Data Integration and Large Scale Analysis
02 Data Warehousing and ETL

Shafaq Siddiqi

Graz University of Technology, Austria

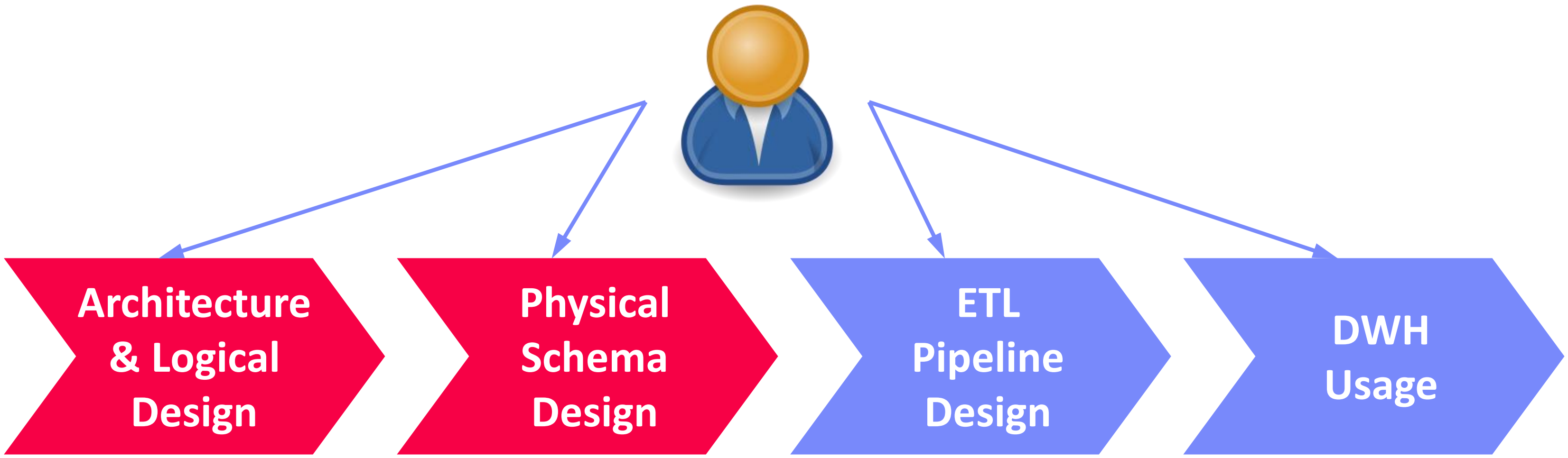
Last update: Oct 14, 2022

Announcements/Org

- **#1 Video Recording**
  - Link in TUbe & TeachCenter
  - Optional attendance (independent of COVID)
  - 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
  - MS these started after 1st of October 2021
  - Submission deadline October 21, 2022

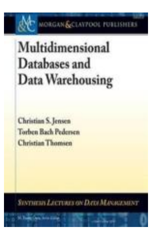
Agenda

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

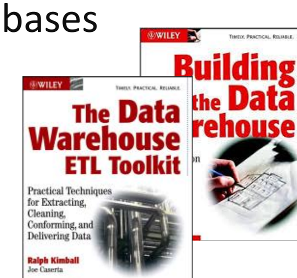


SQL, SQL/OLAP, Data Mining, Machine Learning

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]



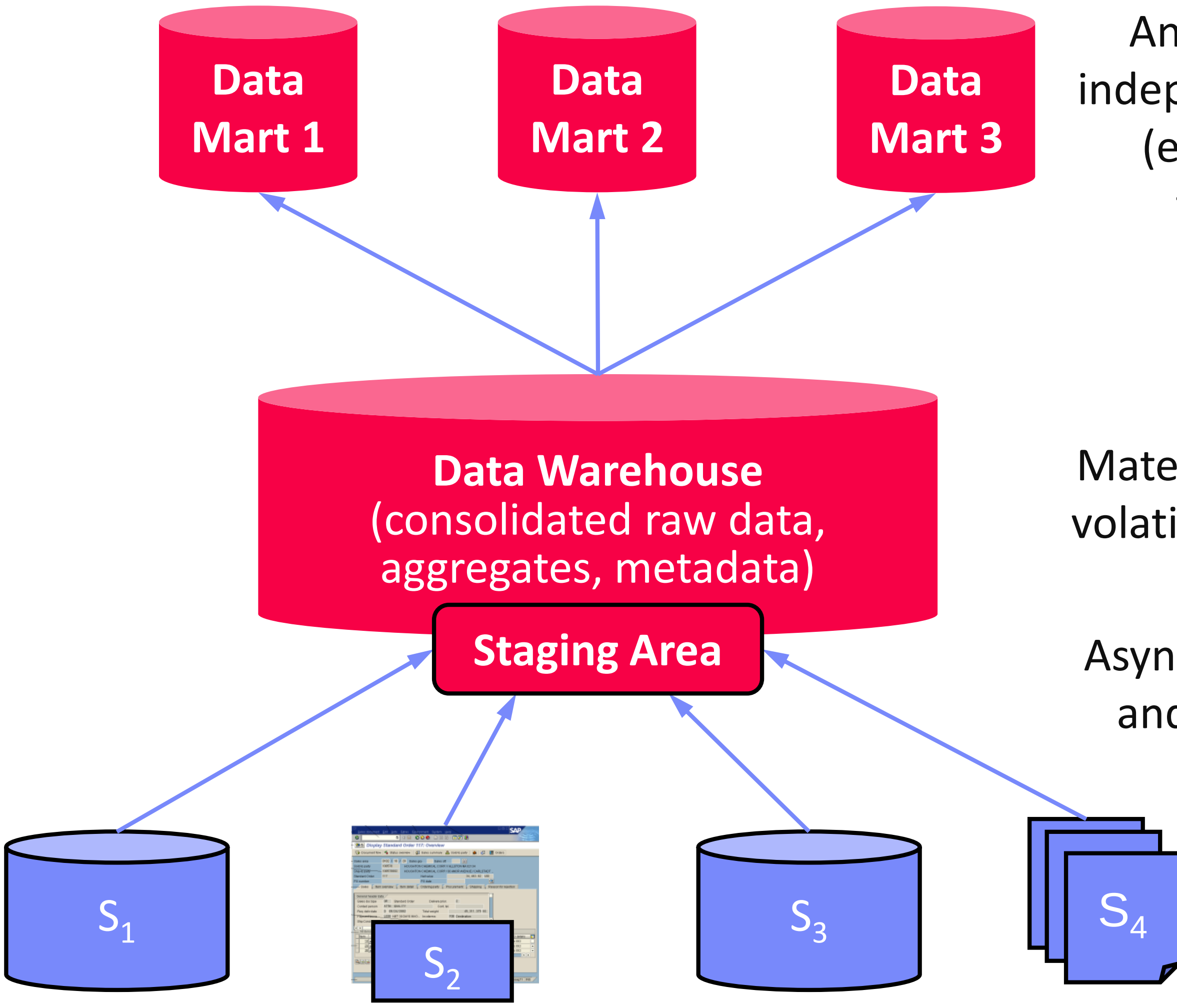
Motivation and Tradeoffs

- **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



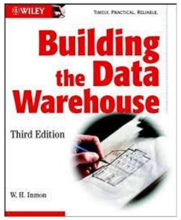
Analysis-centric independent subsets (e.g., geo, org, functional)

Materialized, non-volatile integration

Async replication, and ETL vs ELT

Operational source systems

Data Warehouse Architecture, cont.

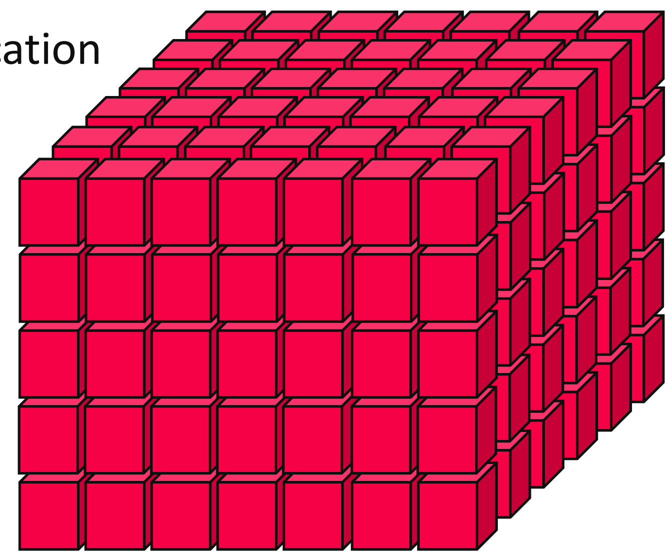


- **Data Warehouse (DWH)**
  - "A *data warehouse is a* ***subject-oriented, integrated, time-varying, non-volatile*** *collection of data in support of the management's decision-making process."* (Bill Inmon)
  - **#1 Subject-oriented:** analysis-centric organization (e.g., sales) → Data Mart
  - **#2 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**)

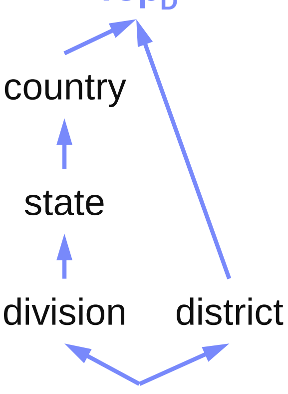
Multi-dimensional Modeling: Data Cube

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

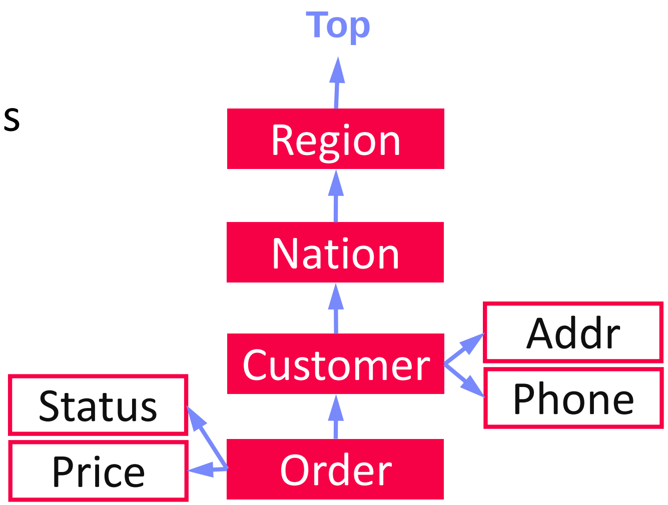


- **Multi-dimensional Schema**
  - Set of **dimension hierarchies** ($D^1,\ldots, D^n$)
  - Set of **measures** ($M^1,\ldots,M^m$)

- **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.



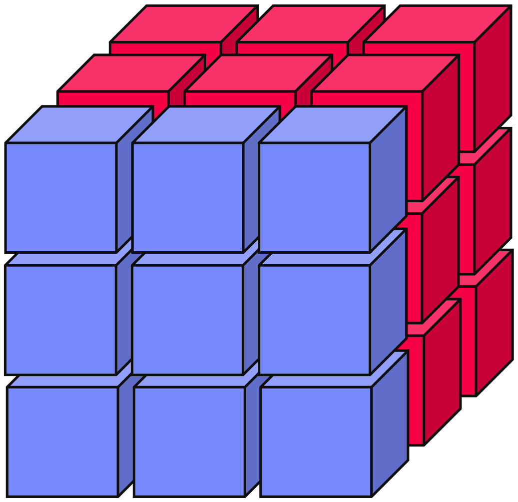
- **Dimension Hierarchy, cont.**
  - Classifying (categorical) vs descriptive attributes
  - **Orthogonal dimensions:** there are no functional dependencies between attributes of different dimensions

- **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

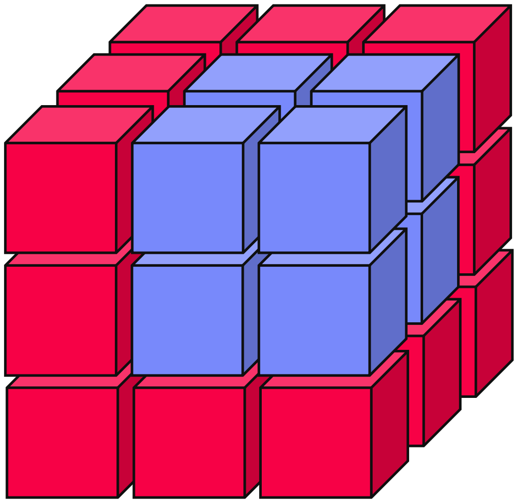
Multi-dimensional Modeling: Operations

- **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



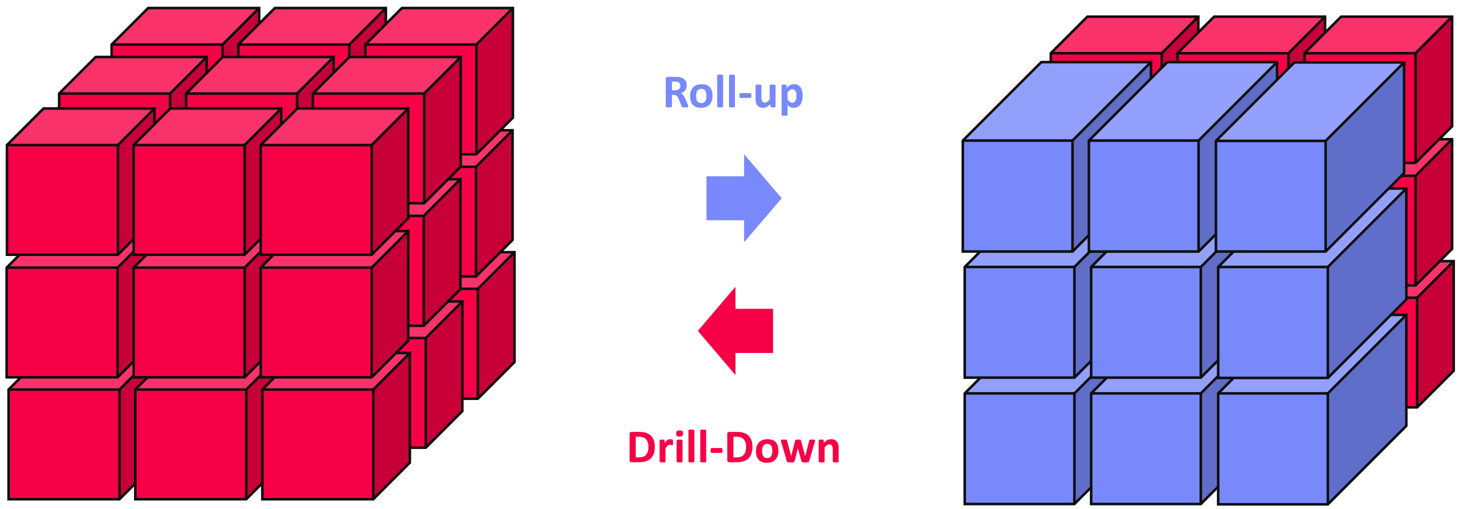
- **Dicing**
  - Select a "sub-cube" by specifying a filter condition on **multiple dimensions**
  - Complex Boolean expressions possible
  - Sometimes slicing used synonym

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



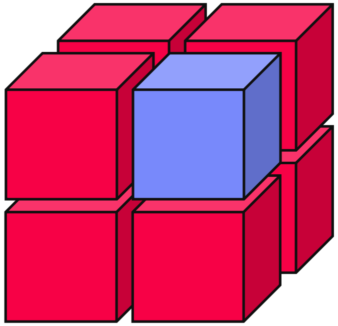
Multi-dimensional Modeling: Operations, cont.

- **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



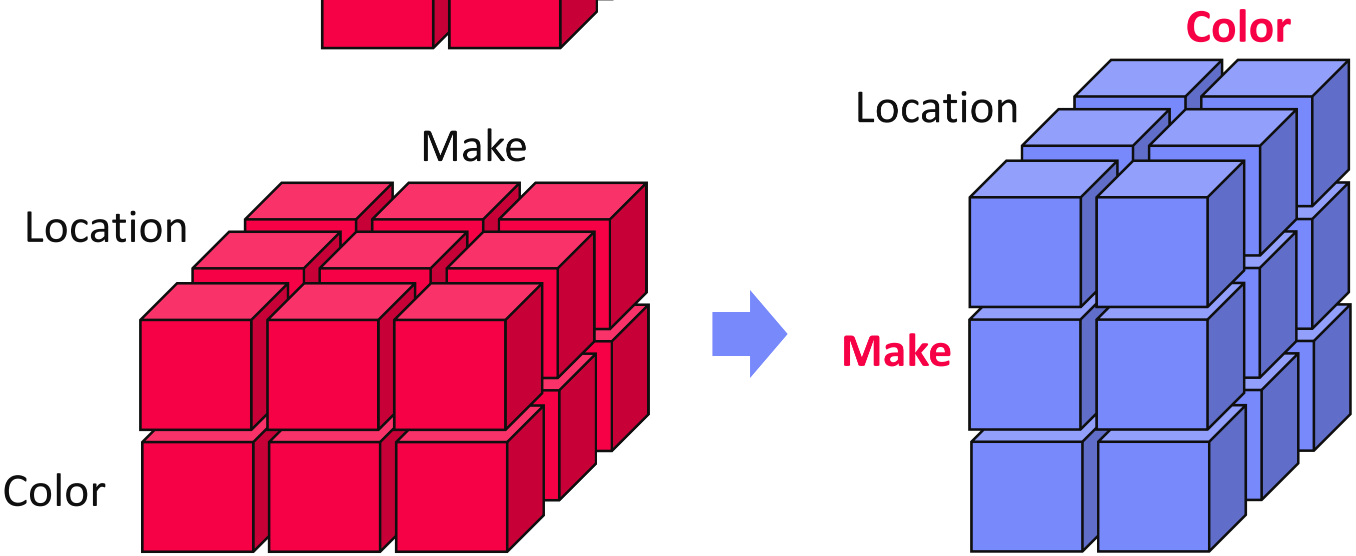
Multi-dimensional Modeling: Operations, cont.

- **Drill-Across**
  - 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]

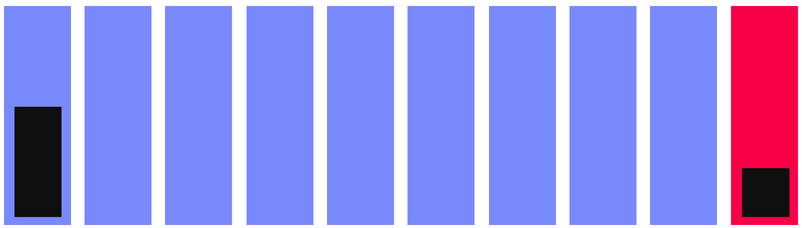
- **Necessary Conditions**
  - Disjoint attribute values
  - Completeness
  - Type compatibility

[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

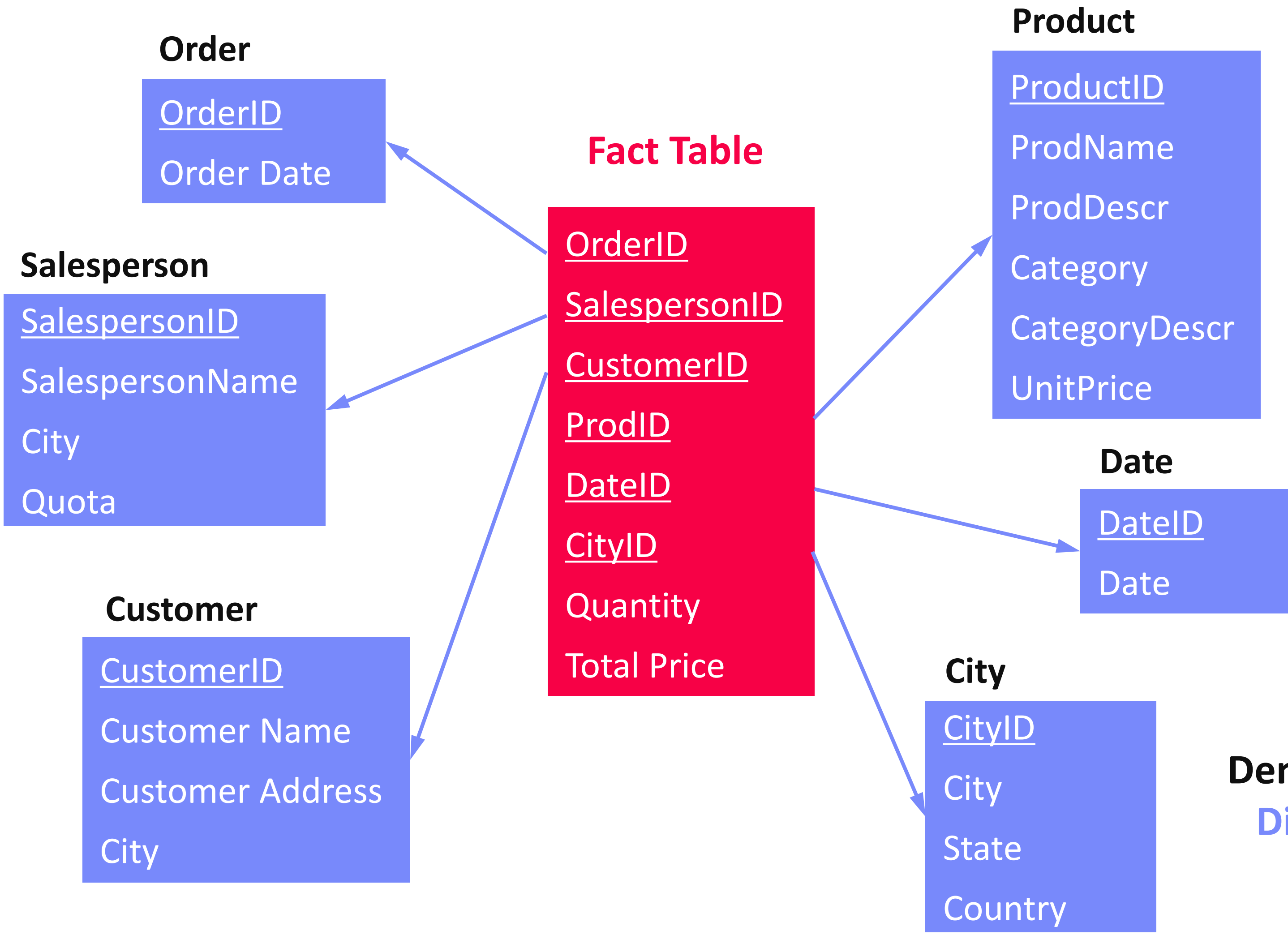
A1 INT	A2 INT	A3 BOOL
3	7	T
1	2	T
3	4	F
1	7	T

Tuple

cardinality: 4
rank: 3

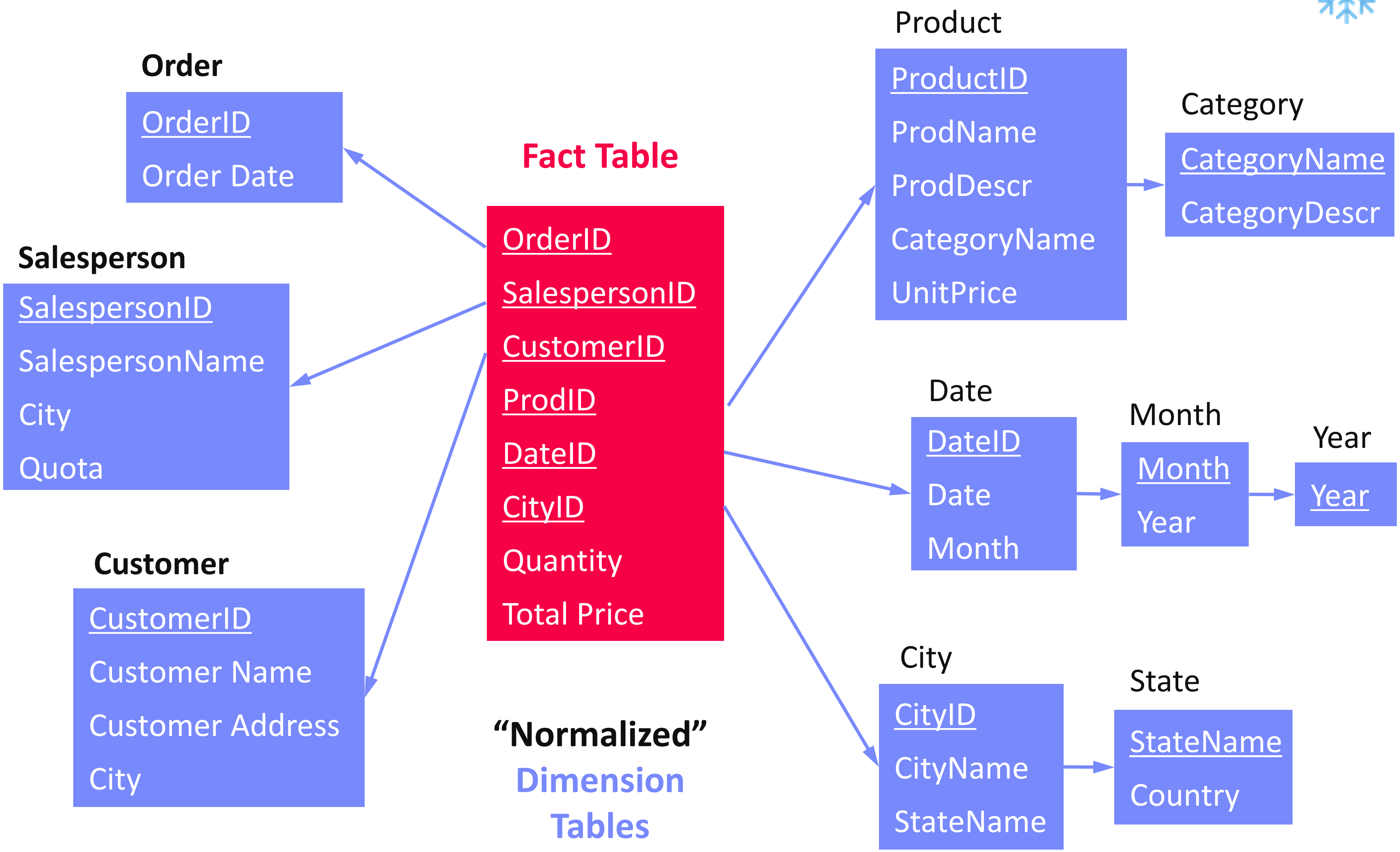
- **Additional Terminology**
  - **Tuple**: row of k elements of a relation
  - **Cardinality** of a relation: number of tuples in the relation
  - **Rank** of a relation: number of attributes
  - **Semantics:** **Set** := no duplicate tuples (in practice: **Bag** := duplicates allowed)
  - **Order of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

ROLAP – Star Schema



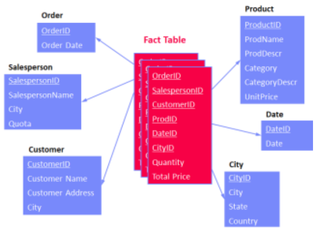
Denormalized Dimension Tables

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

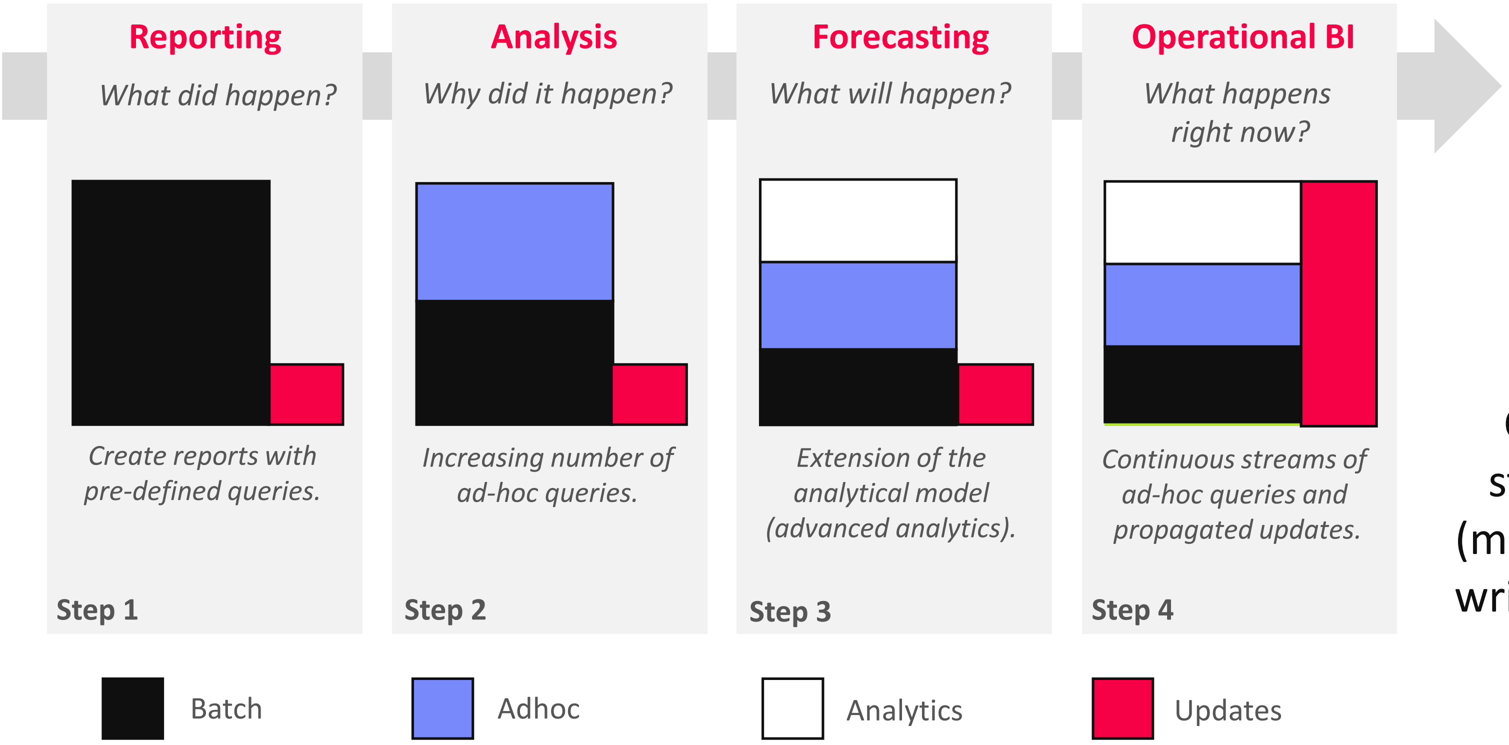
- **OLAP Benchmark Schemas**
  - **TPC-H** (8 tables, normalized schema)
  - **SSB** (5 tables, star schema, simplified TPC-H)
  - **TPC-DS** (24 tables, snow-storm schema)

"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

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**]

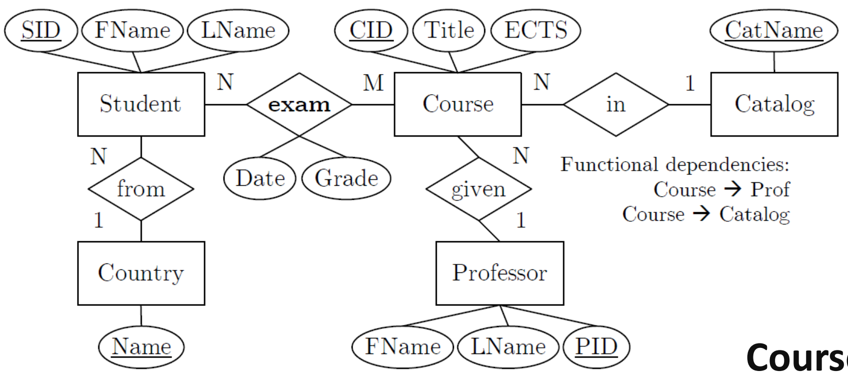
- **#5 Snowflake Data Warehouse**

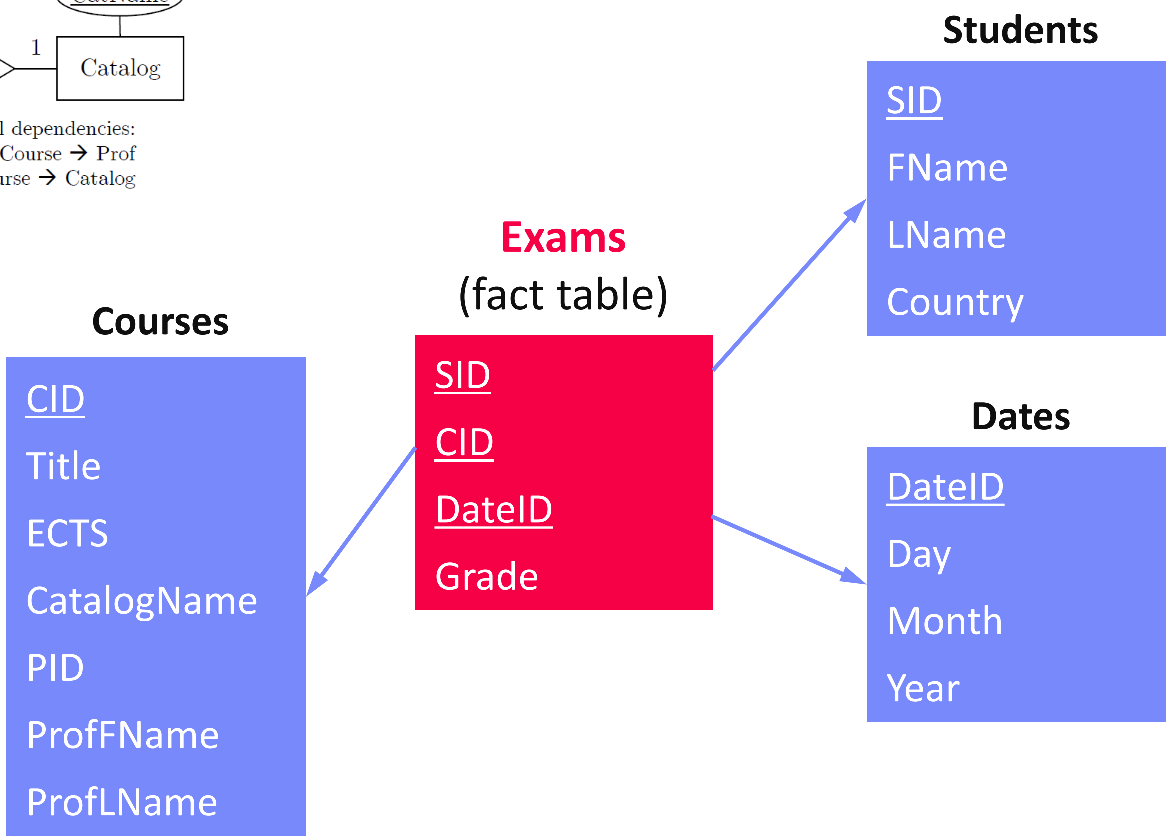
[Benoît Dageville et al.: The Snowflake Elastic Data Warehouse. **SIGMOD 2016**]

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**

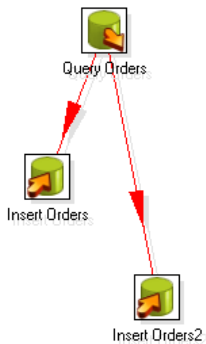
- **#1 Explicit Messages/Triggers**
  - Setup update propagation from the source systems to middleware
  - Asynchronously propagate the updates into the DWH

- **#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

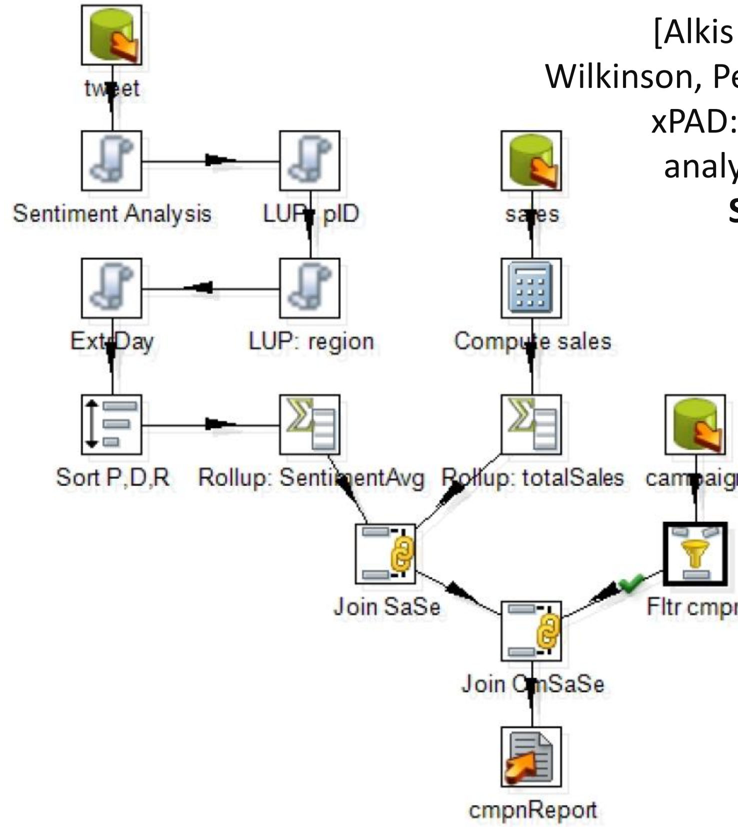
- **#3 Snapshot Differences**
  - Compute difference between old and new snapshot (e.g., files) before loading
  - Broadly applicable but more expensive

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**]

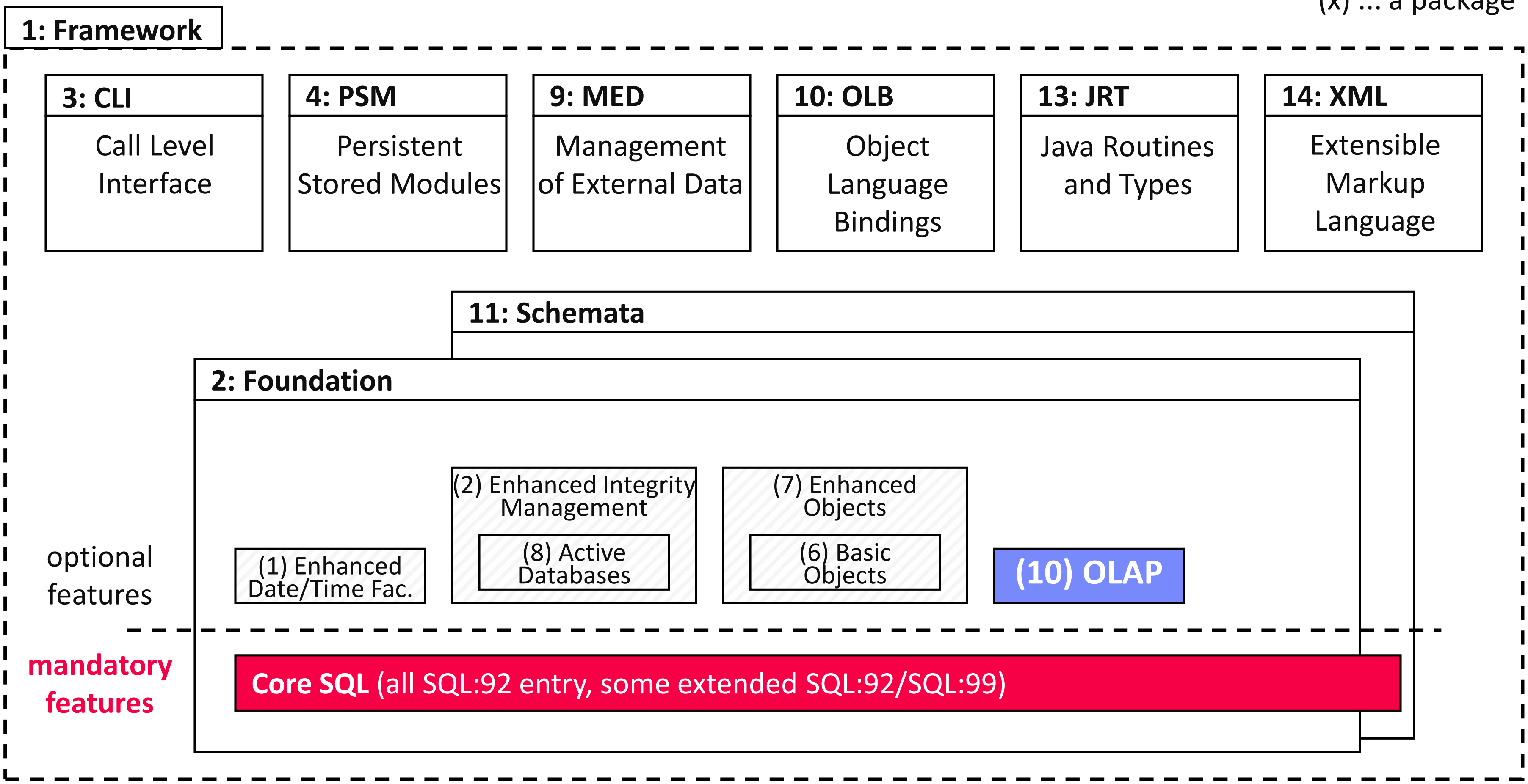

```
//load csv and postgres tables
val csvTable = spark.read.csv("/source/path")
val jdbcTable = spark.read.format("jdbc")
  .option("url", "jdbc:postgresql:...")
  .option("dbtable", "TEST.PEOPLE")
  .load()

//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

Recap: SQL Standard (ANSI/ISO/IEC)

x: ... a part
(x) ... a package



Overview Multi-Groupings

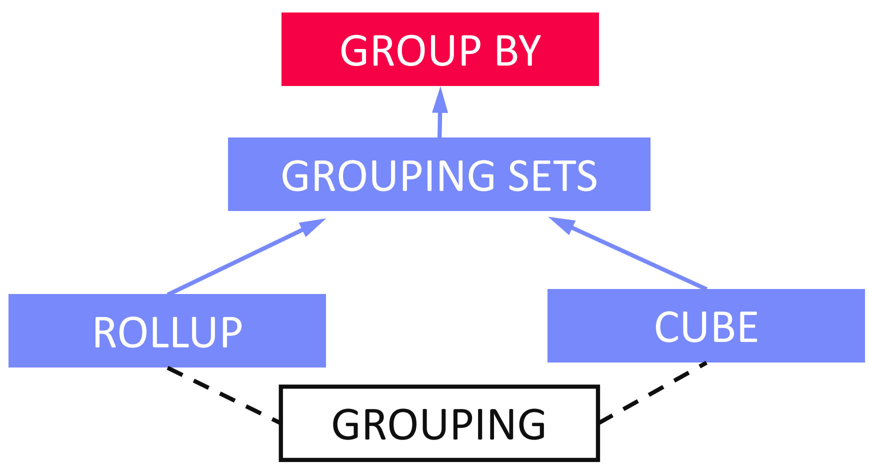
- **Recap: GROUP BY**
  - Group tuples by categorical variables
  - Aggregate per group

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

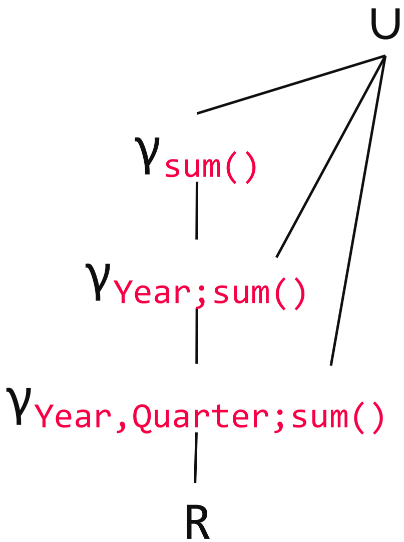
→

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**

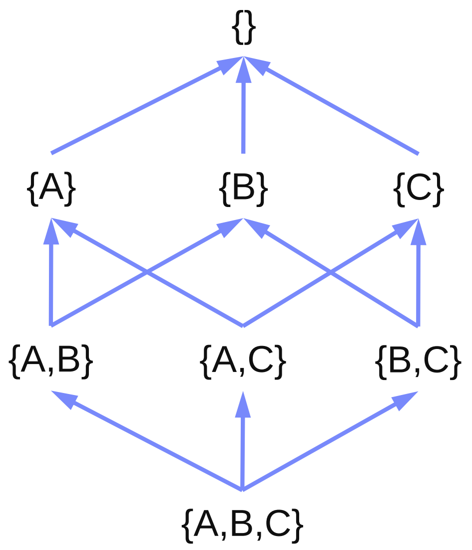
```
SELECT Year, Quarter, SUM(Revenue)
  FROM R
  GROUP BY CUBE(Year,Quarter)
```

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?



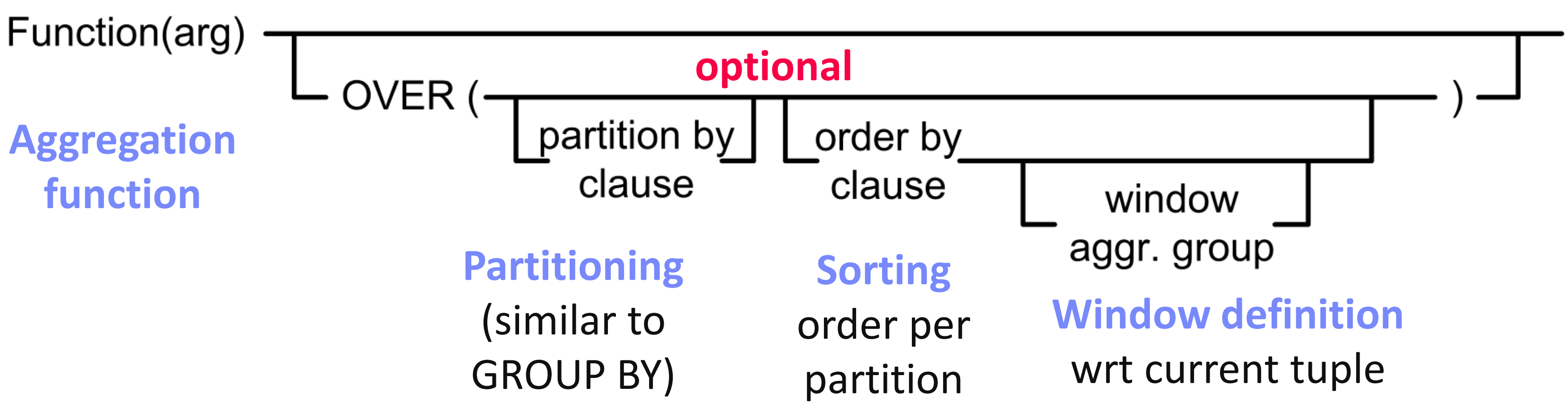
- **Recap: Physical Group-By Operators**
  - SortGroupBy / -Aggregate
  - HashGroupBy / -Aggregate

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

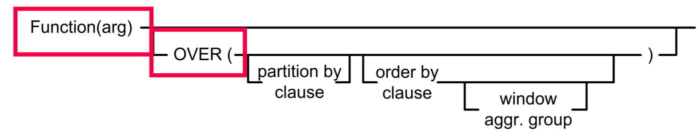
Overview Reporting Functions

- **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**

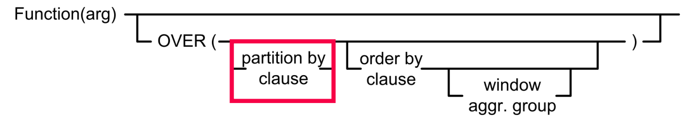
```
SELECT Year, Quarter,
    RANK() OVER (ORDER BY Revenue ASC) AS Rank1,
    DENSE_RANK() OVER (ORDER BY Revenue ASC) AS DRank1,
  FROM R
```

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



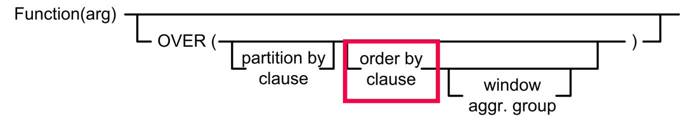
- **Semantics**
  - Select tuples for aggregation via **PARTITON BY** <attribute-list>
- **Example**

```
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



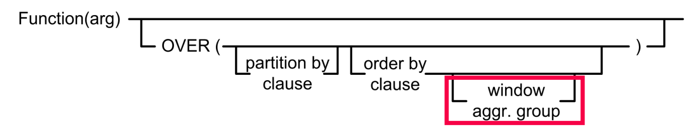
- **Semantics**
  - Define computation per partition via **ORDER BY** <attribute-list>
  - Note: ORDER BY allows cumulative computation → cumsum()
- **Example**

```
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

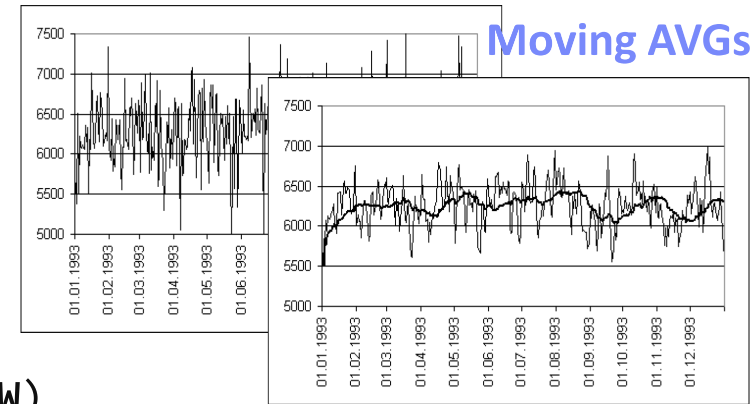


- **Semantics**
  - Define window for computation (e.g., for moving average, cumsum)
- **Example**

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

Measurements

Moving AVGs



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

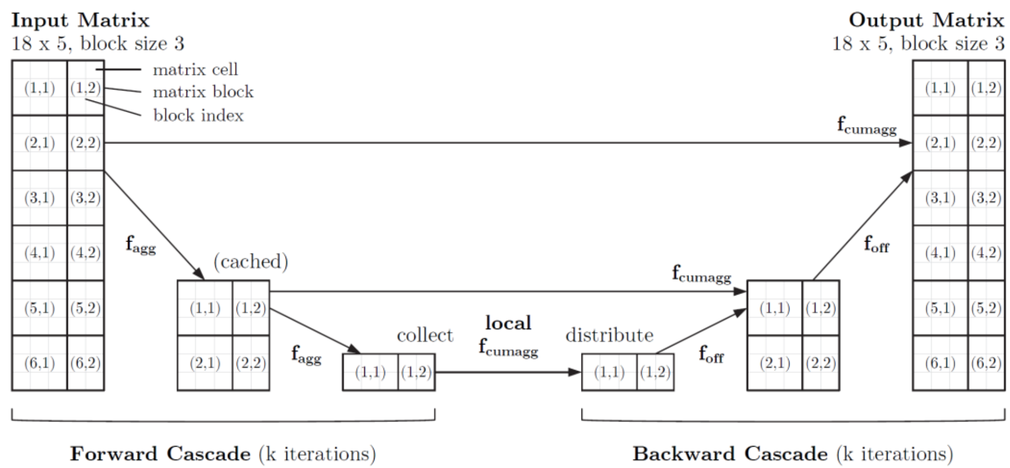
Excursus: Cumulative Aggregates

- **Efficient SQL Window Functions**
  - Partitioning & sorting
  - Segment Tree

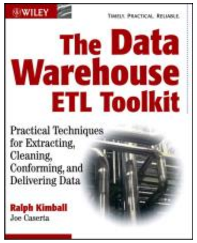
[Viktor Leis, Kan Kundhikanjana, Alfons Kemper, Thomas Neumann: Efficient Processing of Window Functions in Analytical SQL Queries. **PVLDB 8(10), 2015**]

- **Cumulative Aggregates on Distributed Matrices**
  - cumsum(), cummin(), cummax(), cumprod(), cumsumprod()
  - Recursive distributed /local aggregation

[Matthias Boehm, Alexandre V. Evfimievski, Berthold Reinwald: Efficient Data-Parallel Cumulative Aggregates for Large-Scale Machine Learning. **BTW 2019**]



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]