Practical Journal

MACHINE LEARNING

A Practical Report

Submitted in partial fulfillment of the

Requirements for the award of the

Degree

MASTER OF SCIENCE (INFORMATION TECHNOLOGY)

Part 2 – SEM III

Submitted by

Mr. Awan Imran maknojia

Seat No: 1313174

DEPARTMENT OF INFORMATION TECHNOLOGY

VALIA C.L COLLEGE OF COMMERCE & VALIA L.C COLLEGE OF ARTS CES ROAD D.N NAGAR

(Affiliated to University of Mumbai)

MUMBAI, 400053

MAHARASHTRA

2024-2025

VALIA C.L COLLEGE OF COMMERCE & VALIA L.C COLLEGE OF ARTS CES ROAD D.N NAGAR

(Affiliated to

University of Mumbai)

Mumbai- Maharashtra-

400053

DEPARTMENT OF INFORMATION TECHNOLOGY

CERTIFICATE

This is to certify that the practical report of **MACHINE LEARNING** is bonafide work of **Awan Imran maknojia** bearing Seat No: **1313179** submitted in partial fulfilment of the requirements for the award of degree of MASTER OF SCIENCE in INFORMATION TECHNOLOGY from University of Mumbai.

Internal Guide   Coordinator

External Examiner

Date:

College Seal

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PRACTICAL 1

Data Pre-processing and Exploration

(1A) AIM:-Load a CSV dataset. Handle missing values, inconsistent formatting, and outliers.

CODE:-

```
'''Load a CSV dataset. Handle missing values, inconsistent formatting,
and outliers'''
import pandas as pd
import numpy as np
import requests
from io import
StringIO from scipy
import stats

url = 'https://archive.ics.uci.edu/ml/machine-learning-
databases/iris/iris.data'
columns = ['sepal_length', 'sepal_width', 'petal_length',
'petal_width', 'species']
response = requests.get(url)
csv_data =
StringIO(response.text)
df = pd.read_csv(csv_data, header=None, names=columns)

print("Before Data Cleaning:")
print(df.info())
print(df.head())

df_imputed = df.copy()
numeric_cols =
df_imputed.select_dtypes(include=np.number).columns
df_imputed[numeric_cols] =
df_imputed[numeric_cols].fillna(df_imputed[numeric_cols].mean(
))

categorical_cols =
df_imputed.select_dtypes(include='object').columns for col in
categorical_cols:
    df_imputed[col].fillna(df_imputed[col].mode()[0], inplace=True)
```

```
outliers = (z_score> 3)df_cleaned = df_imputed[~np.any(outliers,
axis=1)]

print("\nAfter Data Cleaning:")
print(df_cleaned.info())
print(df_cleaned.head())

print("\nSummary Statistics Before
Cleaning:") print(df.describe())

print("\nSummary Statistics After Cleaning:")
print(df_cleaned.describe())
```

OUTPUT:-

```
PROBLEMS    OUTPUT    DEBUG CONSOLE    TERMINAL    PORTS

After Data Cleaning:
<class 'pandas.core.frame.DataFrame'>
Index: 149 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   sepal_length  149 non-null    float64
 1   sepal_width   149 non-null    float64
 2   petal_length  149 non-null    float64
 3   petal_width   149 non-null    float64
 4   species       149 non-null    object
dtypes: float64(4), object(1)
memory usage: 7.0+ KB
None
   sepal_length  sepal_width  petal_length  petal_width      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

Summary Statistics Before Cleaning:
       sepal_length  sepal_width  petal_length  petal_width
count    150.000000   150.000000    150.000000   150.000000
mean       5.843333     3.054000      3.758667     1.198667
std        0.828066     0.433594      1.764420     0.763161
min        4.300000     2.000000      1.000000     0.100000
25%        5.100000     2.800000      1.600000     0.300000
50%        5.800000     3.000000      4.350000     1.300000
75%        6.400000     3.300000      5.100000     1.800000
max        7.900000     4.400000      6.900000     2.500000

Summary Statistics After Cleaning:
       sepal_length  sepal_width  petal_length  petal_width
count    149.000000   149.000000    149.000000   149.000000
mean       5.844295     3.044966      3.773826     1.204027
std        0.830775     0.420655      1.760543     0.762896
min        4.300000     2.000000      1.000000     0.100000
25%        5.100000     2.800000      1.600000     0.300000
50%        5.800000     3.000000      4.400000     1.300000
75%        6.400000     3.300000      5.100000     1.800000
max        7.900000     4.200000      6.900000     2.500000
```

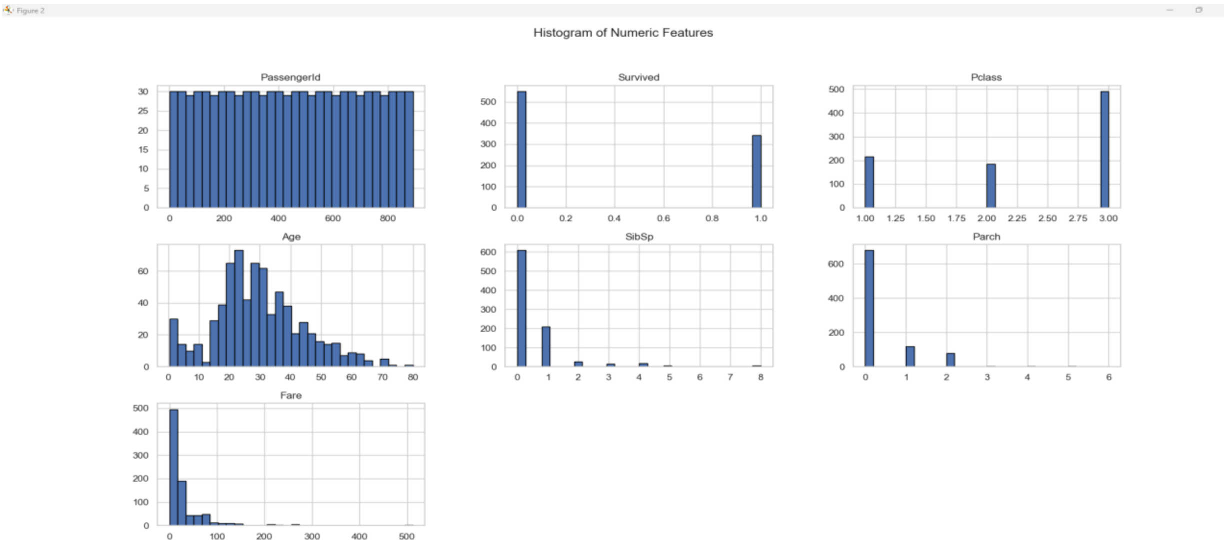
(1B) AIM:- Load a dataset, calculate descriptive summary statistics, create visualizations using different graphs, and identify potential features and target variables.

CODE:-

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

def
    load_dataset(file_url
    ): try:
        data = pd.read_csv(file_url)
        print("Dataset loaded successfully!")
        return data
    except Exception as e:
        print(f"Error loading dataset: {e}")

def descriptive_statistics(data): print("\
    nDescriptive Statistics:")
    print(data.describe(include='all'))
    print("\nMissing Values in Each
    Column:") print(data.isnull().sum())

def create_visualizations(data):
    sns.set(style="whitegrid")

    plt.figure(figsize=(10, 6))
    data.hist(bins=30, edgecolor='black', figsize=(12,
    10)) plt.suptitle('Histogram of Numeric Features')
    plt.show()

    plt.figure(figsize=(10,
    6))
    sns.boxplot(data=data)
    plt.title('Box Plot of Numeric
    Features') plt.show()

    plt.figure(figsize=(10, 6))
    sns.heatmap(data.corr(), annot=True, cmap='coolwarm',
    linewidths=0.5) plt.title('Correlation Heatmap of Numeric Features')
    plt.show()

    plt.figure(figsize=(10,
```

```
    plt.show()

def main():
    file_url =
'https://raw.githubusercontent.com/datasciencedojo/datasets/master/
titanic.csv '
    data = load_dataset(file_url)

    if data is not None:
        descriptive_statistics(data)
        create_visualizations(data)

if _name_== "_main_":
    main()
```

OUTPUT:-



```
PROBLEMS    OUTPUT    DEBUG CONSOLE    TERMINAL    PORTS

PS D:\Viqar\Machine learning> python -u "d:\Viqar\Machine learning\Practical 1b.py"
Dataset loaded successfully!

Descriptive Statistics:
        PassengerId    Survived      Pclass                     Name   Sex         Age       SibSp       Parch  Ticket        Fare    Cabin Embarked
count    891.000000  891.000000  891.000000                      891   891  714.000000  891.000000  891.000000     891  891.000000      204      889
unique          NaN         NaN         NaN                      891     2         NaN         NaN         NaN     681         NaN      147        3
top             NaN         NaN         NaN  Braund, Mr. Owen Harris  male         NaN         NaN         NaN  347082         NaN  B96 B98        S
freq            NaN         NaN         NaN                        1   577         NaN         NaN         NaN       7         NaN        4      644
mean     446.000000    0.383838    2.308642                      NaN   NaN   29.699118    0.523008    0.381594     NaN   32.204208      NaN      NaN
std      257.353842    0.486592    0.836071                      NaN   NaN   14.526497    1.102743    0.806057     NaN   49.693429      NaN      NaN
min        1.000000    0.000000    1.000000                      NaN   NaN    0.420000    0.000000    0.000000     NaN    0.000000      NaN      NaN
25%      223.500000    0.000000    2.000000                      NaN   NaN   20.125000    0.000000    0.000000     NaN    7.910400      NaN      NaN
50%      446.000000    0.000000    3.000000                      NaN   NaN   28.000000    0.000000    0.000000     NaN   14.454200      NaN      NaN
75%      668.500000    1.000000    3.000000                      NaN   NaN   38.000000    1.000000    0.000000     NaN   31.000000      NaN      NaN
max      891.000000    1.000000    3.000000                      NaN   NaN   80.000000    8.000000    6.000000     NaN  512.329200      NaN      NaN

Missing Values in Each Column:
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

(1C) AIM:- Create or Explore datasets to use all pre-processing routines like label encoding, scaling, and binarization.

CODE:-

```
import pandas as pd
from sklearn.preprocessing import LabelEncoder, MinMaxScaler, Binarizer

def load_dataset(url):
    try:
        return
    pd.read_csv(url) except
    Exception as e:
        print(f"Error loading dataset: {e}")
        return None

def preprocess_data(data):
    numeric_cols = data.select_dtypes(include=['number']).columns
    data[numeric_cols] =
    data[numeric_cols].fillna(data[numeric_cols].mean()) for col in
    data.select_dtypes(include='object').columns:
        data[col] =
    LabelEncoder().fit_transform(data[col].astype(str)) scaler =
    MinMaxScaler()
    data[numeric_cols] =
```

```
def main():
    url =
'https://raw.githubusercontent.com/datasciencedojo/datasets/master/
titanic.csv '
    data =
    load_dataset(url) if
    data is not None:
        print("Original
        Data:")
        print(data.head())
        data = preprocess_data(data) print("\
   _    nPreprocessed Data:") print(data.head())

if name_== "_main_":
    main()
```

OUTPUT:-

```
PROBLEMS   OUTPUT   DEBUG CONSOLE   TERMINAL   PORTS

PS D:\Viqar\Machine learning> python -u "d:\Viqar\Machine learning\Practical 1c.py"
Original Data:
   PassengerId  Survived  Pclass                                               Name     Sex   Age  SibSp  Parch            Ticket     Fare Cabin Embarked
0            1         0       3                            Braund, Mr. Owen Harris    male  22.0      1      0         A/5 21171   7.2500   NaN        S
1            2         1       1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1      0          PC 17599  71.2833   C85        C
2            3         1       3                             Heikkinen, Miss. Laina  female  26.0      0      0  STON/O2. 3101282   7.9250   NaN        S
3            4         1       1       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1      0            113803  53.1000  C123        S
4            5         0       3                           Allen, Mr. William Henry    male  35.0      0      0            373450   8.0500   NaN        S

Preprocessed Data:
   PassengerId  Survived  Pclass  Name  Sex  Age  SibSp  Parch  Ticket  Fare  Cabin  Embarked
0          0.0       0.0     1.0   108    1  0.0    0.0    0.0     523   0.0    147         2
1          0.0       1.0     0.0   190    0  0.0    0.0    0.0     596   0.0     81         0
2          0.0       1.0     1.0   353    0  0.0    0.0    0.0     669   0.0    147         2
3          0.0       1.0     0.0   272    0  0.0    0.0    0.0      49   0.0     55         2
4          0.0       0.0     1.0    15    1  0.0    0.0    0.0     472   0.0    147         2
```

PRACTICAL 2

Testing Hypothesis

AIM:- Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data samples. Read the training
data from a. CSV file and generate the final specific hypothesis.

CODE:-

```
import pandas as pd

def find_s_algorithm(data, target_column):
    specific_hypothesis = ['Ø'] * (len(data.columns) -
    1) for _, row in data.iterrows():
        if row[target_column] == "Yes":
            for i in
                range(len(specific_hypothesis)):
                if specific_hypothesis[i] == 'Ø':
                    specific_hypothesis[i] =
                row.iloc[i] elif specific_hypothesis[i]
                != row.iloc[i]:
                    specific_hypothesis[i] =
    '?' return specific_hypothesis

def main():
    dataset = {
        'Sky': ['Sunny', 'Sunny', 'Rainy', 'Sunny', 'Sunny'],
        'Temp': ['Warm', 'Warm', 'Cold', 'Warm', 'Warm'],
        'Humidity': ['Normal', 'High', 'High', 'High', 'Normal'],
        'Wind': ['Strong', 'Strong', 'Strong', 'Strong', 'Strong'],
        'Water': ['Warm', 'Warm', 'Cold', 'Warm', 'Warm'],
        'Forecast': ['Same', 'Same', 'Change', 'Same', 'Same'],
        'EnjoySport': ['Yes', 'Yes', 'No', 'Yes', 'Yes']
    }
    df = pd.DataFrame(dataset)
    df.to_csv("training_data.csv",
    index=False) print("Dataset saved to
    training_data.csv")

    data = pd.read_csv("training_data.csv")
    print("\nTraining Data:")
```

```
    print("\nFinal Specific Hypothesis:")
    print(specific_hypothesis)

if _name_== "_main_":
    main()
```

OUTPUT:-

```
PROBLEMS    OUTPUT    DEBUG CONSOLE    TERMINAL    PORTS

PS D:\Viqar\Machine learning> python -u "d:\Viqar\Machine learning\Practical 2.py"
Dataset saved to training_data.csv

Training Data:
     Sky  Temp Humidity    Wind Water Forecast EnjoySport
0  Sunny  Warm   Normal  Strong  Warm     Same        Yes
1  Sunny  Warm     High  Strong  Warm     Same        Yes
2  Rainy  Cold     High  Strong  Cold   Change         No
3  Sunny  Warm     High  Strong  Warm     Same        Yes
4  Sunny  Warm   Normal  Strong  Warm     Same        Yes

Final Specific Hypothesis:
['Sunny', 'Warm', '?', 'Strong', 'Warm', 'Same']
```

PRACTICAL 3

Linear Models

(3A) AIM:- Simple Linear Regression Fit a linear regression model on a dataset. Interpret coefficients, make predictions, and evaluate performance using metrics like R-squared and MSE.

CODE:-

```
import pandas as pd
from sklearn.model_selection import
train_test_split from sklearn.linear_model import
LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

data = {'X': [1, 2, 3, 4, 5], 'Y': [2.2, 4.1, 6.3, 8.2, 10.1]}
df = pd.DataFrame(data)

X =
df[['X']] Y
= df['Y']

X_train, X_test, Y_train, Y_test = train_test_split(X, Y,
test_size=0.4, random_state=42)

model =
LinearRegression()
model.fit(X_train,
Y_train)

intercept = model.intercept_
coefficient = model.coef_[0]

Y_pred = model.predict(X_test)

mse = mean_squared_error(Y_test,

Y_pred) if len(Y_test) > 1:
    r_squared = r2_score(Y_test,
Y_pred) else:
    r_squared = float('nan')  # Set R-squared to NaN if only one test
    sample

print(f"Intercept: {intercept}")
```

OUTPUT:-

```
PROBLEMS    OUTPUT    DEBUG CONSOLE    TERMINAL    PORTS

PS D:\Viqar\Machine learning> python -u "d:\Viqar\Machine learning\Practical 3a.py"
Intercept: 0.2142857142857153
Coefficient: 2.0071428571428567
MSE: 0.01951530612244882
R-squared: 0.9978316326530613
```

(3B) AIM:- Multiple Linear Regression Extend linear regression to multiple features. Handle feature selection and potential multicollinearity.

CODE:-

```
import pandas as pd
from sklearn.model_selection import train_test_split from
sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from statsmodels.stats.outliers_influence import variance_inflation_factor

data = {
        'Feature1':    [1,   2,   3,   4,     5, 6, 7, 8,     9, 10],
        'Feature2':    [2,   4,   6,   8,     10, 12, 14,     16, 18, 20],
        'Feature3':    [1,   3,   2,   4,     3, 5, 6, 7,     8, 9],
    'Target': [3, 7, 5, 9, 11, 15, 17, 21, 23, 27]
}
df = pd.DataFrame(data)

X = df[['Feature1', 'Feature2', 'Feature3']] Y = df['Target']

vif_data = pd.DataFrame()
vif_data['Feature'] = X.columns
vif_data['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]

print("\nVIF for Features:") print(vif_data)

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
```

```
model =
LinearRegression()
model.fit(X_train,
Y_train)

print("\nIntercept:", model.intercept_)
print("Coefficients:", model.coef_)

Y_pred = model.predict(X_test)

print("MSE:", mean_squared_error(Y_test,
```

OUTPUT:-

```
PROBLEMS   OUTPUT   DEBUG CONSOLE   TERMINAL   PORTS

PS D:\Viqar\Machine learning> python -u "d:\Viqar\Machine learning\Practical 3b.py"
C:\Users\91982\AppData\Local\Programs\Python\Python312\Lib\site-packages\statsmodels\stats\outliers_influence.py:197: RuntimeWarning: divide by zero encountered in scalar divide
  vif = 1. / (1. - r_squared_i)

VIF for Features:
    Feature        VIF
0  Feature1        inf
1  Feature2        inf
2  Feature3  69.271726

Intercept: -1.4322344322344325
Coefficients: [0.33846154 0.67692308 1.21611722]
MSE: 1.1180882609454021
R-squared: 0.9825298709227281
PS D:\Viqar\Machine learning>
```

(3C) AIM:- Regularized Linear Models (Ridge, Lasso, ElasticNet) Implement regression variants like LASSO and Ridge on any generated dataset.

CODE:-

```
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import Ridge, Lasso,
ElasticNet from sklearn.metrics import
mean_squared_error, r2_score

np.random.seed(42)
X = np.random.rand(100, 3)
Y = 3 * X[:, 0] - 2 * X[:, 1] + X[:, 2] + np.random.normal(0, 0.1, 100)
X_train, X_test, Y_train, Y_test = train_test_split(X, Y,
test_size=0.2, random_state=42)

ridge_model = Ridge(alpha=1.0)
ridge_model.fit(X_train, Y_train)
```

```
print("Ridge:", ridge_model.coef_, mean_squared_error(Y_test,
ridge_pred), r2_score(Y_test, ridge_pred))

lasso_model = Lasso(alpha=0.1)
lasso_model.fit(X_train, Y_train)
lasso_pred =
lasso_model.predict(X_test)
print("Lasso:", lasso_model.coef_, mean_squared_error(Y_test,
lasso_pred), r2_score(Y_test, lasso_pred))

elasticnet_model = ElasticNet(alpha=0.1,
l1_ratio=0.5) elasticnet_model.fit(X_train,
Y_train) elasticnet_pred =
elasticnet_model.predict(X_test)
print("ElasticNet:", elasticnet_model.coef_, mean_squared_error(Y_test,
```

OUTPUT:-

```
PROBLEMS    OUTPUT    DEBUG CONSOLE    TERMINAL    PORTS

PS D:\Viqar\Machine learning> python -u "d:\Viqar\Machine learning\Practical 3c.py"
Ridge: [ 2.5807138  -1.77414379  0.90149729] 0.04458190346459917 0.958409870406082
Lasso: [ 1.60397718 -0.98933401  0.        ] 0.31614295332261333 0.705072565837569
ElasticNet: [ 1.38765543 -0.98031813  0.22377714] 0.34657204388252 71 0.6766854912296667
PS D:\Viqar\Machine learning> 
```

PRACTICAL 4

Discriminative Models

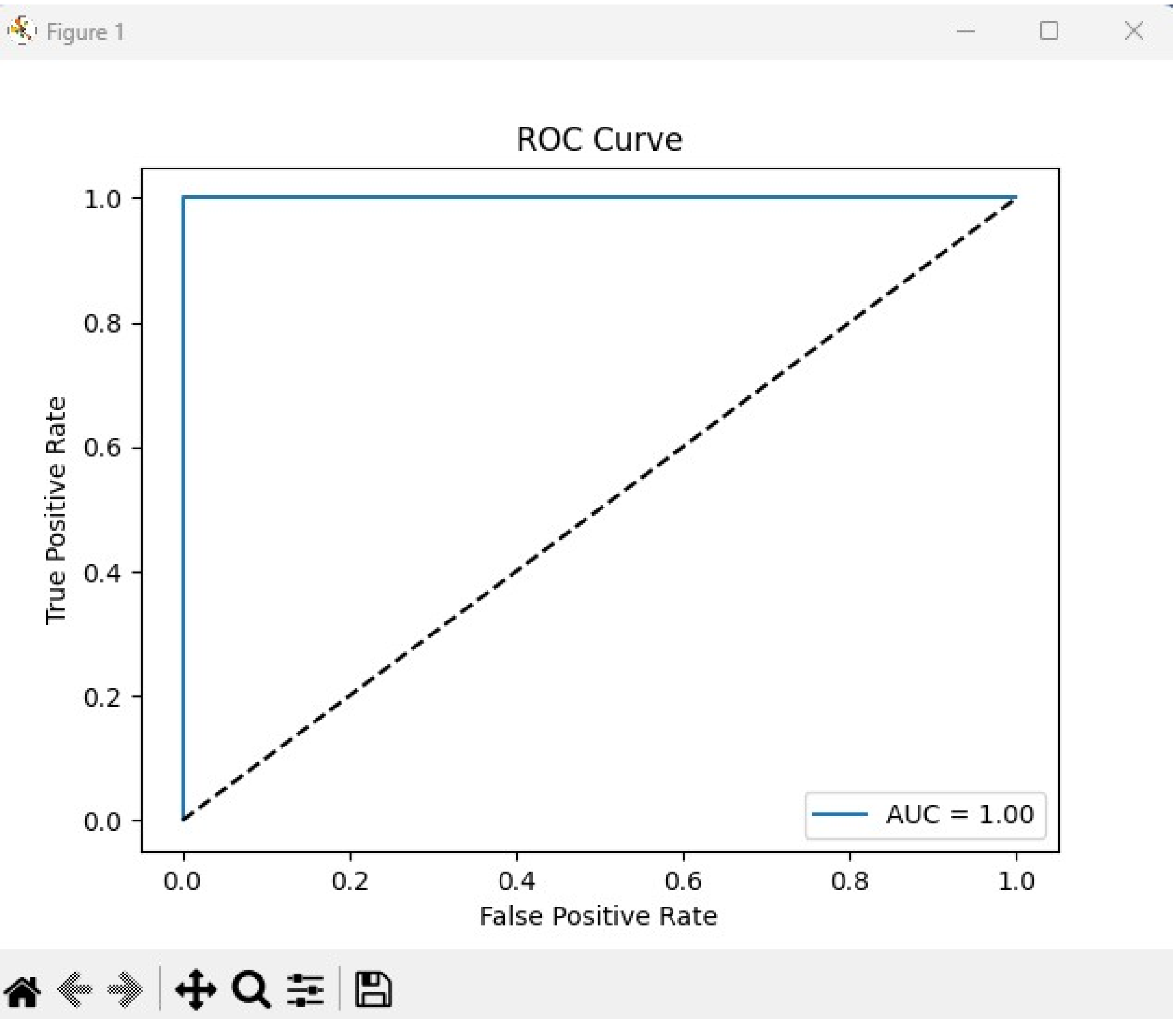
(4A) AIM:- Logistic Regression Perform binary classification using logistic regression. Calculate accuracy, precision, recall, and understand the ROC curve.

CODE:-

```
import numpy as
np import pandas
as pd
from sklearn.model_selection import
train_test_split from sklearn.linear_model import
LogisticRegression
from sklearn.metrics import accuracy_score, precision_score,
recall_score, roc_curve, auc
import matplotlib.pyplot as plt

np.random.seed(42)
X = np.random.rand(100, 2)
Y = (X[:, 0] + X[:, 1] > 1).astype(int)

X_train, X_test, Y_train, Y_test = train_test_split(X, Y,
test_size=0.3, random_state=42)

model = LogisticRegression()
model.fit(X_train, Y_train)

Y_pred = model.predict(X_test)
Y_pred_prob = model.predict_proba(X_test)[:, 1]

print("Accuracy:", accuracy_score(Y_test, Y_pred))
print("Precision:", precision_score(Y_test, Y_pred))
print("Recall:", recall_score(Y_test, Y_pred))

fpr, tpr, _ = roc_curve(Y_test, Y_pred_prob)
plt.plot(fpr, tpr, label=f"AUC = {auc(fpr,
tpr):.2f}") plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel("False Positive
Rate") plt.ylabel("True Positive
Rate") plt.title("ROC Curve")
plt.legend(loc="lower right")
```

OUTPUT:-

```
PROBLEMS   OUTPUT   DEBUG CONSOLE   TERMINAL   PORTS

PS D:\Viqar\Machine learning> python -u "d:\Viqar\Machine learning\tempCodeRunnerFile.py"
Accuracy: 0.8666666666666667
Precision: 1.0
Recall: 0.7333333333333333
```



(4B) AIM:- Implement and demonstrate k-nearest Neighbor algorithm. Read the training data from a
.CSV file and build the model to classify a test sample. Print both correct and wrong predictions.

CODE:-

```
import pandas as pd
import numpy as np
from sklearn.model_selection import
train_test_split from sklearn.preprocessing
import StandardScaler from sklearn.neighbors
import KNeighborsClassifier
from sklearn.metrics import classification_report,
confusion_matrix import urllib.request
import os

url = "https://archive.ics.uci.edu/ml/machine-learning-
databases/iris/iris.data"
dataset_file = "iris.data"

if not os.path.exists(dataset_file):
    urllib.request.urlretrieve(url,
    dataset_file)

columns = ["sepal_length", "sepal_width", "petal_length",
"petal_width", "class"]
data = pd.read_csv(dataset_file, header=None, names=columns)

X = data.iloc[:, :-
1].values y =
data.iloc[:, -1].values

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

scaler = StandardScaler()
X_train =
scaler.fit_transform(X_train) X_test
= scaler.transform(X_test)

k = 3
knn = KNeighborsClassifier(n_neighbors=k)
knn.fit(X_train, y_train)

y_pred = knn.predict(X_test)

conf_matrix = confusion_matrix(y_test,
```

```
print("\nClassification Report:")
print(report)

correct_predictions = np.sum(y_test == y_pred)
incorrect_predictions = np.sum(y_test != y_pred)
print(f"\nCorrect Predictions:
{correct_predictions}") print(f"Incorrect
Predictions: {incorrect_predictions}")

results = pd.DataFrame({"Actual": y_test, "Predicted": y_pred})
print("\nSample Results:")
print(results.head())
```

OUTPUT:-

```
PROBLEMS    OUTPUT    DEBUG CONSOLE    TERMINAL    PORTS

 [ 0  0 11]]

Classification Report:
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        10
Iris-versicolor       1.00      1.00      1.00         9
 Iris-virginica       1.00      1.00      1.00        11

       accuracy                           1.00        30
      macro avg       1.00      1.00      1.00        30
   weighted avg       1.00      1.00      1.00        30


Correct Predictions: 30
Incorrect Predictions: 0

Sample Results:
            Actual        Predicted
0  Iris-versicolor  Iris-versicolor
1      Iris-setosa      Iris-setosa
2   Iris-virginica   Iris-virginica
3  Iris-versicolor  Iris-versicolor
4  Iris-versicolor  Iris-versicolor
```

(4C) AIM:- Build a decision tree classifier or regressor. Control hyperparameters like tree depth to avoid overfitting. Visualize the tree

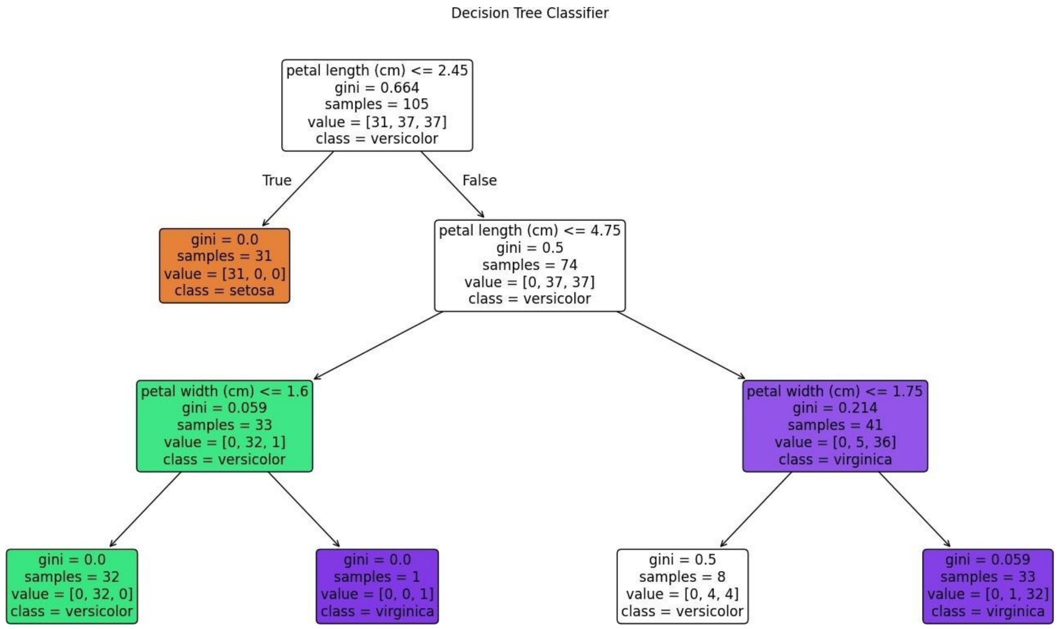
CODE:-

```
import numpy as
np import pandas
as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier,
plot_tree from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt

data = load_iris()
X = data.data
y =
data.target

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

clf = DecisionTreeClassifier(max_depth=3, random_state=42)
clf.fit(X_train, y_train)

y_pred = clf.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy of Decision Tree Classifier: {accuracy:.2f}')

plt.figure(figsize=(12,8))
plot_tree(clf, filled=True,
feature_names=data.feature_names,
class_names=data.target_names, rounded=True)
```

OUTPUT:-

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS

```
PS D:\Viqar\Machine learning> python -u "d:\Viqar\Machine learning\Practical 4C.py"
Accuracy of Decision Tree Classifier: 1.00
```



(4D) AIM:- Implement a Support Vector Machine for any relevant dataset.

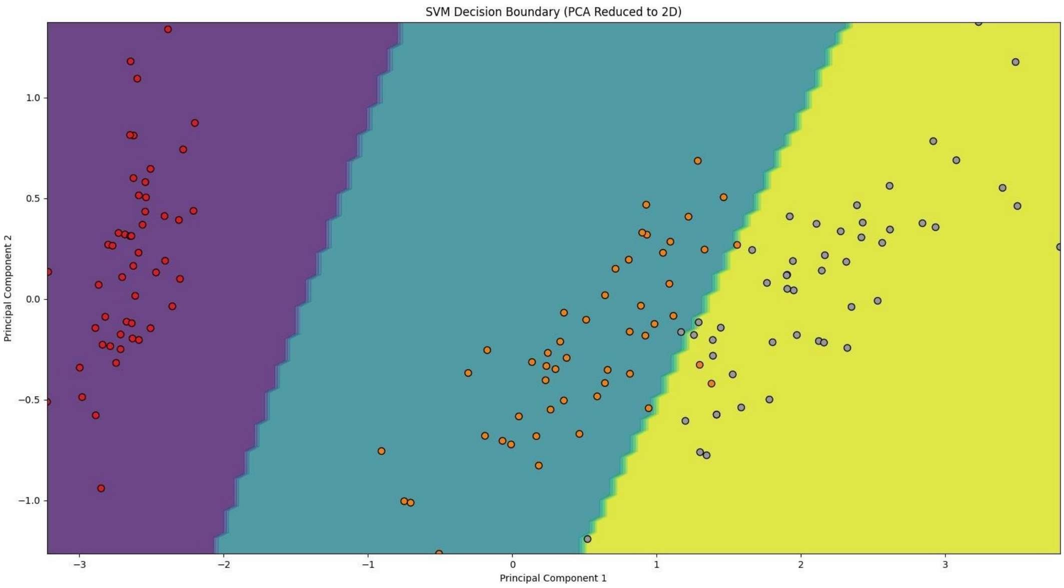
CODE:-

```
import numpy as
np import pandas
as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import
train_test_split from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA

data = load_iris()
X = data.data
y =
data.target

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

svm_clf = SVC(kernel='linear',
random_state=42) svm_clf.fit(X_train,
y_train)
```

```
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)

svm_clf_2d = SVC(kernel='linear',
random_state=42)

xx, yy = np.meshgrid(np.linspace(X_pca[:, 0].min(), X_pca[:, 0].max(), 100),
                     np.linspace(X_pca[:, 1].min(), X_pca[:, 1].max(), 100))
Z = svm_clf_2d.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)

plt.contourf(xx, yy, Z, alpha=0.8)
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, edgecolors='k',
marker='o', s=50,
cmap=plt.cm.Set1)
plt.title("SVM Decision Boundary (PCA Reduced to 2D)")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
```

OUTPUT:-

```
PROBLEMS   OUTPUT   DEBUG CONSOLE   TERMINAL   PORTS

PS D:\Viqar\Machine learning> python -u "d:\Viqar\Machine learning\Practical 4dpy.py"
Accuracy of SVM classifier: 1.00
```



(4E) AIM:- Train a random forest ensemble. Experiment with the number of trees and feature sampling. Compare performance to a single decision tree.

CODE:-

```
import numpy as
np import pandas
as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import
train_test_split from sklearn.tree import
DecisionTreeClassifier from sklearn.ensemble
import RandomForestClassifier from
sklearn.metrics import accuracy_score

data = load_iris()
X = data.data
y =
data.target

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

dt_clf =
DecisionTreeClassifier(random_state=42)
dt_clf.fit(X_train, y_train)
dt_y_pred = dt_clf.predict(X_test)
dt_accuracy = accuracy_score(y_test, dt_y_pred)

rf_clf = RandomForestClassifier(n_estimators=100, max_features='sqrt',
random_state=42)
rf_clf.fit(X_train, y_train)
rf_y_pred =
rf_clf.predict(X_test)
rf_accuracy = accuracy_score(y_test, rf_y_pred)

rf_clf_50 = RandomForestClassifier(n_estimators=50,
max_features='sqrt', random_state=42)
rf_clf_50.fit(X_train, y_train)
rf_50_y_pred =
rf_clf_50.predict(X_test)
```

OUPUT:-

```
PROBLEMS    OUTPUT    DEBUG CONSOLE    TERMINAL    PORTS

PS D:\Viqar\Machine learning> python -u "d:\Viqar\Machine learning\Practical 4e.py"
Decision Tree Accuracy: 1.00
Random Forest (100 trees) Accuracy: 1.00
Random Forest (50 trees) Accuracy: 1.00
```

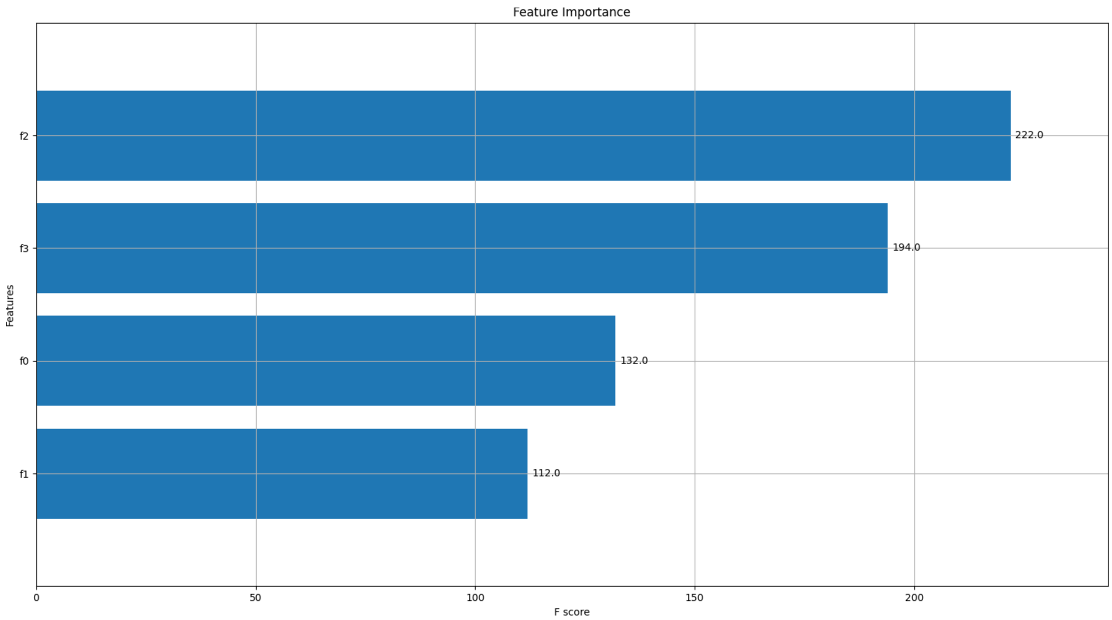
(4F) AIM:- Implement a gradient boosting machine (e.g., XGBoost). Tune hyperparameters and explore feature importance.

CODE:-

```
import numpy as
np import pandas
as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import
train_test_split import xgboost as xgb
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt

data = load_iris()
X = data.data
y =
data.target

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

params = {
    'objective': 'multi:softmax',
    'num_class': 3,
    'max_depth': 3,
    'learning_rate': 0.1,
    'n_estimators': 100,
    'subsample': 0.8,
    'colsample_bytree':
    0.8, 'eval_metric':
    'merror'
}

xgb_model = xgb.XGBClassifier(**params)
```

```
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy of XGBoost model:
{accuracy:.2f}')

xgb.plot_importance(xgb_model, importance_type='weight',
max_num_features=4, height=0.8)
plt.title('Feature
Importance') plt.show()
```

OUTPUT:-




```
PROBLEMS    OUTPUT    DEBUG CONSOLE    TERMINAL    PORTS

PS D:\Viqar\Machine learning> python -u "d:\Viqar\Machine learning\Practical 4f.py"
Accuracy of XGBoost model: 1.00
```

PRACTICAL 5

Generative Models

(5A) AIM:- Implement and demonstrate the working of a Naive Bayesian classifier using a sample data set. Build the model to classify a test sample.

CODE:-

```
import numpy as
np import pandas
as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import
train_test_split from sklearn.naive_bayes import
GaussianNB
from sklearn.metrics import accuracy_score

data = load_iris()
X = data.data
y =
data.target

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

nb_classifier = GaussianNB()
nb_classifier.fit(X_train,
y_train)

y_pred =
nb_classifier.predict(X_test)
accuracy = accuracy_score(y_test,
y_pred)
```

OUTPUT:-

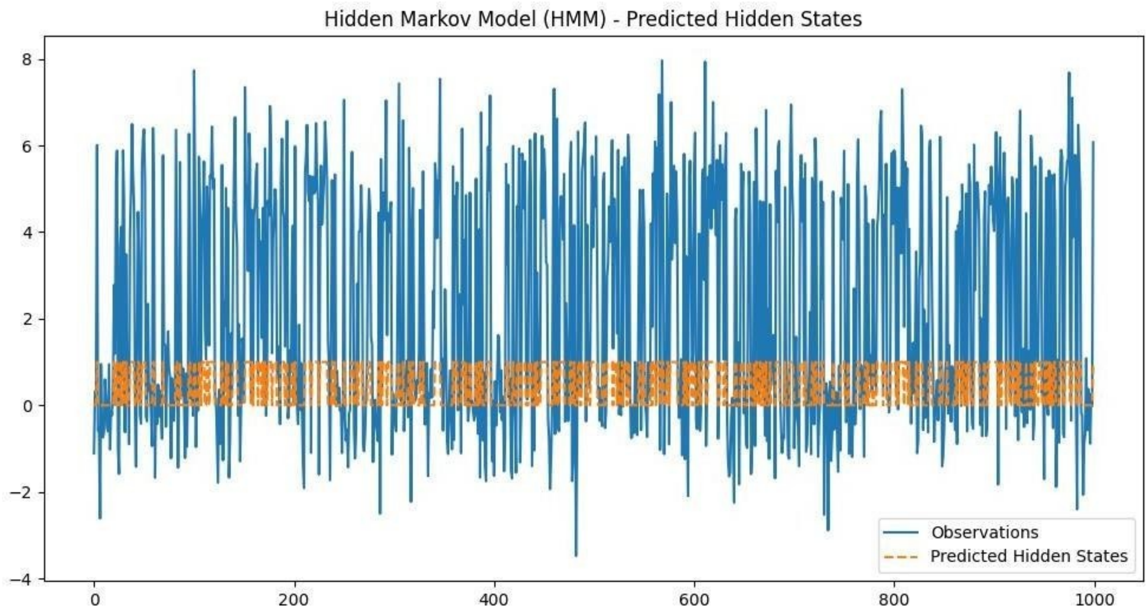
```
PROBLEMS    OUTPUT    DEBUG CONSOLE    TERMINAL    PORTS

PS D:\Viqar\Machine learning> python -u "d:\Viqar\Machine learning\Practical 5a.py"
Accuracy of Naive Bayes classifier: 0.98
Predicted class for the test sample: 1
```

(5B) AIM:- Implement Hidden Markov Models using hmmlearn.

CODE:-

```
import numpy as np
from hmmlearn.hmm import
GaussianHMM import
matplotlib.pyplot as plt

np.random.seed(42)

hidden_states = 2
n_samples = 1000

trans_probs = np.array([[0.7, 0.3], [0.4, 0.6]])
means = np.array([[0.0], [5.0]])

# Covariance matrix needs to be 3D with shape (n_components, n_dim,
n_dim) covars = np.array([[[1.0]], [[1.0]]]) # Correct shape for 'full'
covariance type

model = GaussianHMM(n_components=hidden_states, covariance_type="full",
n_iter=1000)

model.startprob_ = np.array([0.6,
0.4]) model.transmat_ = trans_probs
model.means_ = means
model.covars_ = covars

X, Z = model.sample(n_samples)

model.fit(X)

predicted_states = model.predict(X)

plt.figure(figsize=(12, 6))
plt.plot(X,
label='Observations')
plt.plot(predicted_states, label='Predicted Hidden States',
linestyle='--') plt.legend()
plt.title('Hidden Markov Model (HMM) - Predicted Hidden States')
```

OUTPUT:-




```
PROBLEMS    OUTPUT    DEBUG CONSOLE    TERMINAL    PORTS
PS D:\Viqar\Machine learning> python -u "d:\Viqar\Machine learning\tempCodeRunnerFile.py"
Even though the 'startprob_' attribute is set, it will be overwritten during initialization because 'init_params' contains 's'
Even though the 'transmat_' attribute is set, it will be overwritten during initialization because 'init_params' contains 't'
Even though the 'means_' attribute is set, it will be overwritten during initialization because 'init_params' contains 'm'
Even though the 'covars_' attribute is set, it will be overwritten during initialization because 'init_params' contains 'c'
```

PRACTICAL 6

Probabilistic Models

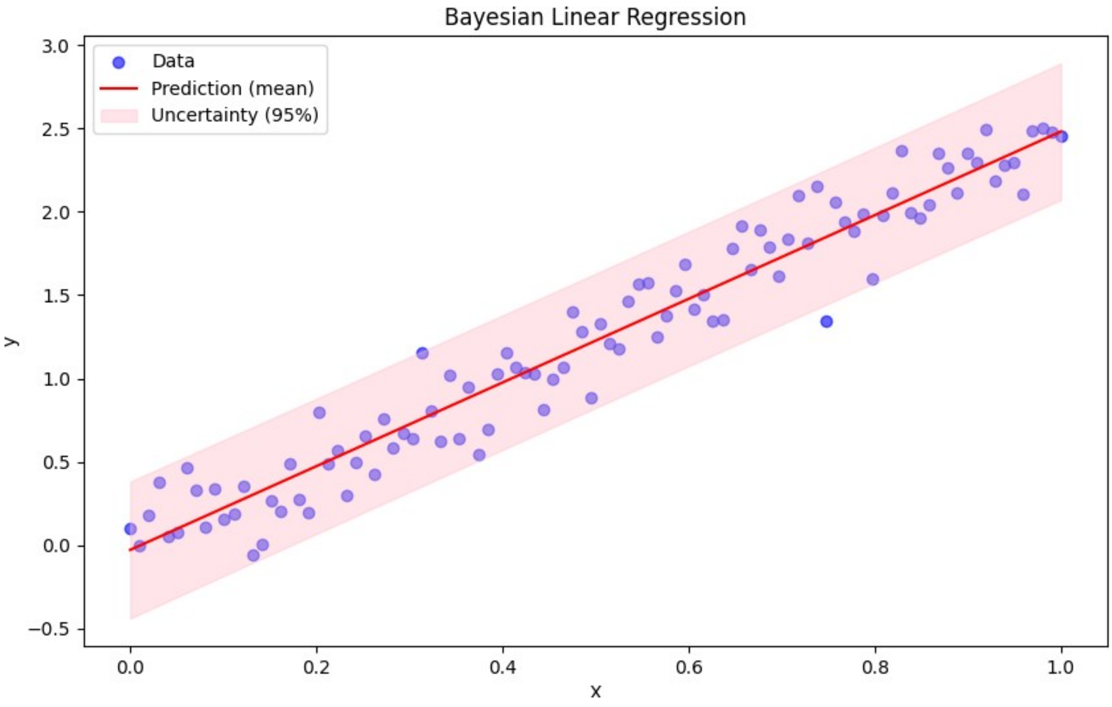
(6A) AIM:- Implement Bayesian Linear Regression to explore prior and posterior distribution.

CODE:-

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

np.random.seed(42)
X = np.linspace(0, 1, 100).reshape(-1, 1)
y = 2.5 * X.squeeze() + np.random.normal(0, 0.2, X.shape[0])

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

class BayesianLinearRegression:
    def _init_(self, alpha=1.0, beta=1.0):
        self.alpha = alpha
        self.beta = beta
        self.w_mean =
        None self.w_cov =
        None

    def fit(self, X, y):
        X = np.hstack((np.ones((X.shape[0], 1)),
        X)) S0_inv = self.alpha *
        np.eye(X.shape[1]) SN_inv = S0_inv +
        self.beta * X.T @ X
        SN = np.linalg.inv(SN_inv)
        mN = self.beta * SN @ X.T @ y
        self.w_mean = mN
        self.w_cov = SN

    def predict(self, X, return_std=False):
        X = np.hstack((np.ones((X.shape[0], 1)),
        X)) mean = X @ self.w_mean
        if return_std:
            variance = 1 / self.beta + np.sum(X @ self.w_cov * X,
            axis=1) return mean, np.sqrt(variance)
        return mean

blr = BayesianLinearRegression(alpha=1.0, beta=25.0)
```

```
X_pred = np.linspace(0, 1, 100).reshape(-1, 1)
y_pred, y_std = blr.predict(X_pred,
return_std=True)

plt.figure(figsize=(10, 6))
plt.scatter(X, y, label="Data", color="blue", alpha=0.6)
plt.plot(X_pred, y_pred, label="Prediction (mean)", color="red")
plt.fill_between(
    X_pred.squeeze(),
    y_pred - 2 *
    y_std, y_pred + 2
    * y_std,
    color="pink",
    alpha=0.4,
    label="Uncertainty (95%)",
)
plt.title("Bayesian Linear Regression")
plt.xlabel("X")
plt.ylabel("y")
plt.legend()
```

OUTPUT:-

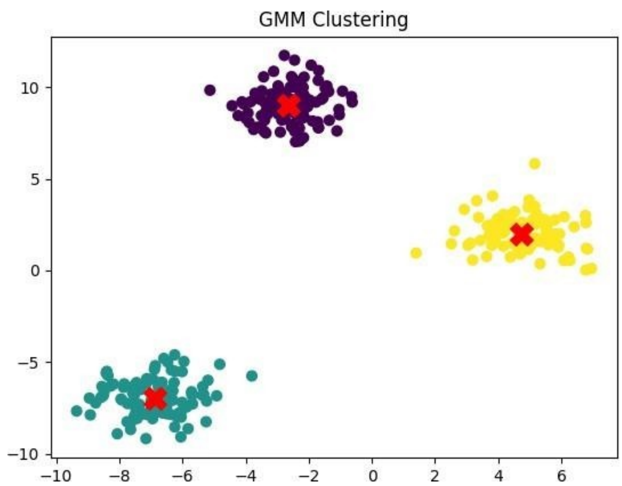


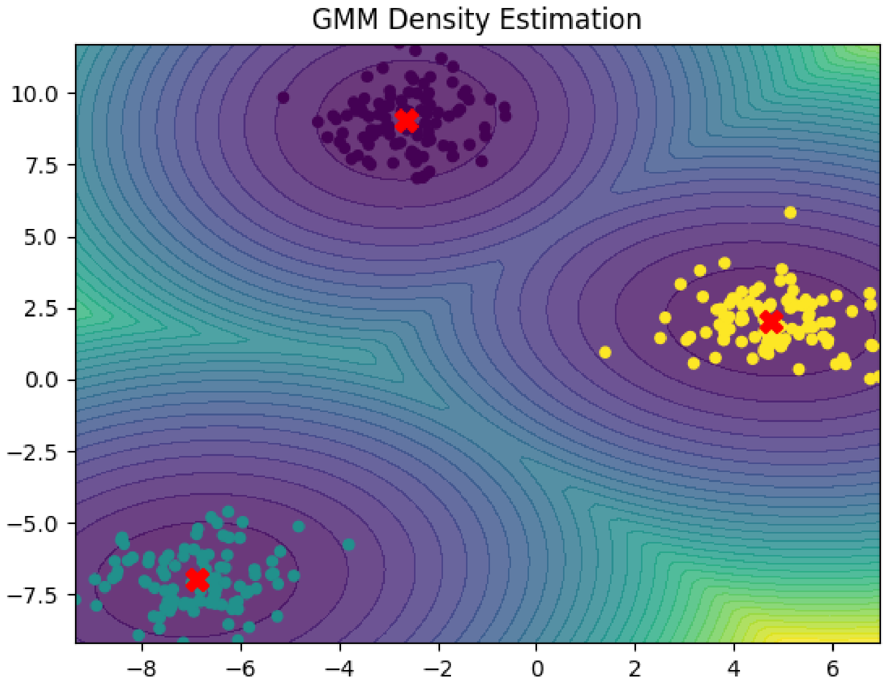
(6B) AIM:- Implement Gaussian Mixture Models for density estimation and unsupervised clustering

CODE:-

```
import numpy as np
from sklearn.mixture import GaussianMixture from
sklearn.datasets import make_blobs import matplotlib.pyplot
as plt

X, _ = make_blobs(n_samples=300, centers=3, cluster_std=1.0, random_state=42)

gmm = GaussianMixture(n_components=3, covariance_type='full', random_state=42).fit(X)
labels = gmm.predict(X)

plt.scatter(X[:, 0], X[:, 1], c=labels, cmap='viridis', s=40)
plt.scatter(gmm.means_[:, 0], gmm.means_[:, 1], c='red', s=200, marker='X') plt.title("GMM Clustering")
plt.show()

x, y = np.linspace(X[:, 0].min(), X[:, 0].max(), 100), np.linspace(X[:, 1].min(), X[:, 1].max(), 100)
X_grid, Y_grid = np.meshgrid(x, y)
grid_points = np.c_[X_grid.ravel(), Y_grid.ravel()]
Z = -gmm.score_samples(grid_points).reshape(X_grid.shape)

plt.contourf(X_grid, Y_grid, Z, levels=30, cmap='viridis', alpha=0.8) plt.scatter(X[:, 0], X[:, 1], c=labels,
cmap='viridis', s=20)
plt.scatter(gmm.means_[:, 0], gmm.means_[:, 1], c='red', s=100, marker='X') plt.title("GMM Density
Estimation") plt.show()
```

OUTPUT:-




GMM Density Estimation
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
−8
−6
−4
−2
0
2
4
6

PRACTICAL 7

Model Evaluation and Hyperparameter Tuning

(7A) AIM:- Implement cross-validation techniques (k-fold, stratified, etc.) for robust model evaluation.

CODE:-

```
import numpy as np

from sklearn.datasets import make_classification
from sklearn.model_selection import KFold, StratifiedKFold, cross_val_score from sklearn.ensemble
import RandomForestClassifier
from sklearn.metrics import accuracy_score

X, y = make_classification(n_samples=1000, n_features=10, n_informative=5, n_redundant=2, random_state=42)

model = RandomForestClassifier(random_state=42)

kf = KFold(n_splits=5, shuffle=True, random_state=42)
kfold_scores = cross_val_score(model, X, y, cv=kf, scoring='accuracy') print("K-Fold Cross-
Validation Scores:", kfold_scores)
print("K-Fold Average Accuracy:", np.mean(kfold_scores))

skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42) stratified_scores =
cross_val_score(model, X, y, cv=skf, scoring='accuracy') print("Stratified K-Fold Cross-Validation
Scores:", stratified_scores) print("Stratified K-Fold Average Accuracy:", np.mean(stratified_scores))

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
model.fit(X_train, y_train) y_pred =
model.predict(X_test)
holdout_accuracy = accuracy_score(y_test, y_pred) print("Holdout
Validation Accuracy:", holdout_accuracy)
```

OUTPUT:-

```
PROBLEMS    OUTPUT    DEBUG CONSOLE    TERMINAL    PORTS

PS D:\Viqar\Machine learning> python -u "d:\Viqar\Machine learning\Practical 7a.py"
K-Fold Cross-Validation Scores: [0.955 0.915 0.9   0.925 0.935]
K-Fold Average Accuracy: 0.9260000000000002
Stratified K-Fold Cross-Validation Scores: [0.925 0.955 0.94  0.925 0.94 ]
Stratified K-Fold Average Accuracy: 0.937
Holdout Validation Accuracy: 0.94
```

(7B) AIM:- Systematically explore combinations of hyperparameters to optimize model performance.(use grid and randomized search)

CODE:-

```
import numpy as np
from sklearn.datasets import
make_classification from sklearn.ensemble
import RandomForestClassifier
from sklearn.model_selection import GridSearchCV,
RandomizedSearchCV from sklearn.model_selection import
train_test_split
from sklearn.metrics import accuracy_score

X, y = make_classification(n_samples=1000, n_features=10, n_informative=5,
n_redundant=2, random_state=42)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=42)

model = RandomForestClassifier(random_state=42)

param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

grid_search = GridSearchCV(estimator=model,
param_grid=param_grid, cv=5, n_jobs=-1, verbose=2,
scoring='accuracy')
grid_search.fit(X_train, y_train)
```

```
print("Best parameters from Grid Search:", grid_search.best_params_)
best_model_grid = grid_search.best_estimator_
```

```
y_pred_grid = best_model_grid.predict(X_test)
grid_accuracy = accuracy_score(y_test,
y_pred_grid) print("Grid Search Model Accuracy:",
grid_accuracy)

param_dist = {
    'n_estimators': [50, 100, 200, 300],
    'max_depth': [None, 10, 20, 30, 40],
    'min_samples_split': [2, 5, 10, 15],
    'min_samples_leaf': [1, 2, 4, 6]
}

random_search = RandomizedSearchCV(estimator=model,
param_distributions=param_dist, n_iter=10, cv=5, n_jobs=-1, verbose=2,
scoring='accuracy', random_state=42)
random_search.fit(X_train, y_train)

print("Best parameters from Randomized Search:",
random_search.best_params_) best_model_random =
random_search.best_estimator_
y_pred_random = best_model_random.predict(X_test)
random_accuracy = accuracy_score(y_test,
```

OUTPUT:-

```
PROBLEMS    OUTPUT    DEBUG CONSOLE    TERMINAL    PORTS

PS D:\Viqar\Machine learning> python -u "d:\Viqar\Machine learning\tempCodeRunnerFile.py"
Fitting 5 folds for each of 108 candidates, totalling 540 fits
[CV] END max_depth=None, min_samples_leaf=1, min_samples_split=2, n_estimators=50; total time=   0.0s
[CV] END max_depth=None, min_samples_leaf=1, min_samples_split=2, n_estimators=50; total time=   0.0s
[CV] END max_depth=20, min_samples_leaf=6, min_samples_split=10, n_estimators=200; total time=   0.4s
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=15, n_estimators=300; total time=   0.5s
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=15, n_estimators=300; total time=   0.5s
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=15, n_estimators=300; total time=   0.5s
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=15, n_estimators=300; total time=   0.6s
[CV] END max_depth=20, min_samples_leaf=1, min_samples_split=15, n_estimators=300; total time=   0.6s
Best parameters from Randomized Search: {'n_estimators': 100, 'min_samples_split': 10, 'min_samples_leaf': 1, 'max_depth': None}
Randomized Search Model Accuracy: 0.9333333333333333
```

Practical 8

Bayesian Learning

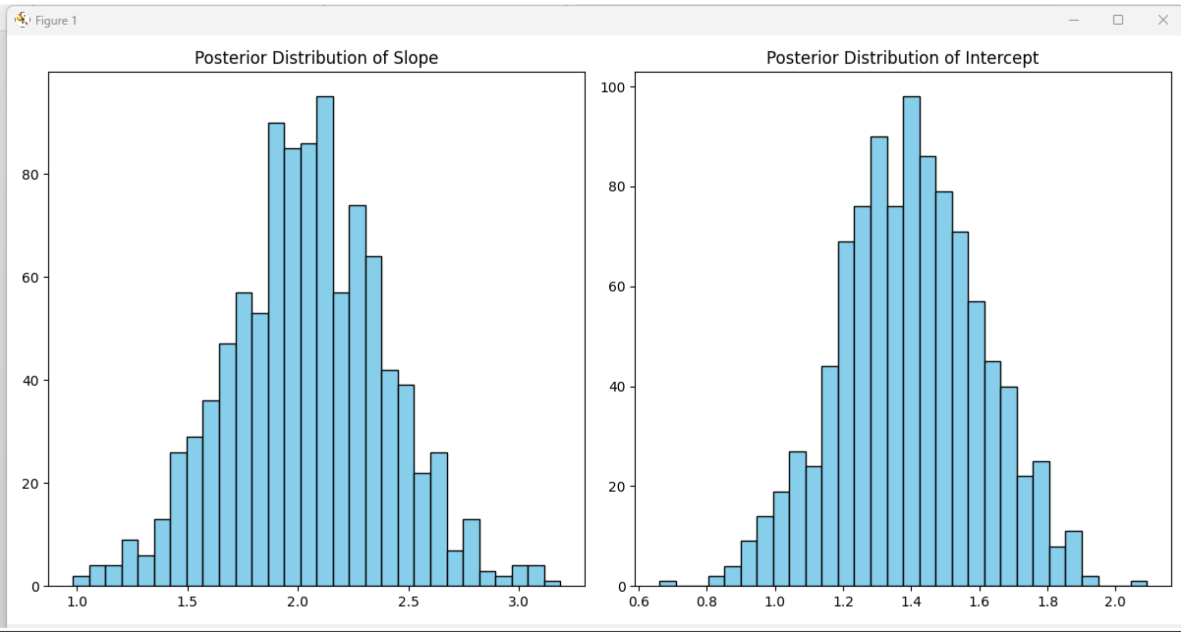
(8A) AIM: Implement Bayesian Learning using inferences.

CODE:-

```
import numpy as np

import matplotlib.pyplot as plt

np.random.seed(42)
X = np.linspace(0, 1, 20)
true_slope = 3
true_intercept = 1
y = true_slope * X + true_intercept + np.random.normal(scale=0.5,
size=X.shape)

plt.scatter(X, y, label="Data")
plt.xlabel("X")
plt.ylabel("y")
plt.legend()
plt.show()

X_ = np.vstack([X, np.ones_like(X)]).T
sigma_prior = 10
mu_prior = np.array([0, 0])
sigma_likelihood = 0.5
sigma_likelihood_inv = np.linalg.inv(sigma_likelihood**2 *
np.eye(len(X)))
X_T = X_.T
covariance_post = np.linalg.inv(X_T @ X_ / sigma_likelihood**2 +
np.eye(2) / sigma_prior**2)
mean_post = covariance_post @ (X_T @ y / sigma_likelihood**2 + mu_prior
/ sigma_prior**2)

num_samples = 1000
posterior_samples = np.random.multivariate_normal(mean_post,
covariance_post, num_samples)

plt.figure(figsize=(12, 6))

plt.subplot(1, 2, 1)
plt.hist(posterior_samples[:, 0], bins=30, color='skyblue',
edgecolor='black') plt.title("Posterior Distribution of Slope")

plt.subplot(1, 2, 2)
```

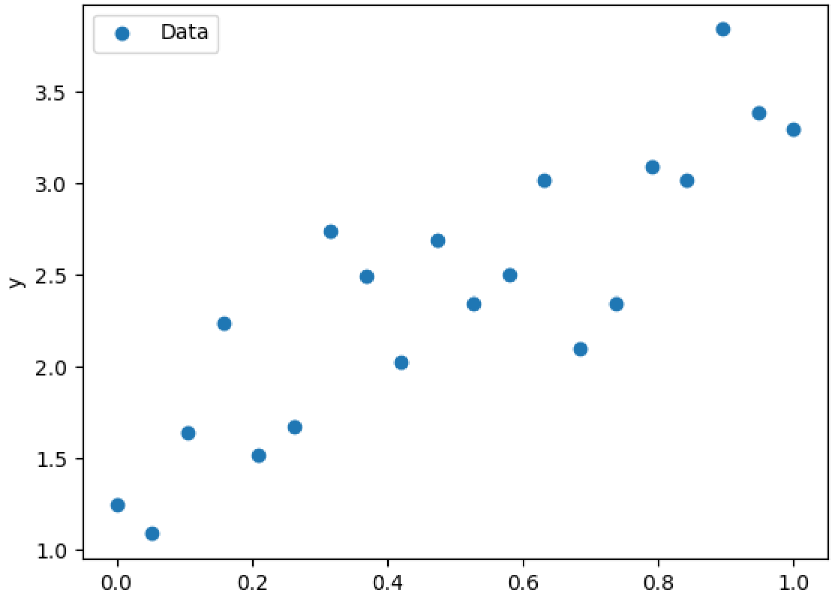
```
plt.hist(posterior_samples[:, 1], bins=30, color='skyblue',
edgecolor='black') plt.title("Posterior Distribution of Intercept")

plt.tight_layout()
plt.show()

plt.scatter(X, y,
label="Data") for sample in
posterior_samples:
    plt.plot(X, sample[0] * X + sample[1], color='red', alpha=0.05)
plt.xlabel("X")
plt.ylabel("y")
plt.legend()
plt.show()

estimated_slope = mean_post[0]
estimated_intercept = mean_post[1]
print(f"Estimated Slope: {estimated_slope}")
print(f"Estimated Intercept: {estimated_intercept}")
```

OUTPUT:-



PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS

```
PS D:\Viqar\Machine learning> python -u "d:\Viqar\Machine learning\Practical 8a.py"
Estimated Slope: 2.052291430826461
Estimated Intercept: 1.3880314999283634
```


Data
y
0.0 0.2 0.4 0.6 0.8 1.0
1.0 1.5 2.0 2.5 3.0 3.5

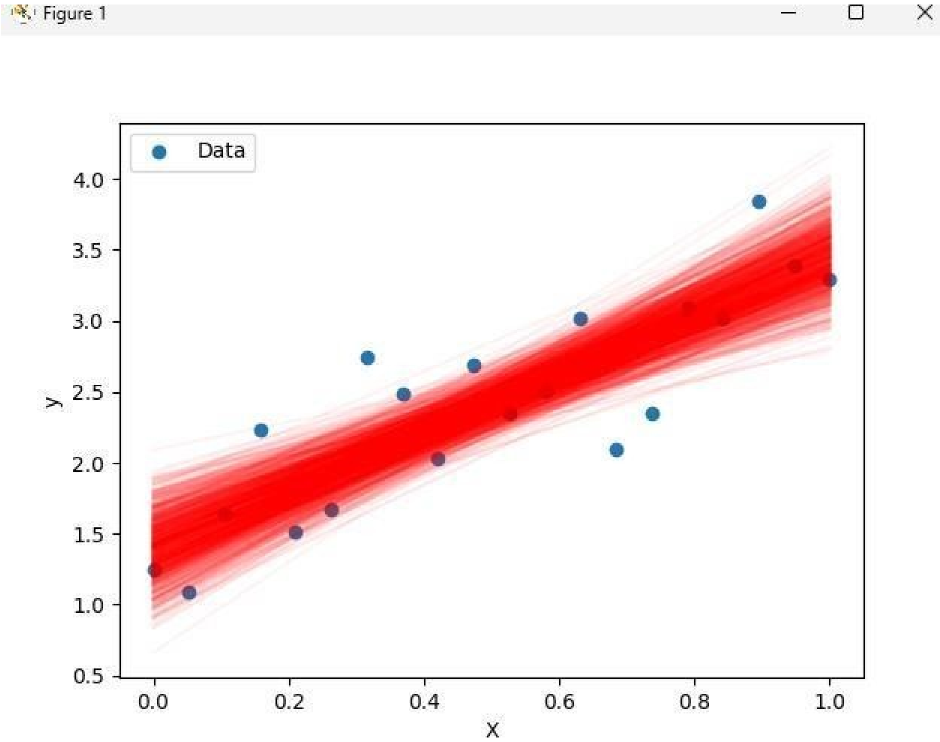


Figure 1
Data
y
X
0.0 0.2 0.4 0.6 0.8 1.0
0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0