PRACTICAL JOURNAL IN

ADVANCED ARTIFICIAL INTELLIGENCE

MACHINE LEARNING

SUBMITTED BY

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IN PARTIAL FULLFILMENT FOR THE DEGREE OF

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|| आ नो भद्राः क्रतवो यन्तु विश्वतः ||

PARLE TILAK VIDYALAYA ASSOCIATION’S
MULUND COLLEGE OF COMMERCE(AUTONOMOUS)
(AFFILIATED TO UNIVERSITY OF MUMBAI)
NAAC RE-ACCREDITED A GRADE – III CYCLE
MULUND WEST, MUMBAI 400080
MAHARASHTRA, INDIA
2024-25

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MAHARASHTRA, INDIA

DEPARTMENT OF INFORMATION TECHNOLOGY

CERTIFICATE

This is to certify that SONAWANE CHAITANYA RAJESH of **M.Sc. I.T. Part II** Roll No 2414559 has successfully completed the practical work in Advanced Artificial Intelligence in partial fulfilment of the requirements for the Semester III of **M.Sc. I.T. Part II** during the academic year **2024-25**.

Teacher In-charge and Coordinator

Examiner

Date:

College Seal

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PRACTICAL 1

AIM: Design a bot using AIML.

CODE:

Step 1: Create the XML file.

Open the notepad, write the following code, and save it as std-startup.xml

```
<aiml version="1.0.1" encoding="UTF-8">
    <!-- std-startup.xml -->
    <!-- Category is an atomic AIML unit -->
    <category>
        <!-- Pattern to match in user input -->
        <!-- If user enters "LOAD AIML B" -->
        <pattern>LOAD AIML B</pattern>
        <!-- Template is the response to the pattern -->
        <!-- This learn an aiml file -->
        <template>
            <learn>basic_chat.aiml</learn>
            <!-- You can add more aiml files here -->
            <!--<learn>more_aiml.aiml</learn>-->
        </template>
    </category>
</aiml>
```

Step 2: Create the aiml file.

Open the notepad, write the following code, and save it as basic_chat.aiml

```
<aiml version="1.0.1" encoding="UTF-8">
      <!-- basic_chat.aiml -->
      <category>
            <pattern>HELLO</pattern>
            <template>
 Well, hello!
 </template>
      </category>
      <category>
            <pattern>WHAT ARE YOU</pattern>
```

```
            <template> I'm a bot, silly! </template>
      </category>
      <category>
            <pattern>MY NAME IS *</pattern>
            <template>
                  <set name = "username">
                        <star/>
                  </set> is the nice name.
            </template>
      </category>
      <category>
            <pattern>I LIKE *</pattern>
            <template>
                  <set name = "liking">
                        <star/>
                  </set> is also my favourite.
            </template>
      </category>
      <category>
            <pattern>MY DOG NAME IS *</pattern>
            <template>
THAT IS INTERESTING THAT YOU HAVE A DOG NAMED
                  <set name ="dog">
                        <star/>
                  </set> .
            </template>
      </category>
      <category>
            <pattern>BYE</pattern>
            <template>
Bye!!!
                  <get name = "username"/> Thanks for talking with me.

            </template>
      </category>
</aiml>
```

Step 3: Install aiml packages

```
pip install aiml
pip install aimlbotkernel
or
pip3 install aiml
pip3 install aimlbotkernel
```

Step 4: Create chatbot.py file

```
import aiml # Create the kernel and learn AIML files
kernel = aiml.Kernel()
kernel.learn("std-startup.xml")
kernel.respond("load aiml b")   # Press CTRL-C to break this loop
while True:
    message = input("Enter your message to the bot: ")
    if message == "quit":
        break
    else:
        bot_response = kernel.respond(message)
        print(bot_response)
```

OUTPUT:

```
Loading std-startup.xml...done (0.03 seconds)
Loading basic_chat.aiml...done (0.00 seconds)
Enter your message to the bot: Hello
Well, hello!
Enter your message to the bot: What are you
I'm a bot, silly!
Enter your message to the bot: My name is Prateek
Prateek  is the nice name.
Enter your message to the bot: I like AIML
AIML  is also my favourite.
Enter your message to the bot: My dog name is Rex
THAT IS INTERESTING THAT YOU HAVE A DOG NAMED  Rex
Enter your message to the bot: Bye
Bye!!!  Prateek  Thanks for talking with me.
Enter your message to the bot:
```

PRACTICAL 2

AIM: Design an Expert system using AIML.

CODE:

Step 1: Create the XML file

Open the notepad, write the following code, and save it as std-startup.xml

```
<aiml version="1.0.1" encoding="UTF-8">
    <!-- std-startup.xml -->
    <!-- Category is an atomic AIML unit -->
    <category>
        <!-- Pattern to match in user input -->
        <!-- If user enters "LOAD AIML B" -->
        <pattern>LOAD AIML B</pattern>
        <!-- Template is the response to the pattern -->
        <!-- This learn an aiml file -->
        <template>
            <learn>basic_chat.aiml</learn>
            <!-- You can add more aiml files here -->
            <!--<learn>more_aiml.aiml</learn>-->
        </template>
    </category>
</aiml>
```

Step 2: Create the aiml file

Open the notepad, write the following code, and save it as basic_chat.aiml

```
<aiml version="1.0.1" encoding="UTF-8">
<!-- basic_chat.aiml -->
 <category>
 <pattern>HELLO</pattern>
 <template>
 WHAT WOULD YOU LIKE TO DISCUSS? : HEALTH, MOVIES
 </template>
 </category>
 <category>
 <pattern>MOVIES</pattern>
```

```
 <template>
 YES <set name = "topic">MOVIES</set>
 </template>
 </category>
 <category>
 <pattern>HEALTH</pattern>
 <template> YES <set name = "topic">HEALTH</set> </template>
 </category>
<topic name ="MOVIES">
<category>
<pattern>*</pattern>
<template>
DO YOU LIKE COMEDY MOVIES?
</template>
</category>
<category>  <pattern>YES</pattern>
<template>
I TOO LIKE COMEDY MOVIES
</template>
</category>
<category>
<pattern>NO</pattern>
<template>
BUT I LIKE COMEDY MOVIES
</template>
</category>
</topic>
<topic name ="HEALTH">
 <category>
<pattern>*</pattern>
<template>
DO YOU HAVE FEVER?
</template>
</category>
<category>
<pattern>YES</pattern>
<template>
 PLEASE TAKE MEDICINES AND PROPER REST
</template>
```

```
</category>
<category>
<pattern>NO</pattern>
<template>
GO OUT FOR A WALK AND LISTEN MUSIC
</template>
</category>
</topic>
 <category>
<pattern>NICE TALKING TO YOU</pattern>
<template>
SAME HERE...!!
</template>
</category>
</aiml>
```

Step 3: Install aiml packages

```
pip install aiml
pip install aimlbotkernel
or
pip3 install aiml
pip3 install aimlbotkernel
```

Step 4: Create chatbot.py file and run chatbot.py

```
import aiml
# Create the kernel and learn AIML files
kernel = aiml.Kernel()
kernel.learn("std-startup.xml")
kernel.respond("load aiml b")
# Press CTRL-C to break this loop
while True:
    message = input("Enter your message to the bot: ")
    if message == "quit":
        break
    else:
        bot_response = kernel.respond(message)
        print(bot_response)
```

OUTPUT:

```
Loading std-startup.xml...done (0.05 seconds)
Loading basic_chat.aiml...done (0.01 seconds)
Enter your message to the bot: Hello
WHAT WOULD YOU LIKE TO DISCUSS? : HEALTH, MOVIES
Enter your message to the bot: Health
YES HEALTH
Enter your message to the bot: I am feeling tired
DO YOU HAVE FEVER?
Enter your message to the bot: No
GO OUT FOR A WALK AND LISTEN MUSIC
Enter your message to the bot: Movies
YES MOVIES
Enter your message to the bot: I love movies
DO YOU LIKE COMEDY MOVIES?
Enter your message to the bot: Yes
I TOO LIKE COMEDY MOVIES
Enter your message to the bot: Nice talking to you
SAME HERE...!!
Enter your message to the bot: Quit
```

PRACTICAL 3

AIM: Implement Bayes Theorem using Python.

CODE:

```
# calculate the probability of cancer patient and diagnostic test
# calculate P(A|B) given P(A), P(B|A), P(B|not A)
def bayes_theorem(p_a, p_b_given_a, p_b_given_not_a):
	# calculate P(not A)
	not_a = 1 - p_a
	# calculate P(B)
	p_b = p_b_given_a * p_a + p_b_given_not_a * not_a
	# calculate P(A|B)
	p_a_given_b = (p_b_given_a * p_a) / p_b
	return p_a_given_b
# P(A)
p_a = 0.0002
# P(B|A)
p_b_given_a = 0.85
# P(B|not A)
p_b_given_not_a = 0.05
# calculate P(A|B)
result = bayes_theorem(p_a, p_b_given_a, p_b_given_not_a)
# summarize
print('P(A|B) = %.3f%%' % (result * 100))
```

OUTPUT:

```
P(A|B) = 0.339%
```

PRACTICAL 4

AIM: Implement Conditional Probability and joint probability using Python.

CODE:

```
import enum, random

class Kid(enum.Enum):

    BOY = 0

    GIRL = 1

def random_kid() -> Kid:

    return random.choice([Kid.BOY, Kid.GIRL])

both_girls = 0

older_girl = 0

either_girl = 0

random.seed(0)

for _ in range(10000):

    younger = random_kid()

    older = random_kid()

    if older == Kid.GIRL:

        older_girl += 1

    if older == Kid.GIRL and younger == Kid.GIRL:

        both_girls += 1

    if older == Kid.GIRL or younger == Kid.GIRL:

        either_girl += 1

print("older girl: ", older_girl)

print("both girl: ", both_girls)

print("either girl: ", either_girl)
```

```
print("P(both | older):", both_girls / older_girl)

print("P(both | either):", both_girls / either_girl)
```

OUTPUT:

```
older girl:  4937
both girl:  2472
either girl:  7464
P(both | older): 0.5007089325501317
P(both | either): 0.3311897106109325
```

PRACTICAL 5

AIM: Write a program for to implement Rule based system. (Prolog).

CODE:

```
go:-
 hypothesis(Disease),
 write('I believe that the patient have '),
 write(Disease),
 nl,
 write('TAKE CARE '),
 undo.
/*Hypothesis that should be tested*/
hypothesis(cold) :- cold, !.
hypothesis(flu) :- flu, !.
hypothesis(typhoid) :- typhoid, !.
hypothesis(measles) :- measles, !.
hypothesis(malaria) :- malaria, !.
hypothesis(unknown). /* no diagnosis*/
/*Hypothesis Identification Rules*/
cold :-
verify(headache),
verify(runny_nose),
verify(sneezing),
verify(sore_throat),
write('Advices and Sugestions:'),
nl,
write('1: Tylenol/tab'),
nl,
write('2: panadol/tab'),
nl,
write('3: Nasal spray'),
nl,
write('Please wear warm cloths Because'),
nl.
flu :-
verify(fever),
```

```
verify(headache),
verify(chills),
verify(body_ache),
write('Advices and Sugestions:'),
nl,
write('1: Tamiflu/tab'),
nl,
write('2: panadol/tab'),
nl,
write('3: Zanamivir/tab'),
nl,
write('Please take a warm bath and do salt gargling Because'),
nl.
typhoid :-
verify(headache),
verify(abdominal_pain),
verify(poor_appetite),
verify(fever),
write('Advices and Sugestions:'),
nl,
write('1: Chloramphenicol/tab'),
nl,
write('2: Amoxicillin/tab'),
nl,
write('3: Ciprofloxacin/tab'),
nl,
write('4: Azithromycin/tab'),
nl,
write('Please do complete bed rest and take soft Diet Because'),
nl.
measles :-
verify(fever),
verify(runny_nose),
verify(rash),
verify(conjunctivitis),
write('Advices and Sugestions:'),
nl,
write('1: Tylenol/tab'),
nl,
```

```
write('2: Aleve/tab'),
nl,
write('3: Advil/tab'),
nl,
write('4: Vitamin A'),
nl,
write('Please Get rest and use more liquid Because'),
nl.
malaria :-
verify(fever),
verify(sweating),
verify(headache),
verify(nausea),
verify(vomiting),
verify(diarrhea),
write('Advices and Sugestions:'),
nl,
write('1: Aralen/tab'),
nl,
write('2: Qualaquin/tab'),
nl,
write('3: Plaquenil/tab'),
nl,
write('4: Mefloquine'),
nl,
write('Please do not sleep in open air and cover your full skin Because'),
nl.
/* how to ask questions */
ask(Question) :-
write('Does the patient have following symptom:'),
write(Question),
write('? '),
read(Response),
nl,
( (Response == yes ; Response == y)
->
assert(yes(Question)) ;
assert(no(Question)), fail).
:- dynamic yes/1,no/1.
```

```
/*How to verify something */
verify(S) :-
(yes(S)
->
true ;
(no(S)
->
fail ;
ask(S))).
/* undo all yes/no assertions*/
undo :- retract(yes(_)),fail.
undo :- retract(no(_)),fail.
undo.
```

OUTPUT:

```
?-
% c:/Users/PrateekKarkera/Downloads/daignosis (1).pl compiled 0.00 sec, 17 clauses
?- go.
Does the patient have following symptom:headache? yes.

Does the patient have following symptom:runny_nose? |: yes.

Does the patient have following symptom:sneezing? |: yes.

Does the patient have following symptom:sore_throat? |: yes.

Advices and Sugestions:
1: Tylenol/tab
2: panadol/tab
3: Nasal spray
Please wear warm cloths Because
I believe that the patient have cold
TAKE CARE
true.

?-
```

PRACTICAL 6

AIM: Design a Fuzzy based application using Python/ R.

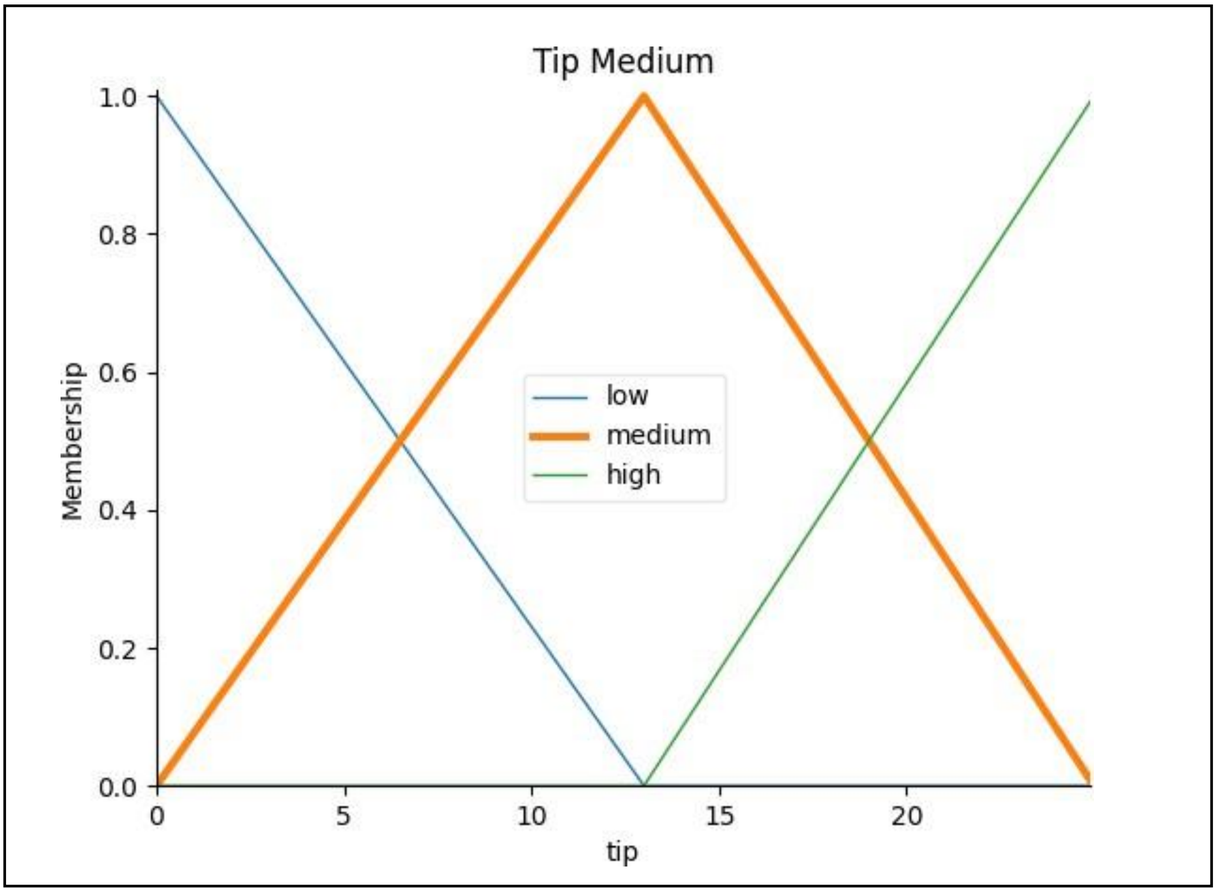
CODE:

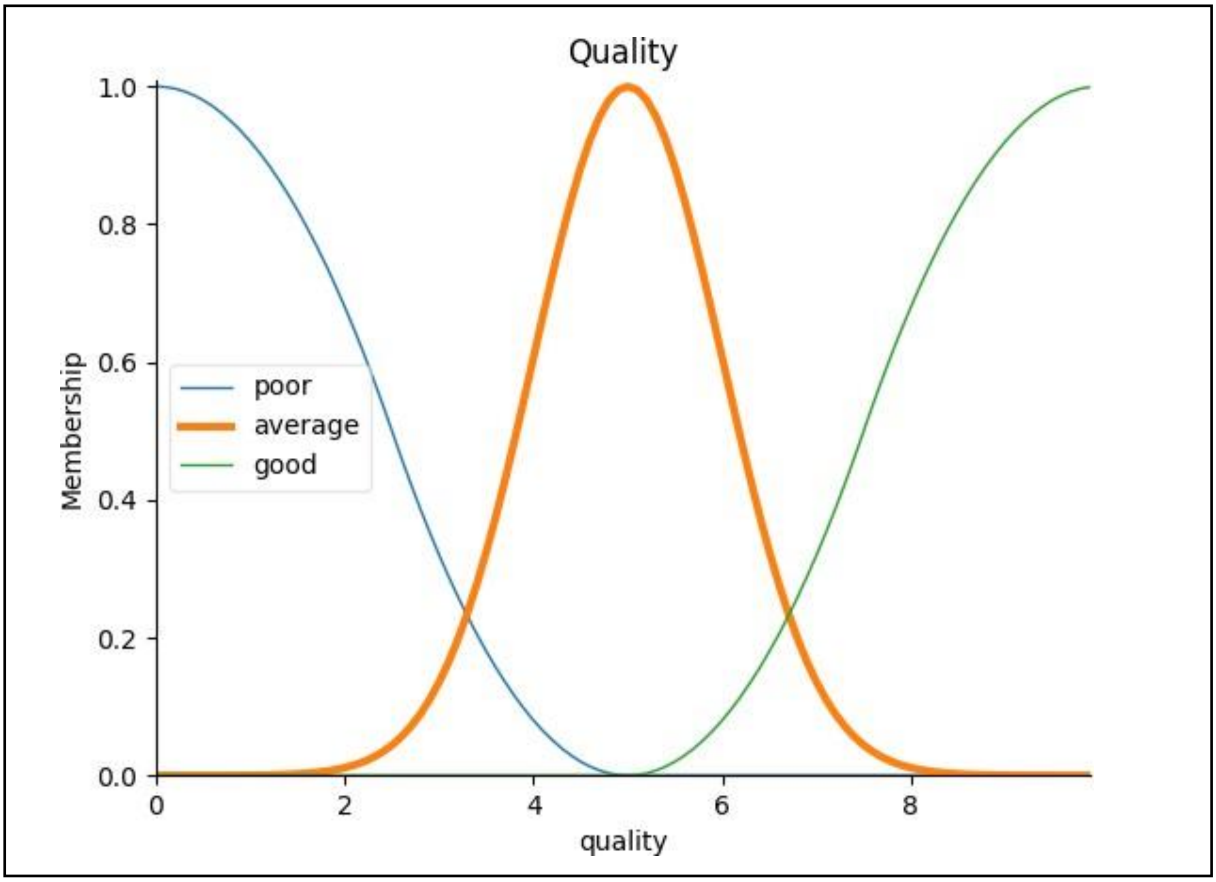
```
import numpy as np

import skfuzzy as fuzz

import matplotlib.pyplot as plt

from skfuzzy import control as ctrl

from mpl_toolkits.mplot3d import Axes3D  # Required for 3D plotting


# New Antecedent/Consequent objects hold universe variables and membership

# functions


quality = ctrl.Antecedent(np.arange(0, 10, 0.1), 'quality')

service = ctrl.Antecedent(np.arange(0, 10, 0.1), 'service')

tip = ctrl.Consequent(np.arange(0, 25, 0.1), 'tip')


quality['poor'] = fuzz.zmf(quality.universe, 0,5)

quality['average'] = fuzz.gaussmf(quality.universe,5,1)

quality['good'] = fuzz.smf(quality.universe,5,10)


service['poor'] = fuzz.zmf(service.universe, 0,5)

service['average'] = fuzz.gaussmf(service.universe,5,1)

service['good'] = fuzz.smf(service.universe,5,10)


tip['low'] = fuzz.trimf(tip.universe, [0, 0, 13])
```

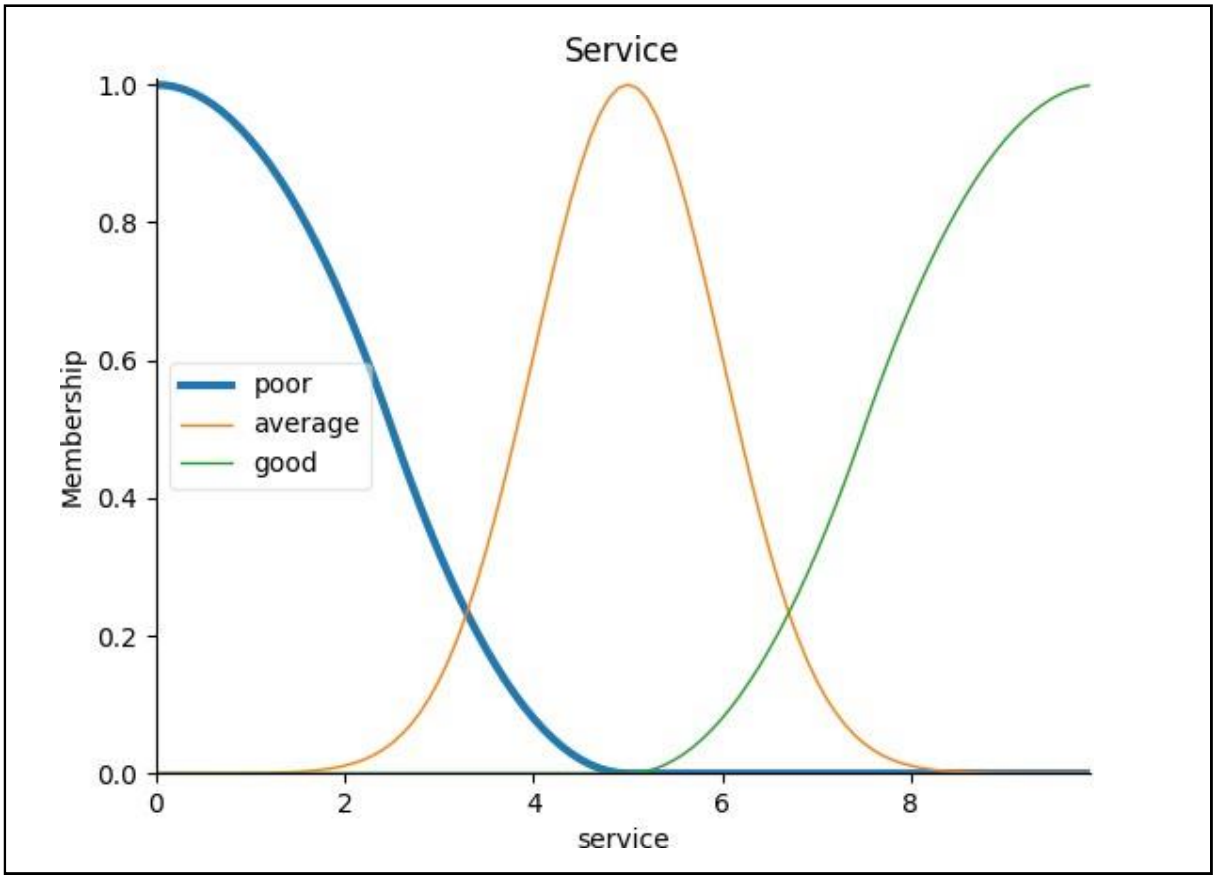
```
tip['medium'] = fuzz.trimf(tip.universe, [0, 13, 25])

tip['high'] = fuzz.trimf(tip.universe, [13, 25, 25])


quality['average'].view()

plt.title('Quality')


service['poor'].view()

plt.title('Service')


tip['medium'].view()

plt.title('Tip Medium')


rule1 = ctrl.Rule(quality['poor'] | service['poor'], tip['low'])

rule2 = ctrl.Rule(service['average'], tip['medium'])

rule3 = ctrl.Rule(service['good'] | quality['good'], tip['high'])

rule1.view()

plt.title('Rule 1')

rule2.view()

plt.title('Rule 2')

rule3.view()

plt.title('Rule 3')tipping_ctrl = ctrl.ControlSystem([rule1, rule2, rule3])

tipping = ctrl.ControlSystemSimulation(tipping_ctrl)

tipping.input['quality'] = 6.5

tipping.input['service'] = 9.8

tipping.compute()

print(tipping.output['tip'])

tip.view(sim=tipping)
```

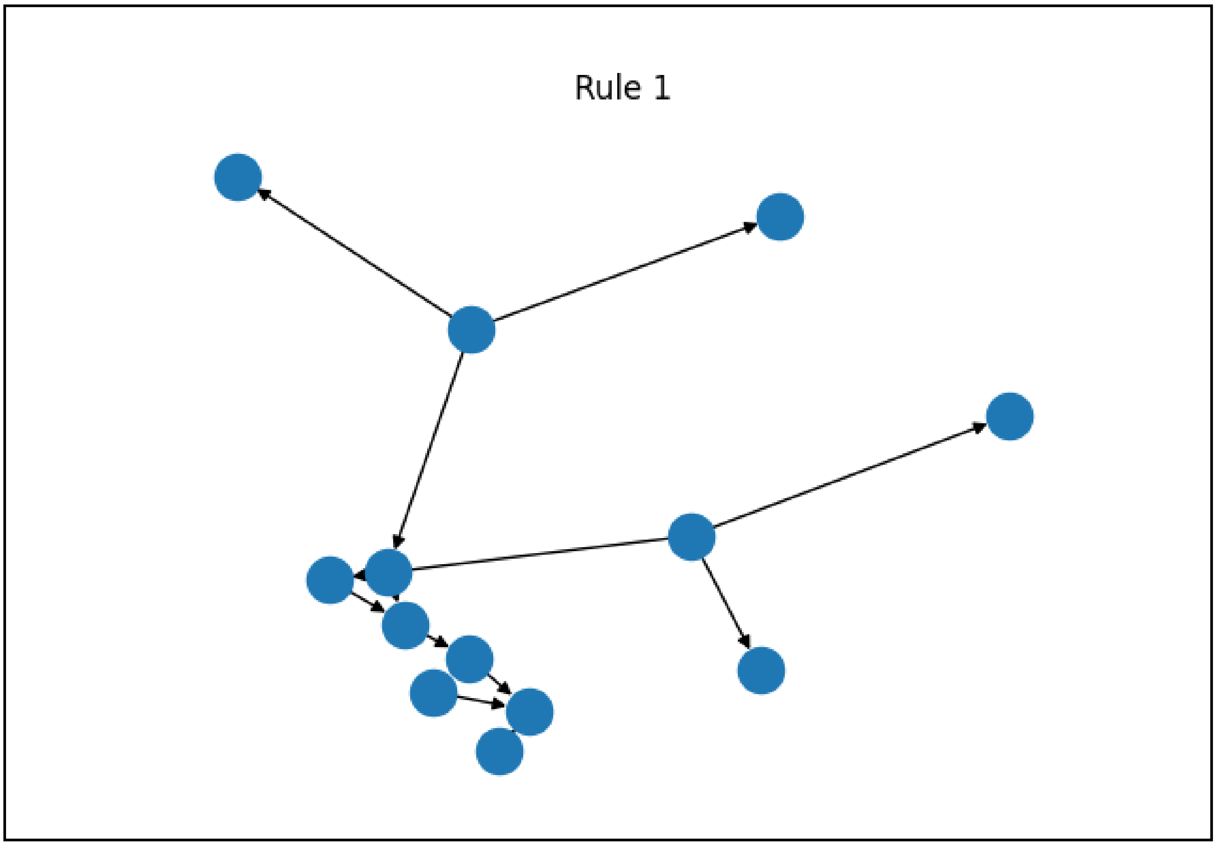
```
plt.title('Result')

plt.show(block=True)
```

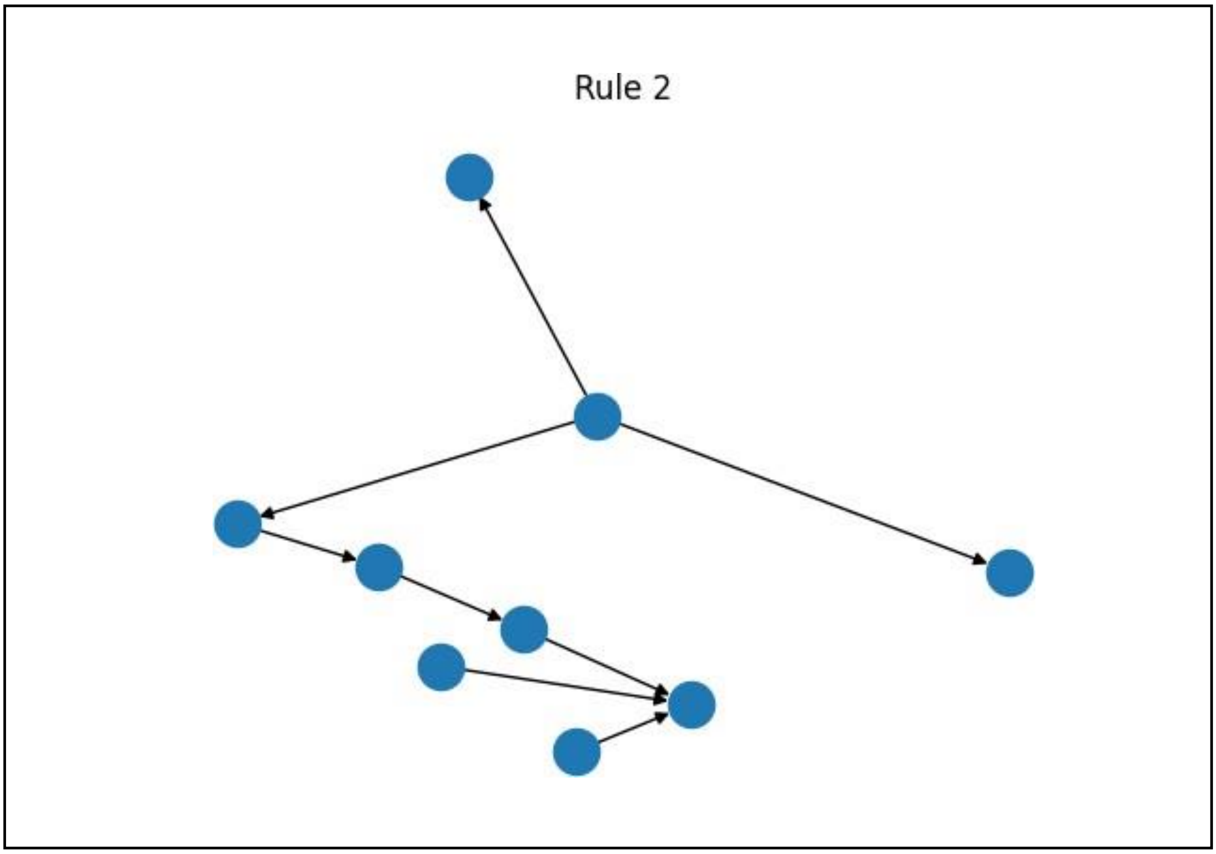
OUTPUT:

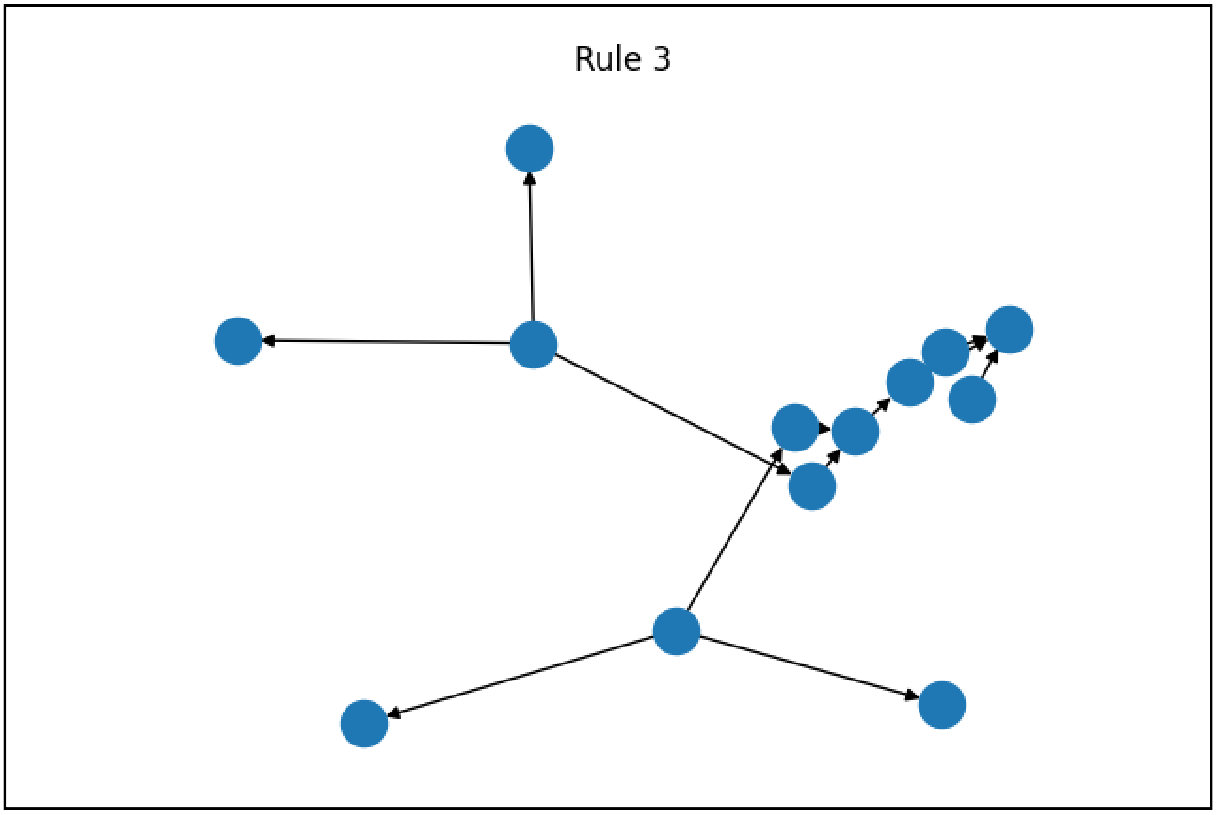


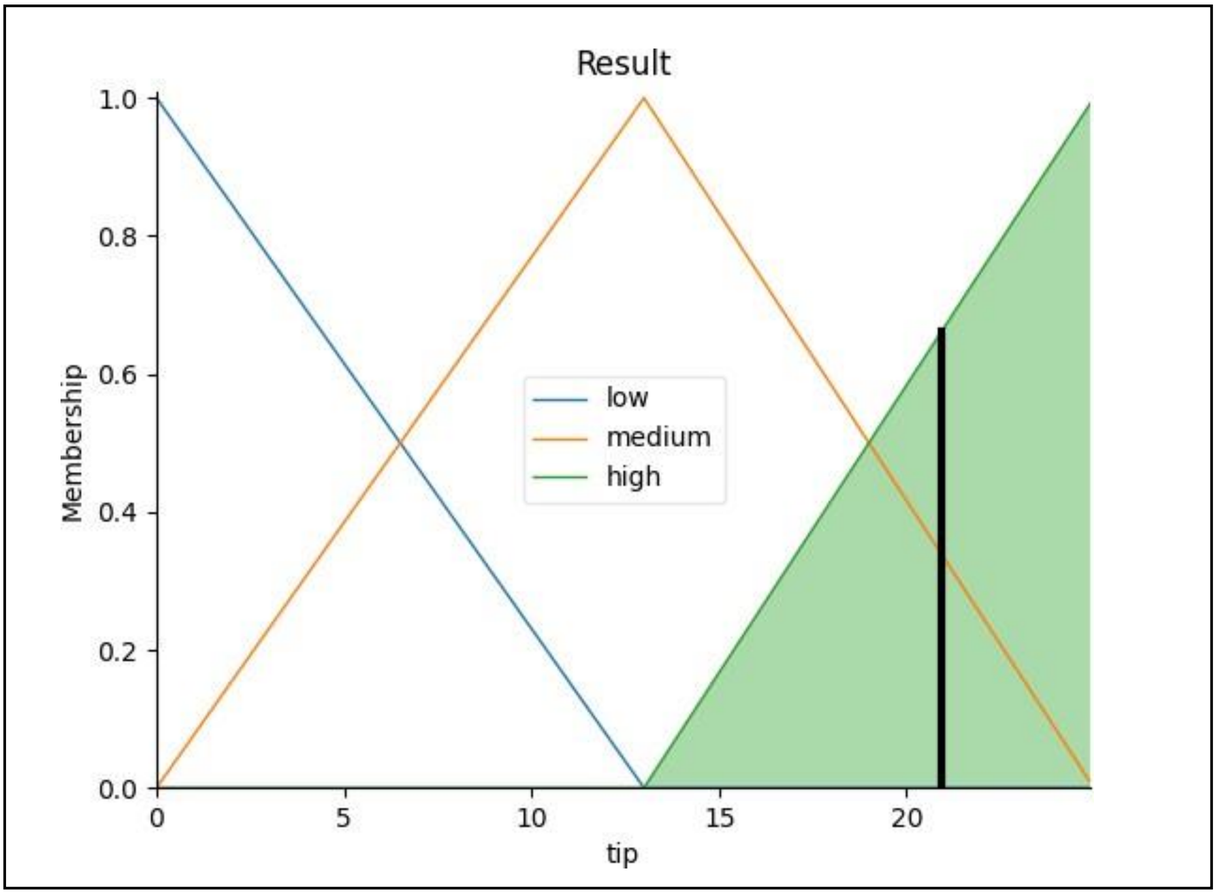

Quality
1.0
0.8
0.6
0.4
0.2
0.0
Membership
poor
average
good
0
2
4
6
8
quality


Service
1.0
0.8
0.6
0.4
0.2
0.0
Membership
poor
average
good
0
2
4
6
8
service


Rule 1


Rule 2


Rule 3


Result
1.0
0.8
0.6
0.4
0.2
0.0
Membership
0
5
10
15
20
tip
low
medium
high

PRACTICAL 7

[A] AIM: Write an application to stimulate supervised learning model.

CODE:

```
from sklearn.model_selection import train_test_split

from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import classification_report, confusion_matrix

from sklearn import datasets

iris=datasets.load_iris()

x = iris.data

y = iris.target

print ('sepal-length', 'sepal-width', 'petal-length', 'petal-width')

print(x)

print('class: 0-Iris-Setosa, 1- Iris-Versicolour, 2- Iris-Virginica')

print(y)

x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.3)

#To Training the model and Nearest nighbors K=5

classifier = KNeighborsClassifier(n_neighbors=5)

classifier.fit(x_train, y_train)

#To make predictions on our test data

y_pred=classifier.predict(x_test)

print('Confusion Matrix')

print(confusion_matrix(y_test,y_pred))

print('Accuracy Metrics')

print(classification_report(y_test,y_pred))
```

OUTPUT:

```
 [5.9 3.  5.1 1.8]]
class: 0-Iris-Setosa, 1- Iris-Versicolour, 2- Iris-Virginica
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2]
Confusion Matrix
[[14  0  0]
 [ 0 15  3]
 [ 0  1 12]]
Accuracy Metrics
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        14
           1       0.94      0.83      0.88        18
           2       0.80      0.92      0.86        13

    accuracy                           0.91        45
   macro avg       0.91      0.92      0.91        45
weighted avg       0.92      0.91      0.91        45
```

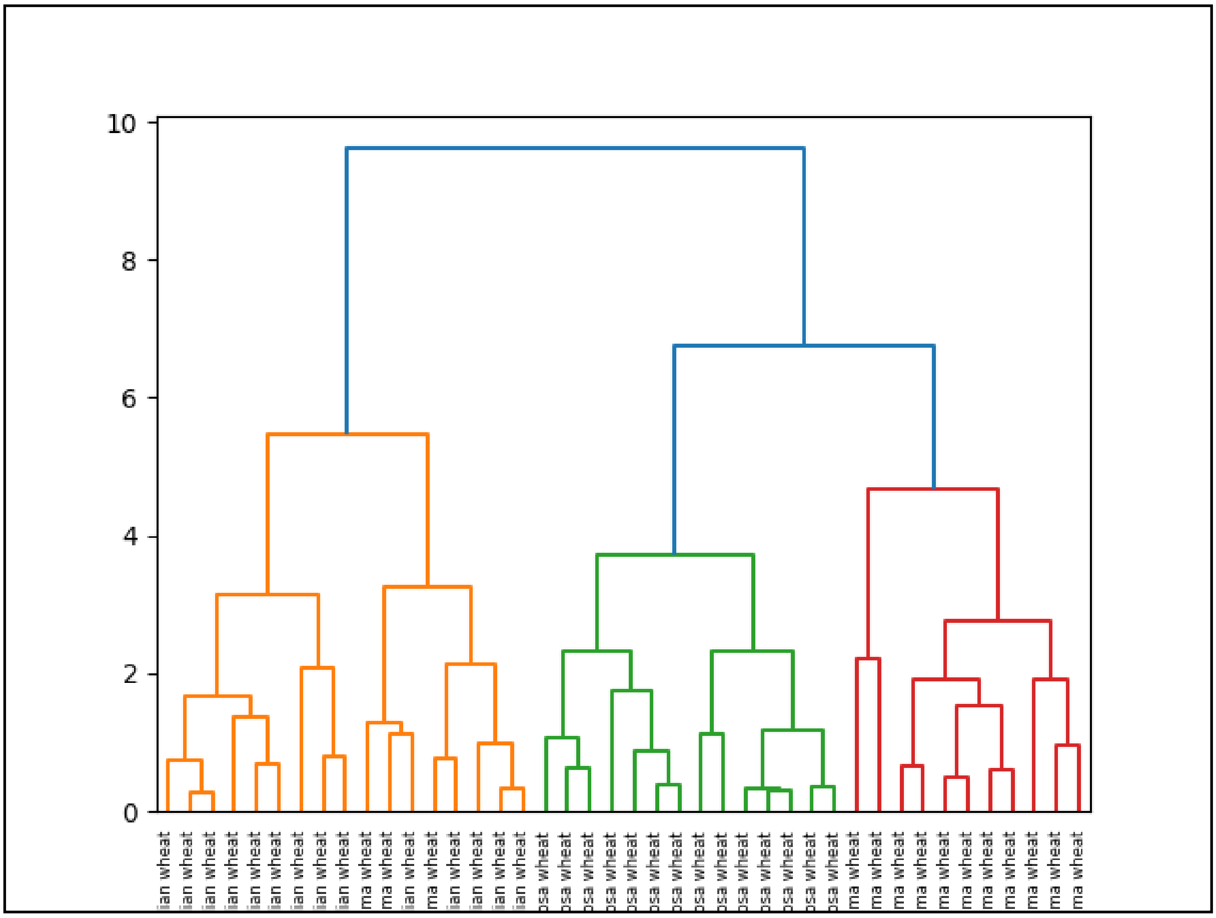
[B] AIM: Write an application to stimulate unsupervised learning model.

CODE:

```
# Importing Modules
from scipy.cluster.hierarchy import linkage, dendrogram
import matplotlib.pyplot as plt
import pandas as pd

# Reading the DataFrame
seeds_df = pd.read_csv("seeds-less-rows.csv")

# Remove the grain species from the DataFrame, save for later
varieties = list(seeds_df.pop('grain_variety'))

# Extract the measurements as a NumPy array
samples = seeds_df.values

"""
Perform hierarchical clustering on samples using the
linkage() function with the method='complete' keyword argument.
Assign the result to mergings.
"""
mergings = linkage(samples, method='complete')

"""
Plot a dendrogram using the dendrogram() function on mergings,
specifying the keyword arguments labels=varieties, leaf_rotation=90,
and leaf_font_size=6.
"""
dendrogram(mergings,
           labels=varieties,
           leaf_rotation=90,
           leaf_font_size=6,
```

```
            )


plt.show()
```

OUTPUT:



PRACTICAL 8

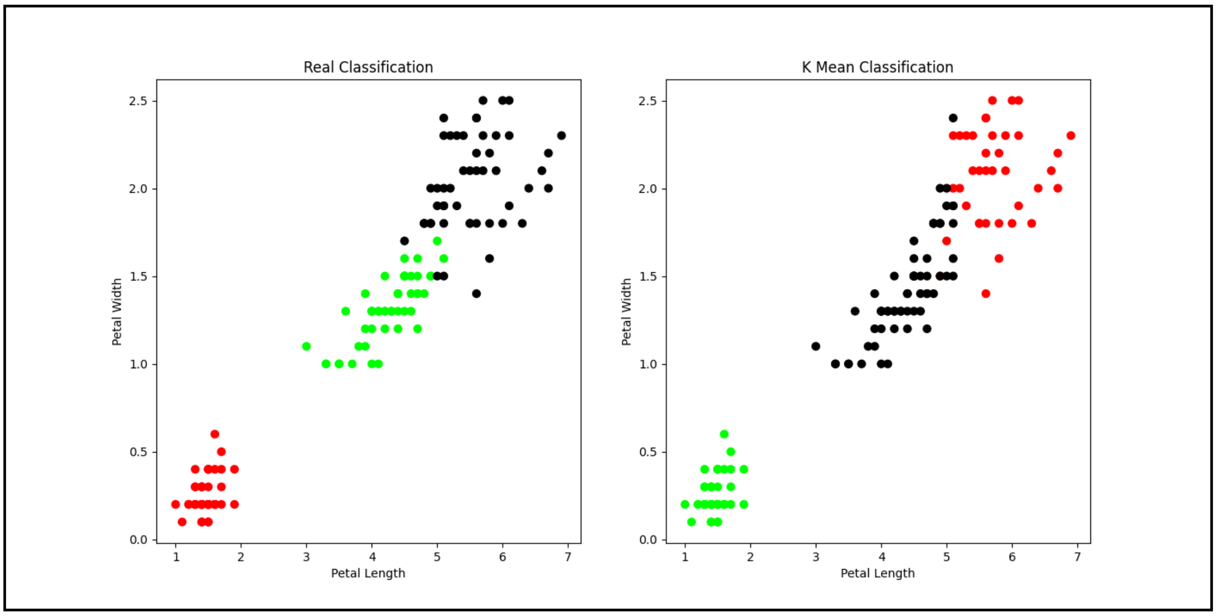
AIM: Write an application to implement clustering algorithm.

CODE:

```
import matplotlib.pyplot as plt

from sklearn import datasets

from sklearn.cluster import KMeans

import sklearn.metrics as sm

import pandas as pd

import numpy as np

iris = datasets.load_iris()

X = pd.DataFrame(iris.data)

X.columns = ['Sepal_Length','Sepal_Width','Petal_Length','Petal_Width']

y = pd.DataFrame(iris.target)

y.columns = ['Targets']

model = KMeans(n_clusters=3)

model.fit(X)

plt.figure(figsize=(14,7))

colormap = np.array(['red', 'lime', 'black'])

# Plot the Original Classifications

plt.subplot(1, 2, 1)

plt.scatter(X.Petal_Length, X.Petal_Width,

c=colormap[y.Targets], s=40)

plt.title('Real Classification')

plt.xlabel('Petal Length')

plt.ylabel('Petal Width')
```

```
# Plot the Models Classifications

plt.subplot(1, 2, 2)

plt.scatter(X.Petal_Length, X.Petal_Width,

c=colormap[model.labels_], s=40)

plt.title('K Mean Classification')

plt.xlabel('Petal Length')

plt.ylabel('Petal Width')

plt.show()

print('The accuracy score of K-Mean: ',sm.accuracy_score(y, model.labels_))

print('The    Confusion    matrix    of    K-Mean:    ',sm.confusion_matrix(y,
model.labels_))
```

OUTPUT:



PRACTICAL 9

AIM: Write an application to implement support vector machine algorithm.

CODE:

```
#Import scikit-learn dataset library

from sklearn import datasets


#Import svm model

from sklearn import svm


# Import train_test_split function

from sklearn.model_selection import train_test_split


#Import scikit-learn metrics module for accuracy calculation

from sklearn import metrics


#Load dataset

cancer = datasets.load_breast_cancer()


# print the names of the 13 features

print("Features: ", cancer.feature_names)


# print the label type of cancer('malignant' 'benign')

print("Labels: ", cancer.target_names)


# print data(feature)shape
```

```
cancer.data.shape

# print the cancer data features (top 5 records)
print(cancer.data[0:5])

# print the cancer labels (0:malignant, 1:benign)
print(cancer.target)

# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(cancer.data,
cancer.target, test_size=0.3,random_state=109) # 70% training and 30% test

#Create a svm Classifier
clf = svm.SVC(kernel='linear') # Linear Kernel

#Train the model using the training sets
clf.fit(X_train, y_train)

#Predict the response for test dataset
y_pred = clf.predict(X_test)



# Model Accuracy: how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))

# Model Precision: what percentage of positive tuples are labeled as such?
print("Precision:",metrics.precision_score(y_test, y_pred))
```

```
# Model Recall: what percentage of positive tuples are labelled as such?

print("Recall:",metrics.recall_score(y_test, y_pred))
```

OUTPUT:

```
Features:  ['mean radius' 'mean texture' 'mean perimeter' 'mean area'
 'mean smoothness' 'mean compactness' 'mean concavity'
 'mean concave points' 'mean symmetry' 'mean fractal dimension'
 'radius error' 'texture error' 'perimeter error' 'area error'
 'smoothness error' 'compactness error' 'concavity error'
 'concave points error' 'symmetry error' 'fractal dimension error'
 'worst radius' 'worst texture' 'worst perimeter' 'worst area'
 'worst smoothness' 'worst compactness' 'worst concavity'
 'worst concave points' 'worst symmetry' 'worst fractal dimension']
Labels:  ['malignant' 'benign']
[[1.799e+01 1.038e+01 1.228e+02 1.001e+03 1.184e-01 2.776e-01 3.001e-01
  1.471e-01 2.419e-01 7.871e-02 1.095e+00 9.053e-01 8.589e+00 1.534e+02
  6.399e-03 4.904e-02 5.373e-02 1.587e-02 3.003e-02 6.193e-03 2.538e+01
  1.733e+01 1.846e+02 2.019e+03 1.622e-01 6.656e-01 7.119e-01 2.654e-01
  4.601e-01 1.189e-01]
 [2.057e+01 1.777e+01 1.329e+02 1.326e+03 8.474e-02 7.864e-02 8.690e-02
  7.017e-02 1.812e-01 5.667e-02 5.435e-01 7.339e-01 3.398e+00 7.408e+01
  5.225e-03 1.308e-02 1.860e-02 1.340e-02 1.389e-02 3.532e-03 2.499e+01
  2.341e+01 1.588e+02 1.956e+03 1.238e-01 1.866e-01 2.416e-01 1.860e-01
  2.750e-01 8.902e-02]
 [1.969e+01 2.125e+01 1.300e+02 1.203e+03 1.096e-01 1.599e-01 1.974e-01
  1.279e-01 2.069e-01 5.999e-02 7.456e-01 7.869e-01 4.585e+00 9.403e+01
  6.150e-03 4.006e-02 3.832e-02 2.058e-02 2.250e-02 4.571e-03 2.357e+01
  2.553e+01 1.525e+02 1.709e+03 1.444e-01 4.245e-01 4.504e-01 2.430e-01
  3.613e-01 8.758e-02]
 [1.142e+01 2.038e+01 7.758e+01 3.861e+02 1.425e-01 2.839e-01 2.414e-01
  1.052e-01 2.597e-01 9.744e-02 4.956e-01 1.156e+00 3.445e+00 2.723e+01
  9.110e-03 7.458e-02 5.661e-02 1.867e-02 5.963e-02 9.208e-03 1.491e+01
  2.650e+01 9.887e+01 5.677e+02 2.098e-01 8.663e-01 6.869e-01 2.575e-01
  6.638e-01 1.730e-01]
 [2.029e+01 1.434e+01 1.351e+02 1.297e+03 1.003e-01 1.328e-01 1.980e-01
  1.043e-01 1.809e-01 5.883e-02 7.572e-01 7.813e-01 5.438e+00 9.444e+01
  1.149e-02 2.461e-02 5.688e-02 1.885e-02 1.756e-02 5.115e-03 2.254e+01
  1.667e+01 1.522e+02 1.575e+03 1.374e-01 2.050e-01 4.000e-01 1.625e-01
  2.364e-01 7.678e-02]]
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 1 0 0 0 0 0 0 0 0 1 0 1 1 1 1 1 0 0 1 0 0 1 1 1 1 0 1 0 0 1 1 1 1 0 1 0 0
 1 0 1 0 0 1 1 1 0 0 1 0 0 0 1 1 1 0 1 1 0 0 1 1 1 0 0 1 1 1 1 0 1 1 0 1 1
 1 1 1 1 1 1 0 0 0 1 0 0 1 1 1 0 0 1 0 1 0 0 1 0 0 1 1 0 1 1 0 1 1 1 1 0 1
 1 1 1 1 1 1 1 1 0 1 1 1 1 0 0 1 0 1 1 0 0 1 1 0 0 1 1 1 1 0 1 1 0 0 0 1 0
 1 0 1 1 1 0 1 1 0 0 1 0 0 0 0 1 0 0 0 1 0 1 0 1 1 0 1 0 0 0 0 1 1 0 0 1 1
 1 0 1 1 1 1 1 0 0 1 1 0 1 1 0 0 1 0 1 1 1 1 0 1 1 1 1 1 0 1 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 1 1 1 1 1 1 0 1 0 1 1 0 1 1 0 1 0 0 1 1 1 1 1 1 1 1 1 1 1 1
 1 0 1 1 0 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 0 1 0 1 1 1 1 0 0 0 1 1
 1 1 0 1 0 1 0 1 1 1 0 1 1 1 1 1 1 1 0 0 0 1 1 1 1 1 1 1 1 1 1 1 0 0 1 0 0
 0 1 0 0 1 1 1 1 1 0 1 1 1 1 1 0 1 1 1 0 1 1 0 0 1 1 1 1 1 1 0 1 1 1 1 1 1
 1 0 1 1 1 1 1 0 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 0 1 0 0 1 0 1 1 1 1 1 0 1 1
 0 1 0 1 1 0 1 0 1 1 1 1 1 1 1 1 0 0 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 0 1
 1 1 1 1 1 1 0 1 0 1 1 0 1 1 1 1 1 0 0 1 0 1 0 1 1 1 1 1 0 1 1 0 1 0 1 0 0
 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 0 1 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 0 0 0 0 0 0 1]
Accuracy: 0.9649122807017544
Precision: 0.9811320754716981
Recall: 0.9629629629629629
```

PRACTICAL 10

AIM: Simulate artificial neural network model with both feedforward and backpropagation approach.

CODE:

```
import numpy as np
X = np.array(([2, 9], [1, 5], [3, 6]), dtype=float)  # two inputs [sleep,study]
y = np.array(([92], [86], [89]), dtype=float) # one output [Expected % in Exams]
X = X / np.amax(X, axis=0)  # maximum of X array longitudinally
y = y / 100


# Sigmoid Function
def sigmoid(x):
    return 1 / (1 + np.exp(-x))


# Derivative of Sigmoid Function
def derivatives_sigmoid(x):
    return x * (1 - x)


# Variable initialization
epoch = 5000  # Setting training iterations
lr = 0.1  # Setting learning rate
inputlayer_neurons = 2  # number of features in data set
hiddenlayer_neurons = 3  # number of hidden layers neurons
output_neurons = 1  # number of neurons at output layer
```

```
# weight and bias initialization
wh = np.random.uniform(size=(inputlayer_neurons, hiddenlayer_neurons))   # weight of the link from input node to hidden node
bh = np.random.uniform(size=(1, hiddenlayer_neurons)) # bias of the link from input node to hidden node
wout = np.random.uniform(size=(hiddenlayer_neurons, output_neurons))   # weight of the link from hidden node to output node
bout = np.random.uniform(size=(1, output_neurons)) # bias of the link from hidden node to output node
# draws a random range of numbers uniformly of dim x*y
for i in range(epoch):
    # Forward Propogation
    hinp1 = np.dot(X, wh)
    hinp = hinp1 + bh
    hlayer_act = sigmoid(hinp)
    outinp1 = np.dot(hlayer_act, wout)
    outinp = outinp1 + bout
    output = sigmoid(outinp)
    # Backpropagation
    EO = y - output
    outgrad = derivatives_sigmoid(output)
    d_output = EO * outgrad
    EH = d_output.dot(wout.T)
    # how much hidden layer weights contributed to error
    hiddengrad = derivatives_sigmoid(hlayer_act)
    d_hiddenlayer = EH * hiddengrad
# dotproduct of nextlayererror and currentlayerop
wout += hlayer_act.T.dot(d_output) * lr
```

```
wh += X.T.dot(d_hiddenlayer) * lr

print("Input: \n" + str(X))

print("Actual Output: \n" + str(y))

print("Predicted Output: \n", output)
```

OUTPUT:

```
Input:
[[0.66666667 1.        ]
 [0.33333333 0.55555556]
 [1.         0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
 [[0.84047843]
 [0.81670721]
 [0.83471132]]
```

Parle Tilak Vidyalaya Association's

MULUND COLLEGE OF COMMERCE (AUTONOMOUS)

(Affiliated to University of Mumbai)

MULUND WEST, MUMBAI 400080

MAHARASHTRA, INDIA

DEPARTMENT OF INFORMATION TECHNOLOGY

CERTIFICATE

This is to certify that SONAWANE CHAITANYA RAJESH of **M.Sc. I.T. Part II** Roll No 2414559 has successfully completed the practical work in Machine Learning in partial fulfilment of the requirements for the Semester III of **M.Sc. I.T. Part II** during the academic year **2024-25**.

Teacher In-charge and Coordinator

Examiner

Date:

College Seal

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Practical 1

1.1 Load a CSV dataset. Handle missing values, inconsistent formatting, and outliers.

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

plt.rcParams["figure.figsize"]      =      [8,6]
sns.set(style="darkgrid")

df         =         sns.load_dataset('titanic')

print(df.head())
```

```
   survived  pclass  sex     age   sibsp  parch  fare     embarked  class
 \
 0  0         3       male    22.0  1      0      7.2500   S         Third
 1  1         1       female  38.0  1      0      71.2833  C         First
 2  1         3       female  26.0  0      0      7.9250   S         Third
 3  1         1       female  35.0  1      0      53.1000  S         First
 4  0         3       male    35.0  0      0      8.0500   S         Third

     who  adult_male deck  embark_town alive  alone
0    man      True  NaN  Southampton   no  False
1   woman      False C     Cherbourg   yes  False
2   woman      False  NaN  Southampton  yes   True
3   woman      False C  Southampton     yes  False
4 man    True  NaN  Southampton    no     True
```

```
print(df.isnull().sum())
```

```
 survived      0
 pclass        0
 sex           0
 age           177
 sibsp         0
 parch         0
 fare          0
 embarked      2
 class         0
 who           0
 adult_male    0
 deck          688
 embark_town   2
 alive         0
```

```
alone      0
dtype: int64
```

```python
df = df[["age", "embarked"]]
print(df.head())
```

```
    age embarked
0  22.0        S
1  38.0        C
2  26.0        S
3  35.0        S
4  35.0        S
```

```python
df.loc[:, 'age'] = df.age.fillna(df.age.median())
df = df.dropna(subset=["embarked"])

print(df.head(20))
```

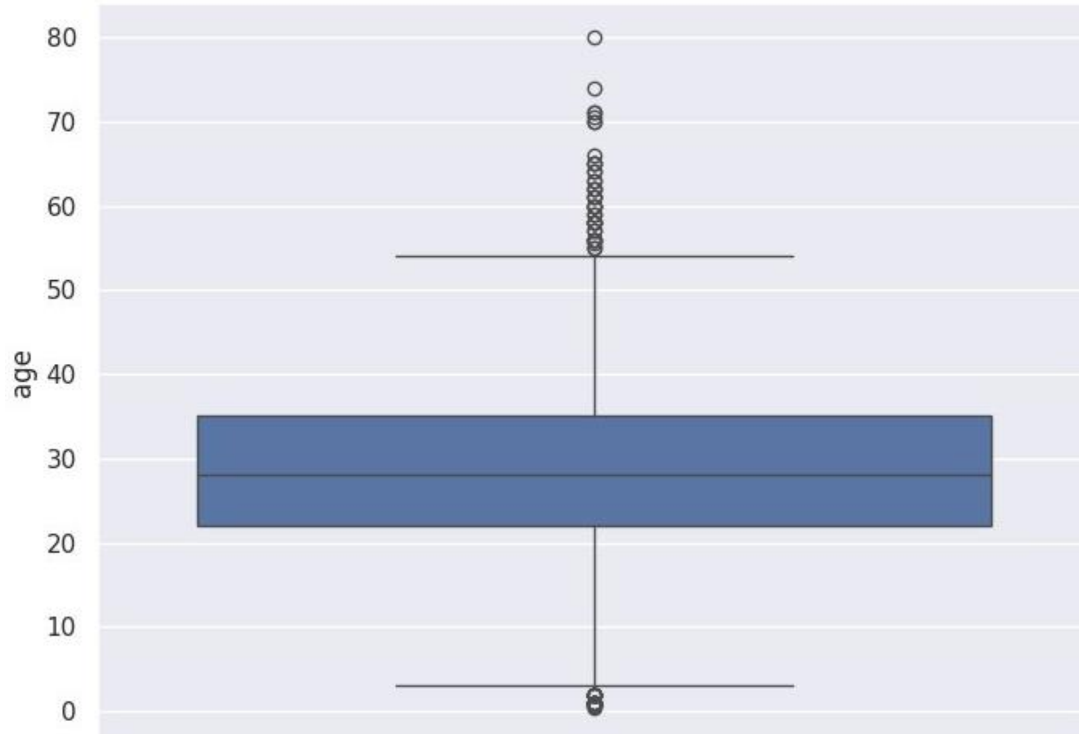
```
     age embarked
0    22.0  S
1    38.0  C
2    26.0  S
3    35.0  S
4    35.0  S
5    28.0  Q
6    54.0  S
7    2.0   S
8    27.0  S
9    14.0  C
10   4.0   S
11  58.0   S
12  20.0   S
13  39.0   S
14  14.0   S
15  55.0   S
16   2.0   Q
17  28.0   S
18  31.0   S
19  28.0   C
```

```python
df.loc[:, 'embarked'] = df.embarked.str.upper()
print(df.embarked.unique())
```

```
['S' 'C' 'Q']
```

```python
sns.boxplot(data=df.age)
```

```
<Axes: ylabel='age'>
```

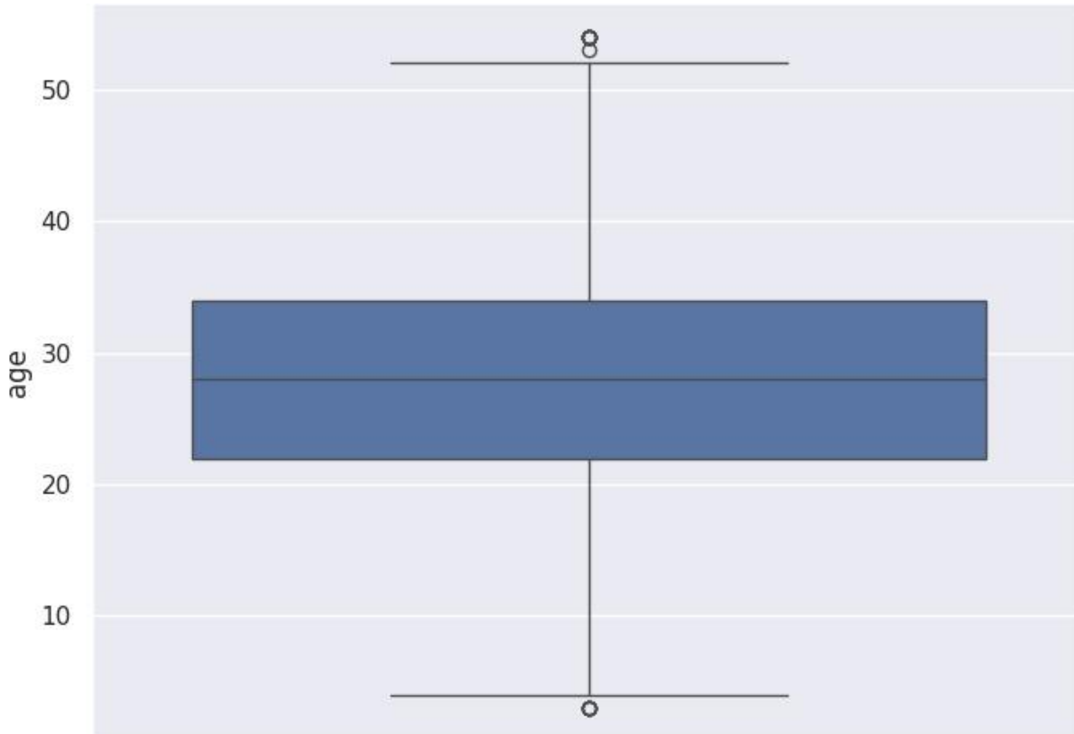



```
Q1 = df.age.quantile(0.25)
Q3 = df.age.quantile(0.75)
IQR = Q3 - Q1

lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

df = df[(df.age >= lower_bound) & (df.age <= upper_bound)]

print(df.head())
```

```
    age embarked
0  22.0 S
1  38.0 C
2  26.0 S
3  35.0 S
4  35.0 S
```

```
sns.boxplot(data=df.age)
```

```
<Axes: ylabel='age'>
```


50
40
30
20
10
age

1.2 Load a dataset, calculate descriptive summary statistics, create visualizations using different graphs, and identify potential features and target variables

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

plt.rcParams["figure.figsize"] = [8,6]
sns.set(style="darkgrid")

df = sns.load_dataset('iris')
print(df.head())
```

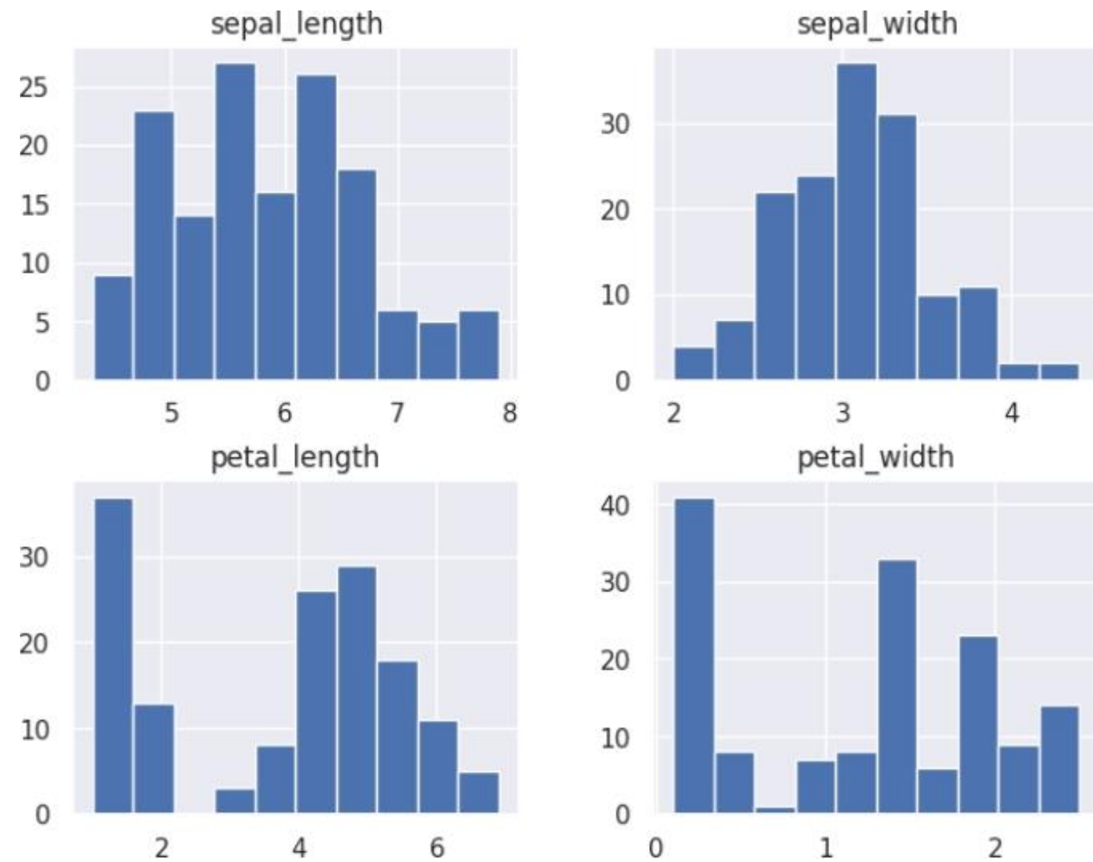
```
   sepal_length  sepal_width  petal_length  petal_width species
0 5.1   3.5   1.4   0.2  setosa
1 4.9   3.0   1.4   0.2  setosa
2 4.7   3.2   1.3   0.2  setosa
3 4.6   3.1   1.5   0.2  setosa
4 5.0   3.6   1.4   0.2  setosa
```

```
summary_statistics = df.describe()
print(summary_statistics)
```

```
       sepal_length  sepal_width  petal_length  petal_width
 count 150.000000    150.000000   150.000000    150.000000
 mean  5.843333      3.057333     3.758000      1.199333
 std   0.828066      0.435866     1.765298      0.762238
 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
```

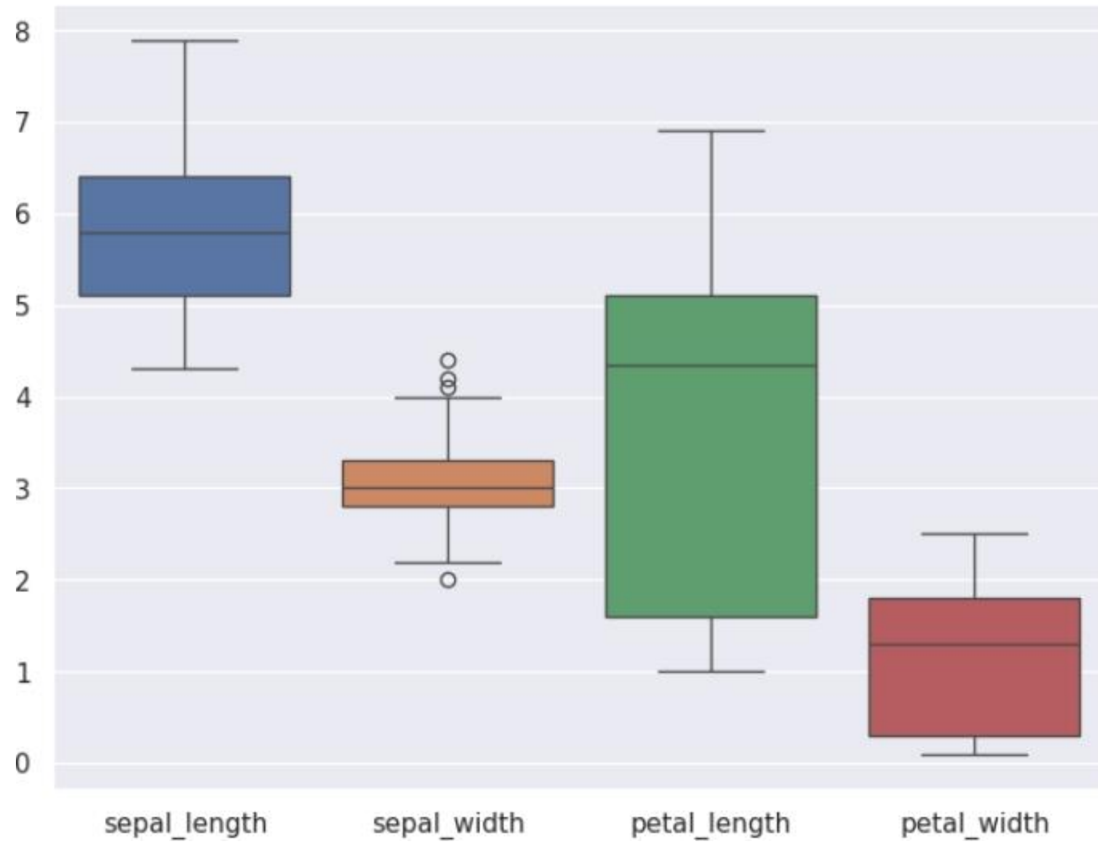
```
#Univariate Visualizations
df.hist()
```

```
array([[<Axes: title={'center': 'sepal_length'}>,
        <Axes: title={'center': 'sepal_width'}>],
       [<Axes: title={'center': 'petal_length'}>,
        <Axes: title={'center': 'petal_width'}>]], dtype=object)
```



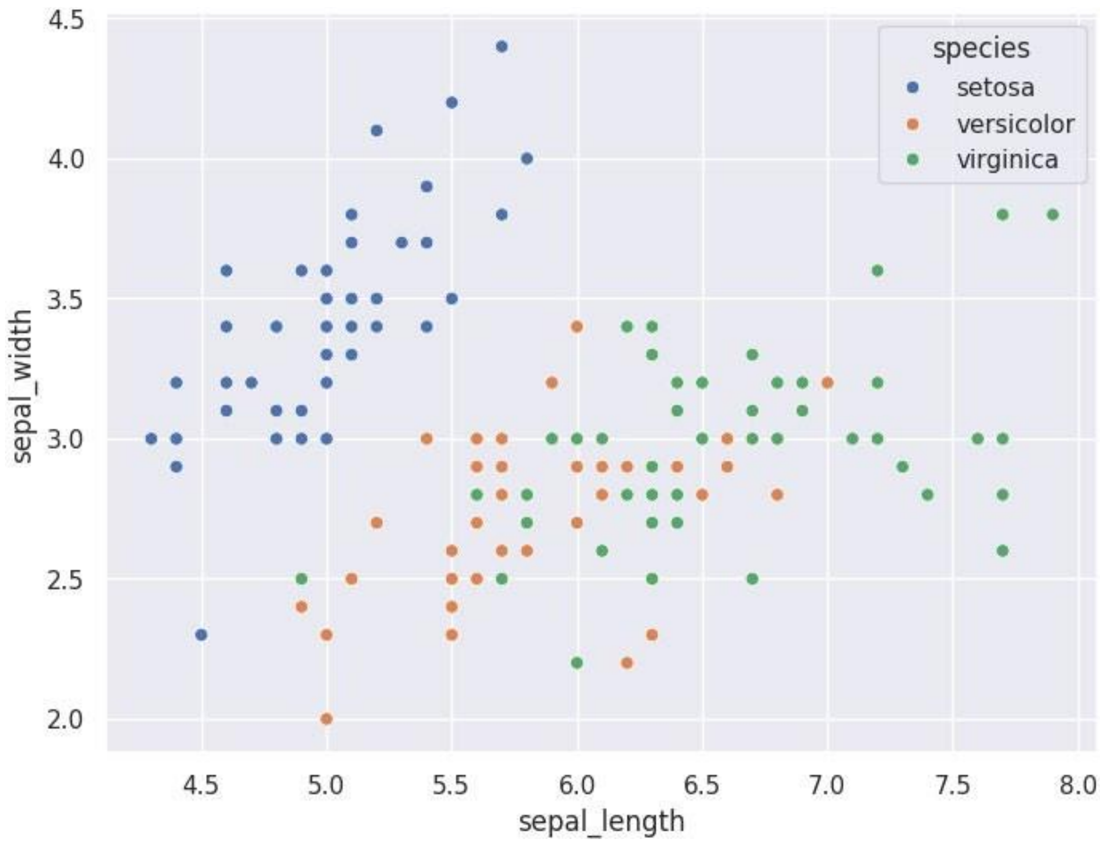

```
sns.boxplot(data=df)
```

```
<Axes: >
```



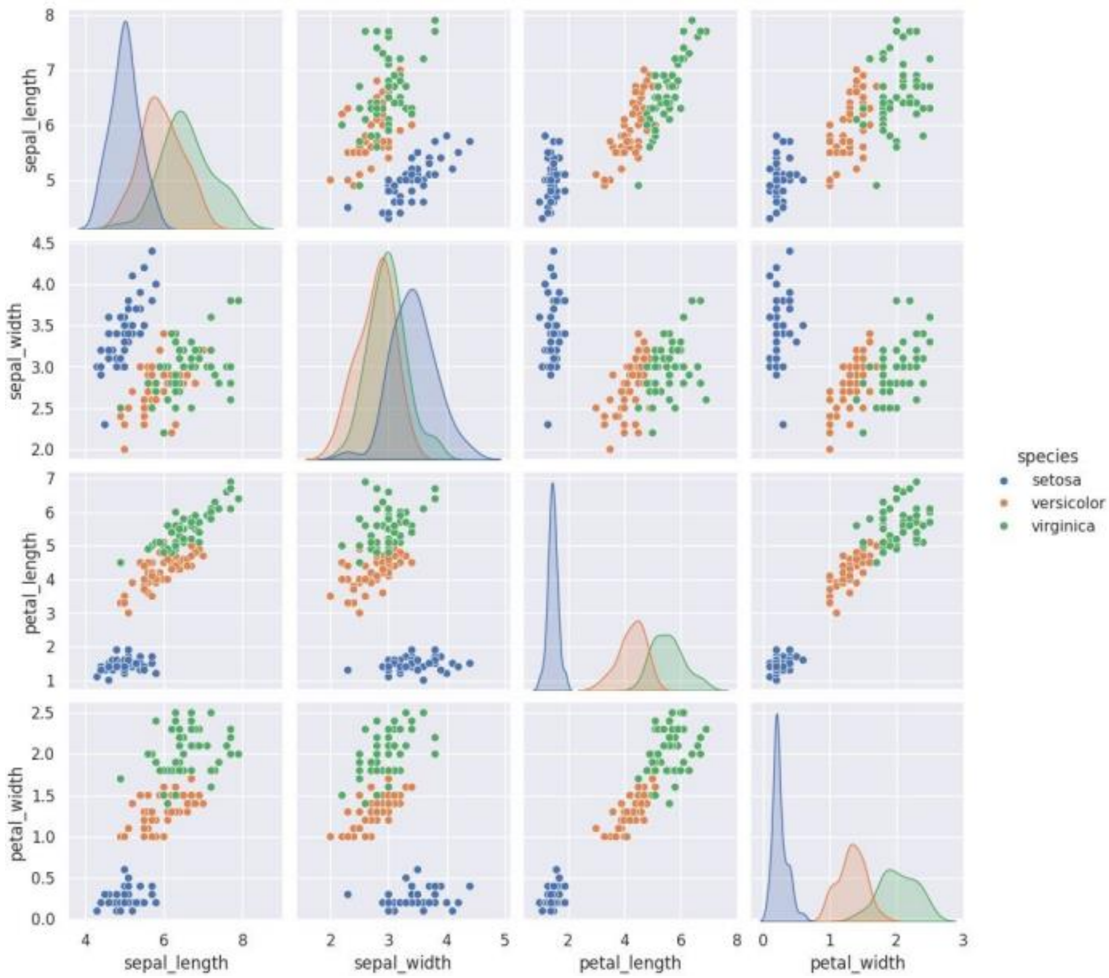

```
sns.scatterplot(data=df, x='sepal_length', y='sepal_width', hue='species')
```

```
<Axes: xlabel='sepal_length', ylabel='sepal_width'>
```



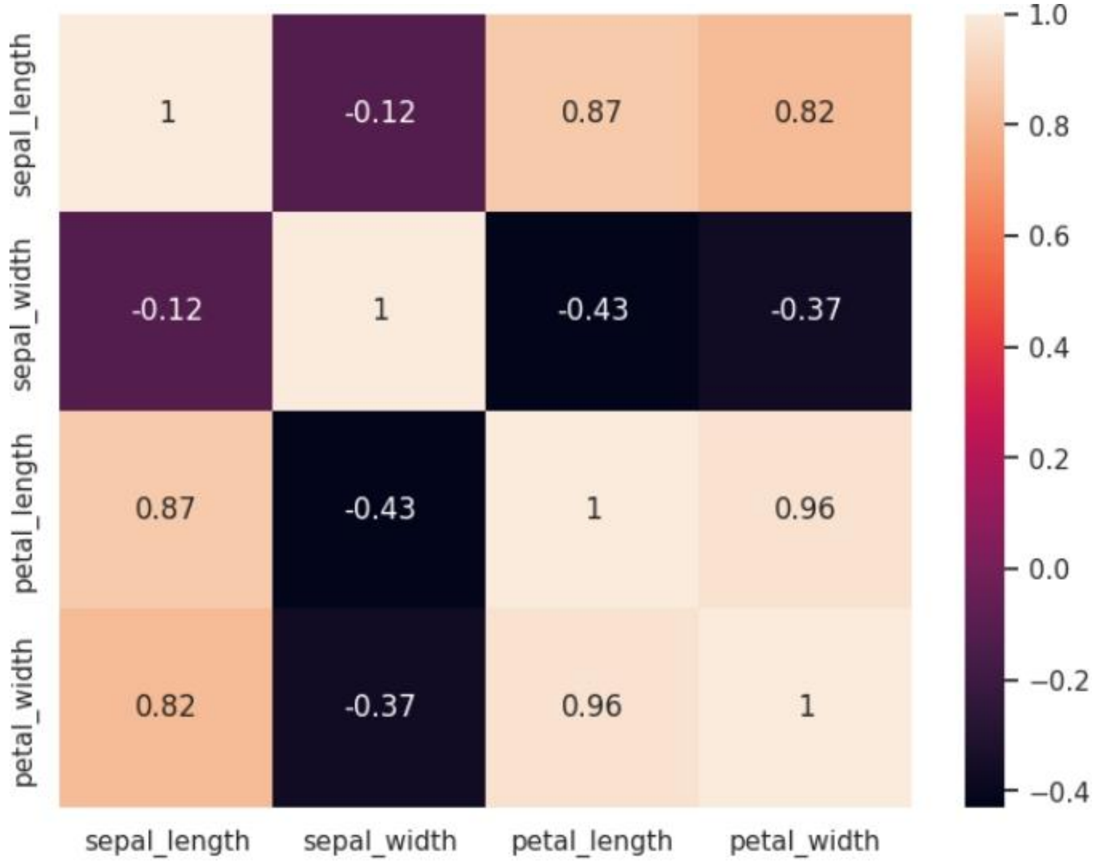

```
sns.pairplot(df, hue="species")
```

```
<seaborn.axisgrid.PairGrid at 0x7fc52c528610>
```




```
#Correleation
numeric_df = df.select_dtypes(include=[np.number])
correlation_matrix = numeric_df.corr()
sns.heatmap(correlation_matrix, annot=True)
```

```
<Axes: >
```




```
potential_features = df.select_dtypes(include=[np.number]).columns.tolist(
)
target_variable = 'species'

print("Potential Features: ", potential_features)
print("Target Variable: ", target_variable)
```

```
Potential Features:  ['sepal_length', 'sepal_width', 'petal_length', 'peta
l_width']
Target Variable:  species
```

1.3 Create or Explore datasets to use all pre-processing routines like label encoding, scaling, and binarization.

```
import seaborn as sns
import pandas as pd
from  sklearn.preprocessing  import  LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import Binarizer

df    =    sns.load_dataset('titanic')
print(df.head())
```

```
   survived  pclass  sex     age   sibsp  parch  fare     embarked  class
 \
 0  0         3       male    22.0  1      0      7.2500   S         Third
 1  1         1       female  38.0  1      0      71.2833  C         First
 2  1         3       female  26.0  0      0      7.9250   S         Third
 3  1         1       female  35.0  1      0      53.1000  S         First
 4  0         3       male    35.0  0      0      8.0500   S         Third

     who  adult_male deck  embark_town alive  alone
0    man       True  NaN  Southampton    no  False
1  woman      False  C      Cherbourg   yes  False
2  woman      False  NaN  Southampton   yes   True
3  woman      False  C  Southampton     yes  False
4    man       True  NaN  Southampton    no    True
```

```
label_encoder = LabelEncoder()
```

0	1
1	0
2	0
3	0
4	1

```
df['sex']    =    label_encoder.fit_transform(df['sex'])
print(df.sex.head())
```

```
Name:  sex,  dtype:  int64
```

```
scaler = StandardScaler()
df[['age',    'fare']]    =    scaler.fit_transform(df[['age',    'fare']])
print(df[['age', 'fare']].head())
```

```
 age         fare
 0 -0.530377 -0.502445
 1  0.571831  0.786845
 2 -0.254825 -0.488854
```

```
    3  0.365167  0.420730
    4  0.365167  -0.486337
```

```
binarizer = Binarizer(threshold=0)
 df[['fare']]          =          binarizer.fit_transform(df[['fare']])
 print(df.fare.head())
```

```
  0  0.0
  1  1.0
  2  0.0
  3  1.0
  4  0.0
 Name:                   fare,                   dtype:                   float6
```

Practical 2

2.1 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. (Create your dataset)

```
import pandas as pd

data = {
    'Material': ['Plastic', 'Metal', 'Glass', 'Metal'],
    'Color': ['White', 'Silver', 'Green', 'Grey'],
    'Size': ['Small', 'Large', 'Small', 'Large'],
    'Recyclable': ['Yes', 'Yes', 'Yes', 'No'],
    'E-Waste': ['No', 'Yes', 'No', 'Yes']
}

df              =             pd.DataFrame(data)
df.to_csv('training_data.csv', index=False)

data = pd.read_csv('training_data.csv')
X = data.iloc[:, :-1]
y     =     data.iloc[:,     -1]

hypothesis = ['0'] * X.shape[1]

for i in range(len(X)):
  if y[i] == 'Yes':
    for j in range(X.shape[1]):
      if    hypothesis[j]    ==    '0':
        hypothesis[j] = X.iloc[i, j]
      elif  hypothesis[j]  !=  X.iloc[i,  j]:
        hypothesis[j] = '?'

print(hypothesis)

['Metal', '?', 'Large', '?']
```

Practical 3

3.1 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

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

np.random.seed(42)
X = 2.5 * np.random.rand(100, 1)
y = 5 + 2 * X + np.random.randn(100, 1)

data = pd.DataFrame({'Feature': X.flatten(), 'Target': y.flatten()})
print(data.head())
```

```
    Feature      Target
0  0.936350  6.959748
1  2.376786  9.454564
2  1.829985  8.751730
3  1.496646  6.005724
4  0.390047  5.560421
```

```
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Feature', y='Target', data=data)
plt.title('Feature vs Target')
plt.show()
```

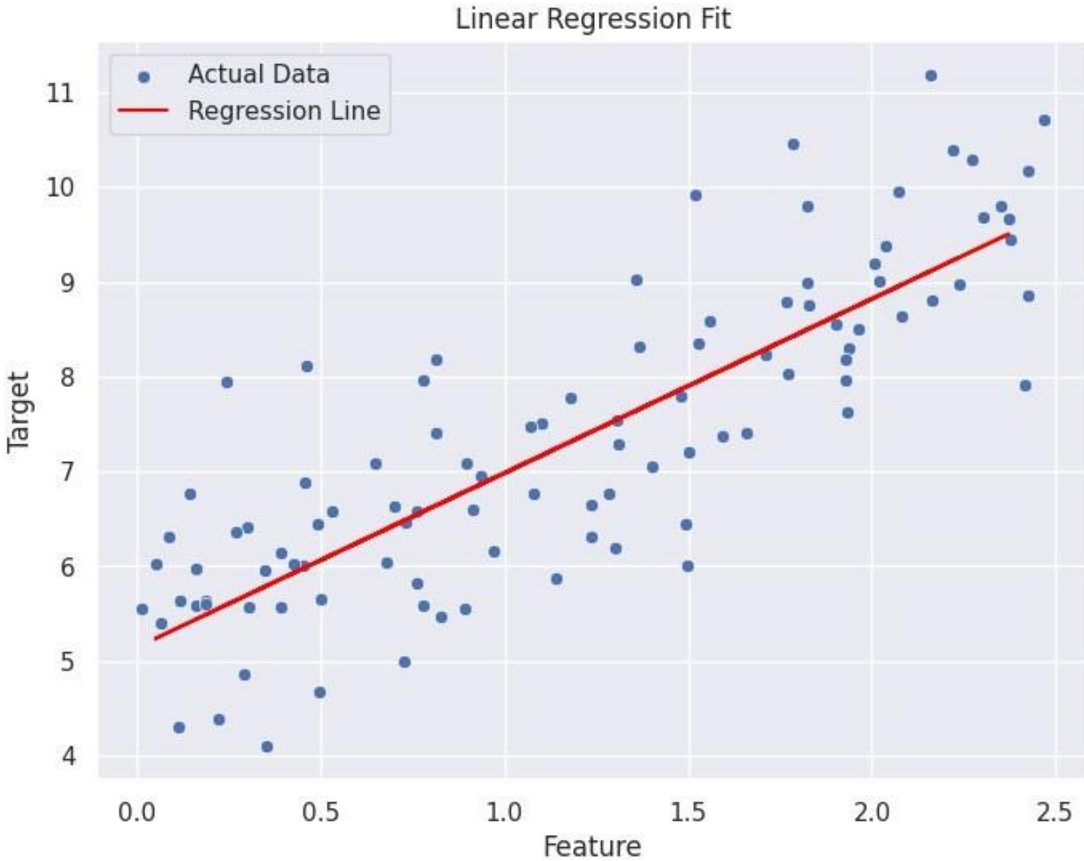

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

model        =        LinearRegression()

model.fit(X_train, y_train)

print(f"Intercept:  {model.intercept_[0]:.2f}")
print(f"Coefficient: {model.coef_[0][0]:.2f}")
```

```
Intercept: 5.14
Coefficient: 1.84
```

```
y_pred = model.predict(X_test)

pred_df = pd.DataFrame({'Actual': y_test.flatten(), 'Predicted': y_pred.flatten()})
print(pred_df.head())
```

```
     Actual  Predicted
0  5.974345   5.435196
1  8.970661   9.257909
2  7.624273   8.694195
```

```
3  7.4032248.189620
4  7.0849326.332951

mse     =     mean_squared_error(y_test,     y_pred)
print(f"Mean Squared Error (MSE): {mse:.2f}")

r2 = r2_score(y_test, y_pred)
print(f"R-squared: {r2:.2f}")

Mean Squared Error (MSE): 0.65
R-squared: 0.73

plt.figure(figsize=(8, 6))
sns.scatterplot(x='Feature',   y='Target',   data=data,   label='Actual   Data')
plt.plot(X_test,     y_pred,     color='red',     label='Regression     Line')
plt.title('Linear Regression Fit')
plt.legend()
plt.show()
```

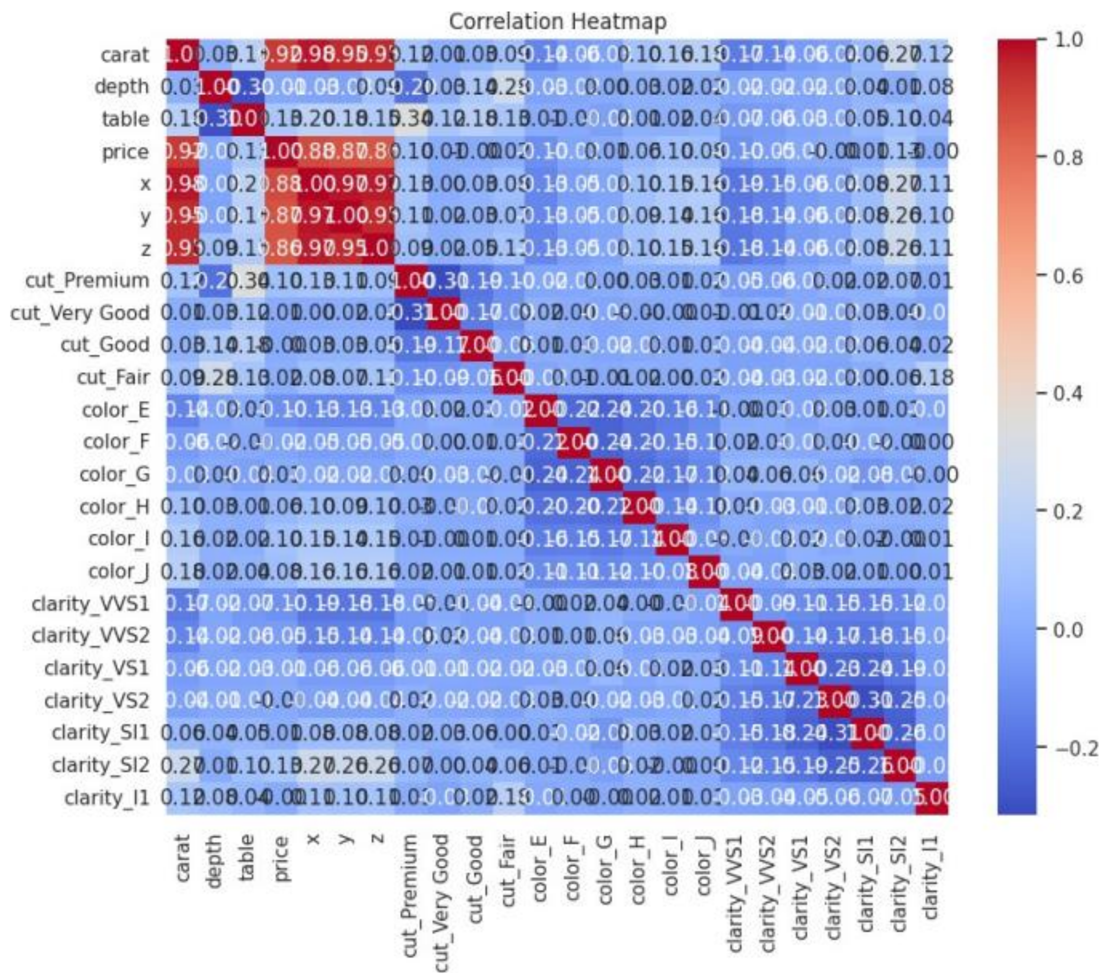


3.2 Multiple Linear Regression Extend linear regression to multiple features. Handle feature selection and potential multicollinearity.

```
import  seaborn  as  sns
import  pandas  as  pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.api as sm
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

df = sns.load_dataset('diamonds')

print("Missing  values  in  the  dataset:")
print(df.isnull().sum())

df = pd.get_dummies(df, drop_first=True)
```

```
Missing values in the dataset:
carat      0
cut        0
color      0
clarity    0
depth      0
table      0
price      0
x          0
y          0
z          0
dtype: int64
```

```
plt.figure(figsize=(10, 8))
sns.heatmap(df.corr(),    annot=True,    cmap='coolwarm',    fmt='.2f')
plt.title("Correlation Heatmap")
plt.show()
```




```
X   =   df[['carat',   'depth',   'table',   'x',   'y',   'z',
        'cut_Premium',    'cut_Good',    'cut_Very    Good',
        'color_E', 'color_F', 'clarity_VVS2', 'clarity_VS1']]
y = df['price']

y = y.astype(float)

X_with_constant = sm.add_constant(X)

X_with_constant  =  X_with_constant.astype(int)

vif = pd.DataFrame()
vif['Features'] = X.columns
vif['VIF'] = [variance_inflation_factor(X_with_constant.values, i+1) for i
in       range(len(X.columns))]
print(vif)
```

	Features	VIF
0	carat	3.613538

```
2 table 1.530672
3 x  19.224267
4 y  15.677513
5 z      5.789510
6 cut_Premium 1.548643
7 cut_Good    1.295429
8 cut_Very Good     1.346362
9 color_E     1.079848
10      color_F     1.060367
11      clarity_VVS21.051655
12      clarity_VS1 1.031049
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, r
andom_state=42)
```

```
print("Data   types   of   X_train:")
print(X_train.dtypes)
print("Data type of y_train:", y_train.dtype)
```

```
Data types of X_train:
carat   float64
depth   float64
table   float64
x                float64
y                float64
z                float64
cut_Premium   bool
cut_Good      bool
cut_Very Good bool
color_E bool
color_F bool
clarity_VVS2  bool
clarity_VS1   bool
dtype: object
Data type of y_train: float64
```

```
X_train   =   X_train.astype(float)
y_train = y_train.astype(float)
```

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

```
print("Intercept:",   model.intercept_)
print("Coefficients:", model.coef_)
```

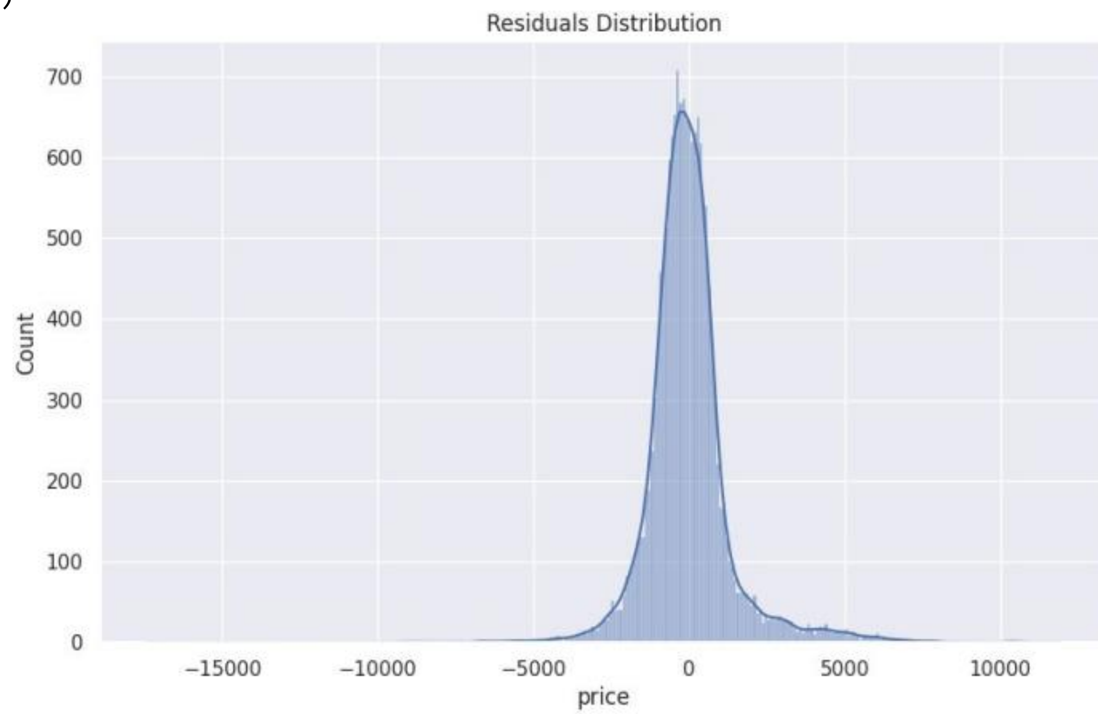
```
Intercept: 17520.480548853404
Coefficients: [ 1.06799558e+04 -1.74848962e+02 -8.87411825e+01 -1.17618393
e+03
  3.03543071e+01  8.16330490e+00 -3.94552416e+01 -1.98436785e+02
```

```
-1.87877044e+01    4.36586414e+02    4.74099129e+02    1.02842658e+03
 6.62232418e+02]
```

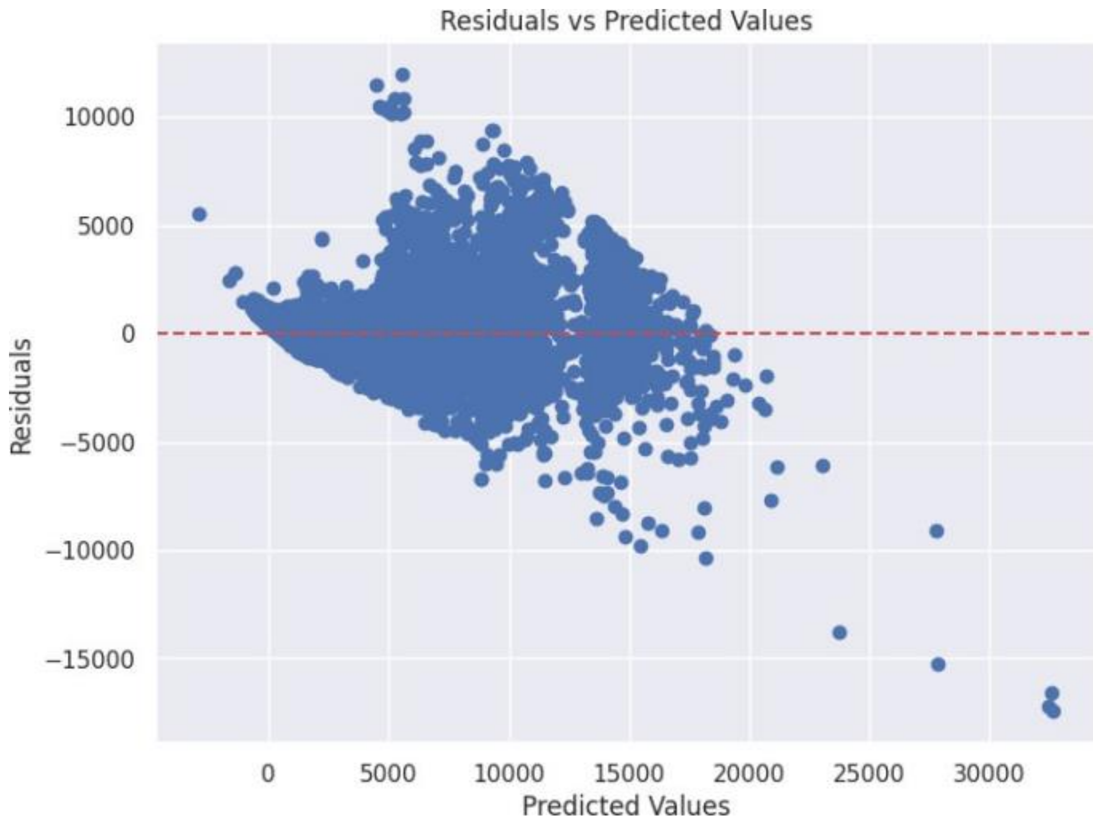
```
y_pred = model.predict(X_test)
mse  =  mean_squared_error(y_test,  y_pred)
r2 = r2_score(y_test, y_pred)

print("Mean Squared Error:", mse)
print("R-squared:", r2)

residuals = y_test - y_pred
```

```
Mean Squared Error: 2018911.748442661
R-squared: 0.8705490836162249
```

```
plt.figure(figsize=(10,                6))
sns.histplot(residuals,         kde=True)
plt.title("Residuals       Distribution")
plt.show()
```




```
plt.scatter(y_pred,              residuals)
plt.axhline(y=0, color='r', linestyle='--')
plt.xlabel("Predicted             Values")
plt.ylabel("Residuals")
plt.title("Residuals vs Predicted Values")
plt.show()
```

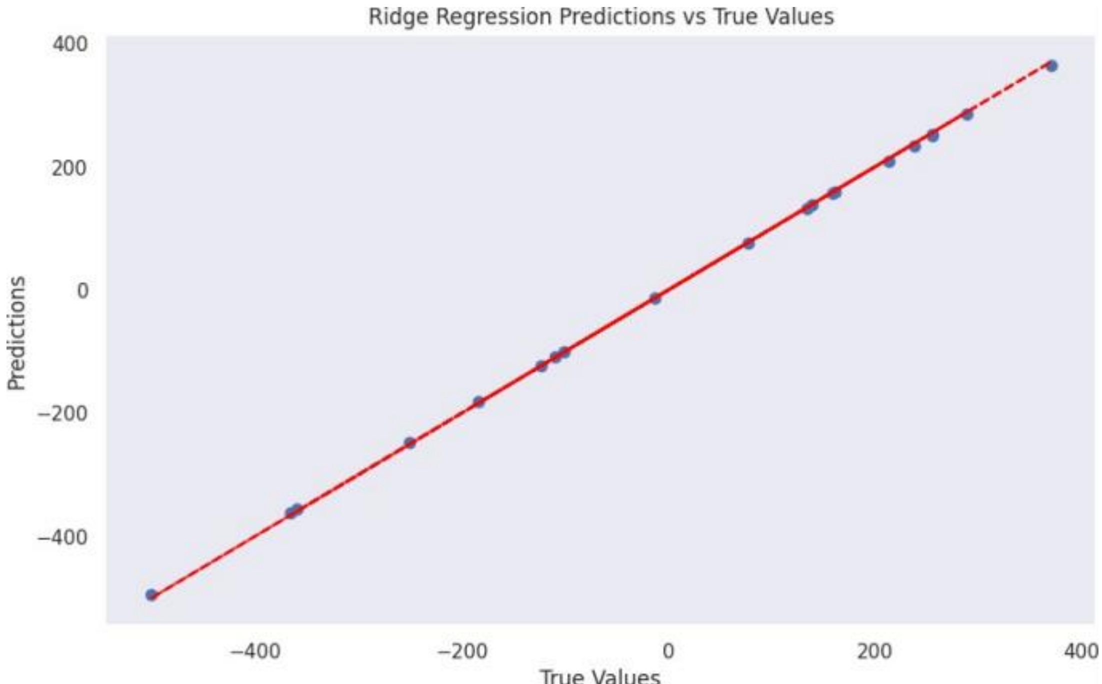


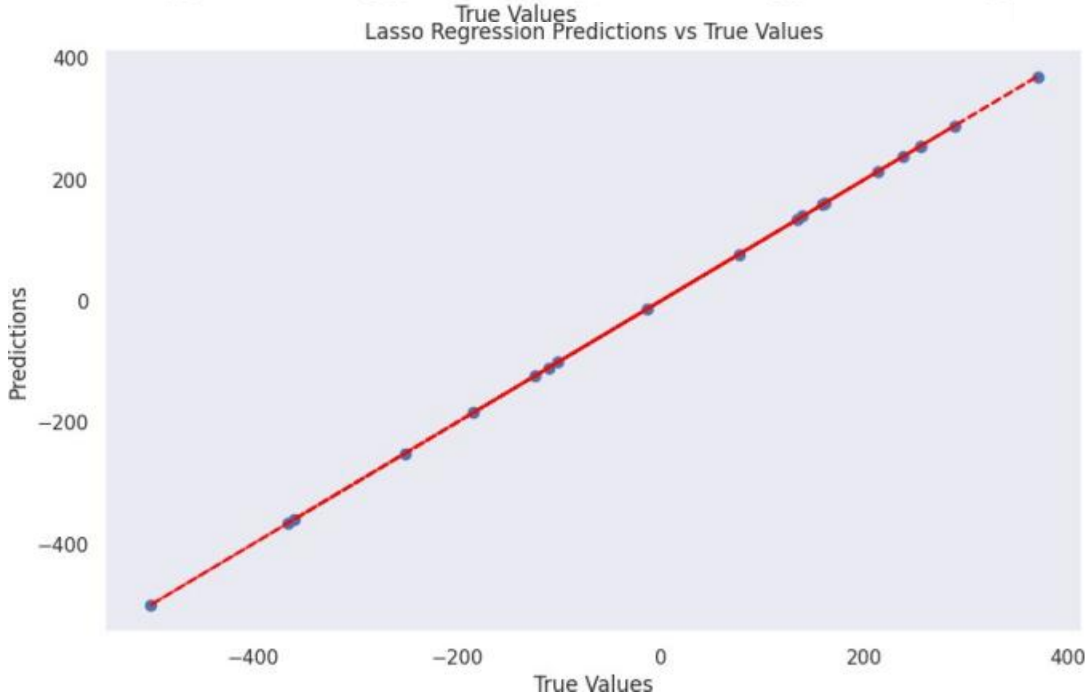

```
X_train_sm      =      sm.add_constant(X_train)
ols_model = sm.OLS(y_train, X_train_sm).fit()
print(ols_model.summary())

                            OLS Regression Results
==========================================================================
====
Dep. Variable:      price R-squared:  0
.870
Model:  OLS   Adj. R-squared:   0
.869
Method: Least Squares     F-statistic:1.935
e+04
Date:   Thu, 24 Oct 2024  Prob (F-statistic): 0.00
Time:   07:44:35    Log-Likelihood:   -3.2835 e+05
No. Observations:   37758 AIC:  6.567
e+05
Df Residuals: 37744 BIC:  6.569
e+05
Df Model:     13
Covariance Type:    nonrobust
==========================================================================
=======
```

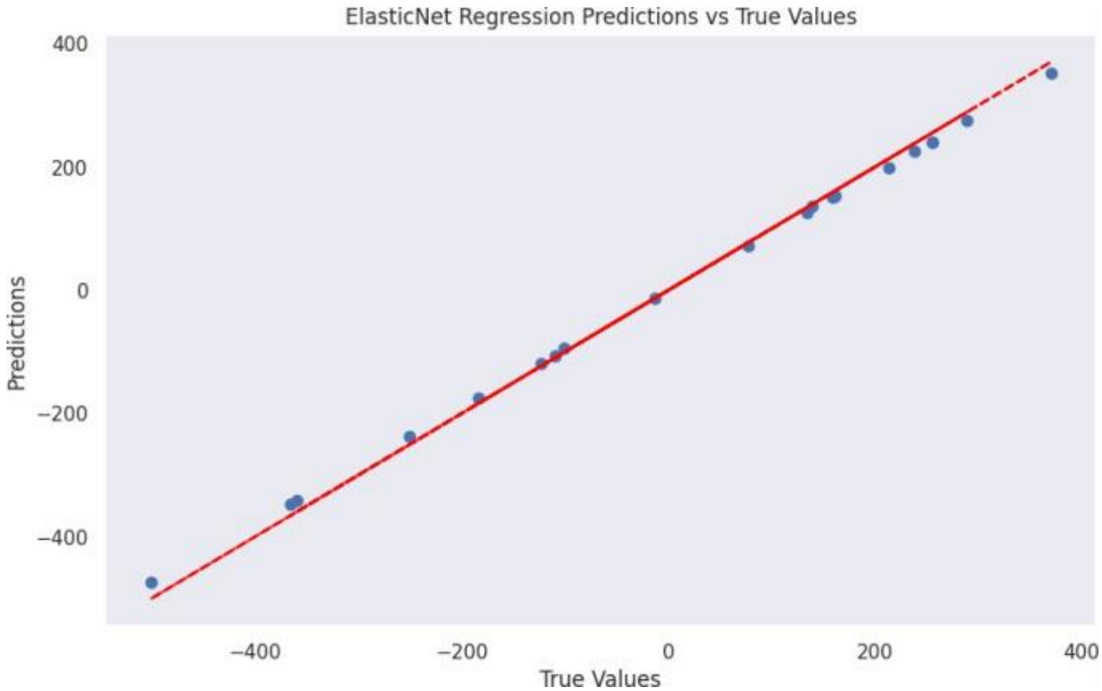
```
                    coef     std err     t      P>|t| [0.025
0.975]
------------------------------------------------------------------------------

const      1.752e+04   537.976     32.5670.000 1.65e+04    1
.86e+04
carat      1.068e+04   72.935146.431     0.000 1.05e+04    1
.08e+04
depth      -174.8490   6.336 -27.595     0.000 -187.268    -
162.430
table      -88.7412    4.144 -21.414     0.000 -96.864
-80.619
x    -1176.1839  46.936-25.059     0.000 -1268.179   -1
084.188
y    30.3543     27.8971.088 0.277 -24.325
85.034
z    8.163343.8890.186 0.852 -77.861
94.188
cut_Premium      -39.4552    21.233-1.8580.063 -81.073
2.163
cut_Good   -198.4368   29.625-6.6980.000 -256.502    -
140.372
cut_Very Good    -18.7877    20.712-0.9070.364 -59.383
21.808
color_E    436.5864    20.10821.7120.000 397.174
475.999
color_F    474.0991    20.08423.6060.000 434.735
513.463
clarity_VVS2     1028.4266   26.28739.1230.000 976.903     1
079.950
clarity_VS1      662.2324    21.07531.4230.000 620.925
703.540
==========================================================================
====
Omnibus:   9105.593    Durbin-Watson:    1
.992
Prob(Omnibus):   0.000 Jarque-Bera (JB): 327369
.326
Skew:      0.453 Prob(JB):
0.00
Kurtosis:  17.397Cond. No.   6.14
e+03
==========================================================================
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
cor rectly specified.
   The condition number is large, 6.14e+03. This might indicate that there are
   strong multicollinearity or other numerical problems.
```

3.3 Multiple Linear Regression Extend linear regression to multiple features. Handle feature selection and potential multicollinearity.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import make_regression
from  sklearn.model_selection  import  train_test_split
from sklearn.linear_model import Ridge, Lasso, ElasticNet
from sklearn.metrics import mean_squared_error

X, y, coef = make_regression(n_samples=100, n_features=10, noise=0.1, coef
=True, random_state=42)

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

ridge_model       =       Ridge(alpha=1.0)
ridge_model.fit(X_train,         y_train)
ridge_pred = ridge_model.predict(X_test)

lasso_model       =       Lasso(alpha=0.1)
lasso_model.fit(X_train,         y_train)
lasso_pred = lasso_model.predict(X_test)

elastic_model       =       ElasticNet(alpha=0.1,       l1_ratio=0.5)
elastic_model.fit(X_train, y_train)
elastic_pred = elastic_model.predict(X_test)

def plot_results(y_test, predictions, model_name):
    plt.figure(figsize=(10,                    6))
    plt.scatter(y_test, predictions)
    plt.plot(y_test, y_test, color='red', linestyle='--')  # y=x line
    plt.title(f'{model_name}    Predictions    vs    True    Values')
    plt.xlabel('True Values')
    plt.ylabel('Predictions')
    plt.grid()
    plt.show()

plot_results(y_test,      ridge_pred,      'Ridge      Regression')
plot_results(y_test,      lasso_pred,      'Lasso      Regression')
plot_results(y_test, elastic_pred, 'ElasticNet Regression')
```


Ridge Regression Predictions vs True Values
400
200
0
−200
−400
Predictions
−400
−200
0
200
400
True Values


Lasso Regression Predictions vs True Values
400
200
0
−200
−400
Predictions
−400
−200
0
200
400
True Values




```
print("Mean Squared Error (MSE):")
print(f"Ridge:      {mean_squared_error(y_test,      ridge_pred):.2f}")
print(f"Lasso:      {mean_squared_error(y_test,      lasso_pred):.2f}")
print(f"ElasticNet: {mean_squared_error(y_test, elastic_pred):.2f}")
```

```
Mean   Squared   Error   (MSE):
Ridge: 11.84
Lasso: 0.18
ElasticNet: 176.03
```

Practical 4

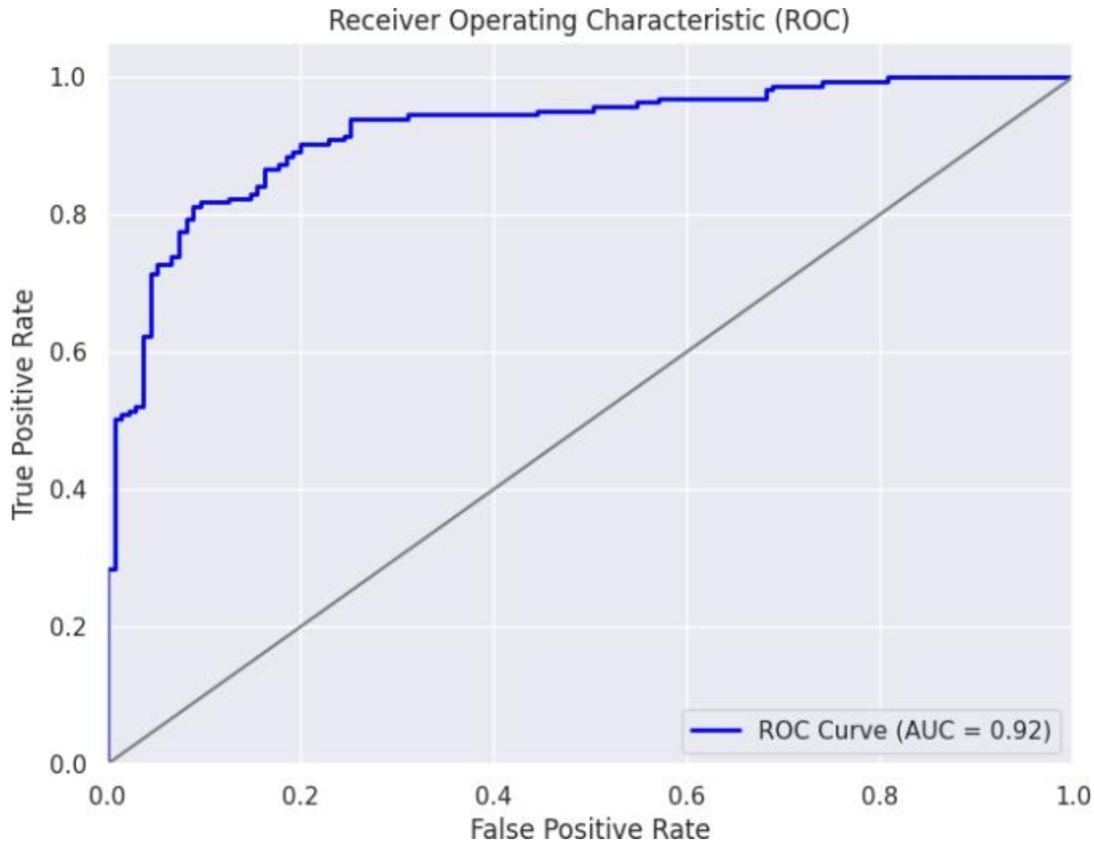
4.1 Logistic Regression Perform binary classification using logistic regression. Calculate accuracy, precision, recall, and understand the ROC curve.

```
import numpy as np
import matplotlib.pyplot as plt
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
from sklearn.datasets import make_classification

X, y = make_classification(n_samples=1000, n_features=10, n_classes=2, ran
dom_state=42)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, r
andom_state=42)
logistic_reg_model   =   LogisticRegression()
logistic_reg_model.fit(X_train,      y_train)
y_pred = logistic_reg_model.predict(X_test)

accuracy   =   accuracy_score(y_test,   y_pred)
precision   =  precision_score(y_test,   y_pred)
recall = recall_score(y_test, y_pred)

print(f"Accuracy:      {accuracy:.2f}")
print(f"Precision:    {precision:.2f}")
print(f"Recall: {recall:.2f}")
```

```
Accuracy: 0.85
Precision: 0.89
Recall: 0.82
```

```
y_prob = logistic_reg_model.predict_proba(X_test)[:, 1]
fpr,   tpr,   thresholds   =   roc_curve(y_test,   y_prob)
roc_auc = auc(fpr, tpr)
plt.figure()
plt.plot(fpr, tpr, color='blue', lw=2, label=f"ROC Curve (AUC = {roc_auc:.
2f})")
plt.plot([0, 1], [0, 1], color='gray', linestyle='-')  # Diagonal line for
random classifier
plt.xlim([0.0, 1.0])
plt.ylim([0.0,              1.05])
plt.xlabel('False  Positive  Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
```

```
plt.legend(loc='lower  right')
plt.show()
```



4.2 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.

```
from sklearn import datasets
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report

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

df   =   pd.DataFrame(data=X,   columns=iris.feature_names)
df['target'] = y
```

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

```
print(df.head())
```

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

```
print(df.isnull().sum())
```

```
sepal length (cm)  0
sepal width (cm)   0
petal length (cm)  0
petal width (cm)   0
target             0
dtype: int6
```

```
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
y = y.astype('category').cat.codes

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, r
andom_state=42)
k = 3
knn = KNeighborsClassifier(n_neighbors=k)
knn.fit(X_train, y_train)

y_pred = knn.predict(X_test)

for i in range(len(y_test)):
    print(f'Predicted:  {iris.target_names[y_pred[i]]},  Actual:  {iris.targe
t_names[y_test.iloc[i]]}')
```

```
Predicted: versicolor, Actual: versicolor Predicted: setosa, Actual: setosa
Predicted: virginica, Actual: virginica Predicted: versicolor, Actual:
versicolor Predicted: versicolor, Actual: versicolor Predicted: setosa,
Actual: setosa Predicted: versicolor, Actual: versicolor Predicted:
virginica, Actual: virginica Predicted: versicolor, Actual: versicolor
Predicted: versicolor, Actual: versicolor Predicted: virginica, Actual:
virginica Predicted: setosa, Actual: setosa Predicted: setosa, Actual:
setosa Predicted: setosa, Actual: setosa Predicted: setosa, Actual: setosa
```

```
Predicted:    setosa,    Actual:    setosa
Predicted: versicolor, Actual: versicolor
Predicted:  virginica,  Actual:  virginica
Predicted: versicolor, Actual: versicolor
Predicted: versicolor, Actual: versicolor
Predicted:  virginica,  Actual:  virginica
Predicted:    setosa,    Actual:    setosa
Predicted:  virginica,  Actual:  virginica
Predicted:    setosa,    Actual:    setosa
Predicted:  virginica,  Actual:  virginica
Predicted:  virginica,  Actual:  virginica
Predicted:  virginica,  Actual:  virginica
Predicted:  virginica,  Actual:  virginica
Predicted:  virginica,  Actual:  virginica
Predicted:    setosa,    Actual:    setosa
Predicted: setosa, Actual: setosa
```

```
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy * 100:.2f}%')
```

```
print(classification_report(y_test, y_pred, target_names=iris.target_names
))
```

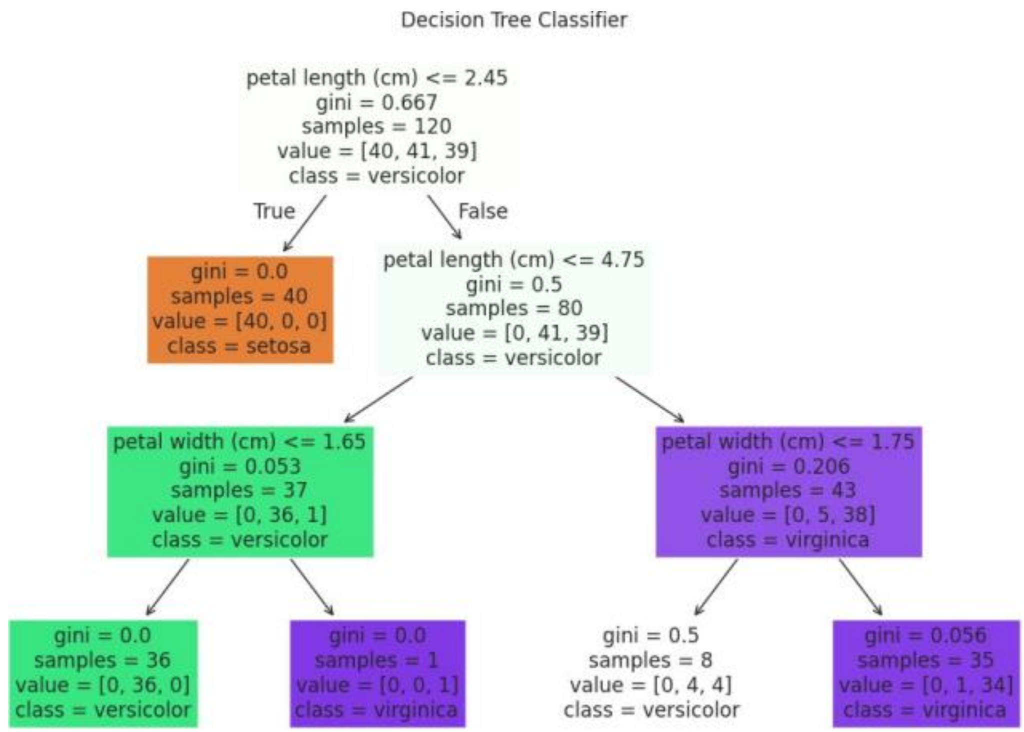
```
Accuracy: 100.00%
              precision    recall   f1-score   support

 setosa        1.00         1.00     1.00       10
 versicolor    1.00         1.00     1.00       9
 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
```

4.3 Build a decision tree classifier or regressor. Control hyperparameters like tree depth to avoid overfitting. Visualize the tree.

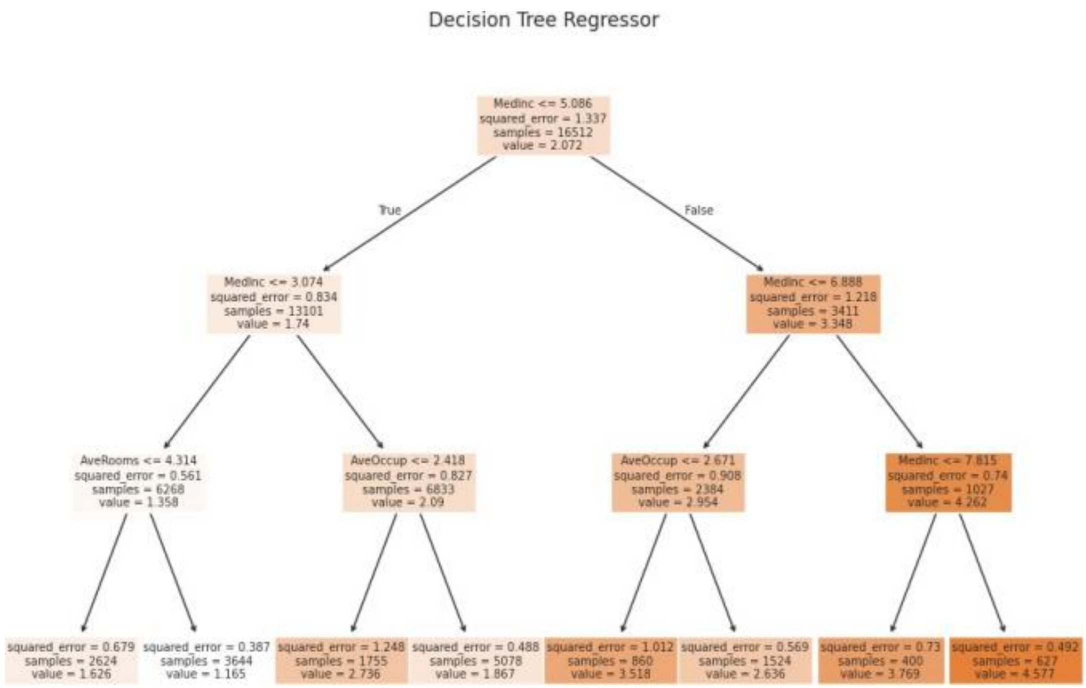
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris, fetch_california_housing
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor, pl
ot_tree
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, mean_squared_error

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

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, r
andom_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: {accuracy:.2f}')
```

```
Accuracy: 1.00
```

```
plt.figure(figsize=(12,8))
plot_tree(clf, filled=True, feature_names=iris.feature_names, class_names=
iris.target_names)
plt.title("Decision Tree Classifier")
plt.show()
```




```
housing = fetch_california_housing()
X_housing  =  housing.data
y_housing = housing.target

X_train_housing, X_test_housing, y_train_housing, y_test_housing = train_t
est_split(X_housing, y_housing, test_size=0.2, random_state=42)

reg = DecisionTreeRegressor(max_depth=3, random_state=42)
reg.fit(X_train_housing, y_train_housing)

y_pred_housing = reg.predict(X_test_housing)

mse = mean_squared_error(y_test_housing, y_pred_housing)
print(f'Mean Squared Error: {mse:.2f}')

Mean Squared Error: 0.64

plt.figure(figsize=(12,8))
plot_tree(reg, filled=True, feature_names=housing.feature_names)
plt.title("Decision Tree Regressor")
plt.show()
```


Decision Tree Regressor
MedInc <= 5.086
squared_error = 1.337
samples = 16512
value = 2.072
True
False
MedInc <= 3.074
squared_error = 0.834
samples = 13101
value = 1.74
MedInc <= 6.888
squared_error = 1.218
samples = 3411
value = 3.348
AveRooms <= 4.314
squared_error = 0.561
samples = 6268
value = 1.358
AveOccup <= 2.418
squared_error = 0.827
samples = 6833
value = 2.09
AveOccup <= 2.671
squared_error = 0.908
samples = 2384
value = 2.954
MedInc <= 7.815
squared_error = 0.74
samples = 1027
value = 4.262
squared_error = 0.679
samples = 2624
value = 1.626
squared_error = 0.387
samples = 3644
value = 1.165
squared_error = 1.248
samples = 1755
value = 2.736
squared_error = 0.488
samples = 5078
value = 1.867
squared_error = 1.012
samples = 860
value = 3.518
squared_error = 0.569
samples = 1524
value = 2.636
squared_error = 0.73
samples = 400
value = 3.769
squared_error = 0.492
samples = 627
value = 4.577

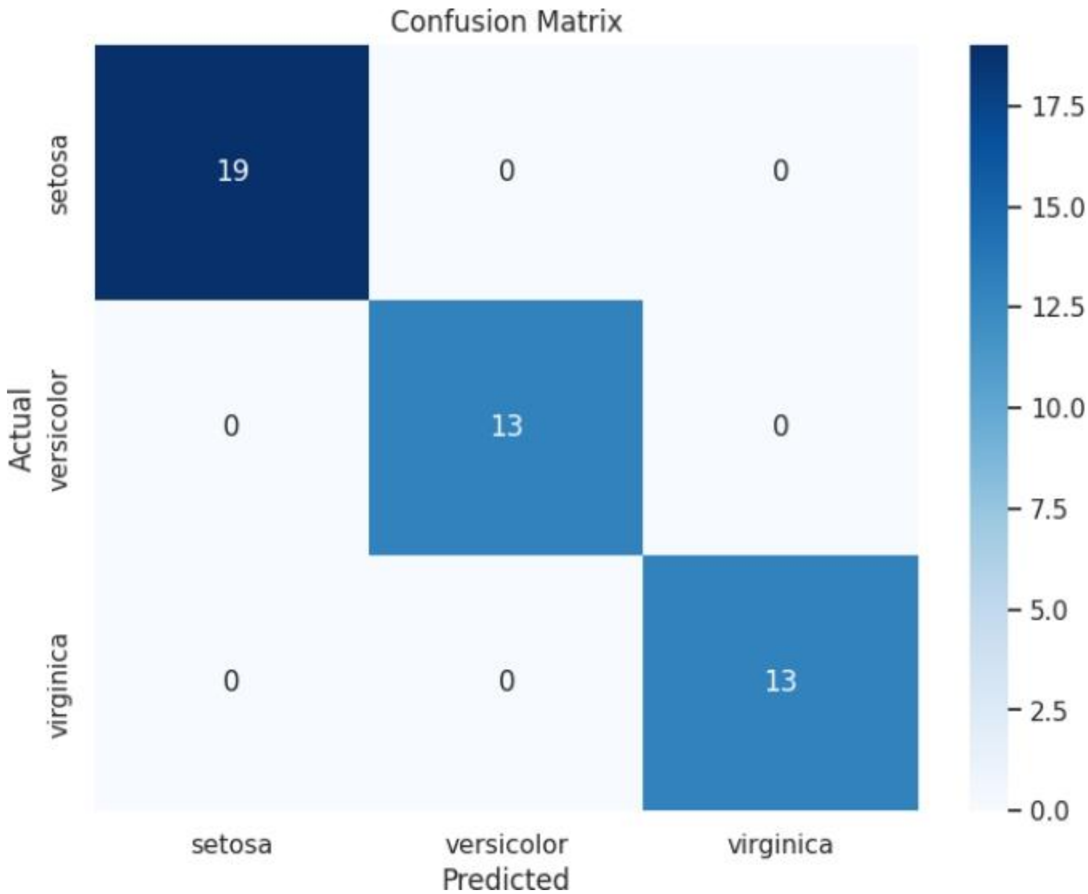
4.4 Implement a Support Vector Machine for any relevant dataset.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, confusion_matrix, classificati
on_report
import seaborn as sns

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

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, r
andom_state=42)
svm_classifier        =        SVC(kernel='linear',        random_state=42)
svm_classifier.fit(X_train, y_train)

y_pred = svm_classifier.predict(X_test)

accuracy   =   accuracy_score(y_test,   y_pred)
print(f"Accuracy: {accuracy:.2f}")

conf_matrix = confusion_matrix(y_test, y_pred)
print("\nConfusion                    Matrix:")
print(conf_matrix)

class_report = classification_report(y_test, y_pred, target_names=iris.tar
get_names)
print("\nClassification      Report:")
print(class_report)
```

```
[[19  0  0]
 [ 0 13  0]
 [ 0  0 13]]
Accuracy:    1.00

Confusion Matrix:




Classification Report:
               precision   recall   f1-score   support

   setosa      1.00        1.00     1.00       19
   versicolor  1.00        1.00     1.00       13
```

```
accuracy                            1.00        45
macro avg       1.00      1.00      1.00        45
weighted avg    1.00      1.00      1.00        45
```

```
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=ir
is.target_names, yticklabels=iris.target_names)
plt.title('Confusion Matrix')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show()
```



4.5 Train a random forest ensemble. Experiment with the number of trees and feature sampling. Compare performance to a single decision tree.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.model_selection import train_test_split
from   sklearn.tree   import   DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classificati
on_report
import seaborn as sns

iris = datasets.load_iris()
X  =  iris.data
y = iris.target
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, r
andom_state=42)
tree_classifier          =          DecisionTreeClassifier(random_state=42)
tree_classifier.fit(X_train, y_train)
y_pred_tree      =      tree_classifier.predict(X_test)
accuracy_tree   =   accuracy_score(y_test,   y_pred_tree)
print(f"Decision Tree Accuracy: {accuracy_tree:.2f}\n")

Decision Tree Accuracy: 1.00


n_trees   =   [1,   5,   10,   50,   100]
accuracy_forest = []
for n in n_trees:
    forest_classifier = RandomForestClassifier(n_estimators=n, random_stat
e=42)
    forest_classifier.fit(X_train,              y_train)
    y_pred_forest   =   forest_classifier.predict(X_test)
    accuracy   =   accuracy_score(y_test,   y_pred_forest)
    accuracy_forest.append(accuracy)
    print(f"Random Forest with {n} trees Accuracy: {accuracy:.2f}")

Random  Forest  with  1  trees  Accuracy:  1.00
Random  Forest  with  5  trees  Accuracy:  1.00
Random  Forest  with  10  trees  Accuracy:  1.00
Random  Forest  with  50  trees  Accuracy:  1.00
Random Forest with 100 trees Accuracy: 1.00

plt.figure(figsize=(10, 6))
plt.plot(n_trees,    accuracy_forest,    marker='o',    label='Random    Forest')
plt.axhline(y=accuracy_tree,  color='r',  linestyle='-',  label='Single  Decis  ion
Tree')
```

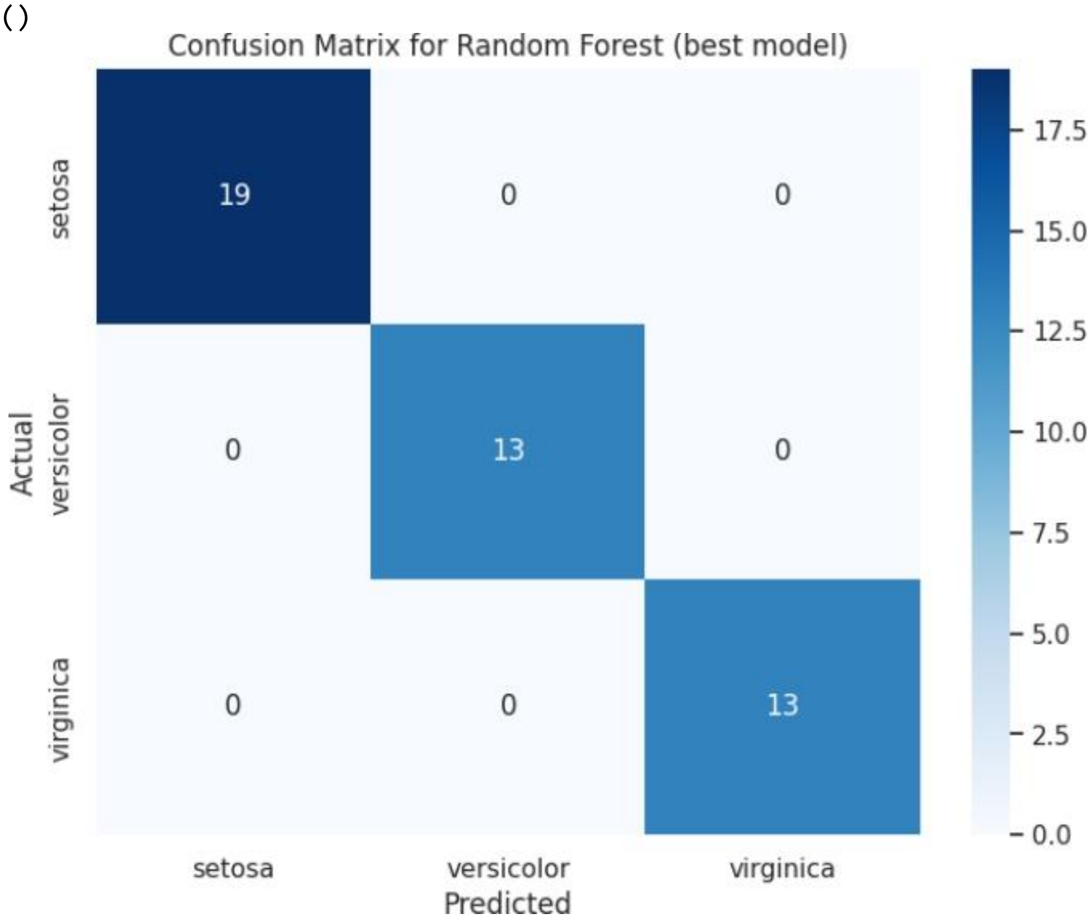
```
plt.title('Model Accuracy Comparison')
plt.xlabel('Number of Trees')
plt.ylabel('Accuracy')
plt.xticks(n_trees) plt.legend()
plt.grid()
plt.show()
```


```
best_n = n_trees[np.argmax(accuracy_forest)]  # Get the best performing nu
mber of trees
best_forest_classifier = RandomForestClassifier(n_estimators=best_n, rando
m_state=42)
best_forest_classifier.fit(X_train,                    y_train)
y_pred_best_forest = best_forest_classifier.predict(X_test)

conf_matrix    =    confusion_matrix(y_test,    y_pred_best_forest)
print("\nConfusion  Matrix  for  Random  Forest  (best  model):")
print(conf_matrix)

Class_report = classification_report(y_test, y_pred_best_forest, target_na
mes=iris.target_names)
print("\nClassification  Report  for  Random  Forest  (best  model):")
print(class_report)
```

```
Confusion Matrix for Random Forest (best model):
 [[19  0 0]
  [ 0 13 0]
  [ 0  0 13]]
```

```
Classification Report for Random Forest (best model):
              precision    recall  f1-score   support

 setosa        1.00        1.00     1.00      19
 versicolor    1.00        1.00     1.00      13
 virginica     1.00        1.00     1.00      13

 accuracy                           1.00      45
 macro avg     1.00        1.00     1.00      45
 weighted avg  1.00        1.00     1.00      45
```

```
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=ir
is.target_names, yticklabels=iris.target_names)
plt.title('Confusion    Matrix    for    Random    Forest    (best    model)')
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.show()
```



4.6 Implement a gradient boosting machine (e.g., XGBoost). Tune hyperparameters and explore feature importance.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import datasets
from sklearn.model_selection import train_test_split, GridSearchCV
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classificati
on_report

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

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, r
andom_state=42)
xgb_model = XGBClassifier(use_label_encoder=False, eval_metric='mlogloss')
xgb_model.fit(X_train, y_train)

param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [3, 4, 5],
    'learning_rate': [0.01, 0.1, 0.2],
    'subsample': [0.8, 1.0]
}
grid_search = GridSearchCV(estimator=xgb_model, param_grid=param_grid, sco
ring='accuracy', cv=3, verbose=1, n_jobs=-1)
grid_search.fit(X_train, y_train)

best_params = grid_search.best_params_
print("Best parameters from GridSearch:", best_params)
```

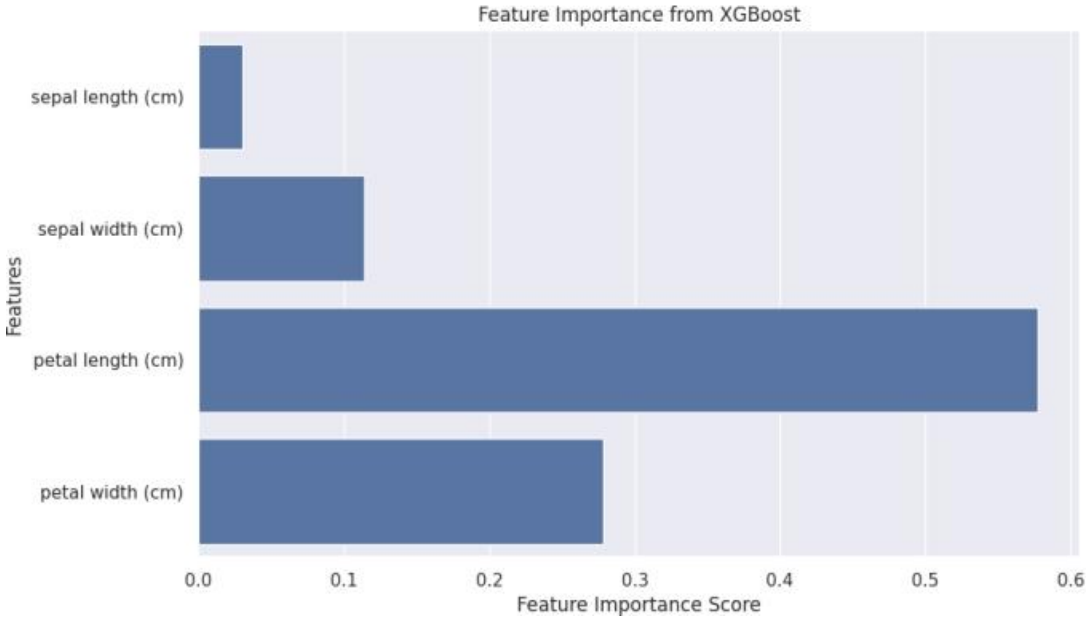
```
Fitting 3 folds for each of 54 candidates, totalling 162 fits
Best parameters from GridSearch: {'learning_rate': 0.01, 'max_depth': 4, '
n_estimators': 100, 'subsample': 0.8}
```

```
best_xgb_model = grid_search.best_estimator_
y_pred = best_xgb_model.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print(f"\nXGBoost Accuracy: {accuracy:.2f}\n")

conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)
```

```
class_report = classification_report(y_test, y_pred, target_names=iris.tar
get_names)
print("\nClassification      Report:")
print(class_report)
```

```
XGBoost Accuracy: 1.00

 Confusion Matrix:
[[19  0  0]
 [ 0 13  0]
 [ 0  0 13]]

 Classification Report:
              precision    recall  f1-score   support

setosa         1.00        1.00     1.00       19
versicolor     1.00        1.00     1.00       13
virginica      1.00        1.00     1.00       13

accuracy                            1.00       45
macro avg      1.00        1.00     1.00       45
weighted avg   1.00        1.00     1.00       45
```

```
plt.figure(figsize=(10,                                              6))
sns.barplot(x=best_xgb_model.feature_importances_,    y=iris.feature_names)
plt.title('Feature Importance from XGBoost')
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.show()
```


Feature Importance from XGBoost
sepal length (cm)
sepal width (cm)
petal length (cm)
petal width (cm)
Features
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Feature Importance Score

Practical 5

5.1 Implement and demonstrate the working of a Naive Bayesian classifier using a sample data set. Build the model to classify a test sample.

```
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, classification_report, confusi
on_matrix

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

df   =   pd.DataFrame(data=X,   columns=iris.feature_names)
df['target'] = y
```

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

```
print(df.head())
```

```
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm
)  \
0                5.1               3.5                1.4               0.
2
1                4.9               3.0                1.4               0.
2
2                4.7               3.2                1.3               0.
2
```

3	4.6	3.1	1.5	0.
2				
4	5.0	3.6	1.4	0.
2				

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, r
andom_state=42)

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

y_pred = gnb.predict(X_test)

accuracy     =     accuracy_score(y_test,     y_pred)
conf_matrix    =    confusion_matrix(y_test,    y_pred)
class_report = classification_report(y_test, y_pred)

print(f"Accuracy:    {accuracy:.2f}")
print("Confusion            Matrix:")
print(conf_matrix)
print("Classification       Report:")
print(class_report)
```

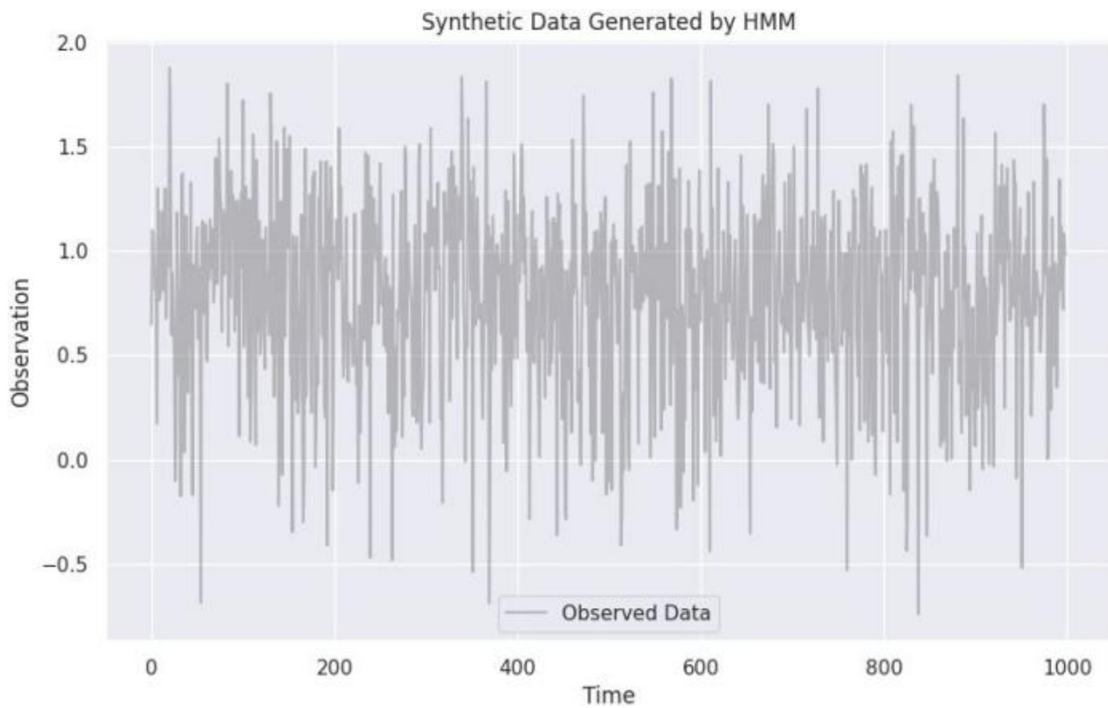
```
Accuracy: 0.98
 Confusion Matrix:
 [[19  0 0]
  [ 0 12 1]
  [ 0  0 13]]
 Classification Report:
              precision    recall   f1-score   support

 0             1.00        1.00     1.00       19
 1             1.00        0.92     0.96       13
 2             0.93        1.00     0.96       13

 accuracy                           0.98       45
 macro avg     0.98        0.97     0.97       45
 weighted avg  0.98        0.98     0.98       45
```

5.2 Implement Hidden Markov Models using hmmlearn

```
!pip install hmmlearn
import numpy as np
import matplotlib.pyplot as plt
from hmmlearn import hmm
```

```
Requirement already satisfied: hmmlearn in /usr/local/lib/python3.10/dist-packages (0.3.2)
Requirement already satisfied: numpy>=1.10 in /usr/local/lib/python3.10/dist-packages (from hmmlearn) (1.26.4)
Requirement already satisfied: scikit-learn!=0.22.0,>=0.16 in /usr/local/lib/python3.10/dist-packages (from hmmlearn) (1.5.2)
Requirement already satisfied: scipy>=0.19 in /usr/local/lib/python3.10/dist-packages (from hmmlearn) (1.13.1)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn!=0.22.0,>=0.16->hmmlearn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn!=0.22.0,>=0.16->hmmlearn) (3.5.0)
```

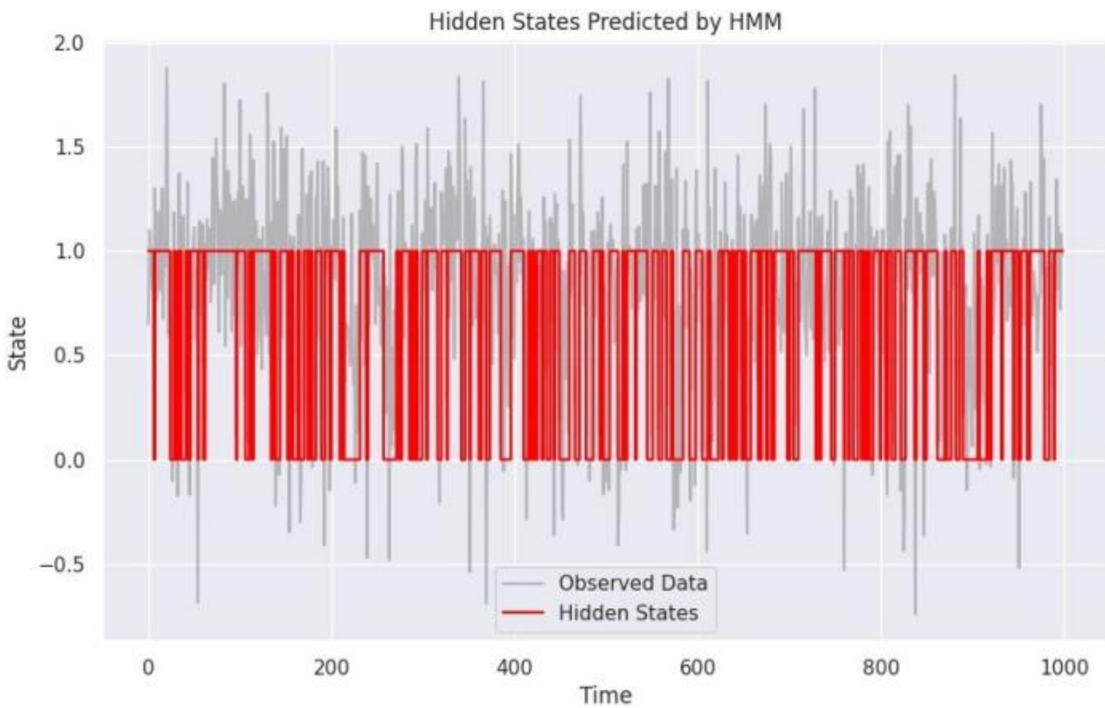
```
np.random.seed(42)

n_samples = 1000
n_states = 2
trans_probs = np.array([[0.7, 0.3],
                        [0.4, 0.6]])
means = np.array([[1.0], [0.5]])
covars = np.array([[0.1], [0.2]])

model = hmm.GaussianHMM(n_components=n_states, covariance_type="diag", n_iter=100)
model.startprob_ = np.array([0.6, 0.4])
model.transmat_ = trans_probs
model.means_ = means
model.covars_ = covars

X, Z = model.sample(n_samples)

plt.figure(figsize=(10, 6))
plt.plot(X, label='Observed Data', color='grey', alpha=0.5)
plt.title('Synthetic Data Generated by HMM')
plt.xlabel('Time')
plt.ylabel('Observation')
plt.legend()
plt.show()
```




```
model.fit(X)
hidden_states = model.predict(X)
```

```
WARNING:hmmlearn.base:Even though the 'startprob_' attribute is set, it wi
ll be overwritten during initialization because 'init_params' contains 's'
WARNING:hmmlearn.base:Even though the 'transmat_' attribute is set, it wil
l be overwritten during initialization because 'init_params' contains 't'
WARNING:hmmlearn.base:Even though the 'means_' attribute is set, it will b
e overwritten during initialization because 'init_params' contains 'm'
WARNING:hmmlearn.base:Even though the 'covars_' attribute is set, it will
be overwritten during initialization because 'init_params' contains 'c'
```

```
plt.figure(figsize=(10, 6))
plt.plot(X, label='Observed Data', color='grey', alpha=0.5)
plt.step(range(n_samples), hidden_states, where="post", label='Hidden Stat
es', color='red')
plt.title('Hidden States Predicted by HMM')
plt.xlabel('Time')
plt.ylabel('State')
plt.legend()
plt.show()
```



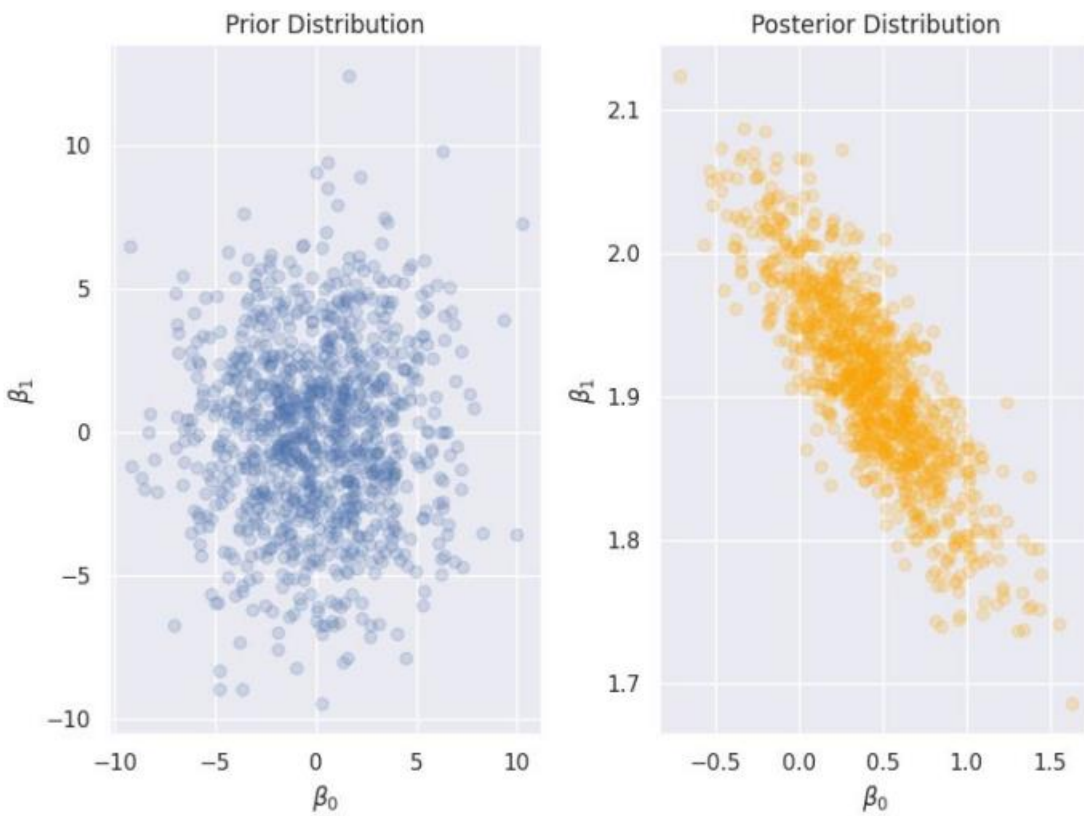

```
print("Transition matrix:\n", model.transmat_)
print("Means:\n",                  model.means_)
print("Covariances:\n", model.covars_)
```

```
Transition         matrix:
 [[0.65865532 0.34134468]
 [0.3121865  0.6878135 ]]
Means:
 [[0.54954006]
 [1.00338912]]
Covariances:
 [[[0.22176075]]

 [[0.09283459]]]
```

Practical 6

6.1 Implement Bayesian Linear Regression to explore prior and posterior distribution.

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import multivariate_normal


np.random.seed(42)
X  =  np.random.rand(100,  1)  *  10
true_beta = np.array([2.0])
y = 2.0 * X.flatten() + np.random.normal(0, 2, size=X.shape[0])
X_b = np.c_[np.ones((X.shape[0], 1)), X]
sigma_0 = 10
sigma_n = 4
sigma_0_inv = 1 / sigma_0
sigma_n_inv = 1 / sigma_n
N = X_b.shape[0]
beta_prior_mean      =      np.zeros(X_b.shape[1])
beta_prior_cov = sigma_0 * np.eye(X_b.shape[1])
posterior_cov  =  np.linalg.inv(sigma_n_inv  *  (X_b.T  @  X_b)  +  sigma_0_inv  *
np.eye(X_b.shape[1]))
posterior_mean = posterior_cov @ (sigma_n_inv * (X_b.T @ y))
beta_samples = np.random.multivariate_normal(posterior_mean, posterior_cov
,                   size=1000)
plt.figure(figsize=(10, 6))
beta_prior_samples  =  np.random.multivariate_normal(beta_prior_mean,  beta_p
rior_cov, size=1000)

<Figure size 1000x600 with 0 Axes>

plt.subplot(1,        2,        1)
plt.title("Prior Distribution")
plt.scatter(beta_prior_samples[:,  0],  beta_prior_samples[:,  1],  alpha=0.2)
plt.xlabel("$\\beta_0$")
plt.ylabel("$\\beta_1$")
plt.subplot(1,          2,          2)
plt.title("Posterior Distribution")
plt.scatter(beta_samples[:, 0], beta_samples[:, 1], alpha=0.2, color='oran
ge')
plt.xlabel("$\\beta_0$")
plt.ylabel("$\\beta_1$")
plt.tight_layout()
plt.show()
```

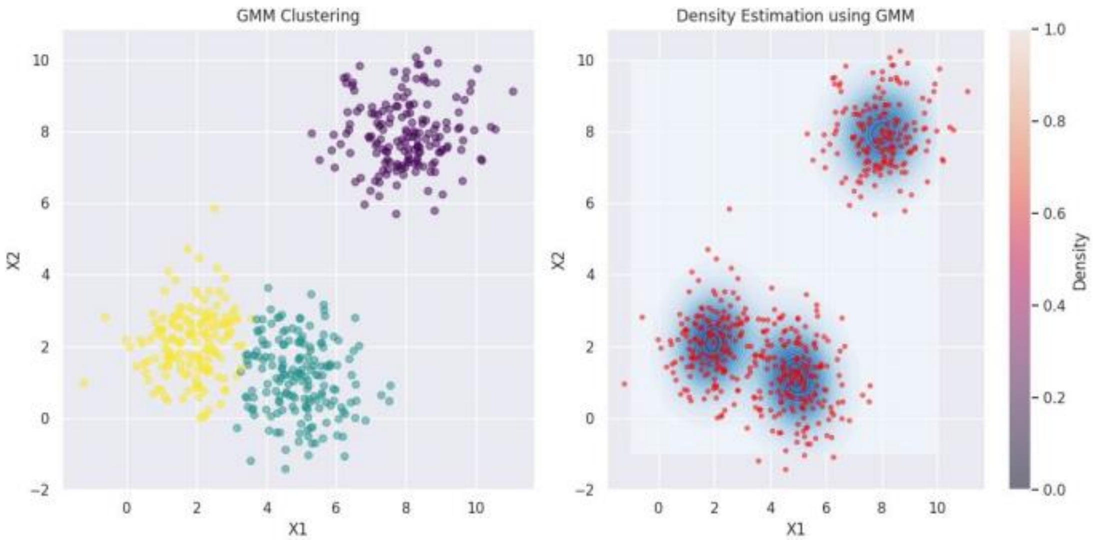



```
print("Posterior      Mean:",      posterior_mean)
print("Posterior Covariance:\n", posterior_cov)
```

```
Posterior    Mean:    [0.42825291    1.90809351]
Posterior Covariance:
 [[ 0.1389247  -0.0211579 ]
 [-0.0211579  0.00451795]]
```

6.2 Implement Gaussian Mixture Models for density estimation and unsupervised clustering

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

np.random.seed(42)
means = [[2, 2], [8, 8], [5, 1]]
covariances = [[[1, 0], [0, 1]], [[1, 0], [0, 1]], [[1, 0], [0, 1]]]
n_samples   =   500
data = np.vstack([
    np.random.multivariate_normal(mean, cov, n_samples // len(means))
    for mean, cov in zip(means, covariances)
])
n_components = len(means)  # Number of clusters
gmm   =   GaussianMixture(n_components=n_components,   covariance_type='full')
gmm.fit(data)
labels = gmm.predict(data)

plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.scatter(data[:,  0],  data[:,  1],  c=labels,  s=30,  cmap='viridis',  alpha=
0.5)
plt.title('GMM                Clustering')
plt.xlabel('X1')
plt.ylabel('X2')
x = np.linspace(-1, 10, 100)
y  =  np.linspace(-1,  10,  100)
X, Y = np.meshgrid(x, y)
XX   =   np.column_stack([X.ravel(),   Y.ravel()])
logprob = gmm.score_samples(XX)
pdf   =   np.exp(logprob).reshape(X.shape)
plt.subplot(1, 2, 2)
plt.contourf(X,   Y,   pdf,   levels=20,   cmap='Blues',   alpha=0.7)
plt.scatter(data[:,   0],   data[:,   1],   c='red',   s=10,   alpha=0.5)
plt.title('Density Estimation using GMM')
plt.xlabel('X1')
plt.ylabel('X2')
plt.colorbar(label='Density')
plt.tight_layout()
plt.show()
```


GMM Clustering
Density Estimation using GMM
X1
X2
Density

Practical 7

7.1 Implement cross-validation techniques (k-fold, stratified, etc.) for robust model evaluation

```
import numpy as np
from sklearn.model_selection import KFold, StratifiedKFold
from sklearn.metrics import accuracy_score
from sklearn.datasets import load_iris
from sklearn.ensemble import RandomForestClassifier

data = load_iris()
X, y = data.data, data.target
model = RandomForestClassifier()
kf = KFold(n_splits=5, shuffle=True, random_state=42)
kf_scores = []
for train_index, test_index in kf.split(X):
    X_train, X_test = X[train_index], X[test_index]
    y_train, y_test = y[train_index], y[test_index]
    model.fit(X_train, y_train)
    predictions = model.predict(X_test)
    score = accuracy_score(y_test, predictions)
    kf_scores.append(score)
print(f'K-Fold Accuracy: {np.mean(kf_scores):.2f} ± {np.std(kf_scores):.2f
}')

K-Fold Accuracy: 0.96 ± 0.02

skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
skf_scores = []
for train_index, test_index in skf.split(X, y):
    X_train, X_test = X[train_index], X[test_index]
    y_train, y_test = y[train_index], y[test_index]
    model.fit(X_train, y_train)
    predictions = model.predict(X_test)
    score = accuracy_score(y_test, predictions)
    skf_scores.append(score)
print(f'Stratified K-Fold Accuracy: {np.mean(skf_scores):.2f} ± {np.std(sk
f_scores):.2f}')

Stratified K-Fold Accuracy: 0.95 ± 0.03
```

7.2 Systematically explore combinations of hyperparameters to optimize model performance.(use grid and randomized search)

```
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split, GridSearchCV, Random
izedSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

data = load_iris()
X, y = data.data, data.target
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,
random_state=42)
model = RandomForestClassifier(random_state=42)
param_grid = {
    'n_estimators': [10, 50, 100],
    'max_depth': [None, 5, 10, 20],
    'min_samples_split': [2, 5, 10],
}
grid_search = GridSearchCV(estimator=model, param_grid=param_grid, scoring
='accuracy',                          cv=5)
grid_search.fit(X_train, y_train)
print("Grid Search Best Parameters:", grid_search.best_params_)
print("Grid Search Best Score:", grid_search.best_score_)

Grid Search Best Parameters: {'max_depth': 5, 'min_samples_split': 5, 'n_e
stimators': 10}
Grid Search Best Score: 0.9636363636363636

param_dist = {
    'n_estimators': np.arange(10, 200, 10),
    'max_depth': [None] + list(np.arange(1, 20, 1)),
    'min_samples_split': np.arange(2, 20, 2),
}
random_search = RandomizedSearchCV(estimator=model, param_distributions=pa
ram_dist, n_iter=50, scoring='accuracy', cv=5, random_state=42)
random_search.fit(X_train, y_train)
print("Randomized Search Best Parameters:", random_search.best_params_)
print("Randomized Search Best Score:", random_search.best_score_)

Randomized Search Best Parameters: {'n_estimators': 120, 'min_samples_spli
t': 16, 'max_depth': None}
Randomized Search Best Score: 0.9636363636363636


best_model = grid_search.best_estimator_
y_pred = best_model.predict(X_test)
```

```
test_accuracy = accuracy_score(y_test, y_pred)
print("Test Set Accuracy using Grid Search Best Model:", test_accuracy)
```

```
Test Set Accuracy using Grid Search Best Model: 1.0
```

Practical 8

8.1 Implement Bayesian Learning using inferences

```
import numpy as np

P_A = 0.5
P_B = 0.5

def likelihood_heads(coin, flips):
    if coin == 'A':
        return (0.5 * flips) * (0.5 * (10 - flips))
    elif coin == 'B':
        return (0.9 * flips) * (0.1 * (10 - flips))

observed_heads = 8
total_flips = 10

likelihood_A = likelihood_heads('A', observed_heads)
likelihood_B = likelihood_heads('B', observed_heads)

marginal_likelihood = (likelihood_A * P_A) + (likelihood_B * P_B)

posterior_A = (likelihood_A * P_A) / marginal_likelihood
posterior_B = (likelihood_B * P_B) / marginal_likelihood

print(f"Posterior Probability of Coin A: {posterior_A:.4f}")
print(f"Posterior Probability of Coin B: {posterior_B:.4f}")
```

```
Posterior Probability of Coin A: 0.7353
Posterior Probability of Coin B: 0.2647
```

Practical 9

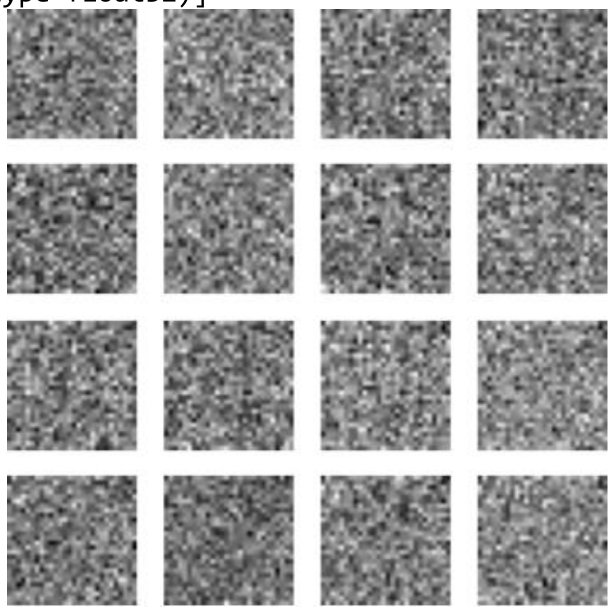
9.1 Set up a generator network to produce samples and a discriminator network to distinguish between real and generated data. (Use a simple small dataset)

```
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras import layers, models

(X_train, _), (_, _) = tf.keras.datasets.mnist.load_data()
X_train  =  (X_train.astype(np.float32)  -  127.5)  /  127.5
X_train = np.expand_dims(X_train, axis=-1)

latent_dim = 100
num_examples_to_generate = 16

def build_generator():
    model              =              models.Sequential()
    model.add(layers.Dense(256,     input_dim=latent_dim))
    model.add(layers.LeakyReLU(alpha=0.2))
    model.add(layers.BatchNormalization())
    model.add(layers.Dense(512))
    model.add(layers.LeakyReLU(alpha=0.2))
    model.add(layers.BatchNormalization())
    model.add(layers.Dense(1024))
    model.add(layers.LeakyReLU(alpha=0.2))
    model.add(layers.BatchNormalization())
    model.add(layers.Dense(28 * 28 * 1, activation='tanh'))
    model.add(layers.Reshape((28, 28, 1)))
    return model

def      build_discriminator():
    model = models.Sequential()
    model.add(layers.Flatten(input_shape=(28,   28,   1)))
    model.add(layers.Dense(512))
    model.add(layers.LeakyReLU(alpha=0.2))
    model.add(layers.Dense(256))
    model.add(layers.LeakyReLU(alpha=0.2))
    model.add(layers.Dense(1,       activation='sigmoid'))
    return model

generator       =       build_generator()
discriminator = build_discriminator()
discriminator.compile(optimizer='adam',   loss='binary_crossentropy',   metric
s=['accuracy'])
```

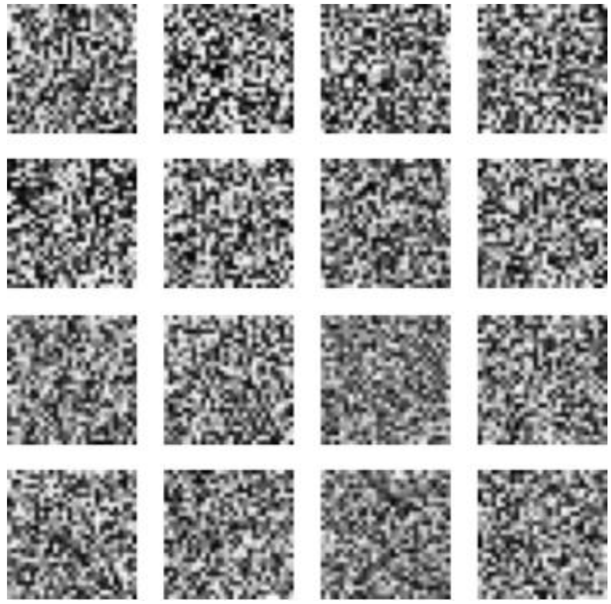
```
discriminator.trainable = False
gan_input = layers.Input(shape=(latent_dim,))
generated_image = generator(gan_input)
gan_output = discriminator(generated_image)
gan = models.Model(gan_input, gan_output)
gan.compile(optimizer='adam', loss='binary_crossentropy')

def generate_and_save_images(model, epoch, test_input):
    predictions = model(test_input)
    predictions = (predictions.numpy() + 1) / 2 # Rescale to [0, 1]

    plt.figure(figsize=(4, 4))
    for i in range(predictions.shape[0]):
        plt.subplot(4, 4, i + 1)
        plt.imshow(predictions[i, :, :, 0], cmap='gray')
        plt.axis('off')
    plt.savefig(f'gan_epoch_{epoch}.png')
    plt.show()

def train_gan(epochs, batch_size):
    random_latent_vectors = tf.random.normal(shape=(num_examples_to_genera
te, latent_dim))

    for epoch in range(epochs):
        idx = np.random.randint(0, X_train.shape[0], batch_size)
        real_images = X_train[idx]

        noise = tf.random.normal(shape=(batch_size, latent_dim))
        fake_images = generator(noise)

        combined_images = tf.concat([real_images, fake_images], axis=0)

        labels = tf.constant([[1.0]] * batch_size + [[0.0]] * batch_size)

        d_loss = discriminator.train_on_batch(combined_images, labels)

        noise = tf.random.normal(shape=(batch_size, latent_dim))
        misleading_labels = tf.constant([[1.0]] * batch_size)

        g_loss = gan.train_on_batch(noise, misleading_labels)

        if epoch % 100 == 0:
            print(f"Epoch: {epoch}")
            print(f"Discriminator Loss: {d_loss[0]}")
            print(f"Generator Loss: {g_loss}")

            generate_and_save_images(generator, epoch, random_latent_vecto
rs)
```

```
epochs = 300
batch_size = 64

train_gan(epochs,  batch_size)
```

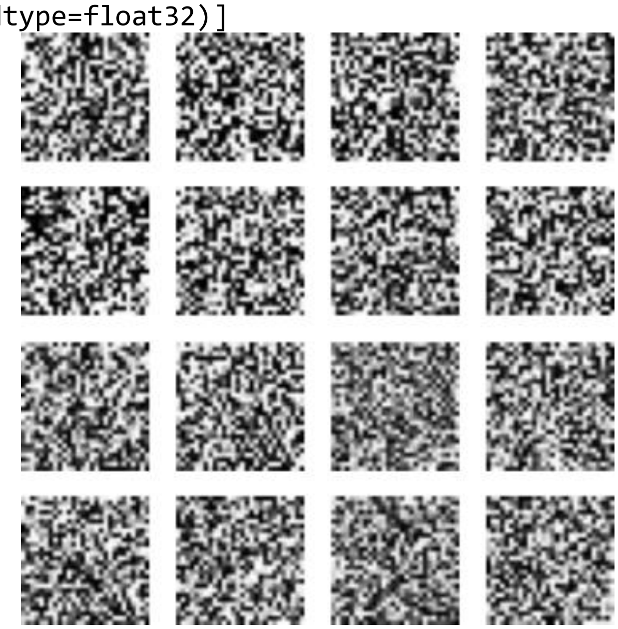
```
Epoch: 0
Discriminator Loss: 0.7258248329162598
Generator Loss: [array(0.72582483, dtype=float32), array(0.72582483, dtype
=float32), array(0.390625, dtype=float32)]
```



```
Epoch: 100
Discriminator Loss: 2.1150412559509277
Generator  Loss:  [array(2.1150413,  dtype=float32),  array(2.1150413,  dtype=f
loat32), array(0.20482673, dtype=float32)]
```



```
Epoch: 200
Discriminator Loss: 2.8626105785369873
Generator Loss: [array(2.8626106, dtype=float32), array(2.8626106, dtype=float32), array(0.20747824, dtype=float32)]
```



Practical 10

10.1 Develop an API to deploy your model and perform predictions

```
# Required Libraries
!pip install pyngrok flask scikit-learn

# Importing Libraries
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
import pickle
from flask import Flask, request, jsonify
from pyngrok import ngrok

# Load dataset
iris = load_iris()
X, y = iris.data, iris.target

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, r
andom_state=42)

# Train a model
model      =      RandomForestClassifier()
model.fit(X_train, y_train)

# Save the model
with  open('model.pkl',  'wb')  as  model_file:
    pickle.dump(model, model_file)

# Load the model
with  open('model.pkl',  'rb')  as  model_file:
    model = pickle.load(model_file)

#  Create  Flask  app
app = Flask(__name__)
port = "5000"

@app.route('/')
def home():
    return "Welcome to the Iris Prediction API! Use the /predict endpoint
to make predictions."

@app.route('/predict', methods=['POST'])
def predict():
    data = request.json
    features = data.get('features')
```

```
    # Ensure the features are in the correct format
    if not features or len(features) != 4:  # Assuming 4 features for
iris dataset
        return  jsonify({'error':  'Invalid  input  format.  Please
provide 4 f eatures.'}), 400

    try:
        prediction = model.predict([features])  # Wrap features in a
        list
to create 2D array
        return jsonify({'prediction': int(prediction[0])})  # Convert
pred iction to int
    except Exception as e:
        return jsonify({'error': str(e)}), 500

#  Start  ngrok  and  print  the  public  URL
ngrok.set_auth_token("api_auth_token")
public_url                              =
ngrok.connect(port).public_url
print("Public URL:", public_url)

# Run the Flask app
if  __name__  ==  '__main__':
    app.run(port=port)
```

```
Requirement        already        satisfied:        pyngrok        in
/usr/local/lib/python3.10/dist-p ackages (7.2.0)
Requirement        already        satisfied:        flask          in
/usr/local/lib/python3.10/dist-pac kages (2.2.5)
Requirement       already       satisfied:       scikit-learn       in
/usr/local/lib/python3.10/d ist-packages (1.5.2)
Requirement       already       satisfied:       PyYAML>=5.1       in
/usr/local/lib/python3.10/di st-packages (from pyngrok) (6.0.2)
Requirement      already      satisfied:      Werkzeug>=2.2.2      in
/usr/local/lib/python3.1 0/dist-packages (from flask) (3.0.4)
Requirement       already       satisfied:       Jinja2>=3.0       in
/usr/local/lib/python3.10/di st-packages (from flask) (3.1.4)
Requirement      already      satisfied:      itsdangerous>=2.0      in
/usr/local/lib/python3
.10/dist-packages (from flask) (2.2.0)
Requirement       already       satisfied:       click>=8.0       in
/usr/local/lib/python3.10/dis t-packages (from flask) (8.1.7)
Requirement       already       satisfied:       numpy>=1.19.5       in
/usr/local/lib/python3.10/    dist-packages    (from    scikit-learn)
(1.26.4)
Requirement       already       satisfied:       scipy>=1.6.0       in
/usr/local/lib/python3.10/d    ist-packages    (from    scikit-learn)
(1.13.1)
Requirement       already       satisfied:       joblib>=1.2.0       in
/usr/local/lib/python3.10/ dist-packages (from scikit-learn) (1.4.2)
Requirement      already      satisfied:     threadpoolctl>=3.1.0     in
/usr/local/lib/pyth on3.10/dist-packages (from scikit-learn) (3.5.0)
Requirement      already      satisfied:      MarkupSafe>=2.0      in
```

```
   /usr/local/lib/python3.1  0/dist-packages  (from  Jinja2>=3.0->flask)
   (2.1.5)
   Public URL: https://2f62-49-43-24-101.ngrok-free.app

  * Serving Flask app '__main__'
  * Debug mode: off

 INFO:werkzeug:WARNING: This is a development server. Do not use it in a
 pr oduction deployment. Use a production WSGI server instead.
  *   Running                 on
 http://127.0.0.1:5000
 INFO:werkzeug:Press  CTRL+C  to
 quit
 INFO:werkzeug:127.0.0.1  -  -  [24/Oct/2024  07:50:42]  "POST  /predict
 HTTP
```