Python Packages

Table of contents

1 Packages for Data Analysis

We will be discussing key Python packages that are commonly used for data analysis such as **pandas**, **matplotlib**, **seaborn**, and **numpy**.

Figure 1: Python Packages

1.1 Packages in Python

- In Python, a *package* is a collection of modules organized within a directory structure, allowing grouping related code components, such as functions, classes, and constants,

into a single namespace.
- This structure enables modularity and reuse across projects, making code easier to maintain, import, and share with others.
- The most common way to import a package is using the `import` statement followed by the name of the package.
- For example, to import the `math` package:

```
import math

math.sqrt(25)
```

```
5.0
```

1.2 Importing Packages with Aliases

- We can also import a package with an *alias* using the `as` keyword.
- This can be useful when we want to use a shorter name for a package in our code.
- For example, to import the `math` package with the alias `m`, we would use the following statement:

```
import math as m

m.sqrt(25)
```

```
5.0
```

1.3 Installing a Package

- If a package is *not* already installed, we can install within our notebook/environment using the following **command line**:

```
%pip install package_name
```

- Example to install **`pandas`**:

```
%pip install pandas
```

```
1 %pip install pandas

Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: pandas in /usr/local/lib/python3.9/dist-packages (1.3.5)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.9/dist-packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.9/dist-packages (from pandas) (2022.7.1)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.9/dist-packages (from pandas) (1.22.4)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.9/dist-packages (from python-dateutil>=2.7.3->pandas) (1.15.0)
```

Notes:

- `pip` stands for 'Pip Installs Packages,' a recursive acronym.
- `pip` is a command-line tool (not a Python statement) typically run in the shell on macOS or Linux or in PowerShell on Windows. However, it can also be run within Jupyter notebooks using magic commands, specifically by prefixing it with `%`.

2 `Pandas`

- `Pandas` is a Python package that is used for data manipulation and analysis.
- It provides data structures for efficiently storing and manipulating large datasets.

Figure 2: Pandas

2.1 The Titanic Dataset

Figure 3: Titantic departing Southampton on April 10, 1912

- The Titanic dataset contains data on the passengers of Titanic, including their survival status, age, gender, class, and other attributes.

2.2 Loading a CSV file with Pandas

```
import pandas as pd

url =
 ↪  'https://web.stanford.edu/class/archive/cs/cs109/cs109.1166/stuff/titanic.csv'
titanic = pd.read_csv(url) # Load Titanic dataset

titanic.shape # The dimension of the dataframe (the table)
```

```
(887, 8)
```

2.3 Viewing `DataFrame`

- Once we have loaded data into a `DataFrame`, we can start exploring it using various Pandas functions.
- The `head()` and `tail` functions are useful functions for quickly viewing the first and last few rows of a `DataFrame`.
  - `head()` for the top records in the `DataFrame`:

```
titanic.head() # Print the first few rows of the DataFrame
```

	Survived	Pclass	Name	Sex	Age	Siblings/Spouses
0	0	3	Mr. Owen Harris Braund	male	22.0	1
1	1	1	Mrs. John Bradley (Florence Briggs Thayer) Cum...	female	38.0	1
2	1	3	Miss. Laina Heikkinen	female	26.0	0
3	1	1	Mrs. Jacques Heath (Lily May Peel) Futrelle	female	35.0	1
4	0	3	Mr. William Henry Allen	male	35.0	0

- `tail()` for the bottom records in the `DataFrame`:

```
titanic.tail() # Print the last few rows of the DataFrame
```

	Survived	Pclass	Name	Sex	Age	Siblings/Spouses Aboard	Parents
882	0	2	Rev. Juozas Montvila	male	27.0	0	0
883	1	1	Miss. Margaret Edith Graham	female	19.0	0	0
884	0	3	Miss. Catherine Helen Johnston	female	7.0	1	2
885	1	1	Mr. Karl Howell Behr	male	26.0	0	0
886	0	3	Mr. Patrick Dooley	male	32.0	0	0

2.4 Basic Statistics

- We can use `Pandas` to calculate basic statistics on our data, such as mean, median, and standard deviation.
- The `describe()` function provides a summary of the basic statistics of each column in the DataFrame.

```
titanic.describe()
```

	Survived	Pclass	Age	Siblings/Spouses Aboard	Parents/Children Aboard	Fare
count	887.000000	887.000000	887.000000	887.000000	887.000000	887.000
mean	0.385569	2.305524	29.471443	0.525366	0.383315	32.3054
std	0.487004	0.836662	14.121908	1.104669	0.807466	49.7820
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.00000
25%	0.000000	2.000000	20.250000	0.000000	0.000000	7.92500
50%	0.000000	3.000000	28.000000	0.000000	0.000000	14.4542
75%	1.000000	3.000000	38.000000	1.000000	0.000000	31.1375
max	1.000000	3.000000	80.000000	8.000000	6.000000	512.329

2.5 Indexing and Selection 1/2

- We can use indexing and selection to retrieve specific data from a `DataFrame`.
- The `iloc[]` function is used for integer-based indexing, where we can specify the row and column numbers.

```
titanic.iloc[2:5]
```

	Survived	Pclass	Name	Sex	Age	Siblings/Spouses Aboard
2	1	3	Miss. Laina Heikkinen	female	26.0	0
3	1	1	Mrs. Jacques Heath (Lily May Peel) Futrelle	female	35.0	1
4	0	3	Mr. William Henry Allen	male	35.0	0

2.6 Indexing and Selection 2/2

- The `loc[]` function is used for label-based indexing, where we can specify the row and column labels.

```python
titanic.loc[2:5, ['Survived', 'Pclass']]
```

	Survived	Pclass
2	1	3
3	1	1
4	0	3
5	0	3

2.7 Comparison of `.loc` and `.iloc` in `pandas DataFrame`

Feature	`.loc` (Label-based)	`.iloc` (Integer-based)
Primary Use	Access data by row and column labels (names)	Access data by row and column integer positions
Syntax	`df.loc[row_label, column_label]`	`df.iloc[row_position, column_position]`
Row/Column Identification	Uses label names for rows and columns	Uses integer positions (like list indexing)
Indexing Type	**Label**-based (requires exact match for labels)	**Integer**-based (0-based index like Python lists)
Row Selection	`df.loc['row_label']`	`df.iloc[row_position]`
Column Selection	`df.loc[:, 'column_label']`	`df.iloc[:, column_position]`
Single Value Access	`df.loc['row_label', 'column_label']`	`df.iloc[row_position, column_position]`
Range Slicing	Inclusive of the endpoint (e.g., `df.loc['A':'C']` includes both `A` and `C`)	Exclusive of the endpoint (e.g., `df.iloc[0:2]` includes only positions `0` and `1`)
Boolean Indexing	Works with Boolean masks for label-based filtering (e.g., `df.loc[df['Age'] > 25]`)	Not typically used with Boolean masks, though possible

2.8 Filtering Data

- We can use Boolean indexing to filter data in a DataFrame based on a certain condition.
- For example, we can filter the Titanic dataset to only show passengers who survived:

```python
# Filter Titanic dataset to only show passengers who survived
survivors = titanic[titanic['Survived'] == 1]
survivors.head()
```

	Survived	Pclass	Name	Sex	Age	Siblings/Spouses
1	1	1	Mrs. John Bradley (Florence Briggs Thayer) Cum...	female	38.0	1
2	1	3	Miss. Laina Heikkinen	female	26.0	0
3	1	1	Mrs. Jacques Heath (Lily May Peel) Futrelle	female	35.0	1
8	1	3	Mrs. Oscar W (Elisabeth Vilhelmina Berg) Johnson	female	27.0	0
9	1	2	Mrs. Nicholas (Adele Achem) Nasser	female	14.0	1

2.9 Grouping and Aggregation

- Grouping: Categorizes data based on one or more columns, creating distinct groups within the dataset.
- Aggregation: Summarizes each group using functions like `sum()`, `mean()`, or `count()`, revealing trends within categories.

2.9.1 Why Use Grouping and Aggregation?

- Grouping and summarizing large datasets make it easier to compare and analyze patterns across different categories.
- Commonly used to calculate summary statistics, such as averages or totals, within groups.
- **Example:** to see grouping and summarization in action, we will group the Titanic dataset by ticket class (`Pclass`) to calculate the average age of passengers in each class.

```python
# Group Titanic dataset by ticket class and calculate the average age for
 ↪ each class
age_by_class = titanic.groupby('Pclass')['Age'].mean()
age_by_class
```

```
Pclass
1    38.788981
2    29.868641
3    25.188747
Name: Age, dtype: float64
```

- Here, `Pclass()` becomes the **index** in the resulting `DataFrame`. While this is useful for quick summaries, it can sometimes make further data manipulation less intuitive.
- Why Use `reset_index()`?
  - Applying `reset_index()` converts the **index** back into a regular column.
  - This makes the `DataFrame` easier to read and more convenient for additional operations (e.g., merging with other `DataFrame` or plotting).
- So, let us apply `reset_index()` to make `Pclass` a *standard* column:

```
# Grouping, aggregation, and reset index
age_by_class = titanic.groupby('Pclass')['Age'].mean().reset_index()
age_by_class
```

	Pclass	Age
0	1	38.788981
1	2	29.868641
2	3	25.188747

- **Final output:** now, `Pclass` appears as a regular column, making it easier to interpret and manipulate.

3 `Matplotlib`

- `Matplotlib` is a Python package used for creating data visualizations.
- It provides a wide range of tools for creating line plots, bar plots, histograms, scatterplots

Figure 4: Matplotlib

3.1 Plotting a Simple Line Graph with `Matplotlib`

Figure 5: Power Station

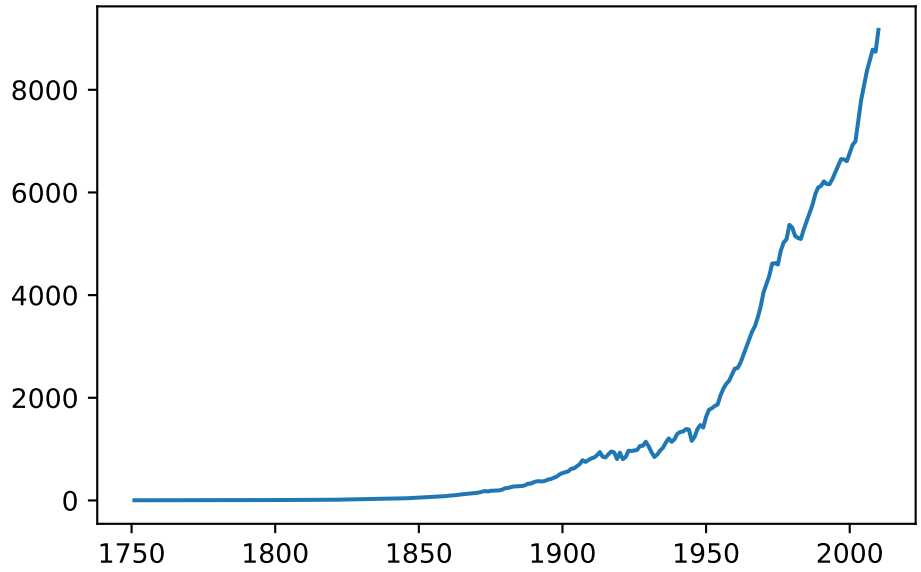
- Let us start with an example of how to use Matplotlib to create a simple line graph for global CO2 emissions from 1960 to 2014.
- Here is the code to load the dataset:

```
import pandas as pd

url =
 ↪  'https://raw.githubusercontent.com/datasets/co2-fossil-global/master/global.csv'
co2 = pd.read_csv(url)

co2.head()
```

	Year	Total	Gas Fuel	Liquid Fuel	Solid Fuel	Cement	Gas Flaring	Per Capita
0	1751	3	0	0	3	0	0	NaN
1	1752	3	0	0	3	0	0	NaN
2	1753	3	0	0	3	0	0	NaN
3	1754	3	0	0	3	0	0	NaN
4	1755	3	0	0	3	0	0	NaN

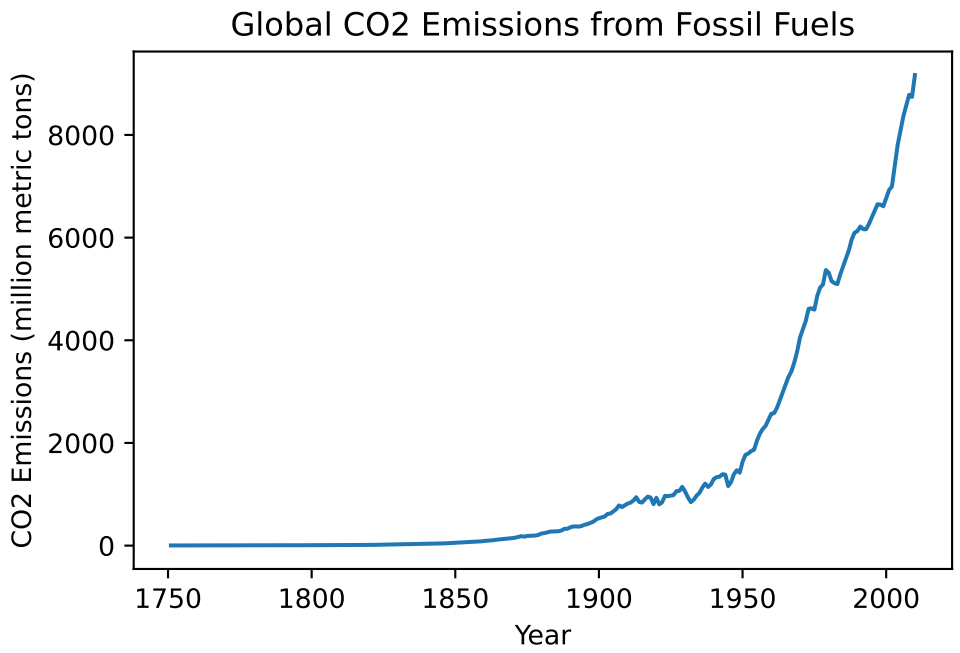
- Now, here is the code to create a line plot using `matplotlib`:

```
import matplotlib.pyplot as plt
plt.plot(co2['Year'], co2['Total'])
```



- Let us add annotations to the plot:

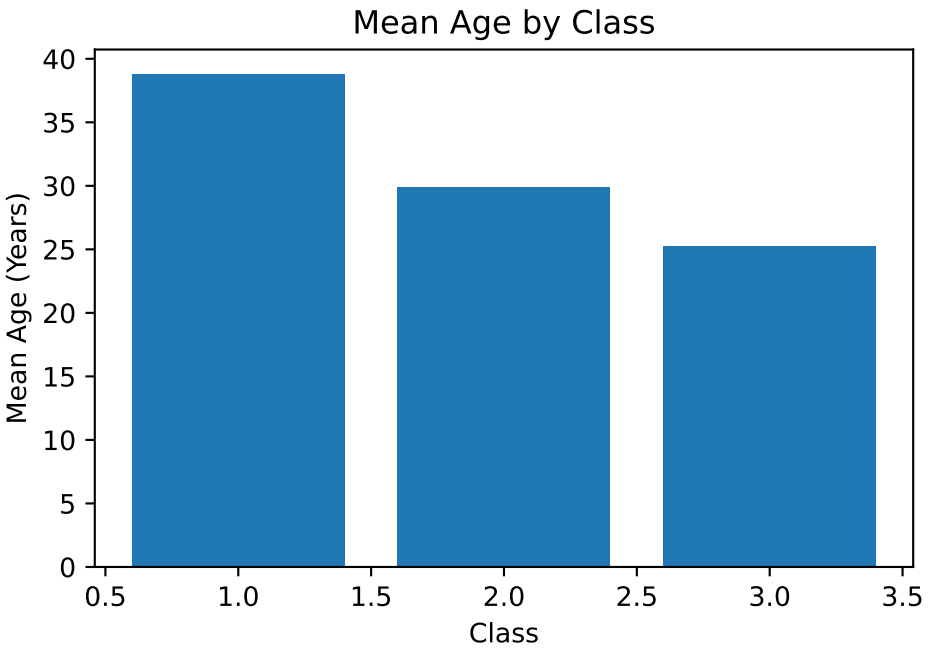
```
import matplotlib.pyplot as plt
plt.plot(co2['Year'], co2['Total'])
plt.xlabel('Year')
plt.ylabel('CO2 Emissions (million metric tons)')
plt.title('Global CO2 Emissions from Fossil Fuels')
plt.show()
```



3.2 Creating a Bar Plot with `Matplotlib`

- We can also use `Matplotlib` to create a bar plot.
- Here is the code to load the dataset and create a bar plot:

```
plt.bar(age_by_class['Pclass'], age_by_class['Age'])

plt.title('Mean Age by Class')
plt.xlabel('Class')
plt.ylabel('Mean Age (Years)')

plt.show()
```



4 `Seaborn`

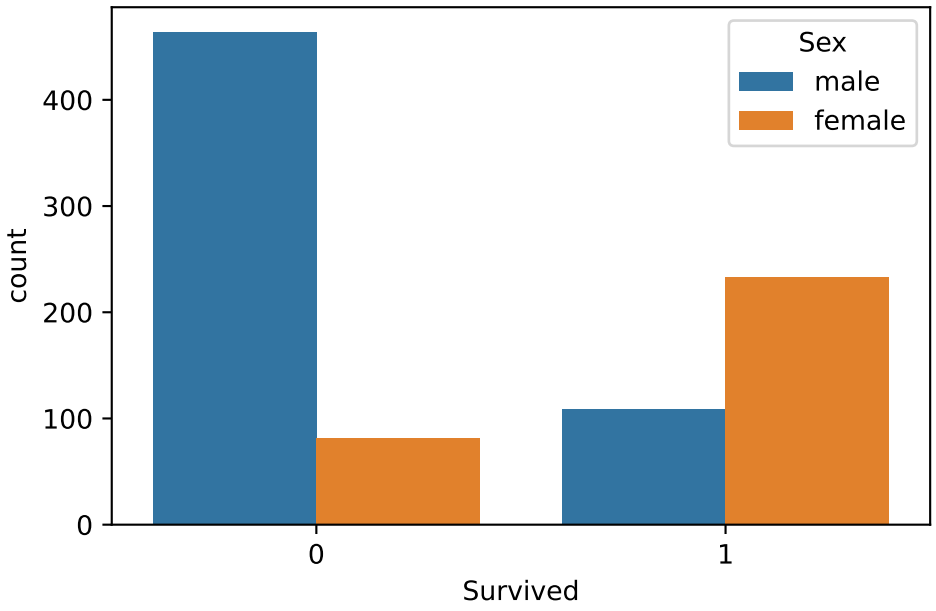
- `Seaborn` is a Python data visualization package based on `Matplotlib`.
- It provides a high-level interface for creating informative and attractive statistical graphics.

Figure 6: Seaborn

- `Seaborn` works well with pandas dataframes and provides tools for visualizing relationships between variables.

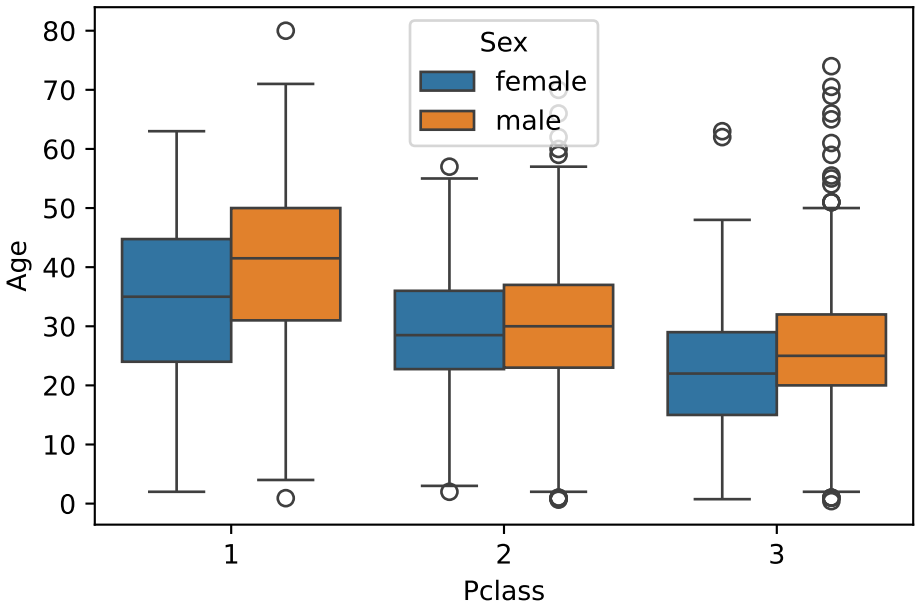
4.1 Titanic: Survived vs. Sex

```
import seaborn as sns
sns.countplot (data = titanic, x = 'Survived', hue = 'Sex')
```



4.2 Titanic: Age vs. Class vs. Age

```
sns.boxplot (data = titanic, x = 'Pclass', y = "Age", hue = 'Sex')
```

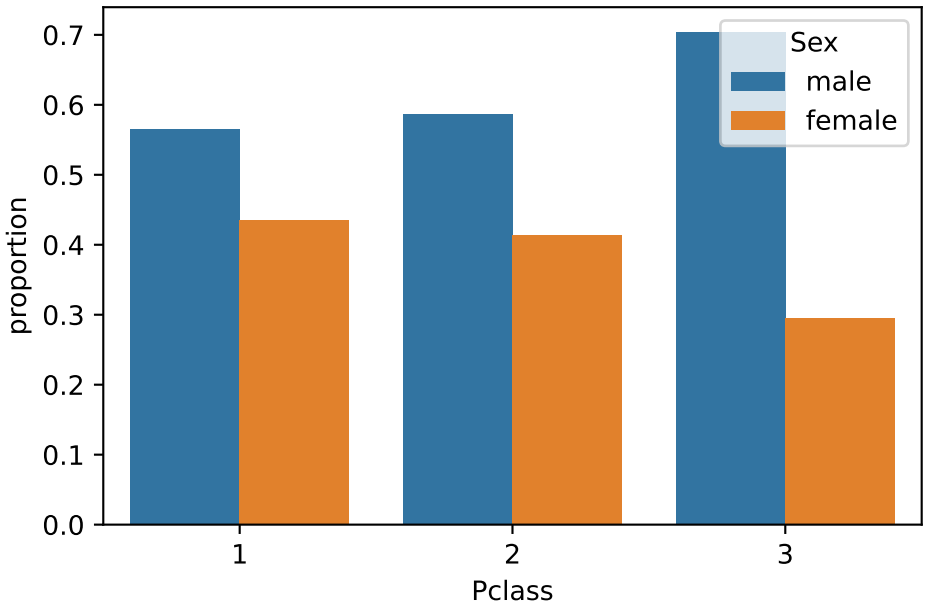


4.3 Titanic: Sex Ratio vs. Class

```
normalized_counts = titanic[['Pclass',
    'Sex']].groupby(['Pclass']).value_counts(normalize=True).reset_index()
normalized_counts.head()
```

	Pclass	Sex	proportion
0	1	male	0.564815
1	1	female	0.435185
2	2	male	0.586957
3	2	female	0.413043
4	3	male	0.704312

```
sns.barplot (data = normalized_counts, x = 'Pclass', y = "proportion", hue =
    'Sex')
```



5 Numpy

- NumPy is a Python package used for numerical computing.
- It provides a wide range of tools for working with arrays and matrices.
- NumPy is used in many scientific computing applications.

Figure 7: NumPy

5.1 Creating a NumPy Array

- To create a NumPy array, we can use the `numpy.array()` function.
- Here is the code to create a NumPy array:

```
import numpy as np

data = [1, 2, 3, 4, 5]
arr = np.array(data)
arr
```

```
array([1, 2, 3, 4, 5])
```

5.2 NumPy Array Operations

- We can perform various operations on NumPy arrays.
- For example, we can add, subtract, multiply, and divide arrays.
- Here is the code to add two arrays:

```
import numpy as np

arr1 = np.array([1, 2, 3])
arr2 = np.array([4, 5, 6])
arr3 = arr1 + arr2
arr3
```

```
array([5, 7, 9])
```

5.3 NumPy Array Indexing and Slicing

- We can also index and slice NumPy arrays.
- Here is the code to create a NumPy array and slice it:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5])
arr[2]
```

```
np.int64(3)
```

```
arr[1:4]
```

```
array([2, 3, 4])
```

5.4 NumPy Broadcasting

- **Broadcasting** is a powerful NumPy feature that allows us to perform operations on arrays of different shapes.
- Here is an example:

```
import numpy as np

# Create a 2D array of shape (3, 4)
arr1 = np.array([[1, 2, 3, 4],
                 [5, 6, 7, 8],
                 [9, 10, 11, 12]])

# Create a 1D array of shape (4,)
arr2 = np.array([2, 2, 2, 2])

# Add the 1D array to each row of the 2D array using broadcasting
result = arr1 + arr2

print(result)
```

```
[[ 3  4  5  6]
 [ 7  8  9 10]
 [11 12 13 14]]
```

- In this example, we have a 2D NumPy array `arr1` with shape `(3, 4)` and a 1D NumPy array `arr2` with shape `(4, )`. We want to add the values in `arr2` to each row of `arr1`.
- Normally, this operation would not be possible because the two arrays have different shapes.
- However, NumPy broadcasting allows us to perform this operation by "stretching" or "broadcasting" the 1D array to match the shape of the 2D array.
- In this case, NumPy broadcasts the 1D array `arr2` to a 2D array of shape `(3, 4)` by duplicating its values along the first dimension. This allows us to perform *element-wise* addition between the two arrays.