Data warehouse design

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Risk factors

- High user expectation
  - the data warehouse is *the* solution of the company's problems
- Data and OLTP process quality
  - incomplete or unreliable data
  - non integrated or non optimized business processes
- "Political" management of the project
  - cooperation with "information owners"
  - system acceptance by end users
  - deployment
    - appropriate training

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Data warehouse design

- Top-down approach
  - the data warehouse provides a global and complete representation of business data
  - significant cost and time consuming implementation
  - complex analysis and design tasks
- Bottom-up approach
  - incremental growth of the data warehouse, by adding data marts on specific business areas
  - separately focused on specific business areas
  - limited cost and delivery time
  - easy to perform intermediate checks

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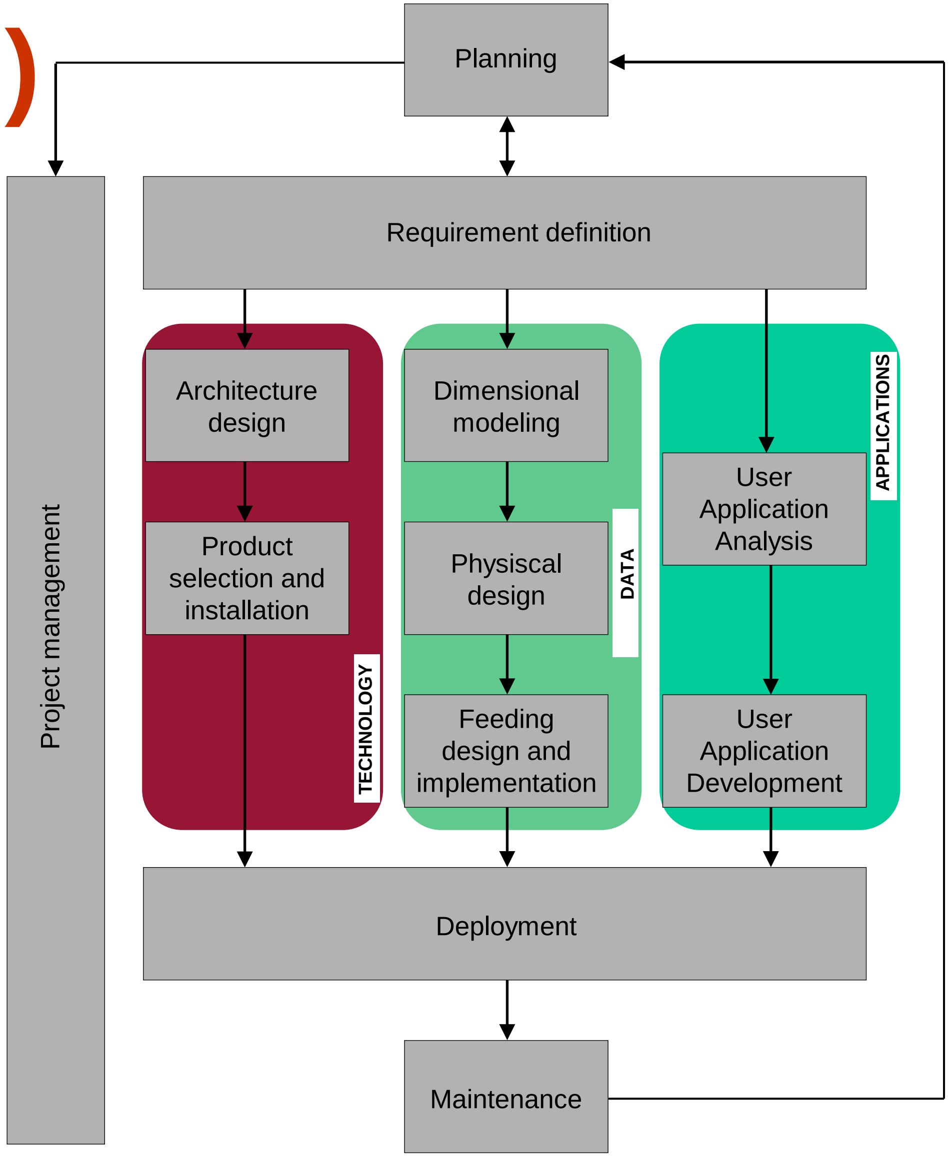
Business Dimensional Lifecycle (Kimball)



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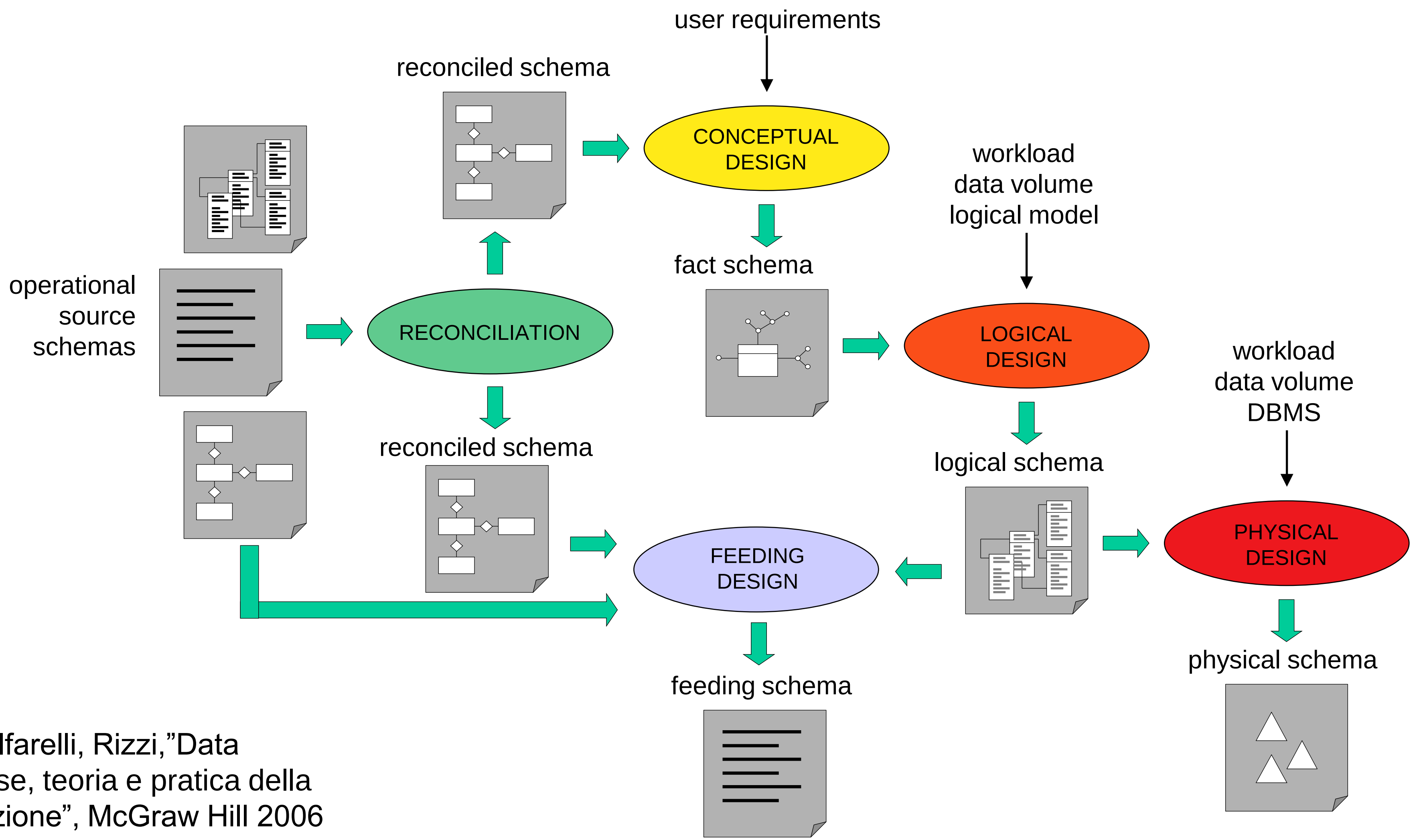
Data mart design



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Requirement analysis

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Requirement analysis

- It collects
  - data analysis requirements to be supported by the data mart
  - implementation constraints due to existing information systems
- Requirement sources
  - business users
  - operational system administrators
- The first selected data mart is
  - crucial for the company
  - feeded by (few) reliable sources

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Application requirements

- Description of relevant events (facts)
  - each fact represents a category of events which are relevant for the company
    - examples: (in the CRM domain) complaints, services
  - characterized by descriptive dimensions (setting the granularity), history span, relevant measures
  - informations are gathered in a glossary
- Workload description
  - periodical business reports
  - queries expressed in natural language
    - example: number of complaints for each product in the last month

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Structural requirements

- Feeding periodicity
- Available space for
  - data
  - derived data (indices, materialized views)
- System architecture
  - level number
  - dependent or independent data marts
- Deployment planning
  - start up
  - training

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Conceptual design

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Conceptual design

- No currently adopted modeling formalism
  - ER model not adequate
- *Dimensional Fact Model* (Golfarelli, Rizzi)
  - graphical model supporting conceptual design
  - for a given fact, it defines a *fact schema* modelling
    - dimensions
    - hierarchies
    - measures
  - it provides design documentation both for requirement review with users, and after deployment

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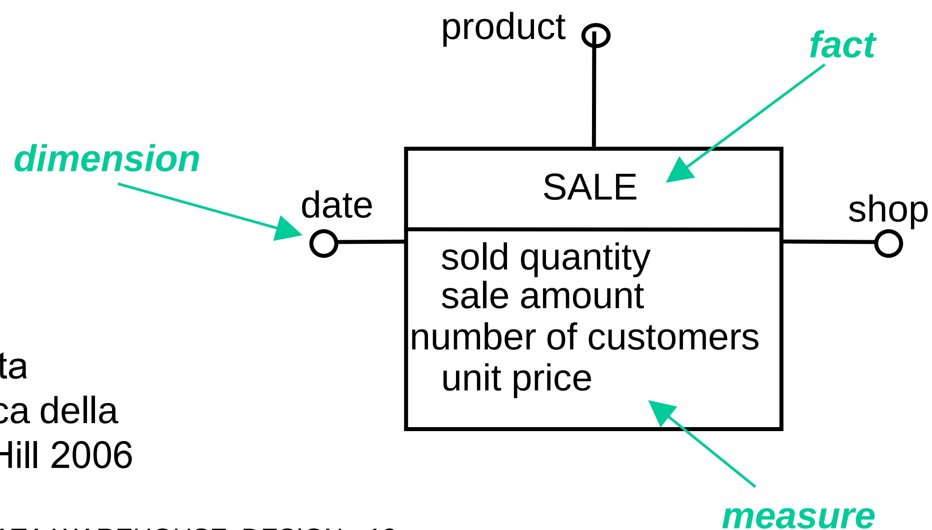
Dimensional Fact Model

- Fact
  - it models a set of relevant events (sales, shippings, complaints)
  - it evolves with time
- Dimension
  - it describes the analysis coordinates of a fact (e.g., each sale is described by the sale date, the shop and the sold product)
  - it is characterized by many, typically categorical, attributes
- Measure
  - it describes a numerical property of a fact (e.g., each sale is characterized by a sold quantity)
  - aggregates are frequently performed on measures



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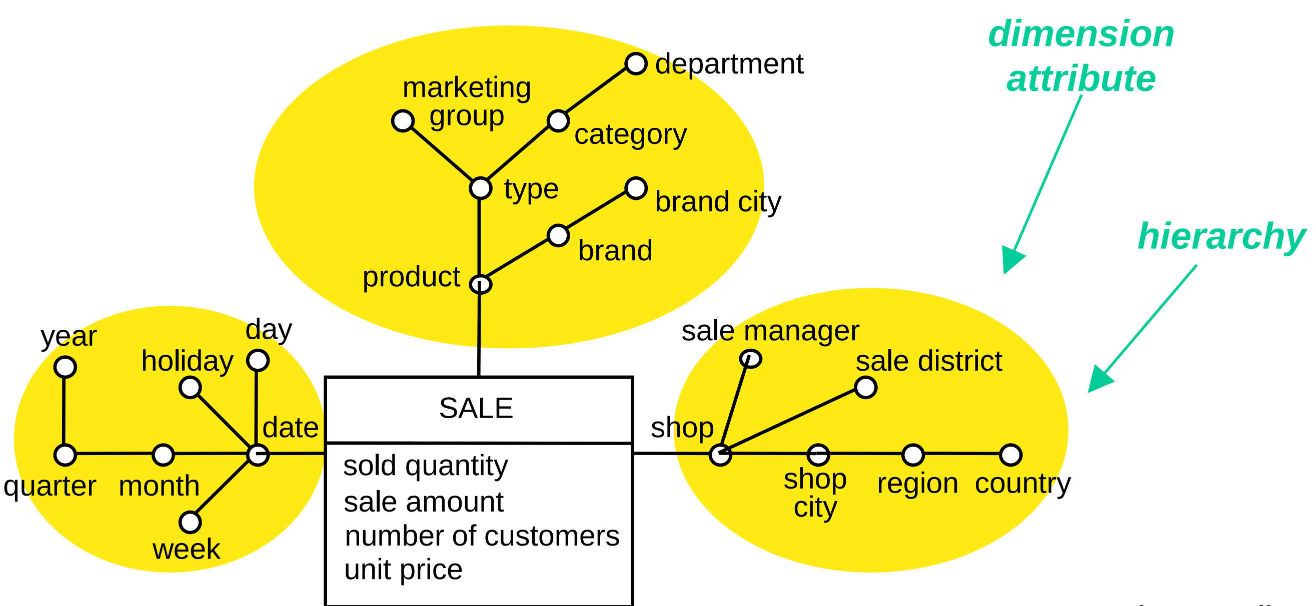
DFM: Hierarchy

- Each dimension can have a set of associated attributes
- The attributes describe the dimension at different abstraction levels and can be structured as a hierarchy
- The hierarchy represents a generalization relationship among a subset of attributes in a dimension (e.g., geografic hierarchy for the shop dimension)
- The hierarchy represents a functional dependency (1:n relationship)



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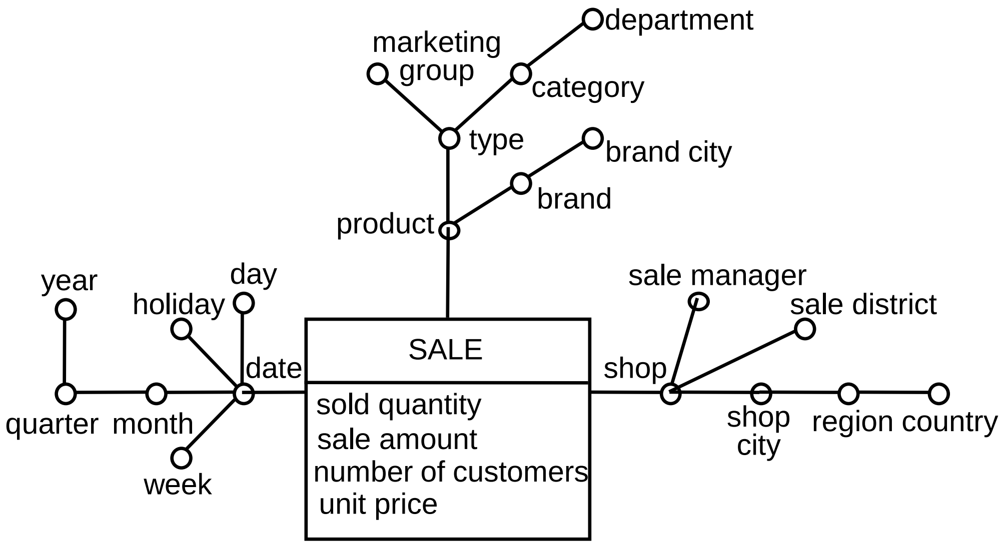
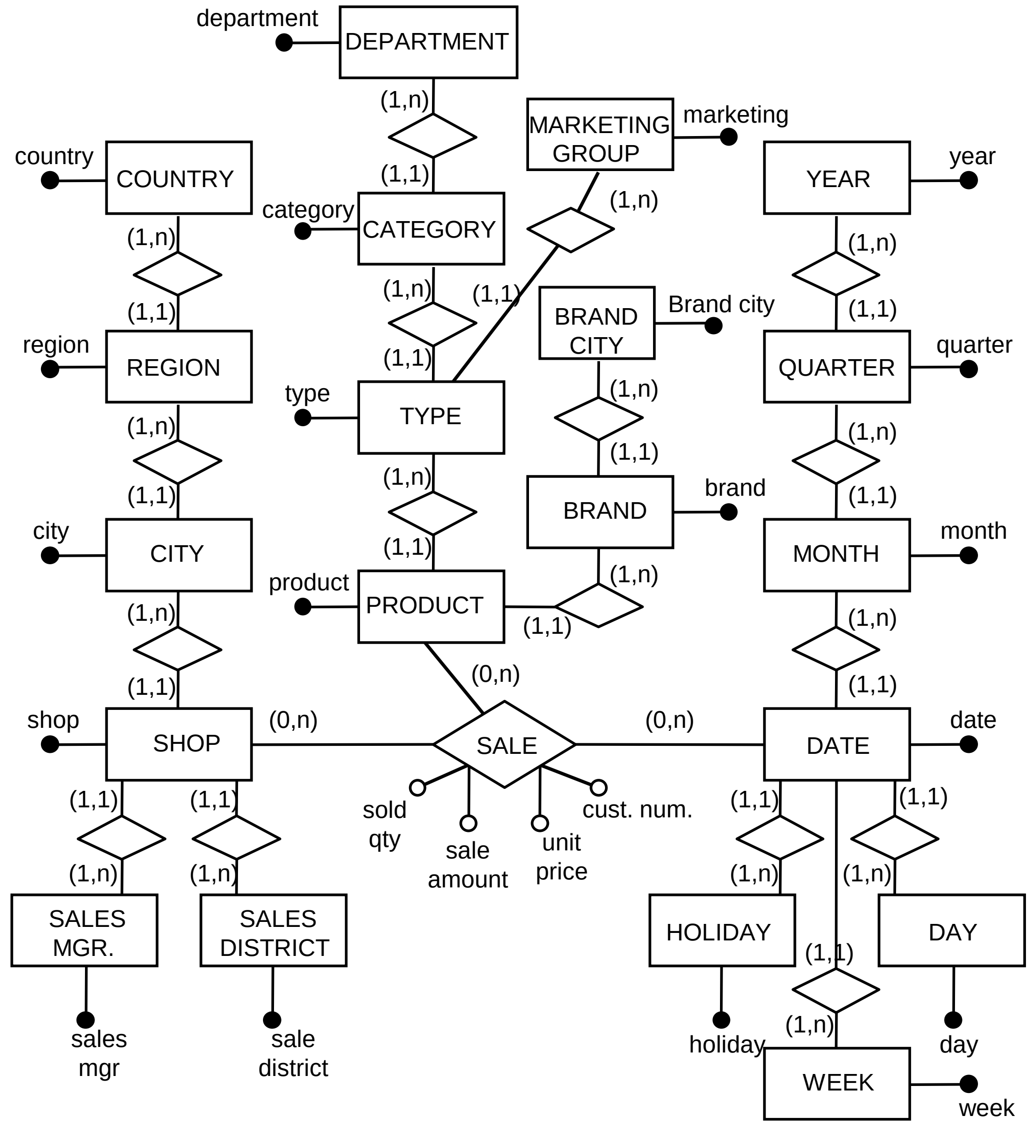
Comparison with ER





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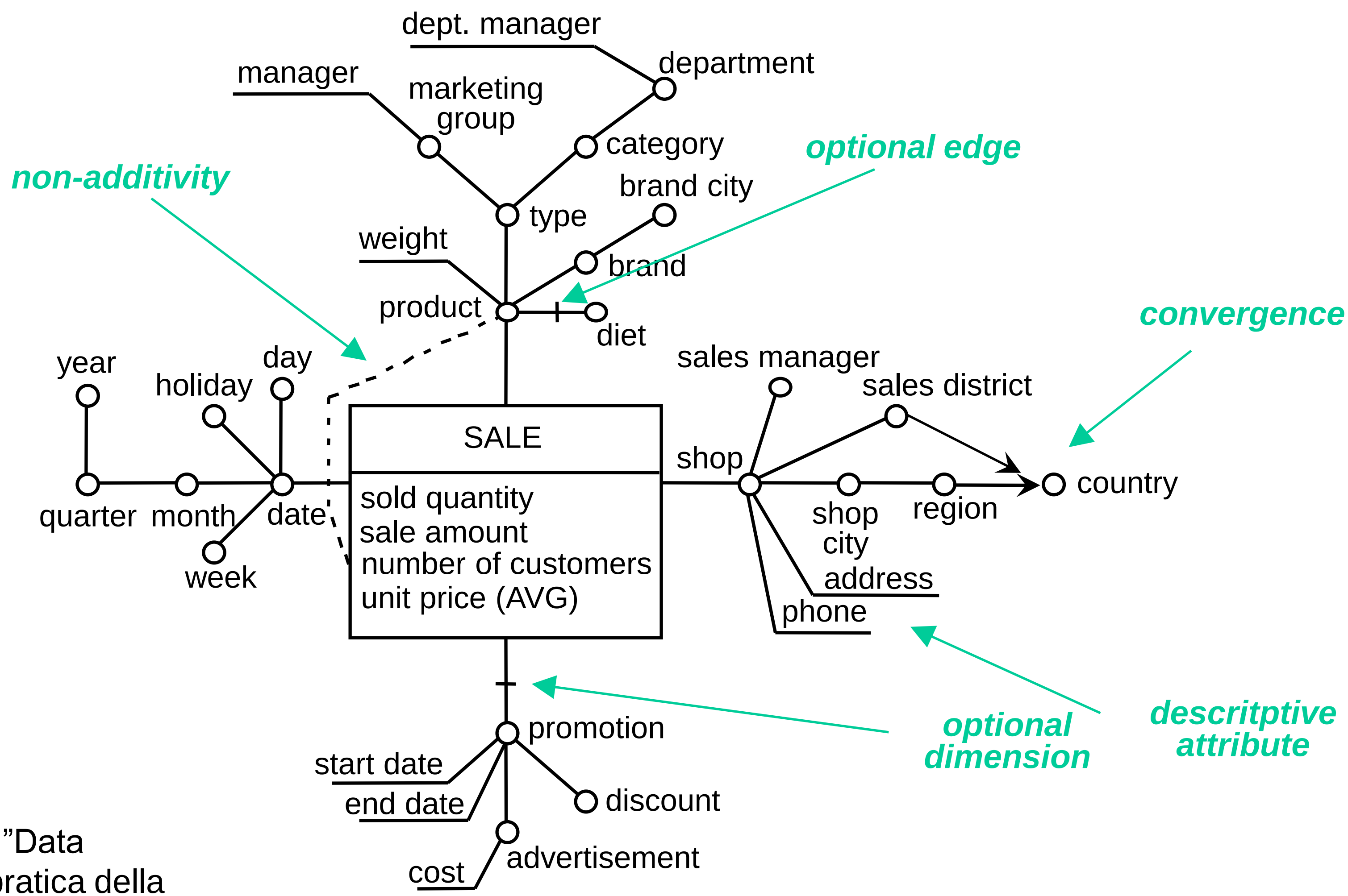
Advanced DFM



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Aggregation

- Aggregation computes measures with a coarser granularity than those in the original fact schema
  - detail reduction is usually obtained by climbing a hierarchy
  - standard aggregate operators: SUM, MIN, MAX, AVG, COUNT
- Measure characteristics
  - additive
  - not additive: cannot be aggregated along a given hierarchy by means of the SUM operator
  - not aggregable

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Measure classification

- Stream measures
  - can be evaluated cumulatively at the end of a time period
  - can be aggregated by means of all standard operators
  - examples: sold quantity, sale amount
- Level measures
  - evaluated at a given time (snapshot)
  - not additive along the time dimension
  - examples: inventory level, account balance
- Unit measures
  - evaluated at a given time and expressed in relative terms
  - not additive along any dimension
  - examples: unit price of a product

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Aggregate operators

category	type	product	I '99 (1999)	II '99 (1999)	III '99 (1999)	IV '99 (1999)	I '00 (2000)	II '00 (2000)	III '00 (2000)	IV '00 (2000)
home cleaning	washing powder	Brillo	100	90	95	90	80	70	90	85
home cleaning	washing powder	Sbianco	20	30	20	10	25	30	35	20
home cleaning	washing powder	Lucido	60	50	60	45	40	40	50	40
home cleaning	soap	Manipulite	15	20	25	30	15	15	20	10
home cleaning	soap	Scent	30	35	20	25	30	30	20	15
food	milk	Latte F Slurp	90	90	85	75	60	80	85	60
food	milk	Latte U Slurp	60	80	85	60	70	70	75	65
food	milk	Yogurt Slurp	20	30	40	35	30	35	35	20
food	soda	Bevimi	20	10	25	30	35	30	20	10
food	soda	Colissima	50	60	45	40	50	60	45	40

category	I'99 (1999)	II'99 (1999)	III'99 (1999)	IV'99 (1999)	I'00 (2000)	II'00 (2000)	III'00 (2000)	IV'00 (2000)
home clean.	225	225	220	200	190	185	215	170
food	240	270	280	240	245	275	260	195

category	type	1999	2000
home cleaning	washing p.	670	605
home cleaning	soap	200	155
food	milk	750	685
food	soda	280	290

category	1999	2000
home clean.	870	760
food	1030	975

From Golfarelli, Rizzi,"Data warehouse, teoria e pratica della progettazione", McGraw Hill 2006

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Aggregate operators

- Distributive
  - can always compute higher level aggregations from more detailed data
  - examples: sum, min, max

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Non distributive operators

Measure: unit price

category	type	product	1999 I'99	1999 II'99	1999 III'99	1999 IV'99
home cleaning	washing powder	Brillo	2	2	2,2	2,5
		Sbianco	1,5	1,5	2	2,5
		Lucido	–	3	3	3
	soap	Manipulite	1	1,2	1,5	1,5
		Scent	1,5	1,5	2	–

category	type	1999 I'99	1999 II'99	1999 III'99	1999 IV'99
home cleaning	wash. p.	1,75	2,17	2,40	2,67
	soap	1,25	1,35	1,75	1,50
	avg:	1,50	1,76	2,08	2,09

category	1999 I'99	1999 II'99	1999 III'99	1999 IV'99
home clean.	1,50	1,84	2,14	2,38

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Aggregate operators

- Distributive
  - can always compute higher level aggregations from more detailed data
  - examples: sum, min, max
- Algebraic
  - can compute higher level aggregations from more detailed data *only* when supplementary support measures are available
  - examples: avg (it requires count)
- Olistic
  - *can not* compute higher level aggregations from more detailed data
  - examples: mode, median

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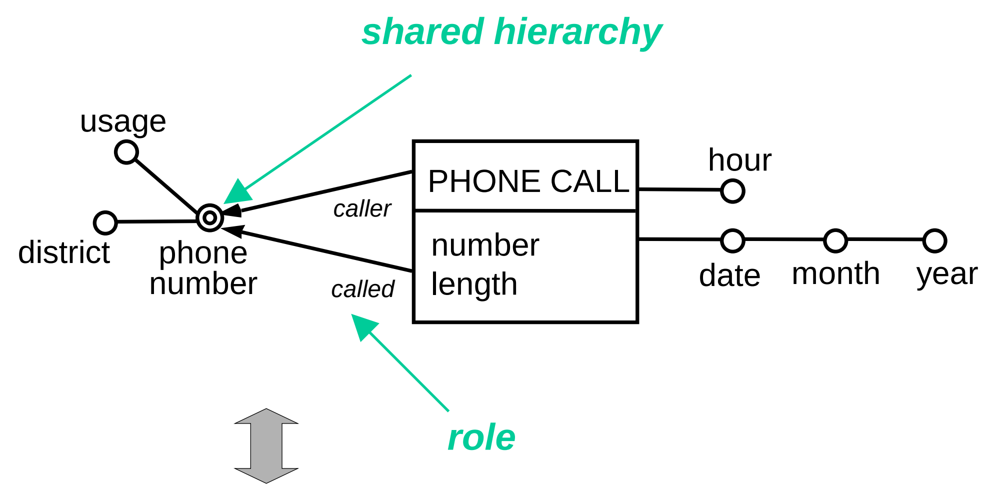

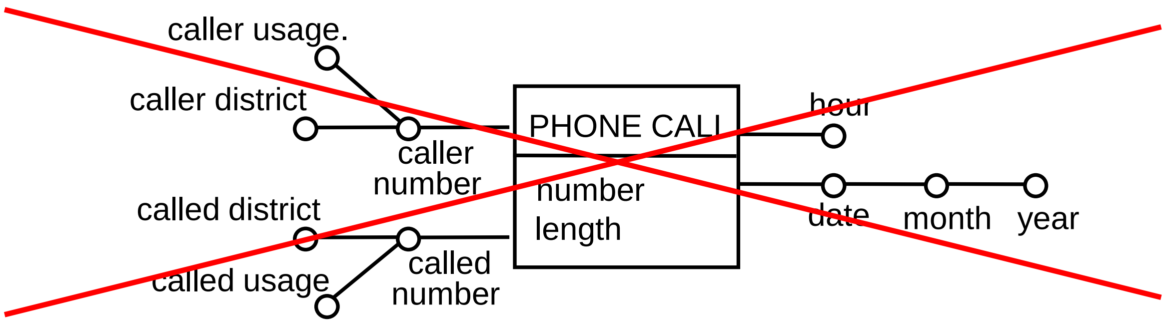

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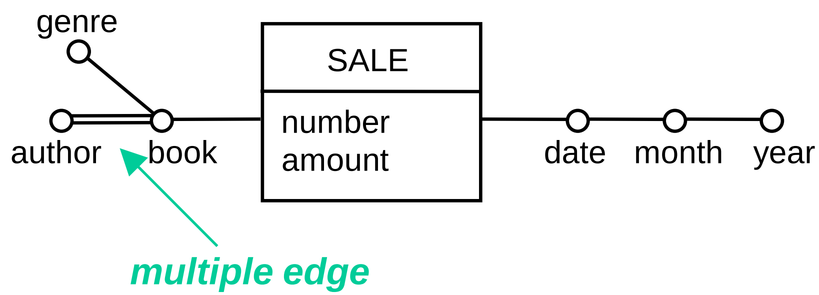

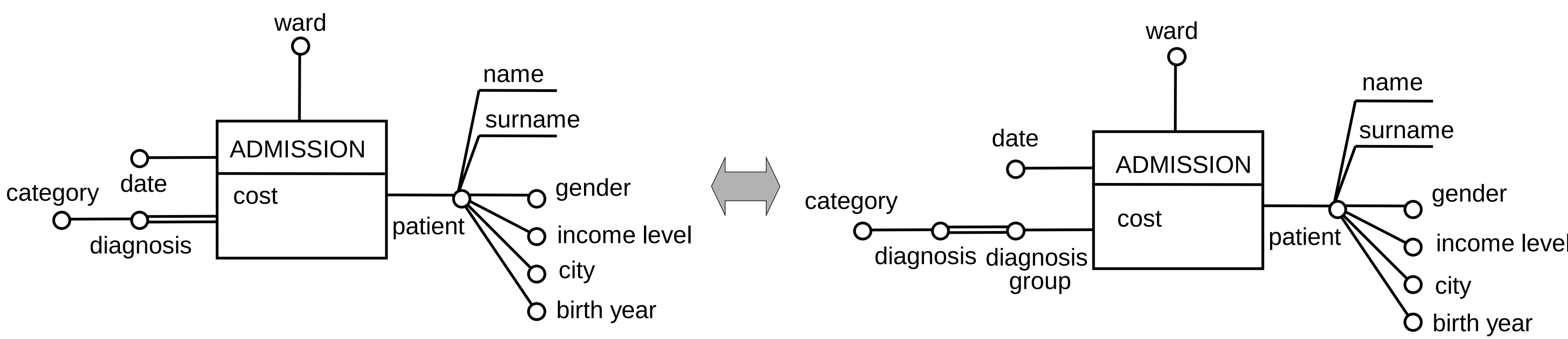

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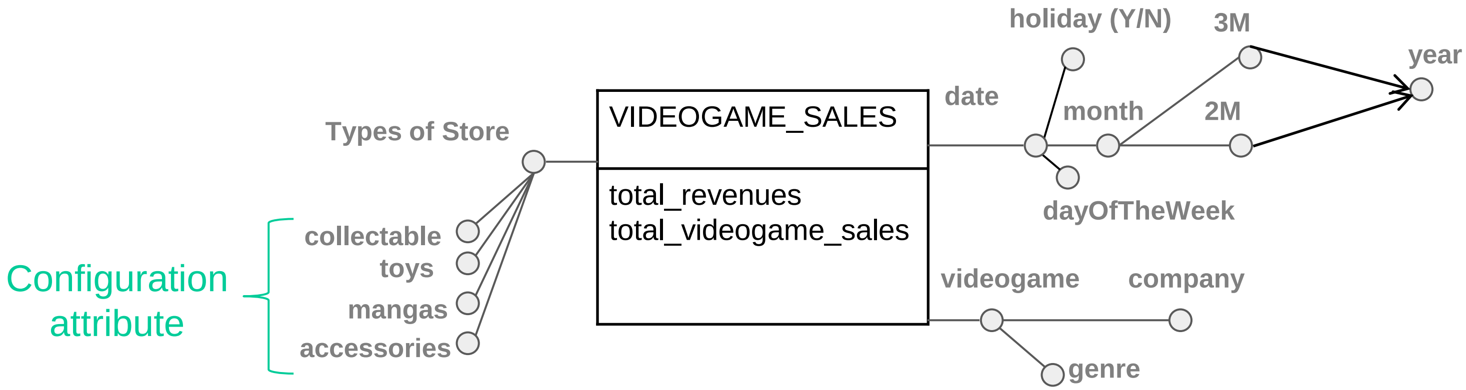
Configuration Attribute

- Multi-valued categorical attribute
  - it can assume several values at the same time
  - characterized by a few distinct values (<=10)
- Representation by enumerating possible values
  - each attribute takes a boolean value (Y/N)
  - easier writing of complex queries



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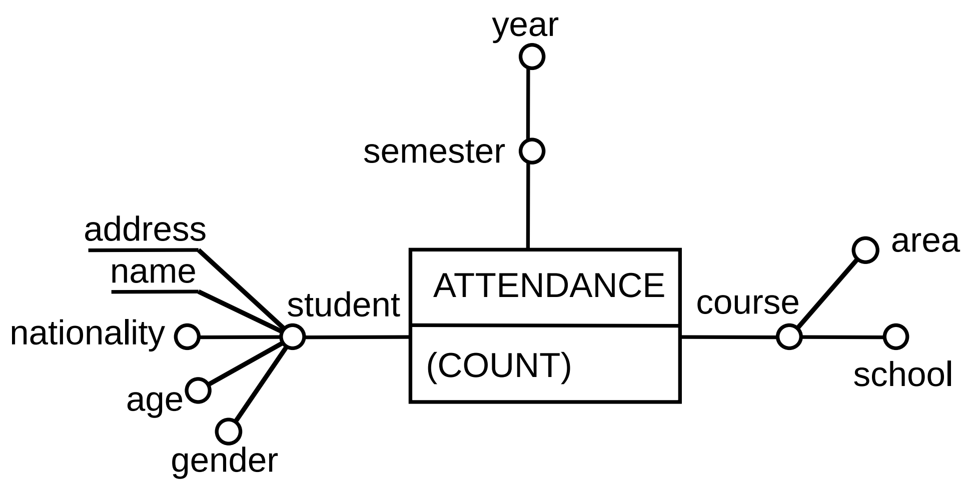
Factless fact schema

- Some events are not characterized by measures
  - empty (i.e., factless) fact schema
  - it records occurrence of an event
- Used for
  - counting occurred events (e.g., course attendance)
  - representing events not occurred (coverage set)



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Representing time

- Data modification over time is explicitly represented by event occurrences
  - time dimension
  - events stored as facts
- Also dimensions may change over time
  - modifications are typically slower
    - slowly changing dimension [Kimball]
  - examples: client demographic data, product description
  - if required, dimension evolution should be explicitly modeled

How to represent time (type I)

- Snapshot of the current value
  - data is overwritten with the current value
  - it overrides the past with the current situation
  - used when an explicit representation of the data change is not needed
  - example
    - customer Mario Rossi changes marital status after marriage
    - all his purchases correspond to the “married” customer

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How to represent time (type II)

- Events are related to the temporally corresponding dimension value
  - after each state change in a dimension
    - a new dimension instance is created
    - new events are related to the new dimension instance
  - events are partitioned after the changes in dimensional attributes
  - example
    - customer Mario Rossi changes marital status after marriage
    - his purchases are partitioned in purchases performed by “unmarried” Mario Rossi and purchases performed by “married” Mario Rossi (a new instance of Mario Rossi)

How to represent time (type III)

- All events are mapped to a dimension value sampled at a given time
  - it requires the explicit management of dimension changes during time
    - the dimension schema is modified by introducing
      - two timestamps: validity start and validity end
      - a new attribute which allows identifying the sequence of modifications on a given instance (e.g., a “master” attribute pointing to the root instance)
    - each state change in the dimension requires the creation of a new instance

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How to represent time (type III)

- Example
  - customer Mario Rossi changes marital status after marriage
  - validity end timestamp of first Mario Rossi instance is given by the marriage date
  - validity start timestamp of the new instance is the same day
  - purchases are partitioned as in type II
  - a new attribute allows tracking all changes of Mario Rossi instance

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Workload

- Workload defined by
  - standard reports
  - approximate estimates discussed with users
- Actual workload difficult to evaluate at design time
  - if the data warehouse succeeds, user and query number may grow
  - query type may vary over time
- Data warehouse tuning
  - performed after system deployment
  - requires monitoring the actual system workload

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Data volume

- Estimation of the space required by the data mart
  - for data
  - for derived data (indices, materialized views)
- To be considered
  - event cardinality for each fact
  - domain cardinality (number of distinct values) for hierarchy attributes
  - attribute length
- It depends on the temporal span of data storage
- Sparsity
  - occurred events are not all combinations of the dimension elements
  - example: the percentage of products actually sold in each shop and day is roughly 10% of all combinations

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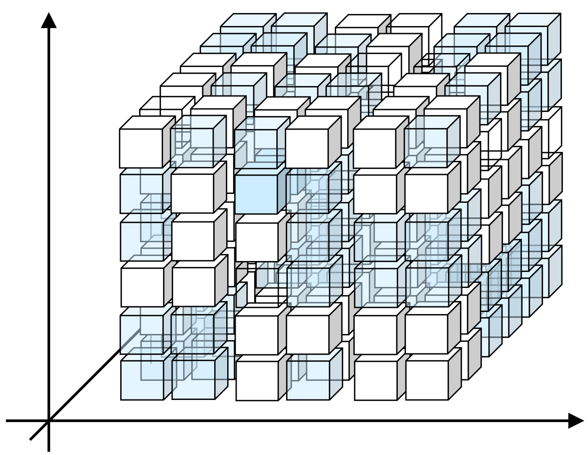
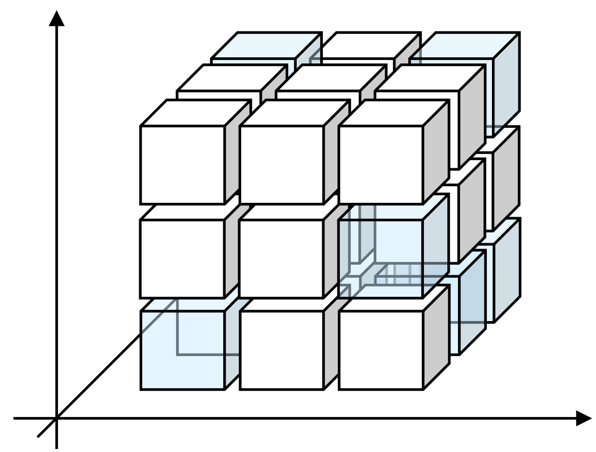
Sparsity

- It decreases with increasing data aggregation level
- May significantly affect the accuracy in estimating aggregated data cardinality





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Logical design

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Logical design

- We address the relational model (ROLAP)
  - inputs
    - conceptual fact schema
    - workload
    - data volume
    - system constraints
  - output
    - relational logical schema
- Based on different principles with respect to traditional logical design
  - data redundancy
  - table denormalization

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Star schema

- Dimensions
  - one table for each dimension
  - surrogate (generated) primary key
  - it contains all dimension attributes
  - hierarchies are not explicitly represented
    - all attributes in a table are at the same level
  - totally denormalized representation
    - it causes data redundancy
- Facts
  - one fact table for each fact schema
  - primary key composed by foreign keys of all dimensions
  - measures are attributes of the fact table

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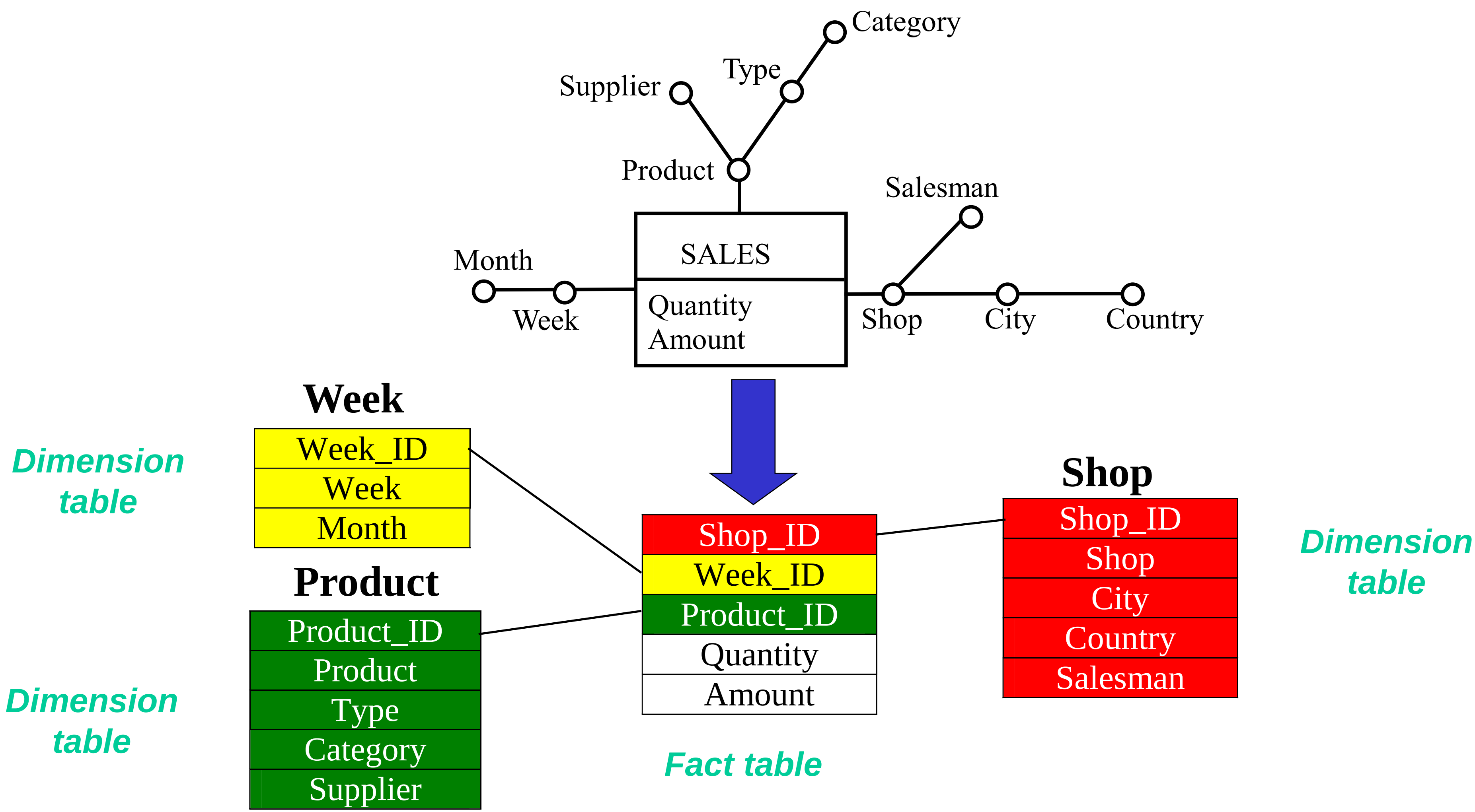
Star schema



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Snowflake schema

- Some functional dependencies are separated, by partitioning dimension data in several tables
  - a new table separates two branches of a dimensional hierarchy (hierarchy is cut on a given attribute)
  - a new foreign key correlates the dimension with the new table
- Decrease in space required for storing the dimension
  - decrease is frequently not significant
- Increase in cost for reading entire dimension
  - one or more joins are needed

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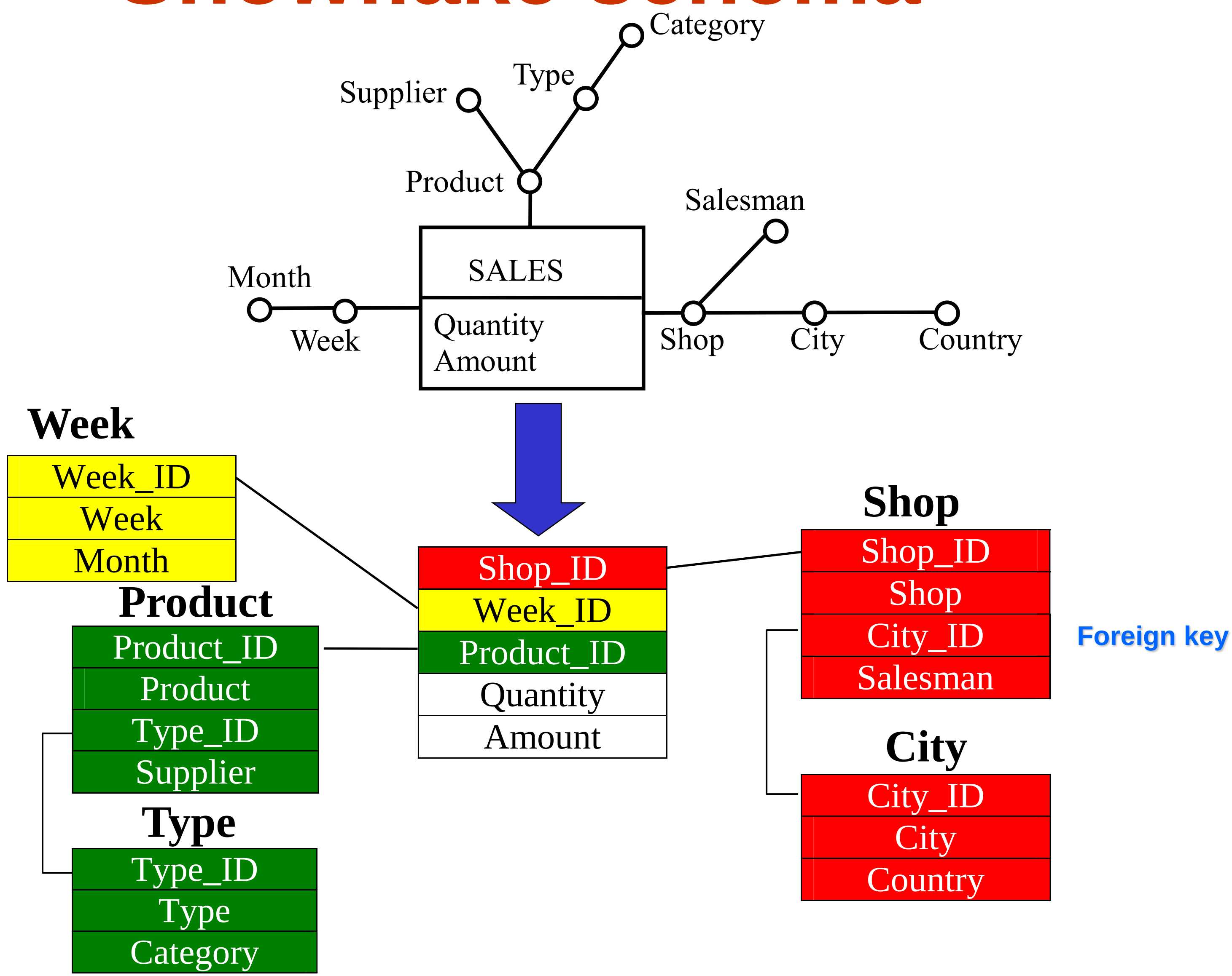
Snowflake schema



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Star or snowflake?

- The snowflake schema is usually not recommended
  - storage space decrease is rarely beneficial
    - most storage space is consumed by the fact table (difference with dimensions is several orders of magnitude)
  - cost of join execution may be significant
- The snowflake schema is rarely used in the data mart design

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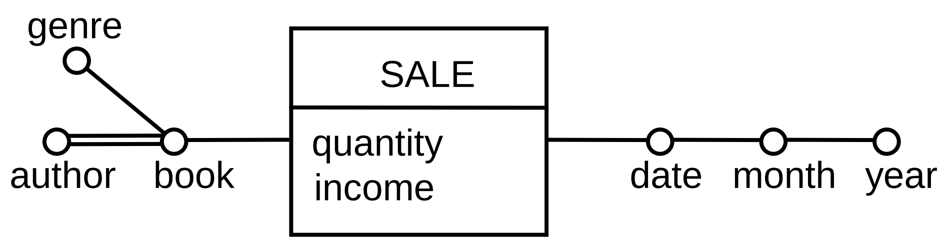
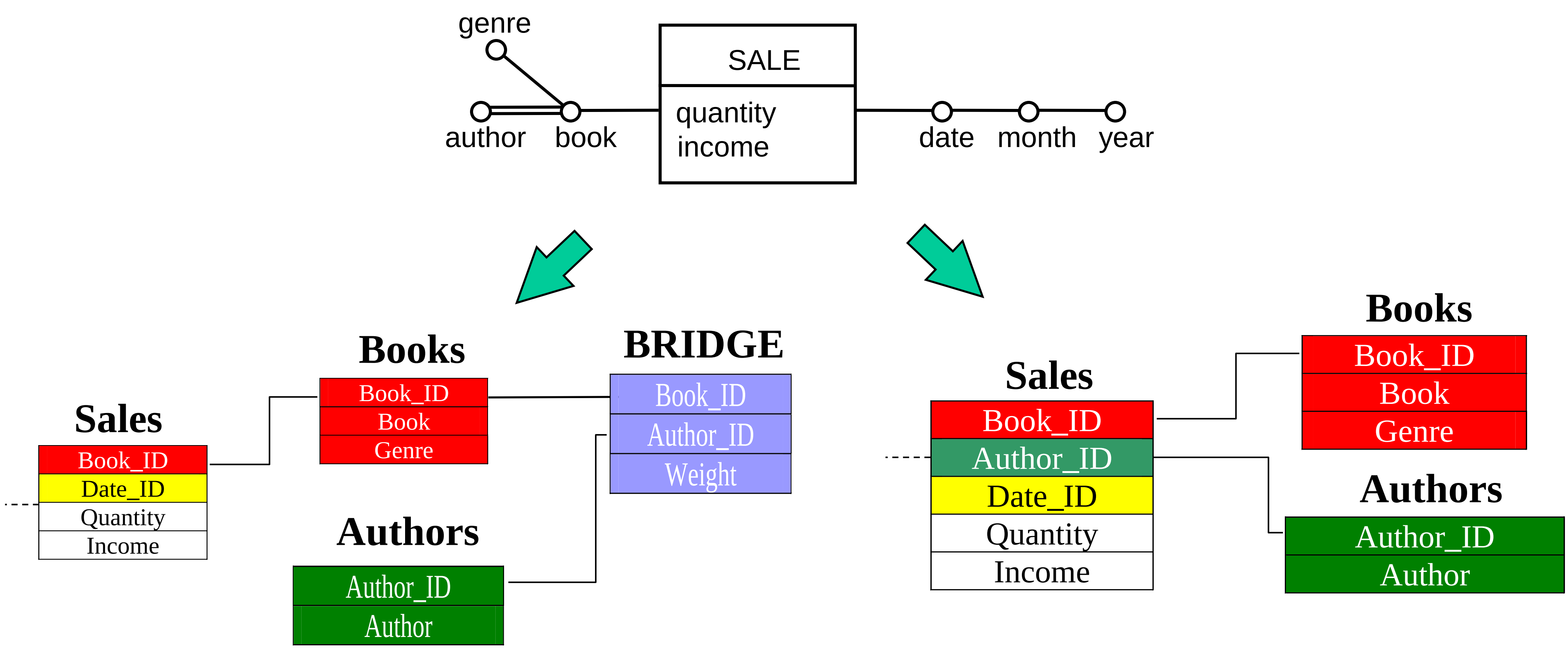
Multiple edges



- Implementation techniques
  - bridge table
    - new table which models many to many relationship
    - new attribute weighting the contribution of tuples in the relationship
  - push down
    - multiple edge integrated in the fact table
    - new corresponding dimension in the fact table

Multiple edges



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Multiple edges

- Queries
  - Weighted query: consider the weight of the multiple edge
    - example: author income
    - by using bridge table:

```
SELECT Author_ID, SUM(Income*Weight)
...
group by Author_ID
```

  - Impact query: do not consider the weight of the multiple edge
    - example: book copies sold for each author
    - by using bridge table:

```
SELECT Author_ID, SUM(Quantity)
...
group by Author_ID
```


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Multiple edges

- Comparison
  - weight is explicited in the bridge table, but wired in the fact table for push down
    - (push down) hard to perform impact queries
    - (push down) weight is computed when feeding the DW
    - (push down) weight modifications are hard
  - push down causes significant redundancy in the fact table
  - query execution cost is lower for push down
    - less joins

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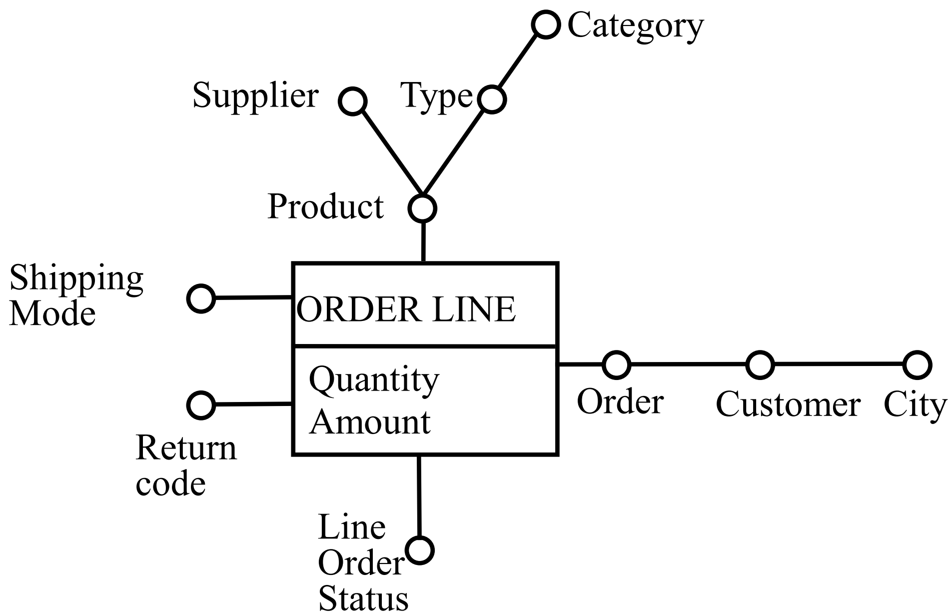
Degenerate dimensions

- Dimensions with a single attribute



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Degenerate dimensions

- Implementations
  - Integration into the fact table
    - for attributes with a (very) small size
  - junk dimension
    - single dimension containing several degenerate dimensions
    - no functional dependencies among attributes in the junk dimension
      - all attribute value combinations are allowed
      - feasible only for attribute domains with small cardinality

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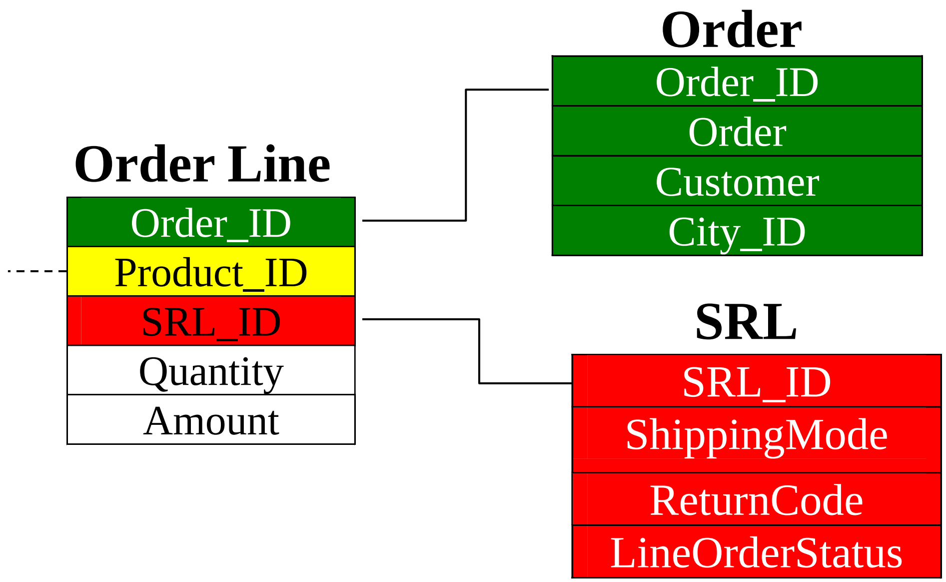
Junk dimension



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