VISVESVARAYA TECHNOLOGICAL UNIVERSITY

“JnanaSangama”, Belgaum -590014, Karnataka.

LAB REPORT
on

MACHINE LEARNING

Submitted by

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in partial fulfillment for the award of the degree of
BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING
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B. M. S. College of Engineering,

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(Affiliated To Visvesvaraya Technological University, Belgaum)

Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the Lab work entitled "Machine Learning Lab" carried out by **SHIVANI GAHLOT (1BM19CS150),** 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 with respect to **Machine Learning - (20CS6PCMAL)** work prescribed for the said degree.

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Index Sheet

Sl. No.	Experiment Title	Page No.

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

CODE:

```
import csv
a = []
with open('/kaggle/input/dataset/data.csv','r') as csvfile:
 for row in csv.reader(csvfile):
 a.append(row)
 print(a)
 print("\n The total number of training instances are : ",len(a))
num_attribute = len(a[0])-1
print("\n The initial hypothesis is : ")
hypothesis = ['0']*num_attribute
print(hypothesis)
for i in range(0, len(a)):
 if a[i][num_attribute] == 'yes':
```

```
for j in range(0, num_attribute):
if hypothesis[j] == '0' or hypothesis[j] == a[i][j]:
hypothesis[j] = a[i][j]
else:
hypothesis[j] = '?'
print("\n The hypothesis for the training instance {} is :\n" .format(i+1),hypothesis)
print("\n The Maximally specific hypothesis for the training instances is :")
print(hypothesis)
```

OUTPUT:

```
The total number of training instances are :  5

The initial hypothesis is :
['0', '0', '0', '0', '0', '0']

The hypothesis for the training instance 1 is :
['0', '0', '0', '0', '0', '0']

The hypothesis for the training instance 2 is :
['sunny', 'warm', 'normal', 'strong', 'warm', 'same']

The hypothesis for the training instance 3 is :
['sunny', 'warm', '?', 'strong', 'warm', 'same']

The hypothesis for the training instance 4 is :
['sunny', 'warm', '?', 'strong', 'warm', 'same']

The hypothesis for the training instance 5 is :
['sunny', 'warm', '?', 'strong', '?', '?']

The Maximally specific hypothesis for the training instances 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.

CODE:

```
import numpy as np
import pandas as pd

data = pd.read_csv('/kaggle/input/dataset/data.csv')
concepts = np.array(data.iloc[:,0:-1])
print(concepts)
target = np.array(data.iloc[:,-1])
print(target)
def learn(concepts, target):
 specific_h = concepts[0].copy()
```

```
print("Initialization of specific_h and general_h")
print(specific_h)
general_h = [["?" for i in range(len(specific_h))] for i in range(len(specific_h))]
print(general_h)

for i, h in enumerate(concepts):
print("For Loop Starts")
if target[i] == "yes":
print("If instance is Positive ")
for x in range(len(specific_h)):
if h[x]!= specific_h[x]:
specific_h[x] ='?'
general_h[x][x] ='?'

if target[i] == "no":
print("If instance is Negative ")
for x in range(len(specific_h)):
if h[x]!= specific_h[x]:
general_h[x][x] = specific_h[x]
else:
general_h[x][x] = '?'

print("Steps of Candidate Elimination Algorithm",i+1)
print(specific_h)
print(general_h)
print("\n")
print("\n")

indices = [i for i, val in enumerate(general_h) if val == ['?', '?', '?', '?', '?', '?']]
for i in indices:
general_h.remove(['?', '?', '?', '?', '?', '?'])
return specific_h, general_h

s_final, g_final = learn(concepts, target)

print("Final Specific_h:", s_final, sep="\n")
print("Final General_h:", g_final, sep="\n")
```

OUTPUT :

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.

CODE:

```
import math
import csv
def load_csv(filename):
 lines=csv.reader(open(filename,"r"));
 dataset = list(lines)
 headers = dataset.pop(0)
 return dataset,headers
```

```
class Node:
 def __init__(self,attribute):
 self.attribute=attribute
 self.children=[]
 self.answer=""

def subtables(data,col,delete):
 dic={}
 coldata=[row[col] for row in data]
 attr=list(set(coldata))

 counts=[0]*len(attr)
 r=len(data)
 c=len(data[0])
 for x in range(len(attr)):
 for y in range(r):
 if data[y][col]==attr[x]:
 counts[x]+=1

 for x in range(len(attr)):
 dic[attr[x]]=[[0 for i in range(c)] for j in range(counts[x])]
 pos=0
 for y in range(r):
 if data[y][col]==attr[x]:
 if delete:
 del data[y][col]
 dic[attr[x]][pos]=data[y]
 pos+=1
 return attr,dic

def entropy(S):
 attr=list(set(S))
 if len(attr)==1:
 return 0

 counts=[0,0]
 for i in range(2):
 counts[i]=sum([1 for x in S if attr[i]==x])/(len(S)*1.0)

 sums=0
 for cnt in counts:


 sums+=-1*cnt*math.log(cnt,2)
 return sums

def compute_gain(data,col):
 attr,dic = subtables(data,col,delete=False)

 total_size=len(data)
 entropies=[0]*len(attr)
 ratio=[0]*len(attr)
```

```
 total_entropy=entropy([row[-1] for row in data])
 for x in range(len(attr)):
 ratio[x]=len(dic[attr[x]])/(total_size*1.0)
 entropies[x]=entropy([row[-1] for row in dic[attr[x]]])
 total_entropy-=ratio[x]*entropies[x]
 return total_entropy

def build_tree(data,features):
 lastcol=[row[-1] for row in data]
 if(len(set(lastcol)))==1:
 node=Node("")
 node.answer=lastcol[0]
 return node

 n=len(data[0])-1
 gains=[0]*n
 for col in range(n):
 gains[col]=compute_gain(data,col)
 split=gains.index(max(gains))
 node=Node(features[split])
 fea = features[:split]+features[split+1:]


 attr,dic=subtables(data,split,delete=True)

 for x in range(len(attr)):
 child=build_tree(dic[attr[x]],fea)
 node.children.append((attr[x],child))
 return node

def print_tree(node,level):
 if node.answer!="":
 print(" "*level,node.answer)
 return

 print(" "*level,node.attribute)
 for value,n in node.children:
 print(" "*(level+1),"└─",value)
 print_tree(n,level+2)


'''Main program'''
dataset,features=load_csv("/kaggle/input/train/ids_train.csv")
node1=build_tree(dataset,features)

print("The decision tree for the dataset using ID3 algorithm is :\n")
print_tree(node1,0)
```

OUTPUT:

```
The decision tree for the dataset using ID3 algorithm is :

 Outlook
   └─ Rain
     Wind
       └─ Weak
         Yes
       └─ Strong
         No
   └─ Sunny
     Humidity
       └─ Normal
         Yes
       └─ High
         No
   └─ Overcast
     Yes
```

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

CODE:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn import metrics

df = pd.read_csv("/kaggle/input/diabetes/diabetes.csv")
feature_col_names = ['num_preg', 'glucose_conc', 'diastolic_bp', 'thickness', 'insulin', 'bmi', 'diab_pred',
'age'] predicted_class_names = ['diabetes']

X = df[feature_col_names].values
y = df[predicted_class_names].values
print(df.head)
xtrain,xtest,ytrain,ytest=train_test_split(X,y,test_size=0.40)
```

```
print ('\n The total number of Training Data :',ytrain.shape)
print ('\n The total number of Test Data :',ytest.shape)

clf = GaussianNB().fit(xtrain,ytrain.ravel())
predicted = clf.predict(xtest)
predictTestData= clf.predict([[6,148,72,35,0,33.6,0.627,50]])

print('\n Confusion matrix')
print(metrics.confusion_matrix(ytest,predicted))
print('\n Accuracy of the classifier is',metrics.accuracy_score(ytest,predicted))
print('\n The value of Precision', metrics.precision_score(ytest,predicted))
print('\n The value of Recall', metrics.recall_score(ytest,predicted))
print("Predicted Value for individual Test Data:", predictTestData)
```

OUTPUT:

```
[145 rows x 9 columns]>

 The total number of Training Data : (87, 1)

 The total number of Test Data : (58, 1)

 Confusion matrix
[[31  7]
 [10 10]]

 Accuracy of the classifier is 0.7068965517241379

 The value of Precision 0.5882352941176471

 The value of Recall 0.5
Predicted Value for individual Test Data: [1]
```

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

CODE:

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

# Importing the dataset
dataset = pd.read_csv('/kaggle/input/years-of-experience-and-salary/Years Experience and
```

```
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:

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

CODE:

```
#Starting with defining the network structure

from pgmpy.models import BayesianModel

from pgmpy.factors.discrete import TabularCPD

from pgmpy.inference import VariableElimination

#Define a Structure with nodes and edges

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())

#Creation of Conditional Probability Table
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])
# Associating the parameters with the model structure.
cancer_model.add_cpds(cpd_poll, cpd_smoke, cpd_cancer, cpd_xray, cpd_dysp)
print('Model generated bt adding conditional probability distribution(cpds)')

# Checking if the cpds are valid for the model.
print('Checking for Correctness of model:', end='')
print(cancer_model.check_model())

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'))


#Inferencing with Bayesian Network
#Computing the probability of Cancer given smoke

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:

```
Inferencing with Bayesian Network

Probability of Cancer given Smoker

Finding Elimination Order: : 0%                                   0/1 [00:00<?, ?it/s]

Eliminating: Pollution: 100%                                   1/1 [00:00<00:00, 30.61it/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 |
+-----------+---------------+
```

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

CODE:

```
import pandas as pd
import matplotlib
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import MinMaxScaler
from matplotlib import pyplot as plt
%matplotlib inline
df = pd.read_csv('/kaggle/input/income/income.csv')
df.head(10)
scaler = MinMaxScaler()
scaler.fit(df[['Age']])
df[['Age']] = scaler.transform(df[['Age']])
scaler.fit(df[['Income($)']])
df[['Income($)']] = scaler.transform(df[['Income($)']])
df.head(10)
plt.scatter(df['Age'], df['Income($)'])
k_range = range(1, 11)
sse = []
for k in k_range:
 kmc = KMeans(n_clusters=k)
 kmc.fit(df[['Age', 'Income($)']])
 sse.append(kmc.inertia_)
sse
plt.xlabel = 'Number of Clusters'
plt.ylabel = 'Sum of Squared Errors'
plt.plot(k_range, sse)
km = KMeans(n_clusters=3)
km


y_predict = km.fit_predict(df[['Age', 'Income($)']])
y_predict
```

```
df['cluster'] = y_predict
df.head()
df0 = df[df.cluster == 0]
df0
df1 = df[df.cluster == 1]
df1
df2 = df[df.cluster == 2]
df2
km.cluster_centers_

p1 = plt.scatter(df0['Age'], df0['Income($)'], marker='+', color='red')
p2 = plt.scatter(df1['Age'], df1['Income($)'], marker='*', color='blue')
p3 = plt.scatter(df2['Age'], df2['Income($)'], marker='^', color='green')
c = plt.scatter(km.cluster_centers_[:,0], km.cluster_centers_[:,1], color='black')
plt.legend((p1, p2, p3, c),
 ('Cluster 1', 'Cluster 2', 'Cluster 3', 'Centroid'))
```

OUTPUT:

18	Nick	1.000000	0.162393	2
19	Alia	0.764706	0.299145	2
20	Sid	0.882353	0.316239	2
21	Abdul	0.764706	0.111111	2

[14]:

```
km.cluster_centers_
```

ut[14]:

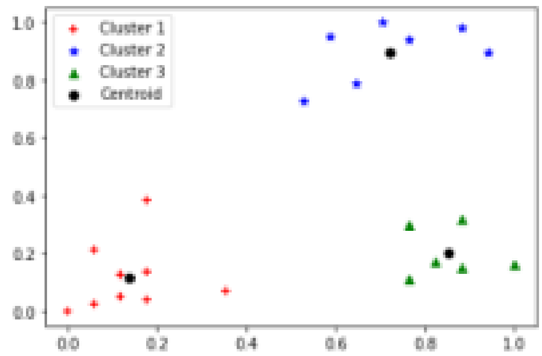
```
array([[0.1372549 , 0.11633428],
       [0.72268908, 0.8974359 ],
       [0.85294118, 0.2022792 ]])
```

[15]:

```
p1 = plt.scatter(df0['Age'], df0['Income($)'], marker='+'
p2 = plt.scatter(df1['Age'], df1['Income($)'], marker='*'
p3 = plt.scatter(df2['Age'], df2['Income($)'], marker='^'
c = plt.scatter(km.cluster_centers_[:,0], km.cluster_cent
plt.legend((p1, p2, p3, c),
           ('Cluster 1', 'Cluster 2', 'Cluster 3', 'Centro
```

ut[15]:

```
<matplotlib.legend.Legend at 0x7f518152d950>
```



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

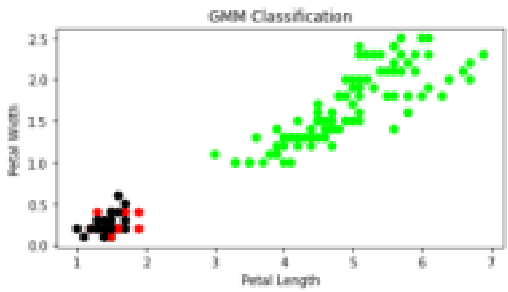
CODE:

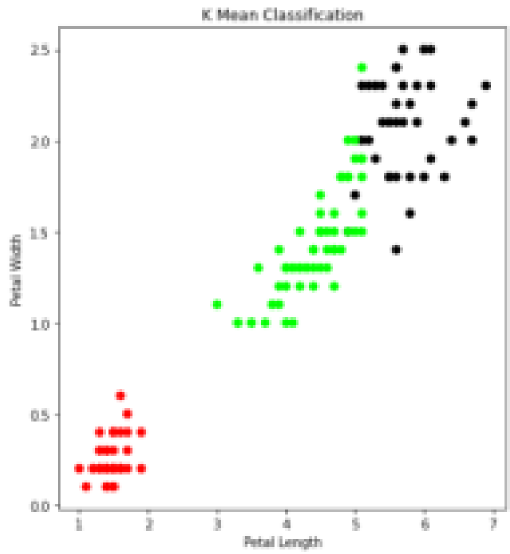
```
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.cluster import KMeans
import sklearn.metrics as sm
import pandas as pd
import numpy as np

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

```
from sklearn import preprocessing
scaler = preprocessing.StandardScaler()
scaler.fit(X)
xsa = scaler.transform(X)
xs = pd.DataFrame(xsa, columns = X.columns)
#xs.sample(5)

from sklearn.mixture import GaussianMixture
gmm = GaussianMixture(n_components=3)
gmm.fit(xs)
y_gmm = gmm.predict(xs)
#y_cluster_gmm
plt.subplot(2, 2, 3)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y_gmm], s=40)
plt.title('GMM Classification')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')

print('The accuracy score of EM: ',sm.accuracy_score(y, y_gmm))
print('The Confusion matrix of EM: ',sm.confusion_matrix(y, y_gmm))
```

OUTPUT:

```
The accuracy score of K-Mean:  0.8933333333333333
The Confusion matrixof K-Mean:  [[50  0  0]
 [ 0 48  2]
 [ 0 14 36]]
The accuracy score of EM:  0.4
The Confusion matrix of EM:  [[10  0 40]
 [ 0 50  0]
 [ 0 50  0]]
```





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

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:

```
Confusion Matrix
[[19  0  0]
 [ 0 14  2]
 [ 0  0 10]]
Accuracy Metrics
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        19
           1       1.00      0.88      0.93        16
           2       0.83      1.00      0.91        10

    accuracy                           0.96        45
   macro avg       0.94      0.96      0.95        45
weighted avg       0.96      0.96      0.96        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.

CODE:

```
from numpy import *
from os import listdir
import matplotlib
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np1
import numpy.linalg as np
from scipy.stats.stats import pearsonr

def kernel(point,xmat, k):
 m,n = np1.shape(xmat)
 weights = np1.mat(np1.eye((m)))
```

```
for j in range(m):
diff = point - X[j]
weights[j,j] = np1.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 = np1.shape(xmat)
ypred = np1.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('/kaggle/input/tipsdataset/tips.csv')
bill = np1.array(data.total_bill)
tip = np1.array(data.tip)

#preparing and add 1 in bill
mbill = np1.mat(bill)
mtip = np1.mat(tip)
# mat is used to convert to n dimesiona to 2 dimensional array form
m= np1.shape(mbill)[1] # print(m) 244 data is stored in m
one = np1.mat(np1.ones(m))
X= np1.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='blue')
ax.plot(xsort[:,1],ypred[SortIndex], color = 'red', linewidth=5)
plt.xlabel('Total bill')
plt.ylabel('Tip')
plt.show();

import numpy as np
from bokeh.plotting import figure, show, output_notebook
from bokeh.layouts import gridplot
from bokeh.io import push_notebook

def local_regression(x0, X, Y, tau):
 # add bias term
 x0 = np.r_[1, x0]

 # Add one to avoid the loss in information
 X = np.c_[np.ones(len(X)), X]
 # fit model: normal equations with kernel
 xw = X.T * radial_kernel(x0, X, tau) # XTranspose * W
 beta = np.linalg.pinv(xw @ X) @ xw @ Y #@ Matrix Multiplication or Dot Product
return x0 @ beta # @ Matrix Multiplication or Dot Product for prediction

 def radial_kernel(x0, X, tau):
 return np.exp(np.sum((X - x0) ** 2, axis=1) / (-2 * tau * tau))
# Weight or Radial Kernal Bias Function

n = 1000
# generate dataset
X = np.linspace(-3, 3, num=n)
print("The Data Set ( 10 Samples) X :\n",X[1:10])
```

```
Y = np.log(np.abs(X ** 2 - 1) + .5)
print("The Fitting Curve Data Set (10 Samples) Y:\n",Y[1:10])
# jitter X
X += np.random.normal(scale=.1, size=n)
print("Normalised (10 Samples) X :\n",X[1:10])

domain = np.linspace(-3, 3, num=300)
print(" Xo Domain Space(10 Samples) :\n",domain[1:10])

def plot_lwr(tau):
 # prediction through regression
 prediction = [local_regression(x0, X, Y, tau) for x0 in domain]
 plot = figure(plot_width=400, plot_height=400)
 plot.title.text='tau=%g' % tau
 plot.scatter(X, Y, alpha=.3)
 plot.line(domain, prediction, line_width=2, color='red')
 return plot

show(gridplot([[plot_lwr(10.), plot_lwr(1.)],

[plot_lwr(0.1), plot_lwr(0.01)]]))

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

def kernel(point,xmat, k):
 m,n = np.shape(xmat)
 weights = np.mat(np.eye((m))) # eye - identity matrix
 for j in range(m):
 diff = point - X[j]
 weights[j,j] = np.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 = np.shape(xmat)
 ypred = np.zeros(m)
 for i in range(m):
 ypred[i] = xmat[i]*localWeight(xmat[i],xmat,ymat,k)
 return ypred

def graphPlot(X,ypred):
 sortindex = X[:,1].argsort(0) #argsort - index of the smallest
 xsort = X[sortindex][:,0]
 fig = plt.figure()
 ax = fig.add_subplot(1,1,1)
 ax.scatter(bill,tip, color='green')
 ax.plot(xsort[:,1],ypred[sortindex], color = 'red', linewidth=5)
 plt.xlabel('Total bill')
 plt.ylabel('Tip')
 plt.show();

# load data points
data = pd.read_csv('/kaggle/input/tipsdataset/tips.csv')
bill = np.array(data.total_bill) # We use only Bill amount and Tips data
tip = np.array(data.tip)

mbill = np.mat(bill) # .mat will convert nd array is converted in 2D array
mtip = np.mat(tip)
m= np.shape(mbill)[1]
one = np.mat(np.ones(m))
```

X = np.hstack((one.T,mbill.T)) # 244 rows, 2 cols

increase k to get smooth curves

ypred = localWeightRegression(X,mtip,3)

graphPlot(X,ypred)

OUTPUT:

```
The Data Set ( 10 Samples) X :
 [-2.99399399 -2.98798799 -2.98198198 -2.97597598 -2.96996997 -2.
 -2.95795796 -2.95195195 -2.94594595]
The Fitting Curve Data Set (10 Samples) Y:
 [2.13582188 2.13156806 2.12730467 2.12303166 2.11874898 2.114456
 2.11015444 2.10584249 2.10152068]
Normalised (10 Samples) X :
 [-3.23963795 -3.01210846 -2.83540045 -3.04102183 -2.96386659 -3.
 -3.0388275  -2.7336852  -3.08914491]
 Xo Domain Space(10 Samples) :
 [-2.97993311 -2.95986622 -2.93979933 -2.91973244 -2.89966555 -2.
 -2.85953177 -2.83946488 -2.81939799]
```