IMPLEMENT A* ALGORITHM

CODE:

```
def aStarAlgo(start_node, stop_node):
     open_set = set(start_node)
     closed\_set = set()
     g = \{\}
     parents = \{\}
     g[start\_node] = 0
     parents[start_node] = start_node
     while len(open\_set) > 0:
       n = None
       for v in open_set:
          if n == None \text{ or } g[v] + heuristic(v) < g[n] + heuristic(n):
            n = v
       if n == stop_node or Graph_nodes[n] == None:
          pass
       else:
          for (m, weight) in get_neighbors(n):
            if m not in open_set and m not in closed_set:
               open_set.add(m)
               parents[m] = n
               g[m] = g[n] + weight
```

```
else:
         if g[m] > g[n] + weight
            g[m] = g[n] + weight
            parents[m] = n
            if m in closed_set:
              closed_set.remove(m)
              open_set.add(m)
  if n == None:
    print('Path does not exist!')
    return None
  if n == stop_node:
    path = []
    while parents[n] != n:
       path.append(n)
       n = parents[n]
    path.append(start_node)
    path.reverse()
    print('Path found: { }'.format(path))
    return path
  open_set.remove(n)
  closed_set.add(n)
print('Path does not exist!')
return None
```

```
def get_neighbors(v):
  if v in Graph_nodes:
     return Graph_nodes[v]
  else:
     return None
def heuristic(n):
     H_dist = {
     'A': 11,
     'B': 6,
     'C': 99,
     'D': 1,
     'E': 7,
     'G': 0,
     }
     return H_dist[n]
Graph\_nodes = \{
  'A': [('B', 2), ('E', 3)],
  'B': [('C', 1),('G', 9)],
  'C': None,
  'E': [('D', 6)],
  'D': [('G', 1)],
}
aStarAlgo('A', 'G')
OUTPUT:
Path found: ['A', 'E', 'D', 'G']
```

['A', 'E', 'D', 'G']

IMPLEMENT AO* ALGORITHM

CODE:

```
class Graph:
  def __init__(self, graph, heuristicNodeList, startNode):
     self.graph = graph
     self.H=heuristicNodeList
     self.start=startNode
     self.parent={ }
     self.status={ }
     self.solutionGraph={}
  def applyAOStar(self):
     self.aoStar(self.start, False)
  def getNeighbors(self, v):
     return self.graph.get(v,")
  def getStatus(self,v):
     return self.status.get(v,0)
  def setStatus(self,v, val):
     self.status[v]=val
  def getHeuristicNodeValue(self, n):
     return self.H.get(n,0)
  def setHeuristicNodeValue(self, n, value):
```

```
def printSolution(self):
    print("FOR GRAPH SOLUTION, TRAVERSE THE GRAPH FROM THE START
NODE:",self.start)
    print("-----")
    print(self.solutionGraph)
   print("-----")
  def computeMinimumCostChildNodes(self, v):
    minimumCost=0
    costToChildNodeListDict={}
    costToChildNodeListDict[minimumCost]=[]
    flag=True
    for nodeInfoTupleList in self.getNeighbors(v):
      cost=0
      nodeList=[]
      for c, weight in nodeInfoTupleList:
        cost=cost+self.getHeuristicNodeValue(c)+weight
        nodeList.append(c)
        if flag==True:
          minimumCost=cost
          costToChildNodeListDict[minimumCost]=nodeList
          flag=False
        else:
          if minimumCost>cost:
            minimumCost=cost
            costToChildNodeListDict[minimumCost] = nodeList\\
```

return minimumCost, costToChildNodeListDict[minimumCost]

self.H[n]=value

```
def aoStar(self, v, backTracking):
    print("HEURISTIC VALUES:", self.H)
    print("SOLUTION GRAPH :", self.solutionGraph)
    print("PROCESSING NODE :", v)
    print("-----")
    if self.getStatus(v) >= 0:
       minimumCost, childNodeList = self.computeMinimumCostChildNodes(v)
       self.setHeuristicNodeValue(v, minimumCost)
       self.setStatus(v,len(childNodeList))
       solved=True
    for childNode in childNodeList:
       self.parent[childNode]=v
      if self.getStatus(childNode)!=-1:
         solved=solved & False
    if solved==True:
       self.setStatus(v,-1)
       self.solutionGraph[v]=childNodeList
    if v!=self.start:
       self.aoStar(self.parent[v], True)
    if backTracking==False:
       for childNode in childNodeList:
         self.setStatus(childNode,0)
         self.aoStar(childNode, False)
h1 = {'A': 1, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 5, 'H': 7, 'I': 7, 'J': 1, 'T': 3}
graph1 = {
  'A': [[('B', 1), ('C', 1)], [('D', 1)]],
  'B': [[('G', 1)], [('H', 1)]],
  'C': [[('J', 1)]],
  'D': [[('E', 1), ('F', 1)]],
```

```
'G': [[('T', 1)]]
}
G1= Graph(graph1, h1, 'A')
G1.applyAOStar()
G1.printSolution()
h2 = {'A': 1, 'B': 6, 'C': 12, 'D': 10, 'E': 4, 'F': 4, 'G': 5, 'H': 7}
graph2 = {
    'A': [[('B', 1), ('C', 1)], [('D', 1)]],
    'B': [[('G', 1)], [('H', 1)]],
    'D': [[('E', 1), ('F', 1)]]
}
G2 = Graph(graph2, h2, 'A')
G2.applyAOStar()
G2.printSolution()
```

```
HEURISTIC VALUES: {'A': 1, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 5, 'H': 7, T: 7, 'J': 1, 'T': 3}

SOLUTION GRAPH: {}

PROCESSING NODE: A

HEURISTIC VALUES: {'A': 7, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 5, 'H': 7, T: 7, 'J': 1, 'T': 3}

SOLUTION GRAPH: {}

PROCESSING NODE: B

HEURISTIC VALUES: {'A': 7, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 5, 'H': 7, T: 7, 'J': 1, 'T': 3}
```

```
SOLUTION GRAPH: {}
PROCESSING NODE: A
HEURISTIC VALUES: {'A': 7, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 5, 'H': 7, 'I': 7, 'J': 1, 'T':
3}
SOLUTION GRAPH: {}
PROCESSING NODE: G
HEURISTIC VALUES: {'A': 7, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 8, 'H': 7, 'I': 7, 'J': 1, 'T':
3}
SOLUTION GRAPH: {}
PROCESSING NODE: B
HEURISTIC VALUES: {'A': 7, 'B': 8, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 8, 'H': 7, 'I': 7, 'J': 1, 'T':
3}
SOLUTION GRAPH: {}
PROCESSING NODE: A
HEURISTIC VALUES: {'A': 9, 'B': 8, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 8, 'H': 7, 'I': 7, 'J': 1, 'T':
3}
SOLUTION GRAPH: {}
PROCESSING NODE: I
HEURISTIC VALUES: {'A': 9, 'B': 8, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 8, 'H': 7, 'I': 0, 'J': 1, 'T':
3}
SOLUTION GRAPH: {'I': []}
PROCESSING NODE: G
HEURISTIC VALUES: {'A': 9, 'B': 8, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 1, 'T':
3}
SOLUTION GRAPH : {'I': [], 'G': ['I']}
```

```
PROCESSING NODE: B
HEURISTIC VALUES: {'A': 9, 'B': 2, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 1, 'T':
3}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G']}
PROCESSING NODE: A
HEURISTIC VALUES: {'A': 3, 'B': 2, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 1, 'T':
3}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G']}
PROCESSING NODE: C
HEURISTIC VALUES: {'A': 3, 'B': 2, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 1, 'T':
3}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G']}
PROCESSING NODE: A
HEURISTIC VALUES: {'A': 3, 'B': 2, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 1, 'T':
3}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G']}
PROCESSING NODE: J
HEURISTIC VALUES: {'A': 3, 'B': 2, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 0, 'T':
3}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G'], 'J': []}
PROCESSING NODE: C
HEURISTIC VALUES: {'A': 3, 'B': 2, 'C': 1, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 0, 'T':
3}
```

PROCESSING NODE: A

SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G'], 'J': [], 'C': ['J']}

FOR GRAPH SOLUTION, TRAVERSE THE GRAPH FROM THE START NODE: A {'I': [], 'G': ['I'], 'B': ['G'], 'J': [], 'C': ['J'], 'A': ['B', 'C']} _____ HEURISTIC VALUES: {'A': 1, 'B': 6, 'C': 12, 'D': 10, 'E': 4, 'F': 4, 'G': 5, 'H': 7} SOLUTION GRAPH : {} PROCESSING NODE: A HEURISTIC VALUES: {'A': 7, 'B': 6, 'C': 12, 'D': 10, 'E': 4, 'F': 4, 'G': 5, 'H': 7} SOLUTION GRAPH: {} PROCESSING NODE : B .-----HEURISTIC VALUES: {'A': 7, 'B': 6, 'C': 12, 'D': 10, 'E': 4, 'F': 4, 'G': 5, 'H': 7} SOLUTION GRAPH: {} PROCESSING NODE: A ______ HEURISTIC VALUES: {'A': 7, 'B': 6, 'C': 12, 'D': 10, 'E': 4, 'F': 4, 'G': 5, 'H': 7} SOLUTION GRAPH: {} PROCESSING NODE: G HEURISTIC VALUES: {'A': 7, 'B': 6, 'C': 12, 'D': 10, 'E': 4, 'F': 4, 'G': 0, 'H': 7} SOLUTION GRAPH: {'G': []} PROCESSING NODE: B ______ HEURISTIC VALUES: {'A': 7, 'B': 1, 'C': 12, 'D': 10, 'E': 4, 'F': 4, 'G': 0, 'H': 7} SOLUTION GRAPH: {'G': [], 'B': ['G']} PROCESSING NODE: A

HEURISTIC VALUES: {'A': 2, 'B': 1, 'C': 12, 'D': 10, 'E': 4, 'F': 4, 'G': 0, 'H': 7}

SOLUTION GRAPH: {'G': [], 'B': ['G']}

PROCESSING NODE: C

HEURISTIC VALUES: {'A': 2, 'B': 1, 'C': 0, 'D': 10, 'E': 4, 'F': 4, 'G': 0, 'H': 7}

SOLUTION GRAPH: {'G': [], 'B': ['G'], 'C': []}

PROCESSING NODE: A

FOR GRAPH SOLUTION, TRAVERSE THE GRAPH FROM THE START NODE: A

['G': [], 'B': ['G'], 'C': [], 'A': ['B', 'C']}

BUILD AN ANN USING BACK PROPOGATION ALGORITHM

CODE: import numpy as np X = np.array(([2, 9], [1, 5], [3, 6]), dtype=float)y = np.array(([92], [86], [89]), dtype=float)X = X/np.amax(X,axis=0)y = y/100def sigmoid (x): return 1/(1 + np.exp(-x))def derivatives_sigmoid(x): return x * (1 - x)epoch=7000 lr=0.1 $inputlayer_neurons = 2$ $hiddenlayer_neurons = 3$ $output_neurons = 1$ wh=np.random.uniform(size=(inputlayer_neurons,hiddenlayer_neurons)) bh=np.random.uniform(size=(1,hiddenlayer_neurons)) wout=np.random.uniform(size=(hiddenlayer_neurons,output_neurons)) bout=np.random.uniform(size=(1,output_neurons)) for i in range(epoch):

```
hinp1=np.dot(X,wh)
  hinp=hinp1 + bh
  hlayer_act = sigmoid(hinp)
  outinp1=np.dot(hlayer_act,wout)
  outinp= outinp1+ bout
  output = sigmoid(outinp)
  EO = y-output
  outgrad = derivatives_sigmoid(output)
  d_output = EO* outgrad
  EH = d\_output.dot(wout.T)
  hiddengrad = derivatives_sigmoid(hlayer_act)
  d_hiddenlayer = EH * hiddengrad
  wout += hlayer_act.T.dot(d_output) *lr
  wh += X.T.dot(d_hiddenlayer) *lr
print("Input: \n" + str(X))
print("Actual Output: \n" + str(y))
print("Predicted Output: \n" ,output)
```

Input:

[[0.666666667 1.]

[0.333333333 0.55555556]

[1. 0.66666667]]

Actual Output:

[[0.92]

[0.86]

[0.89]]

Predicted Output:

[[0.89309893]

[0.87794188]

[0.89899306]]

NAÏVE BAYESIAN CLASSIFIER FOR A GIVEN .CSV FILE

CODE: import csv import random import math def loadCsv(filename): lines = csv.reader(open(filename, "r")); dataset = list(lines) for i in range(len(dataset)): dataset[i] = [float(x) for x in dataset[i]]return dataset def splitDataset(dataset, splitRatio): trainSize = int(len(dataset) * splitRatio) trainSet = [] copy = list(dataset) while len(trainSet) < trainSize: index = random.randrange(len(copy)) trainSet.append(copy.pop(index)) return [trainSet, copy] def separateByClass(dataset): $separated = \{\}$ 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):
  summaries = [(mean(attribute), stdev(attribute)) for attribute in zip(*dataset)]
  del summaries[-1]
  return summaries
def summarizeByClass(dataset):
  separated = separateByClass(dataset)
  summaries = {}
  for class Value, instances in separated.items():
    summaries[classValue] = summarize(instances)
  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 = {}
  for classValue, classSummaries in summaries.items():
    probabilities[classValue] = 1
```

```
for i in range(len(classSummaries)):
     mean, stdev = classSummaries[i]
     x = inputVector[i]
     probabilities[classValue] *= calculateProbability(x, mean, stdev)
     return probabilities
def predict(summaries, inputVector):
  probabilities = calculateClassProbabilities(summaries, inputVector)
  bestLabel, bestProb = None, -1
  for classValue, probability in probabilities.items():
     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 = 'C:\\Users\\DELL\\.jupyter\\pima-indians-diabetes.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)))

summaries = summarizeByClass(trainingSet);

predictions = getPredictions(summaries, testSet)
accuracy = getAccuracy(testSet, predictions)
print('Accuracy of the classifier is : {0}%'.format(accuracy))
main()
```

Split 768 rows into train=514 and test=254 rows

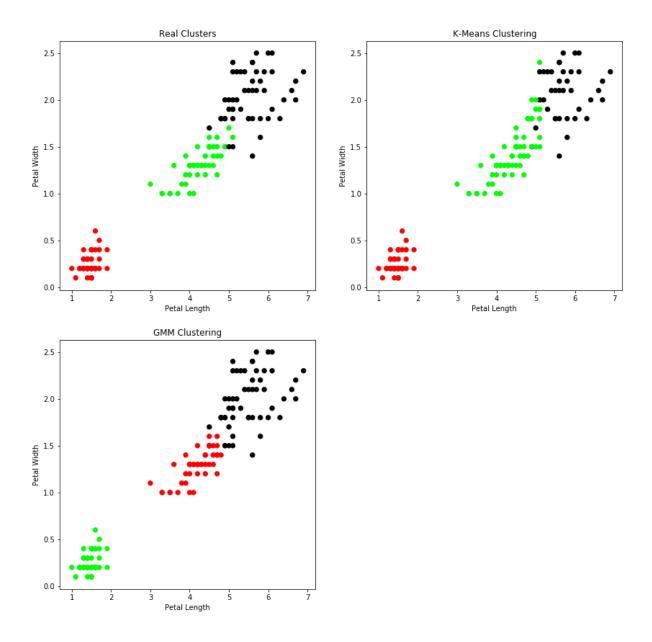
Accuracy of the classifier is: 35.43307086614173%

APPLY EM ALGORITHM TO CLUSTER A SET OF DATA STORE IN A .CSV FILE

CODE: import matplotlib.pyplot as plt from sklearn import datasets from sklearn.cluster import KMeans 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=(14,14)) colormap = np.array(['red', 'lime', 'black']) plt.subplot(2, 2, 1)plt.scatter(X.Petal_Length,X.Petal_Width,c=colormap[y.Targets], s=40) plt.title('Real Clusters') plt.xlabel('Petal Length') plt.ylabel('Petal Width')

```
plt.subplot(2, 2, 2)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[model.labels_], s=40)
plt.title('K-Means Clustering')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
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)
gmm_y = gmm.predict(xs)
plt.subplot(2, 2, 3)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[gmm_y], s=40)
plt.title('GMM Clustering')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
print('Observation: The GMM using EM algorithm based clustering matched the true labels
more closely than the Kmeans.')
```

Observation: The GMM using EM algorithm based clustering matched the true labels more closely than the Kmeans.



IMPLEMENT K-NEAREST NEIGHBOUR ALGORITHM TO CLASSIFY IRIS DATASET

CODE:

```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn import datasets
iris=datasets.load_iris()
print("Iris Data set loaded...")
x_train, x_test, y_train, y_test = train_test_split(iris.data,iris.target,test_size=0.1)
print("Dataset is split into training and testing...")
print("Size of training data and its label",x_train.shape,y_train.shape)
print("Size of training data and its label",x_test.shape, y_test.shape)
for i in range(len(iris.target_names)):
  print("Label", i , "-",str(iris.target_names[i]))
classifier = KNeighborsClassifier(n_neighbors=1)
classifier.fit(x_train, y_train)
y_pred=classifier.predict(x_test)
print("Results of Classification using K-nn with K=1 ")
for r in range(0,len(x_test)):
```

```
print(" Sample:", str(x_test[r]), " Actual-label:", str(y_test[r]), " Predicted-label:",str(y_pred[r]))
print("Classification Accuracy :" , classifier.score(x_test,y_test));
from sklearn.metrics import classification_report, confusion_matrix
print('Confusion Matrix')
print(confusion_matrix(y_test,y_pred))
print('Accuracy Metrics')
print(classification_report(y_test,y_pred))
```

Iris Data set loaded...

Dataset is split into training and testing...

Size of training data and its label (135, 4) (135,)

Size of training data and its label (15, 4) (15,)

Label 0 - setosa

Label 1 - versicolor

Label 2 - virginica

Results of Classification using K-nn with K=1

Sample: [5. 3.5 1.6 0.6] Actual-label: 0 Predicted-label: 0

Sample: [6.6 3. 4.4 1.4] Actual-label: 1 Predicted-label: 1

Sample: [6.7 3. 5.2 2.3] Actual-label: 2 Predicted-label: 2

Sample: [4.8 3. 1.4 0.3] Actual-label: 0 Predicted-label: 0

Sample: [6.3 3.4 5.6 2.4] Actual-label: 2 Predicted-label: 2

Sample: [5.2 4.1 1.5 0.1] Actual-label: 0 Predicted-label: 0

Sample: [5.6 3. 4.5 1.5] Actual-label: 1 Predicted-label: 1

Sample: [6.5 3. 5.5 1.8] Actual-label: 2 Predicted-label: 2

Sample: [6.8 3. 5.5 2.1] Actual-label: 2 Predicted-label: 2

Sample: [5.9 3. 4.2 1.5] Actual-label: 1 Predicted-label: 1

Sample: [7.4 2.8 6.1 1.9] Actual-label: 2 Predicted-label: 2

Sample: [5.6 2.9 3.6 1.3] Actual-label: 1 Predicted-label: 1

Sample: [5.8 2.7 4.1 1.] Actual-label: 1 Predicted-label: 1

Sample: [4.9 3.1 1.5 0.1] Actual-label: 0 Predicted-label: 0

Sample: [7.2 3.6 6.1 2.5] Actual-label: 2 Predicted-label: 2

Classification Accuracy: 1.0

Confusion Matrix

[[4 0 0]

[050]

 $[0\ 0\ 6]]$

Accuracy Metrics

precision recall f1-score support

0 1.00 1.00 1.00 4 1 1.00 1.00 1.00 5

2 1.00 1.00 1.00 6

avg / total 1.00 1.00 1.00 15

IMPLEMENT NON-PARAMETRIC LOCALLY WEIGHTED REGRESSION

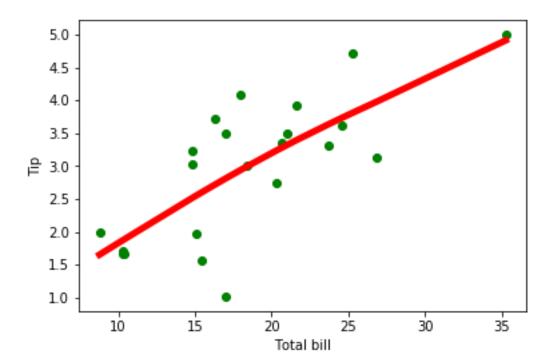
CODE: import matplotlib.pyplot as plt import pandas as pd import numpy as np def kernel(point,xmat, k): m,n = np.shape(xmat)weights = np.mat(np.eye((m)))for j in range(m): diff = point - X[j]weights[j,j] = np.exp(diff*diff.T/(-2.0*k**2)) return weights def localWeight(point,xmat,ymat,k): wei = kernel(point,xmat,k) 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)

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();
data = pd.read_csv('C:\\Users\\DELL\\.jupyter\\10data_tips.csv')
bill = np.array(data.total_bill)
tip = np.array(data.tip)
mbill = np.mat(bill)
mtip = np.mat(tip)
m= np.shape(mbill)[1]
one = np.mat(np.ones(m))
X = np.hstack((one.T,mbill.T))
ypred = localWeightRegression(X,mtip,8)
graphPlot(X,ypred)
```

The following is the output for dataset with 10 examples (10 rows and 2 columns)



The following is the output for dataset with 10 examples (10 rows and 2 columns)

