Armazéns de Dados

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Brief Introduction to Dimensional Data Modeling

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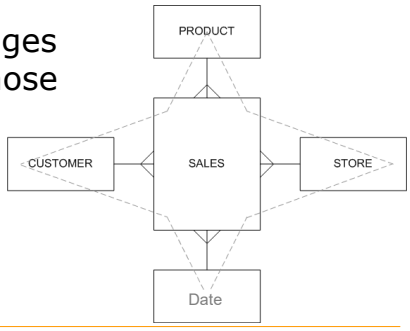
Dimensional Modeling

- Data modeling for DW is also known as **star schema creation**
- Based on **fact tables** and **dimension tables**
- Dimensional model is very **asymmetric**
  - one large dominant table in the center of the schema: **fact table**, with multiple joins connecting to **dimension tables**
- **Dimensional model** packages the data in a format whose design goals are:
  - **User understandability**
  - **Query performance**
  - **Flexibility to change**



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Dimensional Modeling

- **Model simplicity** achieved by the reduced number of tables
  - Business users benefit because **data is easier to understand** and **navigate**
- Has also **performance benefits**
- Dimensional models are gracefully extensible to **accommodate change**
  - Can accommodate **new dimensions** as long as a single value of that dimension is defined for each existing fact row
  - Can accommodate **new facts** to the fact table, when the level of detail is consistent with the existing fact table
  - Can supplement preexisting dimension tables with **new attributes**

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Fact Table

- Primary table in a dimensional model
- Holds
  - Primary key made up by the foreign keys (composite primary key) that connects to dimension tables
  - Numerical measurements of the business (the facts), which may be analyzed using statistical functions
    - units_sold, value_sold, order_cost, units_ordered, …

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Dimension Tables

- Provide the **basis for analyzing data** in the fact table
- Used to answer ***"WHO"***, ***"WHAT"***, ***"WHEN"***, ***"WHERE"*** and ***"WHY"*** questions about the business events stored in the fact table
- Each dimension table has a **non-composite primary key** that usually corresponds to one of the components of the composite key in the fact table

Fact and Dimension Tables

- There is a **1:N** relationship between each **dimension table** and the **fact table**
- **Fact tables** typically have large volumes of rows, while **dimension tables** have a smaller number
  - Key advantage: **JOIN performance is improved** when one large table can be joined with some small tables
  - In many cases the **dimension tables** are small enough to **be fully cached in memory**

Schema Types

- **Star schema**
  - Fact table in the middle connected to a set of dimension tables
- **Snowflake schema**
  - Refinement of star schema where some dimensional table is normalized into a set of smaller dimension tables, forming a snowflake
- **Galaxy schema/Fact constellation**
  - Multiple fact tables share dimension tables, viewed as a collection of star schemas

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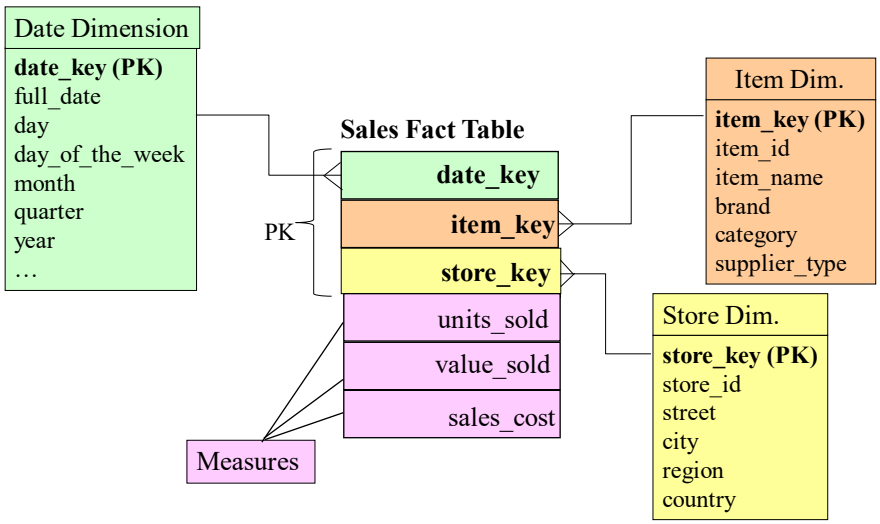
Example of a Star Schema



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Date Dimension Example

date_key	fulldate	day	day_of_week	month	quarter	year	...
...	...	...	...	...	...	...	...
727	28/12/2022	28	wednesday	12	4	2022	...
728	29/12/2022	29	thursday	12	4	2022	...
729	30/12/2022	30	friday	12	4	2022	...
730	31/12/2022	31	saturday	12	4	2022	...
731	01/01/2023	1	sunday	1	1	2023	...
...	...	...	...	...	...	...	...

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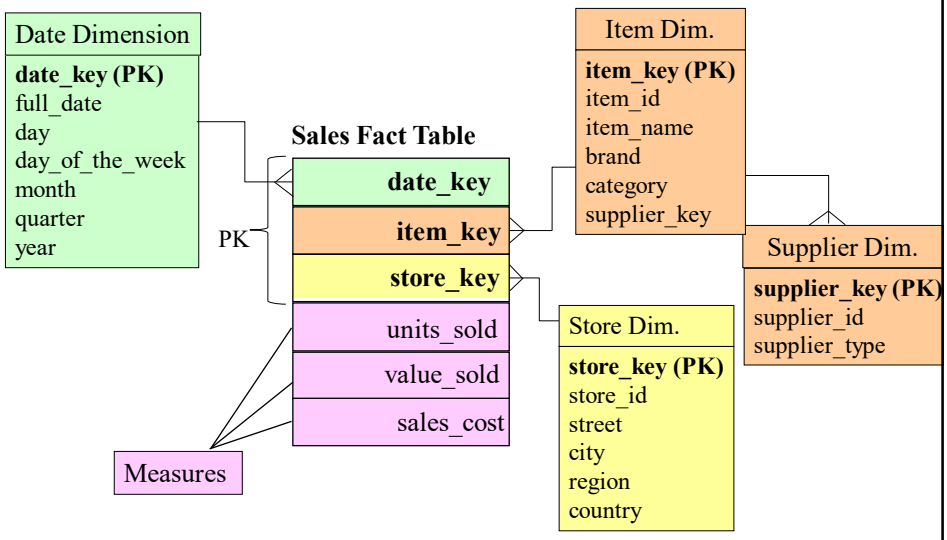
Example of a Snowflake Schema



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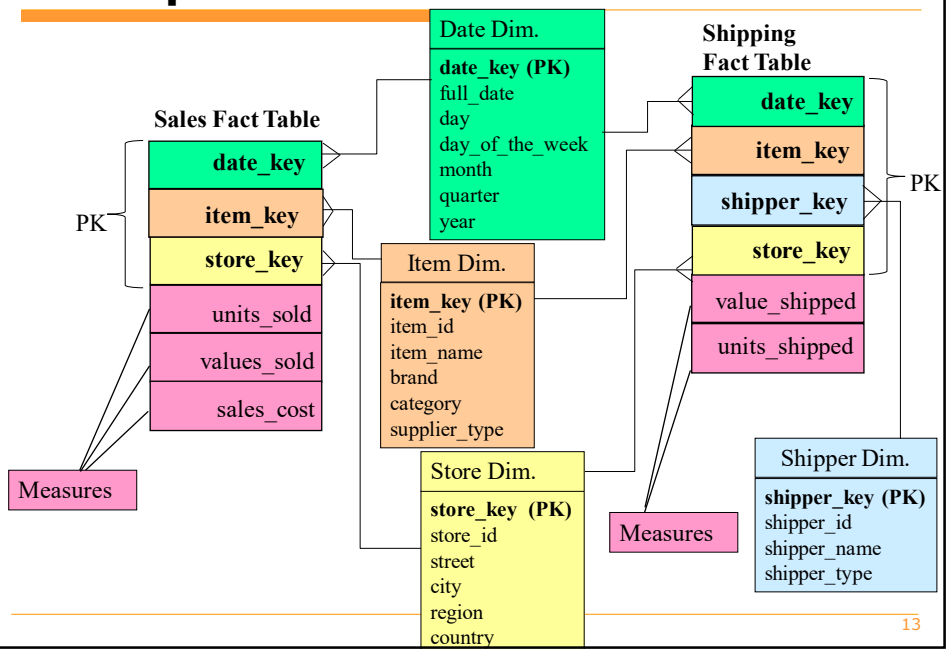
Example of Fact Constellation



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Dimensional Data Modeling

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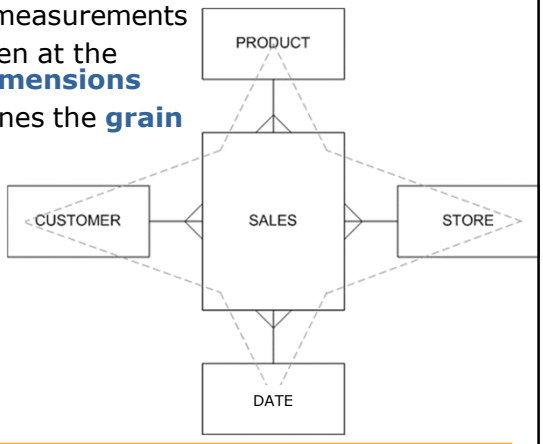
Dimensional Modeling

- Build around the **numerical measurements** of the business
  - Fact tables contain **measurements**
  - Dimension tables contain the **context** surrounding measurements
  - Measurements are taken at the **intersection of all dimensions**
  - List of dimensions defines the **grain of the fact table**



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Fact Table

- Is the **primary table** in a dimensional model
- Holds the **measurements** of the business
- Composed by a **set of foreign keys** that connect to the dimension tables
- Its primary key is made up by **the set or a subset of the foreign keys**
- Role of a **normalized n-ary associative entity**
- All measurements in a fact table must be at the **same grain**

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Importance of the Granularity Level

- **Business perspective** – it dictates the potential capability and flexibility of the DW
  - It is **impossible** to **answer questions** that **require details below the adopted level**
- **Technical perspective** – is one of the **major determinants of the DW size**
  - Has a significant impact on its **operating costs** and **performance**
- **Project perspective** – affects the amount of work that the project team will need to perform to create the DW
  - As the granularity level gets into greater levels of detail, the project team **needs to deal with more attributes and their relationships**

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Fact Table doesn't store "non-events"

- Very important **not to try** to fill the fact table with zeros representing "nothing happened"
  - If there is no sales activity on a given day, in a given store, for a given product, the record must be left out of the fact table
- By only including true activity, **fact tables** tend to be **quite sparse**
- Despite their sparsity, **fact tables usually make up 90% or more of the total space consumed** by a dimensional database

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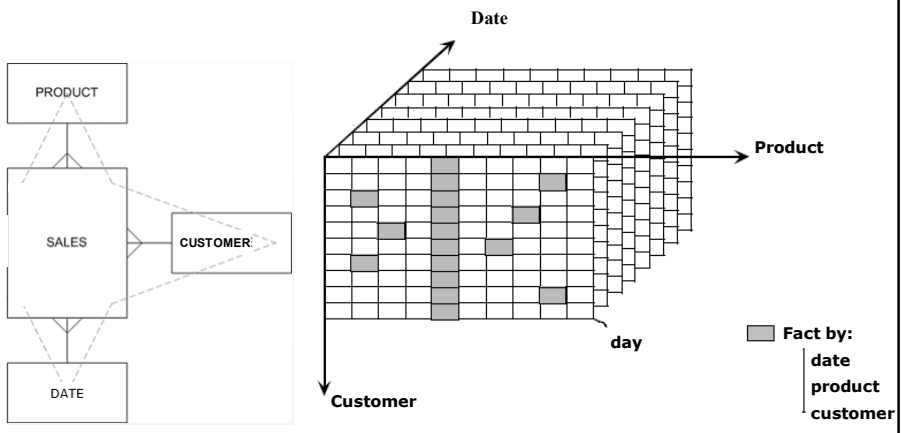
Sparsely Fact Table



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Kind of Facts

- **Additive facts**

  Best and most useful facts because DW applications bring thousands, or even millions of fact rows at a time, and the most useful thing to do is to add them

- **Semi-additive facts**

  Can be added only along some of the dimensions

- **Non-additive facts**

  Simply cannot be added at all – can be counted or averaged

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Kind of Facts

- **Additive facts**

Product Sales			
Product	Day 1	Day 2	Product Total
P1	200 €	300 €	500 €
P2	30 €	20 €	50 €
P3	100 €	300 €	400 €
P4	40 €	60 €	100 €
P5	300 €	100 €	400 €
Day Total	670 €	780 €	1 450 €

- **Semi-additive facts**

Customer Balance			
Customer	Day 1	Day 2	Customer Total
C1	200 €	300 €	500 €
C2	300 €	100 €	400 €
C3	100 €	100 €	200 €
C4	400 €	200 €	600 €
C5	30 €	40 €	70 €
Day Total	1 030 €	740 €	

- **Non-additive facts**

Sales Margin (sales profit / value sold)			
Product	Day 1	Day 2	Product Total
P1	33%	35%	68%
P2	27%	27%	54%
P3	45%	43%	88%
P4	17%	16%	33%
P5	8%	12%	20%
Day Total	130%	133%	263%

Dimension Tables

- Define the details of each transaction
- Dimension tables answer the "**who**", "**what**", "**when**", "**where**" and "**why**" of a business event
  - For example, a sales transaction may be defined by a number of components:
    - Customer: **who** made the purchase
    - Product: **what** was sold
    - Store: **where** it was sold
    - Date: **when** it was sold
    - Promotion: **why** it was sold

Dimension Tables

- **Provide the context for fact tables**, that is, the context for all the **measures**
- Dimension tables have many columns or attributes
  - Usual for a dimension to have between 50 to 100 attributes
  - Relatively small in terms of the number of rows
  - Usually **much smaller than fact tables**
- Best attributes are **textual** and **discrete**
- **Entry points** into the fact table

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Dimension Attributes

- Serve as the primary source of **query constraints**, **groupings**, and **report labels**
- Key to making the DW usable and understandable – **DW is only as good as the dimension attributes**
- Each dimension is defined by its **single primary key – surrogate key**, which serves as the basis for referential integrity with the fact table(s) to which it is joined

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Surrogate Keys

- Joins between dimensions and fact tables should be based on **meaningless integer surrogate keys**
  - Other names: integer keys, *no natural* keys, artificial keys, synthetic keys
- Must be assigned **sequentially**
- **Benefits:**
  - Performance advantages
  - Protects the DW from operational changes
  - Allow the integration of data from multiple operational source systems
  - Allow to define artificial keys without meaning in operational systems, like "not applicable", "no effect", …

Dimension Tables - Hierarchies

- Dimension tables typically are **highly denormalized**
- Often contain **hierarchical relationships** in the business
  - Example: Product dimension table – products roll up into subcategories and then into categories
- Hierarchical descriptive information is **stored redundantly**, to promote **ease of use and query performance**
- Usually small
  - < 10% of total data storage requirements
  - Since dimension tables are geometrically smaller than fact tables, **improving storage efficiency by snow-flaking has virtually no impact on the overall database size**

The Grocery Store

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Grocery Store Business - Brief Description

- The business has **500 large grocery stores** spread over the country. Each store is divided by **departments** such as grocery, frozen foods, dairy, meat, bakery, floral, drugs,… Each store has roughly **60000 individual products** (called **Stock Keeping Units** – **SKUs**) on its shelves. About 40000 SKUs come from outside manufactures and have bar codes called **Universal Product Codes** – **UPCs**.
- The remaining 20000 SKUs come from departments like the meat, bakery, or floral departments and don't have UPC codes. Nevertheless, as a grocery store, these products **also have SKU numbers** assigned to them.
- At the grocery store, management is concerned with the sales of the products as well as maximizing the profit at each store. The most significant management decisions have to do with **pricing**, **promotions** and **good visibility of promotions**.

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Kimball Dimensional Modeling Steps

1. Identify the business process

- Business process is a major operational process supported by some computational system(s) from which data can be collected for the purpose of data warehousing (e.g.: orders)

2. Identify the level of detail (grain)

- Detail level of the data to be represented in the fact table
- Determines the dimensionality of the underlying database and has a profound impact on its size

3. Identify the dimensions

- Choose the dimensions that will apply to each fact table
- For each dimension describe all its attributes

4. Identify the facts

- Choose the measures that will populate each fact table record

Modelling Grocery Store Business

1. Business process

- Sales

2. Granularity level (level of detail)

Options:

- Sales of products by store by promotion and by individual customer ticket transaction
  - ⮑ In this grocery store chain, there is no effective way of identifying individual customers at the cash register
- Sales of products by store by promotion and by day (or by week or by month)
  - ⮑ Weekly or monthly storage item movement would miss too many important analysis, such as difference in sales between Mondays and Saturdays

Best grain for this grocery store chain DW is considered to be the **product (or SKU) sales, by store, by promotion and by day**

Modelling Grocery Store Business

3. Dimensions involved

- Date
- Product
- Store
- Promotion

4. Facts/Measures of interest

- Value sold
- Units sold
- Sales cost
- Sales profit
- Sales margin

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Date Dimension

- **Date dimension** is present in every DW, because every DW is a time series

Date Dimension
date-key
full-date
day-week
day-number-month
day-number-year
week-number
month-name
month-number
semester
quarter
year
last-day-month-flag
season
…

Unlike almost all the other dimensions, **date dimension can be build in advance** – five or ten year of history records can be loaded, as well the next few years

- Surrogate key assigned to the date dimension **should be assigned consecutively in the order of date**
- It's the only dimension where the **surrogate key has a relationship with the underlying semantics** of the dimension

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Time of Day as a Dimension or Fact

- **Time (of day) dimension** has one row per discrete time period necessary to the business
  - Example: each second or minute within a 24-hour period
- **Time (of day) must be separated from the date dimension** to avoid an explosion in the row count
- **Preferred modeling design if we need to support the roll-up of time periods into more summarized groupings** for reporting and analysis, such as 15-minute interval, half-hours, hours, …
- If there is no need to roll up/drill down or filter on time-of-day groups, then **time can be treated as a simple numeric fact**
  - Time of day can be expressed as the number of minutes or seconds since 00:00

Separate Date and Time Dimensions

date_key	fulldate	day	day_of_week	month	quarter	year	...
...	...	...	...	...	...	...	...
727	28/12/2022	28	wednesday	12	4	2022	...
728	29/12/2022	29	thursday	12	4	2022	...
729	30/12/2022	30	friday	12	4	2022	...
730	31/12/2022	31	saturday	12	4	2022	...
...	...	...	...	...	...	...	...

time_key	fulltime	hour	minute	second	period	...
...	...	...	...	...	...	...
1527	11:03:20	11	03	20	Morning	...
1528	11:03:21	11	03	21	Morning	...
1529	11:03:22	11	03	22	Morning	...
1530	11:03:23	11	03	23	Morning	...
...	...	...	...	...	...	...

Separate Date and Time Dimensions

- Nr. of Records for Date Dimension
  - Granularity: day
  - Period: 20 years
  - 365 * 20 + 5 (leap years) = 7 305 records
- Nr. of Records for Time Dimension
  - Granularity: second
  - Period: 24 hours
  - 60 * 60 * 24 = 86 400 records

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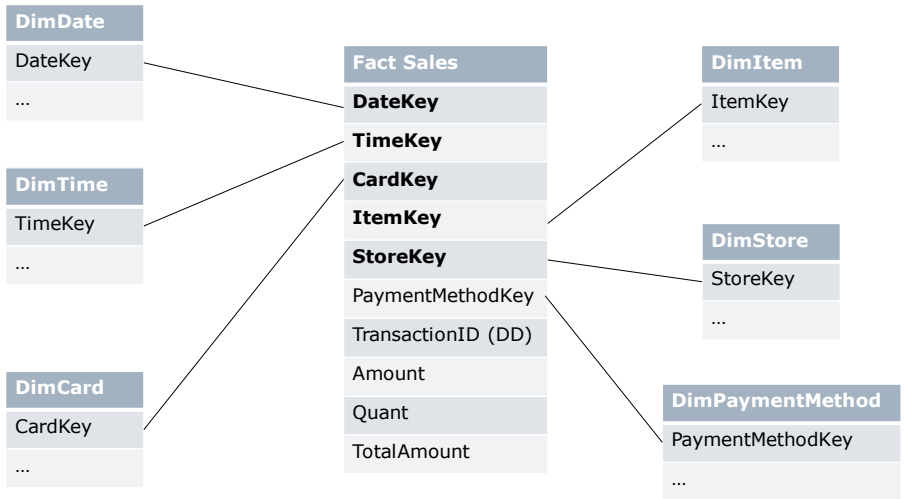
Separe Date and Time Dimensions



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Single Date and Time Dimension

datetime_key	fulldate	day	day_of_week	fulltime	hour	minute	second
…	…	…	…	…	…	…	…
17274	28/12/2022	28	wednesday	11:03:20	11	03	20
17275	28/12/2022	28	wednesday	11:03:21	11	03	21
17276	28/12/2022	28	wednesday	11:03:22	11	03	22
17277	28/12/2022	28	wednesday	11:03:23	11	03	23
17278	28/12/2022	28	wednesday	11:03:24	11	03	24
17279	28/12/2022	28	wednesday	11:03:25	11	03	25
17280	28/12/2022	28	wednesday	11:03:26	11	03	26
17281	28/12/2022	28	wednesday	11:03:27	11	03	27
…	…	…	…	…	…	…	…

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Single Date and Time Dimension

- Nr. of Records for Date Dimension
  - Granularity: day second
  - Period: 24 hours of 20 years
  - (365 * 20 + 5) * (60 * 60 * 24) =
    7 305 * 86 400 = 631 152 000 records

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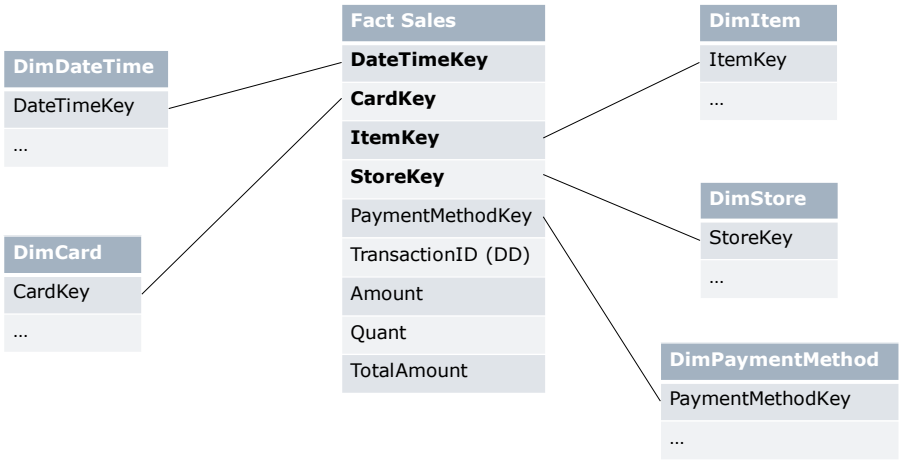
Single Date and Time Dimension



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Product Dimension

Product dimension describes every SKU with as many descriptive attributes as possible, including the **existing hierarchies**

Product Dimension
product-key SKU-description SKU-number package-size brand **subcategory** **category** **department** package-type diet-type weight weight-unit ...

It is possible to **browse** among dimension attributes **whether or not they belong to a hierarchy** and it is possible to **roll up** and **drill down** using the attributes that **belong to a hierarchy**

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Store Dimension

Store dimension describes every store in the grocery chain – **geographic dimension**

Store Dimension
store-key
store-name
store-number
store-address
store-zip
store-city
store-district
store-region
store-manager
open-date
last-remodel-date
store-sqft
grocery-sqft
…

Numeric attributes, however they are clearly a constant attribute of store

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Promotion Dimension

- **Promotion dimension** – describes each promotion condition under which a product is sold in the grocery chain
- **Causal dimension** – describes factors that cause a change in product sales
- Needs a **special register "N/A"** to join sales in fact table without promotion

Promotion Dimension
promotion-key
promotion-name
price-reduction-type
ad-type
display-type
coupon-type
ad-media-name
display-provider
promo-cost
promo-begin-date
promo-end-date
…

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Fact Table

Sales Fact
date-key
product-key
store-key
promotion-key
value-sold
units-sold
sales-cost
sales-profit

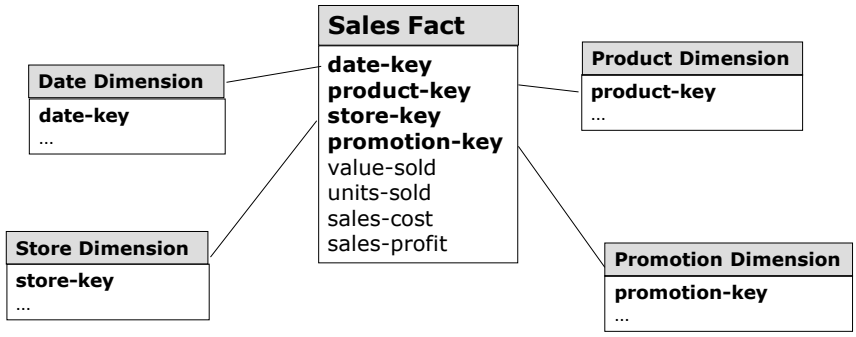
date-key	...	value-sold	units-sold	sales-costs	sales-profit	sales- margin
101	...	780	78	263	517	0,66
102	...	1044	18	580	464	0,44
103	...	213	10	140	73	0,34
104	...	95	19	39	56	0,59
Total		**2132**	**125**	**1022**	**1110**	**0,52**

Business Measures / Facts

Is not stored in the Fact Table

- First three facts are **additive**
- **sales-profit** = value-sold – sales-cost → **additive**
- **sales-margin** = sales-profit / value-sold
  - ↪ **No-additive calculation** – can be calculated for any slice of fact table by calculating the sales profit and value sold before dividing

Grocery Store Business Schema



Advantages:
- Easy to understand
- Better performance
- Easy extensible: new dimensions and new facts

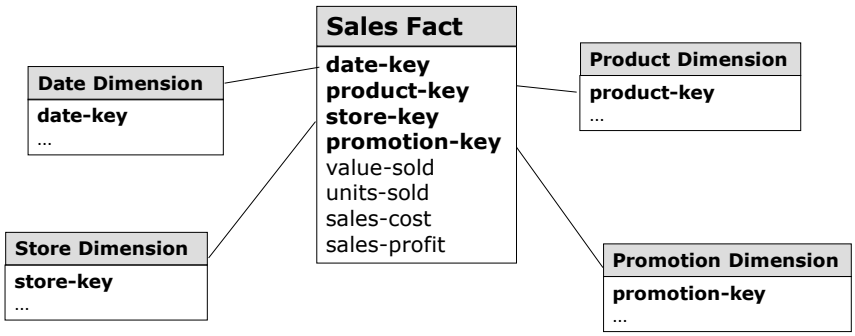
Typical Query on a Star Schema

- **Sales** for the **year of 2019** of the **store "Oxford Street"** by **brand**

```
SELECT p.brand, sum(f.value-sold), sum(f.units-sold)
FROM Product p, Date d, Store s, SalesFact f
WHERE  f.product-key = p.product-key
  AND  f.store-key = s.store-key
  AND  f.date-key = d.date-key
  AND  d.year = 2019
  AND  s.store-name = "Oxford Street"
GROUP BY p.brand
```

- First, **constraints (slicing) are processed** for each dimension
- Each dimension produce **a set of candidate keys**
- Candidate keys **are combined (by Cartesian product) to build the composite keys to be searched in the fact table**
- All rows in the fact table are **selected, grouped and aggregated according to the query**

Grocery Store Business Schema



- Grocery store star schema cannot answer an important question:
  - **What products were on promotion but didn't sell ?**

Factless Fact Table

- Sales fact table **only records products sold** – there are no fact table rows with zero facts
- To know which products on promotion that didn't sell is necessary a **second fact table promotion**
- Promotion coverage fact table
  - Keys: date, product, store, and promotion
  - Grain: **one row for each product on promotion in a store each day**
  - Measures: no measures
    - This kind of fact table without metrics is called **Factless Fact Table**

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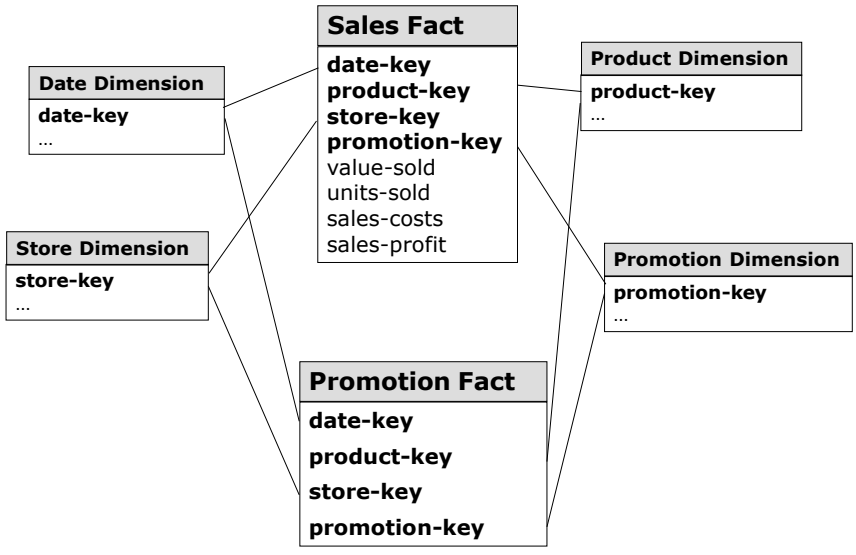
Factless Fact Table (Promotion Fact)



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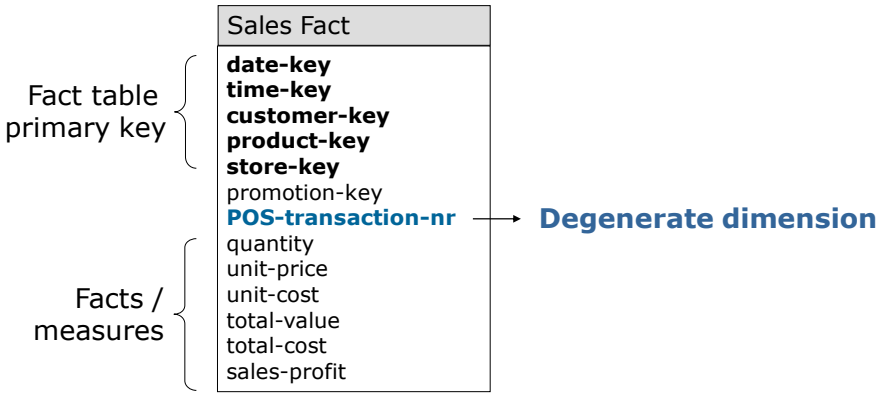
Degenerate Dimension



- Document control numbers such as order numbers, invoice-numbers,… are represented as **degenerate dimensions** – **dimension keys with no corresponding dimension tables**
- Provide a **direct reference to the operational system**

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Dimensional Model for Inventory Periodic Snapshot

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Modelling Inventory Periodic Snapshot

1. **Business process**
   - Inventory
     - Optimized inventory levels can have an impact on profitability
     - Making sure the **right product** is in the **right store** at the **right time** minimizes out-of-stocks and reduces overall inventory carrying costs
2. **Granularity**
   - Daily quantity on stock by product and store
3. **Dimensions**
   - Date
   - Product
   - Store
4. **Facts**
   - Quantity on stock
   - ...

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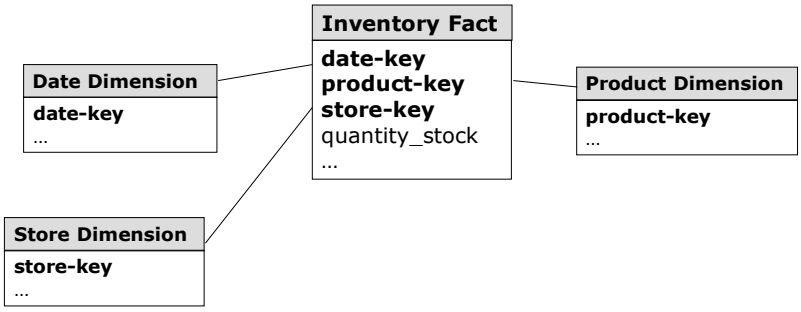
Inventory Periodic Snapshot Schema



- Dimensions **are the same** as on the grocery store schema
- Dimension tables **must have additional attributes useful for inventory analysis**, such as:
  - Product dimension: Minimum reorder quantity
  - Store dimension: Frozen and refrigerated storage square footages

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Fact Table Sizing

- Inventory fact tables are **very dense** by nature – every product must be represented in every store, every day
  - 60000 products × 500 stores × 1095 days (3 years) = 32,85 billion records
  - Size of fact record: 8 bytes
  - Fact table size = 32,85 billion records × 8 bytes = **244,75 GB**
- Dense inventory databases **require some compromises**
  - Keep the last 30 days of inventory at the daily level
  - Revert to weekly inventory the most recent 11 months
  - Revert to monthly inventory snapshots the prior two years
  - Instead of 1095 time snapshots, the number is reduced to:
    - 30 + 48 + 24 = 102 snapshots, which **reduces database size more than a factor of 10**

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Semi-additive Facts

Store	S1	S2
	2 un. P1	3 un. P1
	3 un. P2	1 un. P2
Day 1	1 un. P3	3 un. P3
	4 un. P4	2 un. P4
	3 un. P5	4 un. P5
	1 un. P1	2 un. P2
Day 2	3 un. P2	1 un. P2
	4 un. P3	5 un. P3
	2 un. P4	0 un. P4
	1 un. P5	1 un. P5

- Given a product and a date the **quantity on stock** can be summed-up by stores
- Given a product and a store **it is not possible to sum-up by date**
- Possible aggregations on store S1 for product P4:
  - Average = (4+2)/2=3 → **average over nr. of periods**
  - Min=2
  - Max=4

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Semi-additive Facts

All measures that represent snapshots of a level or balance at one point in time (inventory levels, financial account balances, and measures such as weights) are **inherently non-additive across the date (and time) dimension(s)** – in these cases, the measure may be aggregated usefully across date (and time), for example, **by averaging over the number of periods**

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Enhanced Inventory Facts

- **Quantity on stock** needs to be used in conjunction with additional facts to develop **other metrics**
  - Quantity sold
  - Stock financial value
    - Value of the Inventory Cost (VIC)
      - VIC = Stock Quantity * Unit Cost
    - Value of the Inventory at Latest Selling Price (VILSP)
      - VILSP = Stock Quantity * Unit Price
  - With previous measures is possible to calculate:
    - Gross Profit = VILSP - VIC
    - Gross Margin = Gross Profit / VILSP

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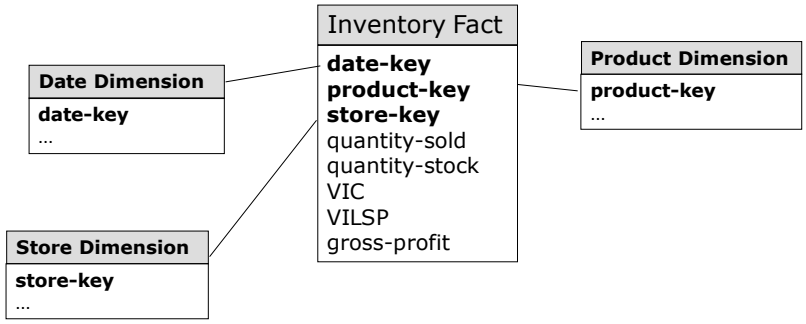
Enhanced Inventory Periodic Snapshot Schema



- Quantity-sold is **additive** across all dimensions
- Measures quantity-stock, VIC, VILSP, and gross-profit **are semi-additive**
- Gross margin is not stored in the fact table because it is **non-additive**

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Slowly Changing Dimensions

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Dimension Characteristics

- Up to this point we have assumed that dimensions are **independent of time**
- While **dimension table attributes are relatively static** in the real world, **their values are not fixed forever**
- **Dimension attributes can change slowly over time**
  - Products change size and weight
  - Customers relocate
  - Stores change layouts
  - Sales staff are assigned to different locations
- In a DW **it is necessary to know the history of values** to **match the history of facts** with the **correct dimensional records** at the time the facts happened

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Slowly Changing Dimension Techniques

- For **each attribute** in dimension tables, it is necessary a **strategy to handle change**
- When an **attribute value changes** in the operational system, the **five strategies most common** to respond to that change are:
  - **Type 1**: Overwrite the value
  - **Type 2**: Add a dimension row
  - **Type 3**: Add a dimension column
  - **Type 4**: New history table
  - **Type 6**: Hybrid approach
- Each strategy results in a **different degree of tracking changes** over time

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Type 1: Overwrite the Value

- **Overwrites the old attribute value** in the dimension row, **replacing it with the current value**
  - Attribute always reflects the most recent assignment
  - No changes are needed elsewhere in the dimension record
  - No keys are affected anywhere in the DW
  - Easiest to implement
  - **It is impossible to track history**
- **Appropriate for corrections or** when there is **no interest in** keeping the **old value**
  - Example: consider an electronic retailer whose marketing person decides that a specific software product **must belong to the Strategy department instead of the Education department**

Product Key	Product Description	Department	SKU Number (Natural Key)
12345	IntelliKidz 1.0	Education	ABC922-Z

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Type 1: Overwrite the Value

Updated row:

Product Key	Product Description	Department	SKU Number (Natural Key)
12345	IntelliKidz 1.0	Strategy	ABC922-Z

- Product key is the dimension key
- SKU is a natural key – must remain inviolate
- No dimension or fact table keys were modified when the IntelliKidz's department changed
- Rows in the fact table still reference product key 12345, regardless of IntelliKidz's departmental location
- **Any previous aggregations on this attribute will change and should be recalculated**
- **No history is recorded**

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Type 2: Add a Dimension Row

- **Create an additional dimension record at the time of the change with the new attribute value**
  - Segments history very accurately between the old description and the new description
- **Predominant technique** for supporting slowly changing dimensions
- **Represents prior history correctly**
- **Gracefully tracks as many dimension changes as required**
- **One downside is to accelerate dimension table growth**

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Type 2: Add a Dimension Row

Product Key	Product Description	Department	SKU Number (Natural Key)	Effective Date	Expired Date
12345	IntelliKidz 1.0	Education	ABC922-Z	11/02/2019	19/09/2020
25984	IntelliKidz 1.0	Strategy	ABC922-Z	19/09/2020	

- Each of the separate surrogate keys identifies **a unique product attribute profile that was true for a span of time**
- In the fact table
  - Fact rows for IntelliKidz prior to the date of change, would reference product key 12345
  - When the product was moved to the Strategy department, fact rows reference product key 25984 to reflect the change
- Constrains
  - On the **department attribute**, precisely differentiate between the two product profiles
  - On the **product description**, brings the complete product history
  - On the count distinct **SKU number** natural key, brings the correct number of products

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Type 2: Add a Dimension Row

- Includes an **effective and expired date stamp on a dimension row with type 2 changes**
  - Date stamp refers to the moment when the attribute values in the row **become valid** (or invalid in case of expiration date)
  - Effective and expiration date attributes **are needed** to know which surrogate key is valid when loading fact records
- **No need to update** existing aggregation tables

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Type 3: Add a Dimension Column

- Sometimes it is useful the ability to **see fact data as if the change never occurred**
- Happens most frequently with sales force reorganizations
  - District boundaries have been redrawn, but some users still want the ability to see **today's sales** in terms of **yesterday's district lines** just to see how they would have done under the old organizational structure
  - For a few transitional months, there may be a desire to track history in terms of the new district and conversely to track new data in terms of old district
- Type 2 SCD **doesn't support** this requirement
- While type 2 strategy partitions history, **it does not allow to associate the new attribute value with old fact history, or vice versa**

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Type 3: Add a Dimension Column

- New dimension row is not created, but rather **a new column is added** to capture the attribute change
- In the case of IntelliKidz
  - Product dimension table is altered to add a **prior department** attribute
  - Prior department attribute is populated with the existing department value (Education)
  - Department attribute is updated to reflect the new value (Strategy)

Product Key	Product Description	Department	Prior Department	SKU Number (Natural Key)
12345	IntelliKidz 1.0	Strategy	Education	ABC922-Z

Type 3: Add a Dimension Column

- **All existing reports and queries use** the new department description immediately
  - Similar effect to Type 1 SCD
  - **Any previous aggregations must be recalculated**
  - Still possible to **analyse/report on the old department value** by querying on the **prior department** attribute
- Allows to see new and historical fact data by either the **new or prior attribute value**
- Appropriate when there is a strong need to **support two views of the world simultaneously**
- Although the change has occurred, it is still logically possible **to act as if it has not**
- **Inappropriate if it is necessary to track the impact of numerous intermediate attribute values** – in this case a type 2 response should be used

Type 4: New History Table

- Idea behind is **almost the same as SCD Type 2**
- Also maintains the historical data **but not in the same table**
- Creates a **new history table** to keep the historical data
- Makes dimensions smaller, reduces complexity and improves performance **if the majority of uses only need the current value**
- Provides a solution to handle **the rapid changes in the dimension tables**, that causes performance and maintenance issues when using SCD Type 2

Type 4: New History Table

First Time Load on 08-10-2020

Source Table

product_id	product_name	unit_price	product_desc	eligible_promotion	Sync
100	Prod1	100.5	Prod desc 1	1	0
101	Prod2	50	Prod desc 2	0	0

Target Table

product_key	product_id	product_name	unit_price	product_desc	eligible_promotion	start_date
1	100	Prod1	100.5	Prod desc 1	1	08-10-2020
2	101	Prod2	50	Prod desc 2	0	08-10-2020

Type 6: Hybrid Approach

- Hybrid approach that **combines the three fundamental SCD techniques**
- Characteristics
  - **Creates a new row** to capture the change (SCD Type 2)
  - **Has an attribute** to reflect an alternative view of the world (SCD Type 3)
  - **Values are overwritten** for all earlier dimension rows for a given change (SCD Type 1)
- **Type 6** = Type 2 + Type 3 + Type 1
- Adds current attributes alongside the historical attributes so measures can be **grouped by the historical or current dimension attribute values**

Type 6: Hybrid Approach

Original row in Product dimension:

Product Key	SKU (NK)	Product Description	Historic Department Name	Current Department Name	Row Effective Date	Row Expiration Date	Current Row Indicator
12345	ABC922-Z	IntelliKidz	Education	Education	2012-01-01		Current