Machine Learning

Lab1:

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

Program:

```
import pandas as pd
import numpy as np
data = pd.read_csv('lab1.csv')
concepts=np.array(data)[:,:-1]
target=np.array(data)[:,-1]
def search(con,tar):
    for i,val in enumerate(tar):
        if val=="yes":
            specifichyp=con[i].copy()
            break
    for i,val in enumerate(con):
        if tar[i]=="yes":
            for x in range(len(specifichyp)):
                if val[x]!=specifichyp[x]:
                    specifichyp[x]="?"
                else:
                    pass
    return specifichyp
print(search(concepts, target))
```

Output:

```
['sunny' 'warm' '?' 'strong' '?' '?']
```

Lab2:

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.

Program:

```
import numpy as np

import pandas as pd

data=pd.read_csv('data.csv')

concepts=np.array(data)[0:,:-1]

target=np.array(data)[0:,-1]


def candidate_elimination(con,tar):

    s_hyp=con[0].copy()

    g_hyp=[["?" for i in range(len(s_hyp))] for i in range(len(s_hyp))]


    for i,val in enumerate(con):

        if tar[i]=="yes":

            for x in range(len(s_hyp)):

                if val[x]!=s_hyp[x]:

                    s_hyp[x]="?"

                    g_hyp[x][x]="?"

        if tar[i]=="no":

            for x in range(len(s_hyp)):

                if val[x]!=s_hyp[x]:

                    g_hyp[x][x]=s_hyp[x]

                else:

                    g_hyp[x][x]="?"

    indices=[i for i,val in enumerate(g_hyp) if val==["?","?","?","?","?","?"]]

    for i in indices:

        g_hyp.remove(["?","?","?","?","?","?"])
```

```
    return s_hyp,g_hyp

s_final,g_final=candidate_elimination(concepts,target)
print(s_final)
print(g_final)
```

Output:

```
['sunny' 'warm' '?' 'strong' '?' '?']
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?']]
```

Lab3:

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.

Program:

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

data = pd.read_csv("3-dataset.csv")
features = [feat for feat in data]
features.remove("answer")

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

def 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])
    #print ("\n",uniq)
    gain = entropy(examples)
    #print ("\n",gain)
    for u in uniq:
        subdata = examples[examples[attr] == u]
        #print ("\n",subdata)
        sub_e = entropy(subdata)
        gain -= (float(len(subdata)) / float(len(examples))) * sub_e
        #print ("\n",gain)
    return gain

def ID3(examples, attrs):
    root = Node()
```

```
max_gain = 0
max_feat = ""
for feature in attrs:
    #print ("\n",examples)
    gain = info_gain(examples, feature)
    if gain > max_gain:
        max_gain = gain
        max_feat = feature
root.value = max_feat
#print ("\nMax feature attr",max_feat)
uniq = np.unique(examples[max_feat])
#print ("\n",uniq)
for u in uniq:
    #print ("\n",u)
    subdata = examples[examples[max_feat] == u]
    #print ("\n",subdata)
    if entropy(subdata) == 0.0:
        newNode = Node()
        newNode.isLeaf = True
        newNode.value = u
        newNode.pred = np.unique(subdata["answer"])
        root.children.append(newNode)
    else:
        dummyNode = Node()
        dummyNode.value = u
        new_attrs = attrs.copy()
        new_attrs.remove(max_feat)
        child = ID3(subdata, new_attrs)
        dummyNode.children.append(child)
        root.children.append(dummyNode)
```

```
    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)
```

```
outlook
        overcast ->  ['yes']

        rain
                wind
                        strong ->  ['no']

                        weak ->  ['yes']

        sunny
                humidity
                        high ->  ['no']

                        normal ->  ['yes']
```

Lab4:

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

Program:

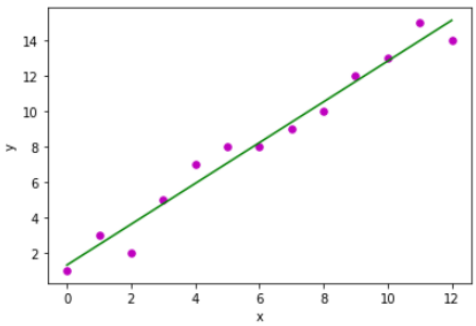
```
import numpy as np
import matplotlib.pyplot as plt
```

```
def estimate_coef(x, y):
    # number of observations/points
    n = np.size(x)

    # mean of x and y vector
    m_x = np.mean(x)
    m_y = np.mean(y)

    # calculating cross-deviation and deviation about x
    SS_xy = np.sum(y*x) - n*m_y*m_x
    SS_xx = np.sum(x*x) - n*m_x*m_x

    # calculating regression coefficients
    b_1 = SS_xy / SS_xx
    b_0 = m_y - b_1*m_x

    return (b_0, b_1)
def plot_regression_line(x, y, b):
    # plotting the actual points as scatter plot
    plt.scatter(x, y, color = "m",
               marker = "o", s = 30)

    # predicted response vector
    y_pred = b[0] + b[1]*x

    # plotting the regression line
    plt.plot(x, y_pred, color = "g")

    # putting labels
```

```
    plt.xlabel('x')
    plt.ylabel('y')

    # function to show plot
    plt.show()

def main():
    # observations / data
    x = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9,10,11,12])
    y = np.array([1, 3, 2, 5, 7, 8, 8, 9, 10, 12,13,15,14])

    # estimating coefficients
    b = estimate_coef(x, y)
    print("Estimated coefficients:\nb_0 = {}  \
        \nb_1 = {}".format(b[0], b[1]))

    # plotting regression line
    plot_regression_line(x, y, b)

if __name__ == "__main__":
    main()
```

Output:

```
Estimated coefficients:
b_0 = 1.3076923076923
b_1 = 1.1538461538461544
```



Lab5:

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

Program:

```
import numpy as np
import pandas as pd
from sklearn import preprocessing
from sklearn.naive_bayes import MultinomialNB
le=preprocessing.LabelEncoder()
clf = MultinomialNB()
data=pd.read_csv('NB.csv')
features=[feat for feat in data]
targetLabel=features[-1]
features.remove(features[-1])
features
diff_values=[]
for f in features:
    for v in data[f]:
        if v not in diff_values:
            diff_values.append(v)

diff_values
dataArray=np.array(data.iloc[:,0:-1])
dataArray
le.fit(diff_values)
list(le.classes_)
trans=[]
for d in dataArray:
```

```
    trans.append(le.transform(d))
trans
target=data[targetLabel]
target
target=np.array(target)
tar=[]
for t in target:
    if t == "yes":
        tar.append(1)
    else:
        tar.append(0)
tar
clf.fit(trans,tar)
predicting=["sunny","cool","high","strong"]
pre_array=le.transform(predicting)
pre_array=np.reshape(pre_array,(1,4))
pre_array
print(clf.predict(pre_array))
```

Output: [0]

Lab6:

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

Program:

```
# importing libraries
import numpy as nm
import matplotlib.pyplot as mtp
import pandas as pd
# Importing the dataset
```

```
dataset = pd.read_csv('Kmeans_data.csv')
x = dataset.iloc[:, [3, 4]].values
#finding optimal number of clusters using the elbow method
from sklearn.cluster import KMeans
wcss_list= []  #Initializing the list for the values of WCSS

#Using for loop for iterations from 1 to 10.
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state= 42)
    kmeans.fit(x)
    wcss_list.append(kmeans.inertia_)
mtp.plot(range(1, 11), wcss_list)
mtp.title('The Elobw Method Graph')
mtp.xlabel('Number of clusters(k)')
mtp.ylabel('wcss_list')
mtp.show()
#training the K-means model on a dataset
kmeans = KMeans(n_clusters=5, init='k-means++', random_state= 42)
y_predict= kmeans.fit_predict(x)
#training the K-means model on a dataset
kmeans = KMeans(n_clusters=5, init='k-means++', random_state= 42)
y_predict= kmeans.fit_predict(x)
```

Output:

Lab7:

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

Program:

```
import pgmpy.models

import pgmpy.inference

import networkx as nx

import pylab as plt

# Create a bayesian network

model = pgmpy.models.BayesianModel([('Burglary', 'Alarm'),

                                ('Earthquake', 'Alarm'),

                                ('Alarm', 'JohnCalls'),

                                ('Alarm', 'MaryCalls')])

# Define conditional probability distributions (CPD)

# Probability of burglary (True, False)

cpd_burglary = pgmpy.factors.discrete.TabularCPD('Burglary', 2, [[0.001], [0.999]])

# Probability of earthquake (True, False)

cpd_earthquake = pgmpy.factors.discrete.TabularCPD('Earthquake', 2, [[0.002], [0.998]])

# Probability of alarm going of (True, False) given a burglary and/or earthquake

cpd_alarm = pgmpy.factors.discrete.TabularCPD('Alarm', 2, [[0.95, 0.94, 0.29, 0.001],

                                                [0.05, 0.06, 0.71, 0.999]],

                                       evidence=['Burglary', 'Earthquake'],

                                       evidence_card=[2, 2])

# Probability that John calls (True, False) given that the alarm has sounded

cpd_john = pgmpy.factors.discrete.TabularCPD('JohnCalls', 2, [[0.90, 0.05],

                                                [0.10, 0.95]],

                                       evidence=['Alarm'],

                                       evidence_card=[2])

# Probability that Mary calls (True, False) given that the alarm has sounded

cpd_mary = pgmpy.factors.discrete.TabularCPD('MaryCalls', 2, [[0.70, 0.01],
```

```
                          [0.30, 0.99]],
                  evidence=['Alarm'],
                  evidence_card=[2])
# Add CPDs to the network structure
model.add_cpds(cpd_burglary, cpd_earthquake, cpd_alarm, cpd_john, cpd_mary)
# Check if the model is valid, throw an exception otherwise
model.check_model()
# Print probability distributions
print('Probability distribution, P(Burglary)')
print(cpd_burglary)
print()
print('Probability distribution, P(Earthquake)')
print(cpd_earthquake)
print()
print('Joint probability distribution, P(Alarm | Burglary, Earthquake)')
print(cpd_alarm)
print()
print('Joint probability distribution, P(JohnCalls | Alarm)')
print(cpd_john)
print()
print('Joint probability distribution, P(MaryCalls | Alarm)')
print(cpd_mary)
print()
# Plot the model
nx.draw(model, with_labels=True)
plt.savefig('C:\\Users\\admin\\Desktop')
plt.close()
# Perform variable elimination for inference
# Variable elimination (VE) is a an exact inference algorithm in bayesian networks
infer = pgmpy.inference.VariableElimination(model)
```

```
# Calculate the probability of a burglary if John and Mary calls (0: True, 1: False)

posterior_probability = infer.query(['Burglary'], evidence={'JohnCalls': 0, 'MaryCalls': 0})

# Print posterior probability

print('Posterior probability of Burglary if JohnCalls(True) and MaryCalls(True)')

print(posterior_probability)

print()

# Calculate the probability of alarm starting if there is a burglary and an earthquake (0: True,
1: False)

posterior_probability = infer.query(['Alarm'], evidence={'Burglary': 0, 'Earthquake': 0})

# Print posterior probability

print('Posterior probability of Alarm sounding if Burglary(True) and Earthquake(True)')

print(posterior_probability)

print()
```

Output:

```
print()
Probability distribution, P(Burglary)
+-------------+-------+
| Burglary(0) | 0.001 |
+-------------+-------+
| Burglary(1) | 0.999 |
+-------------+-------+

Probability distribution, P(Earthquake)
+---------------+-------+
| Earthquake(0) | 0.002 |
+---------------+-------+
| Earthquake(1) | 0.998 |
+---------------+-------+

Joint probability distribution, P(Alarm | Burglary, Earthquake)
+------------+---------------+---------------+---------------+---------------+
| Burglary   | Burglary(0)   | Burglary(0)   | Burglary(1)   | Burglary(1)   |
+------------+---------------+---------------+---------------+---------------+
| Earthquake | Earthquake(0) | Earthquake(1) | Earthquake(0) | Earthquake(1) |
+------------+---------------+---------------+---------------+---------------+
| Alarm(0)   | 0.95          | 0.94          | 0.29          | 0.001         |
+------------+---------------+---------------+---------------+---------------+
| Alarm(1)   | 0.05          | 0.06          | 0.71          | 0.999         |
+------------+---------------+---------------+---------------+---------------+

Joint probability distribution, P(JohnCalls | Alarm)
+--------------+----------+----------+
| Alarm        | Alarm(0) | Alarm(1) |
+--------------+----------+----------+
| JohnCalls(0) | 0.9      | 0.05     |
+--------------+----------+----------+
| JohnCalls(1) | 0.1      | 0.95     |
+--------------+----------+----------+

Joint probability distribution, P(MaryCalls | Alarm)
+--------------+----------+----------+
| Alarm        | Alarm(0) | Alarm(1) |
+--------------+----------+----------+
| MaryCalls(0) | 0.7      | 0.01     |
+--------------+----------+----------+
| MaryCalls(1) | 0.3      | 0.99     |
+--------------+----------+----------+

Finding Elimination Order: : 0%                     0/2 [00:00<?, ?it/s]

Eliminating: Alarm: 100%                             2/2 [00:00<00:00, 67.43it/s]
Posterior probability of Burglary if JohnCalls(True) and MaryCalls(True)
+-------------+-----------------+
| Burglary    |   phi(Burglary) |
+=============+=================+
| Burglary(0) |          0.2842 |
+-------------+-----------------+
| Burglary(1) |          0.7158 |
+-------------+-----------------+

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

  0/0 [00:00<?, ?it/s]
Posterior probability of Alarm sounding if Burglary(True) and Earthquake(True)
+----------+--------------+
| Alarm    |   phi(Alarm) |
+==========+==============+
| Alarm(0) |       0.9500 |
+----------+--------------+
| Alarm(1) |       0.0500 |
+----------+--------------+
```

Lab8:

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

Program:

```
# import libraries
# For plotting
import matplotlib.pyplot as plt
import seaborn as sns
```

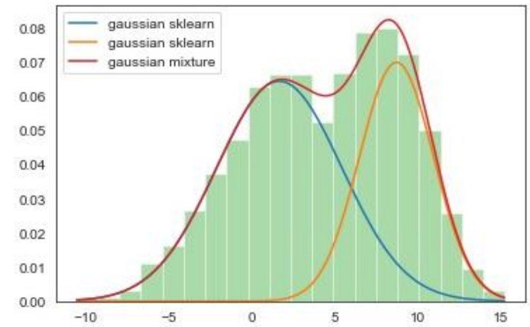
```
sns.set_style("white")
%matplotlib inline
#for matrix math
import numpy as np
#for normalization + probability density function computation
from scipy import stats
#for data preprocessing
import pandas as pd
from math import sqrt, log, exp, pi
from random import uniform
print("import done")
random_seed=36788765
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, max_iter = 100)

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
Gaussian 1: μ = 1.7, σ = 3.8, weight = 0.61
Gaussian 2: μ = 8.8, σ = 2.2, weight = 0.39
```

```
C:\Users\HP\AppData\Local\Programs\Python\Python310\lib
is a deprecated function and will be removed in a futur
l function with similar flexibility) or `histplot` (an
  warnings.warn(msg, FutureWarning)
```



Lab9:

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

Program:

```
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
[[18  0  0]
 [ 0 17  2]
 [ 0  1  7]]
Accuracy Metrics
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        18
           1       0.94      0.89      0.92        19
           2       0.78      0.88      0.82         8

    accuracy                           0.93        45
   macro avg       0.91      0.92      0.91        45
weighted avg       0.94      0.93      0.93        45
```

Lab10:

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

Program:

```
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('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)]]))

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('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,0.3)
SortIndex = X[:,1].argsort(0)
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();
```

Output: