VISVESVARAYA TECHNOLOGICAL UNIVERSITY

“JnanaSangama”, Belgaum -590014, Karnataka.

LAB REPORT
on

MACHINE LEARNING

Submitted by

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in partial fulfillment for the award of the degree of
BACHELOR OF ENGINEERING
in
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B.M.S. COLLEGE OF ENGINEERING
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B. M. S. College of Engineering,
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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 POTANA KUNDANA SAI PRIYA (1BM19CS112), 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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Index Sheet

Course Outcome

LAB-1

FIND-S ALGORITHM

- ## PROGRAM

```
import numpy as np
import pandas as pd

data=pd.read_csv("ENJOYSPORT.csv")
print(data,"\n")

d = np.array(data)[:,:-1]
print("\n The attributes are: ",d)
target = np.array(data)[:,-1]
print("\n The target is: ",target)

def findS(c,t):
    for i, val in enumerate(t):
        if val == 1:
            specific_hypothesis = c[i].copy()
            break

    for i, val in enumerate(c):
        if t[i] == 1:
            for x in range(len(specific_hypothesis)):
                if val[x] != specific_hypothesis[x]:
                    specific_hypothesis[x] = '?'
                else:
                    pass

    return specific_hypothesis

print("\n The final hypothesis is:",findS(d,target))
```

- ## OUTPUT

```
The attributes are:  [['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']
['Sunny' 'Warm' 'High' 'Strong' 'Warm' 'Same']
['Rainy' 'Cold' 'High' 'Strong' 'Warm' 'Change']
['Sunny' 'Warm' 'High' 'Strong' 'Cool' 'Change']]

The target is:  [1 1 0 1]
```

```
def findS(c,t):
    for i, val in enumerate(t):
        if val == 1:
            specific_hypothesis = c[i].copy()
            break

    for i, val in enumerate(c):
        if t[i] == 1:
            for x in range(len(specific_hypothesis)):
                if val[x] != specific_hypothesis[x]:
                    specific_hypothesis[x] = '?'
                else:
                    pass

    return specific_hypothesis

print("\n The final hypothesis is:",findS(d,target))
```

```
The final hypothesis is: ['Sunny' 'Warm' '?' 'Strong' '?' '?']
```

LAB-2

CANDIDATE ELIMINATION ALGORITHM

- ## PROGRAM

```
import numpy as np
import pandas as pd

data=pd.read_csv("ENJOYSPORT.csv")

concepts=  np.array(data)[:,:-1]
print("\n The attributes are: ",concepts)
target = np.array(data)[:,-1]
print("\n The target is: ",target)

def learn(concepts, target):
   specific_h = concepts[0].copy()
   print("initialization of specific_h and general_h")
   print(specific_h)
   general_h = [["?" for i in range(len(specific_h))] for i in range(len(specific_h))]
   print(general_h)

   for i, h in enumerate(concepts):
      print("For Loop Starts")
      if target[i] == 1:
         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] == 0:
         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 ",i+1)
      print(specific_h)
      print(general_h)
      print("\n")
      print("\n")

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

```
    return specific_h, general_h

s_final, g_final = learn(concepts, target)

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

- ## OUTPUT

```
initialization of specific_h and general_h
['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?',
'?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
For Loop Starts
If instance is Positive
 steps  1
['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?',
'?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]


For Loop Starts
If instance is Positive
 steps  2
['Sunny' 'Warm' '?' 'Strong' 'Warm' 'Same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?',
'?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]


For Loop Starts
If instance is Negative
 steps  3
['Sunny' 'Warm' '?' 'Strong' 'Warm' 'Same']
[['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?',
'?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', 'Same']]


For Loop Starts
If instance is Positive
 steps  4
['Sunny' 'Warm' '?' 'Strong' '?' '?']
[['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?',
'?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]


Final Specific_h:
['Sunny' 'Warm' '?' 'Strong' '?' '?']
Final General_h:
[['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?']]
```

LAB-3

ID-3 ALGORITHM

- ## PROGRAM

```
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)
dataset,features=load_csv("tennis.csv")
node1=build_tree(dataset,features)

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

- **OUTPUT**

```
The decision tree for the dataset using ID3 algorithm is
 outlook
   overcast
     yes
   sunny
     humidity
       high
         no
       normal
         yes
   rainy
     windy
       false
         yes
       true
         no
```

LAB-4

NAÏVE BAYES ALGORITHM

- ## PROGRAM

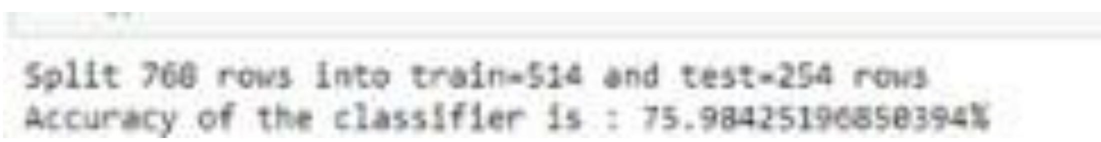
```
#!/usr/bin/env python
# coding: utf-8

# In[1]:


import csv
import random
import math


# In[2]:


def loadcsv(filename):
        lines = csv.reader(open(filename, "r"));
        dataset = list(lines)
        for i in range(len(dataset)):
    #converting strings into numbers for processing
                dataset[i] = [float(x) for x in dataset[i]]

        return dataset


# In[3]:


def splitdataset(dataset, splitratio):
  #67% training size
        trainsize = int(len(dataset) * splitratio);
        trainset = []
        copy = list(dataset);
        while len(trainset) < trainsize:
#generate indices for the dataset list randomly to pick ele for training data
                index = random.randrange(len(copy));
                trainset.append(copy.pop(index))
        return [trainset, copy]


# In[5]:
```

```
def separatebyclass(dataset):
	separated = {} #dictionary of classes 1 and 0
#creates a dictionary of classes 1 and 0 where the values are
#the instances belonging to each class
	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


# In[6]:


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)


# In[7]:


def summarize(dataset): #creates a dictionary of classes
	summaries = [(mean(attribute), stdev(attribute)) for attribute in zip(*dataset)];
	del summaries[-1] #excluding labels +ve or -ve
	return summaries

def summarizebyclass(dataset):
	separated = separatebyclass(dataset);
    #print(separated)
	summaries = {}
	for classvalue, instances in separated.items():
#for key,value in dic.items()
#summaries is a dic of tuples(mean,std) for each class value
		summaries[classvalue] = summarize(instances) #summarize is used to cal to mean and
std
	return summaries


# In[8]:


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 = {} # probabilities contains the all prob of all class of test data
        for classvalue, classsummaries in summaries.items():#class and attribute information as mean
and sd
                probabilities[classvalue] = 1
                for i in range(len(classsummaries)):
                        mean, stdev = classsummaries[i] #take mean and sd of every attribute for class
0 and 1 seperaely
                        x = inputvector[i] #testvector's first attribute
                        probabilities[classvalue] *= calculateprobability(x, mean, stdev);#use normal
dist
        return probabilities


# In[9]:


def predict(summaries, inputvector): #training and test data is passed
        probabilities = calculateclassprobabilities(summaries, inputvector)
        bestLabel, bestProb = None, -1
        for classvalue, probability in probabilities.items():#assigns that class which has he highest prob
                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


# In[10]:


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


# In[12]:
```

```
def main():
            filename = 'naivedataset.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)))
            # prepare model
            summaries = summarizebyclass(trainingset);
            #print(summaries)
   # test model
            predictions = getpredictions(summaries, testset) #find the predictions of test data with the
training data
            accuracy = getaccuracy(testset, predictions)
            print('Accuracy of the classifier is : {0}%'.format(accuracy))

main()
```

- **OUTPUT**



```
Split 768 rows into train=514 and test=254 rows
Accuracy of the classifier is : 75.98425196850394%
```

LAB-5

LINEAR REGRESSION ALGORITHM

- ## PROGRAM

```
#!/usr/bin/env python
# coding: utf-8

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

dataset = pd.read_csv('salary_data.csv')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, 1].values

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)

from sklearn.linear_model import LinearRegression
regressor  = LinearRegression()
regressor.fit(X_train, y_train)

y_pred = regressor.predict(X_test)

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()

viz_test = plt
viz_test.scatter(X_test, y_test, color='red')
viz_test.plot(X_train, regressor.predict(X_train), color='blue')
viz_test.title('Salary VS Experience (Test set)')
viz_test.xlabel('Year of Experience')
viz_test.ylabel('Salary')
viz_test.show()
```

- **OUTPUT**


```
In [9]: 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('Years of Experience')
        viz_test.ylabel('Salary')
        viz_test.show()
```

LAB-6
BAYESIAN NETWORK

- ## PROGRAM

```
from pgmpy.models import BayesianModel
from pgmpy.factors.discrete import TabularCPD
from pgmpy.inference import VariableElimination

cancer_model = BayesianModel([('Pollution', 'Cancer'),
                              ('Smoker', 'Cancer'),
                              ('Cancer', 'Xray'),
                              ('Cancer', 'Dyspnoea')])
print('Bayesian network nodes:')
print('\t', cancer_model.nodes())
print('Bayesian network edges:')
print('\t', cancer_model.edges())

cpd_poll = TabularCPD(variable='Pollution', variable_card=2,
                      values=[[0.9], [0.1]])
cpd_smoke = TabularCPD(variable='Smoker', variable_card=2,
                       values=[[0.3], [0.7]])
cpd_cancer = TabularCPD(variable='Cancer', variable_card=2,
                        values=[[0.03, 0.05, 0.001, 0.02],
                                [0.97, 0.95, 0.999, 0.98]],
                        evidence=['Smoker', 'Pollution'],
                        evidence_card=[2, 2])
cpd_xray = TabularCPD(variable='Xray', variable_card=2,
                      values=[[0.9, 0.2], [0.1, 0.8]],
                      evidence=['Cancer'], evidence_card=[2])
cpd_dysp = TabularCPD(variable='Dyspnoea', variable_card=2,
                      values=[[0.65, 0.3], [0.35, 0.7]],
                      evidence=['Cancer'], evidence_card=[2])
cancer_model.add_cpds(cpd_poll, cpd_smoke, cpd_cancer, cpd_xray, cpd_dysp)
print('Model generated bt adding conditional probability distribution(cpds)')

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

print('Displaying CPDs')
print(cancer_model.get_cpds('Pollution'))
print(cancer_model.get_cpds('Smoker'))
print(cancer_model.get_cpds('Cancer'))
print(cancer_model.get_cpds('Xray'))
print(cancer_model.get_cpds('Dyspnoea'))

cancer_infer = VariableElimination(cancer_model)
print('\nInferencing with Bayesian Network')

print('\nProbability of Cancer given Smoker')
q = cancer_infer.query(variables=['Cancer'], evidence={'Smoker': 1})
print(q)
```

```
print('\nProbability of Cancer given Smoker, Pollution')
q = cancer_infer.query(variables=['Cancer'], evidence={'Smoker': 1,'Pollution': 1})
print(q)
```

- ## OUTPUT

```
Displaying CPDs
+--------------+-----+
| Pollution(0) | 0.9 |
+--------------+-----+
| Pollution(1) | 0.1 |
+--------------+-----+
+-----------+-----+
| Smoker(0) | 0.3 |
+-----------+-----+
| Smoker(1) | 0.7 |
+-----------+-----+
+-----------+--------------+--------------+--------------+--------------+
| Smoker    | Smoker(0)    | Smoker(0)    | Smoker(1)    | Smoker(1)    |
+-----------+--------------+--------------+--------------+--------------+
| Pollution | Pollution(0) | Pollution(1) | Pollution(0) | Pollution(1) |
+-----------+--------------+--------------+--------------+--------------+
| Cancer(0) | 0.03         | 0.05         | 0.001        | 0.02         |
+-----------+--------------+--------------+--------------+--------------+
| Cancer(1) | 0.97         | 0.95         | 0.999        | 0.98         |
+-----------+--------------+--------------+--------------+--------------+
+---------+-----------+-----------+
| Cancer  | Cancer(0) | Cancer(1) |
+---------+-----------+-----------+
| Xray(0) | 0.9       | 0.2       |
+---------+-----------+-----------+
| Xray(1) | 0.1       | 0.8       |
+---------+-----------+-----------+
+-------------+-----------+-----------+
| Cancer      | Cancer(0) | Cancer(1) |
+-------------+-----------+-----------+
| Dyspnoea(0) | 0.65      | 0.3       |
+-------------+-----------+-----------+
| Dyspnoea(1) | 0.35      | 0.7       |
+-------------+-----------+-----------+
```

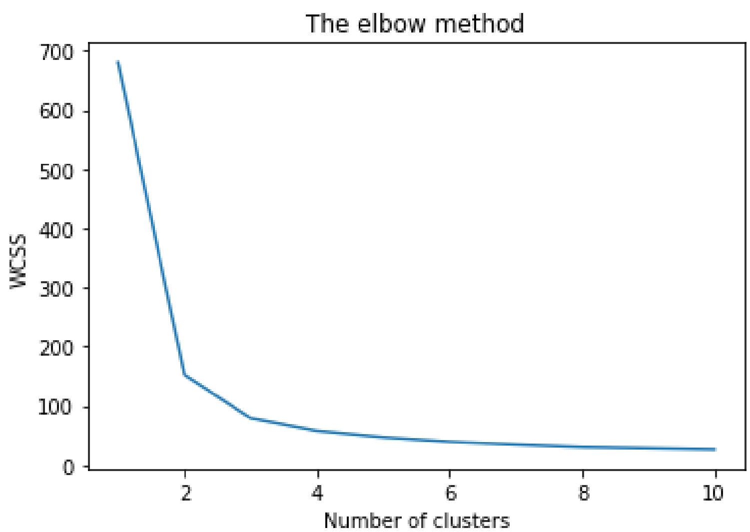
```
Finding Elimination Order: : 100%|██████████| 3/3 [00:00<00:00, 353.00it/s]
Eliminating: Xray: 100%|██████████| 3/3 [00:00<00:00, 188.14it/s]
Finding Elimination Order: : 100%|██████████| 2/2 [00:00<00:00, 367.45it/s]
Eliminating: Xray: 100%|██████████| 2/2 [00:00<00:00, 275.99it/s]
Inferencing with Bayesian Network

Probability of Cancer given Smoker
+-----------+---------------+
| Cancer    |   phi(Cancer) |
+===========+===============+
| Cancer(0) |        0.0029 |
+-----------+---------------+
| Cancer(1) |        0.9971 |
+-----------+---------------+

Probability of Cancer given Smoker, Pollution
+-----------+---------------+
| Cancer    |   phi(Cancer) |
+===========+===============+
| Cancer(0) |        0.0200 |
+-----------+---------------+
| Cancer(1) |        0.9800 |
+-----------+---------------+
```

LAB-7
K MEANS ALGORITHM

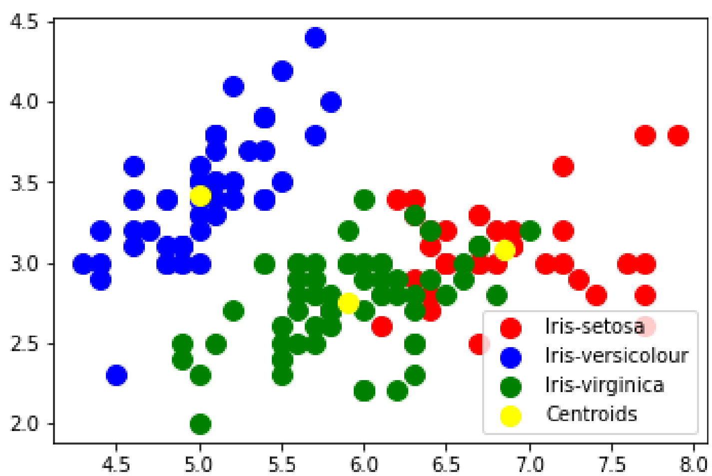
- **PROGRAM**

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

#importing the Iris dataset with pandas
dataset = pd.read_csv('/content/Iris.csv')
x = dataset.iloc[:, [1, 2, 3, 4]].values


from sklearn.cluster import KMeans
wcss = []

for i in range(1, 11):
   kmeans = KMeans(n_clusters = i, init = 'k-means++', max_iter = 300, n_init = 10, random_state = 0)
   kmeans.fit(x)
   wcss.append(kmeans.inertia_)

#Plotting the results onto a line graph, allowing us to observe 'The elbow'
plt.plot(range(1, 11), wcss)
plt.title('The elbow method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS') #within cluster sum of squares
plt.show()


kmeans = KMeans(n_clusters = 3, init = 'k-means++', max_iter = 300, n_init = 10, random_state = 0)
y_kmeans = kmeans.fit_predict(x)


plt.scatter(x[y_kmeans == 0, 0], x[y_kmeans == 0, 1], s = 100, c = 'red', label = 'Iris-setosa')
plt.scatter(x[y_kmeans == 1, 0], x[y_kmeans == 1, 1], s = 100, c = 'blue', label = 'Iris-versicolour')
plt.scatter(x[y_kmeans == 2, 0], x[y_kmeans == 2, 1], s = 100, c = 'green', label = 'Iris-virginica')

#Plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1], s = 100, c = 'yellow', label = 'Centroids')

plt.legend()
```

- **OUTPUT**



]: <matplotlib.legend.Legend at 0x7f10db40fc90>



LAB-8
EM ALGORITHM

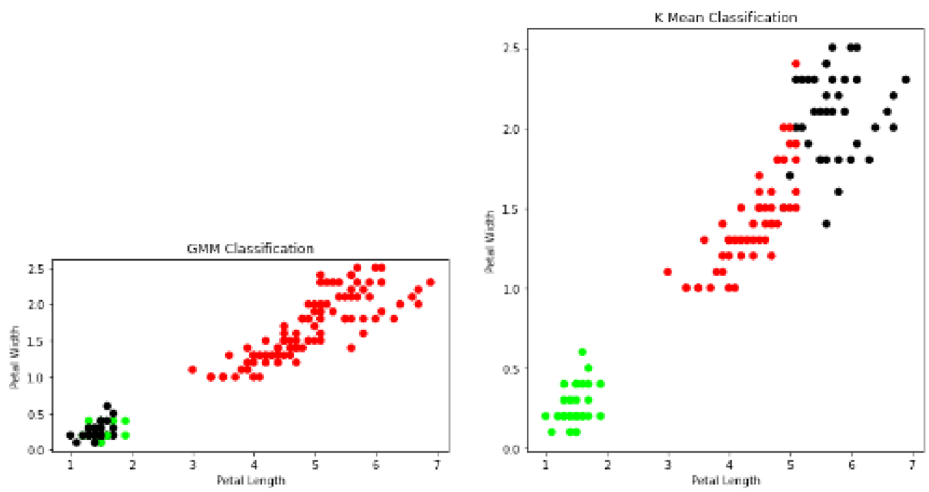
- ## PROGRAM

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

iris = datasets.load_iris()

X = pd.DataFrame(iris.data)
X.columns = ['Sepal_Length','Sepal_Width','Petal_Length','Petal_Width']

y = pd.DataFrame(iris.target)
y.columns = ['Targets']

model = KMeans(n_clusters=3)
model.fit(X)


plt.figure(figsize=(14,7))

colormap = np.array(['red', 'lime', 'black'])

# Plot the Original Classifications
plt.subplot(1, 2, 1)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y.Targets], s=40)
plt.title('Real Classification')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')


# Plot the Models Classifications
plt.subplot(1, 2, 2)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[model.labels_], s=40)
plt.title('K Mean Classification')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
print('The accuracy score of K-Mean: ',sm.accuracy_score(y, model.labels_))
print('The Confusion matrixof K-Mean: ',sm.confusion_matrix(y, model.labels_))


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

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

```
y_gmm = gmm.predict(xs)
#y_cluster_gmm

plt.subplot(2, 2, 3)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y_gmm], s=40)
plt.title('GMM Classification')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')

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

- **OUTPUT**

```
The accuracy score of K-Mean:  0.24
The Confusion matrixof K-Mean:  [[ 0 50  0]
 [48  0  2]
 [14  0 36]]
The accuracy score of EM:  0.0
The Confusion matrix of EM:  [[ 0 10 40]
 [50  0  0]
 [50  0  0]]
```



LAB-9
K NEAREST NEIGHBOUR ALGORITHM

- ## 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

```
 [6.  3.  4.8 1.8]
 [6.9 3.1 5.4 2.1]
 [6.7 3.1 5.6 2.4]
 [6.9 3.1 5.1 2.3]
 [5.8 2.7 5.1 1.9]
 [6.8 3.2 5.9 2.3]
 [6.7 3.3 5.7 2.5]
 [6.7 3.  5.2 2.3]
 [6.3 2.5 5.  1.9]
 [6.5 3.  5.2 2. ]
 [6.2 3.4 5.4 2.3]
 [5.9 3.  5.1 1.8]]
class: 0-Iris-Setosa, 1- Iris-Versicolour, 2- Iris-Virginica
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2]
Confusion Matrix
[[11  0  0]
 [ 0 16  1]
 [ 0  1 16]]
Accuracy Metrics
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        11
           1       0.94      0.94      0.94        17
           2       0.94      0.94      0.94        17

    accuracy                           0.96        45
   macro avg       0.96      0.96      0.96        45
weighted avg       0.96      0.96      0.96        45
```

LAB-10
LOCALLY WEIGHTED REGRESSION ALGORITHM

- ## PROGRAM

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

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
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)]]))
plt.title('K Mean Classification')
plt.xlabel('Petal Length')
```

• OUTPUT

```
The Data Set ( 10 Samples) X :
 [-2.99399399 -2.98798799 -2.98198198 -2.97597598 -2.96996997 -2.963
96396
 -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 :
 [-2.86327233 -2.86956667 -2.82337772 -2.88923105 -2.77788044 -3.023
41724
 -2.95836131 -2.96057068 -2.95988289]
 Xo Domain Space(10 Samples) :
 [-2.97993311 -2.95986622 -2.93979933 -2.91973244 -2.89966555 -2.879
59866
 -2.85953177 -2.83946488 -2.81939799]
ut[4]: Text(0.5, 0, 'Petal Length')
```