# Data Loading, Manipulation, and Visualization

Tópicos de Informática para Automação

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# Data Formats and Structures

# The Spectrum of Data Structure i

Understanding the underlying organization of data is the first step in the pipeline.

1. **Structured Data**

   - **Definition:** Data that adheres to a pre-defined data model and is therefore straightforward to analyze.
   - **Format:** Rows and columns (Tabular).
   - **Schema:** Rigid (Schema-on-write).
   - **Examples:** Relational Databases (SQL), Excel files.

# The Spectrum of Data Structure ii

2. **Unstructured Data**
    - **Definition:** Information that either does not have a pre-defined data model or is not organized in a pre-defined manner.
    - **Format:** Text, Binary, Media.
    - **Schema:** None (Schema-on-read).
    - **Examples:** PDF documents, Video, Audio, Plain Text emails, Social Media posts.

3. **Semi-Structured Data**

   - **Definition:** Data that does not reside in a relational database but has organizational properties that make it easier to analyze. It uses "tags" or "markers" to separate semantic elements and enforce hierarchies.
   - **Format:** Hierarchical trees or Key-Value pairs.
   - **Examples:** JSON, XML, YAML, NoSQL databases.

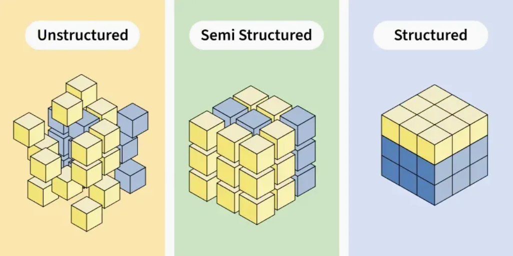



**Figure 1:** Ilustration of [Un|Semi]Structured organization

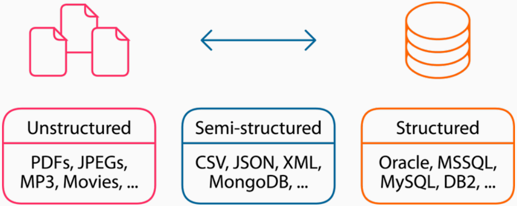



**Figure 2:** Examples of [Un|Semi]Structured Files

# Semi-Structured Formats i

## CSV (Comma Separated Values)

- **Structure:** Flat text file where lines are rows and commas separate columns.
- **Pros:** Universally supported, extremely lightweight.
- **Cons:** No support for types (everything is a string/number), no nesting/hierarchy.

# Semi-Structured Formats ii

**XML (eXtensible Markup Language)**

- **Structure:** Tree-based structure using custom opening/closing tags.
- **Pros:** Standard for legacy web services (SOAP), supports complex hierarchy and schemas (XSD).
- **Cons:** Verbose (heavy storage footprint due to repeated tags), harder to parse than JSON.

**JSON (JavaScript Object Notation)**

- **Structure:** Key-Value pairs using brackets { } for objects and [ ] for arrays.
- **Pros:** The standard for modern Web APIs (REST), native mapping to Python Dictionaries, human-readable.
- **Cons:** Keys are repeated for every record (verbose).

# Semi-Structured Formats iv

**YAML (YAML Ain’t Markup Language)**

- **Structure:** Relies on whitespace indentation to define hierarchy.
- **Pros:** The most human-readable format; perfect for configuration files (Docker, Kubernetes).
- **Cons:** Indentation errors can break the file easily; parsing can be slower than JSON.

## BSON (Binary JSON)

- **Structure:** A binary-encoded serialization of JSON-like documents.
- **Pros:** Optimized for speed (traversal) and space; supports types JSON does not (e.g., `Date`, `BinData`).
- **Cons:** Not human-readable without a decoder. Used primarily in MongoDB.

# Example: “Employee Record” i

Here is a dataset containing two records represented in all formats. Note how “lists” of employees are handled.

**1. CSV**

No native nesting. “Skills” list requires a custom separator (e.g., pipe |).

```
id,name,skills,active
1,"Jane Doe","Python|SQL",true
2,"Bob Smith","Java|C++",false
```

# Example: “Employee Record” ii

## 2. XML

Requires a root tag to wrap multiple children.

```xml
<employees>
    <employee id="1">
        <name>Jane Doe</name>
        <skills><skill>Python</skill><skill>SQL</skill>
        </skills>
        <active>true</active>
    </employee>
    <employee id="2">
        <name>Bob Smith</name>
        <skills><skill>Java</skill><skill>C++</skill>
        </skills>
        <active>false</active>
    </employee>
</employees>
```

## 3. JSON

JSON uses square brackets [ ] to denote a list.

```
{"employees": [{
      "id": 1, "name": "Jane Doe",
      "skills": ["Python", "SQL"], "active": true
    },
    {
      "id": 2, "name": "Bob Smith",
      "skills": ["Java", "C++"], "active": false
    }]
}
```

# Example: “Employee Record” iv

### 4. YAML

YAML uses dashes – to denote list items.

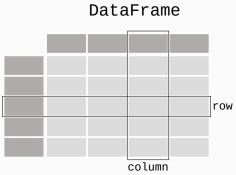
```yaml
employees:
  - id: 1
    name: Jane Doe
    skills: [Python, SQL]
    active: true
  - id: 2
    name: Bob Smith
    skills:
      - Java
      - C++
    active: false
```

# Data Loading & Manipulation

## The DataFrame Concept

A **DataFrame** is the central data structure in data science (used by R, Pandas, Polars, Spark).

- **Conceptual Model:** An in-memory spreadsheet.
- **Structure:**
  - **Index:** Labels for rows (axis 0).
  - **Columns:** Labels for variables (axis 1).
  - **Cells:** The intersection holding the data.
- **Homogeneity:** A single column usually holds a single data type (e.g., all Integers), but different columns can hold different types.



# Pandas

- **Core Philosophy:** Eager execution. Code runs line-by-line immediately, making debugging and exploration intuitive.
- **Key Architecture:**
  - **Single-Threaded:** Primarily runs on a single CPU core.
  - **Index-Based:** Relies heavily on explicit row labels (Indices) for data alignment, which is crucial for time-series analysis.
- **Why use it?**
  - **Unrivaled Ecosystem:** It is the default input for Scikit-Learn, Matplotlib, and thousands of other libraries.
  - **Maturity:** If a data problem exists, there is a StackOverflow answer for how to solve it in Pandas.

# Polars

- **Core Philosophy:** Lazy Evaluation. It builds an optimized query plan before execution to minimize work and memory usage.
- **Key Architecture:**
  - **Multi-Threaded (Rust):** Written in Rust to bypass Python limitations, utilizing **all available CPU cores** for parallel processing.
  - **Apache Arrow:** Uses a columnar memory format that allows for zero-copy data transfer and efficient caching.
- **Why use it?**
  - **Performance:** Significantly faster than Pandas on large datasets (10x-100x speedups are common).
  - **Streaming:** Can process datasets larger than your computer's RAM.

# Library Comparison: Pandas vs. Polars

| Feature | **Pandas** | **Polars** |
|---|---|---|
| **History** | Created in 2008. The industry standard. | Newer (2020s). Built for performance. |
| **Backend** | Python/C / Cython. | **Rust** (Safety & Speed). |
| **Execution** | **Eager**: Runs line-by-line immediately. | **Lazy & Eager**: Can optimize the whole query plan before running. |
| **Parallelism** | Single-threaded (mostly). | **Multi-threaded** (Native parallelization). |
| **Memory** | Copies data often (High RAM usage). | **Arrow Memory Format** (Zero-copy, efficient). |

# Data Cleaning: Missing Values (Imputation) i

Data often has gaps (`NaN` or `Null`). You must decide to **drop** them or **fill** them. Missing data can be filled in with the mean (continous values) or mode (discrete values).

- **Pandas Approach:**

```
# Drop rows with any missing values
df.dropna()


# Fill with Mean (Imputation)
mean_val = df['salary'].mean()
df['salary'].fillna(mean_val, inplace=True)
```

# Data Cleaning: Missing Values (Imputation) ii

- **Polars Approach:**

```
# Drop rows with any missing values
df.drop_nans()

# Fill with Mean
df.with_columns(
    pl.col("salary")
    .fill_null(pl.col("salary")
    .mean())
)
```

# Data Cleaning: Outliers with IQR i

Outliers are extreme values that deviate from other observations. We use the **Interquartile Range (IQR)** to detect them.

**The Math:**

1. **Q1 (25th Percentile):** The middle number between the smallest number and the median.
2. **Q3 (75th Percentile):** The middle number between the median and the highest number.
3. **IQR Formula:**

$$IQR = Q_3 - Q_1$$

# Data Cleaning: Outliers with IQR ii

**The Filter:** Data $D$ is an outlier if:

$$D < (Q_1 - 1.5 \times IQR) \quad \text{or} \quad D > (Q_3 + 1.5 \times IQR)$$

**Implementation (Pandas):**

```
Q1 = df['age'].quantile(0.25)
Q3 = df['age'].quantile(0.75)
IQR = Q3 - Q1
# Filtering
df_clean = df[~((df['age'] < (Q1 - 1.5 * IQR)) |
(df['age'] > (Q3 + 1.5 * IQR)))]
```

**Implementation (Polars):**

```
Q1 = df["age"].quantile(0.25, interpolation="linear")
Q3 = df["age"].quantile(0.75, interpolation="linear")
IQR = Q3 - Q1
# Filtering
df_clean = df.filter(
    pl.col("age").is_between(q1 - 1.5 * iqr, q3 + 1.5 * iqr)
)
```

# Data Scaling i

Scaling the data can help to balance the impact of all variables on the distance calculation and can help to improve the performance of the algorithm.

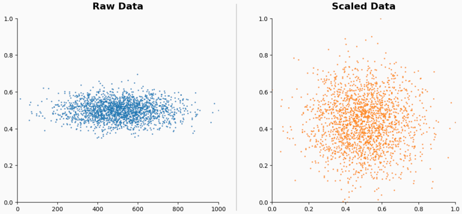



**Figure 4:** Scaling Data

### A. Min-Max Scaling (Normalization)

- **Goal:** Squeeze data into a range $[0, 1]$.
- **Formula:**

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

- **Usage:** Image processing (pixels 0-255), Neural Networks.

### B. Standard Scaling (Z-Score Standardization)

- **Goal:** Center data around Mean=0 with Std Dev=1.

# Data Scaling iii

- **Formula:**

$$Z = \frac{X - \mu}{\sigma}$$

- **Usage:** PCA, Logistic Regression, Clustering.

# Statistics: Correlation & Summaries i

**Summaries (Central Tendency & Dispersion):**

- **Mean:** Average.
- **Median:** Middle value (Robust to outliers).
- **Mode:** Most frequent value.
- **Quartiles:** Distribution checkpoints (25%, 50%, 75%).

**Correlation (Pearson):**

- Measures linear relationship between $-1$ (perfect negative) and $+1$ (perfect positive).
- $0$ means no linear correlation.

**Code Example:**

# Statistics: Correlation & Summaries ii

```
# Pandas/Polars Summary
# Returns count, mean, std,
# min, 25%, 50%, 75%, max
print(df.describe())

# Pandas Correlation Matrix
print(df.corr())
```

# Data Visualization

# Matplotlib vs. Seaborn i

**Matplotlib:**

- **Role:** The engine.
- **Philosophy:** “Make easy things easy and hard things possible.”
- **Control:** Granular control over every axis, tick, line style, and canvas element.
- **Syntax:** Imperative (Step-by-step construction).

**Seaborn:**

- **Role:** The interface.
- **Philosophy:** “Draw attractive and informative statistical graphics.”

# Matplotlib vs. Seaborn ii

- **Control:** Automates color mapping, legends, and statistical aggregation.
- **Syntax:** Declarative (Describe *what* you want, not how to draw it).

# Best Plots for Analysis Types i

## 1. Analysis: Distribution (Univariate)

- **Goal:** See the spread and shape of data.
- **Plot: Histogram** or **KDE** (Kernel Density Estimate).
- **Example:** `sns.histplot(data=df, x="price", kde=True)`

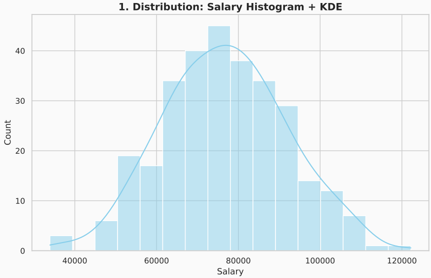



**Figure 5:** Distribution

# Best Plots for Analysis Types ii

## 2. Analysis: Correlation (Bivariate)

- **Goal:** See how two variables relate.
- **Plot: Scatter Plot** or **Heatmap**.
- **Example:** `sns.scatterplot(data=df, x="age", y="salary")`

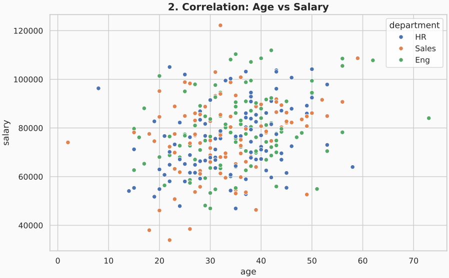



**Figure 6:** Correlation

# Best Plots for Analysis Types iii

## 3. Analysis: Comparison (Categorical)

- **Goal:** Compare values across groups.
- **Plot: Bar Chart** (aggregates) or **Box Plot** (distributions).
- **Example:** `sns.boxplot(data=df, x="department", y="salary")`

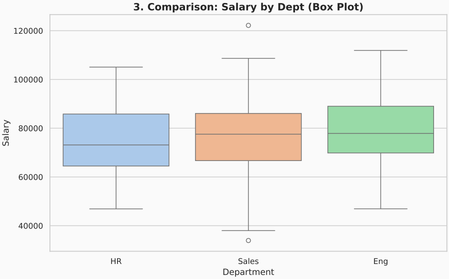



**Figure 7:** Comparison

# Best Plots for Analysis Types iv

## 4. Analysis: Comparison (Distribution Density)

- **Goal:** Compare the distribution and probability.
- **Plot: Violin Plot**.
- **Example:** `sns.violinplot(data=df, x="department", y="salary")`

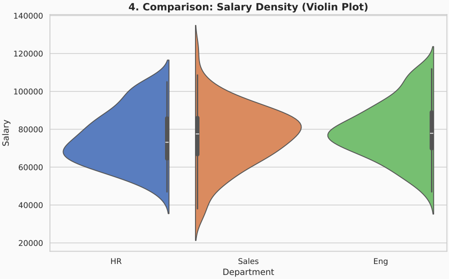



**Figure 8:** Comparison

# Exporting: Raster vs. Vector i

When saving your figures (`plt.savefig`), the extension determines the technology.

| Feature | **Raster (Bitmap)** | **Vector** |
|---|---|---|
| **Formats** | `.png`, `.jpg`, `.bmp` | `.pdf`, `.svg`, `.eps` |
| **Composition** | Grid of colored pixels. | Mathematical formulas (paths, curves). |
| **Scalability** | Loses quality when zoomed (pixelates). | Infinite scalability (sharp at any zoom). |
| **File Size** | Large for high resolution. | Small (unless containing thousands of scatter points). |
| **Usage** | Web, PowerPoints, Quick previews. | **Academic Papers, Printing, Posters.** |

# Jupyter Notebooks

**Jupyter** (JUlia, PYThon, R) is a web-based interactive computing platform. It is a JSON document containing an ordered list of input/output cells.

## The Interactive Framework ii

### Key Features

1. **Literate Programming:** Mixes executable code with narrative text (Markdown), equations (“LaTeX”), and images.
2. **The Kernel:** The computational engine (e.g., IPython) runs in the background. It maintains the “state” (variables remain in memory between cells).
3. **Visualization:** Plots render inline directly below the code that generated them.

# Effective Usage Workflow i

**1. The "Markdown" Cell** Use for documentation. Supports headers (`#`), bolding (`**`), and lists to explain methodology *before* the code.

**2. The "Code" Cell** Runs Python. The last line of a cell is automatically printed (no `print()` needed).

**3. Magic Commands**

- `%matplotlib inline`: Embeds plots in the notebook.
- `%timeit`: Runs a line multiple times to benchmark performance.
- `!pip install X`: Runs shell commands to install libraries inside the notebook.

# Further Reading

# Further Reading

- **Pandas Documentation:** pandas.pydata.org - The definitive guide.
- **Polars User Guide:** pola.rs - Essential for high-performance data manipulation.
- **Seaborn Gallery:** seaborn.pydata.org - Visual inspiration for plots.
- **Matplotlib Anatomy of a Plot:** matplotlib.org - Understanding the object hierarchy.
- **Project Jupyter:** jupyter.org