NumPy Introduction

NumPy is a Python library used for working with arrays.

It also has functions for working in domain of linear algebra, fourier transform, and matrices.

NumPy was created in 2005 by Travis Oliphant. It is an open source project and you can use it freely.

NumPy stands for Numerical Python.

In Python we have lists that serve the purpose of arrays, but they are slow to process.

NumPy aims to provide an array object that is up to 50x faster than traditional Python lists.

The array object in NumPy is called ndarray, it provides a lot of supporting functions that make working with ndarray very easy.

Arrays are very frequently used in data science, where speed and resources are very important.

NumPy arrays are stored at one continuous place in memory unlike lists, so processes can access and manipulate them very efficiently.

This behavior is called locality of reference in computer science.

This is the main reason why NumPy is faster than lists. Also it is optimized to work with latest CPU architectures.

NumPy is a Python library and is written partially in Python, but most of the parts that require fast computation are written in C or C++.

The source code for NumPy is located at this github repository https://github.com/numpy/numpy

github: enables many people to work on the same codebase.

Import NumPy

Once NumPy is installed, import it in your applications by adding the import keyword:

```
import numpy
```

Example

```
1.import numpy

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

print(arr)
```

Output
[1,2,3,4,5]

NumPy as np

NumPy is usually imported under the np alias.

```
import numpy as np
```
Now the NumPy package can be referred to as np instead of numpy

Example

```
import numpy as np

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

print(arr)
```

Checking NumPy Version

The version string is stored under __version__ attribute.

```
import numpy as np

print(np.__version__)
```

Create a NumPy ndarray Object

NumPy is used to work with arrays. The array object in NumPy is called ndarray.

We can create a NumPy ndarray object by using the array() function.

Example

```
import numpy as np

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

print(arr)

print(type(arr))
```

Dimensions in Arrays

A dimension in arrays is one level of array depth (nested arrays).

0-D Arrays

0-D arrays, or Scalars, are the elements in an array. Each value in an array is a 0-D array.

Example

Create a 0-D array with value 42

```
import numpy as np

arr = np.array(42)

print(arr)
```

1-D Arrays

An array that has 0-D arrays as its elements is called uni-dimensional or 1-D array.

These are the most common and basic arrays.

Example

Create a 1-D array containing the values 1,2,3,4,5

```
import numpy as np

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

print(arr)
```

2-D Arrays

An array that has 1-D arrays as its elements is called a 2-D array.

These are often used to represent matrix or 2nd order tensors.

Example

Create a 2-D array containing two arrays with the values 1,2,3 and 4,5,6:

```
import numpy as np

arr = np.array([[1, 2, 3], [4, 5, 6]])

print(arr)
```

3-D arrays

An array that has 2-D arrays (matrices) as its elements is called 3-D array.

These are often used to represent a 3rd order tensor.

Example

Create a 3-D array with two 2-D arrays, both containing two arrays with the values 1,2,3 and 4,5,6:

```
import numpy as np

arr = np.array([[[1, 2, 3], [4, 5, 6]], [[1, 2, 3], [4, 5, 6]]])

print(arr)
```

Check Number of Dimensions ?

NumPy Arrays provides the ndim attribute that returns an integer that tells us how many dimensions the array have.

Example

Check how many dimensions the arrays have:

```
import numpy as np

a = np.array(42)
b = np.array([1, 2, 3, 4, 5])
c = np.array([[1, 2, 3], [4, 5, 6]])
d = np.array([[[1, 2, 3], [4, 5, 6]], [[1, 2, 3], [4, 5, 6]]])

print(a.ndim)
print(b.ndim)
print(c.ndim)
print(d.ndim)
```

Higher Dimensional Arrays

An array can have any number of dimensions.

When the array is created, you can define the number of dimensions by using the ndmin argument.

Example

Create an array with 5 dimensions and verify that it has 5 dimensions:

```
import numpy as np
```

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

print(arr)
print('number of dimensions :', arr.ndim)
```

NumPy Array Indexing

Access Array Elements

Array indexing is the same as accessing an array element.

You can access an array element by referring to its index number.

The indexes in NumPy arrays start with 0, meaning that the first element has index 0, and the second has index 1 etc.

Example

Get the first element from the following array:

```
import numpy as np

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

print(arr[0])
```

Example

Get the second element from the following array.

```
import numpy as np

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

print(arr[1])
```

Example

Get third and fourth elements from the following array and add them.

```
import numpy as np

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

```
print(arr[2] + arr[3])
```

Access 2-D Arrays

To access elements from 2-D arrays we can use comma separated integers representing the dimension and the index of the element.

Think of 2-D arrays like a table with rows and columns, where the dimension represents the row and the index represents the column.

Example

Access the element on the first row, second column:

```
import numpy as np

arr = np.array([[1,2,3,4,5], [6,7,8,9,10]])

print('2nd element on 1st row: ', arr[0, 1])
```

```
import numpy as np

arr = np.array([[1,2,3,4,5], [6,7,8,9,10]])

print('2nd element on 1st row: ', arr[0, 1])
```

Output- 2nd element on 1st row:2

Example

Access the element on the 2nd row, 5th column:

```
import numpy as np

arr = np.array([[1,2,3,4,5], [6,7,8,9,10]])

print('5th element on 2nd row: ', arr[1, 4])
```

Output

5th element on 2nd row:10

NumPy Array Slicing

Slicing arrays

Slicing in python means taking elements from one given index to another given index.

We pass slice instead of index like this: [start:end].

We can also define the step, like this: [start:end:step].

If we don't pass start its considered 0

If we don't pass end its considered length of array in that dimension

If we don't pass step its considered 1

Example

Slice elements from index 1 to index 5 from the following array:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5, 6, 7])

print(arr[1:5])
```

Output:[2,3,4,5]

Example

Slice elements from index 4 to the end of the array:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5, 6, 7])

print(arr[4:])
```

Output:[5,6,7]

Example

Slice elements from the beginning to index 4 (not included):

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5, 6, 7])

print(arr[:4])
```

output:[1,2,3,4]

Negative Slicing

Use the minus operator to refer to an index from the end:

Example

Slice from the index 3 from the end to index 1 from the end:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5, 6, 7])

print(arr[-3:-1])
```

Output:[5,6]

STEP

Use the step value to determine the step of the slicing:

Example

Return every other element from index 1 to index 5:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5, 6, 7])

print(arr[1:5:2])
```

Output-[2,4]

Example

Return every other element from the entire array:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5, 6, 7])

print(arr[::2])
```

Output=[1,3,5,7]

Slicing 2-D Arrays

Example

From the second element, slice elements from index 1 to index 4 (not included):

```
import numpy as np

arr = np.array([[1, 2, 3, 4, 5], [6, 7, 8, 9, 10]])

print(arr[1, 1:4])
```

Output-[7,8,9]

Example

From both elements, return index 2:

```
import numpy as np

arr = np.array([[1, 2, 3, 4, 5], [6, 7, 8, 9, 10]])

print(arr[0:2, 2])
```

Output-[3,8]

Example

From both elements, slice index 1 to index 4 (not included), this will return a 2-D array:

```
import numpy as np

arr = np.array([[1, 2, 3, 4, 5], [6, 7, 8, 9, 10]])

print(arr[0:2, 1:4])
```

Output-

[[2,3,4]

,[7,8,9]]

Data Types in Python

By default Python have these data types:

- strings - used to represent text data, the text is given under quote marks. e.g. ‘ABCD‘
- integer - used to represent integer numbers. e.g. -1, -2, -3
- float - used to represent real numbers. e.g. 1.2, 42.42
- boolean - used to represent True or False.
- complex - used to represent complex numbers. e.g. 1.0 + 2.0j, 1.5 + 2.5j

Data Types in NumPy

NumPy has some extra data types, and refer to data types with one character, like i for integers, u for unsigned integers etc.

Below is a list of all data types in NumPy and the characters used to represent them.

- i - integer
- b - boolean
- u - unsigned integer
- f - float
- c - complex float
- m - timedelta
- M - datetime
- O - object
- S - string

Checking the Data Type of an Array

The NumPy array object has a property called dtype that returns the data type of the array:

U - unicode string

V - fixed chunk of memory for other type (void)

Example

Get the data type of an array object:

```
import numpy as np

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

print(arr.dtype)
```

Output-int64

Example

Get the data type of an array containing strings:

```
import numpy as np

arr = np.array(['apple', 'banana', 'cherry'])

print(arr.dtype)
```

Output-<U6

Creating Arrays With a Defined Data Type

We use the array() function to create arrays, this function can take an optional argument: dtype that allows us to define the expected data type of the array elements:

Example

Create an array with data type string:

```
import numpy as np

arr = np.array([1, 2, 3, 4], dtype='S')

print(arr)
print(arr.dtype)
```

NumPy Array Copy vs View

The Difference Between Copy and View

The main difference between a copy and a view of an array is that the copy is a new array, and the view is just a view of the original array.

The copy owns the data and any changes made to the copy will not affect original array, and any changes made to the original array will not affect the copy.

The view does not own the data and any changes made to the view will affect the original array, and any changes made to the original array will affect the view.

COPY:

Example

Make a copy, change the original array, and display both arrays:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5])
x = arr.copy()
arr[0] = 42

print(arr)
print(x)
```

VIEW:

Example

Make a view, change the original array, and display both arrays:

```
import numpy as np

arr = np.array([1, 2, 3, 4, 5])
x = arr.view()
arr[0] = 42

print(arr)
print(x)
```

Pandas

Pandas is a Python library.

Pandas is used to analyze data.

In our 'Try it Yourself' editor, you can use the Pandas module, and modify the code to see the result.

Example

Load a CSV file into a Pandas DataFrame:

```
import pandas as pd

df = pd.read_csv('data.csv')

print(df.to_string())
```

What is Pandas?

Pandas is a Python library used for working with data sets.

It has functions for analyzing, cleaning, exploring, and manipulating data.

The name 'Pandas' has a reference to both 'Panel Data', and 'Python Data Analysis' and was created by Wes McKinney in 2008.

Why Use Pandas?

Pandas allows us to analyze big data and make conclusions based on statistical theories.

Pandas can clean messy data sets, and make them readable and relevant.

Relevant data is very important in data science.

Import Pandas

Once Pandas is installed, import it in your applications by adding the import keyword:

```
import pandas
```

Example

```
import pandas

mydataset = {
  'cars': ['BMW', 'Volvo', 'Ford'],
  'passings': [3, 7, 2]
}

myvar = pandas.DataFrame(mydataset)

print(myvar)
```

Pandas as pd

Pandas is usually imported under the pd alias.

Example

```
import pandas as pd

mydataset = {
  'cars': ['BMW', 'Volvo', 'Ford'],
  'passings': [3, 7, 2]
}

myvar = pd.DataFrame(mydataset)

print(myvar)
```

Checking Pandas Version

The version string is stored under __version__ attribute.

Example

```
import pandas as pd

print(pd.__version__)
```

Pandas Series

What is a Series?

A Pandas Series is like a column in a table.

It is a one-dimensional array holding data of any type.

Example

Create a simple Pandas Series from a list:

```
import pandas as pd

a = [1, 7, 2]

myvar = pd.Series(a)

print(myvar)
```

Labels

If nothing else is specified, the values are labeled with their index number. First value has index 0, second value has index 1 etc.

This label can be used to access a specified value.

Example

Return the first value of the Series:

```
print(myvar[0])
```

Create Labels

With the index argument, you can name your own labels.

Example

Create your own labels:

```
import pandas as pd

a = [1, 7, 2]

myvar = pd.Series(a, index = ['x', 'y', 'z'])

print(myvar)
```

When you have created labels, you can access an item by referring to the label.

Example

Return the value of 'y':

```
print(myvar['y'])
```

Key/Value Objects as Series

You can also use a key/value object, like a dictionary, when creating a Series.

Example

Create a simple Pandas Series from a dictionary:

```
import pandas as pd

calories = {'day1': 420, 'day2': 380, 'day3': 390}

myvar = pd.Series(calories)

print(myvar)
```

To select only some of the items in the dictionary, use the index argument and specify only the items you want to include in the Series.

Example

Create a Series using only data from 'day1' and 'day2':

```
import pandas as pd

calories = {'day1': 420, 'day2': 380, 'day3': 390}

myvar = pd.Series(calories, index = ['day1', 'day2'])

print(myvar)
```

DataFrames

Data sets in Pandas are usually multi-dimensional tables, called DataFrames.

Series is like a column, a DataFrame is the whole table.

Example

Create a DataFrame from two Series:

```
import pandas as pd

data = {
  'calories': [420, 380, 390],
  'duration': [50, 40, 45]
}

myvar = pd.DataFrame(data)
```

```
print(myvar)
```

What is a DataFrame?

A Pandas DataFrame is a 2 dimensional data structure, like a 2 dimensional array, or a table with rows and columns

Example

Create a simple Pandas DataFrame:

```
import pandas as pd

data = {
  'calories': [420, 380, 390],
  'duration': [50, 40, 45]
}

#load data into a DataFrame object:
df = pd.DataFrame(data)

print(df)
```

Locate Row

As you can see from the result above, the DataFrame is like a table with rows and columns.

Pandas use the `loc` attribute to return one or more specified row(s)

Example

Return row 0:

```
#refer to the row index:
print(df.loc[0])
```

Load Files Into a DataFrame

If your data sets are stored in a file, Pandas can load them into a DataFrame.

Example

Load a comma separated file (CSV file) into a DataFrame:

```
import pandas as pd

df = pd.read_csv('data.csv')

print(df)
```

Read CSV Files

A simple way to store big data sets is to use CSV files (comma separated files).

CSV files contains plain text and is a well know format that can be read by everyone including Pandas.

In our examples we will be using a CSV file called 'data.csv'.

Download data.csv. or Open data.csv

Example

Load the CSV into a DataFrame:

```
import pandas as pd

df = pd.read_csv('data.csv')

print(df.to_string())
```

If you have a large DataFrame with many rows, Pandas will only return the first 5 rows, and the last 5 rows:

Example

Print the DataFrame without the to_string() method:

```
import pandas as pd
```

```
df = pd.read_csv('data.csv')

print(df)
```

max_rows

The number of rows returned is defined in Pandas option settings.

You can check your system's maximum rows with the `pd.options.display.max_rows` statement.

Example

Check the number of maximum returned rows:

```
import pandas as pd

print(pd.options.display.max_rows)
```

In my system the number is `60`, which means that if the DataFrame contains more than `60` rows, the `print(df)` statement will return only the headers and the first and last `5` rows.

You can change the maximum rows number with the same statement.

Example

Increase the maximum number of rows to display the entire DataFrame:

```
import pandas as pd

pd.options.display.max_rows = 9999

df = pd.read_csv('data.csv')

print(df)
```

Pandas Read JSON

Read JSON

Big data sets are often stored, or extracted as JSON.

JSON is plain text, but has the format of an object, and is well known in the world of programming, including Pandas.

In our examples we will be using a JSON file called 'data.json'.

Open data.json.

Example

Load the JSON file into a DataFrame:

```
import pandas as pd

df = pd.read_json('data.json')

print(df.to_string())
```

Pandas - Analyzing DataFrames

Viewing the Data

One of the most used method for getting a quick overview of the DataFrame, is the `head()` method.

The `head()` method returns the headers and a specified number of rows, starting from the top.

Example

Get a quick overview by printing the first 10 rows of the DataFrame:

```
import pandas as pd

df = pd.read_csv('data.csv')

print(df.head(10))
```

There is also a tail() method for viewing the last rows of the DataFrame.

The tail() method returns the headers and a specified number of rows, starting from the bottom.

Example

Print the last 5 rows of the DataFrame:

```
print(df.tail())
```

Pandas - Cleaning Data

Data cleaning means fixing bad data in your data set.

Bad data could be:

- Empty cells
- Data in wrong format
- Wrong data
- Duplicates

Empty Cells

Empty cells can potentially give you a wrong result when you analyze data.

Remove Rows

One way to deal with empty cells is to remove rows that contain empty cells.

This is usually OK, since data sets can be very big, and removing a few rows will not have a big impact on the result.

Example

Return a new Data Frame with no empty cells:

```
import pandas as pd

df = pd.read_csv('data.csv')
```

```
new_df = df.dropna()

print(new_df.to_string())
```

If you want to change the original DataFrame, use the `inplace = True` argument:

Example

Remove all rows with NULL values:

```
import pandas as pd

df = pd.read_csv('data.csv')

df.dropna(inplace = True)

print(df.to_string())
```

Replace Empty Values

Another way of dealing with empty cells is to insert a new value instead.

This way you do not have to delete entire rows just because of some empty cells.

The `fillna()` method allows us to replace empty cells with a value:

Example

Replace NULL values with the number 130:

```
import pandas as pd

df = pd.read_csv('data.csv')

df.fillna(130, inplace = True)
```

Data Visuvalization With Matplotlib and Seaborn

Data visualization is an easier way of presenting the data, however complex it is, to analyze trends and relationships amongst variables with the help of pictorial representation.

The following are the advantages of Data Visualization

- Easier representation of compels data
- Highlights good and bad performing areas
- Explores relationship between data points
- Identifies data patterns even for larger data points

While building visualization, it is always a good practice to keep some below mentioned points in mind

- Ensure appropriate usage of shapes, colors, and size while building visualization
- Plots/graphs using a co-ordinate system are more pronounced
- Knowledge of suitable plot with respect to the data types brings more clarity to the information
- Usage of labels, titles, legends and pointers passes seamless information the wider audience

Python Libraries

There are a lot of python libraries which could be used to build visualization like *matplotlib, vispy, bokeh, seaborn, pygal, folium, plotly, cufflinks*, and *networkx*. Of the many, *matplotlib* and *seaborn* seems to be very widely used for basic to intermediate level of visualizations.

Matplotlib

It is an amazing visualization library in Python for 2D plots of arrays, It is a multi-platform data visualization library built on *NumPy* arrays and designed to work with the broader *SciPy* stack. It was introduced by John Hunter in the year 2002. Let's try to understand some of the benefits and features of *matplotlib*

- It's fast, efficient as it is based on *numpy* and also easier to build
- Has undergone a lot of improvements from the open source community since inception and hence a better library having advanced features as well
- Well maintained visualization output with high quality graphics draws a lot of users to it
- Basic as well as advanced charts could be very easily built
- From the users/developers point of view, since it has a large community support, resolving issues and debugging becomes much easier

Seaborn

Conceptualized and built originally at the Stanford University, this library sits on top of matplotlib. In a sense, it has some flavors of matplotlib while from the visualization point, it is much better than matplotlib and has added features as well. Below are its advantages

- Built-in themes aid better visualization
- Statistical functions aiding better data insights
- Better aesthetics and built-in plots
- Helpful documentation with effective examples

Depending on the number of variables used for plotting the visualization and the type of variables, there could be different types of charts which we could use to understand the relationship. Based on the count of variables, we could have

Univariate plot(involves only one variable)

Bivariate plot(more than one variable in required)

A *Univariate* plot could be for a continuous variable to understand the spread and distribution of the variable while for a discrete variable it could tell us the count

Similarly, a *Bivariate* plot for continuous variable could display essential statistic like correlation, for a continuous versus discrete variable could lead us to very important conclusions like understanding data distribution across different levels of a categorical variable. A *bivariate* plot between two discrete variables could also be developed.

Box plot

A boxplot, also known as a box and whisker plot, the box and the whisker are clearly displayed in the below image. It is a very good visual representation when it comes to measuring the data distribution. Clearly plots the median values, outliers and the quartiles. Understanding data distribution is another important factor which leads to better model building. If data has outliers, box plot is a recommended way to identify them and take necessary actions.

***Syntax**: seaborn.boxplot(x=None, y=None, hue=None, data=None, order=None, hue_order=None, orient=None, color=None, palette=None,*

*saturation=0.75, width=0.8, dodge=True, fliersize=5, linewidth=None, whis=1.5, ax=None, **kwargs)*

Parameters:

x, y, hue: *Inputs for plotting long-form data.*

data: *Dataset for plotting. If x and y are absent, this is interpreted as wide-form.*

color: *Color for all of the elements.*

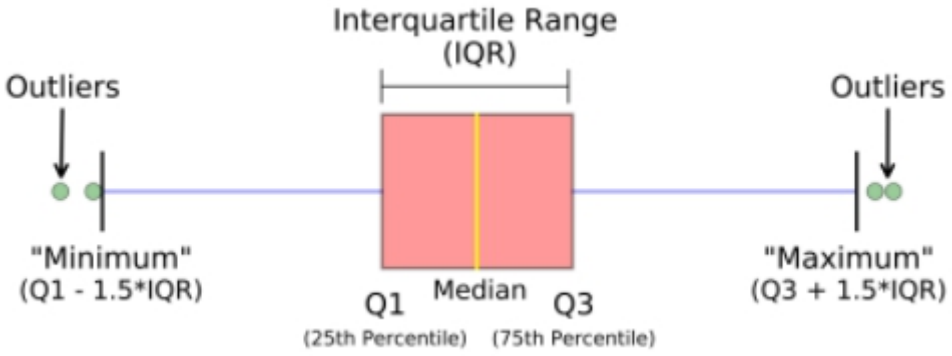
Returns: *It returns the Axes object with the plot drawn onto it.*

The box and whiskers chart shows how data is spread out. Five pieces of information are generally included in the chart

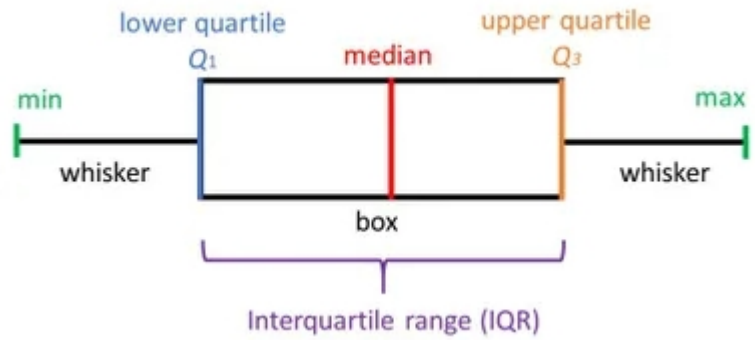
1. The minimum is shown at the far left of the chart, at the end of the left 'whisker'
2. First quartile, Q1, is the far left of the box (left whisker)
3. The median is shown as a line in the center of the box
4. Third quartile, Q3, shown at the far right of the box (right whisker)
5. The maximum is at the far right of the box

As could be seen in the below representations and charts, a box plot could be plotted for one or more than one variable providing very good insights to our data.

Representation of box plot.

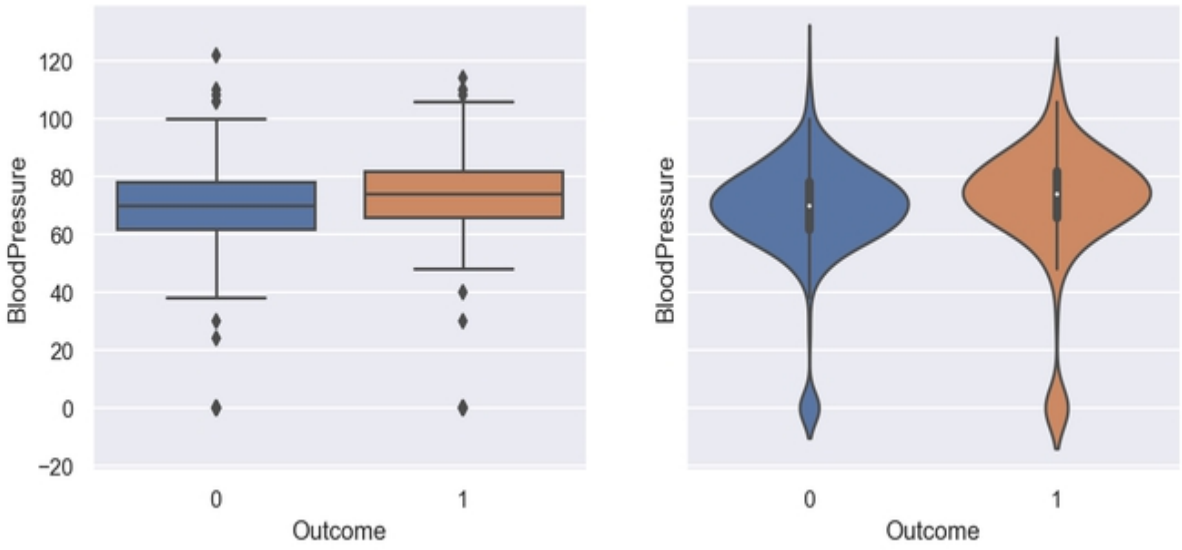


Box plot representing multi-variate categorical variables



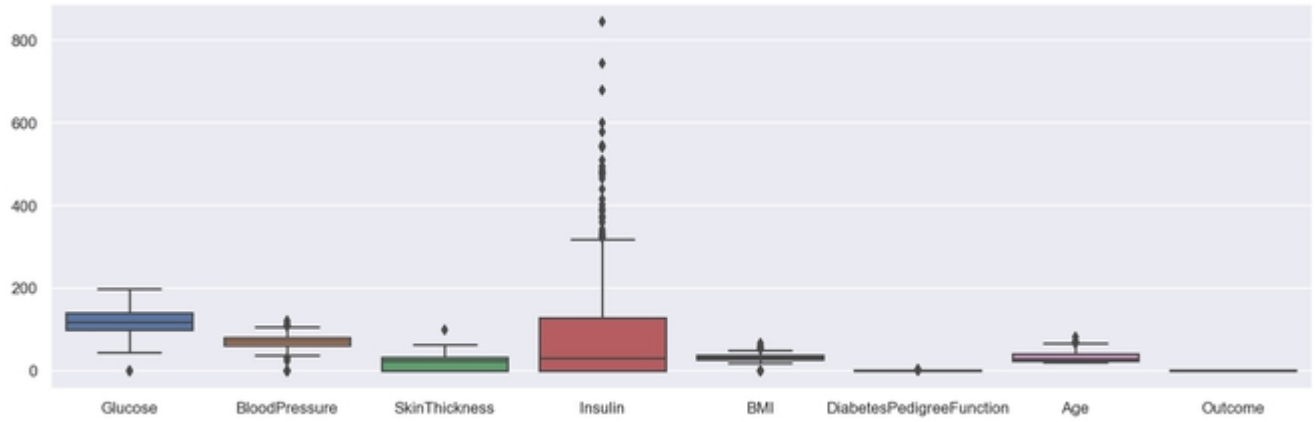
Box plot representing multi-variate categorical variables

```
# import required modules
import matplotlib as plt
import seaborn as sns

# Box plot and violin plot for Outcome vs BloodPressure
_, axes = plt.subplots(1, 2, sharey=True, figsize=(10, 4))

# box plot illustration
sns.boxplot(x='Outcome', y='BloodPressure', data=diabetes, ax=axes[0])

# violin plot illustration
sns.violinplot(x='Outcome', y='BloodPressure', data=diabetes, ax=axes[1])
```




```
# Box plot for all the numerical variables
```

```
sns.set(rc={'figure.figsize': (16, 5)})

# multiple box plot illustration
sns.boxplot(data=diabetes.select_dtypes(include='number'))
```



Output Multiple Box PLot

Scatter Plot

Scatter plots or scatter graphs is a *bivariate* plot having greater resemblance to line graphs in the way they are built. A line graph uses a line on an X-Y axis to plot a continuous function, while a scatter plot relies on dots to represent individual pieces of data. These plots are very useful to see if two variables are correlated. Scatter plot could be 2 dimensional or 3 dimensional.

***Syntax**: seaborn.scatterplot(x=None, y=None, hue=None, style=None, size=None, data=None, palette=None, hue_order=None, hue_norm=None, sizes=None, size_order=None, size_norm=None, markers=True, style_order=None, x_bins=None, y_bins=None, units=None, estimator=None, ci=95, n_boot=1000, alpha='auto', x_jitter=None, y_jitter=None, legend='brief', ax=None, **kwargs)*

Parameters:

***x, y**: Input data variables that should be numeric.*

***data**: Dataframe where each column is a variable and each row is an observation.*

***size**: Grouping variable that will produce points with different sizes.*

***style**: Grouping variable that will produce points with different markers.*

***palette**: Grouping variable that will produce points with different markers.*

***markers**: Object determining how to draw the markers for different levels.*

***alpha**: Proportional opacity of the points.*

***Returns:** This method returns the Axes object with the plot drawn onto it.*

Advantages of a scatter plot

Displays correlation between variables
Suitable for large data sets
Easier to find data clusters
Better representation of each data point

Pie Chart

Pie chart is a *univariate* analysis and are typically used to show percentage or proportional data. The percentage distribution of each class in a variable is provided next to the corresponding slice of the pie. The python libraries which could be used to build a pie chart is *matplotlib* and *seaborn.*

Syntax: *matplotlib.pyplot.pie(data, explode=None, labels=None, colors=None, autopct=None, shadow=False)*

Parameters:

data *represents the array of data values to be plotted, the fractional area of each slice is represented by* ***data/sum(data)****. If sum(data)<1, then the data values returns the fractional area directly, thus resulting pie will have empty wedge of size 1-sum(data).*

labels *is a list of sequence of strings which sets the label of each wedge.*

color *attribute is used to provide color to the wedges.*

autopct *is a string used to label the wedge with their numerical value.*

shadow *is used to create shadow of wedge.*

Below are the advantages of a pie chart

1. Easier visual summarization of large data points
2. Effect and size of different classes can be easily understood
3. Percentage points are used to represent the classes in the data points

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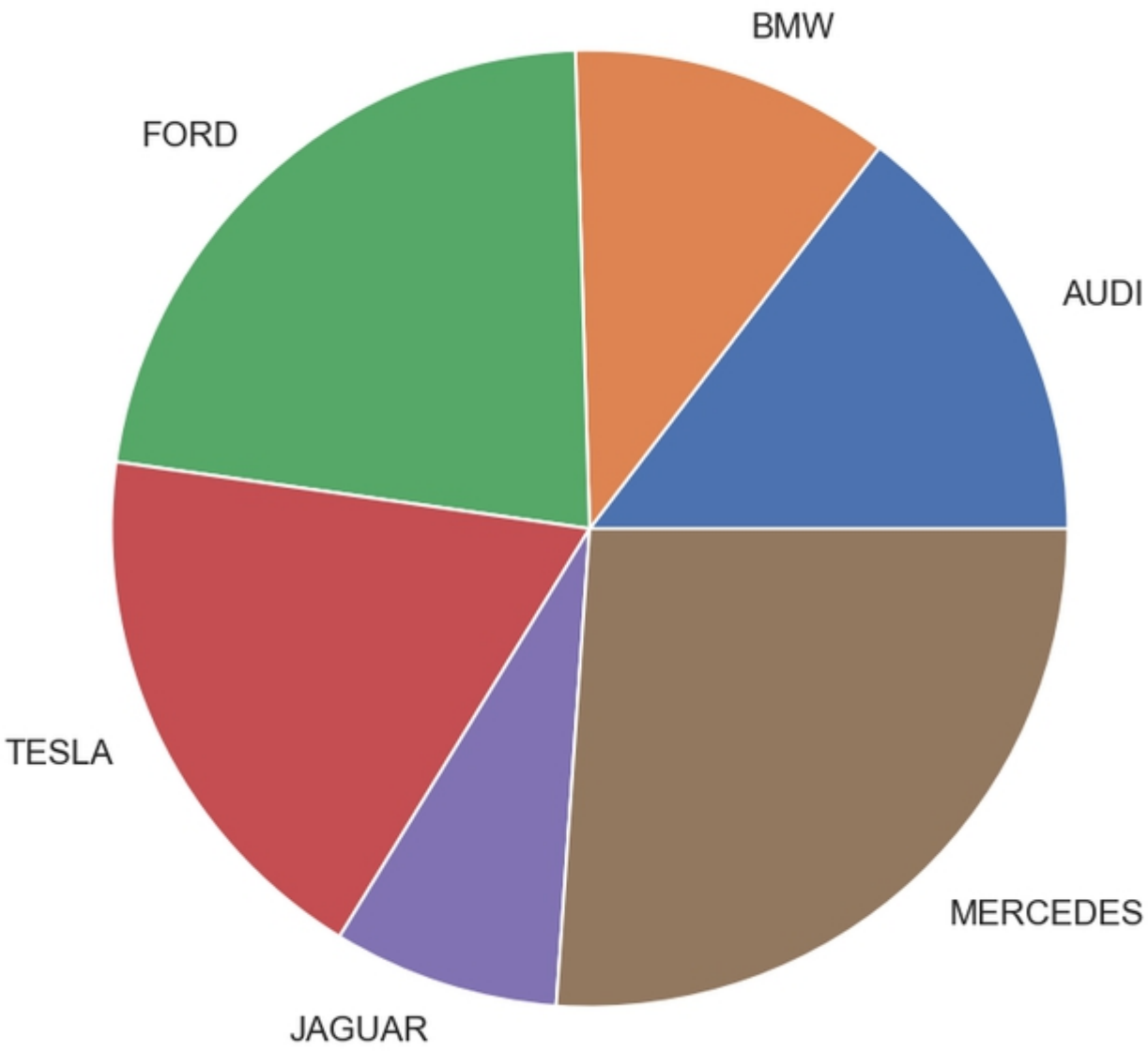
```
# import required module
import matplotlib.pyplot as plt

# Creating dataset
cars = ['AUDI', 'BMW', 'FORD', 'TESLA', 'JAGUAR', 'MERCEDES']
data = [23, 17, 35, 29, 12, 41]

# Creating plot
fig = plt.figure(figsize=(10, 7))
```

```
plt.pie(data, labels=cars)

# Show plot
plt.show()
```



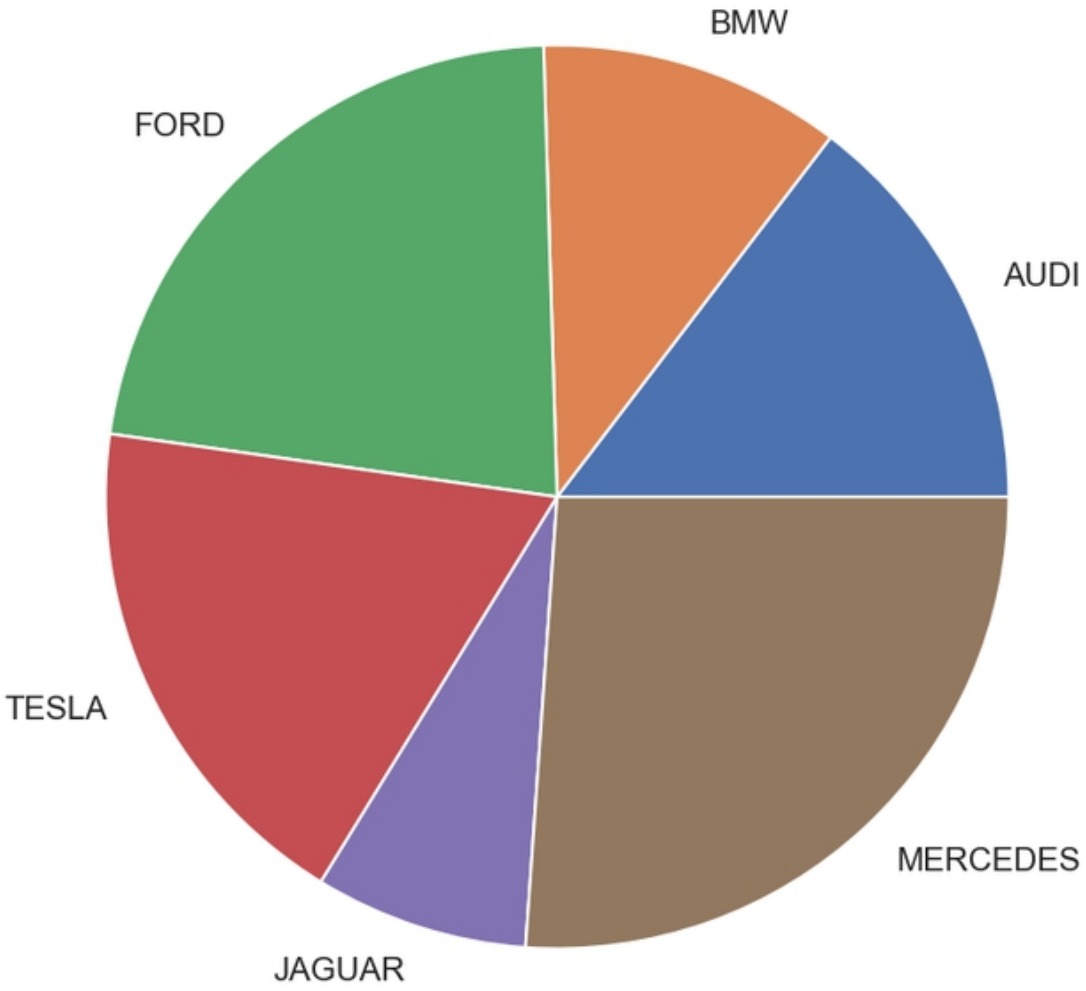

BMW
FORD
AUDI
TESLA
MERCEDES
JAGUAR

Table of difference between Matplotlib and Seaborn

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Features	Matplotlib	Seaborn
Functionality	It is utilized for making basic graphs. Datasets are visualised with the help of bargraphs, histograms, piecharts, scatter plots, lines and so on.	Seaborn contains a number of patterns and plots for data visualization. It uses fascinating themes. It helps in compiling whole data into a single plot. It also provides distribution of data.
Syntax	It uses comparatively complex and lengthy syntax. Example: Syntax for bargraph- matplotlib.pyplot.bar(x_axis, y_axis).	It uses comparatively simple syntax which is easier to learn and understand. Example: Syntax for bargraph- seaborn.barplot(x_axis, y_axis).
Dealing Multiple Figures	We can open and use multiple figures simultaneously. However they are closed distinctly. Syntax to close one figure at a time: matplotlib.pyplot.close(). Syntax to close all the figures: matplotlib.pyplot.close(“all”)	Seaborn sets time for the creation of each figure. However, it may lead to (OOM) out of memory issues

Features	Matplotlib	Seaborn
Visualization	Matplotlib is well connected with Numpy and Pandas and acts as a graphics package for data visualization in python. Pyplot provides similar features and syntax as in MATLAB. Therefore, MATLAB users can easily study it.	Seaborn is more comfortable in handling Pandas data frames. It uses basic sets of methods to provide beautiful graphics in python.
Pliability	Matplotlib is a highly customized and robust	Seaborn avoids overlapping of plots with the help of its default themes
Data Frames and Arrays	Matplotlib works efficiently with data frames and arrays.It treats figures and axes as objects. It contains various stateful APIs for plotting. Therefore plot() like methods can work without parameters.	Seaborn is much more functional and organized than Matplotlib and treats the whole dataset as a single unit. Seaborn is not so stateful and therefore, parameters are required while calling methods like plot()
Use Cases	Matplotlib plots various graphs using Pandas and Numpy	Seaborn is the extended version of Matplotlib which uses Matplotlib along with Numpy and Pandas for plotting graphs