Introduction to Data Manipulation using Python Day 2

Céline Lemarinier

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Py4SHS 2023

- 1 Introduction to datasets and variables
- Retrieving datasets: introduction to databases
- 3 Data Exchange via HTTP Request
- The PyData ecosystem
- 5 Practical use: pandas and seaborn

Organization of the lecture

We will begin by:

- Introducing datasets, variables and statistical estimators;
- Learning about databases and REST API;
- Learning about the PyData ecosystem which allows the manipulation in RAM of datasets.

Bibliography

- Learning SQL: Generate, Manipulate, and Retrieve Data, 3rd Edition, Alan Beaulieu, March 2020, O'Reilly Media, Inc.
- Python for Data Analysis: Data Wrangling with pandas, NumPy, and Jupyter, Wes McKinney, 2022, O'Reilly Media, Inc.
- W3C tutorial on SQL: https://www.w3schools.com/sql/.
- Pandas documentation: https://pandas.pydata.org/.
- Seaborn documentation: https://seaborn.pydata.org/.

Introduction to datasets and variables

Outline

- Introduction to datasets and variables
 - Definition
 - Variables
 - Analyzing variables
- 2 Retrieving datasets: introduction to databases
- 3 Data Exchange via HTTP Request
- 4 The PyData ecosystem
- 6 Practical use: pandas and seaborn

Datasets

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Columns of a table represents a **particular variable** (or **feature**), and each row corresponds to a given **record** of the data set in question for an **individual**.

Datasets

Definition

| | Individual | Variable 1 | Variable 2 | Variable 3 |
|----------|------------|------------|------------|------------|
| Example: | ID1 | 5 | 4 | 1 |
| | ID2 | 2 | 3 | 1 |

Question:

Give the value for:

 $x_{1,3} =$

 $x_{2,1} =$

Variable 1 for individual 1

All data regarding individual 2

Example of dataset

The Iris dataset was introduced by the British statistician and biologist Ronald Fisher in his 1936 paper *The use of multiple measurements in taxonomic problems*.

| ID | Sepal length | Sepal width | Petal length | Specie |
|----|--------------|-------------|--------------|------------|
| 1 | 2.1 | 3.1 | 4.1 | Setosa |
| 2 | 3.1 | 1.1 | 2.1 | Setosa |
| 3 | 4.1 | 5.1 | 3.1 | Versicolor |
| 4 | 1.1 | 2.1 | 2.1 | Virginica |

Example of dataset

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The names of the variables are:
There are _____ individuals.
There are ____ variables.

Variables and features

Variable

A variable is a measurement computed on an individual.

Example: Weight of individual.

Variables and features

Variable

A variable is a measurement computed on an individual.

Example: Weight of individual.

Feature

A feature is a vector descriptive of an individual.

Example: BMI of individual.

Variable analysis highly depends on its type !

Variable analysis highly depends on its type !

Question

Can anyone list the different types of variables that can be encountered in datasets ?

Let's consider a dataset $M=(x_{i,j})_{1\leq n,1\leq m}$, with n individuals and m variables.

Variables

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A variable j can be:

• Numeric: $(x_{i,j})_{1 \le i \le n} \in \mathbb{R}^n$. Example: **Petal width**.

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- Categorical: $(x_{i,j})_{1 \le i \le n} \in \mathcal{X}^n$, with \mathcal{X} a set of distinct values. A special case of categorical variables often encountered . Example: Flower specie.
- Ordinal: $(x_{i,j})_{1 \le i \le n} \in \mathcal{X}^n$, with \mathcal{X} a set of ordered distinct values.

Example: Performance (low, medium, high).

Univariate and multivariate analysis

Univariate analysis

Univariate analysis consists in performing the analysis of a single variable.

Example: Analyze the petal width.

Univariate and multivariate analysis

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Example: Analyze the petal width.

Multivariate analysis

Multivariate analysis consists in analyzing of multiple variables simultaneously, to understand relationships and patterns among variables.

Example: Analyze the petal width within each specie.

To analyze variables, you can perform:

- A visual* analysis: use graphs to better understand the variables.
- A statistical* analysis: use statistical estimators to better understand the variables.

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Analysis depends on the variable type !

A poor analysis of variables can cause misinterpretation of data.

Question

Can anyone give me:

 Possible graphical representation of numeric and categorical variables?

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Analyzing numeric v<u>ariables</u>

Usual indicators include:

 Arithmetical mean: summarize to better understand the overall value.

$$\bar{X} = \frac{1}{N} \sum_{i=1}^{N} x_i$$

Analyzing variables

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 Variance and standard error: measures the dispersion of the data compared to the mean.

$$var(X) = \frac{1}{N} \sum_{i=1}^{N} (x_i - \bar{X})^2$$

$$\sigma(X) = \sqrt{var(X)}$$

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• Quantiles: divide the ordered vectors into equal parts of same 1/4 quantiles, median

Very useful for datasets with a lot of outliers*!

Analyzing numeric variables

Question

Analyzing variables

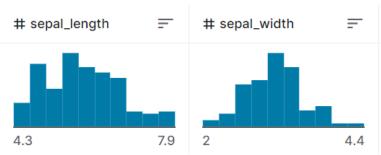
For the vector [0, 3, 4], compute:

- The mean;
- The variance;
- The median.

Representing numeric variables: histograms

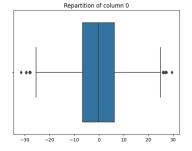
Histograms* consist in:

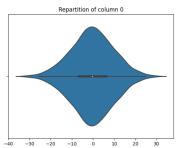
- Dividing the numerical space into intervals of regular length
- Computing the frequency of values per interval



Representing numeric variables: boxplots

Boxplots* and **violin plots*** consist in representing all the values of the variables and their statistical indicators (usually, quantiles and medians).





Representing numerical variables

Question

Given the vector [0, 1, 3, 5, 7, 10, 12, 15]:

- Plot the histogram;
- Plot the boxplot.

Analyzing and representing categorical variables

Categorical variables are often harder to study.

Statistical estimators are:

Analyzing and representing categorical variables

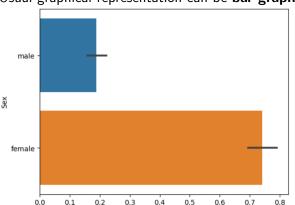
Categorical variables are often **harder** to study.

Statistical estimators are:

- Counts:
- Frequencies.

Analyzing and representing categorical variables

Usual graphical representation can be bar graphs.



Analyzing and representing categorical variables

Question

For vector ["hot", "hot", "hot", "cold", "cold"]:

- Compute count;
- Compute frequency;
- Plot bar graph.

Multivariate analysis

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How can we perform the analysis of **several variables at the** same time?

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How can we perform the analysis of **several variables at the same time**?

Similarly!

- Statistical estimators;
- Graphical representation.

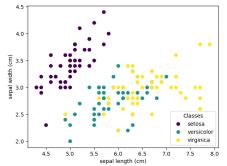
Multivariate analysis: 2 numerical variables

For 2 numerical variables: how does one variable evolve with the other one ?

Multivariate analysis: 2 numerical variables

For 2 numerical variables: how does one variable evolve with the other one ?

- **Correlation**: several ways to compute (Pearson, Spearman ...);
- Scatter plot: visualize one variable in respect to another.



For 1 numerical variable and 1 categorical: how does the value of the numerical variable evolve within each category ?

For 1 numerical variable and 1 categorical: how does the value of the numerical variable evolve within each category ?

Compute **statistical estimators** for each category, called a **grouped by** operation.

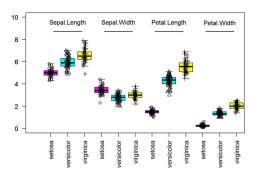
Table: Average Sepal Width for Different Iris Species

| Species | Sepal Width (cm) |
|------------|------------------|
| Setosa | 3.428 |
| Versicolor | 2.770 |
| Virginica | 2.974 |

For 1 numerical variable and 1 categorical: how does the value of the numerical variable evolve within each category ?

For 1 numerical variable and 1 categorical: how does the value of the numerical variable evolve within each category ?

Perform numerical graphs for each category.





Multivariate analysis: 2 categorical variables

How do distribution of individuals differ within each category?

Possible statistical estimator is count/frequency per category, summarized in a **contingency table**.

| | Dog | Cat | Total |
|----------|-----|-----|-------|
| Male | 42 | 10 | 52 |
| Female 9 | | 39 | 48 |
| Total | 51 | 49 | 100 |

Multivariate analysis: 2 categorical variables

How do distribution of individuals differ within each category?

Possible graphical representation is count plot per category.

Questions

Questions?

Introduction to Data Manipulation using Python
Retrieving datasets: introduction to databases

Retrieving datasets: introduction to databases

Outline

- Introduction to datasets and variables
- Retrieving datasets: introduction to databases
 - What is a database ?
 - Relational Databases
 - Tables
 - NoSQL databases
 - MongoDB
 - SQL vs. NoSQL
- 3 Data Exchange via HTTP Request
- 4 The PyData ecosystem

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- Through an API (for example HTTP)
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Today, we will learn how to manipulate single flat files to compute statistical estimators.

Database

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The data and the DBMS, along with the applications that are associated with them, are referred to as a database system, often shortened simply **to database**.

- Data within the most common types of databases in operation today is typically modeled in rows and columns in a series of tables to make processing and data querying efficient.
- The data can then be easily accessed, managed, modified, updated, controlled, and organized.

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- The data can then be easily accessed, managed, modified, updated, controlled, and organized.

Can you remind me the link between rows, columns, individual, features and variables seen in the first part ?

Relational databases

Relational databases

Relational databases* present the data to the user as **relations** (a presentation in tabular form) and provide relational operators to manipulate the data in tabular from.

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- Items in a relational database are organized as a set of tables with columns and rows.
- Relational database technology provides the most efficient and flexible way to access structured information.
- Most relational databases use structured query language (SQL) for writing and querying data.

Examples of tables

This is the kind of data you could find in a Veterinary Clinic.

| Table name : Patients | | | | | | |
|-----------------------|---------|---------|-----------|-----|--------|--|
| Pat_ID | Name | Species | type | age | gender | |
| 1 | Mittens | cat | Tabby | 3 | male | |
| 2 | Loba | dog | Greyhound | 10 | female | |
| 3 | Coco | parrot | Cockatoo | 2 | female | |
| 4 | Ben | dog | Poodle | 5 | male | |

| Table name : Procedures | | | | |
|-------------------------|---------|--------|----------------------|---------------|
| | Proc_ID | Pat_ID | procedure | date |
| | 1 | 1 | neutering | 20 April 2021 |
| | 2 | 2 | fix broken leg | 05 June 2021 |
| | 3 | 3 | vaccination | 10 July 2021 |
| | 4 | 1 | kidney stone removal | 12 March 2022 |

NoSQL databases

NoSQL databases

A **NoSQL*** (Not Only SQL), or non-relational database, allows unstructured and semi-structured data to be stored and manipulated (in contrast to a relational database, which defines how all data inserted into a table must have the same columns).

NoSQL databases grew popular as applications and data became more common and more complex: there are particularly well-suited for use cases like big data, real-time analytics, and web applications.

Types of NoSQL Databases

- **Document Stores**: Stores data in a document format (e.g., JSON or XML). Examples: MongoDB and Couchbase.
- **Key-Value Stores**: Stores data as key-value pairs. Examples: Redis and Amazon DynamoDB.
- Column-Family Stores: Data is organized into columns and column families rather than rows and tables. Examples: Apache Cassandra and HBase.
- Graph Databases: Designed for storing and querying graph-like data structures. Examples: Neo4j and Amazon Neptune.

Example of NoSQL data format: MongoDB Collections

MongoDB

MongoDB is a widely used open-source NoSQL database, which falls under the category of document-oriented databases. It stores data in a **flexible**, **JSON-like documents with dynamic schemas**.

For example, we could have a collection named "animals". One document in this collection would be the equivalent of an individual.

Examples of collections

Data is stored into a JSON like format, the previously seen SQL tables would look like this:

```
"_id": {"$oid":"456gf5465"},
"name": "Mittens",
"Species": "cat",
"type": "Tabby",
"age": 3,
"gender": "male",
"procedures": [
        name: "neutering",
        date: "20 April 2021"
    },
```

Example of collections

Question

How would you store the different procedures of the patients using SQL and No SQL ? Can you list the weaknesses and strengths of each approach ?

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- Data Integrity: Foreign key constraints maintain relationships between tables.

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- High Performance: NoSQL databases excel at read and write operations, especially for specific use cases.
- Unstructured Data: Ideal for managing unstructured or semi-structured data like documents, multimedia, and user-generated content.
- **Rapid Development**: NoSQL databases simplify development by eliminating the need for complex schema migrations.

When to choose SQL or NoSQL

SQL is great for:

- Well-Defined Data: Use SQL for structured, highly relational data where consistency is critical.
- Complex Queries: SQL's rich query language is advantageous for analytical and reporting tasks.
- **Transactions**: When data integrity and transaction management are of utmost importance.

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NoSQL is great for:

- Unstructured Data: Opt for NoSQL to manage diverse and unstructured data types effectively.
- Scalability: Choose NoSQL when dealing with massive amounts of data or high traffic loads.
- Rapid development: as schema is not required, development
 can be started faster (but this can easily backfire in complex
 project!)

Introduction to Data Manipulation using Python Retrieving datasets: introduction to databases SQL vs. NoSQL

Questions regarding the database section ?

Data Exchange via HTTP Request

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REST API

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- Uses standard HTTP operations (GET, POST, PUT, DELETE) to perform actions on resources;
- Operates on a stateless client-server principle;
- Data is usually exchanged in **JSON** or **XML format**.

Characteristics of REST APIs

- Client-server architecture: Communication takes place between a client and a server.
- Stateless: Each request from the client to the server must contain all the information necessary to understand and process the request.
- Uniform interface: Consistent use of resources and HTTP operations.

Usage Example

- **GET**: Retrieve data from a resource.
- POST: Create a new resource.
- PUT: Update an existing resource.
- **DELETE**: Delete a resource.

Usage example

Example of a GET request:

GET /users/123

Example of corresponding data (JSON):

```
"id": 123.
"name": "John Doe",
"email": "john.doe@example.com",
"username": "johndoe",
"profile": {
  "age": 30,
  "gender": "male",
  "location": "New York, NY"
```

Usage example

Example of a GET request:

GET /users/123

Example of corresponding data (XML):

Questions?

Questions regarding the API section ?

The PyData ecosystem

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To do this, Python is very well-suited and provides powerful tools to do so, called the **PyData ecosystem**.

The PyData Ecosystem

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- a collection of open-source libraries and tools built for the Python programming language;
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Question

Can you remind me from yesterday's lecture what is the syntax to install a package in Python ?

Core Libraries

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- NumPy: Core library for numerical computations with multidimensional arrays;
- pandas: Provides data structures like DataFrames and Series for data manipulation and analysis;
- matplotlib: A powerful plotting library for creating static, interactive, and animated visualizations.

Packages for Data Visualization

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- **Plotly**: Offers interactive and web-based visualizations for data exploration and communication.

Because we cannot learn everything in a week, we will focus this afternoon on using **pandas** and **seaborn**.

Packages for Machine Learning

- **scikit-learn**: Comprehensive library for traditional machine learning algorithms and tools.
- Keras/TensorFlow and PyTorch: Deep learning frameworks for building and training neural networks.

Tomorrow, we will use Scikit-learn for our lab session!

Practical use: pandas and seaborn

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- 5 Practical use: pandas and seaborn
 - Manipulating data using pandas and seaborn
 - Pandas
 - Seaborn

Goal

The goal of this lab is to learn **how to manipulate and plot data using**:

- Pandas
- seaborn

We will use as a practice dataset a dataset containing the different lines of Shakespeare's play Romeo and Juliet.

Pandas core component

Pandas

Pandas is a Python package for **easy data manipulation**, which provides support for reading and writing data in various formats (CSV, SQL, XML ...)

Pandas core component

Pandas

Pandas is a Python package for **easy data manipulation**, which provides support for reading and writing data in various formats (CSV, SQL, XML ...)

Pandas provides 2 main objects:

- **DataFrame**: A table-like data structure (similar to the datasets we saw at the beginning of the lecture);
- **Series**: A one-dimensional labeled array (you can think of it as a column in a DataFrame).

Usually, you can decompose your Data Science task in:

Loading the data into RAM;

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 - Standard estimators;
 - Estimators conditioned by other values;
- **5** Creating **meaningful plots** to explore the data.

Creating DataFrames

The first step of your data processing pipeline is to load your data in your RAM by creating a pandas DataFrame.

Creating DataFrames

The first step of your data processing pipeline is to load your data in your RAM by creating a pandas DataFrame.

DataFrames can be **created** from various data sources:

- From dictionaries
- From lists of dictionaries or tuples
- From CSV, Excel, SQL databases, XML ...

Creating a DataFrame from a dictionary

```
import pandas as pd
data = {'Name': ['Alice', 'Bob', 'Charlie'], 'Age':
[25, 30, 22]}
df = pd.DataFrame(data)
```

Data preprocessing: Selection in Pandas

Being able to select columns and/or rows is one of the great advantage of pandas.

- Pandas provides various methods to select specific rows and columns from a DataFrame.
- This allows for targeted data extraction and manipulation based on your analysis needs.

Data preprocessing: Selecting Rows in Pandas

Selecting Rows:

Using integer-based indexing (iloc):

```
# Selecting the first row
first_row = df.iloc[0]
```

```
# Selecting multiple rows
subset = df.iloc[3:7]
```

• Using label-based indexing (loc):
Selecting a row by label
row_data = df.loc['row_label']

Data preprocessing: Selecting Columns in Pandas

Selecting Columns:

```
• Using integer-based indexing (iloc):
    # Selecting a single column by position
    column_data = df.iloc[:, 0]

# Selecting multiple columns by positions
```

```
subset = df.iloc[:, [1, 3, 5]]
```

• Using label-based indexing (loc):

```
# Selecting a single column by label
column_data = df['column_name']
```

```
# Selecting multiple columns by labels
subset = df[['col1', 'col2', 'col3']]
```

Data pre-processing: Filtering Rows by Single Condition

Pandas DataFrame can be filtered on rows by using a *boolean* indexer.

Filtering by Single Condition:

Using comparison operators to filter rows.

```
# Filter rows where Age is greater than 25
adults = df[df['Age'] > 25]

# Filter rows where Name is 'John'
johns = df[df['Name'] == 'John']
```

Data preprocessing: Filtering Rows by Multiple Conditions

• Filtering by Multiple Conditions:

```
Combining conditions using logical operators (&, |).
# Filter rows where Age is greater than 25
and Gender is 'M'
adult_males = df[(df['Age'] > 25)
& (df['Gender'] == 'M')]

# Filter rows where Age is less than 18
or greater than 60
minors_or_seniors = df[(df['Age'] < 18)
| (df['Age'] > 60)]
```

Data preprocessing: Filtering Rows Using String Methods

• Filtering Using String Methods:

• Using string methods to filter rows based on text data.

```
# Filter rows where Name starts with 'A'
a_names = df[df['Name'].str.startswith('A')]
```

```
# Filter rows where Email contains 'example.com'
example_emails = df[df['Email']
.str.contains('example.com')]
```

Data preprocessing: Sorting Data

- **Sorting**: Sorting data based on column values.
 - df.sort_values(by='Age') Sort DataFrame by Age column.

Example

```
# Sort DataFrame by Age in ascending order
sorted_df = df.sort_values(by='Age')
```

Data preprocessing: Adding and Dropping Columns

- Adding and Dropping: Adding or dropping columns or rows.
 - df['Gender'] = ['F', 'M', 'M'] Adding a new column 'Gender'.
 - df.drop('Gender', axis=1, inplace=True) Dropping the 'Gender' column.

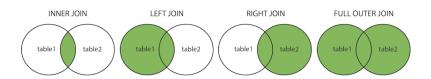
Data preprocessing: Manipulating two datasets

In many cases, **information is split** across several datasets and we need **merging** to retrieve information.

- Merging is a fundamental operation for combining datasets.
- Pandas provides powerful tools to merge DataFrames in various ways.
- Key functions: pd.merge(), df.join(), and df.concat().

Data preprocessing: Different Types of Joins

- Inner Join: Only includes rows with keys present in both DataFrames.
- Outer Join: Includes all rows from both DataFrames, filling in NaN for missing matches.
- Left Join: Includes all rows from the left DataFrame and matching rows from the right DataFrame.
- Right Join: Includes all rows from the right DataFrame and matching rows from the left DataFrame.



Pandas

pd.merge()

- pd.merge(): Merges two DataFrames based on a key column(s).
- Can perform inner, outer, left, and right joins.

```
import pandas as pd
```

```
# Example DataFrames
left = pd.DataFrame({
    'key': ['A', 'B', 'C', 'D'],
    'value': [1, 2, 3, 4]
})
right = pd.DataFrame({
    'key': ['B', 'D', 'E', 'F'],
    'value': [5, 6, 7, 8]
})
```

Result of pd.merge()

• The result of the inner merge:

Example of Outer Join

```
# Outer merge on 'key'
outer_merged_df = pd.merge(left, right, on='key',
how='outer')
```

Result:

| | key | value_x | value_y |
|---|-----|---------|---------|
| 0 | Α | 1.0 | NaN |
| 1 | В | 2.0 | 5.0 |
| 2 | C | 3.0 | NaN |
| 3 | D | 4.0 | 6.0 |
| 4 | Ε | NaN | 7.0 |
| 5 | F | NaN | 8.0 |

Example of Left Join

Example

```
# Left merge on 'key'
left_merged_df = pd.merge(left, right, on='key',
how='left')
```

Result:

```
      key
      value_x
      value_y

      0
      A
      1
      NaN

      1
      B
      2
      5.0

      2
      C
      3
      NaN

      3
      D
      4
      6.0
```

Example of Right Join

```
# Right merge on 'key'
right_merged_df = pd.merge(left, right, on='key',
how='right')
```

Result:

| | key | value_x | value_y |
|---|-----|---------|---------|
| 0 | В | 2.0 | 5 |
| 1 | D | 4.0 | 6 |
| 2 | Ε | NaN | 7 |
| 3 | F | NaN | 8 |

Introduction to Missing Values in Pandas

Values can be missing in datasets for different reasons: abnormal values, failure of measurement...

 Pandas provides various methods to handle missing data effectively.

Detecting Missing Values

• Detecting Missing Values:

• Use the isnull() method to detect missing values.

```
# Detect missing values
missing_values = df.isnull()
```

```
# Summarize missing values per column
missing_summary = df.isnull().sum()
```

• Use the notnull() method to detect non-missing values.

```
# Detect non-missing values
non_missing_values = df.notnull()
```

Handling Missing Values

• Handling Missing Values:

• Use the dropna() method to remove missing values.

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

```
# Drop columns with any missing values
df_cleaned_columns = df.dropna(axis=1)
```

• Use the fillna() method to fill missing values.

```
# Fill missing values with a specific value
df_filled = df.fillna(0)
```

```
# Fill missing values with the mean of the column
df filled mean = df.fillna(df.mean())
```

Replacing Missing Values

Replacing Missing Values:

• Use the replace() method to replace specific values.

```
# Replace missing values with a specific value
df_replaced = df.replace(np.nan, 0)
```

```
# Replace specific values with other values
df_replaced_specific = df.replace(to_replace=np.nan,
value=-1)
```

Computing basic estimators

The second step is the **computation of basic estimators on the dataset**.

Computing basic estimators

The second step is the **computation of basic estimators on the dataset**.

- Display first/last rows of DataFrame: df.head() et df.tail();
- Number of rows and columns: df.shape
- Names of columns: df.columns

Generating Summary Statistics

The third step is the **computation of statistical estimators and general statistical information** on the dataset.

- Generate summary statistics for numerical columns: describe();
- Count occurrences of unique values in a column: df['Age'].value_counts()

Aggregation and Grouping

- Aggregation: Performing group-wise operations and aggregations.
 - df.groupby('Gender')['Age'].mean() Calculate mean Age by Gender.

Seaborn

Introduction to Seaborn

Seaborn

Seaborn is a Python data visualization library relying on pandas, which simplifies the process of creating various types of plots with minimal code..

Key Features of Seaborn

- Seaborn provides a wide range of statistical plots:
 - Scatter plots
 - Line plots
 - Histograms
 - Bar plots
 - Box plots
 - Heatmaps
 - Pair plots

Question

Can you remind me to what variable type each plot corresponds?

Basic Scatter Plot

Scatter plots show the relationship between two variables.

```
import seaborn as sns
import matplotlib.pyplot as plt
# Create a DataFrame
data = sns.load dataset("iris")
# Create a scatter plot
sns.scatterplot(x="sepal length",
                y="sepal_width",
                data=data)
plt.show()
```

Bar Plot

Bar plots display the distribution of a categorical variable.

Customizing Plots

- Seaborn allows customization of plots for better communication:
 - Titles and labels: plt.title(), plt.xlabel(), plt.ylabel()
 - Color palettes: sns.set_palette()
 - Themes: sns.set_theme()
 - Grid and background: sns.grid()
 - Plot styles: sns.set_style()