VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

MACHINE LEARNING
(20CS6PCMAL)

Submitted by

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in partial fulfillment for the award of the degree of
BACHELOR OF ENGINEERING
in
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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 **JOEL NINAN JOHNSON (1BM19CS199),** who is 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 Outcome

CO4	Ability to conduct practical experiments to solve problems using appropriate machine learning techniques.

LAB PROGRAM 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('enjoysport.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 instance 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 instance is
['sunny', 'warm', '?', 'strong', '?', '?']
```

LAB PROGRAM 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.DataFrame(data= pd.read_csv("./enjoysport.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 hypothesis and general hypothesis:")
    print("S0: ",specific_h)
    general_h = [["?" for i in range(len(specific_h))] for i in range(len(specific_h))]
    print("G0: ",general_h)
    for i, h in enumerate(concepts):
        if target[i] == "yes":
            for x in range(len(specific_h)):
                if h[x] != specific_h[x]:
                    specific_h[x] = "?"
                    general_h[x][x] = "?"
        if target[i] == "no":
            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("\nThe steps of Candidate Elimination Algorithm ", i+1)
        print(f"S{i+1}: " ,specific_h)
        actual_general_h= [i for i in general_h if i != ['?', '?', '?', '?', '?', '?']]
        print(f"G{i+1}: ",actual_general_h)
    actual_general_h= [i for i in general_h if i != ["?" for i in range(len(specific_h))]]
    return specific_h, actual_general_h
```

Output:

```
Initialization of specific hypothesis and general hypothesis:
S0:  ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
G0:  [['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],
['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?',
'?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

The steps of Candidate Elimination Algorithm  1
S1:  ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
G1:  []

The steps of Candidate Elimination Algorithm  2
S2:  ['sunny' 'warm' '?' 'strong' 'warm' 'same']
G2:  []

The steps of Candidate Elimination Algorithm  3
S3:  ['sunny' 'warm' '?' 'strong' 'warm' 'same']
G3:  [['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?',
'?'], ['?', '?', '?', '?', '?', 'same']]

The steps of Candidate Elimination Algorithm  4
S4:  ['sunny' 'warm' '?' 'strong' '?' '?']
G4:  [['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?',
'?']]

The final Specific hypothesis is:
['sunny' 'warm' '?' 'strong' '?' '?']
The final General Hypothesis is:
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?']]
```

LAB PROGRAM 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
In [6]:
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)
In [7]:
def classify(node,x_test,features):
    if node.answer!="":
        print(node.answer)
        return
    pos=features.index(node.attribute)
    for value, n in node.children:
        if x_test[pos]==value:
            classify(n,x_test,features)
'''Main program'''
dataset,features=load_csv("id3-dataset.csv")
node1=build_tree(dataset,features)
print("The decision tree for the dataset using ID3 algorithm is")
print_tree(node1,0)
testdata,features=load_csv("id1.csv")
for xtest in testdata:
    print("The test instance:",xtest)
    print("The label for test instance:",end=" ")
    classify(node1,xtest,features)
```

Output:

```
The decision tree for the dataset using ID3 algorithm is
 Outlook
   rain
     Wind
       weak
         yes
       strong
         no
   overcast
     yes
   sunny
     Humidity
       normal
         yes
       high
         no
The test instance: ['rain', 'cool', 'normal', 'strong']
The label for test instance: no
The test instance: ['sunny', 'mild', 'normal', 'strong']
The label for test instance: yes
```

LAB PROGRAM 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 set.

Code:

```
from sklearn.datasets import fetch_20newsgroups
categories = ['alt.atheism', 'soc.religion.christian','comp.graphics', 'sci.med']
news_train = fetch_20newsgroups(subset='train',categories=categories)
news_test = fetch_20newsgroups(subset='test',categories=categories)
print(news_train.keys())
print(news_train['target_names'])
from sklearn.feature_extraction.text import CountVectorizer
count_vect=CountVectorizer()
X_train_tf=count_vect.fit_transform(news_train.data)
print(X_train_tf)
X_train_tf.shape
from sklearn.feature_extraction.text import TfidfTransformer
tfidf_transformer=TfidfTransformer()
X_train_tfidf=tfidf_transformer.fit_transform(X_train_tf)
X_train_tfidf.shape
from sklearn.naive_bayes import MultinomialNB
clf= MultinomialNB().fit(X_train_tfidf, news_train.target)
X_test_tf=count_vect.transform(news_test.data)
X_test_tfidf=tfidf_transformer.transform(X_test_tf)
predicted=clf.predict(X_test_tfidf)
predicted
from sklearn import metrics
from sklearn.metrics import accuracy_score
```

```
print("Accuracy",accuracy_score(news_test.target,predicted))
print(metrics.confusion_matrix(news_test.target,predicted))
```

Output:

```
Accuracy 0.8348868175765646
[[192   2   6 119]
 [  2 347   4  36]
 [  2  11 322  61]
 [  2   2   1 393]]
```

LAB PROGRAM 5:

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

Code:

```
import numpy as np
import pandas as pd
import csv
from pgmpy.estimators import MaximumLikelihoodEstimator
from pgmpy.models import BayesianModel
from pgmpy.inference import VariableElimination
heartDisease = pd.read_csv('heart.csv')
heartDisease = heartDisease.replace('?',np.nan)
print('Sample instances from the dataset are given below')
print(heartDisease.head())
print('\n Attributes and datatypes')
print(heartDisease.dtypes)
model=
BayesianModel([('age','heartdisease'),('sex','heartdisease'),('exang','heartdisease'),('cp','heartdiseas
e'),('heartdisease','restecg'),('heartdisease','chol')])
print('\nLearning CPD using Maximum likelihood estimators')
model.fit(heartDisease,estimator=MaximumLikelihoodEstimator)
print('\n Inferencing with Bayesian Network:')
HeartDiseasetest_infer = VariableElimination(model)
print('\n 1. Probability of HeartDisease given evidence= restecg')
q1=HeartDiseasetest_infer.query(variables=['heartdisease'],evidence={'restecg':1})
print(q1)
print('\n 2. Probability of HeartDisease given evidence= cp ')
q2=HeartDiseasetest_infer.query(variables=['heartdisease'],evidence={'cp':2})
print(q2)
```

Output:

1. Probability of HeartDisease given evidence= restecg

heartdisease	phi(heartdisease)
heartdisease(0)	0.1012
heartdisease(1)	0.0000
heartdisease(2)	0.2392
heartdisease(3)	0.2015
heartdisease(4)	0.4581

2. Probability of HeartDisease given evidence= cp

heartdisease	phi(heartdisease)
heartdisease(0)	0.3610
heartdisease(1)	0.2159
heartdisease(2)	0.1373
heartdisease(3)	0.1537
heartdisease(4)	0.1321

LAB PROGRAM 6:

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

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)
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]]
```

```
Text(0, 0.5, 'Petal Width')
```

LAB PROGRAM 7:

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:

```
from sklearn import datasets
from sklearn.cluster import KMeans
from sklearn.utils import shuffle
import numpy as np
import pandas as pd
iris=datasets.load_iris()
X=iris.data
Y=iris.target
#Shuffle of Data
X,Y = shuffle(X,Y)
model=KMeans(n_clusters=3,init='k-means++',max_iter=10,n_init=1,random_state=3425)
#Training of the model
model.fit(X)
# This is what KMeans thought (Prediction)
Y_Pred=model.labels_
from sklearn.metrics import confusion_matrix
cm=confusion_matrix(Y,Y_Pred)
print(cm)
from sklearn.metrics import accuracy_score
print(accuracy_score(Y,Y_Pred))
#Defining EM Model
from sklearn.mixture import GaussianMixture
model2=GaussianMixture(n_components=3,random_state=3425)
```

#Training of the model

model2.fit(X)

#Predicting classes for our data

Y_predict2= model2.predict(X)

#Accuracy of EM Model

from sklearn.metrics import confusion_matrix

cm=confusion_matrix(Y,Y_predict2)

print(cm)

from sklearn.metrics import accuracy_score

print(accuracy_score(Y,Y_predict2))

Output:

```
#Predicting classes for our data
Y_predict2= model2.predict(X)

#Accuracy of EM Model
from sklearn.metrics import confusion_matrix

cm=confusion_matrix(Y,Y_predict2)
print(cm)

from sklearn.metrics import accuracy_score

print(accuracy_score(Y,Y_predict2))
```

```
[[50  0  0]
 [ 0  5 45]
 [ 0 50  0]]
0.36666666666666664
```

LAB PROGRAM 8:

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('target')
print(Y)
x_train, x_test, y_train, y_test = train_test_split(X,Y,test_size=0.3)
classier = KNeighborsClassifier(n_neighbors=5)
classier.fit(x_train, y_train)
y_pred=classier.predict(x_test)
print('confusion matrix')
print(confusion_matrix(y_test,y_pred))
print('accuracy')
print(classification_report(y_test,y_pred))
```

Output:

```
print('confusion matrix')
print(confusion_matrix(y_test,y_pred))
```

```
confusion matrix
[[16  0  0]
 [ 0 12  1]
 [ 0  0 16]]
```

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

```
accuracy
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        16
           1       1.00      0.92      0.96        13
           2       0.94      1.00      0.97        16

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

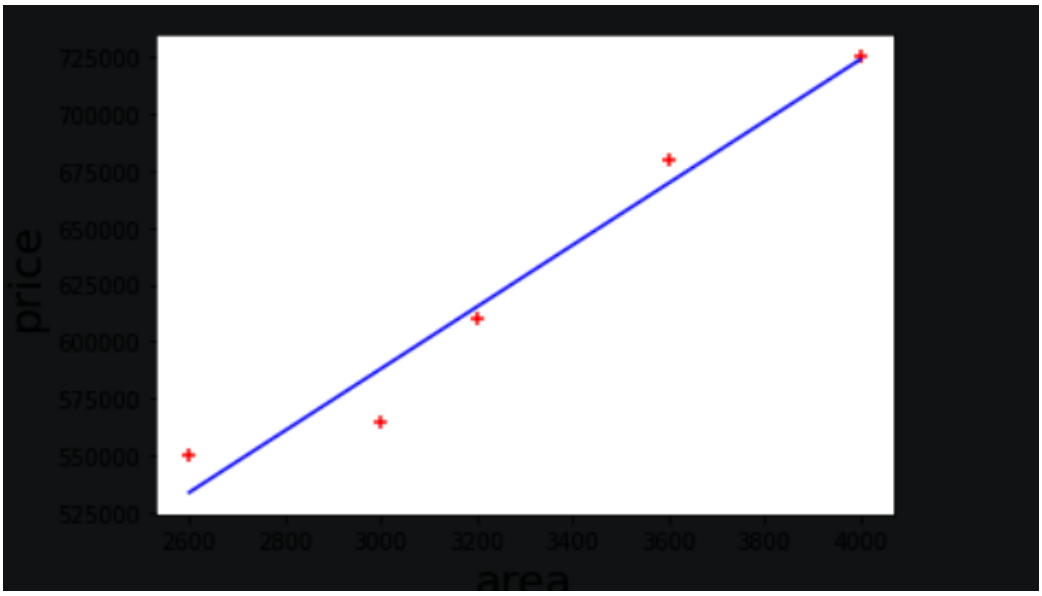
LAB PROGRAM 9:

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

Code:

```
import pandas as pd
import numpy as np
from sklearn import linear_model
import matplotlib.pyplot as plt
df = pd.read_csv(r'/content/homeprices.csv')
df
%matplotlib inline
plt.xlabel('area')
plt.ylabel('price')
plt.scatter(df.area,df.price,color='red',marker='.')
new_df = df.drop('price',axis='columns')
df
Price = df.price
Price
reg = linear_model.LinearRegression()
reg.fit(new_df,Price)
reg.predict([[3300]])
#reg.coef_
reg.predict([[5000]])
plt.xlabel('area',fontsize=20)
plt.ylabel('price',fontsize=20)
plt.scatter(df.area,df.price,color='red',marker='+')
plt.plot(df.area,reg.predict(df[['area']]),color='blue')
```

Output:


725000
700000
675000
650000
625000
600000
575000
550000
525000
price
2600
2800
3000
3200
3400
3600
3800
4000
area

LAB PROGRAM 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.

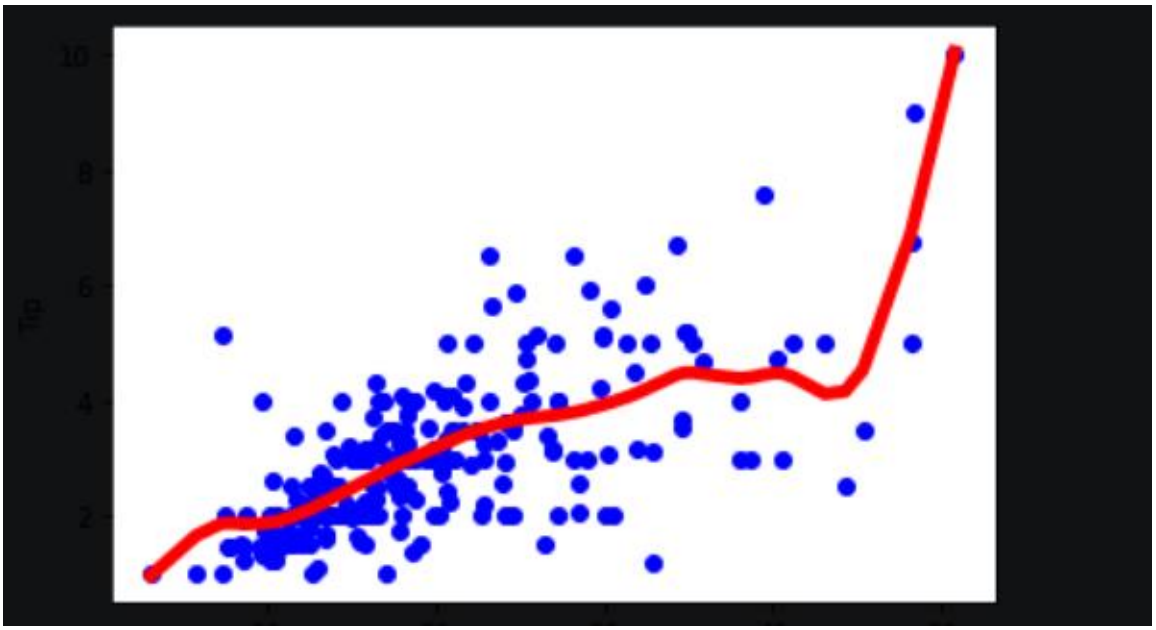
Code:

```
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
data = pd.read_csv('tips.csv')
bill = np1.array(data.total_bill)
tip = np1.array(data.tip)

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]

one = np1.mat(np1.ones(m))
X= np1.hstack((one.T,mbill.T)) # create a stack of bill from ONE

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):
    x0 = np.r_[1, x0]
    X = np.c_[np.ones(len(X)), X]

    xw = X.T * radial_kernel(x0, X, tau)
    beta = np.linalg.pinv(xw @ X) @ xw @ Y
    return x0 @ beta

def radial_kernel(x0, X, tau):
    return np.exp(np.sum((X - x0) ** 2, axis=1) / (-2 * tau * tau))


n = 1000
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])
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 = [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)]]))
```

Output:




```
The Data Set ( 10 Samples) X :
 [-2.99399399 -2.98798799 -2.98198198 -2.97597598 -2.96996997 -2.963963
96
 -2.95795796 -2.95195195 -2.94594595]
The Fitting Curve Data Set (10 Samples) Y :
 [2.13582188 2.13156806 2.12730467 2.12303166 2.11874898 2.11445659
 2.11015444 2.10584249 2.10152068]
Normalised (10 Samples) X :
 [-2.98256634 -2.99368144 -3.05914505 -3.03174286 -3.07963801 -2.859540
46
 -2.92988067 -2.958209   -2.96962333]
 Xo Domain Space(10 Samples) :
 [-2.97993311 -2.95986622 -2.93979933 -2.91973244 -2.89966555 -2.879598
66
 -2.85953177 -2.83946488 -2.81939799]
```