VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning

Submitted by

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in
COMPUTER SCIENCE AND ENGINEERING

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Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the Lab work entitled "**Machine Learning**" carried out by **Arka Sinha (1BM19CS024),** who is a bonafide student of **B. M. S. College of Engineering.** It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum during the year 2022. The Lab report has been approved as it satisfies the academic requirements in respect of a **Machine Learning - (20CS6PCMAL)** work prescribed for the said degree.

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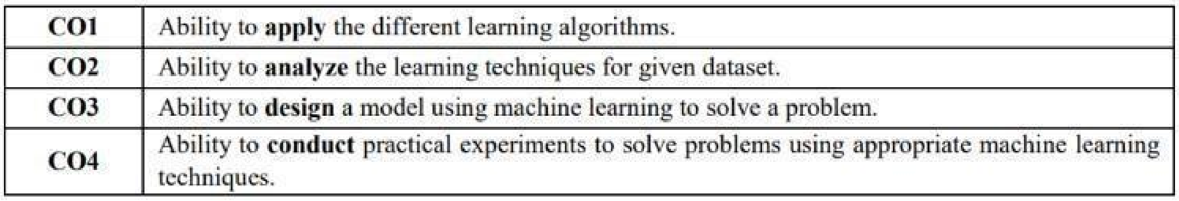
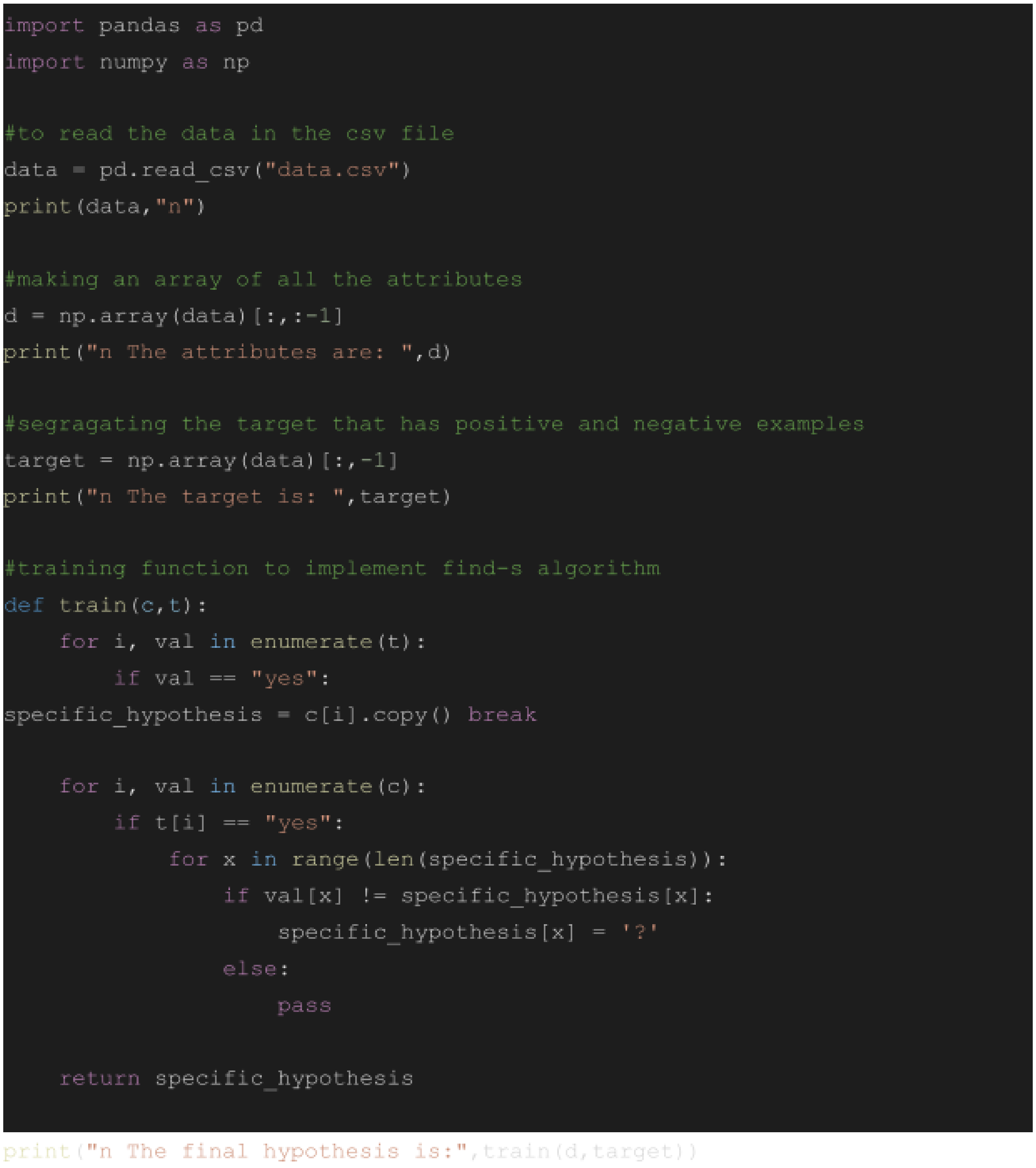
Course Outcomes:



CO1	Ability to **apply** the different learning algorithms.
CO2	Ability to **analyze** the learning techniques for given dataset.
CO3	Ability to **design** a model using machine learning to solve a problem.
CO4	Ability to **conduct** practical experiments to solve problems using appropriate machine learning techniques.

1. Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data samples.



```
import pandas as pd
import numpy as np

#to read the data in the csv file
data = pd.read_csv("data.csv")
print(data,"n")

#making an array of all the attributes
d = np.array(data)[:,:-1]
print("n The attributes are: ",d)

#segragating the target that has positive and negative examples
target = np.array(data)[:,-1]
print("n The target is: ",target)

#training function to implement find-s algorithm
def train(c,t):
    for i, val in enumerate(t):
        if val == "yes":
specific_hypothesis = c[i].copy() break

    for i, val in enumerate(c):
        if t[i] == "yes":
            for x in range(len(specific_hypothesis)):
                if val[x] != specific_hypothesis[x]:
                    specific_hypothesis[x] = '?'
                else:
                    pass

    return specific_hypothesis
print("n The final hypothesis is:",train(d,target))
```

Output

```
    sky air temp humidity    wind water forecast enjoy sport
0   sunn      warm   normal  strong  warm     same         yes
     y
1   sunn      warm     high  strong  warm     same         yes
     y
2   rain      cold     high  strong  warm   change          no
     y
3   sunn      warm     high  strong  cool   change         yes
     y                                                     n
n The attributes are:  [['sunny' 'warm' 'normal' 'strong'
'warm'  'same']
 ['sunny' 'warm' 'high' 'strong' 'warm' 'same']
 ['rainy' 'cold' 'high' 'strong' 'warm' 'change']
 ['sunny' 'warm' 'high' 'strong' 'cool' 'change']]
n The target is:  ['yes' 'yes' 'no' 'yes']
n The final hypothesis is: ['sunny' 'warm' '?' 'strong' '?' '?']
```

2. For a given set of training data examples stored in a .CSV file, implement and demonstrate the Candidate-Elimination algorithm to output a description of the set of all hypotheses consistent with the training examples.

```
import numpy as np
import pandas as
pd
data = pd.read_csv('data.csv')
concepts = np.array(data.iloc[:,0:-1])
print("\nInstances:\n",concepts)
target = np.array(data.iloc[:,-1])
print("\nTarget Values: ",target)
def learn(concepts, target):
    sh = concepts[0].copy()
    print("\nInitialization of specific and genearal hypothesis")
    print("\nSpecific boundary: ", sh)
    gh = [["?" for i in range(len(sh))] for i in range(len(sh))]
    print("\nGeneric boundary: ",gh)
    for i, h in enumerate(concepts):
        print("\nInstance", i+1 , "is ", h)
        if target[i] == "yes":
            print("Instance is positive ")
            for x in range(len(sh)):
                if h[x]!= sh[x]:
                    sh[x] ='?'
                    gh[x][x] ='?'
        if target[i] == "no":
            print("Instance is negative ")
            for x in range(len(sh)):
                if h[x]!= sh[x]:
                    gh[x][x] = sh[x]
                else:
                    gh[x][x] = '?'
        print("Specific boundary after ", i+1, "instance is ", sh)
        print("Generic boundary after ", i+1, "instance is ", gh)
        print("\n")
    indices = [i for i, val in enumerate(gh) if val == ['?', '?', '?', '?',
'?', '?']]
    for i in indices:
        gh.remove(['?', '?', '?', '?', '?', '?'])
    return sh, gh
```

```
sf, gf = learn(concepts, target)
```

```
print("Final specific hypothesis: ", sf,
sep="\n") print("Final general hypothesis: ",
gf, sep="\n")
```

Output

```
Instances:
 [['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
 ['sunny' 'warm' 'high' 'strong' 'warm' 'same']
 ['rainy' 'cold' 'high' 'strong' 'warm' 'change']
 ['sunny' 'warm' 'high' 'strong' 'cool' 'change']]

Target Values:  ['yes' 'yes' 'no' 'yes']

Initialization of specific and genearal hypothesis

Specific boundary:  ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']

Generic boundary:  [['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?',
'?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],
['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

Instance 1 is  ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
Instance is positive
Specific boundary after  1 instance is  ['sunny' 'warm' 'normal' 'strong'
'warm' 'same']
Generic boundary after  1 instance is  [['?', '?', '?', '?', '?', '?'],
['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?',
'?',
'?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?',
'?', '?']]


Instance 2 is  ['sunny' 'warm' 'high' 'strong' 'warm'
'same'] Instance is positive
Specific boundary after  2 instance is  ['sunny' 'warm' '?' 'strong' 'warm'
'same']
Generic boundary after  2 instance is  [['?', '?', '?', '?', '?', '?'],
['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?',
'?',
'?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?',
'?', '?']]


Instance 3 is  ['rainy' 'cold' 'high' 'strong' 'warm' 'change']
Instance is negative
Specific boundary after  3 instance is  ['sunny' 'warm' '?' 'strong' 'warm'
'same']
Generic boundary after  3 instance is  [['sunny', '?', '?', '?', '?', '?'],
['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?',
'?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?',
'?', '?', 'same']]
```

```
Instance 4 is  ['sunny' 'warm' 'high' 'strong' 'cool' 'change']
Instance is positive
Specific boundary after  4 instance is  ['sunny' 'warm' '?' 'strong'
'?' '?']
Generic boundary after  4 instance is  [['sunny', '?', '?', '?', '?', '?'],
['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?',
'?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?',
'?', '?', '?']]


Final specific hypothesis:
['sunny' 'warm' '?' 'strong' '?' '?']
Final general hypothesis:
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?']]
```

3. Write a program to demonstrate the working of the Decision tree based ID3 algorithm. Use an appropriate data set for building the decision tree and apply this knowledge to classify a new sample

```python
import pandas as pd
import math
import numpy as np
import pprint


data=pd.read_csv("tennis.csv")
print("\n Input Data Set is:\n", data)
features = [f for f in data]
features.remove("answer")


class Node:
    def __init__(self):
        self.children = []
        self.value = ""
        self.isLeaf = False
        self.pred = ""

def find_entropy(examples):
    pos = 0.0
    neg = 0.0
    for _, row in examples.iterrows():
        if row["answer"] == "yes":
            pos += 1
        else:
            neg += 1
    if pos == 0.0 or neg == 0.0:
        return 0.0
    else:
        p = pos / (pos + neg)
        n = neg / (pos + neg)
        return -(p * math.log(p, 2) + n * math.log(n, 2))

def info_gain(examples, attr):
    uniq = np.unique(examples[attr])
    gain = find_entropy(examples)
    for u in uniq:
        subdata = examples[examples[attr] == u]
        sub_e = find_entropy(subdata)
        gain -= (float(len(subdata)) / float(len(examples))) *
sub_e
    return gain


def id3(examples, attrs):
  root = Node()

  max_gain = 0
  max_feat = ""
  for feature in attrs:
      gain = info_gain(examples, feature)
      if gain > max_gain:
          max_gain = gain
          max_feat = feature
  root.value = max_feat
  uniq = np.unique(examples[max_feat])
  for u in uniq:
      subdata = examples[examples[max_feat] == u]
      if find_entropy(subdata) == 0.0:
          newNode = Node()
          newNode.isLeaf = True
          newNode.value = u
          newNode.pred = np.unique(subdata["answer"])
          root.children.append(newNode)
      else:
          tempNode = Node()
          tempNode.value = u
          new_attrs = attrs.copy()
          new_attrs.remove(max_feat)
          child       =       id3(subdata,
          new_attrs)
          tempNode.children.append(child
          )
          root.children.append(tempNode)
  return root


def printTree(root: Node, depth=0):
    for i in range(depth):
        print("\t", end="")
print(root.value, end="")
if root.isLeaf:
        print(" : ",
    root.pred) print()
    for child in root.children:
        printTree(child, depth +
        1)

root = id3(data, features)
print("Final decision
tree:\n") printTree(root)
```

Output

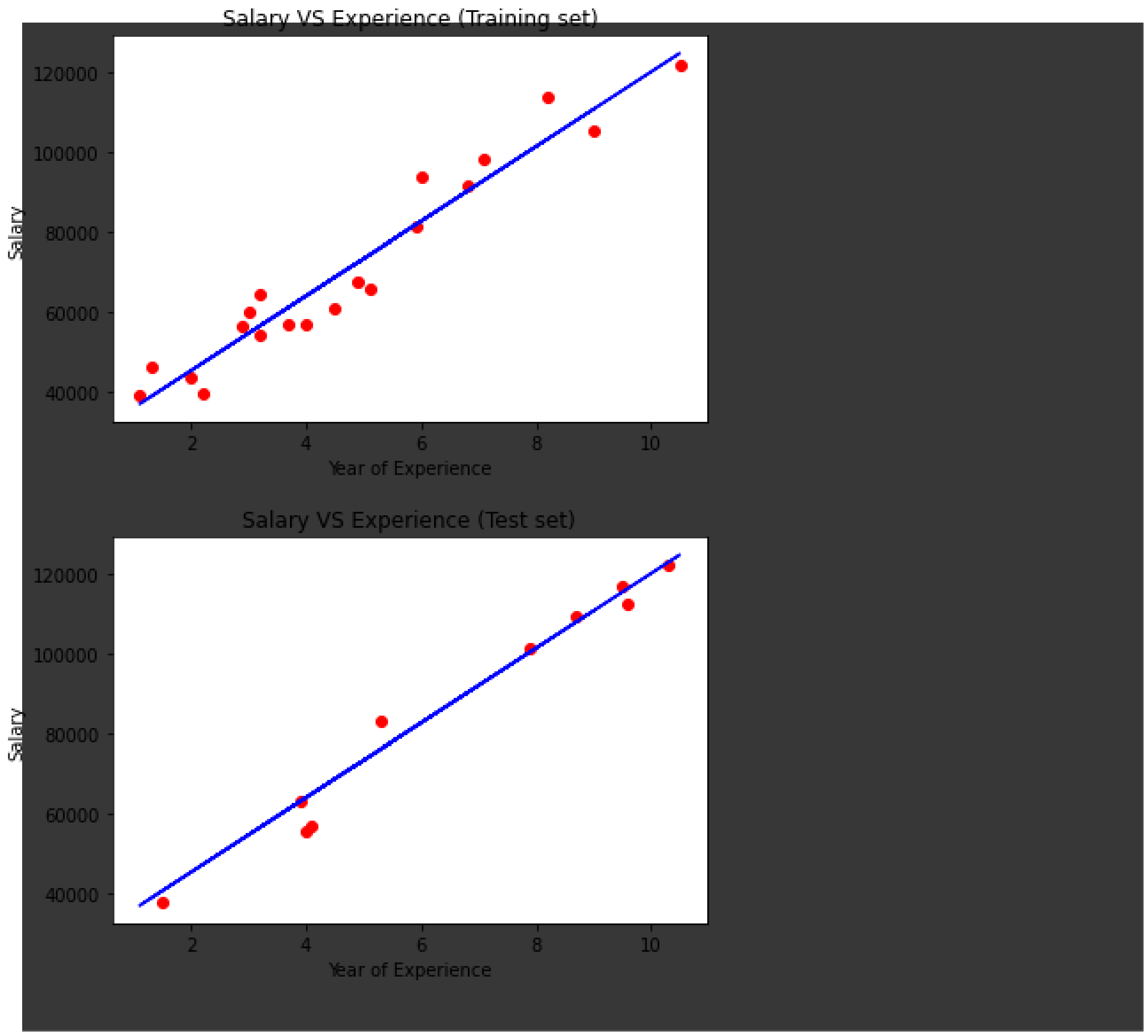
```
 Input Data Set is:
      outlook temperature humidity    wind answer
```

```
Final decision tree:
outlook
     overcast :  ['yes']

     rain
           wind
                 strong :  ['no']

                 weak :  ['yes']

     sunny
           humidity
                 high :  ['no']

                 normal :  ['yes']
```

4. Write a program to implement the Naïve Bayesian classifier for a sample training data set stored as a .CSV file. Compute the accuracy of the classifier, considering few test data sets.

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

# Importing the dataset
#dataset =
pd.read_csv('181105_missing-data.csv') dataset =
pd.read_csv('salary.csv')
X = dataset.iloc[:, :-1].values #get a copy of dataset exclude last column
y = dataset.iloc[:, 1].values #get array of dataset in column 1st

# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=1/3,
random_state=0)
# Fitting Simple Linear Regression to the Training set
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)

# Predicting the Test set results
y_pred =
regressor.predict(X_test)

# Visualizing the Training set results
viz_train = plt
viz_train.scatter(X_train, y_train, color='red')
viz_train.plot(X_train, regressor.predict(X_train), color='blue')
viz_train.title('Salary VS Experience (Training set)')
viz_train.xlabel('Year of Experience')
viz_train.ylabel('Salary')
viz_train.show()

# Visualizing the Test set results
viz_test = plt
viz_test.scatter(X_test, y_test, color='red')
viz_test.plot(X_train, regressor.predict(X_train), color='blue')
viz_test.title('Salary VS Experience (Test set)')
viz_test.xlabel('Year of Experience')
viz_test.ylabel('Salary')
viz_test.show()
```

Output



5. Write a program to construct a Bayesian network considering training data. Use this model to make predictions.

```
import csv
import random
import math
def loadcsv(filename):
  lines = csv.reader(open("naive.csv", "r"));
  dataset = list(lines)
  for i in range(len(dataset)):
       #converting strings into numbers for processing
    dataset[i] = [float(x) for x in dataset[i]]

  return dataset

def splitdataset(dataset, splitratio):
    #67% training size
  trainsize = int(len(dataset) * splitratio);
  trainset = []
  copy = list(dataset);
  while len(trainset) < trainsize:
#generate indices for the dataset list randomly to pick ele for training
data
    index = random.randrange(len(copy));
    trainset.append(copy.pop(index))
  return [trainset, copy]

def separatebyclass(dataset):
  separated = {} #dictionary of classes 1 and 0
#creates a dictionary of classes 1 and 0 where the values are
#the instances belonging to each class
  for i in range(len(dataset)):
    vector = dataset[i]
    if (vector[-1] not in separated):
      separated[vector[-1]] = []
    separated[vector[-1]].append(vector)
  return separated

def mean(numbers):
  return sum(numbers)/float(len(numbers))
```

```
def stdev(numbers):
  avg = mean(numbers)
  variance = sum([pow(x-avg,2) for x in numbers])/float(len(numbers)-1)
  return math.sqrt(variance)

def summarize(dataset): #creates a dictionary of classes
  summaries = [(mean(attribute), stdev(attribute)) for attribute in
zip(*dataset)];
  del summaries[-1] #excluding labels +ve or -ve
  return summaries

def summarizebyclass(dataset):
  separated = separatebyclass(dataset);
    #print(separated)
  summaries = {}
  for classvalue, instances in separated.items():
#for key,value in dic.items()
#summaries is a dic of tuples(mean,std) for each class value
    summaries[classvalue] = summarize(instances) #summarize is used to cal
to mean and std
  return summaries

def calculateprobability(x, mean, stdev):
  exponent = math.exp(-(math.pow(x-mean,2)/(2*math.pow(stdev,2))))
  return (1 / (math.sqrt(2*math.pi) * stdev)) * exponent

def calculateclassprobabilities(summaries, inputvector):
  probabilities = {} # probabilities contains the all prob of all class of
test data
  for classvalue, classsummaries in summaries.items():#class and attribute
information as mean and sd
    probabilities[classvalue] = 1
    for i in range(len(classsummaries)):
      mean, stdev = classsummaries[i] #take mean and sd of every attribute
for class 0 and 1 seperaely
      x = inputvector[i] #testvector's first attribute
      probabilities[classvalue] *= calculateprobability(x, mean,
stdev);#use normal dist
  return probabilities
def predict(summaries, inputvector): #training and test data is passed
  probabilities = calculateclassprobabilities(summaries, inputvector)
  bestLabel, bestProb = None, -1
  for classvalue, probability in probabilities.items():#assigns that class
which has he highest prob
    if bestLabel is None or probability > bestProb:
```

```
    bestProb = probability
    bestLabel = classvalue
  return bestLabel

def getpredictions(summaries, testset):
  predictions = []
  for i in range(len(testset)):
    result = predict(summaries, testset[i])
    predictions.append(result)
  return predictions

def getaccuracy(testset, predictions):
  correct = 0
  for i in range(len(testset)):
    if testset[i][-1] == predictions[i]:
      correct += 1
  return (correct/float(len(testset))) * 100.0
def main():
  filename = 'naivedata.csv'
  splitratio = 0.67
  dataset = loadcsv(filename);

  trainingset, testset = splitdataset(dataset, splitratio)
  print('Split {0} rows into train={1} and test={2}
rows'.format(len(dataset), len(trainingset), len(testset)))
  # prepare model
  summaries = summarizebyclass(trainingset);
  #print(summaries)
    # test model
  predictions = getpredictions(summaries, testset) #find the predictions of
test data with the training data
  accuracy = getaccuracy(testset, predictions)
  print('Accuracy of the classifier is : {0}%'.format(accuracy))

main()
```

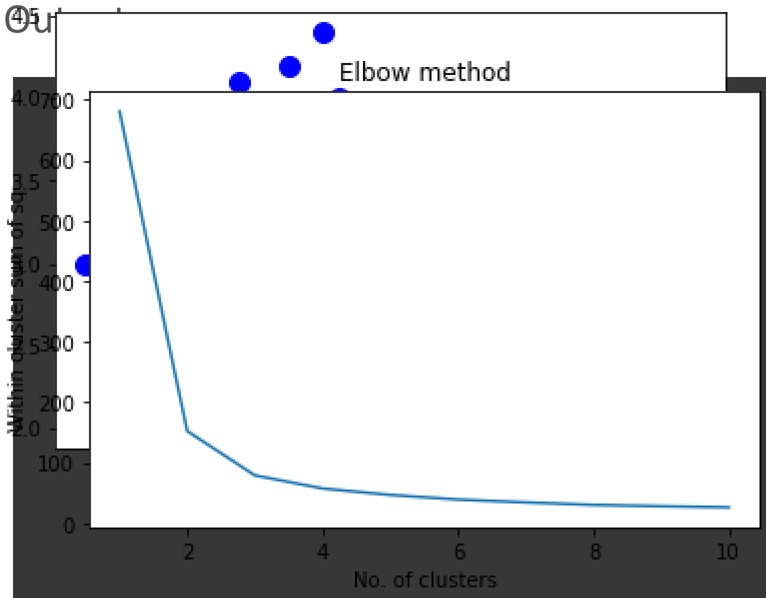
Output

```
Split 767 rows into train=513 and test=254 rows
Accuracy of the classifier is : 74.80314960629921%
```

6. Apply k-Means algorithm to cluster a set of data stored in a .CSV file

```python
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
dataset = pd.read_csv('iris.csv')
x = dataset.iloc[:, [1, 2, 3, 4]].values
from sklearn.cluster import KMeans
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', max_iter = 300,
n_init = 10, random_state = 0)
    kmeans.fit(x)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('Elbow method')
plt.xlabel('No. of clusters')
plt.ylabel('Within cluster sum of sq')
plt.show()
kmeans = KMeans(n_clusters = 3, init = 'k-means++', max_iter = 300, n_init =
10, random_state = 0)
y_kmeans = kmeans.fit_predict(x)
plt.scatter(x[y_kmeans == 0, 0], x[y_kmeans == 0, 1], s = 100, c = 'red',
label = 'Iris-setosa')
plt.scatter(x[y_kmeans == 1, 0], x[y_kmeans == 1, 1], s = 100, c = 'blue',
label = 'Iris-versicolour')
plt.scatter(x[y_kmeans == 2, 0], x[y_kmeans == 2, 1], s = 100, c = 'green',
label = 'Iris-virginica')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1], s =
100, c = 'yellow', label = 'Centroids')
plt.legend()
```

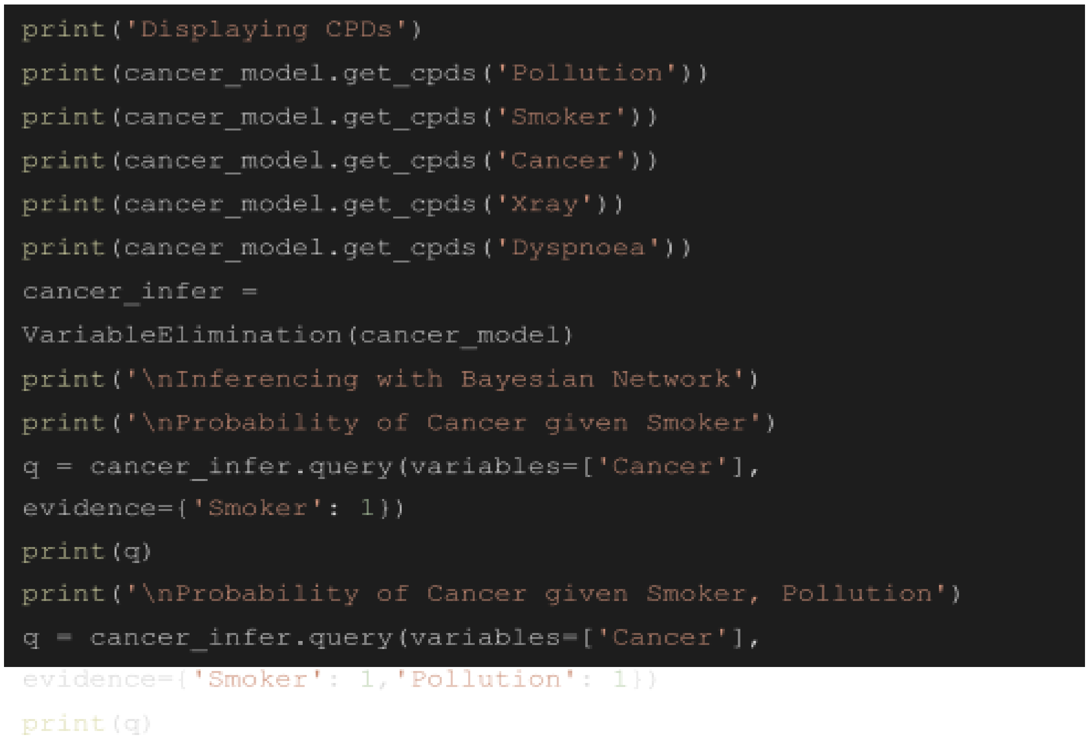
Ou


Elbow method
Within cluster sum of sq
No. of clusters
0
100
200
300
400
500
600
700
2
4
6
8
10
2.0
2.5
3.0
3.5
4.0
4.5

```
<matplotlib.legend.Legend at 0x7fc6098efad0>
```

7. Apply EM algorithm to cluster a set of data stored in a .CSV file. Compare the results of k-Means algorithm and EM algorithms.

```
!pip install pgmpy
from pgmpy.models import BayesianModel
from pgmpy.factors.discrete import TabularCPD
from pgmpy.inference import
VariableElimination
cancer_model = BayesianModel([('Pollution', 'Cancer'),
                              ('Smoker', 'Cancer'),
                              ('Cancer', 'Xray'),
                              ('Cancer', 'Dyspnoea')])
print('Bayesian network nodes:')
print('\t', cancer_model.nodes())
print('Bayesian network edges:')
print('\t', cancer_model.edges())
cpd_poll = TabularCPD(variable='Pollution', variable_card=2,
                     values=[[0.9], [0.1]])
cpd_smoke = TabularCPD(variable='Smoker', variable_card=2,
                      values=[[0.3], [0.7]])
cpd_cancer = TabularCPD(variable='Cancer', variable_card=2,
                       values=[[0.03, 0.05, 0.001, 0.02],
                               [0.97, 0.95, 0.999, 0.98]],
                       evidence=['Smoker', 'Pollution'],
                       evidence_card=[2, 2])
cpd_xray = TabularCPD(variable='Xray', variable_card=2,
                     values=[[0.9, 0.2], [0.1, 0.8]],
                     evidence=['Cancer'], evidence_card=[2])
cpd_dysp = TabularCPD(variable='Dyspnoea', variable_card=2,
                     values=[[0.65, 0.3], [0.35, 0.7]],
                     evidence=['Cancer'], evidence_card=[2])
cancer_model.add_cpds(cpd_poll, cpd_smoke, cpd_cancer, cpd_xray,
cpd_dysp)
print('Model generated bt adding conditional probability
distribution(cpds)')
print('Checking for Correctness of model:', end='')
print(cancer_model.check_model())
'''print('All local dependencies are as
follows') cancer_model.get_independencies()
'''
```



```python
print('Displaying CPDs')
print(cancer_model.get_cpds('Pollution'))
print(cancer_model.get_cpds('Smoker'))
print(cancer_model.get_cpds('Cancer'))
print(cancer_model.get_cpds('Xray'))
print(cancer_model.get_cpds('Dyspnoea'))
cancer_infer =
VariableElimination(cancer_model)
print('\nInferencing with Bayesian Network')
print('\nProbability of Cancer given Smoker')
q = cancer_infer.query(variables=['Cancer'],
evidence={'Smoker': 1})
print(q)
print('\nProbability of Cancer given Smoker, Pollution')
q = cancer_infer.query(variables=['Cancer'],
evidence={'Smoker': 1,'Pollution': 1})
print(q)
```

Output

```
Looking in indexes: https://pypi.org/simple,
https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting pgmpy
  Downloading pgmpy-0.1.19-py3-none-any.whl (1.9 MB)
     |████████████████████████████████| 1.9 MB 5.0 MB/s
Requirement already satisfied: joblib in /usr/local/lib/python3.7/dist-packages
(from pgmpy) (1.1.0)
Requirement already satisfied: pandas in /usr/local/lib/python3.7/dist-packages (from
pgmpy) (1.3.5)
Requirement already satisfied: pyparsing in /usr/local/lib/python3.7/dist-packages
(from pgmpy) (3.0.9)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.7/dist-packages
(from pgmpy) (1.0.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from
pgmpy) (1.21.6)
Requirement already satisfied: torch in /usr/local/lib/python3.7/dist-packages (from
pgmpy) (1.11.0+cu113)
Requirement already satisfied: tqdm in /usr/local/lib/python3.7/dist-packages (from
pgmpy) (4.64.0)
Requirement already satisfied: networkx in /usr/local/lib/python3.7/dist-packages
(from pgmpy) (2.6.3)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages (from
pgmpy) (1.4.1)
Requirement already satisfied: statsmodels in /usr/local/lib/python3.7/dist-packages
```

```
(from pgmpy) (0.10.2)
Requirement already satisfied: python-dateutil>=2.7.3 in
/usr/local/lib/python3.7/dist-packages (from pandas->pgmpy) (2.8.2)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-packages
(from pandas->pgmpy) (2022.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages
(from python-dateutil>=2.7.3->pandas->pgmpy) (1.15.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.7/dist-packages (from scikit-learn->pgmpy) (3.1.0)
Requirement already satisfied: patsy>=0.4.0 in
/usr/local/lib/python3.7/dist-packages (from statsmodels->pgmpy) (0.5.2)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.7/dist-packages (from torch->pgmpy) (4.1.1)
Installing collected packages: pgmpy
Successfully installed pgmpy-0.1.19
/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19:
FutureWarning: pandas.util.testing is deprecated. Use the functions in the public API at
pandas.testing instead.
  import pandas.util.testing as
tm Bayesian network nodes:
        ['Pollution', 'Cancer', 'Smoker', 'Xray', 'Dyspnoea']
Bayesian network edges:
        [('Pollution', 'Cancer'), ('Cancer', 'Xray'), ('Cancer', 'Dyspnoea'), ('Smoker', 'Cancer')]
Model generated bt adding conditional probability distribution(cpds)
Checking for Correctness of
model:True Displaying CPDs
+--------------+-----+
| Pollution(0) | 0.9 |
+--------------+-----+
| Pollution(1) | 0.1 |
+--------------+-----+
+-----------+-----+
| Smoker(0) | 0.3 |
+-----------+-----+
| Smoker(1) | 0.7 |
+-----------+-----+
+-----------+--------------+--------------+--------------+--------------+
| Smoker    | Smoker(0)    | Smoker(0)    | Smoker(1)    | Smoker(1)    |
+-----------+--------------+--------------+--------------+--------------+
| Pollution | Pollution(0) | Pollution(1) | Pollution(0) | Pollution(1) |
+-----------+--------------+--------------+--------------+--------------+
| Cancer(0) | 0.03         | 0.05         | 0.001        | 0.02         |
+-----------+--------------+--------------+--------------+--------------+
| Cancer(1) | 0.97         | 0.95         | 0.999        | 0.98         |
+-----------+--------------+--------------+--------------+--------------+
+---------+-----------+-----------+
| Cancer  | Cancer(0) | Cancer(1) |
+---------+-----------+-----------+
| Xray(0) | 0.9       | 0.2       |
+---------+----------+----------+
| Xray(1) | 0.1      | 0.8      |
+---------+----------+----------+
+-------------+----------+----------+
| Cancer      | Cancer(0) | Cancer(1) |
+-------------+----------+----------+
| Dyspnoea(0) | 0.65     | 0.3      |
+-------------+----------+----------+
| Dyspnoea(1) | 0.35     | 0.7      |
+-------------+----------+----------+
Inferencing with Bayesian Network
Probability of Cancer given Smoker
/usr/local/lib/python3.7/dist-packages/pgmpy/models/BayesianModel.py:10:
FutureWarning: BayesianModel has been renamed to BayesianNetwork. Please use
BayesianNetwork class, BayesianModel will be removed in future.
  FutureWarning,
```

```
Finding Elimination Order: : 100%
1/1 [00:00<00:00, 8.95it/s]
Eliminating: Pollution: 100%
1/1 [00:00<00:00, 14.21it/s]
```

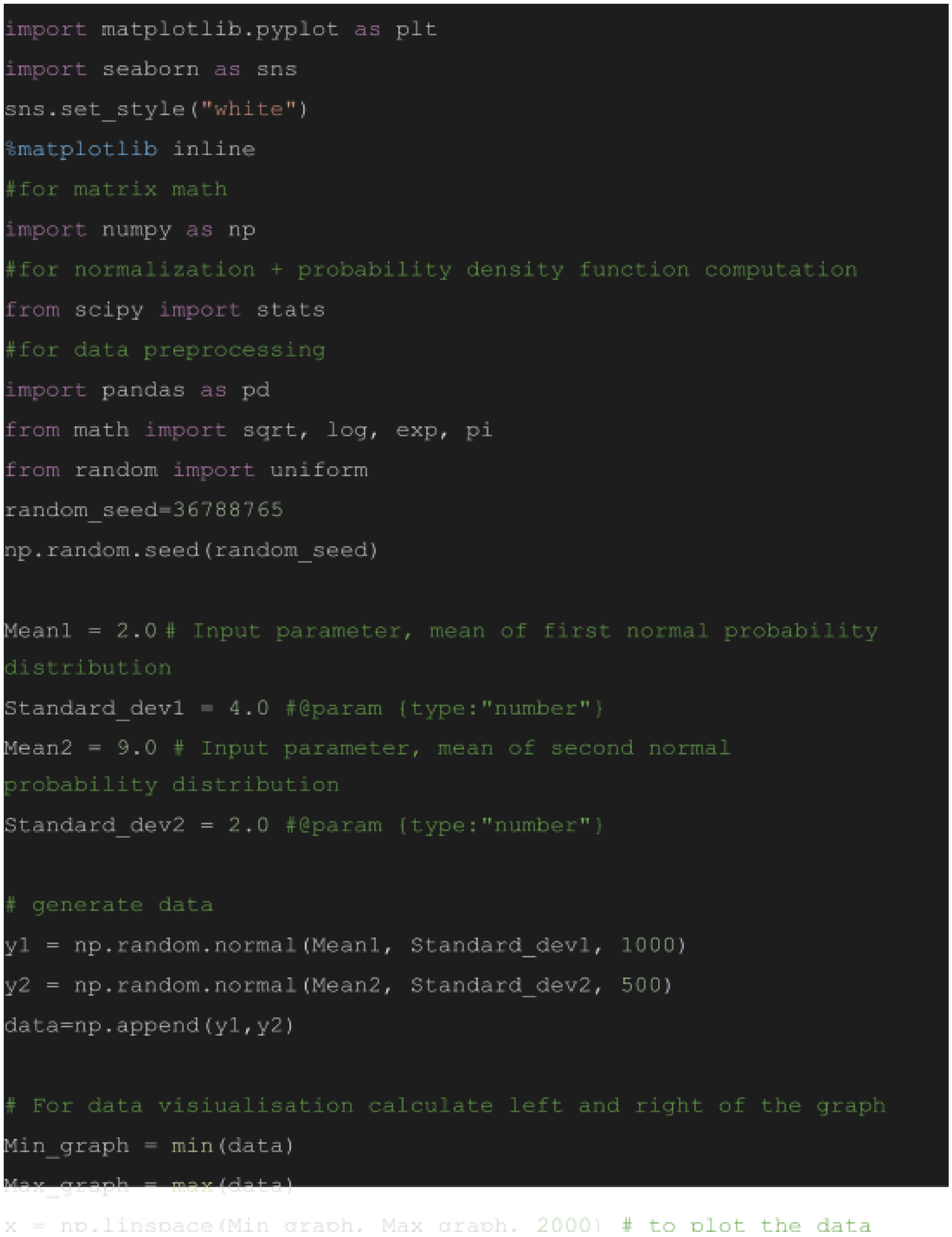
```
+-----------+---------------+
| Cancer    | phi(Cancer) |
+===========+===============+
| Cancer(0) |        0.0029 |
+-----------+---------------+
| Cancer(1) |        0.9971 |
+-----------+---------------+
```

Probability of Cancer given Smoker, Pollution

```
Finding Elimination Order: :
0/0 [00:00<?, ?it/s]
0/0 [00:00<?, ?it/s]
```

```
+-----------+---------------+
| Cancer    | phi(Cancer) |
+===========+===============+
| Cancer(0) |        0.0200 |
+-----------+---------------+
| Cancer(1) |        0.9800 |
+-----------+---------------+
```

8. Implement the Linear Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs.

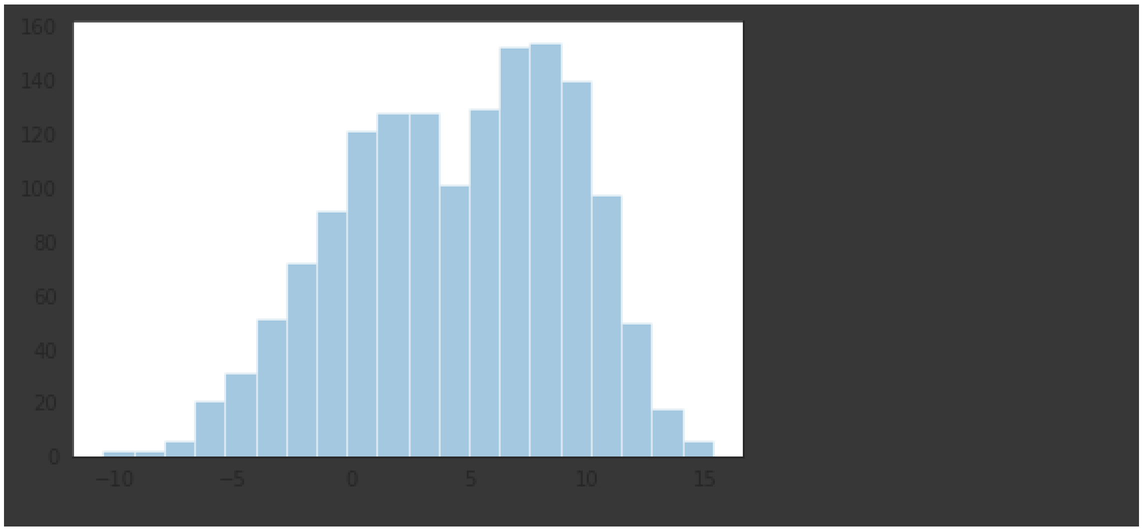


```
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style("white")
%matplotlib inline
#for matrix math
import numpy as np
#for normalization + probability density function computation
from scipy import stats
#for data preprocessing
import pandas as pd
from math import sqrt, log, exp, pi
from random import uniform
random_seed=36788765
np.random.seed(random_seed)

Mean1 = 2.0 # Input parameter, mean of first normal probability
distribution
Standard_dev1 = 4.0 #@param {type:"number"}
Mean2 = 9.0 # Input parameter, mean of second normal
probability distribution
Standard_dev2 = 2.0 #@param {type:"number"}

# generate data
y1 = np.random.normal(Mean1, Standard_dev1, 1000)
y2 = np.random.normal(Mean2, Standard_dev2, 500)
data=np.append(y1,y2)

# For data visiualisation calculate left and right of the graph
Min_graph = min(data)
Max_graph = max(data)
x = np.linspace(Min_graph, Max_graph, 2000) # to plot the data
```

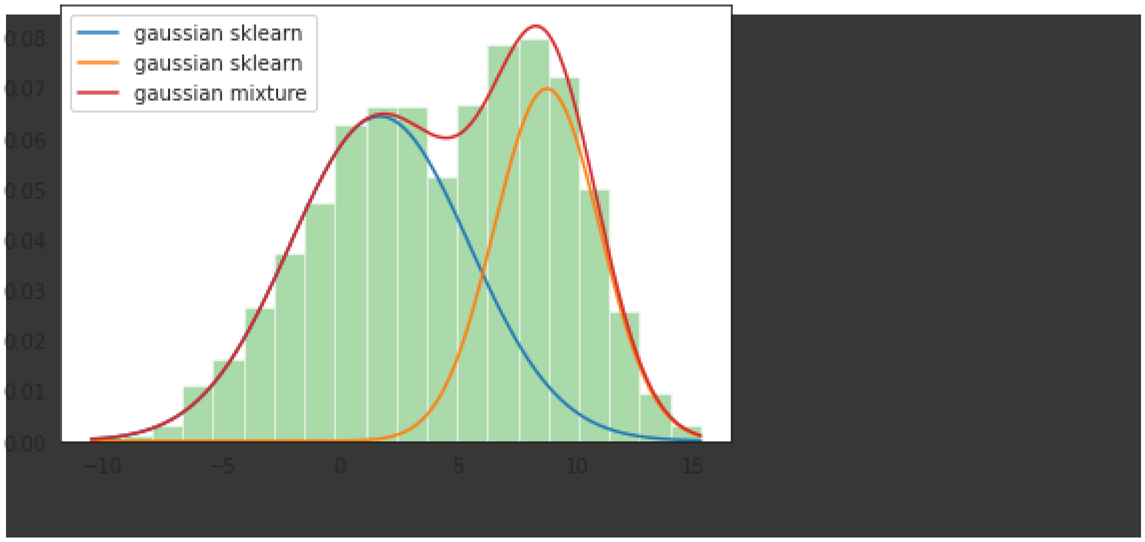
```
print('Input Gaussian {:}: μ = {:.2}, σ = {:.2}'.format("1", Mean1,
Standard_dev1))
print('Input Gaussian {:}: μ = {:.2}, σ = {:.2}'.format("2", Mean2,
Standard_dev2))
sns.distplot(data, bins=20, kde=False);

from sklearn.mixture import GaussianMixture
gmm = GaussianMixture(n_components = 2, tol=0.000001)
gmm.fit(np.expand_dims(data, 1)) # Parameters: array-like, shape
(n_samples, n_features), 1 dimension dataset so 1 feature
Gaussian_nr = 1
print('Input Gaussian {:}: μ = {:.2}, σ = {:.2}'.format("1", Mean1,
Standard_dev1))
print('Input Gaussian {:}: μ = {:.2}, σ = {:.2}'.format("2", Mean2,
Standard_dev2))
for mu, sd, p in zip(gmm.means_.flatten(),
np.sqrt(gmm.covariances_.flatten()),
gmm.weights_):
    print('Gaussian {:}: μ = {:.2}, σ = {:.2}, weight =
{:.2}'.format(Gaussian_nr, mu, sd, p))
    g_s = stats.norm(mu, sd).pdf(x) * p
    plt.plot(x, g_s, label='gaussian sklearn');
    Gaussian_nr += 1
sns.distplot(data, bins=20, kde=False, norm_hist=True)
gmm_sum = np.exp([gmm.score_samples(e.reshape(-1, 1)) for e in x])
#gmm gives log probability, hence the exp() function
plt.plot(x, gmm_sum, label='gaussian mixture');
plt.legend();
```

Output

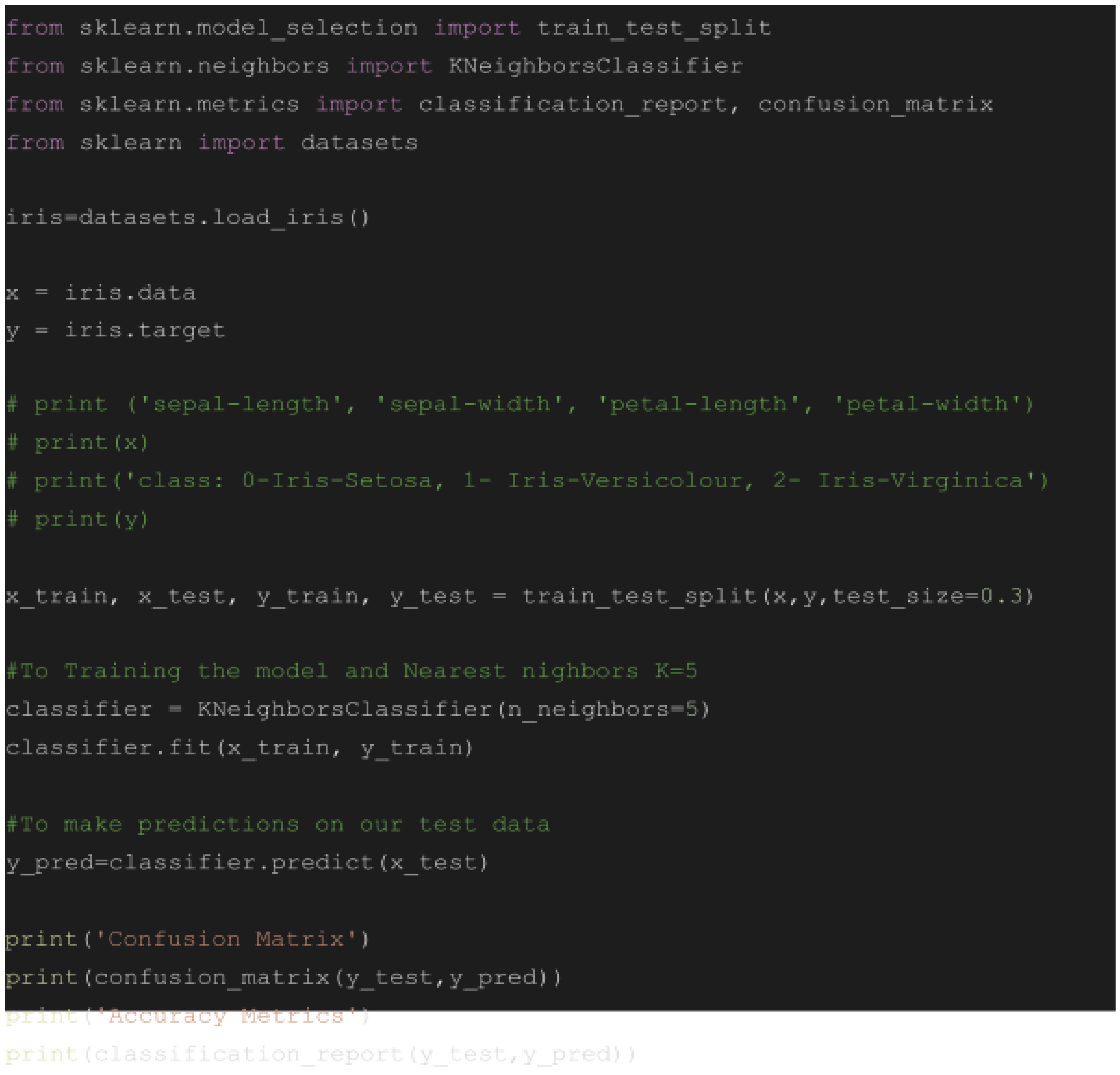
```
Input Gaussian 1: μ = 2.0, σ = 4.0
Input Gaussian 2: μ = 9.0, σ = 2.0
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619:  FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please adapt
your code to use either `displot` (a figure-level function with similar flexibility) or `histplot`
(an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



```
Input Gaussian 1: μ = 2.0, σ = 4.0
Input Gaussian 2: μ = 9.0, σ = 2.0
Gaussian 1: μ = 1.7, σ = 3.8, weight = 0.61
Gaussian 2: μ = 8.8, σ = 2.2, weight = 0.39
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619:  FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



9. Write a program to implement k-Nearest Neighbour algorithm to classify the iris data set. Print both correct and wrong predictions.

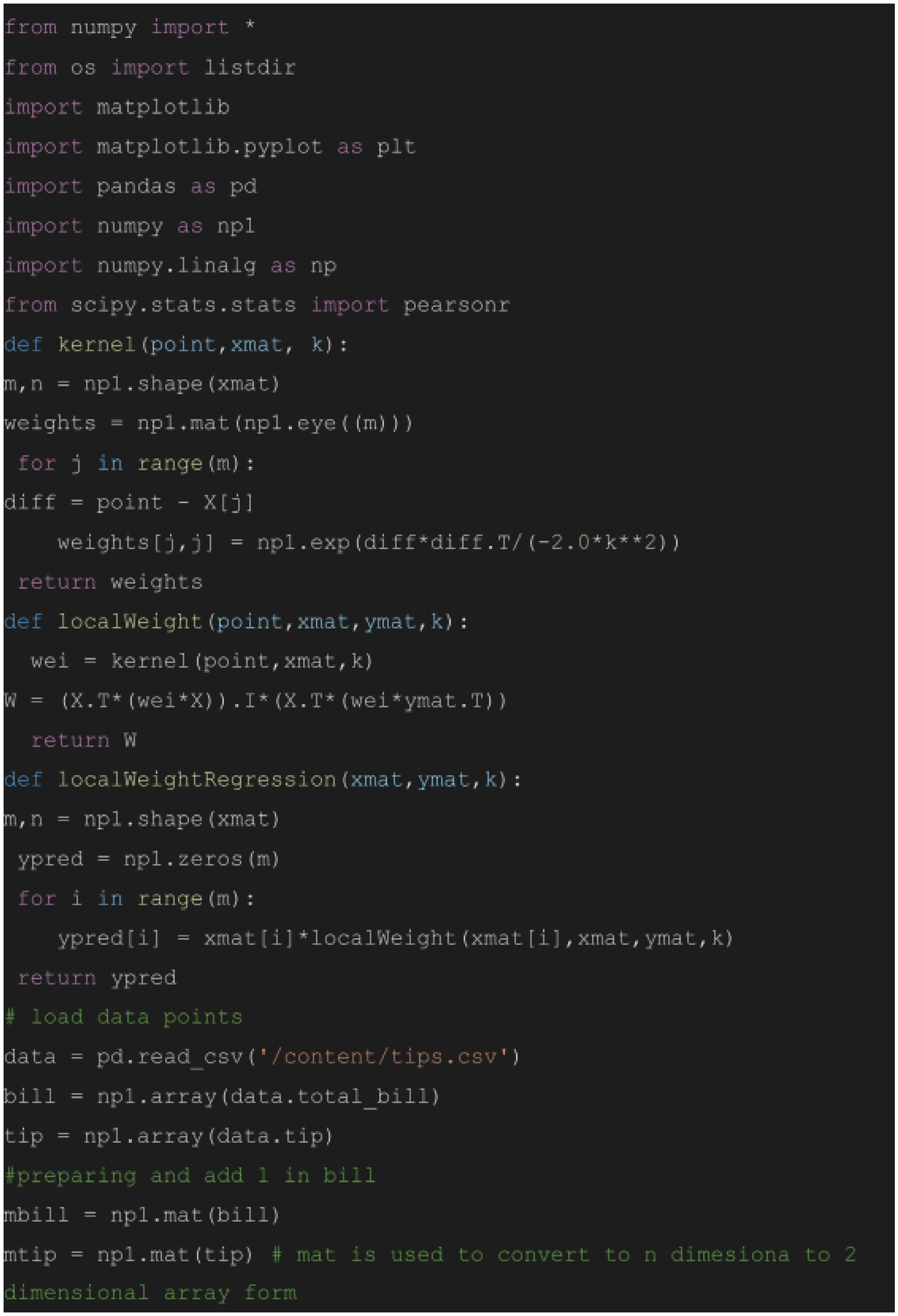


```python
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn import datasets

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

```
Confusion Matrix
[illegible]
 [ 0  2 18]]
Accuracy Metrics
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        14
           1       0.83      0.91      0.87        11
           2       0.95      0.90      0.92        20

    accuracy                           0.93        45
   macro avg       0.93      0.94      0.93        45
weighted avg       0.94      0.93      0.93        45
```

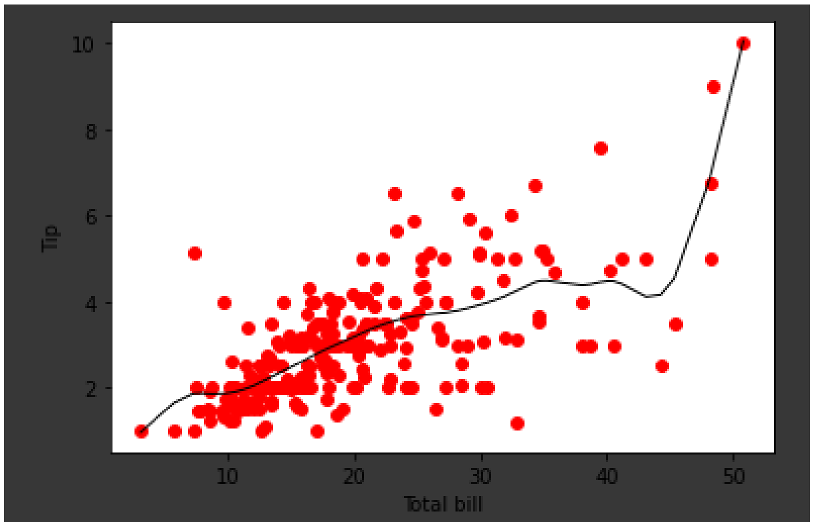
10. Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs.



```
from numpy import *
from os import listdir
import matplotlib
import matplotlib.pyplot as plt
import pandas as pd
import numpy as npl
import numpy.linalg as np
from scipy.stats.stats import pearsonr
def kernel(point,xmat, k):
m,n = npl.shape(xmat)
weights = npl.mat(npl.eye((m)))
 for j in range(m):
diff = point - X[j]
    weights[j,j] = npl.exp(diff*diff.T/(-2.0*k**2))
 return weights
def localWeight(point,xmat,ymat,k):
  wei = kernel(point,xmat,k)
W = (X.T*(wei*X)).I*(X.T*(wei*ymat.T))
  return W
def localWeightRegression(xmat,ymat,k):
m,n = npl.shape(xmat)
 ypred = npl.zeros(m)
 for i in range(m):
    ypred[i] = xmat[i]*localWeight(xmat[i],xmat,ymat,k)
 return ypred
# load data points
data = pd.read_csv('/content/tips.csv')
bill = npl.array(data.total_bill)
tip = npl.array(data.tip)
#preparing and add 1 in bill
mbill = npl.mat(bill)
mtip = npl.mat(tip) # mat is used to convert to n dimesiona to 2
dimensional array form
```

```
X= npl.hstack((one.T,mbill.T)) # create a stack of bill from
ONE #print(X)
#set k here
ypred =
localWeightRegression(X,mtip,2)
SortIndex = X[:,1].argsort(0)
xsort =
X[SortIndex][:,0] fig =
plt.figure()
ax = fig.add_subplot(1,1,1)
ax.scatter(bill,tip,
color='red')
ax.plot(xsort[:,1],ypred[SortIndex], color = 'black',
linewidth=1) plt.xlabel('Total bill')
plt.ylabel('Tip
') plt.show()
```

Output



```
0       sunny         hot     high    weak    no
1       sunny         hot     high  strong    no
2    overcast         hot     high    weak   yes
3        rain        mild     high    weak   yes
4        rain        cool   normal    weak   yes
5        rain        cool   normal  strong    no
6    overcast        cool   normal  strong   yes
7       sunny        mild     high    weak    no
8       sunny        cool   normal    weak   yes
9        rain        mild   normal    weak   yes
10      sunny        mild   normal  strong   yes
11   overcast        mild     high  strong   yes
```

```
12  overcast          hot   normal    weak    yes
13      rain         mild     high  strong     no
```