JCEI'S JAIHIND COLLEGE OF ENGINEERING, KURAN

DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

LAB MANUAL

Computer Laboratory I

Subject Code: 417525

Prepared By:

Prof. Said S. K.

Computer Laboratory -I

Course Code	Course Name	Teaching Scheme (Hrs./ Week)	Credits
417525	Computer Laboratory-I: Machine Learning	4	2
417525	Computer Laboratory-I: Data Modeling and Visualization	4	2

Course Objectives:

- Apply regression, classification and clustering algorithms for creation of ML models
- Introduce and integrate models in the form of advanced ensembles
- Conceptualized representation of Data objects
- Create associations between different data objects, and the rules
- Organized data description, data semantics, and consistency constraints of data

Course Outcomes:

After completion of the course, learners should be able to-

CO1: Implement regression, classification and clustering models
CO2: Integrate multiple machine learning algorithms in the form of ensemble learning
CO3: Apply reinforcement learning and its algorithms for real world applications
CO4: Analyze the characteristics, requirements of data and select an appropriate data model
CO5: Apply data analysis and visualization techniques in the field of exploratory data science
CO6: Evaluate time series data.

Operating System recommended: 64-bit Open source Linux or its derivative

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			A. Implement K-Means clustering on Iris.csv dataset. Determine the number of clusters using the elbow method. Dataset Link: https://www.kaggle.com/datasets/uciml/iris **B.** Implement K-Mediod Algorithm on a credit card dataset. Determine the number of clusters using the Silhouette Method. Dataset link: https://www.kaggle.com/datasets/arjunbhasin2013/ccdata	
	5	A5	**Ensemble Learning (Any one)** **A.** Implement Random Forest Classifier model to predict the safety of the car. Dataset link: https://www.kaggle.com/datasets/elikplim/car-evaluation-data-set **B.** Use different voting mechanism and Apply AdaBoost (Adaptive Boosting), Gradient Tree Boosting (GBM), XGBoost classification on Iris dataset and compare the performance of three models using different evaluation measures. Dataset Link: https://www.kaggle.com/datasets/uciml/iris	65
	6	A6	**Reinforcement Learning (Any one)** **A.** Implement Reinforcement Learning using an example of a maze environment that the agent needs to explore. **B.** Solve the Taxi problem using reinforcement learning where the agent acts as a taxi driver to pick up a passenger at one location and then drop the passenger off at their destination. C. Build a Tic-Tac-Toe game using reinforcement learning in Python by using following tasks a. Setting up the environment b. Defining the Tic-Tac-Toe game c. Building the reinforcement learning model d. Training the model e. Testing the model	70
	Part II: Data Modeling and Visualization			
	7	B2	**Interacting with Web APIs** **Problem Statement:** Analyzing Weather Data from OpenWeatherMap API **Dataset:** Weather data retrieved from OpenWeatherMap API **Description**: The goal is to interact with the OpenWeatherMap API to retrieve weather data for a specific location and perform data modeling and visualization to analyze weather patterns over time. **Tasks to Perform:** 1. Register and obtain API key from OpenWeatherMap. 2. Interact with the OpenWeatherMap API using the API key to retrieve weather data for a specific location. 3. Extract relevant weather attributes such as temperature, humidity, wind speed, and precipitation from the API response.	76

			4. Clean and preprocess the retrieved data, handling missing values or inconsistent formats. 5. Perform data modeling to analyze weather patterns, such as calculating average temperature, maximum/minimum values, or trends over time. 6. Visualize the weather data using appropriate plots, such as line charts, bar plots, or scatter plots, to represent temperature changes, precipitation levels, or wind speed variations. 7. Apply data aggregation techniques to summarize weather statistics by specific time periods (e.g., daily, monthly, seasonal). 8. Incorporate geographical information, if available, to create maps or geospatial visualizations representing weather patterns across different locations. 9. Explore and visualize relationships between weather attributes, such as temperature and humidity, using correlation plots or heatmaps.	
	8	B3	**Data Cleaning and Preparation** **Problem Statement**: Analyzing Customer Churn in a Telecommunications Company **Dataset:** "Telecom_Customer_Churn.csv" **Description:** The dataset contains information about customers of a telecommunications company and whether they have churned (i.e., discontinued their services). The dataset includes various attributes of the customers, such as their demographics, usage patterns, and account information. The goal is to perform data cleaning and preparation to gain insights into the factors that contribute to customer churn. **Tasks to Perform:** 1. Import the "Telecom_Customer_Churn.csv" dataset. 2. Explore the dataset to understand its structure and content. 3. Handle missing values in the dataset, deciding on an appropriate strategy. 4. Remove any duplicate records from the dataset. 5. Check for inconsistent data, such as inconsistent formatting or spelling variations, and standardize it. 6. Convert columns to the correct data types as needed. 7. Identify and handle outliers in the data. 8. Perform feature engineering, creating new features that may be relevant to predicting customer churn. 9. Normalize or scale the data if necessary. 10. Split the dataset into training and testing sets for further analysis. 11. Export the cleaned dataset for future analysis or modeling.	84
	9	B4	**Data Wrangling** **Problem Statement:** Data Wrangling on Real Estate Market **Dataset:** "RealEstate_Prices.csv"	93

			Description: The dataset contains information about housing prices in a specific real estate market. It includes various attributes such as property characteristics, location, sale prices, and other relevant features. The goal is to perform data wrangling to gain insights into the factors influencing housing prices and prepare the dataset for further analysis or modeling. **Tasks to Perform:** 1. Import the "RealEstate_Prices.csv" dataset. Clean column names by removing spaces, special characters, or renaming them for clarity. 2. Handle missing values in the dataset, deciding on an appropriate strategy (e.g., imputation or removal). 3. Perform data merging if additional datasets with relevant information are available (e.g., neighborhood demographics or nearby amenities). 4. Filter and subset the data based on specific criteria, such as a particular time period, property type, or location. 5. Handle categorical variables by encoding them appropriately (e.g., one-hot encoding or label encoding) for further analysis. 6. Aggregate the data to calculate summary statistics or derived metrics such as average sale prices by neighborhood or property type. 7. Identify and handle outliers or extreme values in the data that may affect the analysis or modeling process	
	10	B5	**Data Visualization using matplotlib** **Problem Statement:** Analyzing Air Quality Index (AQI) Trends in a City **Dataset:** "City_Air_Quality.csv" **Description:** The dataset contains information about air quality measurements in a specific city over a period of time. It includes attributes such as date, time, pollutant levels (e.g., PM2.5, PM10, CO), and the Air Quality Index (AQI) values. The goal is to use the matplotlib library to create visualizations that effectively represent the AQI trends and patterns for different pollutants in the city. **Tasks to Perform:** 1. Import the "City_Air_Quality.csv" dataset. 2. Explore the dataset to understand its structure and content. 3. Identify the relevant variables for visualizing AQI trends, such as date, pollutant levels, and AQI values. 4. Create line plots or time series plots to visualize the overall AQI trend over time. 5. Plot individual pollutant levels (e.g., PM2.5, PM10, CO) on separate line plots to visualize their trends over time. 6. Use bar plots or stacked bar plots to compare the AQI values across different dates or	111

			time periods. 7. Create box plots or violin plots to analyze the distribution of AQI values for different pollutant categories. 8. Use scatter plots or bubble charts to explore the relationship between AQI values and pollutant levels. 9. Customize the visualizations by adding labels, titles, legends, and appropriate color schemes	
	11	B6	**Data Aggregation** **Problem Statement:** Analyzing Sales Performance by Region in a Retail Company **Dataset:** "Retail_Sales_Data.csv" **Description:** The dataset contains information about sales transactions in a retail company. It includes attributes such as transaction date, product category, quantity sold, and sales amount. The goal is to perform data aggregation to analyze the sales performance by region and identify the top-performing regions. **Tasks to Perform:** 1. Import the "Retail_Sales_Data.csv" dataset. 2. Explore the dataset to understand its structure and content. 3. Identify the relevant variables for aggregating sales data, such as region, sales amount, and product category. 4. Group the sales data by region and calculate the total sales amount for each region. 5. Create bar plots or pie charts to visualize the sales distribution by region. 6. Identify the top-performing regions based on the highest sales amount. 7. Group the sales data by region and product category to calculate the total sales amount for each combination. 8. Create stacked bar plots or grouped bar plots to compare the sales amounts across different regions and product categories.	126
			Part III: Mini Project(Mandatory Assignments)	
	12		Mini Project (Mandatory- Group Activity) It is recommended that group of 3 to 5 students should undergo a mini project (considering the Machine Learning and Data modeling and Visualizing concepts) as content beyond syllabus. Some of the problem statements are mentioned below: 1. Development of a happiness index for schools (including mental health and well-being parameters, among others) with self-assessment facilities. 2. Automated Animal Identification and Detection of Species 3. Sentimental analysis on Govt. Released Policies 4. Identification of Flood Prone Roads 5. Identification of Missing Bridges which would increase the connectivity between regions Note: Instructor can also assign similar problem statements References: For Dataset https://data.gov.in/ For Problem statements: https://sih.gov.in/sih2022PS	

Lab Assignment No.	1A
Title	To use PCA Algorithm for dimensionality reduction. You have a dataset that includes measurements for different variables on wine (alcohol, ash, magnesium, and so on). Apply PCA algorithm & transform this data so that most variations in the measurements of the variables are captured by a small number of principal components so that it is easier to distinguish between red and white wine by inspecting these principal components
Roll No.	
Class	BE
Date of Completion	
Subject	Computer Laboratory-I
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 1 A (Group A)

- **Aim:** To use PCA Algorithm for dimensionality reduction. You have a dataset that includes measurements for different variables on wine (alcohol, ash, magnesium, and so on). Apply PCA algorithm & transform this data so that most variations in the measurements of the variables are captured by a small number of principal components so that it is easier to distinguish between red and white wine by inspecting these principal components

- **Outcome: At end of this experiment, student will be able understand the scheduler, and how its behaviour influences the performance of the system**

- **Hardware Requirement:**

- 6 GB free disk space.
- 2 GB RAM.
- 2 GB of RAM, plus additional RAM for virtual machines.
- 6 GB disk space for the host, plus the required disk space for the virtual machine(s).
- Virtualization is available with the KVM hypervisor
- Intel 64 and AMD64 architectures

- **Software Requirement:**

Jupyter Nootbook/Ubuntu

- **Theory:**

Principal Component Analysis (PCA)

PCA is an unsupervised machine learning algorithm. PCA is mainly used for dimensionality reduction in a dataset consisting of many variables that are highly correlated or lightly correlated with each other while retaining the variation present in the dataset up to a maximum extent.

It is also a great tool for exploratory data analysis for making predictive models.

PCA performs a linear transformation on the data so that most of the variance or information in your high-dimensional dataset is captured by the first few principal components. The first principal component will capture the most variance, followed by the second principal component, and so on.

Each principal component is a linear combination of the original variables. Because all the principal components are orthogonal to each other, there is no redundant information. So, the total variance in the data is defined as the sum of the variances of the individual component. So decide the total number of principal components according to cumulative variance ‘‘explained’’ by them.

Implementation:

```
import pandas as pd
from sklearn.decomposition import PCA
```

```
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

df = pd.read_csv("C:/Users/HP/Dropbox/PC/Downloads/Wine.csv")

df.keys()

print(df['DESCR'])

df.head(5)
```

```
   Alcohol  Malic_Acid   Ash  Ash_Alcanity  Magnesium  Total_Phenols  \
0    14.23        1.71  2.43          15.6        127           2.80
1    13.20        1.78  2.14          11.2        100           2.65
2    13.16        2.36  2.67          18.6        101           2.80
3    14.37        1.95  2.50          16.8        113           3.85
4    13.24        2.59  2.87          21.0        118           2.80

   Flavanoids  Nonflavanoid_Phenols  Proanthocyanins  Color_Intensity   Hue  \
0        3.06                  0.28             2.29             5.64  1.04
1        2.76                  0.26             1.28             4.38  1.05
2        3.24                  0.30             2.81             5.68  1.03
3        3.49                  0.24             2.18             7.80  0.86
4        2.69                  0.39             1.82             4.32  1.04

   OD280  Proline  Customer_Segment
0   3.92     1065                 1
1   3.40     1050                 1
2   3.17     1185                 1
3   3.45     1480                 1
4   2.93      735                 1
```

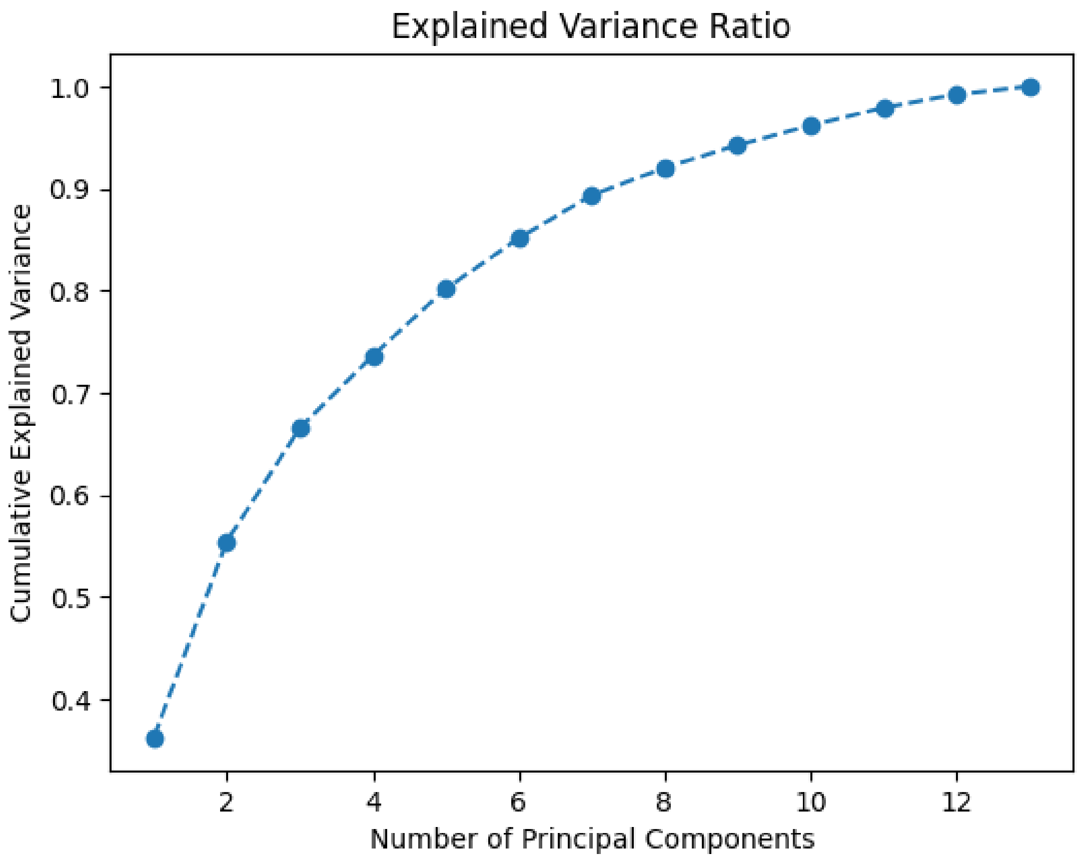
```
df.Customer_Segment.unique()
```

```
array([1, 2, 3], dtype=int64)
```

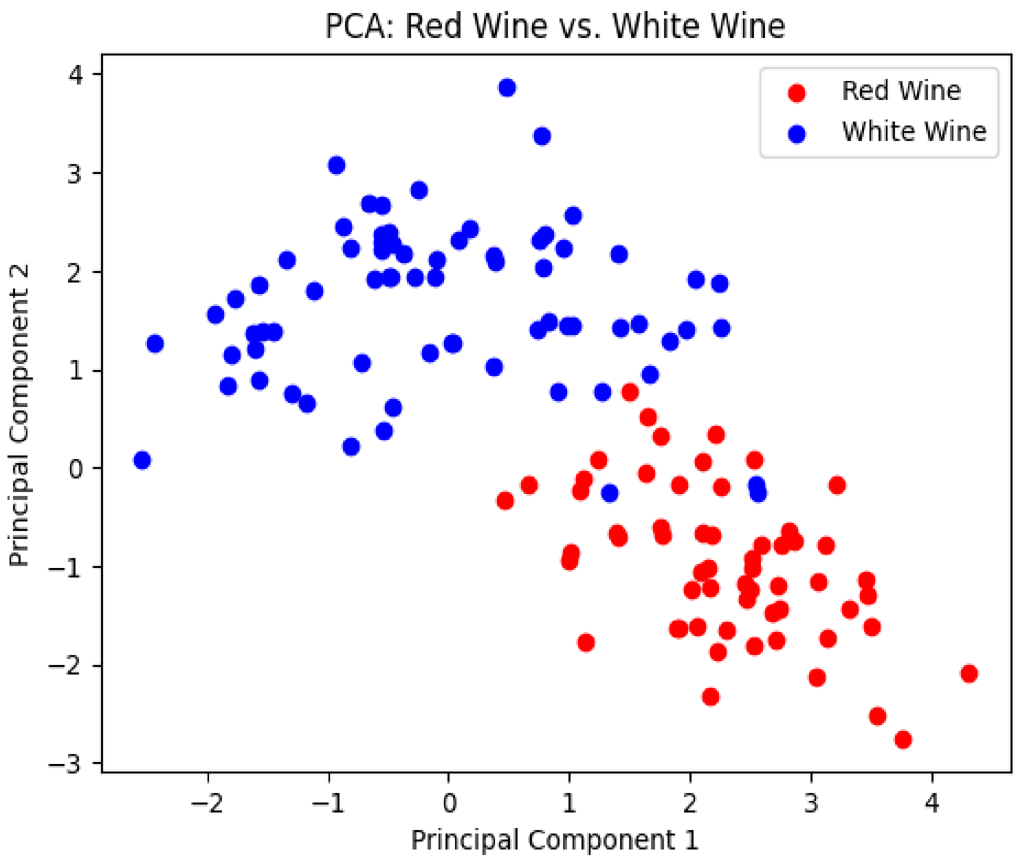
```
print(df.isnull().sum())       #checking is null
```

```
Alcohol                 0
Malic_Acid              0
Ash                     0
Ash_Alcanity            0
Magnesium               0
Total_Phenols           0
Flavanoids              0
Nonflavanoid_Phenols    0
Proanthocyanins         0
Color_Intensity         0
Hue                     0
OD280                   0
```

```
Proline              0
Customer_Segment     0
dtype: int64

X = df.drop('Customer_Segment', axis=1)  # Features
y = df['Customer_Segment']  # Target variable

for col in X.columns:
   sc = StandardScaler()                        #Standardize features by removing the mean and scaling to unit variance.z = (x - u) / s  mean=0, Stddeviation=1
   X[col] = sc.fit_transform(X[[col]])          #Fit to data, then transform it.Compute the mean and std to be used for later scaling.

X.head(5)

    Alcohol  Malic_Acid       Ash  Ash_Alcanity  Magnesium  Total_Phenols  \
0  1.518613   -0.562250  0.232053     -1.169593   1.913905       0.808997
1  0.246290   -0.499413 -0.827996     -2.490847   0.018145       0.568648
2  0.196879    0.021231  1.109334     -0.268738   0.088358       0.808997
3  1.691550   -0.346811  0.487926     -0.809251   0.930918       2.491446
4  0.295700    0.227694  1.840403      0.451946   1.281985       0.808997

   Flavanoids  Nonflavanoid_Phenols  Proanthocyanins  Color_Intensity  \
0    1.034819             -0.659563         1.224884         0.251717
1    0.733629             -0.820719        -0.544721        -0.293321
2    1.215533             -0.498407         2.135968         0.269020
3    1.466525             -0.981875         1.032155         1.186068
4    0.663351              0.226796         0.401404        -0.319276

        Hue     OD280   Proline
0  0.362177  1.847920  1.013009
1  0.406051  1.113449  0.965242
2  0.318304  0.788587  1.395148
3 -0.427544  1.184071  2.334574
4  0.362177  0.449601 -0.037874

pca = PCA()
X_pca = pca.fit_transform(X)

explained_variance_ratio = pca.explained_variance_ratio_

plt.plot(range(1, len(explained_variance_ratio) + 1), explained_variance_ratio.cumsum(), marker='o',
linestyle='--')
plt.xlabel('Number of Principal Components')
plt.ylabel('Cumulative Explained Variance')
plt.title('Explained Variance Ratio')
plt.show()
```




```
n_components = 12  # Choose the desired number of principal components you want to reduce a dimention to
pca = PCA(n_components=n_components)
X_pca = pca.fit_transform(X)

X_pca.shape

X.shape

red_indices = y[y == 1].index
white_indices = y[y == 2].index

plt.scatter(X_pca[red_indices, 0], X_pca[red_indices, 1], c='red', label='Red Wine')
plt.scatter(X_pca[white_indices, 0], X_pca[white_indices, 1], c='blue', label='White Wine')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend()
plt.title('PCA: Red Wine vs. White Wine')
plt.show()
```



#Conclusion: Here we have reduce the dimention now we can able to apply any algorithm like classification, Regression etc.

Lab Assignment No.	1B
Title	Apply LDA Algorithm on Iris Dataset and classify which species a given flower belongs to. Dataset Link:https://www.kaggle.com/datasets/uciml/iris
Roll No.	
Class	BE
Date of Completion	
Subject	Computer Laboratory-I
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 1 B

- **Aim**: Apply LDA Algorithm on Iris Dataset and classify which species a given flower belongs to. Dataset Link:https://www.kaggle.com/datasets/uciml/iris

- **Hardware Requirement:**

- 6 GB free disk space.
- 2 GB RAM.
- 2 GB of RAM, plus additional RAM for virtual machines.
- 6 GB disk space for the host, plus the required disk space for the virtual machine(s).
- Virtualization is available with the KVM hypervisor
- Intel 64 and AMD64 architectures

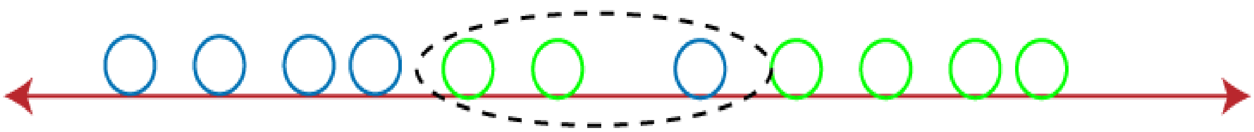
- **Software Requirement:**
  Jupyter Nootbook/Ubuntu

- **Theory:**

  Linear Discriminant Analysis (LDA) is one of the commonly used dimensionality reduction techniques in machine learning to solve more than two-class classification problems. It is also known as Normal Discriminant Analysis (NDA) or Discriminant Function Analysis (DFA).

  This can be used to project the features of higher dimensional space into lower-dimensional space in order to reduce resources and dimensional costs. In this topic, "Linear Discriminant Analysis (LDA) in machine learning", we will discuss the LDA algorithm for classification predictive modeling problems, limitation of logistic regression, representation of linear Discriminant analysis model, how to make a prediction using LDA, how to prepare data for LDA, extensions to LDA and much more. So, let's start with a quick introduction to Linear Discriminant Analysis (LDA) in machine learning.

Although the logistic regression algorithm is limited to only two-class, linear Discriminant analysis is applicable for more than two classes of classification problems.
Linear Discriminant analysis is one of the most popular dimensionality reduction techniques used for supervised classification problems in machine learning. It is also considered a pre-processing step for modeling differences in ML and applications of pattern classification.
Whenever there is a requirement to separate two or more classes having multiple features efficiently, the Linear Discriminant Analysis model is considered the most common technique to solve such classification problems. For e.g., if we have two classes with multiple features and need to separate them efficiently. When we classify them using a single feature, then it may show overlapping.

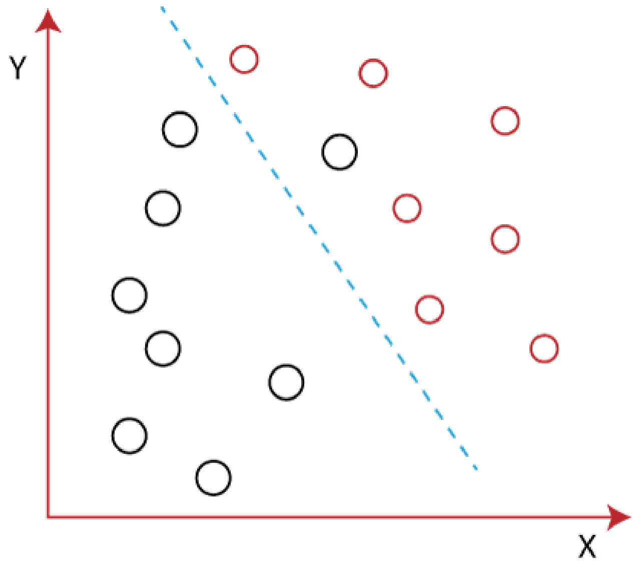


Overlapping

To overcome the overlapping issue in the classification process, we must increase the number of features regularly.

Example:

Let's assume we have to classify two different classes having two sets of data points in a 2-dimensional plane as shown below image:



However, it is impossible to draw a straight line in a 2-d plane that can separate these data points efficiently but using linear Discriminant analysis; we can dimensionally reduce the 2-D plane into the 1-D plane. Using this technique, we can also maximize the separability between multiple classes.

Implementation:

```
import pandas as pd
```

Reference Link: https://medium.com/@betulmesci/dimensionality-reduction-with-principal-component-analysis-and-linear-discriminant-analysis-on-iris-dc1731c07fad

```
df = pd.read_csv("Iris.csv")

print(df)
```

```
Id  SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm  \
0    1            5.1           3.5            1.4           0.2
1    2            4.9           3.0            1.4           0.2
2    3            4.7           3.2            1.3           0.2
3    4            4.6           3.1            1.5           0.2
4    5            5.0           3.6            1.4           0.2
..  ...           ...           ...            ...           ...
145  146          6.7           3.0            5.2           2.3
146  147          6.3           2.5            5.0           1.9
147  148          6.5           3.0            5.2           2.0
148  149          6.2           3.4            5.4           2.3
149  150          5.9           3.0            5.1           1.8

            Species
0       Iris-setosa
1       Iris-setosa
2       Iris-setosa
3       Iris-setosa
4       Iris-setosa
..              ...
145  Iris-virginica
146  Iris-virginica
147  Iris-virginica
148  Iris-virginica
149  Iris-virginica

[150 rows x 6 columns]
```

```
df.Species.unique()
```

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

```
X = df.drop(['Id','Species'],axis=1)
y = df['Species']
```

```
from sklearn.preprocessing import StandardScaler

# Scale the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

# Create an instance of LDA
lda = LinearDiscriminantAnalysis(n_components=2)

# Apply LDA on the scaled features
X_lda = lda.fit_transform(X_scaled, y)
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_lda, y, test_size=0.2, random_state=42)

# Train a logistic regression classifier
classifier = LogisticRegression()
classifier.fit(X_train, y_train)
```

```
LogisticRegression()
```

```
# Suppose you have a new flower with the following measurements:
new_flower = [[6.7,3.0,5.2,2.3 ]]  # Sepal length, sepal width, petal length, petal width

# Scale the new flower using the same scaler used for training
new_flower_scaled = scaler.transform(new_flower)

# Apply LDA on the scaled new flower
new_flower_lda = lda.transform(new_flower_scaled)

# Predict the species of the new flower
predicted_species = classifier.predict(new_flower_lda)

# Map the predicted label to the actual species
species_mapping = {'Iris-setosa': 0, 'Iris-versicolor': 1, 'Iris-virginica': 2}
predicted_species_name = species_mapping[predicted_species[0]]

# Print the predicted species
print("Predicted species:", predicted_species_name)
```

```
Predicted species: 2

/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but StandardScaler was fitted with feature names
  warnings.warn
```

Lab Assignment No.	2A
Title	Predict the price of the Uber ride from a given pickup point to the agreed drop-off location. Perform following tasks: 1. Pre-process the dataset. 2. Identify outliers. 3. Check the correlation. 4. Implement linear regression and ridge, Lasso regression models. 5. Evaluate the models and compare their respective scores like R2, RMSE, etc. Dataset link: https://www.kaggle.com/datasets/yasserh/uber-fares-dataset
Roll No.	
Class	BE
Date of Completion	
Subject	Computer Laboratory-I
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 2 A

- **Aim**: Predict the price of the Uber ride from a given pickup point to the agreed drop-off location. Perform following
tasks: 1. Pre-process the dataset. 2. Identify outliers. 3. Check the correlation. 4. Implement linear regression and ridge, Lasso regression models. 5. Evaluate the models and compare their respective scores like R2, RMSE, etc.
Dataset link: https://www.kaggle.com/datasets/yasserh/uber-fares-dataset

- **Hardware Requirement:**

  - 6 GB free disk space.
  - 2 GB RAM.
  - 2 GB of RAM, plus additional RAM for virtual machines.
  - 6 GB disk space for the host, plus the required disk space for the virtual machine(s).
  - Virtualization is available with the KVM hypervisor
  - Intel 64 and AMD64 architectures

- **Software Requirement:**
Jupyter Nootbook/Ubuntu

- **Theory:**

Regression analysis is a statistical method to model the relationship between a dependent (target) and independent (predictor) variables with one or more independent variables. More specifically, Regression analysis helps us to understand how the value of the dependent variable is changing corresponding to an independent variable when other independent variables are held fixed. It predicts continuous/real values such as temperature, age, salary, price, etc.

Why do we use Regression Analysis?

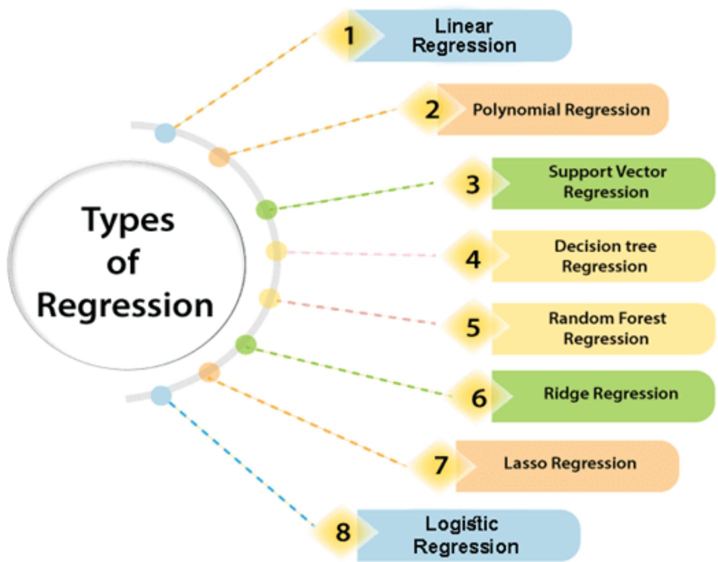
As mentioned above, Regression analysis helps in the prediction of a continuous variable. There are various scenarios in the real world where we need some future predictions such as weather condition, sales prediction, marketing trends, etc., for such case we need some technology which can make predictions more accurately. So for such case we need Regression analysis which is a statistical method and used in machine learning and data science. Below are some other reasons for using Regression analysis:

- Regression estimates the relationship between the target and the independent variable.
- It is used to find the trends in data.
- It helps to predict real/continuous values.
- By performing the regression, we can confidently determine the most important factor, the least important factor, and how each factor is affecting the other factors.

Types of Regression

There are various types of regressions which are used in data science and machine learning. Each type has its own importance on different scenarios, but at the core, all the regression methods analyze the effect of the independent variable on dependent variables. Here we are discussing some important types of regression which are given below:

- Linear Regression
- Logistic Regression
- Polynomial Regression
- Support Vector Regression
- Decision Tree Regression
- Random Forest Regression
- Ridge Regression
- Lasso Regression:



Lab Assignment No.	2B
Title	Use the diabetes data set from UCI and Pima Indians Diabetes data set for performing the following: a. Univariate analysis: Frequency, Mean, Median, Mode, Variance, Standard Deviation, Skewness and Kurtosis b. Bivariate analysis: Linear and logistic regression modeling c. Multiple Regression analysis d. Also compare the results of the above analysis for the two data sets Dataset link: https://www.kaggle.com/datasets/uciml/pima-indians-diabetes-database
Roll No.	
Class	BE
Date of Completion	
Subject	Computer Laboratory-I
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 2 B

- **Aim**: Use the diabetes data set from UCI and Pima Indians Diabetes data set for performing the following: a. Univariate analysis: Frequency, Mean, Median, Mode, Variance, Standard Deviation, Skewness and Kurtosis b. Bivariate analysis: Linear and logistic regression modeling c. Multiple Regression analysis d. Also compare the results of the above analysis for the two data sets Dataset link: https://www.kaggle.com/datasets/uciml/pima-indians-diabetes-database

- **Hardware Requirement:**

▪ 6 GB free disk space.
▪ 2 GB RAM.
▪ 2 GB of RAM, plus additional RAM for virtual machines.
▪ 6 GB disk space for the host, plus the required disk space for the virtual machine(s).
▪ Virtualization is available with the KVM hypervisor
▪ Intel 64 and AMD64 architectures

- **Software Requirement:**
  Jupyter Nootbook/Ubuntu

- **Theory:**

Descriptive statistics are brief informational coefficients that summarize a given data set, which can be either a representation of the entire population or a sample of a population. Descriptive statistics are broken down into measures of central tendency and measures of variability (spread). Measures of central tendency include the mean, median, and mode, while measures of variability include standard deviation, variance, minimum and maximum variables, kurtosis, and skewness.

Types of Descriptive Statistics

All descriptive statistics are either measures of central tendency or measures of variability, also known as measures of dispersion.

Central Tendency

Measures of central tendency focus on the average or middle values of data sets, whereas measures of variability focus on the dispersion of data. These two measures use graphs, tables and general discussions to help people understand the meaning of the analyzed data.

Measures of central tendency describe the center position of a distribution for a data set. A person analyzes the frequency of each data point in the distribution and describes it using the mean, median, or mode, which measures the most common patterns of the analyzed data set.

Measures of Variability

Measures of variability (or the measures of spread) aid in analyzing how dispersed the distribution is for a set of data. For example, while the measures of central tendency may give a person the average of a data set, it does not describe how the data is distributed within the set.

So while the average of the data maybe 65 out of 100, there can still be data points at both 1 and 100. Measures of variability help communicate this by describing the shape and spread of the data set. Range, quartiles, absolute deviation, and variance are all examples of measures of variability.

Consider the following data set: 5, 19, 24, 62, 91, 100. The range of that data set is 95, which is calculated by subtracting the lowest number (5) in the data set from the highest (100).

Distribution

Distribution (or frequency distribution) refers to the quantity of times a data point occurs. Alternatively, it is the measurement of a data point failing to occur. Consider a data set: male, male, female, female, female, other. The distribution of this data can be classified as:

- The number of males in the data set is 2.
- The number of females in the data set is 3.
- The number of individuals identifying as other is 1.
- The number of non-males is 4.

Univariate vs. Bivariate

In descriptive statistics, univariate data analyzes only one variable. It is used to identify characteristics of a single trait and is not used to analyze any relationships or causations.

For example, imagine a room full of high school students. Say you wanted to gather the average age of the individuals in the room. This univariate data is only dependent on one factor: each person's age. By gathering this one piece of information from each person and dividing by the total number of people, you can determine the average age.

Bivariate data, on the other hand, attempts to link two variables by searching for correlation. Two types of data are collected, and the relationship between the two pieces of information is analyzed together. Because multiple variables are analyzed, this approach may also be referred to as multivariate.

Descriptive Statistics vs. Inferential Statistics

Descriptive statistics have a different function than inferential statistics, data sets that are used to make decisions or apply characteristics from one data set to another.

Imagine another example where a company sells hot sauce. The company gathers data such as the count of sales, average quantity purchased per transaction, and average sale per day of the week. All of this information is descriptive, as it tells a story of what actually happened in the past. In this case, it is not being used beyond being informational.

Let's say the same company wants to roll out a new hot sauce. It gathers the same sales data above, but it crafts the information to make predictions about what the sales of the new hot sauce will be. The act of using descriptive statistics and applying characteristics to a different data set makes the data set inferential statistics. We are no longer simply summarizing data; we are using it predict what will happen regarding an entirely different body of data (the new hot sauce product).

Implementation:

```
import numpy as np
import pandas as pd

df = pd.read_csv("C:/Users/HP/Dropbox/PC/Downloads/diabetes.csv")

df.shape

(768, 9)

df.head()

   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            6      148             72             35        0  33.6
1            1       85             66             29        0  26.6
2            8      183             64              0        0  23.3
3            1       89             66             23       94  28.1
4            0      137             40             35      168  43.1

   DiabetesPedigreeFunction  Age  Outcome
0                     0.627   50        1
1                     0.351   31        0
2                     0.672   32        1
3                     0.167   21        0
4                     2.288   33        1

df.describe()

       Pregnancies     Glucose  BloodPressure  SkinThickness     Insulin  \
count   768.000000  768.000000     768.000000     768.000000  768.000000
mean      3.845052  120.894531      69.105469      20.536458   79.799479
std       3.369578   31.972618      19.355807      15.952218  115.244002
min       0.000000    0.000000       0.000000       0.000000    0.000000
25%       1.000000   99.000000      62.000000       0.000000    0.000000
50%       3.000000  117.000000      72.000000      23.000000   30.500000
75%       6.000000  140.250000      80.000000      32.000000  127.250000
max      17.000000  199.000000     122.000000      99.000000  846.000000

              BMI  DiabetesPedigreeFunction         Age     Outcome
count  768.000000                768.000000  768.000000  768.000000
mean    31.992578                  0.471876   33.240885    0.348958
std      7.884160                  0.331329   11.760232    0.476951
min      0.000000                  0.078000   21.000000    0.000000
25%     27.300000                  0.243750   24.000000    0.000000
50%     32.000000                  0.372500   29.000000    0.000000
75%     36.600000                  0.626250   41.000000    1.000000
max     67.100000                  2.420000   81.000000    1.000000
```

Univariate analysis: Frequency, Mean, Median, Mode, Variance, Standard Deviation,

Skewness and Kurtosis

```
for column in df.columns:
    print(f"Column: {column}")
    print(f"Frequency:\n{df[column].value_counts()}\n")
    print(f"Mean: {df[column].mean()}")
    print(f"Median: {df[column].median()}")
    print(f"Mode:\n{df[column].mode()}")
    print(f"Variance: {df[column].var()}")
    print(f"Standard Deviation: {df[column].std()}")
    print(f"Skewness: {df[column].skew()}")
    print(f"Kurtosis: {df[column].kurt()}")
    print("----------\n")
```

```
Column: Pregnancies
Frequency:
1     135
0     111
2     103
3      75
4      68
5      57
6      50
7      45
8      38
9      28
10     24
11     11
13     10
12      9
14      2
15      1
17      1
Name: Pregnancies, dtype: int64

Mean: 3.8450520833333335
Median: 3.0
Mode:
0    1
Name: Pregnancies, dtype: int64
Variance: 11.35405632062142
Standard Deviation: 3.3695780626988623
Skewness: 0.9016739791518588
Kurtosis: 0.15921977754746486
----------

Column: Glucose
Frequency:
99     17
```

```
100    17
111    14
129    14
125    14
       ..
191     1
177     1
44      1
62      1
190     1
Name: Glucose, Length: 136, dtype: int64

Mean: 120.89453125
Median: 117.0
Mode:
0     99
1    100
Name: Glucose, dtype: int64
Variance: 1022.2483142519557
Standard Deviation: 31.97261819513622
Skewness: 0.17375350179188992
Kurtosis: 0.6407798203735053
----------

Column: BloodPressure
Frequency:
70    57
74    52
78    45
68    45
72    44
64    43
80    40
76    39
60    37
0     35
62    34
66    30
82    30
88    25
84    23
90    22
86    21
58    21
50    13
56    12
52    11
54    11
```

```
75      8
92      8
65      7
85      6
94      6
48      5
96      4
44      4
100     3
106     3
98      3
110     3
55      2
108     2
104     2
46      2
30      2
122     1
95      1
102     1
61      1
24      1
38      1
40      1
114     1
Name: BloodPressure, dtype: int64

Mean: 69.10546875
Median: 72.0
Mode:
0    70
Name: BloodPressure, dtype: int64
Variance: 374.6472712271838
Standard Deviation: 19.355807170644777
Skewness: -1.8436079833551302
Kurtosis: 5.180156560082496
----------

Column: SkinThickness
Frequency:
0     227
32     31
30     27
27     23
23     22
33     20
28     20
18     20
31     19
19     18
39     18
29     17
40     16
25     16
26     16
22     16
```

37 16
41 15
35 15
36 14
15 14
17 14
20 13
24 12
42 11
13 11
21 10
46 8
34 8
12 7
38 7
11 6
43 6
16 6
45 6
14 6
44 5
10 5
48 4
47 4
49 3
50 3
8 2
7 2
52 2
54 2
63 1
60 1
56 1
51 1
99 1

Name: SkinThickness, dtype: int64

Mean: 20.536458333333332
Median: 23.0
Mode:
0 0
Name: SkinThickness, dtype: int64
Variance: 254.47324532811953
Standard Deviation: 15.952217567727677
Skewness: 0.10937249648187608
Kurtosis: -0.520071866153013

Column: Insulin
Frequency:
0 374
105 11
130 9
140 9
120 8
...
73 1
171 1
255 1
52 1
112 1
Name: Insulin, Length: 186, dtype: int64

Mean: 79.79947916666667

```
Median: 30.5
Mode:
0    0
Name: Insulin, dtype: int64
Variance: 13281.180077955281
Standard Deviation: 115.24400235133837
Skewness: 2.272250858431574
Kurtosis: 7.2142595543487715
----------

Column: BMI
Frequency:
32.0    13
31.6    12
31.2    12
0.0     11
32.4    10
        ..
36.7     1
41.8     1
42.6     1
42.8     1
46.3     1
Name: BMI, Length: 248, dtype: int64

Mean: 31.992578124999998
Median: 32.0
Mode:
0    32.0
Name: BMI, dtype: float64
Variance: 62.15998395738257
Standard Deviation: 7.8841603203754405
Skewness: -0.42898158845356543
Kurtosis: 3.290442900816981
----------

Column: DiabetesPedigreeFunction
Frequency:
0.258    6
0.254    6
0.268    5
0.207    5
0.261    5
        ..
1.353    1
0.655    1
0.092    1
0.926    1
```

0.171 1
Name: DiabetesPedigreeFunction, Length: 517, dtype: int64

Mean: 0.47187630208333325
Median: 0.3725
Mode:
0 0.254
1 0.258
Name: DiabetesPedigreeFunction, dtype: float64
Variance: 0.10977863787313938
Standard Deviation: 0.33132859501277484
Skewness: 1.919911066307204
Kurtosis: 5.5949535279830584

Column: Age
Frequency:
22 72
21 63
25 48
24 46
23 38
28 35
26 33
27 32
29 29
31 24
41 22
30 21
37 19
42 18
33 17
38 16
36 16
32 16
45 15
34 14
46 13
43 13
40 13
39 12
35 10
50 8
51 8
52 8
44 8
58 7
47 6
54 6
49 5
48 5
57 5
53 5
60 5
66 4
63 4
62 4
55 4
67 3
56 3
59 3
65 3
69 2
61 2
72 1
81 1
64 1
70 1
68 1

Name: Age, dtype: int64

Mean: 33.240885416666664
Median: 29.0

```
Mode:
0    22
Name: Age, dtype: int64
Variance: 138.30304589037365
Standard Deviation: 11.76023154067868
Skewness: 1.1295967011444805
Kurtosis: 0.6431588885398942
----------

Column: Outcome
Frequency:
0    500
1    268
Name: Outcome, dtype: int64

Mean: 0.3489583333333333
Median: 0.0
Mode:
0    0
Name: Outcome, dtype: int64
Variance: 0.22748261625380098
Standard Deviation: 0.4769513772427971
Skewness: 0.635016643444986
Kurtosis: -1.600929755156027
----------
```

Bivariate analysis: Linear and logistic regression modeling

```
from sklearn.linear_model import LinearRegression, LogisticRegression

# Prepare the data
X_linear = df[['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI', 'DiabetesPedigreeFunction', 'Age']]
y_linear = df['Outcome']

# Fit the linear regression model
model_linear = LinearRegression()
model_linear.fit(X_linear, y_linear)

# Print the coefficients
print('Linear Regression Coefficients:')
for feature, coef in zip(X_linear.columns, model_linear.coef_):
    print(f'{feature}: {coef}')

# Make predictions
predictions_linear = model_linear.predict(X_linear)
```

```
Linear Regression Coefficients:
Glucose: 0.005932504680360896
```

```
BloodPressure: -0.00227883712542089
SkinThickness: 0.00016697889986787442
Insulin: -0.0002096169514137912
BMI: 0.013310837289280066
DiabetesPedigreeFunction: 0.1376781570786881
Age: 0.005800684345071733
```

```
# Prepare the data
X_logistic = df[['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI', 'DiabetesPedigreeFunction', 'Age']]
y_logistic = df['Outcome']

# Fit the logistic regression model
model_logistic = LogisticRegression()
model_logistic.fit(X_logistic, y_logistic)

# Print the coefficients
print('Logistic Regression Coefficients:')
for feature, coef in zip(X_logistic.columns, model_logistic.coef_[0]):
    print(f'{feature}: {coef}')

# Make predictions
predictions_logistic = model_logistic.predict(X_logistic)
```

```
Logistic Regression Coefficients:
Glucose: 0.03454477124790582
BloodPressure: -0.01220824032665116
SkinThickness: 0.0010051963882454211
Insulin: -0.0013499454083243116
BMI: 0.08780751006435426
DiabetesPedigreeFunction: 0.8191678019528903
Age: 0.032699759788267134
```

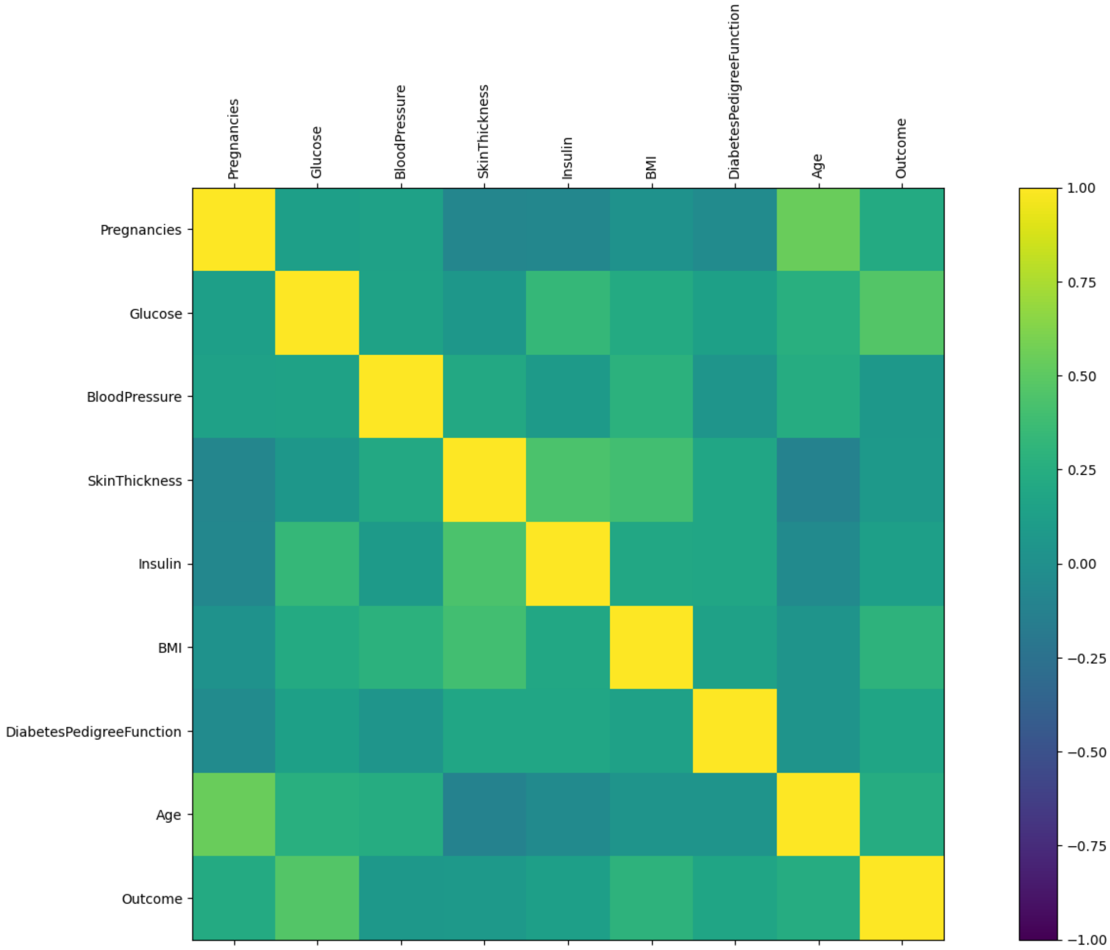
Multiple Regression analysis

```
import statsmodels.api as sm

# Split the dataset into the independent variables (X) and the dependent variable (y)
X = df.drop('Outcome', axis=1)  # Independent variables
y = df['Outcome']  # Dependent variable

# Add a constant column to the independent variables
X = sm.add_constant(X)

# Fit the multiple regression model
model = sm.OLS(y, X)
results = model.fit()

# Print the regression results
print(results.summary())
```

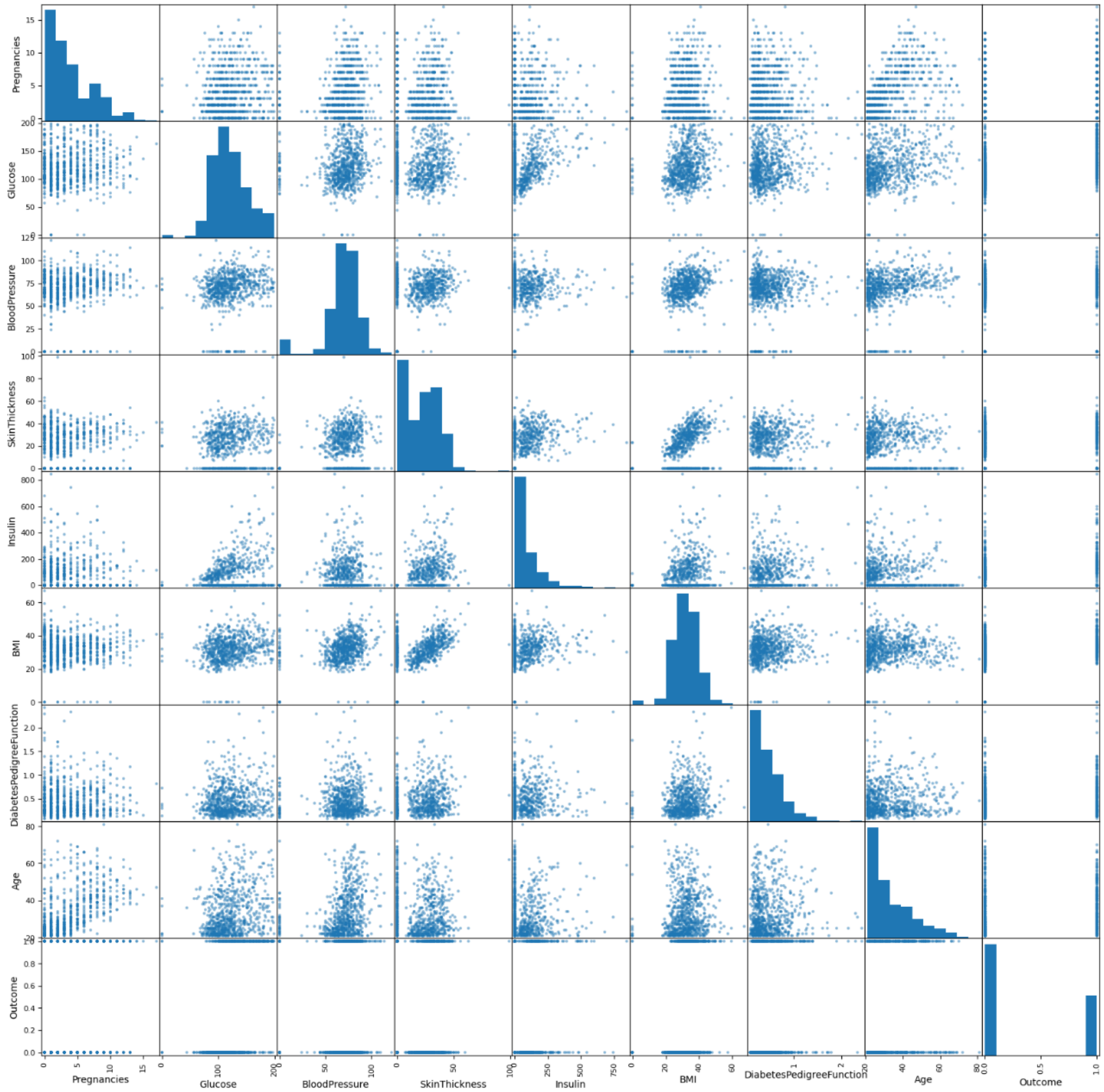
```
                    OLS Regression Results
==============================================================================
Dep. Variable:              Outcome   R-squared:                       0.303
Model:                          OLS   Adj. R-squared:                  0.296
Method:               Least Squares   F-statistic:                     41.29
Date:              Sat, 08 Jul 2023   Prob (F-statistic):           7.36e-55
Time:                      15:59:17   Log-Likelihood:                -381.91
No. Observations:               768   AIC:                             781.8
Df Residuals:                   759   BIC:                             823.6
Df Model:                         8
Covariance Type:          nonrobust
============================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------------
const                     -0.8539      0.085     -9.989      0.000      -1.022      -0.686
Pregnancies                0.0206      0.005      4.014      0.000       0.011       0.031
Glucose                    0.0059      0.001     11.493      0.000       0.005       0.007
BloodPressure             -0.0023      0.001     -2.873      0.004      -0.004      -0.001
SkinThickness              0.0002      0.001      0.139      0.890      -0.002       0.002
Insulin                   -0.0002      0.000     -1.205      0.229      -0.000       0.000
BMI                        0.0132      0.002      6.344      0.000       0.009       0.017
DiabetesPedigreeFunction   0.1472      0.045      3.268      0.001       0.059       0.236
Age                        0.0026      0.002      1.693      0.091      -0.000       0.006
==============================================================================
Omnibus:                       41.539   Durbin-Watson:                   1.982
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               31.183
Skew:                           0.395   Prob(JB):                     1.69e-07
Kurtosis:                       2.408   Cond. No.                     1.10e+03
==============================================================================
```

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.1e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

```
fig = pyplot.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(corr, vmin=-1, vmax=1)
fig.colorbar(cax)
ticks = np.arange(0,9,1)
ax.set_xticks(ticks)
ax.set_yticks(ticks)
names = df.columns
# Rotate x-tick labels by 90 degrees
ax.set_xticklabels(names,rotation=90)
ax.set_yticklabels(names)
pyplot.show()
```




```
# Import required package
from pandas.plotting import scatter_matrix
pyplot.rcParams['figure.figsize'] = [20, 20]
# Plotting Scatterplot Matrix
scatter_matrix(df)
pyplot.show()
```


Pregnancies
Glucose
BloodPressure
SkinThickness
Insulin
BMI
DiabetesPedigreeFunction
Age
Outcome

Lab Assignment No.	3A
Title	Implementation of Support Vector Machines (SVM) for classifying images of handwritten digits into their respective numerical classes (0 to 9).
Roll No.	
Class	BE
Date of Completion	
Subject	Computer Laboratory-I
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 3 A

- **Aim**: Implementation of Support Vector Machines (SVM) for classifying images of handwritten digits into their respective numerical classes (0 to 9).

- **Hardware Requirement:**

▪ 6 GB free disk space.
▪ 2 GB RAM.
▪ 2 GB of RAM, plus additional RAM for virtual machines.
▪ 6 GB disk space for the host, plus the required disk space for the virtual machine(s).
▪ Virtualization is available with the KVM hypervisor
▪ Intel 64 and AMD64 architectures

- **Software Requirement:**
  Jypiter Nootbook/Ubuntu

- **Theory:**

Classification Analysis: Definition

This analysis is a data mining technique used to determine the structure and categories within a given dataset. Classification analysis is commonly used in machine learning, text analytics, and statistical modelling. Above all, it can help identify patterns or groupings between individual observations, enabling researchers to understand their datasets better and make more accurate predictions.

Classification analysis is used to group or classify objects according to shared characteristics. Moreover, this analysis can be used in many applications, from segmenting customers for marketing campaigns to forecasting stock market trends.

Classification Analysis Example

- Classifying images

One example of a classification analysis is the use of supervised learning algorithms to classify images. In this case, the algorithm is provided with an image dataset (the training set) that contains labelled images.
The algorithm uses labels to learn how to distinguish between different types of objects in the picture. Once trained, it can then be used to classify new images as belonging to one category or another.

- Customer Segmentation

Another example of classification analysis would be customer segmentation for marketing campaigns. Classification algorithms group customers into segments based on their characteristics and behaviours.
This helps marketers target specific groups with tailored content, offers, and promotions that are more likely to appeal to them.

- Stock Market Prediction

Finally, classification analysis can also be used for stock market prediction. Classification algorithms can identify patterns between past stock prices and other economic indicators, such as interest rates or unemployment figures. By understanding these correlations, analysts can better predict future market trends and make more informed investment decisions.

These are just some examples of how classification analysis can be applied to various scenarios. Unquestionably, classification algorithms can be used to analyse datasets in any domain, from healthcare and finance to agriculture and logistics.

Classification Analysis Techniques

This analysis is a powerful technique used in data science to analyse and categorise data. Classification techniques are used in many areas, from predicting customer behaviours to finding patterns and trends in large datasets.
This analysis can help businesses make informed decisions about marketing strategies, product development, and more. So, let’s delve into the various techniques

1. Supervised Learning

Supervised learning algorithms require labelled data. This means the algorithm is provided with a dataset that has already been categorised or labelled with class labels. The algorithm then uses this label to learn how to distinguish between different class objects in the data. Once trained, it can use its predictive power to classify new datasets.

2. Unsupervised Learning

Unsupervised learning algorithms do not require labelled data. Instead, they use clustering and dimensionality reduction techniques to identify patterns in the dataset without any external guidance. These algorithms help segment customers or identify outlier items in a dataset.

3. Deep Learning

Deep learning is a subset/division of machine learning technologies that use artificial neural networks. These algorithms are capable of learning from large datasets and making complex decisions. Deep learning can be used for tasks such as image classification, natural language processing, and predictive analytics.
Classification algorithms can help uncover patterns in the data that could not be detected using traditional methods. By using classification analysis, businesses can gain valuable insights into their customers’ behaviours and preferences, helping them make more informed decisions.

Implementation:

```
# Import Libraries

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

Handwritten Digit Recognition

Use the sklearn.dataset load_digits() method. It loads the handwritten digits dataset. The returned data is in the form of a Dictionary. The 'data' attribute contains a flattenned array of 64 (each digit image is of 8*8 pixels) elements representing the digits.

The 'target' attribute is the 'class' of Digit (0-9) Each individual digit is represented through a flattendded 64 digit array numbers of Greyscale values. There are 1797 samples in total and each class or digit has roughly 180 samples.

```
from sklearn.datasets import load_digits
digits = load_digits(n_class=10)

digits

{'data': array([[ 0.,  0.,  5., ...,  0.,  0.,  0.],
       [ 0.,  0.,  0., ..., 10.,  0.,  0.],
```

```
        [ 0.,  0.,  0., ..., 16.,  9.,  0.],
        ...,
        [ 0.,  0.,  1., ...,  6.,  0.,  0.],
        [ 0.,  0.,  2., ..., 12.,  0.,  0.],
        [ 0.,  0., 10., ..., 12.,  1.,  0.]]),
 'target': array([0, 1, 2, ..., 8, 9, 8]),
 'frame': None,
 'feature_names': ['pixel_0_0',
  'pixel_0_1',
  'pixel_0_2',
  'pixel_0_3',
  'pixel_0_4',
  'pixel_0_5',
  'pixel_0_6',
  'pixel_0_7',
  'pixel_1_0',
  'pixel_1_1',
  'pixel_1_2',
  'pixel_1_3',
  'pixel_1_4',
  'pixel_1_5',
  'pixel_1_6',
  'pixel_1_7',
  'pixel_2_0',
  'pixel_2_1',
  'pixel_2_2',
  'pixel_2_3',
  'pixel_2_4',
  'pixel_2_5',
  'pixel_2_6',
  'pixel_2_7',
  'pixel_3_0',
  'pixel_3_1',
  'pixel_3_2',
  'pixel_3_3',
  'pixel_3_4',
  'pixel_3_5',
  'pixel_3_6',
  'pixel_3_7',
  'pixel_4_0',
  'pixel_4_1',
  'pixel_4_2',
  'pixel_4_3',
  'pixel_4_4',
  'pixel_4_5',
  'pixel_4_6',
  'pixel_4_7',
  'pixel_5_0',
  'pixel_5_1',
  'pixel_5_2',
  'pixel_5_3',
  'pixel_5_4',
  'pixel_5_5',
  'pixel_5_6',
  'pixel_5_7',
  'pixel_6_0',
  'pixel_6_1',
  'pixel_6_2',
  'pixel_6_3',
  'pixel_6_4',
  'pixel_6_5',
  'pixel_6_6',
  'pixel_6_7',
  'pixel_7_0',
  'pixel_7_1',
  'pixel_7_2',
  'pixel_7_3',
  'pixel_7_4',
  'pixel_7_5',
  'pixel_7_6',
  'pixel_7_7'],

 'target_names': array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
 'images': array([[[ 0.,  0.,  5., ...,  1.,  0.,  0.],
         [ 0.,  0., 13., ..., 15.,  5.,  0.],
         [ 0.,  3., 15., ..., 11.,  8.,  0.],
         ...,
         [ 0.,  4., 11., ..., 12.,  7.,  0.],
         [ 0.,  2., 14., ..., 12.,  0.,  0.],
```

```
 [ 0.,  0.,  6., ...,  0.,  0.,  0.]],

[[ 0.,  0.,  0., ...,  5.,  0.,  0.],
 [ 0.,  0.,  0., ...,  9.,  0.,  0.],
 [ 0.,  0.,  3., ...,  6.,  0.,  0.],
 ...,
 [ 0.,  0.,  1., ...,  6.,  0.,  0.],
 [ 0.,  0.,  1., ...,  6.,  0.,  0.],
 [ 0.,  0.,  0., ..., 10.,  0.,  0.]],

[[ 0.,  0.,  0., ..., 12.,  0.,  0.],
 [ 0.,  0.,  3., ..., 14.,  0.,  0.],
 [ 0.,  0.,  8., ..., 16.,  0.,  0.],
 ...,
 [ 0.,  9., 16., ...,  0.,  0.,  0.],
 [ 0.,  3., 13., ..., 11.,  5.,  0.],
 [ 0.,  0.,  0., ..., 16.,  9.,  0.]],

...,

[[ 0.,  0.,  1., ...,  1.,  0.,  0.],
 [ 0.,  0., 13., ...,  2.,  1.,  0.],
 [ 0.,  0., 16., ..., 16.,  5.,  0.],
 ...,
 [ 0.,  0., 16., ..., 15.,  0.,  0.],
 [ 0.,  0., 15., ..., 16.,  0.,  0.],
 [ 0.,  0.,  2., ...,  6.,  0.,  0.]],

[[ 0.,  0.,  2., ...,  0.,  0.,  0.],
 [ 0.,  0., 14., ..., 15.,  1.,  0.],
 [ 0.,  4., 16., ..., 16.,  7.,  0.],
 ...,
 [ 0.,  0.,  0., ..., 16.,  2.,  0.],
 [ 0.,  0.,  4., ..., 16.,  2.,  0.],
 [ 0.,  0.,  5., ..., 12.,  0.,  0.]],

[[ 0.,  0., 10., ...,  1.,  0.,  0.],
 [ 0.,  2., 16., ...,  1.,  0.,  0.],
 [ 0.,  0., 15., ..., 15.,  0.,  0.],
 ...,
 [ 0.,  4., 16., ..., 16.,  6.,  0.],
 [ 0.,  8., 16., ..., 16.,  8.,  0.],
 [ 0.,  1.,  8., ..., 12.,  1.,  0.]]]]),
```

'DESCR': ".. _digits_dataset:\n\nOptical recognition of handwritten digits dataset\n--\n\n**Data Set Characteristics:**\n\n   :Number of Instances: 1797\n   :Number of Attributes: 64\n   :Attribute Information: 8x8 image of integer pixels in the range 0..16.\n   :Missing Attribute Values: None\n   :Creator: E. Alpaydin (alpaydin '@' boun.edu.tr)\n   :Date: July; 1998\n\nThis is a copy of the test set of the UCI ML hand-written digits datasets\nhttps://archive.ics.uci.edu/ml/datasets/Optical+Recognition+of+Handwritten+Digits\n\nThe data set contains images of hand-written digits: 10 classes where\neach class refers to a digit.\n\nPreprocessing programs made available by NIST were used to extract\nnormalized bitmaps of handwritten digits from a preprinted form. From a\ntotal of 43 people, 30 contributed to the training set and different 13\nto the test set. 32x32 bitmaps are divided into nonoverlapping blocks of\n4x4 and the number of on pixels are counted in each block. This generates\nan input matrix of 8x8 where each element is an integer in the range\n0..16. This reduces dimensionality and gives invariance to small\ndistortions.\n\nFor info on NIST preprocessing routines, see M. D. Garris, J. L. Blue, G.\nT. Candela, D. L. Dimmick, J. Geist, P. J. Grother, S. A. Janet, and C.\nL. Wilson, NIST Form-Based Handprint Recognition System, NISTIR 5469,\n1994.\n\n.. topic:: References\n\n - C. Kaynak (1995) Methods of Combining Multiple Classifiers and Their\n   Applications to Handwritten Digit Recognition, MSc Thesis, Institute of\n   Graduate Studies in Science and Engineering, Bogazici University.\n - E. Alpaydin, C. Kaynak (1998) Cascading Classifiers, Kybernetika.\n - Ken Tang and Ponnuthurai N. Suganthan and Xi Yao and A. Kai Qin.\n   Linear dimensionalityreduction using relevance weighted LDA. School of\n   Electrical and Electronic Engineering Nanyang Technological University.\n   2005.\n - Claudio Gentile. A New Approximate Maximal Margin Classification\n   Algorithm. NIPS. 2000.\n"}

```
digits['data'][0].reshape(8,8)
```

```
array([[ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.],
       [ 0.,  0., 13., 15., 10., 15.,  5.,  0.],
       [ 0.,  3., 15.,  2.,  0., 11.,  8.,  0.],
       [ 0.,  4., 12.,  0.,  0.,  8.,  8.,  0.],
       [ 0.,  5.,  8.,  0.,  0.,  9.,  8.,  0.],
       [ 0.,  4., 11.,  0.,  1., 12.,  7.,  0.],
       [ 0.,  2., 14.,  5., 10., 12.,  0.,  0.],
       [ 0.,  0.,  6., 13., 10.,  0.,  0.,  0.]])
```

```
digits['data'][0]
```

```
array([ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.,  0.,  0., 13., 15., 10.,
       15.,  5.,  0.,  0.,  3., 15.,  2.,  0., 11.,  8.,  0.,  0.,  4.,
       12.,  0.,  0.,  8.,  8.,  0.,  0.,  5.,  8.,  0.,  0.,  9.,  8.,
        0.,  0.,  4., 11.,  0.,  1., 12.,  7.,  0.,  0.,  2., 14.,  5.,
       10., 12.,  0.,  0.,  0.,  0.,  6., 13., 10.,  0.,  0.,  0.])
```

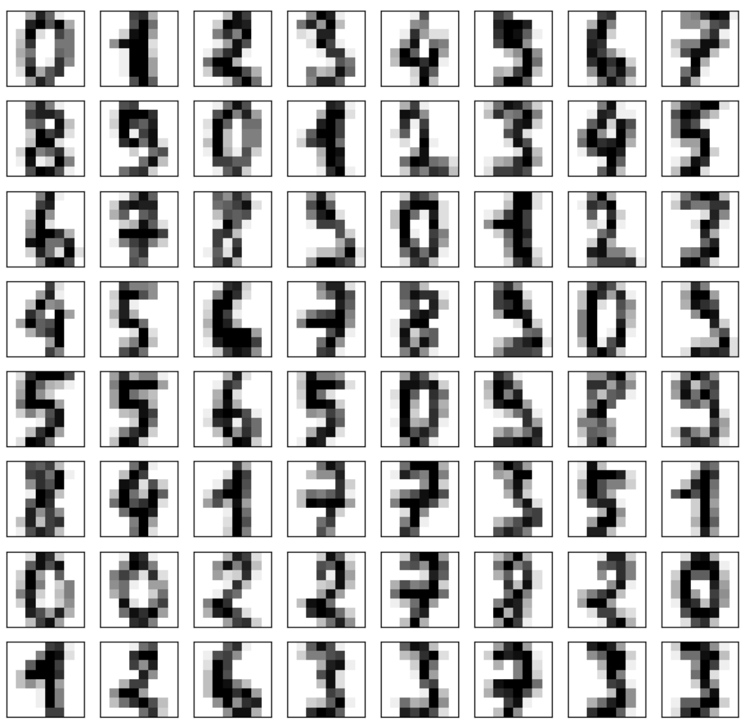
```
digits['images'][1]
```

```
array([[ 0.,  0.,  0., 12., 13.,  5.,  0.,  0.],
       [ 0.,  0.,  0., 11., 16.,  9.,  0.,  0.],
       [ 0.,  0.,  3., 15., 16.,  6.,  0.,  0.],
       [ 0.,  7., 15., 16., 16.,  2.,  0.,  0.],
       [ 0.,  0.,  1., 16., 16.,  3.,  0.,  0.],
       [ 0.,  0.,  1., 16., 16.,  6.,  0.,  0.],
       [ 0.,  0.,  1., 16., 16.,  6.,  0.,  0.],
       [ 0.,  0.,  0., 11., 16., 10.,  0.,  0.]])
```

```
digits['target'][0:9]
```

```
array([0, 1, 2, 3, 4, 5, 6, 7, 8])
```

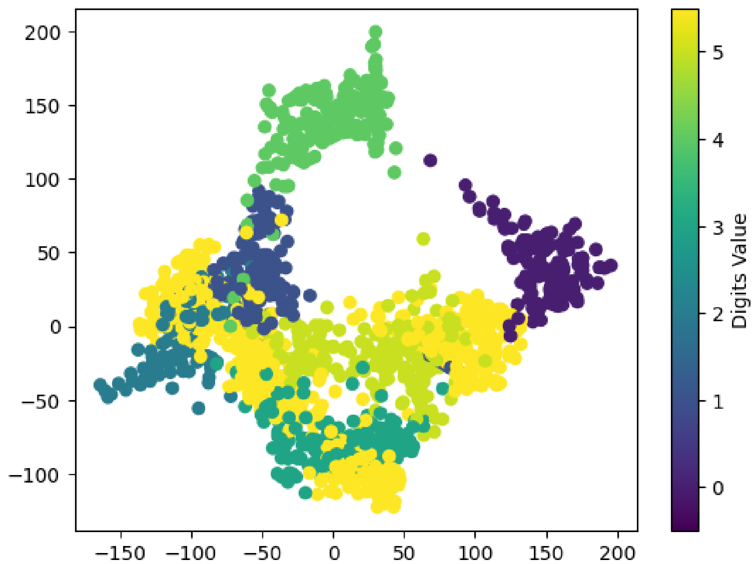
```
digits['target'][0]

0

digits.images[0]

array([[ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.],
       [ 0.,  0., 13., 15., 10., 15.,  5.,  0.],
       [ 0.,  3., 15.,  2.,  0., 11.,  8.,  0.],
       [ 0.,  4., 12.,  0.,  0.,  8.,  8.,  0.],
       [ 0.,  5.,  8.,  0.,  0.,  9.,  8.,  0.],
       [ 0.,  4., 11.,  0.,  1., 12.,  7.,  0.],
       [ 0.,  2., 14.,  5., 10., 12.,  0.,  0.],
       [ 0.,  0.,  6., 13., 10.,  0.,  0.,  0.]])

# Each Digit is represented in digits.images as a matrix of 8x8 = 64 pixels. Each of the 64 values represent
# a greyscale. The Greyscale are then plotted in the right scale by the imshow method.

fig, ax = plt.subplots(8,8, figsize=(10,10))
for i, axi in enumerate(ax.flat):
    axi.imshow(digits.images[i], cmap='binary')
    axi.set(xticks=[], yticks=[])
```



```
# Plotting - Clustering the data points after using Manifold Learning

from sklearn.manifold import Isomap

iso = Isomap(n_components=2)
```

```
projection = iso.fit_transform(digits.data)     # digits.data - 64 dimensions to 2 dimensions

plt.scatter(projection[:, 0], projection[:, 1], c=digits.target, cmap="viridis")

plt.colorbar(ticks=range(10), label='Digits Value')
plt.clim(-0.5, 5.5)
```

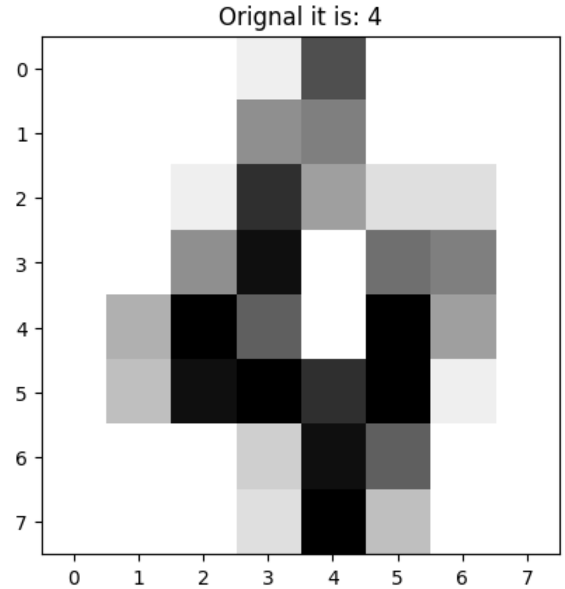
```
/usr/local/lib/python3.10/dist-packages/sklearn/manifold/_isomap.py:373: UserWarning: The number of connected components of the neighbors graph is 2 > 1. Completing the graph to fit Isomap might be slow. Increase the number of neighbors to avoid this issue.
  self._fit_transform(X)
/usr/local/lib/python3.10/dist-packages/scipy/sparse/_index.py:103: SparseEfficiencyWarning: Changing the sparsity structure of a csr_matrix is expensive. lil_matrix is more efficient.
  self._set_intXint(row, col, x.flat[0])
```




```
print(projection[:, 0][70], projection[:, 1][70])
```

```
-56.60683580684862 61.95022367117501
```

```
def view_digit(index):
    plt.imshow(digits.images[index] , cmap = plt.cm.gray_r)
    plt.title('Orignal it is: '+ str(digits.target[index]))
    plt.show()

view_digit(4)
```



Use the Support Vector Machine Classifier to train the Data

Use part of the data for train and part of the data for test (predicion)

```
main_data = digits['data']
targets = digits['target']

from sklearn import svm

svc = svm.SVC(gamma=0.001 , C = 100)

# GAMMA is a parameter for non linear hyperplanes.
# The higher the gamma value it tries to exactly fit the training data set
# C is the penalty parameter of the error term.
# It controls the trade off between smooth decision boundary and classifying the training points correctly.

svc.fit(main_data[:1500] , targets[:1500])

predictions = svc.predict(main_data[1501:])

list(zip(predictions , targets[1501:]))
```

```
[(7, 7),
 (4, 4),
 (6, 6),
 (3, 3),
 (1, 1),
 (3, 3),
 (9, 9),
 (1, 1),
 (7, 7),
 (6, 6),
 (8, 8),
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 (3, 3),
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 (9, 9),
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 (1, 1),
 (7, 7),
 (5, 5),
 (4, 4),
 (4, 4),
 (7, 7),
 (2, 2),
 (8, 8),
 (2, 2),
```

(2, 2),
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(7, 7),
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(5, 5),
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(2, 2),
(8, 8),
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(1, 1),

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(4, 4),
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```
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(4, 4),
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(9, 9),
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(2, 2),
(0, 0),
(0, 0),
(1, 1),
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(7, 7),
(4, 4),
(6, 6),
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(7, 7),
(6, 6),
(8, 8),
(4, 4),
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(1, 1),
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(0, 0),
(5, 5),
(3, 3),
(6, 6),
(9, 9),
(6, 6),
(1, 1),
(7, 7),
(5, 5),
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(2, 2),
(8, 8),
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(9, 9),
(5, 5),
(4, 4),
(8, 8),
(8, 8),
(4, 4),
(9, 9),
(0, 0),
(8, 8),
(9, 9),
(8, 8)]
```

Create the Confusion Matric for Performance Evaluation

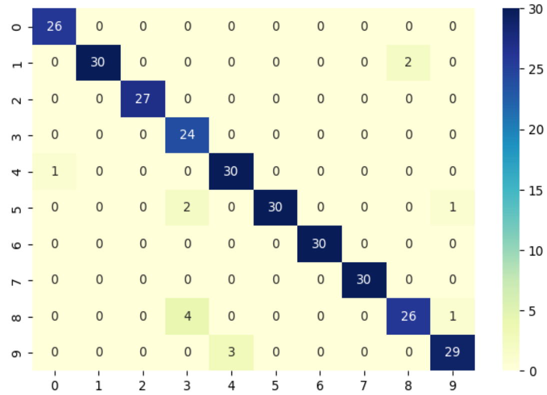
```
from sklearn.metrics import confusion_matrix
import seaborn as sns

cm = confusion_matrix(predictions, targets[1501:])

conf_matrix = pd.DataFrame(data = cm)
```

```
plt.figure(figsize = (8,5))

sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu");
```



```
cm

array([[26,  0,  0,  0,  0,  0,  0,  0,  0,  0],
       [ 0, 30,  0,  0,  0,  0,  0,  0,  2,  0],
       [ 0,  0, 27,  0,  0,  0,  0,  0,  0,  0],
       [ 0,  0,  0, 24,  0,  0,  0,  0,  0,  0],
       [ 1,  0,  0,  0, 30,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  2,  0, 30,  0,  0,  0,  1],
       [ 0,  0,  0,  0,  0,  0, 30,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0, 30,  0,  0],
       [ 0,  0,  0,  4,  0,  0,  0,  0, 26,  1],
       [ 0,  0,  0,  0,  3,  0,  0,  0,  0, 29]])
```

Print the Classification Report

```
from sklearn.metrics import classification_report

print(classification_report(predictions, targets[1501:]))
```

	precision	recall	f1-score	support
0	0.96	1.00	0.98	26
1	1.00	0.94	0.97	32
2	1.00	1.00	1.00	27
3	0.80	1.00	0.89	24
4	0.91	0.97	0.94	31
5	1.00	0.91	0.95	33
6	1.00	1.00	1.00	30
7	1.00	1.00	1.00	30
8	0.93	0.84	0.88	31
9	0.94	0.91	0.92	32
accuracy			0.95	296

macro avg	0.95	0.96	0.95	296
weighted avg	0.96	0.95	0.95	296

Lab Assignment No.	4A
Title	Implement K-Means clustering on Iris.csv dataset. Determine the number of clustersusing the elbow method.Dataset Link: https://www.kaggle.com/datasets/uciml/iris
Roll No.	
Class	BE
Date of Completion	
Subject	Computer Laboratory-I
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 4 A

- **Aim**: Implement K-Means clustering on Iris.csv dataset. Determine the number of clusters using the elbow method.Dataset Link: https://www.kaggle.com/datasets/uciml/iris

- **Hardware Requirement:**

▪ 6 GB free disk space.
▪ 2 GB RAM.
▪ 2 GB of RAM, plus additional RAM for virtual machines.
▪ 6 GB disk space for the host, plus the required disk space for the virtual machine(s).
▪ Virtualization is available with the KVM hypervisor
▪ Intel 64 and AMD64 architectures

- **Software Requirement:**
  Jupyter Nootbook/Ubuntu

- **Theory:**

K-means clustering algorithm computes the centroids and iterates until we it finds optimal centroid. It assumes that the number of clusters are already known. It is also called flat clustering algorithm. The number of clusters identified from data by algorithm is represented by 'K' in K-means.

In this algorithm, the data points are assigned to a cluster in such a manner that the sum of the squared distance between the data points and centroid would be minimum. It is to be understood that less variation within the clusters will lead to more similar data points within same cluster.

Working of K-Means Algorithm

We can understand the working of K-Means clustering algorithm with the help of following steps −

Step 1 − First, we need to specify the number of clusters, K, need to be generated by this algorithm.
Step 2 − Next, randomly select K data points and assign each data point to a cluster. In simple words, classify the data based on the number of data points.
Step 3 − Now it will compute the cluster centroids.
Step 4 − Next, keep iterating the following until we find optimal centroid which is the assignment of data points to the clusters that are not changing any more −

4.1 − First, the sum of squared distance between data points and centroids would be computed.

4.2 − Now, we have to assign each data point to the cluster that is closer than other cluster (centroid).

4.3 − At last compute the centroids for the clusters by taking the average of all data points of that cluster.

K-means follows Expectation-Maximization approach to solve the problem. The Expectation-step is used for assigning the data points to the closest cluster and the Maximization-step is used for computing the centroid of each cluster.

While working with K-means algorithm we need to take care of the following things −

While working with clustering algorithms including K-Means, it is recommended to standardize the data because such algorithms use distance-based measurement to determine the similarity between data points.

Due to the iterative nature of K-Means and random initialization of centroids, K-Means may stick in a local optimum and may not converge to global optimum. That is why it is recommended to use different initializations of centroids

Implementation:

Importing the libraries and the data

```
import pandas as pd # Pandas (version : 1.1.5)
import numpy as np # Numpy (version : 1.19.2)
import matplotlib.pyplot as plt # Matplotlib (version :  3.3.2)
from sklearn.cluster import KMeans # Scikit Learn (version : 0.23.2)
import seaborn as sns # Seaborn (version : 0.11.1)
plt.style.use('seaborn')
```

Importing the data from .csv file

First we read the data from the dataset using read_csv from the pandas library.

```
data = pd.read_csv('data\iris.csv')
```

Viewing the data that we imported to pandas dataframe object

```
data
```

```
     Id  SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm  \
0     1            5.1           3.5            1.4           0.2
1     2            4.9           3.0            1.4           0.2
2   3          4.7       3.2          1.3          0.2
3     4            4.6           3.1            1.5           0.2
4     5            5.0           3.6            1.4           0.2
..  ...            ...       ...       ...       ...
145  146           6.7           3.0            5.2           2.3
146  147           6.3           2.5            5.0           1.9
147  148           6.5           3.0            5.2           2.0
148  149           6.2       3.4          5.4          2.3
149  150           5.9           3.0            5.1           1.8

           Species
0      Iris-setosa
1      Iris-setosa
2      Iris-setosa
3      Iris-setosa
4      Iris-setosa
..             ...
145  Iris-virginica
146  Iris-virginica
147  Iris-virginica
148  Iris-virginica
149  Iris-virginica

[150 rows x 6 columns]
```

Viewing and Describing the data

Now we view the Head and Tail of the data using head() and tail() respectively.

data.head()

```
   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
```

data.tail()

```
      Id  SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm  \
145  146    6.7    3.0    5.2    2.3
146  147    6.3    2.5    5.0    1.9
147  148    6.5    3.0    5.2    2.0
148  149    6.2    3.4    5.4    2.3
149  150    5.9    3.0    5.1    1.8

          Species
145  Iris-virginica
146  Iris-virginica
147  Iris-virginica
148  Iris-virginica
149  Iris-virginica
```

Checking the sample size of data - how many samples are there in the dataset using len().

len(data)

150

Checking the dimensions/shape of the dataset using shape.

data.shape

(150, 6)

Viewing Column names of the dataset using columns

data.columns

```
Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',
       'Species'],
      dtype='object')
```

for i,col in enumerate(data.columns):

```
print(f'Column number {1+i} is {col}')
```

Column number 1 is Id

Column number 2 is SepalLengthCm

Column number 3 is SepalWidthCm

Column number 4 is PetalLengthCm

Column number 5 is PetalWidthCm

Column number 6 is Species

So, our dataset has 5 columns named:

- Id
- SepalLengthCm
- SepalWidthCm
- PetalLengthCm
- PetalWidthCm
- Species.

View datatypes of each column in the dataset using dtype.

```
data.dtypes
```

```
Id              int64
SepalLengthCm   float64
SepalWidthCm    float64
PetalLengthCm   float64
PetalWidthCm    float64
Species         object
dtype: object
```

Gathering Further information about the dataset using info()

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             150 non-null    int64
```

```
 1   SepalLengthCm  150 non-null    float64
 2   SepalWidthCm   150 non-null    float64
 3   PetalLengthCm  150 non-null    float64
 4   PetalWidthCm   150 non-null    float64
 5   Species        150 non-null    object
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

Describing the data as basic statistics using describe()

data.describe()

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
std	43.445368	0.828066	0.433594	1.764420	0.763161
min	1.000000	4.300000	2.000000	1.000000	0.100000
25%	38.250000	5.100000	2.800000	1.600000	0.300000
50%	75.500000	5.800000	3.000000	4.350000	1.300000
75%	112.750000	6.400000	3.300000	5.100000	1.800000
max	150.000000	7.900000	4.400000	6.900000	2.500000

Checking the data for inconsistencies and further cleaning the data if needed.

Checking data for missing values using isnull().

data.isnull()

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	False	False	False	False	False	False
1	False	False	False	False	False	False
2	False	False	False	False	False	False
3	False	False	False	False	False	False
4	False	False	False	False	False	False
..	...	...	...	...	...	...
145	False	False	False	False	False	False
146	False	False	False	False	False	False
147	False	False	False	False	False	False

```
148  False      False          False          False          False   False
149  False      False          False          False          False   False

[150 rows x 6 columns]
```

Checking summary of missing values

```
data.isnull().sum()
Id               0
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

The 'Id' column has no relevence therefore deleting it would be better.

Deleting 'customer_id' colummn using drop().

```
data.drop('Id', axis=1, inplace=True)
data.head()
   SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm      Species
0            5.1           3.5            1.4           0.2  Iris-setosa
1            4.9           3.0            1.4           0.2  Iris-setosa
2            4.7           3.2            1.3           0.2  Iris-setosa
3            4.6           3.1            1.5           0.2  Iris-setosa
4            5.0           3.6            1.4           0.2  Iris-setosa
```

Modelling

K - Means Clustering

K-means clustering is a clustering algorithm that aims to partition n observations into k clusters. Initialisation – K initial “means” (centroids) are generated at random Assignment – K clusters are created by associating each observation with the nearest centroid Update – The centroid of the clusters becomes the new mean, Assignment and Update are repeated iteratively until convergence The end result is that the sum of squared errors is minimised between points and their respective centroids. We will use KMeans Clustering. At first we will find the optimal clusters based on inertia and using elbow method. The distance between the centroids and the data points should be less.

First we need to check the data for any missing values as it can ruin our model.

data.isna().sum()

```
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

We conclude that we don't have any missing values therefore we can go forward and start the clustering procedure.

We will now view and select the data that we need for clustering.

data.head()

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

Checking the value count of the target column i.e. 'Species' using value_counts()

data['Species'].value_counts()

```
Iris-setosa       50
Iris-versicolor   50
```

```
Iris-virginica     50
Name: Species, dtype: int64
```

Splitting into Training and Target data

Target Data

```
target_data = data.iloc[:,4]
target_data.head()
```

```
0     Iris-setosa
1     Iris-setosa
2     Iris-setosa
3     Iris-setosa
4     Iris-setosa
Name: Species, dtype: object
```

Training data

```
clustering_data = data.iloc[:,[0,1,2,3]]
clustering_data.head()
```

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
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

Now, we need to visualize the data which we are going to use for the clustering. This will give us a fair idea about the data we're working on.

```
fig, ax = plt.subplots(figsize=(15,7))
sns.set(font_scale=1.5)
ax = sns.scatterplot(x=data['SepalLengthCm'],y=data['SepalWidthCm'], s=70, color='#f73434',
```

```
edgecolor='#f73434', linewidth=0.3)
 ax.set_ylabel('Sepal Width (in cm)')
 ax.set_xlabel('Sepal Length (in cm)')
 plt.title('Sepal Length vs Width', fontsize = 20)
 plt.show()
```

This gives us a fair Idea and patterns about some of the data.

Determining No. of Clusters Required

The Elbow Method

The Elbow method runs k-means clustering on the dataset for a range of values for k (say from 1-10) and then for each value of k computes an average score for all clusters. By default, the distortion score is computed, the sum of square distances from each point to its assigned center.

When these overall metrics for each model are plotted, it is possible to visually determine the best value for k. If the line chart looks like an arm, then the “elbow” (the point of inflection on the curve) is the best value of k. The “arm” can be either up or down, but if there is a strong inflection point, it is a good indication that the underlying model fits best at that point.

We use the Elbow Method which uses Within Cluster Sum Of Squares (WCSS) against the the number of clusters (K Value) to figure out the optimal number of clusters value. WCSS measures sum of distances of observations from their cluster centroids which is given by the below formula.

formula

where Yi is centroid for observation Xi. The main goal is to maximize number of clusters and in limiting case each data point becomes its own cluster centroid.

With this simple line of code we get all the inertia value or the within the cluster sum of square.

```
from sklearn.cluster import KMeans
 wcss=[]
 for i in range(1,11):
```

```
    km = KMeans(i)
    km.fit(clustering_data)
    wcss.append(km.inertia_)
np.array(wcss)
```

```
array([680.8244      , 152.36870648,  78.94084143,  57.31787321,
        46.53558205,  38.93096305,  34.29998554,  30.21678683,
        28.23999745,  25.95204113])
```

Inertia can be recognized as a measure of how internally coherent clusters are.

Now, we visualize the Elbow Method so that we can determine the number of optimal clusters for our dataset.

```
fig, ax = plt.subplots(figsize=(15,7))
ax = plt.plot(range(1,11),wcss, linewidth=2, color="red", marker ="8")
plt.axvline(x=3, ls='--')
plt.ylabel('WCSS')
plt.xlabel('No. of Clusters (k)')
plt.title('The Elbow Method', fontsize = 20)
plt.show()
```

It is clear, that the optimal number of clusters for our data are 3, as the slope of the curve is not steep enough after it. When we observe this curve, we see that last elbow comes at k = 3, it would be difficult to visualize the elbow if we choose the higher range.

Clustering

Now we will build the model for creating clusters from the dataset. We will use n_clusters = 3 i.e. 3 clusters as we have determined by the elbow method, which would be optimal for our dataset.

Our data set is for unsupervised learning therefore we will use fit_predict() Suppose we were working with supervised learning data set we would use fit_tranform()

```
from sklearn.cluster import KMeans
```

```
kms = KMeans(n_clusters=3, init='k-means++')
kms.fit(clustering_data)
```

```
KMeans(n_clusters=3)
```

Now that we have the clusters created, we will enter them into a different column

```
clusters = clustering_data.copy()
clusters['Cluster_Prediction'] = kms.fit_predict(clustering_data)
clusters.head()
```

```
   SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm  \
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

   Cluster_Prediction
0                   1
1                   1
2                   1
3                   1
4                   1
```

We can also get the centroids of the clusters by the cluster_centers_ attribute of KMeans algorithm.

```
kms.cluster_centers_
```

```
array([[5.9016129 , 2.7483871 , 4.39354839, 1.43387097],
       [5.006     , 3.418     , 1.464     , 0.244     ],
       [6.85      , 3.07368421, 5.74210526, 2.07105263]])
```

Now we have all the data we need, we just need to plot the data. We will plot the data using scatterplot which will allow us to observe different clusters in different colours.

```
fig, ax = plt.subplots(figsize=(15,7))
 plt.scatter(x=clusters[clusters['Cluster_Prediction'] == 0]['SepalLengthCm'],
            y=clusters[clusters['Cluster_Prediction'] == 0]['SepalWidthCm'],
            s=70,edgecolor='teal', linewidth=0.3, c='teal', label='Iris-versicolor')



 plt.scatter(x=clusters[clusters['Cluster_Prediction'] == 1]['SepalLengthCm'],
            y=clusters[clusters['Cluster_Prediction'] == 1]['SepalWidthCm'],
            s=70,edgecolor='lime', linewidth=0.3, c='lime', label='Iris-setosa')



 plt.scatter(x=clusters[clusters['Cluster_Prediction'] == 2]['SepalLengthCm'],
            y=clusters[clusters['Cluster_Prediction'] == 2]['SepalWidthCm'],
            s=70,edgecolor='magenta', linewidth=0.3, c='magenta', label='Iris-virginica')

 plt.scatter(x=kms.cluster_centers_[:, 0], y=kms.cluster_centers_[:, 1], s = 170, c = 'yellow', label =
'Centroids',edgecolor='black', linewidth=0.3)
 plt.legend(loc='upper right')
 plt.xlim(4,8)
 plt.ylim(1.8,4.5)
 ax.set_ylabel('Sepal Width (in cm)')
 ax.set_xlabel('Sepal Length (in cm)')
 plt.title('Clusters', fontsize = 20)
 plt.show()
```

Lab Assignment No.	5B
Title	Use different voting mechanism and Apply AdaBoost (Adaptive Boosting), Gradient Tree Boosting (GBM), XGBoost classification on Iris dataset and compare the performance of three models using different evaluation measures. Dataset Link https://www.kaggle.com/datasets/uciml/iris
Roll No.	
Class	BE
Date of Completion	
Subject	Computer Laboratory-I
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 5 B

- **Aim**: Use different voting mechanism and Apply AdaBoost (Adaptive Boosting), Gradient Tree Boosting (GBM), XGBoost classification on Iris dataset and compare the performance of three models using different evaluation measures. Dataset Link https://www.kaggle.com/datasets/uciml/iris

Hardware Requirement:

- 6 GB free disk space.
- 2 GB RAM.
- 2 GB of RAM, plus additional RAM for virtual machines.
- 6 GB disk space for the host, plus the required disk space for the virtual machine(s).
- Virtualization is available with the KVM hypervisor
- Intel 64 and AMD64 architectures

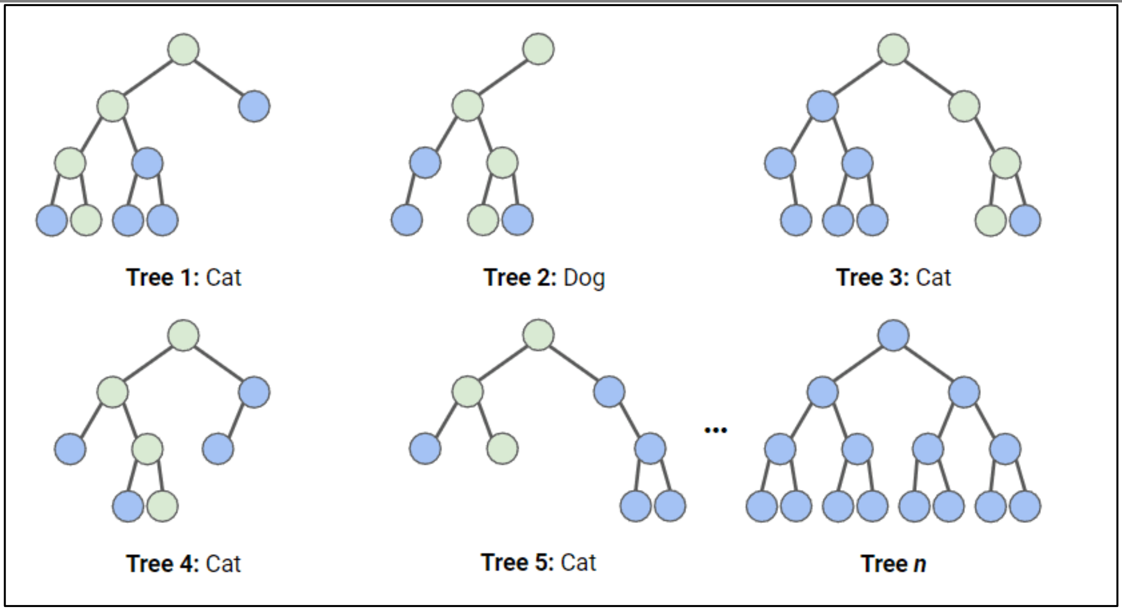
- **Software Requirement:**
  Jypiter Nootbook/Ubuntu

- **Theory:**

Imagine you have a complex problem to solve, and you gather a group of experts from different fields to provide their input. Each expert provides their opinion based on their expertise and experience. Then, the experts would vote to arrive at a final decision.

In a random forest classification, multiple decision trees are created using different random subsets of the data and features. Each decision tree is like an expert, providing its opinion on how to classify the data. Predictions are made by calculating the prediction for each decision tree, then taking the most popular result. (For regression, predictions use an averaging technique instead.)

In the diagram below, we have a random forest with n decision trees, and we've shown the first 5, along with their predictions (either "Dog" or "Cat"). Each tree is exposed to a different number of features and a different sample of the original dataset, and as such, every tree can be different. Each tree makes a prediction. Looking at the first 5 trees, we can see that 4/5 predicted the sample was a Cat. The green circles indicate a hypothetical path the tree took to reach its decision. The random forest would count the number of predictions from decision trees for Cat and for Dog, and choose the most popular prediction.



Implementation:

```
import pandas as pd
 from sklearn.datasets import load_digits
 digits = load_digits()

dir(digits)

['DESCR', 'data', 'feature_names', 'frame', 'images', 'target', 'target_names']

%matplotlib inline
 import matplotlib.pyplot as plt

plt.gray()
 for i in range(4):
     plt.matshow(digits.images[i])

<Figure size 640x480 with 0 Axes>

df = pd.DataFrame(digits.data)
 df.head()

        0    1    2     3     4     5    6    7    8    9  ...   54   55   56  \
 0  0.0  0.0  5.0  13.0   9.0   1.0  0.0  0.0  0.0  0.0  ...  0.0  0.0  0.0
 1  0.0  0.0  0.0  12.0  13.0   5.0  0.0  0.0  0.0  0.0  ...  0.0  0.0  0.0
 2  0.0  0.0  0.0   4.0  15.0  12.0  0.0  0.0  0.0  0.0  ...  5.0  0.0  0.0
 3  0.0  0.0  7.0  15.0  13.0   1.0  0.0  0.0  0.0  8.0  ...  9.0  0.0  0.0
 4  0.0  0.0  0.0   1.0  11.0   0.0  0.0  0.0  0.0  0.0  ...  0.0  0.0  0.0
```

```
     57   58    59    60    61   62   63
0  0.0  6.0  13.0  10.0   0.0  0.0  0.0
1  0.0  0.0  11.0  16.0  10.0  0.0  0.0
2  0.0  0.0   3.0  11.0  16.0  9.0  0.0
3  0.0  7.0  13.0  13.0   9.0  0.0  0.0
4  0.0  0.0   2.0  16.0   4.0  0.0  0.0

[5 rows x 64 columns]
```

```
df['target'] = digits.target

df[0:12]
```

```
     0    1     2     3     4     5     6    7    8    9  ...   55   56   57  \
0   0.0  0.0   5.0  13.0   9.0   1.0   0.0  0.0  0.0  0.0  ...  0.0  0.0  0.0
1   0.0  0.0   0.0  12.0  13.0   5.0   0.0  0.0  0.0  0.0  ...  0.0  0.0  0.0
2   0.0  0.0   0.0   4.0  15.0  12.0   0.0  0.0  0.0  0.0  ...  0.0  0.0  0.0
3   0.0  0.0   7.0  15.0  13.0   1.0   0.0  0.0  0.0  8.0  ...  0.0  0.0  0.0
4   0.0  0.0   0.0   1.0  11.0   0.0   0.0  0.0  0.0  0.0  ...  0.0  0.0  0.0
5   0.0  0.0  12.0  10.0   0.0   0.0   0.0  0.0  0.0  0.0  ...  0.0  0.0  0.0
6   0.0  0.0   0.0  12.0  13.0   0.0   0.0  0.0  0.0  0.0  ...  0.0  0.0  0.0
7   0.0  0.0   7.0   8.0  13.0  16.0  15.0  1.0  0.0  0.0  ...  0.0  0.0  0.0
8   0.0  0.0   9.0  14.0   8.0   1.0   0.0  0.0  0.0  0.0  ...  0.0  0.0  0.0
9   0.0  0.0  11.0  12.0   0.0   0.0   0.0  0.0  0.0  2.0  ...  0.0  0.0  0.0
10  0.0  0.0   1.0   9.0  15.0  11.0   0.0  0.0  0.0  0.0  ...  0.0  0.0  0.0
11  0.0  0.0   0.0   0.0  14.0  13.0   1.0  0.0  0.0  0.0  ...  0.0  0.0  0.0

      58    59    60    61   62   63  target
0    6.0  13.0  10.0   0.0  0.0  0.0       0
1    0.0  11.0  16.0  10.0  0.0  0.0       1
2    0.0   3.0  11.0  16.0  9.0  0.0       2
3    7.0  13.0  13.0   9.0  0.0  0.0       3
4    0.0   2.0  16.0   4.0  0.0  0.0       4
5    9.0  16.0  16.0  10.0  0.0  0.0       5
6    1.0   9.0  15.0  11.0  3.0  0.0       6
7   13.0   5.0   0.0   0.0  0.0  0.0       7
8   11.0  16.0  15.0  11.0  1.0  0.0       8
9    9.0  12.0  13.0   3.0  0.0  0.0       9
10   1.0  10.0  13.0   3.0  0.0  0.0       0
11   0.0   1.0  13.0  16.0  1.0  0.0       1

[12 rows x 65 columns]
```

Train and the model and prediction

```
X = df.drop('target',axis='columns')
y = df.target
```

```
from sklearn.model_selection import train_test_split
 X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2)
```

```
from sklearn.ensemble import RandomForestClassifier
 model = RandomForestClassifier(n_estimators=20)
 model.fit(X_train, y_train)
```

RandomForestClassifier(n_estimators=20)

```
model.score(X_test, y_test)
```

0.9805555555555555

```
y_predicted = model.predict(X_test)
```

Confusion Matrix

```
from sklearn.metrics import confusion_matrix
 cm = confusion_matrix(y_test, y_predicted)
 cm
```

```
array([[32,  0,  0,  0,  0,  0,  0,  0,  0,  0],
       [ 0, 30,  0,  0,  0,  0,  0,  0,  0,  0],
       [ 0,  0, 32,  0,  0,  0,  0,  0,  0,  0],
       [ 0,  0,  0, 37,  0,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0, 35,  0,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0, 41,  1,  0,  0,  1],
       [ 0,  0,  0,  0,  1,  0, 35,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  0,  0, 52,  0,  2],
       [ 1,  0,  0,  0,  0,  0,  0,  0, 32,  0],
       [ 0,  0,  0,  0,  1,  0,  0,  0,  0, 27]])
```

```
%matplotlib inline
 import matplotlib.pyplot as plt
 import seaborn as sn
 plt.figure(figsize=(10,7))
 sn.heatmap(cm, annot=True)
 plt.xlabel('Predicted')
 plt.ylabel('Truth')
```

Text(95.72222222222221, 0.5, 'Truth')

Lab Assignment No.	6C
Title	Build a Tic-Tac-Toe game using reinforcement learning in Python by using following tasks a. Setting up the environment b. Defining the Tic-Tac-Toe game c. Building the reinforcement learning model d. Training the model e. Testing the model
Roll No.	
Class	BE
Date of Completion	
Subject	Computer Laboratory-I
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 6 C

- **Aim**: Build a Tic-Tac-Toe game using reinforcement learning in Python by using following tasks
  a. Setting up the environment
  b. Defining the Tic-Tac-Toe game
  c. Building the reinforcement learning model
  d. Training the model
  e. Testing the model

- **Hardware Requirement:**

▪ 6 GB free disk space.
▪ 2 GB RAM.
▪ 2 GB of RAM, plus additional RAM for virtual machines.
▪ 6 GB disk space for the host, plus the required disk space for the virtual machine(s).
▪ Virtualization is available with the KVM hypervisor
▪ Intel 64 and AMD64 architectures

- **Software Requirement:**
  Jypiter Nootbook/Ubuntu

- **Theory:**

In reinforcement learning, developers devise a method of rewarding desired behaviors and punishing negative behaviors. This method assigns positive values to the desired actions to encourage the agent and negative values to undesired behaviors. This programs the agent to seek long-term and maximum overall reward to achieve an optimal solution.

These long-term goals help prevent the agent from stalling on lesser goals. With time, the agent learns to avoid the negative and seek the positive. This learning method has been adopted in artificial intelligence (AI) as a way of directing unsupervised machine learning through rewards and penalties.

Common reinforcement learning algorithms

Rather than referring to a specific algorithm, the field of reinforcement learning is made up of several algorithms that take somewhat different approaches. The differences are mainly due to their strategies for exploring their environments.

- State-action-reward-state-action (SARSA). This reinforcement learning algorithm starts by giving the agent what's known as a *policy*. The policy is essentially a probability that tells it the odds of certain actions resulting in rewards, or beneficial states.

- Q-learning. This approach to reinforcement learning takes the opposite approach. The agent receives no policy, meaning its exploration of its environment is more self-directed.
- Deep Q-Networks. These algorithms utilize neural networks in addition to reinforcement learning techniques. They utilize the self-directed environment exploration of reinforcement learning. Future actions are based on a random sample of past beneficial actions learned by the neural network.

Implementation:

```
import numpy as np

class TicTacToeEnvironment:
    def __init__(self):
    self.state = [0] * 9
    self.is_terminal = False

    def reset(self):
    self.state = [0] * 9
    self.is_terminal = False

    def get_available_moves(self):
    return [i for i, mark in enumerate(self.state) if mark == 0]

    def make_move(self, move, player_mark):
    self.state[move] = player_mark

    def check_win(self, player_mark):
  winning_states = [
    [0, 1, 2], [3, 4, 5], [6, 7, 8],  # rows
    [0, 3, 6], [1, 4, 7], [2, 5, 8],  # columns
    [0, 4, 8], [2, 4, 6]  # diagonals
    ]
    for state_indices in winning_states:
    if all(self.state[i] == player_mark for i in state_indices):
        self.is_terminal = True
        return True
    return False
```

```
        def is_draw(self):
        return 0 not in self.state

class QLearningAgent:
        def __init__(self, learning_rate=0.9, discount_factor=0.9, exploration_rate=0.3):
        self.learning_rate = learning_rate
        self.discount_factor = discount_factor
        self.exploration_rate = exploration_rate
        self.q_table = np.zeros((3**9, 9))

        def get_state_index(self, state):
      state_index = 0
        for i, mark in enumerate(state):
         state_index += (3 ** i) * (mark + 1)
        return state_index

        def choose_action(self, state, available_moves):
      state_index = self.get_state_index(state)
        if np.random.random() < self.exploration_rate:
        return np.random.choice(available_moves)
        else:
        return np.argmax(self.q_table[state_index, available_moves])

        def update_q_table(self, state, action, next_state, reward):
      state_index = self.get_state_index(state)
      next_state_index = self.get_state_index(next_state) if next_state is not None else None
      max_q_value = np.max(self.q_table[next_state_index]) if next_state is not None else 0
        self.q_table[state_index, action] = (1 - self.learning_rate) * self.q_table[state_index, action] + \
                                    self.learning_rate * (reward + self.discount_factor * max_q_value)

def evaluate_agents(agent1, agent2, num_episodes=1000):
    environment = TicTacToeEnvironment()
    agent1_wins = 0
    agent2_wins = 0
        draws = 0

        for _ in range(num_episodes):
      environment.reset()
      current_agent = agent1
        while not environment.is_terminal:
         available_moves = environment.get_available_moves()
```

```
            current_state = environment.state.copy()
            action = current_agent.choose_action(current_state, available_moves)
            environment.make_move(action, 1 if current_agent == agent1 else -1)

            if environment.check_win(1 if current_agent == agent1 else -1):
                current_agent.update_q_table(current_state, action, None, 10)
                if current_agent == agent1:
                    agent1_wins += 1
                else:
                    agent2_wins += 1
                break
            elif environment.is_draw():
                current_agent.update_q_table(current_state, action, None, 0)
                draws += 1
                break

            next_state = environment.state.copy()
            reward = 0
            if environment.check_win(1 if current_agent == agent1 else -1):
                reward = -10
            current_agent.update_q_table(current_state, action, next_state, reward)

            current_agent = agent2 if current_agent == agent1 else agent1

    return agent1_wins, agent2_wins, draws

# Create agents
agent1 = QLearningAgent()
agent2 = QLearningAgent()

# Evaluate agents
agent1_wins, agent2_wins, draws = evaluate_agents(agent1, agent2)

# Print results
print(f"Agent 1 wins: {agent1_wins}")
print(f"Agent 2 wins: {agent2_wins}")
print(f"Draws: {draws}")
```

```
Agent 1 wins: 458
Agent 2 wins: 470
Draws: 72
```

TicTacToeEnvironment:

This class represents the Tic-Tac-Toe game environment. It maintains the current state of the game, checks for a win or draw, and provides methods to reset the game and make moves.

The __init__ method initializes the game state and sets the terminal flag to False.

The reset method resets the game state and the terminal flag.

The get_available_moves method returns a list of indices representing the available moves in the current game state.

The make_move method updates the game state by placing a player's mark at the specified move index.

The check_win method checks if a player has won the game by examining the current state.

The is_draw method checks if the game has ended in a draw.

QLearningAgent:

This class represents the Q-learning agent. It learns to play Tic-Tac-Toe by updating a Q-table based on the rewards received during gameplay.

The __init__ method initializes the learning rate, discount factor, exploration rate, and the Q-table.

The get_state_index method converts the current game state into a unique index for indexing the Q-table.

The choose_action method selects the action (move) to be taken based on the current game state and the exploration-exploitation tradeoff using the epsilon-greedy policy.

The update_q_table method updates the Q-table based on the current state, action, next state, and the reward received.

evaluate_agents:

This function performs the evaluation of two Q-learning agents by playing multiple episodes of Tic-Tac-Toe games.

It takes the two agents and the number of episodes to play as input.

In each episode, the environment is reset, and the agents take turns making moves until the game is over (either a win or a draw).

The agents update their Q-tables based on the rewards received during the episode.

The function keeps track of the wins and draws for each agent and returns the counts.

Main code:

The main code creates two Q-learning agents, agent1 and agent2, using the QLearningAgent class.

The evaluate_agents function is called to evaluate the agents by playing a specified number of episodes.

The results (number of wins and draws) for each agent are printed.

The Q-learning algorithm involves the following steps:

The agents choose their moves based on the current game state and the exploration-exploitation policy.
The environment updates the game state based on the chosen moves.
The environment checks if the game has ended (win or draw).
The agents update their Q-tables based on the rewards received.
The agents continue playing until the specified number of episodes is completed.

Lab Assignment No.	7B
Title	Interacting with Web APIs Analyzing Weather Data from OpenWeatherMap API
Roll No.	
Class	BE
Date of Completion	
Subject	Computer Laboratory-I
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 7 (Group B)

- **Aim**: Interacting with Web APIs
  Problem Statement: Analyzing Weather Data from OpenWeatherMap API
  Dataset: Weather data retrieved from OpenWeatherMap API
  Description: The goal is to interact with the OpenWeatherMap API to retrieve weather data for a specific location and perform data modeling and visualization to analyze weather patterns over time.

  Tasks to Perform:

  1. Register and obtain API key from OpenWeatherMap.
  2. Interact with the OpenWeatherMap API using the API key to retrieve weather data for a specific location.
  3. Extract relevant weather attributes such as temperature, humidity, wind speed, and precipitation from the API response.
  4. Clean and preprocess the retrieved data, handling missing values or inconsistent formats.
  5. Perform data modeling to analyze weather patterns, such as calculating average temperature, maximum/minimum values, or trends over time.
  6. Visualize the weather data using appropriate plots, such as line charts, bar plots, or scatter plots, to represent temperature changes, precipitation levels, or wind speed variations.
  7. Apply data aggregation techniques to summarize weather statistics by specific time periods (e.g., daily, monthly, seasonal).
  8. Incorporate geographical information, if available, to create maps or geospatial visualizations representing weather patterns across different locations.
  9. Explore and visualize relationships between weather attributes, such as temperature and humidity, using correlation plots or heatmaps.

- **Hardware Requirement:**

▪ 6 GB free disk space.
▪ 2 GB RAM.
▪ 2 GB of RAM, plus additional RAM for virtual machines.
▪ 6 GB disk space for the host, plus the required disk space for the virtual machine(s).
▪ Virtualization is available with the KVM hypervisor
▪ Intel 64 and AMD64 architectures

- **Software Requirement:**
  Jypiter Nootbook/Ubuntu

Implementation:

```
import requests
```

```
import pandas as pd
import datetime

# Set your OpenWeatherMap API key
api_key = 'fb365aa6104829b44455572365ff3b4e'
```

Get the lat(itude) and lon(gitude) from here.

```
# Set the location for which you want to retrieve weather data
lat = 18.184135
lon = 74.610764

#https://openweathermap.org/api/one-call-3#how    How to use api call
# Construct the API URL
api_url = f"http://api.openweathermap.org/data/2.5/forecast?lat={lat}&lon={lon}&appid={api_key}"


# Send a GET request to the API
response = requests.get(api_url)
weather_data = response.json()        #pass response to weather_data object(dictionary)
```

```
weather_data.keys()
```

```
dict_keys(['cod', 'message', 'cnt', 'list', 'city'])
```

```
weather_data['list'][0]
```


```
{'dt': 1690189200,
 'main': {'temp': 298.21,
  'feels_like': 298.81,
  'temp_min': 298.1,
  'temp_max': 298.21,
  'pressure': 1006,
  'sea_level': 1006,
  'grnd_level': 942,
  'humidity': 78,
  'temp_kf': 0.11},
 'weather': [{'id': 804,
   'main': 'Clouds',
   'description': 'overcast clouds',
   'icon': '04d'}],
 'clouds': {'all': 100},
 'wind': {'speed': 6.85, 'deg': 258, 'gust': 12.9},
 'visibility': 10000,
 'pop': 0.59,
 'sys': {'pod': 'd'},
 'dt_txt': '2023-07-24 09:00:00'}
```

```
len(weather_data['list'])

40

weather_data['list'][0]['weather'][0]['description']

{"type":"string"}

#getting the data from dictionary and taking into one variable
 # Extract relevant weather attributes using list comprehension
 temperatures = [item['main']['temp'] for item in weather_data['list']]          #it will extract all values (40)
and putting into one variable
 timestamps = [pd.to_datetime(item['dt'], unit='s') for item in weather_data['list']]
 temperature = [item['main']['temp'] for item in weather_data['list']]
 humidity = [item['main']['humidity'] for item in weather_data['list']]
 wind_speed = [item['wind']['speed'] for item in weather_data['list']]
 weather_description = [item['weather'][0]['description'] for item in weather_data['list']]

 # Create a pandas DataFrame with the extracted weather data
 weather_df = pd.DataFrame({
         'Timestamp': timestamps,
         'Temperature': temperatures,
         'humidity': humidity,
         'wind_speed': wind_speed,
         'weather_description': weather_description,
 })

 # Set the Timestamp column as the DataFrame's index
 weather_df.set_index('Timestamp', inplace=True)

max_temp = weather_df['Temperature'].max()

max_temp

298.9

min_temp = weather_df['Temperature'].min()

min_temp

294.92

# Clean and preprocess the data

 # Handling missing values
 weather_df.fillna(0, inplace=True)  # Replace missing values with 0 or appropriate value

 # Handling inconsistent format (if applicable)
 weather_df['Temperature'] = weather_df['Temperature'].apply(lambda x: x - 273.15 if isinstance(x, float)
```

```
else x)   # Convert temperature from Kelvin to Celsius

# Print the cleaned and preprocessed data
print(weather_df)

                     Temperature  humidity  wind_speed weather_description
Timestamp
2023-07-24 09:00:00        25.06        78        6.85     overcast clouds
2023-07-24 12:00:00        24.52        81        6.92          light rain
2023-07-24 15:00:00        23.73        84        7.18          light rain
2023-07-24 18:00:00        23.69        83        6.44          light rain
2023-07-24 21:00:00        23.06        85        5.54          light rain
2023-07-25 00:00:00        22.28        92        4.57       moderate rain
2023-07-25 03:00:00        22.46        92        3.95       moderate rain
2023-07-25 06:00:00        22.98        90        6.10       moderate rain
2023-07-25 09:00:00        24.55        79        6.46          light rain
2023-07-25 12:00:00        23.53        84        5.00          light rain
2023-07-25 15:00:00        22.87        88        5.00     overcast clouds
2023-07-25 18:00:00        22.77        89        3.93     overcast clouds
2023-07-25 21:00:00        22.56        84        5.47     overcast clouds
2023-07-26 00:00:00        22.35        87        3.97     overcast clouds
2023-07-26 03:00:00        23.05        85        3.47          light rain
2023-07-26 06:00:00        23.34        85        3.84          light rain
2023-07-26 09:00:00        23.08        89        4.16          light rain
2023-07-26 12:00:00        24.09        83        5.52          light rain
2023-07-26 15:00:00        23.10        87        5.59          light rain
2023-07-26 18:00:00        22.43        91        5.42          light rain
2023-07-26 21:00:00        22.29        92        5.17          light rain
2023-07-27 00:00:00        22.53        90        5.31          light rain
2023-07-27 03:00:00        22.78        88        4.30          light rain
2023-07-27 06:00:00        22.83        90        5.19       moderate rain
2023-07-27 09:00:00        22.57        91        6.65       moderate rain
2023-07-27 12:00:00        22.28        91        5.27       moderate rain
2023-07-27 15:00:00        22.03        93        5.12          light rain
2023-07-27 18:00:00        21.82        92        4.65          light rain
2023-07-27 21:00:00        21.77        90        5.27          light rain
2023-07-28 00:00:00        22.01        88        5.41          light rain
2023-07-28 03:00:00        23.30        81        6.19     overcast clouds
2023-07-28 06:00:00        25.19        72        7.19          light rain
2023-07-28 09:00:00        24.95        76        7.22          light rain
2023-07-28 12:00:00        24.72        75        6.93     overcast clouds
2023-07-28 15:00:00        23.41        83        5.12     overcast clouds
2023-07-28 18:00:00        22.76        86        4.56     overcast clouds
2023-07-28 21:00:00        22.63        87        4.15     overcast clouds
2023-07-29 00:00:00        22.74        84        4.35     overcast clouds
2023-07-29 03:00:00        23.87        77        6.16     overcast clouds
2023-07-29 06:00:00        25.75        66        7.23     overcast clouds
```

```
import matplotlib.pyplot as plt

 daily_mean_temp = weather_df['Temperature'].resample('D').mean()
 daily_mean_humidity = weather_df['humidity'].resample('D').mean()
 daily_mean_wind_speed = weather_df['wind_speed'].resample('D').mean()

 # Plot the mean daily temperature over time (Line plot)
 plt.figure(figsize=(10, 6))
 daily_mean_temp.plot(color='red', linestyle='-', marker='o')
 plt.title('Mean Daily Temperature')
 plt.xlabel('Date')
 plt.ylabel('Temperature (°C)')
 plt.grid(True)
 plt.show()

 # Plot the mean daily humidity over time (Bar plot)
 plt.figure(figsize=(10, 6))
 daily_mean_humidity.plot(kind='bar', color='blue')
 plt.title('Mean Daily Humidity')
 plt.xlabel('Date')
 plt.ylabel('Humidity (%)')
 plt.grid(True)
 plt.show()

 # Plot the relationship between temperature and wind speed (Scatter plot)
 plt.figure(figsize=(10, 6))
 plt.scatter(weather_df['Temperature'], weather_df['wind_speed'], color='green')
 plt.title('Temperature vs. Wind Speed')
 plt.xlabel('Temperature (°C)')
 plt.ylabel('Wind Speed (m/s)')
 plt.grid(True)
 plt.show()

###Heatmap

import seaborn as sns

 heatmap_data = weather_df[['Temperature', 'humidity']]
 sns.heatmap(heatmap_data, annot=True, cmap='coolwarm')
 plt.title('Temperature vs Humidity Heatmap')
 plt.show()

 # Create a scatter plot to visualize the relationship between temperature and humidity
 plt.scatter(weather_df['Temperature'], weather_df['humidity'])
 plt.xlabel('Temperature (°C)')
 plt.ylabel('Humidity (%)')
```

```
plt.title('Temperature vs Humidity Scatter Plot')
plt.show()
```

###Geospatial Map

```
import requests
import pandas as pd
import geopandas as gpd
import folium

# Set your OpenWeatherMap API key
api_key = 'fb365aa6104829b44455572365ff3b4e'

# Specify the locations for which you want to retrieve weather data
locations = ['London', 'Paris', 'New York']

weather_df = pd.DataFrame()

# Retrieve weather data for each location
for location in locations:
    # Construct the API URL
    api_url = f'http://api.openweathermap.org/data/2.5/weather?q={location}&appid={api_key}'

    # Send a GET request to the API
    response = requests.get(api_url)
    weather_data = response.json()
    # Extract relevant weather attributes
    temperature = weather_data['main']['temp']
    humidity = weather_data['main']['humidity']
    wind_speed = weather_data['wind']['speed']
    latitude = weather_data['coord']['lat']
    longitude = weather_data['coord']['lon']
    # Create a DataFrame for the location's weather data
    location_df = pd.DataFrame({
    'Location': [location],
    'Temperature': [temperature],
    'Humidity': [humidity],
    'Wind Speed': [wind_speed],
    'Latitude': [latitude],
    'Longitude': [longitude]
    })

    # Append the location's weather data to the main DataFrame
    weather_df = weather_df.append(location_df, ignore_index=True)
```

```
<ipython-input-17-68826faaad0a>:41: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  weather_df = weather_df.append(location_df, ignore_index=True)
```

```
<ipython-input-17-68826faaad0a>:41: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  weather_df = weather_df.append(location_df, ignore_index=True)
<ipython-input-17-68826faaad0a>:41: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  weather_df = weather_df.append(location_df, ignore_index=True)
```

```
weather_df
```

	Location	Temperature	Humidity	Wind Speed	Latitude	Longitude
0	London	289.02	88	3.60	51.5085	-0.1257
1	Paris	290.96	83	6.17	48.8534	2.3488
2	New York	296.82	61	4.47	40.7143	-74.0060

```
# Load a world map shapefile using geopandas
world_map = gpd.read_file(gpd.datasets.get_path('naturalearth_cities'))

# Rename the column used for merging in the world map DataFrame
world_map.rename(columns={'name': 'Location'}, inplace=True)

# Merge the weather data with the world map based on location
weather_map = world_map.merge(weather_df, on='Location')

# Create a folium map centered around the mean latitude and longitude of all locations
map_center = [weather_df['Latitude'].mean(), weather_df['Longitude'].mean()]
weather_map_folium = folium.Map(location=map_center, zoom_start=2)

# Add weather markers to the folium map
for index, row in weather_map.iterrows():
        location = [row['Latitude'], row['Longitude']]
        temperature = row['Temperature']
        marker_text = f'Temperature: {temperature} K'
    folium.Marker(location, popup=marker_text, icon=folium.Icon(icon='cloud', color='red')).add_to(weather_map_folium)
# display the folium map
weather_map_folium
```

```
<ipython-input-19-c9bd718791be>:2: FutureWarning: The geopandas.dataset module is deprecated and will be removed in GeoPandas 1.0. You can get the original 'naturalearth_cities' data from https://www.naturalearthdata.com/downloads/110m-cultural-vectors/.
  world_map = gpd.read_file(gpd.datasets.get_path('naturalearth_cities'))
```

```
<folium.folium.Map at 0x7f242a56f430>
```

```
type(weather_map_folium)
```

```
folium.folium.Map
```

Lab Assignment No.	8B
Title	Analyzing Customer Churn in a Telecommunications Company
Roll No.	
Class	BE
Date of Completion	
Subject	Computer Laboratory-I
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 8 (Group B)

- **Aim**: Data Cleaning and Preparation
  Problem Statement: Analyzing Customer Churn in a Telecommunications Company
  Dataset: "Telecom_Customer_Churn.csv"
  Description: The dataset contains information about customers of a telecommunications company and whether they have churned (i.e., discontinued their services). The dataset includes various attributes of the customers, such as their demographics, usage patterns, and account information. The goal is to perform data cleaning and preparation to gain insights into the factors that contribute to customer churn.

- **Tasks to Perform:**
  1. Import the "Telecom_Customer_Churn.csv" dataset.
  2. Explore the dataset to understand its structure and content.
  3. Handle missing values in the dataset, deciding on an appropriate strategy.
  4. Remove any duplicate records from the dataset.
  5. Check for inconsistent data, such as inconsistent formatting or spelling variations, and standardize it.
  6. Convert columns to the correct data types as needed.
  7. Identify and handle outliers in the data.

- **Hardware Requirement:**

- 6 GB free disk space.
- 2 GB RAM.
- 2 GB of RAM, plus additional RAM for virtual machines.
- 6 GB disk space for the host, plus the required disk space for the virtual machine(s).
- Virtualization is available with the KVM hypervisor
- Intel 64 and AMD64 architectures

- **Software Requirement:**
  Jypiter Nootbook/Ubuntu

Implementation:

Import necessary libraries

```
import pandas as pd              #data manipulation
 import numpy as np              #numerical computations
 from sklearn.model_selection import train_test_split          # scikit-learn for machine learning models
split the dataset into training and testing sets for model evaluation
 from sklearn import metrics                        #evaluating the performance of machine learning models
```

Load the dataset

```
data = pd.read_csv("Telecom_Customer_Churn.csv")
 print(data.index)
```

RangeIndex(start=0, stop=7043, step=1)

Explore the dataset

```
print(data)
```

```
        customerID  gender  SeniorCitizen Partner Dependents  tenure  \
0    7590-VHVEG  Female             0        Yes       No   1
1    5575-GNVDE    Male             0        No        No   34
2    3668-QPYBK     Male            0        No        No   2
3    7795-CFOCW     Male            0        No        No   45
4    9237-HQITU  Female             0        No        No   2
...        ...       ...       ...        ...       ...       ...
7038  6840-RESVB   Male             0        Yes       Yes  24
7039  2234-XADUH  Female            0        Yes       Yes  72
7040  4801-JZAZL  Female            0    Yes        Yes     11
7041  8361-LTMKD  Male              1        Yes       No   4
7042  3186-AJIEK   Male             0        No        No   66

     PhoneService       MultipleLines InternetService OnlineSecurity  ...  \
0             No  No phone service             DSL             No  ...
1            Yes             No            DSL            Yes  ...
2            Yes             No            DSL            Yes  ...
3             No  No phone service             DSL             Yes  ...
4            Yes             No      Fiber optic            No  ...
...          ...             ...            ...        ...  ...
7038         Yes                  Yes            DSL              Yes  ...
7039         Yes                  Yes     Fiber optic             No  ...
7040          No  No phone service             DSL             Yes  ...
7041         Yes                  Yes     Fiber optic             No  ...
7042         Yes              No  Fiber optic             Yes  ...

     DeviceProtection TechSupport StreamingTV StreamingMovies          Contract  \
0                No         No      No              No  Month-to-month
1               Yes         No        No            No      One year
2                No         No      No              No  Month-to-month
3               Yes        Yes             No             No      One year
4                No         No      No          No  Month-to-month
...             ...         ...     ...             ...            ...
7038              Yes       Yes     Yes             Yes     One year
7039              Yes       No      Yes             Yes       One year
7040               No       No      No              No  Month-to-month
7041               No       No      No              No  Month-to-month
```

```
7042            Yes       Yes      Yes              Yes     Two year

     PaperlessBilling            PaymentMethod MonthlyCharges  TotalCharges  \
0               Yes        Electronic check        29.85             29.85
1                No                 Mailed check            56.95            1889.5
2                  Yes              Mailed check            53.85            108.15
3                No  Bank transfer (automatic)          42.30            1840.75
4               Yes        Electronic check        70.70             151.65
...             ...                   ...           ...        ...
7038            Yes                 Mailed check            84.80            1990.5
7039            Yes       Credit card (automatic)          103.20           7362.9
7040            Yes                 Electronic check        29.60            346.45
7041            Yes                 Mailed check            74.40            306.6
7042            Yes  Bank transfer (automatic)          105.65           6844.5

        Churn
0       No
1       No
2         Yes
3       No
4       Yes
...     ...
7038   No
7039   No
7040   No
7041   Yes
7042   No

[7043 rows x 21 columns]
```

```
print(data.columns)
```

```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
         'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
      'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
      'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
      'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
     dtype='object')
```

```
data.shape
```

```
(7043, 21)
```

```
print(data.head())
```

```
   customerID  gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  7590-VHVEG  Female              0        Yes        No   1          No
1  5575-GNVDE       Male              0        No        No    34        Yes
2  3668-QPYBK       Male              0        No        No    2          Yes
```

```
3  7795-CFOCW      Male          0        No       No    45      No
4  9237-HQITU  Female            0        No       No    2       Yes

     MultipleLines InternetService OnlineSecurity  ... DeviceProtection  \
0  No phone service             DSL             No  ...             No
1               No             DSL            Yes  ...            Yes
2               No             DSL            Yes  ...             No
3  No phone service             DSL            Yes  ...            Yes
4               No     Fiber optic             No  ...             No

  TechSupport StreamingTV StreamingMovies        Contract PaperlessBilling  \
0          No          No              No  Month-to-month              Yes
1          No          No              No        One year               No
2          No          No              No  Month-to-month              Yes
3         Yes          No              No        One year               No
4          No          No              No  Month-to-month              Yes

               PaymentMethod MonthlyCharges  TotalCharges Churn
0           Electronic check          29.85         29.85    No
1               Mailed check          56.95        1889.5    No
2               Mailed check          53.85        108.15   Yes
3  Bank transfer (automatic)          42.30       1840.75    No
4           Electronic check          70.70        151.65   Yes

[5 rows x 21 columns]
```

print(data.tail())

```
      customerID  gender  SeniorCitizen Partner Dependents  tenure  \
7038  6840-RESVB    Male              0     Yes        Yes      24
7039  2234-XADUH  Female              0     Yes        Yes      72
7040  4801-JZAZL  Female              0     Yes        Yes      11
7041  8361-LTMKD    Male              1     Yes         No       4
7042  3186-AJIEK    Male              0      No         No      66

     PhoneService     MultipleLines InternetService OnlineSecurity  ...  \
7038          Yes               Yes             DSL            Yes  ...
7039          Yes               Yes     Fiber optic             No  ...
7040           No  No phone service             DSL            Yes  ...
7041          Yes               Yes     Fiber optic             No  ...
7042          Yes                No     Fiber optic            Yes  ...

     DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
7038              Yes         Yes         Yes             Yes        One year
7039              Yes          No         Yes             Yes        One year
7040               No          No          No              No  Month-to-month
7041               No          No          No              No  Month-to-month
7042              Yes         Yes         Yes             Yes        Two year
```

```
     PaperlessBilling              PaymentMethod MonthlyCharges  TotalCharges  \
7038              Yes                Mailed check          84.80        1990.5
7039              Yes     Credit card (automatic)         103.20        7362.9
7040              Yes            Electronic check          29.60        346.45
7041              Yes                Mailed check          74.40         306.6
7042              Yes   Bank transfer (automatic)         105.65        6844.5

     Churn
7038    No
7039    No
7040    No
7041   Yes
7042    No

[5 rows x 21 columns]
```

```
# to know unique values
data.nunique()
```

```
customerID          7043
gender                 2
SeniorCitizen          2
Partner                2
Dependents             2
tenure                73
PhoneService           2
MultipleLines          3
InternetService        3
OnlineSecurity         3
OnlineBackup           3
DeviceProtection       3
TechSupport            3
StreamingTV            3
StreamingMovies        3
Contract               3
PaperlessBilling       2
PaymentMethod          4
MonthlyCharges      1585
TotalCharges        6531
Churn                  2
dtype: int64
```

Handle Missing Values

```
# data.isna().sum() is used to count the number of missing values (NaN values) in each column of a pandas DataFrame called data.
data.isna().sum()
```

```
customerID          0
 gender           0
 SeniorCitizen      0
 Partner          0
 Dependents        0
 tenure           0
 PhoneService       0
 MultipleLines      0
 InternetService    0
 OnlineSecurity     0
 OnlineBackup       0
 DeviceProtection   0
 TechSupport        0
 StreamingTV        0
 StreamingMovies    0
 Contract          0
 PaperlessBilling   0
 PaymentMethod      0
 MonthlyCharges     0
 TotalCharges       0
 Churn            0
 dtype: int64
```

isna() and isnull() are essentially the same method in Pandas, and they both return a boolean mask of the same shape as the input object, indicating where missing values (NaN or None) are present.

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

```
customerID          0
 gender           0
 SeniorCitizen      0
 Partner          0
 Dependents        0
 tenure           0
 PhoneService       0
 MultipleLines      0
 InternetService    0
 OnlineSecurity     0
 OnlineBackup       0
 DeviceProtection   0
 TechSupport        0
 StreamingTV        0
 StreamingMovies    0
 Contract          0
 PaperlessBilling   0
 PaymentMethod      0
 MonthlyCharges     0
 TotalCharges       0
 Churn            0
```

dtype: int64

Remove Duplicate Records

```
# Check the number of rows before removing duplicates
print("Number of rows before removing duplicates:", len(data))
```

Number of rows before removing duplicates: 7043

```
# Remove duplicate records
data_cleaned = data.drop_duplicates()

# Check the number of rows after removing duplicates
print("Number of rows after removing duplicates:", len(data_cleaned))
```

Number of rows after removing duplicates: 7043

```
data.describe()
```

	SeniorCitizen	tenure	MonthlyCharges
count	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692
std	0.368612	24.559481	30.090047
min	0.000000	0.000000	18.250000
25%	0.000000	9.000000	35.500000
50%	0.000000	29.000000	70.350000
75%	0.000000	55.000000	89.850000
max	1.000000	72.000000	118.750000

```
#Measure of frequency destribution
unique, counts = np.unique(data['tenure'], return_counts=True)
print(unique, counts)
```

```
[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71
 72] [ 11 613 238 200 176 133 110 131 123 119 116  99 117 109  76  99  80  87
  97  73  71  63  90  85  94  79  79  72  57  72  72  65  69  64  65  88
  50  65  59  56  64  70  65  65  51  61  74  68  64  66  68  68  80  70
  68  64  80  65  67  60  76  76  70  72  80  76  89  98 100  95 119 170
 362]
```

```
#Measure of frequency destribution
unique, counts = np.unique(data['MonthlyCharges'], return_counts=True)
print(unique, counts)
```

```
[ 18.25  18.4   18.55 ... 118.6  118.65 118.75] [1 1 1 ... 2 1 1]
```

```
#Measure of frequency destribution
```

```
unique, counts = np.unique(data['TotalCharges'], return_counts=True)
print(unique, counts)
```

[' ' '100.2' '100.25' ... '999.45' '999.8' '999.9'] [11 1 1 ... 1 1 1]

```
# sns.pairplot(data) creates a grid of pairwise plots of the variables in a dataset, which can help you quickly visualize the relationships between different pairs of variables.
import seaborn as sns           #Seaborn library for data visualization
sns.pairplot(data)
```

<seaborn.axisgrid.PairGrid at 0x7fb9cc97a680>

Check for Outliers

```
#checking boxplot for Fare column
import matplotlib.pyplot as plt         #pyplot module from the Matplotlib library
plt.boxplot(data['tenure'])
plt.show()
```

```
plt.boxplot(data['MonthlyCharges'])
plt.show()
```

Split the Data

```
X = data.drop("Churn", axis=1)
y = data["Churn"]
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

X_train.shape

(5634, 20)

y_train.shape

(5634,)

X_test.shape

(1409, 20)

y_test.shape

(1409,)

Export the cleaned data

```
# Export the cleaned dataset to a CSV file
data.to_csv("Cleaned_Telecom_Customer_Churn.csv", index=False)
```

Lab Assignment No.	9B
Title	Data Wrangling on Real Estate Market
Roll No.	
Class	BE
Date of Completion	
Subject	Computer Laboratory-I
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 9 (Group B)

- **Aim**: Data Wrangling

  Problem Statement: Data Wrangling on Real Estate Market

  Dataset: "RealEstate_Prices.csv"

  Description: The dataset contains information about housing prices in a specific real estate market. It includes various attributes such as property characteristics, location, sale prices, and other relevant features. The goal is to perform data wrangling to gain insights into the factors influencing housing prices and prepare the dataset for further analysis or modeling.

Tasks to Perform:

1. Import the "RealEstate_Prices.csv" dataset. Clean column names by removing spaces, special characters, or renaming them for clarity.
2. Handle missing values in the dataset, deciding on an appropriate strategy (e.g., imputation or removal).
3. Perform data merging if additional datasets with relevant information are available (e.g., neighborhood demographics or nearby amenities).
4. Filter and subset the data based on specific criteria, such as a particular time period, property type, or location.
5. Handle categorical variables by encoding them appropriately (e.g., one-hot encoding or label encoding) for further analysis.
6. Aggregate the data to calculate summary statistics or derived metrics such as average sale prices by neighborhood or property type.
7. Identify and handle outliers or extreme values in the data that may affect the analysis or modeling process.

- **Hardware Requirement:**

▪ 6 GB free disk space.
▪ 2 GB RAM.
▪ 2 GB of RAM, plus additional RAM for virtual machines.
▪ 6 GB disk space for the host, plus the required disk space for the virtual machine(s).
▪ Virtualization is available with the KVM hypervisor
▪ Intel 64 and AMD64 architectures

- **Software Requirement:**

  Jypiter Nootbook/Ubuntu

Implementation:

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

```
%matplotlib inline
import matplotlib
matplotlib.rcParams["figure.figsize"] = (20,10)
```

Data Wrangling is the process of gathering, collecting, and transforming Raw data into another format for better understanding, decision-making, accessing, and analysis in less time. Data Wrangling is also known as Data Munging.

```
df1 = pd.read_csv("/content/Bengaluru_House_Data.csv")
df1.head()
```

```
          area_type   availability                  location       size  \
0  Super built-up  Area         19-Dec  Electronic City Phase II      2 BHK
1            Plot  Area  Ready To Move          Chikka Tirupathi  4 Bedroom
2        Built-up  Area  Ready To Move               Uttarahalli      3 BHK
3  Super built-up  Area  Ready To Move        Lingadheeranahalli      3 BHK
4  Super built-up  Area  Ready To Move                  Kothanur      2 BHK

   society total_sqft  bath  balcony   price
0  Coomee        1056   2.0      1.0   39.07
1  Theanmp       2600   5.0      3.0  120.00
2      NaN       1440   2.0      3.0   62.00
3  Soiewre       1521   3.0      1.0   95.00
4      NaN       1200   2.0      1.0   51.00
```

```
df1.shape
```

```
(13320, 9)
```

```
df1.columns
```

```
Index(['area_type', 'availability', 'location', 'size', 'society',
       'total_sqft', 'bath', 'balcony', 'price'],
      dtype='object')
```

```
df1['area_type']

0        Super built-up  Area
 1                Plot  Area
 2            Built-up  Area
 3        Super built-up  Area
 4        Super built-up  Area
              ...
 13315          Built-up  Area
 13316 Super built-up  Area
 13317             Built-up  Area
 13318 Super built-up  Area
 13319 Super built-up  Area
 Name: area_type, Length: 13320, dtype: object

df1['area_type'].unique()

array(['Super built-up  Area', 'Plot  Area', 'Built-up  Area',
       'Carpet  Area'], dtype=object)

df1['area_type'].value_counts()

Super built-up  Area   8790
 Built-up  Area         2418
 Plot  Area             2025
 Carpet  Area           87
 Name: area_type, dtype: int64
```

Drop features that are not required to build our model

```
df2 = df1.drop(['area_type','society','balcony','availability'],axis='columns')
 df2.shape

(13320, 5)
```

```
df2.isnull().sum()

location       1
 size          16
 total_sqft    0
 bath          73
 price         0
 dtype: int64

df2.shape

(13320, 5)

df3 = df2.dropna()
 df3.isnull().sum()

location       0
 size          0
 total_sqft    0
 bath          0
 price         0
 dtype: int64

df3.shape

(13246, 5)

df3['size'].unique()

array(['2 BHK', '4 Bedroom', '3 BHK', '4 BHK', '6 Bedroom', '3 Bedroom',
       '1 BHK', '1 RK', '1 Bedroom', '8 Bedroom', '2 Bedroom',
       '7 Bedroom', '5 BHK', '7 BHK', '6 BHK', '5 Bedroom', '11 BHK',
       '9 BHK', '9 Bedroom', '27 BHK', '10 Bedroom', '11 Bedroom',
       '10 BHK', '19 BHK', '16 BHK', '43 Bedroom', '14 BHK', '8 BHK',
       '12 Bedroom', '13 BHK', '18 Bedroom'], dtype=object)
```

```
df3['bhk'] = df3['size'].apply(lambda x: int(x.split(' ')[0]))
```

```
<ipython-input-15-4c4c73fbe7f4>:1: SettingWithCopyWarning:
 A value is trying to be set on a copy of a slice from a DataFrame.
 Try using .loc[row_indexer,col_indexer] = value instead


 See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
   df3['bhk'] = df3['size'].apply(lambda x: int(x.split(' ')[0]))
```

```
df3.head()
```

	location	size	total_sqft	bath	price	bhk
0	Electronic City Phase II	2 BHK	1056	2.0	39.07	2
1	Chikka Tirupathi	4 Bedroom	2600	5.0	120.00	4
2	Uttarahalli	3 BHK	1440	2.0	62.00	3
3	Lingadheeranahalli	3 BHK	1521	3.0	95.00	3
4	Kothanur	2 BHK	1200	2.0	51.00	2

```
df3.bhk.unique()
```

```
array([ 2,  4,  3,  6,  1,  8,  7,  5, 11,  9, 27, 10, 19, 16, 43, 14, 12,
       13, 18])
```

```
df3[df3.bhk>20]
```

	location	size	total_sqft	bath	price	bhk
1718	2Electronic City Phase II	27 BHK	8000	27.0	230.0	27
4684	Munnekollal	43 Bedroom	2400	40.0	660.0	43

```
df3.total_sqft.unique()
```

```
array(['1056', '2600', '1440', ..., '1133 - 1384', '774', '4689'],
      dtype=object)
```

Explore total_sqft feature

```
def is_float(x):
    try:
        float(x)
    except:
        return False
    return True
```

```
df3[~df3['total_sqft'].apply(is_float)].head(10)
```

	location	size	total_sqft	bath	price	bhk
30	Yelahanka	4 BHK	2100 - 2850	4.0	186.000	4
122	Hebbal	4 BHK	3067 - 8156	4.0	477.000	4
137	8th Phase JP Nagar	2 BHK	1042 - 1105	2.0	54.005	2
165	Sarjapur	2 BHK	1145 - 1340	2.0	43.490	2
188	KR Puram	2 BHK	1015 - 1540	2.0	56.800	2
410	Kengeri	1 BHK	34.46Sq. Meter	1.0	18.500	1
549	Hennur Road	2 BHK	1195 - 1440	2.0	63.770	2
648	Arekere	9 Bedroom	4125Perch	9.0	265.000	9
661	Yelahanka	2 BHK	1120 - 1145	2.0	48.130	2
672	Bettahalsoor	4 Bedroom	3090 - 5002	4.0	445.000	4

```
def convert_sqft_to_num(x):
    tokens = x.split('-')
    if len(tokens) == 2:
        return (float(tokens[0])+float(tokens[1]))/2
    try:
        return float(x)
    except:
        return None
```

```
convert_sqft_to_num('2100 - 2850')
```

```
2475.0

convert_sqft_to_num('34.46Sq. Meter')

df4 = df3.copy()
 df4.total_sqft = df4.total_sqft.apply(convert_sqft_to_num)
 df4

                    location        size  total_sqft  bath   price  bhk
 0     Electronic City Phase II          2 BHK          1056.0   2.0   39.07     2
 1          Chikka Tirupathi  4 Bedroom      2600.0   5.0  120.00    4
 2               Uttarahalli     3 BHK          1440.0   2.0   62.00     3
 3        Lingadheeranahalli  3 BHK          1521.0   3.0   95.00     3
 4                 Kothanur      2 BHK          1200.0   2.0   51.00     2
 ...                      ...        ...        ...   ...   ...  ...
 13315              Whitefield  5 Bedroom      3453.0   4.0  231.00    5
 13316          Richards Town         4 BHK          3600.0   5.0  400.00    4
 13317          Raja Rajeshwari Nagar         2 BHK          1141.0   2.0   60.00     2
 13318        Padmanabhanagar       4 BHK          4689.0   4.0  488.00    4
 13319           Doddathoguru         1 BHK          550.0   1.0   17.00      1

 [13246 rows x 6 columns]

df4 = df4[df4.total_sqft.notnull()]
 df4

                    location        size  total_sqft  bath   price  bhk
 0     Electronic City Phase II          2 BHK          1056.0   2.0   39.07     2
 1          Chikka Tirupathi  4 Bedroom      2600.0   5.0  120.00    4
 2               Uttarahalli     3 BHK          1440.0   2.0   62.00     3
 3        Lingadheeranahalli  3 BHK          1521.0   3.0   95.00     3
 4                 Kothanur     2 BHK     1200.0   2.0   51.00    2
 ...                      ...        ...        ...   ...   ...  ...
```

```
13315         Whitefield  5 Bedroom     3453.0   4.0  231.00    5
13316        Richards Town        4 BHK        3600.0   5.0  400.00    4
13317        Raja Rajeshwari Nagar        2 BHK        1141.0   2.0   60.00    2
13318       Padmanabhanagar       4 BHK        4689.0   4.0  488.00    4
13319         Doddathoguru        1 BHK        550.0   1.0   17.00     1

[13200 rows x 6 columns]
```

For below row, it shows total_sqft as 2475 which is an average of the range 2100-2850

```
df4.loc[30]
```

```
location        Yelahanka
size           4 BHK
total_sqft      2475.0
bath              4.0
price           186.0
bhk                 4
Name: 30, dtype: object
```

```
(2100 + 2850)/2
```

```
2475.0
```

Add new feature called price per square feet

```
df5 = df4.copy()
df5['price_per_sqft'] = df5['price']*100000/df5['total_sqft']
df5.head()
```

```
                    location         size  total_sqft  bath   price  bhk  \
0  Electronic City Phase II     2 BHK          1056.0   2.0   39.07    2
1        Chikka Tirupathi  4 Bedroom          2600.0   5.0  120.00    4
2            Uttarahalli          3 BHK          1440.0   2.0   62.00    3
```

```
3     Lingadheeranahalli   3 BHK   1521.0  3.0  95.00   3
4              Kothanur    2 BHK   1200.0  2.0  51.00   2

   price_per_sqft
0     3699.810606
1     4615.384615
2     4305.555556
3     6245.890861
4     4250.000000
```

```
df5_stats = df5['price_per_sqft'].describe()
df5_stats
```

```
count   1.320000e+04
mean    7.920759e+03
std     1.067272e+05
min     2.678298e+02
25%     4.267701e+03
50%     5.438331e+03
75%     7.317073e+03
max     1.200000e+07
Name: price_per_sqft, dtype: float64
```

```
df5.to_csv("bhp.csv",index=False)
```

Examine locations which is a categorical variable. We need to apply dimensionality reduction technique here to reduce number of locations

```
len(df5.location.unique())
```

1298

```
df5.location = df5.location.apply(lambda x: x.strip())
location_stats = df5['location'].value_counts(ascending=False)
```

location_stats

```
Whitefield                 533
Sarjapur  Road             392
Electronic City            304
Kanakpura Road             264
Thanisandra                235
                          ...
Rajanna Layout               1
Subramanyanagar              1
Lakshmipura Vidyaanyapura    1
Malur Hosur Road             1
Abshot Layout                1
Name: location, Length: 1287, dtype: int64
```

len(location_stats[location_stats>10])

240

len(location_stats)

1287

len(location_stats[location_stats<=10])

1047

Any location having less than 10 data points should be tagged as "other" location. This way number of categories can be reduced by huge amount. Later on when we do one hot encoding, it will help us with having fewer dummy columns

location_stats_less_than_10 = location_stats[location_stats<=10]
location_stats_less_than_10

BTM 1st Stage 10

```
Gunjur Palya             10
Nagappa Reddy Layout       10
Sector 1 HSR Layout        10
Thyagaraja Nagar           10
                        ..
Rajanna Layout             1
Subramanyanagar            1
Lakshmipura Vidyaanyapura          1
Malur Hosur Road           1
Abshot Layout              1
Name: location, Length: 1047, dtype: int64
```

```
len(df5.location.unique())
```

```
1287
```

```
df5.location = df5.location.apply(lambda x: 'other' if x in location_stats_less_than_10 else x)
len(df5.location.unique())
```

```
241
```

```
df5.head(10)
```

```
                 location       size  total_sqft  bath   price  bhk  \
0  Electronic City Phase II      2 BHK      1056.0   2.0   39.07    2
1          Chikka Tirupathi  4 Bedroom      2600.0   5.0  120.00    4
2               Uttarahalli      3 BHK      1440.0   2.0   62.00    3
3        Lingadheeranahalli      3 BHK      1521.0   3.0   95.00    3
4                  Kothanur      2 BHK      1200.0   2.0   51.00    2
5                Whitefield      2 BHK      1170.0   2.0   38.00    2
6          Old Airport Road      4 BHK      2732.0   4.0  204.00    4
7              Rajaji Nagar      4 BHK      3300.0   4.0  600.00    4
8              Marathahalli      3 BHK      1310.0   3.0   63.25    3
9                     other  6 Bedroom      1020.0   6.0  370.00    6
```

```
   price_per_sqft
0     3699.810606
1     4615.384615
2     4305.555556
3     6245.890861
4     4250.000000
5     3247.863248
6     7467.057101
7    18181.818182
8     4828.244275
9    36274.509804
```

normally square ft per bedroom is 300 (i.e. 2 bhk apartment is minimum 600 sqft

```
df5[df5.total_sqft/df5.bhk<300].head()
```

```
             location       size  total_sqft  bath  price  bhk  \
9               other  6 Bedroom      1020.0   6.0  370.0    6
45         HSR Layout  8 Bedroom       600.0   9.0  200.0    8
58      Murugeshpalya  6 Bedroom      1407.0   4.0  150.0    6
68  Devarachikkanahalli  8 Bedroom    1350.0   7.0   85.0    8
70              other  3 Bedroom       500.0   3.0  100.0    3

    price_per_sqft
9     36274.509804
45    33333.333333
58    10660.980810
68     6296.296296
70    20000.000000
```

Check above data points. We have 6 bhk apartment with 1020 sqft. Another one is 8 bhk and total sqft is 600. These are clear data errors that can be removed safely

```
df5.shape

(13200, 7)

df6 = df5[~(df5.total_sqft/df5.bhk<300)]
df6.shape

(12456, 7)

df6.columns

Index(['location', 'size', 'total_sqft', 'bath', 'price', 'bhk',
       'price_per_sqft'],
      dtype='object')

plt.boxplot(df6['total_sqft'])
plt.show()

Q1 = np.percentile(df6['total_sqft'], 25.) # 25th percentile of the data of the given feature
Q3 = np.percentile(df6['total_sqft'], 75.) # 75th percentile of the data of the given feature
IQR = Q3-Q1 #Interquartile Range
ll = Q1 - (1.5*IQR)
ul = Q3 + (1.5*IQR)
upper_outliers = df6[df6['total_sqft'] > ul].index.tolist()
lower_outliers = df6[df6['total_sqft'] < ll].index.tolist()
bad_indices = list(set(upper_outliers + lower_outliers))
drop = True
if drop:
    df6.drop(bad_indices, inplace = True, errors = 'ignore')

<ipython-input-51-c46bdd7d51e2>:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame


See the caveats in the documentation: https://pandas.pydata.org/pandas-
```

```
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df6.drop(bad_indices, inplace = True, errors = 'ignore')

plt.boxplot(df6['bath'])
 plt.show()

Q1 = np.percentile(df6['bath'], 25.) # 25th percentile of the data of the given feature
 Q3 = np.percentile(df6['bath'], 75.) # 75th percentile of the data of the given feature
 IQR = Q3-Q1 #Interquartile Range
 ll = Q1 - (1.5*IQR)
 ul = Q3 + (1.5*IQR)
 upper_outliers = df6[df6['bath'] > ul].index.tolist()
 lower_outliers = df6[df6['bath'] < ll].index.tolist()
 bad_indices = list(set(upper_outliers + lower_outliers))
 drop = True
 if drop:
    df6.drop(bad_indices, inplace = True, errors = 'ignore')

<ipython-input-54-cdb575bb4e89>:11: SettingWithCopyWarning:
 A value is trying to be set on a copy of a slice from a DataFrame


 See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df6.drop(bad_indices, inplace = True, errors = 'ignore')

plt.boxplot(df6['price'])
 plt.show()

Q1 = np.percentile(df6['price'], 25.) # 25th percentile of the data of the given feature
 Q3 = np.percentile(df6['price'], 75.) # 75th percentile of the data of the given feature
 IQR = Q3-Q1 #Interquartile Range
 ll = Q1 - (1.5*IQR)
 ul = Q3 + (1.5*IQR)
```

```
upper_outliers = df6[df6['price'] > ul].index.tolist()
lower_outliers = df6[df6['price'] < ll].index.tolist()
bad_indices = list(set(upper_outliers + lower_outliers))
drop = True
if drop:
    df6.drop(bad_indices, inplace = True, errors = 'ignore')
```

```
<ipython-input-56-e0f097c1f625>:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df6.drop(bad_indices, inplace = True, errors = 'ignore')
```

```
plt.boxplot(df6['bhk'])
plt.show()
```

```
Q1 = np.percentile(df6['bhk'], 25.) # 25th percentile of the data of the given feature
Q3 = np.percentile(df6['bhk'], 75.) # 75th percentile of the data of the given feature
IQR = Q3-Q1 #Interquartile Range
ll = Q1 - (1.5*IQR)
ul = Q3 + (1.5*IQR)
upper_outliers = df6[df6['bhk'] > ul].index.tolist()
lower_outliers = df6[df6['bhk'] < ll].index.tolist()
bad_indices = list(set(upper_outliers + lower_outliers))
drop = True
if drop:
    df6.drop(bad_indices, inplace = True, errors = 'ignore')
```

```
<ipython-input-58-c12c1120f543>:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
```

```
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df6.drop(bad_indices, inplace = True, errors = 'ignore')

plt.boxplot(df6['price_per_sqft'])
plt.show()

Q1 = np.percentile(df6['price_per_sqft'], 25.) # 25th percentile of the data of the given feature
Q3 = np.percentile(df6['price_per_sqft'], 75.) # 75th percentile of the data of the given feature
IQR = Q3-Q1 #Interquartile Range
ll = Q1 - (1.5*IQR)
ul = Q3 + (1.5*IQR)
upper_outliers = df6[df6['price_per_sqft'] > ul].index.tolist()
lower_outliers = df6[df6['price_per_sqft'] < ll].index.tolist()
bad_indices = list(set(upper_outliers + lower_outliers))
drop = True
if drop:
    df6.drop(bad_indices, inplace = True, errors = 'ignore')

<ipython-input-60-d349eb2f1f03>:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame


See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df6.drop(bad_indices, inplace = True, errors = 'ignore')

df6.shape

(10090, 7)

X = df6.drop(['price'],axis='columns')
X.head(3)

                  location   size  total_sqft  bath  bhk  price_per_sqft
0  Electronic City Phase II  2 BHK    1056.0   2.0    2     3699.810606
```

```
2          Uttarahalli  3 BHK      1440.0   2.0    3        4305.555556
3    Lingadheeranahalli  3 BHK     1521.0   3.0    3        6245.890861
```

```
X.shape
```

```
(10090, 6)
```

```
y = df6.price
 y.head(3)
```

```
0        39.07
 2       62.00
 3       95.00
 Name: price, dtype: float64
```

```
len(y)
```

```
10090
```

```
from sklearn.model_selection import train_test_split
 X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=10)
```

```
X_train.shape
```

```
(8072, 6)
```

```
y_train.shape
```

```
(8072,)
```

```
X_test.shape
```

```
(2018, 6)
```

```
y_test.shape
```

```
(2018,)
```

Lab Assignment No.	10B
Title	Data Visualization using matplotlib
Roll No.	
Class	BE
Date of Completion	
Subject	Computer Laboratory-I
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 10 (Group B)

- **Aim**: Data Visualization using matplotlib
  Problem Statement: Analyzing Air Quality Index (AQI) Trends in a City
  Dataset: "City_Air_Quality.csv"
  Description: The dataset contains information about air quality measurements in a specific city over a period of time. It includes attributes such as date, time, pollutant levels (e.g., PM2.5, PM10, CO), and the Air Quality Index (AQI) values. The goal is to use the matplotlib library to create visualizations that effectively represent the AQI trends and patterns for different pollutants in the city.
  Tasks to Perform:
  1. Import the "City_Air_Quality.csv" dataset.
  2. Explore the dataset to understand its structure and content.
  3. Identify the relevant variables for visualizing AQI trends, such as date, pollutant levels, and AQI values.
  4. Create line plots or time series plots to visualize the overall AQI trend over time.
  5. Plot individual pollutant levels (e.g., PM2.5, PM10, CO) on separate line plots to visualize their trends over time.
  6. Use bar plots or stacked bar plots to compare the AQI values across different dates or time periods.
  7. Create box plots or violin plots to analyze the distribution of AQI values for different pollutant categories.
  8. Use scatter plots or bubble charts to explore the relationship between AQI values and pollutant levels.
  9. Customize the visualizations by adding labels, titles, legends, and appropriate color schemes.

- **Hardware Requirement:**

- 6 GB free disk space.
- 2 GB RAM.
- 2 GB of RAM, plus additional RAM for virtual machines.
- 6 GB disk space for the host, plus the required disk space for the virtual machine(s).
- Virtualization is available with the KVM hypervisor
- Intel 64 and AMD64 architectures

- **Software Requirement:**
  Jypiter Nootbook/Ubuntu

Implementation:

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

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.impute import SimpleImputer

%matplotlib inline
data = pd.read_csv("data.csv")
print(data.index)
RangeIndex(start=0, stop=49005, step=1)
sns.set(style="ticks", rc = {'figure.figsize':(20,15)})
# Supressing update warnings
import warnings
warnings.filterwarnings('ignore')
```

Checking the dataset

We can see that there are quite a number of NaNs in the dataset. To proceed with the EDA, we must handle these NaNs by either removing them or filling them. I will be doing both.

```
# checking the original dataset
print(data.isnull().sum())
print(data.shape)
data.info()
stn_code                      15764
sampling_date                     0
state                             0
location                          0
agency                        16355
type                            994
so2                            1312
no2                             858
rspm                           2696
spm                           28659
location_monitoring_station    2537
pm2_5                         49005
```

```
date                          1
dtype: int64
(49005, 13)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 49005 entries, 0 to 49004
Data columns (total 13 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   stn_code                      33241 non-null  float64
 1   sampling_date                 49005 non-null  object
 2   state                         49005 non-null  object
 3   location                      49005 non-null  object
 4   agency                        32650 non-null  object
 5   type                          48011 non-null  object
 6   so2                           47693 non-null  float64
 7   no2                           48147 non-null  float64
 8   rspm                          46309 non-null  float64
 9   spm                           20346 non-null  float64
 10  location_monitoring_station  46468 non-null  object
 11  pm2_5                         0 non-null      float64
 12  date                          49004 non-null  object
dtypes: float64(6), object(7)
memory usage: 4.9+ MB
```

Cleaning the dataset

Removing NaNs Looking at the dataset head, we can conclude that the following columns:

1. stn_code
1. agency
2. sampling_date
3. location_monitoring_agency

do not add much to the dataset in terms of information that can't already be extracted from other columns. Therefore, we drop these columns.

Since date also has missing values, we will drop the rows containing these values as they're of little use as well.

Cleaning values Since the geographical nomenclature has changed over time, we change it here as well to correspond to more accurate insights.

The type column

Currently, the type column has several names for the same type and therefore, it is better to clean it up and make it more uniform.

```
# Cleaning up the data


 # cleaning up name changes

 data.state = data.state.replace({'Uttaranchal':'Uttarakhand'})
 data.state[data.location == "Jamshedpur"] = data.state[data.location ==
'Jamshedpur'].replace({"Bihar":"Jharkhand"})

 #changing types to uniform format

 types = {
         "Residential": "R",
         "Residential and others": "RO",
    "Residential, Rural and other Areas": "RRO",
         "Industrial Area": "I",
         "Industrial Areas": "I",
         "Industrial": "I",
         "Sensitive Area": "S",
         "Sensitive Areas": "S",
         "Sensitive": "S",
         np.nan: "RRO"
 }
 data.type = data.type.replace(types)
data.head()
```

```
         state   location type  so2   no2  rspm  spm  pm2_5    date
0  Andhra Pradesh  Hyderabad  RRO  4.8  17.4   NaN  NaN         NaN  1990-02-01
1  Andhra Pradesh  Hyderabad    I  3.1   7.0   NaN  NaN     NaN  1990-02-01
2  Andhra Pradesh  Hyderabad  RRO  6.2  28.5   NaN  NaN         NaN  1990-02-01
3  Andhra Pradesh  Hyderabad  RRO  6.3  14.7   NaN  NaN         NaN  1990-03-01
4  Andhra Pradesh  Hyderabad    I  4.7   7.5   NaN  NaN     NaN  1990-03-01
```

```
# defining columns of importance, which shall be used reguarly
VALUE_COLS = ['so2', 'no2', 'rspm', 'spm', 'pm2_5']
```

Filling NaNs Since our pollutants column contain a lot of NaNs, we must fill them to have consistent data. If we drop the rows containing NaNs, we will be left with nothing.

I use the SimpleImputer from sklearn.imputer (v0.20.2) to fill the missing values in every column with the mean.

```
# invoking SimpleImputer to fill missing values
imputer = SimpleImputer(missing_values=np.nan, strategy='mean')
data[VALUE_COLS] = imputer.fit_transform(data[VALUE_COLS])
---------------------------------------------------------------------------
ValueError                              Traceback (most recent call last)
<ipython-input-16-7a53965e699d> in <cell line: 3>()
      1 # invoking SimpleImputer to fill missing values
      2 imputer = SimpleImputer(missing_values=np.nan, strategy='mean')
----> 3 data[VALUE_COLS] = imputer.fit_transform(data[VALUE_COLS])

/usr/local/lib/python3.10/dist-packages/pandas/core/frame.py in __setitem__(self, key, value)
   3966             self._setitem_frame(key, value)
   3967         elif isinstance(key, (Series, np.ndarray, list, Index)):
-> 3968             self._setitem_array(key, value)
   3969         elif isinstance(value, DataFrame):
   3970             self._set_item_frame_value(key, value)

/usr/local/lib/python3.10/dist-packages/pandas/core/frame.py in _setitem_array(self, key, value)
   4017
   4018         elif isinstance(value, np.ndarray) and value.ndim == 2:
```

```
-> 4019             self._iset_not_inplace(key, value)
   4020
   4021         elif np.ndim(value) > 1:

/usr/local/lib/python3.10/dist-packages/pandas/core/frame.py in _iset_not_inplace(self, key, value)
   4044         if self.columns.is_unique:
   4045         if np.shape(value)[-1] != len(key):
-> 4046                 raise ValueError("Columns must be same length as key")
   4047
   4048         for i, col in enumerate(key):

ValueError: Columns must be same length as key
# checking to see if the dataset has any null values left over and the format
print(data.isnull().sum())
data.tail()
state          0
location       0
type           0
so2            1312
no2            858
rspm           2696
spm            28659
pm2_5          49005
date           1
dtype: int64
        state    location type   so2   no2   rspm       spm  pm2_5  \
49000  Chandigarh  Chandigarh   RO   6.0  15.0   47.0  125.0      NaN
49001  Chandigarh  Chandigarh   RO   NaN  12.0   54.0  161.0      NaN
49002  Chandigarh  Chandigarh   RO   NaN  10.0  116.0  196.0      NaN
49003  Chandigarh  Chandigarh   RO   NaN   9.0   38.0  154.0      NaN
49004  Chandigarh  Chandigarh   RO  10.0  27.0   43.0  152.0      NaN
```

```
          date
49000  2005-03-23
49001  2005-03-25
49002  2005-03-28
49003  2005-03-30
49004         NaN
```

Plotting pollutant levels as yearly averages for states

```
# defining a function that plots SO2, NO2, RSPM and SPM yearly average levels for a given state
# since data is available monthly, it was resampled to a year and averaged to obtain yearly averages
# years for which no data was collected has not been imputed
def plot_for_state(state):
    fig, ax = plt.subplots(2,2, figsize=(20,12))
    fig.suptitle(state, size=20)
    state = aqi[aqi.state == state]
    state = state.reset_index().set_index('date')[VALUE_COLS].resample('Y').mean()
    state.so2.plot(legend=True, ax=ax[0][0], title="so2")
    ax[0][0].set_ylabel("so2 (µg/m3)")
    ax[0][0].set_xlabel("Year")

    state.no2.plot(legend=True, ax=ax[0][1], title="no2")
    ax[0][1].set_ylabel("no2 (µg/m3)")
    ax[0][1].set_xlabel("Year")

    state.rspm.plot(legend=True, ax=ax[1][0], title="rspm")
    ax[1][0].set_ylabel("RSPM (PM10 µg/m3)")
    ax[1][0].set_xlabel("Year")

    state.spm.plot(legend=True, ax=ax[1][1], title="spm")
    ax[1][1].set_ylabel("SPM (PM10 µg/m3)")
    ax[1][1].set_xlabel("Year")
```

```
plot_for_state("Uttar Pradesh")
```

Plotting Uttar Pradesh, we see that SO2 levels have fallen in the state while NO2 levels have risen. Information about RSPM and SPM can't be concluded since a lot of data is missing.

Plotting highest and lowest ranking states

```
# defining a function to find and plot the top 10 and bottom 10 states for a given indicator (defaults to SO2)
def top_and_bottom_10_states(indicator="so2"):
    fig, ax = plt.subplots(2,1, figsize=(20, 12))

    ind = data[[indicator, 'state']].groupby('state',
as_index=False).median().sort_values(by=indicator,ascending=False)
    top10 = sns.barplot(x='state', y=indicator, data=ind[:10], ax=ax[0], color='red')
    top10.set_title("Top 10 states by {} (1991-2016)".format(indicator))
    top10.set_ylabel("so2 (µg/m3)")
    top10.set_xlabel("State")

    bottom10 = sns.barplot(x='state', y=indicator, data=ind[-10:], ax=ax[1], color='green')
    bottom10.set_title("Bottom 10 states by {} (1991-2016)".format(indicator))
    bottom10.set_ylabel("so2 (µg/m3)")
    bottom10.set_xlabel("State")
top_and_bottom_10_states("so2")
top_and_bottom_10_states("no2")
```

Plotting for SO2, we can see that the top state is Uttarakhand, while the bottom state is Meghalaya.

Plotting for NO2, we can see that the top state is West Bengal, while the bottom state is Mizoram.

Plotting the highest ever recorded levels

```
# defining a function to find the highest ever recorded levels for a given indicator (defaults to SO2) by state
# sidenote: mostly outliers
def highest_levels_recorded(indicator="so2"):
    plt.figure(figsize=(20,10))
    ind = data[[indicator, 'location', 'state', 'date']].groupby('state', as_index=False).max()
    highest = sns.barplot(x='state', y=indicator, data=ind)
    highest.set_title("Highest ever {} levels recorded by state".format(indicator))
```

```
    plt.xticks(rotation=90)
highest_levels_recorded("no2")
 highest_levels_recorded("rspm")
```

Plotting for NO2, we can see that Rajasthan recorded the highest ever NO2 level. Plotting for RSPM, we can see that Uttar Pradesh recorded the highest ever RSPM level.

Plotting yearly trends

```
# defining a function to plot the yearly trend values for a given indicator (defaults to SO2) and state (defaults to overall)
 def yearly_trend(state="", indicator="so2", ):
    plt.figure(figsize=(20,12))
    data['year'] = data.date.dt.year
    if state is "":
    year_wise = data[[indicator, 'year', 'state']].groupby('year', as_index=False).median()
    trend = sns.pointplot(x='year', y=indicator, data=year_wise)
    trend.set_title('Yearly trend of {}'.format(indicator))
    else:
    year_wise = data[[indicator, 'year', 'state']].groupby(['state','year']).median().loc[state].reset_index()
    trend = sns.pointplot(x='year', y=indicator, data=year_wise)
    trend.set_title('Yearly trend of {} for {}'.format(indicator, state))
yearly_trend()
 yearly_trend("Bihar", "no2")
---------------------------------------------------------------------------
 AttributeError                    Traceback (most recent call last)
 <ipython-input-42-e79267482a54> in <cell line: 1>()
 ----> 1 yearly_trend()
    2 yearly_trend("Bihar", "no2")

 <ipython-input-30-93f123e178ba> in yearly_trend(state, indicator)
    2 def yearly_trend(state="", indicator="so2", ):
    3     plt.figure(figsize=(20,12))
 ----> 4        data['year'] = data.date.dt.year
```

```
      5     if state is "":
      6         year_wise = data[[indicator, 'year', 'state']].groupby('year', as_index=False).median()

/usr/local/lib/python3.10/dist-packages/pandas/core/generic.py in __getattr__(self, name)
   5900         ):
   5901             return self[name]
-> 5902         return object.__getattribute__(self, name)
   5903
   5904     def __setattr__(self, name: str, value) -> None:

/usr/local/lib/python3.10/dist-packages/pandas/core/accessor.py in __get__(self, obj, cls)
    180             # we're accessing the attribute of the class, i.e., Dataset.geo
    181             return self._accessor
--> 182         accessor_obj = self._accessor(obj)
    183         # Replace the property with the accessor object. Inspired by:
    184         # https://www.pydanny.com/cached-property.html

/usr/local/lib/python3.10/dist-packages/pandas/core/indexes/accessors.py in __new__(cls, data)
    510             return PeriodProperties(data, orig)
    511
--> 512         raise AttributeError("Can only use .dt accessor with datetimelike values")

AttributeError: Can only use .dt accessor with datetimelike values
<Figure size 2000x1200 with 0 Axes>
```

Plotting for SO2, we can see the yearly trend for sulphur dioxide levels in the country. Plotting for NO2 in West Bengal, we can see the yearly trend.

Plotting a heatmap for a particular indicator

```
# defining a function to plot a heatmap for yearly median average for a given indicator (defaults to SO2)
def indicator_by_state_and_year(indicator="so2"):
    plt.figure(figsize=(20, 20))
    hmap = sns.heatmap(
```

```
        data=data.pivot_table(values=indicator, index='state', columns='year', aggfunc='median', margins=True),
                annot=True, linewidths=.5, cbar=True, square=True, cmap='inferno', cbar_kws={'label': "Annual
Average"})

        hmap.set_title("{} by state and year".format(indicator))
indicator_by_state_and_year('no2')
---------------------------------------------------------------------------
 KeyError                          Traceback (most recent call last)
 <ipython-input-35-39c9f3640fe4> in <cell line: 1>()
 ----> 1 indicator_by_state_and_year('no2')

 <ipython-input-34-3c4f9130ffd5> in indicator_by_state_and_year(indicator)
        3       plt.figure(figsize=(20, 20))
        4       hmap = sns.heatmap(
 ----> 5      data=data.pivot_table(values=indicator, index='state', columns='year', aggfunc='median',
margins=True),
          6           annot=True, linewidths=.5, cbar=True, square=True, cmap='inferno', cbar_kws={'label':
"Annual Average"})
        7

 /usr/local/lib/python3.10/dist-packages/pandas/core/frame.py in pivot_table(self, values, index, columns,
aggfunc, fill_value, margins, dropna, margins_name, observed, sort)
   8729         from pandas.core.reshape.pivot import pivot_table
   8730
 -> 8731        return pivot_table(
   8732         self,
   8733         values=values,

 /usr/local/lib/python3.10/dist-packages/pandas/core/reshape/pivot.py in pivot_table(data, values, index, columns,
aggfunc, fill_value, margins, dropna, margins_name, observed, sort)
        95      return table.__finalize__(data, method="pivot_table")
```

```
     96
---> 97     table = __internal_pivot_table(
     98     data,
     99     values,

/usr/local/lib/python3.10/dist-packages/pandas/core/reshape/pivot.py in __internal_pivot_table(data, values, index, columns, aggfunc, fill_value, margins, dropna, margins_name, observed, sort)
    164     values = list(values)
    165
--> 166     grouped = data.groupby(keys, observed=observed, sort=sort)
    167     msg = (
    168     "pivot_table dropped a column because it failed to aggregate. This behavior "

/usr/local/lib/python3.10/dist-packages/pandas/core/frame.py in groupby(self, by, axis, level, as_index, sort, group_keys, squeeze, observed, dropna)
   8400     axis = self._get_axis_number(axis)
   8401
-> 8402     return DataFrameGroupBy(
   8403     obj=self,
   8404     keys=by,

/usr/local/lib/python3.10/dist-packages/pandas/core/groupby/groupby.py in __init__(self, obj, keys, axis, level, grouper, exclusions, selection, as_index, sort, group_keys, squeeze, observed, mutated, dropna)
    963         from pandas.core.groupby.grouper import get_grouper
    964
--> 965     grouper, exclusions, obj = get_grouper(
    966             obj,
    967             keys,

/usr/local/lib/python3.10/dist-packages/pandas/core/groupby/grouper.py in get_grouper(obj, key, axis, level, sort, observed, mutated, validate, dropna)
```

```
    886             in_axis, level, gpr = False, gpr, None
    887             else:
--> 888             raise KeyError(gpr)
    889     elif isinstance(gpr, Grouper) and gpr.key is not None:
    890             # Add key to exclusions

KeyError: 'year'
<Figure size 2000x2000 with 0 Axes>
```

Plotting pollutant average by type

```
# defining a function to plot pollutant averages by type for a given indicator
def type_avg(indicator=""):
    type_avg = data[VALUE_COLS + ['type', 'date']].groupby("type").mean()
    if indicator is not "":
    t = type_avg[indicator].plot(kind='bar')
    plt.xticks(rotation = 0)
    plt.title("Pollutant average by type for {}".format(indicator))
    else:
    t = type_avg.plot(kind='bar')
    plt.xticks(rotation = 0)
    plt.title("Pollutant average by type")
type_avg('so2')
```

Plotting pollutant averages by locations/state

```
# defining a function to plot pollutant averages for a given indicator (defaults to SO2) by locations in a given state
def location_avgs(state, indicator="so2"):
    locs = data[VALUE_COLS + ['state', 'location', 'date']].groupby(['state', 'location']).mean()
    state_avgs = locs.loc[state].reset_index()
    sns.barplot(x='location', y=indicator, data=state_avgs)
    plt.title("Location-wise average for {} in {}".format(indicator, state))
    plt.xticks(rotation = 90)
location_avgs("Bihar", "no2")
```

Lab Assignment No.	11B
Title	Analyzing Sales Performance by Region in a Retail Company
Roll No.	
Class	BE
Date of Completion	
Subject	Computer Laboratory-J
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 11 (Group B)

- **Aim**: Data Aggregation
  Problem Statement: Analyzing Sales Performance by Region in a Retail Company
  Dataset: "Retail_Sales_Data.csv"
  Description: The dataset contains information about sales transactions in a retail company. It includes attributes such as transaction date, product category, quantity sold, and sales amount. The goal is to perform data aggregation to analyze the sales performance by region and identify the top-performing regions.
- **Tasks to Perform:**
  1. Import the "Retail_Sales_Data.csv" dataset.
  2. Explore the dataset to understand its structure and content.
  3. Identify the relevant variables for aggregating sales data, such as region, sales amount, and product category.
  4. Group the sales data by region and calculate the total sales amount for each region.
  5. Create bar plots or pie charts to visualize the sales distribution by region.
  6. Identify the top-performing regions based on the highest sales amount.
  7. Group the sales data by region and product category to calculate the total sales amount for each combination.
  8. Create stacked bar plots or grouped bar plots to compare the sales amounts across different regions and product categories.

- **Hardware Requirement:**

- 6 GB free disk space.
- 2 GB RAM.
- 2 GB of RAM, plus additional RAM for virtual machines.
- 6 GB disk space for the host, plus the required disk space for the virtual machine(s).
- Virtualization is available with the KVM hypervisor
- Intel 64 and AMD64 architectures

- **Software Requirement:**
  Jypiter Nootbook/Ubuntu

Implementation:

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

Data Aggregation is important for deriving granular insights about individual customers and for better understanding their perception and expectations regarding the product.

Regardless of the size and type, every business organization needs valuable data and insights to combat the day-to-day challenges of the competitive market. If a business wants to thrive in the market, then it must understand its target audience and customer preferences, and in this, big data plays a vital role.

What is Data Aggregation?

About Dataset

dataset contains shopping information from 10 different shopping malls between 2021 and 2023. We have gathered data from various age groups and genders to provide a comprehensive view of shopping habits in Istanbul. The dataset includes essential information such as invoice numbers, customer IDs, age, gender, payment methods, product categories, quantity, price, order dates, and shopping mall locations.

Attribute Information:

invoice_no: Invoice number. Nominal. A combination of the letter 'I' and a 6-digit integer uniquely assigned to each operation.

customer_id: Customer number. Nominal. A combination of the letter 'C' and a 6-digit integer uniquely assigned to each operation.

gender: String variable of the customer's gender.

age: Positive Integer variable of the customers age.

category: String variable of the category of the purchased product.

quantity: The quantities of each product (item) per transaction. Numeric.

price: Unit price. Numeric. Product price per unit in Turkish Liras (TL).

payment_method: String variable of the payment method (cash, credit card or debit card) used for the transaction.

invoice_date: Invoice date. The day when a transaction was generated.

shopping_mall: String variable of the name of the shopping mall where the transaction was made.

dataset source: https://www.kaggle.com/datasets/mehmettahiraslan/customer-shopping-dataset

```
#df = pd.read_csv("/content/customer_shopping_data.csv")
df= pd.read_csv("/content/customer_shopping_data.csv")
df.head()
```

```
 invoice_no customer_id  gender  age  category  quantity    price  \
0   I138884   C241288  Female   28  Clothing       5.0  1500.40
1   I317333   C111565    Male   21     Shoes       3.0  1800.51
2   I127801   C266599    Male   20  Clothing     1.0   300.08
3   I173702   C988172  Female   66     Shoes       5.0  3000.85
4   I337046   C189076  Female   53     Books       4.0     60.60

  payment_method invoice_date   shopping_mall
0    Credit Card     5/8/2022          Kanyon
1     Debit Card   12/12/2021  Forum Istanbul
2           Cash    9/11/2021       Metrocity
3    Credit Card   16/05/2021    Metropol AVM
4           Cash   24/10/2021          Kanyon
```

To check the count of records grouped by region/branch of the mall

```
df.groupby("shopping_mall").count()
```

```
                   invoice_no  customer_id  gender   age  category  quantity  \
shopping_mall
Cevahir AVM              1349         1349    1349  1349      1349      1349
Emaar Square Mall        1341         1341    1341  1341      1341      1341
Forum Istanbul           1343         1343    1343  1343      1343      1343
Istinye Park             2709         2709    2709  2709      2709      2709
Kanyon                   5481         5481    5481  5481      5481      5481
Mall of Istanbul         5588         5588    5588  5588      5588      5588
```

```
Metrocity            4193         4193   4193  4193    4193    4193
Metropol AVM         2856         2856   2856  2856    2856    2856
Viaport Outlet      1389          1389   1389  1389    1389    1389
Zorlu Center         1392         1392   1392  1392    1392    1392

                  price  payment_method  invoice_date
shopping_mall
Cevahir AVM        1349             1349             1349
Emaar Square Mall   1341            1341             1341
Forum Istanbul     1343        1343            1343
Istinye Park       2709        2709            2709
Kanyon             5481        5481            5481
Mall of Istanbul   5588        5588            5588
Metrocity          4193        4193            4193
Metropol AVM        2856            2856             2856
Viaport Outlet     1389        1389            1389
Zorlu Center       1392        1392            1392
```

To check the count of records grouped by the product categories

```
df.groupby("category").count()
```

```
                invoice_no  customer_id  gender   age  quantity  price  \
category
Books                1397         1397   1397  1397    1397   1397
Clothin              1        1        1    1         0        0
Clothing             9433         9433   9433  9433    9433   9433
Cosmetics            4224         4224   4224  4224    4224   4224
Food & Beverage      4158         4158   4158  4158    4158   4158
Shoes                2773         2773   2773  2773    2773   2773
Souvenir          1402       1402    1402  1402     1402   1402
Technology           1435         1435   1435  1435    1435   1435
```

```
Toys              2819         2819    2819  2819      2819   2819

              payment_method  invoice_date  shopping_mall
category
Books             1397         1397          1397
Clothin           0        0            0
Clothing          9433         9433          9433
Cosmetics         4224         4224          4224
Food & Beverage       4158         4158          4158
Shoes             2773         2773          2773
Souvenir          1402         1402        1402
Technology        1435         1435          1435
Toys              2819         2819          2819
```

```
# total sales for each mall branch

 branch_sales = df.groupby("shopping_mall").sum()
```

<ipython-input-13-64840580634c>:3: FutureWarning: The default value of numeric_only in DataFrameGroupBy.sum is deprecated. In a future version, numeric_only will default to False. Either specify numeric_only or select only columns which should be valid for the function.
  branch_sales = df.groupby("shopping_mall").sum()

```
# total sales for each category of product

 category_sales = df.groupby("category").sum()
```

<ipython-input-14-732f2a6af039>:3: FutureWarning: The default value of numeric_only in DataFrameGroupBy.sum is deprecated. In a future version, numeric_only will default to False. Either specify numeric_only or select only columns which should be valid for the function.
  category_sales = df.groupby("category").sum()

In the above two cells, the sum method will return sums for all numeric values. For some attributes such as age, this sum is not relevant.

#to get the top performing branches

```
branch_sales.sort_values(by = "price", ascending = False)
```

shopping_mall	age	quantity	price
Mall of Istanbul	243751	16680.0	3874873.68
Kanyon	237767	16464.0	3774006.38
Metrocity	183003	12585.0	2799049.70
Metropol AVM	123899	8530.0	1886384.39
Istinye Park	118686	8202.0	1874608.87
Viaport Outlet	59666	4107.0	989716.52
Zorlu Center	60844	4181.0	983379.89
Emaar Square Mall	58286	4008.0	927215.95
Cevahir AVM	57069	4059.0	913555.36
Forum Istanbul	58716	4063.0	895712.68

to get the top selling categories

```
category_sales.sort_values(by = "price", ascending = False)
```

category	age	quantity	price
Clothing	1497054	103558	31075684.64
Shoes	436027	30217	18135336.89
Technology	216669	15021	15772050.00
Cosmetics	657937	45465	1848606.90
Toys	437032	30321	1086704.64
Food & Beverage	640605	44277	231568.71
Books	216882	14982	226977.30

Souvenir 216922 14871 174436.83

```
# to get total sales for each combination of branch and product_category

 combined_branch_category_sales = df.groupby(["shopping_mall", "category"]).sum()
```

```
<ipython-input-16-994273aad95b>:3: FutureWarning: The default value of numeric_only in DataFrameGroupBy.sum is deprecated. In a future version, numeric_only will default to False. Either specify numeric_only or select only columns which should be valid for the function.
  combined_branch_category_sales = df.groupby(["shopping_mall", "category"]).sum()
```

```
combined_branch_category_sales

# pie chart for sales by branch

 plt.pie(branch_sales["price"], labels = branch_sales.index)
 plt.show()

# pie chart for sales by product category

 plt.pie(category_sales["price"], labels = category_sales.index)
 plt.show()

combined_pivot = df.pivot_table(index="shopping_mall", columns="category", values="price", aggfunc="sum")

# grouped bar chart for sales of different categories at different branches

 combined_pivot.plot(kind="bar", figsize=(10, 6))
 plt.show()
```