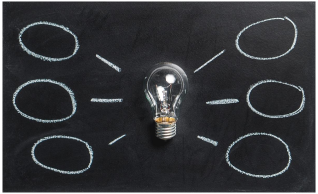
Julian Kunkel

Data Models & Data Processing Strategies



Learning Objectives

- Define important terminology for data handling and data processing
- Sketch the ETL process used in data warehouses
- Sketch a typical HPDA data analysis workflow
- Sketch the lambda architecture
- Construct suitable data models for a given use-case and discuss their pro/cons
- Define relevant semantics for data access (in data models)

Outline

Terminology

Data [1, 10]

- **Raw data**: collected information that is not derived from other data
- **Derived data/data product**: data produced with some computation/functions
- **View**: presents derived data to answer specific questions
  - Convenient for users (only see what you need) + faster than re-computation
  - Convenient for administration (e.g., manage permissions)
  - Data access can be optimized

Processing makes data valuable!

Dealing with unstructured data

- We need to extract information from raw unstructured data
  - e.g., perform text-processing using techniques from computer linguistics
- **Semantic normalization** is the process of reshaping free-form information into a structured form of data [11]
- Store raw data when your processing algorithm improves over time

Data Management in Projects Involves Various Considerations

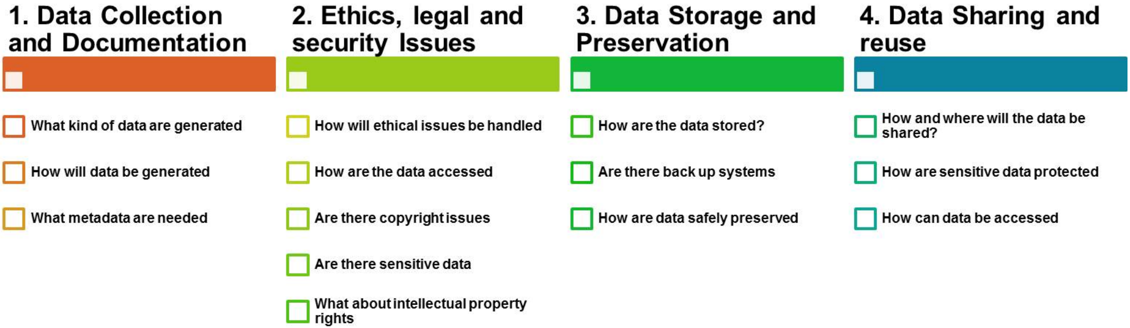


Figure: Data Management Plan. Source: https://www.uzh.ch/blog/hbz/2018/11/15/data-management-plan-in-a-nutshell/

- **Data management plan (DMP)**: describes the strategies and measures for handling research data during and after a project
- **Data life cycle**: creation, distribution, use, maintenance & disposition
  - For every data object, should define its life cycle
- **Information lifecycle management** (ILM): business term; practices, tools and policies to manage the data life cycle in a cost-effective way

Terminology for Managing Data [1, 10]

- **Data governance**: *"control that ensures that the data entry ... meets precise standards such as business rule, a data definition and data integrity constraints in the data model"* [10]
  - Think about reasons that invalidate data that lead to catastrophic results...
  - Example: missinterpretation of data value "NaN" as "0" in a survey
- **Data provenance**: the documentation of input, transformations of data and involved systems to support analysis, tracing and reproducibility
  - e.g., Input (file.csv) ⇒Calculate means via x.py (result: means.csv) ⇒Create diagrams via d.py (result fig1.pdf)
- **Data-lineage** (Datenherkunft): forensics; allows to identify the source data used to generate data products (part of data provenance)
  - e.g., fig1.pdf has been produced from ... using Z...
  - I'm able to reproduce results and track errors from the product
- **Service level agreements** (SLAs): contract defining quality, e.g., performance/reliability & responsibilities between service user/provider

Outline

Process Model [13]

- Process Model: *A model describing processes*
- **Process** [15]:
  - *"A series of events to produce a result, especially as contrasted to product."*
- Qualities of descriptions
  - Descriptive: Describe the events that occur during the process
  - Prescriptive
    - Define the intended process and how it is executed
    - Rules and guideliness steering the process
  - Explanatory
    - Provide rationales for the process
    - Describe requirements
    - Establish links between processes
- **Workflow**
  - *A defined process, i.e., all events/processing steps are clearly defined*

Data-Cleaning and Ingestion

- Importing of raw data into a big data system is an important process
  - Wrong data results in wrong conclusions: Garbage in – Garbage out
- **Data wrangling**: process & procedures to clean/convert data from one format to another [1]
  - **Data extraction**: identify relevant data sets and extract raw data
  - **Data munging**: cleaning raw data, converting it to a format for consumption
- **ETL process** (Extract, Transform, Load): data warehouse term for importing data (from databases) into a data warehouse

Necessary steps

- Define and document data governance policies to ensure data quality
  - Identifying and dealing with duplicates, time(stamp) synchronization
  - Handling of missing values (NULL or replace them with default values)
- Document the conducted transformations (for data provenance)
  - Data sources
  - Conversions of data types, complex transformations
  - Extraction of information from unstructured data (semantic normalization)
- Implementation of the procedures for bulk loading and cleaning of data

Datawarehousing ETL Process

- Extract: read data from source (transactional) databases
- Transform: alter data on the fly
  - Perform quality control
  - Treat errors and uncertainty to improve quality
  - Change the layout to fit the schema of the data warehouse
- Load: integrate the data into the data warehouse
  - Restructure data to fit needs of business users
  - Rely on batch integration of large quantities of data

Data Analysis Workflow

The traditional approach proceeds in phases:

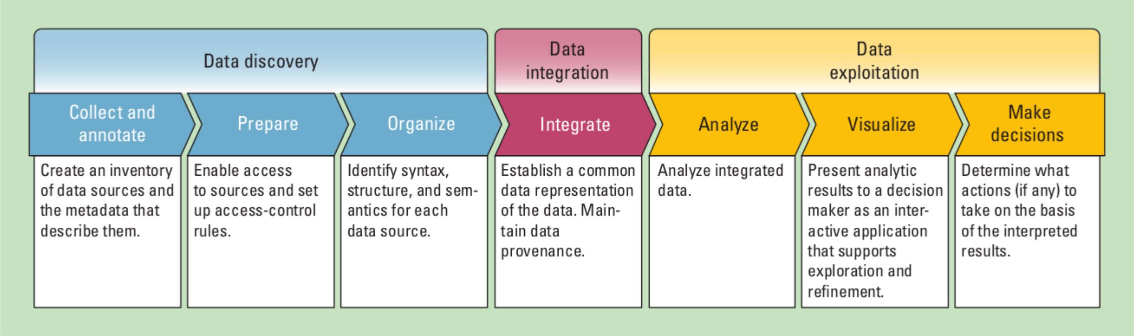


Figure: Source: Gilbert Miller, Peter Mork From Data to Decisions: A Value Chain for Big Data.

- Analysis tools: machine learning, statistics, interactive visualization
- Limitation: Interactivity by browsing through prepared results
- Indirect feedback between visualization and analysis

Programming (High-Performance) BigData Analytics

High-level concepts

- SQL and derivatives
- Domain-specific languages (Cypher, PigLatin)

Programming languages

- Java interfaces are widely available but low-level
- Scala language increases productivity over Java
- Python and R have connectors to popular BigData solutions

In the exercises, we are using primarily Python

Programming Paradigms[14]

Programming paradigms are process models for computation

- Fundamental style and abstraction level for computer programming
  - **Imperative** (e.g., Procedural)
  - **Declarative** (e.g., Functional, **Dataflow**, Logic)
  - **Data-driven** programming (describe patterns and transformations)
  - **Multi-paradigm** support several at the same time (e.g., **SQL**)
- Goals: productivity of the users and performance upon execution
  - Tool support for development, deployment and testing
  - Performance depends on single core efficiency but importantly parallelism
- **Parallelism** is an important aspect for processing of large data
  - In HPC, there are language extensions, libraries to specify parallelism
    - PGAS, Message Passing, OpenMP, data flow e.g., OmpSs, ...
  - In BigData Analytics, libraries and domain-specific languages
    - MapReduce, SQL, data-flow, streaming and data-driven

Domain-specific Language (DSL)

- DSLs are a contrast to general-purpose languages (GPL)
- Specialized programming language to an application domain
  - Mathematics, e.g., statistics, modeling
  - Description of graphs, e.g., graphviz (dot)
  - Processing of big data (Apache Pig)
- Standalone vs. embedded DSLs
  - Embedding into a GPL (e.g., regex, SQL) with library support
  - Standalone requires to provide its own toolchain (e.g., compiler)
  - Source-to-source compilation (DSL to GPL) an alternative
- Abstraction level
  - High-level: only covers (scientific) domain
  - Low-level: includes technical details (e.g., about hardware)

Tools for Data Exploration

Mandatory features

- Interactive
- Rich set: visualization, data manipulations, algorithms
- Real-time processing of big data

Tools (excerpt)

- Closed source: SAS, Spotfire, Domo, Tableau
- Open source: **R, Python/Jupyter**/Bokeh, GoogleVis
- Other open source tools, see [19]

Requirements

- Usability
- Flexible
- Performance

Productivity

Productivity is a very important metric for Big Data tools

Development environments

1. Text editor; workflow: edit, save, (compile), run on a server
   - Notepad, gedit
2. Interactive shell; type code and execute it
   - Python, SQL frontend
3. IDE; optimized workflow of the text editor, may run code on a server
   - NetBeans, Eclipse, VisualStudio
4. Interactive lab notebook; type code and store it together with results
   - Examples: Jupyter, Apache Zeppelin
   - Embedded in GitHub:
     https://github.com/jakevdp/PythonDataScienceHandbook/blob/master/code_listings/03.11-Working-with-Time-Series.ipynb
5. Lab notebook + IDE;
   - Examples: Spyder

Alternative Processing Technology

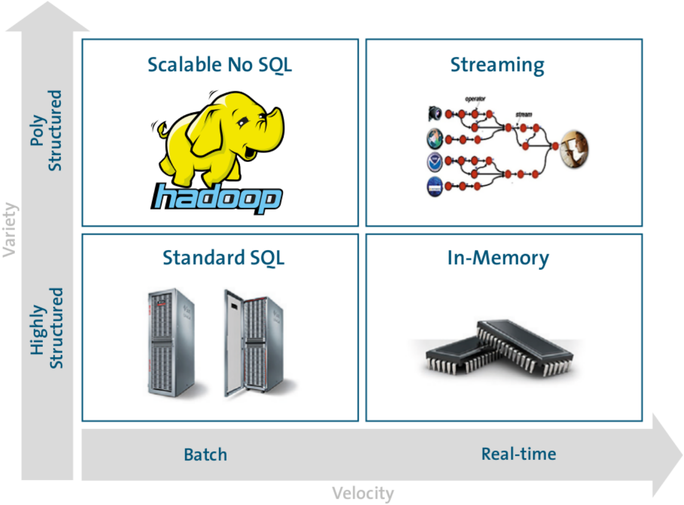
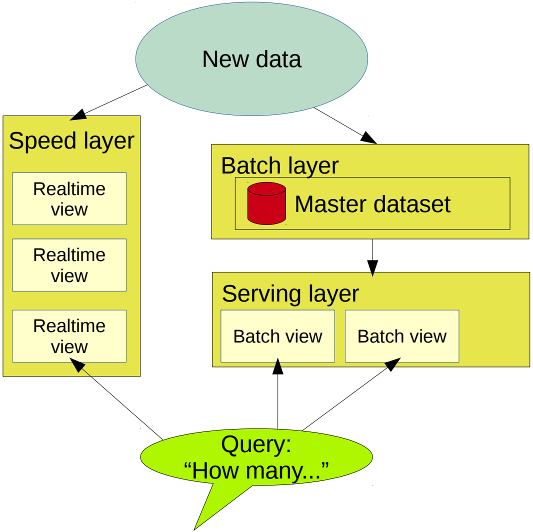


Figure: Source: Forrester Webinar. Big Data: Gold Rush Or Illusion? [4]

The Lambda Architecture [11]

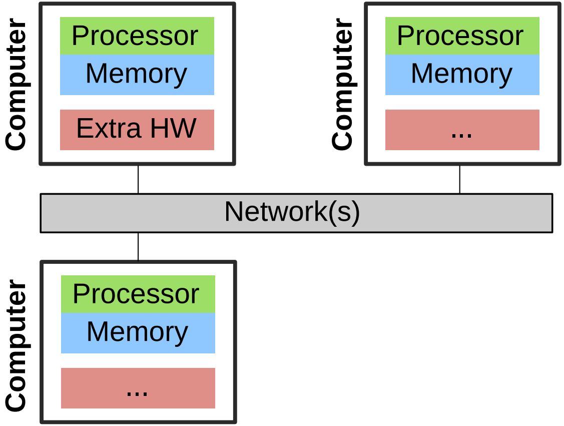


- **Goal**: Interactive Processing
- Batch layer pre-processes data
  - Master dataset is immutable/never changed
  - Operations are periodically performed
- Serving layer offers performance optimized views
- Speed layer serves deltas of batch and recent activities, may approximate results
- Robust: Errors/inaccuracies of realtime views are corrected in batch view

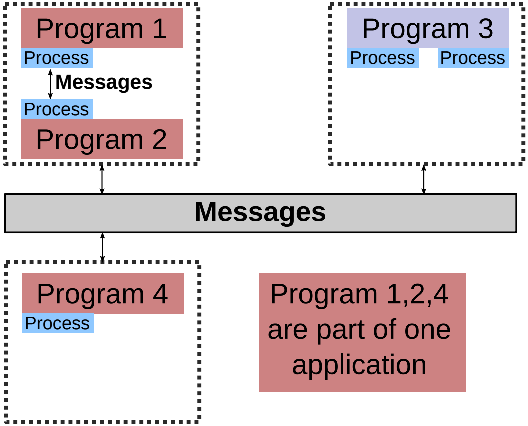
Reminder: Distributed System and Distributed Program

- **Must map a workflow to processes and hardware of a distributed system**
- A **distributed program** (DP) runs on a distributed system

Hardware perspective



Software perspective (mapped to hw)



Group Work

- Discuss the processing stages of a "use case" of your exercise
  - How is data processed?
  - How does the use case map to the ETL and data analysis workflow?
  - Is this an interactive process?
  - What programming paradigm is used?
  - What tools are used?
  - How were the tools mapped to hardware?
  - How did they manage data? Is there a data management plan, a defined life cycle?
- If you haven't done the exercise participate in the discussion
  - Google or come up with an example of your choice...
- Time: 10 min
- Organization: breakout groups - please use your mic or chat

Outline

Data Models[12] and their Instances [12]

- A data model describes how information is organized in a system
  - It is a tool to specify, access and process information
  - A model provide operations for accessing and manipulating data that follow certain semantics
  - Typical information is some kind of entity (virtual object) (e.g., car)
- **Logical model**: abstraction expressing objects and operations
- **Physical model**: maps logical structures onto hardware resources (e.g., files, bytes)

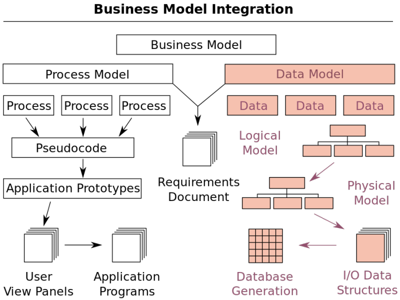


Figure: Source: [12]

- DM theory: Formal methods for describing data models with tool support
- Applying theory creates a **data model instance** for a specific application

[1]: The term is often used ambivalently for a data (meta) model concept/theory or an instance

Operations

- Operations define how you can interact with the data
  - Minimal: Need to somehow store and retrieve data
  - Users may want to search for data, update existing data
- May want to offload some operations to the server side: active storage
  - Reduce data, e.g., compute mean/sum
  - Conditional updates

Typical Operations

- POSIX: create, open, write (anywhere), read (anywhere)
  - Does not distinguish between write and update
- CRUD: Create, Read, Update, Delete
- Amazon S3: Put (Overwrite), Get (Partially), Delete

Selection of Theory (concepts) for Data Models

- I/O Middelware: NetCDF, HDF5, ADIOS
  - Self-describing formats containing N-dim variables with metadata
- Relational model (tuples and tables)
  - Can be physically stored in, e.g., a CSV file or database
- Relational model + raster data
  - Operations for N-dimensional data (e.g., pictures, scientific data)
- NoSQL data models: Not only SQL[13], lacks features of databases
  - Example DB models: columnar, document, key-value, named graph
- Fact-based: built on top of atomic facts, well-suited for BI [11]

Data modeling [10]

The process in software-engineering of creating a data model instance for an information system

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[13] Sometimes people also call it No SQL

Semantics

Semantics describe I/O operations and their behavior

- Application programming interface (API)
- **Concurrency**: Behavior of simultaneously executed operations
  - Atomicity: Are partial modifications visible to other clients
  - Visibility: When are changes visible to other clients
  - Isolation: Are operations influencing other ongoing operations
- **Availability**: Readiness to serve operations
  - Robustness of the system for typical (hardware and software) errors
  - Scalability: availability and performance behavior depending on the number of clients, concurrent requests, request size, ...
  - Partition tolerance: Continue to operate even if network breaks partially
- **Durability**: Modifications should be stored on persistent storage
  - Consistency: Any operation leaves a consistent (correct) system state

Consensus [17]

- **Consensus**: several processes agree (decide) for a single data value
  - Processes may propose a value (any time)
- Consensus and consistency of distributed processes are related
- Consensus protocols such as Paxos ensure cluster-wide consistency
  - They tolerate typical errors in distributed systems
  - Hardware faults and concurrency/race conditions
  - Byzantine protocols additionally deal with forged (lying) information
- Properties of consensus
  - Agreement: Every correct process must agree on the same value
  - Integrity: All correct process decide upon at most one value v. If one decides v, then v has been proposed by some process
  - Validity: If all process propose the same value v, then all correct processes decide v
  - Termination: Every correct process decides upon a value

Example Semantics

POSIX I/O

- Atomicity and isolation for individual operations, locking possible

ACID

- Strict semantics for database systems to prevent data loss
- Atomicity, consistency, isolation and durability for **transactions**

BASE

- BASE is a typical semantics for Big Data due to the CAP theorem
- Basically Available replicated Soft state with Eventual consistency [26]
  - Availability: Always serve but may return a failure, retry may be needed
  - Soft state: State of the system may change over time without requests due to eventual consistency
  - Consistency: If no updates are made any more, the last state becomes visible to all clients after some time (eventually)
- Big data solutions usually exploit the immutability of data

Relational Model [10]

- Database model based on first-order predicate logic
  - Theoretic foundations: relational algebra and relational calculus
- Data is represented as tuples
  - In its original style, it does not support collections
- Relation/Table: groups tuples with similar semantics
  - Table consists of rows and named columns (attributes)
  - No (identical) duplicate of a row allowed
- Schema: specify structure of tables
  - Datatypes (domain of attributes)
  - Consistency via constraints
  - Organization and optimizations

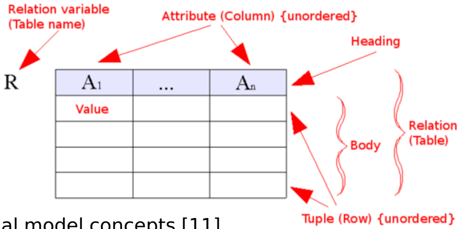

Figure: Source: Relational model concepts [11]

Example Relational Model for Students Data

Matrikel	Name	Birthday
242	Hans	22.04.1955
245	Fritz	24.05.1995

Table: Student table

ID	Name
1	Big Data Analytics
2	Hochleistungsrechnen

Table: Lecture table

Matrikel	LectureID
242	1
242	2
245	2

Table: Attends table representing a relation

Columnar Model

- Data is stored in rows and columns (similar to tables)
- A column is a tuple (name, value and timestamp)
- Each row can contain different columns
  - Columns can store complex objects, e.g., collections
- Wide columnar model: very sparse table of 100k+ columns
- Example technology: HBase, Cassandra, Accumulo

Row/Column:	student name	matrikel	lectures	lecture name
1	"Max Mustermann"	4711	[3]	-
2	"Nina Musterfrau"	4712	[3,4]	-
3	-	-	-	"Big Data Analytics"
4	-	-	-	"Hochleistungsrechnen"

Table: Example columnar model for the students, each value has its own timestamp (not shown). Note that lectures and students should be modeled with two tables

Key-Value Store

- Data is stored as value and addressed by a key
- The value can be complex objects, e.g., JSON or collections
- Keys can be forged to simplify lookup (evtl. tables with names)
- Example technology: CouchDB, BerkeleyDB, Memcached, BigTable

Key	Value
stud/4711	<name>Max Mustermann</name><attended><id>1</id></attended>
stud/4712	<name>Nina Musterfrau</name><attended><id>1</id><id>2</id></attended>
lec/1	<name>Big Data Analytics</name>
lec/2	<name>Hochleistungsrechnen</name>

Table: Example key-value model for the students with embedded XML

Document Model

- Collection of documents
- Documents contain semi-structured data (JSON, XML)
- Addressing to lookup documents are implementation specific
  - e.g., bucket/document key, (sub) collections, hierarchical namespace
- References between documents are possible
- Example technology: MongoDB, Couchbase, DocumentDB

```xml
<students>
  <student><name>Max Mustermann</name><matrikel>4711</matrikel>
    <lecturesAttended><id>1</id></lecturesAttended>
  </student>
  <student><name>Nina Musterfrau</name><matrikel>4712</matrikel>
    <lecturesAttended><id>1</id><id>2</id></lecturesAttended>
  </student>
</students>
```

Table: Example XML document storing students. Using a bucket/key namespace, the document could be addressed with key: "uni/stud" in the bucket "app1"

Graph

- Entities are stored as nodes and relations as edges in the graph
- Properties/Attributes provide additional information as key/value
- Example technology: Neo4J, InfiniteGraph

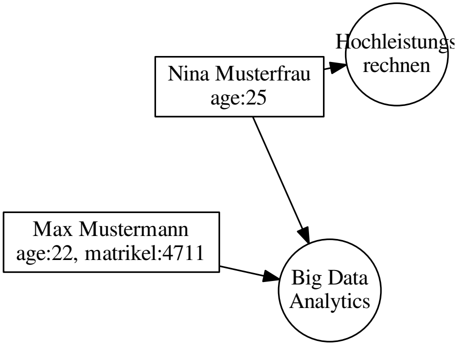

Figure: Graph representing the students (attributes are not shown)

Fact-Based Model [11][15]

- Store raw data as timestamped atomic facts aka log files of change/current status
- Never delete true facts: Immutable data
- Make individual facts unique to prevent duplicates

Example: social web page

- Record all changes to user profiles as facts
- Benefits
  - Allows reconstruction of the profile state at any time
  - Can be queried at any time[14]

Example: purchases

- Record each item purchase as facts together with location, time, ...

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14 If the profile is changed recently, the query may return an old state.

15 Note that the definitions in the data warehousing (OLAP) and big data [11] domains are slightly different

From Big Data to the Data Lake

- With cheap storage costs, people promote the concept of the data lake
- Combines data from many sources (data silos) and of any type and model
- Allows for conducting future analysis and not miss any opportunity

Attributes of the data lake

- Collect everything: all time all data: raw sources and processed data
  - Decide during analysis which data is important, e.g., no “schema“ until read
- Dive in anywhere: enable users across multiple business units to
  - Refine, explore and enrich data on their terms
- Flexible access: shared infrastructure supports various patterns
  - Batch, interactive, online, search

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http://hortonworks.com/blog/enterprise-hadoop-journey-data-lake/

Group Work

- Discuss the use case to store information about students with each data model
- Which data model would you prefer, why?
- Time: 10 min
- Organization: breakout groups - please use your mic or chat

Summary

- Data-cleaning and ingestion is a key to successful modeling
- Big data can be considered to be immutable (remember: data lake)
- Data models describe how information is organized
  - Various I/O middleware, relational model
  - NoSQL: Column, document, key-value, graphs
- Semantics describe operations and behavior, e.g., POSIX, ACID, BASE
- Process models and programming paradigms describe how to
  - transform and analyze data
- Apache ecosystem offers means for batch and real-time processing
- Lambda architecture is a concept for enabling real-time processing

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