DATA WAREHOUSING

INTRODUCTION TO DATA SCIENCE

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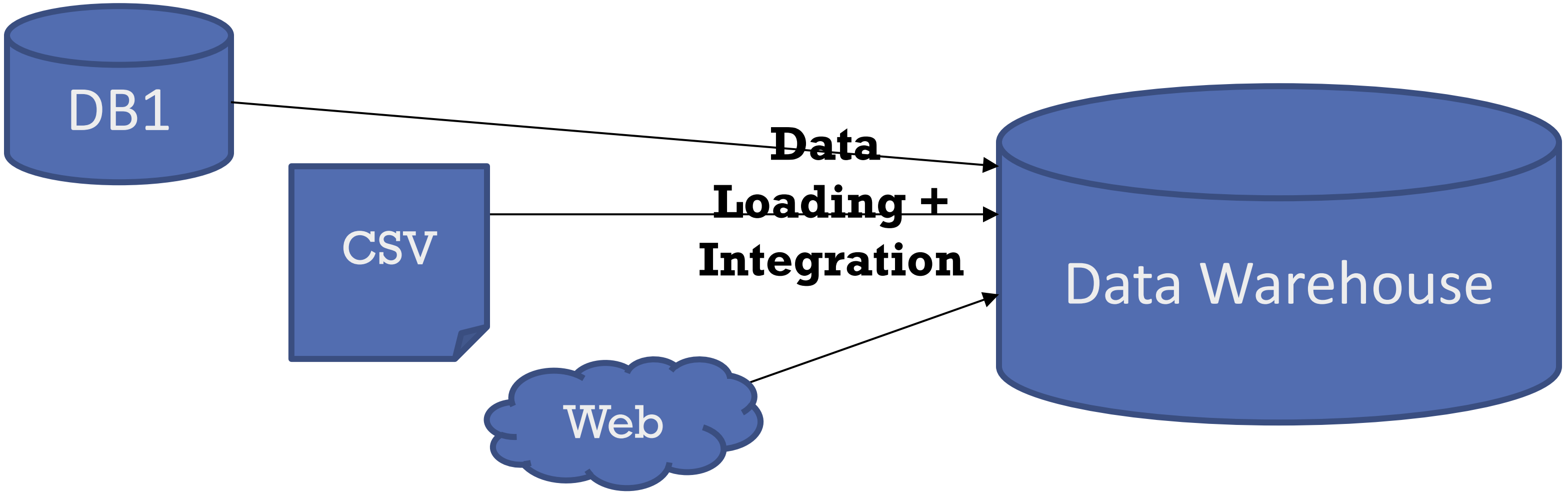
DATA WAREHOUSES

Definition: A data warehouse is a **database that is optimized for analytical workloads** which **integrates data from independent and heterogeneous data sources**



DB1

CSV

Web

Data Loading + Integration

Data Warehouse

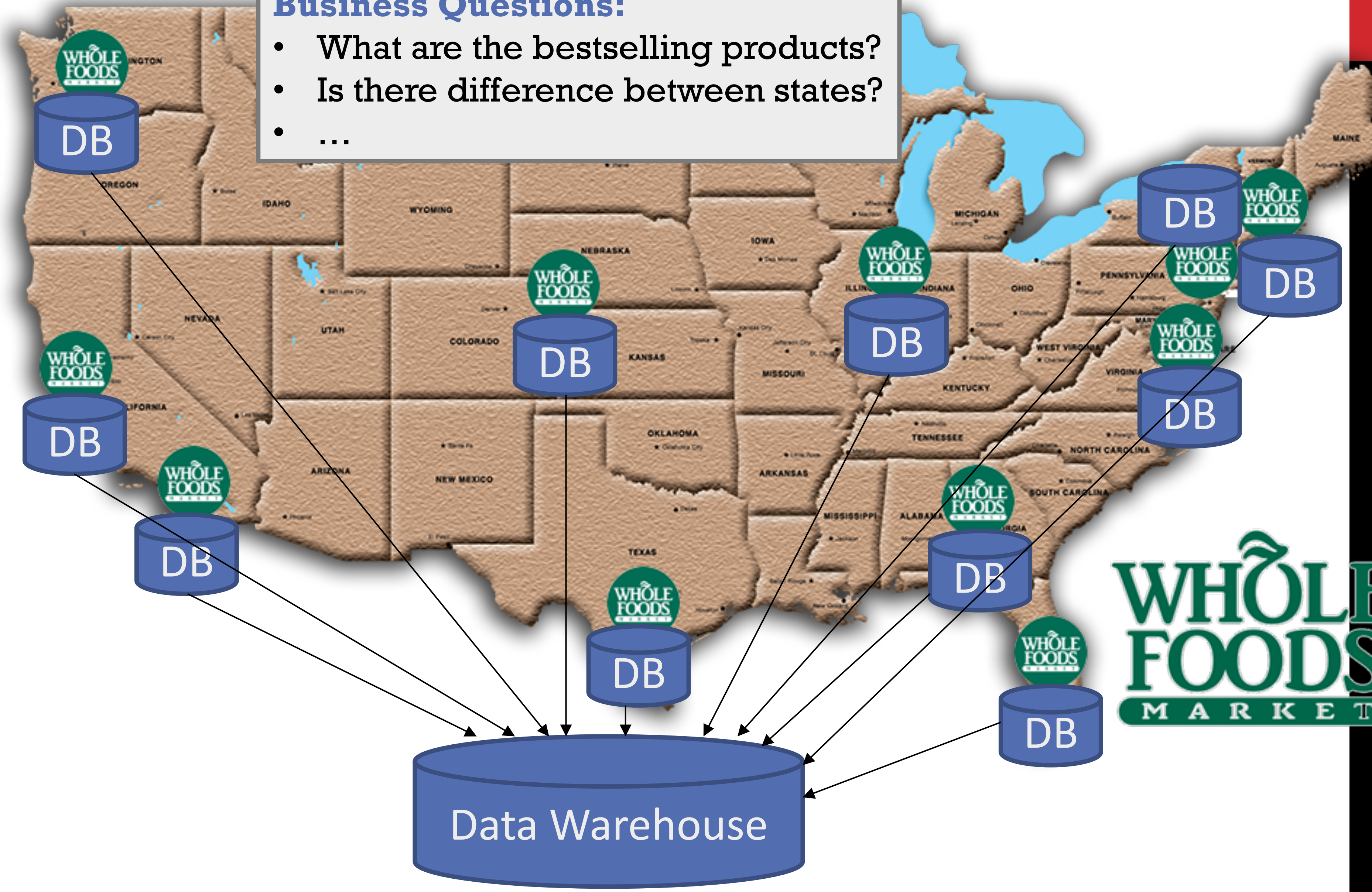
Heterogeneous Data Sources

Decision Support / Data Mining

ENTERPRISE SCENARIO: WHOLEFOODS

Business Questions:

- What are the bestselling products?
- Is there difference between states?
- …



OTHER APPLICATION DOMAINS

Restaurant Chains (McDonalds, etc.)

Retailers (Nike, …)

Insurance Companies

Banks

…

HISTORY OF DATABASES

Age of Online Transaction Processing - OLTP (> 1970)

- **Goal: have access to up-to-date business transactions**
- 60s: IMS (hierarchical data model) => financial domain
- 80s: Oracle (relational data model) => most other domains (ERP, CRM)

Age of Online Analytical Processing - OLAP (> 1990)

- **Goal: make business decisions**
- 90s: Data-warehousing extensions to relational databases
- Recently: New systems like in-memory column stores

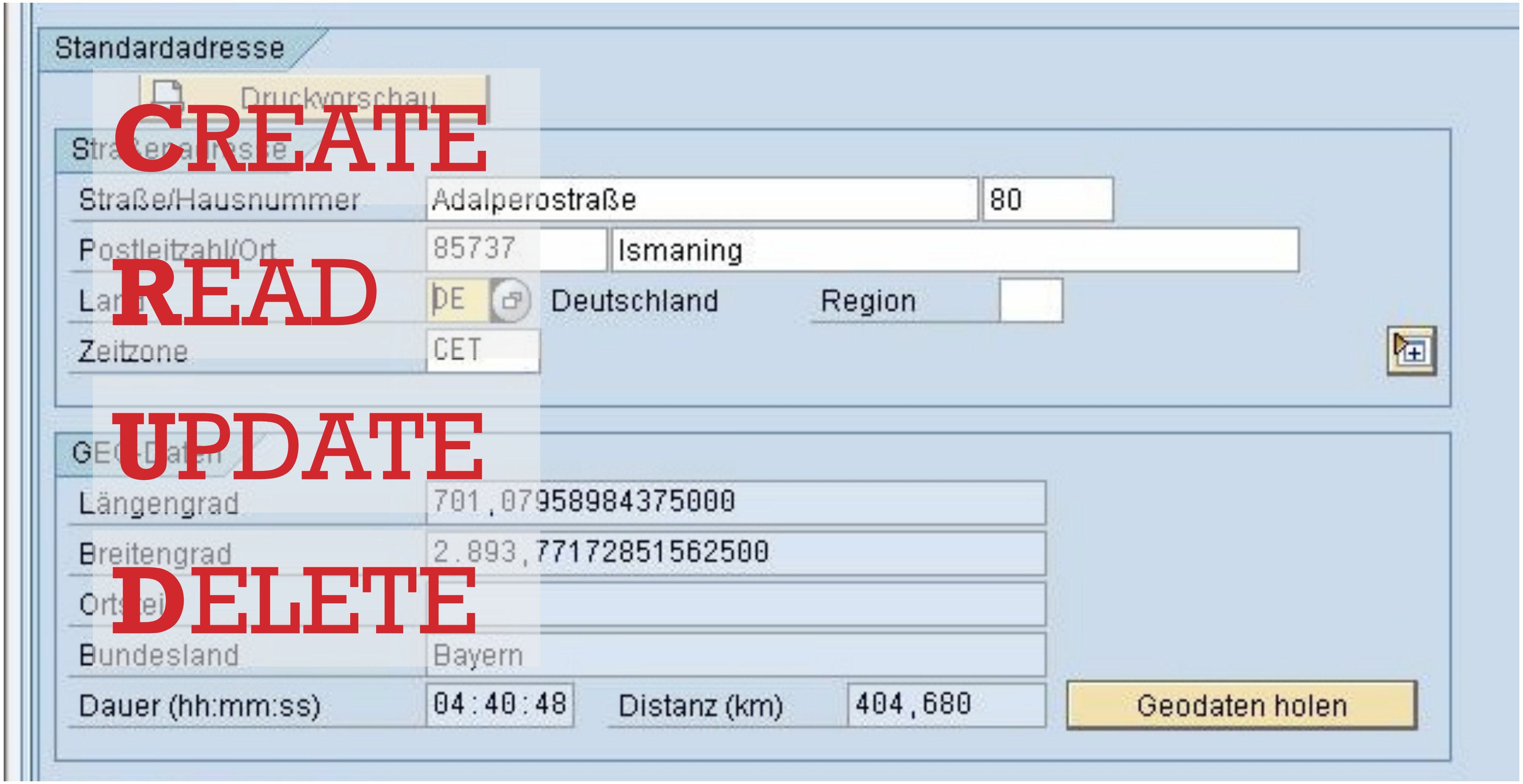
OLTP VS. OLAP

Online Transaction Processing (OLTP)

- Current state of data is important
- Queries read / update only few records; AKA point queries or CRUD workloads (Create, Read, Update, Delete)
- Data Modeling: Avoid redundancy, normalize schemas

Goal: High throughput of transactions (Oracle 1995)

EXAMPLE: CUSTOMER DATA (OLTP)



CREATE

READ

UPDATE

DELETE

Standardadresse

Straßenadresse

Straße/Hausnummer	Adalperostraße	80		
Postleitzahl/Ort	85737	Ismaning		
Land	DE	Deutschland	Region	
Zeitzone	CET			

GEO-Daten

Längengrad	701,07958984375000			
Breitengrad	2.893,77172851562500			
Ortsteil				
Bundesland	Bayern			
Dauer (hh:mm:ss)	04:40:48	Distanz (km)	404,680	Geodaten holen

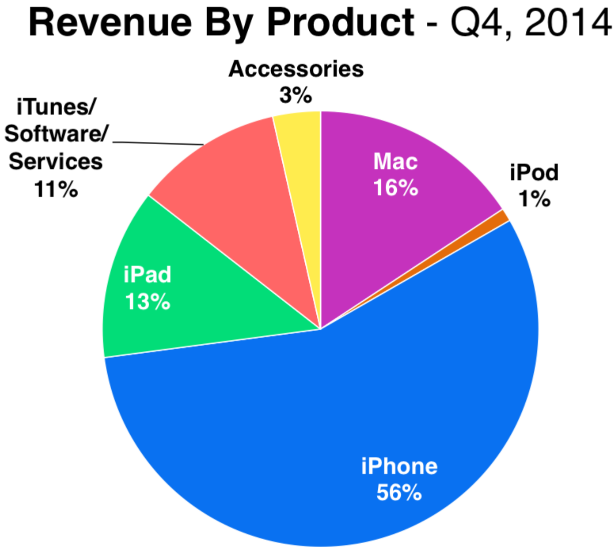
OLTP VS. OLAP

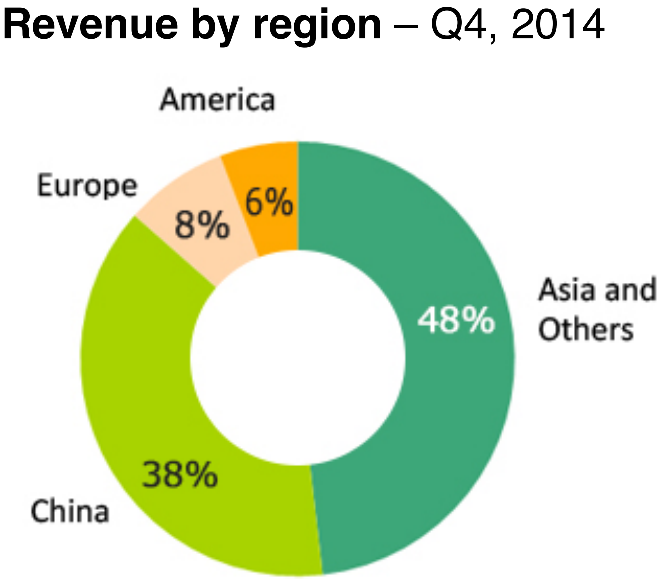
Online Analytical Processing

- History of data is important (not only the current state)
- Big queries (aggregate data, joins);
  - No Updates, only bulk loads
  - Data freshness is not that important!
- Modeling: Redundancy is a feature (i.e., de-normalized schemas are preferred)

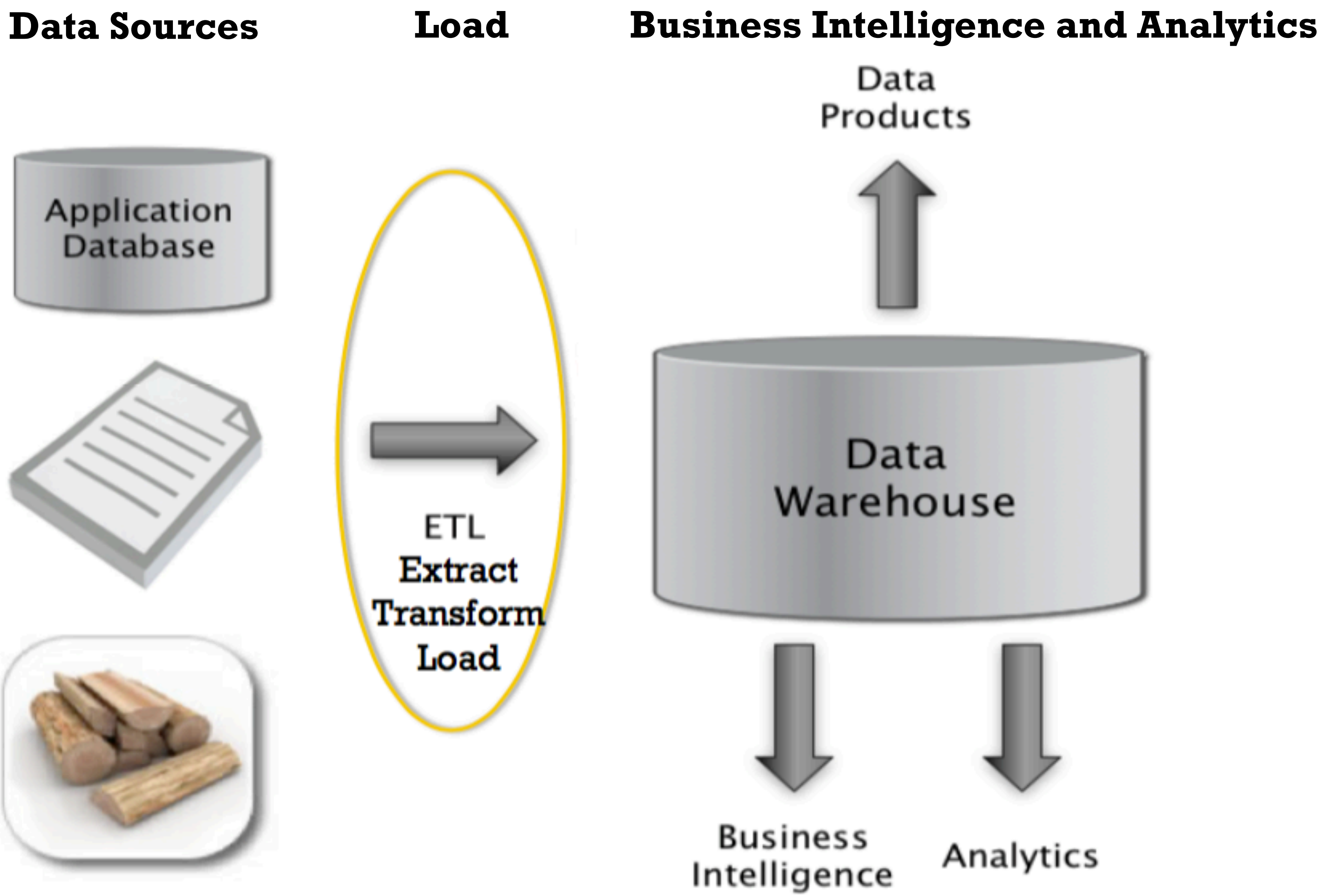
Goal: Low latency of "big" queries (<= 500ms)

EXAMPLE: REVENUE (OLAP)





THE BIG PICTURE



FOR THE BUSINESS PERSON

Data Sources

- CSV files

ETL

- Copy and paste to Excel
- References + functions

Data Warehouse

- Excel Sheets

Business Intelligence and Analytics

- Excel functions
- Excel charts

FOR THE BUSINESS PERSON

Data Sources

- Web scraping, web services API
- Databases

ETL

- Visual transformation tools
- Informatica, IBM DataStage, Ab Initio, Talend

Data Warehouse

- Teradata, Oracle, IBM DB2, Microsoft SQL Server

Business Intelligence and Analytics

- Business Objects, Cognos, Microstrategy
- SAS, SPSS, R

FOR THE "HIP" WEB ENTERPRISE

Data Sources

- Logs from the services tier
- User clicks, user comments, web crawl data…

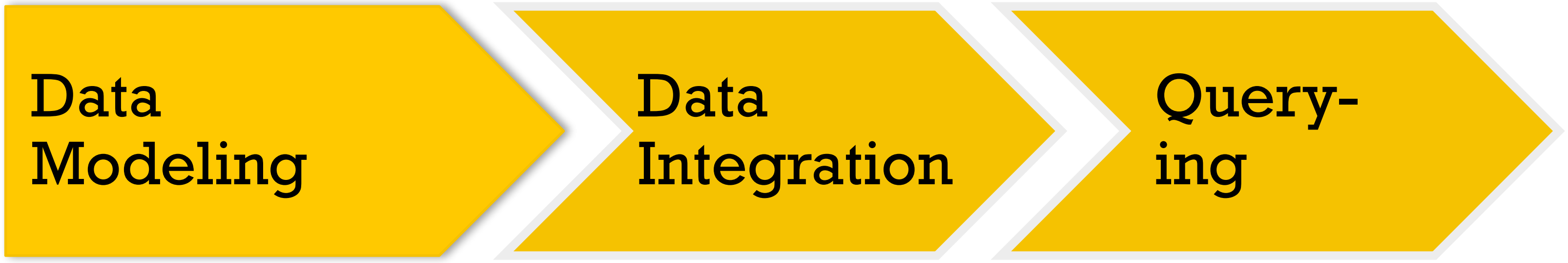
ETL

- Flume, Sqoop, Pig,/Crunch, Oozie (Workflow Scheduler)
- Hadoop/Hive, Spark/SparkSQL

Business Intelligence and Analytics

- Custom web-based dashboards
- R

DATA WAREHOUSING STEPS

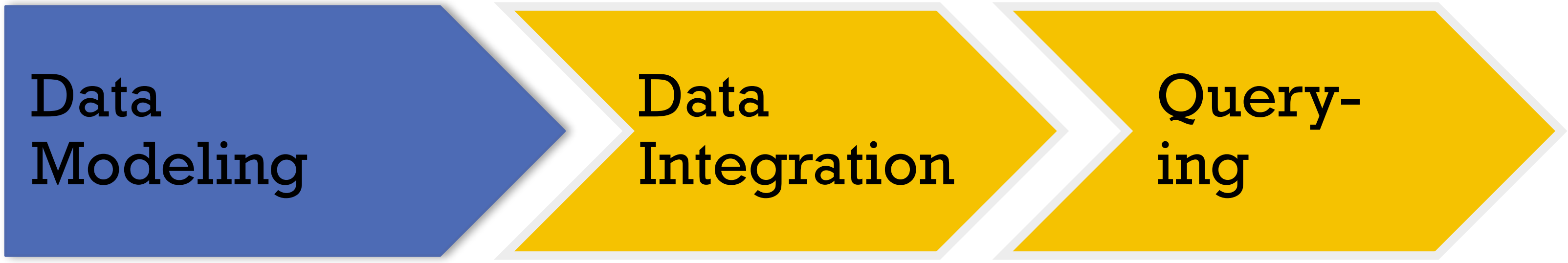


Data Modeling

Data Integration

Query-ing

DATA WAREHOUSING STEPS

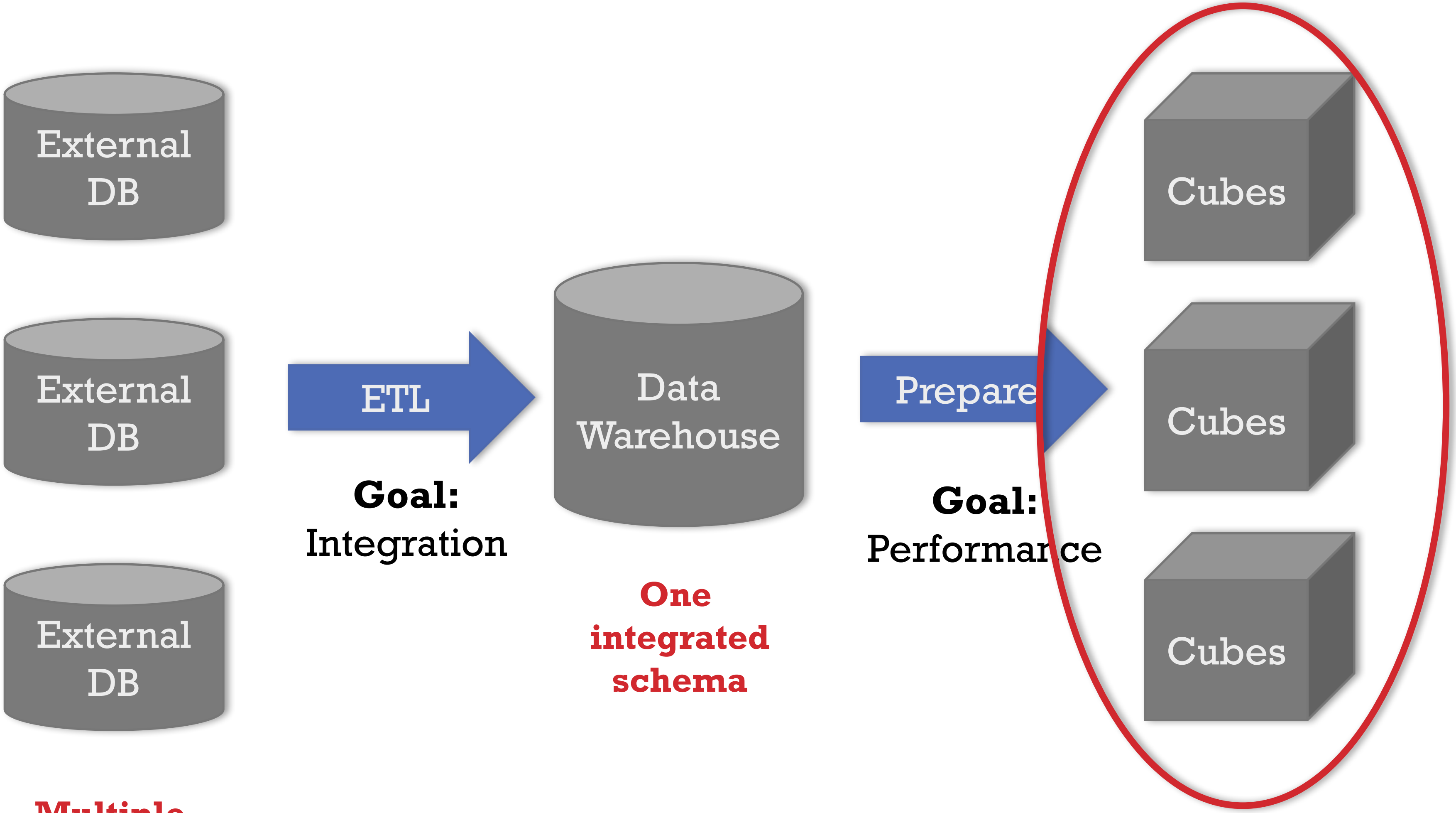


Data Modeling

Data Integration

Query-ing

A MORE TECHNICAL VIEW

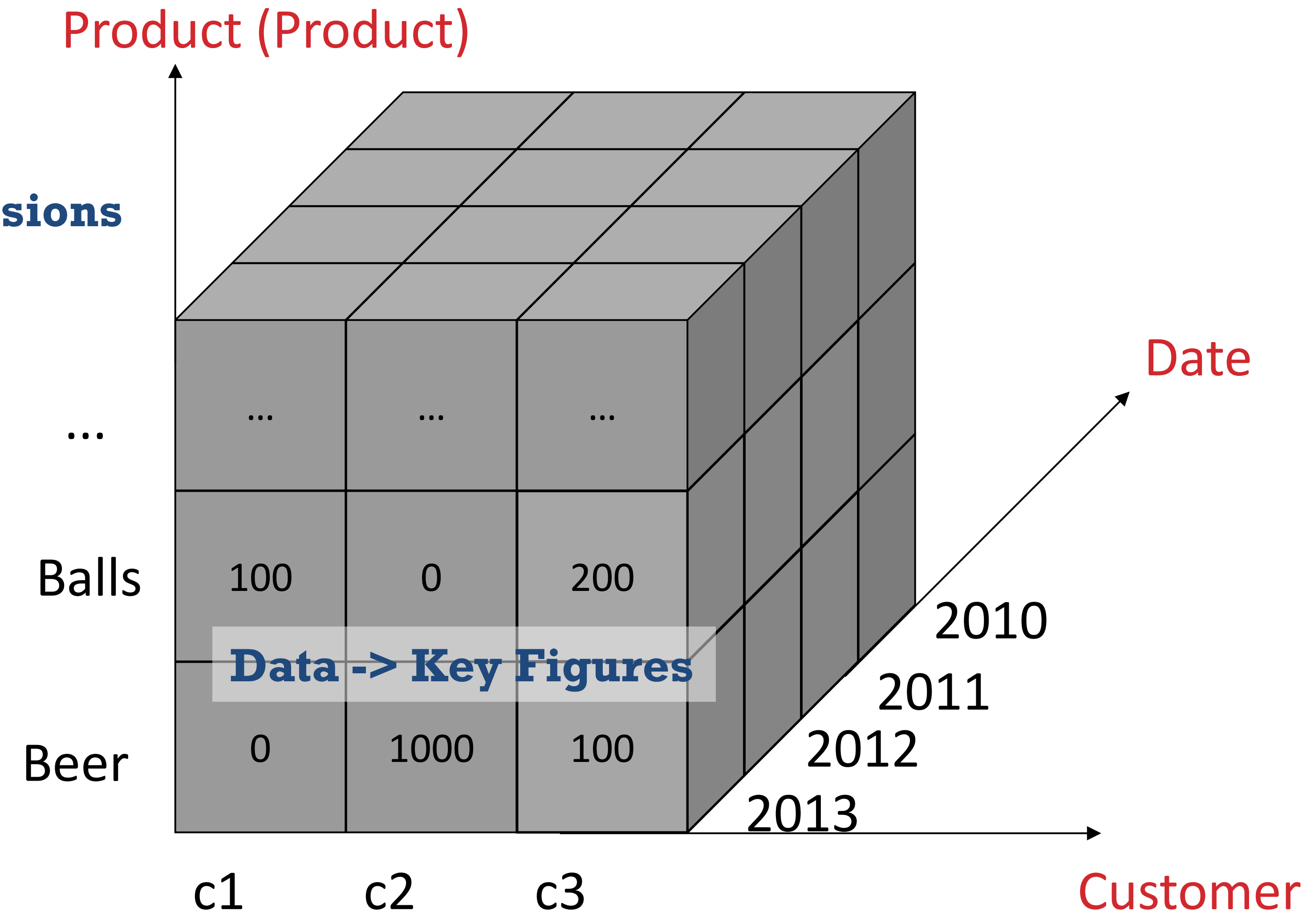


Multiple independent schemata

One integrated schema

Derived analytical schemata

CUBE: MULTIDIMENSIONAL DATA MODEL

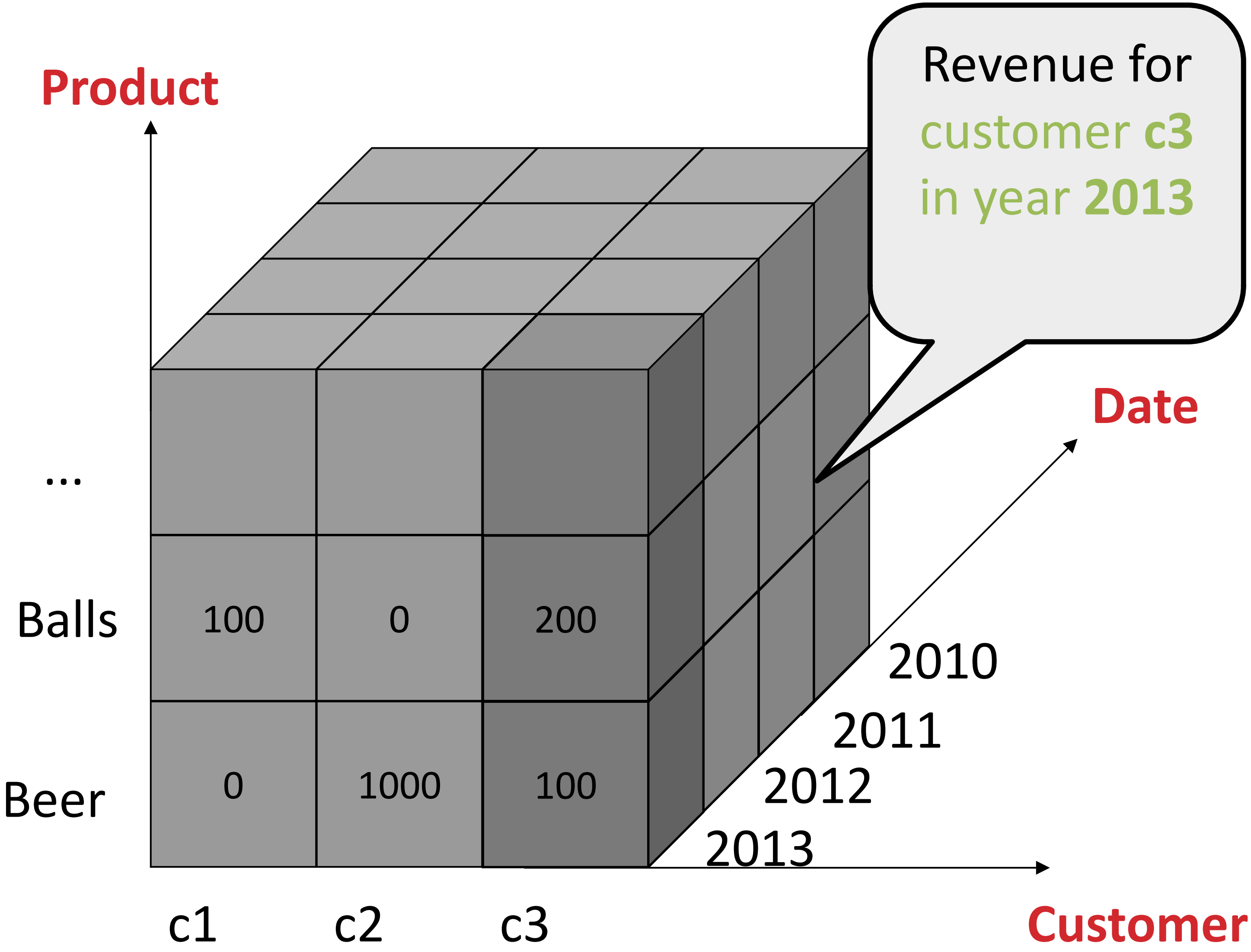


Axis -> Dimensions

Data -> Key Figures

	c1	c2	c3
…	…	…	…
Balls	100	0	200
Beer	0	1000	100

MULTIDIMENSIONAL DATA (CUBE)



	c1	c2	c3
Balls	100	0	200
Beer	0	1000	100

Revenue for customer **c3** in year **2013**

DATA OPERATIONS

Slice: Cut a slice out of the cube (e.g. **product=„Beer“**)

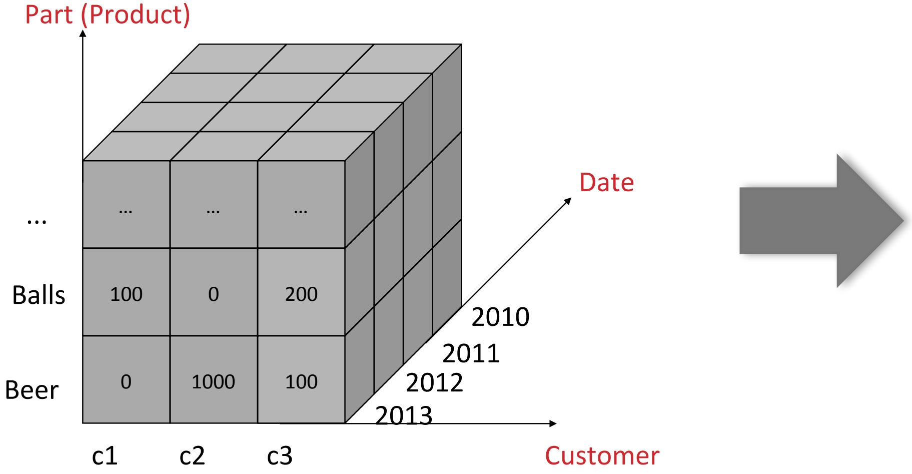
Dice: Cut a smaller cube out of the data
(e.g. **product=„Beer“ and year=2013**)

Drill-down: Show details on the next level of detail
(e.g., **zoom into from sales per month to sales per week**)

Roll-up: Aggregate data along a hierarchy
(e.g., **zoom out from sales per month to sales per year**)

RELATIONAL OLAP (ROLAP)

ROLAP: Store multidimensional cube data in a **relational database**



	c1	c2	c3
…	…	…	…
Balls	100	0	200
Beer	0	1000	100

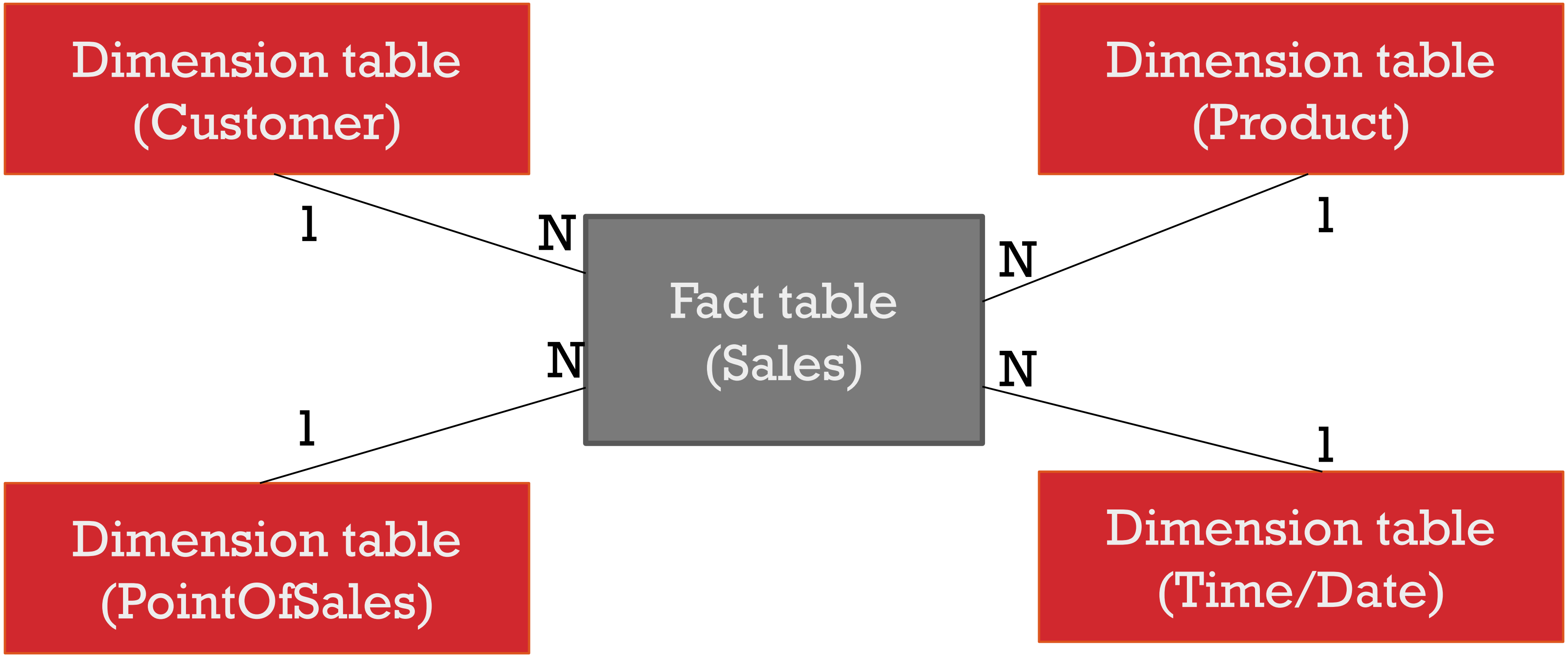
Relational Schema?

Star-Schema:

Fact table: Store key figures (e.g., revenue, number of products sold, margin, …)

Dimension tables: Store values on the axis!

STAR-SCHEMA (ROLAP)


Dimension table (Customer)
Dimension table (Product)
1
N
N
1
Fact table (Sales)
N
N
1
1
Dimension table (PointOfSales)
Dimension table (Time/Date)

DIMENSION TABLE

Data in dimension tables:

- Distinct values of one axis of the cube (e.g. dates, product names, …)
- Many different data types (texts, dates, ...)
- Often de-normalized (why?)

One dimension table is typically the **Time / Date table**

Used to …

- **Select data in fact table** (e.g. revenue in 2011): by joining dimension table with fact table
- **Group results** (e.g., revenue grouped by year)

EXAMPLE: DIMENSION TABLE (CUSTOMER)

custkey	lastName	firstName	city	Country	region
1	Binnig	Carsten	Mannheim	Germany	Europe
2	Tellex	Stephanie	Providence	USA	North America
…	…	…	…	…	…

PK

Attributes for selection and grouping

FACT TABLE

Data in fact tables

- Numeric key figures for aggregation e.g. revenue
- Foreign keys to dimensions (tables: customer, Product, date, …)
- Mostly numeric data

Key figures are used for **aggregations** (e.g., total of orders, quantity of sales)

Data in fact table is **constantly growing**!

Primary key of fact table: Composed of all foreign keys

EXAMPLE: FACT TABLE (SALES)

custkey	product key	date key	…	revenue	quantity
1	1	1	…	1000	10
1	2	1	…	100	1
2	1	3	…	800	9
…	…	…	…	…	…

Foreign Keys to dimension tables

Key figures

DIMENSIONS: HIERARCHIES

Dimensions often **describe a hierarchy** (i.e., 1:N relationships between entities)

Static hierarchies: Levels in hierarchy is fixed
(e.g. Year->Month->Day or Region->Country->City)

Flexible hierarchies: Dynamic number of levels
(e.g. management hierarchies, bill of materials – BOM)

STATIC HIERARCHIES

Levels of a hierarchy are represented by **different columns**

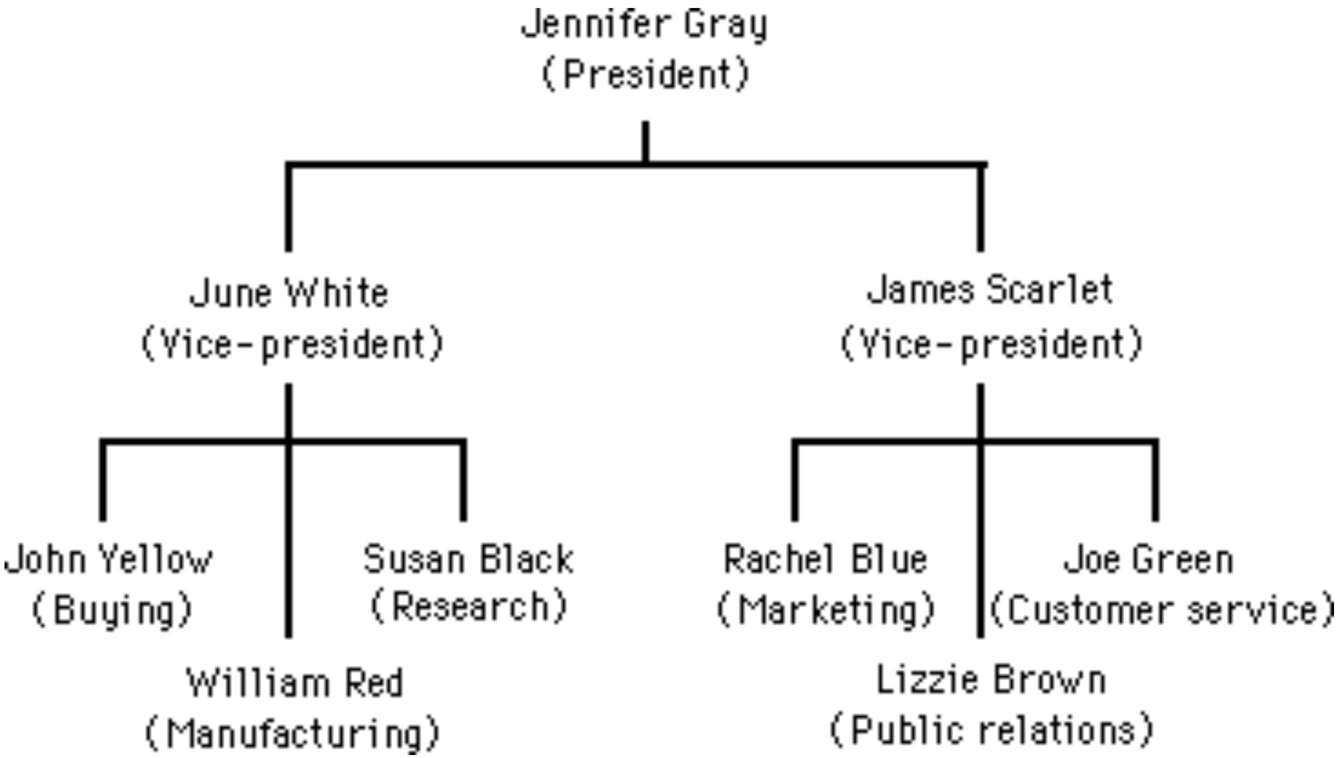
Region->Country->City

City	Country	Region
Mannheim	Germany	Europe
Mosbach	Germany	Europe
…	…	…

Year->Month->Day

Year	Month	Day
2012	01	1
2012	01	2
…	…	…
2012	01	31
…	…	…

FLEXIBEL HIERARCHIES



Jennifer Gray
(President)

June White
(Vice-president)

James Scarlet
(Vice-president)

John Yellow
(Buying)

Susan Black
(Research)

William Red
(Manufacturing)

Rachel Blue
(Marketing)

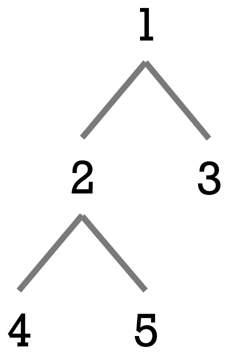
Joe Green
(Customer service)

Lizzie Brown
(Public relations)

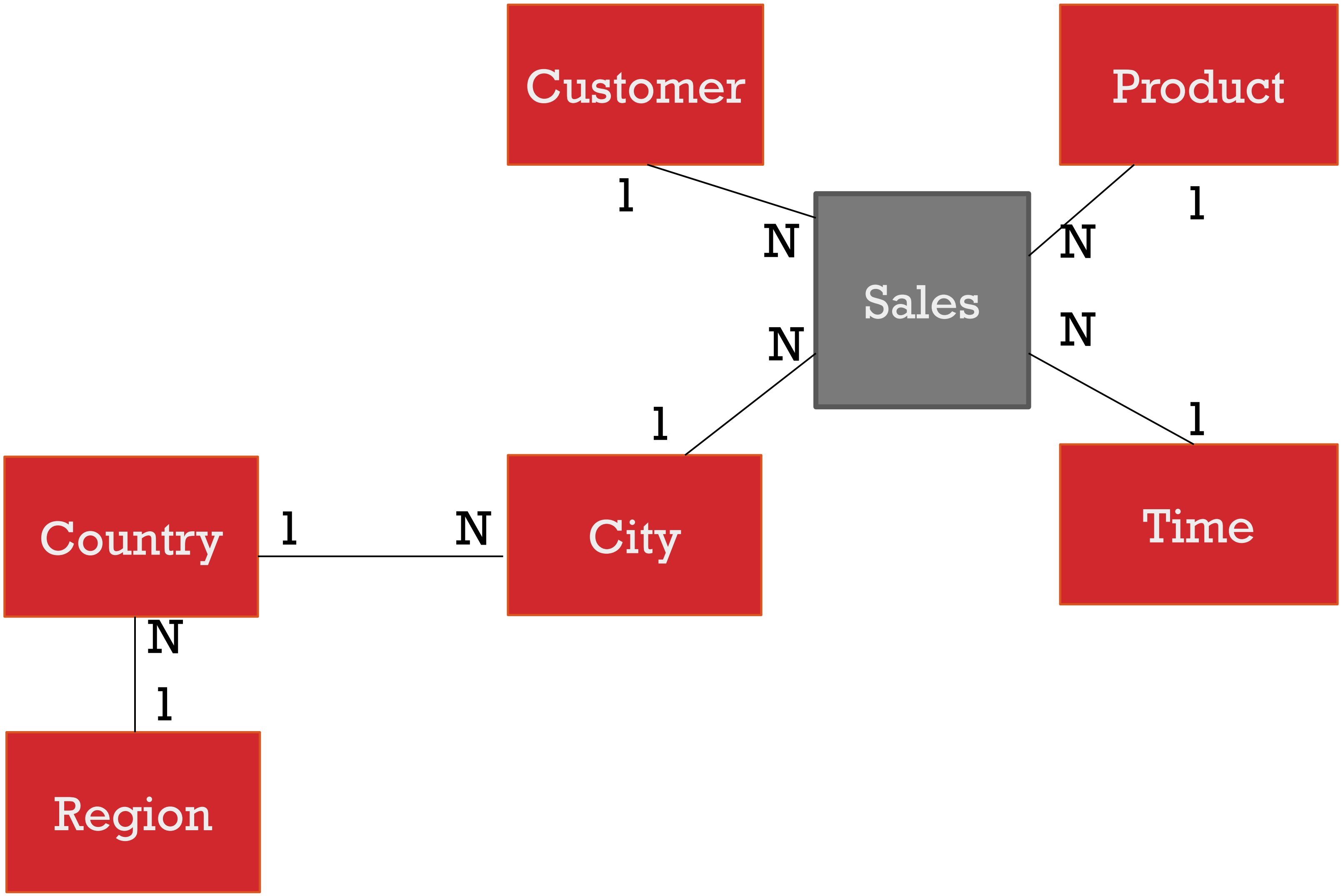
FLEXIBEL HIERARCHIES

Levels of hierarchy are represented as **recursive relationships (e.g., management hierarchy)**

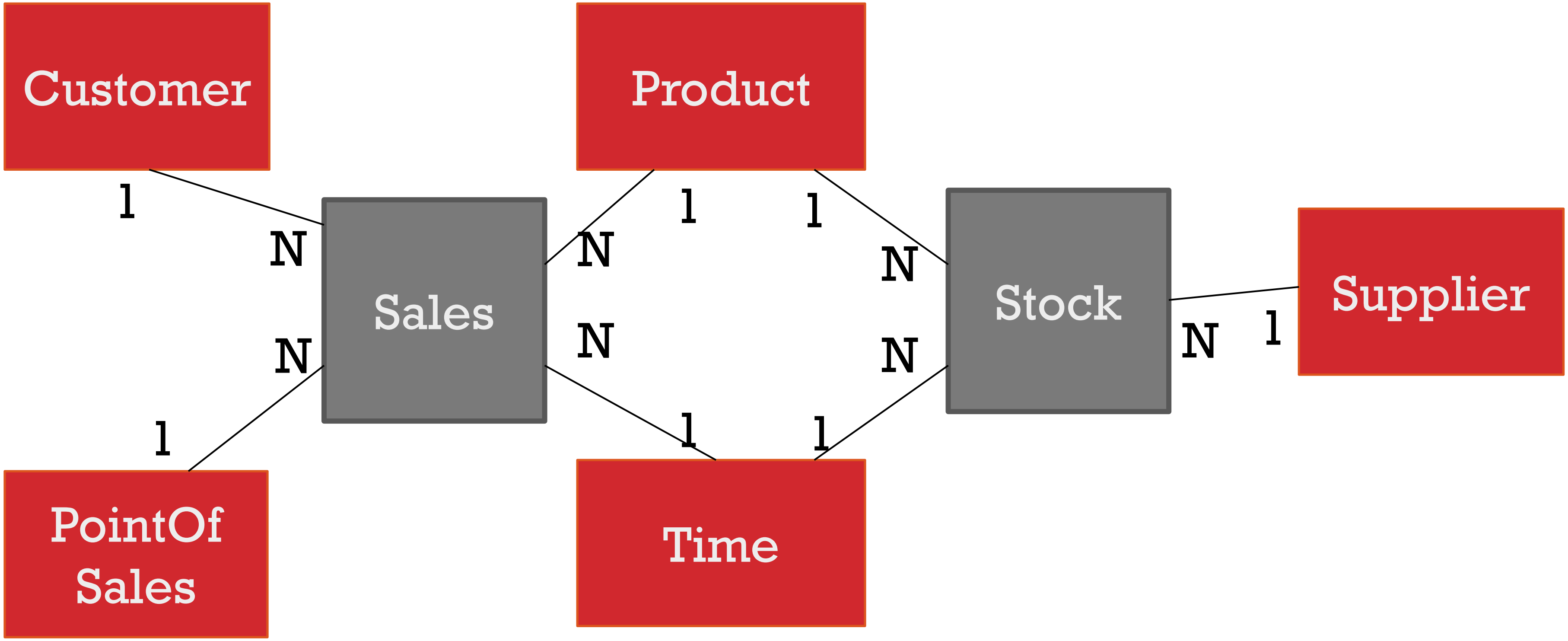
empKey	lastName	bossKey
1	…	NULL
2	…	1
3	…	1
4	…	2
5	…	2



OTHER SCHEMATA: SNOWFLAKE

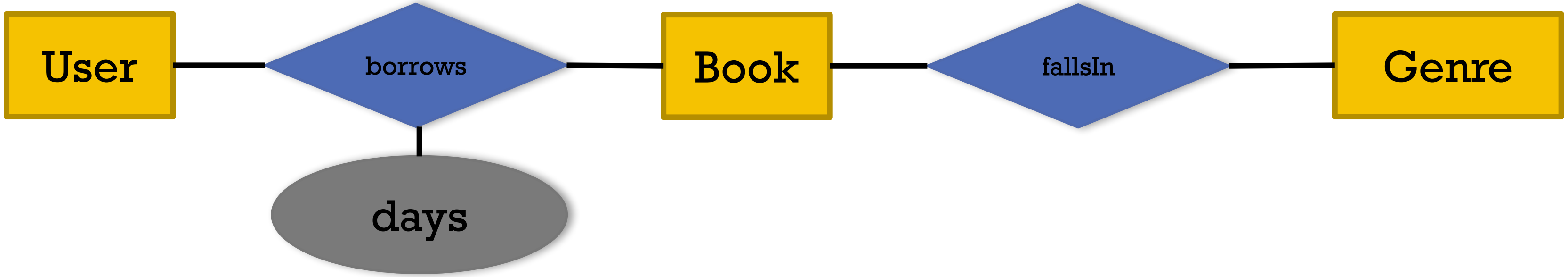


OTHER SCHEMATA: GALAXY



CLICKER QUESTION

An OLTP database tracks which user has borrowed which books for how long. We want to be able to answer questions like 'who are the users with the longest lending (per book, per genre)?'



How should the fact table look like?

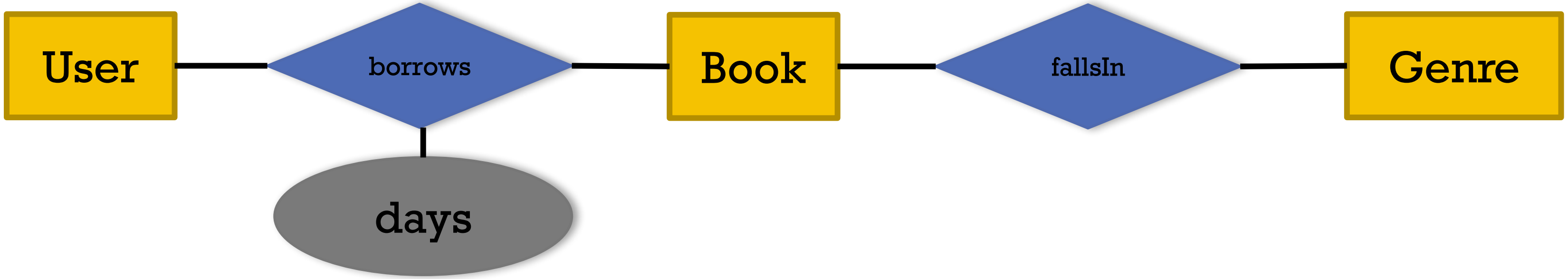
A) Lendings(bookId, genreId, userId, days)

B) Lendings(bookId, genreID, days)

C) Lendings(bookId, userId, days)

CLICKER QUESTION

An OLTP database tracks which user has borrowed which books for how long. We want to be able to answer questions like 'who are the users with the longest lending (per book, per genre)?'



How should the fact table look like?

A) Lendings(bookId, genreId, userId, days)

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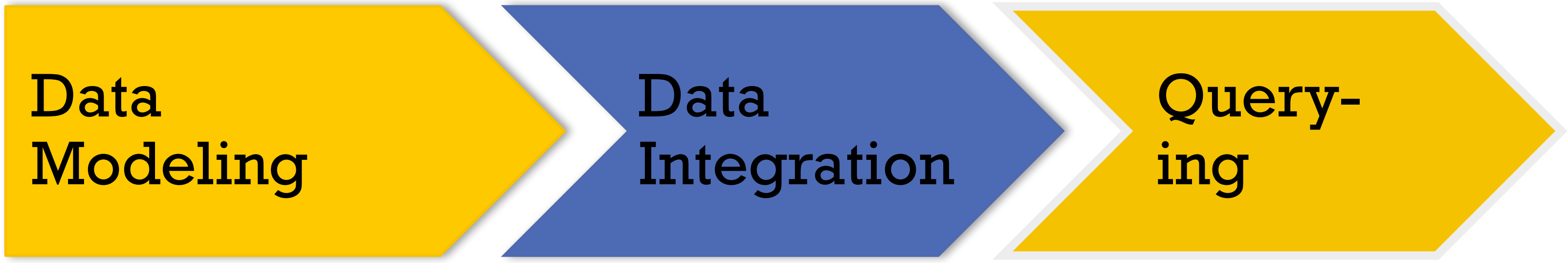
C) Lendings(bookId, userId, days)

DATA WAREHOUSING STEPS

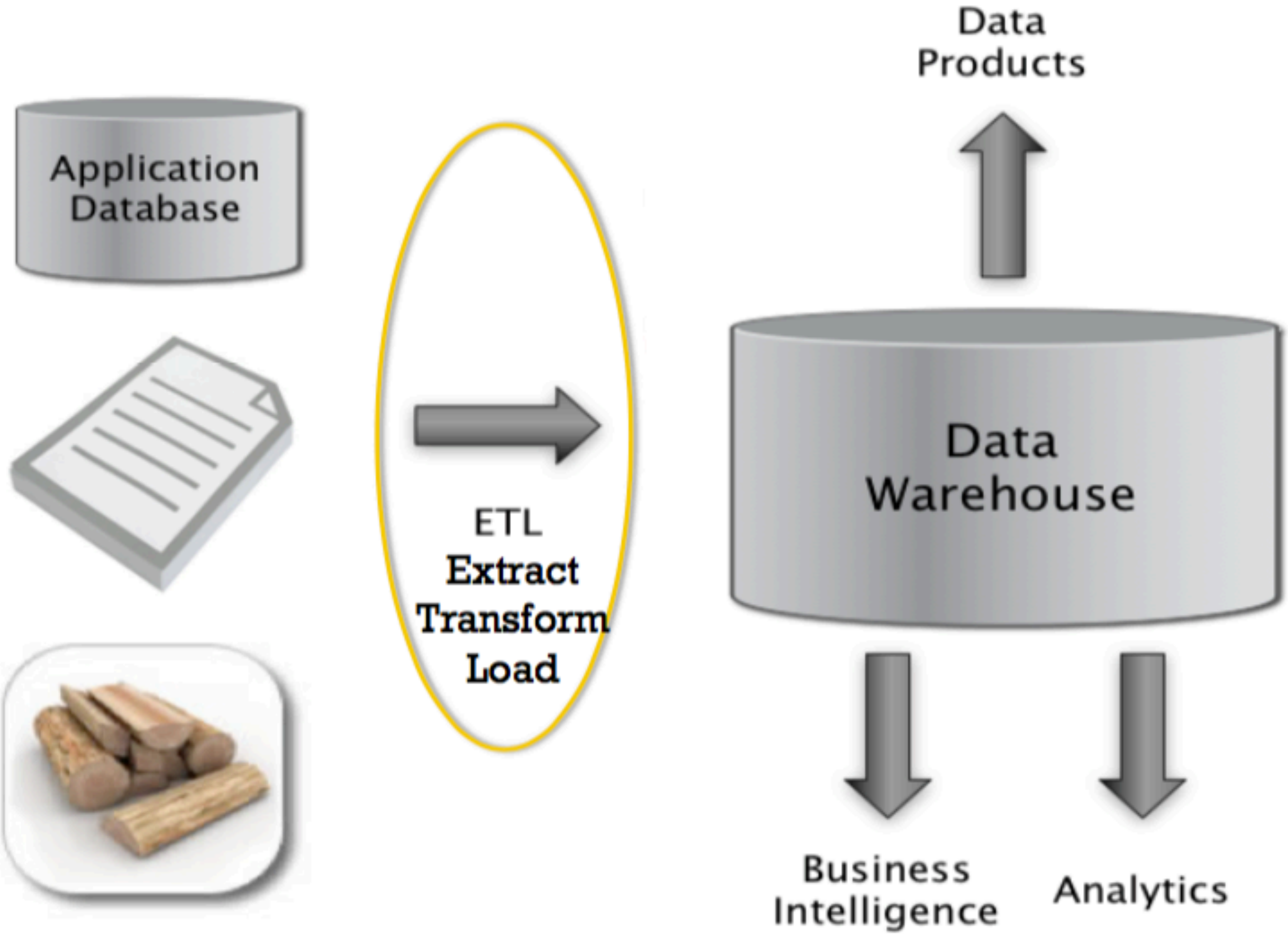


Data Modeling

Data Integration

Query-ing

THE BIG PICTURE



DATA INTEGRATION

Data integration is done by ETL Processes

- **Extract:** extract data out of an operational data source
- **Transform:** cleanse it and transform it into the target schema (e.g., split first and last names)
- **Load:** append it to the tables of a data warehouse

Operational Sources: files, databases, event logs, ...

Sink (Data Warehouse): RDBMS, specialized OLAP engines, …

ETL WORFLOWS

The ETL pipeline or workflow often consists of many sequential steps

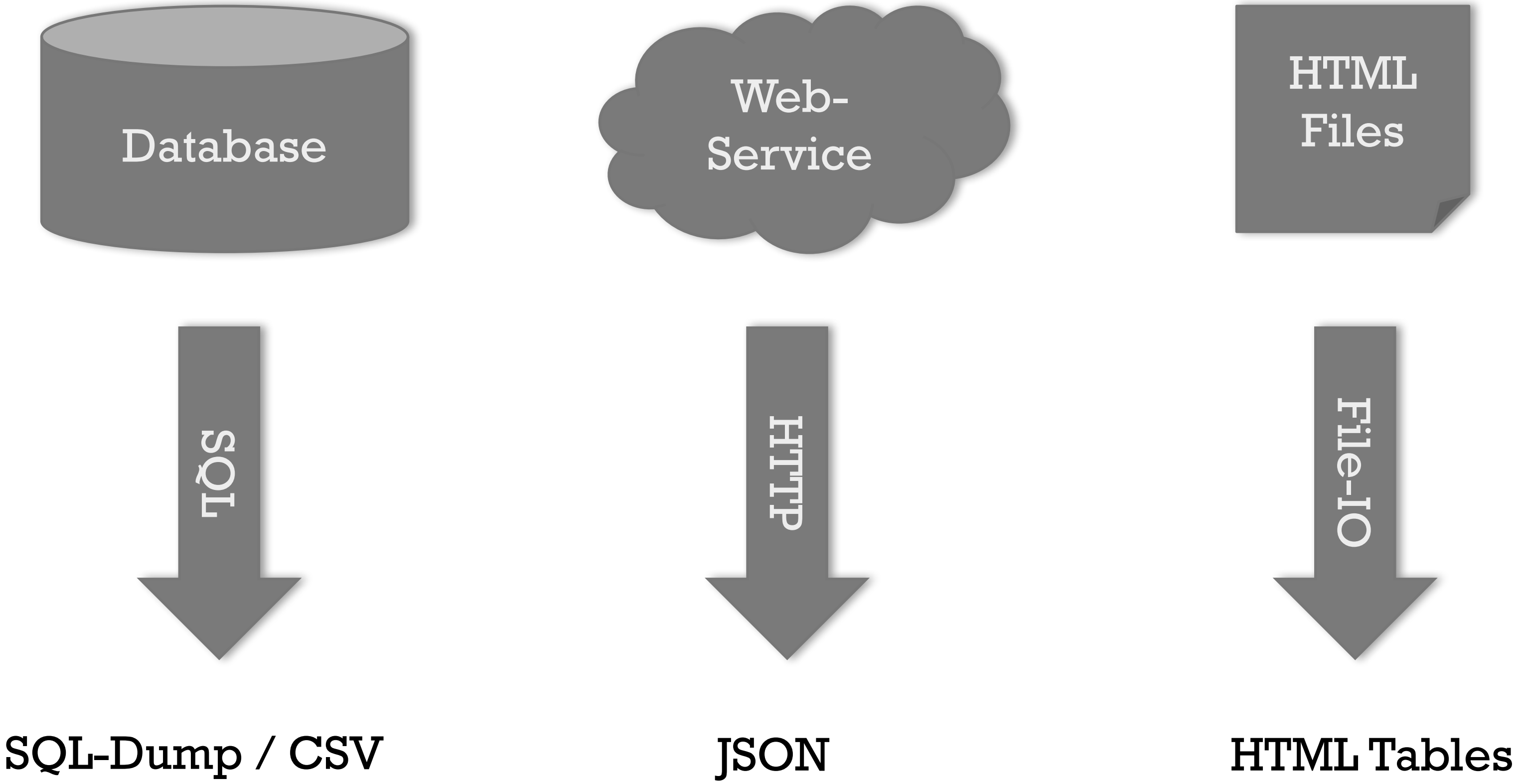
- Often a mix of tools involved (Web-Service APIs, tools to reformat data, …)
- Analogy: Unix pipes and filters -> $ cat data_science.txt | wc | mail -s "word count" hammer@example.com

If the workflow is to be run more than once, it can be scheduled

- Scheduling can be time-based or event-based

Transformations are most complex Product (Separate slides on Data Integration!)

EXTRACT DATA



Database

SQL

SQL-Dump / CSV

Web-Service

HTTP

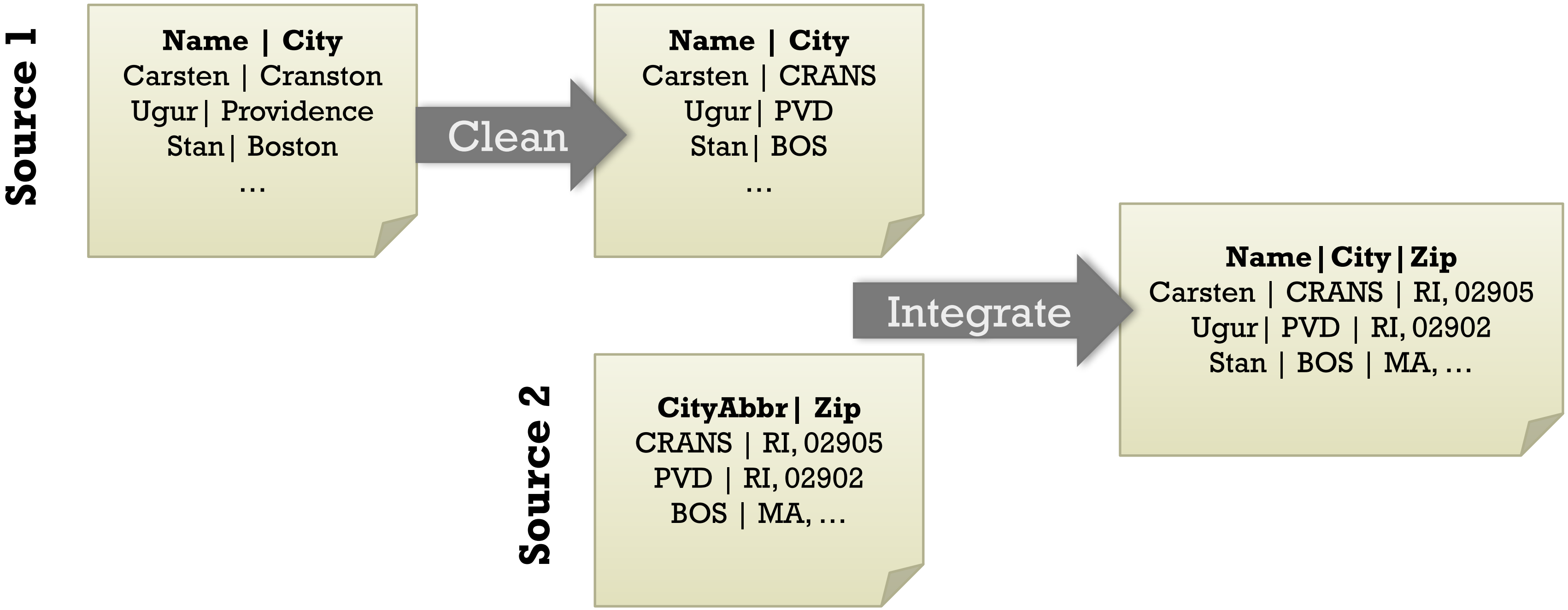
JSON

HTML Files

File-IO

HTML Tables

TRANSFORM DATA



Name | City
Carsten | Cranston
Ugur| Providence
Stan| Boston
…

Name | City
Carsten | CRANS
Ugur| PVD
Stan| BOS
…

CityAbbr| Zip
CRANS | RI, 02905
PVD | RI, 02902
BOS | MA, …

Name|City|Zip
Carsten | CRANS | RI, 02905
Ugur| PVD | RI, 02902
Stan | BOS | MA, …

Typical Tasks

- Clean Data (e.g., add missing values, correct mis-spellings, …)
- Integrate Data when using multiple sources (e.g., schema matching)
- Execute relational transformations (e.g., joins)

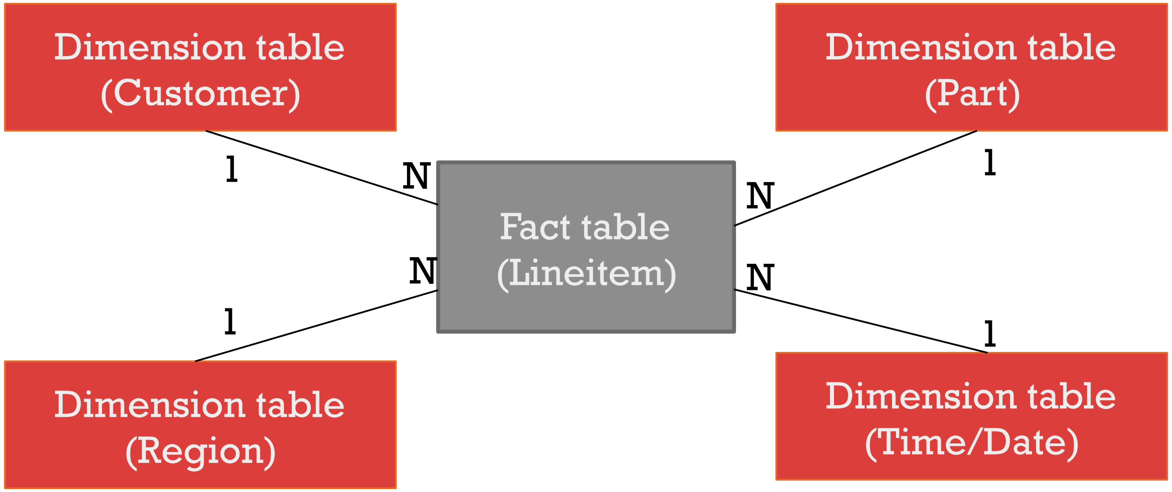
LOAD DATA

Name | City | Zip
Carsten | CRANS | RI, 02905
Ugur | PVD | RI, 02902
Stan | BOS | MA, …

…

…

Load into Warehouse
(e.g., generate keys)



Dimension table (Customer)

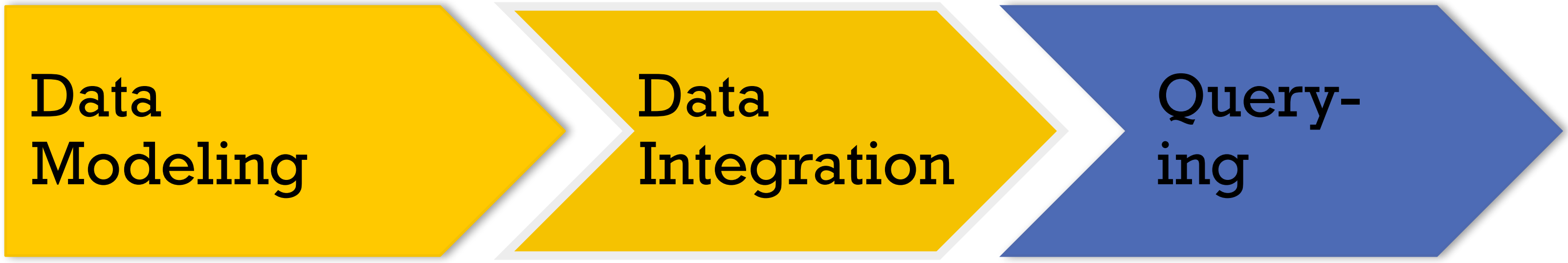
Dimension table (Part)

Fact table (Lineitem)

Dimension table (Region)

Dimension table (Time/Date)

DATA WAREHOUSING STEPS

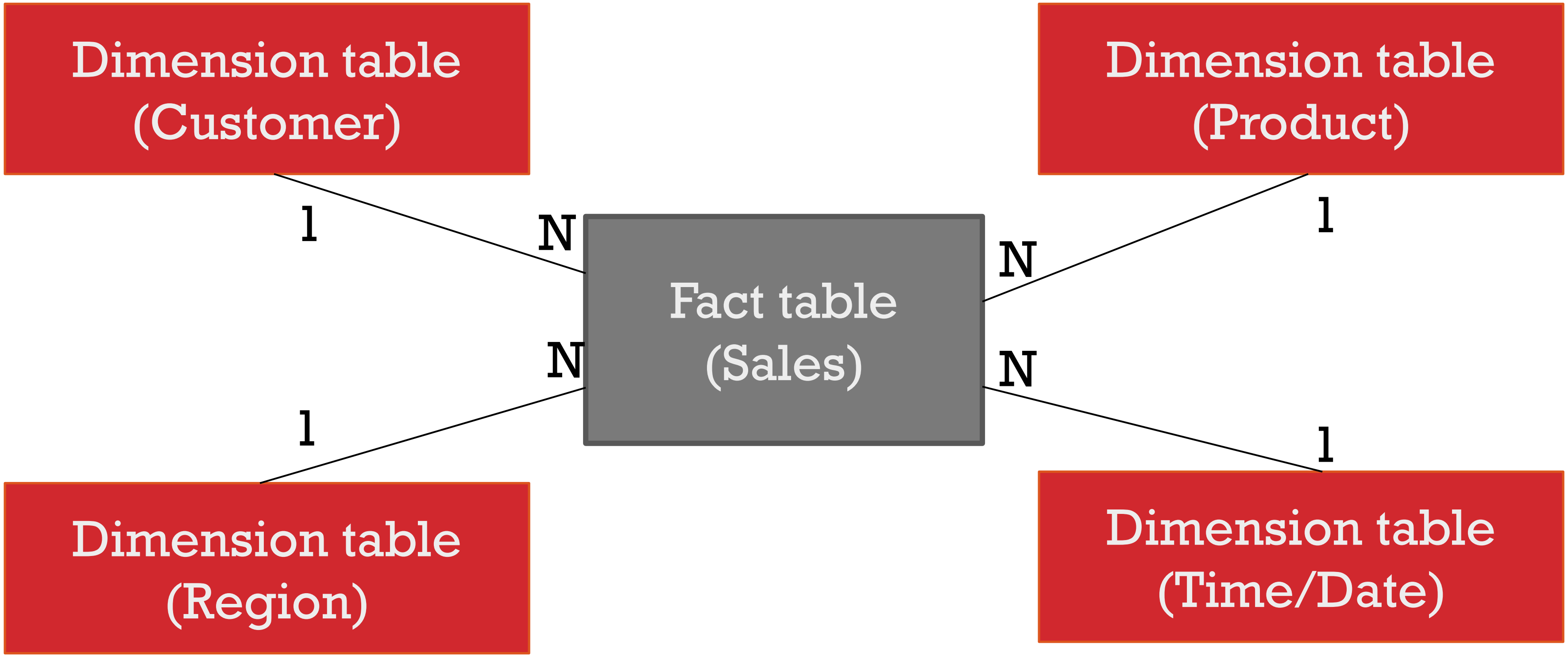


Data Modeling

Data Integration

Query-ing

RECAP: STAR-SCHEMA (ROLAP)


Dimension table (Customer)
Dimension table (Product)
1
N
N
1
Fact table (Sales)
N
N
1
1
Dimension table (Region)
Dimension table (Time/Date)

STAR-QUERY

Star query = typical query pattern for star schema

Example: Total revenue in a given year (e.g. 2013) per product

Join of multiple dimension tables with fact table +

- **Selection (WHERE):** on attributes in dimension tables
- **Grouping (GROUP BY):** on attributes in dimension tables
- **Aggregation (SUM, AVG, COUNT, … and HAVING-clause):** on attributes in fact table

EXAMPLE: STAR-QUERY

Total revenue in 2013 per product

```
select sum(revenue) as total, by p.ProductKey,
p.name

from Linitem l, Customer c, Product p, Date d

where l.custKey = c.custKey

and l.ProductKey = p.ProductKey

and l.dateKey = d.dateKey

And d.year = 2013

group by p.ProductKey, p.name
```

CLICKER QUESTION

The following star schema is used to track user who borrowed which books over time

Dimensions:

Book(bookId, title)

User(userId, name, DOB)

Genre(genreId, title)

Fact Table:
Lendings(bookId, userId, genreId, days)

CLICKER QUESTION (CNT)

Book(bookId, title)

User(userId, name, DOB)

Genre(genreId, title)

Lendings(bookId, userId, genreId, days)

Which SQL query returns the total number of books from the genre “Fantasy” for more than 90 days on average?

```
A) SELECT g.genre, COUNT(*)
   FROM BorrowedBooks bb, Books b , Genre g
   WHERE bb.bookID=b.bookID AND
   bb.genreID=g.genreID AND
   g.genre=‘Fantasy’ AND
   bb.days > 90
   GROUP BY b.genre
```

```
B) SELECT genre, COUNT(*)
   FROM BorrowedBooks bb, Genre g
   WHERE bb.genreID=g.genreID AND
   g.genre=‘Fantasy’
   HAVING AVG(bb.days) > 90
```

CLICKER QUESTION (CNT)

Book(bookId, title)

User(userId, name, DOB)

Genre(genreId, title)

Lendings(bookId, userId, genreId, days)

Which SQL query returns the total number of books from the genre "Fantasy" for more than 90 days on average?

```
A) SELECT g.genre, COUNT(*)
   FROM BorrowedBooks bb, Books b , Genre g
   WHERE bb.bookID=b.bookID AND
   bb.genreID=g.genreID AND
   g.genre='Fantasy' AND
   bb.days > 90
   GROUP BY b.genre
```

```
B) SELECT genre, COUNT(*)
   FROM BorrowedBooks bb, Genre g
   WHERE bb.genreID=g.genreID AND
   g.genre='Fantasy'
   HAVING AVG(bb.days) > 90
```

SQL-EXTENSIONS

SQL has **different extensions** to support **analytical queries**

Rollup (Grouping Sets)/ Cube: special grouping by different sets of dimensional attributes

Top(k)/Limit: Top-k results ordered by a given key figure (e.g., top-10 customer which produced maximal total revenue)

Skyline: Finding optimal along multiple dimensions (e.g., hotels that are cheap and are close to the beach)

ROLLUP

Rollup: special grouping by different sets along a hierarchy

Example (IBM DB2):

```
select sum(revenue) as total, region, country, city
from Linitem l, Customer c
where l.custKey = c.custKey
group by rollup(region, country, city)
```

Query groups result by the following attribute sets: (region), (region, country) and (region, country, city)

EXAMPLE: ROLLUP

total	region	country	city	
1.435.789	Europe	-	-	(region)
232.199	Europe	France	-	(region, Country)
634.124	Europe	Germany	-	
119.566	Europe	Germany	Munich	(region, Country, city)
35.234	Europe	Germany	Mannheim	
…	…	…	…	
210.199	Europe	France	Paris	
…	…	…	…	

GROUPING SETS

Alternative for Rollup: Grouping sets define the set of group-by attributes explicitly

Example (Oracle):

```
select sum(total) as total, region, Country, city
from Linitem l, Customer c
where l.custKey = c.custKey
group by grouping sets((region, country),
(region, country, city))
```

Query groups result by the following attribute combiCountrys: (region, Country) und (region, Country, city)

EXAMPLE: GROUPING SETS

total	region	Country	city
232.199	Europe	France	-
634.124	Europe	Germany	-
119.566	Europe	Germany	Munich
35.234	Europe	Germany	Mannheim
…	…	…	…
210.199	Europe	France	Paris
…	…	…	…

(region, country)

(region, country, city)

TOP(K) OR LIMIT

Top-k/ LIMIT functionality:

- Sort aggregated result
- Limit result size by given k

Example (PostgreSQL):

```
select sum(total) as total, region
from Linitem l, Customer c
where l.custKey = c.custKey
group by region
order by total
limit 5;
```

SKYLINE

Skyline is a **multi-dimensional top(k)**

- Skyline returns all **tuples that are not dominated by any other point** in the given set of dimensions
- Qualifying tuples also known as „**Pareto-Optimum**"

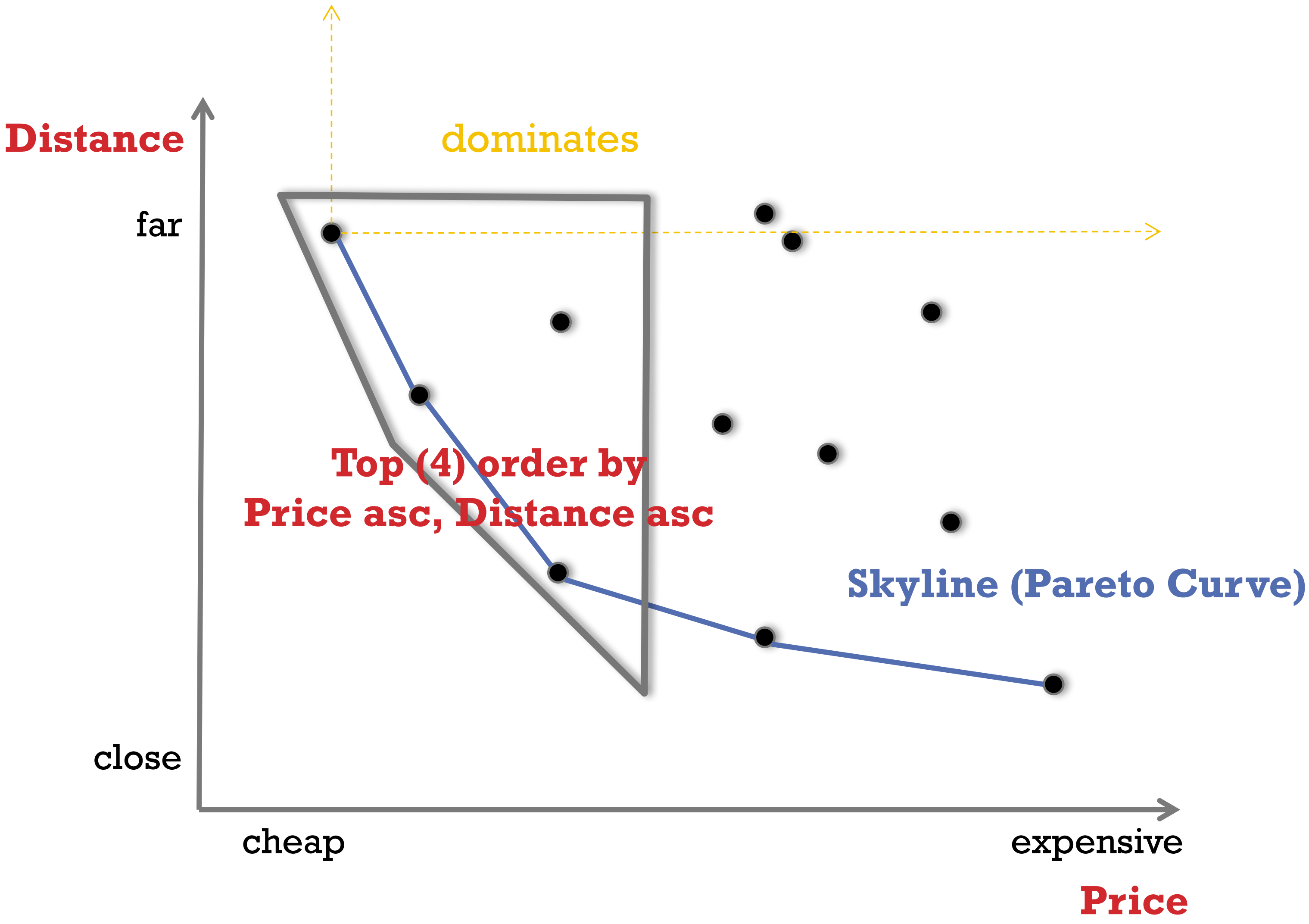
Example: Hotels low distance to beach + low price

```
select *

from hotels h

skyline of h.distance min, p.price min
```

EXAMPLE: SKYLINE (HOTELS)



SUMMARY

Data Modeling

- Multi-dimensional Model / Cube
- Star Schema / Snowflake Schema
- Hierarchies

ETL-Processes

SQL Extensions

- ROLLUP / GROUPING SETS
- TOP(k)
- SKYLINE

WHAT IS A GOOD DATA WAREHOUSE?

“A Data Warehouse is a

- **subject-oriented,**
- **integrated,**
- **non-volatile and time-variant**

collection of data in **support of managements decisions”**

(W. H. Inmon, Building the Data Warehouse, 1996)

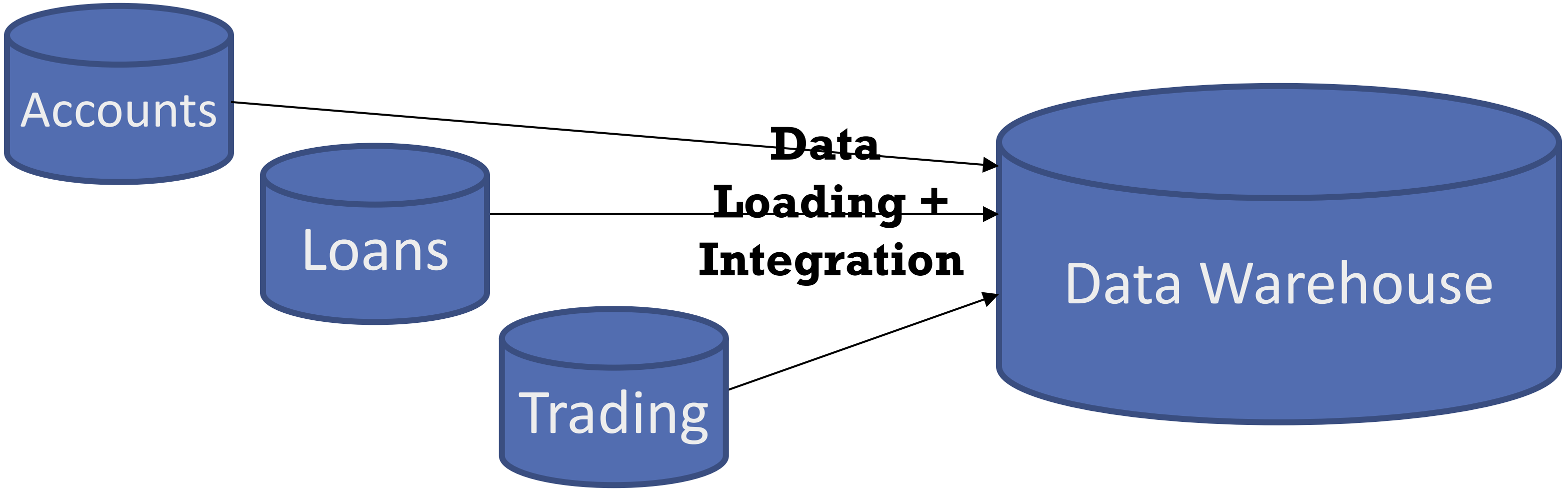
SUBJECT ORIENTED DATABASE

Operational Databases:

- Are **application oriented** (e.g., bank accounts, loans, …)
- Each DB manages only a **subset-of the overall data**

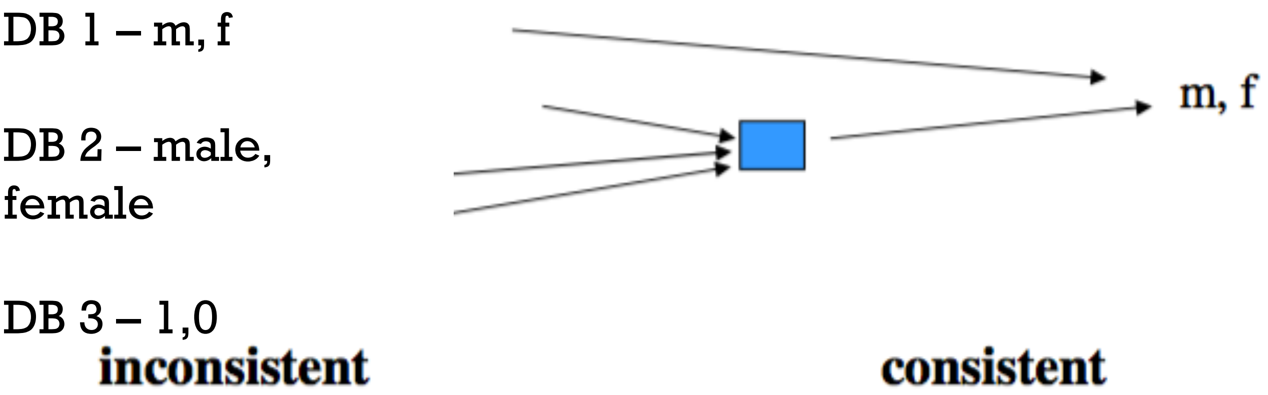
Data Warehouses:

- **Global view** on all data about a given subject / entity (e.g., customer)
- **Not targeted** towards **one application**



INTEGRATED DATABASE

A data warehouse **integrates (inconsistent) data** coming from different sources in a **consistent way**



DB 1 – m, f

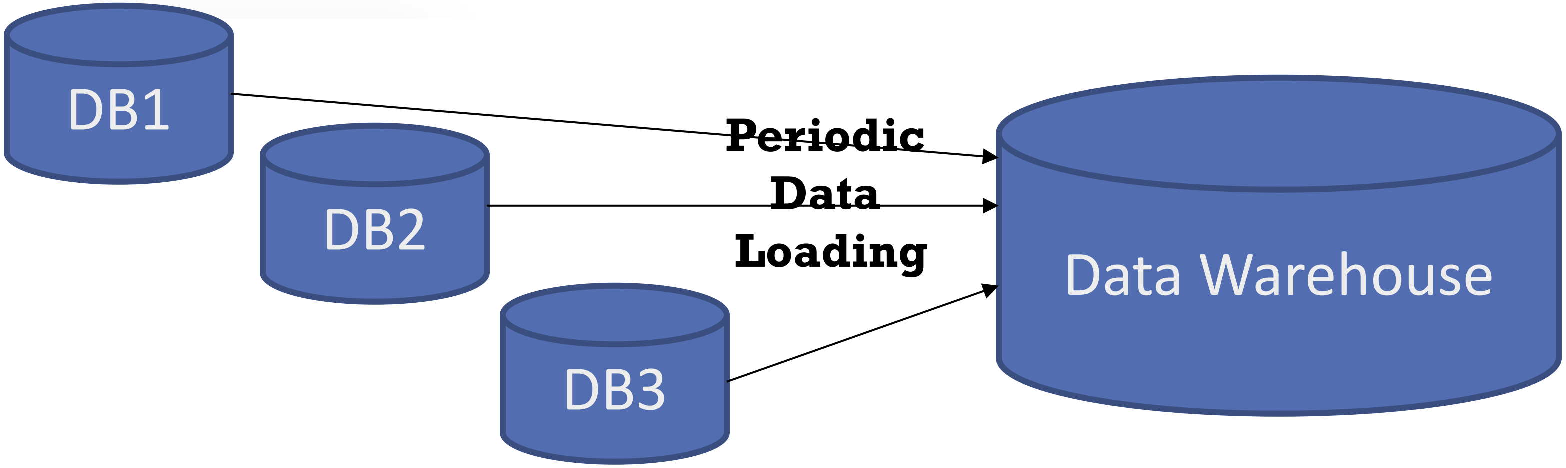
DB 2 – male, female

DB 3 – 1,0

m, f

inconsistent

consistent

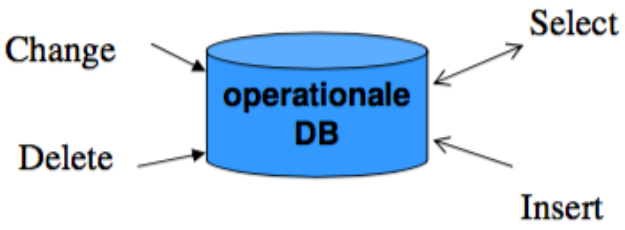


NON-VOLATILE AND TIME-VARIANT

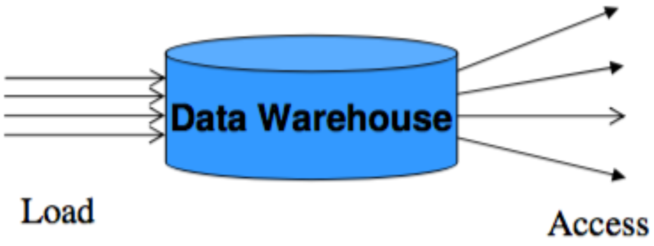
Operational Databases represents the **most up-to-date snapshot**

Data Warehouses represents the **history of all changes:**

- New Data is only appended / never updated
- All entries have a timestamp
- Comparison over time are possible



updated constantly



snapshotted data