Data Warehouse/Data Mart Conceptual Modeling and Design Dimensional Fact Model (DFM)

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Methodological Framework
Conceptual Modelling: the Dimensionnal Fact Model (DFM)

Plan

Bibliographie

- **Books**
  - Golfarelli M., Rizzi S., "Data Warehouse Design : Modern Principles and Methodologies", McGrawHill, 2009.
  - Kimball R., Ross, M., "Entrepôts de données : guide pratique de modélisation dimensionnelle", 2°édition, Ed. Vuibert, 2003.
  - S. Rizzi. "Conceptual modeling solutions for the data warehouse". In Data Warehousing and Mining: Concepts, Methodologies, Tools, and Applications, J. Wang (Ed.), Information Science Reference, pp. 208-227, 2008.
  - M. Golfarelli, D. Maio, S. Rizzi. "Conceptual Design of Data Warehouses from E/R Schemes". Proceedings 31st Hawaii International Conference on System Sciences (HICSS-31), vol. VII, Kona, Hawaii, pp. 334-343, 1998.
- **Courses**
  - Course of M. Golfarelli M. and S. Rizzi, University of Bologna
  - Courses of M. Böhlen and J. Gamper J., Free University of Bolzano

1. Methodological framework

- **Conceptual Design & Logical Design**
- **Life-Cycle**
- **Top-Down, Botton-Up and Mixed Strategies**
- **Design Phases**
- **Schemata derivations for DMs design**

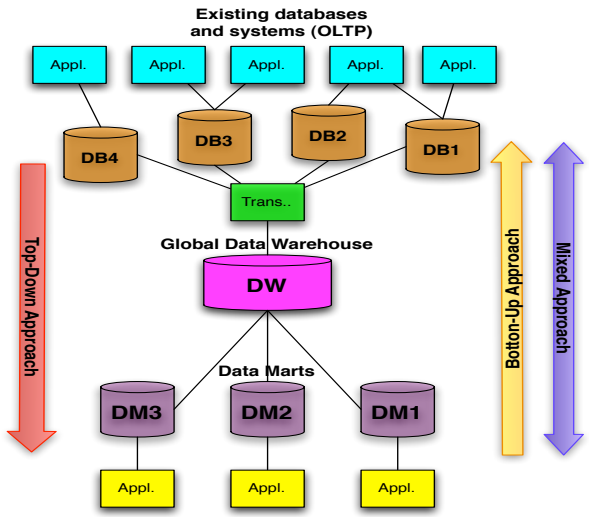
Conceptual Design & Logical Design

- **Entite-Relation models** are not very useful in modeling DWs
- DW is conceptualy based on a **multidimensional view of data :**
  - *But there is still **no agreement** on HOW to develop its conceptual design !*
- **Most of the time, DW design is at the logical level** : a multidimensional model (star/snowflake schema) is directly designed :
  - *But a **star/snowflake schema** is nothing but a **relational schema***
  - *it contains only the definition of a **set of relations** and **integrity constraints** !*
- **A better approach:**
  - 1) **design** first a **conceptual model** : **Conceptual Design**
  - 2) which is then ***translated*** into a **logical model : Logical Design**

Methodological Framework

- Building a DW is a **very complex task**, which requires an **accurate planning** aimed at devising satisfactory answers to organizational and architectural questions
- A large number of organizations **lack experience and skills** that are required to meet the challenges involved in DW projects
- Major cause of DW failures lies in the **absence of a global view of the design process**, of a **design methodology**
- **Design Methodologies** are necessary to **minimizing the risks for failure**
- **3 main strategies for DW design:**
  - **Top-Down strategy**
  - **Botton-Up strategy**
  - **Mixed strategy**

Various strategies



Top-Down Approach:

1. Design of DW
2. Design of DMs

Bottom-Up Approach:

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

Mixed Approach:

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

Top-Down Strategy

Analyze global business needs, **plan** how to develop a **DW, design** it, and implement it as a **whole with its DMs**

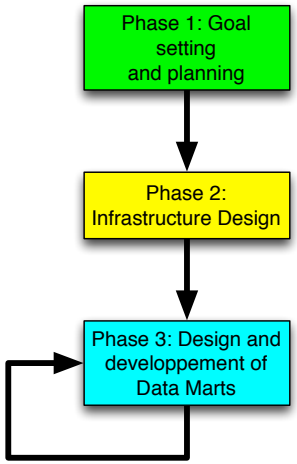
(+) Stengths:

- Promising: it is **based on a global picture** of the goal to achieve, and in principle it ensures consistent, well integrated DW

(-) Weakness:

- High-cost estimates with **long-term implementations** discourage company managers from embarking on these kind of projects.
- Analyzing and integrating all relevant sources at the same time is a **very difficult task**: they are all available and stable at the same time.
- **Extremely difficult to forecast** the specific needs of every department involved in a project, which leads to specific DMs
- As **no working DW system is going to be delivered in the short term**, users cannot check for this project to be useful, so they lose trust and interest in it.

Life-Cycle with a Top-Down strategy



Phase 1 : Goal setting and planning of the DW

- set system goals, borders, and size
- select an approach for design and implementation
- estimate costs and benefits
- analyze risks and expectations
- examine the skills of the working team

Phase 2 : Infrastructure design of the DW

- analyze and compare the possible architectural solutions
- assess the available technologies and tools
- create a preliminary plan of the whole DW system

Phase 3 : Design and development of DMs

- Every iteration causes a new DM and new applications to be created and progressively added to the DW system

Botton-Up Strategy

- **DW is incrementally built** and several **DM are iteratively created**
- **Each DM is based on a set of facts** that are linked to a **specific department** and that can be interesting for a user group

(+) Stengths:

- Leads to concrete **results in a short time**
- Does **not require huge investments**
- Enables designers to investigate **one area at a time**
- Gives managers a **quick feedback** about the actual benefits of the system being built

(-) Weakness:

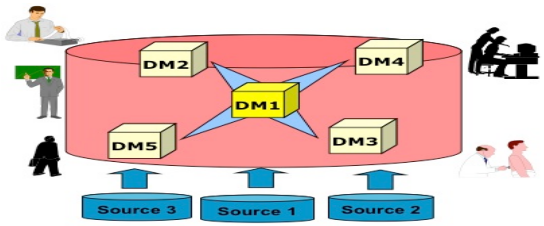
- Keeps the interest for the project constantly high may determine a **partial vision of the business domain**.

=> Mixed strategy …

Mixed Strategy

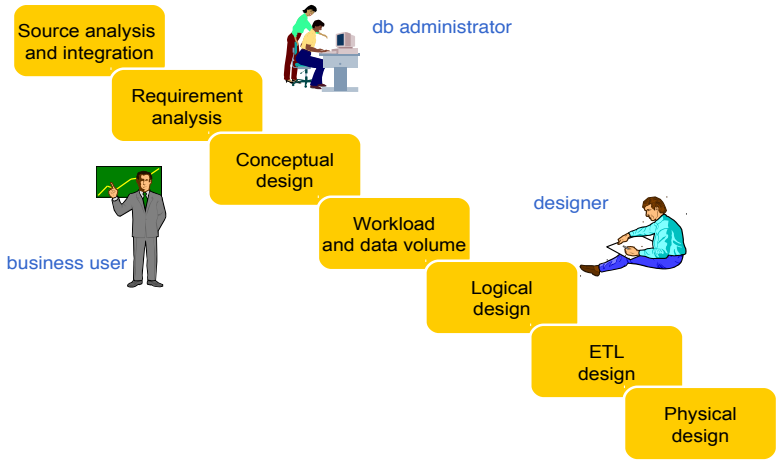
Top-Down and **Bottom-Up** strategies should be **mixed :**

- **When planning a DW**, a *bottom-up strategy* should be followed
- **One Data Mart (DM) at a time** is **identified** and **prototyped** according to *a top-down strategy* by building a *conceptual schema* for each *fact* of interest
- The **first DM (DM1) to prototype** :
  - is the one *playing* the most *strategic role* for the enterprise
  - should be a *backbone* for the whole DW
  - should lean on available and consistent data sources

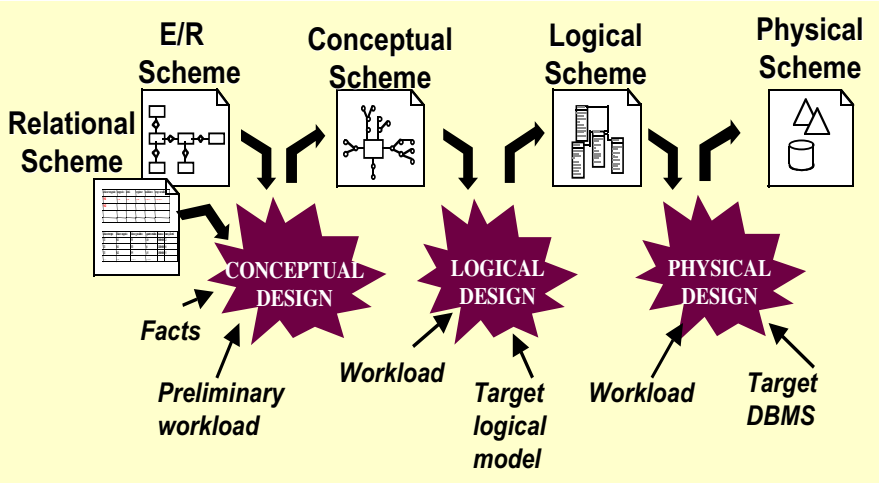


Main Data Warehouse/Mart Design Steps

Each Data Mart (DM) will be designed according these steps:



Schemata derivations for DMs design



2. Conceptual Design of Data Mart: The Dimensionnal Fact Model

- **Fact schema**
- **Dimension hierarchies**
- **Fact schema and fact instances**
- **Additive attributes**
- **Semi-additive and non-additive attributes**
- **Overlapping compatible fact schemata**
- ***Representing query patterns on a fact schema***

Conceptual Design of a Data Mart (DM)

- **Conceptual Design** is based on the documentation of the underlying operational information system (IS):
  - ***Relational schemata*** *or*
  - ***E/R schemata***

- **Steps:**
  1. Find facts
  2. For each fact:
     a) Navigate functional dependencies
     b) Drop useless attributes
     c) Define dimensions and measures

The Dimensionnal Fact Model (DFM)

The **Dimensional Fact Model (DFM)** has be proposed by Golfarelli M., Rizzi S. to support a Conceptual Design of DW

The DFM is a **graphical conceptual model** for **Data Mart design**

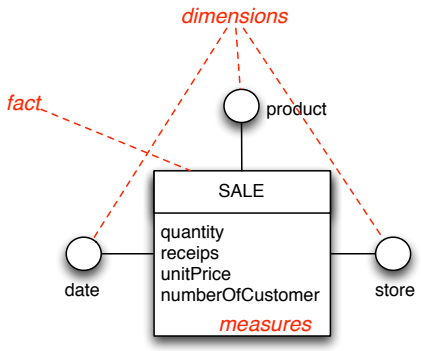
The **aim** of the **DFM** is to :

1. Provide an efficient **support to Conceptual Design**
2. Create an environment in which **user queries may be formulated intuitively**
3. Make **communication possible between designers and end users** with the goal of formalizing requirement specifications
4. Build a **stable platform for logical design** (independently of the target logical model)
5. Provide **clear and expressive design documentation**

The conceptual representation generated by the DFM consists of **a set of fact schemata** that basically model *facts, measures, dimensions, and hierarchies*.

Exemple of Fact Schema

Ex : a simple 3-dimensional fact schema « SALE » for a chain of stores :



- A ***fact schema*** is structured as a **tree whose root is a fact**
- A **Conceptual Model** of a DW consists of a **set of *fact schemata***

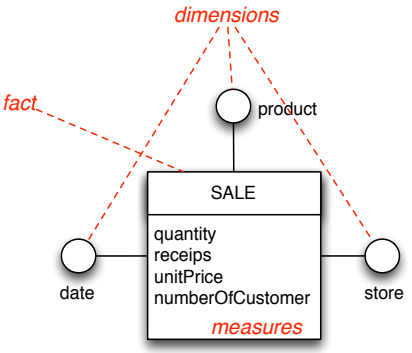
Fact, Measure and Dimension

A **fact** is a *concept relevant* to decision-making processes :

- It models a set of ***events*** (ex: in a compagny: sales, shipments, purchases, ...)
- It has ***dynamic properties*** or evolve in some way *over* ***time***
- It has one or more ***numeric*** and ***continuously valued attributes*** which *"**measure**"* the fact from different points of view

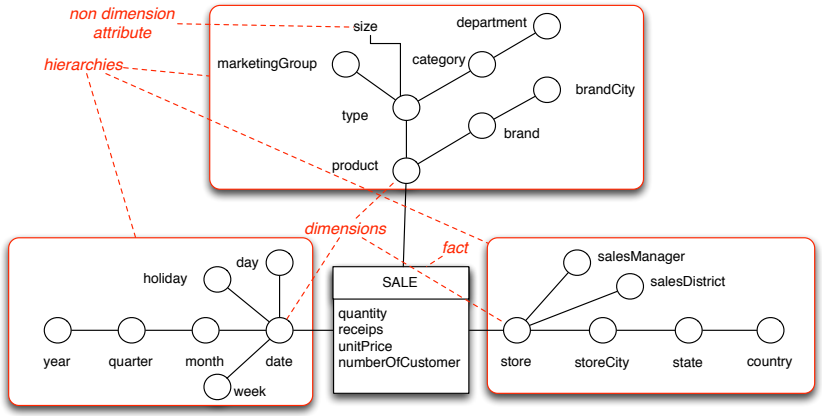
- a **measure** is a *numerical property of a fact* and describes a *quantitative fact aspect* that is relevant to analysis : Ex : every sale is quantified by its ***quantity, receips, unitPrice, numberOfCustomer***

- a **dimension** is a fact property with a finite domain and describes an analysis axes of the fact : Ex : typical dimensions for the sales fact are ***product***, ***store***, and ***date***



Dimension Hierarchies (1)

- **Hierarchy** determines **how fact instances** may be **aggregated** and **selected** significantly for the decision-making process and determines the ***granularity*** adopted for representing facts.
- **Hierarchies** are **subtrees rooted** in ***dimensions***:



Dimension hierarchies (2)

In dimension hierarchies :

- **nodes** represented by **circles** are *dimension attributes* which may assume a discrete set of values.

  Ex : week, month, product, …

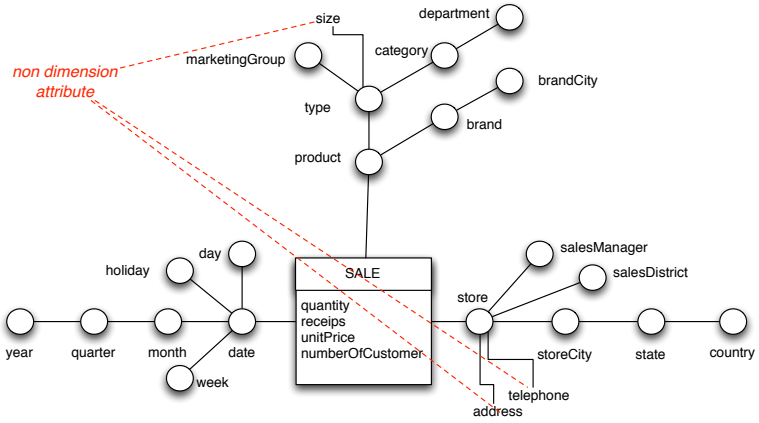
- ***arcs*** represent *relationships between pairs of attributes:* these relationships are functional dependencies:

  Ex: product -> type; type -> category; category -> department …

- ***dimension attributes*** in the nodes along each sub-path of the hierarchy starting from the dimension define ***progressive granularities.***

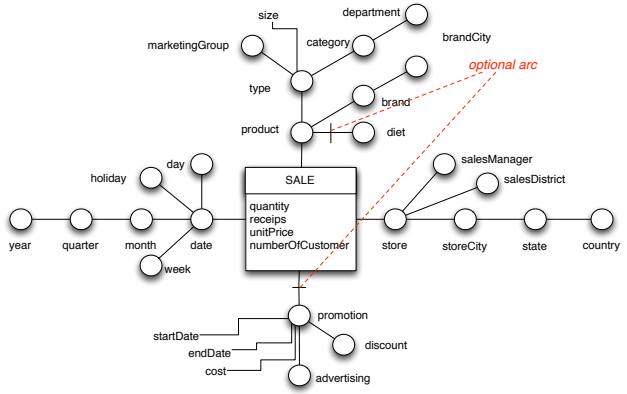
Advanced Modeling: Descriptives Attributes

non-dimension attributes contains additional information about an attribute of the hierarchy: it cannot be used for aggregation ! *Ex : **size** : aggregating sales according to the **size** of the product would not make sense!*



Advanced Modeling: Optional Arcs

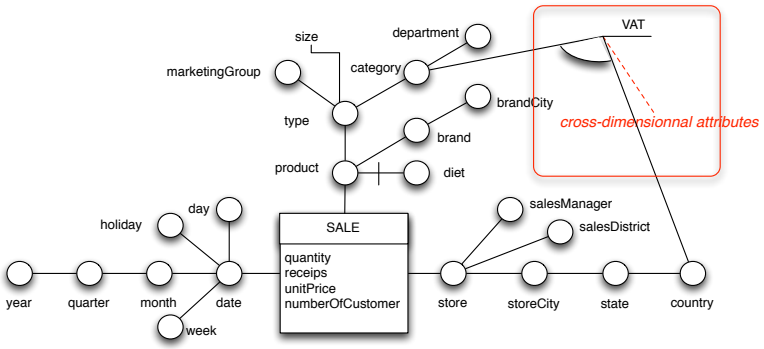
Optional arcs *(marked by a dash)* express *optional relationships* between pairs of attributes (useful for logical design) *Ex : **diet**, **promotion**. The **diet** attribute takes a value (such as cholesterol-free, gluten-free, or sugar-free) only for food products; for the other products, it is undefined.*



Advanced Modeling: Cross-Dimensional Attributes

Cross-dimensional attribute is a *dimensionnal* or *descriptive attribute* whose value is defined by the combination of 2 or more dimensional attributes, possibly belonging to different hierarchies.

Ex : if a product Value Added Tax (VAT) depends both on the product category and on the country where the product is sold, you can use a cross-dimensional attribute to represent it:



Advanced Modeling: Convergence

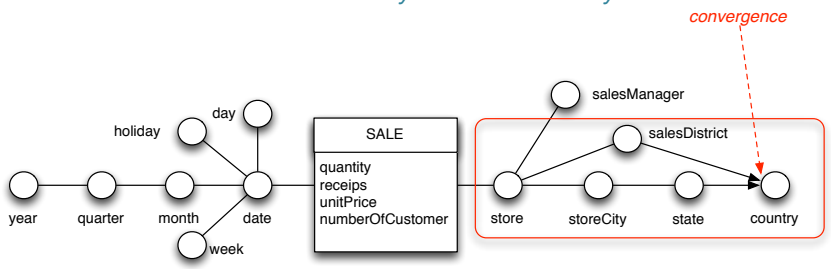
A **convergence** takes place when **2 dimensional attributes** within a hierarchy are connected by 2 or more alternative paths of many-to-one associations *(Graphically, use of arrows)*.

Ex : in store dimension, store are grouped into sales districts and no inclusive relationship exists between districts and states, but each district is part of only one country:

Store -> salesDistrict -> country

or

Store -> storeCity -> state -> country



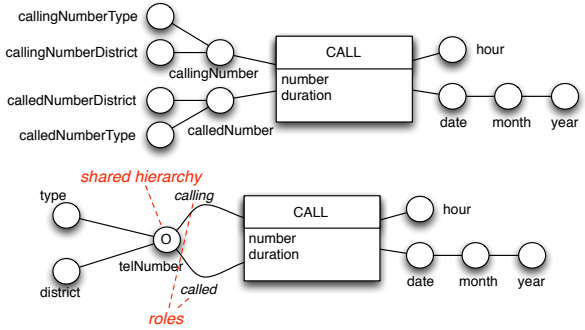
Advanced Modeling: Shared Hierarchies

Shared hierarchies exist when entire *portion of hierarchies are frequently replicated* 2 or more time in fact schemata

In particular in time hierarchies, 2 or more date-type dimensions with different meaning can easily exist in a same fact, and need to build a month-year hierarchy on each one of them

=> an abreviation is introduced

Ex: calling and called phone numbers …

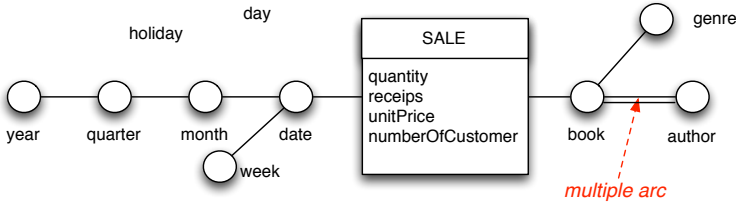


Advanced Modeling: Multiple Arcs

Multiple arc models a **many-to-many association between the 2 dimensional attributes** it connects *(Graphically, denoted by doubling of the arc)*

Ex : in a fact schema modeling the sales of books, whose dimensions are date and book. It would certainly be interesting to aggregate and select sales on the basis of book authors.

However, it would not be accurate to model author as a dimensional child attribute of book because many different authors can write many books. Then, the relationship between books and authors is modeled as a multiple arc:



Advanced modeling: Additivity (1)

3 Types of measure :

- *Flow measure*: refer to time *(ex: number of products sold in a day)*
- *Level measure*: evaluated at particular time (*ex: number of products in inventory)*
- *Unit measure*: evaluated at particular time but are expressed in relative terms *(ex: product unit price, discount percentage)*
- Suitable operators for aggregation:

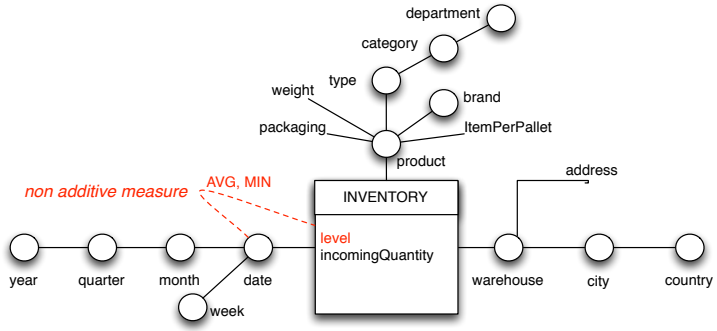
	Temporal hierarchies	*Nontemporal hierarchies*
Flow measures	**SUM**, AVG, MIN, MAX	**SUM**, AVG, MIN, MAX
Level measures	AVG, MIN, MAX	**SUM**, AVG, MIN, MAX
Unit measures	AVG, MIN, MAX	AVG, MIN, MAX

3 Natures of measure :

- *additive* along a dimension when can be used the SUM aggregation operator
- *non-additive* along a dimension if the aggregation operator is not **SUM** (ex: inventory level)
- a non-additive measure is *non-aggregable* if no operator exists (ex: unitPrice product)

Advanced Modeling: Additivity (2)

- Along all the dimensions by **default** measures are **additive** (operator SUM)
- **Non-additive measure** can be **explicitely specified with its operator(s)** used for aggregation – other that SUM *(Ex: AVG and MIN for inventory **level** measure for time dimension)*



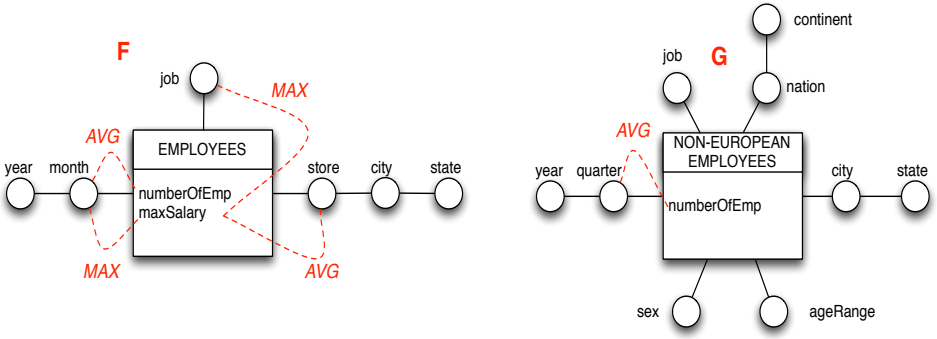
Overlapping Compatible Fact Schemata (1)

- Different facts are represented in different fact schemata
- Queries the user formulates on the DW may require comparing fact attributes taken from distinct, though related, schemata (*drill across* in OLAP)
- 2 fact schemata are said ***compatible*** if they share at least one dimension attribute
- 2 compatible schemata *F* and *G* may be ***overlapped*** to create a resulting schema *H*
- Without conflict between attribute dependencies in the 2 schemata:
  - the set of the **fact attributes in *H*** is the **union** of the sets in *F* and *G*
  - the **dimensions in *H*** are the **intersection of those in *F* and *G***, assuming that a given dimension is common to *F* and *G* if at least one dimension attribute is shared
  - **each hierarchy in *H includes*** all and only the **dimension attributes** included in the corresponding hierarchies of both *F* and *G*.

Overlapping Compatible Fact Schemata (2)

Consider the 2 fact schemata :

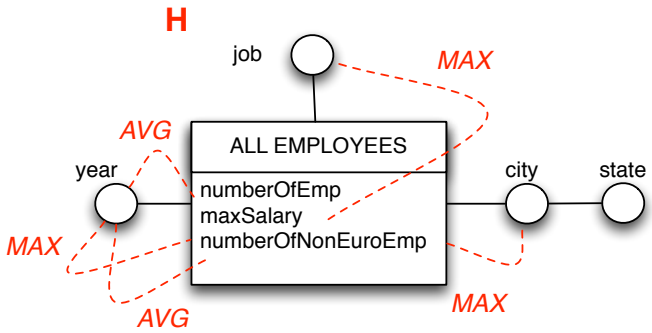
- F represents all employees of an enterprise
- G only the non-European employees.



F and G are compatible, they share the ***time***, ***job*** and ***store*** dimensions

Overlapping Compatible Fact Schemata (3)

- Schema resulting from *overlapping* F and G is H:



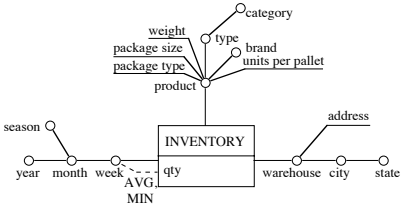
- H can be used, for instance, to *calculate the percentage of non-European employees for each city, job and year*.

Overlapping Compatible Fact Schemata (4)

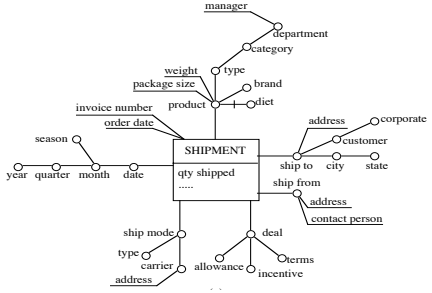
- In some cases, aggregation along a dimension can be carried out at different abstraction levels even if the corresponding dimension attributes were not explicitly shown.
  - *Ex: a **month** attribute within a time hierarchy, fact instances can be aggregated by **quarter**, **semester** and **year** by performing a simple calculation.*
  - *Thus, given the F and G fact schemata, attribute **quarter** could in principle be **added** to the time dimension in the resulting schema H*
  - On the other hand, the designer must keep in mind that, by adopting this solution, the time for extracting data by quarter will **increase significantly**
  - thus, the best solution would probably be to **add explicitly the *quarter*** attribute to the time hierarchy in the employee fact schema.

Overlapping compatible fact schemata (5)

Fact schema INVENTORY :



Fact schema SHIPMENT:



Fact schema overlaping INVENTORY and SHIPMENT: