Group A

Assignment No: 1

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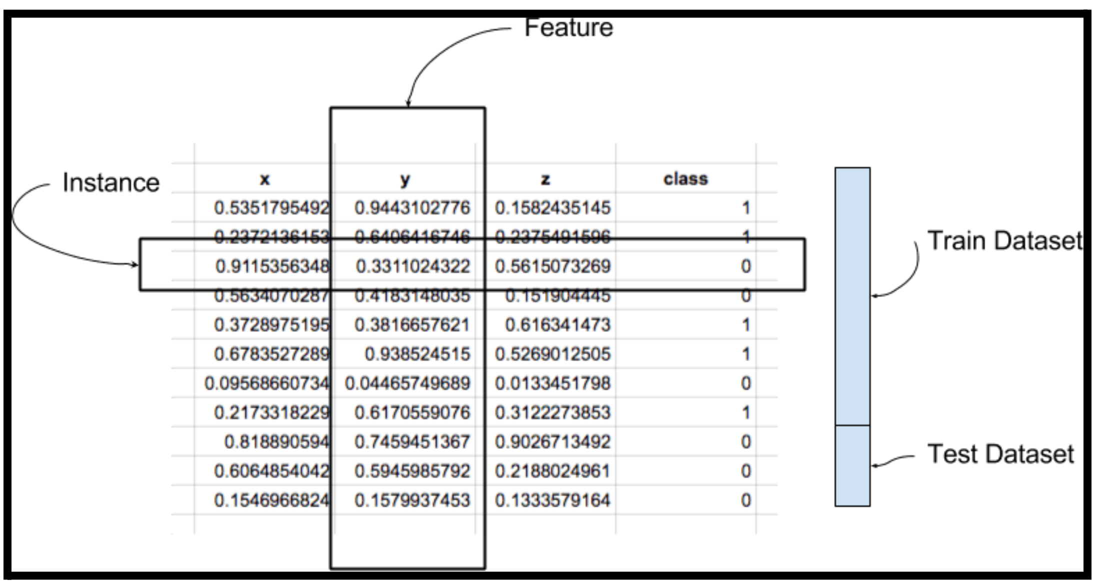
1. **Introduction to Dataset**

A dataset is a collection of records, similar to a relational database table. Records are similar to table rows, but the columns can contain not only strings or numbers, but also nested data structures such as lists, maps, and other records.



Instance: A single row of data is called an instance. It is an observation from the domain.

Feature: A single column of data is called a feature. It is a component of an observation and is also called an attribute of a data instance. Some features may be inputs to a model (the predictors) and others may be outputs or the features to be predicted.

Data Type: Features have a data type. They may be real or integer-valued or may have a categorical or ordinal value. You can have strings, dates, times, and more complex types, but typically they are reduced to real or categorical values when working with traditional machine learning methods.

Datasets: A collection of instances is a dataset and when working with machine learning methods we typically need a few datasets for different purposes.

Training Dataset: A dataset that we feed into our machine learning algorithm to train our model.

Testing Dataset: A dataset that we use to validate the accuracy of our model but is not used to train the model. It may be called the validation dataset.

Data Represented in a Table:

Data should be arranged in a two-dimensional space made up of rows and columns. This type of data structure makes it easy to understand the data and pinpoint any problems. An example of some raw data stored as a CSV (comma separated values).

```
1., Avatar, 18-12-2009, 7.8
2., Titanic, 18-11-1997,
3., Avengers Infinity War, 27-04-2018, 8.5
```

The representation of the same data in a table is as follows:

S.No	Movie	Release Date	Ratings (IMDb)
1.	Avatar	18-12-2009	7.8
2.	Titanic	18-11-1997	*Na*
3.	Avengers Infinity War	27-04-2018	8.5

Pandas Data Types

A data type is essentially an internal construct that a programming language uses to understand how to store and manipulate data.

A possible confusing point about pandas data types is that there is some overlap between pandas, python and numpy. This table summarizes the key points:

Pandas dtype	Python type	NumPy type	Usage
object	str or mixed	string_, unicode_, mixed types	Text or mixed numeric and non-numeric values
int64	int	int_, int8, int16, int32, int64, uint8, uint16, uint32, uint64	Integer numbers
float64	float	float_, float16, float32, float64	Floating point numbers
bool	bool	bool_	True/False values
datetime64	NA	datetime64[ns]	Date and time values
timedelta[ns]	NA	NA	Differences between two datetimes
category	NA	NA	Finite list of text values

2. Python Libraries for Data Science

a. Pandas

Pandas is an open-source Python package that provides high-performance, easy-to-use data structures and data analysis tools for the labeled data in Python programming language.

What can you do with Pandas?

1. Indexing, manipulating, renaming, sorting, merging data frame
2. Update, Add, Delete columns from a data frame
3. Impute missing files, handle missing data or NANs
4. Plot data with histogram or box plot

b. NumPy

One of the most fundamental packages in Python, NumPy is a general-purpose array-processing package. It provides high-performance multidimensional array objects and tools to work with the arrays. NumPy is an efficient container of generic multi-dimensional data.

NumPy’s main object is the homogeneous multidimensional array. It is a table of elements or numbers of the same datatype, indexed by a tuple of positive integers. In NumPy, dimensions are called axes and the number of axes is called rank. NumPy’s array class is called ndarray aka array.

What can you do with NumPy?

1. Basic array operations: add, multiply, slice, flatten, reshape, index arrays
2. Advanced array operations: stack arrays, split into sections, broadcast arrays
3. Work with DateTime or Linear Algebra
4. Basic Slicing and Advanced Indexing in NumPy Python

c. Matplotlib

This is undoubtedly my favorite and a quintessential Python library. You can create stories with the data visualized with Matplotlib. Another library from the SciPy Stack, Matplotlib plots 2D figures.

What can you do with Matplotlib?

Histogram, bar plots, scatter plots, area plot to pie plot, Matplotlib can depict a wide range of visualizations. With a bit of effort and tint of visualization capabilities, with Matplotlib, you can create just any visualizations:Line plots

- Scatter plots
- Area plots
- Bar charts and Histograms
- Pie charts
- Stem plots
- Contour plots
- Quiver plots

- Spectrograms

Matplotlib also facilitates labels, grids, legends, and some more formatting entities with Matplotlib.

d. Seaborn

So when you read the official documentation on Seaborn, it is defined as the data visualization library based on Matplotlib that provides a high-level interface for drawing attractive and informative statistical graphics. Putting it simply, seaborn is an extension of Matplotlib with advanced features.

What can you do with Seaborn?

1. Determine relationships between multiple variables (correlation)
2. Observe categorical variables for aggregate statistics
3. Analyze univariate or bi-variate distributions and compare them between different data subsets
4. Plot linear regression models for dependent variables
5. Provide high-level abstractions, multi-plot grids
6. Seaborn is a great second-hand for R visualization libraries like corrplot and ggplot.

e. 5. Scikit Learn

Introduced to the world as a Google Summer of Code project, Scikit Learn is a robust machine learning library for Python. It features ML algorithms like SVMs, random forests, k-means clustering, spectral clustering, mean shift, cross-validation and more... Even NumPy, SciPy and related scientific operations are supported by Scikit Learn with Scikit Learn being a part of the SciPy Stack.

What can you do with Scikit Learn?

1. Classification: Spam detection, image recognition
2. Clustering: Drug response, Stock price
3. Regression: Customer segmentation, Grouping experiment outcomes
4. Dimensionality reduction: Visualization, Increased efficiency

5. Model selection: Improved accuracy via parameter tuning
6. Pre-processing: Preparing input data as a text for processing with machine learning algorithms.

3. Description of Dataset:

The Iris dataset was used in R.A. Fisher's classic 1936 paper, The Use of Multiple Measurements in Taxonomic Problems, and can also be found on the UCI Machine Learning Repository.

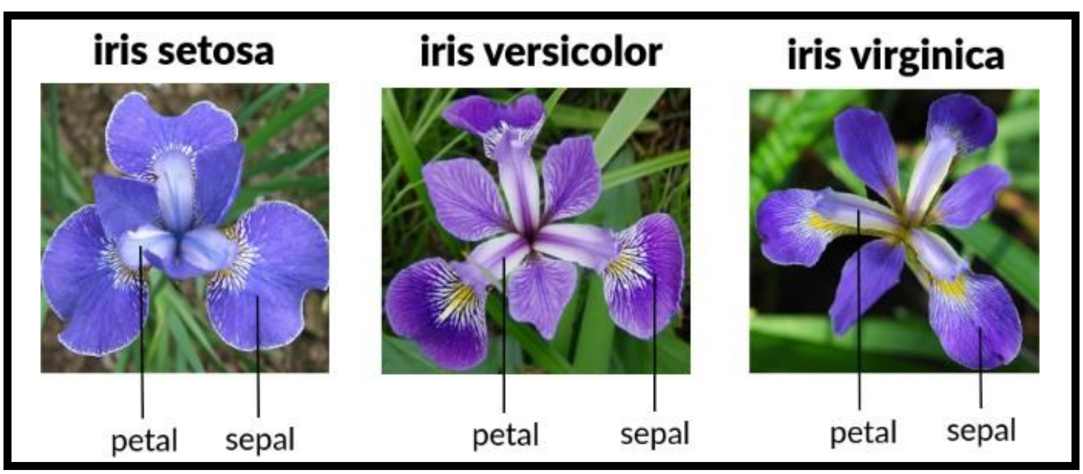
It includes three iris species with 50 samples each as well as some properties about each flower. One flower species is linearly separable from the other two, but the other two are not linearly separable from each other.

Total Sample- 150

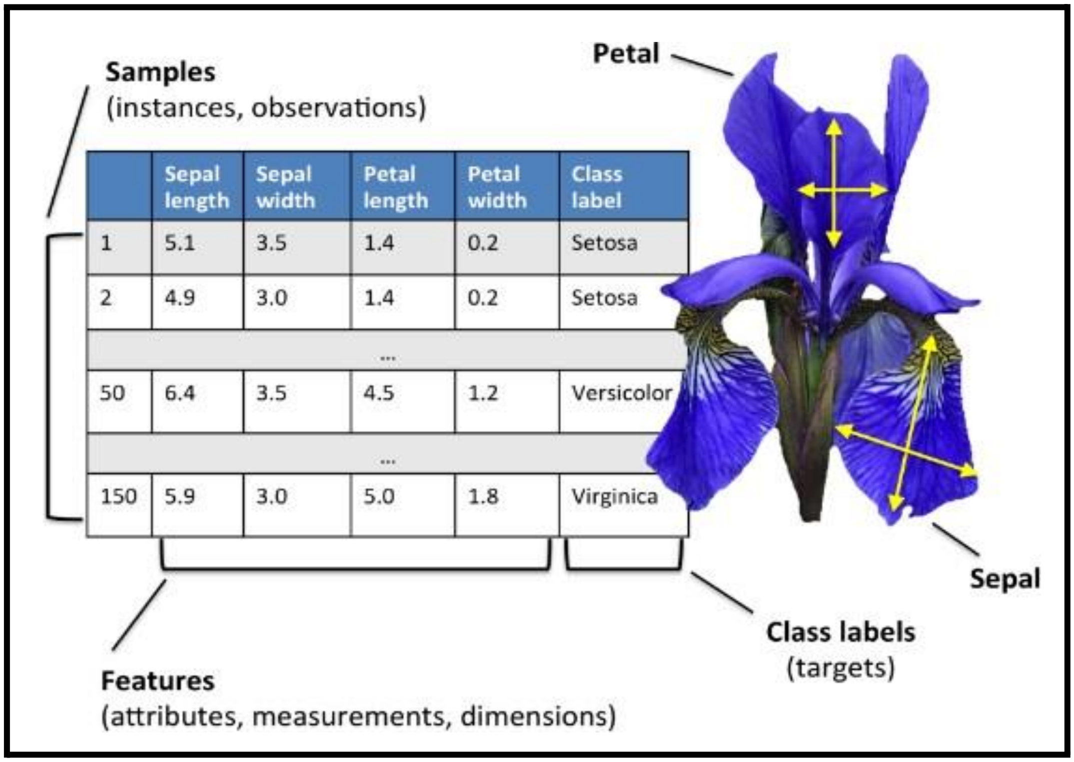
The columns in this dataset are:

1. Id
2. SepalLengthCm
3. SepalWidthCm
4. PetalLengthCm
5. PetalWidthCm
6. Species

3 Different Types of Species each contain 50 Sample-



Description of Dataset-



4. Panda Dataframe functions for Load Dataset

 # The columns of the resulting DataFrame have different dtypes.

iris.dtypes

1. The dataset is downloads from UCI repository.

csv_url = 'https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data'

2. Now Read CSV File as a Dataframe in Python from from path where you saved the same The Iris data set is stored in .csv format. '.csv' stands for comma separated values. It is easier to load .csv files in Pandas data frame and perform various analytical operations on it.

   Load Iris.csv into a Pandas data frame —

   `Syntax-`

   iris = pd.read_csv(csv_url, header = None)

3. The csv file at the UCI repository does not contain the variable/column names. They are located in a separate file.

col_names = ['Sepal_Length','Sepal_Width','Petal_Length','Petal_Width','Species']

4. read in the dataset from the UCI Machine Learning Repository link and specify column names to use

   iris = pd.read_csv(csv_url, names = col_names)

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

5. **Panda Dataframe functions for Data Preprocessing :**

Dataframe Operations:

Sr. No	**Data Frame Function**	**Description**
1	**dataset.head(n=5)**	**Return the first n rows.**
2	**dataset.tail(n=5)**	**Return the last n rows.**
3	**dataset.index**	The index (row labels) of the Dataset.
4	**dataset.columns**	The column labels of the Dataset.
5	**dataset.shape**	Return a tuple representing the dimensionality of the Dataset.
6	**dataset.dtypes**	Return the dtypes in the Dataset. This returns a Series with the data type of each column. The result's index is the original Dataset's columns.

		Columns with mixed types are stored with the object dtype.
7	**dataset.columns.values**	Return the columns values in the Dataset in array format
8	**dataset.describe(include='all')**	Generate descriptive statistics. to view some basic statistical details like percentile, mean, std etc. of a data frame or a series of numeric values. Analyzes both numeric and object series, as well as Dataset column sets of mixed data types.
9	**dataset['Column name]**	Read the Data Column wise.
10	**dataset.sort_index(axis=1, ascending=False)**	Sort object by labels (along an axis).
11	**dataset.sort_values(by="Column name")**	Sort values by column name.
12	**dataset.iloc[5]**	Purely integer-location based indexing for selection by position.
13	**dataset[0:3]**	Selecting via [], which slices the rows.
14	**dataset.loc[:, ["Col_name1", "col_name2"]]**	Selection by label
15	**dataset.iloc[:n, :]**	a subset of the first n rows of the original data
16	**dataset.iloc[:, :n]**	a subset of the first n columns of the original data
17	**dataset.iloc[:m, :n]**	a subset of the first m rows and the first n columns

Few Examples of iLoc to slice data for iris Dataset

Sr. No	Data Frame Function	Description	Output
1	**dataset.iloc[3:5, 0:2]**	Slice the data	Id SepalLengthCm 3 4 4.6 4 5 5.0
2	**dataset.iloc[[1, 2, 4], [0, 2]]**	By lists of integer position locations, similar to the NumPy/Python style:	Id SepalWidthCm 1 2 3.0 2 3 3.2 4 5 3.6
3	**dataset.iloc[1:3, :]**	For slicing rows explicitly:	Id SepalLengthCm SepalWidthCm PetalLengthCm PetalWidthCm Species 1 2 4.9 3.0 1.4 0.2 Iris-setosa 2 3 4.7 3.2 1.3 0.2 Iris-setosa
4	**dataset.iloc[:, 1:3]**	For slicing Column explicitly:	SepalLengthCm SepalWidthCm 0 5.1 3.5 1 4.9 3.0 2 4.7 3.2 3 4.6 3.1
4	**dataset.iloc[1, 1]**	For getting a value explicitly:	4.9
5	**dataset['SepalLengthCm'].iloc[5]**	Accessing Column and Rows by position	5.4

<table>
<tr>
<td>6</td>
<td>cols_2_4=dataset.columns[2:4]

dataset[cols_2_4]</td>
<td>Get Column Name then get data from column</td>
<td>
<table>
<tr><th></th><th>SepalWidthCm</th><th>PetalLengthCm</th></tr>
<tr><td>0</td><td>3.5</td><td>1.4</td></tr>
<tr><td>1</td><td>3.0</td><td>1.4</td></tr>
<tr><td>2</td><td>3.2</td><td>1.3</td></tr>
<tr><td>3</td><td>3.1</td><td>1.5</td></tr>
</table>
</td>
</tr>
<tr>
<td>7</td>
<td>dataset[dataset.columns[2:4]].iloc[5:10]</td>
<td>in one Expression answer for the above two commands</td>
<td>
<table>
<tr><th></th><th>SepalWidthCm</th><th>PetalLengthCm</th></tr>
<tr><td>5</td><td>3.9</td><td>1.7</td></tr>
<tr><td>6</td><td>3.4</td><td>1.4</td></tr>
<tr><td>7</td><td>3.4</td><td>1.5</td></tr>
<tr><td>8</td><td>2.9</td><td>1.4</td></tr>
<tr><td>9</td><td>3.1</td><td>1.5</td></tr>
</table>
</td>
</tr>
</table>

Checking of Missing Values in Dataset:

- **isnull()** is the function that is used to check missing values or null values in pandas python.
- isna() function is also used to get the count of missing values of column and row wise count of missing values
- The dataset considered for explanation is:

	Name	State	Gender	Score
0	George	Arizona	M	63.0
1	Andrea	Georgia	F	48.0
2	micheal	Newyork	M	56.0
3	maggie	Indiana	F	75.0
4	Ravi	Florida	M	NaN
5	Xien	California	M	77.0
6	Jalpa	NaN	NaN	NaN
7	NaN	NaN	NaN	NaN

a. **is there any missing values in dataframe as a whole**

Function: DataFrame.isnull()

Output:

```
    Name  State  Gender  Score
0  False  False   False  False
1  False  False   False  False
2  False  False   False  False
3  False  False   False  False
4  False  False   False   True
5  False  False   False  False
6  False   True    True   True
7   True   True    True   True
```

b. **is there any missing values across each column**

Function: DataFrame.isnull().any()

Output:

```
Name      True
State     True
Gender    True
Score     True
dtype: bool
```

c. **count of missing values across each column using isna() and isnull()**

In order to get the count of missing values of the entire dataframe isnull() function is used. sum() which does the column wise sum first and doing another sum() will get the count of missing values of the entire dataframe.

Function: dataframe.isnull().sum().sum()

Output : 8

d. **count row wise missing value using isnull()**

Function: dataframe.isnull().sum(axis = 1)

Output:

```
0    0
1    0
2    0
3    0
4    1
5    0
6    3
7    4
dtype: int64
```

e. **count Column wise missing value using isnull()**

Method 1:

Function: dataframe.isnull().sum()

Output:

```
Name      1
State     2
Gender    2
Score     3
dtype: int64
```

Method 2:

unction: dataframe.isna().sum()

```
Name      1
State     2
Gender    2
Score     3
dtype: int64
```

f. **count of missing values of a specific column.**

Function:dataframe.col_name.isnull().sum()

```
df1.Gender.isnull().sum()
```

Output: 2

g. **groupby count of missing values of a column.**

In order to get the count of missing values of the particular column by group in pandas we will be using isnull() and sum() function with apply() and groupby() which performs the group wise count of missing values as shown below.

Function:

```
df1.groupby(['Gender'])['Score'].apply(lambda x:
x.isnull().sum())
```

Output:

```
Gender
F    0
M    1
Name: Score, dtype: int64
```

6. **Panda functions for Data Formatting and Normalization**

The Transforming data stage is about converting the data set into a format that can be analyzed or modelled effectively, and there are several techniques for this process.

a. **Data Formatting:** Ensuring all data formats are correct (e.g. object, text, floating number, integer, etc.) is another part of this initial 'cleaning' process. If you are working with dates in Pandas, they also need to be stored in the exact format to use special date-time functions.

Functions used for data formatting

Sr. No	Data Frame Function	Description	Output

1.	**df.dtypes**	To check the data type	`df.dtypes`
			`sepal length (cm)    float64`
			`sepal width (cm)     float64`
			`petal length (cm)    float64`
			`petal width (cm)     float64`
			`dtype: object`

2.	**df['petal length (cm)']= df['petal length (cm)'].astype("int")**	To change the data type (data type of 'petal length (cm)'changed to int)	`df.dtypes`
			`sepal length (cm)    float64`
			`sepal width (cm)     float64`
			`petal length (cm)      int64`
			`petal width (cm)     float64`
			`dtype: object`

b. Data normalization: Mapping all the nominal data values onto a uniform scale (e.g. from 0 to 1) is involved in data normalization. Making the ranges consistent across variables helps with statistical analysis and ensures better comparisons later on.It is also known as Min-Max scaling.

Algorithm:

Step 1 : Import pandas and sklearn library for preprocessing

```
from sklearn import preprocessing
```

Step 2: Load the iris dataset in dataframe object df

Step 3: Print iris dataset.

```
df.head()
```

Step 5: Create a minimum and maximum processor object

```
min_max_scaler = preprocessing.MinMaxScaler()
```

Step 6: Separate the feature from the class label

```
x=df.iloc[:,:4]
```

Step 6: Create an object to transform the data to fit minmax processor

```
x_scaled = min_max_scaler.fit_transform(x)
```

Step 7: Run the normalizer on the dataframe

```
df_normalized = pd.DataFrame(x_scaled)
```

Step 8: View the dataframe

```
df_normalized
```

Output: After Step 3:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

Output after step 8:

	0	1	2	3
0	0.222222	0.625000	0.067797	0.041667
1	0.166667	0.416667	0.067797	0.041667
2	0.111111	0.500000	0.050847	0.041667
3	0.083333	0.458333	0.084746	0.041667
4	0.194444	0.666667	0.067797	0.041667

7. Panda Functions for handling categorical variables

- **Categorical variables** have values that **describe a 'quality' or 'characteristic'** of a data unit, like **'what type' or 'which category'.**
- Categorical variables fall into **mutually exclusive (in one category or in another)** and **exhaustive (include all possible options)** categories. Therefore, categorical variables are qualitative variables and t**end to be represented by a non-numeric value.**

- Categorical features refer **to string type data** and can be easily understood by human beings. But in case of a **machine, it cannot interpret the categorical data directly**. Therefore, the categorical data must be **translated into numerical data that can be understood by machine.**

There are many ways to convert categorical data into numerical data. Here the three most used methods are discussed.

a. Label Encoding: Label Encoding refers to **converting the labels into a numeric form** so as to convert them into the machine-readable form. **It is an important preprocessing step for the structured dataset** in supervised learning.

Example : Suppose we have a column Height in some dataset. After applying label encoding, the Height column is converted into:

Height
Tall
Medium
Short

Height
0
1
2

where 0 is the label for tall, 1 is the label for medium, and 2 is a label for short height.

Label Encoding on iris dataset: For iris dataset the target column which is Species. It contains three species Iris-setosa, Iris-versicolor, Iris-virginica.

Sklearn Functions for Label Encoding:

- **`preprocessing.LabelEncoder` :** It Encode labels with value between 0 and n_classes-1.
- **`fit_transform(y)`:**

  `Parameters:` `yarray-like of shape (n_samples,)`
  `Target values.`

  `Returns:` `yarray-like of shape (n_samples,)`
  `Encoded labels.`

This transformer should be used to encode target values, and not the input.

Algorithm:

Step 1 : Import pandas and sklearn library for preprocessing

```
from sklearn import preprocessing
```

Step 2: Load the iris dataset in dataframe object df

Step 3: Observe the unique values for the Species column.

```
df['Species'].unique()
```

```
output: array(['Iris-setosa', 'Iris-versicolor',
'Iris-virginica'], dtype=object)
```

Step 4: define label_encoder object knows how to understand word labels.

```
label_encoder = preprocessing.LabelEncoder()
```

Step 5: Encode labels in column 'species'.

```
df['Species']= label_encoder.fit_transform(df['Species'])
```

Step 6: Observe the unique values for the Species column.

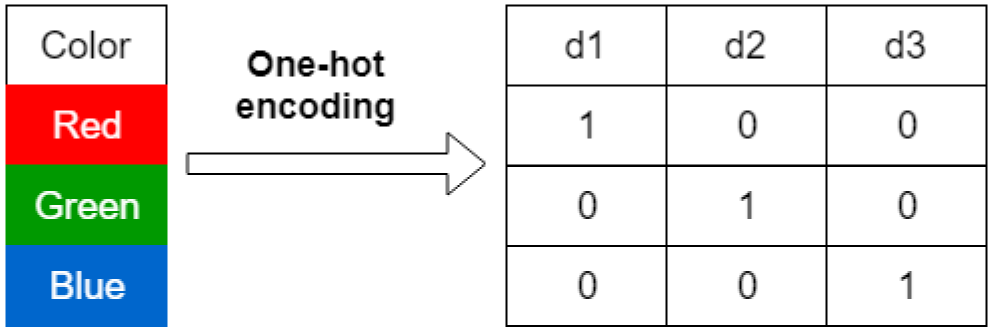
```
df['Species'].unique()
Output: array([0, 1, 2], dtype=int64)
```

- Use LabelEncoder when there are only two possible values of a categorical feature. For example, features having value such as yes or no. Or, maybe, gender features when there are only two possible values including male or female.

Limitation: Label encoding converts the data in machine-readable form, but it assigns a **unique number(starting from 0) to each class of data**. This may lead to the generation of **priority issues in the data sets**. A label with a high value may be considered to have high priority than a label having a lower value.

b. One-Hot Encoding:

In one-hot encoding, we create a new set of dummy (binary) variables that is equal to the number of categories (k) in the variable. For example, let’s say we have a categorical variable Color with three categories called “Red”, “Green” and “Blue”, we need to use three dummy variables to encode this variable using one-hot encoding. A dummy (binary) variable just takes the value 0 or 1 to indicate the exclusion or inclusion of a category.



In one-hot encoding,

“Red” color is encoded as **[1 0 0]** vector of size 3.

“Green” color is encoded as **[0 1 0]** vector of size 3.

“Blue” color is encoded as **[0 0 1]** vector of size 3.

One-hot encoding on iris dataset: For iris dataset the target column which is Species. It contains three species Iris-setosa, Iris-versicolor, Iris-virginica.

Sklearn Functions for One-hot Encoding:

- **`sklearn.preprocessing.OneHotEncoder():`** Encode categorical integer features using a one-hot aka one-of-K scheme

Algorithm:

Step 1 : Import pandas and sklearn library for preprocessing

```
from sklearn import preprocessing
```

Step 2: Load the iris dataset in dataframe object df

Step 3: Observe the unique values for the Species column.

```
df['Species'].unique()
```

```
output: array(['Iris-setosa', 'Iris-versicolor',
'Iris-virginica'], dtype=object)
```

Step 4: Apply label_encoder object for label encoding the Observe the unique values for the Species column.

```
df['Species'].unique()
```

```
Output: array([0, 1, 2], dtype=int64)
```

Step 5: Remove the target variable from dataset

```
features_df=df.drop(columns=['Species'])
```

Step 6: Apply one_hot encoder for Species column.

```
enc = preprocessing.OneHotEncoder()
```

```
enc_df=pd.DataFrame(enc.fit_transform(df[['Species']])).toarray()
```

Step 7: Join the encoded values with Features variable

```
df_encode = features_df.join(enc_df)
```

Step 8: Observe the merge dataframe

```
df_encode
```

Step 9: Rename the newly encoded columns.

```
df_encode.rename(columns = {0:'Iris-Setosa',
1:'Iris-Versicolor',2:'Iris-virginica'}, inplace = True)
```

Step 10: Observe the merge dataframe

```
df_encode
```

Output after Step 8:

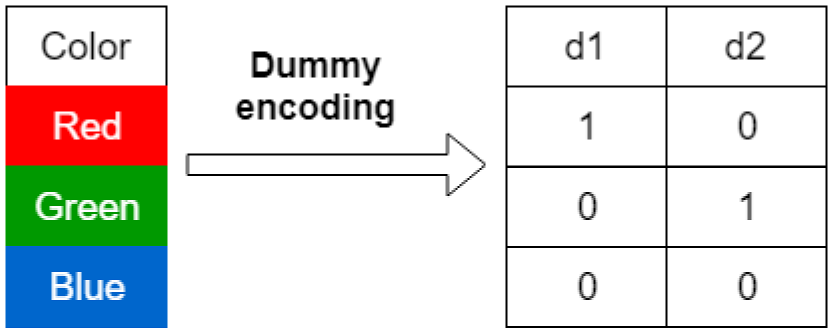
	Sepal_Length	Sepal_Width	Petal_Length	Petal_Width	0	1	2
0	5.1	3.5	1.4	0.2	1.0	0.0	0.0
1	4.9	3.0	1.4	0.2	1.0	0.0	0.0
2	4.7	3.2	1.3	0.2	1.0	0.0	0.0
3	4.6	3.1	1.5	0.2	1.0	0.0	0.0
4	5.0	3.6	1.4	0.2	1.0	0.0	0.0

Output after Step 10:

	Sepal_Length	Sepal_Width	Petal_Length	Petal_Width	Iris-Setosa	Iris-Versicolor	Iris-virginica
0	5.1	3.5	1.4	0.2	1.0	0.0	0.0
1	4.9	3.0	1.4	0.2	1.0	0.0	0.0
2	4.7	3.2	1.3	0.2	1.0	0.0	0.0
3	4.6	3.1	1.5	0.2	1.0	0.0	0.0
4	5.0	3.6	1.4	0.2	1.0	0.0	0.0

c. Dummy Variable Encoding

Dummy encoding also uses dummy (binary) variables. Instead of creating a number of dummy variables that is equal to the number of categories (k) in the variable, dummy encoding uses k-1 dummy variables. To encode the same Color variable with three categories using the dummy encoding, we need to use only two dummy variables.



In dummy encoding,

“Red” color is encoded as **[1 0]** vector of size 2.

“Green” color is encoded as **[0 1]** vector of size 2.

“Blue” color is encoded as **[0 0]** vector of size 2.

Dummy encoding removes a duplicate category present in the one-hot encoding.

Pandas Functions for One-hot Encoding with dummy variables:

- **`pandas.get_dummies(data, prefix=None, prefix_sep='_', dummy_na=False, columns=None, sparse=False, drop_first=False, dtype=None)`**: Convert categorical variable into dummy/indicator variables.
- **Parameters**:

  data:array-like, Series, or DataFrame

  Data of which to get dummy indicators.

  prefixstr: list of str, or dict of str, default None

  String to append DataFrame column names.

  prefix_sep: str, default ‘_’

  If appending prefix, separator/delimiter to use. Or pass a list or dictionary as with prefix.

  dummy_nabool: default False

  Add a column to indicate NaNs, if False NaNs are ignored.

  columns: list:like, default None

Column names in the DataFrame to be encoded. If columns is None then all the columns with object or category dtype will be converted.

sparse: bool: default False

Whether the dummy-encoded columns should be backed by a SparseArray (True) or a regular NumPy array (False).

drop_first:bool, default False

Whether to get k-1 dummies out of k categorical levels by removing the first level.

dtype: dtype, default np.uint8

Data type for new columns. Only a single dtype is allowed.

- **Return :** DataFrame with Dummy-coded data.

Algorithm:

Step 1 : Import pandas and sklearn library for preprocessing

```
from sklearn import preprocessing
```

Step 2: Load the iris dataset in dataframe object df

Step 3: Observe the unique values for the Species column.

```
df['Species'].unique()
```

output: array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=object)

Step 4: Apply label_encoder object for label encoding the Observe the unique values for the Species column.

```
df['Species'].unique()
Output: array([0, 1, 2], dtype=int64)
```

Step 6: Apply one_hot encoder with dummy variables for Species column.

```
one_hot_df = pd.get_dummies(df, prefix="Species",
columns=['Species'], drop_first=True)
```

Step 7: Observe the merge dataframe

```
one_hot_df
```

	Sepal_Length	Sepal_Width	Petal_Length	Petal_Width	Species_1	Species_2
0	5.1	3.5	1.4	0.2	0	0
1	4.9	3.0	1.4	0.2	0	0
2	4.7	3.2	1.3	0.2	0	0
3	4.6	3.1	1.5	0.2	0	0
4	5.0	3.6	1.4	0.2	0	0
...	...	...	...	...	...	...

Conclusion- In this way we have explored the functions of the python library for Data Preprocessing, Data Wrangling Techniques and How to Handle missing values on Iris Dataset.

Assignment Question

1. **Explain Data Frame with Suitable example.**
2. **What is the limitation of the label encoding method?**
3. **What is the need of data normalization?**
4. **What are the different Techniques for Handling the Missing Data?**

Group A

Assignment No: 2

Contents for Theory:

1. **Creation of Dataset using Microsoft Excel.**
2. **Identification and Handling of Null Values**
3. **Identification and Handling of Outliers**
4. **Data Transformation for the purpose of :**
    a. **To change the scale for better understanding**
    b. **To decrease the skewness and convert distribution into normal distribution**

Theory:

1. **Creation of Dataset using Microsoft Excel.**

The dataset is created in "CSV" format.

- The name of dataset is **StudentsPerformance**
- **The features of the dataset are:** Math_Score, Reading_Score, Writing_Score, Placement_Score, Club_Join_Date .
- **Number of Instance**s: 30
- **The response variable is**: Placement_Offer_Count .
- **Range of Values:**
  Math_Score [60-80], Reading_Score[75-,95], ,Writing_Score [60,80], Placement_Score[75-100], Club_Join_Date [2018-2021].
- **The response variable is** the number of placement offers facilitated to particular students, which is largely depend on Placement_Score

To fill the values in the dataset the **RANDBETWEEN** is used. Returns a random integer number between the numbers you specify

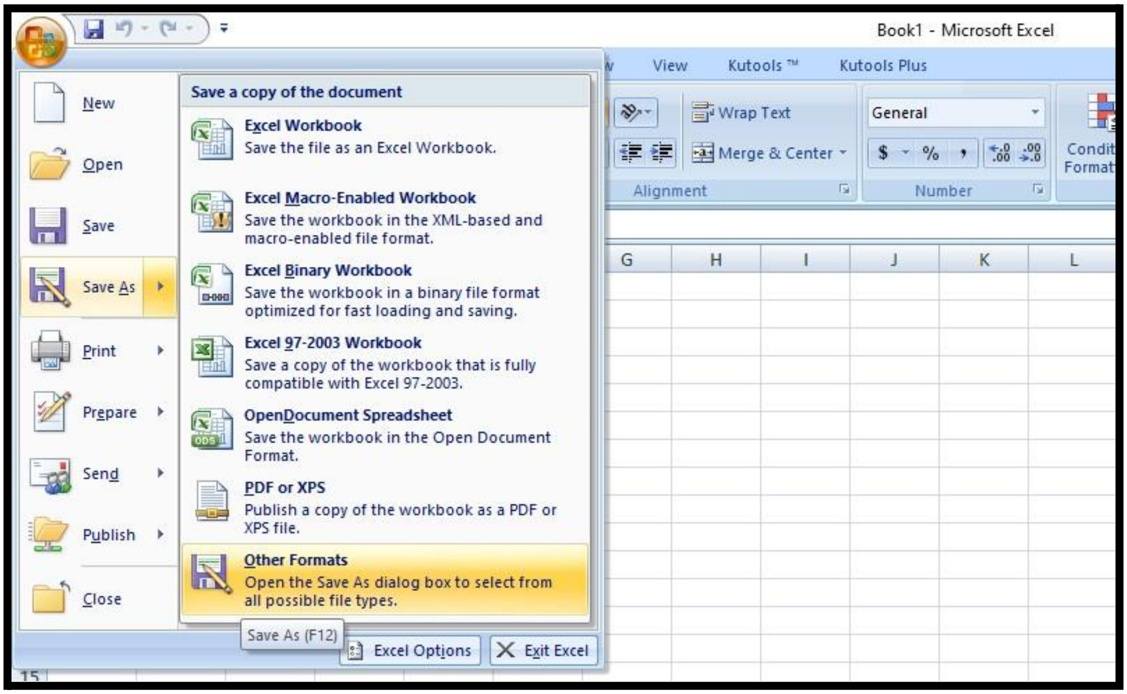
Syntax : RANDBETWEEN(bottom, top) Bottom The smallest integer and

Top The largest integer RANDBETWEEN will return.

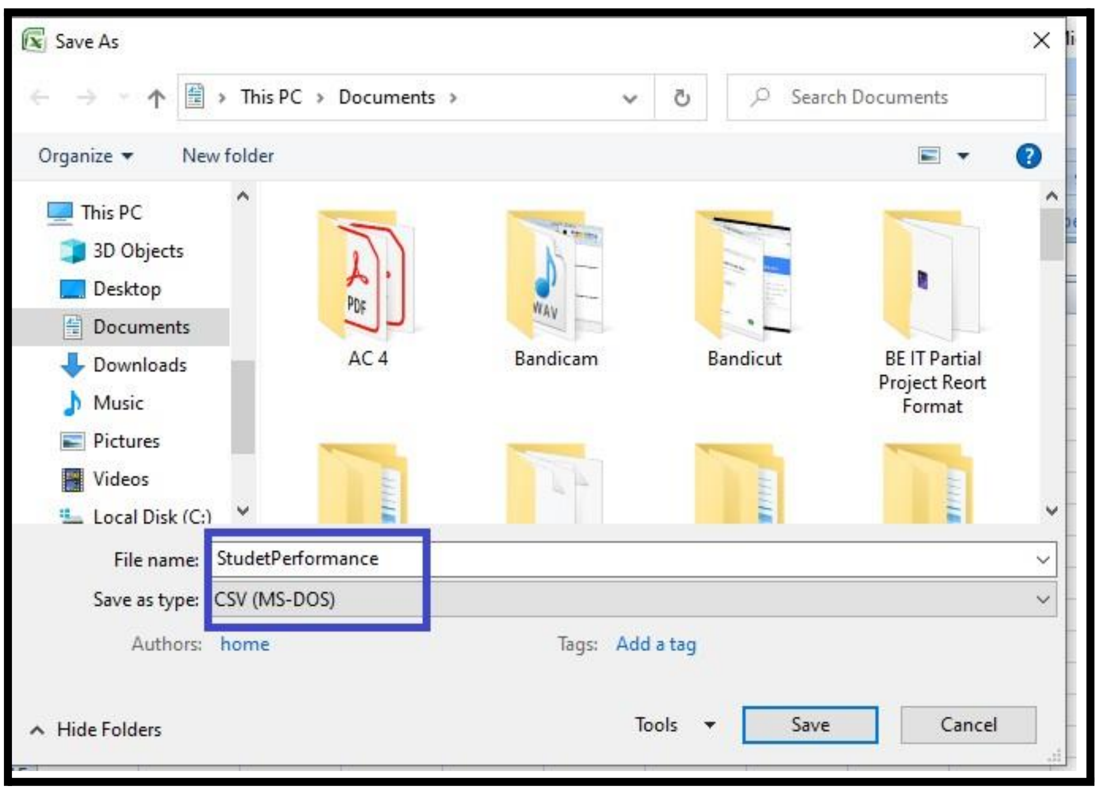
For better understanding and visualization, 20% impurities are added into each variable to the dataset.

The step to create the dataset are as follows:

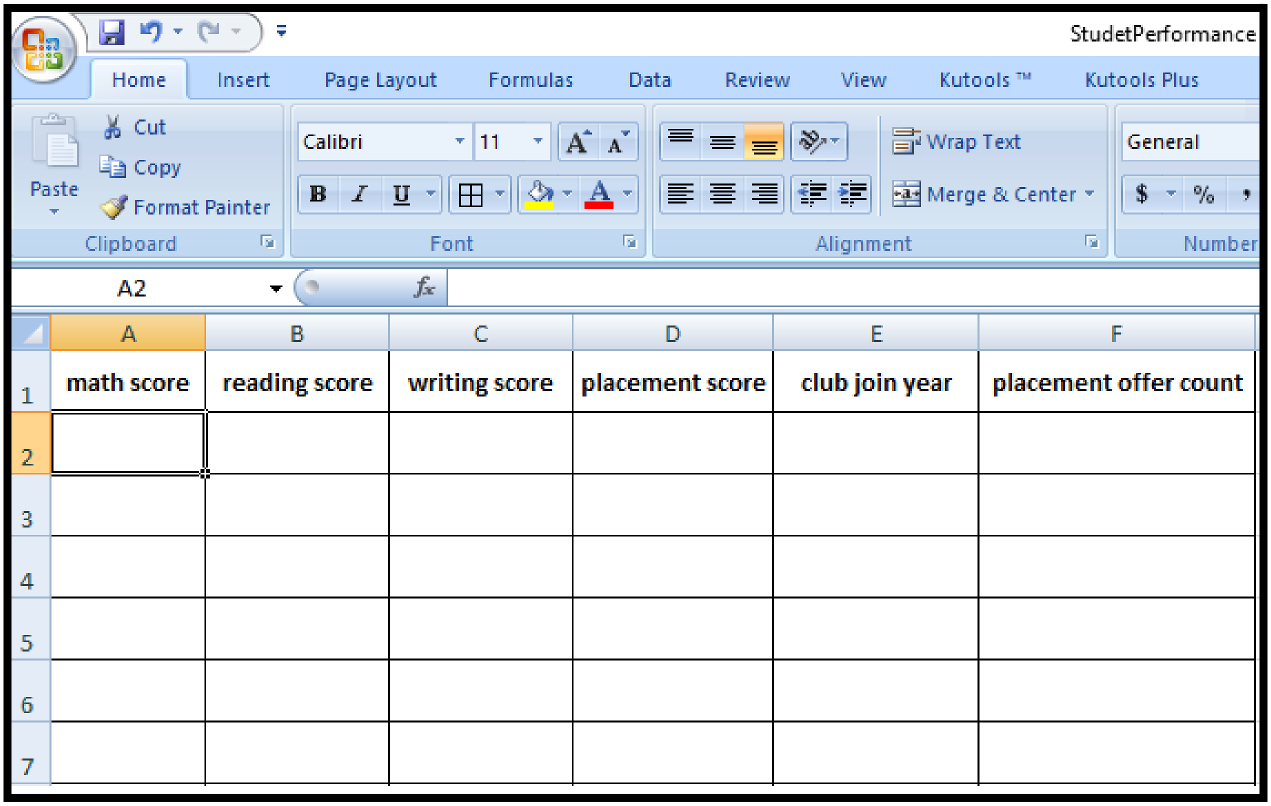
Step 1: Open Microsoft Excel and click on Save As. Select Other .Formats



Step 2: Enter the name of the dataset and Save the dataset astye CSV(MS-DOS).

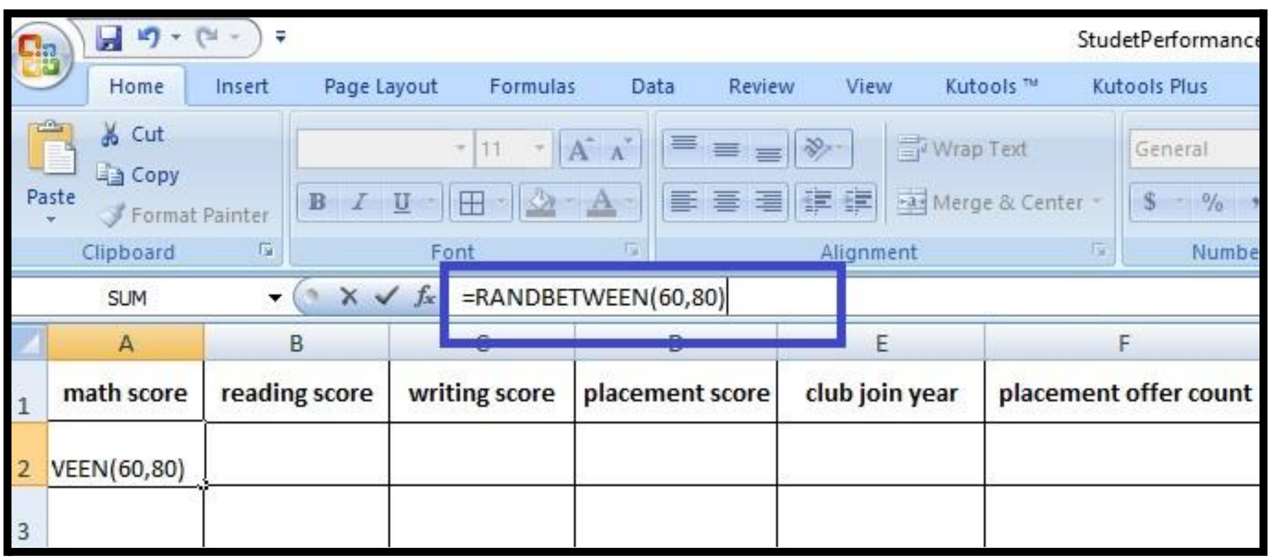


Step 3: Enter the name of features as column header.



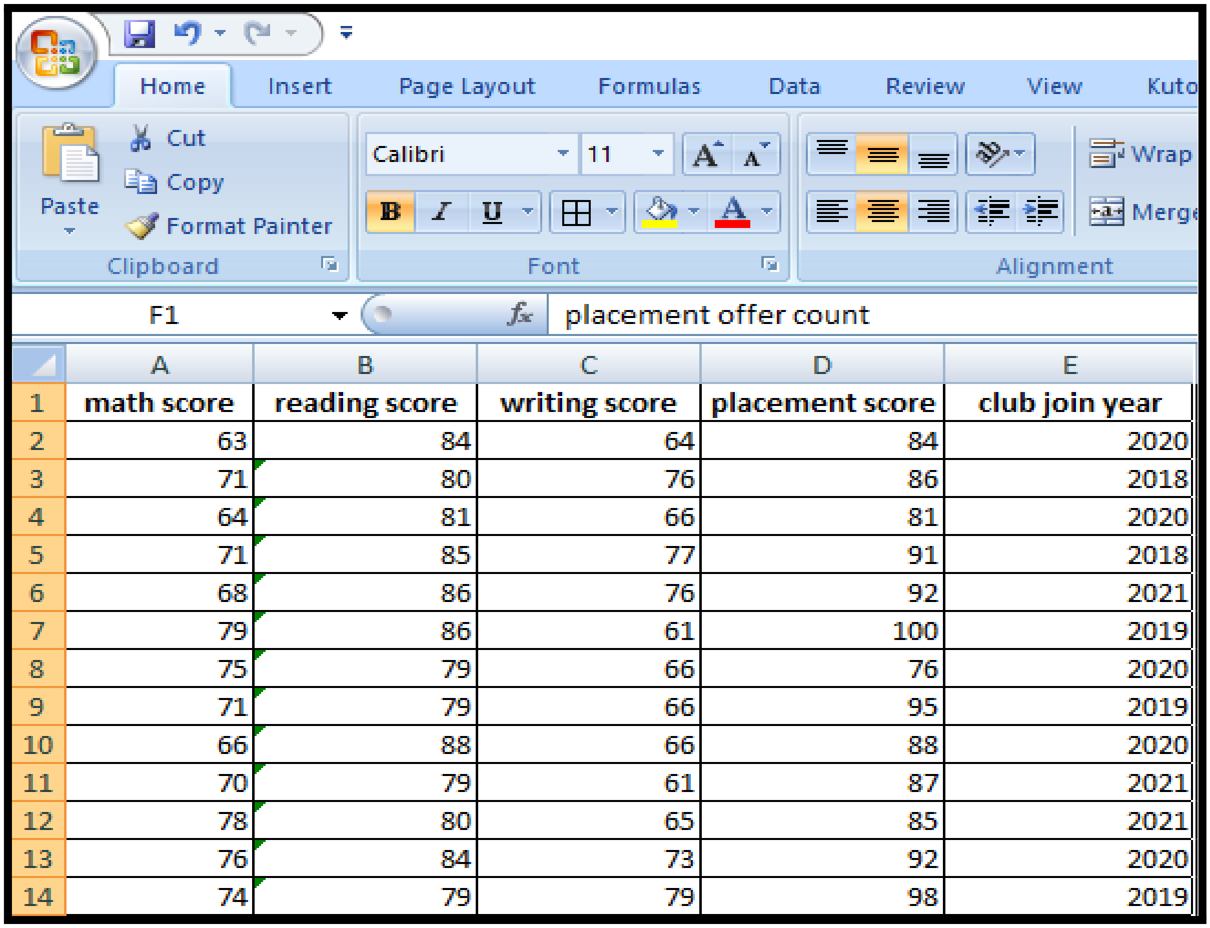
Step 3: Fill the dara by using **RANDOMBETWEEN** function. For every feature , fill the data by considering above spectified range.

one example is given:



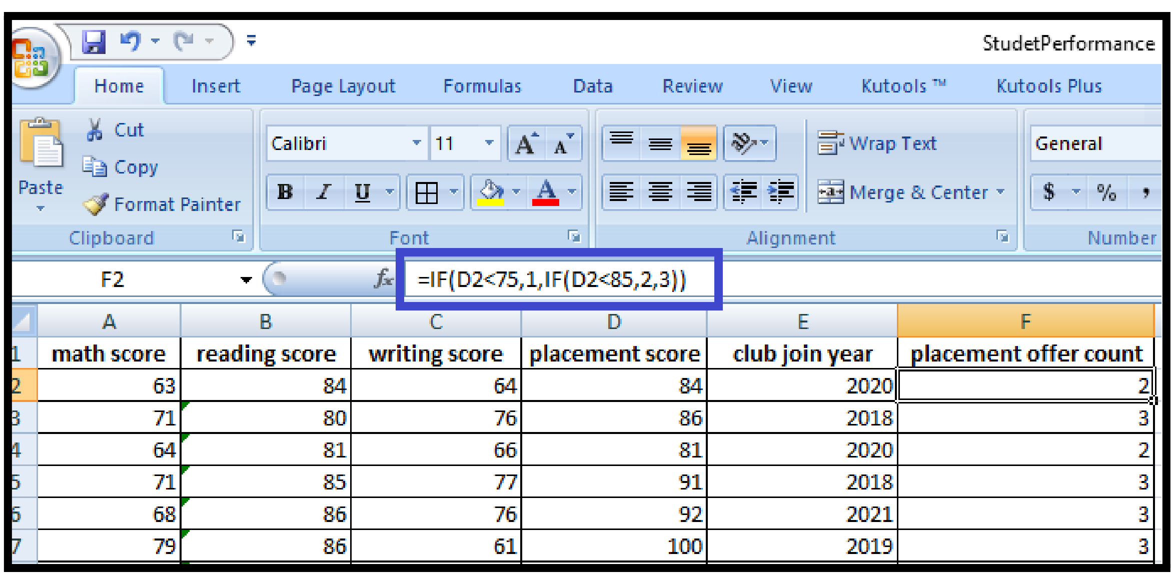
Scroll down the cursor for 30 rows to create 30 instances.

Repeat this for the features, Reading_Score, Writing_Score, Placement_Score, Club_Join_Date.



	A	B	C	D	E
1	math score	reading score	writing score	placement score	club join year
2	63	84	64	84	2020
3	71	80	76	86	2018
4	64	81	66	81	2020
5	71	85	77	91	2018
6	68	86	76	92	2021
7	79	86	61	100	2019
8	75	79	66	76	2020
9	71	79	66	95	2019
10	66	88	66	88	2020
11	70	79	61	87	2021
12	78	80	65	85	2021
13	76	84	73	92	2020
14	74	79	79	98	2019

The placement count largely depends on the placement score. It is considered that if placement score <75, 1 offer is facilitated; for placement score >75 , 2 offer is facilitated and for else (>85) 3 offer is facilitated. Nested If formula is used for ease of data filling.



	A	B	C	D	E	F
1	math score	reading score	writing score	placement score	club join year	placement offer count
2	63	84	64	84	2020	2
3	71	80	76	86	2018	3
4	64	81	66	81	2020	2
5	71	85	77	91	2018	3
6	68	86	76	92	2021	3
7	79	86	61	100	2019	3

Step 4: In 20% data, fill the impurities. The range of math score is [60,80], updating a few instances values below 60 or above 80. Repeat this for Writing_Score [60,80], Placement_Score[75-100], Club_Join_Date [2018-2021].

	A	B	C	D	E
1	math score	reading score	writing score	placement score	club join year
2	68	94	64	90	2018
3	72	85	70	86	2018
4	94	90	64	91	2020

Step 5: To violate the ruleof response variable, update few valus . If placement scoreis greater then 85, facilated only 1 offer.

	A	B	C	D	E	F
1	math score	reading score	writing score	placement score	club join year	placement offer count
2	70	91	64	87	2019	3
3	77	75	67	81	2020	2
4	94	84	73	99	2019	3
5	78	84	77	96	2020	1

The dataset is created with the given description.

2. Identification and Handling of Null Values

Missing Data can occur when no information is provided for one or more items or for a whole unit. Missing Data is a very big problem in real-life scenarios. Missing Data can also refer to as NA(Not Available) values in pandas. In DataFrame sometimes many datasets simply arrive with missing data, either because it exists and was not collected or it never existed. For Example, Suppose different users being surveyed may choose not to share their income, some users may choose not to share the address in this way many datasets went missing.

In Pandas missing data is represented by two value:

1. **None**: None is a Python singleton object that is often used for missing data in Python code.
2. **NaN** : NaN (an acronym for Not a Number), is a special floating-point value recognized by all systems that use the standard IEEE floating-point representation.

Pandas treat None and NaN as essentially interchangeable for indicating missing or null values. To facilitate this convention, there are several useful functions for detecting, removing, and replacing null values in Pandas DataFrame :

- isnull()
- notnull()
- dropna()
- fillna()
- replace()

1. Checking for missing values using isnull() and notnull()

- **Checking for missing values using isnull()**

In order to check null values in Pandas DataFrame, isnull() function is used. This function return dataframe of Boolean values which are True for NaN values**.**

Algorithm:

Step 1 : Import pandas and numpy in order to check missing values in Pandas DataFrame

```
import pandas as pd
import numpy as np
```

Step 2: Load the dataset in dataframe object df

```
df=pd.read_csv("/content/StudentsPerformanceTest1.csv")
```

Step 3: Display the data frame

```
df
```

	gender	math score	reading score	writing score	Placement Score	placement offer count	Region
0	female	72	72	74.0	78.0	1	Pune
1	female	69	90	88.0	NaN	2	na
2	female	90	95	93.0	74.0	2	Nashik
3	male	47	57	NaN	78.0	1	Na
4	male	na	78	75.0	81.0	3	Pune
5	female	71	Na	78.0	70.0	4	na
6	male	12	44	52.0	12.0	2	Nashik
7	male	NaN	65	67.0	49.0	1	Pune
8	male	5	77	89.0	55.0	0	NaN

Step 4: Use isnull() function to check null values in the dataset.

```
df.isnull()
```

	gender	math score	reading score	writing score	Placement Score	placement offer count	Region
0	False	False	False	False	False	False	False
1	False	False	False	False	True	False	False
2	False	False	False	False	False	False	False
3	False	False	False	True	False	False	False
4	False	False	False	False	False	False	False
5	False	False	False	False	False	False	False
6	False	False	False	False	False	False	False
7	False	True	False	False	False	False	False
8	False	False	False	False	False	False	True

Step 5: To create a series true for NaN values for specific columns. for example math score in dataset and display data with only math score as NaN

```
series = pd.isnull(df["math score"])
df[series]
```

	gender	math score	reading score	writing score	Placement Score	placement offer count	Region
7	male	NaN	65	67.0	49.0	1	Pune

- **Checking for missing values using notnull()**

In order to check null values in Pandas Dataframe, notnull() function is used. This function return dataframe of Boolean values which are False for NaN values.

Algorithm:

Step 1 : Import pandas and numpy in order to check missing values in Pandas DataFrame

```
import pandas as pd
import numpy as np
```

Step 2: Load the dataset in dataframe object df

```
df=pd.read_csv("/content/StudentsPerformanceTest1.csv")
```

Step 3: Display the data frame

```
df
```

	gender	math score	reading score	writing score	Placement Score	placement offer count	Region
0	female	72	72	74.0	78.0	1	Pune
1	female	69	90	88.0	NaN	2	na
2	female	90	95	93.0	74.0	2	Nashik
3	male	47	57	NaN	78.0	1	Na
4	male	na	78	75.0	81.0	3	Pune
5	female	71	Na	78.0	70.0	4	na
6	male	12	44	52.0	12.0	2	Nashik
7	male	NaN	65	67.0	49.0	1	Pune
8	male	5	77	89.0	55.0	0	NaN

Step 4: Use notnull() function to check null values in the dataset.

```
df.notnull()
```

	gender	math score	reading score	writing score	Placement Score	placement offer count	Region
0	True	True	True	True	True	True	True
1	True	True	True	True	False	True	True
2	True	True	True	True	True	True	True
3	True	True	True	False	True	True	True
4	True	True	True	True	True	True	True
5	True	True	True	True	True	True	True
6	True	True	True	True	True	True	True
7	True	False	True	True	True	True	True
8	True	True	True	True	True	True	False

Step 5: To create a series true for NaN values for specific columns. for example math score in dataset and display data with only math score as NaN

```
series1 = pd.notnull(df["math score"])
df[series1]
```

	gender	math score	reading score	writing score	Placement Score	placement offer count	Region
0	female	72	72	74.0	78.0	1	Pune
1	female	69	90	88.0	NaN	2	na
2	female	90	95	93.0	74.0	2	Nashik
3	male	47	57	NaN	78.0	1	Na
4	male	na	78	75.0	81.0	3	Pune
5	female	71	Na	78.0	70.0	4	na
6	male	12	44	52.0	12.0	2	Nashik
8	male	5	77	89.0	55.0	0	NaN

See that there are also categorical values in the dataset, for this, you need to use Label Encoding or One Hot Encoding.

- `from sklearn.preprocessing import LabelEncoder`
- `le = LabelEncoder()`
- `df['gender'] = le.fit_transform(df['gender'])`
- `newdf=df`

```
df
```

	gender	math score	reading score	writing score	Placement Score	placement offer count	Region
0	0	72	72	74.0	78.0	1	Pune
1	0	69	90	88.0	NaN	2	na
2	0	90	95	93.0	74.0	2	Nashik
3	1	47	57	NaN	78.0	1	Na
4	1	na	78	75.0	81.0	3	Pune
5	0	71	Na	78.0	70.0	4	na
6	1	12	44	52.0	12.0	2	Nashik
7	1	NaN	65	67.0	49.0	1	Pune
8	1	5	77	89.0	55.0	0	NaN

2. Filling missing values using dropna(), fillna(), replace()

In order to fill null values in a datasets, fillna(), replace() functions are used. These functions replace NaN values with some value of their own. All these functions help in filling null values in datasets of a DataFrame.

- **For replacing null values with NaN**

```
missing_values = ["Na", "na"]
```

```
df = pd.read_csv("StudentsPerformanceTest1.csv", na_values =
missing_values)
df
```

	gender	math score	reading score	writing score	Placement Score	placement offer count	Region
0	female	72.0	72.0	74.0	78.0	1	Pune
1	female	69.0	90.0	88.0	NaN	2	NaN
2	female	90.0	95.0	93.0	74.0	2	Nashik
3	male	47.0	57.0	NaN	78.0	1	NaN
4	male	NaN	78.0	75.0	81.0	3	Pune
5	female	71.0	NaN	78.0	70.0	4	NaN
6	male	12.0	44.0	52.0	12.0	2	Nashik
7	male	NaN	65.0	67.0	49.0	1	Pune
8	male	5.0	77.0	89.0	55.0	0	NaN

- **Filling null values with a single value**

Step 1 : Import pandas and numpy in order to check missing values in Pandas DataFrame

```
import pandas as pd
import numpy as np
```

Step 2: Load the dataset in dataframe object df

```
df=pd.read_csv("/content/StudentsPerformanceTest1.csv")
```

Step 3: Display the data frame

```
df
```

Step 4: filling missing value using fillna()

```
ndf=df
ndf.fillna(0)
```

	gender	math score	reading score	writing score	Placement Score	placement offer count	Region
0	female	72	72	74.0	78.0	1	Pune
1	female	69	90	88.0	0.0	2	na
2	female	90	95	93.0	74.0	2	Nashik
3	male	47	57	0.0	78.0	1	Na
4	male	na	78	75.0	81.0	3	Pune
5	female	71	Na	78.0	70.0	4	na
6	male	12	44	52.0	12.0	2	Nashik
7	male	0	65	67.0	49.0	1	Pune
8	male	5	77	89.0	55.0	0	0

Step 5: filling missing values using mean, median and standard deviation of that column.

data['math score'] = data['math score'].fillna(data['math score'].mean())

data["math score"] = data["math score"].fillna(data["math score"].median())

data['math score"] = data["math score"].fillna(data["math score"].std())

replacing missing values in forenoon column with minimum/maximum number of that column

data["math score"] = data["math score"].fillna(data["math score"].min())

data["math score"] = data["math score"].fillna(data["math score"].max())

- **Filling null values in dataset**
  To fill null values in dataset use inplace=true

```
m_v=df['math score'].mean()
df['math score'].fillna(value=m_v, inplace=True)
df
```

	gender	math score	reading score	writing score	Placement Score	placement offer count
0	female	72.000	72	74	78	1
1	female	69.000	90	88	70	2
2	female	90.000	95	93	74	2
3	male	47.000	57	44	78	1
4	male	11.000	78	75	81	3
5	female	71.000	83	78	70	4
6	male	12.000	44	52	12	2
7	male	47.125	65	67	49	1
8	male	5.000	77	89	55	0

- **Filling a null values using replace() method**

  Following line will replace Nan value in dataframe with value -99

```
ndf.replace(to_replace = np.nan, value = -99)
```

	gender	math score	reading score	writing score	Placement Score	placement offer count	Region
0	female	72	72	74.0	78.0	1	Pune
1	female	69	90	88.0	-99.0	2	na
2	female	90	95	93.0	74.0	2	Nashik
3	male	47	57	-99.0	78.0	1	Na
4	male	na	78	75.0	81.0	3	Pune
5	female	71	Na	78.0	70.0	4	na
6	male	12	44	52.0	12.0	2	Nashik
7	male	-99	65	67.0	49.0	1	Pune
8	male	5	77	89.0	55.0	0	-99

- **Deleting null values using dropna() method**
  In order to drop null values from a dataframe, dropna() function is used. This function drops Rows/Columns of datasets with Null values in different ways.
  1. Dropping rows with at least 1 null value
  2. Dropping rows if all values in that row are missing
  3. Dropping columns with at least 1 null value.
  4. Dropping Rows with at least 1 null value in CSV file

Algorithm:

Step 1 : Import pandas and numpy in order to check missing values in Pandas DataFrame

```
import pandas as pd
import numpy as np
```

Step 2: Load the dataset in dataframe object df

```
df=pd.read_csv("/content/StudentsPerformanceTest1.csv")
```

Step 3: Display the data frame

```
df
```

Step 4 : To drop rows with at least 1 null value

```
ndf.dropna()
```

	gender	math score	reading score	writing score	Placement Score	placement offer count	Region
0	female	72	72	74.0	78.0	1	Pune
2	female	90	95	93.0	74.0	2	Nashik
4	male	na	78	75.0	81.0	3	Pune
5	female	71	Na	78.0	70.0	4	na
6	male	12	44	52.0	12.0	2	Nashik

Step 5: To Drop rows if all values in that row are missing

```
ndf.dropna(how = 'all')
```

	gender	math score	reading score	writing score	Placement Score	placement offer count	Region
0	female	72	72	74.0	78.0	1	Pune
1	female	69	90	88.0	NaN	2	na
2	female	90	95	93.0	74.0	2	Nashik
3	male	47	57	NaN	78.0	1	Na
4	male	na	78	75.0	81.0	3	Pune
5	female	71	Na	78.0	70.0	4	na
6	male	12	44	52.0	12.0	2	Nashik
7	male	NaN	65	67.0	49.0	1	Pune
8	male	5	77	89.0	55.0	0	NaN

Step 6: To Drop columns with at least 1 null value.

```
ndf.dropna(axis = 1)
```

	gender	reading score	placement offer count
0	female	72	1
1	female	90	2
2	female	95	2
3	male	57	1
4	male	78	3
5	female	Na	4
6	male	44	2
7	male	65	1
8	male	77	0

Step 7 : To drop rows with at least 1 null value in CSV file.

making new data frame with dropped NA values

```
new_data = ndf.dropna(axis = 0, how ='any')
new_data
```

	gender	math score	reading score	writing score	Placement Score	placement offer count	Region
0	female	72	72	74.0	78.0	1	Pune
2	female	90	95	93.0	74.0	2	Nashik
4	male	na	78	75.0	81.0	3	Pune
5	female	71	Na	78.0	70.0	4	na
6	male	12	44	52.0	12.0	2	Nashik

3. Identification and Handling of Outliers

3.1 Identification of Outliers

One of the most important steps as part of data preprocessing is detecting and treating the outliers as they can negatively affect the statistical analysis and the training process of a machine learning algorithm resulting in lower accuracy.

- **1. What are Outliers?**

We all have heard of the idiom ‘odd one out' which means something unusual in comparison to the others in a group.

Similarly, an Outlier is an observation in a given dataset that lies far from the rest of the observations. That means an outlier is vastly larger or smaller than the remaining values in the set.

- **2. Why do they occur?**

An outlier may occur due to the variability in the data, or due to experimental error/human error.

They may indicate an experimental error or heavy skewness in the data(heavy-tailed distribution).

- **3. What do they affect?**

In statistics, we have three measures of central tendency namely Mean, Median, and Mode. They help us describe the data.

Mean is the accurate measure to describe the data when we do not have any outliers present. Median is used if there is an outlier in the dataset. Mode is used if there is an outlier AND about ½ or more of the data is the same.

‘Mean’ is the only measure of central tendency that is affected by the outliers which in turn impacts Standard deviation.

- Example:

Consider a small dataset, sample= [15, 101, 18, 7, 13, 16, 11, 21, 5, 15, 10, 9]. By looking at it, one can quickly say ‘101’ is an outlier that is much larger than the other values.

```
+--------------------+-------------------+
| with outlier       | without outlier   |
+--------------------+-------------------+
| Mean: 20.08        | Mean: 12.72       |
| Median: 14.0       | Median: 13.0      |
| Mode: 15           | Mode: 15          |
| Variance: 614.74   | Variance: 21.28   |
| Std dev: 24.79     | Std dev: 4.61     |
+--------------------+-------------------+
```

fig. Computation with and without outlier

From the above calculations, we can clearly say the Mean is more affected than the Median.

○ **4. Detecting Outliers**

If our dataset is small, we can detect the outlier by just looking at the dataset. But what if we have a huge dataset, how do we identify the outliers then? We need to use visualization and mathematical techniques.

Below are some of the techniques of detecting outliers

- Boxplots
- Scatterplots
- Z-score
- Inter Quantile Range(IQR)

4.1 Detecting outliers using Boxplot:

It captures the summary of the data effectively and efficiently with only a simple box and whiskers. Boxplot summarizes sample data using 25th, 50th, and 75th percentiles. One can just get insights(quartiles, median, and outliers) into the dataset by just looking at its boxplot.

Algorithm:

Step 1 : Import pandas and numpy libraries

```
import pandas as pd
import numpy as np
```

Step 2: Load the dataset in dataframe object df

```
df=pd.read_csv("/content/demo.csv")
```

Step 3: Display the data frame

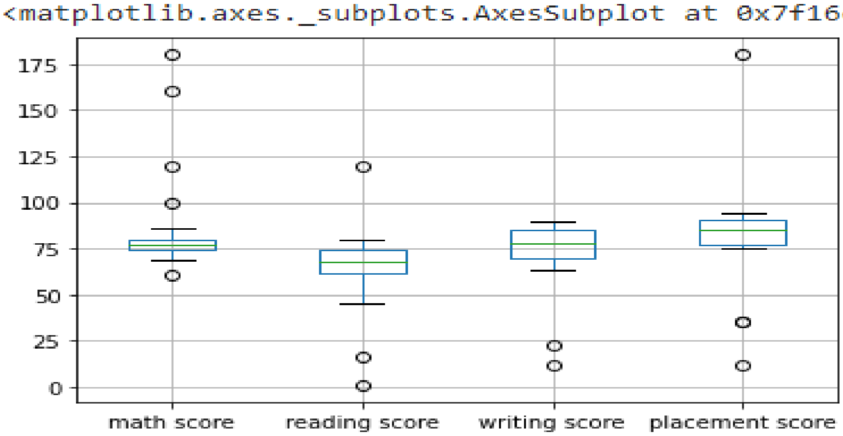
```
df
```

	math score	reading score	writing score	placement score	placement offer count
0	80	68	70	89	3
1	71	61	85	91	3
2	79	16	87	77	2
3	61	77	74	76	2
4	78	71	67	90	3
5	73	68	90	80	2
6	77	62	70	35	2
7	74	45	80	12	1
8	76	60	79	77	2
9	75	65	85	87	3
10	160	67	12	83	2
11	79	72	88	180	2
12	80	80	78	94	3

Step 4: Select the columns for boxplot and draw the boxplot.

```
col = ['math score', 'reading score' , 'writing
score','placement score']
df.boxplot(col)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f16c473d250>



Step 5: We can now print the outliers for each column with reference to the box plot.

```
print(np.where(df['math score']>90))
print(np.where(df['reading score']<25))
print(np.where(df['writing score']<30))
```

4.2 Detecting outliers using Scatterplot:

It is used when you have paired numerical data, or when your dependent variable has multiple values for each reading independent variable, or when trying to determine the relationship between the two variables. In the process of utilizing the scatter plot, one can also use it for outlier detection.

To plot the scatter plot one requires two variables that are somehow related to each other. So here Placement score and Placement count features are used.

Algorithm:

Step 1 : Import pandas , numpy and matplotlib libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

Step 2: Load the dataset in dataframe object df

```
df=pd.read_csv("/content/demo.csv")
```

Step 3: Display the data frame

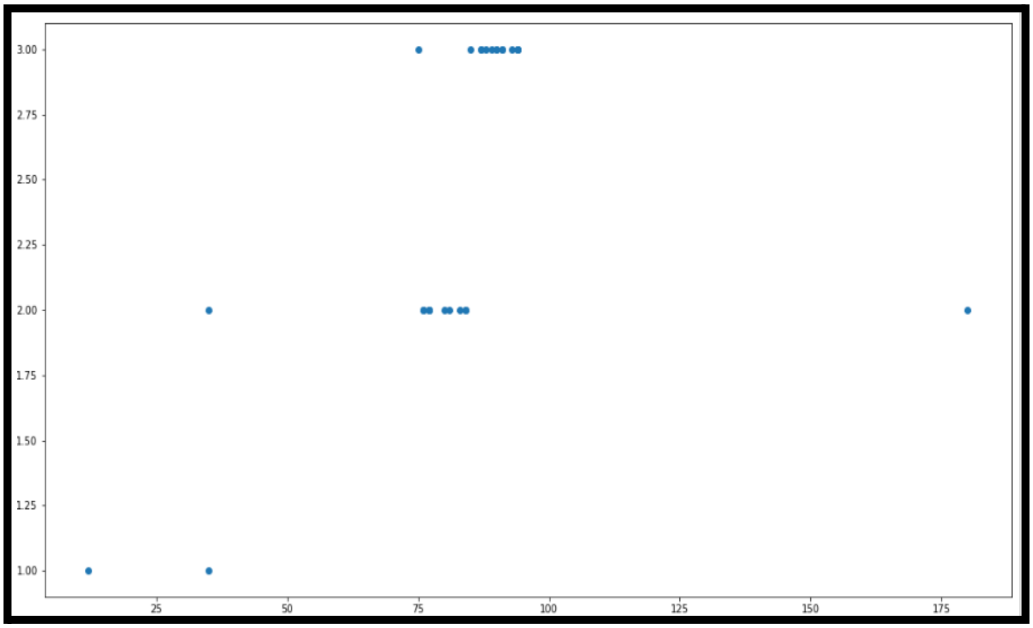
```
df
```

Step 4: Draw the scatter plot with placement score and placement offer count

```
fig, ax = plt.subplots(figsize = (18,10))
ax.scatter(df['placement score'], df['placement offer
count'])
plt.show()
```

Labels to the axis can be assigned (Optional)

```
ax.set_xlabel('(Proportion non-retail business
acres)/(town)')
ax.set_ylabel('(Full-value property-tax rate)/(
$10,000)')
```



Step 5: We can now print the outliers with reference to scatter plot.

```
print(np.where((df['placement score']<50) & (df['placement offer count']>1)))
print(np.where((df['placement score']>85) & (df['placement offer count']<3)))
```

4.3 Detecting outliers using Z-Score:

Z-Score is also called a standard score. This value/score helps to understand how far is the data point from the mean. And after setting up a threshold value one can utilize z score values of data points to define the outliers.

Zscore = (data_point -mean) / std. deviation

Algorithm:

Step 1 : Import numpy and stats from scipy libraries

```
import numpy as np
from scipy import stats
```

Step 2: Calculate Z-Score for mathscore column

```
z = np.abs(stats.zscore(df['math score']))
```

Step 3: Print Z-Score Value. It prints the z-score values of each data item of the column

```
print(z)
```

```
[0.17564553 0.5282877  0.21482799 0.92011234 0.25401045 0.44992277
 0.29319292 0.41074031 0.33237538 0.37155785 2.95895157 0.21482799
 0.17564553 0.25401045 0.37155785 0.25401045 0.05944926 0.17564553
 0.37155785 0.0972806  0.60665263 0.60800375 0.48910524 0.41074031
 0.37155785 3.74260085 0.48910524 0.5282877  1.39165302]
```

Step 4: Now to define an outlier threshold value is chosen.

```
threshold = 0.18
```

Step 5: Display the sample outliers

```
sample_outliers = np.where(z <threshold)
sample_outliers
```

```
(array([ 0, 12, 16, 17, 19]),)
```

4.4 Detecting outliers using Inter Quantile Range(IQR):

IQR (Inter Quartile Range) Inter Quartile Range approach to finding the outliers is the most commonly used and most trusted approach used in the research field.

IQR = Quartile3 – Quartile1

To define the outlier base value is defined above and below datasets normal range namely Upper and Lower bounds, define the upper and the lower bound (1.5*IQR value is considered) :

upper = Q3 +1.5*IQR

lower = Q1 – 1.5*IQR

In the above formula as according to statistics, the 0.5 scale-up of IQR (new_IQR = IQR + 0.5*IQR) is taken.

Algorithm:

Step 1 : Import numpy library

```
import numpy as np
```

Step 2: Sort Reading Score feature and store it into sorted_rscore.

```
sorted_rscore= sorted(df['reading score'])
```

Step 3: Print sorted_rscore

```
sorted_rscore
```

Step 4: Calculate and print Quartile 1 and Quartile 3

```
q1 = np.percentile(sorted_rscore, 25)
```

```
q3 = np.percentile(sorted_rscore, 75)
print(q1,q3)
```

```
62.0 74.0
```

Step 5: Calculate value of IQR (Inter Quartile Range)

```
IQR = q3-q1
```

Step 6: Calculate and print Upper and Lower Bound to define the outlier base value.

```
lwr_bound = q1-(1.5*IQR)
upr_bound = q3+(1.5*IQR)
print(lwr_bound, upr_bound)
```

```
44.0 92.0
```

Step 7: Print Outliers

```
r_outliers = []
for i in sorted_rscore:
  if (i<lwr_bound or i>upr_bound):
    r_outliers.append(i)
print(r_outliers)
```

```
[1, 16, 120]
```

3.2 Handling of Outliers:

For removing the outlier, one must follow the same process of removing an entry from the dataset using its exact position in the dataset because in all the above methods of detecting the outliers end result is the list of all those data items that satisfy the outlier definition according to the method used.

Below are some of the methods of treating the outliers

- Trimming/removing the outlier
- Quantile based flooring and capping
- Mean/Median imputation

- **Trimming/removing the outlier:**

  In this technique, we remove the outliers from the dataset. Although it is not a good practice to follow.

```
new_df=df
for i in sample_outliers:
  new_df.drop(i,inplace=True)
new_df
```

	math score	reading score	writing score	placement score	placement offer count
1	71	61	85	91	3
2	79	16	87	77	2
3	61	77	74	76	2
4	78	71	67	90	3
5	73	68	90	80	2
6	77	62	70	35	2
7	74	45	80	12	1
8	76	60	79	77	2
9	75	65	85	87	3
10	160	67	12	83	2
11	79	72	88	180	2
13	78	69	71	90	3
14	75	1	71	81	2
15	78	62	79	93	3
18	75	62	86	87	3

Here Sample_outliers are `(array([ 0, 12, 16, 17 ]),)` So instances with index 0, 12 ,16 and 17 are deleted.

- **Quantile based flooring and capping:**

  In this technique, the outlier is capped at a certain value above the 90th percentile value or floored at a factor below the 10th percentile value

```
df=pd.read_csv("/demo.csv")
df_stud=df
ninetieth_percentile = np.percentile(df_stud['math score'], 90)
b = np.where(df_stud['math score']>ninetieth_percentile,
ninetieth_percentile, df_stud['math score'])
print("New array:",b)
```

```
New array: [ 80.  71.  79.  61.  78.  73.  77.  74.  76.  75. 104.  79.  80.  78.
  75.  78.  86.  80.  75.  82.  69. 100.  72.  74.  75. 104.  72.  71.
 104.]
```

```
df_stud.insert(1,"m score",b,True)
df_stud
```

	math score	m score	reading score	writing score	placement score	placement offer count
0	80	80.0	68	70	89	3
1	71	71.0	61	85	91	3
2	79	79.0	16	87	77	2
3	61	61.0	77	74	76	2
4	78	78.0	71	67	90	3
5	73	73.0	68	90	80	2
6	77	77.0	62	70	35	2
7	74	74.0	45	80	12	1

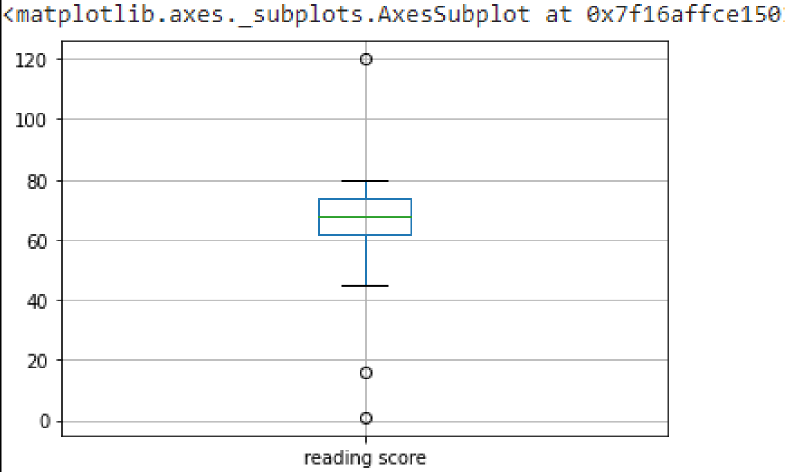
- **Mean/Median imputation:**

  As the mean value is highly influenced by the outliers, it is advised to replace the outliers with the median value.

  1. Plot the box plot for reading score

     ```
     col = ['reading score']
     df.boxplot(col)
     ```

     ```
     <matplotlib.axes._subplots.AxesSubplot at 0x7f16affce150>
     ```

  2. Outliers are seen in box plot.
  3. Calculate the median of reading score by using sorted_rscore

     ```
     median=np.median(sorted_rscore)
     median
     ```

  4. Replace the upper bound outliers using median value

     ```
     refined_df=df
     ```

```
refined_df['reading score'] = np.where(refined_df['reading
score'] >upr_bound, median,refined_df['reading score'])
```

5. Display redefined_df

	math score	m score	reading score	writing score	placement score	placement offer count
0	80	80.0	68.0	70	89	3
1	71	71.0	61.0	85	91	3
2	79	79.0	16.0	87	77	2
3	61	61.0	77.0	74	76	2
4	78	78.0	71.0	67	90	3
5	73	73.0	68.0	90	80	2
6	77	77.0	62.0	70	35	2
7	74	74.0	45.0	80	12	1
8	76	76.0	60.0	79	77	2
9	75	75.0	65.0	85	87	3
10	160	104.0	67.0	12	83	2

6. Replace the lower bound outliers using median value

```
refined_df['reading score'] = np.where(refined_df['reading
score'] <lwr_bound, median,refined_df['reading score'])
```

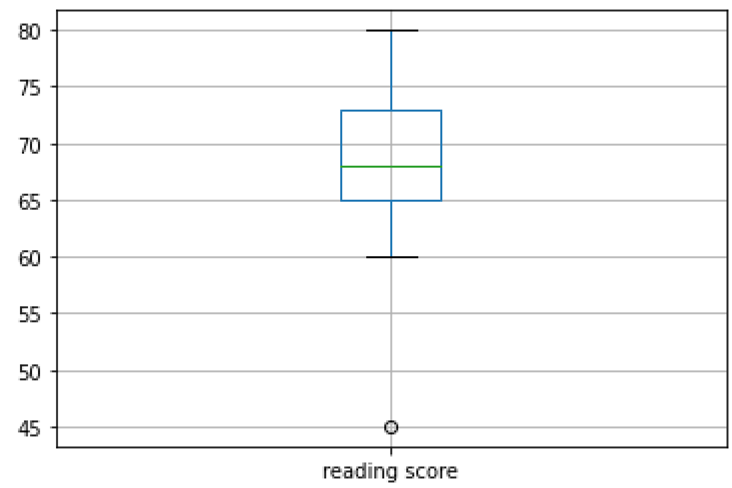
7. Display redefined_df

	math score	m score	reading score	writing score	placement score	placement offer count
0	80	80.0	68.0	70	89	3
1	71	71.0	61.0	85	91	3
2	79	79.0	68.0	87	77	2
3	61	61.0	77.0	74	76	2
4	78	78.0	71.0	67	90	3
5	73	73.0	68.0	90	80	2
6	77	77.0	62.0	70	35	2
7	74	74.0	45.0	80	12	1
8	76	76.0	60.0	79	77	2
9	75	75.0	65.0	85	87	3
10	160	104.0	67.0	12	83	2

8. Draw the box plot for redefined_df

```
col = ['reading score']
refined_df.boxplot(col)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f16aff6f090>



4. **Data Transformation for the purpose of :**

Data transformation is the process of converting raw data into a format or structure that would be more suitable for model building and also data discovery in general.The process of data transformation can also be referred to as extract/transform/load (ETL). The extraction phase involves identifying and pulling data from the various source systems that create data and then moving the data to a single repository. Next, the raw data is cleansed, if needed. It's then transformed into a target format that can be fed into operational systems or into a data warehouse, a date lake or another repository for use in business intelligence and analytics applications. The transformation The data are transformed in ways that are ideal for mining the data. The data transformation involves steps that are.

- **Smoothing:** It is a process that is used to remove noise from the dataset using some algorithms It allows for highlighting important features present in the dataset. It helps in predicting the patterns
- **Aggregation**: Data collection or aggregation is the method of storing and presenting data in a summary format. The data may be obtained from multiple data sources to

integrate these data sources into a data analysis description. This is a crucial step since the accuracy of data analysis insights is highly dependent on the quantity and quality of the data used.

- **Generalization**:It converts low-level data attributes to high-level data attributes using concept hierarchy. For Example Age initially in Numerical form (22, 25) is converted into categorical value (young, old).
- **Normalization:** Data normalization involves converting all data variables into a given range. Some of the techniques that are used for accomplishing normalization are:
  - **Min–max normalization**: This transforms the original data linearly.
  - **Z-score normalization**: In z-score normalization (or zero-mean normalization) the values of an attribute (A), are normalized based on the mean of A and its standard deviation.
  - **Normalization by decimal scaling**: It normalizes the values of an attribute by changing the position of their decimal points
- **Attribute or feature construction**.
  - **New attributes constructed from the given ones**: Where new attributes are created & applied to assist the mining process from the given set of attributes. This simplifies the original data & makes the mining more efficient.

    In this assignment , The purpose of this transformation should be one of the following reasons:

a. **To change the scale for better understanding (Attribute or feature construction)**

Here the Club_Join_Date is transferred to Duration.

Algorithm:

Step 1 : Import pandas and numpy libraries

```
import pandas as pd
import numpy as np
```

Step 2: Load the dataset in dataframe object df

```
df=pd.read_csv("/content/demo.csv")
```

Step 3: Display the data frame

```
df
```

```
df
```

	math score	reading score	writing score	placement score	placement offer count	club join year
0	80	68	70	89	3	2019
1	71	61	85	91	3	2019
2	79	16	87	77	2	2018
3	61	77	74	76	2	2020
4	78	71	67	90	3	2019

Step 3: Change the scale of Joining year to duration.

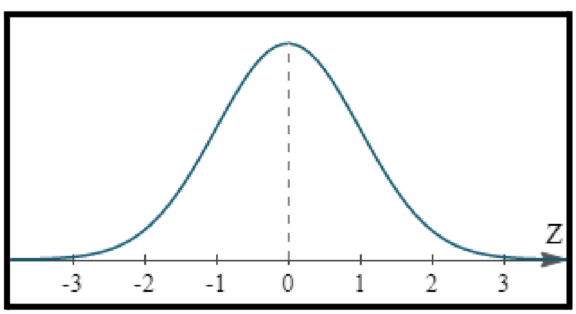
```
[11] df
```

	math score	reading score	writing score	placement score	placement offer count	club join year	Duration
0	80	68	70	89	3	2019	3
1	71	61	85	91	3	2019	3
2	79	16	87	77	2	2018	4
3	61	77	74	76	2	2020	2
4	78	71	67	90	3	2019	3

b. To decrease the skewness and convert distribution into normal distribution (Normalization by decimal scaling)

Data Skewness: It is asymmetry in a statistical distribution, in which the curve appears distorted or skewed either to the left or to the right. Skewness can be quantified to define the extent to which a distribution differs from a normal distribution.

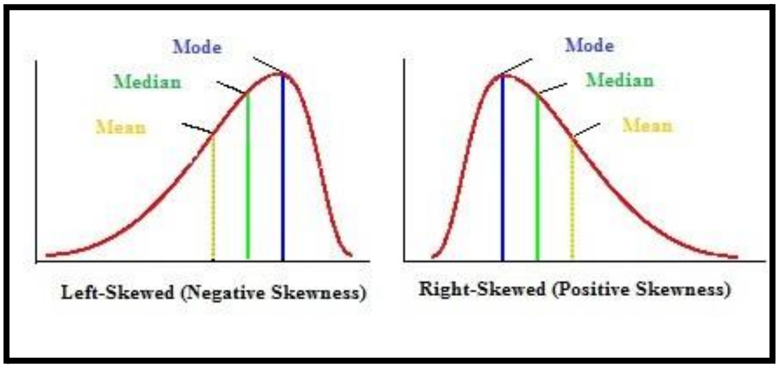
Normal Distribution: In a normal distribution, the graph appears as a classical, symmetrical "bell-shaped curve." The mean, or average, and the mode, or maximum point on the curve, are equal.



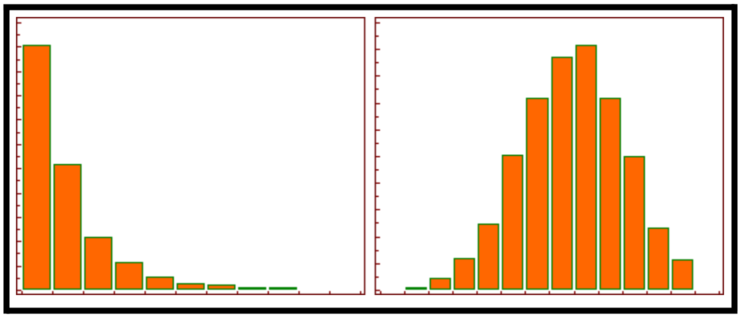
Positively Skewed Distribution

A positively skewed distribution means that the extreme data results are larger. This skews the data in that it brings the mean (average) up. The mean will be larger than the median in a Positively skewed distribution.

A negatively skewed distribution means the opposite: that the extreme data results are smaller. This means that the mean is brought down, and the median is larger than the mean in a negatively skewed distribution.



Reducing skewness A data transformation may be used to reduce skewness. A distribution that is symmetric or nearly so is often easier to handle and interpret than a skewed distribution. The logarithm, x to log base 10 of x, or x to log base e of x (ln x), or x to log base 2 of x, is a strong transformation with a major effect on distribution shape. It is commonly used for reducing right skewness and is often appropriate for measured variables. It can not be applied to zero or negative values.



Algorithm:

Step 1 : Detecting outliers using Z-Score for the Math_score variable and remove the outliers.

Step 2: Observe the histogram for math_score variable.

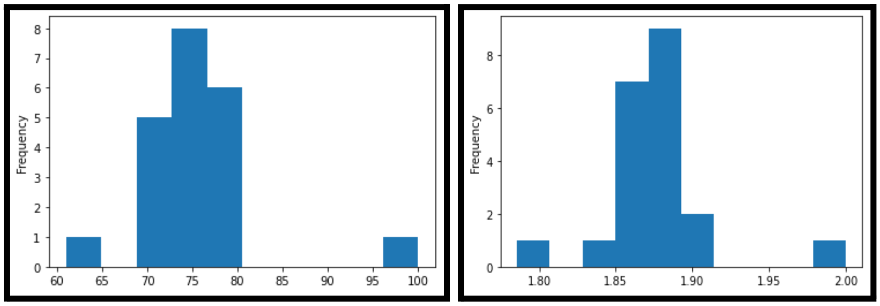
```
import matplotlib.pyplot as plt
new_df['math score'].plot(kind = 'hist')
```

Step 3: Convert the variables to logarithm at the scale 10.

```
df['log_math'] = np.log10(df['math score'])
```

Step 4: Observe the histogram for math_score variable.

```
df['log_math'].plot(kind = 'hist')
```



It is observed that skewness is reduced at some level.

Conclusion: In this way we have explored the functions of the python library for Data Identifying and handling the outliers. Data Transformations Techniques are explored with the purpose of creating the new variable and reducing the skewness from datasets.

Assignment Question:

1. **Explain the methods to detect the outlier.**
2. **Explain data transformation methods**
3. **Write the algorithm to display the statistics of Null values present in the dataset.**
4. **Write an algorithm to replace the outlier value with the mean of the variable.**

.

Group A

Assignment No: 3

Contents for Theory:

1. Summary statistics

2. Types of Variables

3. Summary statistics of income grouped by the age groups

4. Display basic statistical details on the iris dataset.

---

1. Summary statistics:

- **What is Statistics?**

Statistics is the science of collecting data and analysing them to infer proportions (sample) that are representative of the population. In other words, statistics is interpreting data in order to make predictions for the population.

Branches of Statistics:

There are two branches of Statistics.

DESCRIPTIVE STATISTICS : Descriptive Statistics is a statistics or a measure that describes the data.

INFERENTIAL STATISTICS : Using a random sample of data taken from a population to describe and make inferences about the population is called Inferential Statistics.

Descriptive Statistics

Descriptive Statistics is summarising the data at hand through certain numbers like mean, median etc. so as to make the understanding of the data easier. It does not involve any generalisation or inference beyond what is available. This means that the descriptive statistics are just the representation of the data (sample) available and not based on any theory of probability.

Commonly Used Measures

1. Measures of Central Tendency
2. Measures of Dispersion (or Variability)

- **Measures of Central Tendency**

  A Measure of Central Tendency is a one number summary of the data that typically describes the centre of the data. This one number summary is of three types.

a. **Mean :** Mean is defined as the ratio of the sum of all the observations in the data to the total number of observations. This is also known as Average. Thus mean is a number around which the entire data set is spread.

Consider the following data points.

17, 16, 21, 18, 15, 17, 21, 19, 11, 23

$$\boxed{Mean = \frac{17+16+21+18+15+17+21+19+11+23}{10} = \frac{178}{10} = 17.8}$$

b. **Median** : Median is the point which divides the entire data into two equal halves. One-half of the data is less than the median, and the other half is greater than the same. Median is calculated by first arranging the data in either ascending or descending order.

  - If the number of observations is odd, the median is given by the middle observation in the sorted form.
  - If the number of observations are even, median is given by the mean of the two middle observations in the sorted form.

  An important point to note is that the order of the data (ascending or descending) does not affect the median.

To calculate Median, let's arrange the data in ascending order.

11, 15, 16, 17, 17, 18, 19, 21, 21, 23

Since the number of observations is even (10), median is given by the average of the two middle observations (5th and 6th here).

$$\boxed{Median = \frac{5^{th}\ Obs + 6^{th}\ Obs}{2} = \frac{17+18}{2} = 17.5}$$

c. **Mode :** Mode is the number which has the maximum frequency in the entire data set, or in other words,mode is the number that appears the maximum number of times. A data can have one or more than one mode.

- If there is only one number that appears the maximum number of times, the data has one mode, and is called Uni-modal.
- If there are two numbers that appear the maximum number of times, the data has two modes, and is called Bi-modal.
- If there are more than two numbers that appear the maximum number of times, the data has more than two modes, and is called Multi-modal.

Consider the following data points.

17, 16, 21, 18, 15, 17, 21, 19, 11, 23

Mode is given by the number that occurs the maximum number of times. Here, 17 and 21 both occur twice. Hence, this is a Bimodal data and the modes are 17 and 21.

- **Measures of Dispersion (or Variability)**

Measures of Dispersion describes the spread of the data around the central value (or the Measures of Central Tendency)

1. **Absolute Deviation from Mean** — The Absolute Deviation from Mean, also called Mean Absolute Deviation (MAD), describes the variation in the data set, in the sense that it tells the average absolute distance of each data point in the set. It is calculated as

$$\boxed{Mean\ \ Absolute\ \ Deviation = \frac{1}{N}\sum_{i=1}^{N}\left|X_i - \overline{X}\right|}$$

2. **Variance** — Variance measures how far are data points spread out from the mean. A high variance indicates that data points are spread widely and a small variance indicates that the data points are closer to the mean of the data set. It is calculated as

$$\boxed{Variance = \frac{1}{N}\sum_{i=1}^{N}\left(X_i - \overline{X}\right)^2}$$

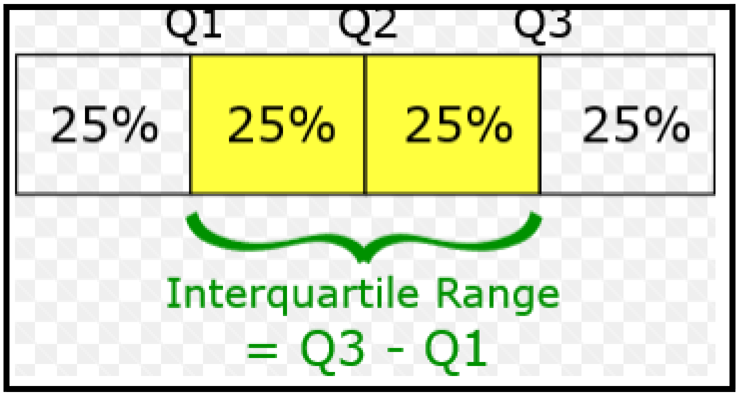
3. **Standard Deviation** — The square root of Variance is called the Standard Deviation. It is calculated as

$$\boxed{Std\ \ Deviation = \sqrt{Variance} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(X_i - \overline{X}\right)^2}}$$

4. **Range** — Range is the difference between the Maximum value and the Minimum value in the data set. It is given as

$$\boxed{Range = Maximum - Minimum}$$

5. **Quartiles** — Quartiles are the points in the data set that divides the data set into four equal parts. Q1, Q2 and Q3 are the first, second and third quartile of the data set.
   - 25% of the data points lie below Q1 and 75% lie above it.
   - 50% of the data points lie below Q2 and 50% lie above it. Q2 is nothing but Median.
   - 75% of the data points lie below Q3 and 25% lie above it.



6. **Skewness** — The measure of asymmetry in a probability distribution is defined by Skewness. It can either be positive, negative or undefined.

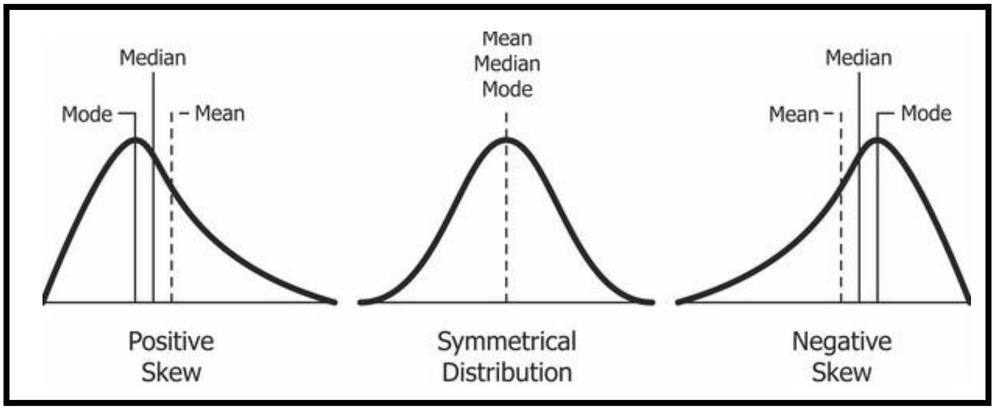
$$Skewness = \frac{3\,(Mean - Median)}{Std\ \ Deviation}$$

Positive Skew — This is the case when the tail on the right side of the curve is bigger than that on the left side. For these distributions, mean is greater than the mode.

Negative Skew — This is the case when the tail on the left side of the curve is bigger than that on the right side. For these distributions, mean is smaller than the mode.

The most commonly used method of calculating Skewness is

If the skewness is zero, the distribution is symmetrical. If it is negative, the distribution is Negatively Skewed and if it is positive, it is Positively Skewed.



Python Code:

1. **Mean**

To find mean of all columns

Syntax:

```
df.mean()
```

Output:

```
CustomerID                100.50
Age                        38.85
Annual Income (k$)         60.56
Spending Score (1-100)     50.20
dtype: float64
```

To find mean of specific column

Syntax:

```
df.loc[:,'Age'].mean()
```

Output:

```
38.85
```

To find mean row wise

Syntax:

```
df.mean(axis=1)[0:4]
```

Output:

```
0    18.50
1    29.75
2    11.25
3    30.00
dtype: float64
```

2. Median

To find median of all columns

Syntax:

```
df.median()
```

Output:

```
CustomerID                100.5
Age                        36.0
Annual Income (k$)         61.5
Spending Score (1-100)     50.0
dtype: float64
```

To find median of specific column

Syntax:

```
df.loc[:,'Age'].median()
```

Output:

```
36.0
```

To find median row wise

Syntax:

```
df.median(axis=1)[0:4]
```

Output:

```
0    17.0
1    18.0
2    11.0
3    19.5
dtype: float64
```

3. Mode

To find mode of all columns

Syntax:

```
df.mode()
```

Output:

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Female	32.0	54.0	42.0
1	2	NaN	NaN	78.0	NaN
2	3	NaN	NaN	NaN	NaN
3	4	NaN	NaN	NaN	NaN
4	5	NaN	NaN	NaN	NaN
...	...	...	...	...	...
195	196	NaN	NaN	NaN	NaN
196	197	NaN	NaN	NaN	NaN
197	198	NaN	NaN	NaN	NaN
198	199	NaN	NaN	NaN	NaN
199	200	NaN	NaN	NaN	NaN

200 rows × 5 columns

In the Genre Column mode is Female, for column Age mode is 32 etc. If a particular column does not have mode all the values will be displayed in the column.

To find the mode of a specific column.

Syntax:

```
df.loc[:,'Age'].mode()
```

Output:

```
32
```

4. Minimum

To find minimum of all columns

Syntax:

```
df.min()
```

Output:

```
CustomerID                    1
Genre                    Female
Age                          18
Annual Income (k$)           15
Spending Score (1-100)        1
dtype: object
```

To find minimum of Specific column

Syntax:

```
df.loc[:,'Age'].min(skipna = False)
```

Output:

```
18
```

5. Maximum

To find Maximum of all columns

Syntax:

```
df.max()
```

Output:

```
CustomerID                 200
Genre                     Male
Age                         70
Annual Income (k$)         137
Spending Score (1-100)      99
dtype: object
```

To find Maximum of Specific column

Syntax:

```
df.loc[:,'Age'].max(skipna = False)
```

Output:

```
70
```

6. Standard Deviation

To find Standard Deviation of all columns

Syntax:

```
df.std()
```

Output:

```
CustomerID                57.879185
Age                       13.969007
Annual Income (k$)        26.264721
Spending Score (1-100)    25.823522
dtype: float64
```

To find Standard Deviation of specific column

Syntax:

```
df.loc[:,'Age'].std()
```

Output:

```
13.969007331558883
```

To find Standard Deviation row wise

Syntax:

```
df.std(axis=1)[0:4]
```

Output:

```
0    15.695010
1    35.074920
2     8.057088
3    32.300671
dtype: float64
```

2. Types of Variables:

A variable is a characteristic that can be measured and that can assume different values. Height, age, income, province or country of birth, grades obtained at school and type of housing are all examples of variables.

Variables may be classified into two main categories:

- Categorical and
- Numeric.

Each category is then classified in two subcategories: nominal or ordinal for categorical variables, discrete or continuous for numeric variables.

- **Categorical variables**

A categorical variable (also called qualitative variable) refers to a characteristic that can't be quantifiable.
Categorical variables can be either nominal or ordinal.

- **Nominal Variable**
  A nominal variable is one that describes a name, label or category without natural order. In the given table, the variable "mode of transportation for travel to work" is also nominal.

Method of travel to work for Canadians

Mode of transportation for travel to work	Number of people
Car, truck, van as driver	9,929,470
Car, truck, van as passenger	923,975
Public transit	1,406,585
Walked	881,085
Bicycle	162,910
Other methods	146,835

- **Ordinal Variable**

  An ordinal variable is a variable whose values are defined by an order relation between the different categories. In the following table, the variable "behaviour" is ordinal because the category "Excellent" is better than the category "Very good," which is better than the category "Good," etc. There is some natural ordering, but it is limited since we do not know by how much "Excellent" behaviour is better than "Very good" behaviour.

Student behaviour ranking

Behaviour	Number of students
Excellent	5
Very good	12
Good	10
Bad	2
Very bad	1

- **Numerical Variables**

  A numeric variable (also called quantitative variable) is a quantifiable characteristic whose values are numbers (except numbers which are codes standing up for categories). Numeric variables may be either continuous or discrete.

  - **Continuous variables**

A variable is said to be continuous if it can assume an infinite number of real values within a given interval.

For instance, consider the height of a student. The height can't take any values. It can't be negative and it can't be higher than three metres. But between 0 and 3, the number of possible values is theoretically infinite. A student may be 1.6321748755 … metres tall.

- **Discrete variables**

  As opposed to a continuous variable, a discrete variable can assume only a finite number of real values within a given interval.

  An example of a discrete variable would be the score given by a judge to a gymnast in competition: the range is 0 to 10 and the score is always given to one decimal (e.g. a score of 8.5)

3. Summary statistics of income grouped by the age groups

Problem Statement: For example, if your categorical variable is age groups and quantitative variable is income, then provide summary statistics of income grouped by the age groups. Create a list that contains a numeric value for each response to the categorical variable.

Categorical Variable: Genre

Quantitative Variable : Age

Syntax:

```
df.groupby(['Genre'])['Age'].mean()
```

Output:

```
Genre
Female    38.098214
Male      39.806818
Name: Age, dtype: float64
```

Categorical Variable: Genre

Quantitative Variable : Income

Syntax:

```
df_u=df.rename(columns= {'Annual Income
k$)':'Income'},inplace=False)
```

```
(df_u.groupby(['Genre']).Income.mean())
```

Output:

```
Genre
Female    59.250000
Male      62.227273
Name: Income, dtype: float64
```

To create a list that contains a numeric value for each response to the categorical variable.

```
from sklearn import preprocessing
enc = preprocessing.OneHotEncoder()
enc_df = pd.DataFrame(enc.fit_transform(df[['Genre']]).toarray())
enc_df
```

	0	1
0	0.0	1.0
1	0.0	1.0
2	1.0	0.0
3	1.0	0.0
4	1.0	0.0

To concat numerical list to dataframe

```
df_encode =df_u.join(enc_df)
df_encode
```

	CustomerID	Genre	Age	Income	Spending Score (1-100)	0	1
0	1	Male	19	15	39	0.0	1.0
1	2	Male	21	15	81	0.0	1.0
2	3	Female	20	16	6	1.0	0.0
3	4	Female	23	16	77	1.0	0.0
4	5	Female	31	17	40	1.0	0.0
...	...	...	...	...	...	...	...
195	196	Female	35	120	79	1.0	0.0
196	197	Female	45	126	28	1.0	0.0
197	198	Male	32	126	74	0.0	1.0
198	199	Male	32	137	18	0.0	1.0
199	200	Male	30	137	83	0.0	1.0

200 rows × 7 columns

4. Display basic statistical details on the iris dataset.

Algorithm:

1. Import Pandas Library
2. The dataset is downloaded from UCI repository.

   csv_url = 'https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data'
3. Assign Column names

```
col_names =
['Sepal_Length','Sepal_Width','Petal_Length','Petal_Width','Species']
```

4. Load Iris.csv into a Pandas data frame

```
iris = pd.read_csv(csv_url, names = col_names)
```

5. Load all rows with Iris-setosa species in variable irisSet

```
irisSet = (iris['Species']== 'Iris-setosa')
```

6. To display basic statistical details like percentile, mean,standard deviation etc. forIris-setosa use describe

```
print('Iris-setosa')
print(iris[irisSet].describe())
```

7. Load all rows with Iris-versicolor species in variable irisVer

```
irisVer = (iris['Species']== 'Iris-versicolor')
```

8. To display basic statistical details like percentile, mean,standard deviation etc. forIris-versicolor use describe

```
print('Iris-versicolor')

print(iris[irisVer].describe())
```

9. Load all rows with Iris-virginica species in variable irisVir

```
irisVir = (iris['Species']== 'Iris-virginica')
```

10. To display basic statistical details like percentile, mean,standard deviation etc. forIris-virginica use describe

```
print('Iris-virginica')

print(iris[irisVir].describe())
```

```
Iris-setosa
       Sepal_Length  Sepal_Width  Petal_Length  Petal_Width
count      50.00000    50.000000     50.000000     50.00000
mean        5.00600     3.418000      1.464000      0.24400
std         0.35249     0.381024      0.173511      0.10721
min         4.30000     2.300000      1.000000      0.10000
25%         4.80000     3.125000      1.400000      0.20000
50%         5.00000     3.400000      1.500000      0.20000
75%         5.20000     3.675000      1.575000      0.30000
max         5.80000     4.400000      1.900000      0.60000
Iris-versicolor
       Sepal_Length  Sepal_Width  Petal_Length  Petal_Width
count     50.000000    50.000000     50.000000    50.000000
mean       5.936000     2.770000      4.260000     1.326000
std        0.516171     0.313798      0.469911     0.197753
min        4.900000     2.000000      3.000000     1.000000
25%        5.600000     2.525000      4.000000     1.200000
50%        5.900000     2.800000      4.350000     1.300000
75%        6.300000     3.000000      4.600000     1.500000
max        7.000000     3.400000      5.100000     1.800000
Iris-virginica
       Sepal_Length  Sepal_Width  Petal_Length  Petal_Width
count      50.00000    50.000000     50.000000     50.00000
mean        6.58800     2.974000      5.552000      2.02600
std         0.63588     0.322497      0.551895      0.27465
min         4.90000     2.200000      4.500000      1.40000
25%         6.22500     2.800000      5.100000      1.80000
50%         6.50000     3.000000      5.550000      2.00000
75%         6.90000     3.175000      5.875000      2.30000
max         7.90000     3.800000      6.900000      2.50000
```

Conclusion:

Descriptive statistics summarises or describes the characteristics of a data set. Descriptive statistics consists of two basic categories of measures:

- measures of central tendency and
- measures of variability (or spread).

Measures of central tendency describe the centre of a data set. It includes the mean, median, and mode.

Measures of variability or spread describe the dispersion of data within the set and it includes standard deviation, variance, minimum and maximum variables.

Assignment Questions:

1. **Explain Measures of Central Tendency with examples.**
2. **What are the different types of variables? Explain with examples.**
3. **Which method is used to statistic the dataframe? write the code.**

.

Group A

Assignment No: 4

Contents for Theory:

1. Linear Regression : Univariate and Multivariate

2. Least Square Method for Linear Regression

3. Measuring Performance of Linear Regression

4. Example of Linear Regression

5. Training data set and Testing data set

---

1. **Linear Regression:** It is a machine learning algorithm based on supervised learning. It targets prediction values on the basis of independent variables.
   - It is preferred to find out the relationship between forecasting and variables.
   - A linear relationship between a dependent variable (X) is continuous; while independent variable(Y) relationship may be continuous or discrete. A linear relationship should be available in between predictor and target variable so known as Linear Regression.
   - Linear regression is popular because the cost function is Mean Squared Error (MSE) which is equal to the average squared difference between an observation's actual and predicted values.
   - It is shown as an equation of line like :

     Y = m*X + b + e

     Where : b is intercepted, m is slope of the line and e is error term.

   This equation can be used to predict the value of target variable Y based on given predictor variable(s) X, as shown in Fig. 1.

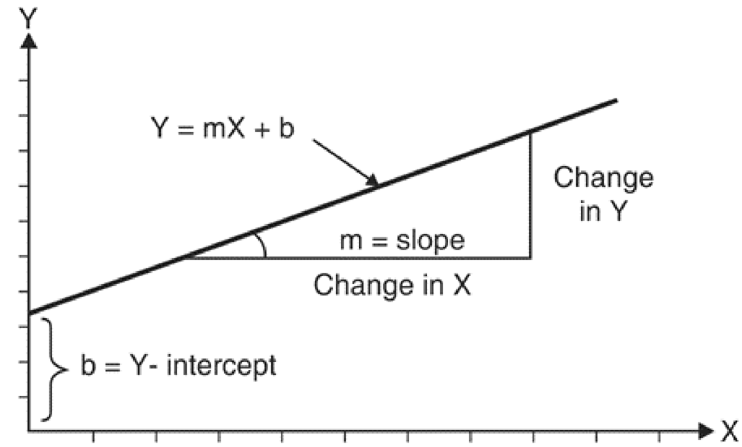
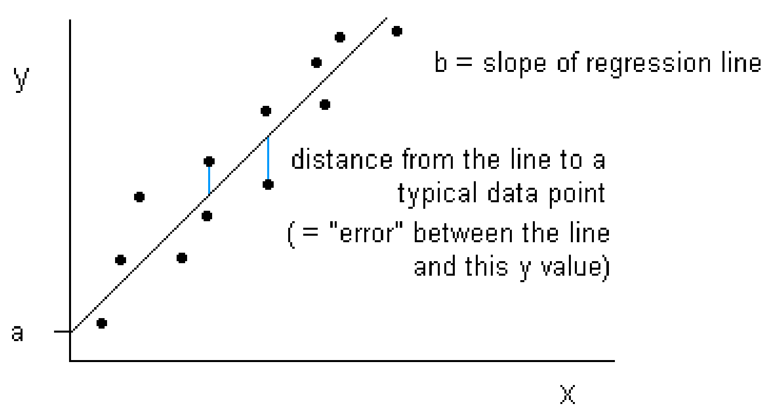


Fig. 1: geometry of linear regression

- Fig. 2 shown below is about the relation between weight (in Kg) and height (in cm), a linear relation. It is an approach of studying in a statistical manner to summarise and learn the relationships among continuous (quantitative) variables.
- Here a variable, denoted by ‘x’ is considered as the predictor, explanatory, or independent variable.
- Another variable, denoted ‘y’, is considered as the response, outcome, or dependent variable. While "predictor" and "response" used to refer to these variables.
- Simple linear regression technique concerned with the study of only one predictor variable.

Fig.2 : Relation between weight (in Kg) and height (in cm)



MultiVariate Regression :It concerns the study of two or more predictor variables. Usually a transformation of the original features into polynomial features from a given degree is preferred and further Linear Regression is applied on it.

- A simple linear model Y = a + bX is in original feature will be transformed into polynomial feature is transformed and further a linear regression applied to it and it will be something like

$$Y=a + bX + cX2$$

- If a high degree value is used in transformation the curve becomes over-fitted as it captures the noise from data as well.

2. Least Square Method for Linear Regression

- Linear Regression involves establishing linear relationships between dependent and independent variables. Such a relationship is portrayed in the form of an equation also known as the linear model.
- A simple linear model is the one which involves only one dependent and one independent variable. Regression Models are usually denoted in Matrix Notations.
- However, for a simple univariate linear model, it can be denoted by the regression equation

$$\hat{y} = \beta_0 + \beta_1 x \qquad (1)$$

where $\hat{y}$ is the dependent or the response variable

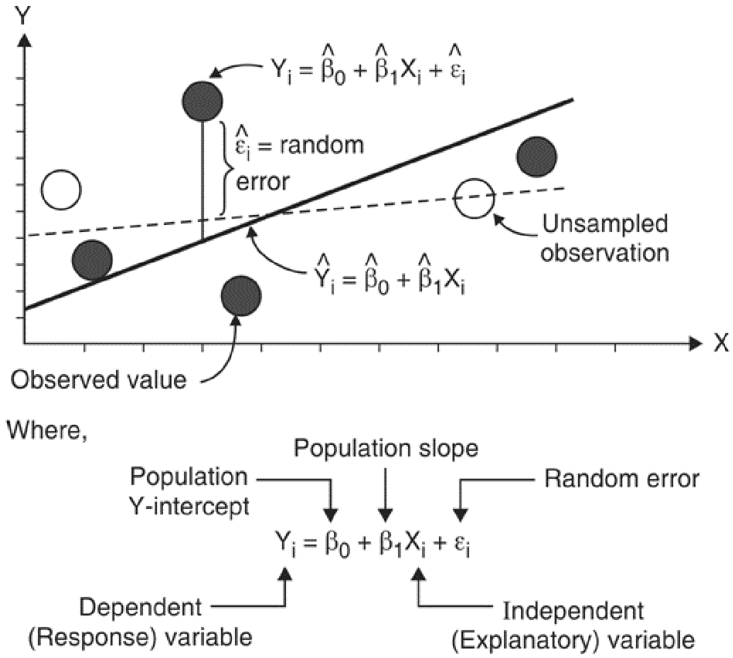
x is the independent or the input variable

β_0 is the value of y when x=0 or the y intercept

β_1 is the value of slope of the line ε is the error or the noise

- This linear equation represents a line also known as the 'regression line'. The least square estimation technique is one of the basic techniques used to guess the values of the parameters and based on a sample set.
- This technique estimates parameters β_0 and β_1 and by trying to minimise the square of errors at all the points in the sample set. The error is the deviation of the actual sample
- data point from the regression line. The technique can be represented by the equation.

$$\min \sum_{i=0}^{n} (\hat{y} - y)^2 \qquad (2)$$



Using differential calculus on equation 1 we can find the values of β_0 and β_1 such that the sum of squares (that is equation 2) is minimum.

$$\beta_1 = \sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y}) / \sum_{i=1}^{n} (x_i - \bar{x})^2 \qquad (3)$$

$$\beta_0 = \bar{y} - \beta_1 \bar{x} \qquad (4)$$

Once the Linear Model is estimated using equations (3) and (4), we can estimate the value of the dependent variable in the given range only. Going outside the range is called extrapolation which is inaccurate if simple regression techniques are used.

3. Measuring Performance of Linear Regression

Mean Square Error:

The Mean squared error (MSE) represents the error of the estimator or predictive model created based on the given set of observations in the sample. Two or more regression models created using a given sample data can be compared based on their MSE. The lesser the MSE, the better the regression model is. When the linear regression model is trained using a given set of observations, the model with the least mean sum of squares error (MSE) is selected as the best model. The Python or R packages select the best-fit model as the model with the lowest MSE or lowest RMSE when training the linear regression models.

Mathematically, the MSE can be calculated as the average sum of the squared difference between the actual value and the predicted or estimated value represented by the regression model (line or plane).

$$MSE = \frac{1}{n} \Sigma \underbrace{\left(y - \widehat{y} \right)}_{\substack{\text{The square of the difference} \\ \text{between actual and} \\ \text{predicted}}}^{2}$$

An MSE of zero (0) represents the fact that the predictor is a perfect predictor.

RMSE:

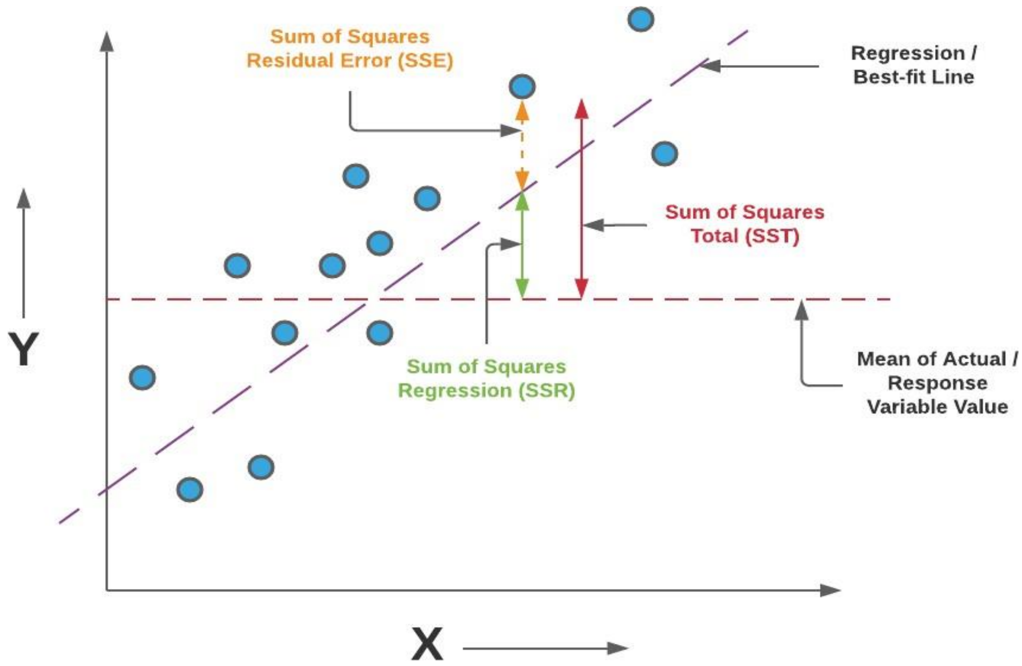
Root Mean Squared Error method that basically calculates the least-squares error and takes a root of the summed values.

Mathematically speaking, Root Mean Squared Error is the square root of the sum of all errors divided by the total number of values. This is the formula to calculate RMSE

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{1}{n} (\hat{y}_i - y_i)^2}$$

RMSE - Least Squares Regression Method - Edureka

R-Squared :



R-Squared is the ratio of the sum of squares regression (SSR) and the sum of squares total (SST).

SST : total sum of squares (SST), regression sum of squares (SSR), Sum of square of errors (SSE) are all showing the variation with different measures.

$$SST = \sum_{i=1} (y_i - \bar{y})^2$$

$$SSR = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2$$

$$SSE = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

$$R^2 = \frac{SSR}{SST} = \frac{\sum(\hat{y}_i - \bar{y})^2}{\sum(y_i - \bar{y})^2}$$

A value of R-squared closer to 1 would mean that the regression model covers most part of the variance of the values of the response variable and can be termed as a good model.

One can alternatively use MSE or R-Squared based on what is appropriate and the need of the hour. However, the disadvantage of using MSE rather than R-squared is that it will be difficult to gauge the performance of the model using MSE as the value of MSE can vary from 0 to any larger number. However, in the case of R-squared, the value is bounded between 0 and .

4. Example of Linear Regression

Consider following data for 5 students.

Each Xi (i = 1 to 5) represents the score of ith student in standard X and corresponding Yi (i = 1 to 5) represents the score of ith student in standard XII.

(i) Linear regression equation best predicts standard XIIth score

(ii) Interpretation for the equation of Linear Regression

(iii) If a student's score is 80 in std X, then what is his expected score in XII standard?

Student	Score in X standard (Xi)	Score in XII standard (Yi)
1	95	85
2	85	95
3	80	70
4	70	65
5	60	70

x	**y**	$x - \bar{x}$	$y - \bar{y}$	$(x - \bar{x})^2$	$(x - \bar{x})(y - \bar{y})$
95	85	17	8	289	136
85	95	7	18	49	126
80	70	2	-7	4	-14
70	65	-8	-12	64	96

60	70	-18	-7	324	126
$\bar{x} = 78$	$\bar{y} = 77$			$\Sigma\ (x - \bar{x})^2 = 730$	$\Sigma\ (x - \bar{x})(y - \bar{y}) = 470$

(i) linear regression equation that best predicts standard XIIth score

$$\hat{y} = \beta_0 + \beta_1 x$$

$$\beta_1 = \sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y}) / \sum_{i=1}^{n} (x_i - \bar{x})^2$$

$$\beta_1 = 470/730 = 0.644$$

$$\beta_0 = \bar{y} - \beta_1 \bar{x}$$

$$\beta_0 = 77 - (0.644 * 78) = 26.768$$

$$\hat{y} = 26.76 + 0.644\,x$$

(ii) Interpretation of the regression line.

Interpretation 1

For an increase in value of x by 0.644 units there is an increase in value of y in one unit.

Interpretation 2

Even if x = 0 value of independent variable, it is expected that value of y is 26.768

Score in XII standard (Yi) is 0.644 units depending on Score in X standard (Xi) but other factors will also contribute to the result of XII standard by 26.768 .

(iii) If a student's score is 80 in std X, then his expected score in XII standard is 78.288

For x = 65 the y value will be

$$\hat{y} = 26.76 + 0.644 * 65 = 68.38$$

5. Training data set and Testing data set

- Machine Learning algorithm has two phases
  1. Training and 2. Testing.
- The input of the training phase is training data, which is passed to any machine learning algorithm and machine learning model is generated as output of the training phase.
- The input of the testing phase is test data, which is passed to the machine learning model and prediction is done to observe the correctness of mode.

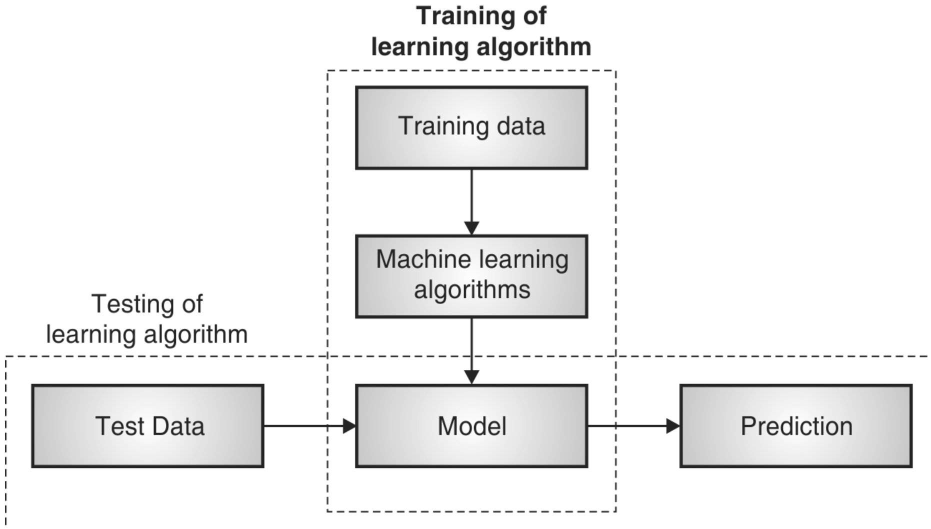


Fig. 1.3.1 : Training and Testing Phase in Machine Learning

(a) Training Phase

- Training dataset is provided as input to this phase.
- Training dataset is a dataset having attributes and class labels and used for training Machine Learning algorithms to prepare models.
- Machines can learn when they observe enough relevant data. Using this one can model algorithms to find relationships, detect patterns, understand complex problems and make decisions**.**
- Training error is the error that occurs by applying the model to the same data from which the model is trained**.**
- In a simple way the actual output of training data and predicted output of the model does not match the training error E_{in} is said to have occurred.
- Training error is much easier to compute.

(b) Testing Phase

    - Testing dataset is provided as input to this phase.
    - Test dataset is a dataset for which class label is unknown. It is tested using model
    - A test dataset used for assessment of the finally chosen model.
- Training and Testing dataset are completely different.
- Testing error is the error that occurs by assessing the model by providing the unknown data to the model.
- In a simple way the actual output of testing data and predicted output of the model does not match the testing error E_{out} is said to have occurred.
- E_{out} is generally observed larger than E_{in}.

(c) Generalization

- Generalization is the prediction of the future based on the past system.
- It needs to generalize beyond the training data to some future data that it might not have seen yet.
- The ultimate aim of the machine learning model is to minimize the generalization error.
- The generalization error is essentially the average error for data the model has never seen.
- In general, the dataset is divided into two partition training and test sets.
- The fit method is called on the training set to build the model.
- This fit method is applied to the model on the test set to estimate the target value and evaluate the model's performance.
- The reason the data is divided into training and test sets is to use the test set to estimate how well the model trained on the training data and how well it would perform on the unseen data.

Algorithm (Synthesis Dataset):

Step 1: Import libraries and create alias for Pandas, Numpy and Matplotlib

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

Step 2: Create a Dataframe with Dependent Variable(x) and independent variable y.

```
x=np.array([95,85,80,70,60])
y=np.array([85,95,70,65,70])
```

Step 3 : Create Linear Regression Model using Polyfit Function:

```
model= np.polyfit(x, y, 1)
```

Step 4: Observe the coefficients of the model.

```
model
```

Output:

```
array([ 0.64383562, 26.78082192])
```

Step 5: Predict the Y value for X and observe the output.

```
predict = np.poly1d(model)
predict(65)
```

Output:

```
68.63
```

Step 6: Predict the y_pred for all values of x.

```
y_pred=  predict(x)
y_pred
```

Output:

```
array([81.50684932, 87.94520548, 71.84931507, 68.63013699, 71.84931507])
```

Step 7: Evaluate the performance of Model (R-Suare)

R squared calculation is not implemented in numpy… so that one should be borrowed from sklearn.

```
from sklearn.metrics import r2_score
r2_score(y, y_pred)
```

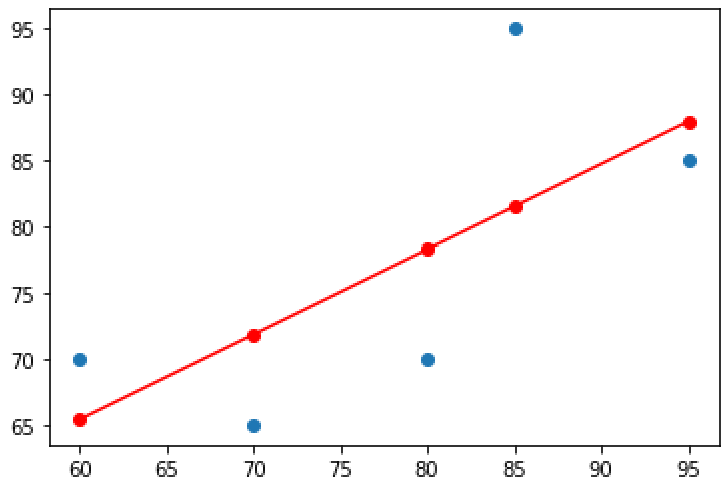
Output:

```
0.4803218090889323
```

Step 8: Plotting the linear regression model

```
y_line = model[1] + model[0]* x
plt.plot(x, y_line, c = 'r')
plt.scatter(x, y_pred)
plt.scatter(x,y,c='r')
```

Output:



Algorithm (Boston Dataset):

Step 1: Import libraries and create alias for Pandas, Numpy and Matplotlib

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

Step 2: Import the Boston Housing dataset

```
from sklearn.datasets import load_boston
boston = load_boston()
```

Step 3: Initialize the data frame

```
data = pd.DataFrame(boston.data)
```

Step 4: Add the feature names to the dataframe

```
data.columns = boston.feature_names
data.head()
```

Step 5: Adding target variable to dataframe

```
data['PRICE'] = boston.target
```

Step 6: Perform Data Preprocessing(Check for missing values)

```
data.isnull().sum()
```

Step 7: Split dependent variable and independent variables

```
x = data.drop(['PRICE'], axis = 1)
y = data['PRICE']
```

Step 8: splitting data to training and testing dataset.

```
from sklearn.model_selection import train_test_split
xtrain, xtest, ytrain, ytest =
train_test_split(x, y, test_size =0.2,random_state = 0)
```

Step 9: Use linear regression(Train the Machine) to Create Model

```
import sklearn
from sklearn.linear_model import LinearRegression
lm = LinearRegression()
model=lm.fit(xtrain, ytrain)
```

Step 10: Predict the y_pred for all values of train_x and test_x

```
ytrain_pred = lm.predict(xtrain)
ytest_pred = lm.predict(xtest)
```

Step 11:Evaluate the performance of Model for train_y and test_y

```
df=pd.DataFrame(ytrain_pred,ytrain)
df=pd.DataFrame(ytest_pred,ytest)
```

Step 12: Calculate Mean Square Paper for train_y and test_y

```
from sklearn.metrics import mean_squared_error, r2_score
mse = mean_squared_error(ytest, ytest_pred)
print(mse)
mse = mean_squared_error(ytrain_pred,ytrain)
```

```
print(mse)
```

Output:

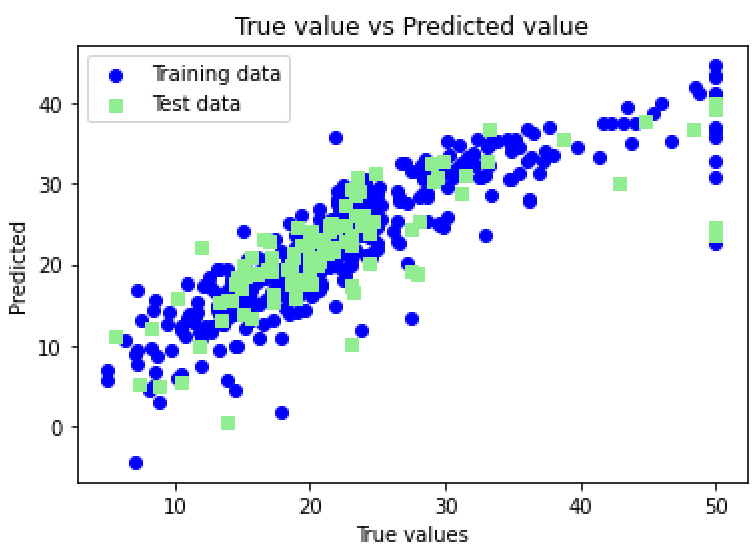
```
33.44897999767638
mse = mean_squared_error(ytest, ytest_pred)
print(mse)
```

Output:

```
19.32647020358573
```

Step 13: Plotting the linear regression model

```
lt.scatter(ytrain ,ytrain_pred,c='blue',marker='o',label='Training data')
plt.scatter(ytest,ytest_pred ,c='lightgreen',marker='s',label='Test data')
plt.xlabel('True values')
plt.ylabel('Predicted')
plt.title("True value vs Predicted value")
plt.legend(loc= 'upper left')
#plt.hlines(y=0,xmin=0,xmax=50)
plt.plot()
plt.show()
```



Conclusion:

In this way we have done data analysis using linear regression for Boston Dataset and predict the price of houses using the features of the Boston Dataset.

Assignment Question:

1) **Compute SST, SSE, SSR, MSE, RMSE, R Square for the below example .**

Student	Score in X standard (Xi)	Score in XII standard (Yi)

1	95	85
2	85	95
3	80	70
4	70	65
5	60	70

2) **Comment on whether the model is best fit or not based on the calculated values.**
3) **Write python code to calculate the RSquare for Boston Dataset.**
   (Consider the linear regression model created in practical session)

.

Group A

Assignment No: 5

Contents for Theory:

1. Logistic Regression

2. Differentiate between Linear and Logistic Regression

3. Sigmoid Function

4. Types of LogisticRegression

5. Confusion Matrix Evaluation Metrics

---

1. **Logistic Regression:** Classification techniques are an essential part of machine learning and data mining applications. Approximately 70% of problems in Data Science are classification problems. There are lots of classification problems that are available, but logistic regression is common and is a useful regression method for solving the binary classification problem. Another category of classification is Multinomial classification, which handles the issues where multiple classes are present in the target variable. For example, the IRIS dataset is a very famous example of multi-class classification. Other examples are classifying article/blog/document categories.

   Logistic Regression can be used for various classification problems such as spam detection. Diabetes prediction, if a given customer will purchase a particular product or will they churn another competitor, whether the user will click on a given advertisement link or not, and many more examples are in the bucket.

   Logistic Regression is one of the most simple and commonly used Machine Learning algorithms for two-class classification. It is easy to implement and can be used as the baseline for any binary classification problem. Its basic fundamental concepts are also constructive in deep learning. Logistic regression describes and estimates the relationship between one dependent binary variable and independent variables.

Logistic regression is a statistical method for predicting binary classes. The outcome or target variable is dichotomous in nature. Dichotomous means there are only two possible classes. For example, it can be used for cancer detection problems. It computes the probability of an event occurring.

It is a special case of linear regression where the target variable is categorical in nature. It uses a log of odds as the dependent variable. Logistic Regression predicts the probability of occurrence of a binary event utilising a logit function.

Linear Regression Equation:

$$y = \beta0 + \beta1X1 + \beta2X2 + \ldots\ldots + \beta nXn$$

Where, y is a dependent variable and x1, x2 ... and Xn are explanatory variables.

Sigmoid Function:

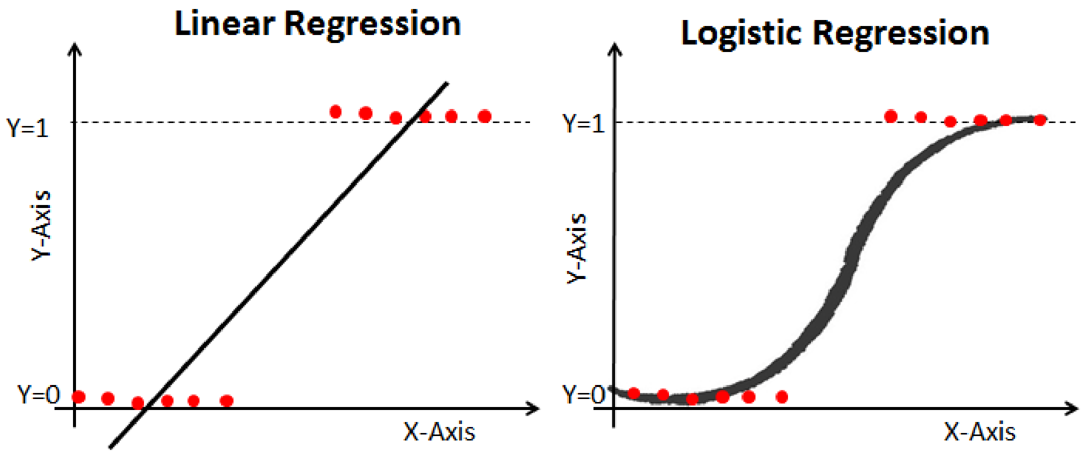
$$p = 1/1 + e^{-y}$$

Apply Sigmoid function on linear regression:

$$p = 1/1 + e^{-(\beta0+\beta1X1+\beta2X2 \ldots\ldots \beta nXn)}$$

2. Differentiate between Linear and Logistic Regression

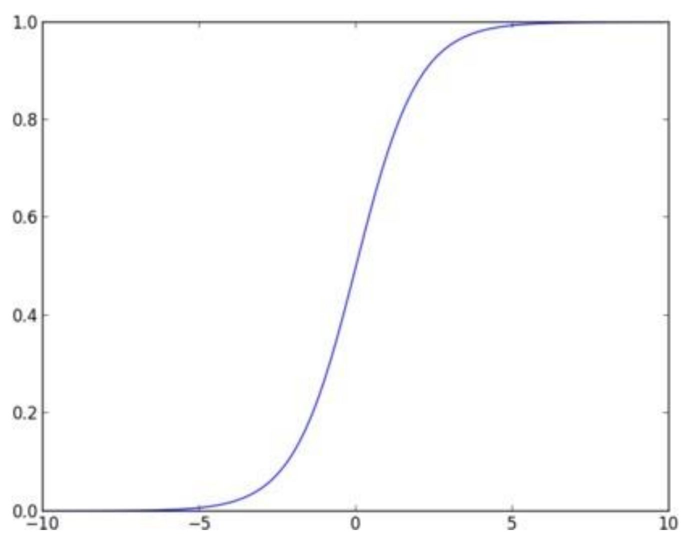
Linear regression gives you a continuous output, but logistic regression provides a constant output. An example of the continuous output is house price and stock price. Example's of the discrete output is predicting whether a patient has cancer or not, predicting whether the customer will churn. Linear regression is estimated using Ordinary Least Squares (OLS) while logistic regression is estimated using Maximum Likelihood Estimation (MLE) approach.



3. Sigmoid Function

The sigmoid function, also called logistic function, gives an 'S' shaped curve that can take any real-valued number and map it into a value between 0 and 1. If the curve goes to positive infinity, y predicted will become 1, and if the curve goes to negative infinity, y predicted will become 0. If the output of the sigmoid function is more than 0.5, we can classify the outcome as 1 or YES, and if it is less than 0.5, we can classify it as 0 or NO. The outputcannotFor example: If the output is 0.75, we can say in terms of probability as: There is a 75 percent chance that a patient will suffer from cancer.

$$f(x) = \frac{1}{1+e^{-(x)}}$$



4. Types of LogisticRegression

Binary Logistic Regression: The target variable has only two possible outcomes such as Spam or Not Spam, Cancer or No Cancer.

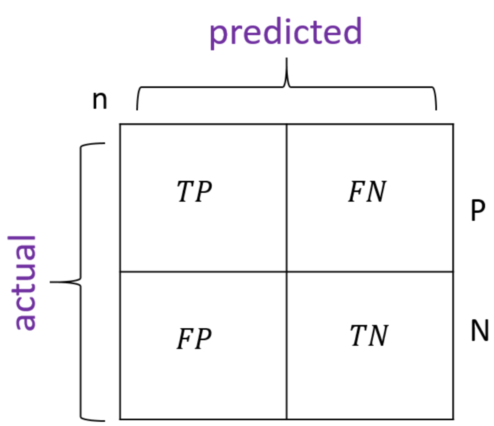
Multinomial Logistic Regression: The target variable has three or more nominal categories such as predicting the type of Wine.

Ordinal Logistic Regression: the target variable has three or more ordinal categories such as restaurant or product rating from 1 to 5.

5. Confusion Matrix Evaluation Metrics

Contingency table or Confusion matrix is often used to measure the performance of classifiers. A confusion matrix contains information about actual and predicted classifications done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix.

The following table shows the confusion matrix for a two class classifier.



Confusion matrix

Here each row indicates the actual classes recorded in the test data set and the each column indicates the classes as predicted by the classifier.
Numbers on the descending diagonal indicate correct predictions, while the ascending diagonal concerns prediction errors.

Some Important measures derived from confusion matrix are:

- **Number of positive (Pos) :** Total number instances which are labelled as positive in a given dataset.
- **Number of negative (Neg)** : Total number instances which are labelled as negative in a given dataset.

- **Number of True Positive (TP) :** Number of instances which are actually labelled as positive and the predicted class by classifier is also positive.
- **Number of True Negative (TN) :** Number of instances which are actually labelled as negative and the predicted class by classifier is also negative.
- **Number of False Positive (FP) :** Number of instances which are actually labelled as negative and the predicted class by classifier is positive.
- **Number of False Negative (FN):** Number of instances which are actually labelled as positive and the class predicted by the classifier is negative.
- **Accuracy:** Accuracy is calculated as the number of correctly classified instances divided by total number of instances.

  The ideal value of accuracy is 1, and the worst is 0. It is also calculated as the sum of true positive and true negative (TP + TN) divided by the total number of instances.

$$\text{acc} = \frac{TP + TN}{TP + FP + TN + FN} = \frac{TP + TN}{Pos + Neg}$$

- **Error Rate:** Error Rate is calculated as the number of incorrectly classified instances divided by total number of instances.

  The ideal value of accuracy is 0, and the worst is 1. It is also calculated as the sum of false positive and false negative (FP + FN) divided by the total number of instances.

$$\text{err} = \frac{FP + FN}{TP + FP + TN + FN} = \frac{FP + FN}{Pos + Neg} \qquad Or$$

$$err = 1 - acc$$

- **Precision:** It is calculated as the number of correctly classified positive instances divided by the total number of instances which are predicted positive. It is also called confidence value. The ideal value is 1, whereas the worst is 0.
-

$$\text{precision} = \frac{TP}{TP + FP}$$

- **Recall: .**It is calculated as the number of correctly classified positive instances divided by the total number of positive instances. It is also called recall or sensitivity. The ideal value of sensitivity is 1, whereas the worst is 0.

  It is calculated as the number of correctly classified positive instances divided by the total number of positive instances.

$$\text{recall} = \frac{TP}{TP + FN}$$

Algorithm (Boston Dataset):

Step 1: Import libraries and create alias for Pandas, Numpy and Matplotlib

Step 2: Import the Social_Media_Adv Dataset

Step 3: Initialize the data frame

Step 4: Perform Data Preprocessing

- Convert Categorical to Numerical Values if applicable
- Check for Null Value
- Covariance Matrix to select the most promising features
- Divide the dataset into Independent(X) and Dependent(Y)variables.
- Split the dataset into training and testing datasets
- Scale the Features if necessary.

Step 5: Use Logistic regression(Train the Machine) to Create Model

```
# import the class
from sklearn.linear_model import LogisticRegression
# instantiate the model (using the default parameters)
logreg = LogisticRegression()
# fit the model with data
logreg.fit(xtrain,ytrain)
# y_pred=logreg.predict(xtest)
```

Step 6: Predict the y_pred for all values of train_x and test_x

Step 7:Evaluate the performance of Model for train_y and test_y

Step 8: Calculate the required evaluation parameters

```
from sklearn.metrics import
precision_score,confusion_matrix,accuracy_score,recall_score
cm= confusion_matrix(ytest, y_pred)
```

Conclusion:

In this way we have done data analysis using logistic regression for Social Media Adv. and evaluate the performance of model.

Value Addition: Visualising Confusion Matrix using Heatmap

Assignment Question:

1) **Consider the binary classification task with two classes positive and negative. Find out TP,TP, FP, TN, FN, Accuracy, Error rate, Precision, Recall**

N = 165	Predicted YES	Predicted NO
Actual YES	TP = 150	FN = 10
Actual NO	FP = 20	TN = 100

2) **Comment on whether the model is best fit or not based on the calculated values.**
3) **Write python code for the preprocessing mentioned in step 4. and Explain every step in detail.**

.

Group A

Assignment No: 6

Contents for Theory:

1. **Concepts used in Naïve Bayes classifier**
2. **Naive Bayes Example**
3. **Confusion Matrix Evaluation Metrics**

---

1. Concepts used in Naïve Bayes classifier

- Naïve Bayes Classifier can be used for Classification of categorical data.
  - Let there be a 'j' number of classes. C={1,2,….j}
  - Let, input observation is specified by 'P' features. Therefore input observation x is given , x = {F1,F2,…..Fp}
  - The Naïve Bayes classifier depends on Bayes' rule from probability theory.
- Prior probabilities: Probabilities which are calculated for some event based on no other information are called Prior probabilities.

For example, P(A), P(B), P(C) are prior probabilities because while calculating P(A), occurrences of event B or C are not concerned i.e. no information about occurrence of any other event is used.

Conditional Probabilities:

$$\boldsymbol{P\left(\frac{A}{B}\right) = \frac{P(A \cap B)}{P(B)} \quad if\ P(B) \neq 0} \qquad \dots\dots(1)$$

$$\boldsymbol{P\left(\frac{B}{A}\right) = \frac{P(B \cap A)}{P(A)}} \qquad \dots\dots\dots(2)$$

From equation (1) and (2) ,

$$P(A \cap B) = P\left(\frac{A}{B}\right).P(B) = P\left(\frac{B}{A}\right).P(A)$$

$$\therefore \qquad P\left(\frac{A}{B}\right) = \frac{P\left(\frac{B}{A}\right).P(A)}{P(B)}$$

Is called the Bayes Rule.

2. Example of Naive Bayes

We have a dataset with some features Outlook, Temp, Humidity, and Windy, and the target here is to predict whether a person or team will play tennis or not.

Outlook	Temp	Humidity	Windy	Play
sunny	hot	high	FALSE	no
sunny	hot	high	TRUE	no
overcast	hot	high	FALSE	yes
rainy	mild	high	FALSE	yes
rainy	cool	normal	FALSE	yes
rainy	cool	normal	TRUE	no
overcast	cool	normal	TRUE	yes
sunny	mild	high	FALSE	no
sunny	cool	normal	FALSE	yes
rainy	mild	normal	FALSE	yes
sunny	mild	normal	TRUE	yes
overcast	mild	high	TRUE	yes
overcast	hot	normal	FALSE	yes
rainy	mild	high	TRUE	no

$$X = [\underbrace{\text{Outlook}}_{x_1}, \underbrace{\text{Temp}}_{x_2}, \underbrace{\text{Humidity}}_{x_3}, \underbrace{\text{Windy}}_{x_4}$$

$$C_k = [\underbrace{\text{Yes}}_{C_1}, \underbrace{\text{No}}_{C_2}]$$

Conditional Probability

Here, we are predicting the probability of class1 and class2 based on the given condition. If I try to write the same formula in terms of classes and features, we will get the following equation

$$P(C_k \mid X) = \frac{P(X \mid C_k) * P(C_k)}{P(X)}$$

Now we have two classes and four features, so if we write this formula for class C1, it will be something like this.

$$P(C_1 \mid x_1 \cap x_2 \cap x_3 \cap x_4) = \frac{P(x_1 \cap x_2 \cap x_3 \cap x_4 \mid C_1) * P(C_1)}{P(x_1 \cap x_2 \cap x_3 \cap x_4)}$$

Here, we replaced Ck with C1 and X with the intersection of X1, X2, X3, X4. You might have a question, It’s because we are taking the situation when all these features are present at the same time.

The Naive Bayes algorithm assumes that all the features are independent of each other or in other words all the features are unrelated. With that assumption, we can further simplify the above formula and write it in this form

$$\boxed{P(C_1 \mid x_1 \cap x_2 \cap x_3 \cap x_4) = \frac{P(x_1 \mid C_1) * P(x_2 \mid C_1) * P(x_3 \mid C_1) * P(x_4 \mid C_1) * P(C_1)}{P(x_1) * P(x_2) * P(x_3) * P(x_4)}}$$

This is the final equation of the Naive Bayes and we have to calculate the probability of both C1 and C2.For this particular example.

Outlook	Temp	Humidity	Windy	Play
Rainy	Cool	High	True	?

$$P(Yes \mid X) = P(Rainy \mid Yes) \times P(Cool \mid Yes) \times P(High \mid Yes) \times P(True \mid Yes) \times P(Yes)$$

$$P(Yes \mid X) = 2/9 \times 3/9 \times 3/9 \times 3/9 \times 9/14 = 0.00529 \rightarrow 0.2 = \frac{0.00529}{0.02057 + 0.00529}$$

$$P(No \mid X) = P(Rainy \mid No) \times P(Cool \mid No) \times P(High \mid No) \times P(True \mid No) \times P(No)$$

$$P(No \mid X) = 3/5 \times 1/5 \times 4/5 \times 3/5 \times 5/14 = 0.02057 \rightarrow 0.8 = \frac{0.02057}{0.02057 + 0.00529}$$

P (N0 | Today) > P (Yes | Today) So, the prediction that golf would be played is ‘No’.

Algorithm (Iris Dataset):

Step 1: Import libraries and create alias for Pandas, Numpy and Matplotlib

Step 2: Import the Iris dataset by calling URL.

Step 3: Initialize the data frame

Step 4: Perform Data Preprocessing

- Convert Categorical to Numerical Values if applicable
- Check for Null Value
- Divide the dataset into Independent(X) and Dependent(Y)variables.
- Split the dataset into training and testing datasets
- Scale the Features if necessary.

Step 5: Use Naive Bayes algorithm(Train the Machine) to Create Model

```
# import the class
from sklearn.naive_bayes import GaussianNB
gaussian = GaussianNB()
gaussian.fit(X_train, y_train)
```

Step 6: Predict the y_pred for all values of train_x and test_x

```
Y_pred = gaussian.predict(X_test)
```

Step 7:Evaluate the performance of Model for train_y and test_y

```
accuracy = accuracy_score(y_test,Y_pred)
```

```
precision =precision_score(y_test, Y_pred,average='micro')
recall =  recall_score(y_test, Y_pred,average='micro')
```

Step 8: Calculate the required evaluation parameters

```
from sklearn.metrics import
precision_score,confusion_matrix,accuracy_score,recall_score
cm = confusion_matrix(y_test, Y_pred)
```

Conclusion:

In this way we have done data analysis using Naive Bayes Algorithm for Iris dataset and evaluated the performance of the model.

Value Addition: Visualising Confusion Matrix using Heatmap

Assignment Question:

1) Consider the observation for the car theft scenario having 3 attributes colour, Type and origin.

Example No.	Color	Type	Origin	Stolen?
1	Red	Sports	Domestic	Yes
2	Red	Sports	Domestic	No
3	Red	Sports	Domestic	Yes
4	Yellow	Sports	Domestic	No
5	Yellow	Sports	Imported	Yes
6	Yellow	SUV	Imported	No
7	Yellow	SUV	Imported	Yes
8	Yellow	SUV	Domestic	No
9	Red	SUV	Imported	No
10	Red	Sports	Imported	Yes

Find the probability of car theft having scenarios Red SUV and Domestic.

2) Write python code for the preprocessing mentioned in step 4. and Explain every step in detail.

.

Group A

Assignment No: 7

Contents for Theory:

1. **Basic concepts of Text Analytics**
2. **Text Analysis Operations using natural language toolkit**
3. **Text Analysis Model using TF-IDF.**
4. **Bag of Words (BoW)**

---

1. Basic concepts of Text Analytics

One of the most frequent types of day-to-day conversion is text communication. In our everyday routine, we chat, message, tweet, share status, email, create blogs, and offer opinions and criticism. All of these actions lead to a substantial amount of unstructured text being produced. It is critical to examine huge amounts of data in this sector of the online world and social media to determine people's opinions.

Text mining is also referred to as text analytics. Text mining is a process of exploring sizable textual data and finding patterns. Text Mining processes the text itself, while NLP processes with the underlying metadata. Finding frequency counts of words, length of the sentence, presence/absence of specific words is known as text mining. Natural language processing is one of the components of text mining. NLP helps identify sentiment, finding entities in the sentence, and category of blog/article. Text mining is preprocessed data for text analytics. In Text Analytics, statistical and machine learning algorithms are used to classify information.

2. Text Analysis Operations using natural language toolkit

NLTK(natural language toolkit) is a leading platform for building Python programs to work with human language data. It provides easy-to-use interfaces and lexical resources such as WordNet, along with a suite of text processing libraries for classification, tokenization, stemming, tagging, parsing, and semantic reasoning and many more.

Analysing movie reviews is one of the classic examples to demonstrate a simple NLP Bag-of-words model, on movie reviews.

2.1. Tokenization:

Tokenization is the first step in text analytics. The process of breaking down a text paragraph into smaller chunks such as words or sentences is called Tokenization. Token is a single entity that is the building blocks for a sentence or paragraph.

- Sentence tokenization : split a paragraph into **list of sentences** using **sent_tokenize()** method
- Word tokenization : split a sentence into **list of words** using **word_tokenize()** method

2.2. Stop words removal

Stopwords considered as noise in the text. Text may contain stop words such as is, am, are, this, a, an, the, etc. In NLTK for removing stopwords, you need to create a list of stopwords and filter out your list of tokens from these words.

2.3. Stemming and Lemmatization

Stemming is a normalization technique where lists of tokenized words are converted into shortened root words to remove redundancy. Stemming is the process of reducing inflected (or sometimes derived) words to their word stem, base or root form.

A computer program that stems word may be called a stemmer.

E.g.

A stemmer reduces the words like fishing, fished, and fisher to the stem fish.

The stem need not be a word, for example the Porter algorithm reduces, argue, argued, argues, arguing, and argus to the stem argu .

Lemmatization in NLTK is the algorithmic process of finding the lemma of a word depending on its meaning and context. Lemmatization usually refers to the morphological analysis of words, which aims to remove inflectional endings. It helps in returning the base or dictionary form of a word known as the lemma.
Eg. Lemma for studies is study

1) Lemmatization Vs Stemming

Stemming algorithm works by cutting the suffix from the word. In a broader sense cuts either the beginning or end of the word.

On the contrary, Lemmatization is a more powerful operation, and it takes into consideration morphological analysis of the words. It returns the lemma which is the base form of all its inflectional forms. In-depth linguistic knowledge is required to create dictionaries and look for the proper form of the word. Stemming is a general operation while lemmatization is an intelligent operation where the proper form will be looked in the dictionary. Hence, lemmatization helps in forming better machine learning features.

2.4. POS Tagging

POS (Parts of Speech) tell us about grammatical information of words of the sentence by assigning specific token (Determiner, noun, adjective , adverb , verb,Personal Pronoun etc.) as tag (DT,NN ,JJ,RB,VB,PRP etc) to each words.
Word can have more than one POS depending upon the context where it is used. We can use POS tags as statistical NLP tasks. It distinguishes a sense of word which is very helpful in text realization and infer semantic information from text for sentiment analysis.

3. Text Analysis Model using TF-IDF.

Term frequency–inverse document frequency(TFIDF) , is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus.

- **Term Frequency (TF)**

It is a measure of the frequency of a word (w) in a document (d). TF is defined as the ratio of a word's occurrence in a document to the total number of words in a document. The denominator term in the formula is to normalize since all the corpus documents are of different lengths.

$$TF(w,d) = \frac{occurences\ of\ w\ in\ document\ d}{total\ number\ of\ words\ in\ document\ d}$$

Example:

Documents	Text	Total number of words in a document
A	Jupiter is the largest planet	5
B	Mars is the fourth planet from the sun	8

The initial step is to make a vocabulary of unique words and calculate TF for each document. TF will be more for words that frequently appear in a document and less for rare words in a document.

- **Inverse Document Frequency (IDF)**

  It is the measure of the importance of a word. Term frequency (TF) does not consider the importance of words. Some words such as' of', 'and', etc. can be most frequently present but are of little significance. IDF provides weightage to each word based on its frequency in the corpus D.

$$IDF(w,D) = \ln\left(\frac{Total\ number\ of\ documents\ (N)\ in\ corpus\ D}{number\ of\ documents\ containing\ w}\right)$$

In our example, since we have two documents in the corpus, N=2.

Words	TF (for A)	TF (for B)	IDF
Jupiter	1/5	0	ln(2/1) = 0.69
Is	1/5	1/8	ln(2/2) = 0
The	1/5	2/8	ln(2/2) = 0
largest	1/5	0	ln(2/1) = 0.69
Planet	1/5	1/8	ln(2/2) = 0
Mars	0	1/8	ln(2/1) = 0.69
Fourth	0	1/8	ln(2/1) = 0.69
From	0	1/8	ln(2/1) = 0.69
Sun	0	1/8	ln(2/1) = 0.69

- **Term Frequency — Inverse Document Frequency (TFIDF)**

  It is the product of TF and IDF.

  TFIDF gives more weightage to the word that is rare in the corpus (all the documents).

  TFIDF provides more importance to the word that is more frequent in the document.

$$TFIDF\ (w, d, D) = TF(w, d) * IDF(w, D)$$

Words	TF (for A)	TF (for B)	IDF	TFIDF (A)	TFIDF (B)
Jupiter	1/5	0	ln(2/1) = 0.69	0.138	0
Is	1/5	1/8	ln(2/2) = 0	0	0
The	1/5	2/8	ln(2/2) = 0	0	0
largest	1/5	0	ln(2/1) = 0.69	0.138	0
Planet	1/5	1/8	ln(2/2) = 0	0.138	0
Mars	0	1/8	ln(2/1) = 0.69	0	0.086
Fourth	0	1/8	ln(2/1) = 0.69	0	0.086
From	0	1/8	ln(2/1) = 0.69	0	0.086
Sun	0	1/8	ln(2/1) = 0.69	0	0.086

After applying TFIDF, text in A and B documents can be represented as a TFIDF vector of dimension equal to the vocabulary words. The value corresponding to each word represents the importance of that word in a particular document.

TFIDF is the product of TF with IDF. Since TF values lie between 0 and 1, not using ***ln*** can result in high IDF for some words, thereby dominating the TFIDF. We don't want that, and therefore, we use ***ln*** so that the IDF should not completely dominate the TFIDF.

- **Disadvantage of TFIDF**

It is unable to capture the semantics. For example, funny and humorous are synonyms, but TFIDF does not capture that. Moreover, TFIDF can be computationally expensive if the vocabulary is vast.

4. **Bag of Words (BoW)**

Machine learning algorithms cannot work with raw text directly. Rather, the text must be converted into vectors of numbers. In natural language processing, a common technique for extracting features from text is to place all of the words that occur in the text in a bucket. This approach is called a bag of words model or BoW for short. It's referred to as a "bag" of words because any information about the structure of the sentence is lost.

Algorithm for Tokenization, POS Tagging, stop words removal, Stemming and Lemmatization:

Step 1: Download the required packages

```
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
nltk.download('averaged_perceptron_tagger')
```

Step 2: Initialize the text

```
text= "Tokenization is the first step in text analytics. The process of breaking down a text paragraph into smaller chunks such as words or sentences is called Tokenization."
```

Step 3: Perform Tokenization

```
#Sentence Tokenization
from nltk.tokenize import sent_tokenize
tokenized_text= sent_tokenize(text)
print(tokenized_text)

#Word  Tokenization
from nltk.tokenize import word_tokenize
tokenized_word=word_tokenize(text)
print(tokenized_word)
```

Step 4: Removing Punctuations and Stop Word

```
# print stop words of English
from nltk.corpus import stopwords
stop_words=set(stopwords.words("english"))
print(stop_words)

text= "How to remove stop words with NLTK library in Python?"
text= re.sub('[^a-zA-Z]', ' ',text)
tokens = word_tokenize(text.lower())
filtered_text=[]
for w in tokens:
    if w not in stop_words:
        filtered_text.append(w)
print("Tokenized Sentence:",tokens)
print("Filterd Sentence:",filtered_text)
```

Step 5 : Perform Stemming

```
from nltk.stem import PorterStemmer
e_words= ["wait", "waiting", "waited", "waits"]
ps =PorterStemmer()
for w in e_words:
    rootWord=ps.stem(w)
print(rootWord)
```

Step 6: Perform Lemmatization

```
from nltk.stem import   WordNetLemmatizer
wordnet_lemmatizer = WordNetLemmatizer()
text = "studies studying cries cry"
tokenization = nltk.word_tokenize(text)
for w in tokenization:
    print("Lemma      for      {}      is      {}".format(w,
    wordnet_lemmatizer.lemmatize(w)))
```

Step 7: Apply POS Tagging to text

```
import nltk
from nltk.tokenize import word_tokenize
data="The pink sweater fit her perfectly"
words=word_tokenize(data)
for word in words:
    print(nltk.pos_tag([word]))
```

Algorithm for Create representation of document by calculating TFIDF

Step 1: Import the necessary libraries.

```
import pandas as pd
from sklearn.feature_extraction.text import TfidfVectorizer
```

Step 2: Initialize the Documents.

```
documentA = 'Jupiter is the largest Planet'
documentB = 'Mars is the fourth planet from the Sun'
```

Step 3: Create BagofWords (BoW) for Document A and B.

```
bagOfWordsA = documentA.split(' ')
bagOfWordsB = documentB.split(' ')
```

Step 4: Create Collection of Unique words from Document A and B.

```
uniqueWords = set(bagOfWordsA).union(set(bagOfWordsB))
```

Step 5: Create a dictionary of words and their occurrence for each document in the corpus

```
numOfWordsA = dict.fromkeys(uniqueWords, 0)
for word in bagOfWordsA:
    numOfWordsA[word] += 1
    numOfWordsB = dict.fromkeys(uniqueWords, 0)
for word in bagOfWordsB:
    numOfWordsB[word] += 1
```

Step 6: Compute the term frequency for each of our documents.

```
def computeTF(wordDict, bagOfWords):
tfDict = {}
bagOfWordsCount = len(bagOfWords)
for word, count in wordDict.items():
    tfDict[word] = count / float(bagOfWordsCount)
return tfDict
tfA = computeTF(numOfWordsA, bagOfWordsA)
tfB = computeTF(numOfWordsB, bagOfWordsB)
```

Step 7: Compute the term Inverse Document Frequency.

```
def computeIDF(documents):
import math
N = len(documents)

idfDict = dict.fromkeys(documents[0].keys(), 0)
for document in documents:
    for word, val in document.items():
        if val > 0:
```

```
            idfDict[word] += 1

    for word, val in idfDict.items():
        idfDict[word] = math.log(N / float(val))
    return idfDict
    idfs = computeIDF([numOfWordsA, numOfWordsB])
    idfs
```

Step 8: Compute the term TF/IDF for all words.

```
def computeTFIDF(tfBagOfWords, idfs):
tfidf = {}
for word, val in tfBagOfWords.items():
    tfidf[word] = val * idfs[word]
return tfidf
tfidfA = computeTFIDF(tfA, idfs)
tfidfB = computeTFIDF(tfB, idfs)
df = pd.DataFrame([tfidfA, tfidfB])
df
```

Conclusion:

In this way we have done text data analysis using TF IDF algorithm

Assignment Question:

2) **Perform Stemming for** `text = "studies studying cries cry".` **Compare the results generated with Lemmatization. Comment on your answer how Stemming and Lemmatization differ from each other.**

3) **Write Python code for removing stop words from the below documents, conver the documents into lowercase and calculate the TF, IDF and TFIDF score for each document.**

```
documentA = 'Jupiter is the largest Planet'
documentB = 'Mars is the fourth planet from the Sun'
```

.

Group A

Assignment No: 8

Contents for Theory:

1. **Seaborn Library Basics**
2. **Know your Data**
3. **Finding patterns of data.**
4. **Checking how the price of the ticket (column name: 'fare') for each passenger is distributed by plotting a histogram.**

Theory:

Data Visualisation plays a very important role in Data mining. Various data scientists spent their time exploring data through visualisation. To accelerate this process we need to have a well-documentation of all the plots.

Even plenty of resources can't be transformed into valuable goods without planning and architecture

1. **Seaborn Library Basics**

Seaborn is a Python data visualisation library based on matplotlib. It provides ahigh-level interface for drawing attractive and informative statistical graphics.

For the installation of Seaborn, you may run any of the following in your command line.

```
pip install seaborn
conda install seaborn
```

To import seaborn you can run the following command.

```
import seaborn as sns
```

2. **Know your data**

The dataset that we are going to use to draw our plots will be the Titanic dataset, which is downloaded by default with the Seaborn library. All you have to do is use the load_dataset function and pass it the name of the dataset.

Let's see what the Titanic dataset looks like. Execute the following script:

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns


dataset = sns.load_dataset('titanic')

dataset.head()
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alone
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no	False
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	False
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes	True
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes	False
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no	True

The dataset contains 891 rows and 15 columns and contains information about the passengers who boarded the unfortunate Titanic ship. The original task is to predict whether or not the passenger survived depending upon different features such as their age, ticket, cabin they boarded, the class of the ticket, etc. We will use the Seaborn library to see if we can find any patterns in the data.

3. Finding patterns of data.

Patterns of data can be find out with the help of different types of plots

Types of plots are:

A. Distribution Plots

a. Dist-Plot

b. Joint Plot

d. Rug Plot

B. Categorical Plots

a. Bar Plot

b. Count Plot

c. Box Plot

d. Violin Plot

C. Advanced Plots

a. Strip Plot

b. Swarm Plot

D. Matrix Plots

a. Heat Map

b. Cluster Map

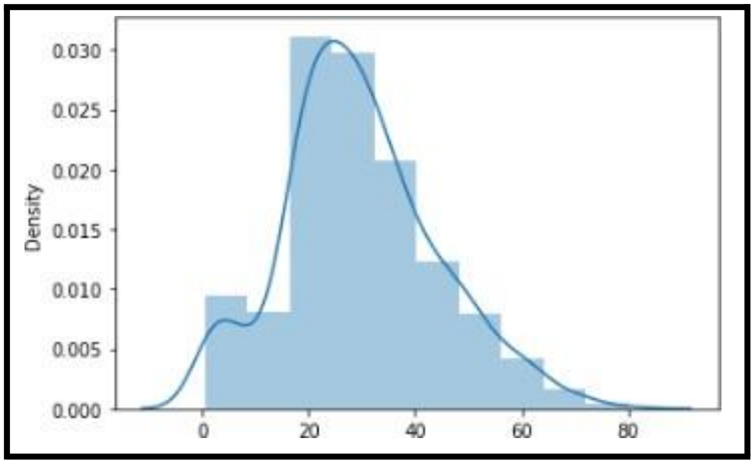
A. Distribution Plots:

These plots help us to visualise the distribution of data. We can use these plots to understand the mean, median, range, variance, deviation, etc of the data.

a. Distplot

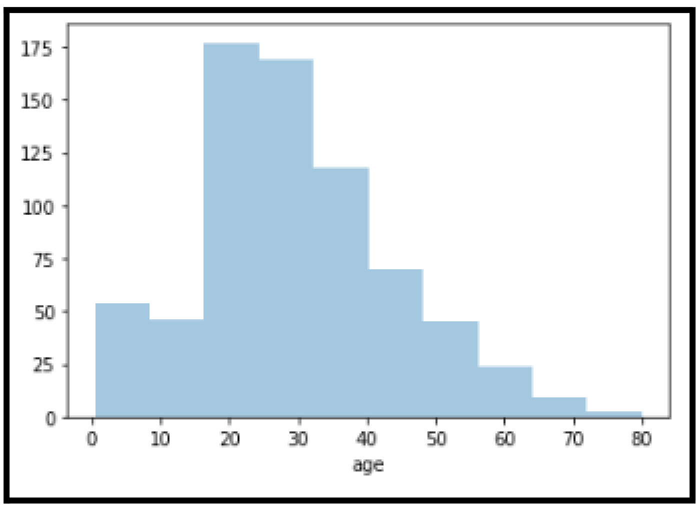
- Dist plot gives us the histogram of the selected continuous variable.
- It is an example of a univariate analysis.
- We can change the number of bins i.e. number of vertical bars in a histogram

```
import seaborn as sns

sns.distplot(x = dataset['age'], bins = 10)
```



The line that you see represents the kernel density estimation. You can remove this line by passing False as the parameter for the kde attribute as shown below

```
sns.distplot(dataset['age'], bins = 10,kde=False)
```



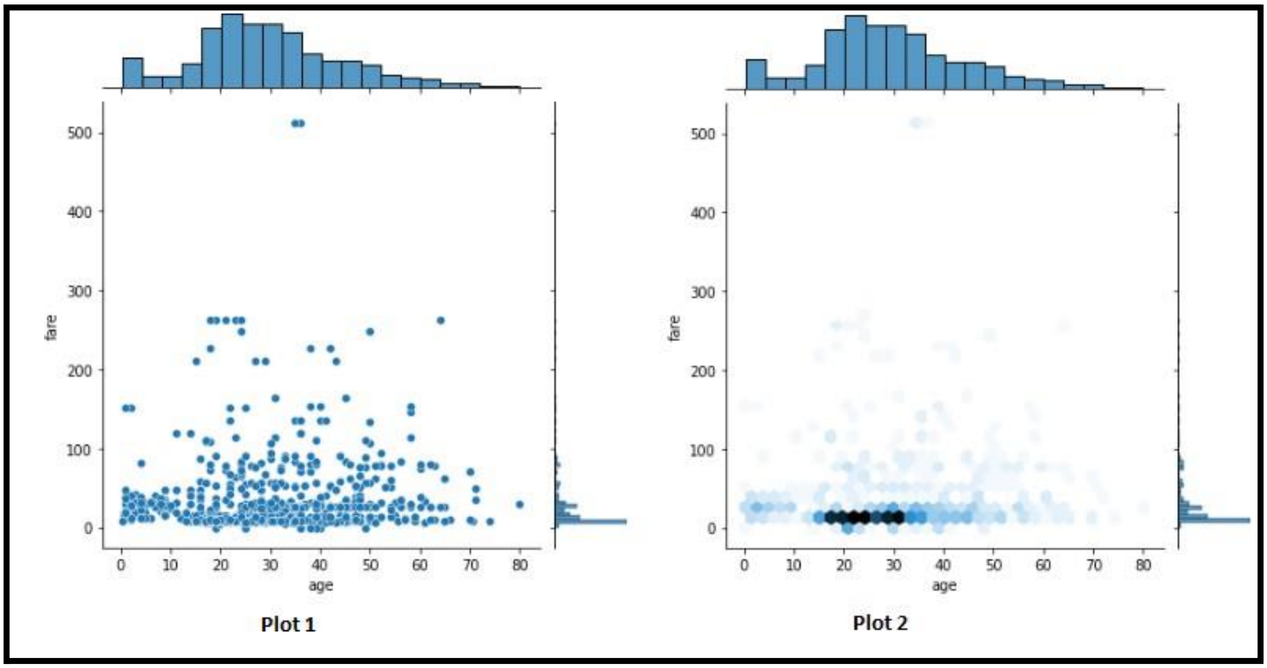
Here the x-axis is the age and the y-axis displays frequency. For example, for bins = 10, there are around 50 people having age 0 to 10

i.b. Joint Plot

- It is the combination of the distplot of two variables.
- It is an example of bivariate analysis.

- We additionally obtain a scatter plot between the variables to reflect their linear relationship. We can customise the scatter plot into a hexagonal plot, where, the more the colour intensity, the more will be the number of observations.

```
import seaborn as sns

# For Plot 1

sns.jointplot(x = dataset['age'], y = dataset['fare'], kind =
'scatter')

# For Plot 2

sns.jointplot(x = dataset['age'], y = dataset['fare'], kind = 'hex')
```



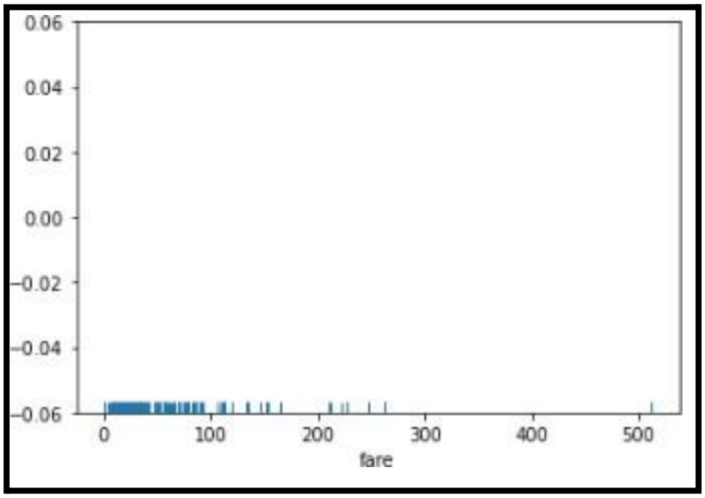
- From the output, you can see that a joint plot has three parts. A distribution plot at the top for the column on the x-axis, a distribution plot on the right for the column on the y-axis and a scatter plot in between that shows the mutual distribution of data for both the columns. You can see that there is no correlation observed between prices and the fares.
- You can change the type of the joint plot by passing a value for the kind parameter. For instance, if instead of a scatter plot, you want to display the distribution of data in the form of a hexagonal plot, you can pass the value hex for the kind parameter.

- In the hexagonal plot, the hexagon with the most number of points gets darker colour. So if you look at the above plot, you can see that most of the passengers are between the ages of 20 and 30 and most of them paid between 10-50 for the tickets.

a. c. The Rug Plot

b. The rugplot() is used to draw small bars along the x-axis for each point in the dataset. To plot a rug plot, you need to pass the name of the column. Let's plot a rug plot for fare.

```
sns.rugplot(dataset['fare'])
```



From the output, you can see that most of the instances for the fares have values between 0 and 100.

These are some of the most commonly used distribution plots offered by the Python's Seaborn Library. Let's see some of the categorical plots in the Seaborn library.

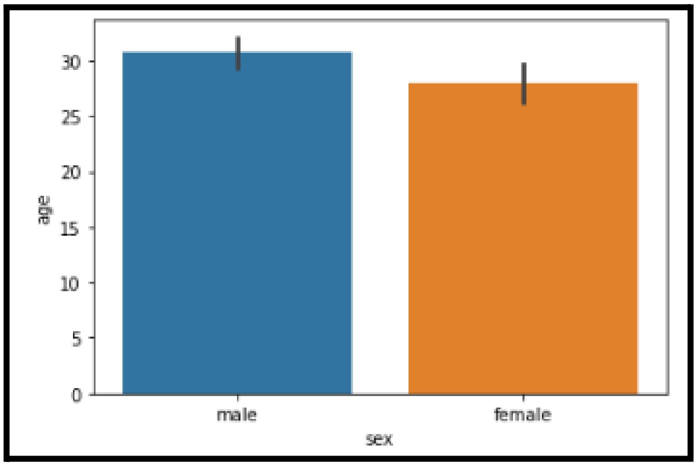
2. Categorical Plots

Categorical plots, as the name suggests, are normally used to plot categorical data. The categorical plots plot the values in the categorical column against another categorical column or a numeric column. Let's see some of the most commonly used categorical data.

b. The Bar Plot

The barplot() is used to display the mean value for each value in a categorical column, against a numeric column. The first parameter is the categorical column, the second parameter is the numeric column while the third parameter is the dataset. For instance, if you want to know the mean value of the age of the male and female passengers, you can use the bar plot as follows.

```
sns.barplot(x='sex', y='age', data=dataset)
```

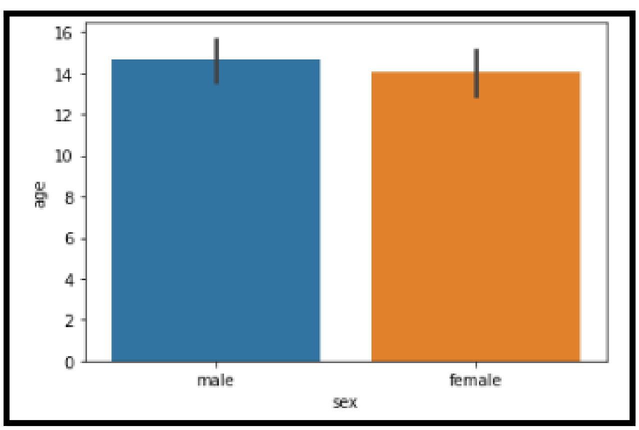


From the output, you can clearly see that the average age of male passengers is just less than 40 while the average age of female passengers is around 33.

In addition to finding the average, the bar plot can also be used to calculate other aggregate values for each category. To do so, you need to pass the aggregate function to the estimator. For instance, you can calculate the standard deviation for the age of each gender as follows:

```
import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

sns.barplot(x='sex', y='age', data=dataset, estimator=np.std)
```

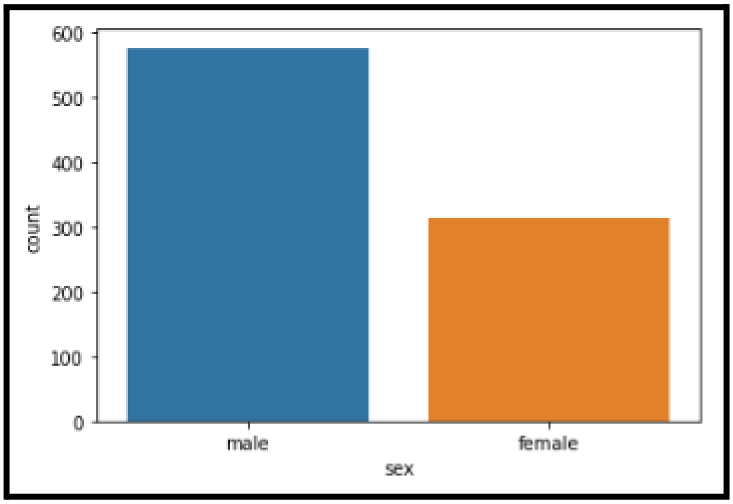
Notice, in the above script we use the std aggregate function from the numpy library to calculate the standard deviation for the ages of male and female passengers. The output looks like this:



c. The Count Plot

The count plot is similar to the bar plot, however it displays the count of the categories in a specific column. For instance, if we want to count the number of males and women passenger we can do so using count plot as follows:

```
sns.countplot(x='sex', data=dataset)
```

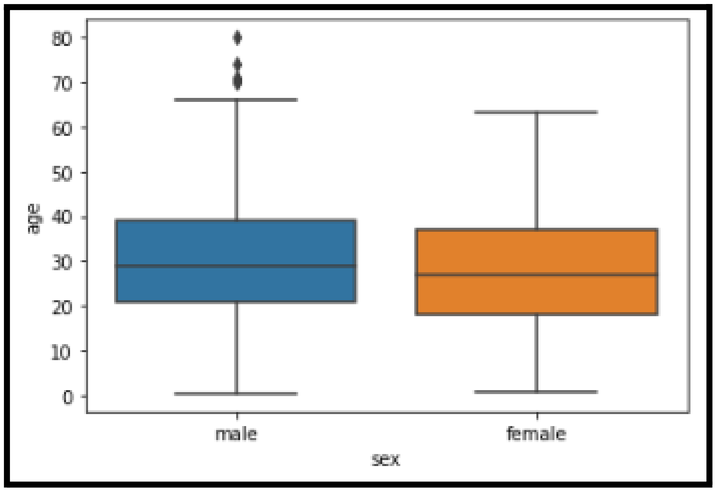


d. The Box Plot

The box plot is used to display the distribution of the categorical data in the form of quartiles. The centre of the box shows the median value. The value from the lower whisker to the bottom of the box shows the first quartile. From the bottom of the box to the middle of the box lies the second quartile. From the middle of the box to the top of the box lies the third quartile and finally from the top of the box to the top whisker lies the last quartile.

Now let's plot a box plot that displays the distribution for the age with respect to each gender. You need to pass the categorical column as the first parameter (which is sex in our case) and the numeric column (age in our case) as the second parameter. Finally, the dataset is passed as the third parameter, take a look at the following script:

```
sns.boxplot(x='sex', y='age', data=dataset)
```

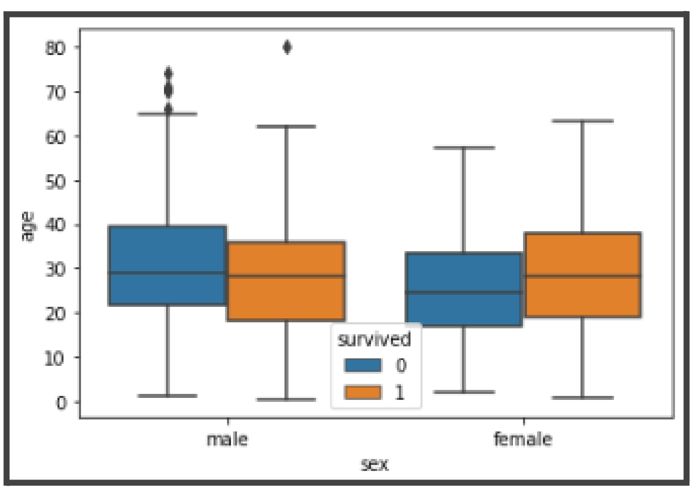


Let's try to understand the box plot for females. The first quartile starts at around 1 and ends at 20 which means that 25% of the passengers are aged between 1 and 20. The second quartile starts at around 20 and ends at around 28 which means that 25% of the passengers are aged between20 and 28. Similarly, the third quartile starts and ends between 28 and 38, hence 25% passengers are aged within this range and finally the fourth or last quartile starts at 38 and ends around 64.

If there are any outliers or the passengers that do not belong to any of the quartiles, they are called outliers and are represented by dots on the box plot.

You can make your box plots more fancy by adding another layer of distribution. For instance, if you want to see the box plots of forage of passengers of both genders, along with the information about whether or not they survived, you can pass the survived as value to the hue parameter as shown below:

```
sns.boxplot(x='sex', y='age', data=dataset, hue="survived")
```



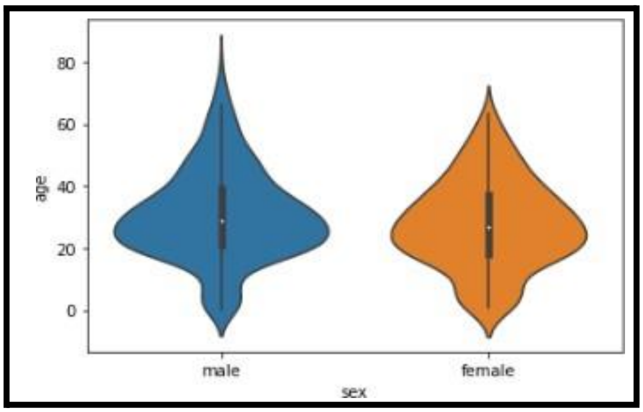
Now in addition to the information about the age of each gender, you can also see the distribution of the passengers who survived. For instance, you can see that among the male passengers, on average more younger people survived as compared to the older ones. Similarly, you can see that the variation among the age of female passengers who did not survive is much greater than the age of the surviving female passengers.

e. The Violin Plot

The violin plot is similar to the box plot, however, the violin plot allows us to display all the components that actually correspond to the data point. The violinplot() function is used to plot the violin plot. Like the box plot, the first parameter is the categorical column, the second parameter is the numeric column while the third parameter is the dataset.

Let's plot a violin plot that displays the distribution for the age with respect to each gender.

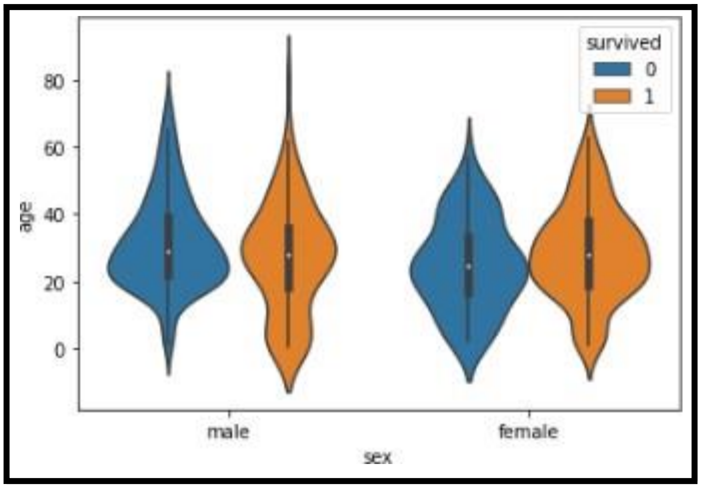
```
sns.violinplot(x='sex', y='age', data=dataset)
```



You can see from the figure above that violin plots provide much more information about the data as compared to the box plot. Instead of plotting the quartile, the violin plot allows us to see all the components that actually correspond to the data. The area where the violin plot is thicker has a higher number of instances for the age. For instance, from the violin plot for males, it is clearly evident that the number of passengers with age between 20 and 40 is higher than all the rest of the age brackets.

Like box plots, you can also add another categorical variable to the violin plot using the hue parameter as shown below:

```
sns.violinplot(x='sex', y='age', data=dataset, hue='survived')
```



Now you can see a lot of information on the violin plot. For instance, if you look at the bottom of the violin plot for the males who survived (left-orange), you can see that it is thicker than the bottom of the violin plot for the males who didn't survive (left-blue). This means that the number of young male passengers who survived is greater than the number of young male passengers who did not survive

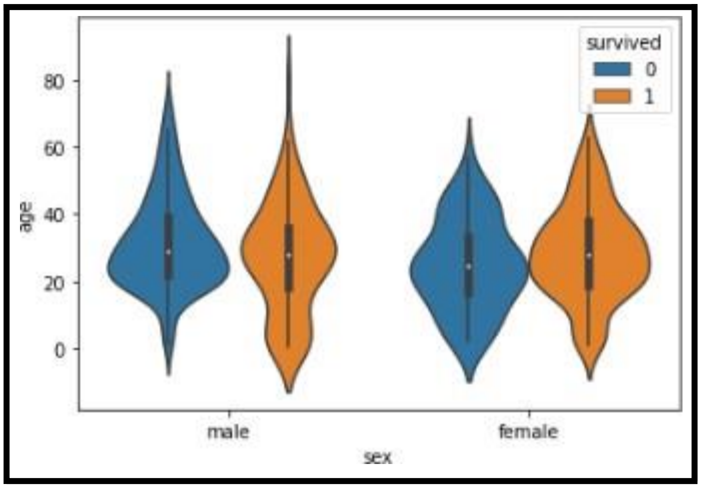
Advanced Plots:

a. The Strip Plot

The strip plot draws a scatter plot where one of the variables is categorical. We have seen scatter plots in the joint plot and the pair plot sections where we had two numeric variables. The strip plot is different in a way that one of the variables is categorical in this case, and for each category in the categorical variable, you will see a scatter plot with respect to the numeric column.

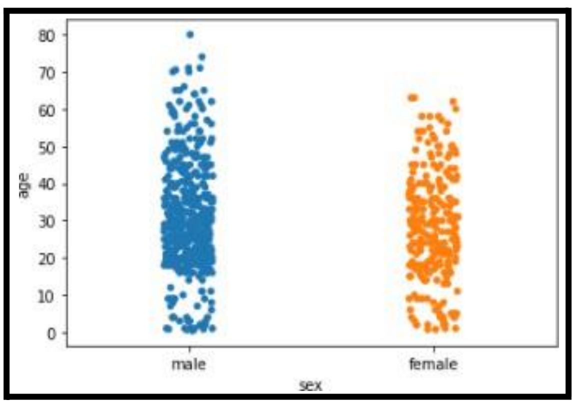
The stripplot() function is used to plot the violin plot. Like the box plot, the first parameter is the categorical column, the second parameter is the numeric column while the third parameter is the dataset. Look at the following script:

```
sns.stripplot(x='sex', y='age', data=dataset, jitter=False)
```



You can see the scattered plots of age for both males and females. The data points look like strips. It is difficult to comprehend the distribution of data in this form. To better comprehend the data, pass True for the jitter parameter which adds some random noise to the data. Look at the following script:

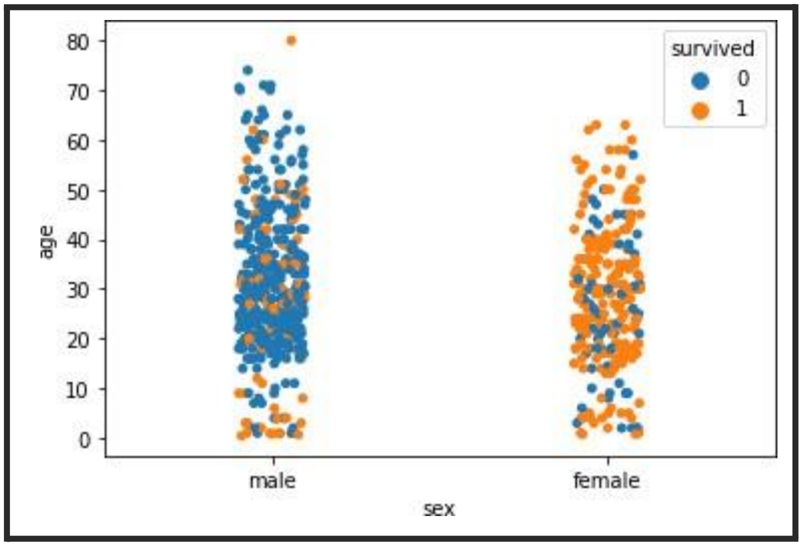
```
sns.stripplot(x='sex', y='age', data=dataset, jitter=True)
```



Now you have a better view for the distribution of age across the genders.

Like violin and box plots, you can add an additional categorical column to strip plot using hue parameter as shown below:

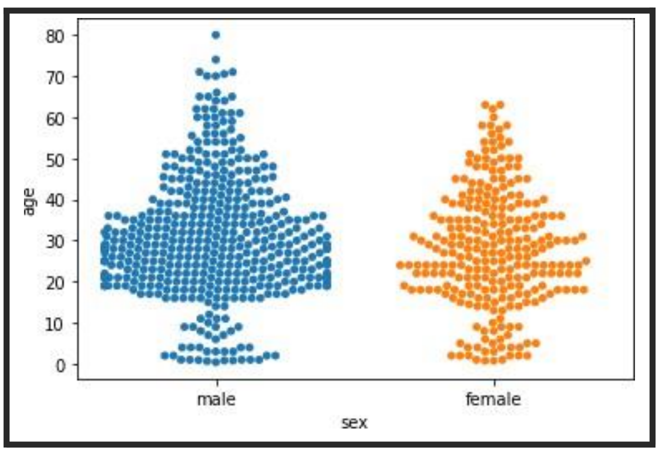
```
sns.stripplot(x='sex', y='age', data=dataset, jitter=True, hue='survived')
```



b. The Swarm Plot

The swarm plot is a combination of the strip and the violin plots. In the swarm plots, the points are adjusted in such a way that they don't overlap. Let's plot a swarm plot for the distribution of age against gender. The swarmplot() function is used to plot the violin plot. Like the box plot, the first parameter is the categorical column, the second parameter is the numeric column while the third parameter is the dataset. Look at the following script:

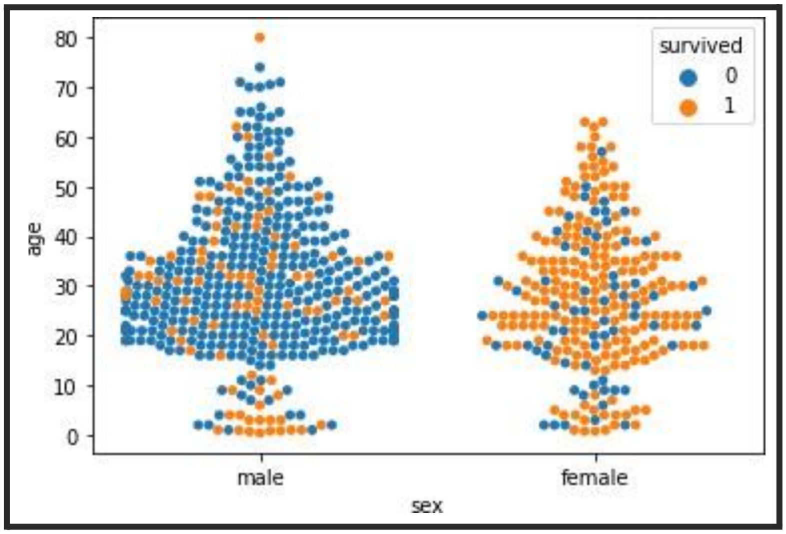
```
sns.swarmplot(x='sex', y='age', data=dataset)
```



You can clearly see that the above plot contains scattered data points like the strip plot and the data points are not overlapping. Rather they are arranged to give a view similar to that of a violin plot.

Let's add another categorical column to the swarm plot using the hue parameter.

```
sns.swarmplot(x='sex', y='age', data=dataset, hue='survived')
```



From the output, it is evident that the ratio of surviving males is less than the ratio of surviving females. Since for the male plot, there are more blue points and less orange points. On the other hand, for females, there are more orange points (surviving) than the blue points (not surviving). Another observation is that amongst males of age less than 10, more passengers survived as compared to those who didn't.

1. Matrix Plots

Matrix plots are the type of plots that show data in the form of rows and columns. Heat maps are the prime examples of matrix plots.

a. Heat Maps

Heat maps are normally used to plot correlation between numeric columns in the form of a matrix. It is important to mention here that to draw matrix plots, you need to have meaningful information on rows as well as columns. Let's plot the first five rows of the Titanic dataset to see if both the rows and column headers have meaningful information. Execute the following script:

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

dataset = sns.load_dataset('titanic')

dataset.head()
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alone
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no	False
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	False
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes	True
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes	False
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no	True

From the output, you can see that the column headers contain useful information such as passengers surviving, their age, fare etc. However the row headers only contain indexes 0, 1, 2, etc. To plot matrix plots, we need useful information on both columns and row headers. One way to do this is to call the corr() method on the dataset. The corr() function returns the correlation between all the numeric columns of the dataset. Execute the following script:

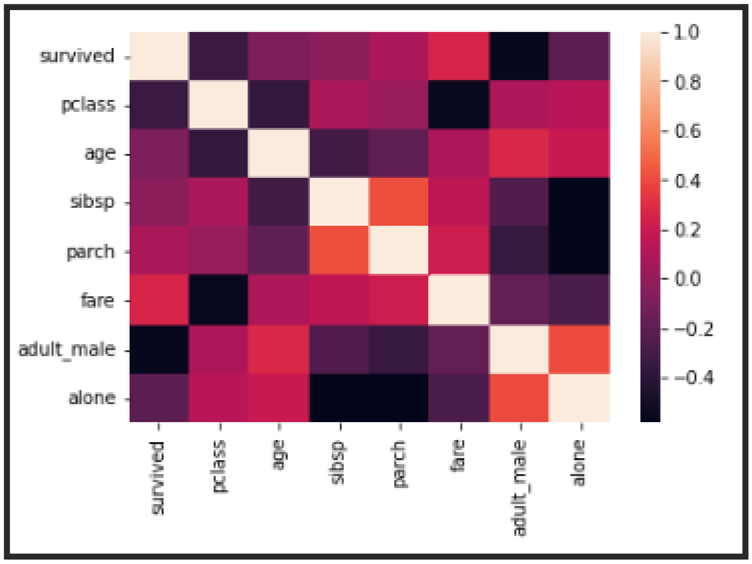
```
dataset.corr()
```

In the output, you will see that both the columns and the rows have meaningful header information, as shown below:

	survived	pclass	age	sibsp	parch	fare	adult_male	alone
survived	1.000000	-0.338481	-0.077221	-0.035322	0.081629	0.257307	-0.557080	-0.203367
pclass	-0.338481	1.000000	-0.369226	0.083081	0.018443	-0.549500	0.094035	0.135207
age	-0.077221	-0.369226	1.000000	-0.308247	-0.189119	0.096067	0.280328	0.198270
sibsp	-0.035322	0.083081	-0.308247	1.000000	0.414838	0.159651	-0.253586	-0.584471
parch	0.081629	0.018443	-0.189119	0.414838	1.000000	0.216225	-0.349943	-0.583398
fare	0.257307	-0.549500	0.096067	0.159651	0.216225	1.000000	-0.182024	-0.271832
adult_male	-0.557080	0.094035	0.280328	-0.253586	-0.349943	-0.182024	1.000000	0.404744
alone	-0.203367	0.135207	0.198270	-0.584471	-0.583398	-0.271832	0.404744	1.000000

Now to create a heat map with these correlation values, you need to call the heatmap() function and pass it your correlation dataframe. Look at the following script:

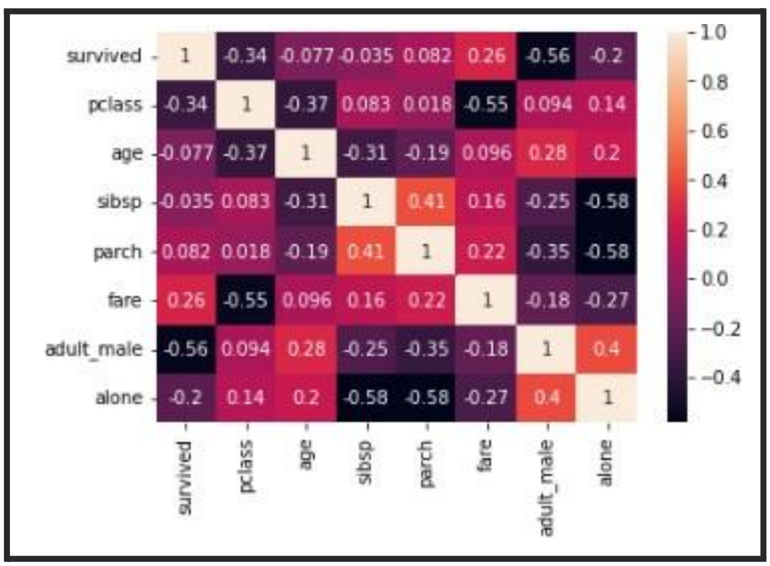
```
corr = dataset.corr()

sns.heatmap(corr)
```



From the output, it can be seen that what heatmap essentially does is that it plots a box for every combination of rows and column value. The colour of the box depends upon the gradient. For instance, in the above image if there is a high correlation between two features, the corresponding cell or the box is white, on the other hand if there is no correlation, the corresponding cell remains black.

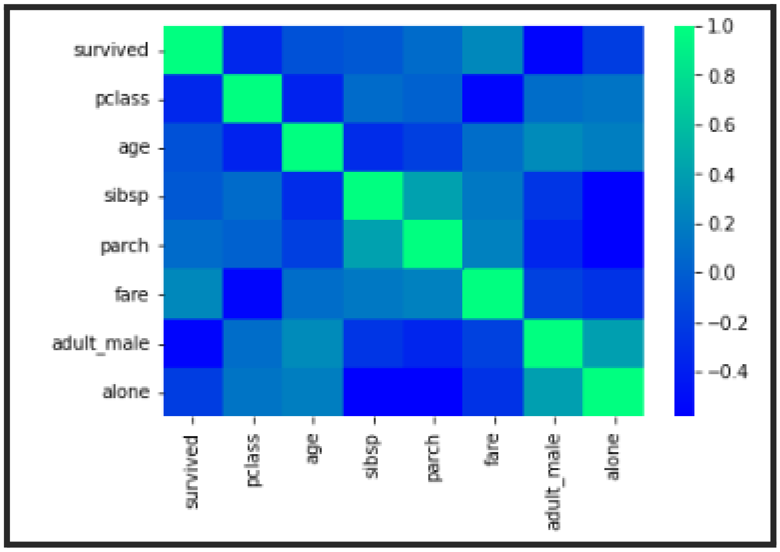
The correlation values can also be plotted on the heatmap by passing True for the annot parameter. Execute the following script to see this in action:

```
corr = dataset.corr()

sns.heatmap(corr, annot=True)
```



You can also change the colour of the heatmap by passing an argument for the cmap parameter. For now, just look at the following script:

```
corr = dataset.corr()

sns.heatmap(corr)
```



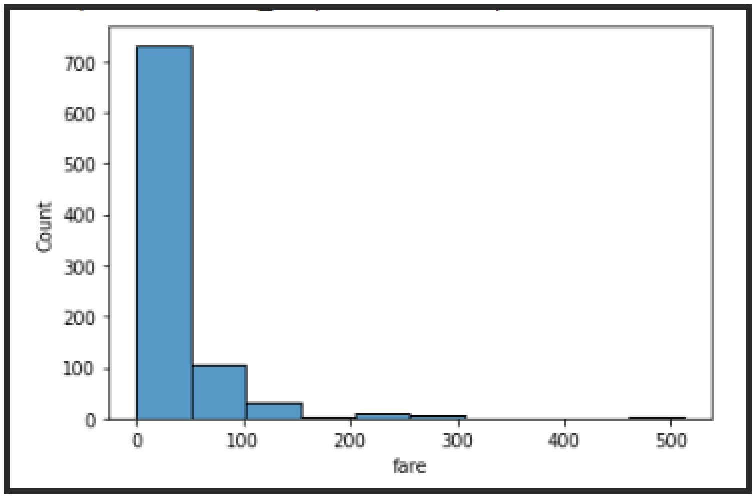
b. Cluster Map:

In addition to the heat map, another commonly used matrix plot is the cluster map. The cluster map basically uses Hierarchical Clustering to cluster the rows and columns of the matrix.

Let's plot a cluster map for the number of passengers who travelled in a specific month of a specific year. Execute the following script:

4. Checking how the price of the ticket (column name: 'fare') for each passenger is distributed by plotting a histogram.

```
import seaborn as sns

dataset = sns.load_dataset('titanic')

sns.histplot(dataset['fare'], kde=False, bins=10)
```



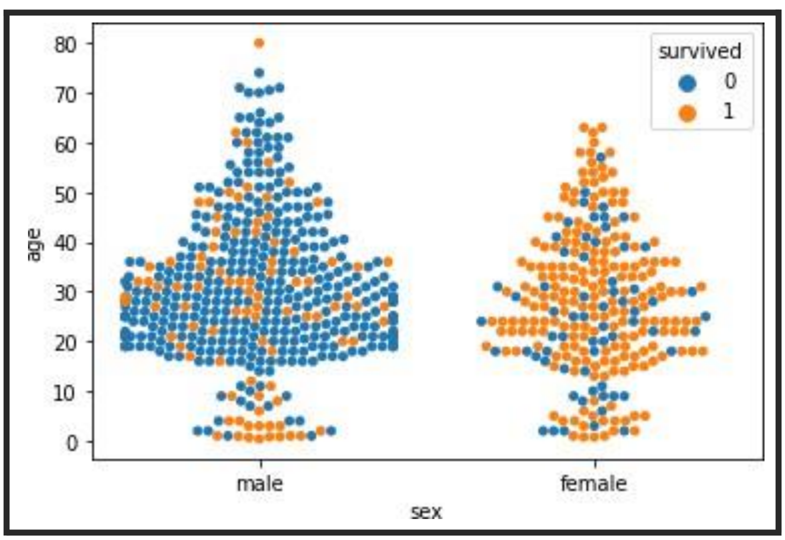
From the histogram, it is seen that for around 730 passengers the price of the ticket is 50. For 100 passengers the price of the ticket is 100 and so on.

Conclusion-

Seaborn is an advanced data visualisation library built on top of Matplotlib library. In this assignment, we looked at how we can draw distributional and categorical plots using the Seaborn library. We have seen how to plot matrix plots in Seaborn. We also saw how to change plot styles and use grid functions to manipulate subplots.

Assignment Questions

1. **List out different types of plot to find patterns of data**
2. **Explain when you will use distribution plots and when you will use categorical plots.**
3. **Write the conclusion from the following swarm plot (consider titanic dataset)**



4. Which parameter is used to add another categorical variable to the violin plot, Explain with syntax and example.

Group A

Assignment No: 9

Contents for Theory:

1. **Exploratory Data Analysis**
2. **Univariate Analysis**

Exploratory Data Analysis

There are various techniques to understand the data, And the basic need is the knowledge of Numpy for mathematical operations and Pandas for data manipulation. Titanic dataset is used. For demonstrating some of the techniques, use an inbuilt dataset of seaborn as tips data which explains the tips each waiter gets from different customers.

Import libraries and loading Data

```
import numpy as np

import pandas pd
import matplotlib.pyplot as plt

import seaborn as sns

from seaborn import load_dataset

#titanic dataset

data = pd.read_csv("titanic_train.csv")

#tips dataset

tips = load_dataset("tips")
```

Univariate Analysis

Univariate analysis is the simplest form of analysis where we explore a single variable. Univariate analysis is performed to describe the data in a better way. we perform Univariate analysis of Numerical and categorical variables differently because plotting uses different plots.

Categorical Data:

A variable that has text-based information is referred to as categorical variables. Now following are various plots which we can use for visualizing Categorical data.

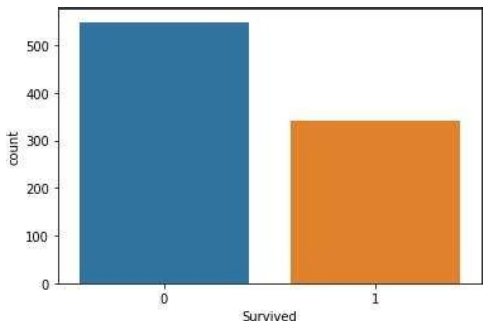
1) CountPlot:

Countplot is basically a count of frequency plot in form of a bar graph. It plots the count of each category in a separate bar. When we use the pandas' value counts function on any column. It is the same visual form of the value counts function. In our data-target variable is survived and it is categorical so plot a countplot of this.

sns.countplot(data['Survived'])

plt.show()

OUTPUT:

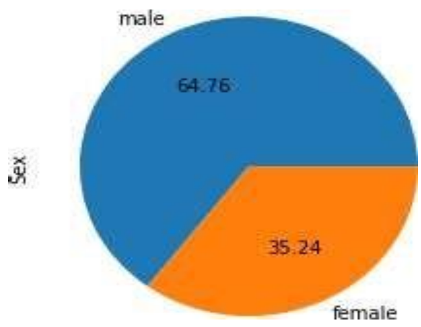


2) Pie Chart:

The pie chart is also the same as the countplot, only gives us additional information about the percentage presence of each category in data means which category is getting how much weightage in data. Now we check about the Sex column, what is a percentage of Male and Female members traveling.

```
data['Sex'].value_counts().plot(kind="pie", autopct="%.2f")
plt.show()
```

OUTPUT:



Numerical Data:

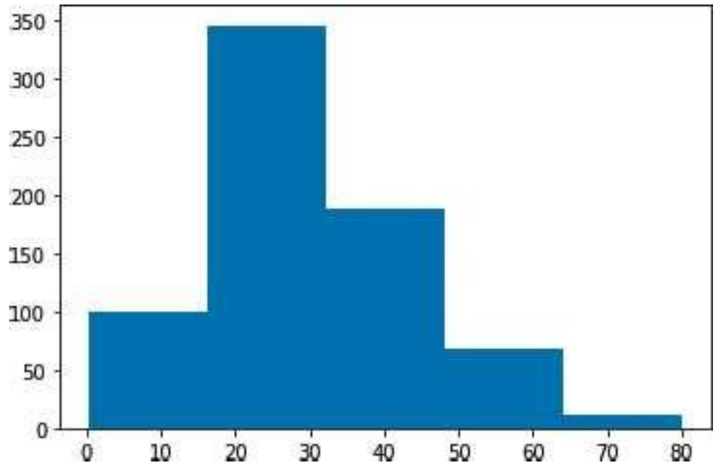
Analyzing Numerical data is important because understanding the distribution of variables helps to further process the data. Most of the time, we will find much inconsistency with numerical data so we have to explore numerical variables.

1) Histogram:

A histogram is a value distribution plot of numerical columns. It basically creates bins in various ranges in values and plots it where we can visualize how values are distributed. We can have a look where more values lie like in positive, negative, or at the center(mean). Let's have a look at the Age column.

```
plt.hist(data['Age'], bins=5)
plt.show()
```

OUTPUT:



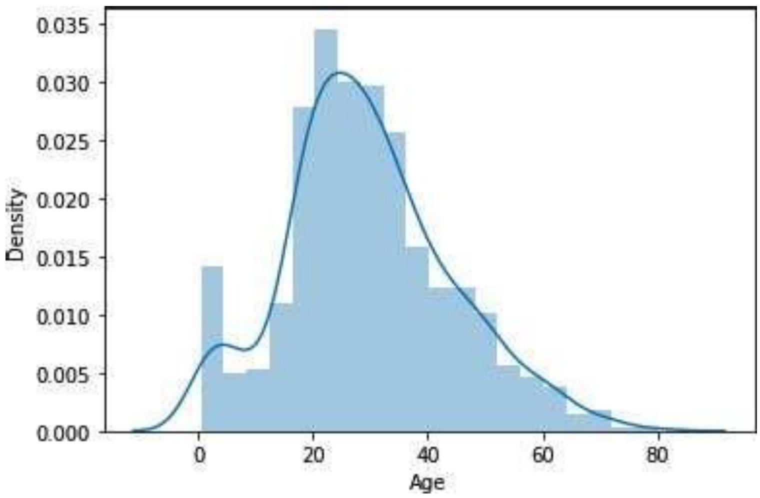
2) Distplot:

Distplot is also known as the second Histogram because it is a slight improvement version of the Histogram. Distplot gives us a KDE(Kernel Density Estimation) over histogram which explains PDF(Probability Density Function) which means what is the probability of each value occurring in this column.

sns.distplot(data['Age'])

plt.show()

OUTPUT:



3) Boxplot:

Boxplot is a very interesting plot that basically plots a 5 number summary. to get 5 number summary some terms we need to describe.

- Median – Middle value in series after sorting
- Percentile ~~–~~Gives any number which is number of values present before this percentile like for example 50 under 25th percentile so it explains total of 50 values are there below 25th percentile
- Minimum and Maximum – These are not minimum and maximum values, rather they describe the lower and upper boundary of standard deviation which is calculated using Interquartile range(IQR).

IQR = Q3 - Q1

Lower_boundary = Q1 - 1.5 * IQR

Upper_bounday = Q3 + 1.5 * IQR

Here Q1 and Q3 is 1st quantile (25th percentile) and 3rd Quantile(75th percentile).

Bivariate/ Multivariate Analysis:

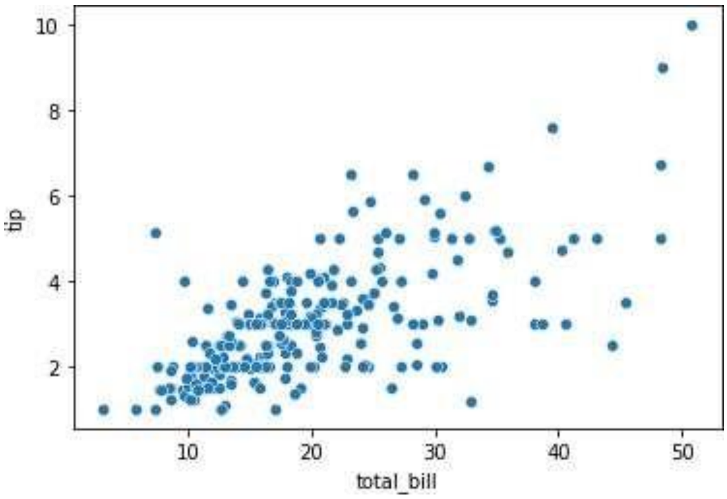
We have study about various plots to explore single categorical and numerical data. Bivariate Analysis is used when we have to explore the relationship between 2 different variables and we have to do this because, in the end, our main task is to explore the relationship between variables to build a powerful model. And when we analyze more than 2 variables together then it is known as Multivariate Analysis. we will work on different plots for Bivariate as well on Multivariate Analysis.

Explore the plots when both the variable is numerical.

1) Scatter Plot:

To plot the relationship between two numerical variables scatter plot is a simple plot to do. Let us see the relationship between the total bill and tip provided using a scatter plot.

```
sns.scatterplot(tips["total_bill"], tips["tip"])
```



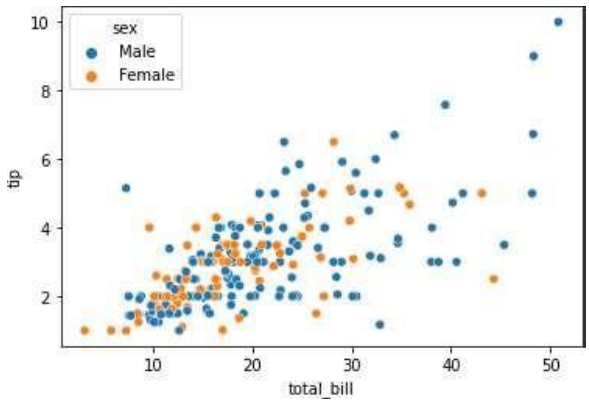
Multivariate analysis with scatter plot:

We can also plot 3 variable or 4 variable relationships with scatter plot. suppose we want to find the separate ratio of male and female with total bill and tip provided.

sns.scatterplot(tips["total_bill"], tips["tip"], hue=tips["sex"])

plt.show()

OUTPUT:

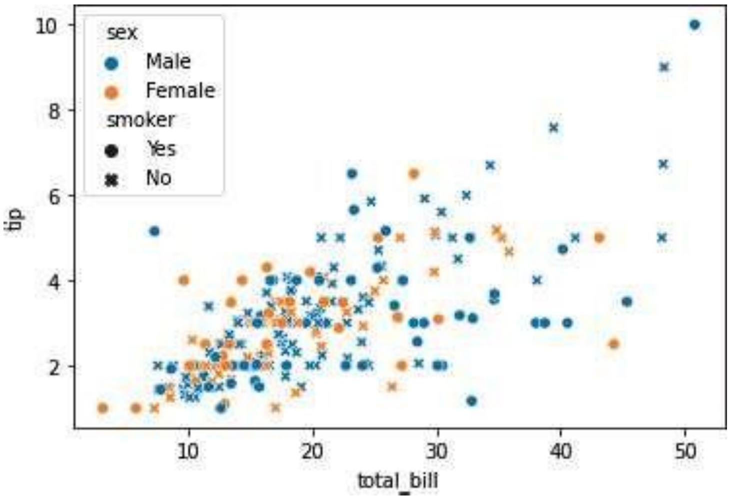


We can also see 4 variable multivariate analyses with scatter plots using style argument. Suppose along with gender we also want to know whether the customer was a smoker or not so we can do this.

sns.scatterplot(tips["total_bill"], tips["tip"], hue=tips["sex"], style=tips['smoker'])

plt.show()

OUTPUT:



Numerical and Categorical:

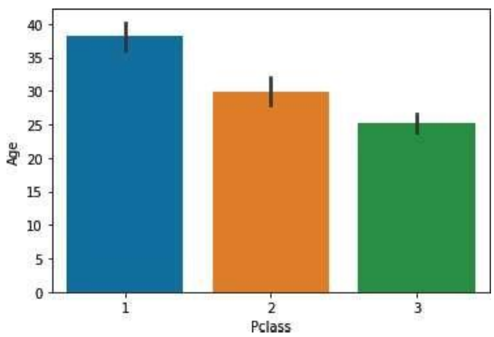
If one variable is numerical and one is categorical then there are various plots that we can use for Bivariate and Multivariate analysis.

1) Bar Plot:

Bar plot is a simple plot which we can use to plot categorical variable on the x-axis and numerical variable on y-axis and explore the relationship between both variables. The blacktip on top of each bar shows the confidence Interval. let us explore P-Class with age.

```
sns.barplot(data['Pclass'], data['Age'])

plt.show()
```

OUTPUT:



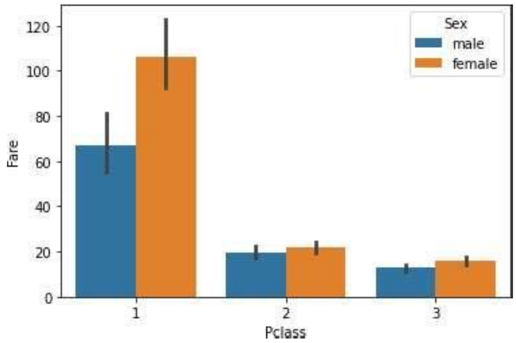
Multivariate analysis using Bar plot:

Hue's argument is very useful which helps to analyze more than 2 variables. Now along with the above relationship we want to see with gender.

sns.barplot(data['Pclass'], data['Fare'], hue = data["Sex"])

plt.show()

OUTPUT:

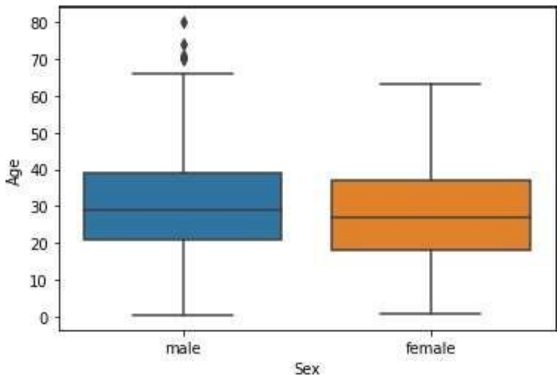


2) Boxplot:

We have already study about boxplots in the Univariate analysis above. we can draw a separate boxplot for both the variable. let us explore gender with age using a boxplot.

sns.boxplot(data['Sex'], data["Age"])

OUTPUT:

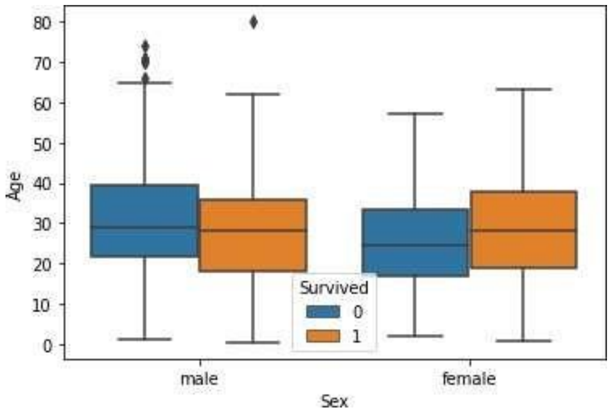


Multivariate analysis with boxplot:

Along with age and gender let's see who has survived and who has not.

sns.boxplot(data['Sex'], data["Age"], data["Survived"]) plt.show()

OUTPUT:



3) Distplot:

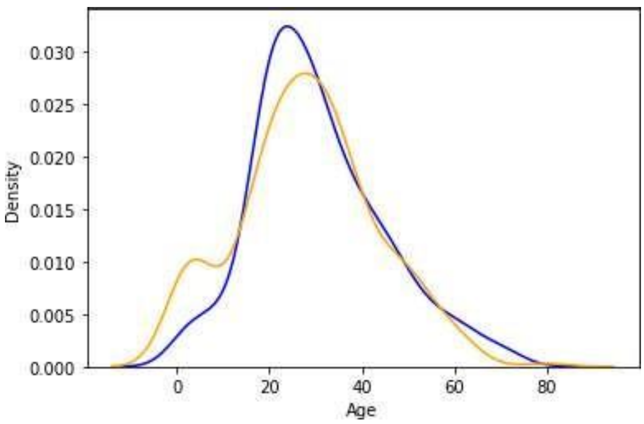
Distplot explains the PDF function using kernel density estimation. Distplot does not have a hue parameter but we can create it. Suppose we want to see the probability of people with an age range that of survival probability and find out whose survival probability is high to the age range of death ratio.

sns.distplot(data[data['Survived'] == 0]['Age'], hist=False, color="blue")

sns.distplot(data[data['Survived'] == 1]['Age'], hist=False, color="orange")

plt.show()

OUTPUT:



In above graph, the blue one shows the probability of dying and the orange plot shows the survival probability. If we observe it we can see that children's survival probability is higher than death and which is the opposite in the case of aged peoples. This small analysis tells sometimes some big things about data and it helps while preparing data stories.

Categorical and Categorical:

Now, we will work on categorical and categorical columns.

1) Heatmap:

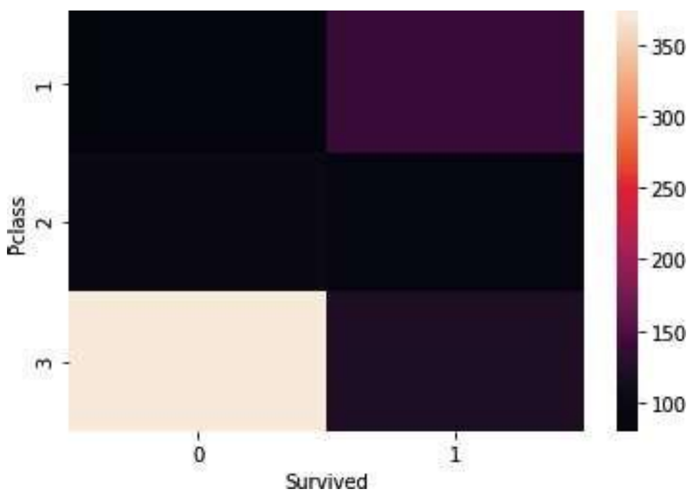
If you have ever used a crosstab function of pandas then Heatmap is a similar visual representation of that only. It basically shows that how much presence of one category concerning another category is present in the dataset. let me show first with crosstab and then with heatmap.

pd.crosstab(data['Pclass'], data['Survived'])

Survived	0	1
Pclass		
1	80	136
2	97	87
3	372	119

Now with heatmap, we have to find how many people survived and died.

sns.heatmap(pd.crosstab(data['Pclass'], data['Survived']))

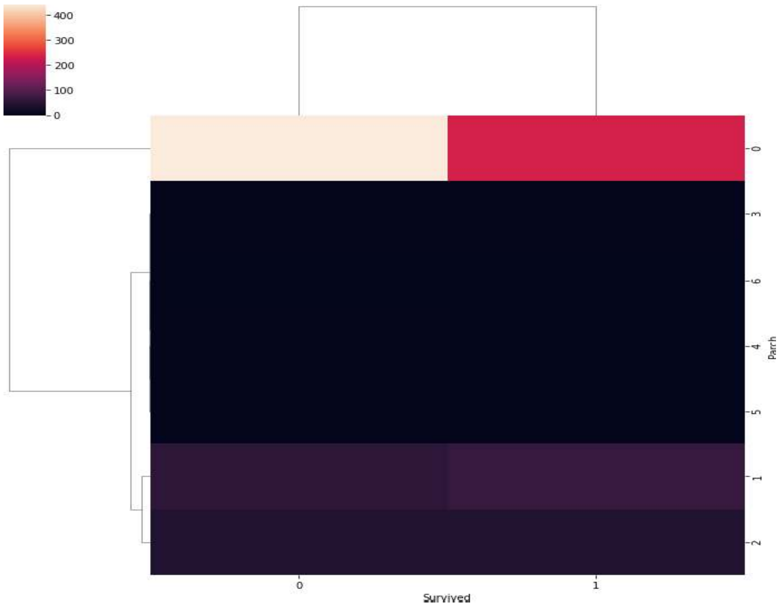


2) Cluster map:

We can also use a cluster map to understand the relationship between two categorical variables. A cluster map basically plots a dendrogram that shows the categories of similar behavior together.

```
sns.clustermap(pd.crosstab(data['Parch'], data['Survived']))

plt.show()
```

OUTPUT:



Conclusion-

In this way we have explored the functions of the python library for Data Preprocessing, Data Wrangling Techniques and How to Handle missing values on Iris Dataset.

Assignment Questions

1. Write down the code to use inbuilt dataset 'titanic' using seaborn library.
2. Write code to plot a box plot for distribution of age with respect to each gender along with the information about whether they survived or not.
3. Write the observations from the box plot.

Group A

Assignment No: 10

Contents for Theory:

Implement a dataset into a dataframe. Implement the following operations:

1. Display data set details.
2. Calculate min, max ,mean, range, standard deviation, variance.
3. Create histograph using hist function.
4. Create boxplot using boxplot function.

Theory:

How to Find the Mean, Median, Mode, Range, and Standard Deviation

Simplify comparisons of sets of number, especially large sets of number, by calculating the center values using mean, mode and median. Use the ranges and standard deviations of the sets to examine the variability of data.

Calculating Mean

The mean identifies the average value of the set of numbers. For example, consider the data set containing the values 20, 24, 25, 36, 25, 22, 23.

Formula

To find the mean, use the formula: Mean equals the sum of the numbers in the data set divided by the number of values in the data set. In mathematical terms: Mean=(sum of all terms)÷(how many terms or values in the set).

Adding Data Set

Add the numbers in the example data set: 20+24+25+36+25+22+23=175.

Finding Divisor

Divide by the number of data points in the set. This set has seven values so divide by 7.

Finding Mean

Insert the values into the formula to calculate the mean. The mean equals the sum of the values (175) divided by the number of data points (7). Since 175÷7=25, the mean of this data set equals 25. Not all mean values will equal a whole number.

Calculating Range

Range shows the mathematical distance between the lowest and highest values in the data set. Range measures the variability of the data set. A wide range indicates greater variability in the data, or perhaps a single outlier far from the rest of the data. Outliers may skew, or shift, the mean value enough to impact data analysis.

Identifying Low and High Values

In the sample group, the lowest value is 20 and the highest value is 36.

Calculating Range

To calculate range, subtract the lowest value from the highest value. Since 36-20=16, the range equals 16.

Calculating Standard Deviation

Standard deviation measures the variability of the data set. Like range, a smaller standard deviation indicates less variability.

Formula

Finding standard deviation requires summing the squared difference between each data point and the mean $[\sum(x-\mu)^2]$, adding all the squares, dividing that sum by one less than the number of values (N-1), and finally calculating the square root of the dividend.

Mathematically, start with calculating the mean.

Calculating the Mean

Calculate the mean by adding all the data point values, then dividing by the number of data points. In the sample data set, 20+24+25+36+25+22+23=175. Divide the sum, 175, by the number of data points, 7, or 175÷7=25. The mean equals 25.

Squaring the Difference

Next, subtract the mean from each data point, then square each difference. The formula looks like this: $\sum(x-\mu)^2$, where $\sum$ means sum, x represents each data set value and μ represents the mean value. Continuing with the example set, the values become: 20-25=-5 and $-5^2=25$; 24-25=-1 and $-1^2=1$; 25-25=0 and $0^2=0$; 36-25=11 and $11^2=121$; 25-25=0 and $0^2=0$; 22-25=-3 and $-3^2=9$; and 23-25=-2 and $-2^2=4$.

Adding the Squared Differences

Adding the squared differences yields: 25+1+0+121+0+9+4=160. The example data set has 7 values, so N-1 equals 7-1=6. The sum of the squared differences, 160, divided by 6 equals approximately 26.6667.

Standard Deviation

Calculate the standard deviation by finding the square root of the division by N-1. In the example, the square root of 26.6667 equals approximately 5.164. Therefore, the standard deviation equals approximately 5.164.

Evaluating Standard Deviation

Standard deviation helps evaluate data. Numbers in the data set that fall within one standard deviation of the mean are part of the data set. Numbers that fall outside of two standard deviations are extreme values or outliers. In the example set, the value 36 lies more than two standard deviations from the mean, so 36 is an outlier. Outliers may represent erroneous data or may suggest unforeseen circumstances and should be carefully considered when interpreting data.

Facilities: Windows/Linux Operating Systems, RStudio, jdk.

Application:

1. The histogram is suitable for visualizing distribution of numerical data over a continuous interval, or a certain time period. The histogram organizes large amounts of data, and produces visualization quickly, using a single dimension.

2. The box plot allows quick graphical examination of one or more data sets. Box plots may seem more primitive than a histogram but they do have some advantages. They take up less space and are therefore particularly useful for comparing distributions between several groups or sets of data. Choice of number and width of bins techniques can heavily influence the appearance of a histogram, and choice of bandwidth can heavily influence the appearance of a kernel density estimate.

3. Data Visualization Application lets you quickly create insightful data visualizations, in minutes.

Data visualization tools allow anyone to organize and present information intuitively. They enables users to share data visualizations with others.

Input:

Structured Dataset: Iris

Dataset File: iris.csv

Output:

1. Display Dataset Details.
2. Calculate Min, Max, Mean, Variance value and Percentiles of probabilities also Display Specific use quantile.
3. Display the Histogram using Hist Function.
4. Display the Boxplot using Boxplot Function.

Conclusion:

Hence, we have studied using dataset into a dataframe and compare distribution and identify outliers.

Assignment Questions

1. **For the iris dataset, list down the features and their types.**
2. **Write a code to create a histogram for each feature. (iris dataset)**
3. **Write a code to create a boxplot for each feature. (iris dataset)**
4. **Identify the outliers from the boxplot drawn for iris dataset.**