

B.M.S. COLLEGE OF ENGINEERING BENGALURU

Autonomous Institute, Affiliated to VTU



Lab Record

Machine Learning

Submitted in partial fulfillment for the 6th Semester Laboratory

Bachelor of Technology
in
Computer Science and Engineering

Submitted by:

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B.M.S. COLLEGE OF ENGINEERING
DEPARTMENT OF COMPUTER SCIENCE AND
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CERTIFICATE

This is to certify that the Machine Learning (20CS6PCMAL) laboratory has been carried out by SAKSHI SRIVASTAVA(1BM18CS090) during the 6th Semester Mar-June-2021.

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Lab Program	Unit #	Program Details
1	1	Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data samples.
2	1	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.
3	1	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.
4	3	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
5	3	Write a program to construct a Bayesian network considering training data. Use this model to make predictions.
6	3	Apply k-Means algorithm to cluster a set of data stored in a .CSV file.
7	3	Apply EM algorithm to cluster a set of data stored in a .CSV file. Compare the results of k-Means algorithm and EM algorithm.
8	4	Write a program to implement k-Nearest Neighbour algorithm to classify the iris data set. Print both correct and wrong predictions.
9	4	Implement the Linear Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs.
10	4	Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs.

Lab 01: Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data samples. Read the training data from a .CSV file.

FIND-S Algorithm:

1. Initialize h to the most specific hypothesis in H
2. For each positive training instance x For each attribute constraint a_i in h
 - If the constraint a_i is satisfied by x
 - Then do nothing
 - Else replace a_i in h by the next more general constraint that is satisfied by x
3. Output hypothesis h

In [18]:

```
import csv
```

In [19]:

```
data = []

# Print data
with open('enjoysport.csv', 'r') as csvfile:
    for line in csv.reader(csvfile):
        data.append(line)
        print(line)

['sky', 'airtemp', 'humidity', 'wind', 'water', 'forecast', 'enjoysport']
['sunny', 'warm', 'normal', 'strong', 'warm', 'same', 'yes']
['sunny', 'warm', 'high', 'strong', 'warm', 'same', 'yes']
['rainy', 'cold', 'high', 'strong', 'warm', 'change', 'no']
['sunny', 'warm', 'high', 'strong', 'cool', 'change', 'yes']
```

In [20]:

```
num_attribute = len(data[0])-1
print("\n The initial hypothesis is : ")
hypothesis = ['0'] * num_attribute
print(hypothesis)
```

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

In [21]:

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

```
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', '?', '?']

In [22]:

```
print("\n The Maximally specific hypothesis for the training instance is ")  
print(hypothesis)
```

```
  The Maximally specific hypothesis for the training instance is  
['sunny', 'warm', '?', 'strong', '?', '?']
```

In []:

Lab 02: Candidate Elimination algorithm

In [1]:

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

```
data = pd.read_csv('enjoysport.csv')
concepts = np.array(data.iloc[:,0:-1])
print(concepts)
target = np.array(data.iloc[:,-1])
print(target)
```

```
[['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
 ['sunny' 'warm' 'high' 'strong' 'warm' 'same']
 ['rainy' 'cold' 'high' 'strong' 'warm' 'change']
 ['sunny' 'warm' 'high' 'strong' 'cool' 'change']]
['yes' 'yes' 'no' 'yes']
```

In [2]:

```
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
```

In [3]:

```
s_final, g_final = learn(concepts, target)
```

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

```
initialization of specific_h and general_h
['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
[['?', '?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?', '?']]
```

```
, '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
For Loop Starts
If instance is Positive
    steps of Candidate Elimination Algorithm 1
['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
```

```
For Loop Starts
If instance is Positive
    steps of Candidate Elimination Algorithm 2
['sunny' 'warm' '?' 'strong' 'warm' 'same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
```

```
For Loop Starts
If instance is Negative
    steps of Candidate Elimination Algorithm 3
['sunny' 'warm' '?' 'strong' 'warm' 'same']
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
```

```
For Loop Starts
If instance is Positive
    steps of Candidate Elimination Algorithm 4
['sunny' 'warm' '?' 'strong' '?' '?']
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
```

```
Final Specific_h:
['sunny' 'warm' '?' 'strong' '?' '?']
Final General_h:
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?']]
```

```
In [ ]:
```

Lab 03: 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.

In [1]:

```
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)

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)

```

In [2]:

```

dataset, features=load_csv("id3.csv")
model=build_tree(dataset, features)

print("The decision tree for the dataset using ID3 algorithm is")
print_tree(model, 0)
testdata, features=load_csv("id3_test.csv")

for xtest in testdata:
    print("The test instance:", xtest)
    print("The label for test instance:", end=" ")
    classify(model, xtest, features)

```

The decision tree for the dataset using ID3 algorithm is

```

Outlook
  overcast
  yes
  sunny
    Humidity
      normal
      yes
      high
      no
  rain
    Wind

```

weak
yes
strong
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 04: 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.

In [101]:

```
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 classvalue, 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 nb(filename, split):
    splitratio = split/100
    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))

```

In [102]:

```
nb('pima_indian.csv', 90)
```

Split 365 rows into train=328 and test=37 rows
Accuracy of the classifier is : 62.16216216216216%

In [103]:

```
nb('nb1.csv', 50)
```

Split 212 rows into train=106 and test=106 rows
Accuracy of the classifier is : 69.81132075471697%

In [104]:

```
nb('nb2.csv', 70)
```

Split 191 rows into train=133 and test=58 rows
Accuracy of the classifier is : 87.93103448275862%

In []:

Lab 05: Write a program to construct a Bayesian network considering training data. Use this model to make predictions.

In [19]:

```
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
```

In [27]:

```
heartDisease = pd.read_csv('heart.csv')
heartDisease = heartDisease.replace('?', np.nan)
```

In [32]:

```
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', 'heartdisease'), ('heartdisease', 'restecg'), ('heartdisease', 'chol')])
print('\n Learning 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)
```

Sample instances from the dataset are given below

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	\
0	63	1	1	145	233	1	2	150	0	2.3	3	
1	67	1	4	160	286	0	2	108	1	1.5	2	
2	67	1	4	120	229	0	2	129	1	2.6	2	
3	37	1	3	130	250	0	0	187	0	3.5	3	
4	41	0	2	130	204	0	2	172	0	1.4	1	

	ca	thal	heartdisease
0	0	6	0
1	3	3	2
2	2	7	1
3	0	3	0
4	0	3	0

Attributes and datatypes

age	int64
sex	int64
cp	int64
trestbps	int64
chol	int64
fbs	int64
restecg	int64
thalach	int64
exang	int64
oldpeak	float64
slope	int64

ca object
thal object
heartdisease int64
dtype: object

Learning CPD using Maximum likelihood estimators

Finding Elimination Order: : 0%| | 0/5 [00:00<?, ?it/s]
0%| | 0/5 [00:00<?, ?it/s]
Eliminating: chol: 0%| | 0/5 [00:00<?, ?it/s]
Eliminating: exang: 0%| | 0/5 [00:00<?, ?it/s]
Eliminating: age: 0%| | 0/5 [00:00<?, ?it/s]
Eliminating: sex: 0%| | 0/5 [00:00<?, ?it/s]
Eliminating: cp: 100%| | 5/5 [00:00<00:00, 304.89it/s]
Finding Elimination Order: : 100%| | 5/5 [00:00<00:00, 246.56it/s]
0%| | 0/5 [00:00<?, ?it/s]
Inferencing with Bayesian Network:

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

Finding Elimination Order: : 0%| | 0/5 [00:00<?, ?it/s]
0%| | 0/5 [00:00<?, ?it/s]
Eliminating: restecg:0%| | 0/5 [00:00<?, ?it/s]
Eliminating: chol: 0%| | 0/5 [00:00<?, ?it/s]
Finding Elimination Order: : 100%| | 5/5 [00:00<00:00, 913.23it/s]

Eliminating: age: 0%| | 0/5 [00:00<?, ?it/s]
Eliminating: sex: 100%| | 5/5 [00:00<00:00, 324.37it/s]

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

In []:

Lab 06: Apply k-Means algorithm to cluster a set of data.

In []:

```
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
```

In []:

```
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'])
```

In [5]:

```
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')
```

Out[5]:

Text(0, 0.5, 'Petal Width')

In [4]:

```
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 matrix of K-Mean: ', sm.confusion_matrix(y, model.labels_))
```

```
The accuracy score of K-Mean: 0.44
The Confusion matrix of K-Mean: [[50  0  0]
 [ 0  2 48]
 [ 0 36 14]]
```

In []:

Lab 07: Apply EM algorithm to cluster a set of data. Compare the results of k-Means algorithm and EM algorithm.

In [1]:

```
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'])
```

<Figure size 1008x504 with 0 Axes>

In [2]:

```
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')
```

Out[2]:

Text(0, 0.5, 'Petal Width')

In [3]:

```
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 matrix of K-Mean: ', sm.confusion_matrix(y, model.labels_))
```

The accuracy score of K-Mean: 0.09333333333333334
The Confusion matrix of K-Mean:
[[0 50 0]
 [2 0 48]
 [36 0 14]]

In [4]:

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


In [5]:

```
from sklearn.mixture import GaussianMixture
gmm = GaussianMixture(n_components=3)
gmm.fit(xs)

y_gmm = gmm.predict(xs)
```

In [6]:

```
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))
```

```
The accuracy score of EM:  0.9666666666666667
The Confusion matrix of EM: [[50    0   0]
 [ 0 45   5]
 [ 0   0 50]]
```

Lab 08: Write a program to implement k-Nearest Neighbour algorithm to classify the iris data set. Print both correct and wrong predictions.

In [1]:

```
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
```

In [2]:

```
print ('sepal-length', 'sepal-width', 'petal-length', 'petal-width')
print(x)
print('class: 0-Iris-Setosa, 1- Iris-Versicolour, 2- Iris-Virginica')
print(y)
```

sepal-length sepal-width petal-length petal-width

```
[5.1 3.5 1.4 0.2]
[4.9 3.  1.4 0.2]
[4.7 3.2 1.3 0.2]
[4.6 3.1 1.5 0.2]
[5.  3.6 1.4 0.2]
[5.4 3.9 1.7 0.4]
[4.6 3.4 1.4 0.3]
[5.  3.4 1.5 0.2]
[4.4 2.9 1.4 0.2]
[4.9 3.1 1.5 0.1]
[5.4 3.7 1.5 0.2]
[4.8 3.4 1.6 0.2]
[4.8 3.  1.4 0.1]
[4.3 3.  1.1 0.1]
[5.8 4.  1.2 0.2]
[5.7 4.4 1.5 0.4]
[5.4 3.9 1.3 0.4]
[5.1 3.5 1.4 0.3]
[5.7 3.8 1.7 0.3]
[5.1 3.8 1.5 0.3]
[5.4 3.4 1.7 0.2]
[5.1 3.7 1.5 0.4]
[4.6 3.6 1.  0.2]
[5.1 3.3 1.7 0.5]
[4.8 3.4 1.9 0.2]
[5.  3.  1.6 0.2]
[5.  3.4 1.6 0.4]
[5.2 3.5 1.5 0.2]
[5.2 3.4 1.4 0.2]
[4.7 3.2 1.6 0.2]
[4.8 3.1 1.6 0.2]
[5.4 3.4 1.5 0.4]
[5.2 4.1 1.5 0.1]
[5.5 4.2 1.4 0.2]
[4.9 3.1 1.5 0.2]
[5.  3.2 1.2 0.2]
[5.5 3.5 1.3 0.2]
[4.9 3.6 1.4 0.1]
[4.4 3.  1.3 0.2]
[5.1 3.4 1.5 0.2]
[5.  3.5 1.3 0.3]
[4.5 2.3 1.3 0.3]
[4.4 3.2 1.3 0.2]
[5.  3.5 1.6 0.6]
[5.1 3.8 1.9 0.4]
```

[4.8 3. 1.4 0.3]
[5.1 3.8 1.6 0.2]
[4.6 3.2 1.4 0.2]
[5.3 3.7 1.5 0.2]
[5. 3.3 1.4 0.2]
[7. 3.2 4.7 1.4]
[6.4 3.2 4.5 1.5]
[6.9 3.1 4.9 1.5]
[5.5 2.3 4. 1.3]
[6.5 2.8 4.6 1.5]
[5.7 2.8 4.5 1.3]
[6.3 3.3 4.7 1.6]
[4.9 2.4 3.3 1.]
[6.6 2.9 4.6 1.3]
[5.2 2.7 3.9 1.4]
[5. 2. 3.5 1.]
[5.9 3. 4.2 1.5]
[6. 2.2 4. 1.]
[6.1 2.9 4.7 1.4]
[5.6 2.9 3.6 1.3]
[6.7 3.1 4.4 1.4]
[5.6 3. 4.5 1.5]
[5.8 2.7 4.1 1.]
[6.2 2.2 4.5 1.5]
[5.6 2.5 3.9 1.1]
[5.9 3.2 4.8 1.8]
[6.1 2.8 4. 1.3]
[6.3 2.5 4.9 1.5]
[6.1 2.8 4.7 1.2]
[6.4 2.9 4.3 1.3]
[6.6 3. 4.4 1.4]
[6.8 2.8 4.8 1.4]
[6.7 3. 5. 1.7]
[6. 2.9 4.5 1.5]
[5.7 2.6 3.5 1.]
[5.5 2.4 3.8 1.1]
[5.5 2.4 3.7 1.]
[5.8 2.7 3.9 1.2]
[6. 2.7 5.1 1.6]
[5.4 3. 4.5 1.5]
[6. 3.4 4.5 1.6]
[6.7 3.1 4.7 1.5]
[6.3 2.3 4.4 1.3]
[5.6 3. 4.1 1.3]
[5.5 2.5 4. 1.3]
[5.5 2.6 4.4 1.2]
[6.1 3. 4.6 1.4]
[5.8 2.6 4. 1.2]
[5. 2.3 3.3 1.]
[5.6 2.7 4.2 1.3]
[5.7 3. 4.2 1.2]
[5.7 2.9 4.2 1.3]
[6.2 2.9 4.3 1.3]
[5.1 2.5 3. 1.1]
[5.7 2.8 4.1 1.3]
[6.3 3.3 6. 2.5]
[5.8 2.7 5.1 1.9]
[7.1 3. 5.9 2.1]
[6.3 2.9 5.6 1.8]
[6.5 3. 5.8 2.2]
[7.6 3. 6.6 2.1]
[4.9 2.5 4.5 1.7]
[7.3 2.9 6.3 1.8]
[6.7 2.5 5.8 1.8]
[7.2 3.6 6.1 2.5]
[6.5 3.2 5.1 2.]
[6.4 2.7 5.3 1.9]
[6.8 3. 5.5 2.1]
[5.7 2.5 5. 2.]
[5.8 2.8 5.1 2.4]
[6.4 3.2 5.3 2.3]
[6.5 3. 5.5 1.8]

[illegible]

```
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.3)

classifier = KNeighborsClassifier(n_neighbors=5)
classifier.fit(x_train, y_train)

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))
```

```
[[10  0  0]
 [ 0 16  1]
 [ 0  0 18]]
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	10
1	1.00	0.94	0.97	17
2	0.95	1.00	0.97	18
accuracy			0.98	45
macro avg	0.98	0.98	0.98	45
weighted avg	0.98	0.98	0.98	45

Lab 09: Implement the Linear Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs.

In [1]:

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

In [2]:

```
#Dataset link = https://drive.google.com/file/d/1f0_x8Zq02oRAoKo_HJkQRtShYOJcP6b7/view?usp=sharing
dataset = pd.read_csv('salaryData.csv')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, 1].values
```

In [3]:

```
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)
```

In [4]:

```
# Fitting Simple Linear Regression to the Training set
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[4]:

```
LinearRegression()
```

In [5]:

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

In [6]:

```
# 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()
```

In [7]:

```
# 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()
```

In []:

Lab 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.

In [1]:

```
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
```

In [2]:

```
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
```

In [3]:

```
def localWeight(point,xmat,yamat,k):
    wei = kernel(point,xmat,k)
    W = (X.T*(wei*X)).I*(X.T*(wei*yamat.T))
    return W
```

In [4]:

```
def localWeightRegression(xmat,yamat,k):
    m,n = np1.shape(xmat)
    ypred = np1.zeros(m)
    for i in range(m):
        ypred[i] = xmat[i]*localWeight(xmat[i],xmat,yamat,k)
    return ypred
```

In [5]:

```
#Load data points
#Download link: https://drive.google.com/file/d/1MGcwt0-82AAnpBprzGXAUHprSATKxH6J/view?usp=sharing
data = pd.read_csv('tips.csv')
bill = np1.array(data.total_bill)
tip = np1.array(data.tip)
```

In [6]:

```
#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]
```

In [7]:

```
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()
```

In [8]:

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

In [9]:

```
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
    # predict value
    return x0 @ beta # @ Matrix Multiplication or Dot Product for prediction
```

In [10]:

```
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
```

In [11]:

```
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])
```

```
The Data Set ( 10 Samples) X :
[-2.99399399 -2.98798799 -2.98198198 -2.97597598 -2.96996997 -2.96396396
-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 :
[-2.96229046 -2.99034099 -2.95074819 -2.91932923 -3.0688763 -2.92705678
-2.88695919 -2.87853339 -2.99439943]
Xo Domain Space(10 Samples) :
[-2.97993311 -2.95986622 -2.93979933 -2.91973244 -2.89966555 -2.87959866
-2.85953177 -2.83946488 -2.81939799]
```

In [12]:

```
def plot_lwr(tau):
    # prediction through regression
    prediction = [local_regression(x0, X, Y, tau) for x0 in domain]
    plot = figure(plot_width=600, plot_height=600)
    plot.title.text='tau=%g' % tau
    plot.scatter(X, Y, alpha=.3)
    plot.line(domain, prediction, line_width=2, color='red')
    return plot
```


In [13]:

```
show(gridplot([
    plot_lwr(10.), plot_lwr(1.)],
    plot_lwr(0.1), plot_lwr(0.01)]))
```



