
Group A

Assignment No: 1

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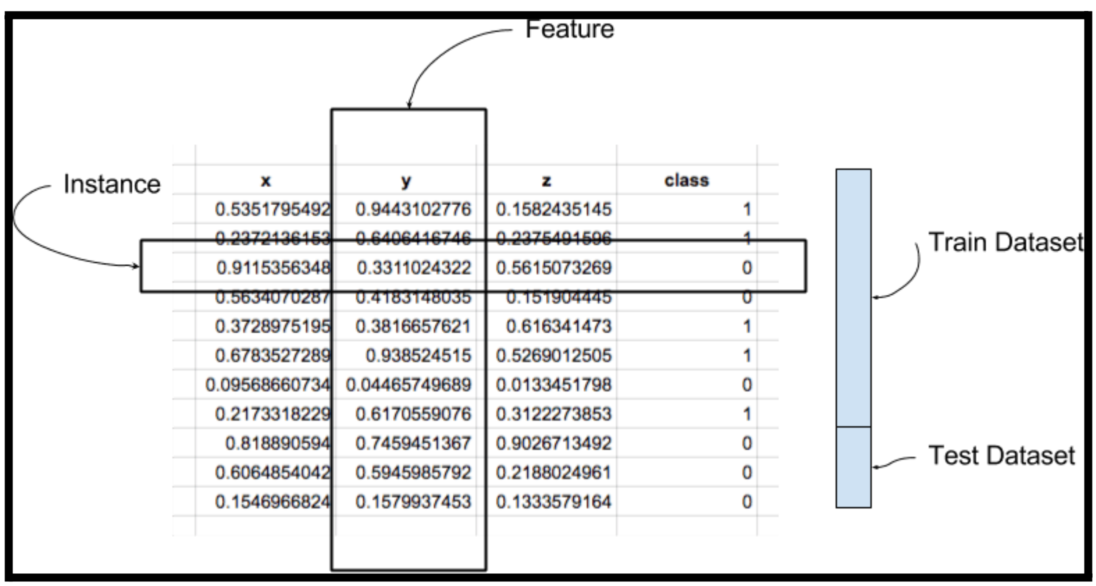
1. **Introduction to Dataset**

   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.

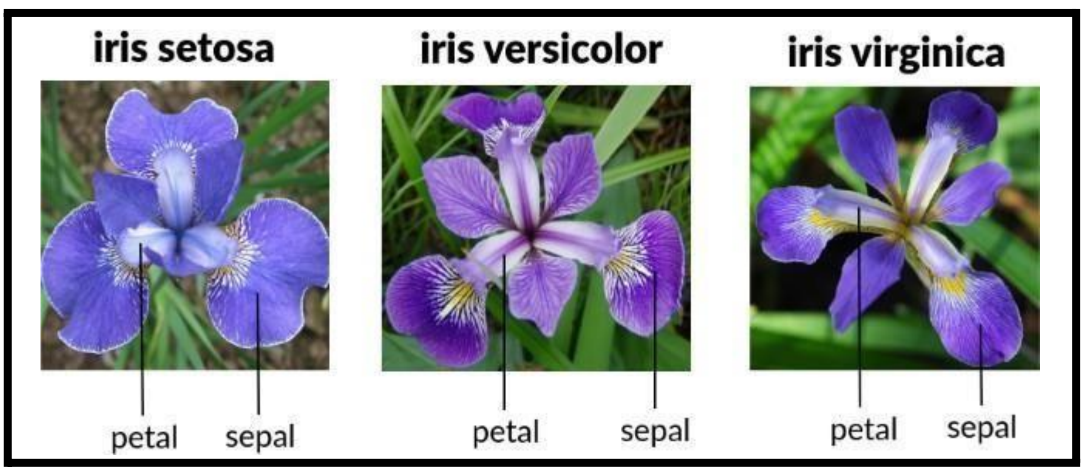
It includes three iris species with 50 samples each as well as some properties about each flower. One flower species is linearly separable from the other two, but the other two are not linearly separable from each other.

Total Sample- 150

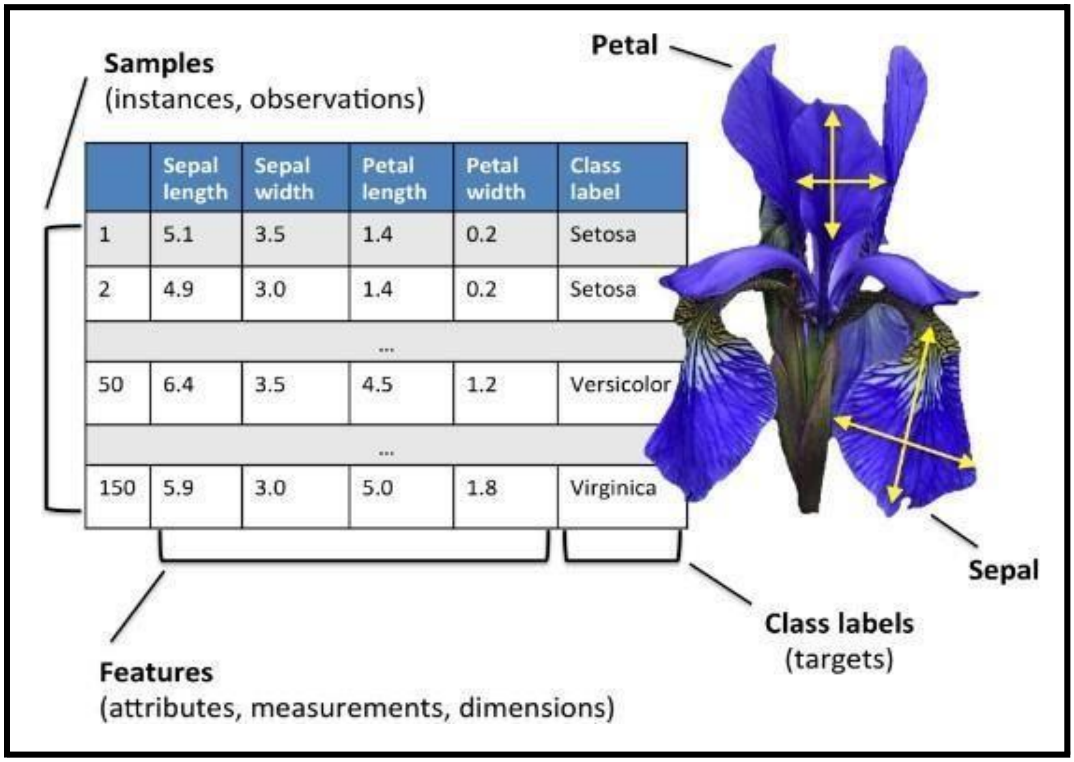
The columns in this dataset are:

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

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

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

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.

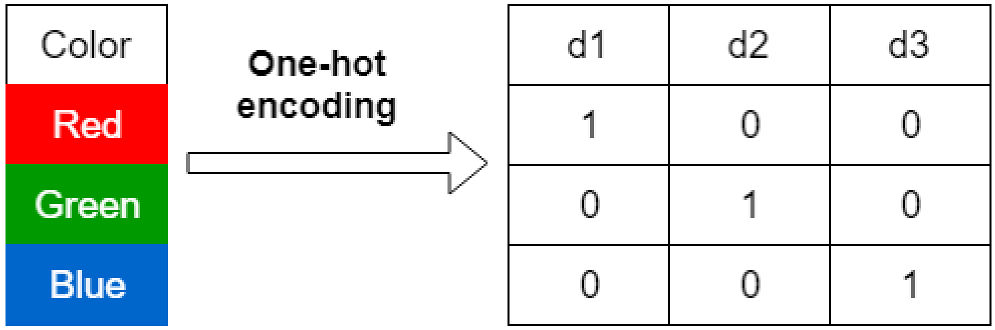
```
df['Species'].unique()
Output: array([0, 1, 2], dtype=int64)
```

- 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:

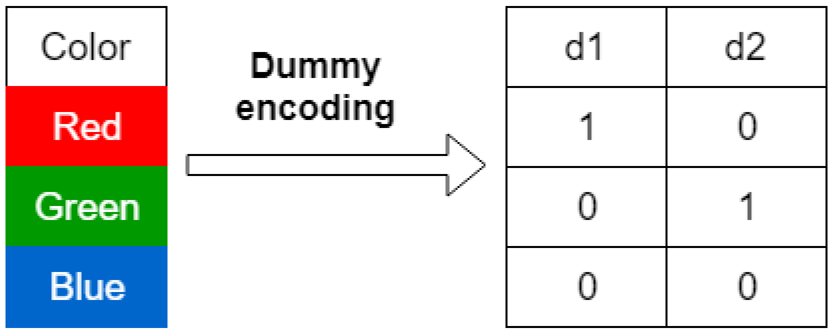
	Sepal_Length	Sepal_Width	Petal_Length	Petal_Width	0	1	2
0	5.1	3.5	1.4	0.2	1.0	0.0	0.0
1	4.9	3.0	1.4	0.2	1.0	0.0	0.0
2	4.7	3.2	1.3	0.2	1.0	0.0	0.0
3	4.6	3.1	1.5	0.2	1.0	0.0	0.0
4	5.0	3.6	1.4	0.2	1.0	0.0	0.0

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

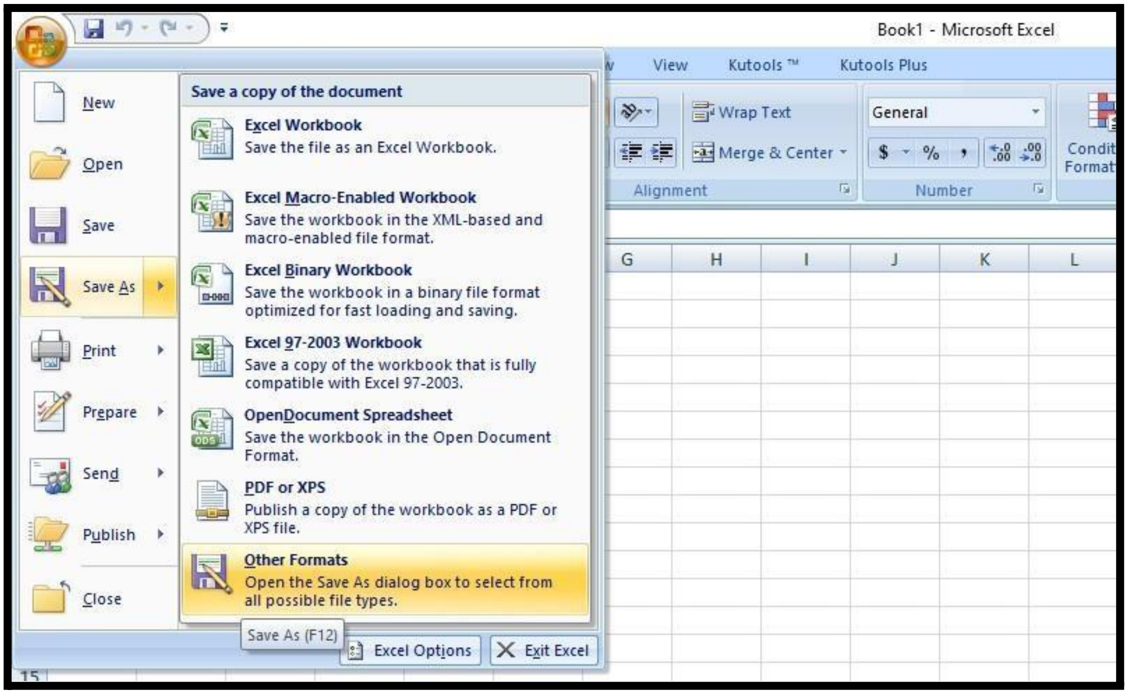
Syntax : RANDBETWEEN(bottom, top) Bottom The smallest integer and

Top The largest integer RANDBETWEEN will return.

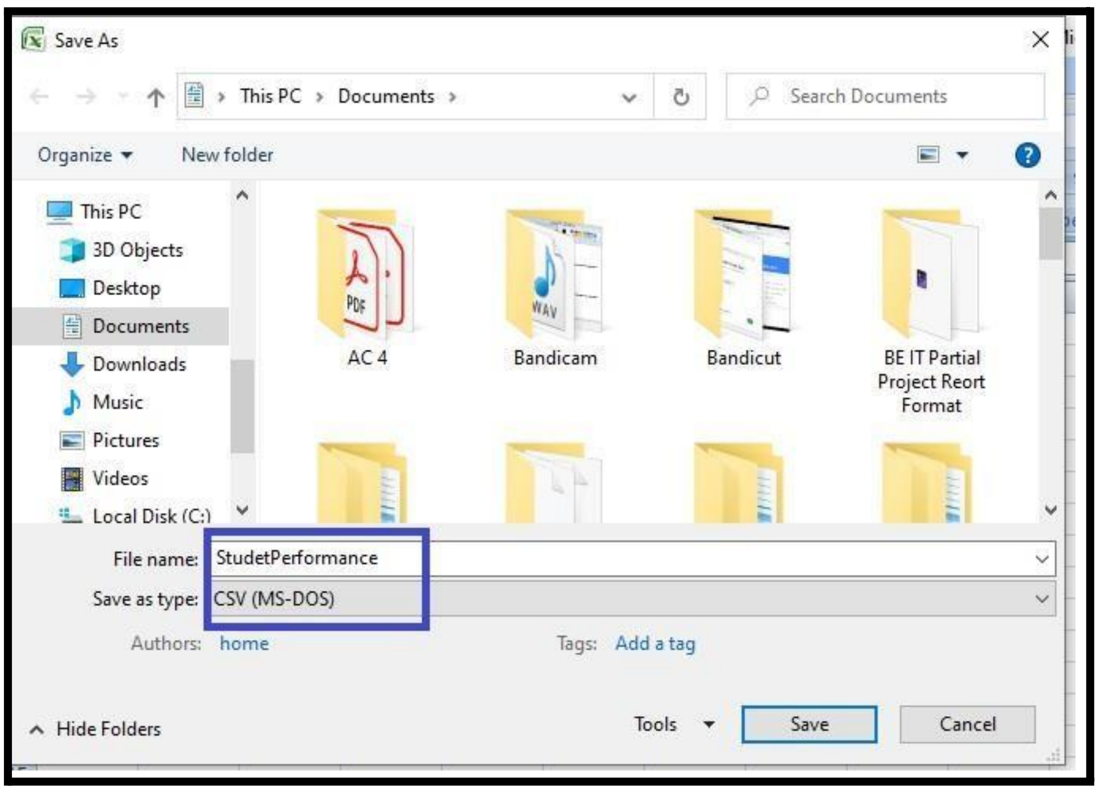
For better understanding and visualization, 20% impurities are added into each variable to the dataset.

The step to create the dataset are as follows:

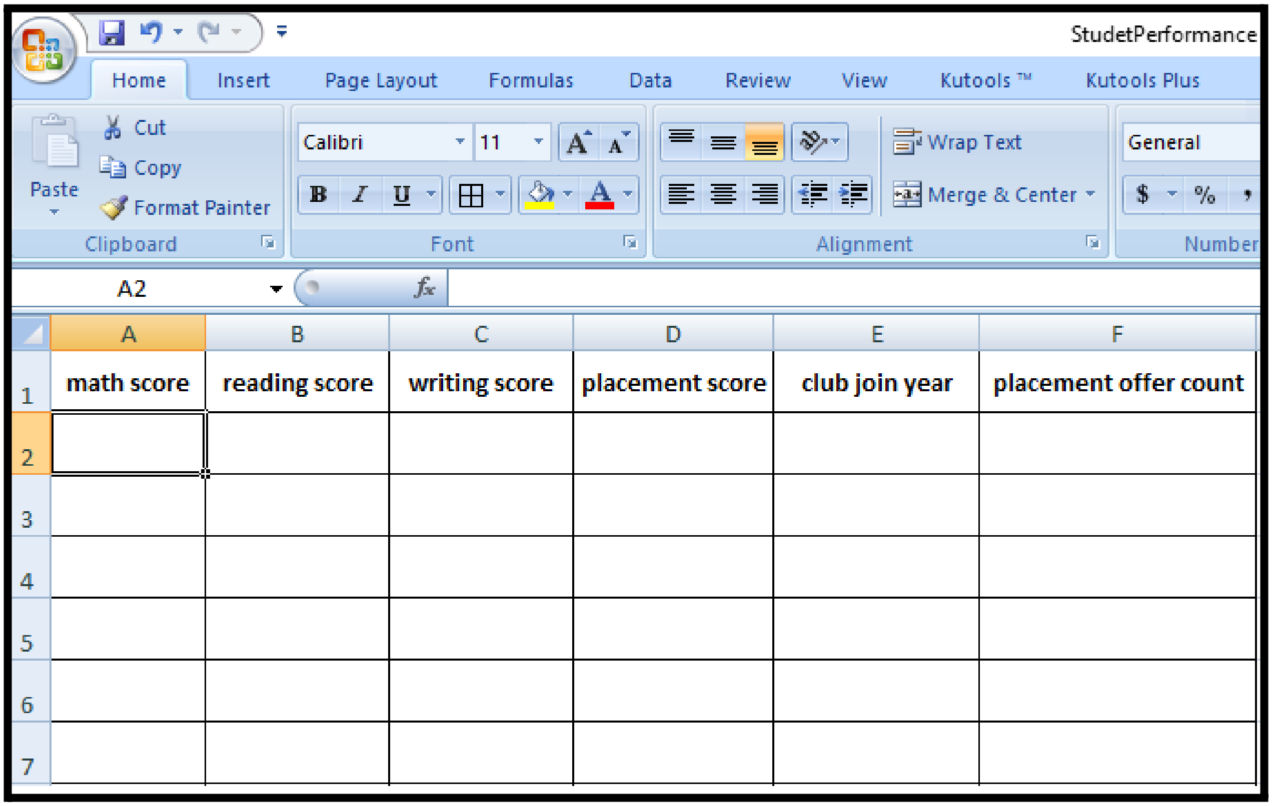
Step 1: Open Microsoft Excel and click on Save As. Select Other .Formats



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

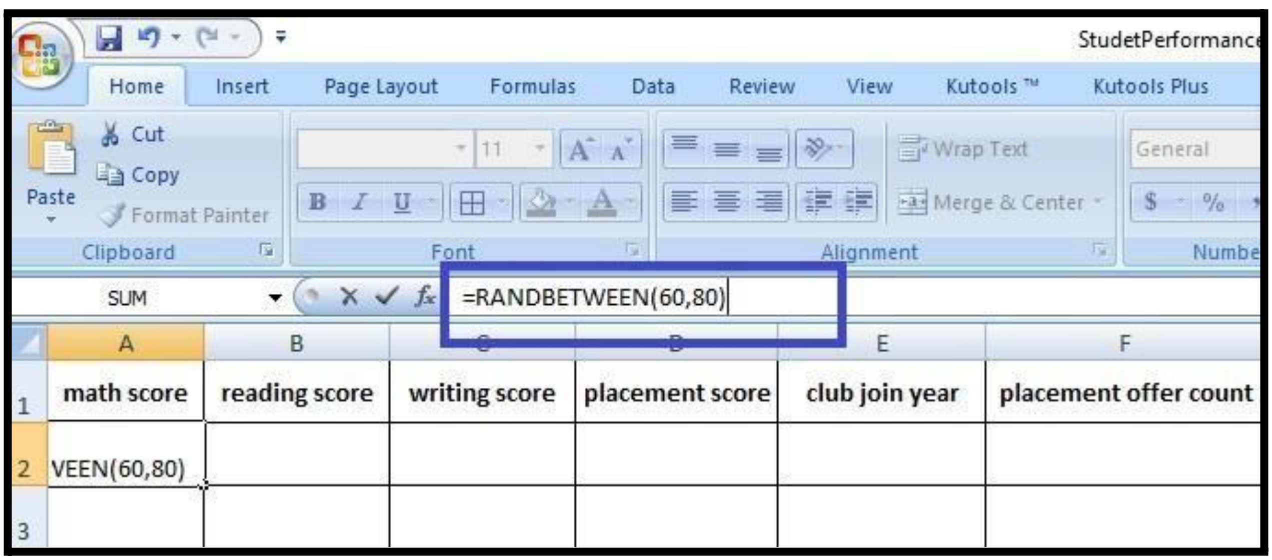


Step 3: Enter the name of features as column header.



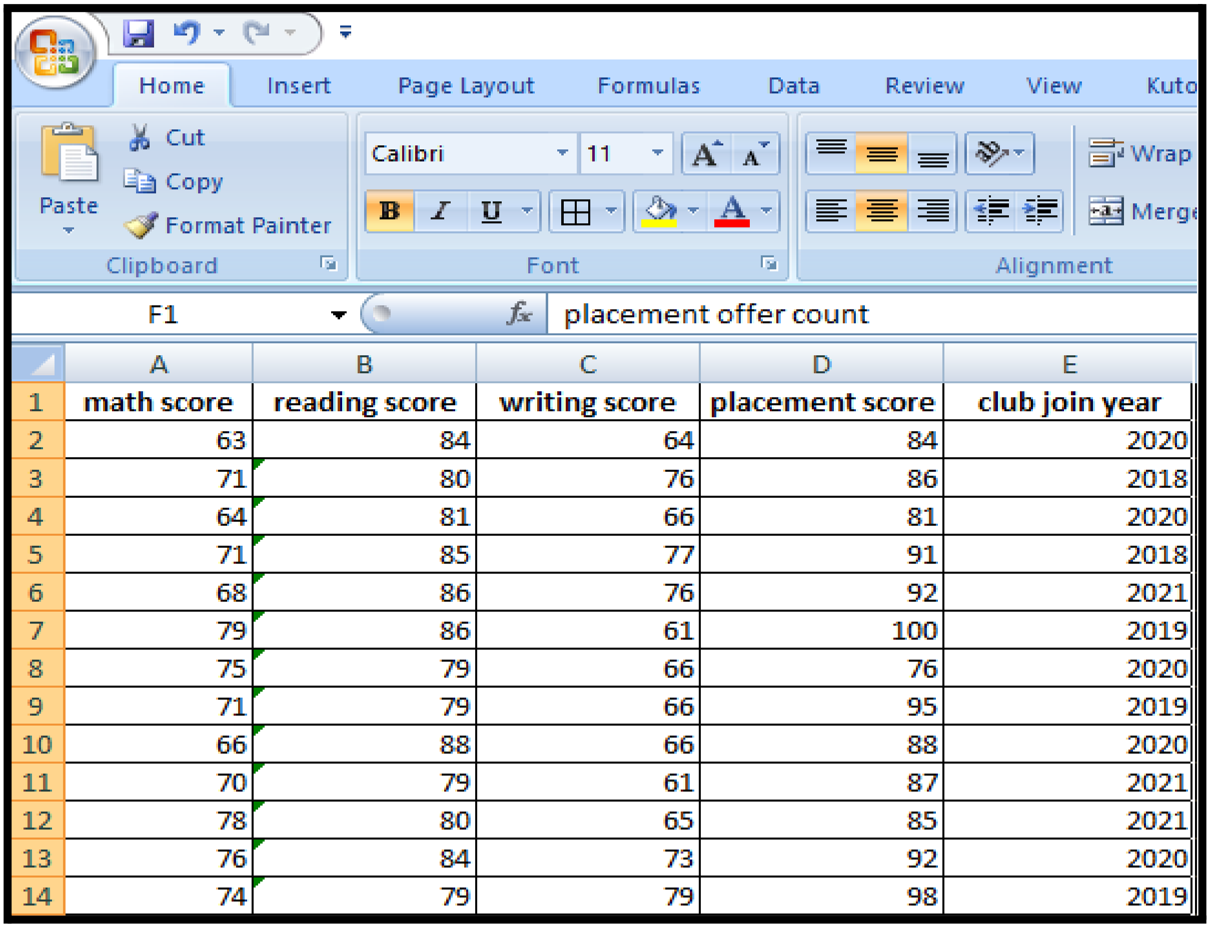
Step 3: Fill the dara by using **RANDOMBETWEEN** function. For every feature , fill the data by considering above spectified range.

one example is given:



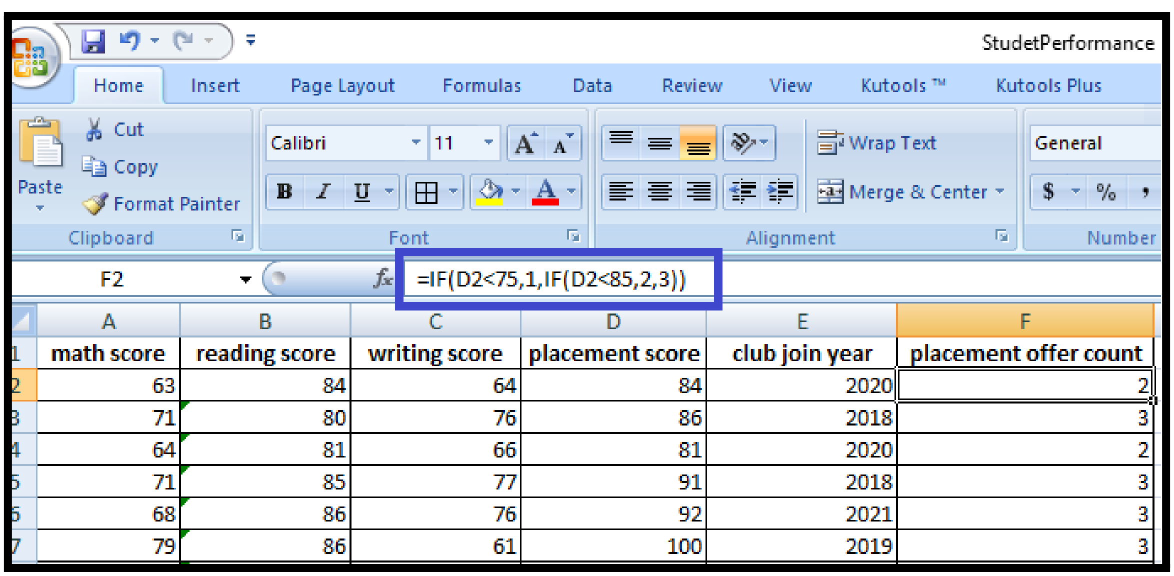
Scroll down the cursor for 30 rows to create 30 instances.

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

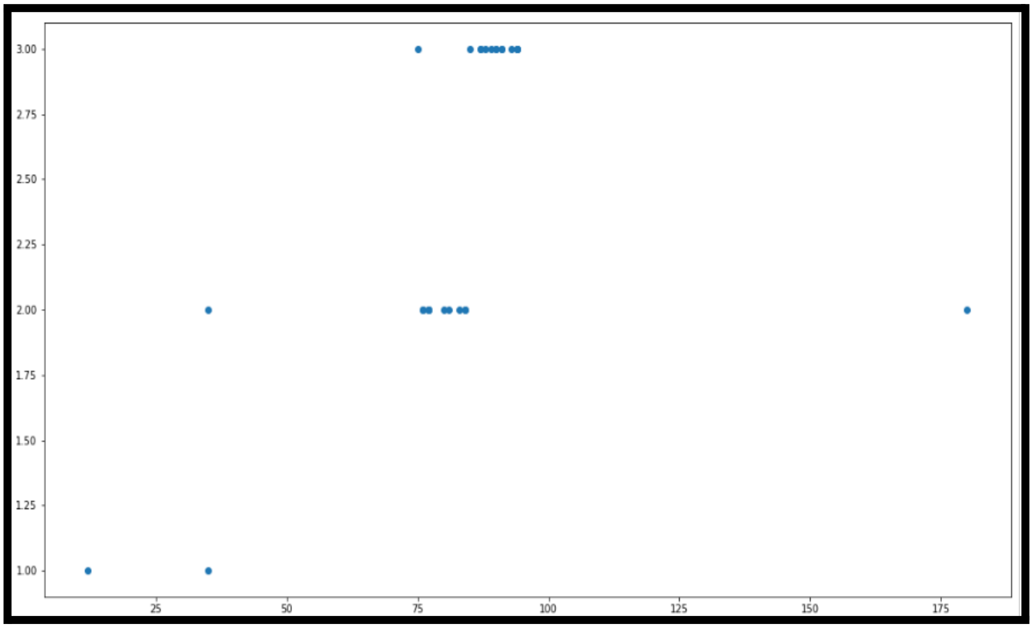
```
df
```

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

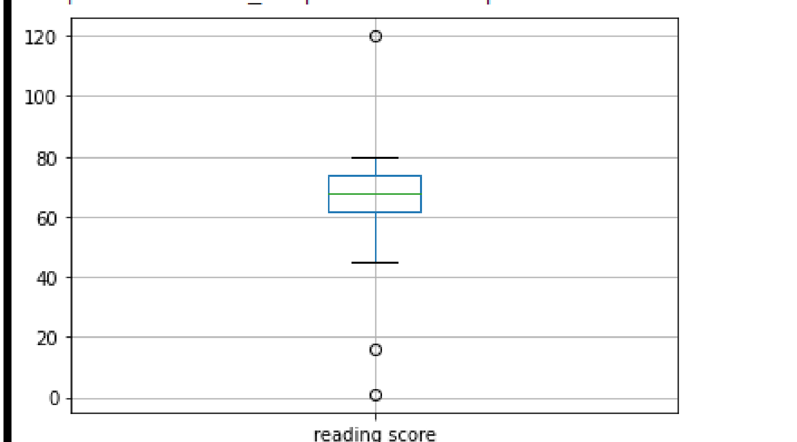
- **Mean/Median imputation:**

  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

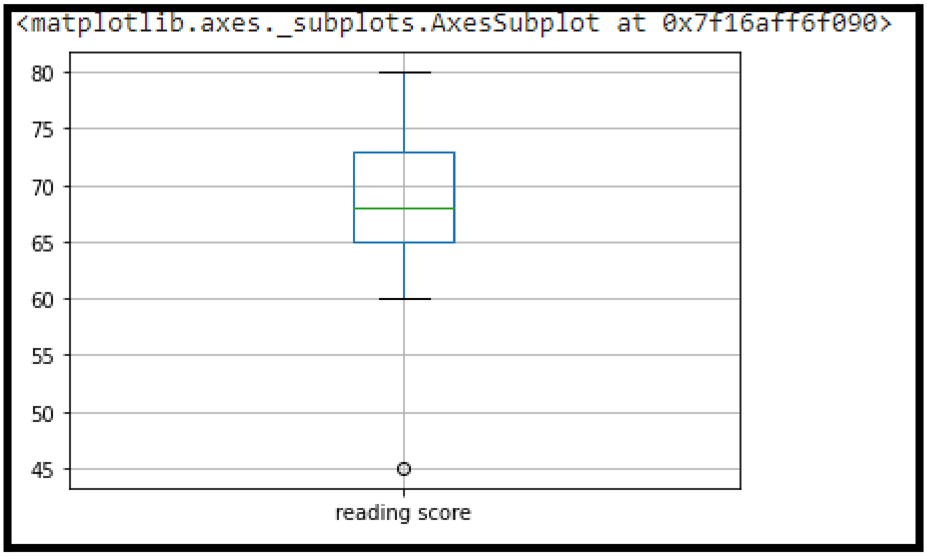
```
refined_df['reading score'] = np.where(refined_df['reading
score'] <lwr_bound, median,refined_df['reading score'])
```

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)
```



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.

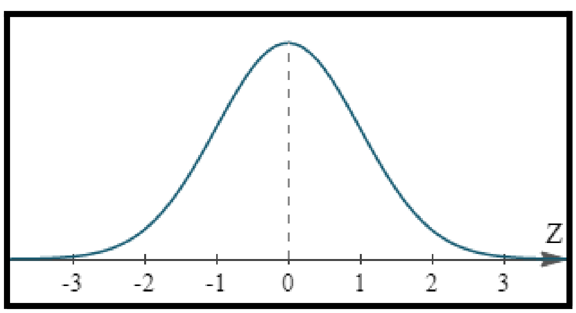
```
[11] df
```

	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.

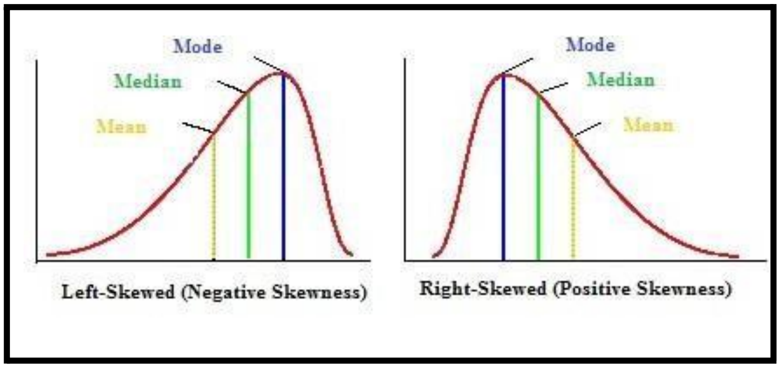
Normal Distribution: In a normal distribution, the graph appears as a classical, symmetrical "bell-shaped curve." The mean, or average, and the mode, or maximum point on the curve, are equal.



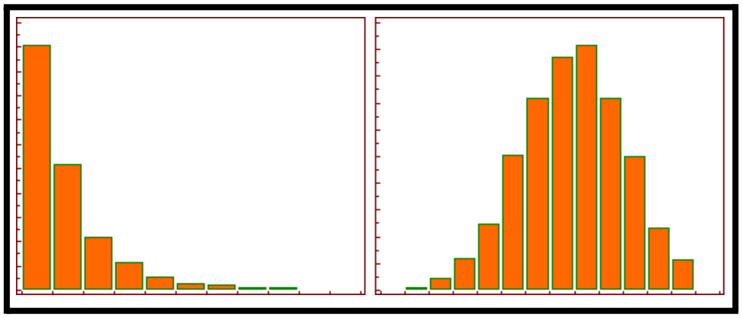
Positively Skewed Distribution

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.

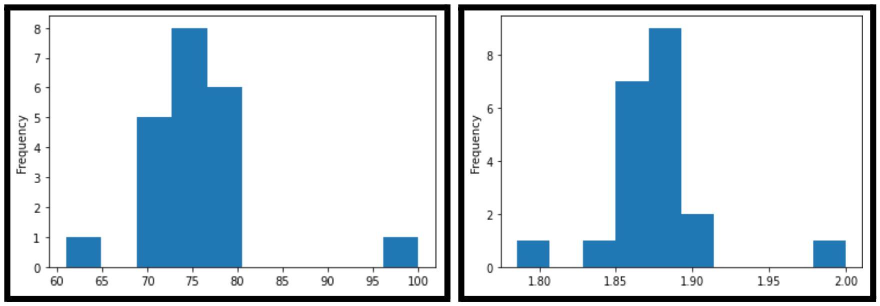
```
import matplotlib.pyplot as plt
new_df['math score'].plot(kind = 'hist')
```

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

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

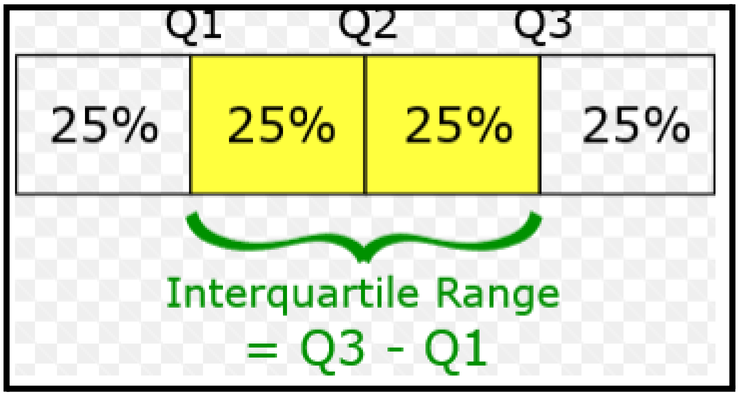
3. **Standard Deviation** — The square root of Variance is called the Standard Deviation. It is calculated as

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

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.

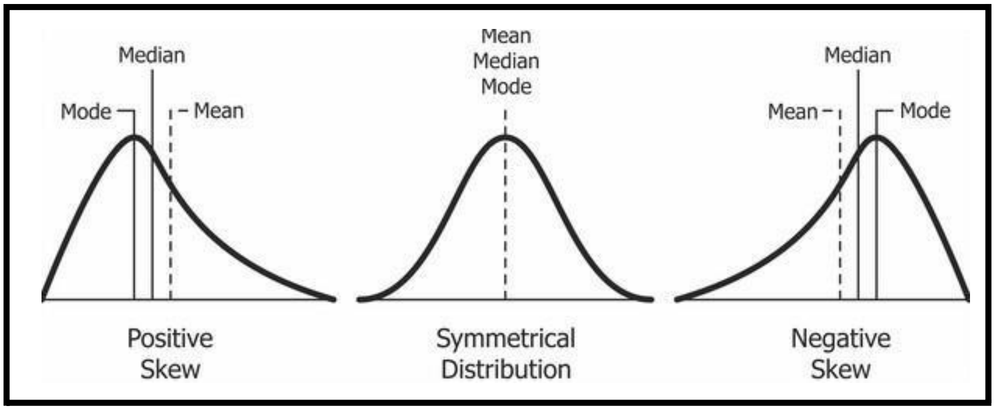
$$Skewness = \frac{3\,(Mean - Median)}{Std\ \ Deviation}$$

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.

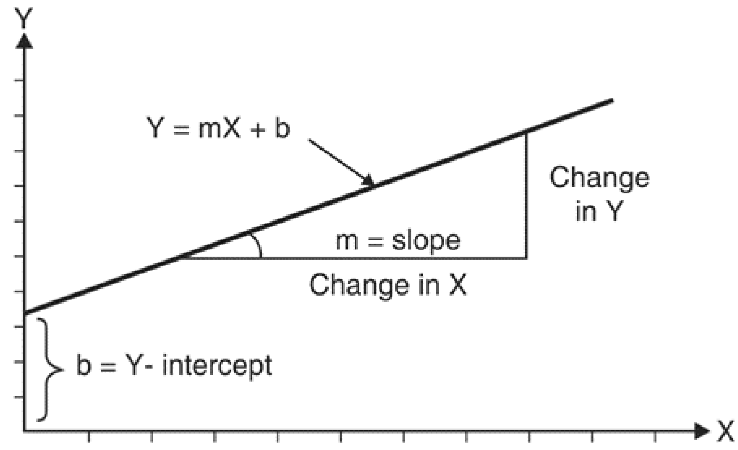
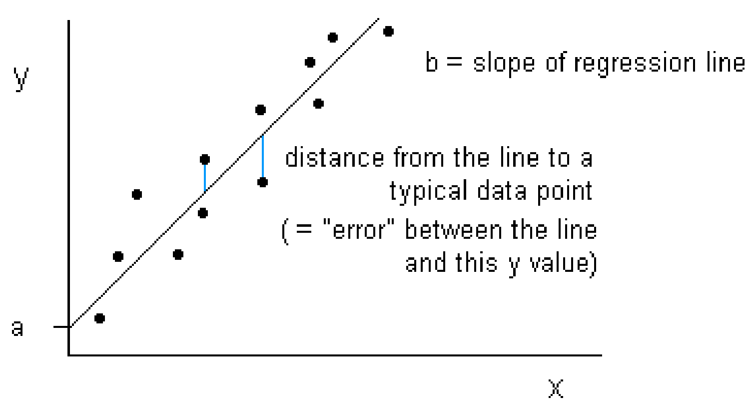


Fig. 1: geometry of linear regression

- 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

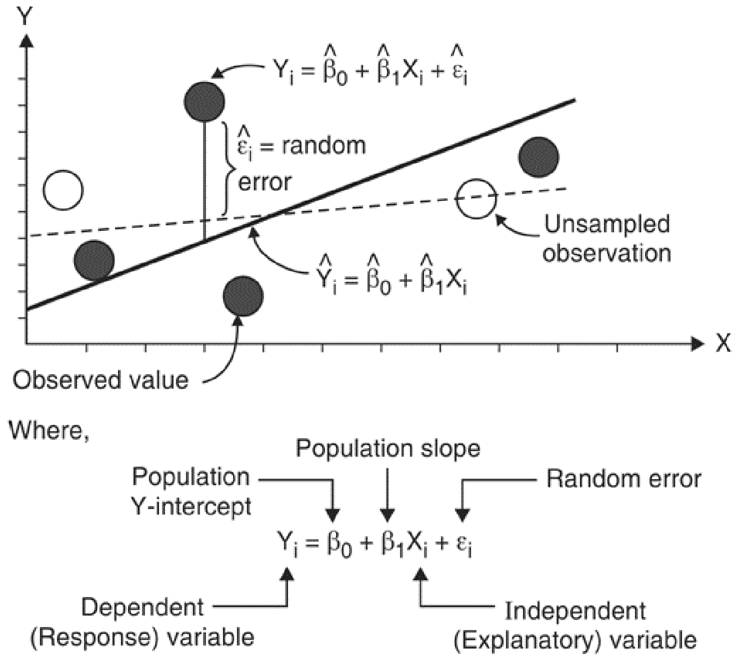
x is the independent or the input variable

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).

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

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

RMSE:

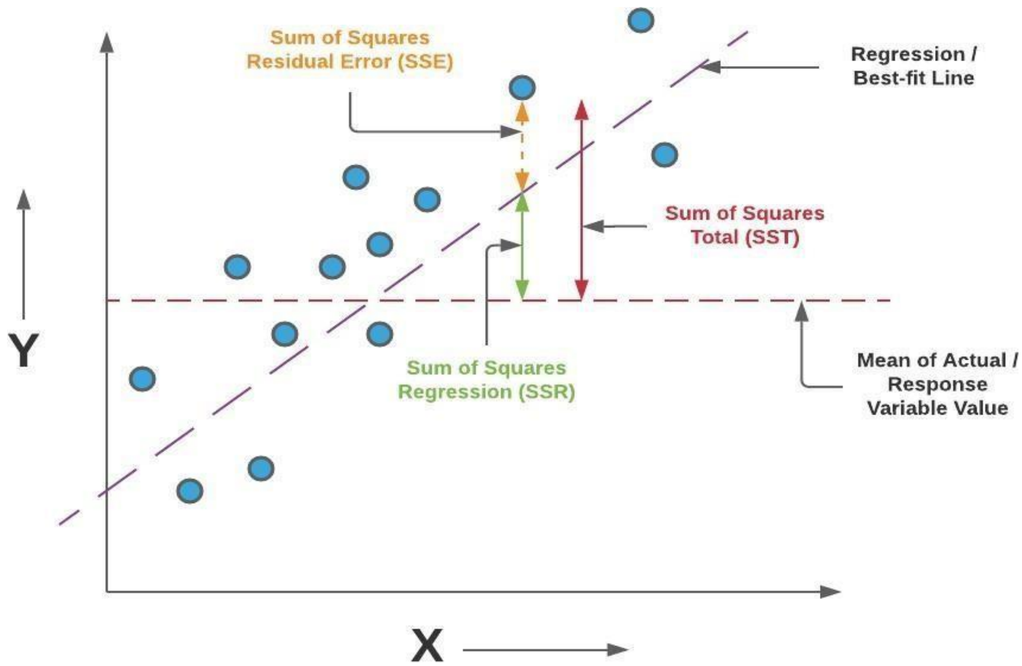
Root Mean Squared Error method that basically calculates the least-squares error and takes a root of the summed values.

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.

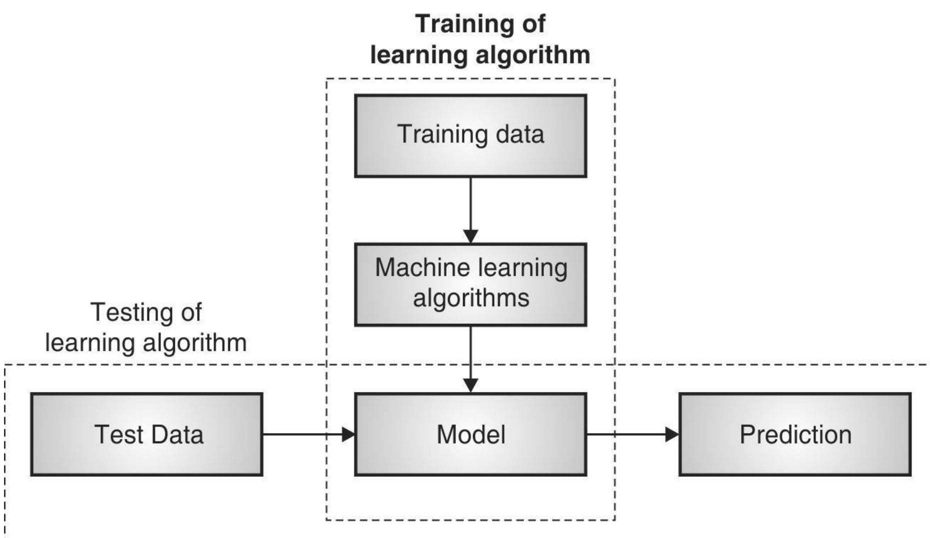


Fig. 1.3.1 : Training and Testing Phase in Machine Learning

(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)
```

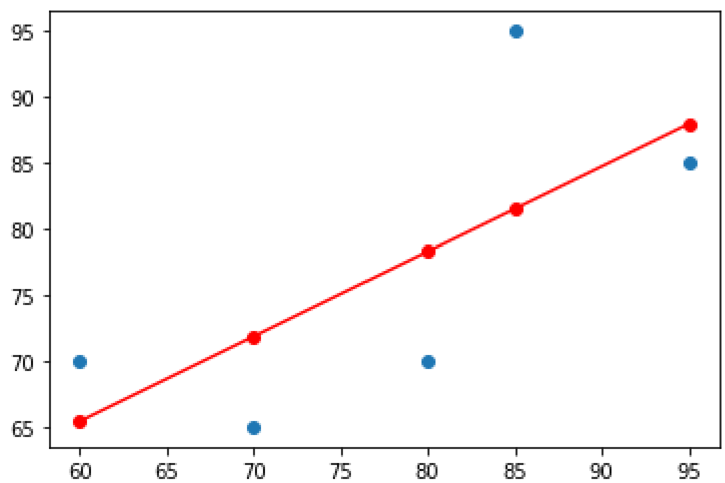
Output:

```
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:

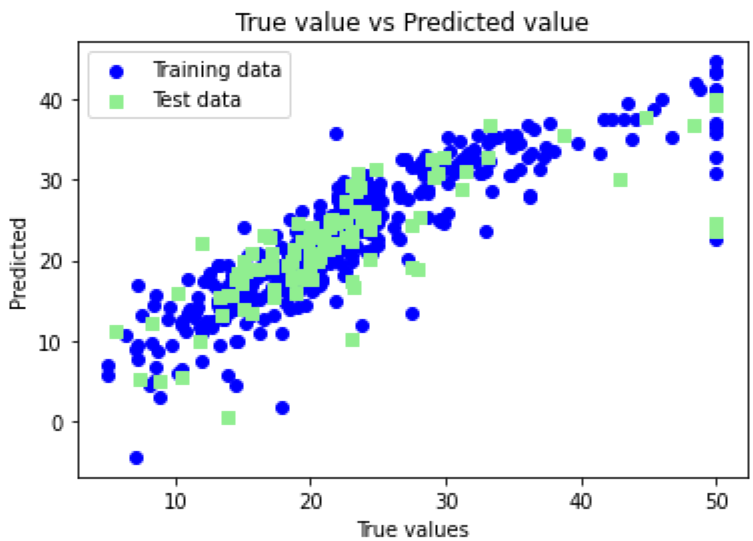
```
33.44897999767638
mse = mean_squared_error(ytest, ytest_pred)
print(mse)
```

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)

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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

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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:

$$y = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots\ldots + \beta nXn$$

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

Sigmoid Function:

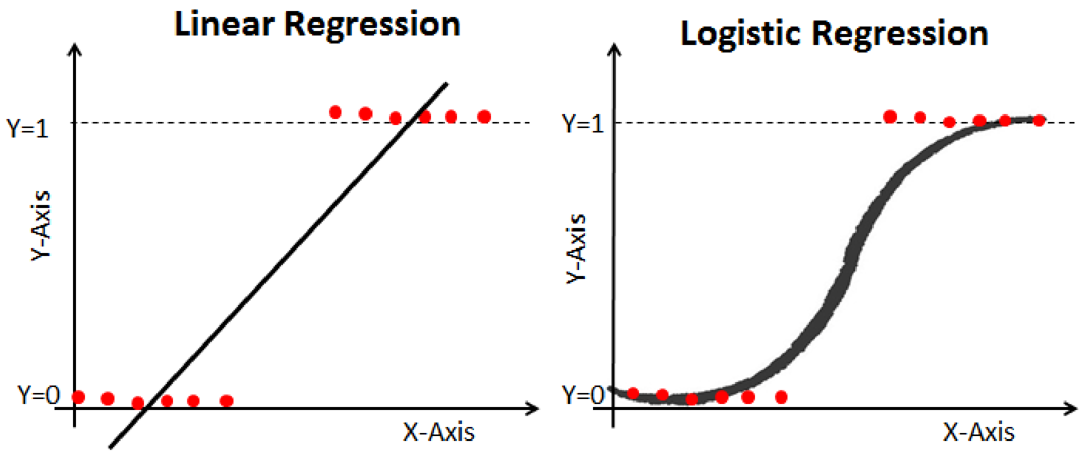
$$p = 1/1 + e^{-y}$$

Apply Sigmoid function on linear regression:

$$p = 1/1 + e^{-(\beta 0 + \beta 1X1 + \beta 2X2 \ldots\ldots \beta nXn)}$$

2. Differentiate between Linear and Logistic Regression

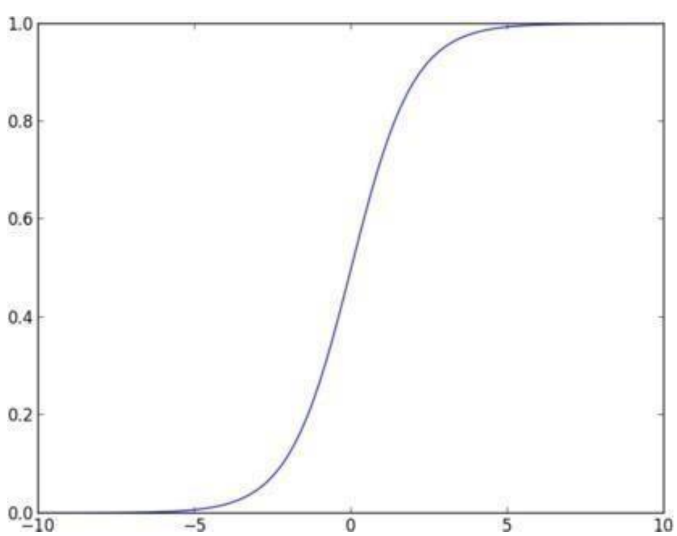
Linear regression gives you a continuous output, but logistic regression provides a constant output. An example of the continuous output is house price and stock price. Example's of the discrete output is predicting whether a patient has cancer or not, predicting whether the customer will churn. Linear 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.

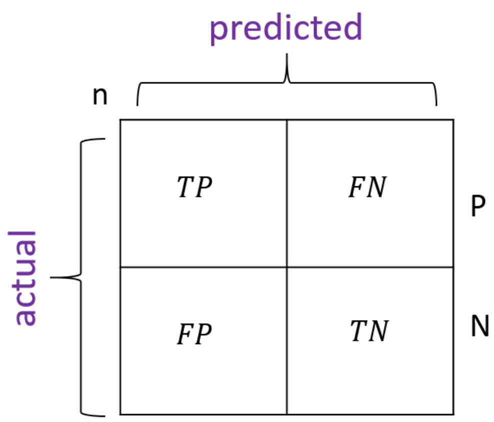
Multinomial Logistic Regression: The target variable has three or more nominal categories such as predicting the type of Wine.

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.**

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Group A

Assignment No: 6

Contents for Theory:

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

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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:

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

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

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	?

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

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

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

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

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.

1. Write python code for the preprocessing mentioned in step 4. and Explain every step indetail.

2. ata frame? write the cod