Dr. D. Y. Patil Pratishthan's

DR. D. Y. PATIL INSTITUTE OF ENGINEERING, MANAGEMENT & RESEARCH

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Department of Artificial Intelligence and Data Science

LAB MANUAL

Computer Laboratory
Semester-I

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Computer Laboratory -I

Course Code	Course Name	Teaching Scheme (Hrs./ Week)	Credits
417526	Computer Laboratory-I: Machine Learning	4	2
417526	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 scienceCO6: Evaluate time series data.

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

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4	A4	**Clustering Analysis (Any one)**	51
		A. 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 **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. Datasetlink: https://www.kaggle.com/datasets/elikplim/car-evaluation-data-set **B.** Use different voting mechanism and Apply AdaBoost (Adaptive Boosting), GradientTree 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 toanalyze weather patterns over time. **Tasks to Perform:** Register and obtain API key from OpenWeatherMap. 2. Interact with the OpenWeatherMap API using the API key to retrieve weather data for aspecific location. 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. 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 telecommunicationscompany 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:** Import the "Telecom_Customer_Churn.csv" dataset. Explore the dataset to understand its structure and content. 3. Handle missing values in the dataset, deciding on an appropriate strategy. 4. Removeany duplicate records from the dataset. 5. Check for inconsistent data, such as inconsistent formatting or spelling variations, andstandardize it. Convert columns to the correct data types as needed. Identify and handle outliers in the data. 8. Perform feature engineering, creating new features that may be relevant to predictingcustomer churn. Normalize or scale the data if necessary. 10. Split the dataset into training and testing sets for further analysis. 11. Export thecleaned dataset for future analysis or modeling.	84
9	B4	**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, saleprices, and other relevant features. The goal is to perform data wrangling to gain insightsinto 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 orlabel encoding) for further analysis. 6. Aggregate the data to calculate summary statistics or derived metrics such as averagesale prices by neighborhood or property type. 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 trendsand patterns for different pollutants in the city. **Tasks to Perform:** Import the "City_Air_Quality.csv" dataset. 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. 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. 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 differentpollutant categories. 8. Use scatter plots or bubble charts to explore the relationship between AQI values andpollutant levels. 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:** Import the "Retail_Sales_Data.csv" dataset. 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. Group the sales data by region and calculate the total sales amount for each region. Create bar plots or pie charts to visualize the sales distribution by region. 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 amountfor each combination. 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 (consideringthe 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-beingparameters, among others) with self-assessment facilities. Automated Animal Identification and Detection of Species Sentimental analysis on Govt. Released Policies Identification of Flood Prone Roads 5. Identification of Missing Bridges which would increase the connectivity between regions Note: Instructor can also assign similar problem statementsReferences: 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-II :Quantum AI
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 PCAalgorithm & 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:**

<u>Principal Component Analysis (PCA)</u>

PCA is an unsupervised machine learning algorithm. PCA is mainly used for dimensionality reduction in a datasetconsisting 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        1.712.43           15.6127           2.80
                1    13.20        1.782.14           11.2100           2.65
                2    13.16        2.362.67           18.6101           2.80
                3    14.37        1.952.50           16.8113           3.85
                4    13.24        2.592.87           21.0118           2.80

Flavanoids  Nonflavanoid_Phenols  Proanthocyanins  Color_Intensity  Hue  \
                0       3.060.28                             2.29         5.64 1.04
                1       2.760.26                             1.28         4.38 1.05
                2       3.240.30                             2.81         5.68 1.03
                3       3.490.24                             2.18         7.80 0.86
                4       2.690.39                             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 tounit 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 andstd to be used for later scaling.
```

```
X.head(5)
```

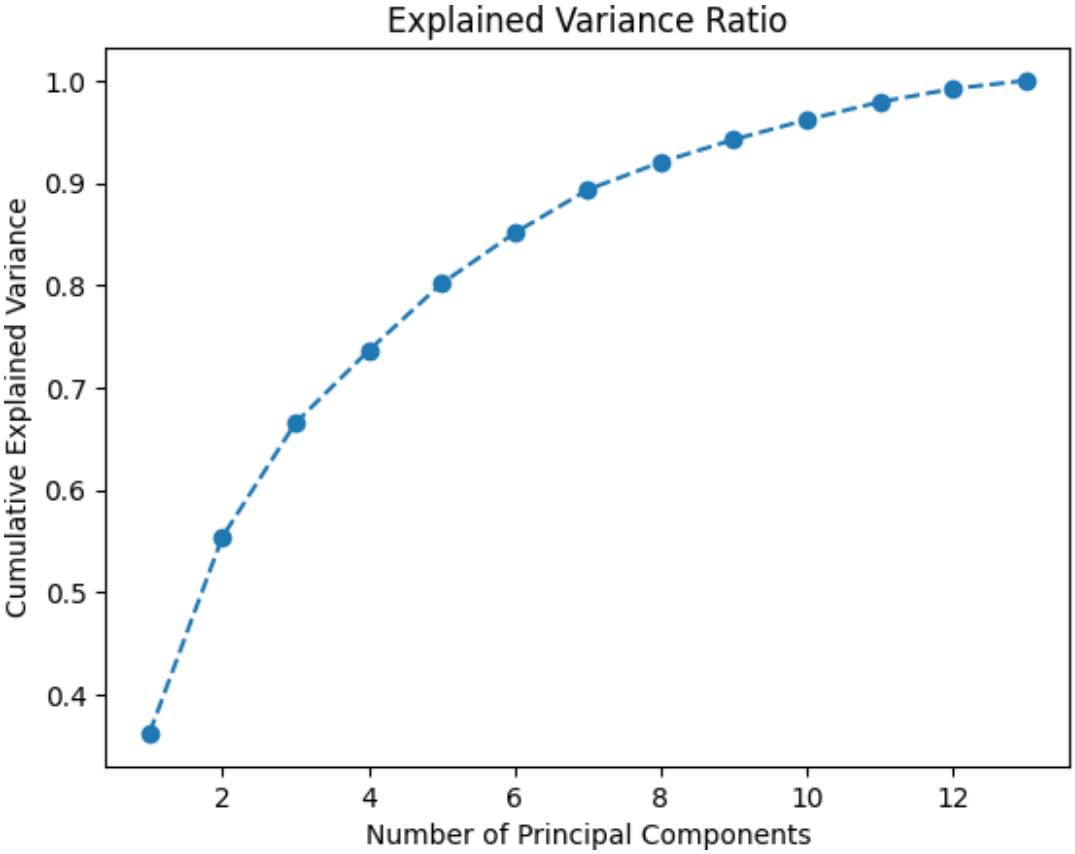
	Alcohol	Malic_Acid	Ash	Ash_Alcanity	Magnesium	Total_Phenols	\
0	1.518613	-0.562250	0.232053	-1.169593	1.913905	0.808997	
1	0.246290	-0.499413	-0.827996	-2.490847	0.018145	0.568648	
2	0.196879	0.021231	1.109334	-0.268738	0.088358	0.808997	
3	1.691550	-0.346811	0.487926	-0.809251	0.930918	2.491446	
4	0.295700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

	Flavanoids	Nonflavanoid_Phenols	Proanthocyanins	Color_Intensity	\
0	-0.659563	1.224884	0.251717	1.03481	
9					
1	-0.820719	-0.544721	-0.293321	0.73362	
9					
2	-0.498407	2.135968	0.269020	1.21553	
3					
3	-0.981875	1.032155	1.186068	1.46652	
5					
4	0.226796	0.401404	-0.319276	0.66335	
1					

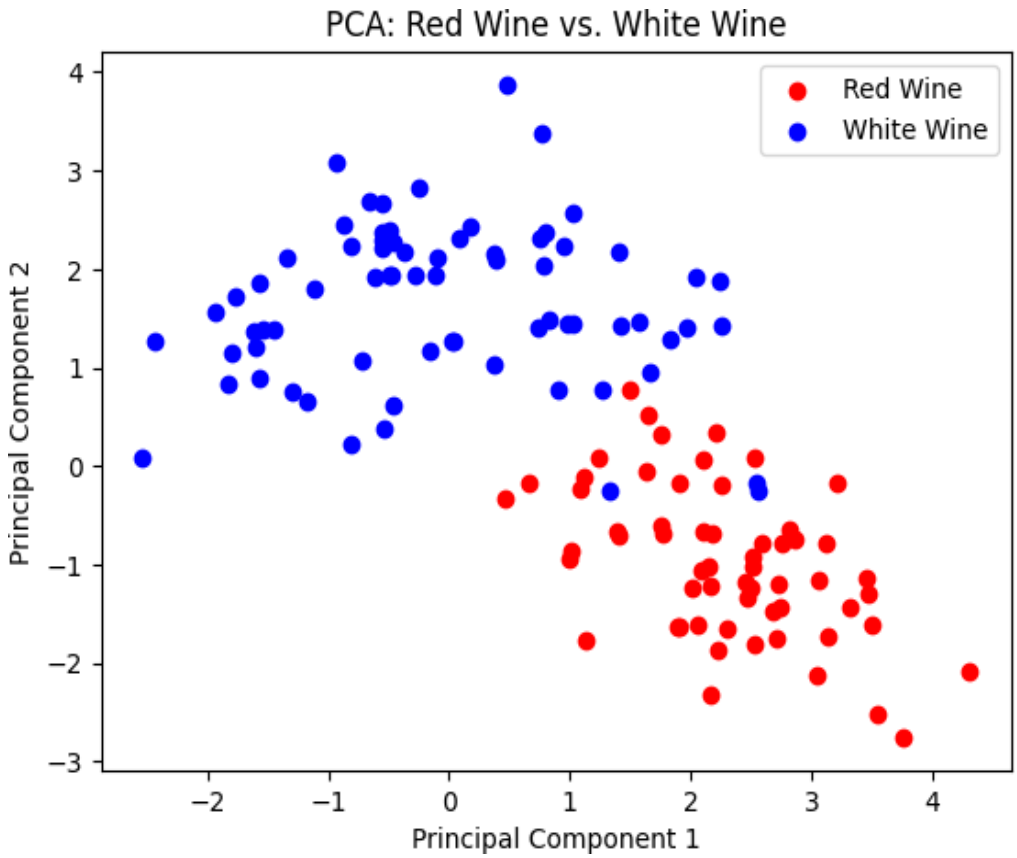
	Hue	OD280	Proline
0	0.362177	1.847920	1.013009
1	0.406051	1.113449	0.965242
2	0.318304	0.788587	1.395148
3	-0.427544	1.184071	2.334574
4	0.362177	0.449601	-0.037874

```
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.shapeX.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-II :Quantum AI
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 1 B (Group A)

- **Aim**: Apply LDA Algorithm on Iris Dataset and classify which species a given flower belongs to DatasetLink: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

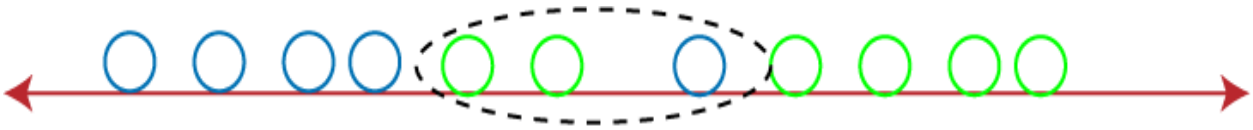
- **Software Requirement:**
  Jupyter Nootbook/Ubuntu

- **Theory:**

Linear Discriminant Analysis (LDA) is one of the commonly used dimensionality reduction techniques inmachine 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 differencesin 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. Fore.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.

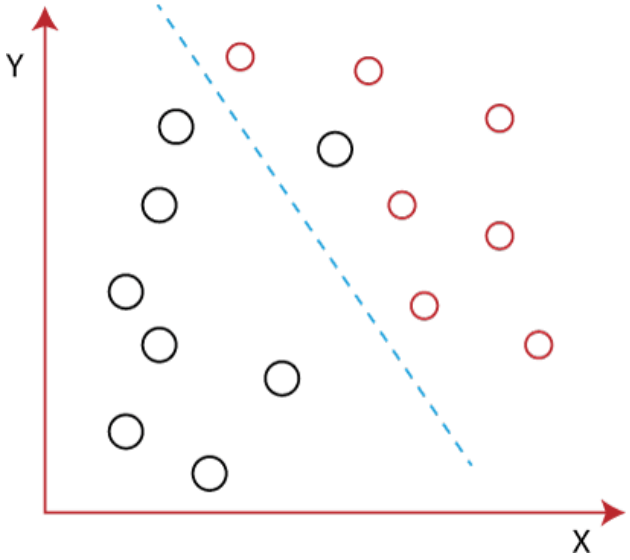


Overlapping

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

Example:

Let's assume we have to classify two different classes having two sets of data points in a 2-dimensional plane asshown 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.uniqu()

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 classifierclassifier = 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-II :Quantum AI
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 2 A (Group 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 andridge, 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.

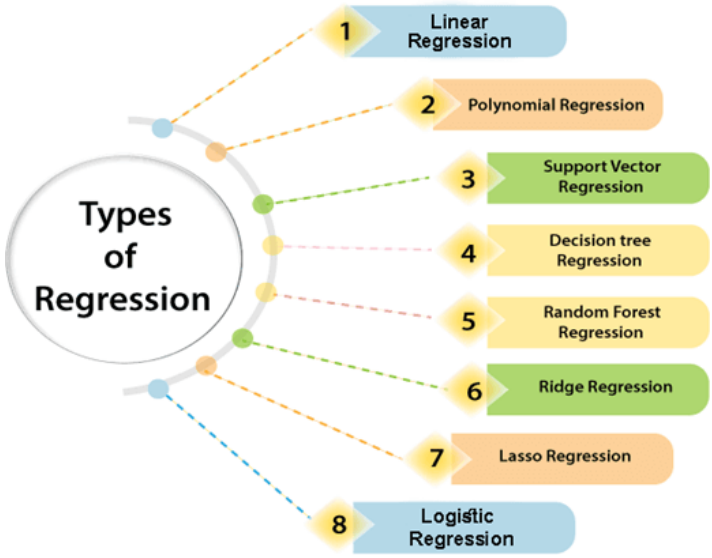
  Why do we use Regression Analysis?
  As mentioned above, Regression analysis helps in the prediction of a continuous variable. There are various scenarios in the real world where we need some future predictions such as weather condition, sales prediction, marketing trends, etc., for such case we need some technology which can make predictions more accurately. So forsuch 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 importantfactor, 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-II :Quantum AI
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 2 B (Group A)

- **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 ofdispersion.

Central Tendency

Measures of central tendency focus on the average or middle values of data sets, whereas measures of variabilityfocus 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 themost 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 traitand 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 theindividuals in the room. This univariate data is only dependent on one factor: each person's age. By gathering this onepiece 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 variablesare 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          0.37250029.000000   0.000000
       75%          36.600000          0.62625041.000000   1.000000
       max    67.100000                  2.42000081.000000   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: PregnanciesFrequency:
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: GlucoseFrequency:
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
Me dian: 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: BloodPressu reFrequency:
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:
```

Skin Thickness Frequency:

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

3716	456
4115	146
3515	445
3614	105
1514	484
1714	474
2013	493
2412	503
4211	82
1311	72
2110	522
468	542
348	631
127	601
387	561
116	511
436	991
166	

Name: SkinThickness, dtype: int64

Mean: 20.536458333333332
Median: 23.0Mode:
0 0
Name: SkinThickness, dtype: int64Variance: 254.47324532811953
Standard Deviation: 15.952217567727677
Skewness: 0.10937249648187608
Kurtosis: -0.520071866153013

Column: InsulinFrequency

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

                                  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: int64Mean: 31.992578124999998
 Median: 32.0Mode:
 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: 0.3725Mode:
0 0.254

1 0.258
Name: DiabetesPedigreeFunction, dtype: float64Variance:
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
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

```
3912                                                    70  1
3510                                                    68  1
508

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: OutcomeFrequency:
0       500
1       268
Name: Outcome, dtype: int64

Mean: 0.3489583333333333
Median: 0.0Mode:
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

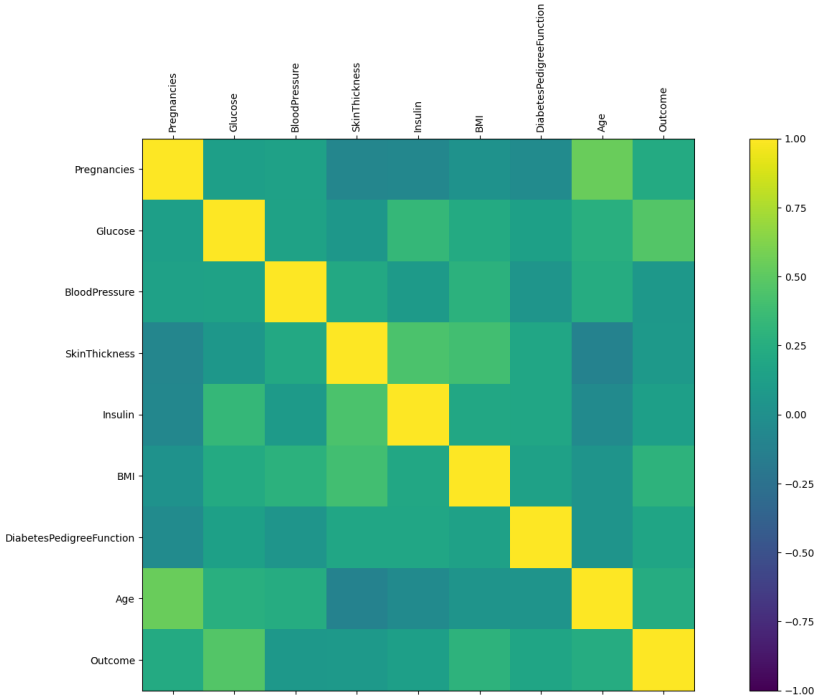
Omnibus:	41.539	Durbin-Watson:	1.982
Prob(Omnibus):	0.000	Jarque-Bera (JB):	31.183
Skew:	0.395	Prob(JB):	1.69e-07
Kurtosis:	2.408	Cond. No.....	1.10e+03

Notes:

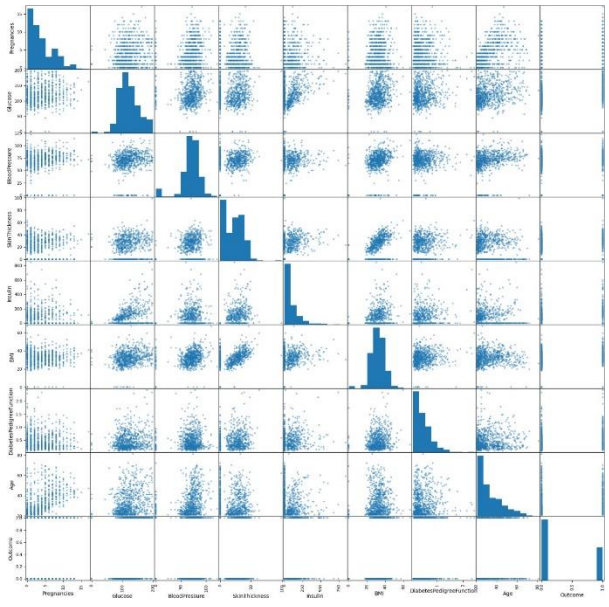
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.1e+03. This might indicate that there arestrong 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_matrixpyplot.rcParams['figure.figsize'] = [20, 20] # Plotting Scatterplot Matrix scatter_matrix(df)
pyplot.show()
```



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

EXPERIMENT NO. 3 A (Group A)

- **Aim**: Implementation of Support Vector Machines (SVM) for classifying images of handwritten digits into theirrespective 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, itcan 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 analysiscan 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, itcan 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. Classificationalgorithms 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 toappeal 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 investmentdecisions.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 agricultureand logistics.

Classification Analysis Techniques

This analysis is a powerful technique used in data science to analyse and categorise data. Classification techniquesare 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, andmore. 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 distinguishbetween 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 segmentcustomers 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 fortasks 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_digitsdigits = 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\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.]])
```

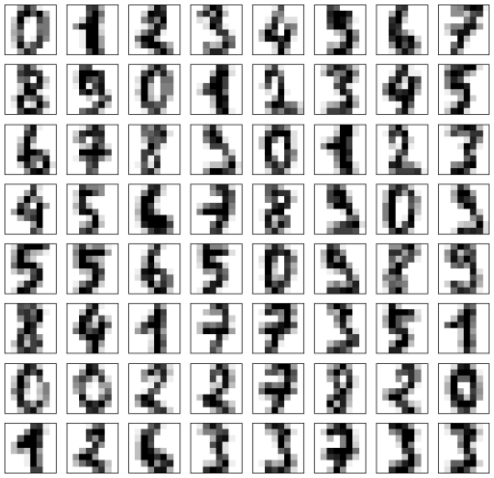
```
digits['target'][0:9]
```

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

```
digits.images[0]
```

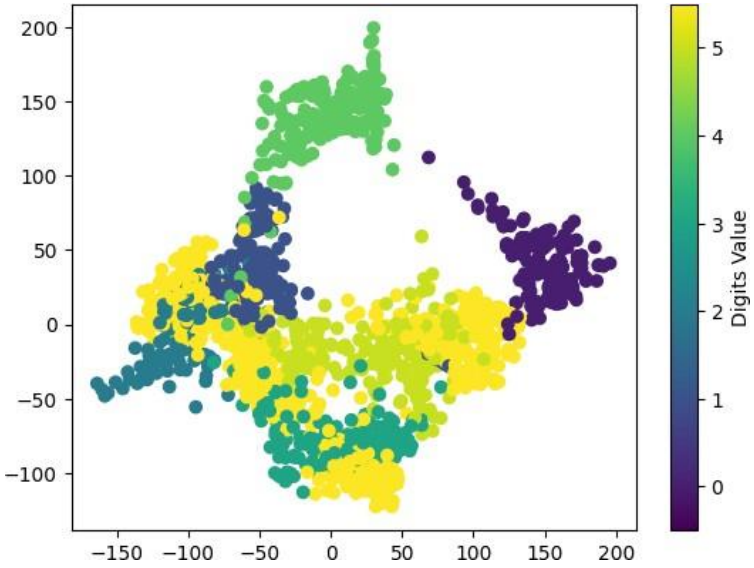
```
array([[ 0.,  0.,  5., 13.,  9.,  1.,  0.,  0.],
                        [ 0.,  0., 13., 15., 10., 15.,  5.,  0.],
                        [ 0.,  3., 15.,  2.,  0., 11.,  8.,  0.],
                        [ 0.,  4., 12.,  0.,  0.,  8.,  8.,  0.],
                        [ 0.,  5.,  8.,  0.,  0.,  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 Isomapiso = 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: Changingthe sparsity structure of a csr_matrix is expensive. lil_matrix is more efficient.
self._set_intXint(row, col, x.flat[0])
```

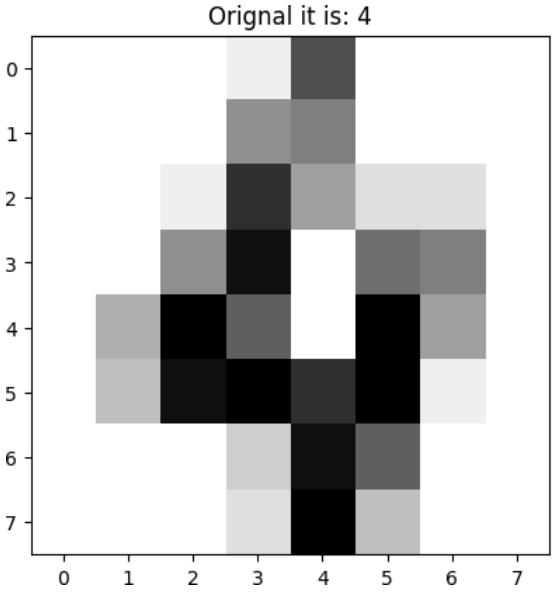



```
print(projection[:, 0][70], projection[:, 1][70])
```

-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:]))
```

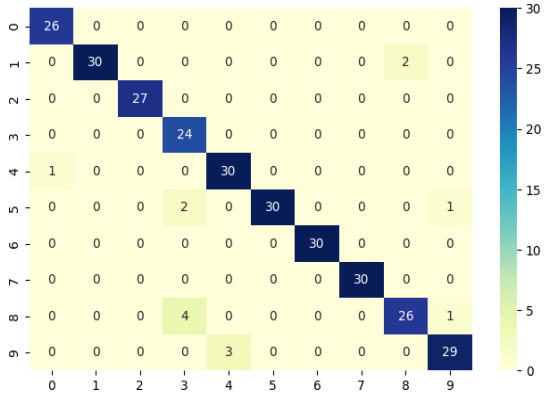
```
[(7, 7),
(4, 4),
(6, 6),
(3, 3),
(1, 1),
(3, 3),
(9, 9),
(1, 1),
(7, 7),
(6, 6),
(8, 8),
(9, 9),
(0, 0),
(1, 1),
(2, 2),
(3, 3),
(4, 4),
(5, 5),
(6, 6),
(7, 7),
(8, 8),
(9, 9),
(0, 0),
(1, 1),
(2, 2),
(8, 3),
(4, 4),
(5, 5),
(6, 6),
(7, 7),
(8, 8),
(8, 8),
(4, 4),
(3, 3),
(1, 1),
(4, 4),
(0, 0),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

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

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

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
   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-II :Quantum AI
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 4 A (Group A)

- **Aim**: 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

- **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 assumesthat the number of clusters are already known. It is also called flat clustering algorithm. The number of clustersidentified 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 distancebetween 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 assignmentof 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 ofeach 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 standardizethe 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 usedifferent 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 objectdata

	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 5.1 3.5 1.4 0.2
SepalWidthCm Iris-setosa
PetalLengthCm
PetalWidthCm Species 0 1

1	24.9	3.0	1.4	0.2	Iris-setosa
2	34.7	3.2	1.3	0.2	Iris-setosa
3	44.6	3.1	1.5	0.2	Iris-setosa
4	55.0	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)

150150

Checking the dimensions/shape of the dataset using shape.data.shape

(150, 6)

Viewing Column names of the dataset using columnsdata.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 SepalLengthCmColumn number 3 is SepalWidthCm Column number 4 is

PetalLengthCmColumn 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 float64SepalWidthCm float64PetalLengthCm 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 valuesdata.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' columnn 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

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 dataTarget 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: objectTraining data

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

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
0		5.13.5	1.4	0.2
1		4.93.0	1.4	0.2
2		4.73.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4		5.03.6	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) andthen 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 bestvalue 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 ofclusters (K Value) to figure out the optimal number of clusters value.

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

```
from sklearn.cluster import KMeanswcss=[]
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 tovisualize 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 columnclusters = 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-II :Quantum AI
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 5 B (Group A)

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 dataand features. Each decision tree is like an expert, providing its opinion on how to classify the data. Predictions aremade 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_digitsdigits = 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    89  ...   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 0.06.0  13.0  10.0  0.0  0.0  0.0
                     1 0.00.0  11.0 16.0  10.0  0.0  0.0
                     2 0.00.0  3.0 11.0  16.0  9.0  0.0
                     3 0.07.0  13.0  13.0  9.0  0.0  0.0
                     4 0.00.0  2.0  16.0  4.0  0.0  0.0

 [5 rows x 64 columns] df['target'] = digits.targetdf[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  13.05.0     0.00.0     0.0 0.0  ...  0.0  0.00.0
                    2  0.0  0.0  0.0      4.0 15.012.0    0.00.0     0.0 0.0  ...  0.0  0.00.0
                    3  0.0  0.0  7.0    15.0  13.01.0     0.00.0     0.0 8.0  ...  0.0  0.00.0
                    4  0.0  0.0  0.0      1.0 11.00.0     0.00.0  0.0 0.0  ...  0.0    0.00.0
                    5  0.0  0.0   12.0   10.0  0.00.0    0.0 0.0  0.0  0.0  ...  0.0  0.0  0.0
                    6  0.0  0.0  0.0    12.0  13.00.0    0.0 0.0  0.0  0.0  ...  0.0  0.0  0.0
                    7  0.0  0.0  7.0      8.0 13.016.0  15.0  1.0  0.0  0.0  ...  0.0  0.0  0.0
                    8  0.0  0.0  9.0    14.0   8.01.0    0.0 0.0  0.0  0.0  ...  0.0  0.0  0.0
                    9  0.0  0.0   11.0   12.0  0.00.0    0.0 0.0  0.0  2.0  ...  0.0  0.0  0.0
                   10  0.0 0.0    1.0    9.0 15.011.0  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 RandomForestClassifiermodel =
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_matrixcm = 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 pltimport 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 inPython by using following tasks Setting up the environment Defining the Tic-Tac-Toe game Building the reinforcement learning model Training the model Testing the model
Roll No.	
Class	BE
Date of Completion	
Subject	Computer Laboratory-II :Quantum AI
Assessment Marks	
Assessor's Sign	

EXPERIMENT NO. 6 C (Group A)

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 valuesto 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 avoidthe negative and seek the positive. This learning method has been adopted in artificial intelligence (AI) as a wayof 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 theagent 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 Truereturn 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_rateself.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 Nonemax_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 += 1else:
       agent2_wins += 1break
 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 currentgame 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 onthe 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 theexploration-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 thereward received.

evaluate_agents:

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

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-II :Quantum AI
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 datafor 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 fora specific location.
3. Extract relevant weather attributes such as temperature, humidity, wind speed, andprecipitation from the API response.
4. Clean and preprocess the retrieved data, handling missing values or inconsistentformats.
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, orscatter plots, to represent temperature changes, precipitation levels, or wind speed variations.
7. Apply data aggregation techniques to summarize weather statistics by specific timeperiods (e.g., daily, monthly, seasonal).
8. Incorporate geographical information, if available, to create maps or geospatialvisualizations representing weather patterns across different locations.
9. Explore and visualize relationships between weather attributes, such as temperatureand 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

- **Theory:**

What is a Web API?

- **Web API** (Application Programming Interface) is a set of rules and protocols that allows different software applications to communicate with each other over the web. It provides a standardized way for software to request and exchange data.

How Web APIs Work:

- **Requests and Responses:** Communication with a web API typically involves sending HTTP requests to a server and receiving HTTP responses. The request specifies the desired data or action, while the response contains the data or confirmation of the action.
- **Endpoints:** APIs consist of various endpoints, which are specific URLs that define where and how you can interact with the API to get or send data.
- **Methods:** Common HTTP methods used in APIs include GET (retrieve data), POST (send data), PUT (update data), and DELETE (remove data).

OpenWeatherMap API

1. **Overview:**
- OpenWeatherMap provides weather data, including current conditions, forecasts, and historical data. The API enables developers to integrate weather information into their applications or services.
2. **Key Features:**
- **Current Weather Data:** Provides real-time weather information for specific locations, including temperature, humidity, wind speed, and weather conditions.
- **Forecast Data:** Offers short-term (hourly) and long-term (daily) weather forecasts.
- **Historical Data:** Gives past weather data for analysis and comparison.
3. **Interacting with OpenWeatherMap API:**
- **API Key:** To use the OpenWeatherMap API, you need an API key, which is a unique identifier that allows you to authenticate requests.
- **Endpoints:** Examples of endpoints include /weather for current weather data and /forecast for weather forecasts. Each endpoint requires specific parameters, such as location (city name or coordinates) and the API key.
- **Parameters:** Requests to the API often need parameters like city name, geographic coordinates, or the desired units of measurement (e.g., Celsius or Fahrenheit).
4. **Response Format:**
- The API typically returns data in JSON format, which is a lightweight and easy-to-parse format for structured data. JSON responses include various fields such as temperature, weather description, and timestamps.
5. **Usage and Analysis:**

- **Data Extraction:** Extract the relevant data from the JSON response, such as temperature trends or weather conditions.
- **Visualization:** Use tools and libraries (like Python's Matplotlib or JavaScript's D3.js) to visualize weather data, such as creating graphs or charts to display temperature changes over time.
- **Insights:** Analyze weather patterns to derive insights, such as identifying trends or making weather-related decisions.

By understanding these concepts, you can effectively interact with the OpenWeatherMap API to retrieve and analyze weather data for various applications, from simple weather apps to more complex data-driven analyses.

Implementation:

```
import requests
import pandas as pdimport datetime

# Set your OpenWeatherMap API key
 api_key = 'fb365aa6104829b44455572365ff3b4e'Get the lat(itude) and lon(gitude)

# Set the location for which you want to retrieve weather datalat = 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 APIresponse = 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 dataweather_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 indexweather_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 dataprint(weather_df)
```

Timestamp	Temperature	humidity	wind_speed	weather_description
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 gpdimport folium

# Set your OpenWeatherMap API key
api_key = 'fb365aa6104829b44455572365ff3b4e'

# Specify the locations for which you want to retrieve weather datalocations = ['London', 'Paris', 'New
York']
weather_df = pd.DataFrame()
# Retrieve weather data for each locationfor 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 APIresponse = 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 datalocation_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
willbe 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
willbe 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  Longitude0       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 locationweather_map =
world_map.merge(weather_df, on='Location')

# Create a folium map centered around the mean latitude and longitude of all locationsmap_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 mapfor 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 mapweather_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-II :Quantum AI
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 companyand 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 contributeto 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

Theory:

1. **Data Cleaning:**
   - **Purpose:** Data cleaning involves identifying and correcting errors or inconsistencies in the data to improve its quality and ensure accuracy. Clean data is essential for reliable analysis and decision-making.
   - **Common Tasks:**

- **Handling Missing Values:** Missing data can be addressed by imputation (filling in missing values) or by removing incomplete records, depending on the context and the amount of missing data.
- **Removing Duplicates:** Duplicate records can skew results and should be identified and removed.
- **Correcting Errors:** Data entry errors, inconsistencies, and typos need to be corrected to ensure data integrity.
- **Standardizing Formats:** Consistent formatting of data (e.g., dates, categorical values) is necessary for accurate analysis.

2. **Data Preparation:**

- **Purpose:** Data preparation involves transforming raw data into a format suitable for analysis. This step includes organizing, structuring, and enriching data to support effective analytical processes.
- **Common Tasks:**

- **Data Transformation:** This includes normalization (scaling numeric values), encoding categorical variables (e.g., converting categories into numerical values), and creating derived features (e.g., calculating customer tenure from join dates).
- **Data Integration:** Combining data from multiple sources (e.g., CRM systems, billing databases) to create a comprehensive dataset.
- **Feature Engineering:** Creating new features that can help improve the performance of analytical models. For example, calculating the average monthly spend or identifying usage patterns.
- **Splitting Data:** Dividing data into training and testing sets for model evaluation.

Analyzing Customer Churn

1. **Understanding Customer Churn:**

- **Definition:** Customer churn refers to the loss of customers over time. In telecommunications, churn might be defined as the percentage of customers who cancel their service within a specific period.
- **Impact:** High churn rates can significantly impact revenue and profitability, making it crucial to understand and address the reasons behind customer attrition.

2. **Data Requirements:**

- **Customer Demographics:** Information about customer age, gender, location, etc.
- **Service Usage:** Details about how customers use services, including call duration, data usage, and service types.
- **Billing Information:** Records of payments, outstanding balances, and billing cycles.
- **Customer Interaction:** Data on customer interactions with support, complaints, and service requests.

3. **Analytical Techniques:**

- **Exploratory Data Analysis (EDA):** Analyzing patterns, trends, and relationships in the data to understand factors influencing churn.
- **Predictive Modeling:** Using statistical and machine learning models to predict which customers are likely to churn. Common algorithms include logistic regression, decision trees, and random forests.
- **Churn Segmentation:** Identifying different segments of customers who are at risk of churning and understanding the unique characteristics of each segment.

4. **Actionable Insights:**

- **Retention Strategies:** Based on analysis, develop strategies to improve customer retention, such as personalized offers, targeted marketing campaigns, or enhanced customer support.
- **Performance Metrics:** Monitor metrics like churn rate, retention rate, and customer lifetime value to evaluate the effectiveness of retention strategies.

In summary, data cleaning and preparation are critical for ensuring that the data used in churn analysis is accurate and reliable. By carefully cleaning and preparing the data, and applying appropriate analytical techniques, telecommunications companies can gain valuable insights into customer churn and develop strategies to reduce it.

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 modelssplit 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)
```

```
Expl ore the datasetprint(data)
```

```
tenure \      customerID  gender  SeniorCitizen Partner Dependents
        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             NoNo phone service             DSL             No  ...
                1            YesNo                           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 \
Yes          Electronic check          29.85          29.85
No           Mailed check              56.95          1889.5
2             Yes          Mailed check 53.85          108.15
No  Bank transfer (automatic)           42.30          1840.75
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         No34         Yes
                2  3668-QPYBK    Male                  0    No         No2          Yes
                3  7795-CFOCW Male                     0    No         No45      No
                 4  9237-HQITU Female                  0    No         No2       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          NoNo                 NoMonth-to-month         Yes
                1          NoNo                 NoOne year               No
                2          NoNo                 NoMonth-to-month         Yes
                3          Yes          No          No          One year              No
                4          NoNo                 NoMonth-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 \
                  70386840-RESVB  Male                  0Yes          Yes24
                  70392234-XADUH  Female                0Yes          Yes72
                  70404801-JZAZL  Female                0Yes          Yes11
                  70418361-LTMKD Male                   1Yes           No4
```

```
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
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 valuesdata.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 thesame 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: 7043data.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 visualizationsns.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-II :Quantum AI
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 averagesale prices by neighborhood or property type.
7. Identify and handle outliers or extreme values in the data that may affect the analysisor 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

- **Theory:**

In this lab experiment, students will engage in data wrangling activities focusing on the real estate market. The primary objective is to clean, transform, and organize raw real estate data to make it suitable for analysis. This process involves handling missing values, correcting inconsistencies, transforming data types, and deriving new variables. Students will utilize various data wrangling techniques and tools to prepare the dataset for further analysis, such as predictive modeling or market trend analysis.

Objectives:

1. Understand the importance and process of data wrangling in data analysis.
2. Gain hands-on experience with data cleaning, transformation, and integration techniques.
3. Learn to handle real-world data challenges, such as missing values, outliers, and inconsistent data.
4. Prepare a clean and well-structured dataset suitable for analysis and modeling in the real estate market.

Tasks:

1. **Data Import:** Import raw real estate data from various sources, such as CSV files, databases, or APIs.
2. **Data Cleaning:** Identify and handle missing values, remove duplicates, and correct inconsistent entries.
3. **Data Transformation:** Convert data types, normalize data, and create new variables through feature engineering.
4. **Data Integration:** Merge data from multiple sources to create a comprehensive dataset.
5. **Exploratory Data Analysis (EDA):** Perform initial analysis to understand the data distribution, identify patterns, and gain insights.
6. **Documentation:** Document the data wrangling process, including the steps taken and decisions made during data cleaning and transformation.

Tools and Technologies:

- Python (Pandas, NumPy)
- Jupyter Notebook
- SQL (for database integration)
- Data visualization tools (Matplotlib, Seaborn)

By the end of this lab experiment, students will be equipped with practical skills in data wrangling, essential for any data analysis or data science project. The cleaned and structured real estate dataset will serve as a foundation for further analysis, such as price prediction models or market trend analysis.

Implementation:

```
Import  pandas as pdimport numpy as np

from matplotlib import pyplot as plt
%matplotlib inlineimport 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: objectdf1['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: int64df2.shape (13320, 5)

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

location	0
size	0
total_sqft	0
bath	0

price 0

dtype: int64df3.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 Bedroom2400 40.0 660.0 43df3.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 Falsereturn 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]))/2try:

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 2100-2850df4.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 feetdf5 = 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	34	
	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+03std 1.067272e+05 min 2.678298e+02
25% 4.267701e+03

50% 5.438331e+03

75% 7.317073e+03max 1.200000e+07

Name: price_per_sqft, dtype: float64df5.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: int64len(location_stats[location_stats>10])

240

len(location_stats)1287

len(location_stats[location_stats<=1 0])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 10Gunjur 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: int64len(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-copydf6.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 featureIQR = 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 featureIQR = 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 featureIQR = 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-copydf6.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 featureQ3 =

```
np.percentile(df6['price_per_sqft'], 75.) # 75th percentile of the data of the given featureIQR = 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 = Trueif 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    1440.02.0  3     4305.555556
  3                       Lingadheeranahalli  3       1521.03.0  3     6245.890861

 X.shape (10090, 6)

y = df6.pricey.head(3)

                    0       39.07
                        2   62.00
                        3   95.00
  Name: price, dtype: float64len(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-II :Quantum AI
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 matplotliblibrary 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, pollutantlevels, 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 tovisualize their trends over time.
6. Use bar plots or stacked bar plots to compare the AQI values across different dates ortime periods.
7. Create box plots or violin plots to analyze the distribution of AQI values for differentpollutant categories.
8. Use scatter plots or bubble charts to explore the relationship between AQI values andpollutant levels.
9. Customize the visualizations by adding labels, titles, legends, and appropriate colorschemes.

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 this lab experiment, students will explore data visualization techniques using Matplotlib to analyze Air Quality Index (AQI) trends in a specific city. The primary objective is to learn how to effectively visualize time-series data and other relevant variables to gain insights into air quality trends over time. Students will practice creating various types of plots and graphs to represent AQI data and interpret the visualizations to understand the underlying patterns.

Objectives:

1. Understand the importance of data visualization in data analysis and interpretation.
2. Gain proficiency in using Matplotlib for creating various types of visualizations.
3. Analyze and visualize AQI trends to identify patterns, anomalies, and seasonal variations.
4. Develop skills in presenting data insights through clear and informative visualizations.

Tasks:

1. **Data Collection:** Obtain historical AQI data for a specific city from a reliable source (e.g., government websites, Kaggle datasets).
2. **Data Preparation:** Clean and preprocess the data, ensuring it is in a suitable format for visualization.
3. **Exploratory Data Analysis (EDA):** Conduct initial analysis to understand the data distribution and identify key variables.
4. **Time-Series Visualization:** Create line plots to visualize AQI trends over time, highlighting significant changes and patterns.
5. **Seasonal Analysis:** Use bar charts or box plots to analyze seasonal variations in AQI.
6. **Correlation Analysis:** Create scatter plots to examine relationships between AQI and other variables, such as temperature or humidity.
7. **Geospatial Visualization (Optional):** Use heatmaps or geographical plots to visualize AQI distribution across different regions of the city.
8. **Data Annotation:** Enhance visualizations with annotations, legends, and titles to improve clarity and interpretability.
9. **Documentation:** Document the data visualization process, including the steps taken, visualizations created, and insights derived.

Tools and Technologies:

- Python
- Matplotlib
- Pandas (for data manipulation)
- Jupyter Notebook

By the end of this lab experiment, students will have practical experience in using Matplotlib to create informative and aesthetically pleasing visualizations. They will be able to analyze AQI trends, identify patterns, and present their findings through effective visual representations, which are crucial skills in data science and analytics.

Implementation:

```
import numpy as np import pandas as pd
import matplotlib.pyplot as pltimport 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 theseNaNs by either removing them or filling them. I will be doing both.

```
# checking the original datasetprint(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 49004Data 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	objectdtypes: 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 makeit 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 wedrop 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 formatprint(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
              statelocation 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
  49004NaN
```

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. Informationabout 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 seethat 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 tooverall)
def yearly_trend(state="", indicator="so2", ):plt.figure(figsize=(20,12))
data['year'] = data.date.dt.yearif 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()
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)
    # we're accessing the attribute of the class, i.e., Dataset.geo
    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 WestBengal, 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_table8730
-> 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 indicatordef 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 statedef 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-II :Quantum AI
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. Itincludes 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 andidentify 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, salesamount, 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 salesamount for each combination.
8. Create stacked bar plots or grouped bar plots to compare the sales amounts acrossdifferent 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

Theory:

In this lab experiment, students will learn about data aggregation techniques to analyze sales performance by region in a retail company. The primary objective is to aggregate and summarize sales data to identify

regional performance trends, highlight top-performing regions, and uncover potential areas for improvement. Students will gain hands-on experience in grouping and summarizing data using various aggregation methods and tools.

Objectives:

1. Understand the concept and importance of data aggregation in data analysis.
2. Learn how to aggregate and summarize data to derive meaningful insights.
3. Analyze sales performance data to identify trends and patterns across different regions.
4. Develop skills in using data aggregation techniques to support business decision-making.

Tasks:

1. **Data Collection:** Obtain sales data for a retail company, including sales figures, product categories, and regional information.
2. **Data Preparation:** Clean and preprocess the data to ensure it is suitable for aggregation.
3. **Grouping Data:** Group sales data by region to facilitate aggregation and analysis.
4. **Aggregation Techniques:** Use various aggregation functions (e.g., sum, mean, median) to summarize sales data by region.
5. **Performance Metrics:** Calculate key performance metrics such as total sales, average sales, and sales growth rates for each region.
6. **Trend Analysis:** Analyze trends in sales performance across different regions and time periods.
7. **Visualization:** Create visualizations (e.g., bar charts, pie charts, heatmaps) to represent aggregated sales data and highlight regional performance.
8. **Comparison:** Compare the performance of different regions and identify top-performing and underperforming areas.
9. **Documentation:** Document the data aggregation process, including the steps taken, methods used, and insights derived.

Tools and Technologies:

- Python
- Pandas (for data manipulation and aggregation)
- Jupyter Notebook
- Data visualization tools (Matplotlib, Seaborn)

By the end of this lab experiment, students will be proficient in data aggregation techniques and capable of analyzing sales performance data to support business decisions. They will be able to aggregate and summarize data effectively, create insightful visualizations, and provide recommendations based on their analysis. These skills are essential for data analysts and business intelligence professionals.

Implementation:

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

Data Aggregation is important for deriving granular insights about individual customers and for betterunderstanding 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 understandits 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, paymentmethods, 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 assignedto 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 5.01500.40

1 I317333 C111565 Male 21 Shoes 3.0 1800.51

2 I127801 C266599 Male 20 Clothing 1.0300.08

3 I173702 C988172 Female 66 Shoes 5.0 3000.85

4 I337046 C189076 Female 53 Books 4.060.60

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 AVM4 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 13491349 13491349

Emaar Square Mall 1341 13411341 1341 1341 1341

Forum Istanbul 1343 1343 13431343 13431343

Istinye Park 2709 2709 27092709 27092709

Kanyon	5481	5481	54815481	54815481			
Mall of Istanbul	5588	5588	55885588	55885588			
Metrocity	4193	4193	41934193	4193	4193		
Metropol AVM	2856	2856	28562856	2856	2856		
Viaport Outlet	1389	1389	13891389	1389	1389		
Zorlu Center	1392	1392	13921392	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	13971397	1397	1397
Clothin	1	1	1 1	0	0
Clothing	9433	9433	94339433	9433	9433
Cosmetics	4224	4224	42244224	4224	4224
Food & Beverage	4158	4158	41584158	4158	4158
Shoes	2773	2773	27732773	2773	2773

Souvenir	1402	1402	1402	1402	1402	1402
Technology	1435	1435	1435	1435	1435	1435
Toys	2819	2819	2819	2819	2819	2819

category	payment_method	invoice_date	shopping_mall
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 specifynumeric_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 specifynumeric_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)age quantity price

shopping_mall

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)

age quantity price

category

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
specifynumeric_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()
```