



# Week 1: Introduction to Jupyter Notebook, NumPy, and Pandas

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# Jupyter Notebook, NumPy, and Pandas:

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Why it is important to learn them:

- **Jupyter Notebook:** Interactive Data Exploration
- **NumPy:** Efficient Numerical Computing
- **Pandas:** Data Manipulation and Analysis

# Understanding Jupyter Notebooks

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- Jupyter Notebook is a **web-based interactive computing environment** that allows users to create and share documents containing live code, equations, visualizations, and narrative text.
- Jupyter Notebook is not just a code editor; it revolutionizes the way we work with code, data, and explanations.
- Jupyter Notebook is particularly well-suited for various **data-related tasks**, including **data exploration, analysis, and visualization**.

# Jupyter Notebooks Features

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## Live Code Execution:

- Jupyter allows users to execute code in a step-by-step manner, making it **easy to understand** and **visualize each stage** of data analysis.
- Code cells can be executed **individually**, allowing for an **iterative** and **interactive** coding experience.
- Execute code cells **one by one** to see **immediate results**, making it **easier to debug** and understand the **impact of each code segment**.

# Jupyter Notebooks Features

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## Rich Media Integration:

- Supports the [inclusion of images, charts, and interactive visualizations](#) directly in the notebook, enhancing the storytelling aspect of data analysis.

## Narrative Text Support:

- Enables the [inclusion of descriptive text alongside code](#), facilitating the creation of a [comprehensive](#) and [well-documented analysis](#).

# Introduction to NumPy

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- NumPy is a powerful library for **numerical computing** in Python, providing support for **large, multi-dimensional** arrays and matrices.

## **NumPy arrays:** Efficient Handling of Numeric Data

- NumPy arrays are multi-dimensional, and resizable data structures.
- NumPy provides a powerful **array object** that allows **efficient manipulation of large datasets**, making **numerical operations more straightforward and faster**.
- NumPy **includes a wide range of mathematical functions** for array manipulation, linear algebra, and statistical operations, crucial for data manipulation and analysis.

# Why Use NumPy Arrays?

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## ➤ Homogeneous Data Storage:

NumPy arrays are homogeneous, meaning they contain **elements of the same data type**.

Arrays enforce homogeneity, ensuring consistent data types within the same array.

## ➤ Vectorized Operations:

Operations on NumPy arrays are vectorized, **eliminating the need for explicit loops** and making computations faster.

## ➤ Broadcasting:

Broadcasting allows for **operations on arrays of different shapes and sizes**, providing flexibility in array manipulation.

# Example

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Creating a NumPy array and performing a mathematical operation (squaring) on its elements.

```
▶ import numpy as np

# Create a NumPy array
arr = np.array([1, 2, 3, 4, 5])

# Perform a mathematical operation
arr_squared = arr ** 2

print(arr_squared)

[ 1  4  9 16 25]
```



# Lists VS NumPy arrays

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➤ While lists in Python and arrays in NumPy may seem similar, there are key differences between the two. Here's an overview of the distinctions:

## 1. Homogeneity:

List (Python):

Lists can contain **elements of different data types**.

You can have a mix of integers, floats, strings, etc., in a single list.

Array (NumPy):

NumPy arrays are homogeneous, meaning **they hold elements of the same data type**.

This homogeneity allows for more efficient storage and operations.

# Lists VS NumPy arrays

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## 2. Vectorized Operations:

List (Python):

Operations on lists generally **require explicit loops**.

Performing mathematical operations on each element of a list typically involves iterating through the list using a loop.

Array (NumPy):

NumPy arrays support vectorized operations.

**Operations can be applied to entire arrays without the need for explicit loops**, leading to faster and more concise code.

# Lists VS NumPy arrays

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## 3. Memory Efficiency:

List (Python):

Lists are generally **less memory-efficient**.

Each element in a list carries additional information such as type and reference information.

Array (NumPy):

NumPy arrays are **more memory-efficient**.

They store elements in contiguous memory locations, reducing the overhead associated with each element.

# Lists VS NumPy arrays

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## 4. Functionality and Methods:

List (Python):

Lists offer a **basic set of functionalities and methods** for general-purpose use.

They lack specialized methods for numerical operations.

Array (NumPy):

NumPy arrays come with an **extensive set of functions and methods optimized for numerical computations**.

NumPy provides tools for linear algebra, statistical operations, and more.

# Lists VS NumPy arrays

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## 5. Broadcasting:

List (Python):

Lists **do not support broadcasting**.

Operations on lists typically require compatible shapes or explicit looping.

Array (NumPy):

NumPy arrays **support broadcasting**, enabling operations on arrays of **different shapes and sizes**.

# Example

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In the example, array B is broadcasted to the shape of A, allowing the addition operation to be performed element-wise.

The value B is effectively treated as if it were replicated along a new axis to match the shape of A.

```
▶ import numpy as np

# Example of Broadcasting
A = np.array([[1, 2, 3],
              [4, 5, 6]])

B = np.array([10, 20, 30])

# Broadcasting automatically adjusts the shape of B to (2, 3) to match A
result = A + B

print(result)

[[11 22 33]
 [14 25 36]]
```

# Introduction to Pandas

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- **DataFrame Structure**: Pandas introduces two primary data structures: **Series (1-dimensional)** and **DataFrames (2-dimensional)**, making it easy to work with structured data.
- **Data Cleaning and Transformation**: Pandas provides **powerful tools for handling missing data, filtering, and transforming datasets**, ensuring data is in a suitable format for analysis.

# Pandas Series

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## ➤ A One-Dimensional Labeled Array

- The Pandas Series is a one-dimensional labeled array that **can hold any data type**.
- It consists of **data and associated labels** (index).
- It's particularly useful when working with **single-dimensional datasets** or when **extracting a single column from a DataFrame**.



# Why Use Series?

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## ➤ Labeled Indexing:

Series provides **labeled indexing**, making it **easy to access and manipulate** data using meaningful labels.

## ➤ Homogeneous Data:

Ensures homogeneity within a column, simplifying operations on the entire set of data.

## ➤ Integration with NumPy:

Series seamlessly integrates with NumPy, allowing for the application of various mathematical and statistical operations.

# Example

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Creating a Pandas Series to represent a one-dimensional array of ages.

```
▶ import pandas as pd

# Create a Pandas Series
ages = pd.Series([25, 30, 35], name='Age')

print(ages)
```

```
0    25
1    30
2    35
Name: Age, dtype: int64
```

# DataFrame

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## ➤ A Two-Dimensional Tabular Data Structure

- The DataFrame is a two-dimensional, tabular data structure **similar to a spreadsheet or SQL table**.
- It consists of **rows** and **columns**, where **each column can have a different data type**.
- The DataFrame is a tabular representation of data, where information is organized into rows and columns.
- Each column is essentially a Pandas Series.

# Why Use DataFrames?

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## ➤ Flexibility and Versatility:

DataFrames provide a flexible and versatile structure to **handle diverse datasets** with ease.

Columns can be of different data types, allowing for **mixed data within the same structure**.

## ➤ Efficient Data Manipulation:

Operations on columns, rows, and the entire DataFrame are **vectorized**, leading to **efficient and fast data manipulations**.

## ➤ Integration with Other Tools:

DataFrames seamlessly integrate with other libraries such as NumPy and Matplotlib, forming a comprehensive ecosystem for data analysis.

# Example

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Creating a Pandas DataFrame to organize and display structured data.

```
▶ import pandas as pd

# Create a Pandas DataFrame
data = {'Name': ['Alice', 'Bob', 'Charlie'],
        'Age': [25, 30, 35],
        'City': ['New York', 'San Francisco', 'Los Angeles']}

df = pd.DataFrame(data)

print(df)
```

	Name	Age	City
0	Alice	25	New York
1	Bob	30	San Francisco
2	Charlie	35	Los Angeles

# What is a CSV File?

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- CSV stands for **Comma-Separated Values**.
- It is a **plain text file** where each line represents a row, and **values are separated by commas (or other delimiters)**.
- CSV files are a common format for **storing structured data**.

## CSV Structure:

- **Rows** represent **records**, and **columns** represent **fields**.
- The **first row** often contains **headers**, defining the **names of the fields**.

# Read CSV file using *read\_csv* function

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- Before using this function, we must import the Pandas library.
- Like any other function, it can take parameters. Here is the Pandas read CSV syntax with its parameters.

```
pandas.read_csv(filepath_or_buffer, sep= ' , ' , header= 'infer' , index_col= None, usecols= None, nrows= None)
```

Parameters: (there are more other parameters)

- filepath\_or\_buffer: Location of the csv file. It accepts any string path or URL of the file.
- sep: It stands for separator, default is ' , '.
- header: It accepts int, a list of int, row numbers to use as the column names, and the start of the data. If no names are passed, i.e., header=None, then, it will display the first column as 0, the second as 1, and so on.
- usecols: Retrieves only selected columns from the CSV file.
- nrows: Number of rows to be displayed from the dataset.
- index\_col: If None, there are no index numbers displayed along with records.

# Example

## Creating a Pandas DataFrame object from a CSV file

```
In [1]: # Import pandas Library
import pandas as pd

# Creating a dataframe by reading a CSV file
df = pd.read_csv('./dataset.csv')
```

```
In [2]: df
```

Out[2]:

	Year	Age	Role	City	Education	Experience	Salary
0	2018	47	Helpdeskmanager	Apeldoorn	HBO	25	4950
1	2018	42	Applicatiebeheerder	Almelo	HAVO	10	4086
2	2018	42	BI Consultant	NaN	MBO	25	4400
3	2018	39	Software Engineer	Amsterdam	MBO	6	3600
4	2018	38	IT Consultant	Mierlo	HBO	15	4900
...	...	...	...	...	...	...	...
95	2018	24	Software Engineer	Zuid Holland	HBO	2	2413
96	2018	23	Servicedeskmedewerker	Randstad	MBO	3	2200
97	2018	23	Software Engineer	Friesland	MBO	5	3250
98	2018	23	Infrastructure Specialist	NaN	HBO	0	2200
99	2018	23	Web Developer	Nijmegen	MBO	2	1850

100 rows × 7 columns



# Example

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## Methods and attributes of DataFrame class

In [3]: `df.shape`

Out[3]: (100, 7)

In [4]: `# Display the first 5 rows of the dataset`  
`df.head()`

Out[4]:

	Year	Age	Role	City	Education	Experience	Salary
0	2018	47	Helpdeskmanager	Apeldoorn	HBO	25	4950
1	2018	42	Applicatiebeheerder	Almelo	HAVO	10	4086
2	2018	42	BI Consultant	NaN	MBO	25	4400
3	2018	39	Software Engineer	Amsterdam	MBO	6	3600
4	2018	38	IT Consultant	Mierlo	HBO	15	4900

# Integration of Jupyter, NumPy, and Pandas


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- Loading data
  - Performing basic operations
  - Visualizing results
- The provided example demonstrates the integration by loading a dataset, performing basic analysis using NumPy and Pandas, and displaying the results within the Jupyter Notebook.

# Example

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Integrating Jupyter, NumPy, and Pandas to load a dataset, perform basic analysis, and display the results directly in the notebook.

```
In [5]:  # Import necessary libraries  
import pandas as pd  
import numpy as np  
  
# Creating a dataframe by reading a CSV file  
df = pd.read_csv('./dataset.csv')  
  
# Perform basic analysis using Pandas and NumPy  
max_value = df['Salary'].max()  
mean_value = np.mean(df['Salary'])  
  
# Display results in the Jupyter Notebook  
mean_value, max_value
```

```
Out[5]: (3510.75, 10000)
```

# Exercise

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❑ Install Anaconda on your computer. Open Anaconda navigator and run Jupyter Notebook.

❑ Jupyter:

- Create a new Jupyter Notebook.
- Create markdown cells and code cells
- Write and execute a code cell to print a message of your choice.

# Exercise

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## □ NumPy:

- Create a NumPy array with values from 1 to 10.
- Calculate the mean and standard deviation of the array.
- Feel free to experiment and test your understanding of the concepts we've covered.

# Exercise

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## □ Pandas:

- Create a Pandas DataFrame with at least three columns.
- Use DataFrame methods to display summary statistics and the first few rows.

# Exercise

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- ❑ Load given dataset into Pandas and conduct initial data exploration

Explore the data, check the first few rows, and try some basic operations to familiarize yourself with Pandas functionalities.

Here's a list of attributes and methods that you can try on your own created Pandas DataFrames.

These exercises will help you get hands-on experience with data manipulation and exploration using Pandas.

# Exercise: DataFrame Attributes:

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**shape**: Returns the dimensions of the DataFrame (number of rows, number of columns).

Example: `df.shape`

**columns**: Returns the column labels of the DataFrame.

Example: `df.columns`

**index**: Returns the row labels of the DataFrame.

Example: `df.index`

**dtypes**: Returns the data type of each column.

Example: `df.dtypes`



# Exercise: DataFrame Methods:

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**head(n)**: Returns the first n rows of the DataFrame.

Example: `df.head(3)`

**tail(n)**: Returns the last n rows of the DataFrame.

Example: `df.tail(3)`

**info()**: Provides a concise summary of the DataFrame, including data types and non-null values.

Example: `df.info()`

**describe()**: Generates descriptive statistics for numerical columns.

Example: `df.describe()`