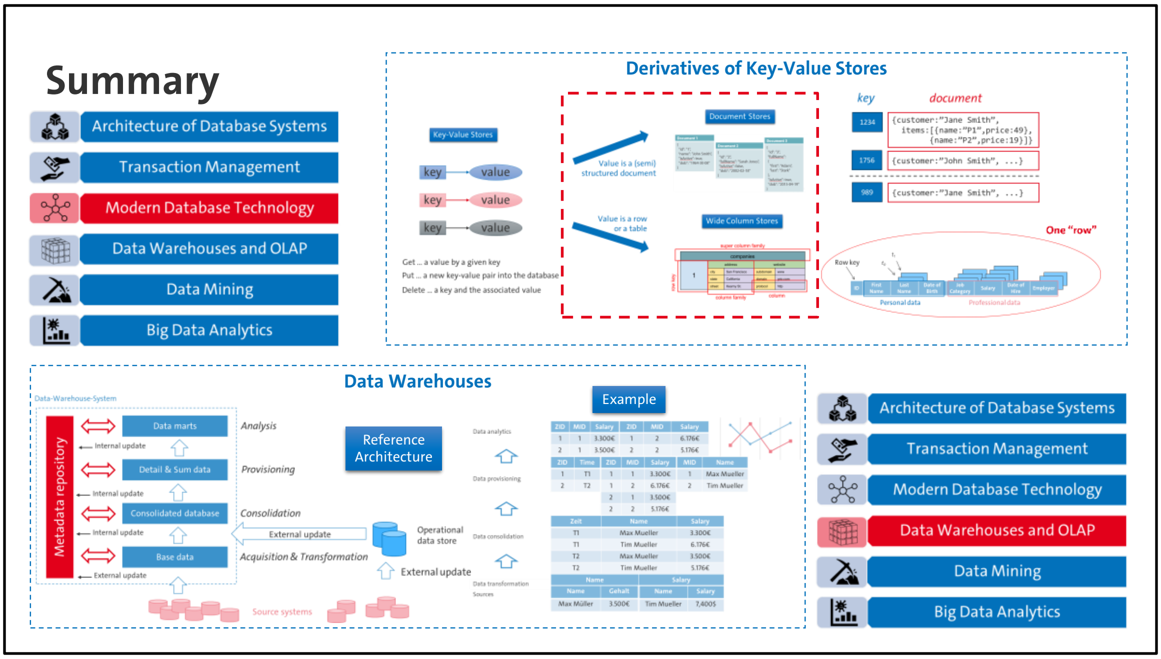
Summary
Architecture of Database Systems
Transaction Management
Modern Database Technology
Data Warehouses and OLAP
Data Mining
Big Data Analytics
Derivatives of Key-Value Stores
Key-Value Stores
key
value
Get ... a value by a given key
Put ... a new key-value pair into the database
Delete ... a key and the associated value
Value is a (semi) structured document
Document Stores
Value is a row or a table
Wide Column Stores
key
document
1234
{customer:"Jane Smith", items:[{name:"P1",price:49}, {name:"P2",price:19}]}
1756
{customer:"John Smith", ...}
989
{customer:"Jane Smith", ...}
One "row"
Row key
Personal data
Professional data
Data Warehouses
Data-Warehouse-System
Metadata repository
Data marts
Internal update
Detail & Sum data
Consolidated database
Base data
External update
Analysis
Provisioning
Consolidation
Acquisition & Transformation
Source systems
Reference Architecture
Operational data store
External update
Data analytics
Data provisioning
Data consolidation
Data transformation
Sources
Example
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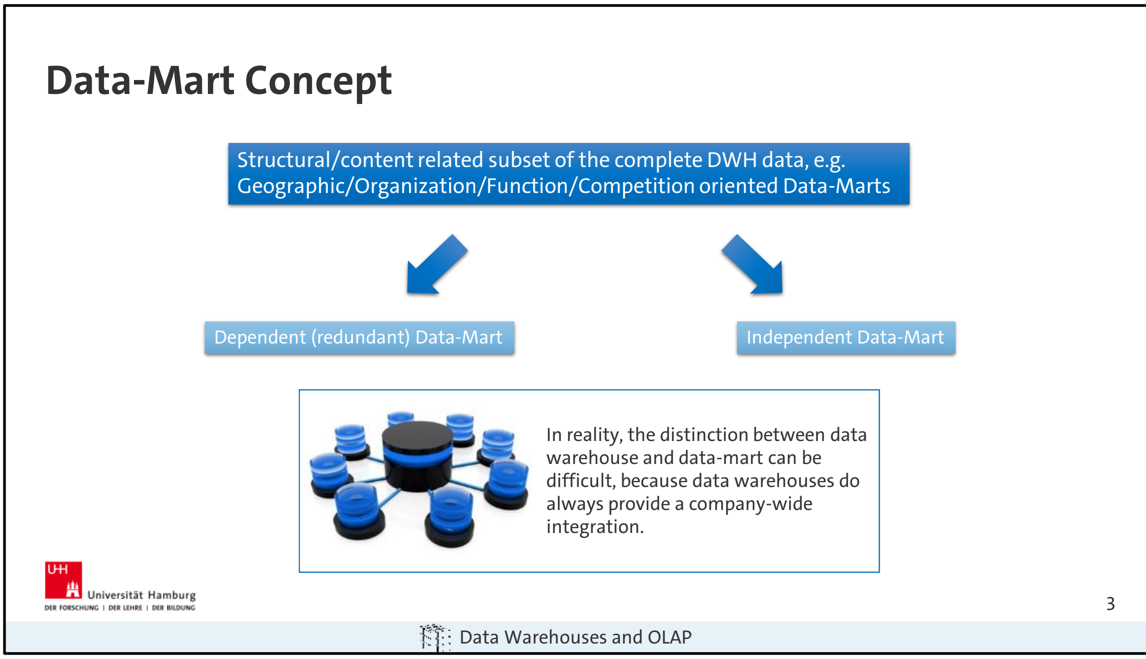


Why?

- Read-optimized layer: Data is stored in a denormalized data model for better read performance and better end user usability/understanding
- The Data Mart Layer is providing typically aggregated data or data with less history (e.g. latest years only) in a denormalized data model
- Dividing independent topics, ideally one subject per data mart
- Privacy aspects
- Reduction of data volume → Queries on the whole data warehouse can become a bottleneck
- Performance/Load distribution

DWH 2.0

- Structured and “unstructured” data
- Life cycle of data with different storage areas

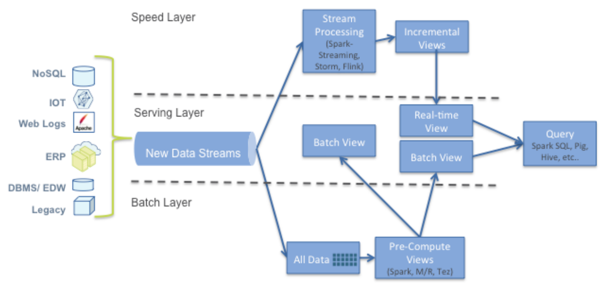
Hot data: High speed, expensive storage for most recent data

Cold data: Low speed, inexpensive, large storage for old data; archival data model with compression

- Metadata s an integral part of the DWH, not just an afterthought

W.H. H. Inmon, Derek Strauss, Genia Neushloss: DW 2.0: The Architecture for the Next Generation of Data Warehousing

Lambda Architecture (Big Data)



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Batch Layer

- DWH alike, correct & complete
- Output in Read-only DB, complete replacement
- Hadoop/Spark de facto standard

Speed Layer

- Stream processing
- Real-time, latency is king, „batch gap“
- Correct-/completeness minor concern
- Apache Storm, Spark etc.
- Output into fast NoSQL DBs
- Indexes most recently added data

Serving Layer

- Query processing
- Stores outputs, builds views
- Druid, Cassandra, HBase

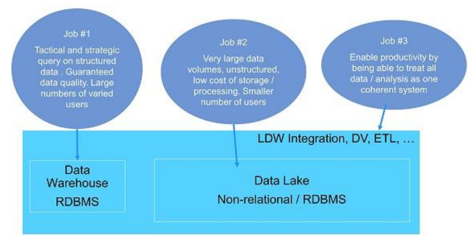
Example: Streaming service analytics

→ Speed layer: we need information about service issues → aggregate only needed to check if any threshold is hit and the system must react

→ Batch layer: analytics about user groups

Logical Data Warehouse

- Focus on Jobs to be done
- **DWH**
  - Query processing on structured data
  - Guaranteed quality
- **Data Lake**
  - Very large volumes of unstructured data
- **Logical Data Warehouse**
  - Provide access to both underlying systems
  - Requires ETL functionality
  - Virtual integration



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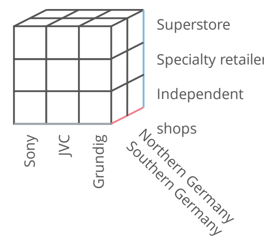
[https://blogs.gartner.com/henry-cook/2018/01/28/the-logical-data-warehouse-and-its-jobs-to-be-done/]

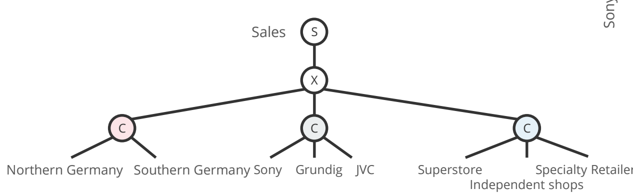
Data Lakes

- With cheap storage costs, people promote the concept of the data lake
  - Combines data from many sources and of any type
  - Allows for conducting future analysis and not miss any opportunity
- Collect everything
  - All data, both raw sources over extended periods of time as well as any processed data
  - Decide during analysis which data is important, e.g., no “schema“ until read
- Dive in anywhere
  - Enable users across multiple business units to refine, explore and enrich data on their terms
- Flexible access
  - Enable multiple data access patterns across a shared infrastructure: batch, interactive, online, search, and others

Multidimensional Modelling

Sales		Sony	JVC	Grundig
Northern Germany	Superstore			
	Specialty retailer			
	Independent shops			
Southern Germany	Superstore			
	Specialty retailer			
	Independent shops			





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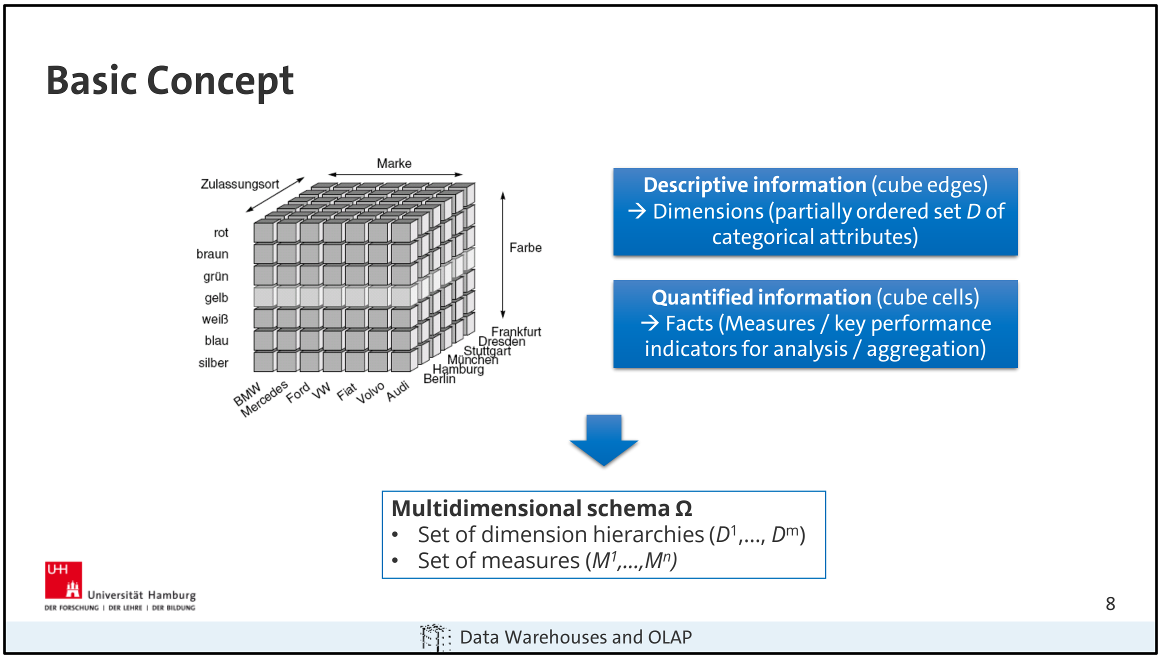
Static table also called “summary table”

Motivation: Reporting and interactive Analysis
- OLAP (Online Analytical Processing) on multidimensional data model
- Data Mining: Search for unknown patterns or relations in data
- Visualization



Central data structure: multidimensional cube

- Descriptive data (categorical attributes)
- Quantified data (sum attributes)

Multidimensional modeling

"Predict" analytic patterns of users

- Drill-paths for navigations operators
- Limit to ***meaningful*** aggregation options

Data structures

- **Descriptive information** (cube edges) → dimensions
  - Hierarchies, dimensional attributes
  - Structural basis for selection and aggregation
- **Quantified information** (cube cells) → facts
  - Measures / key performance indicators for analysis / aggregation

Goal

- Orthogonal dimensional descriptions
- Clear separation of measures

Dimensions / Dimension hierarchy

- Partially ordered set D of categorical attributes

$(\{D_1, \ldots, D_n, Top_D\}; \rightarrow)$

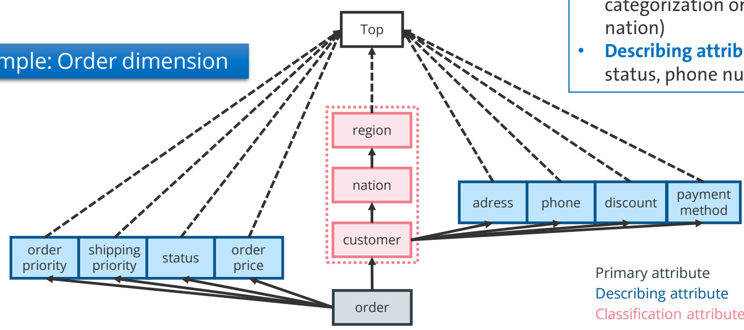
- Top_D is a generic maximum element w.r.t. "→", i.e.
  $\forall i\ (1 \leq i \leq n): D_i \rightarrow Top_D$
- There is a Di with finest granularity, i.e. $D_i \rightarrow D_j$ for all D_j
- "→" denotes the functional dependency
- Partial ordering allows arbitrary parallel hierarchies

!!!Multidimensional Model is conceptual not physical!!

Schema of a Dimension

Roles of categorical attributes
- **Primary attribute**: finest granularity (e.g. order)
- **Classification attribute:** implies multi-stage categorization on value level (e.g. customer, nation)
- **Describing attribute:** additional description (e.g. status, phone number)

Example: Order dimension



Orthogonality
- No functional dependencies between attributes from different dimensions

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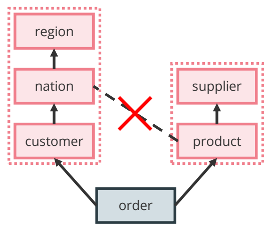
There is a functional dependency A→B if for all a∈A there is exactly one b∈B, e.g. Germany → Europe, but not Europe → Germany

Schema of a Dimension

Example: Multiple hierarchies

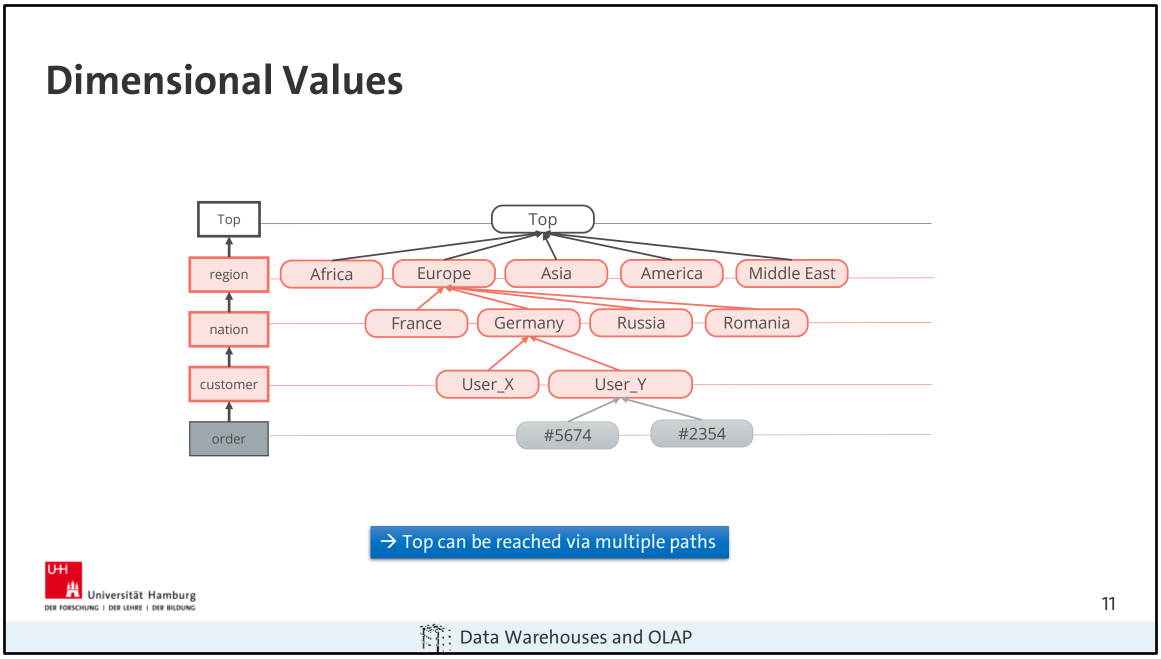


Not modelled here: products sold only in some nations

Primary attribute
Describing attribute
Classification attribute

Orthogonality

- No functional dependencies between attributes from different dimensions



Functional dependencies define tree structure on instances

- Functional dependency corresponds to 1:N-relation!
- Every path from a classification attribute to Top defines a classification hierarchy

Facts and Measures

Quantifying part of a multidimensional data schema

Fact

- Defined as F = (G, SumType)
- Granularity: G = {G1,...,Gn}
- Subset of all categorical attributes of all existing dimensional hierarchies $D_1, \ldots, D_n$
- Summation type: SumTyp $\in$ {FLOW, STOCK, VPU}

Example: Delivered quantity with granularity G={orderNo, partNo, supplierNo}

Measure

- M = (G, f($F_1,\ldots,F_k$), SumType)
- Calculation formula f()
  - Scalar function +,-,•,/,mod etc., e.g. sales tax= quantity • price • tax rate
  - Aggregation functions, e.g. SUM(), MAX(), COUNT(), e.g. SUM(quantity • price)
  - Order-based functions, e.g. cumulation, top-k calculations
- Non-empty subset of all existing Facts $F_1,\ldots,F_k$

Example
Fact: Number and price per product
Scalar measure: Sum of price and sales tax for one product
Aggregated measure: Aggregated price for a completed order
Order-based measure: The k most expensive products of the order

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Summability

Problem

- Not all functions can be summed up (median, quantiles, standard deviation)
- Even simple aggregation functions (SUM, AVG, MIN, MAX, COUNT, ...) cannot be aggregated further at will

Change of granularity

- *$G = (G_1,\ldots,G_n)$ is finer (same) $G' = (G_1',\ldots,G_k')$, i.e. $G \leq G'$ iff, for each $G_j' \in G'$ exists a $G_i \in G$, s.t. $G_i \rightarrow G_j'$*
- Coarsening / refinement of granularity adding / removing categorical attributes
- Example

  (orderNo, partNo) ≤ (customerNo, brand) ≤ (market segment)

Necessary characteristics for summability

- Disjointness, completeness, type compatibility

Characteristics of Summability

Disjointness

→An individual value is considered **exactly once** during calculation

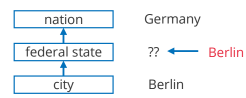
→General: Summability is given if functional dependencies exist between the categories that should be summed up

Number of students	2020	2021	2022	Total
Computer science	15	17	13	**28**
Economics	10	15	11	**21**
Total	**25**	**32**	**24**	**49**

Case 1: sum by year gives correct results
Case 2: sum up number of computer science students
- naive: 15+17+13 = 45 gives wrong result (2 year overlap)
- Assume faculty founding in 2020: 15 + (17 - 15) + (13 - 2) = 28

Completeness

→Measures on higher aggregation-level are completely derived from measures of lower aggregation-levels



Number of restaurants	2010	2011	2012	2013
Dresden	34	38	31	29
Leipzig	123	121	128	131
Chemnitz	21	18	24	27
OTHER	11	13	13	12
Total	**189**	**190**	**196**	**199**

- Number of restaurants in the triangle Dresden-Leipzig-Chemnitz
- OTHER for inns, not located in one of the cities

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Data Warehouses and OLAP

- Possibly, the whole space cannot be captured
  - Example: assume Berlin is not modeled as a federal state (city → federal state)
  - Weak functional dependency (A⇒B): for each a∈A exists at most one b∈B
  - example: city⇒ federal state
- Remove weak functional dependencies
  - NULL, OTHER, dummy values

Summation types

Summability

	FLOW	STOCK: aggregation over temporal dimension?		VPU
		no	yes	
MIN/MAX	✓	✓		✓
SUM	✓	✓	✗	✗
AVG	✓	✓		✓
COUNT	✓	✓		✓

FLOW
Can be aggregated freely, usually measured in <thing> per time

STOCK
States which can be aggregated freely except for a temporal dimension

Value-per-Unit
States which cannot be summed (except for min, max, and avg), e.g. exchange rate
→ Values of different points in time might not be aggregated into one value

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Summation Types

Flow (event at time T)

- Can be aggregated freely
- Examples: order quantity of a certain item per day, number of traffic deaths per month, sales, earnings per year,…

Stock (status at time T)

- Can be aggregated freely, without a temporal dimension
- Items in stock over time → disjointness voided
- Example: number of school kids per month,

Value-Per-Unit (VPU)

- Current states, that cannot be summed
- Use of COUNT()-, MIN()-, MAX()- und AVG() is allowed
- Example: exchange rate, unit costs, …

Exercise Summation Types

	FLOW	STOCK	VPU
Inventory			
Value added tax rate			
Ordered items per day			
#inhabitants per city			
Stock price			
Exams per semester			
SWS (Semesterwochenstunden/ semester hours)			
Exam grade			

The Data Cube

Data cube: C = (DS,M)

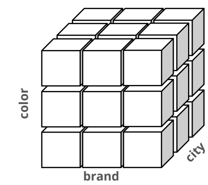
- Set of dimensional hierarchies: $DS = \{D^1, \ldots, D^n\}$
- Set of fact-based measures: $M = \{M^1, \ldots, M^m\}$

Domain of a data cube

- Cartesian product of all value ranges of all attributes of the cube schema

Data cube instance

- All cube cells from the cube domain



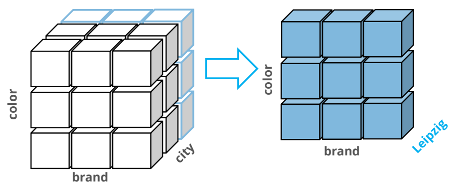
Cube is just a metaphor!

- Almost never, all cells are present (sparsity)
- Non-existent values on the implementation level become NULL or 0 on the model level!

There are usually more than 3 dimensions!

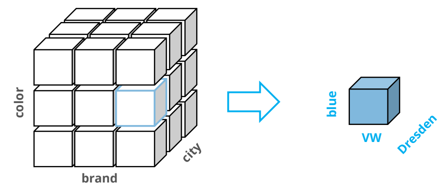
Operations on Data Cubes I

Slicing → Select "slices of a cube"
→ Selection via specification of classification attributes of **one** dimension

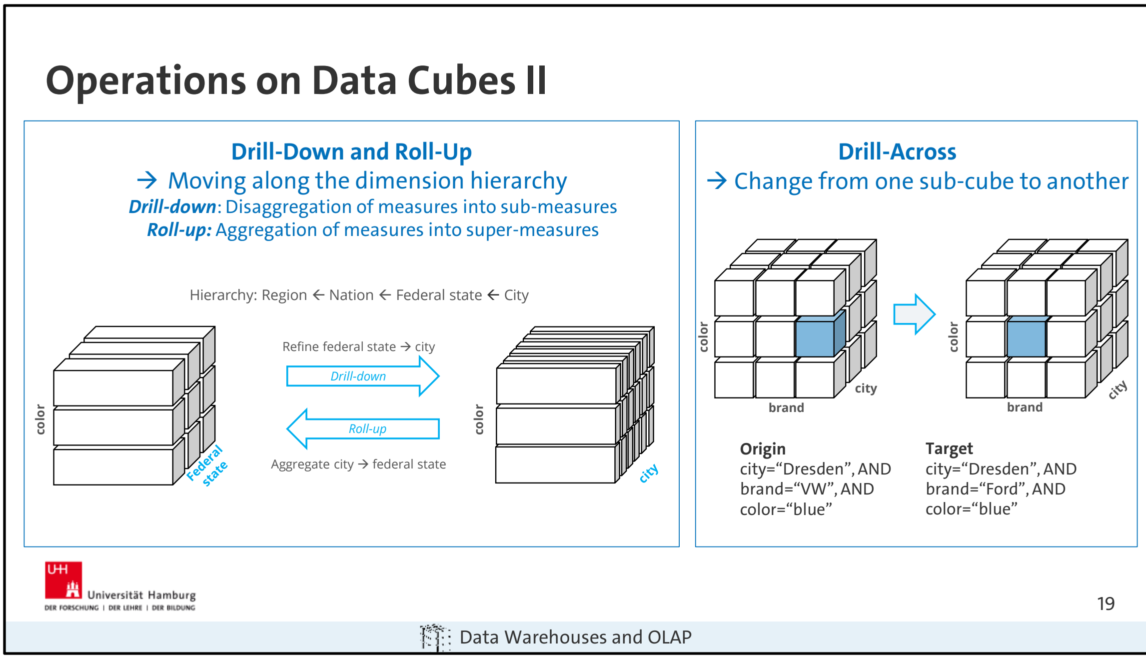


city="Leipzig"

Dicing → Select a sub-cube
→ Selection by specification of classification attributes of **multiple** dimensions



city="Dresden", AND
brand="VW", AND
color="blue"



Drill-Down and Roll-Up

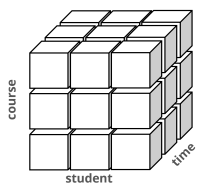
- Changes granularity, not Categorization

Drill-Across

- Dimension stays on the same hierarchy-level, but selection value changes
- Also change of data cube (Join of multiple data cubes)

Exercise Data Cube

- Which operations are described? (slicing, dicing, roll-up, drill-down, drill-across)
- How could you visualize the results?



a) name = “Jane Doh”
b) refine name → first
c) student=“Jane Doh” AND time = “2 pm” AND course = “AD”
d) time = “4 pm” AND course = “Math I”
e) aggregate first → name
f) student=“Jane Doh” AND time = “2 pm” AND course = “AD”
   → student=“Jane Doh” AND time = “10 am” AND course = “AD”

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Data Cube in PostgreSQL

- Install extension: CREATE EXTENSION cube;
- Create a cube: SELECT cube(array[X,Y,Z]); //creates cube with dimensions X, Y, and Z
- Selected functions:
  - Cube_union (cube,cube)
  - Cube_inter(cube,cube) → intersection
  - cube_subset (cube, integer[]) → new cube from existing group using list of dimension indexes, e.g. for dicing
- Rollup is a separate function and a subclause of GROUP BY

rollup (x,y,z)
(assuming the hierarchy is x > y > z) →
(x, y, z)
(x, y)
(x)
()

cube (x,y,z) →
(x, y, z)
(x, y)
(y, z)
(x, z)
(x)
(y)
(z)
()

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https://www.postgresql.org/docs/current/cube.html
https://www.timescale.com/learn/postgresql-extensions-cube

- Cube can also be used in GROUP BY
- Common use of rollup: aggregation of data by year, month, and day

Multidimensional database design

<table>
<tr><th></th><th>Classical relational database design</th><th colspan="2">Multidimensional database design</th></tr>
<tr><td>Conceptual schema (semi-formal)</td><td>Variants of entity-relationship modelling</td><td colspan="2">Different modelling languages, e.g. mE/R, mUML, ADAPT,...</td></tr>
<tr><td rowspan="2">Logical schema (formal)</td><td rowspan="2">Relations with attributes</td><td colspan="2">Data cube: facts and measures</td></tr>
<tr><td colspan="2">Dimensional hierarchy with categorical attributes: classifying and describing attributes</td></tr>
<tr><td>Internal/physical schema</td><td>Memory organisation (primary/secondary indexes, partitioning,...)</td><td>Relational storage (ROLAP): Star/Snowflake schema patterns</td><td>Multidimensional storage (MOLAP): native implementation</td></tr>
</table>

ROLAP = Relational OLAP
MOLAP = Multidimensional OLAP
HOLAP → Hybrid solution