

# DECISION SUPPORT SYSTEMS Module I: DECISION SUPPORT DATABASES

Course home page, teaching material, and recorded lessons:

http://didawiki.di.unipi.it/doku.php/mds/dsd/

#### INTRODUCTION TO DATA WAREHOUSES



- Today, an introduction to
  - What is a Data Warehouse (DW)
  - · What do we model in a DW
- · and some tests of your knowledge of SQL
  - · we will recall relational algebra and SQL starting next week

#### DEFINITION



A DW is a decision support database with historical, nonvolatile data, pulled together primarily from operational business systems, structured and tuned to facilitate analysis of the performance of key business processes, worthy of improvement.

The first definition of data warehouse was provided by William Inmon in 1990, One of the two fathers of DW (the other is Ralph Kimball)

### A DW is a specialized database

- static (non volatile),
- with integrated data from different data sources,
- organized to analyze subjects of interest,
- with historical data,
- used to produce summarized data to support decision-making processes.

#### WHY SEPARATE DB AN DW?



### To promote the high performance of both systems

- Special data organization, and implementation techniques are needed to support multidimensional OLAP analysis.
- Complex data analysis would degrade performance of operational DBMS.

### The systems have different structures, contents, and uses of the data

- Decision support requires historical data which operational DBs do not typically maintain.
- Decision support requires aggregation of data from heterogeneous sources: operational DBs, external sources.
- Different sources typically use inconsistent data representations, codes and formats which have to be reconciled.

#### DATA WAREHOUSING



**Data warehousing** is the process to bring data from operational (OLTP) sources into a single data warehouse for (OLAP) analysis with Business Intelligence applications.

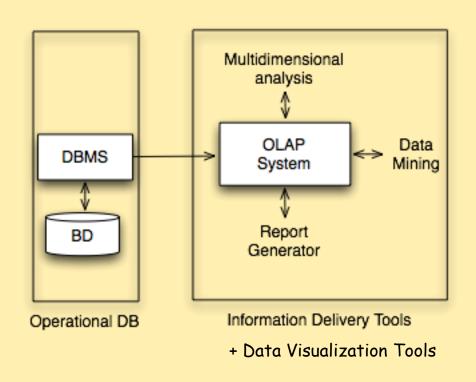
OLTP (On Line Transaction Processing)

OLAP (On Line Analytical Processing)

#### DATA WAREHOUSING ARCHITECTURES



### Single-Layer Architecture



Business Intelligence

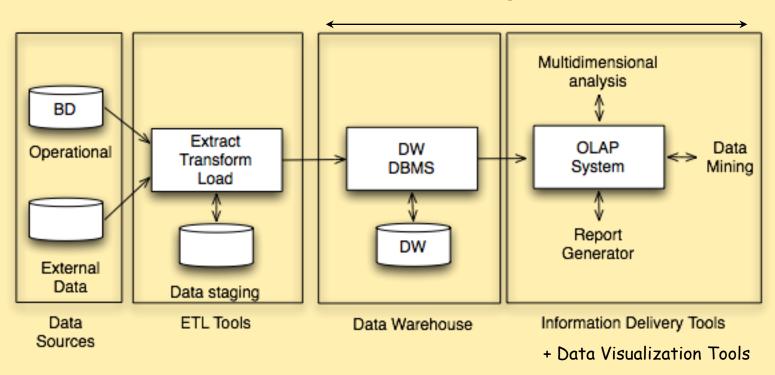
OLAP (On Line Analytical Processing)

### DATA WAREHOUSING ARCHITECTURES

## Three-Layer Architecture



DSS



Business Intelligence

OLAP (On Line Analytical Processing)

#### WHAT IS MODELED IN A DW?



### Computer science is a science of abstraction:

Creating the right model for thinking about a real-world problem that can be understood by computer users and that can be represented and manipulated inside a computer.

The attention here is on modeling the world in data organized as collections of logically related structured data called decision support databases (DW).

What is modeled in a DW?

#### **EXAMPLE:**

### https://community.microstrategy.com/s/gallery





### WHAT IS MODELED IN A DW?



### Managers think about a business process in terms of

facts,

A fact is an observation of the performance of a business process (the subject of analysis) (e.g. a sale)

measures,

The **measures** are numerical attributes of a fact (e.g. qty, revenue, etc),

dimensions,

The dimensions give facts their context. In general a dimension is described by a set of attributes, otherwise is called degenerate. (e.g. sales revenue by product category, by month time, and by city market).

and hierarchies,

The attributes of a dimension may be related via a hierarchy of relationships (e.g. a month is related to the quarter and the year attributes).

#### FACTS ANALYSIS



Managers are interested in aggregate data: the sum, average minimum, maximum, ..., of measures of data groups with equal values of some dimensions or dimensional attributes.

Metrics and Key Performance Indicators (KPI)

Total sales revenue, by products.

### FACTS ANALYSIS: AN SQL EXERCISE



### Total revenue, by Product (SQL ?)

#### SALES

Product	Store	Date	Revenue
p1	m1	d1	120
p2	m1	d1	110
p1	m3	d1	500
p2	m2	d1	800
p1	m1	d2	400
p1	m2	d2	300

Product	Store	Date	Revenue
p1	m1	d1	120
p1	m3	d1	500
p1	m1	d2	400
p1	m2	d2	300
p2	m1	d1	110
p2	m2	d1	800

Product	Total Revenue	
p1	1320	
p2	910	

### FACTS ANALYSIS: AN SQL EXERCISE



### Total revenue, by Product (SQL?)

#### SALES

Product	Store	Date	Revenue
p1	m1	d1	120
p2	m1	d1	110
p1	m3	d1	500
p2	m2	d1	800
p1	m1	d2	400
p1	m2	d2	300

**SELECT** Product

, SUM(Revenue) AS TotalRevenue

FROM Sales

**GROUP BY** Product;

Product	Store	Date	Revenue
p1	m1	d1	120
p1	m3	d1	500
p1	m1	d2	400
p1	m2	d2	300
p2	m1	d1	110
p2	m2	d1	800

Product	Total Revenue
p1	1320
p2	910

### FACTS ANALYSIS



Managers think in term of business dimensions to analyze the data.

Total revenue by Product.

Total revenue by Product, by Market

Revenue I	by Product
Product	Revenue (€)
0.4	
P1	130
P2	910

Revenue by Product and Market			
Product	Market	Revenue (€)	
P1	M1 M2	520 300	
P2	M3 M1 M2	500 110 800	

### FACTS ANALYSIS WITH SUBTOTALS



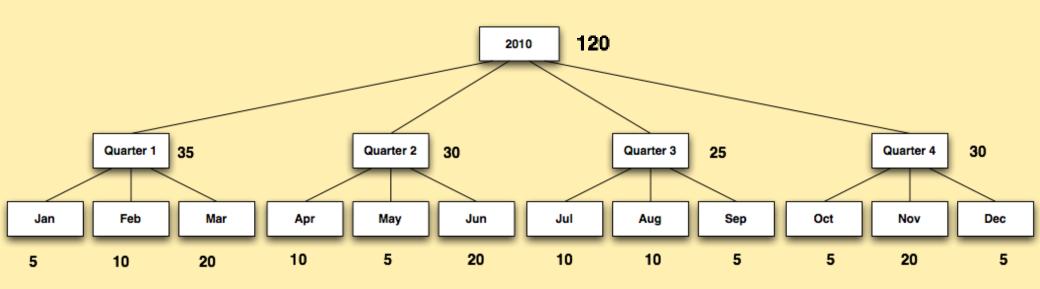
Revenue by Product and Market			
Product	Market	Revenue (€)	
P1	M1 M2 M3	520 300 500	
P1	Total	1 320	
P2	M1 M2	110 800	
P2	Total	910	
Total		2 2 3 0	

#### FACTS ANALYSIS



Managers analyse measure aggregates by business dimensions, and then in various levels of details, by exploiting dimensional attributes hierarchies.

Total Revenue, by Month Total Revenue, by Quarter Total Revenue, by Year Example with Sales of Year 2010



### WHAT IS MODELED IN A DW: DIMENSIONAL HIERARCHIES



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A dimensional attributes hierarchy models attributes dependency, i.e. a functional dependency between attributes, using the relational model terminology.

### ■ **Definition 8.1** *Functional Dependency*

Given a relation schema R and X, Y subsets of attributes of R, a functional dependency  $X \to Y$  (X determines Y) is a constraint that specifies that for every possible instance r of R and for any two tuples  $t_1, t_2 \in r$ ,  $t_1[X] = t_2[X]$  implies  $t_1[Y] = t_2[Y]$ .

For example, the dimension **Date** has attributes **Month**, **Quarter**, **Year**. Can we define a **dimensional hierarchy** among them?

Month → Quarter → Year

### DIMENSIONAL HIERARCHIES





 $\textbf{Date} \qquad \qquad \textbf{Month} \rightarrow \textbf{Quarter} \rightarrow \textbf{Year}$ 

PkDate	Month	Quarter	Year
20080101	1	1	2008
20080102	1	1	2008
20090101	1	1	2009
20090102	1	1	2009

### DIMENSIONAL HIERARCHIES





 $\textbf{Date} \qquad \qquad \textbf{Month} \rightarrow \textbf{Quarter} \rightarrow \textbf{Year}$ 

PkDate	Month	Quarter	Year
20080101	1	1	2008
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20090101	1	1	2009
20090102	1	1	2009

### USEFULNESS OF HIERARCHIES (SQL)



Sales(Product,..., Month, Quarter, Year, Revenue)

Month  $\rightarrow$  Quarter

V = SELECT Month, SUM(Revenue) AS SRM

FROM Sales

WHERE Year = 2010

GROUP BY Month:

For the year 2010, the total Revenue,

by Month

Q = SELECT Quarter, SUM(Revenue) AS SRQ

FROM Sales

WHERE Year = 2010

For the year 2010, the total Revenue,

GROUP BY Quarter; by Quarter.

If the result of V is materialized, then may we compute Q from V only?

### USEFULNESS OF HIERARCHIES (SQL)



Sales(Product,..., Month, Quarter, Year, Revenue)

Month → Quarter

FROM Sales

WHERE Year = 2010

GROUP BY Month, Quarter;

For the year 2010, the total Revenue, by Month, by Quarter

FROM Sales

WHERE Year = 2010

GROUP BY Quarter;

For the year 2010, the total Revenue, by Quarter.

If the result of V' is materialized, then may we compute Q from V' only?

$$Q = SELECT$$
 Quarter, Sum(SRMQ) AS SRQ

FROM V

GROUP BY Quarter

# USEFULNESS OF HIERARCHIES AND DISTRIBUTIVE AGGREGATION FUNCTIONS



$$V = V_1 \cup V_2$$

$$V_1 \cap V_2 = \emptyset$$

#### Distributive

E.g., sum(), min(), max(), count()

### Algebraic

E.g., avg(), standard\_deviation().

#### Holistic

E.g., median(), mode(), rank().