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Data Integration and Analysis
02 Data Warehousing and ETL

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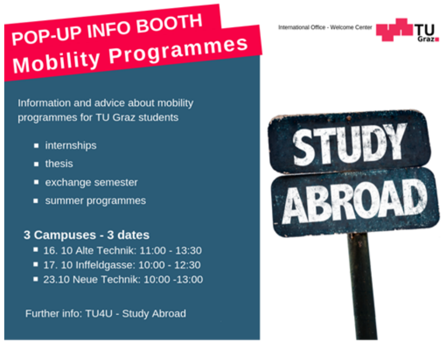
Announcements/Org

- **#1 Video Recording**
  - Link in **TeachCenter** & **TUbe** (lectures will be public)
  - Since 2nd lecture

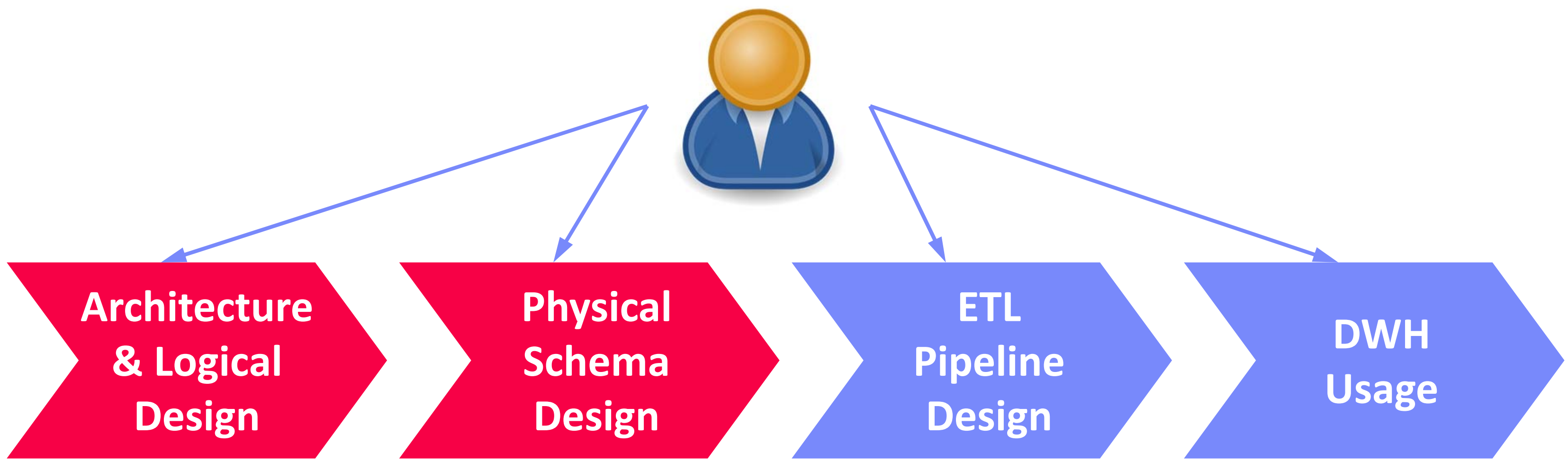
- **#2 Study Abroad Info**
  - **Oct 17, 10am** @ Inffeldgasse
  - Internships, master theses,
    study courses, summer programs



- **#3 Workshop - Focus on FAIR**
  - **Nov 7**, **9.30am – 4pm** (all day)
  - Student reach-out BS, MS, PhD
  - Invited speakers from EGI, TU Delft, Uni. Vienna,
    Uni. Barcelona, UCL, and TU Graz/Know-Center

Agenda

- **Data Warehousing (DWH)**
- **Extraction, Transformation, Loading (ETL)**
- **SQL/OLAP Extensions**



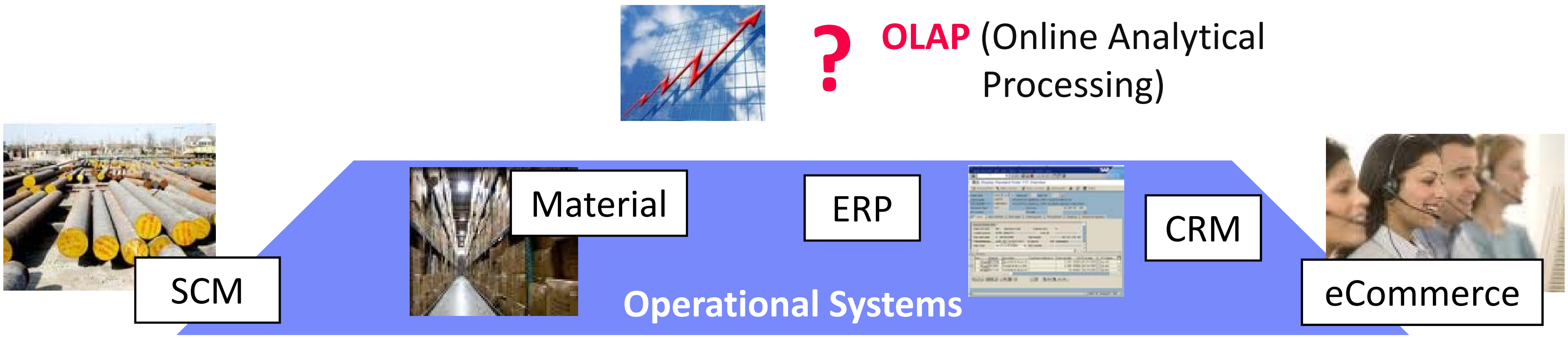
SQL, SQL/OLAP,
Data Mining,
Machine Learning

Data Warehousing

[Wolfgang Lehner: Datenbanktechnologie für Data-Warehouse-Systeme. Konzepte und Methoden, Dpunkt Verlag, 1-373, 2003]

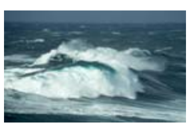
Motivation and Tradeoffs

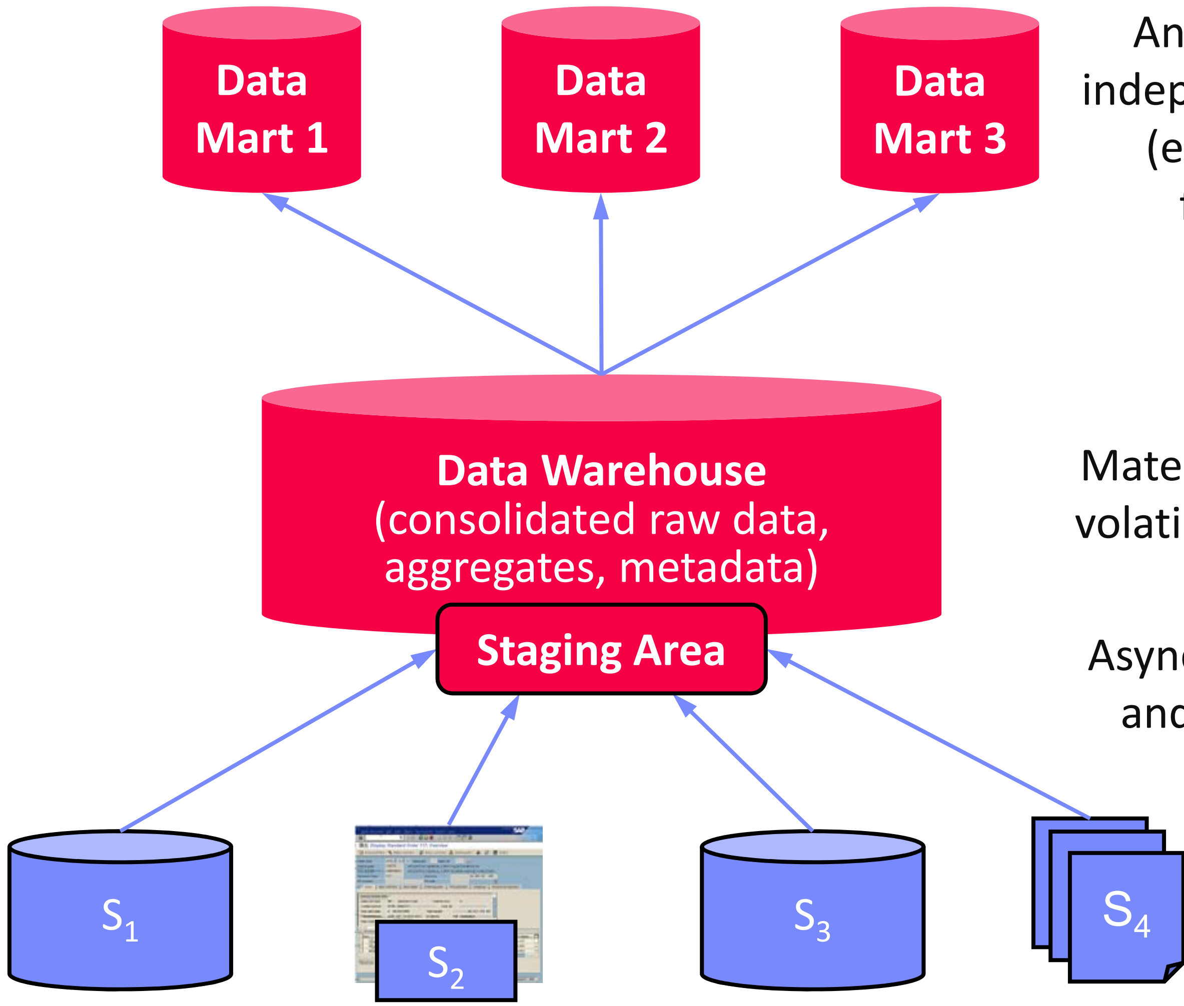
- **Goal:** Queries over consolidated and cleaned data of several, potentially heterogeneous, data sources



- **Tradeoffs**
  - **Analytical query performance:** write vs read optimized data stores
  - **Virtualization:** overhead of remote access, source systems affected
  - **Consistency:** sync vs async changes, time regime → up-to-date?
  - **Others:** history, **flexibility**, **redundancy**, effort for **data exchange**

Data Warehouse Architecture





Analysis-centric independent subsets (e.g., geo, org, functional)

Materialized, non-volatile integration

Async replication, and ETL vs ELT

Operational source systems

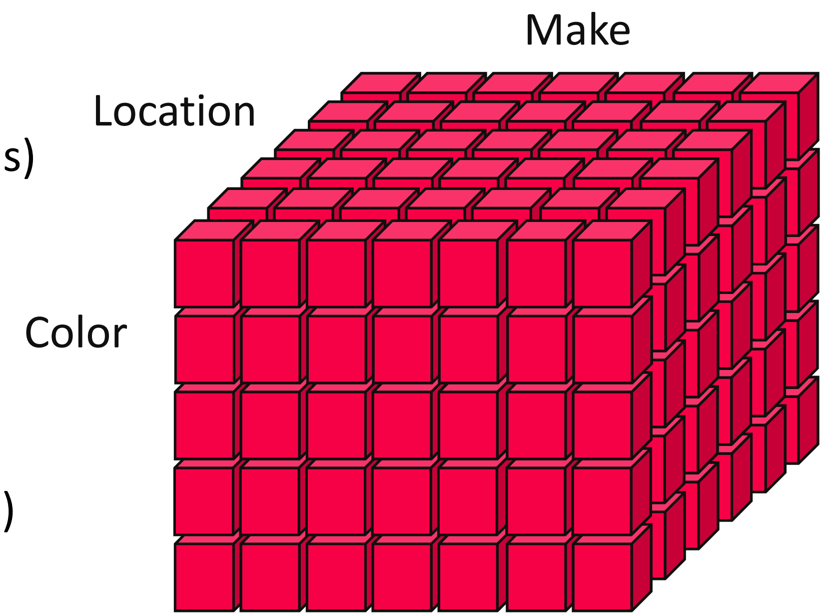
Data Warehouse Architecture, cont.

- **Data Warehouse (DWH)**
  - "A *data warehouse is a **subject-oriented, integrated, time-varying, non-volatile** collection of data in support of the management's decision-making process."* (Bill Inmon)
  - **#1 Subject-oriented:** analysis-centric organization (e.g., sales) → Data Mart
  - **#2 Integrated:** consistent data from different data sources
  - **#3 Time-varying:** History (snapshots of sources), and temporal modelling
  - **#4 Non-volatile:** Read-only access, limited to periodic data loading by admin

- **Different DWH Instantiations**
  - **Single DWH system** with virtual/materialized views for data marts
  - Separate systems for consolidated DWH and aggregates/data marts (**dependent data marts**)
  - Data-Mart-local staging areas and ETL (**independent data marts**)

Multi-dimensional Modeling: Data Cube

- **Central Metaphor: Data Cube**
  - Qualifying data (categories, dimensions)
  - Quantifying data (cells)
  - Often sparse (0 for empty cells)

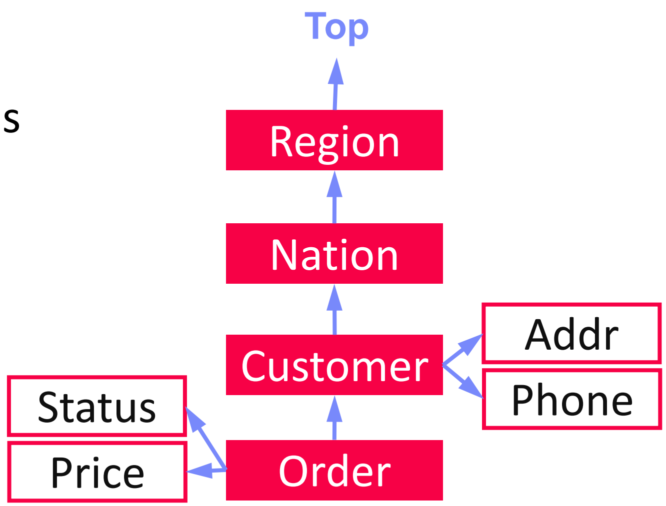


- **Multi-dimensional Schema**
  - Set of **dimension hierarchies** ($D^1,\ldots, D^n$)
  - Set of **measures** ($M^1,\ldots,M^m$)

- **Dimension Hierarchy**
  - Partially-ordered set D of categorical attributes ($\{D_1,\ldots,D_n, Top_D\};\rightarrow$)
  - Generic **maximum element**
    $\forall i(1 \leq i \leq n): D_i \rightarrow Top_D$
  - Existing **minimum element** (primary attribute)
    $\exists i(1 \leq i \leq n)\forall j(1 \leq i \leq n, i \neq j): D_i \rightarrow D_j$

Multi-dimensional Modeling: Data Cube, cont.

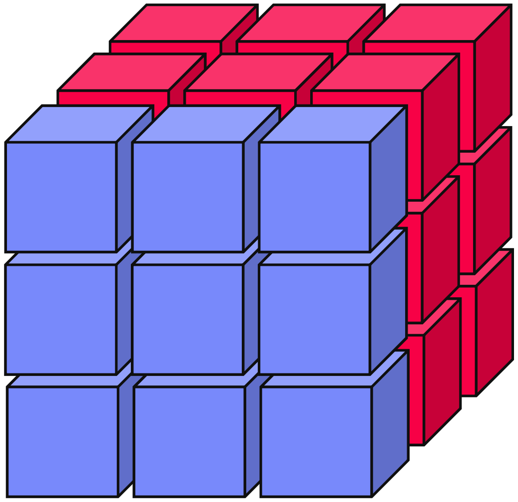
- **Dimension Hierarchy, cont.**
  - Classifying (categorical) vs descriptive attributes
  - **Orthogonal dimensions:** there are no functional dependencies between attributes of different dimensions



- **Fact F**
  - Base tuples w/ measures of summation type
  - Granularity G as subset of categorical attributes
- **Measure M**
  - Computation function over non-empty subset of facts $f(F_1, \ldots, F_k)$ in schema
  - Scalar function vs aggregation function
  - Granularity G as subset of categorical attributes

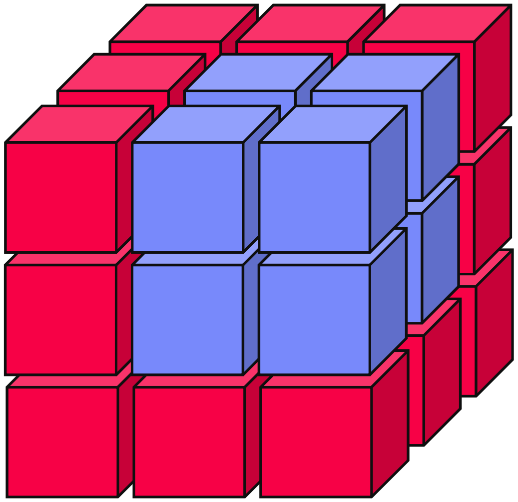
Multi-dimensional Modeling: Operations

- **Slicing**
  - Select a “slice” of the cube by specifying a filter condition on one of the dimensions (categorical attributes)
  - Same data granularity but subset of dimensions



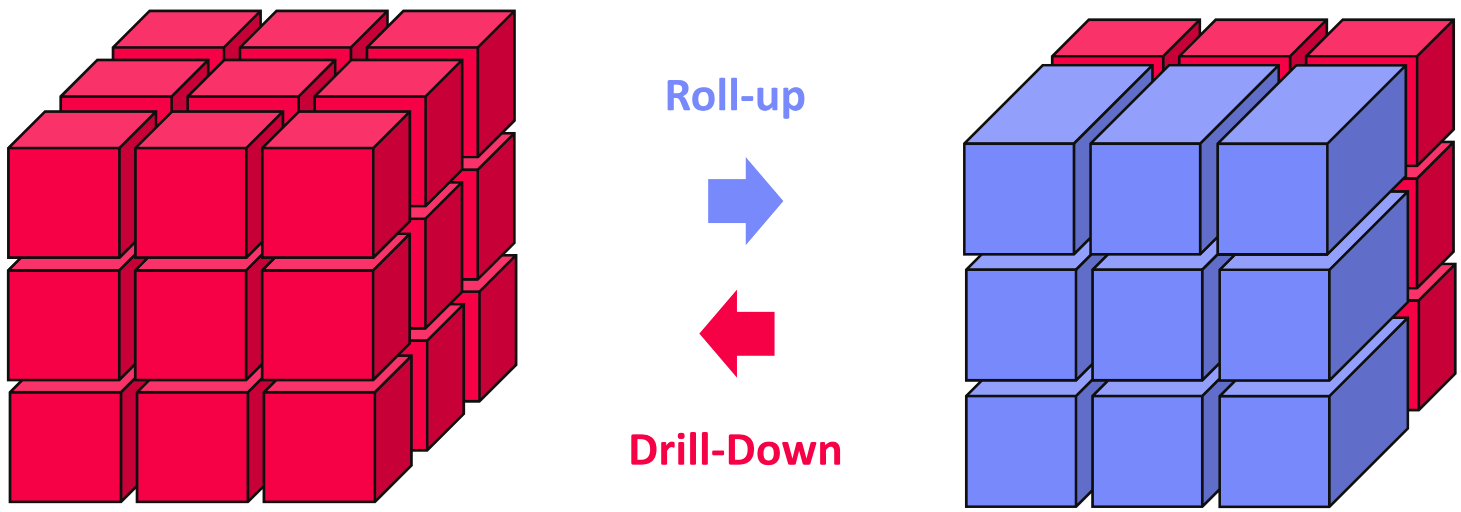
- **Dicing**
  - Select a “sub-cube” by specifying a filter condition on multiple dimensions
  - Complex Boolean expressions possible
  - Sometimes slicing used synonym

Example: `Location=Graz` **AND** `Color=White` **AND** `Make=BMW`



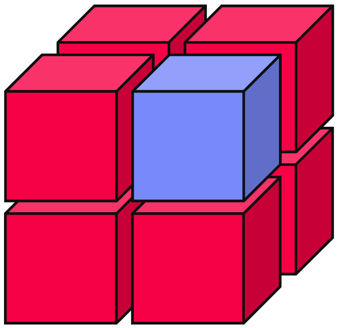
Multi-dimensional Modeling: Operations, cont.

- **Roll-up** (similar Merge - remove dim)
  - Aggregation of facts or measures into coarser-grained aggregates (measures)
  - Same dimensions but different granularity
- **Drill-Down** (similar Split add dim)
  - Disaggregation of measures into finer-grained measures



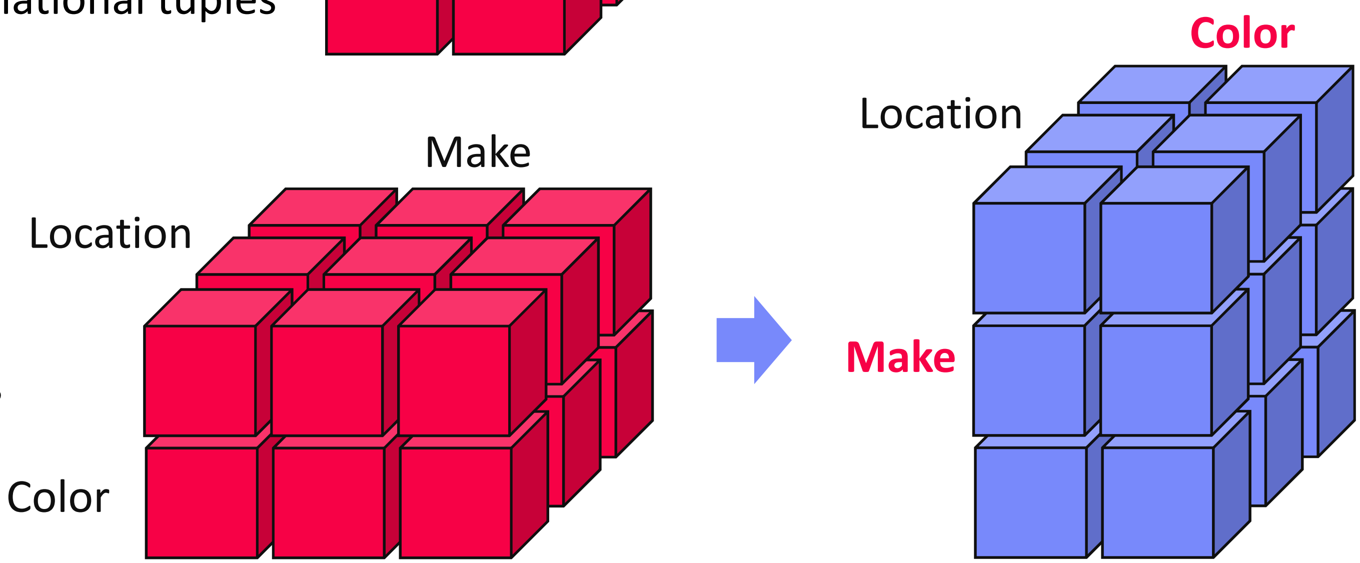
Multi-dimensional Modeling: Operations, cont.

- **Drill-Across**
  - Navigate to neighboring cells at same granularity (changed selection)
- **Drill-Through**
  - Drill-Down to smallest granularity of underlying data store (e.g., RDBMS)
  - E.g., find relational tuples



FName	LName	Local	Make	Color
Matthias	Boehm	Graz	BMW	White
…	…	…	…	…

- **Pivot**
  - Rotate cube by exchanging dimensions



Aggregation Types

- **Recap: Classification of Aggregates**
  - Additive aggregation functions (SUM, COUNT)
  - Semi-additive aggregation functions (MIN, MAX)
  - Additively computable aggregation functions (AVG, STDDEV, VAR)
  - Aggregation functions (MEDIAN, QUANTILES)

- **Beware Summation Types of Measures**
  - Disjointness, completeness, type compatibility
  - FLOW: arbitrary aggregation possible
  - STOCK: aggregation possible, except over temporal dimension
  - VPU: value-per-unit typically cannot be aggregated

[TUGraz online]

# Stud	16/17	17/18	18/19	19/20	Total
CS	1,153	1,283	1,321	(1,184)	?
SEM	928	970	939	(838)	?
ICE	804	868	846	(742)	?
Total	2,885	3,121	3,106	2,764	?

Aggregation Types, cont.

- **Additivity**

	FLOW	STOCK: Temporal Agg?		VPU
		Yes	No	
MIN/MAX	✔	✔		✔
SUM	✔	✗	✔	✗
AVG	✔	✔		✔
COUNT	✔	✔		✔

- **Type Compatibility** (addition/ subtraction)

	FLOW	STOCK	VPU
FLOW	FLOW	STOCK	✗
STOCK		STOCK	✗
VPU			VPU

Data Cube Mapping and MDX

- **MOLAP (Multi-Dim. OLAP)**
  - OLAP server with native multi-dimensional data storage
  - Dedicated query language: Multidimensional Expressions (MDX)
  - E.g., IBM Cognos Powerplay, Essbase

[https://docs.microsoft.com/en-us/analysis-services/multidimensional-models/mdx]

```
SELECT
  {[Measures].[Sales],
   [Measures].[Tax]} ON COLUMNS,
  {[Date].[Fiscal].[Year].&[2002],
   [Date].[Fiscal].[Year].&[2003] } ON ROWS
FROM [Adventure Works]
WHERE ([Sales Territory].[Southwest])
```

- **ROLAP (Relation OLAP)**
  - OLAP server w/ storage in RDBMS
  - E.g., all commercial RDBMS vendors
- **HOLAP (Hybrid OLAP)**
  - OLAP server w/ storage in RDBMS and multi-dimensional in-memory caches and data structures

Requires mapping to relational model

[**Example systems**: https://en.wikipedia.org/wiki/Comparison_of_OLAP_servers]

Recap: Relational Data Model

- **Domain D (value domain): e.g., Set S, INT, Char[20]**
- **Relation R**
  - **Relation schema** RS:
    Set of k attributes $\{A_1,\ldots,A_k\}$
  - **Attribute** A_j: value domain $D_j = dom(A_j)$
  - **Relation:** subset of the Cartesian product over all value domains D_j
    $R \subseteq D_1 \times D_2 \times \ldots \times D_k, k \geq 1$

Attribute

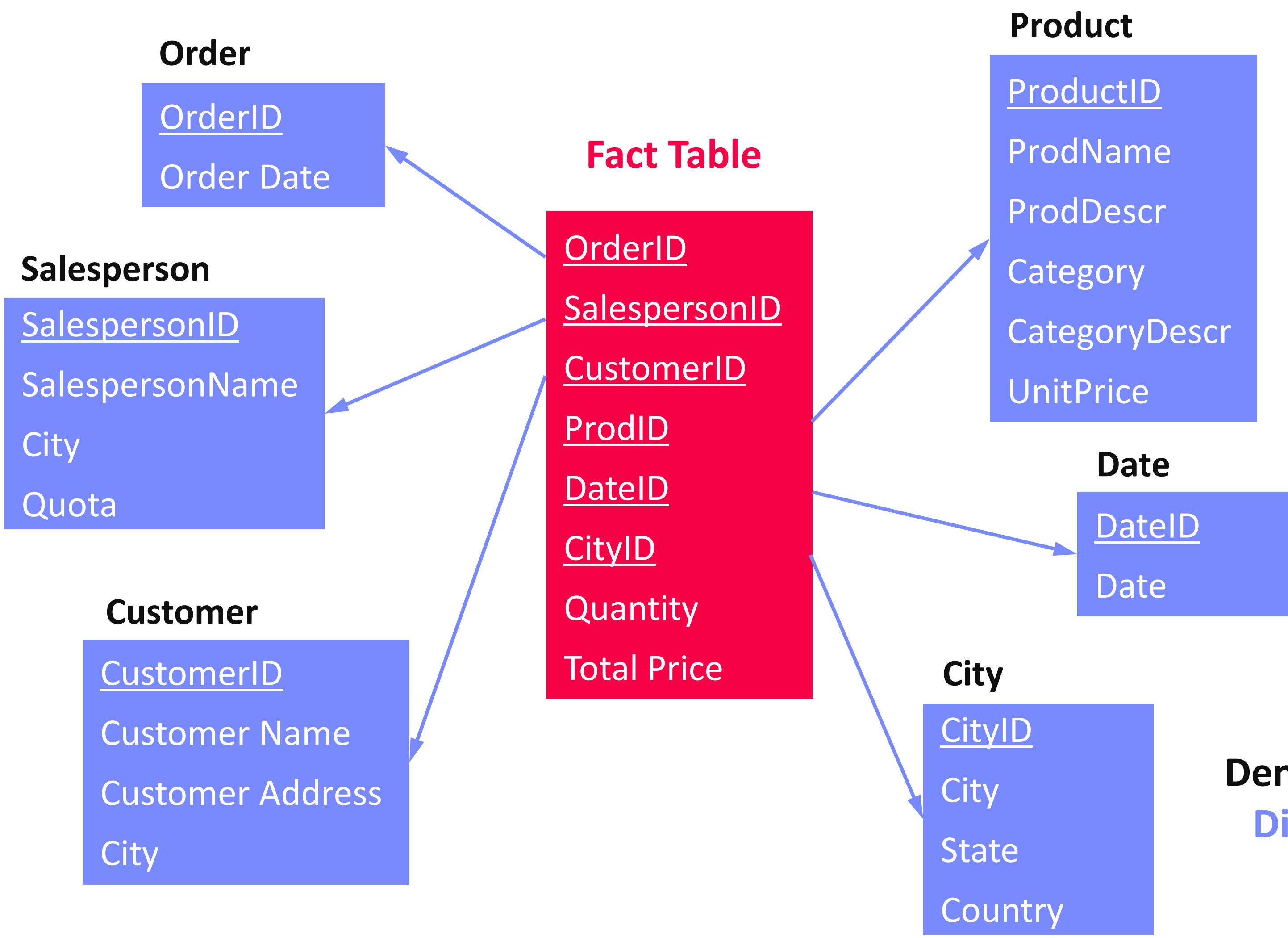
A1 INT	A2 INT	A3 BOOL
3	7	T
1	2	T
3	4	F
1	7	T

Tuple

cardinality: 4
rank: 3

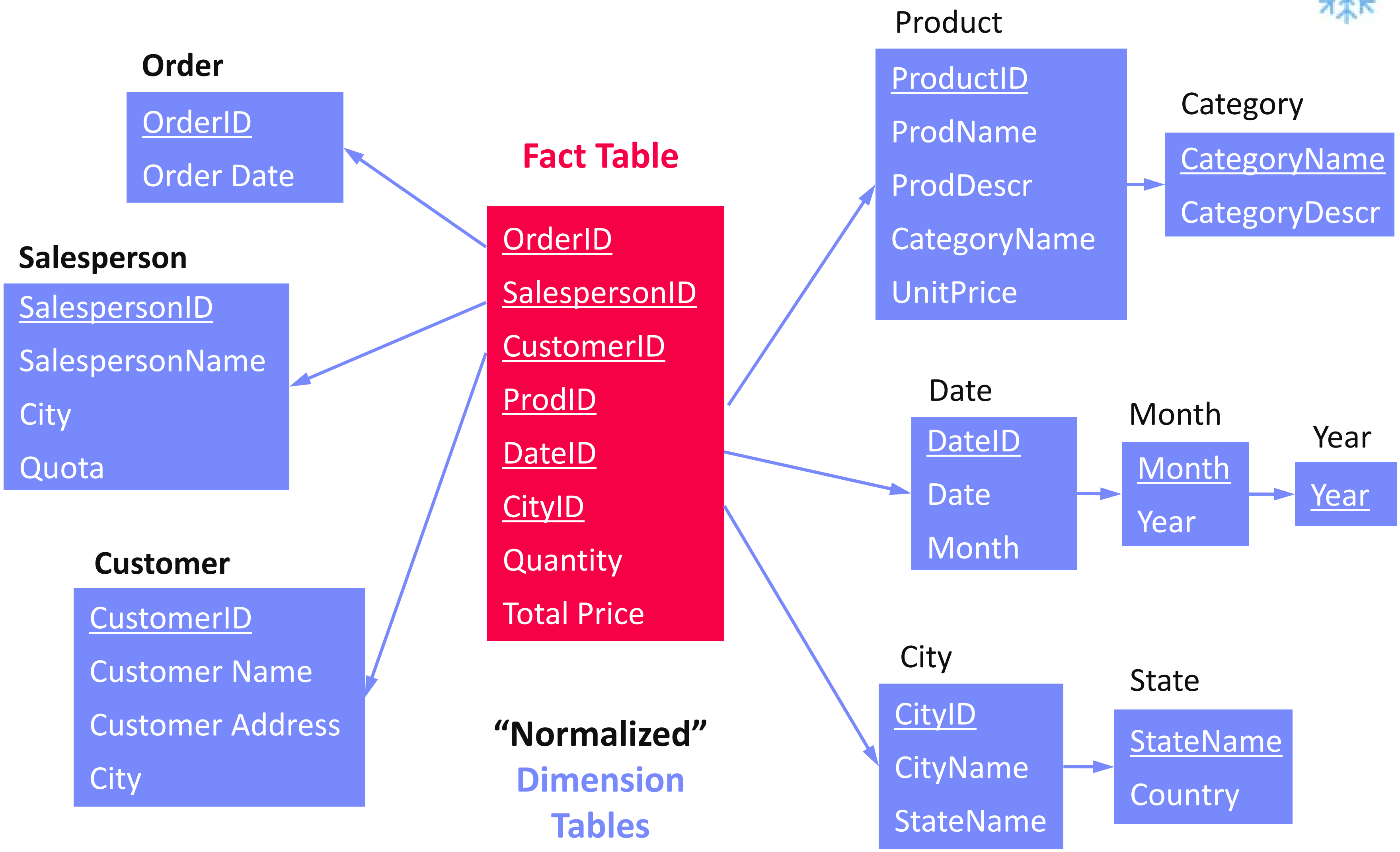
- **Additional Terminology**
  - **Tuple**: row of k elements of a relation
  - **Cardinality** of a relation: number of tuples in the relation
  - **Rank** of a relation: number of attributes
  - **Semantics:** Set := no duplicate tuples (in practice: Bag := duplicates allowed)
  - **Order of tuples and attributes is irrelevant**

ROLAP – Star Schema



Denormalized Dimension Tables

ROLAP – Snowflake Schema



ROLAP – Other Schemas

- **Galaxy Schema**
  - Similar to star-schema but with **multiple fact tables** and potentially shared dimension tables
  - Multiple stars → Galaxy

- **Snow-Storm Schema**
  - Similar to snow-flake-schema but with **multiple fact tables** and potentially shared dimension tables
  - Multiple snow flakes → snow storm

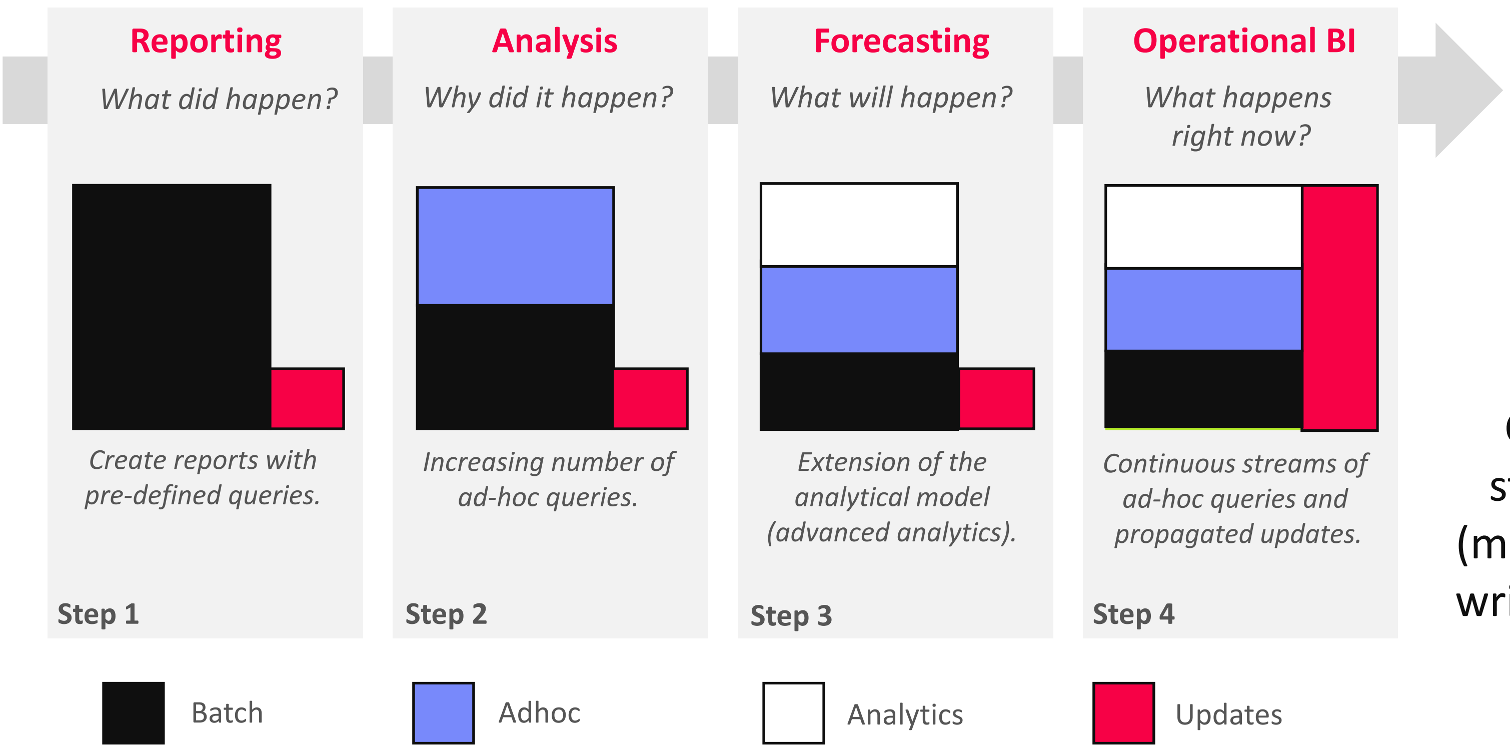
- **OLAP Benchmark Schemas**
  - **TPC-H** (8 tables, normalized schema)
  - **SSB** (5 tables, star schema, simplified TPC-H)
  - **TPC**-DS (24 tables, snow-storm schema)

"TPC-D and its successors, TPC-H and TPC-R assumed a 3rd Normal Form (3NF) schema. However, over the years the industry has expanded towards star schema approaches."

[Raghunath Othayoth Nambiar, Meikel Poess: The Making of TPC- DS. **VLDB 2006**]

Evolution of DWH/OLAP Workloads

- **Goals: Advanced analytics and Operational BI**



SotA: Column stores w/ (multi-stage) write buffers

Excursus: MAD Skills

- **In the days of Kings and Priests**
  - Computers and Data: Crown Jewels
  - Executives depend on computers
    - But cannot work with them directly
  - The DBA “Priesthood”
    - And their Acronymia: EDW, BI, OLAP

- **The architected Enterprise DWH**
  - Rational behavior … **for a bygone era**
  - “There is no point in bringing data … into the data warehouse environment without integrating it.”

    —Bill Inmon, Building the Data Warehouse, 2005

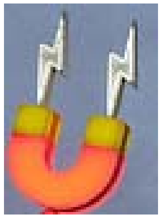
Excursus: MAD Skills, cont.

1. mad skills **92** up,

To be able to do/perform amazing/unexpected things

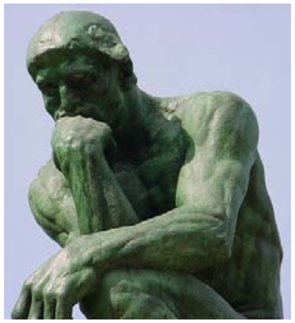
I gots me mad skills, yo.
To be said after performing an extraordinairy feat.

- **Magnetic**
  - **„Attract data and practitioners“**
  - Use all available data, irrespective of data quality



- **Agile**
  - **„Rapid iteration: ingest, analyze, productionalize“**
  - Continuous and fast evolution of physical and logical structures (ELT)

- **Deep**
  - **„Sophisticated analytics in Big Data“**
  - Ad-hoc advanced analytics and statistics



[J. Cohen, B. Dolan, M. Dunlap, J. M. Hellerstein, C. Welton: **MAD Skills**: New Analysis Practices for Big Data. **PVLDB 2(2) 2009**]

Trend: Cloud Data Warehousing

- **#1 Google Big Query**

[Google, Kazunori Sato: An Inside Look at Google BigQuery, Google **White Paper 2012**]

- **#2 Amazon Redshift**

[Anurag Gupta, Deepak Agarwal, Derek Tan, Jakub Kulesza, Rahul Pathak, Stefano Stefani, Vidhya Srinivasan: Amazon Redshift and the Case for Simpler Data Warehouses. **SIGMOD 2015**]

- **#3 Microsoft Azure Data Warehouse**

- **#4 IBM BlueMix dashDB**

[IBM: IBM dashDB - Cloud-based data warehousing as-a-service, built for analytics, IBM **White Paper 2015**]

- **#5 Snowflake Data Warehouse**

[Benoît Dageville et al.: The Snowflake Elastic Data Warehouse. **SIGMOD 2016**]

Extraction, Transformation, Loading (ETL)

Extract-Transform-Load (ETL) Overview

- **Overview**
  - ETL process refers to the overall process of obtaining data from the source systems, cleaning and transforming it, and loading it into the DWH
  - Subsumes many integration and cleaning techniques
- **#1 ETL**
  - Extract data from heterogeneous sources
  - Transform data via dedicated data flows or in staging area
  - Load cleaned and transformed data into DWH
- **#2 ELT**
  - Extract data from heterogeneous sources
  - Load raw data directly into DWH
  - Perform data transformations inside the DWH via SQL

  → allows for **automatic optimization of execution plans**

Types of Heterogeneity

[J. Hammer, M. Stonebraker, and O. Topsakal: THALIA: Test Harness for the Assessment of Legacy Information Integration Approaches. U Florida, TR05-001, **2005**]

- **Heterogeneity**
  - **Semantic Heterogeneity**
    - **Attribute Heterogeneity**
      1. Synonyms/Homonyms
      2. Simple Mapping (mathematical)
      3. Union Types
      4. Complex Mappings
      5. Language Expressions
    - **Missing Data**
      6. Nulls (Missing Values)
      7. Virtual Columns
      8. Semantic Incompatibility
  - **Structural Heterogeneity**
    9. Same Attribute in different structure
    10. Handling Sets
    11. Attribute name does not define semantics
    12. Attribute composition

Corrupted Data

- **Heterogeneity of Data Sources**
  - Update anomalies on denormalized data / eventual consistency
  - Changes of app/preprocessing over time (US vs us) → inconsistencies
- **Human Error**
  - Errors in semi-manual data collection, laziness (see default values), bias
  - Errors in data labeling (especially if large-scale: crowd workers / users)
- **Measurement/Processing Errors**
  - Unreliable HW/SW and measurement equipment (e.g., batteries)
  - Harsh environments (temperature, movement) → aging

Uniqueness & duplicates **Contradictions & wrong values** **Missing Values** **Ref. Integrity**

[**Credit:** Felix Naumann]

ID	Name	BDay	Age	Sex	Phone	Zip
3	Smith, Jane	05/06/1975	44	F	999-9999	98120
3	John Smith	38/12/1963	55	M	867-4511	11111
7	Jane Smith	05/06/1975	24	F	567-3211	98120

Zip	City
98120	San Jose
90001	Lost Angeles

Typos

ETL – Planning and Design Phase

- **Architecture, Flows, and Schemas**
  - #1 Plan requirements, architecture, tools
  - #2 Design high-level integration flows (systems, integration jobs)
  - #3 Data understanding (copy/code books, meta data)
  - #4 Design dimension loading (static, dynamic incl keys)
  - #5 Design fact table loading
- **Data Integration and Cleaning**
  - #5 Types of data sources (snapshot, APIs, query language, logs)
  - #6 Prepare schema mappings → see **04 Schema Matching and Mapping**
  - #7 Change data capture and incremental loading (diff, aggregates)
  - #8 Transformations, enrichments, and deduplication → **05 Entity Linking**
  - #9 Data validation and cleansing → see **06 Data Cleaning and Data Fusion**
- **Optimization**
  - #10 Partitioning schemes for loaded data (e.g., per month)
  - #11 Materialized views and incremental maintenance

Events and Change Data Capture

- **Goal: Monitoring operations of data sources for detecting changes**

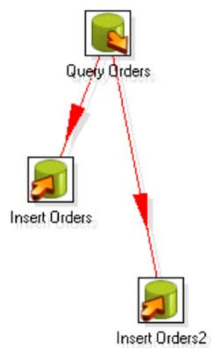
- **#1 Explicit Messages/Triggers**
  - Setup update propagation from the source systems to middleware
  - Asynchronously propagate the updates into the DWH

- **#2 Log-based Capture**
  - Parse system logs / provenance to retrieve changes since last loading
  - Sometimes combined w/ replication → **03 MoM, EAI, and Replication**
  - Leverage explicit audit columns or internal timestamps

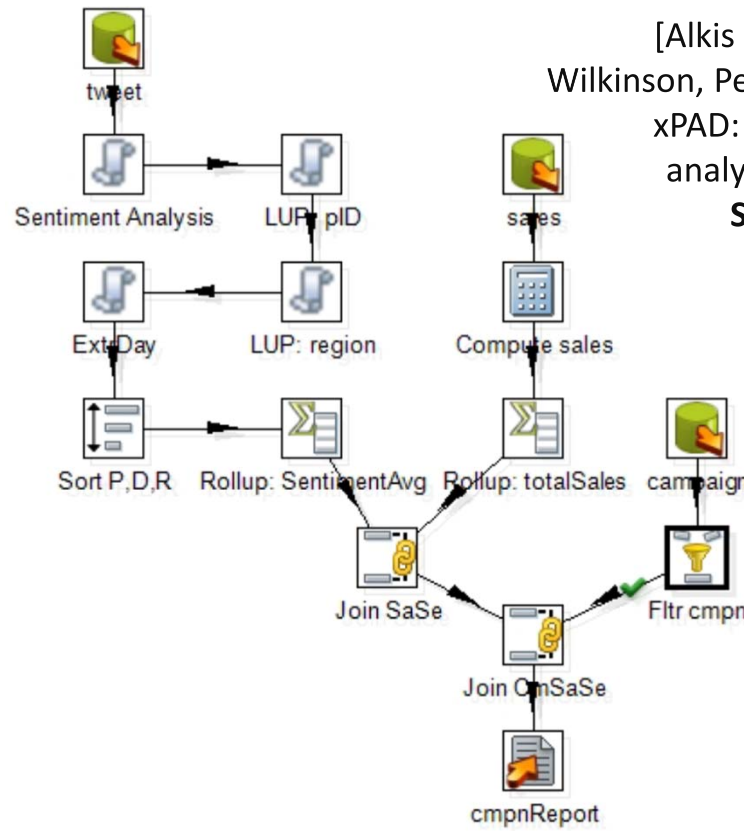
- **#3 Snapshot Differences**
  - Compute difference between old and new snapshot (e.g., files) before loading
  - Broadly applicable but more expensive

Example ETL Flow

- **Example Flows** (Pentaho Data Integration, since 2015 Hitachi)



[Matthias Boehm, Uwe Wloka, Dirk Habich, Wolfgang Lehner: GCIP: exploiting the generation and optimization of integration processes. **EDBT 2009**]

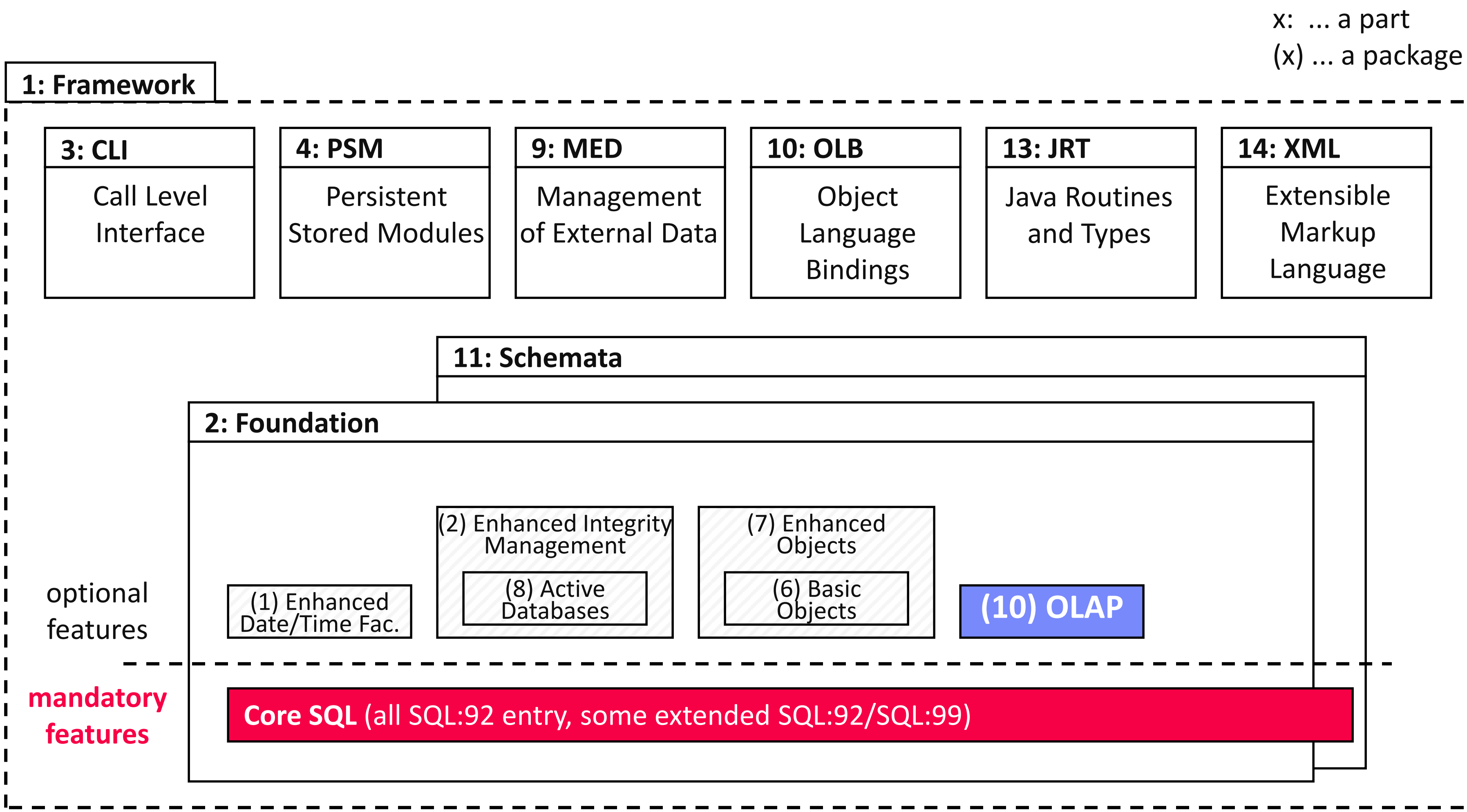


[Alkis Simitsis, Kevin Wilkinson, Petar Jovanovic: xPAD: a platform for analytic data flows. **SIGMOD 2013**]

- **Other Tools**
  - IBM IS, Informatica, SAP BO, MS Integration Services
  - Open Source: Pentaho Data Integration, Scriptella ETL, CloverETL, Talend

SQL/OLAP Extensions

Recap: SQL Standard (ANSI/ISO/IEC)



Overview Multi-Groupings

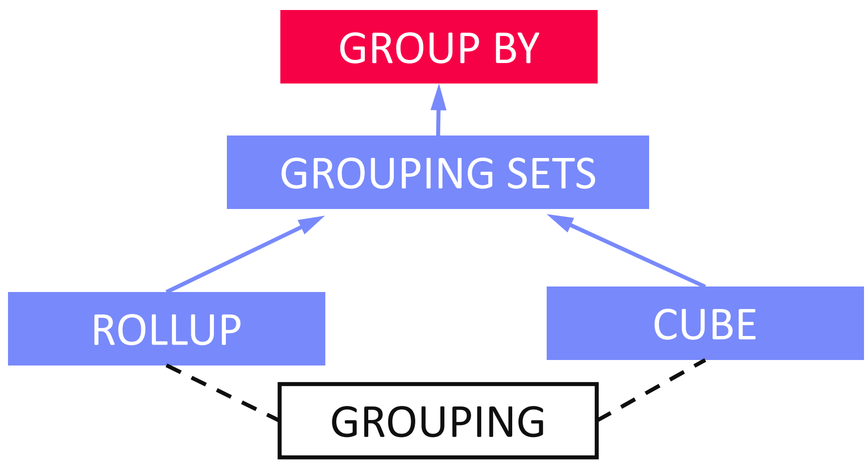
- **Recap: GROUP BY**
  - Group tuples by categorical variables
  - Aggregate per group

Year	Quarter	Revenue
2004	1	10
2004	2	20
2004	3	10
2004	4	20
2005	1	30

```
SELECT Year, SUM(Revenue)
  FROM Sales
  GROUP BY Year
```

Year	SUM
2004	60
2005	30

- **Grouping Extensions**



Grouping Sets

```
GROUP BY GROUPING SETS
  ((<attribute-list>), …)
```

- **Semantics**
  - Grouping by multiple group-by attribute lists w/ consistent agg function
  - Equivalent to multiple GROUP BY, connected by UNION ALL

- **Example**

```
SELECT Year, Quarter, SUM(Revenue)
  FROM R
  GROUP BY GROUPING SETS
    ((), (Year), (Year,Quarter))
```

Year	Quarter	Revenue
2004	1	10
2004	2	20
2004	3	10
2004	4	20
2005	1	30

→

Year	Quarter	SUM
-	-	90
2004	-	60
2005	-	30
2004	1	10
2004	2	20
2004	3	10
2004	4	20
2005	1	30

Rollup (see also multi-dim ops)

```
GROUP BY ROLLUP
  (<attribute-list>)
```

- **Semantics**
  - Hierarchical grouping along dimension hierarchy
  - `GROUP BY ROLLUP (A1,A2,A3)`
    `:= GROUP BY GROUPING SETS((),(A1),(A1,A2),(A1,A2,A3))`

- **Example**

```
SELECT Year, Quarter, SUM(Revenue)
  FROM R
  GROUP BY ROLLUP(Year,Quarter)
```

Year	Quarter	Revenue
2004	1	10
2004	2	20
2004	3	10
2004	4	20
2005	1	30

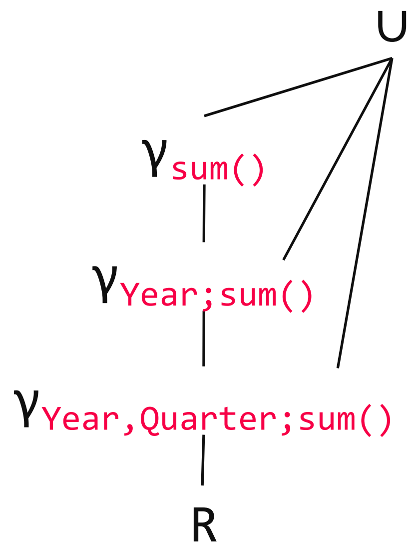
→

Year	Quarter	SUM
-	-	90
2004	-	60
2005	-	30
2004	1	10
2004	2	20
2004	3	10
2004	4	20
2005	1	30

Rollup, cont. and Grouping

- **Operator Implementation**
  - Aggregation towers for (semi-)additive aggregation functions
  - Example

```
SELECT Year, Quarter, SUM(Revenue)
  FROM R
  GROUP BY ROLLUP(Year,Quarter)
```



- **GROUPING Semantics**
  - Used with ROLLUP or CUBE to identify computed tuples
  - Example

```
SELECT Year, Quarter, SUM(Revenue),
    GROUPING(Quarter) AS Flag
  FROM R
  GROUP BY ROLLUP (Year, Quarter)
```

Cube

`GROUP BY CUBE(<attribute-list>)`

- **Semantics**
  - Computes aggregate for all 2^n combinations for n grouping attributes
  - Equivalent to enumeration via `GROUPING SETS`
- **Example**

```
SELECT Year, Quarter, SUM(Revenue)
  FROM R
  GROUP BY CUBE(Year,Quarter)
```

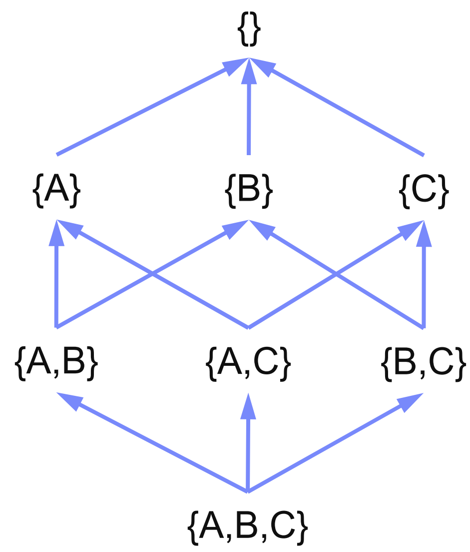
Year	Quarter	Revenue
2004	1	10
2004	2	20
2004	3	10
2004	4	20
2005	1	30

→

Year	Quarter	SUM
-	-	90
2004	-	60
2005	-	30
-	1	40
-	2	20
-	3	10
-	4	20
2004	1	10
2004	2	20
2004	3	10
2004	4	20
2005	1	30

Cube, cont.

- **Operator Implementation**
  - Aggregation lattice for (semi-)additive aggregation functions
  - **But: multiple alternative paths**
    → how to select the cheapest?



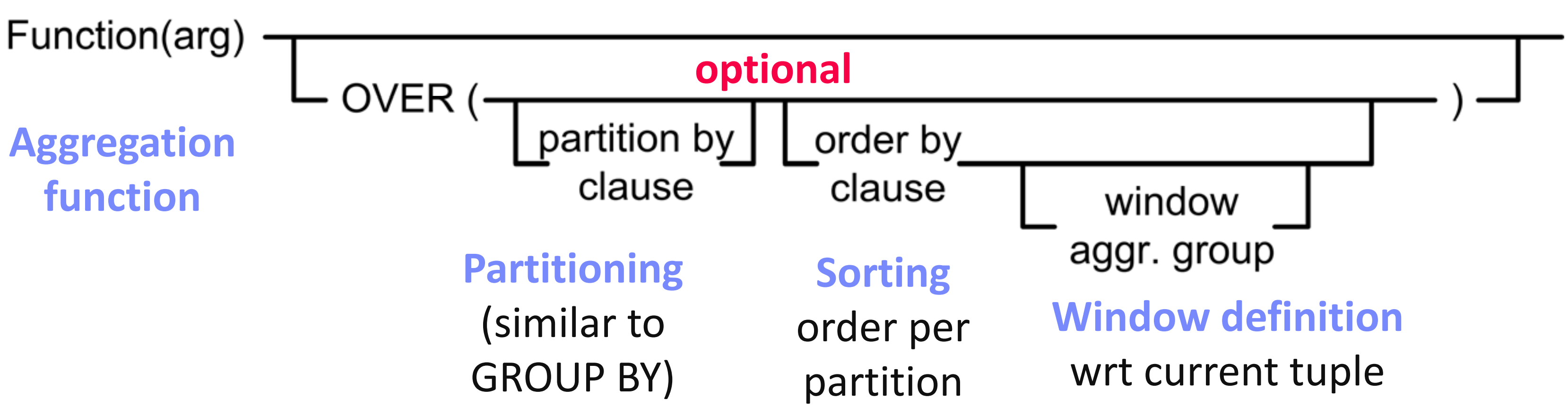
- **Recap: Physical Group-By Operators**
  - SortGroupBy / -Aggregate
  - HashGroupBy / -Aggregate

- **Cube Implementation Strategies**
  - #1: Some operators can share sorted order (e.g., {A,B} -> {A})
  - #2: Subsets with different cardinality → pick smallest intermediates

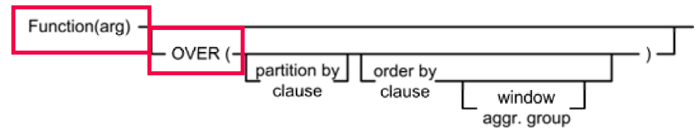
Overview Reporting Functions

- **Motivation and Problem**
  - Scalar functions as well as grouping + aggregation
  - For many advanced use cases **not flexible enough**

- **Reporting Functions**
  - Separate partitioning (grouping) and aggregation via OVER
  - Allows local partitioning via windows and ranking/numbering



RF – Aggregation Function



- **Semantics**
  - Operates over window and returns value for every tuple
  - `RANK(), DENSE_RANK(), PERCENT_RANK(), CUME_DIST(), ROW_NUMBER()`
- **Example**

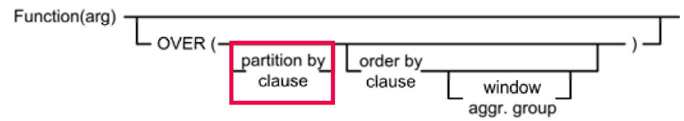
```
SELECT Year, Quarter,
    RANK() OVER (ORDER BY Revenue ASC) AS Rank1,
    DENSE_RANK() OVER (ORDER BY Revenue ASC) AS DRank1,
  FROM R
```

Year	Quarter	Revenue
2004	1	10
2004	2	20
2004	3	10
2004	4	20
2005	1	30

OVER() represents all tuples

Year	Quarter	Rank1	DRank1
2004	1	1	1
2004	3	1	1
2004	2	3	2
2004	4	3	2
2005	1	5	3

RF – Partitioning



- **Semantics**
  - Select tuples for aggregation via **PARTITON BY** <attribute-list>
- **Example**

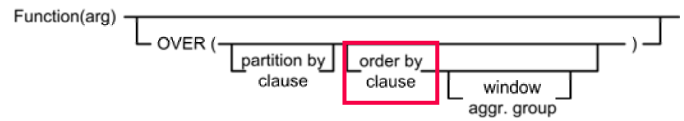
```
SELECT Year, Quarter, Revenue,
    SUM(Revenue) OVER(PARTITION BY Year)
  FROM R
```

Year	Quarter	Revenue
2004	1	10
2004	2	20
2004	3	10
2004	4	20
2005	1	30

→

Year	Quarter	Revenue	SUM
2004	1	10	60
2004	2	20	60
2004	3	10	60
2004	4	20	60
2005	1	30	30

RF – Partition Sorting



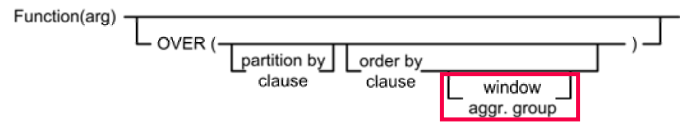
- **Semantics**
  - Define computation per partition via **`ORDER BY`** `<attribute-list>`
  - Note: `ORDER BY` allows cumulative computation → `cumsum()`
- **Example**

```
SELECT Year, Quarter, Revenue,
    SUM(Revenue) OVER(PARTITION BY Year ORDER BY Quarter)
  FROM R
```

Year	Quarter	Revenue
2004	1	10
2004	2	20
2004	3	10
2004	4	20
2005	1	30

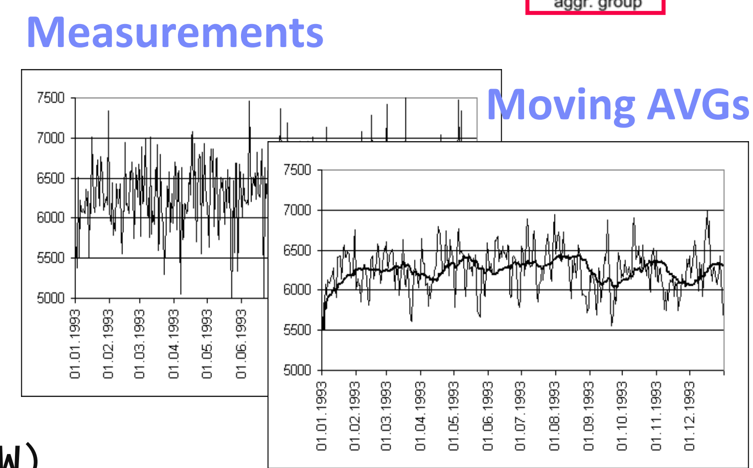
Year	Quarter	Revenue	SUM
2004	1	10	10
2004	2	20	30
2004	3	10	40
2004	4	20	60
2005	1	30	30

RF – Windowing



- **Semantics**
  - Define window for computation (e.g., for moving average, cumsum)
- **Example**

```
SELECT Year, Quarter, Revenue, AVG(Revenue)
  OVER (ORDER BY Year, Quarter
    ROWS BETWEEN 1 PRECEDING AND CURRENT ROW)
  FROM R
```

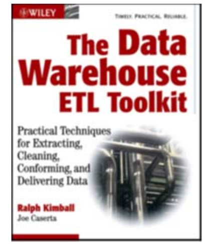


Year	Quarter	Revenue
2004	1	10
2004	2	20
2004	3	10
2004	4	20
2005	1	30

Year	Quarter	Revenue	AVG
2004	1	10	10
2004	2	20	15
2004	3	10	15
2004	4	20	15
2005	1	30	25

Summary and Q&A

- **Data Warehousing (DWH)**
  - DWH architecture
  - Multidimensional modeling
- **Extraction, Transformation, Loading (ETL)**
  - ETL process, errors, and data flows
- **SQL/OLAP Extensions**
  - Multi-grouping operations
  - Reporting functions



"There is a profound cultural assumption in the business world that *if only we could see all of our data, we could manage our businesses more effectively*. This cultural assumption is so deeply rooted that we take it for granted. Yet this is the mission of the data warehouse, and this is why the data warehouse is a permanent entity […] even as it morphs and changes its shape." -- Ralph Kimball, Joe Caserta; 2004

- **Next Lectures (Data Integration Architectures)**
  - **03 Message-oriented Middleware, EAI, and Replication** [Oct 18]
  - **04 Schema Matching and Mapping** [Oct 25]
  - **05 Entity Linking and Deduplication** [Nov 08]
  - **06 Data Cleaning and Data Fusion** [Nov 15]