Evolution of Database Systems

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Review of the Previous Lecture

- Mining of massive datasets,
- Operational and analytical database systems,
- Data mining: discovering models for data,
- Different aspects of data mining:
  - ideas,
  - data,
  - computational power,
  - human computation,
  - statistics,
  - algorithms.
- Many amazing implementations of data mining.

Outline

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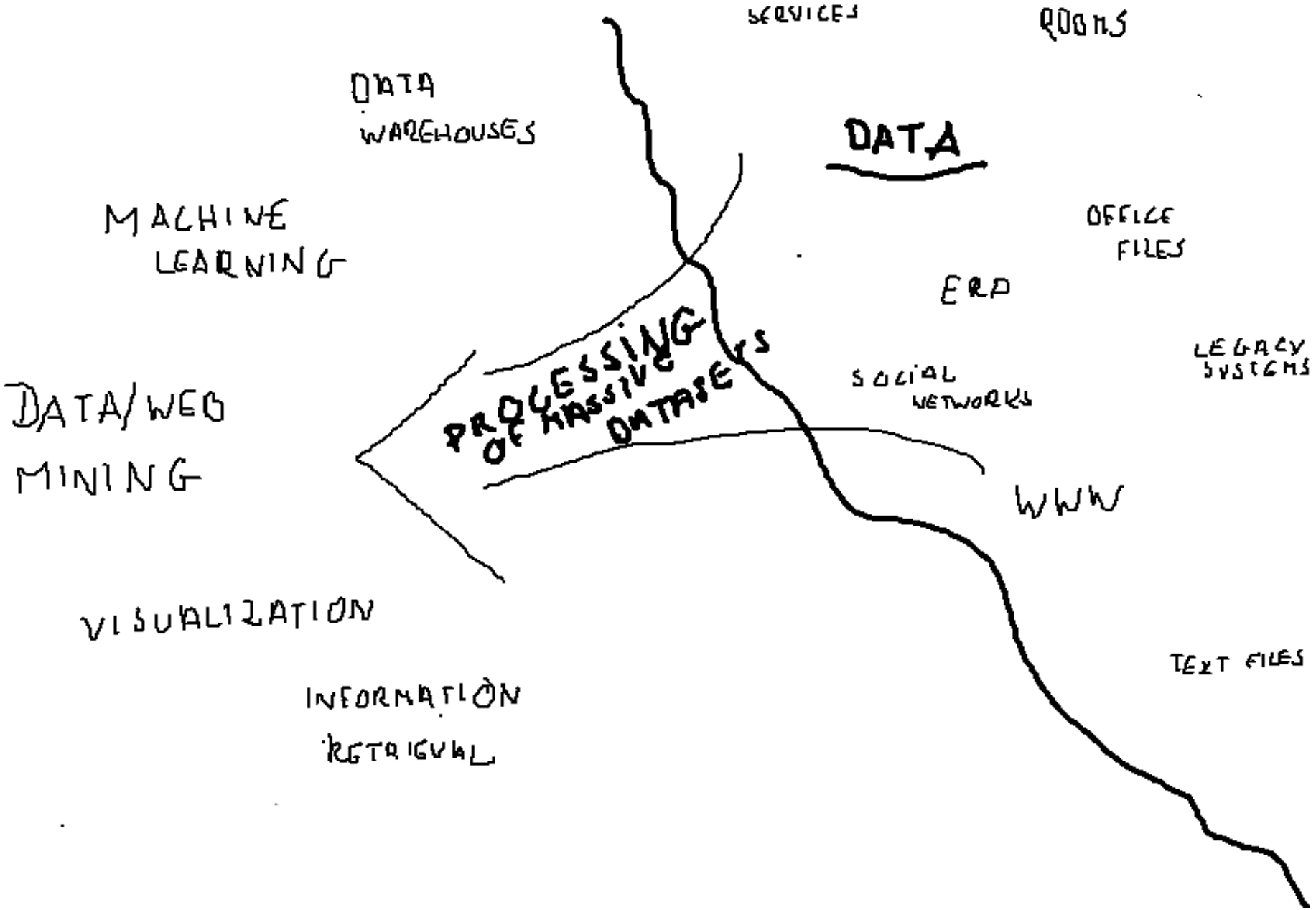
SERVICES
ROOMS
DATA WAREHOUSES
DATA
MACHINE LEARNING
OFFICE FILES
ERP
LEGACY SYSTEMS
SOCIAL NETWORKS
DATA/WEB MINING
PROCESSING OF MASSIVE DATABASES
WWW
VISUALIZATION
TEXT FILES
INFORMATION RETRIEVAL

Data management

- **Data** is a vital organizational resource.
- Data needs to be managed like other important business assets.
- Most organizations could not survive without quality data about their internal operations and external environment.

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  - Enable durability, the recovery of the database in the face of failures,
  - Control access to data from many users at once in isolation and ensure the actions on data to be performed completely.

Data models

- **Data model** is an abstract model that defines how data is represented and accessed.
  - **Logical data model** – from a user's point of view
  - **Physical data model** – from a computer's point of view.
- Data model defines:
  - Data objects and types, relationships between data objects, and constraints imposed on them.
  - Operations for defining, searching and updating data.

Approaches to data management

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- NoSQL and BigData

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- *NewSQL*

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- NoSQL and BigData
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- **The choice of the approach strongly depends on a given application!**

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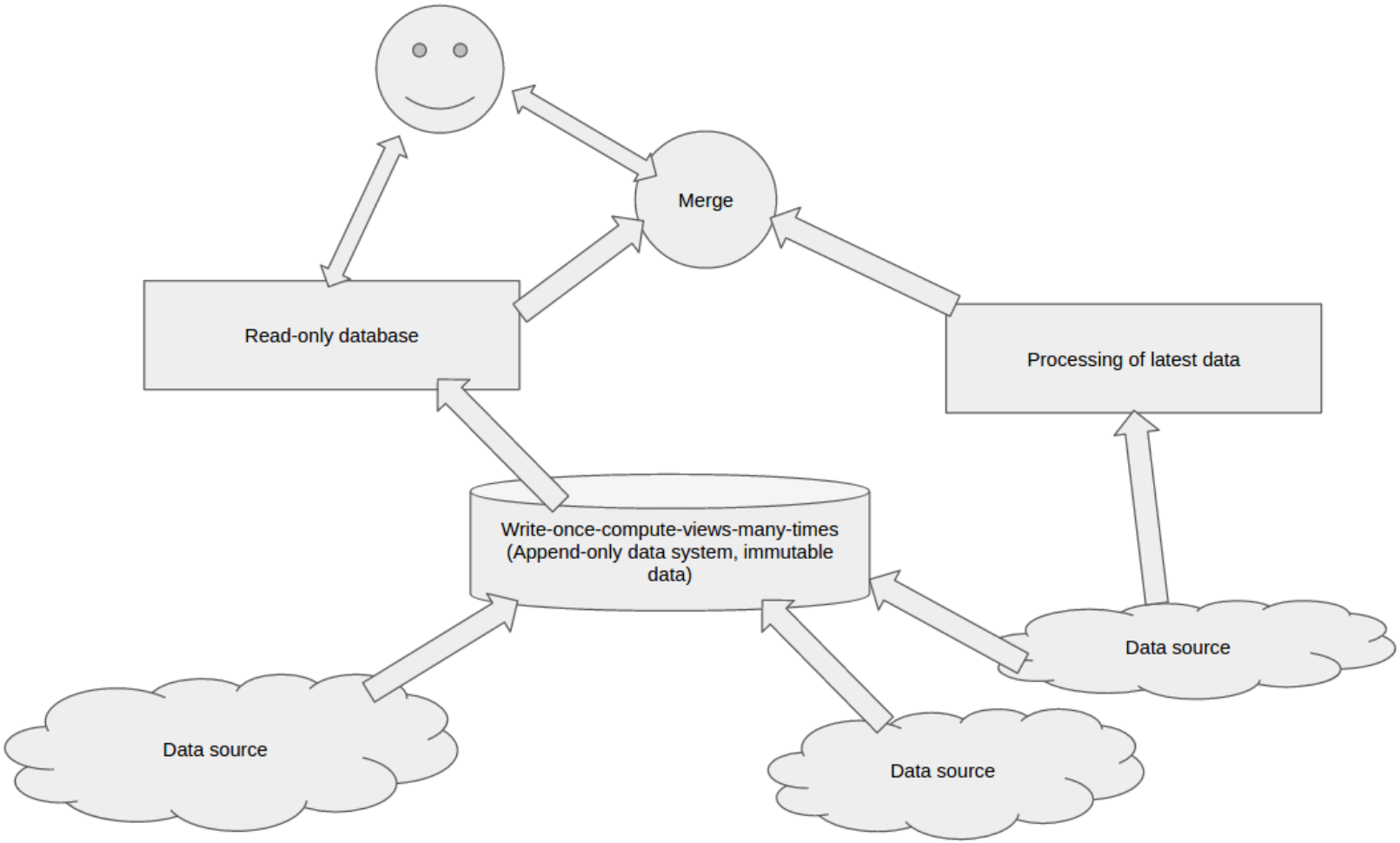
  - **Main tasks**: effective processing of multidimensional queries concerning huge volumes of data.
  - Database systems of a **write-once-read-many-times** type.

Outline

Analytical database systems

- Data warehouses,
- Business intelligence,
- Computational and analytical tools,
- Scientific databases.

Analytical database systems



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  - **Time-variant**: the time horizon for the data warehouse is significantly longer than that of operational systems.

Example

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- University authorities decided to analyze teaching performance by using the data collected in databases owned by the university containing information about students, instructors, lectures, faculties, etc.
- They would like to get answers for the following queries:
  - What is the average score of students over academic years?
  - What is the number of students over academic years?
  - What is the average score by faculties, instructors, etc.?
  - What is the distribution of students over faculties, semesters, etc.?
  - ...

Example

- An exemplary query could be the following:

```
SELECT Instructor, Academic_year, AVG(Grade)
FROM Data_Warehouse
GROUP BY Instructor, Academic_year
```

- And the result:

Academic_year	Name	AVG(Grade)
2013/14	Stefanowski	4.2
2014/15	Stefanowski	4.5
2013/14	Słowiński	4.1
2014/15	Słowiński	4.3
2014/15	Dembczyński	4.6

Motivation

- The result is also commonly given as a pivot table:

AVG(Grade)	Academic_year	
Name	2013/2014	2014/2015
Stefanowski	4.2	4.5
Słowiński	4.1	4.3
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  - How to prepare an integrated view of data and move data from operational to analytical system?

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  - Periodically refresh data in the data warehouse.

There are typically a number of different dimensions from which a given pool of data can be analyzed. This plural perspective, or Multidimensional Conceptual View appears to be the way most business persons naturally view their enterprise.

E.F. Codd, S.B. Codd and C.T. Salley, 1993

Conceptual schemes of data warehouses

- Three main goals for logical design:
  - Simplicity:
    - Users should understand the design,
    - Data model should match users' conceptual model,
    - Queries should be easy and intuitive to write.
  - Expressiveness:
    - Include enough information to answer all important queries,
    - Include all relevant data (without irrelevant data).
  - Performance:
    - An efficient physical design should be possible to apply.

Three basic conceptual schemes

- Star schema,
- Snowflake schema,
- Fact constellations.

Star schema

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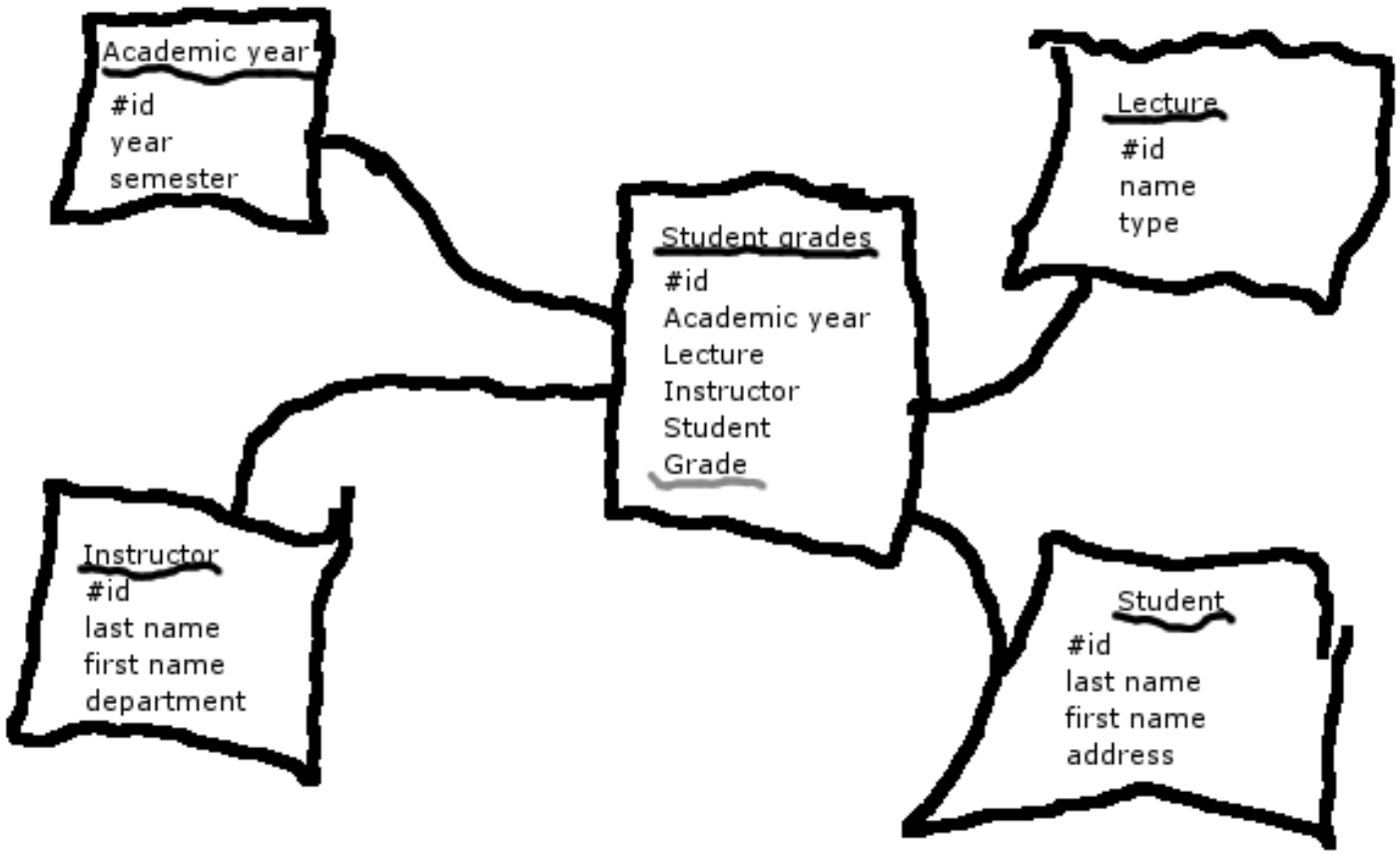
- A single table in the middle connected to a number of dimension tables.



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  - Represent information about dimensions (student, academic year, etc.).
  - Each dimension has a set of descriptive attributes.

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- The aggregated fact columns are the matter of the analysis.

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- Dimension tables describe facts stored in the fact table.

Fact table vs. Dimension tables

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Facts contain numbers, dimensions contain labels

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- Denormalization helps cover up the inefficiencies inherent in relational database software.
- **Normalize until it hurts, denormalize until it works** :)

Data models in OLAP systems

- Relational,
- Multidimensional.

Multidimensional data model

- Retail sales data:

Location:Vancouver				
Time (quarters)	Items			
	TV	Computer	Phone	Security
Q1	605	825	14	400
Q2	680	952	31	512
Q3	812	1023	30	501
Q4	927	1038	38	580

Multidimensional data model

- Similar information for other cities:

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	TV	Computer	Phone	Security
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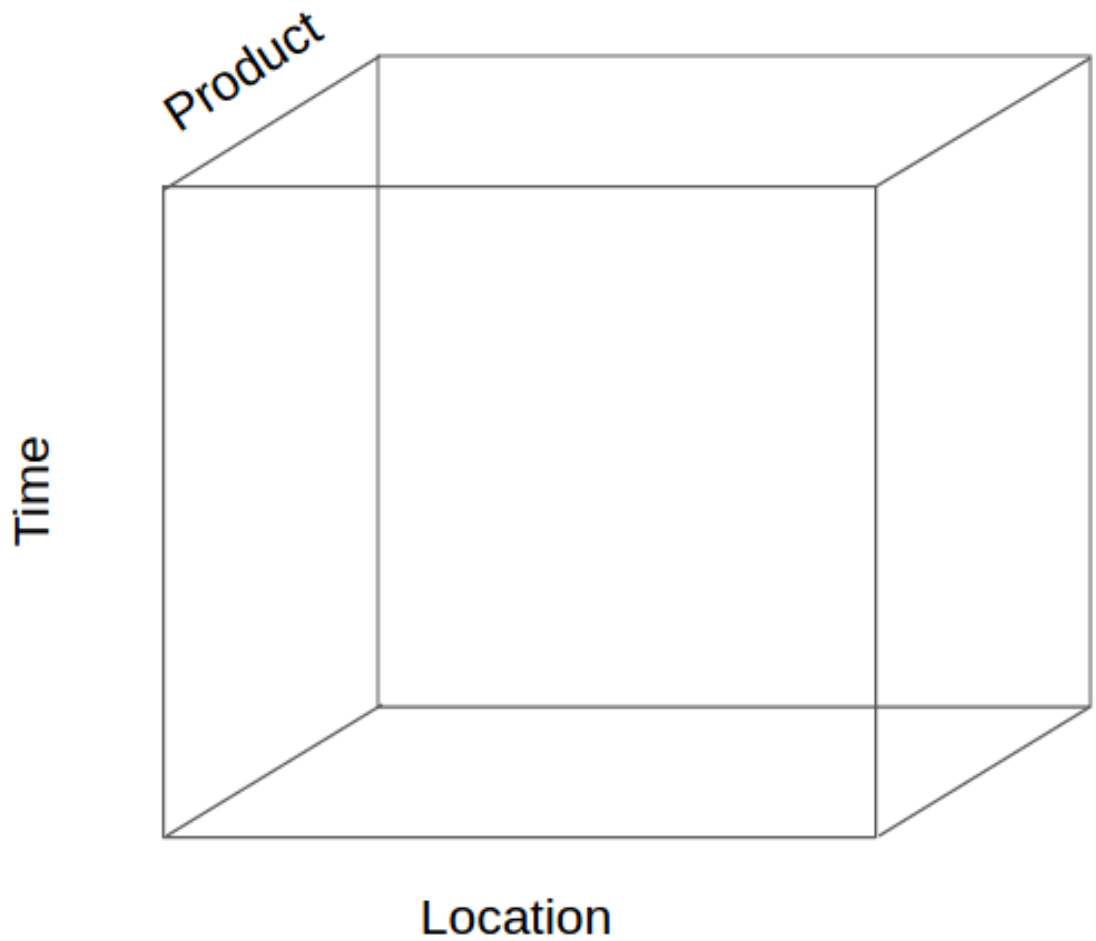
Q2	680	952	31	512
Q3	812	1023	30	501
Q4	927	1038	38	580

Location:Toronto				
Time (quarters)	Items			
	TV	Computer	Phone	Security
Q1	1087	968	38	872
Q2	1130	1024	41	952
Q3	1034	1048	45	1002
Q4	1142	1091	52	984

Location:Chicago				
Time (quarters)	Items			
	TV	Computer	Phone	Security
Q1	854	882	89	623
Q2	943	890	64	698
Q3	1023	924	59	789
Q4	1129	992	63	870

Location:New York				
Time (quarters)	Items			
	TV	Computer	Phone	Security
Q1	818	746	43	591
Q2	894	769	52	682
Q3	940	795	58	728
Q4	978	864	59	784

Multidimensional cube



- More dimensions possible.

Different levels of aggregation

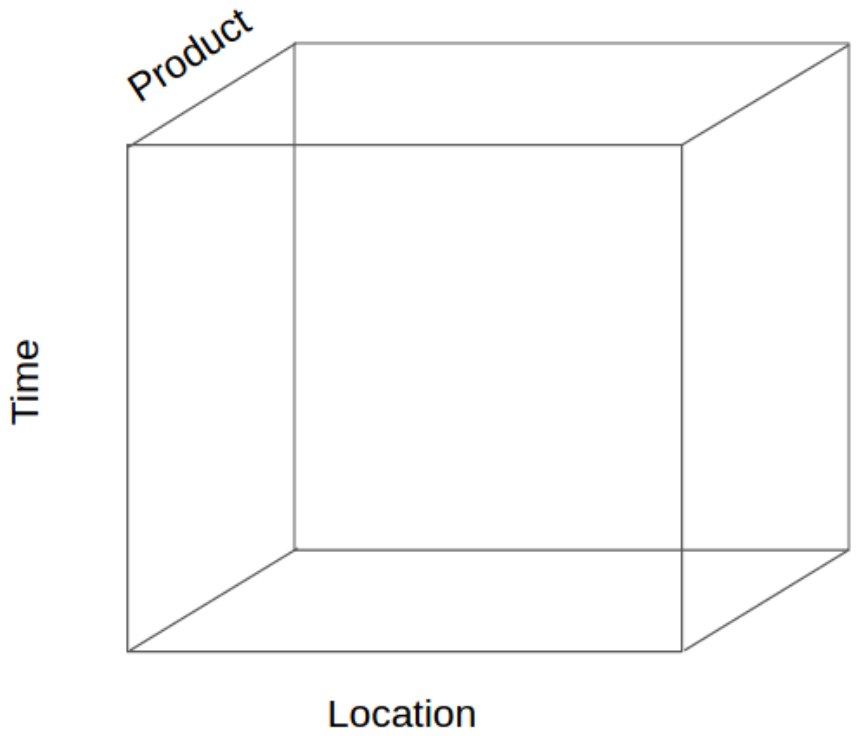
- Sales(time, product, *)

Time (quarters)	Items			
	TV	Computer	Phone	Security
Q1	3364	3421	184	2486
Q2	3647	3635	188	2817
Q3	3809	3790	186	3020
Q4	4176	3985	212	3218

- Sales(time, *, *); Sales(*, *, *)

Operators in multidimensional data model

- Roll up – summarize data along a dimension hierarchy.
- Drill down – go from higher level summary to lower level summary or detailed data.
- Slice and dice – corresponds to selection and projection.
- Pivot – reorient cube.
- Raking, Time functions, etc.



Exploring the cube

Time (quarters)	Items			
	TV	Computer	Phone	Security
Q1	3364	3421	184	2486
Q2	3647	3635	188	2817
Q3	3809	3790	186	3020
Q4	4176	3985	212	3218

$\Leftrightarrow$

Time		Items			
		TV	Computer	Phone	Security
Q1		3364	3421	184	2486
Q2		3647	3635	188	2817
Q3		3809	3790	186	3020
Q4	October	1172	960	105	1045
	November	1005	1340	45	987
	December	1999	1685	62	1186

OLTP vs. OLAP

	OLTP	OLAP
users	clerk, IT professional	knowledge worker
function	day to day operations	decision support
DB design	application-oriented	subject-oriented
Data	current, up-to-date, detailed, flat, relational	isolated, historical, summarized, multidimensional, integrated, consolidated
usage	repetitive	ad-hoc
access	read/write,	lots of scans
unit of work	short, simple transaction	complex query
# records accessed	tens	millions
#users	thousands	hundreds
db size	100MB-GB	100GB-TB
metric	transaction throughput	query throughput, response

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  - No declarative query language (requires more programming, but new paradigms like MapReduce appear)

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  - graph database systems.
- Design for different purposes, also for OLTP and OLAP.

BigData – a lot of Vs[1]

- **Volume**: the quantity of generated and stored data.
- **Variety**: the type and nature of the data.
- **Velocity**: the speed at which the data is generated and processed.
- **Variability**: inconsistency of the data.
- **Veracity**: the quality of captured data.

[1] `https://en.wikipedia.org/wiki/Big_data`

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- Data schemas: star schema, flexible schemas.

Outline

Summary

- Significant difference between operational and analytical systems.
- Different data models dedicated to particular applications.
- OLAP vs. OLTP.
- Relational model vs. multidimensional model.
- Star schema.
- NoSQL = "Not only traditional relational DBMS."
- Processing of massive datasets.

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