Intelligent techniques for processing large and structured data

Lecture 1

Faculty of Mathematics and Computer Science
Babeș-Bolyai University

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Motto: From Raw Data to Actionable Knowledge

Introduction into Data Analysis, Data Mining, and Knowledge Discovery

AGENDA

- Course organization
- Why this course exists?
- Let’s get to know the audience
- Evaluation
- What is Data?
- What is Data Analysis?
- What is Data Mining?
- What is Knowledge Discovery?
- Types of Data
- Industry Pipeline for Large & Structured Data
- Key Takers

Course organization

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Course organization

- Instructors
  - Course: Teaching Assistant PhD Sergiu Limboi
  - Laboratory: Associate Teacher Andreea Gabrian

- Team channel code: j8zn8u3

- Course structure:
  - Lectures 2 hours per week
  - Laboratories 2 hours per week

- Additional information
  - All materials will be posted on GitHub: https://github.com/SergiuLimboi/Intelligent-techniques-for-processing-structured-and-large-data/tree/main
  - MS Teams will be used for announcements (e.g., exam dates, invited guests, etc.)

Why this course exists?

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Why this course exists?

- “Do all real datasets look like a Pandas table?”
- “What breaks first when data becomes large: the algorithm or the infrastructure?”
- “If a model works on 10,000 rows, will it work on 100 million?”
- “If your data is clean but your pipeline is slow, where is the real problem?”
- “Is structured data really simple?”
- “In large-scale systems, what is more important: accuracy, speed, or reliability?”

Why this course exists?

- This course assumes you already know Machine Learning (ML).

- We will focus on what ML *cannot* naturally handle

- Most AI students can:
  - Train a model;
  - Tune hyperparameters;
  - Get a good accuracy score.

- But real projects fail because:
  - The data is wrong;
  - The problem is wrongly defined;
  - The evaluation is misleading;
  - The dataset is biased or incomplete.

- This course is NOT about “better models”. It is about getting the right knowledge from data.

Why this course exists?

- Typical student mindset
  - “ I just load the data and try Random Forest/ ANN/ etc. and compute some evaluation measures.”
- Professional mindset
  - “What does the data represent, how was it generated, and what decision will be made based on it?”

Let’s get to know the audience

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Let’s get to know the audience

Go to www.menti.com and enter the code **7361 1112**

or use the QR code

Evaluation

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Evaluation

- Evaluation structure:
  - Written exam (during the official exam session): 40%
  - Laboratory assignments (3 assignments during the semester): **10%**
  - Project development (during the semester): 50%

- To successfully pass the course, students must obtain:
  - Minimum grade of 5 in the Written Exam
  - Minimum grade of 5 in the Project
  - Both conditions must be fulfilled independently.

- To be eligible for the exam session, students must meet the following requirements:
  - Number of laboratory attendances: 8 out of 12
  - Number of turned laboratory assignments 2 out of 3
  - A minimum grade of 5 in the project

Evaluation

- Additional Points
  - **In-class quizzes** conducted throughout the semester may provide bonus points.
  - **Attendance at invited lectures** will be rewarded with additional points added to the final grade.

- Project timeline:
  - Project development will start in **Week 5** of the semester.

- The project will consist of the following components:
  - Project development (an application with a minimal UI is required)
  - Research report
  - Presentation during the final laboratory session

What is Data?

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What is Data?

- Data = recorded observations
- Data ≠ information
- Data ≠ knowledge
- Information = data plus context and meaning
- Knowledge = information + understanding, interpretation and validation
- Examples:
  - Numbers (prices, temperature)
  - Categories (gender, product type)
  - Text (reviews, comments)
  - Images/ signals
  - etc.

What is Data Analysis?

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What is Data Analysis?

- Process of systematically inspecting, cleaning, transforming and modelling data to discover useful information, draw conclusions, and support decision-making.

- Answers:
  - What happened?
  - How often?
  - What trends exist?

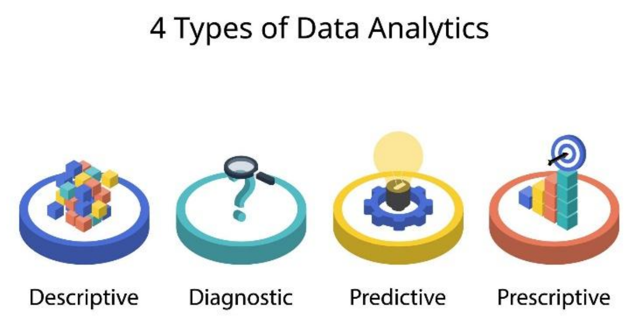
- Key concepts of Data Analysis:
  - Data collection
  - Data cleaning
  - Data transformation
  - Exploratory Data Analysis (EDA)
  - Interpretation

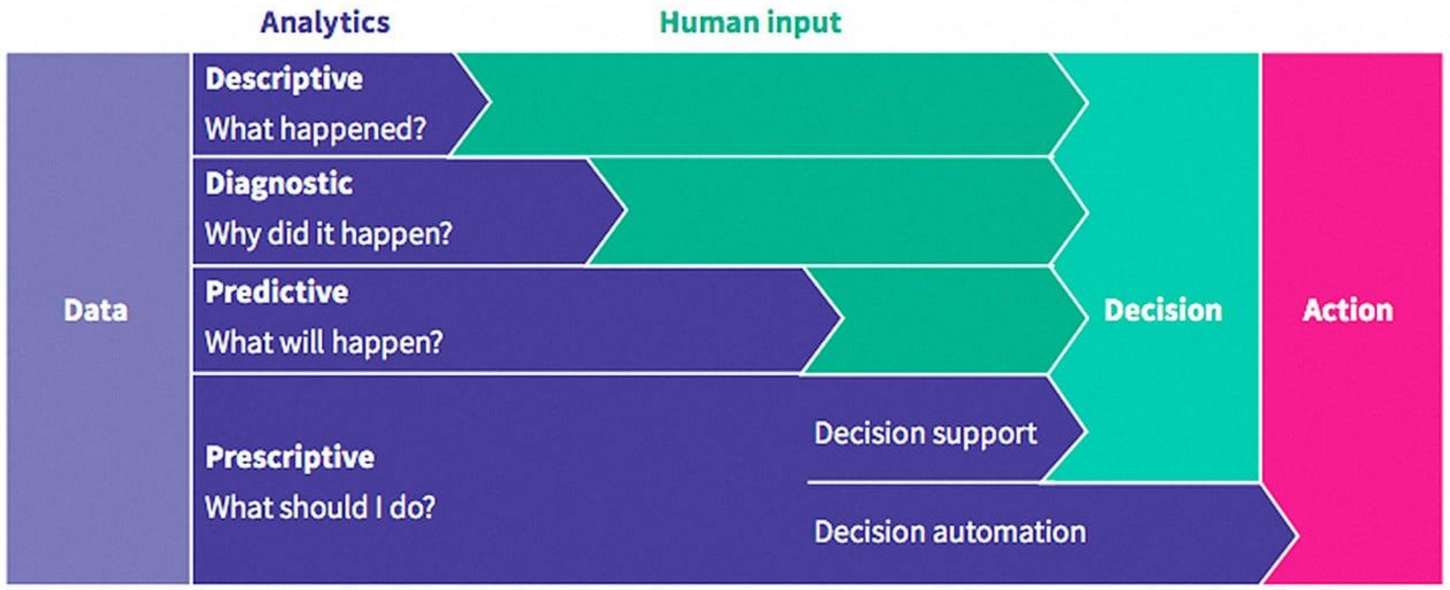
What is Data Analysis?

- Why is Data Analysis Important?
  - Problem-solving;
  - Performance tracking;
  - Informed decision-making.

- The role of a Data Analyst:
  - Data interpretation
  - Reporting
  - Decision support
  - Tool proficiency
  - Collaboration

Types of Data Analysis





Descriptive Analysis (What happened?)

- Summarizes historical data to understand **what has already occurred**.

- **Typical outputs**
  - Averages, totals, percentages;
  - Tables and dashboards;
  - Line charts, bar charts.

- **Examples**
  - Monthly sales report;
  - Average exam score;
  - Number of users per day.

- **Methods**
  - Basic statistics (mean, median, variance);
  - Aggregations (group by, counts);
  - Data visualization.

Diagnostic Analysis (Why did it happened?)

- Investigates **causes and relationships** behind observed outcomes.

- **Typical outputs**
  - Correlations
  - Comparisons between groups
  - Root-cause explanations

- **Examples**
  - Why did sales drop in March?
  - Why did website traffic decrease after the redesign?
  - Why did customer satisfaction decline this quarter?

- **Methods**
  - Correlation analysis
  - Segmentation
  - Hypothesis testing
  - Drill-down analysis

Predictive Analysis (What is likely to happen?)

- Uses historical data to **forecast future outcomes**.

- **Typical outputs**
  - Predictions;
  - Probabilities;
  - Forecasted trends.

- **Examples**
  - What will next month’s demand be?
  - Which customers are at highest risk of leaving in the next 3 months?

- **Methods**
  - Regression models;
  - Classification algorithms;
  - Time-series forecasting;
  - It can imply Machine learning models.

Prescriptive Analysis (What should we do?)

- Recommends **actions or decisions** based on predictions and constraints.

- **Typical outputs**
  - Optimal actions;
  - Decision rules;
  - What-if scenarios.

- **Examples**
  - What price should we set?
  - Which customers should receive a discount?

- **Methods**
  - Optimization;
  - Simulation;
  - Business rules + Machine Learning.

What is Data Mining?

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What is Data Mining?

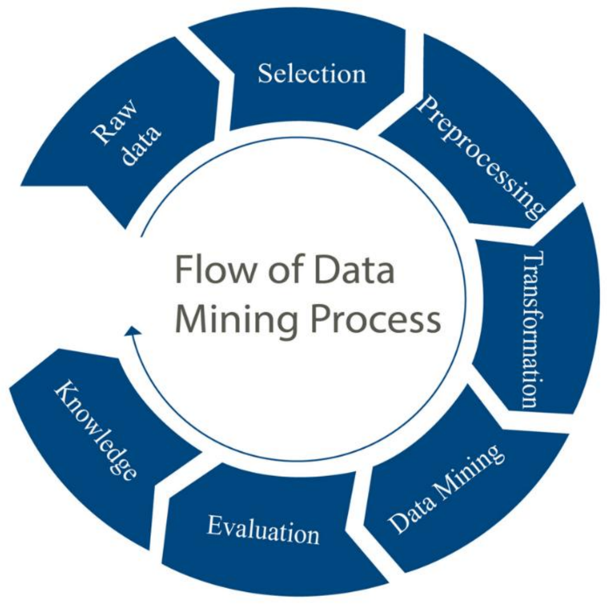
- **Data Mining** is the process of extracting valuable information from large databases that was previously unknown and using it to make informed business decisions.

- Why is Data Mining Important?
  - Insight extraction: transforms complex data sets into understandable and actionable information;
  - Decision-making support: helps businesses make data-driven decisions;
  - Pattern recognition : reveals trends and relationships that were previously hidden.

Why Data Mining?

- Fraud detection
- User profile
- Market analysis
- Time-based pattern mining
- Association rules
- House price prediction
- Energy consumption prediction
- Spam detection
- Credit risk detection
- Medical diagnosis
- etc.

What is Data Mining?



- The role of Data Mining professionals:
  - Data transformation
  - Driving innovation
  - Application across fields
  - Communication & decision support

- Data mining professionals don't just build models — they explain data.

- Data mining does NOT work on raw data

What is Knowledge Discovery?

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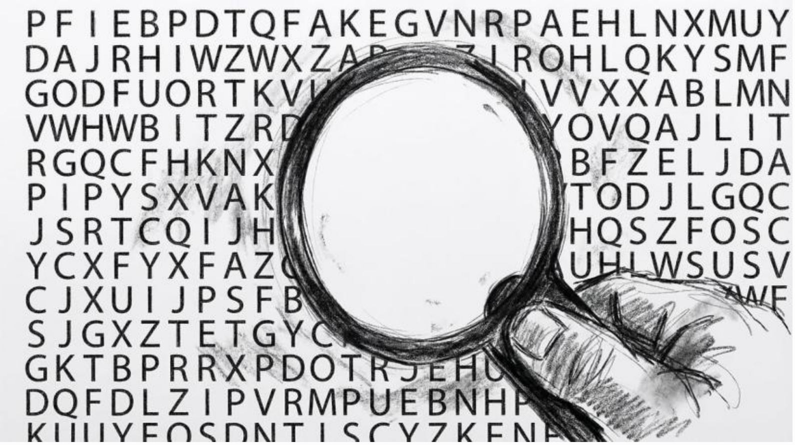
What is Knowledge Discovery?

- **Knowledge Discovery** is the process of identifying valid, novel, and useful patterns in data, transforming raw data into meaningful information.

- **Key Concepts of Knowledge Discovery:**
  - Data selection;
  - Data preprocessing;
  - Data mining;
  - Pattern evolution;
  - Knowledge representation.

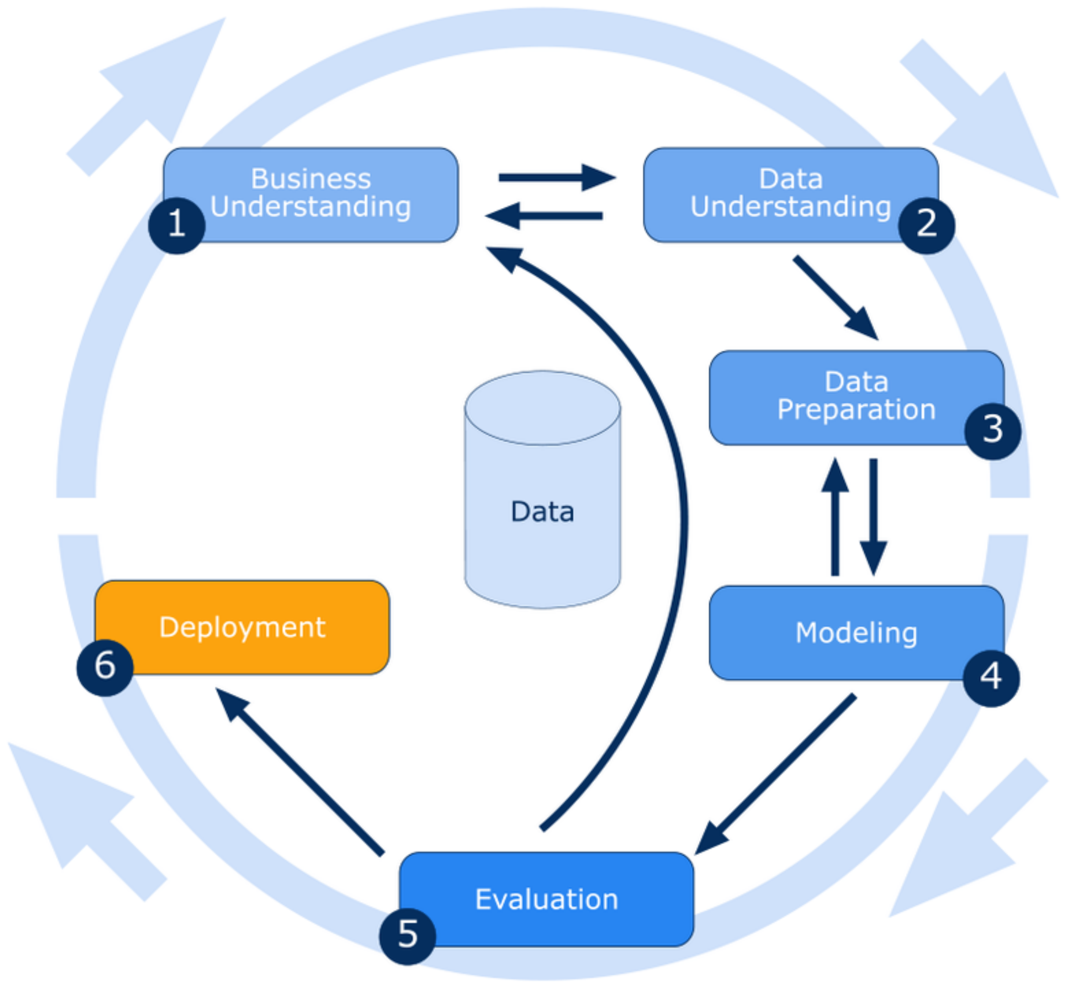


What is Knowledge Discovery?

- The Data Analyst acts as the **bridge between raw data and knowledge**, ensuring that discovered patterns are **understandable, valid, and useful.**

- The role of a Data Analysist in Knowledge Discovery:
  - Data preparation;
  - Pattern identification;
  - Result interpretation;
  - Knowledge presentation;
  - Business alignment.

The Knowledge Discovery Process



The Knowledge Discovery Process

- Step 1- Business Understanding
  - What question are we answering?
  - Who uses the result?
  - What decision depends on it?

- Step 2 – Data Understanding
  - What data do we have?
  - Where does it come from?
  - What does each column mean?
  - What is missing and why?
  - Observation: Many datasets are **not random samples**.

The Knowledge Discovery Process

- Step 3: Data Preparation (Most Time-Consuming)
  - Cleaning
  - Filtering
  - Encoding
  - Feature engineering
  - Aggregations
  - Etc.
  - In real projects: 60%-70% of the effort
  - This is where **domain knowledge matters more than algorithms**.

- Step 4: Data Mining/ Modelling Pattern mining
  - Classification
  - Anomaly detection
  - Regression
  - Clustering
  - This step is often less than 20% of total effort

The Knowledge Discovery Process

- Step 5- Evaluation
  - Is the result correct?
  - Is it useful?
  - Is it stable?
  - Includes: metrics, validation strategies, error analysis, sanity checks

- Step 6- Deployment = Interpretation & use (knowledge extraction)
  - Reports
  - Dashboards
  - Decisions
  - Monitoring

Data Analysis vs. Data Mining vs. Machine Learning vs. Knowledge Discovery

- **Data Analysis:** understand & describe data
- **Data Mining:** discover hidden patterns
- **Machine Learning:** algorithms that learn patterns
- **Knowledge Discovery** focuses on interpretation and meaning.

- **Knowledge Discovery**→ the **whole journey** from raw data to insight
- **Data Mining**→ the **core step** where patterns are extracted
- **Machine Learning**→ the **toolbox of algorithms** used inside data mining
- **Data Analysis**→ supports **every step** (before, during, after)

Types of Data

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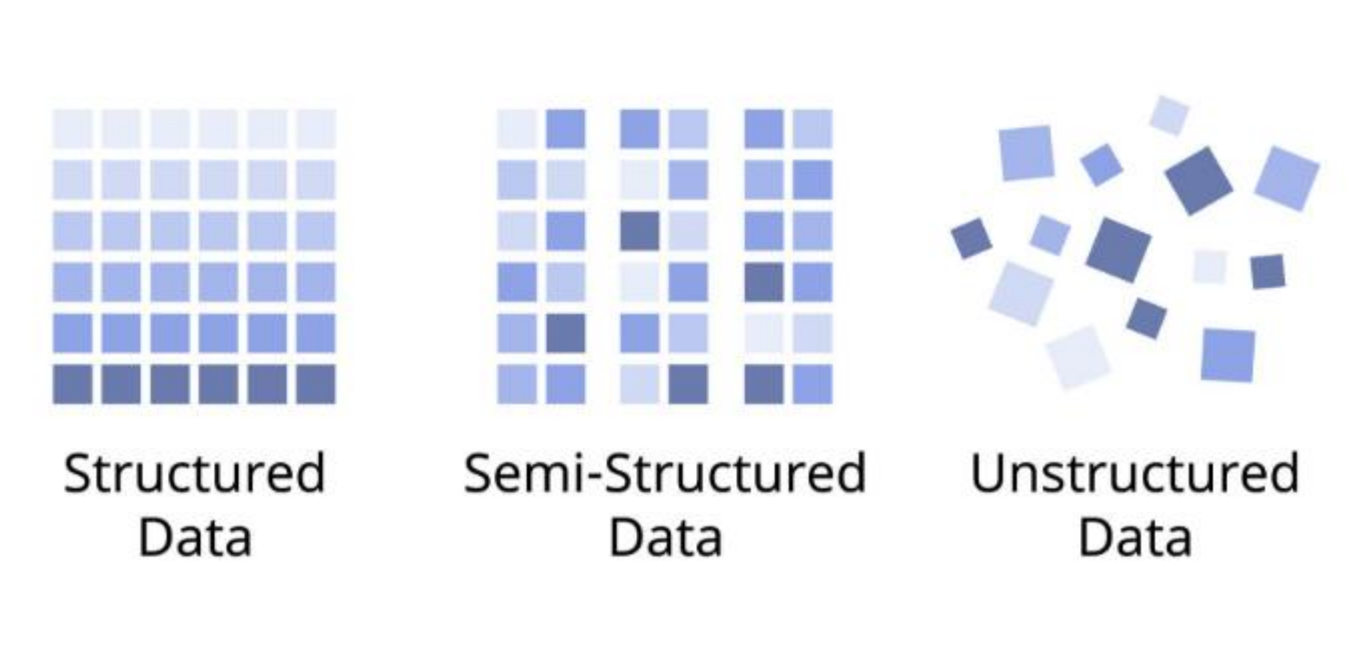
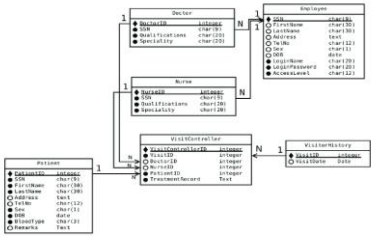
Types of Data

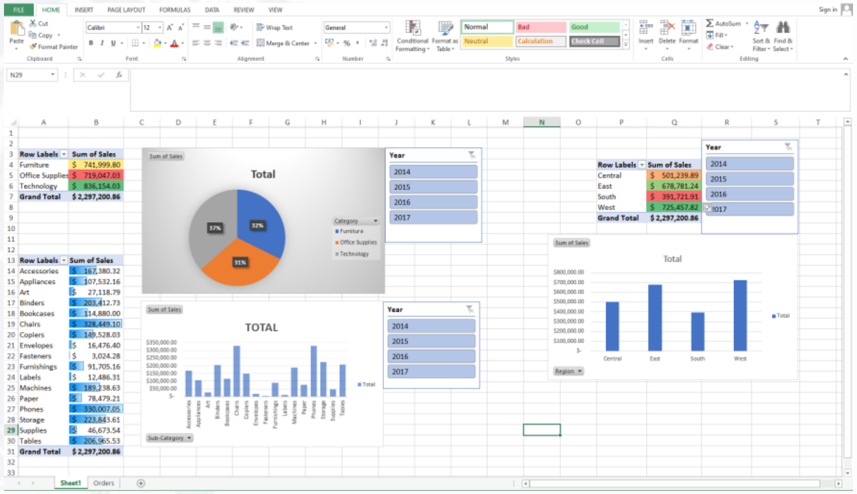


Structured data



- Data organized in a **fixed schema**, where every instance has the same attributes.

- Characteristics:
  - Rows and columns
  - Well-defined data types
  - Easy to store in databases
- Examples:
  - SQL tables
  - CSV/ Excel files
  - Transaction records



Row Labels	Sum of Sales
Furniture	$ 741,999.80
Office Supplies	$ 719,047.03
Technology	$ 836,154.03
Grand Total	$ 2,297,200.86

Row Labels	Sum of Sales
Accessories	$ 167,380.32
Appliances	$ 107,532.16
Art	$ 27,118.79
Binders	$ 203,412.73
Bookcases	$ 114,880.00
Chairs	$ 328,449.10
Copiers	$ 149,528.03
Envelopes	$ 16,476.40
Fasteners	$ 3,024.28
Furnishings	$ 91,705.16
Labels	$ 12,486.31
Machines	$ 189,238.63
Paper	$ 78,479.21
Phones	$ 330,007.05
Storage	$ 223,843.61
Supplies	$ 46,673.54
Tables	$ 206,965.53
Grand Total	$ 2,297,200.86

Row Labels	Sum of Sales
Central	$ 501,239.89
East	$ 678,781.24
South	$ 391,721.91
West	$ 725,457.82
Grand Total	$ 2,297,200.86

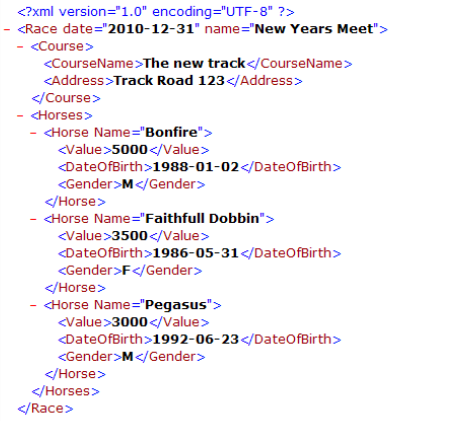
- Structured data is **easy to query**, but **hard to design correctly**.

Semi-structured data

- Data with **some structure**, but not a fixed schema.

- Characteristics:
  - flexible attributes
  - nested fields
  - schema may vary per instance

- Examples:
  - JSON
  - XML
  - API responses



```
<?xml version="1.0" encoding="UTF-8" ?>
- <Race date="2010-12-31" name="New Years Meet">
  - <Course>
      <CourseName>The new track</CourseName>
      <Address>Track Road 123</Address>
    </Course>
  - <Horses>
    - <Horse Name="Bonfire">
        <Value>5000</Value>
        <DateOfBirth>1988-01-02</DateOfBirth>
        <Gender>M</Gender>
      </Horse>
    - <Horse Name="Faithfull Dobbin">
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        <Gender>F</Gender>
      </Horse>
    - <Horse Name="Pegasus">
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        <DateOfBirth>1992-06-23</DateOfBirth>
        <Gender>M</Gender>
      </Horse>
    </Horses>
</Race>
```
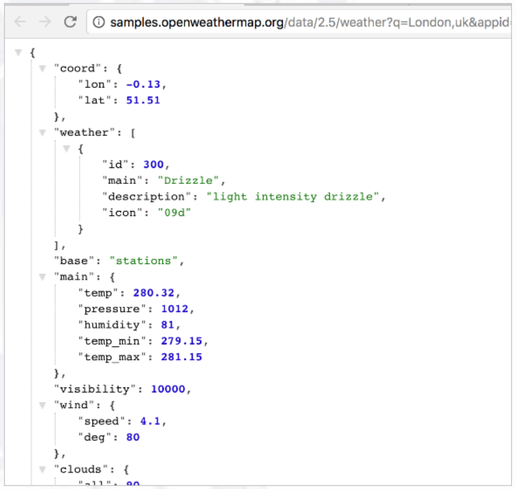
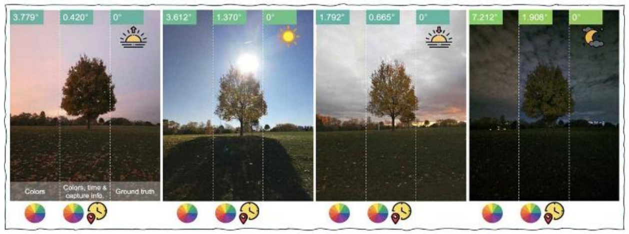



samples.openweathermap.org/data/2.5/weather?q=London,uk&appid

```
{
  "coord": {
     "lon": -0.13,
     "lat": 51.51
  },
  "weather": [
     {
        "id": 300,
        "main": "Drizzle",
        "description": "light intensity drizzle",
        "icon": "09d"
     }
  ],
  "base": "stations",
  "main": {
     "temp": 280.32,
     "pressure": 1012,
     "humidity": 81,
     "temp_min": 279.15,
     "temp_max": 281.15
  },
  "visibility": 10000,
  "wind": {
     "speed": 4.1,
     "deg": 80
  },
  "clouds": {
     "all": 90
```

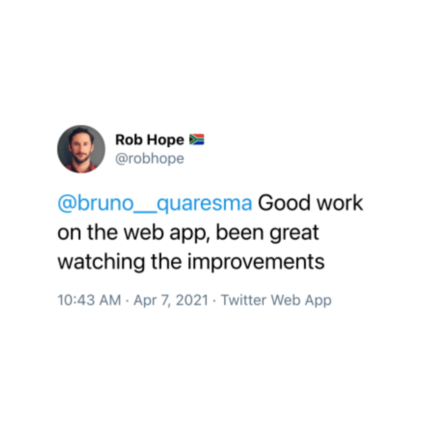
- Harder to query, requires parsing and normalization before mining.

Unstructured data



- Data without predefined organization.

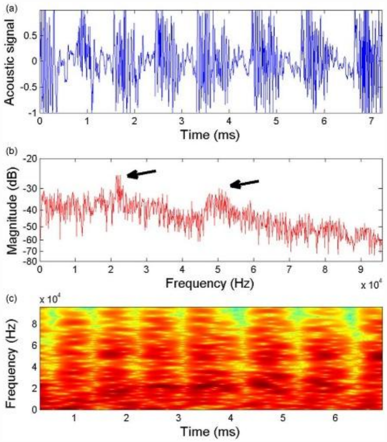
- Examples:
  - text documents
  - images
  - audio
  - video
  - social media posts



Rob Hope 🇿🇦
@robhope

@bruno__quaresma Good work on the web app, been great watching the improvements

10:43 AM · Apr 7, 2021 · Twitter Web App



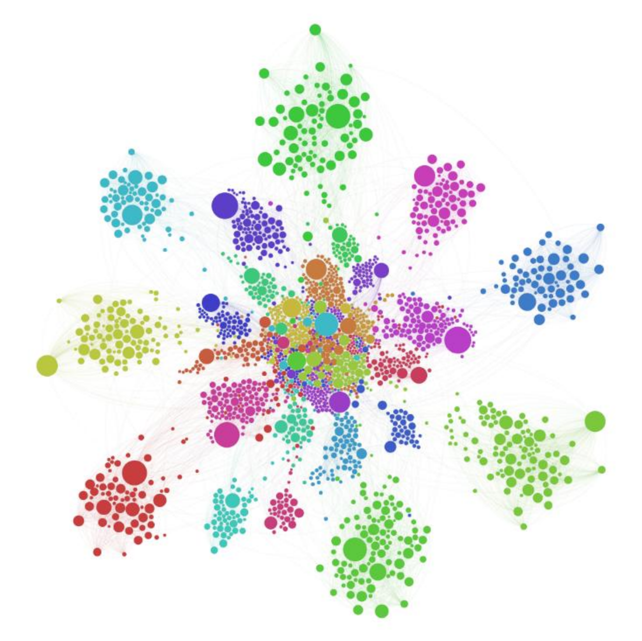
- Even unstructured data is often **converted into structured form** before mining (e.g., features, embeddings).

Why this course focuses on structured data?

- Most business data is structured
- Decisions rely on tables
- Pipelines are more complex than models
- Scalability issues appear here first

Large Data

- **Large data** refers to datasets that:
  - Do **not** fit in memory on a single machine
  - Require distributed storage & processing
  - Need specialized frameworks
- Typical characteristics:
  - Millions to billions of records
  - Tens of GBs → TBs → PBs
  - High velocity (data arrives continuously)
  - Often semi-structured and unstructured
- Examples:
  - Social media stream (tweets)
  - Transactional data at scale
  - Logs



Large vs. Small Data

Small	**Large**
Pandas works	Pandas struggles
Quick experiments	Need planning
Few joins	Complex joins
Fast feedback	Performance matters

- Large ≠ Big Data buzzword
- Large = **practical processing difficulty**

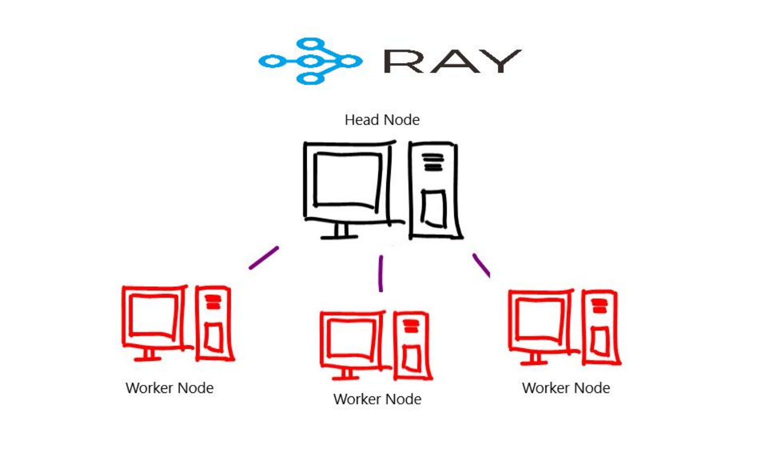
Why Large Structured Data?

- Common issues:
  - Memory limits
  - Slow joins
  - Slow processing
  - Imbalanced data
  - Wrong aggregation logic
  - Hidden bias.

- Using future information when predicting the past
  → model looks “amazing”
  → completely useless in reality

Tools & Mindset

- Tools:
  - Pandas (baseline)
  - Polars/ PySpark/ Dask/ Ray (for scale)
  - ML libraries



- Mindset:
  - Thinking
  - Reasoning
  - Correctness

- **All industrial systems aim to produce structured data** for decision-making.

Industry Pipeline for Large & Structured Data

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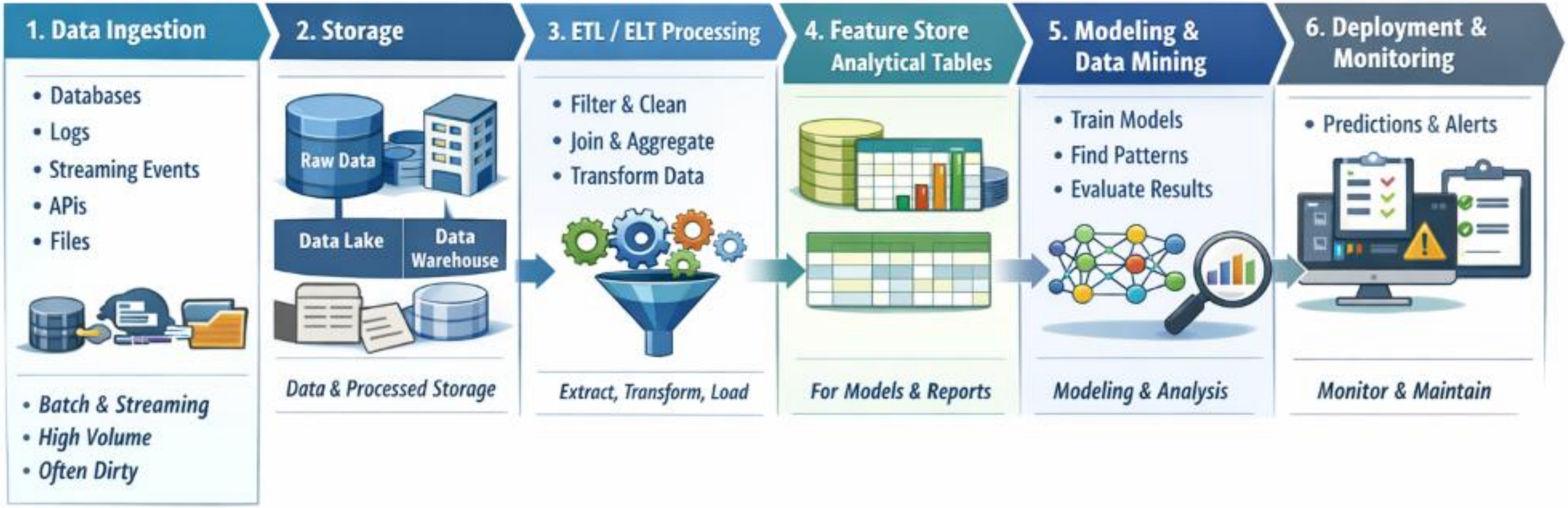
Industry Pipeline for Large & Structured Data



Step 1: Data Ingestion

- **Goal:** Bring data into the system.
- **Sources:**
  - databases
  - logs
  - streaming events
  - APIs
  - Files

- **Key properties:**
  - batch or streaming
  - high volume
  - often dirty

Step 2: Storage

- Storage is not just “where data lives”
- Storage defines how data can be used
- Wrong storage → slow pipelines, wrong results
- Common layers:
  - raw data storage (data lake)
  - processed data storage (warehouse)
- Raw data is almost never used directly for modelling.
- What goes in a data lake?
  - Database dumps, logs, CSV files, JSON files, etc.
- What goes in a data warehouse?
  - Cleaned and transformed data (e.g., aggregated tables)

Step 3: ETL/ ELT Processing

- ETL = Extract, Transform, Load
- Operations include:
  - filtering
  - joining tables
  - aggregations
  - feature computation
  - data validation

- This step creates **analysis-ready structured datasets**.

Step 4: Feature Store/ Analytical Tables

- At this stage:
  - Data is clean
  - Schema is stables
  - Features are well-defined

- This data feeds:
  - Machine Learning models
  - Dashboards
  - Reports

- Feature computation is done at step 3 (e.g., compute number of purchases per user, average transaction values, etc.)

- Feature engineering is done at step 4 (e.g., selecting useful features for a ML model, define feature semantics,

Step 5: Modelling & Data Mining

- **At this stage, we can:**
  - Train predictive models
  - Discover patterns in data
  - Evaluate results and performance

- Models are **consumers**, not owners of data.

Step 6: Deployment & Monitoring

- Deployment = using results in real systems

- Outputs are:
  - Predictions;
  - Scores;
  - Clusters;
  - Alerts – triggered when conditions are met.

- Monitoring checks:
  - data drift (e.g., feature no longer look the same, changes in input data)
  - model degradation (e.g., performance decreases over time)
  - pipeline failures (e.g., missing data, delayed pipelines)

Key Takers

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Key Takers

- Data mining is a **process**, not an algorithm
- Machine Learning is a **tool**, not the goal
- Structured data drives real-world decisions
- Raw data is almost never used directly
- Pipelines matter more than models
- Knowledge must be **useful and explainable**

Thank you for your attention — questions, thoughts, or challenges?

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