Slides credit: Matthias Boehm

SCIENCE
PASSION
TECHNOLOGY

Data Integration and Large Scale Analysis
02 Data Warehousing and ETL

Shafaq Siddiqi

Graz University of Technology, Austria

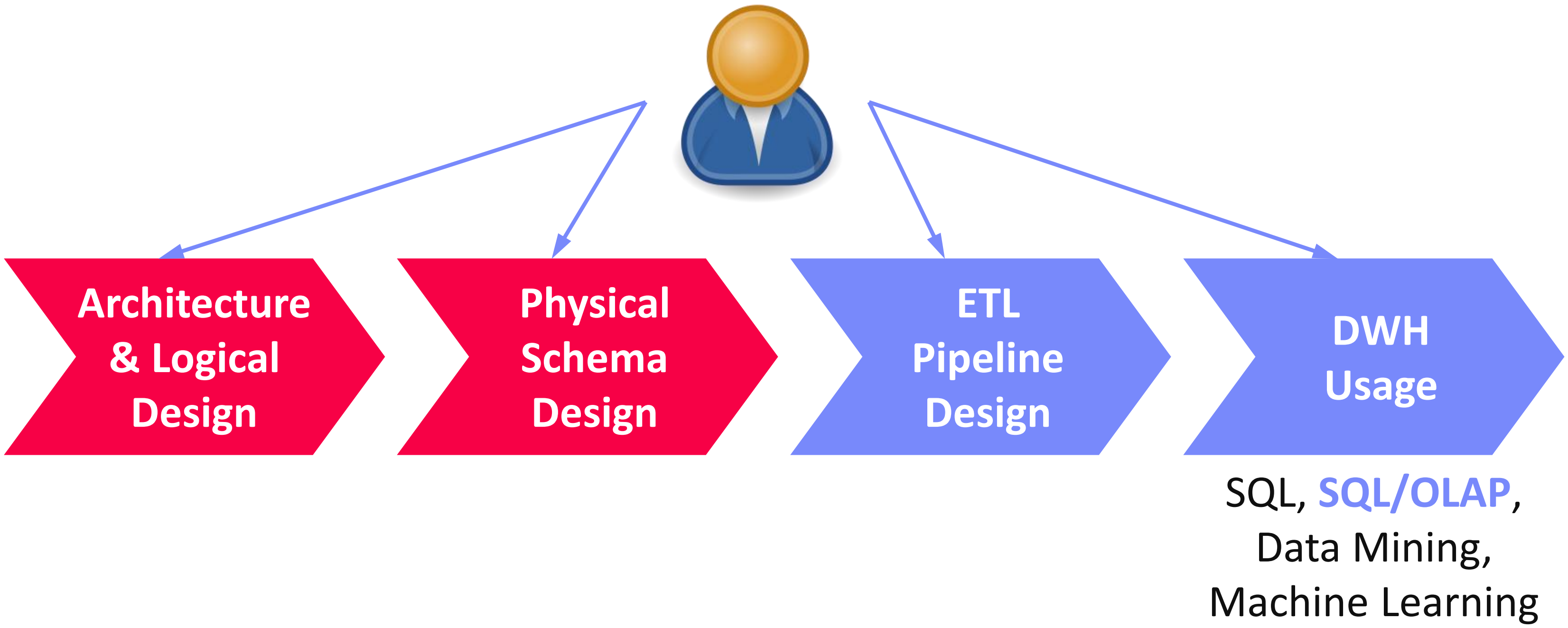
Announcements/Org

- **#1 Video Recording**
  - Link in **TUbe** & **TeachCenter**
  - Optional attendance
  - In-person and video-recorded lectures
    - **HS i5** or Webex: https://tugraz.webex.com/meet/shafaq.siddiqi

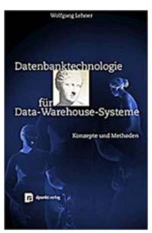
- WKO Research Grants
  - https://www.tugraz.at/en/research/research-at-tu-graz/services-fuer-forschende/foerderprogramme-und-preise-an-der-tu-graz/#c87088
  - Submission deadline October 20, 2023

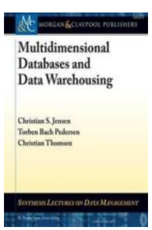
Agenda

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

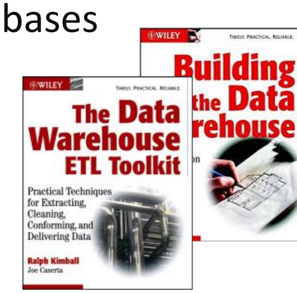


Data Warehousing





1. [**Wolfgang Lehner:** Datenbanktechnologie für Data-Warehouse-Systeme. Konzepte und Methoden, Dpunkt Verlag, 1-373, 2003]
2. [**C. S. Jensen, T. B. Pedersen, C. Thomsen.** Multidimensional Databases and Data Warehousing. Morgan and Claypool Publishers. 2010]



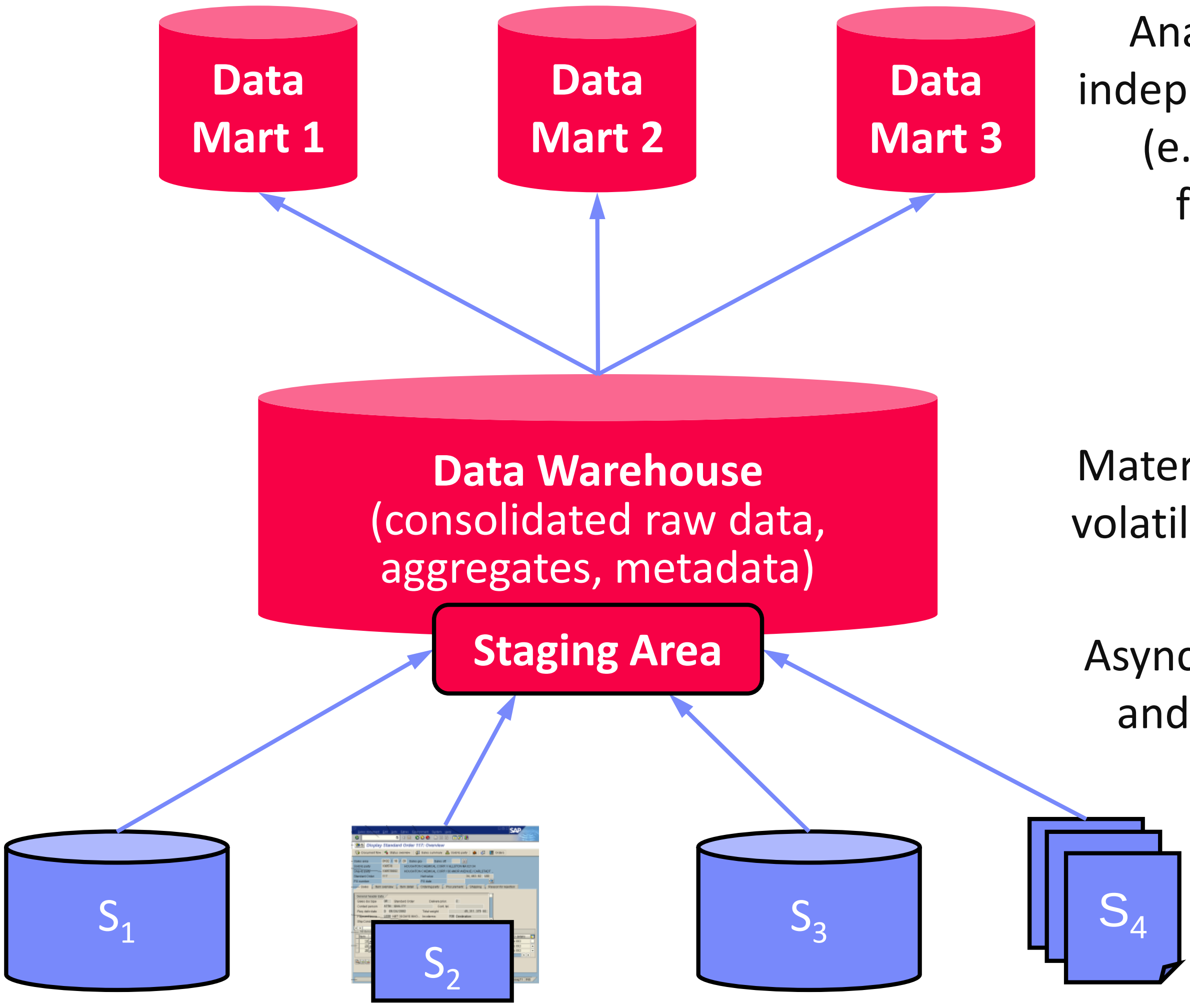
Motivation and Tradeoffs

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

? **OLTP** (Online Transaction Processing) **vs OLAP** (Online Analytical Processing)

- **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)

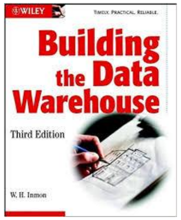
Materialized, non-volatile integration

Async replication, and ETL vs ELT

Operational source systems

Data Warehouse Architecture, cont.

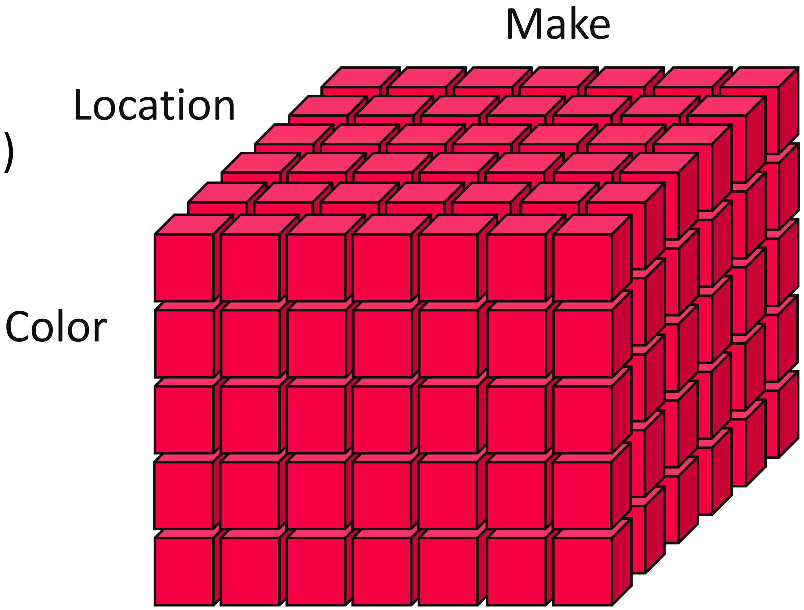
- **Data Warehouse (DWH)**
  - "A *data warehouse is a **subject-oriented, integrated, time-varying, non-volatile** collection of data in support of the management's decision-making process."* (Bill Inmon)



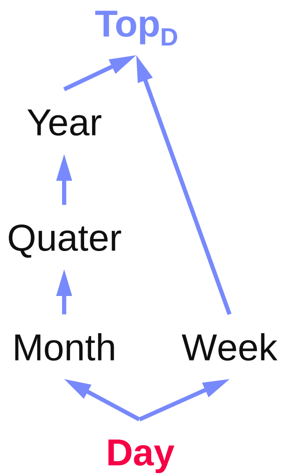
  - **#1 Subject-oriented:** analysis-centric organization (e.g., sales) → Data Mart
  - **#2 Integrated:** consistent data from different data sources
  - **#3 Time-varying:** History (snapshots of sources), and temporal modelling
  - **#4 Non-volatile:** Read-only access, limited to periodic data loading 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

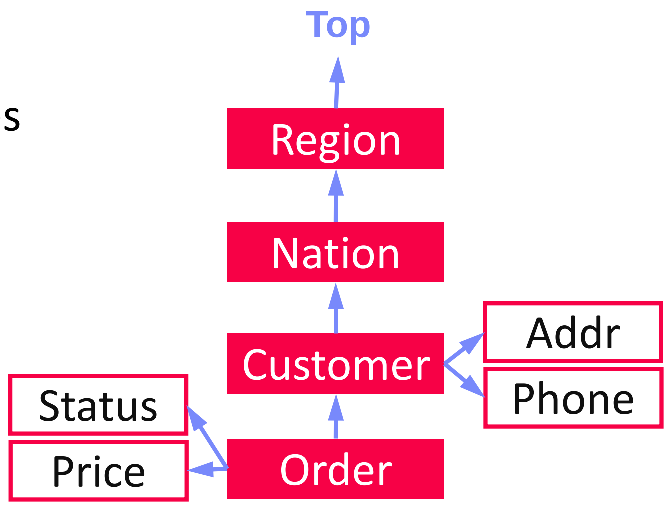


- **Central Metaphor: Data Cube**
  - Qualifying data (categories, dimensions)
  - Quantifying data (cells)
  - Often sparse (0 for empty cells)
- **Multi-dimensional Schema**
  - Set of **dimension hierarchies** (D^1,…, D^n)
  - Set of **measures** (M^1,…,M^m)
- **Dimension Hierarchy**
  - Partially-ordered set D of categorical attributes ({D_1,…,D_n, Top_D};→)
  - 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

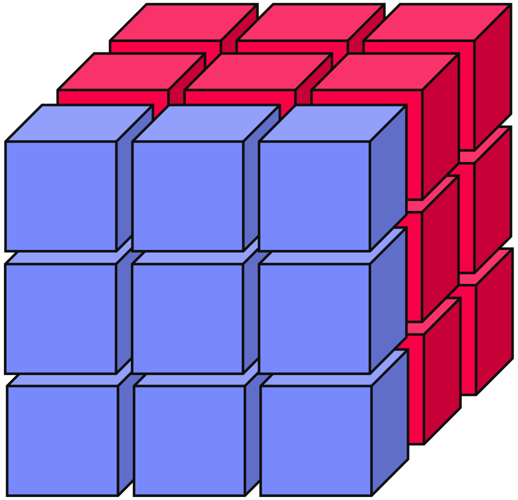


- **Fact F**
  - Base tuples w/ measures of summation type
  - Granularity G as subset of categorical attributes

- **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

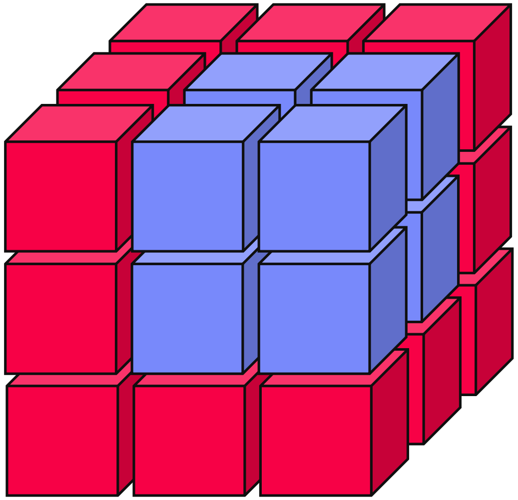
Multi-dimensional Modeling: Operations

- **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



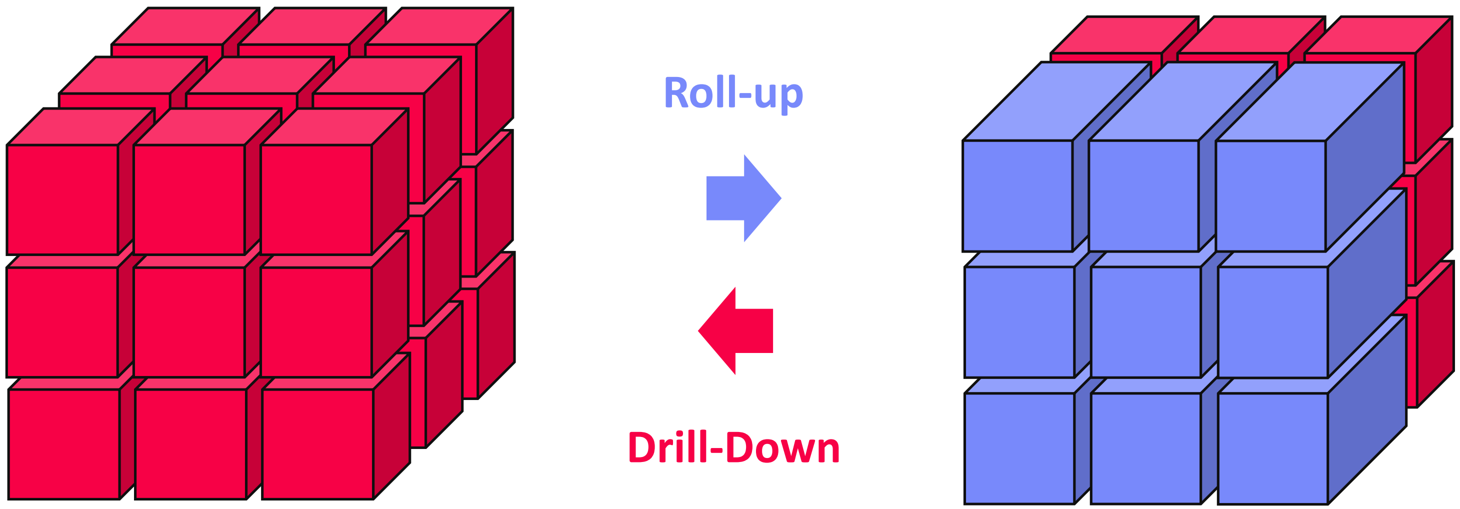
- **Dicing**
  - Select a "sub-cube" by specifying a filter condition on multiple dimensions
  - Complex Boolean expressions possible
  - Sometimes slicing used synonym

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



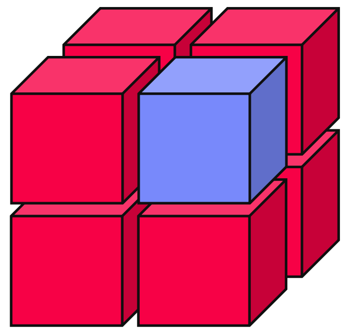
Multi-dimensional Modeling: Operations, cont.

- **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



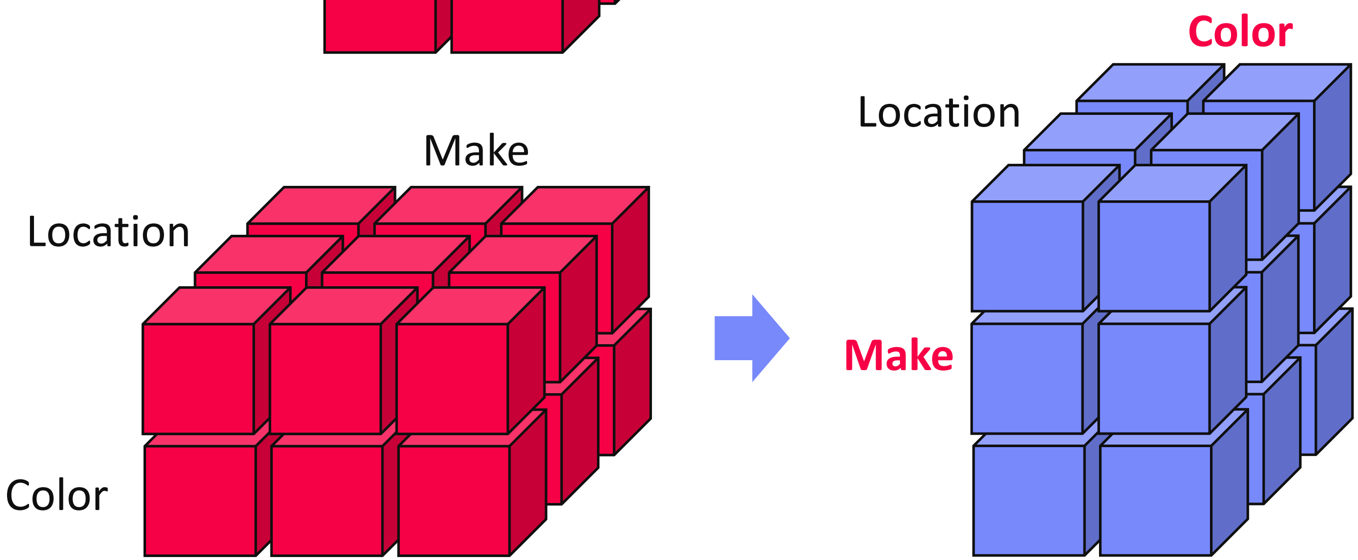
Multi-dimensional Modeling: Operations, cont.

- **Drill-Across**
  - Change from one cube to another
- **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)

- **Summation Types of Measures**
  - **FLOW:** arbitrary aggregation possible
  - **STOCK:** aggregation possible, except over temporal dim
  - **VPU:** value-per-unit typically (e.g., price)

[Hans-Joachim Lenz, Arie Shoshani: Summarizability in OLAP and Statistical Data Bases. SSDBM 1997]

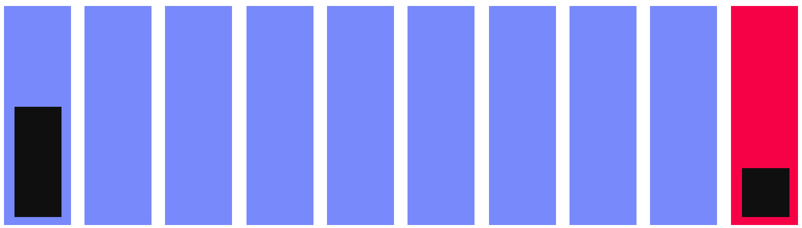
- **Necessary Conditions**
  - Disjoint attribute values
  - Completeness
  - Type compatibility

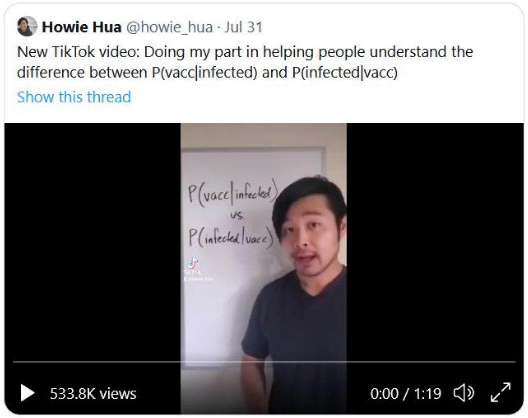
[TUGraz online]

# Stud	16/17	17/18	18/19	19/20	20/21	Total
CS	1,153	1,283	1,321	1,343	1368	?
SEM	928	970	939	944	985	?
ICE	804	868	846	842	849	?
Total	2,885	3,121	3,106	3,129	3,202	?

Excursus: Other Misleading Statistics

- **Problem Setting**
  - 100 people (**90 vaccinated**, **10 non-vaccinated**)
  - **5** infected vaccinated, **2** infected non-vaccinated





[https://twitter.com/howie_hua/status/1421502809862664197]

- **P(vacc|infected) = 5/7 = 0.71 → misleading**
- **P(infected|vacc) = 5/90 = 0.056**
- **P(infected|non-vacc) = 2/10 = 0.2**

[see also Simpson's Paradox in **06 Data Cleaning**]

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
    $\mathbf{R \subseteq D_1 \times D_2 \times \ldots \times D_k, k \geq 1}$

Attribute

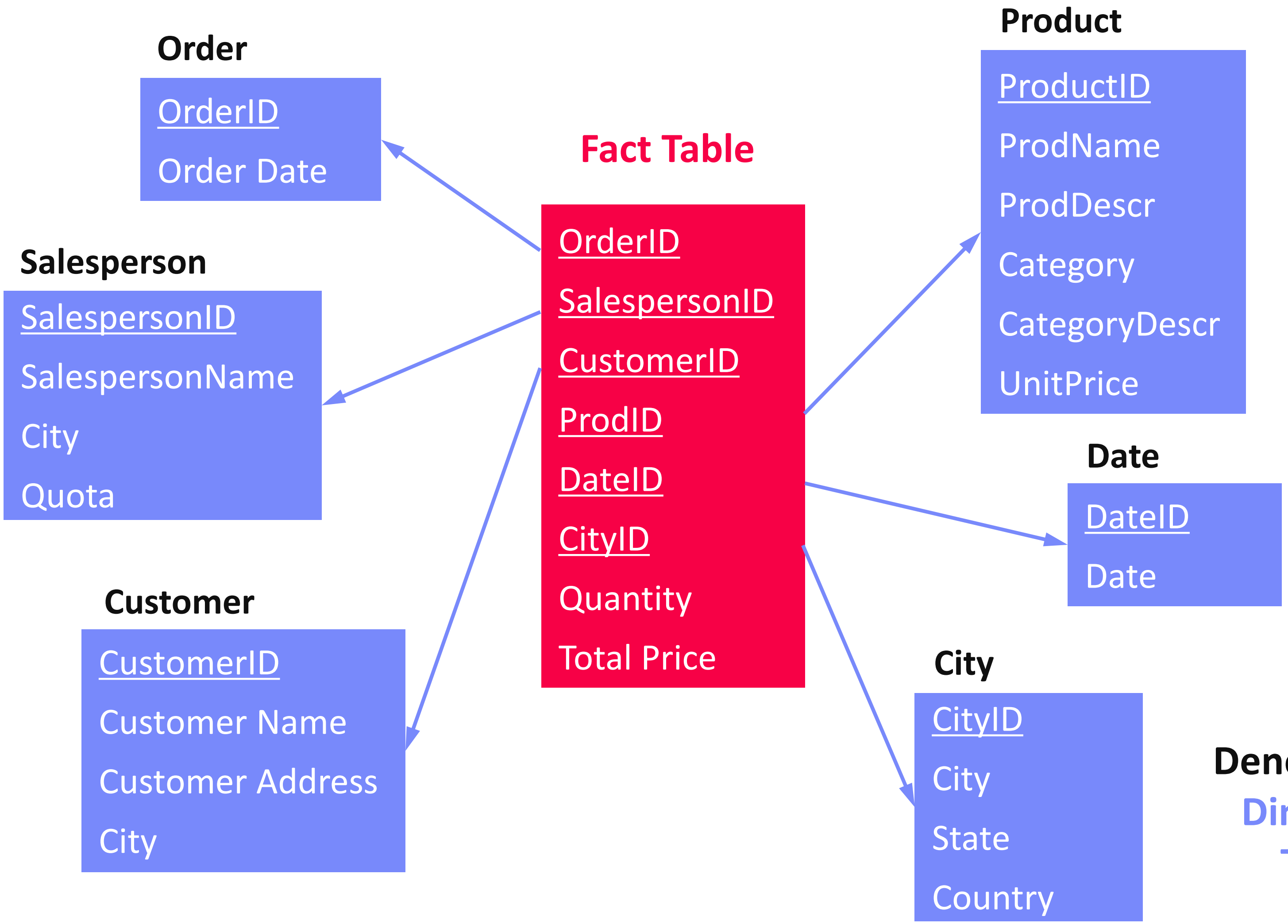
A1 INT	A2 INT	A3 BOOL
3	7	T
1	2	T
3	4	F
1	7	T

Tuple

cardinality: 4
rank: 3

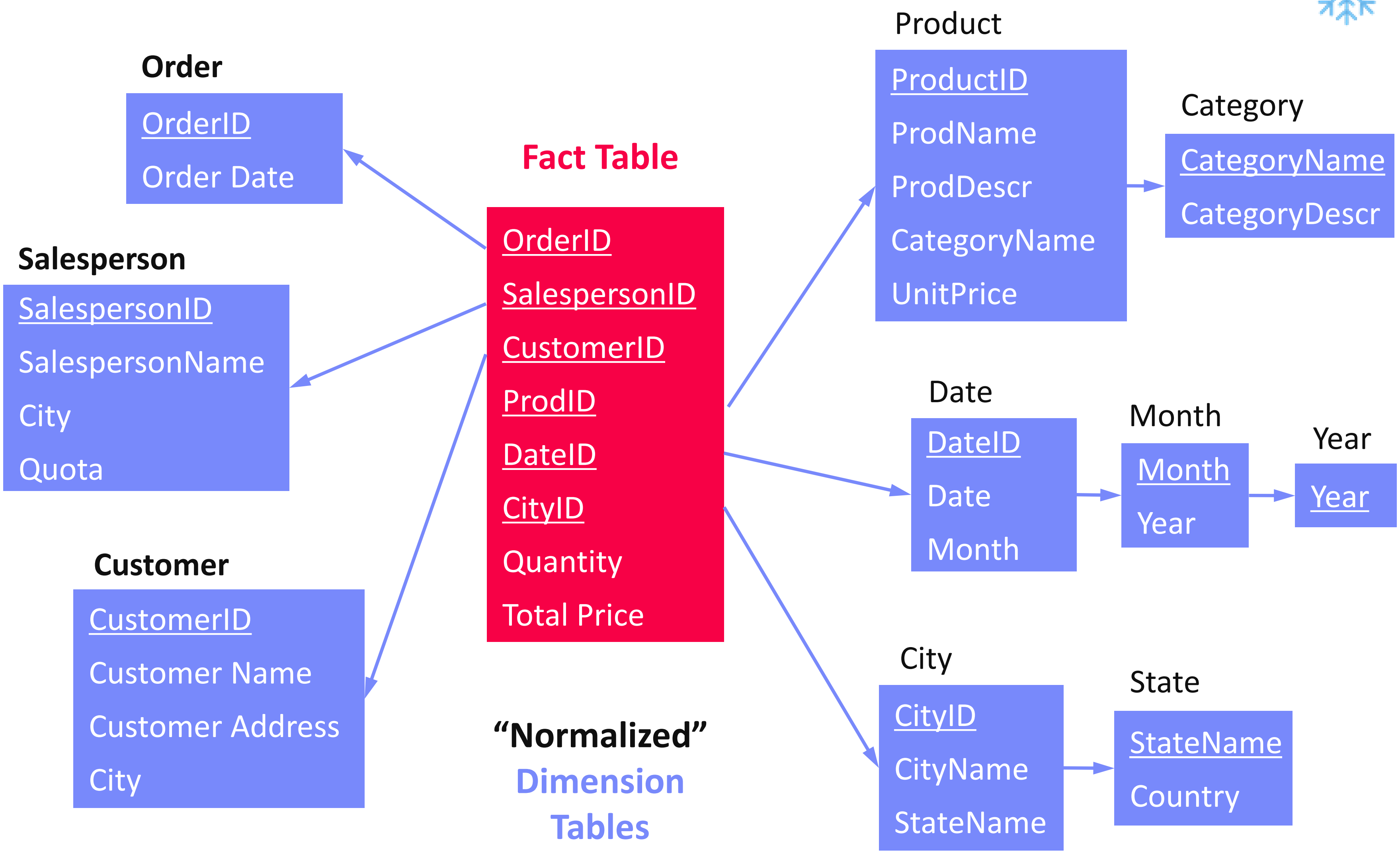
- **Additional Terminology**
  - **Tuple**: row of k elements of a relation
  - **Cardinality** of a relation: number of tuples in the relation
  - **Rank** of a relation: number of attributes
  - **Semantics:** **Set** := no duplicate tuples (in practice: **Bag** := duplicates allowed)
  - **Order of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

ROLAP – Star Schema



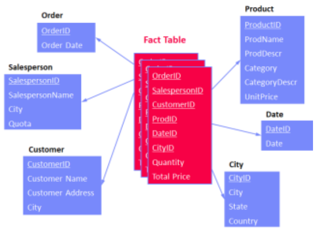
Denormalized Dimension Tables

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

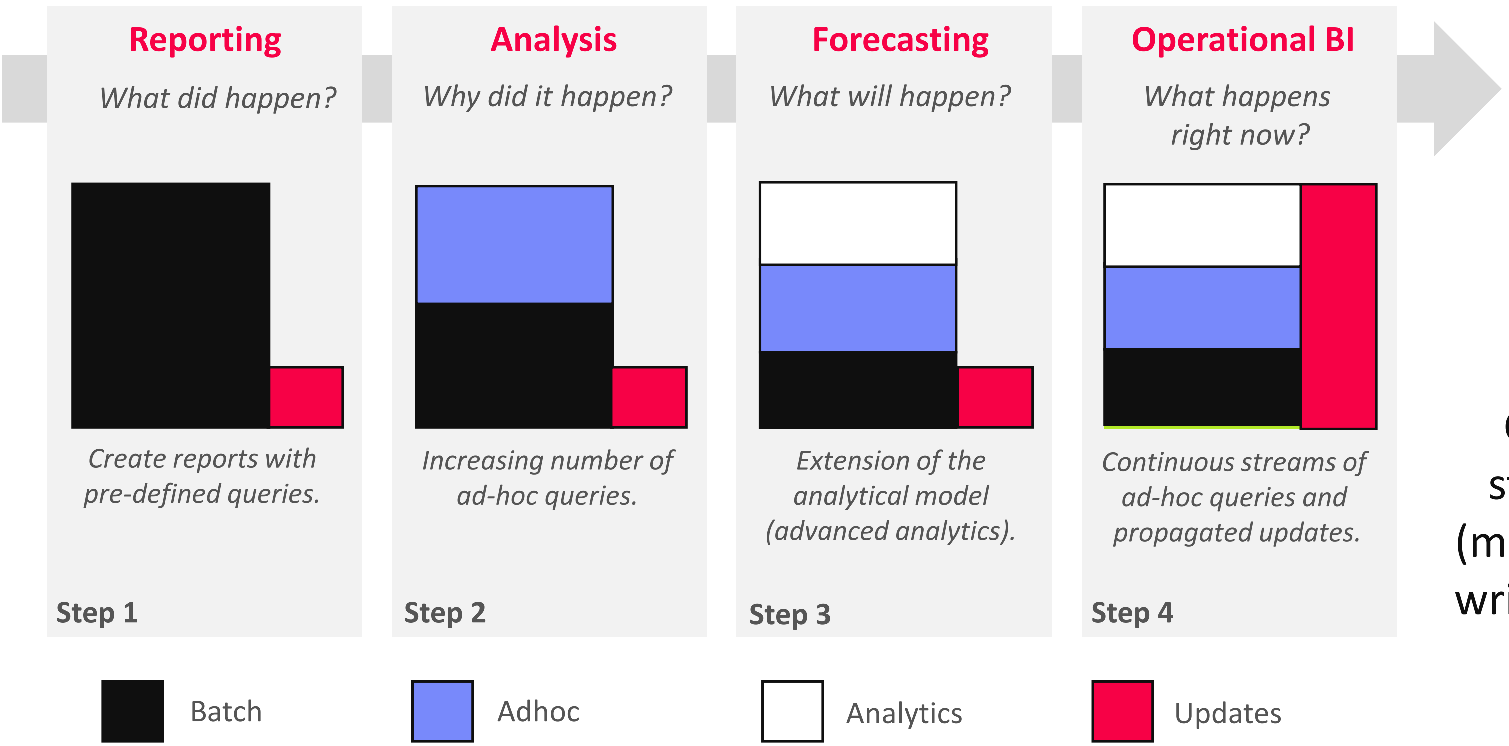
- **OLAP Benchmark Schemas**
  - **TPC-H** (8 tables, normalized schema)
  - **SSB** (5 tables, star schema, simplified TPC-H)
  - **TPC-DS** (24 tables, snow-storm schema)

  "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**

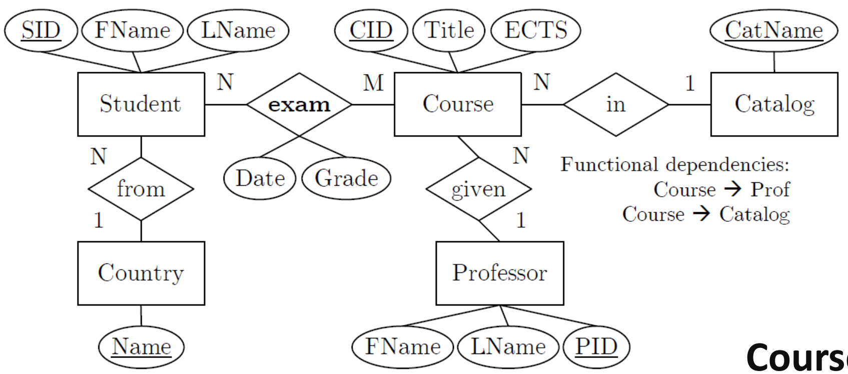


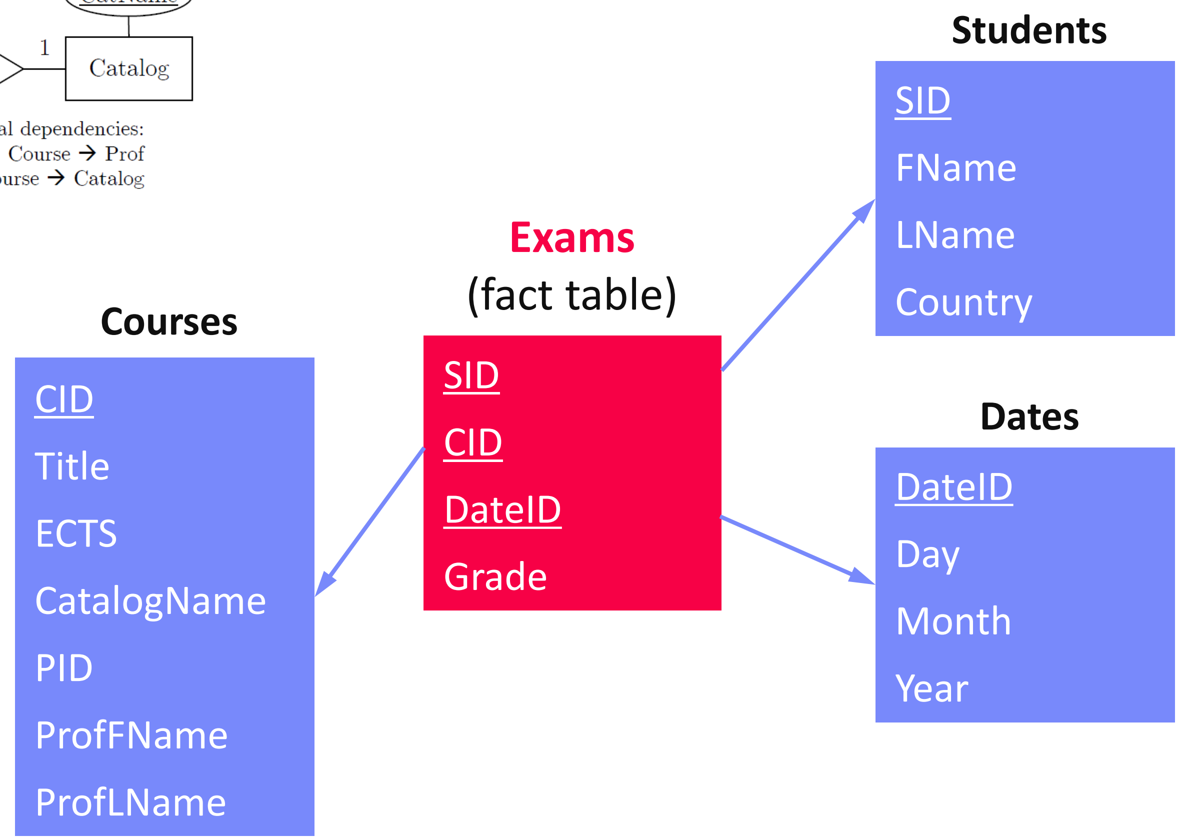
SotA: Column stores w/ (multi-stage) write buffers

BREAK (and Test Yourself)

[Exam Feb 08, 2021]

- **Task: Given below ER diagram, create a ROLAP star schema. Data types can be ignored, but indicate PK and FK constraints. (9/100 points)**





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 (Instructor vs lecturer)
2. Simple Mapping (mathematical 12 hr vs 12 hr)
3. Union Types (String, urls)
4. Complex Mappings (Units/Credits)
5. Language Expressions (Databse vs Datenbank)

Missing Data

6. Nulls (Missing Values)
7. Virtual Columns
8. Semantic Incompatibility (Concept does not exist)

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**

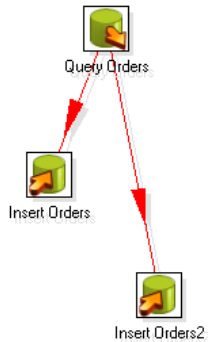
- **#1 Explicit Messages/Triggers**
  - Setup update propagation from the source systems to middleware
  - Asynchronously propagate the updates into the DWH

- **#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

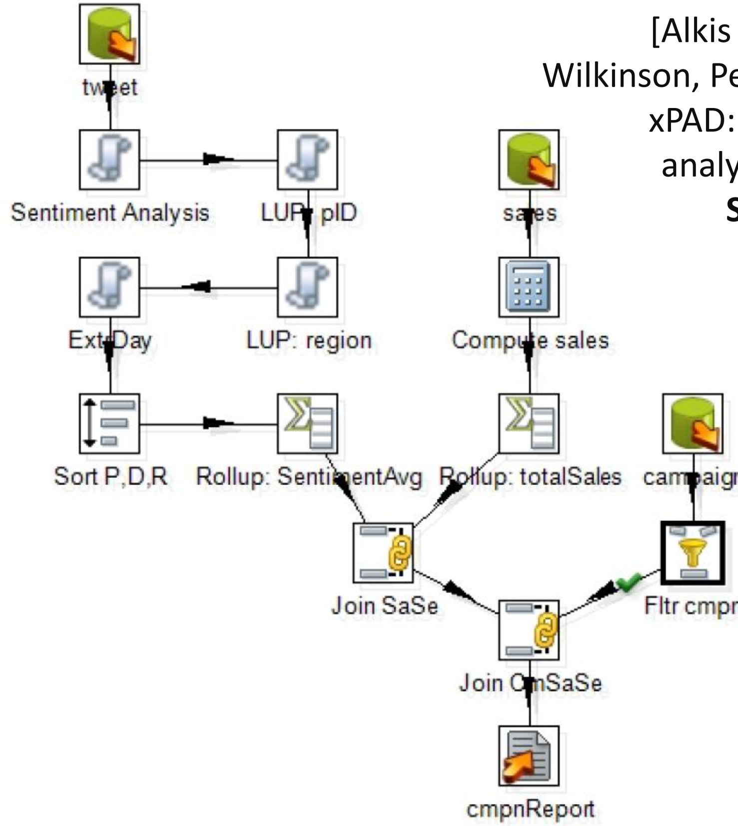
- **#3 Snapshot Differences**
  - Compute difference between old and new snapshot (e.g., files) before loading
  - Broadly applicable but more expensive

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

ETL via Apache Spark

- **Example**
  - Distributed ETL pipeline processing

[Xiao Li: Building Robust ETL Pipelines with Apache Spark, **Spark Summit 2017**]


```
//load csv and postgres tables
val csvTable = spark.read.csv("/source/path")
val jdbcTable = spark.read.format("jdbc")
  .option("url", "jdbc:postgresql:...")
  .option("dbtable", "TEST.PEOPLE")
  .load()

//join tables, filter and write as parquet
csvTable
  .join(jdbcTable, Seq("name"), "outer")
  .filter("id <= 2999")
  .write.mode("overwrite")
  .format("parquet")
  .saveAsTable("outputTableName")
```

11 Distributed, Data-Parallel Computation

SQL/OLAP Extensions

Overview Multi-Groupings

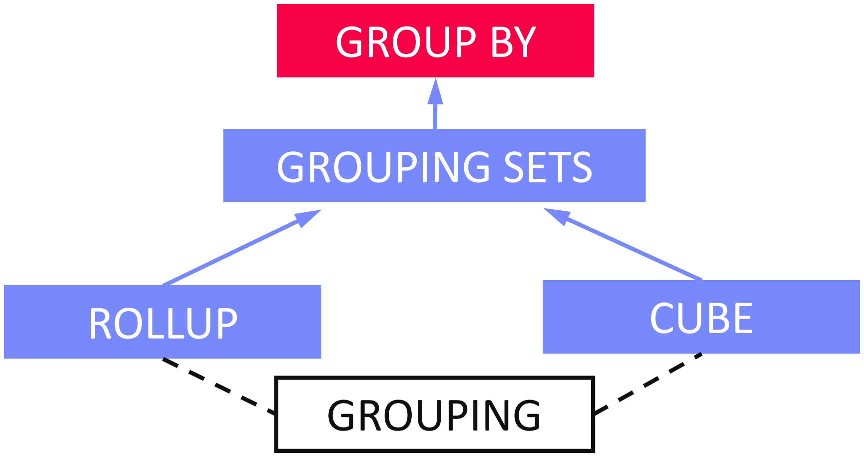
- **Recap: GROUP BY**
  - Group tuples by categorical variables
  - Aggregate per group

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

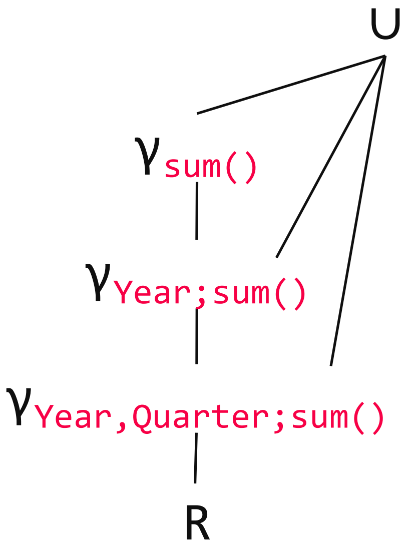
→

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**
  - With ROLLUP or CUBE to identify aggregates
  - NULL group vs NULL due to aggregation
  - Example

```
SELECT Team, SUM(Revenue),
       GROUPING(Team) AS Agg
  FROM R
  GROUP BY ROLLUP (Team)
```

Team	Revenue	Agg
NULL	10	0
Sales	40	0
Tech	20	0
NULL	70	1

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**

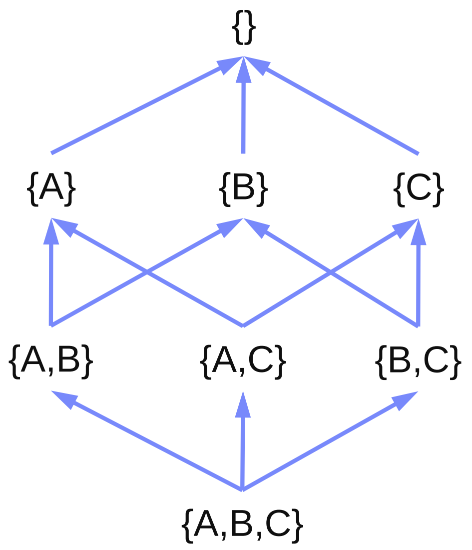
```
SELECT Year, Quarter, SUM(Revenue)
  FROM R
  GROUP BY CUBE(Year,Quarter)
```

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?

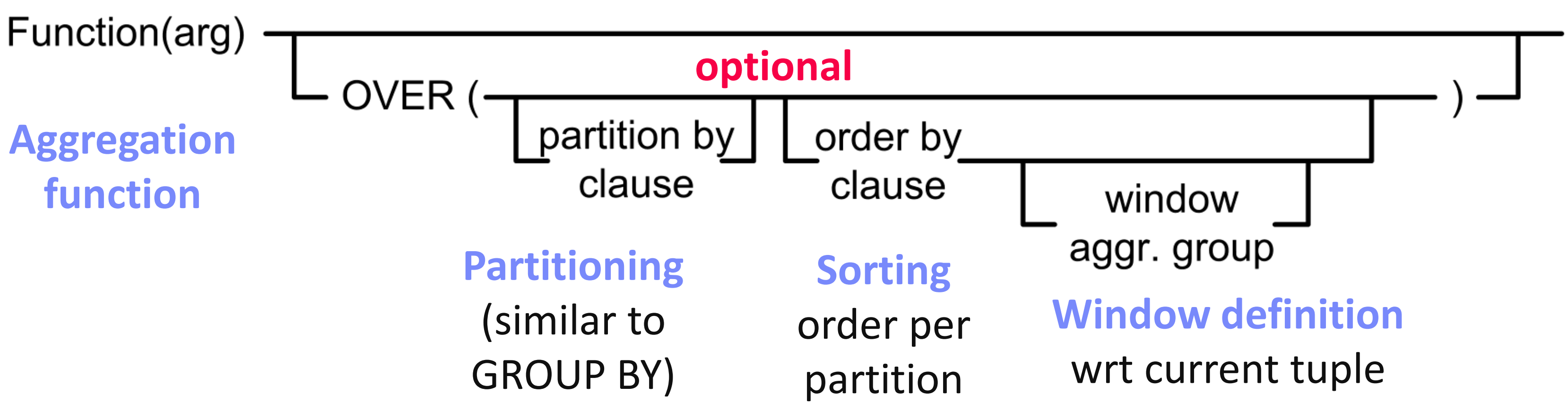


- **Recap: Physical Group-By Operators**
  - SortGroupBy / -Aggregate
  - HashGroupBy / -Aggregate

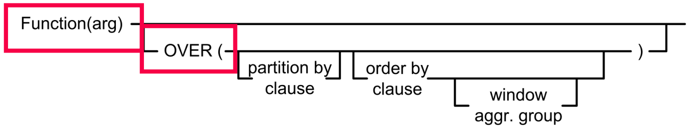
- **Cube Implementation Strategies**
  - #1: Some operators can share sorted order (e.g., {A,B} -> {A})
  - #2: Subsets with different cardinality → pick smallest intermediates

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**

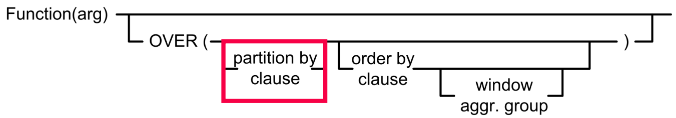
```
SELECT Year, Quarter,
    RANK() OVER (ORDER BY Revenue ASC) AS Rank1,
    DENSE_RANK() OVER (ORDER BY Revenue ASC) AS DRank1,
  FROM R
```

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



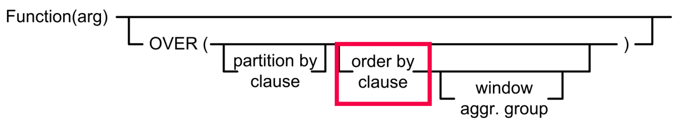
- **Semantics**
  - Select tuples for aggregation via **`PARTITON BY`** `<attribute-list>`
- **Example**

```
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



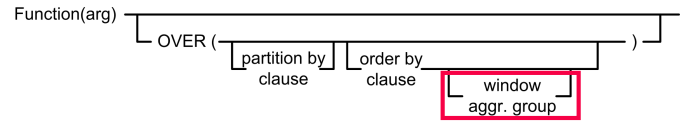
- **Semantics**
  - Define computation per partition via **ORDER BY** <attribute-list>
  - Note: ORDER BY allows cumulative computation → cumsum()
- **Example**

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

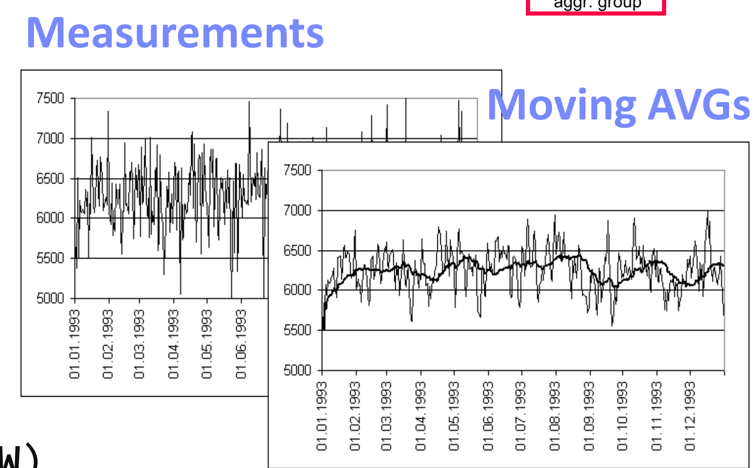
Year	Quarter	Revenue
2004	1	10
2004	2	20
2004	3	10
2004	4	20
2005	1	30

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

Trend: Cloud Data Warehousing

10 Distributed Data Storage

- **#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**

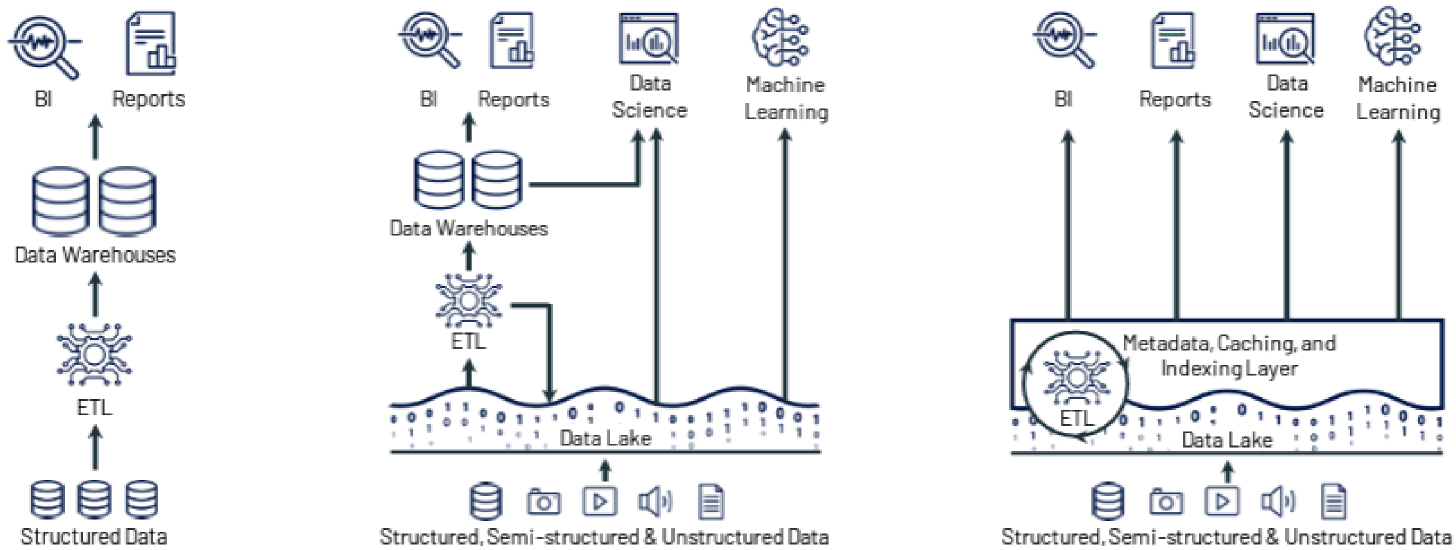
[IBM: IBM dashDB - Cloud-based data warehousing as-a-service, built for analytics, IBM **White Paper 2015**]

- **#5 Snowflake Data Warehouse**

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

Trend: Data Lakes and Lakehouse

10 Distributed Data Storage

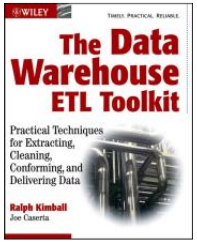


(a) First-generation platforms. (b) Current two-tier architectures. (c) Lakehouse platforms.

[Matei Zahari et. al, Lakehouse: A New Generation of Open Platforms that Unify Data Warehousing and Advanced Analytics. **CIDR 2021**]

[Alkis Simitsis et. al., The History, Present, and Future of ETL Technology, **DOLAP 2023]**

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 21]
  - **04 Schema Matching and Mapping** [Oct 28]
  - **05 Entity Linking and Deduplication** [Nov 04]
  - **06 Data Cleaning and Data Fusion** [Nov 11]