Experiment 7

Aim : Support Vector Machine (SVM)

To implement support vector machine(SVM) in python from scratch

Description :

A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples. In two dimentional space this hyperplane is a line dividing a plane in two parts where in each class lay in either side.

Advantages and Disadvantages of SVM :

Let us now look at some advantages and disadvantages of SVM.

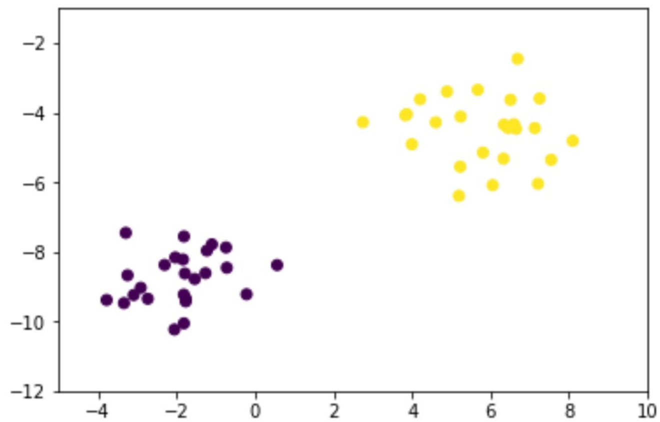
Advantages – SVMs can model nonlinear phenomena by the choice of an appropriate kernel method. SVMs generally provide precise predictions. SVMs determine the optimal hyperplane by the nearest points (support vectors) only and not by distant points. This thus enhances the robustness of the model in some cases.

Disadvantage – The models are opaque. Although you can explain them with a decision tree, there is a risk of loss or precision. SVMs are very sensitive to the choice of the kernel parameters. The difficulty in choosing the correct kernel parameters may compel you to test many possible values. As a result, the computation time is sometimes lengthy.

Code and Output :

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
np.random.seed(6)
import math
```

In [2]:
```
from sklearn.datasets.samples_generator import make_blobs

(X,y) =  make_blobs(n_samples=50,n_features=2,centers=2,cluster_std=1.05,random_sta
te=40)
#we need to add 1 to X values (we can say its bias)
X1 = np.c_[np.ones((X.shape[0])),X]

plt.scatter(X1[:,1],X1[:,2],marker='o',c=y)
plt.axis([-5,10,-12,-1])
plt.show()
```



In [3]:
```
postiveX=[]
negativeX=[]
for i,v in enumerate(y):
    if v==0:
        negativeX.append(X[i])
    else:
        postiveX.append(X[i])

#our data dictionary
data_dict = {-1:np.array(negativeX), 1:np.array(postiveX)}
```

In [4]:
```
#all the required variables
w=[] #weights 2 dimensional vector
b=[] #bias

max_feature_value=float('-inf')
min_feature_value=float('+inf')

for yi in data_dict:
    if np.amax(data_dict[yi])>max_feature_value:
        max_feature_value=np.amax(data_dict[yi])

    if np.amin(data_dict[yi])<min_feature_value:
        min_feature_value=np.amin(data_dict[yi])

learning_rate = [max_feature_value * 0.1, max_feature_value * 0.01, max_feature_val
ue * 0.001,]
```

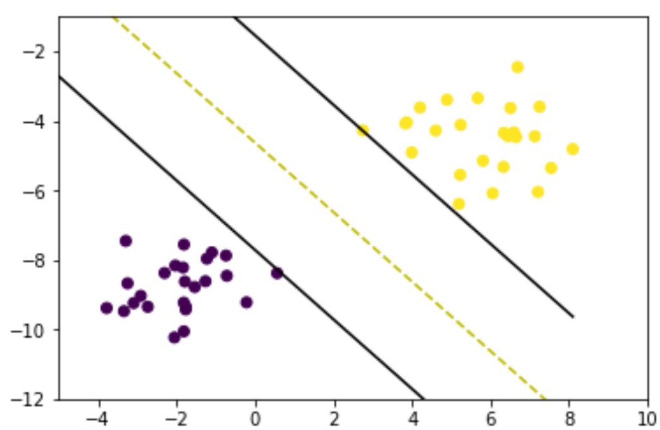
In [5]:
```
def SVM_Training(data_dict):
    i=1
    global w
    global b
    # { ||w||: [w,b] }
    length_Wvector = {}
    transforms = [[1,1],[-1,1],[-1,-1],[1,-1]]

    b_step_size = 2
    b_multiple = 5
    w_optimum = max_feature_value*0.5

    for lrate in learning_rate:

        w = np.array([w_optimum,w_optimum])
        optimized = False
        while not optimized:
            #b=[-maxvalue to maxvalue] we wanna maximize the b values so check for
every b value
            for b in np.arange(-1*(max_feature_value*b_step_size), max_feature_valu
e*b_step_size, lrate*b_multiple):
                for transformation in transforms:  # transforms = [[1,1],[-1,1],[-1
,-1],[1,-1]]
                    w_t = w*transformation

                    correctly_classified = True

                    # every data point should be correct
                    for yi in data_dict:
                        for xi in data_dict[yi]:
                            if yi*(np.dot(w_t,xi)+b) < 1:  # we want  yi*(np.dot(w_
t,xi)+b) >= 1 for correct classification
                                correctly_classified = False

                    if correctly_classified:
                        length_Wvector[np.linalg.norm(w_t)] = [w_t,b] #store w, b f
or minimum magnitude

            if w[0] < 0:
                optimized = True
            else:
                w = w - lrate

        norms = sorted([n for n in length_Wvector])

        minimum_wlength = length_Wvector[norms[0]]
        w = minimum_wlength[0]
        b = minimum_wlength[1]

        w_optimum = w[0]+lrate*2
```

In [6]:
```
SVM_Training(data_dict)
```

In [7]:
```
colors = {1:'r',-1:'b'}
fig = plt.figure()
ax = fig.add_subplot(1,1,1)
```

In [8]:
```
def visualize(data_dict):


        #[[ax.scatter(x[0],x[1],s=100,color=colors[i]) for x in data_dict[i]] for i
in data_dict]

        plt.scatter(X1[:,1],X1[:,2],marker='o',c=y)

        # hyperplane = x.w+b
        # v = x.w+b
        # psv = 1
        # nsv = -1
        # dec = 0
        def hyperplane_value(x,w,b,v):
            return (-w[0]*x-b+v) / w[1]

        datarange = (min_feature_value*0.9,max_feature_value*1.)
        hyp_x_min = datarange[0]
        hyp_x_max = datarange[1]

        # (w.x+b) = 1
        # positive support vector hyperplane
        psv1 = hyperplane_value(hyp_x_min, w, b, 1)
        psv2 = hyperplane_value(hyp_x_max, w, b, 1)
        ax.plot([hyp_x_min,hyp_x_max],[psv1,psv2], 'k')

        # (w.x+b) = -1
        # negative support vector hyperplane
        nsv1 = hyperplane_value(hyp_x_min, w, b, -1)
        nsv2 = hyperplane_value(hyp_x_max, w, b, -1)
        ax.plot([hyp_x_min,hyp_x_max],[nsv1,nsv2], 'k')

        # (w.x+b) = 0
        # positive support vector hyperplane
        db1 = hyperplane_value(hyp_x_min, w, b, 0)
        db2 = hyperplane_value(hyp_x_max, w, b, 0)
        ax.plot([hyp_x_min,hyp_x_max],[db1,db2], 'y--')

        plt.axis([-5,10,-12,-1])
        plt.show()
```

In [9]:
```
visualize(data_dict)
```



In [10]:
```python
def predict(features):
        # sign( x.w+b )
        dot_result = np.sign(np.dot(np.array(features),w)+b)
        return dot_result.astype(int)

for i in X[:5]:
    print(predict(i),end=',  ')
```

```
1,  1,  -1,  1,  -1,
```

In [11]:
```python
l=[]
for xi in X:

    l.append(predict(xi[:6]))
l=np.array(l).astype(int)
l
```

Out[11]:
```
array([ 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])
```

In [12]:
```python
X[4]
```

Out[12]:
```
array([-1.8171622 , -9.22909875])
```

In [13]:
```python
for i, v in enumerate(y):
    if v==0:
        y[i]=-1
y
```

Out[13]:
```
array([ 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])
```

In [14]:
```python
error = sum((l-y)**2)
```

In [15]:
```python
error
```

Out[15]:
```
0
```

Finding and Learning :

Support Vector Machine, it is the most popular machine learning algorithm. It is the maximal-margin classifier that explains how actually SVM works. It is implemented practically using kernel. And the learning of the hyperplane in linear SVM is done by transforming the problem using liear algebra.