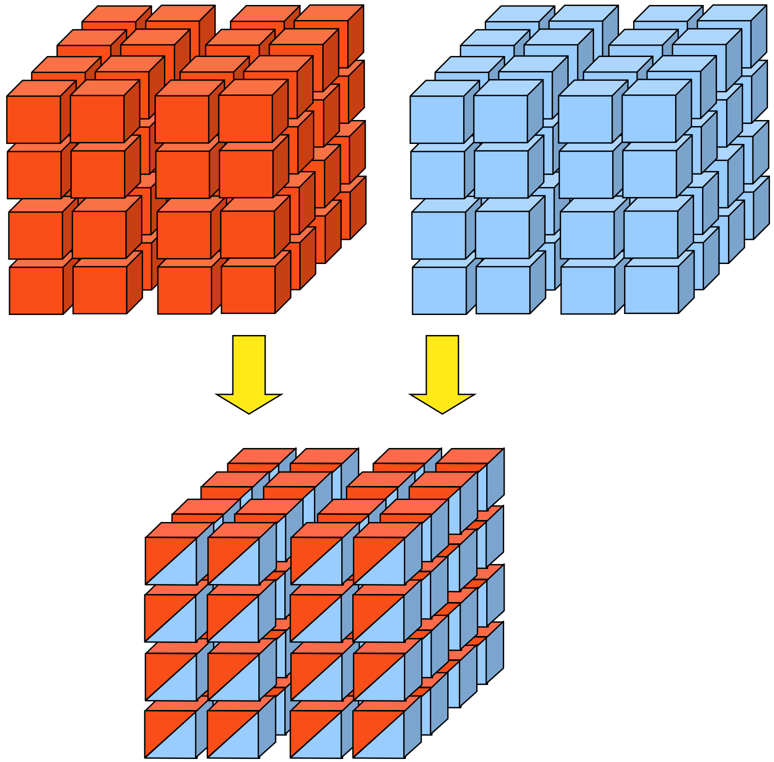
OLAP: operators

Category	Year	Metrics / Customer Region	Revenue: Northeast	Mid Atlantic	Southeast	Central	South	Northwest	Southwest
Books	2005		$416,183	$316,104	$36,517	$207,850	$137,502	$19,062	$187,368
	2006		$534,932	$401,908	$42,027	$239,806	$138,683	$22,655	$183,275
Electronics	2005		$1,860,172	$6,517,723	$1,226,825	$3,719,752	$915,633	$1,434,575	$3,625,191
	2006		$2,403,311	$8,253,620	$1,451,397	$4,631,259	$999,611	$1,615,848	$4,298,985
Movies	2005		$112,560	$138,611	$118,179	$153,556	$119,566	$27,060	$362,858
	2006		$148,785	$188,567	$147,445	$203,547	$145,434	$35,878	$463,470
Music	2005		$78,507	$99,631	$25,528	$383,911	$38,373	$27,933	$95,083
	2006		$104,925	$126,851	$35,215	$485,174	$43,424	$33,860	$110,689

pivoting

Metrics / Customer Region / Year	Revenue: Northeast		Mid Atlantic		Southeast		Central		South		Nort
Category	2005	2006	2005	2006	2005	2006	2005	2006	2005	2006	2
Books	$416,183	$534,932	$316,104	$401,908	$36,517	$42,027	$207,850	$239,806	$137,502	$138,683	$
Electronics	$1,860,172	$2,403,311	$6,517,723	$8,253,620	$1,226,825	$1,451,397	$3,719,752	$4,631,259	$915,633	$999,611	$1,
Movies	$112,560	$148,785	$138,611	$188,567	$118,179	$147,445	$153,556	$203,547	$119,566	$145,434	$
Music	$78,507	$104,925	$99,631	$126,851	$25,528	$35,215	$383,911	$485,174	$38,373	$43,424	$

OLAP: operators



drill-across

It combines data in different cubes to obtain a new cube.

OLAP: operators

	Metrics	Revenue							
	Quarter	2005 Q1	2005 Q2	2005 Q3	2005 Q4	2006 Q1	2006 Q2	2006 Q3	2006 Q4
Category									
Books		$319,767	$313,339	$336,862	$350,617	$348,483	$387,849	$407,392	$419,563
Electronics		$4,448,112	$4,299,411	$4,918,673	$5,633,676	$5,411,499	$5,714,783	$5,999,174	$6,528,576
Movies		$228,108	$232,201	$264,471	$307,611	$299,531	$326,270	$334,143	$373,182
Music		$168,843	$169,462	$193,234	$217,427	$212,438	$228,289	$239,112	$260,298

+ discount data
(having same aggregation level)

drill-across

	Quarter	2005 Q1		2005 Q2		2005 Q3		2005 Q4		2006 Q1	
	Metrics	Discount	Revenue	Discount	Revenue	Discount	Revenue	Discount	Revenue	Discount	Re
Category											
Books		$ 0	$319,767	$ 10,845	$313,339	$ 9,497	$336,862	$ 18,279	$350,617	$ 0	
Electronics		$ 0	$4,448,112	$ 150,366	$4,299,410	$ 143,395	$4,918,673	$ 302,884	$5,633,675	$ 0	$5
Movies		$ 0	$228,108	$ 8,025	$232,201	$ 7,948	$264,471	$ 16,649	$307,611	$ 0	
Music		$ 0	$168,843	$ 6,143	$169,462	$ 5,563	$193,234	$ 11,047	$217,427	$ 0	

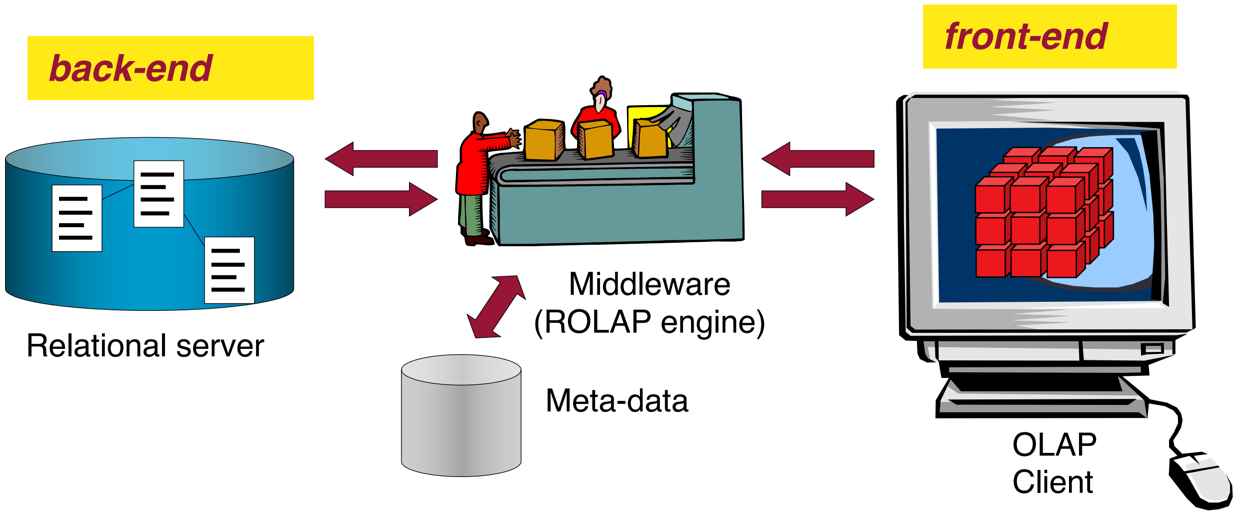
Drilling across the sales cube (Revenue measure) and the promotion cube (Discount measure)

Implementing the multidimensional data model: ROLAP

- Stands for *Relational* OLAP: an implementation based on relational DBMSs
- Motivated by the huge amount of literature written about the relational model, the broadly available corporate experience with relational database usage and management, and the top performance and flexibility standards of relational DBMSs. However,
  - ✓ the relational model does not include the concepts of dimension, measure, and hierarchy: you must create specific types of schemata that allow one to represent multidimensional schemata in terms of relational ones => Star Schema.
  - ✓ Performance problems (costly join operations over large tables) =>*denormalization*.
- Since ROLAP uses a relational database, it requires more processing time and/or disk space to perform some of the tasks that multidimensional databases are designed for. However, ROLAP supports larger user groups and greater amounts of data.
- As is typical of relational databases, some queries are created and their results are stored in advance (in materialized views)

Implementing the multidimensional data model: ROLAP

- From an architectural viewpoint, adopting ROLAP requires specialized middleware, also called *multidimensional or ROLAP engine*, between relational back-end servers and front-end components.
- The user submits a request for multidimensional analysis and the ROLAP engine converts the request to SQL for submission to the database. Then, the engine converts the resulting data from SQL to a multidimensional format before it is returned to the client for viewing.



We will see more on ROLAP solutions later on in these slides

Implementing the multidimensional data model: MOLAP

- It is based on an ad-hoc logical model, where multidimensional data and operations can be natively represented.
- Events and Aggregation:

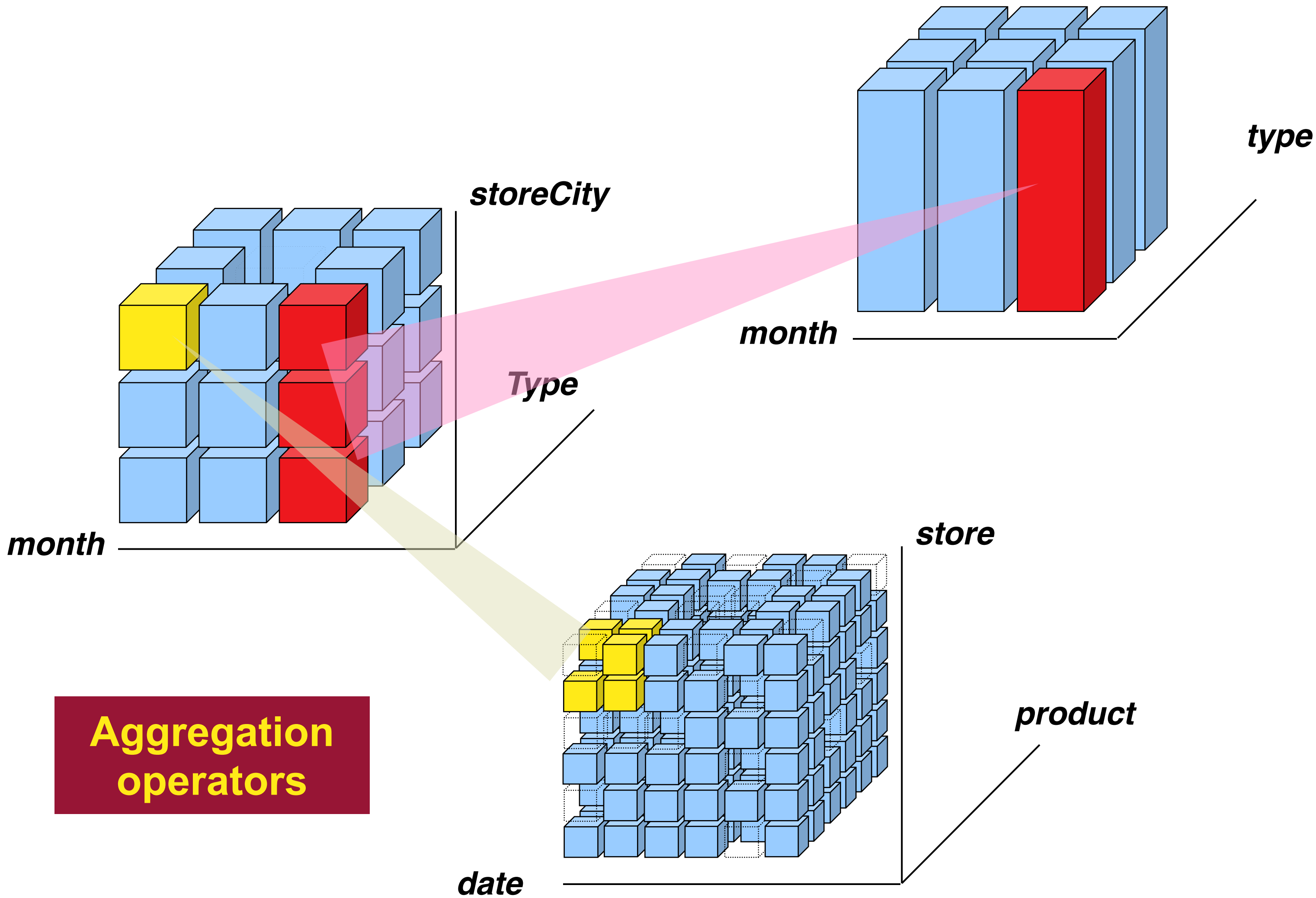
A primary event is a particular occurrence of a fact, identified by one n-ple made up of a value for each dimension. A value for each measure is associated with each primary event.

- ✓ In reference to sales, for example, a possible primary event records that 10 packages of Shiny detergent were sold for total sales of $25 on 10/10/2008 in the SmartMart store.

Given some dimensional attributes, each n-ple of their values identifies a secondary event which aggregates all corresponding primary events. To any secondary event a value is associated for each measure. Such a value sums up all the values of the same measure in the corresponding primary events.

- ✓ Thus, hierarchies define the way you can aggregate primary events and effectively select them for decision-making process; while the dimension in which a hierarchy takes root defines its finest aggregation granularity, the other dimensional attributes correspond to a gradually increasing granularity.

Events and Aggregation



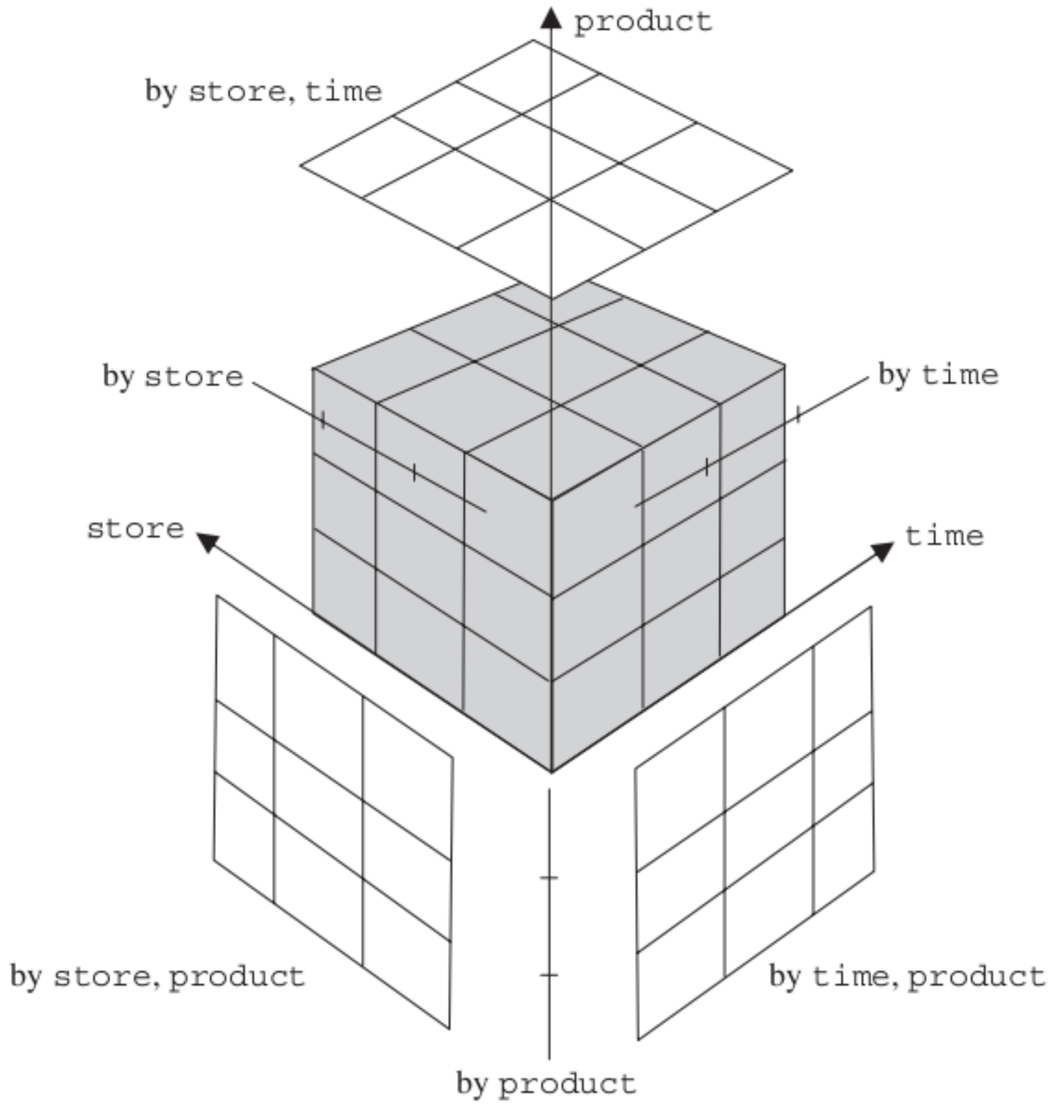
Aggregation operators

MOLAP – data cube

- Given a primary cube including all the primary events, i.e., the facts, its *data cube* consists of the primary cube surrounded by a collection of secondary coarse-grained cubes, which aggregate the primary cube along one or more dimensions and include secondary events.
- All the secondary cubes do not need to be physically available because you can calculate them by aggregating their primary cube along one. Nevertheless, you may need to store some or all the secondary cubes to improve the query response time.
- Data cubes thus act as a logical structure for the multidimensional model.
- Data cubes are stored in arrays. Each array element is associated with a set of coordinates on a value space. Access to data is positional, through the array coordinates.

MOLAP

The figure shows data cubes for a simple SALE fact containing three dimensions (store, time, and product), without any hierarchy. Along with the primary cube (in gray), this figure shows three two-dimensional secondary cubes (by store-product; by store-time; by time-product). product), and three one-dimensional secondary cubes (by store; by time; by product). The 0-dimensional cube is not shown.



MOLAP

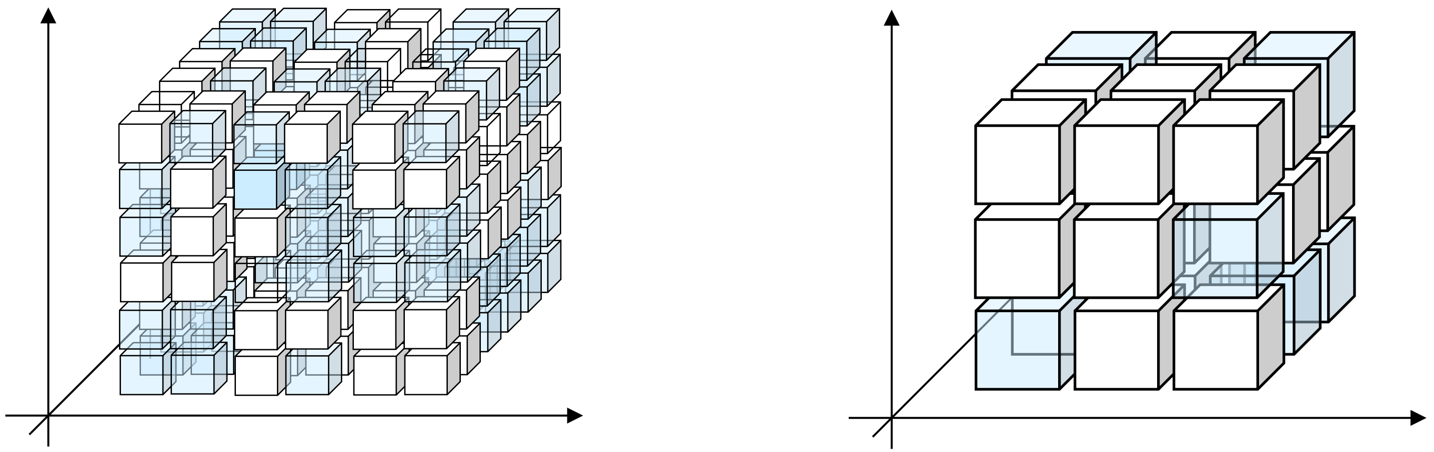
- ✓ The big advantage of the MOLAP approach with respect to the ROLAP one is that multidimensional operations can be simply and naturally realized, without the need of resorting to joins. For this reason, MOLAP system performance is excellent.
- ✓ However, no standard for the logical model at the basis of MOLAP approach currently exists, and the various implementations present very many differences one another: They simply share the usage of optimization techniques specifically designed for *sparsity management*.
- ✓ No standard query language: each vendor tends to propose a proprietary one (*Microsoft Multidimensional Expressions* is a popular language that can be considered as standard de facto)
- ✓ Loading process is often slow.
- ✓ Some products may handle only up to ten dimensions with limited cardinality

MOLAP: The problem of sparsity

- In the multidimensional model, a set of coordinates corresponds to a possible event even if this does not actually took place.
- Typically, the number of occurred events is far less than possible events (around 20%).
- Keeping track of events that did not occur leads to a waste of resources and reduces the performance of the system.
  - ✓ ROLAP: can store only useful cells (occurred events).
  - ✓ MOLAP: calls for complex techniques to minimize the space required to keep track of not occurred events.

MOLAP: The problem of sparsity

- We can group cubes into “chunks”, and classify these as sparse or dense chunks. MOLAP systems try to materialize mainly dense chunks.



- Variuos strategies are possible (Hybrid OLAP):
  - Store dense chunks in MOLAP mode and sparse chunks in ROLAP mode.
  - Store primary cubes in ROLAP mode and secondary cubes in MOLAP mode (aggregation reduces sparsity).
  - Store frequently accessed data in MOLAP mode and the remaining data in ROLAP mode.

Need of a Design Methodology

- Many organizations lack the experience and skills required to meet the challenges involved in data warehousing projects.
- The lack of a methodological approach prevents data warehousing projects from being carried out successfully.
- Methodological approaches are created by closely studying similar experiences and minimizing the risks for failure by basing new approaches on a constructive analysis of previous mistakes.

Facts

- Fact types are concepts on which data mart end users base their decision-making process. Each fact (instance of a fact type) describes a category of events taking place in an organization. They have to be identified in the *Requirement Analysis phase.*
  - ✓ Designers should also have clear ideas on fact dimensions. Focusing on the dimensions of a fact leads to the definition of fact granularity, i.e., the highest detail level for data to be represented in the data warehouse. Selecting a granularity level for fact representation is the result of a delicate compromise between two opposite needs: the need for maximum usage flexibility, which implies the same granularity level as operational sources, and the need for top performance, which implies a concise synthesis of data.
  - ✓ Most facts need a historical interval to be defined -- that is, a period of time covered by the events stored in a data mart.

Typical facts of different application fields

Application Field	Data Mart	Facts
Business, manufacturing	Supplies	Purchases, stock inventory, distribution
	Production	Packaging, inventory, delivery, manufacturing
	Demand management	Sales, invoices, orders, shipments, complaints
	Marketing	Promotions, customer retention, advertising campaigns
Finance	Banks	Checking accounts, bank transfers, mortgage loans, loans
	Investments	Securities, stock exchange transactions
	Services	Credit cards, bill payment through standing orders
Health service	Division	Admissions, discharges, transfers, surgical operations, diagnosis, prescriptions
	Accident & emergency	Admissions, tests, discharges
	Epidemiology	Diseases, outbreaks, treatments, vaccinations
Transportation	Goods	Demand, supply, transport
	Passengers	Demand, supply, transport
	Maintenance	Operations
Telecommunications	Traffic management	Network traffic, calls
	Customer relationship management	Customer retention, complaints, services

Conceptual Modeling for DWs

- It is well known that an accurate conceptual design is the fundamental requirement for the construction of a well-documented data stores that completely meets the requirements.

- While it is universally acknowledged that a DW relies (at the logical level) on the multidimensional model, there is no agreement on the methodology for conceptual modeling in DWs.

- The Entity/Relationship (ER) model is widely used in organizations for the documentation of information systems based on the relational model (even though not always in a formal and completely understood way), it is not suitable to model a DW.

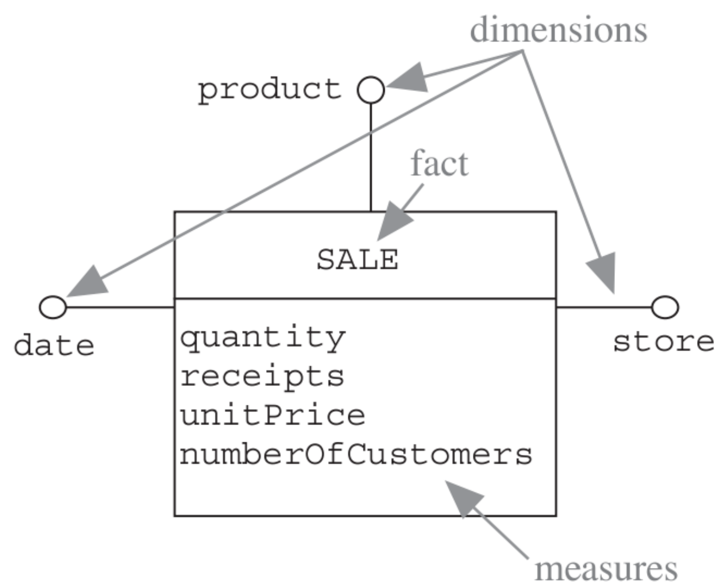
The Dimensional Fact Model

- DFM is a graphical conceptual model for data marts, designed for:
  - ✓ Effectively supporting the conceptual design.
  - ✓ Creating an environment in which user queries may be formulated intuitively.
  - ✓ Making communication possible between designers and end users to refine requirement specifications.
  - ✓ Building a stable platform from which starting the logical design (*indipendent from the target logical model*).
  - ✓ Providing clear and expressive design documentation.

- The conceptual representation generated by the DFM consists of a set of fact schemata. Each fact schema basically models facts, measures, dimensions, and hierarchies.

DFM: basic constructs

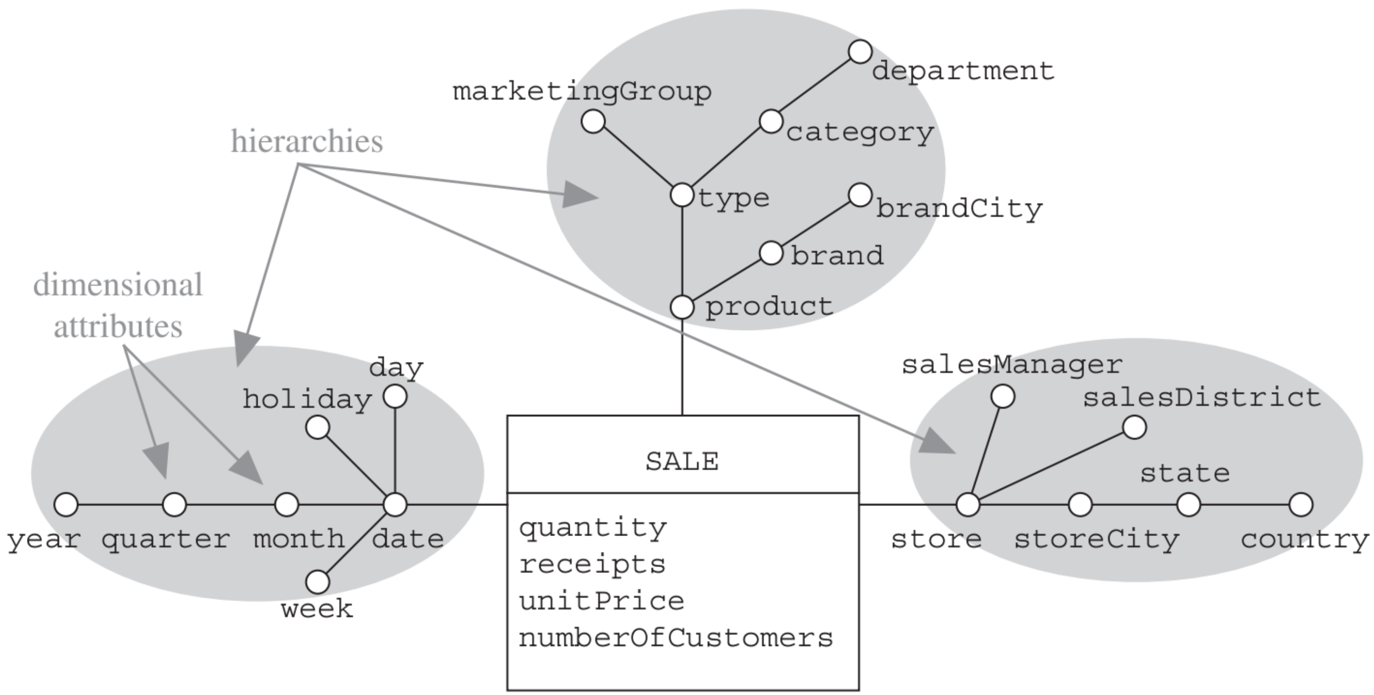
- A fact type (or simply fact) is a concept relevant to decision-making processes. It typically models a set of events taking place within an organization (e.g., sales, shipments, purchases, and complaints, etc.). It is essential that a fact have dynamic properties or evolve in some way over time
- A *measure* is a numerical property of a fact and describes a quantitative fact aspect that is relevant to analysis (e.g., each sale is measured by the number of units sold, the unit price, and the total receipts)
- A *dimension* is a fact property with a finite domain and describes an analysis coordinate of the fact (typical dimensions for the sales fact are products, stores, and dates)
- The values associated to a fact by the various dimensions identify the fact



Note: A fact can also have no measures, as in the case when you are interested in recording only the occurrence of an event

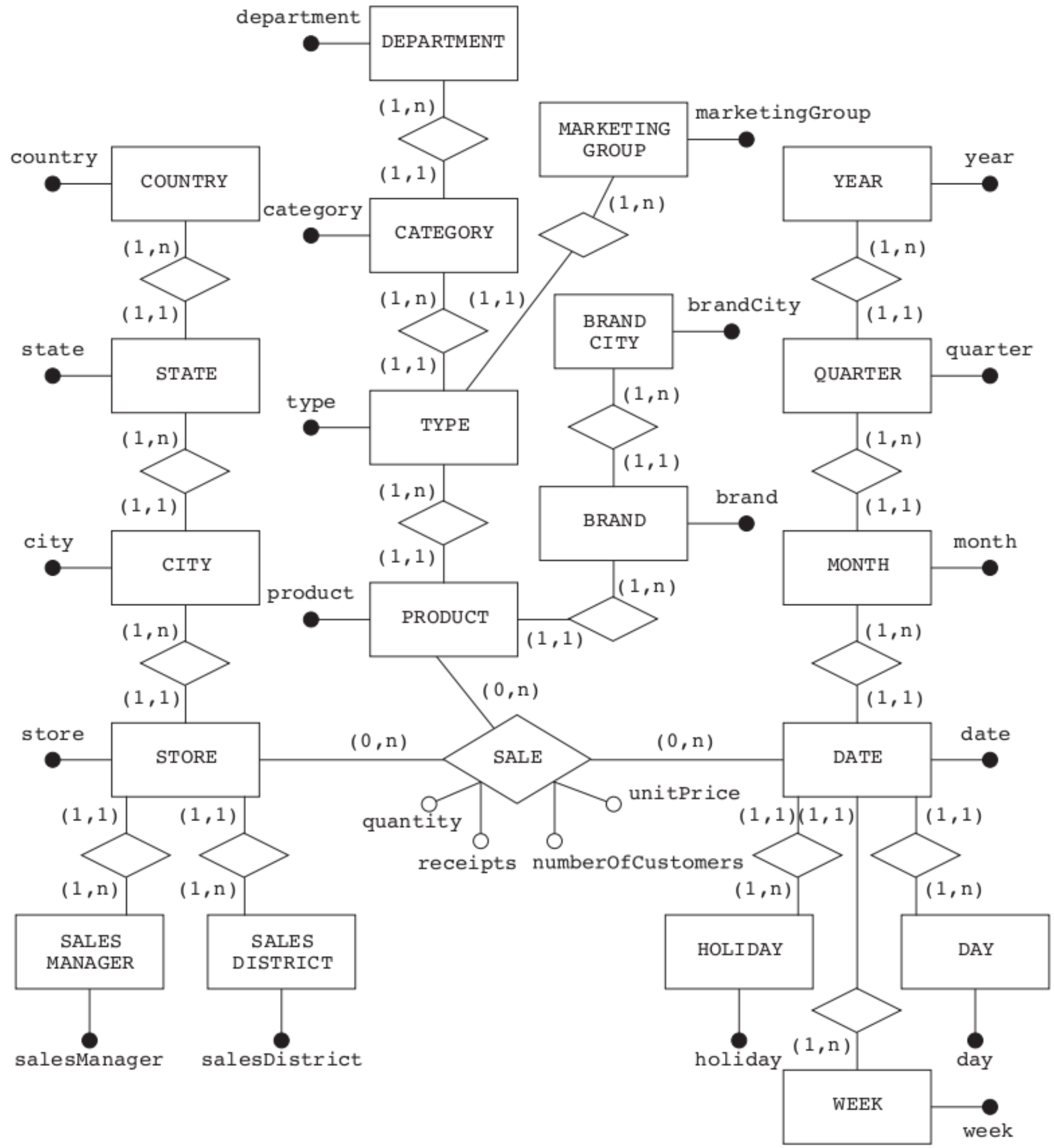
DFM: basic constructs

- The general term dimensional attributes stands for the dimensions and other possible attributes, always with discrete values, that describe them (for example, a *product* dimension is described by its *type*, the *category* it belongs to, its *brand*, the *department* in which it is sold)
- A hierarchy is a directed tree whose nodes are dimensional attributes and whose arcs model many-to-one associations between dimensional attributes. It includes a dimension, positioned at the trees root, and all of the dimensional attributes that describe it.



DFM: correspondence with ER diagrams

Note: *Though the ER is expressive enough to show facts, dimensions, and measures, it does not represent these concepts as first-class citizen*

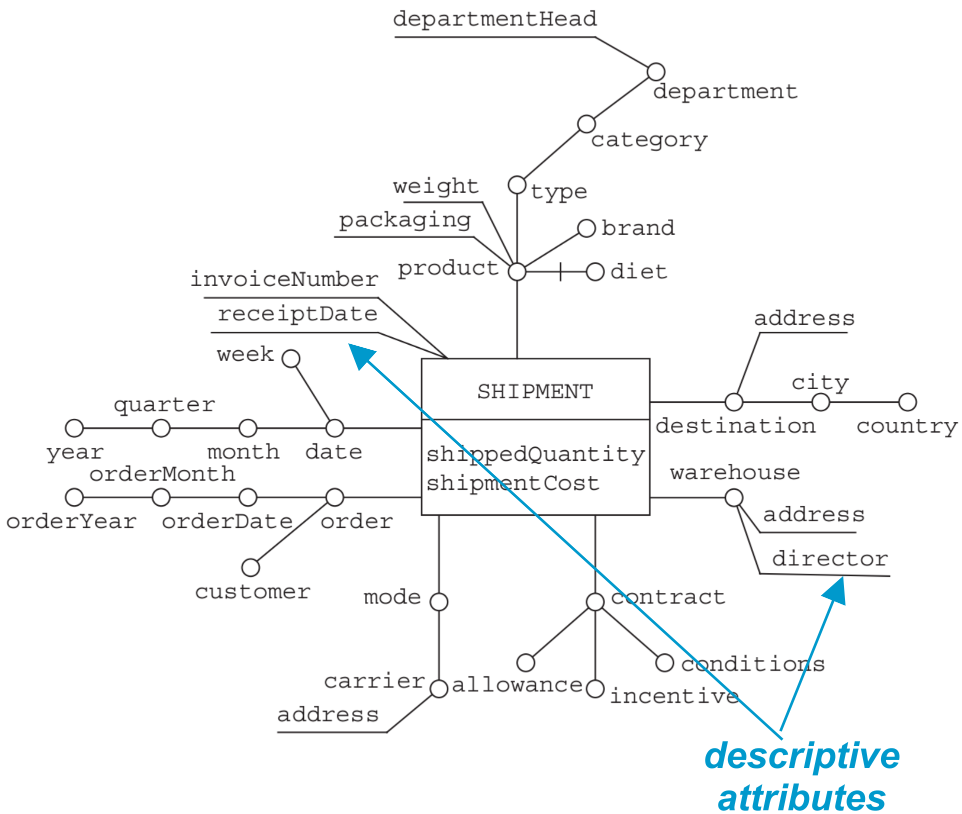


“Naming conventions”

- All dimensional attributes in a fact schema must have different names.
- Similar names can be differentiated by qualifying them with the name of the dimensional attribute that comes before them in hierarchies.
  - ✓ For instance, *brandCity* and *storeCity*.
- Names of dimensional attributes should not explicitly refer to the fact they belong to
  - ✓ For instance, *shippedProduct* and *shipmentDate have to be avoided*
- Attributes with the same meaning in different fact schemata must have the same name.

DFM: descriptive attributes

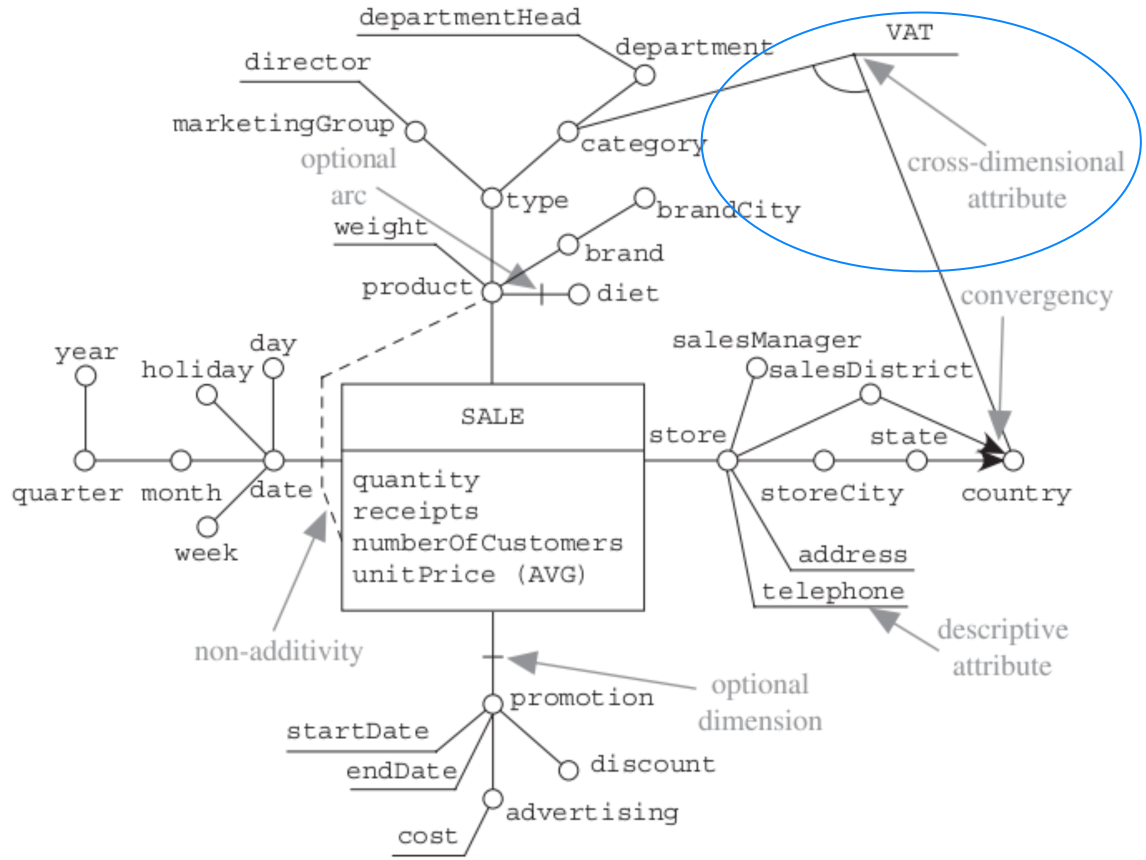
- A *descriptive attribute* is functionally determined by a dimensional attribute of a hierarchy and specifies a property of this dimensional attribute. Descriptive attributes often are tied to dimensional attributes by one-to-one associations and do not actually add useful levels of aggregation. They can also be directly connected to a fact if they describe primary events, but it is neither possible nor interesting to use it to identify single events or to make calculations



Note: *In an ER representation of such model, you can model descriptive attributes as attributes of the entities corresponding to dimensional attributes or the relationship modeling the fact*

DFM: cross dimensional attribute

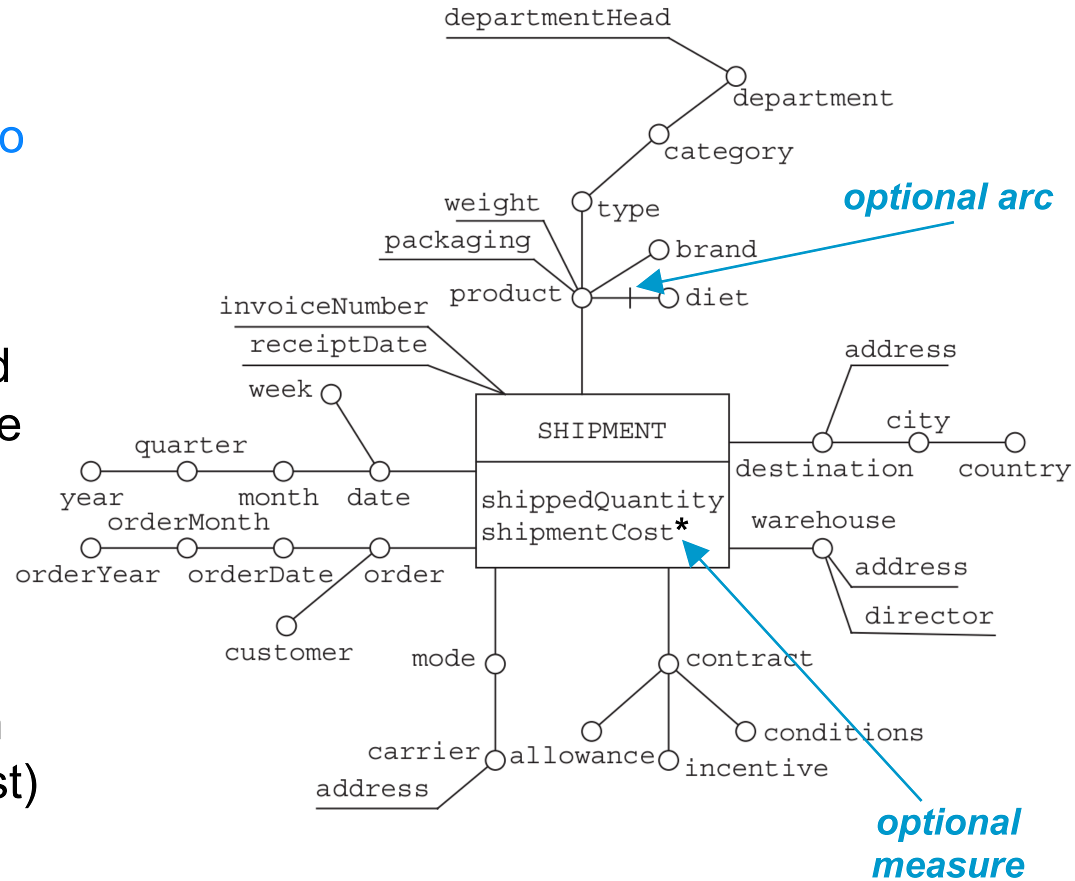
A cross-dimensional attribute is a *descriptive* attribute whose value is defined by the combination of two or more dimensional attributes. For example, a product Value Added Tax (VAT) depends both on the product category and on the country where the product is sold.



Note: *In an ER representation of such model, VAT is an attribute of a relationship between CATEGORY and COUNTRY, to which both such entities participate with cardinality (1,n)*

DFM: optional attributes

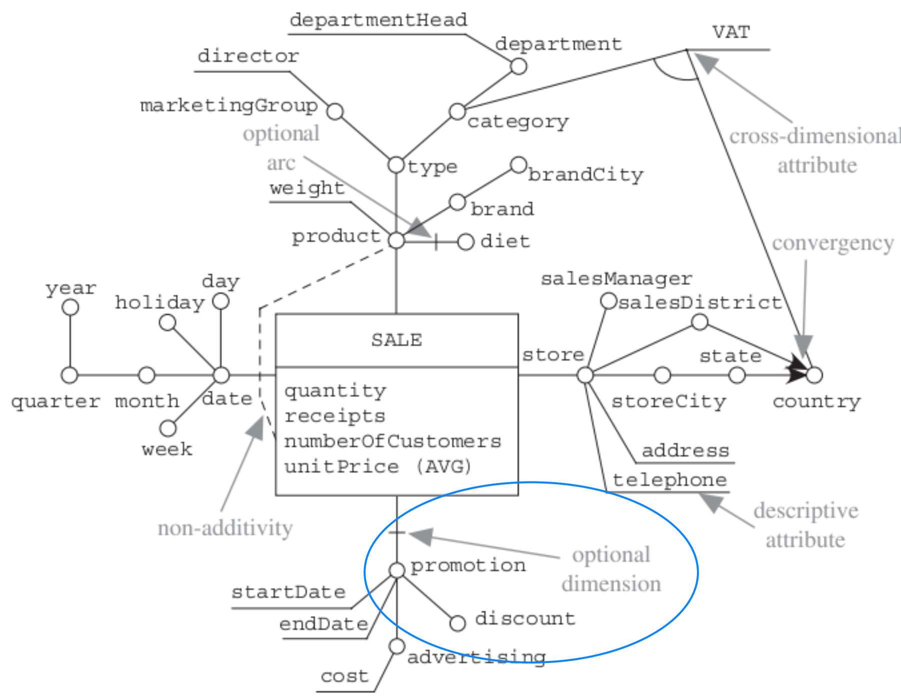
- Some arcs can be marked as *optional.*
- If the optionality is associated to a dimensional attribute *A* (as *diet* in the figure), this means that *A* and all possible descendents may be undefined for one or more instances of the fact to which the arc is (indirectly) associated
- If the optionality concerns a measure, then the name of the measure attribute appears with the symbol * (see shipmentCost)



Note: *In an ER representation of such model, the minimum cardinality of the association from PRODUCT to DIET is 0 rather than 1*

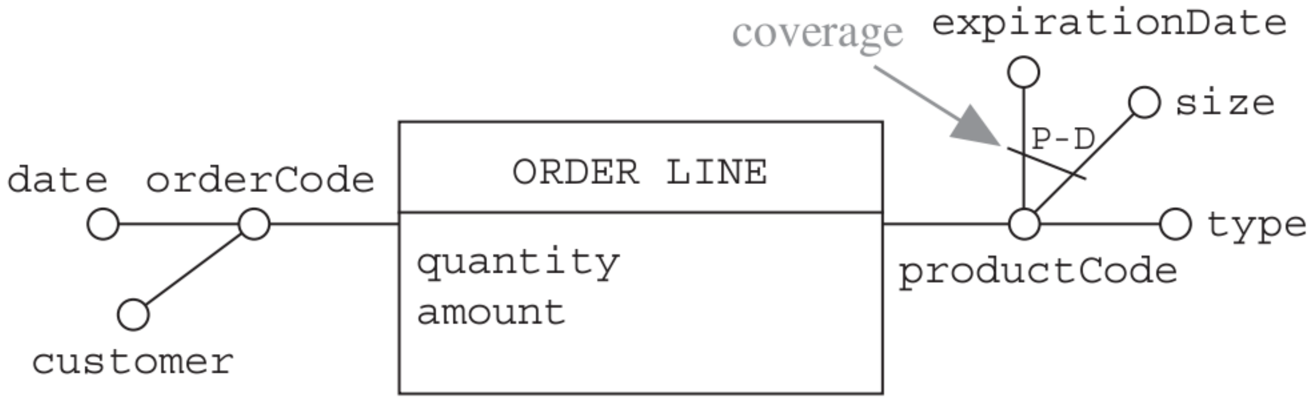
DFM: optional dimensions

- If the optionality is associated to a dimension *d*, this means that some primary events exist that are identified only by the other dimensions



***Note: :** In an ER representation of such model, the SALE has to be reified and identified by its participation to the relationships towards DATE, PRODUCT, and STORE. Also, it has a (0,n) participation to a relationship towards PROMOTION*

DFM: coverage



A coverage can be specified on two or more arcs that exit from the same dimensional attribute *A*. It can be:

- total (T): every value of *A* is associated to a value for at least one of the child attributes of *A*
- partial (P): there are values for A for which all the children are undefined

and

- disjoint (D): every value of *A* is associated to a value for at most one of the child attributes of A
- overlapping (O): values of A exist linking to values of two or more children

DFM: coverage

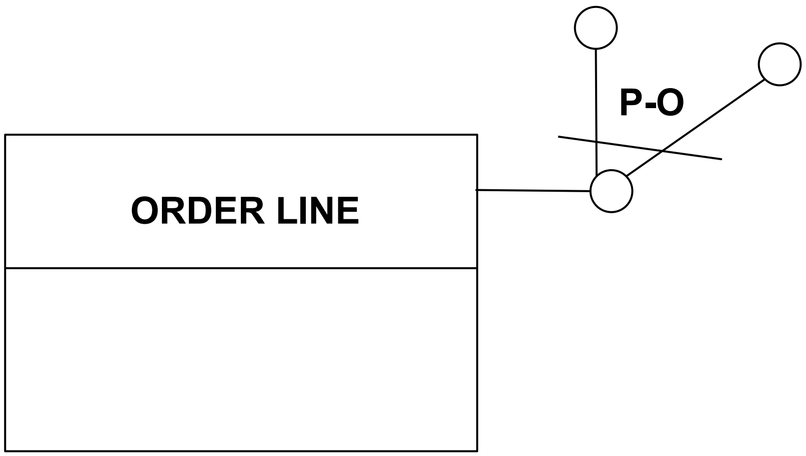
T-D -> every value of *A* is associated to a value for exactly one of the child attributes of *A*

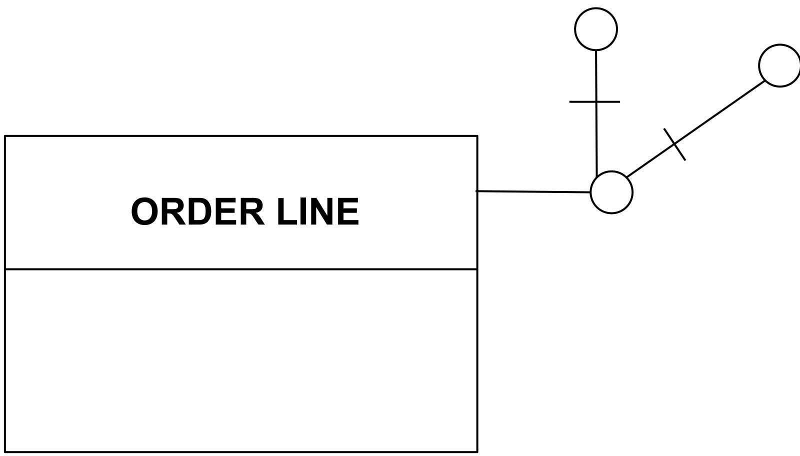
P-D -> every value of A is associated to a value for at most one of the child attributes of A

T-O -> every value of A is associated to a value for at least one of the child attributes of A (but even more)

P-O -> no constraints, but optionality

A P-O coverage is in fact equivalent to two optional dimensional attributes

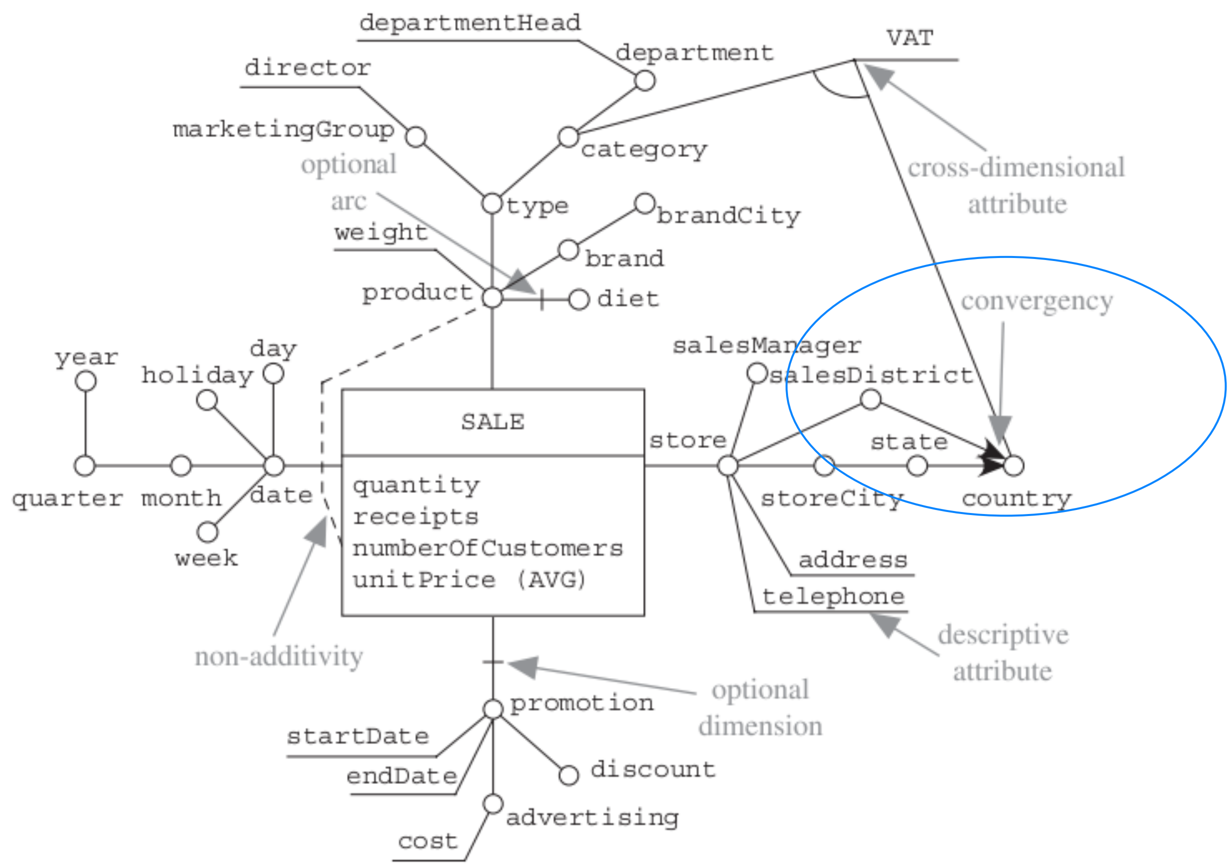




Note: *In an ER representation, coverage is expressed through external constraints regulating the participation of the entity corresponding to the attribute A to the relationships towards the entities corresponding to the attributes of the coverage*

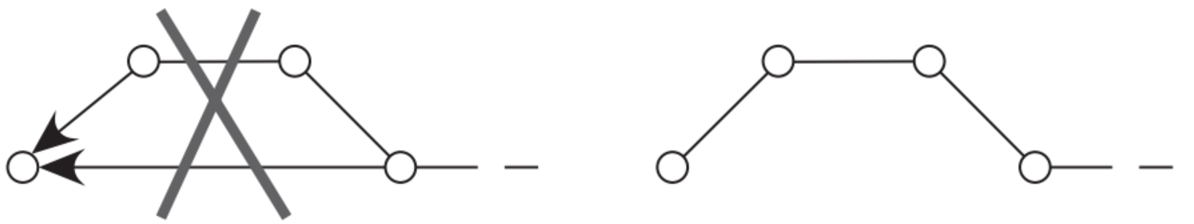
DFM: convergence

Convergence is an integrity constraint. For example, the country of the state of the city of a store, has to be the same of the salesDistrict of the store.



Note: : *In an ER representation of such model, convergence has to be specified through an external constraint*

DFM: convergence

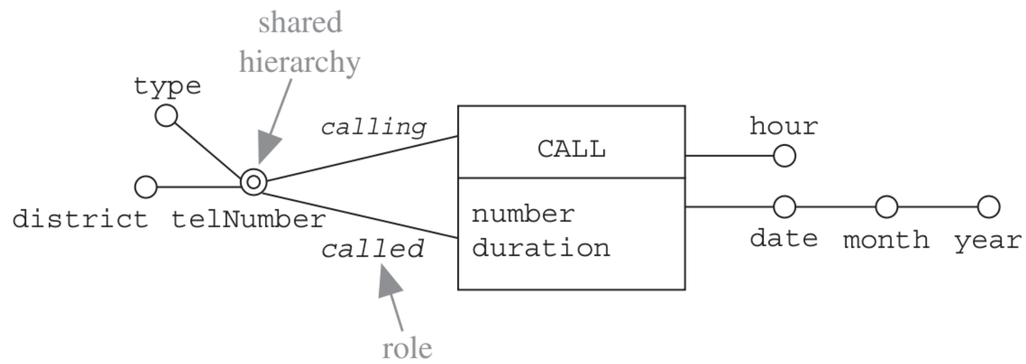


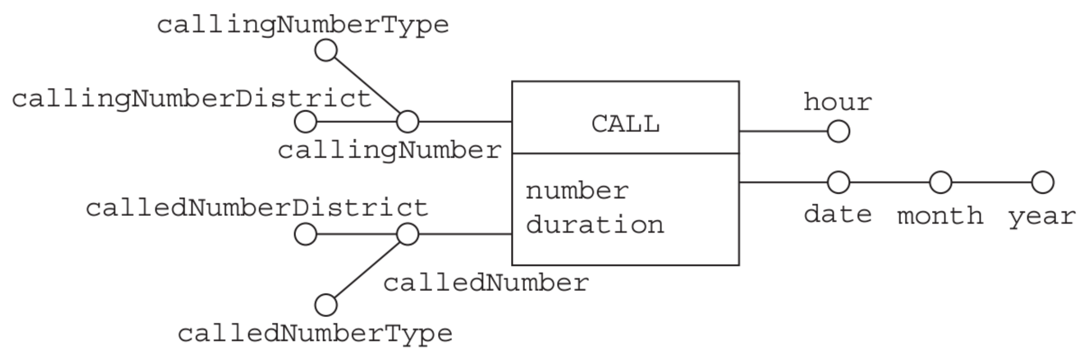
a hierarchy like this, in which one of the alternate paths does not include intermediate attributes, does not have a reason to exist. In the right-hand side we give the correct representation of this redundant convergence.

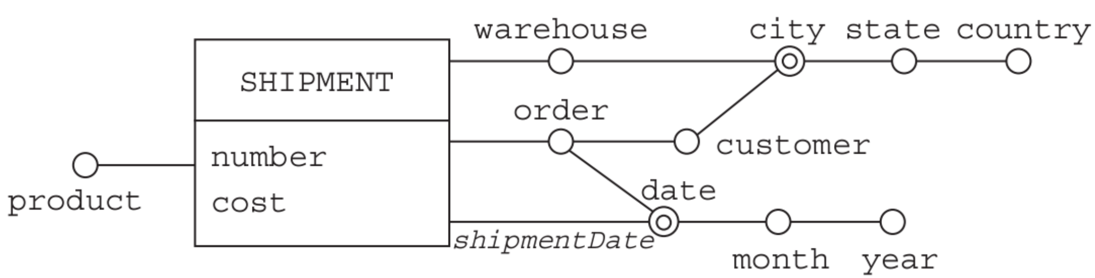
The convergence is completely obvious in virtue of the transitive property holding for functional dependencies.

DFM: shared hierarchy

Shared hierarchy:
Avoids to replicate two or more times *entire portions* of hierarchies in a fact schema. If the sharing is on the overall hierarchy, a <u>role</u> is specified through an arc label

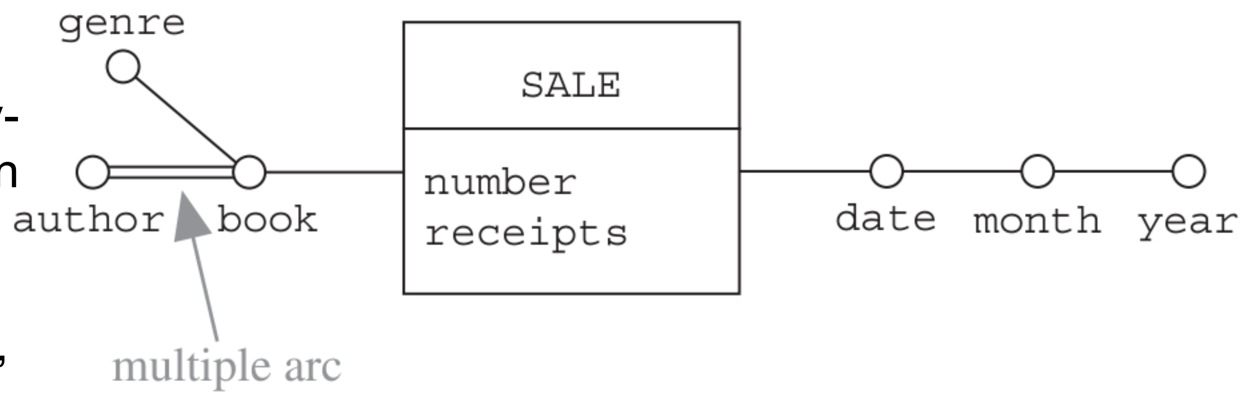




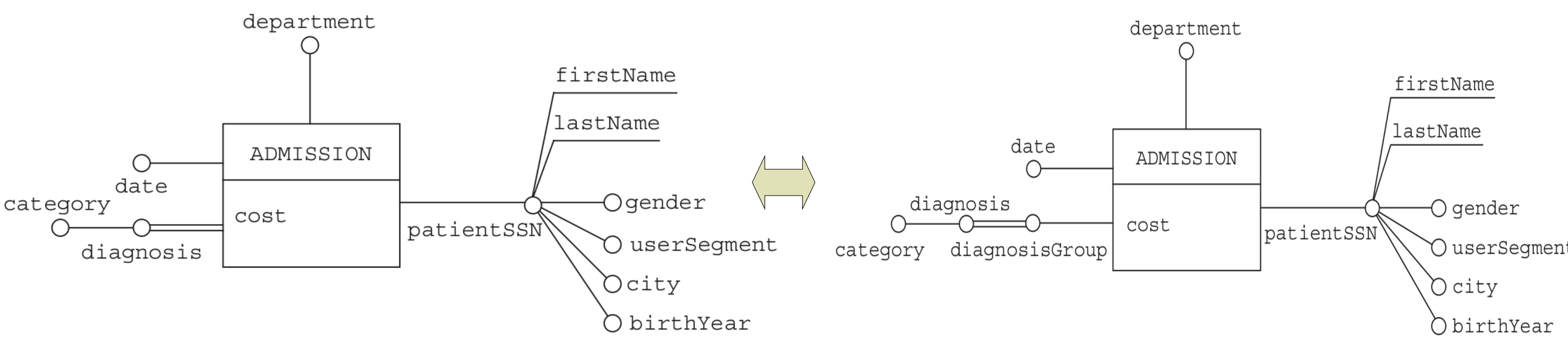


DFM: multiple arcs

Multiple arc:
Allows for modeling many-to-many relations between dimensional attributes (instead of many-to-one relations). In the example, a book can have more than one author.



Multiple arc entering a dimension:
A fact is identified by a tuple containing a value for each dimension. In the example, the value for diagnosis is, in fact, a "group of diagnosis"



Note: *In an ER representation of such model, the relationship corresponding to a multiple arc is a many-to-many relationship.*

Additivity

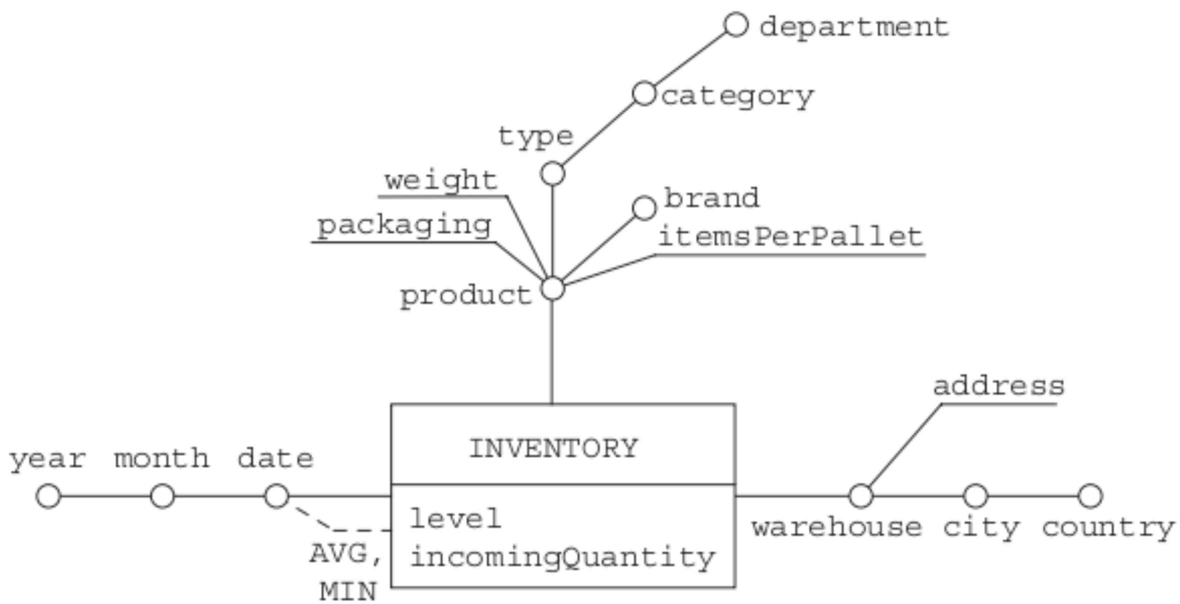
- Aggregation requires the definition of a suitable operator to compose the measure values that mark primary events into values to be assigned to secondary events.
- From this viewpoint, measures can be classified into three categories:
  - ✓ Flow Measures: refer to a timeframe, at the end of which they are evaluated cumulatively for such timeframe (the number of products sold in a day, monthly receipts, and yearly number of births).
  - ✓ Level Measures: are evaluated at particular times (the number of products in inventory, the number of inhabitants in a city).
  - ✓ Unit Measures: are evaluated at particular times but are expressed in relative terms (product unit price, discount percentage, currency exchange).

	Temporal Hierarchies	Nontemporal Hierarchies
Flow Measures	SUM, AVG, MIN, MAX	SUM, AVG, MIN, MAX
Level Measures	AVG, MIN, MAX	SUM, AVG, MIN, MAX
Unit Measures	AVG, MIN, MAX	AVG, MIN, MAX

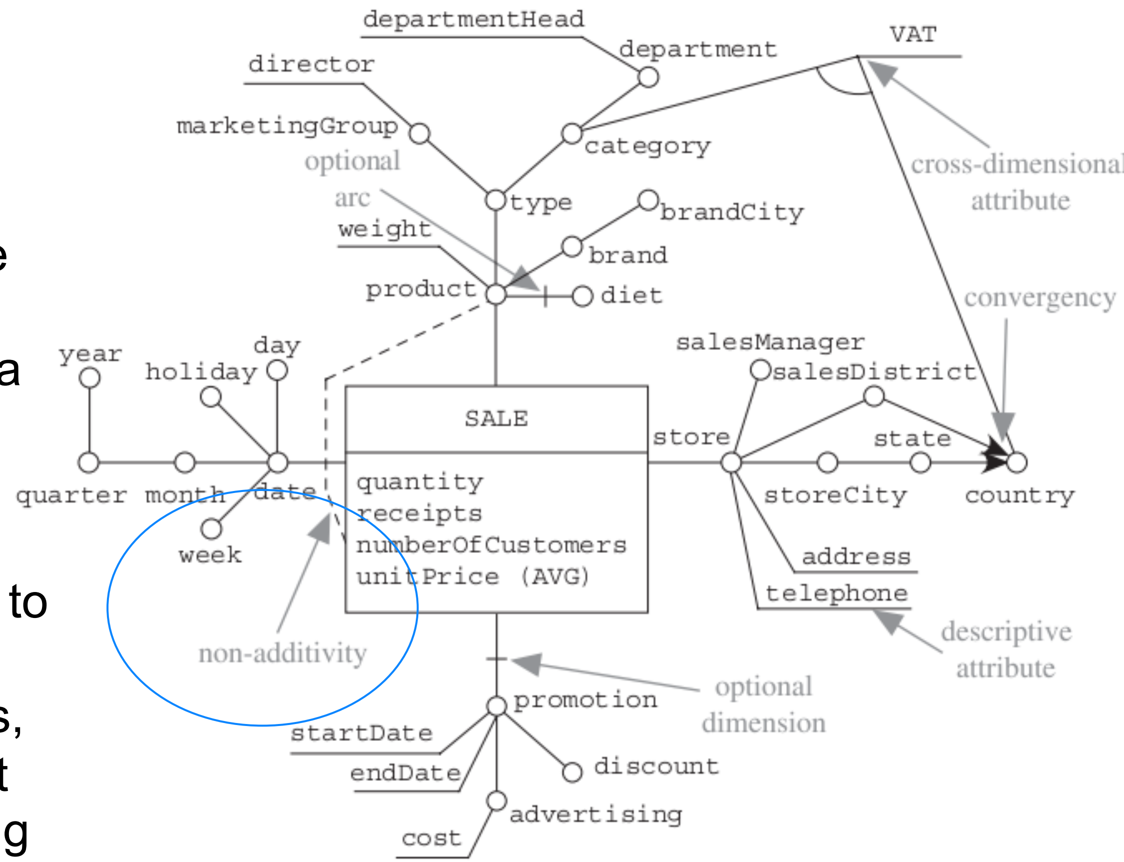
Valid Aggregation Operators for Three Types of Measures

Additivity

- A measure is called additive along a dimension when you can use the SUM operator to aggregate its values along the dimension hierarchy. If this is not the case, it is called non-additive.
- A measure is connected to the dimensions along which it is non-additive via a dashed line labeled with the usable aggregation operators.
- Example: level is non-additive along date dimension, but it is additive along the other dimensions.



Additivity

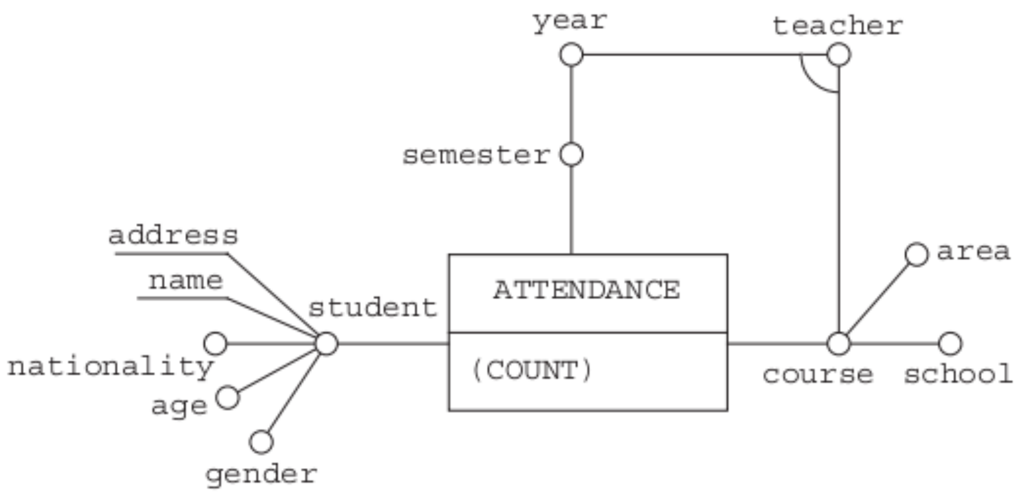


In the sales fact schema, the numberOfCustomers measure (i.e., estimated through the number of receipts issued for a product in a certain date in a certain store) is non-additive along the product dimension: Indeed, a single receipt refers to several products (possibly of different types). In other words, a customer might have bought various products, and summing numberOfCustomers along the product dimension would mean to count a customer several time. In this case this measure is also considered *non-aggregable* at all (missing labels)

If a measure shows the same type of additivity on all of the dimensions, you can mark the aggregation operator on it: unitPrice is a non-addivite unit measure.

Empty fact schemata

- A fact schema is said to be empty if it does not have any measures
  - ✓ If this is the case, primary events only record the occurrence of events in an application domain

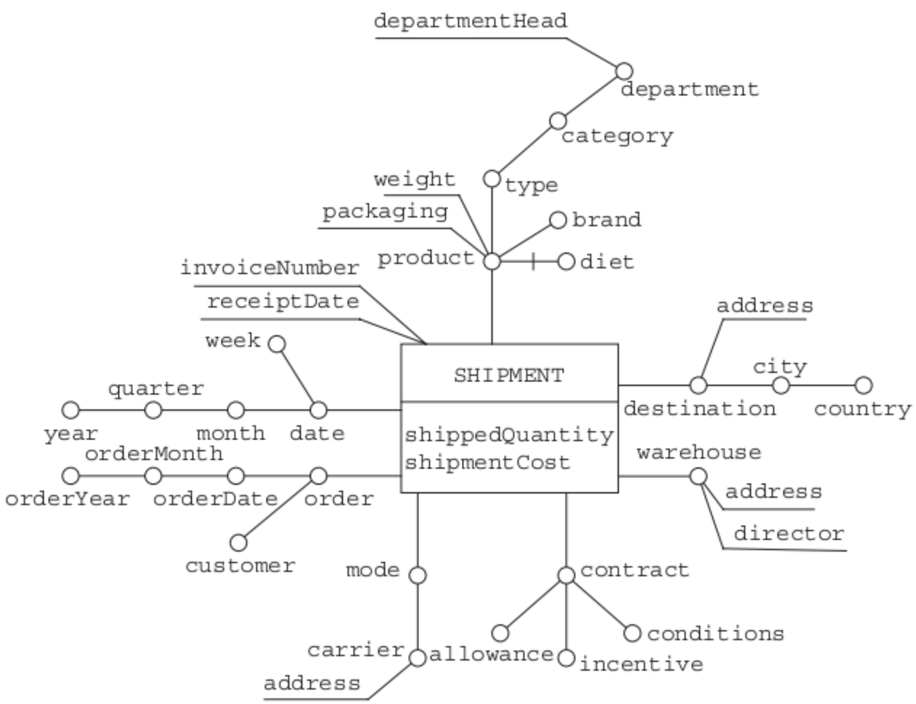


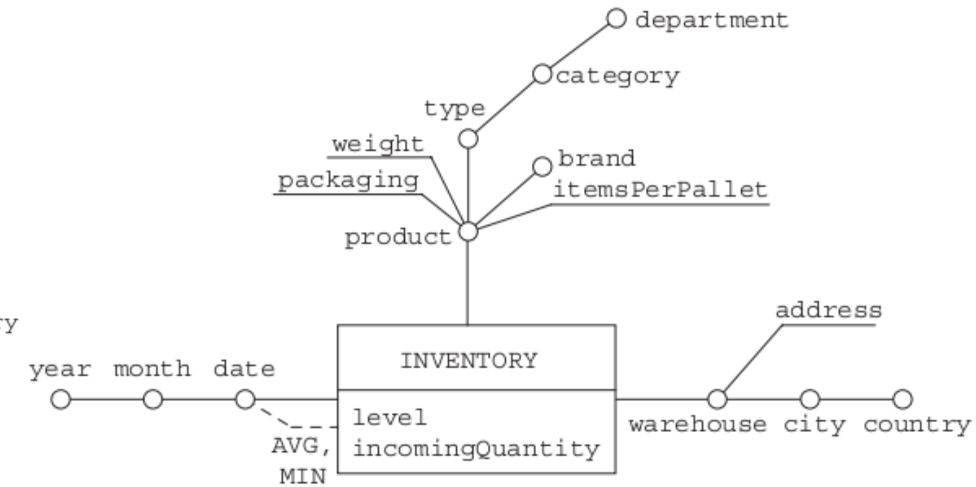
(COUNT) indicates that the information represented by a secondary event is the number of primary events corresponding to it

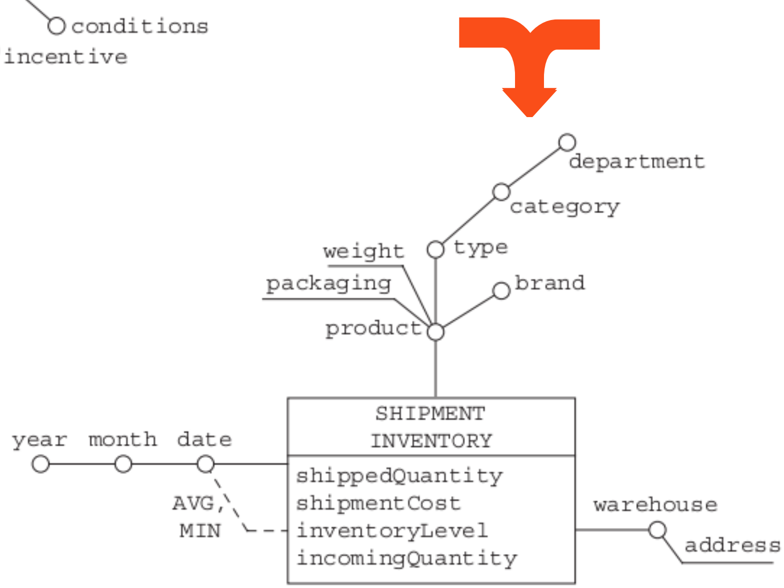
Overlapping fact schemata

- Separate fact schemata represent different facts in the DFM. However, part of the queries may require a comparison of the measures from two or more facts correlating to each other. In OLAP terminology, these are called drill-across queries
- To perform such queries we need to define which are the measures and which are the aggregation patterns that can be used when 2 or more fact schemata are queried. In an overlapping schema:
  - ✓ Measures are the union of the measures of the various schema
  - ✓ Hierarchies include only the attributes that occur in all hierarchies
  - ✓ The domain of each attribute is the intersection of the domains of the corresponding attributes in the original schema.

Overlapping fact schemata







Integrity constraints in DFM

- One can always add <u>integrity constraints</u> as separate sentences added to the graphical representation

- Popular types of integrity contraints are:
  - ✓ Conditions on possible missing values of dimensional attributes
  - ✓ Functional dependencies between attributes
  - ✓ More restricted conditions on the indentification of facts. For example one can assert that a proper subset of the dimensions acts as an identifier for a fact type

Logical Models for Data Marts

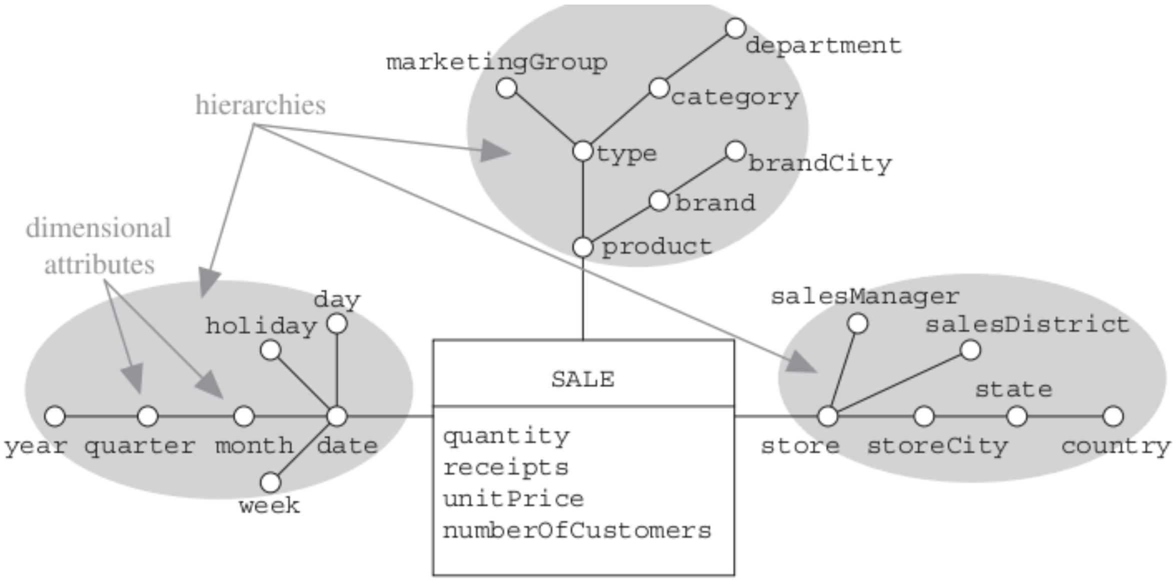
- Conceptual modeling does not depend on the logical model the designer has selected in the architecture design phase, but the topics related to logical modeling clearly do.
- As already said, multidimensional structure can be represented using two distinct logical models:
  - ✓ MOLAP (*Multidimensional On-Line Analytical Processing*) stores data using structures that are intrinsically multidimensional (e.g., multidimensional vectors).
  - ✓ ROLAP (*Relational On-Line Analytical Processing*) makes use of the well-known relational model to represent multidimensional data.

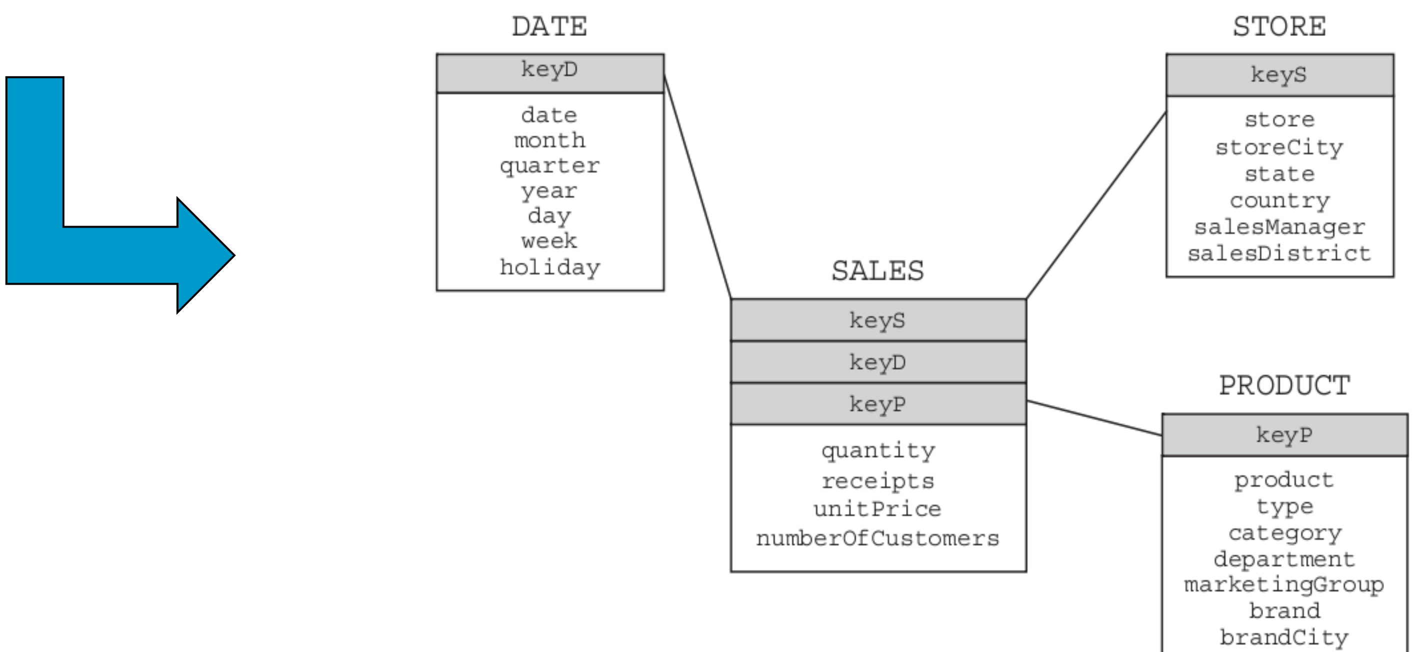
ROLAP: The star schema

In what follows we concentrate on ROLAP systems

- Multidimensional modeling in relational systems is based on the so-called star schema and star schema variants.
- A star schema is constituted by:
  - ✓ A set of relations $DT_1, \ldots, DT_n$ called dimension tables. Each of them corresponds to a dimension. Every DT_i features a primary (typically surrogate) key k_i and a set of attributes describing its dimension at different aggregation levels.
  - ✓ A fact table *FT* referencing all the dimension tables. An FT primary key is the composition of the set of foreign keys $k_1, \ldots, k_n$ referencing dimension tables (or a subset, in case a specific integrity constraint asserts this condition). An *FT* also contains an attribute for every measure.

Star schema: structure





Star schema: instances

SALES

keyS	keyD	keyP	quantity	receipts	…..
1	1	1	170	85	…..
2	1	2	320	160	…..
3	2	3	412	412	…..
…..	…..	…..	…..	…..	…..

Fact Table

STORE

keyS	store	storeCity	state	…..
1	COOP1	Columbus	Ohio	…..
2	COOP2	Austin	Texas	…..
3	COOP3	Austin	Texas	…..
…..	…..	…..	…..	…..

Dimension Table

PRODUCT

keyP	product	type	category	brand	…..
1	Slurp Milk	Dairy product	Food	Slurp	…..
2	Fresh Milk	Dairy product	Food	Fresh	…..
3	Slurp Yogurt	Dairy product	Food	Slurp	…..
…..	…..	…..	…..	…..	…..

Dimension Table

DATE

keyD	date	month	year	…..
1	9/2/2008	9/2008	2008	…..
2	10/3/2008	10/2008	2008	…..
3	10/5/2008	10/2008	2008	…..
…..	…..	…..	…..	…..

Dimension Table

Star schema: comments

- Dimension tables are completely denormalized (cf., e.g., the functional dependencies *product* $\rightarrow$ *type; type* $\rightarrow$ *category*)
  - 👍 A join is sufficient to obtain all data connected to a certain dimension
  - 👎 High redundancy in the data due to denormalization (even though redundancy is in the dimensional tables, whose size is often negligible)

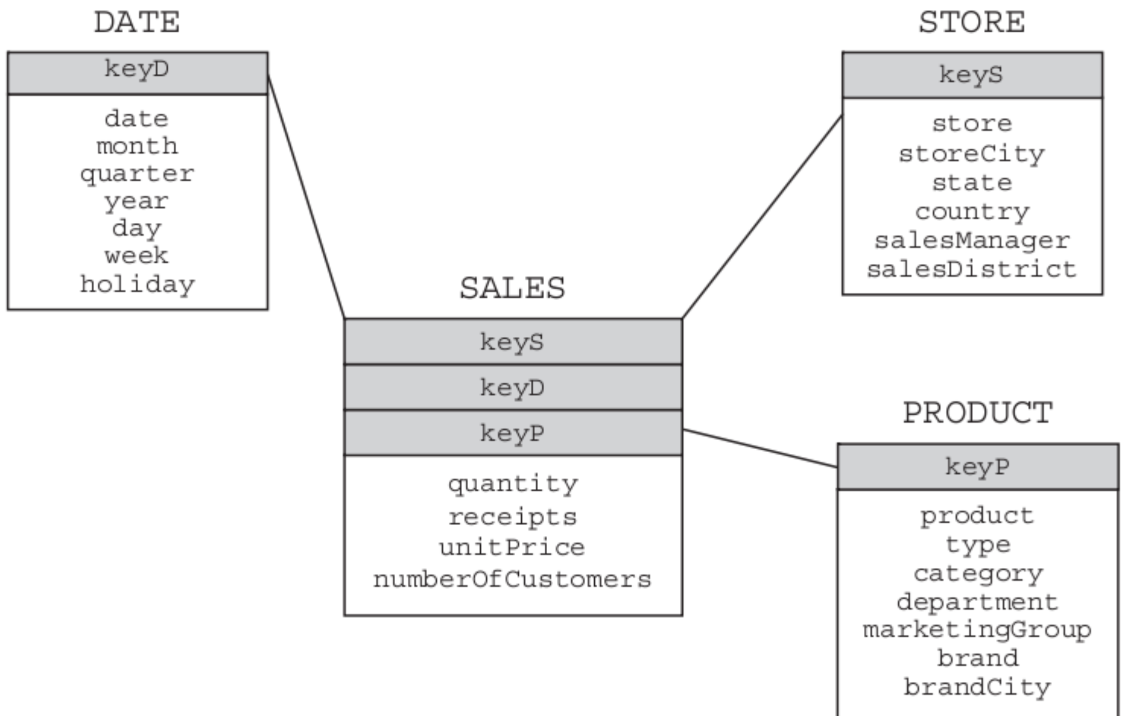
- Fact Table contains tuples at the chosen level of aggregation
  - 👎 For very fine-grained facts, fact table can be very large and this can negatively affect access time to data

- No sparsity problems: we store only tuples corresponding to points in the multidmensional space for which an event occurred

Integrity constraints in the Star schema

- As in the case of DFM, one can always add <u>integrity constraints</u> as separate sentences added to the graphical representation
- By default, all attributes are «not null». An asterisc is used to assert that null values may appear in an attribute.
- As in DFM, popular types of integrity contraints are:
  - ✓ Functional dependencies between attributes
  - ✓ More restricted conditions on the indentification of facts. For example one can assert that a proper subset of the dimensions acts as an identifier for a fact type (this is denoted by underlying the identifying attributes)

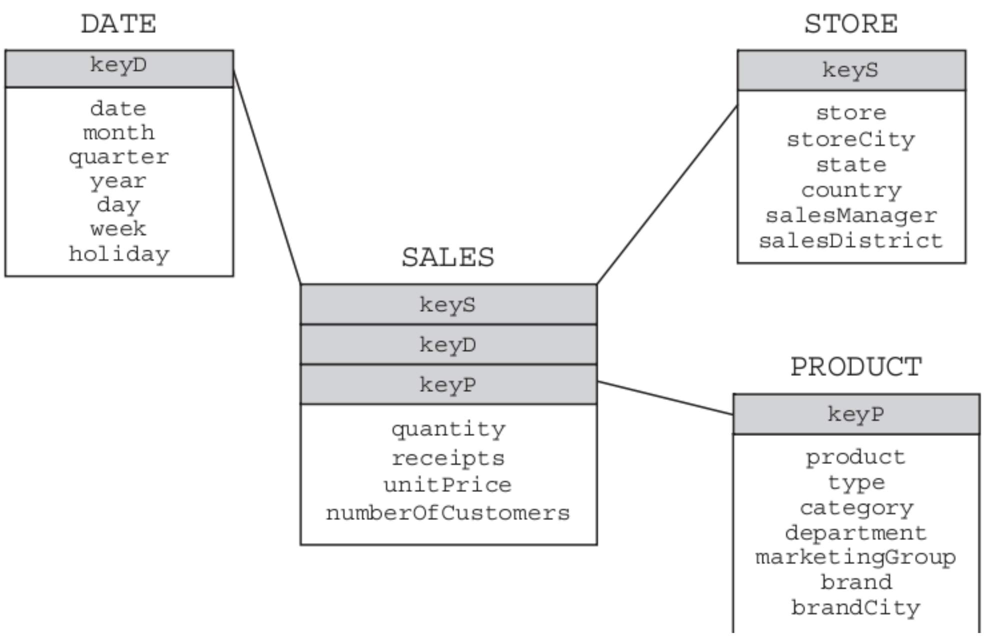
OLAP queries over star schemata




```
SELECT *
FROM SALES AS FT, PRODUCT AS DT1, STORE AS DT2, DATA AS DT3
WHERE FT.keyP = DT1.keyP AND FT.keyS = DT2.keyS AND
      FT.keyD = DT3.keyD
```

A multidimensional view of data is obtained when you join the fact table to its dimension tables

OLAP queries over star schemata



SALES (store.storeCity, date.week, product.type; product.categoy= ‘Food’).quantity

```
SELECT storeCity, week, type, sum(quantity)
FROM SALES AS FT, PRODUCT AS DT1, STORE AS DT2, DATA AS DT3
WHERE FT.keyP = DT1.keyP AND FT.keyS = DT2.keyS AND
      FT.keyD = DT3.keyD AND DT1.category='Food'
GROUP BY storeCity, week, type
```

Snowflake schema

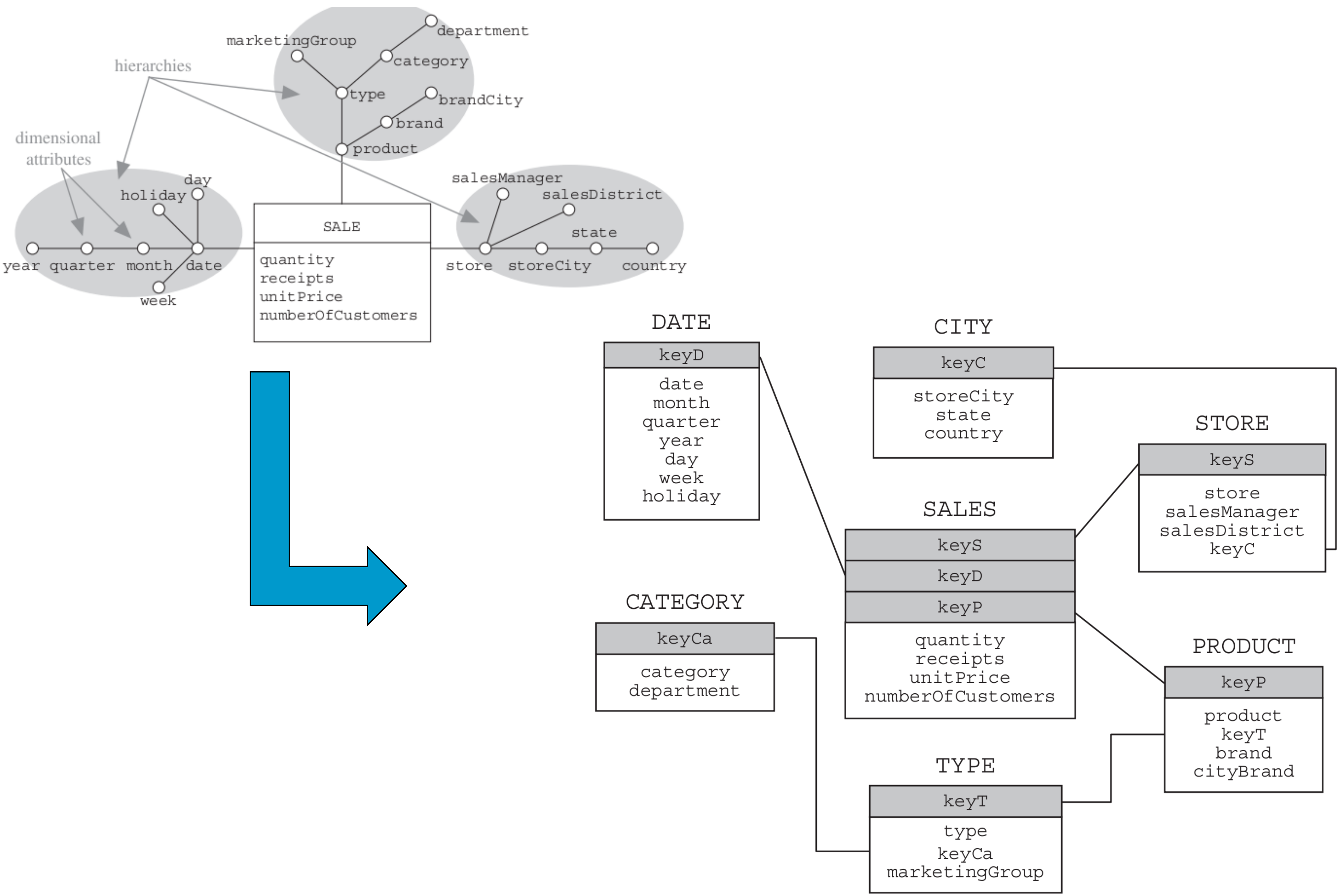
- Dimension tables are not in third normal form. For example, the STORE dimension table includes the transitive functional dependencies store→storeCity, storeCity→state.

- *Snowflake schema* reduces the denormalization of the dimension tables DT_i in the star schemata by eliminating some of (or all) the transitive dependencies that characterize them.

- A dimension table $DT_{i,j}$ in a snowflake schema is characterized by:
  - ✓ one primary key (typically surrogate) $d_{i,j}$
  - ✓ a subset of DT_i attributes functionally depending on $d_{i,j}$
  - ✓ some foreign keys, each referencing another $DT_{i,k}$ table, necessary for any DT_i information to be properly reconstructed

- We call *primary* the dimension tables whose keys are referenced in the fact table, *secondary* the remaining ones.

Snowflake schema: structure



Snowflake schema: instances

keyT	type	keyCa
1	A	1
2	B	2

keyP	product	brand	keyT
1	P1	F1	1
2	P2	F1	1
3	P3	F2	2
4	P4	F2	2

keyCa	category	department
1	D	Z
2	F	T

keyD	week	month
1	Jan1	Jan.
2	Jan2	Jan.
3	Feb1	Feb.
4	Feb2	Feb.

keyS	keyD	keyP	quantity	recepits
1	1	1	100	100
1	2	1	150	150
3	3	4	350	350
4	4	4	200	200

keyS	store	keyC	salesManager
1	N1	1	R1
2	N2	1	R1
3	N3	2	R2
4	N4	2	R2

keyC	storeCity	country
1	Austin	I
2	Miami	I

For ease of exposition, not all the dimensional attributes and measures are considered in this instantiation of the snowflake schema

Snowflake schema: comments

- The disk space required for data storage decreases by virtue of normalization.
- Snowflake schemata, however, need new surrogate keys to be added in order to express the relationships between primary and secondary dimension tables.
- Processing the queries that involve only fact table attributes and primary dimension table attributes is streamlined because their joins involve smaller tables
- The time needed for queries of secondary dimension table attributes is longer because of a larger number of necessary joins.

Snowflake schema normalization

- When you decompose a dimension table to design a snowflake schema, you should check for an appropriate set of attributes to be inserted in the new relation
- To break down a schema effectively, you need, for all those attributes that directly or transitively depend on the snowflaking attribute (that is, on the natural key of the new relation), to be part of the new relation.

STORE

keyS
store
storeCity
state
country
salesManager

keyS $\rightarrow$ store
store $\rightarrow$ storeCity
storeCity $\rightarrow$ state
state $\rightarrow$ country
store $\rightarrow$ salesManager

STORE

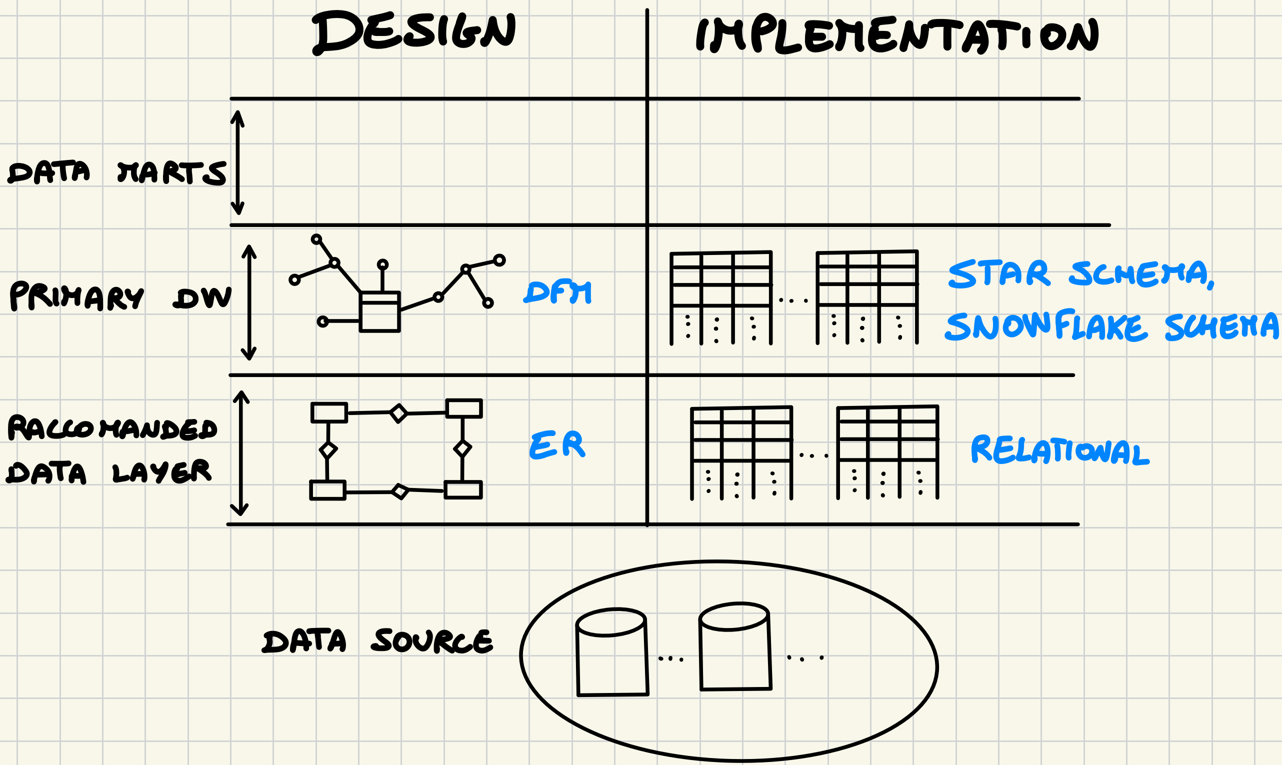
keyS
store
keyC
salesManager

keyS $\rightarrow$ store
store $\rightarrow$ keyC
store $\rightarrow$ salesManager

CITY

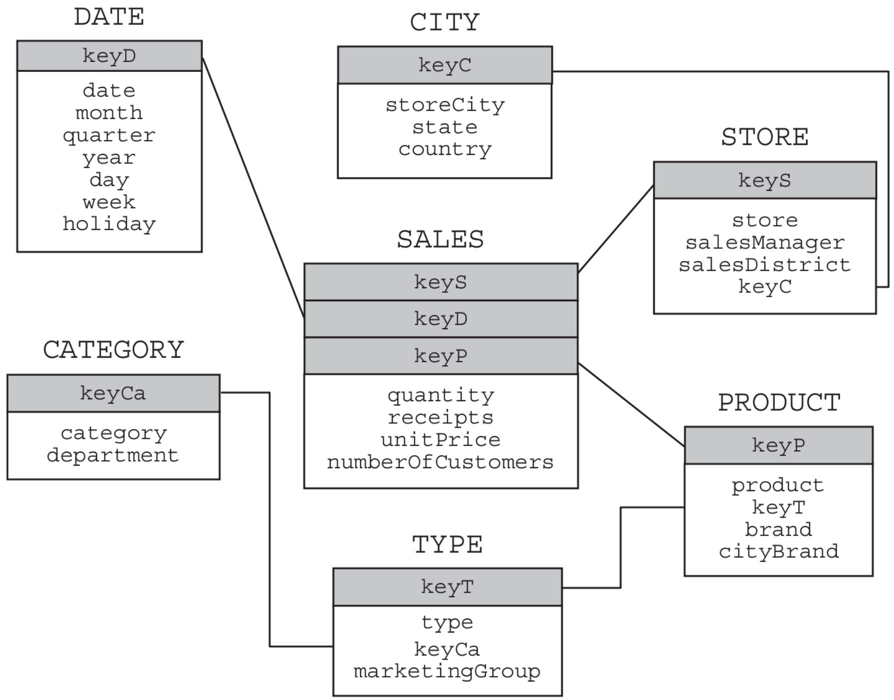
keyC
storeCity
state
country

keyC $\rightarrow$ storeCity
storeCity $\rightarrow$ state
state $\rightarrow$ country



DESIGN
IMPLEMENTATION
DATA MARTS
PRIMARY DW
DFM
STAR SCHEMA,
SNOWFLAKE SCHEMA
RACCOMANDED
DATA LAYER
ER
RELATIONAL
DATA SOURCE

OLAP queries over snowflake schemata



SALES (store.storeCity, date.week, product.type; product.categoy= ‘Food’).quantity

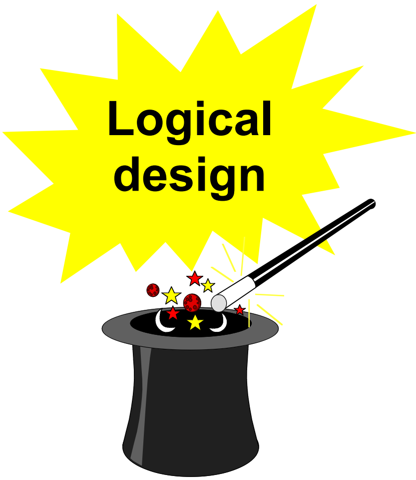
```
SELECT storeCity, week, type, sum(quantity)
FROM SALES AS FT, PRODUCT AS DT1, STORE AS DT2, DATE AS DT3,
     TYPE AS DT4, CATEGORY AS DT5, CITY AS DT6
WHERE FT.keyP = DT1.keyP AND FT.keyS = DT2.keyS AND
      FT.keyD = DT3.keyD AND DT6.keyC=DT2.keyC AND
      DT4.keyT=DT1.keyT AND DT5.keyCa=DT4.keyCa AND
      DT5.category=‘Food’
GROUP BY storeCity, week, type;
```

Logical Design

- The logical design phase includes a set of steps that, starting from the conceptual schema, make it possible to define the logical schema of a data mart.

INPUT

Conceptual schema
Workload
Data volume
System constraints



OUTPUT

Logical schema

- Requires radically different techniques from those used for operational databases:
  - ✓ Data redundancy
  - ✓ Denormalizations of relational tables

Logical design

- Main steps in DW logical design are:

  1. Choosing the logical schema to adopt
     (e.g., star/snowflake schema)
  2. Translating fact schemata into logical schemata
  3. Materializing views
  4. Realizing some forms of optimization

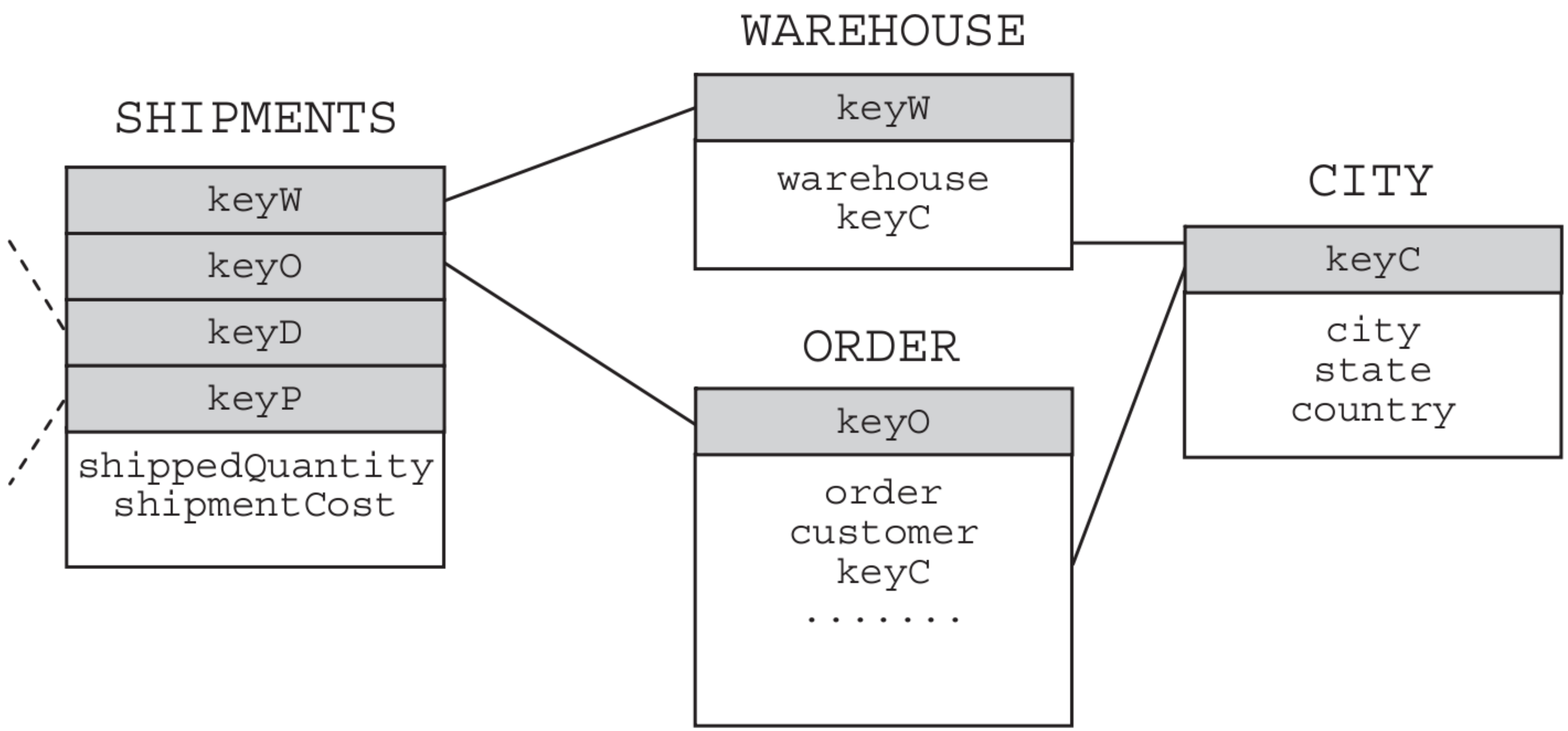
Star vs Snowflake

- There are discordant opinions on snowflaking:
  - ✓ Some authors consider it an embellishment that is in conflict with the founding philosophy of data warehousing

- Snowflaking can be beneficial when:
  - ✓ the ratio between secondary dimension table cardinality and the primary dimension table one is very high. For example, if there were many products of each type, but few product types, normalization would save a remarkable amount of space, and the extra cost of a join, which is necessary to retrieve information on product types, would be small

Star vs Snowflake

- Snowflaking can be beneficial when
  - ✓ part of a hierarchy is common to more than one dimension



The secondary dimension table can be re-used for various hierarchies

From fact schemata to star schemata

- The basic rule for the translation of a fact schema into a star schema is the following

Create a fact table containing the key attributes, all the measures and descriptive attributes directly connected with the fact, and for each hierarchy, create a dimension table that contains all attributes.

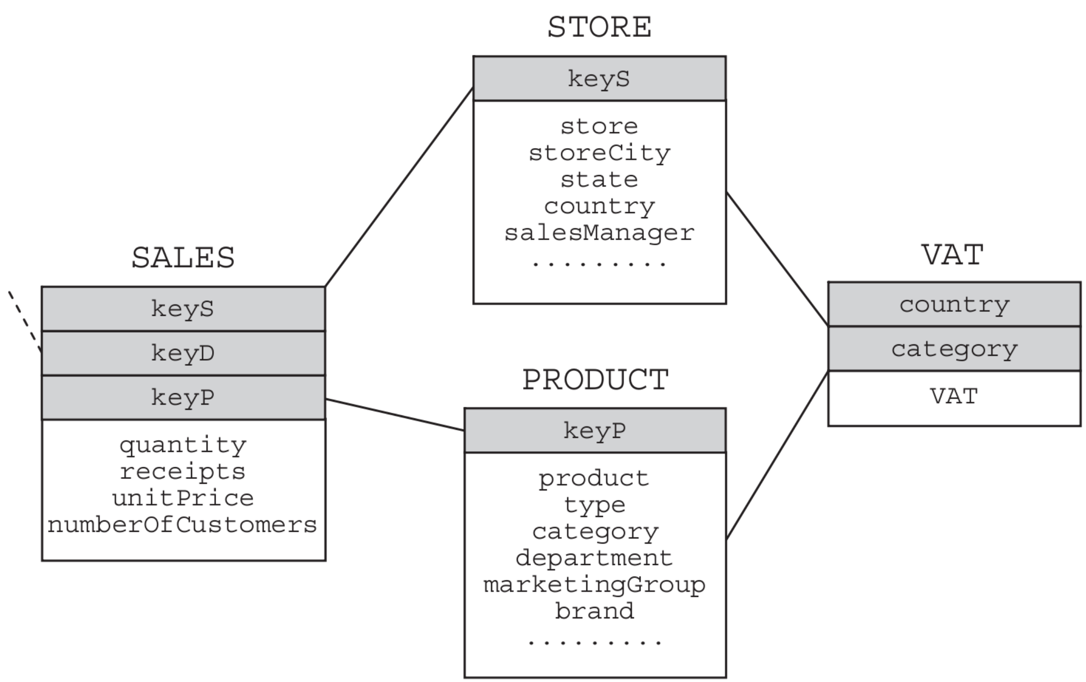
- In addition to this simple rule, the correct translation of a fact schema requires an in-depth discussion of the advanced constructs of the DFM.

Descriptive attributes

- Contain information that will not be used to perform aggregations but that is considered useful.
  - ✓ When connected to a dimensional attribute, it has to be included in the dimension table that contains the attribute.
  - ✓ If connected directly to the fact, it has to be included in the fact table.
- It only makes sense if it is compatible with the level of granularity of the event described in the fact table, so if connected directly to the fact table it will be omitted in the aggregated views. Also, if it is connected to a dimensional attribute, it can be included only in the dimensional tables that contain the attribute it refers to.

Cross-dimensional attributes

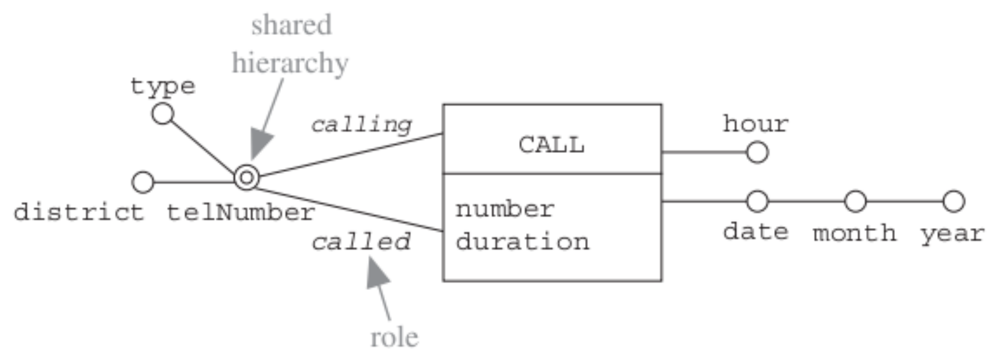
- From the conceptual point of view, a cross-dimensional attribute b defines a many-to-many relationship between two or more dimensional attributes a1,...,am.
- Its translation into a logical schema requires you to enter a new table that includes b and has a1,...,am as key attribute.

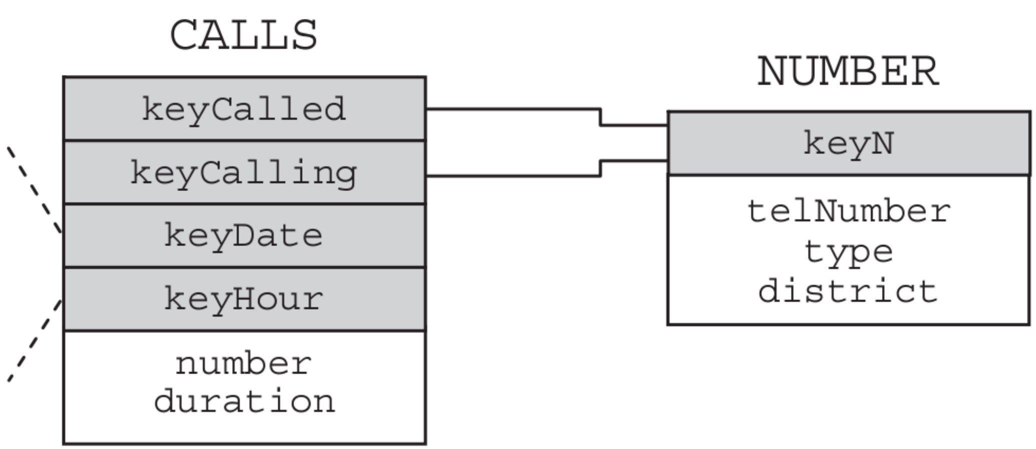


The choice between surrogate or non-surrogate keys for the new table should be made according to the space occupation that they cause

Shared Hierarchies

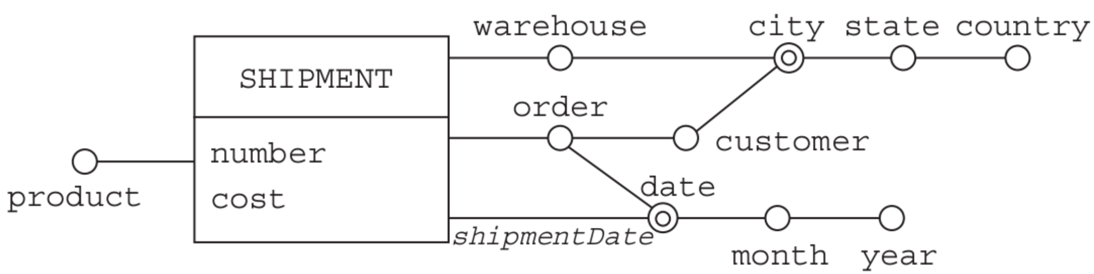
- If a hierarchy occurs several times in the same fact (or in different facts) it is not convenient to introduce redundant copies of the related dimension table.
- If two (or more) hierarchies contain exactly the same attributes it is sufficient to simply import the key twice (or more) in the fact table connected to them

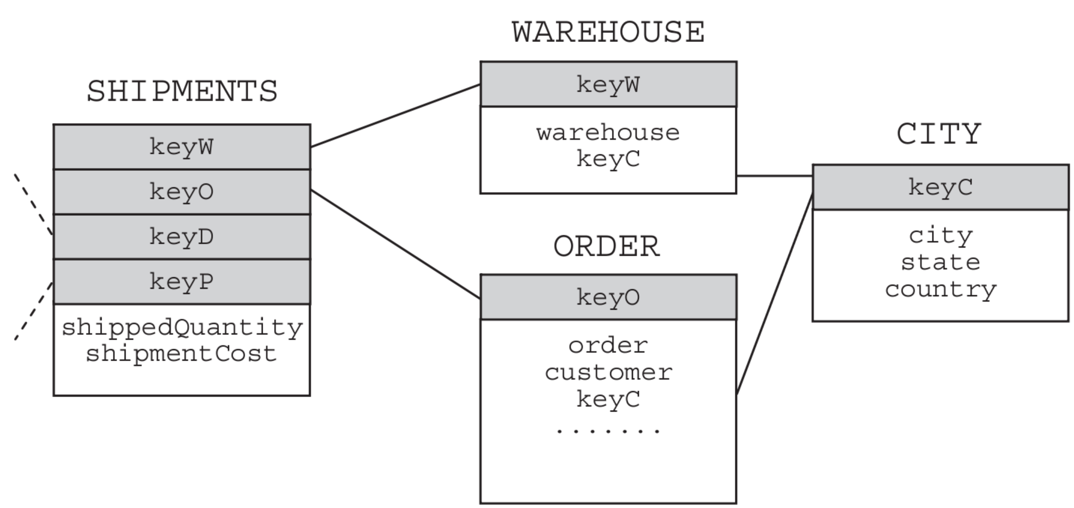




Shared hierarchies

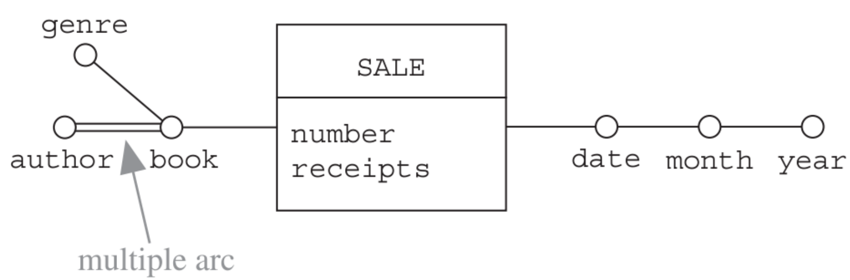
- If the two hierarchies share only some of the attributes, you need to decide if:
  I. Introducing additional redundancy in the diagram by duplicating hierarchies and replicating the common fields.
  II. Snowflaking the schema on the first shared attribute, and thus introducing a third table common to both the dimension table.

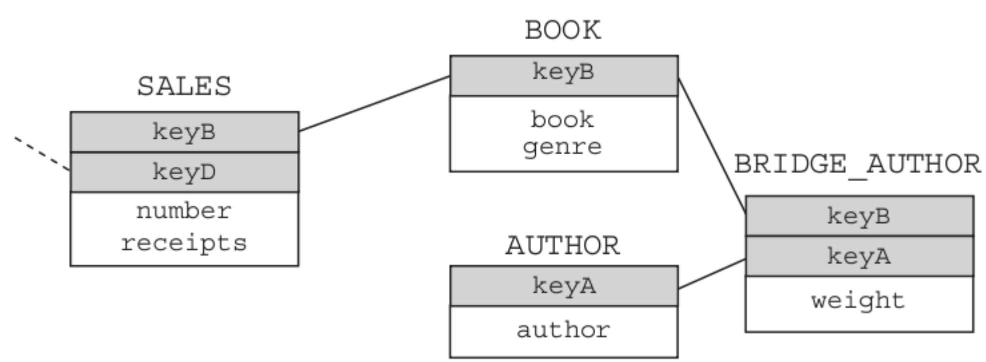




Multiple arcs

- Although it is not very common, some hierarchies can also model many-to-many relations.
- The most obvious design solution is to insert an additional table (bridge table) that models the multiple arc:
  - ✓ The key of the bridge table is the combination of the attributes connected by the multiple arc.
  - ✓ An (optional) *weight* attribute makes it also possible to consider to assign (in terms of a percentage) different relevance to the participating tuples





Multiple arcs

BOOK

keyB	book	genre
1	Facts & Crimes	Technical
2	Sounds Logical	Technical
3	The Right Measure	Current affairs
4	Facts: How and Why	Current affairs
5	The 4th Dimension	Science fiction

AUTHOR

keyA	author
1	Matteo Golfarelli
2	Stefano Rizzi

BRIDGE_AUTHOR

keyB	keyA	weight
1	1	0.5
1	2	0.5
2	1	1.0
3	2	1.0
4	1	0.5
4	2	0.5
5	1	1.0

SALES

keyB	keyD	number	receipts
1	1	3	150
2	1	5	250
3	1	10	300
4	1	4	80
5	1	8	400