

MACHINE LEARNING PROGRAMS OUTPUT VERIFIED

PROGRAM: 01

```
from sklearn.datasets import make_blobs
```

```
from matplotlib import pyplot as plt
```

```
from matplotlib import style
```

```
from sklearn.datasets import make_blobs
```

```
from matplotlib import pyplot as plt
```

```
from matplotlib import style
```

```
style.use("fivethirtyeight")
```

```
X, y = make_blobs(n_samples = 100, centers = 3,
```

```
                  cluster_std = 1, n_features = 2)
```

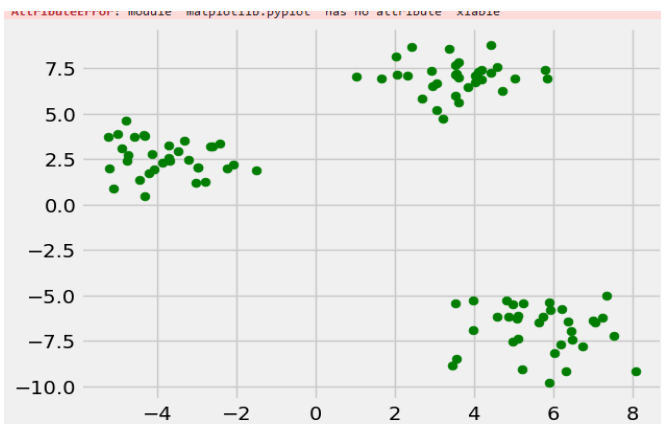
```
plt.scatter(X[:, 0], X[:, 1], s = 40, color = 'g')
```

```
plt.xlabel("X")
```

```
plt.ylabel("Y")
```

```
plt.show()
```

```
plt.clf()
```



[]:

PROGREAM: 02

```
from IPython.display import HTML
```

```
import pandas as pd
```

```
import numpy as np
```

```
import base64
```

```
def create_download_link(df, title = "Download CSV file", filename = "data.csv"):
```

```
    csv = df.to_csv()
```

```
    b64 = base64.b64encode(csv.encode())
```

```
    payload = b64.decode()
```

```
    html = '<a download="{filename}" href="data:text/csv;base64,{payload}" target="_blank">{title}</a>'
```

```
    html = html.format(payload=payload,title=title,filename=filename)
```

```
    return HTML(html)
```

```
df = pd.DataFrame(np.random.randn(50, 4), columns=list('ABCD'))
```

```
create_download_link(df)
```

```
[6]: from IPython.display import HTML
import pandas as pd
import numpy as np
import base64
```

```
[14]: def create_download_link(df,title = "Download CSV file", filename = "data.csv"):
    csv = df.to_csv()
    b64 = base64.b64encode(csv.encode())
    payload = b64.decode()
    html = '<a download="{filename}" href="data:text/csv;base64,{payload}" target="_blank">{title}</a>'
    html = html.format(payload=payload,title=title,filename=filename)
    return HTML(html)
df = pd.DataFrame(np.random.randn(50, 4), columns=list('ABCD'))
create_download_link(df)
```

```
[14]: Download CSV file
```

```
[ ]:
```

PROGRESSION: 03

```
from pandas import read_csv

from numpy import set_printoptions

from sklearn.feature_selection import SelectKBest

from sklearn.feature_selection import chi2

path = r'D:\squad\book.csv'

names = ['preg', 'plas', 'hello']

dataframe = read_csv(path, names=names)

array = dataframe.values

print(dataframe)
```

	preg	plas	pres	skin	test	mass	pedi	age	class
0.0	variance	skewness	Curtosis	Entropy	class	NaN	NaN	NaN	NaN
1.0	3.6216	8.661	-2.8073	-0.4469	0	NaN	NaN	NaN	NaN
2.0	4.5459	8.1674	-2.4586	-1.462	0	NaN	NaN	NaN	NaN
3.0	3.866	-2.6383	1.9242	0.10645	0	NaN	NaN	NaN	NaN
4.0	3.4566	9.5228	-4.0112	-3.594	0	NaN	NaN	NaN	NaN

PROGRAM: 04

```
from sklearn.metrics import confusion_matrix

from sklearn.metrics import accuracy_score

from sklearn.metrics import classification_report

from sklearn.metrics import roc_auc_score

from sklearn.metrics import log_loss

X_actual = [1, 1, 0, 1, 0, 0, 1, 0, 0, 0]

Y_predic = [1, 0, 1, 1, 1, 0, 1, 1, 0, 0]

results = confusion_matrix(X_actual, Y_predic)

print ('Confusion Matrix :')

print(results)

print ('Accuracy Score is',accuracy_score(X_actual, Y_predic))

print ('Classification Report : ')

print (classification_report(X_actual, Y_predic))

print('AUC-ROC:',roc_auc_score(X_actual, Y_predic))

print('LOGLOSS Value is',log_loss(X_actual, Y_predic))
```

```
Confusion Matrix :
[[3 3]
 [1 3]]
Accuracy Score is 0.6
Classification Report :
              precision    recall  f1-score   support

     0       0.75        0.50        0.60         6
     1       0.50        0.75        0.60         4

   accuracy          0.60         10
  macro avg          0.62         10
 weighted avg          0.65         10

AUC-ROC: 0.625
LOGLOSS Value is 14.41746135564686
```

PROGREAM: 05

```
from sklearn.datasets import load_iris

iris = load_iris()

X = iris.data

y=iris.target

from sklearn.model_selection import train_test_split

X_train,X_test,y_train, y_test=train_test_split(X,y,test_size=0.4,random_state=1)

from sklearn.naive_bayes import GaussianNB

gnb=GaussianNB()

gnb.fit(X_train, y_train)

y_pred=gnb.predict(X_test)

from sklearn import metrics

print("GaussianNaiveBayes model accuracy(in %):", metrics.accuracy_score(y_test,y_pred)*100)
```

```
GaussianNaiveBayes model accuracy(in %): 95.0
```

```
[ ]:
```

PROGREAM: 06

PROGREAM: 07

```
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'])

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')

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_))

from sklearn import preprocessing

scaler = preprocessing.StandardScaler()

scaler.fit(X)

xsa = scaler.transform(X)

xs = pd.DataFrame(xsa, columns = X.columns)

from sklearn.mixture import GaussianMixture

gmm = GaussianMixture(n_components=3)

gmm.fit(xs)

y_gmm = gmm.predict(xs)

plt.subplot(2, 2, 3)

plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y_gmm], s=40)

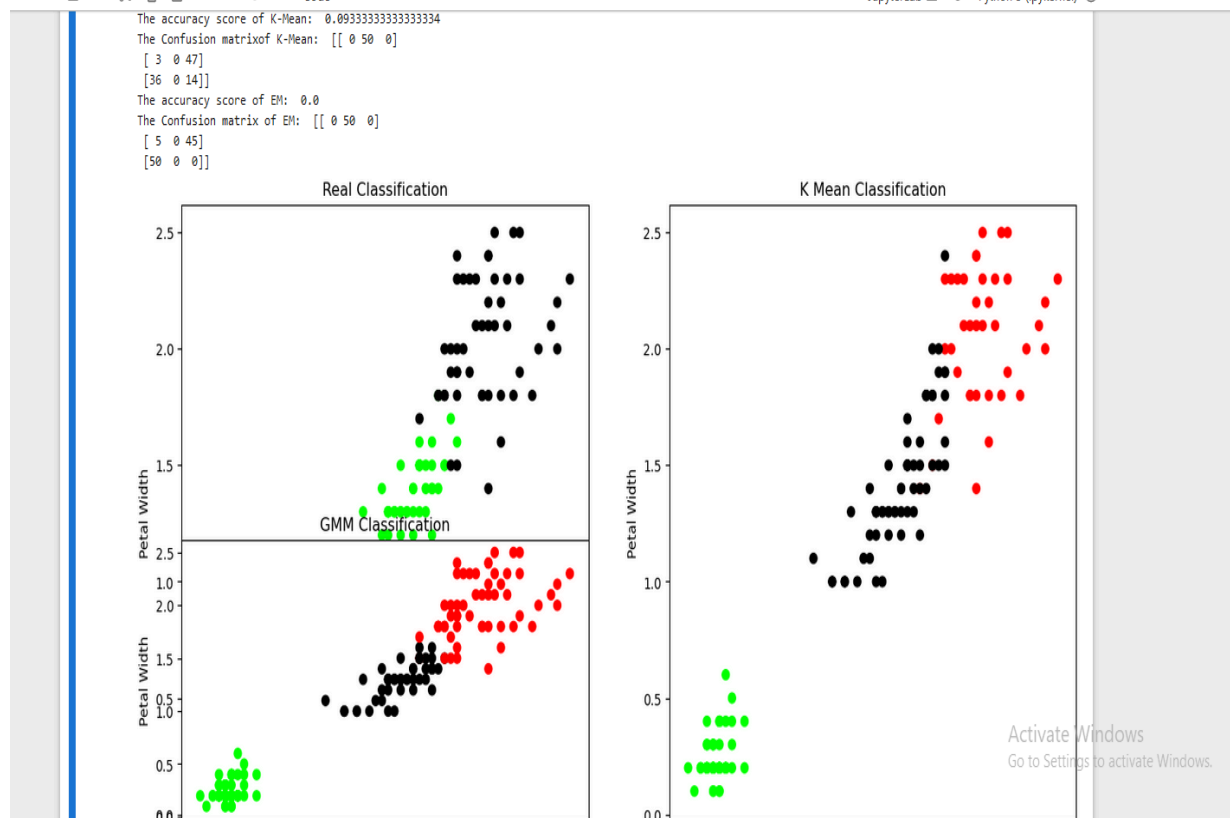
plt.title('GMM Classification')

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))
```



PROGREAN: 08

PROGREAN: 09

```
from sklearn.datasets import make_classification
```

```
from sklearn import tree
```

```
from sklearn.model_selection import train_test_split
```

```
X, t = make_classification(100, 5, n_classes=2, shuffle=True, random_state=10)
```



```
X_train, X_test, t_train, t_test = train_test_split(
X, t, test_size=0.3, shuffle=True, random_state=1)

model = tree.DecisionTreeClassifier()

model = model.fit(X_train, t_train)

predicted_value = model.predict(X_test)

print(predicted_value)

tree.plot_tree(model)

zeroes = 0

ones = 0

for i in range(0, len(t_train)):

    if t_train[i] == 0:

        zeroes += 1

    else:

        ones += 1

    print(zeroes)

    print(ones)

val = 1 - ((zeroes/70)*(zeroes/70) + (ones/70)*(ones/70))

print("Gini :", val)

match = 0

UnMatch = 0

for i in range(30):

    if predicted_value[i] == t_test[i]:

        match += 1
```

else:

UnMatch += 1

accuracy = match/30

print("Accuracy is: ", accuracy)

```
for i in range(30):
    if predicted_value[i] == t_test[i]:
        match += 1
    else:
        UnMatch += 1
accuracy = match/30
print("Accuracy is: ", accuracy)
```

```
[0 1 0 1 0 0 0 0 0 0 1 0 0 1 0 0 0 0 1 1 0 1 0 0 0 1 1 1 0 0]
```

0

1

2

2

2

3

3

4

3

5

3

6

6

7

6

8

7

PROGREAN:10

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/100

def sigmoid (x):

return 1/(1 + np.exp(-x))

```

def derivatives_sigmoid(x):
    return x * (1 - x)

epoch=5

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 ("-----Epoch-", i+1, "Starts ----- ")

print("Input: \n" + str(X))

print("Actual Output: \n" + str(y))

print("Predicted Output: \n" ,output)

print ("-----Epoch-", i+1, "Ends ----- \n")

print("Input: \n" + str(X))

print("Actual Output: \n" + str(y))

print("Predicted Output: \n" ,output)

```

```

-----Epoch- 5 Starts -----
Input:
[[0.66666667 1.          ]
 [0.33333333 0.55555556]
 [1.          0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
[[0.91052119]
 [0.89787668]
 [0.90937736]]
-----Epoch- 5 Ends -----

Input:
[[0.66666667 1.          ]
 [0.33333333 0.55555556]
 [1.          0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
[[0.91052119]
 [0.89787668]
 [0.90937736]]

```

PROGREAM:11

```
import numpy as np

import matplotlib.pyplot as plt

from sklearn import svm, datasets

iris = datasets.load_iris()

X = iris.data[:, :2]

y = iris.target

C = 1.0

svc = svm.SVC(kernel='linear', C = 1).fit(X, y)

x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1

y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1

h = (x_max / x_min)/100

xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
np.arange(y_min, y_max, h))

plt.subplot(1, 1, 1)

Z = svc.predict(np.c_[xx.ravel(), yy.ravel()])

Z = Z.reshape(xx.shape)

plt.contourf(xx, yy, Z, cmap = plt.cm.Paired, alpha = 0.8)

plt.scatter(X[:, 0], X[:, 1], c = y, cmap = plt.cm.Paired)

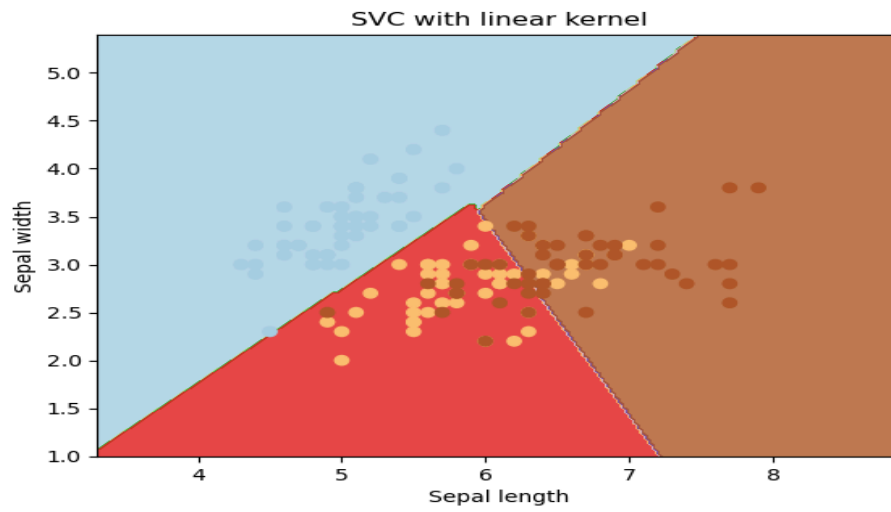
plt.xlabel('Sepal length')

plt.ylabel('Sepal width')

plt.xlim(xx.min(), xx.max())

plt.title('SVC with linear kernel')
```

```
plt.show()
```



```
[ ]:
```

PROGREAM:12

```
import pandas as pd

import numpy as np

from sklearn.linear_model import LogisticRegression

from sklearn.model_selection import train_test_split

import seaborn as sns

import matplotlib.pyplot as plt

from sklearn import metrics

Data= pd.read_csv(r"C:\divya ml\diabetes.csv")

Data.head().transpose()

Data.describe ()
```

```
[5]:
```

	0.38076	0.05068	0.061696	0.021872	0.021872.1	-1.044223
count	1.0	1.0	1.0	1.0	1.0	1.0
mean	441.0	441.0	441.0	441.0	441.0	441.0
std	NaN	NaN	NaN	NaN	NaN	NaN
min	441.0	441.0	441.0	441.0	441.0	441.0
25%	441.0	441.0	441.0	441.0	441.0	441.0
50%	441.0	441.0	441.0	441.0	441.0	441.0
75%	441.0	441.0	441.0	441.0	441.0	441.0
max	441.0	441.0	441.0	441.0	441.0	441.0