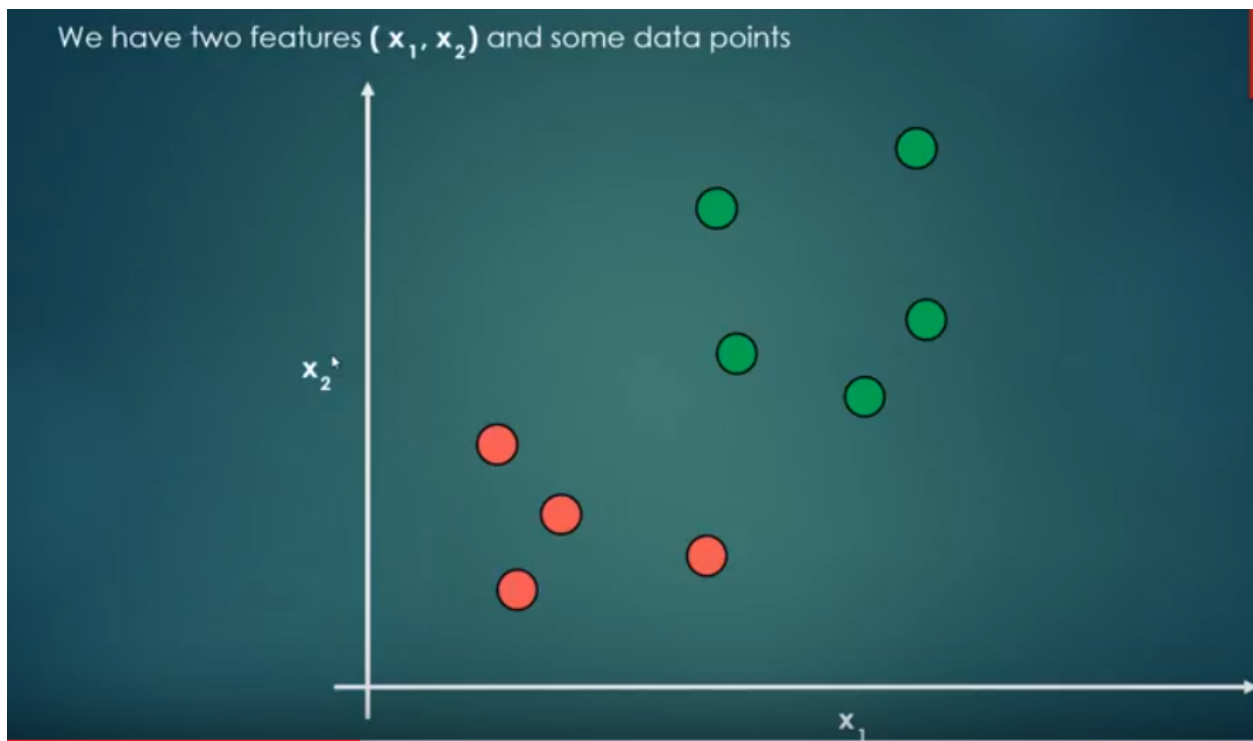


## Support vector machine (SVM)

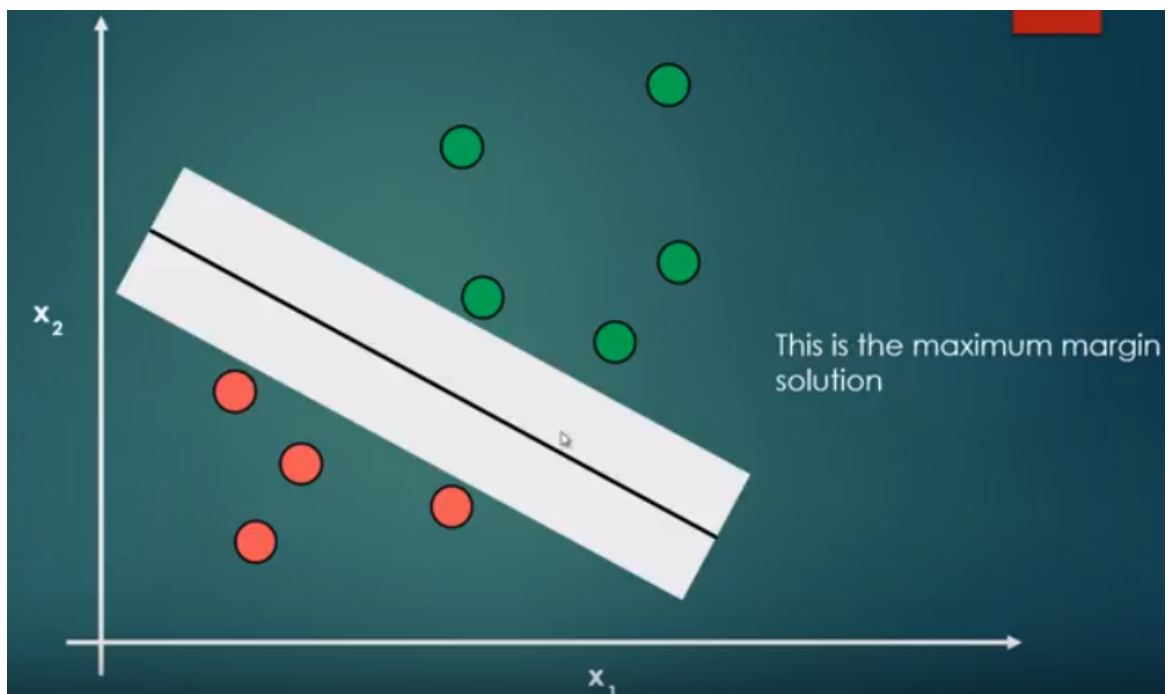
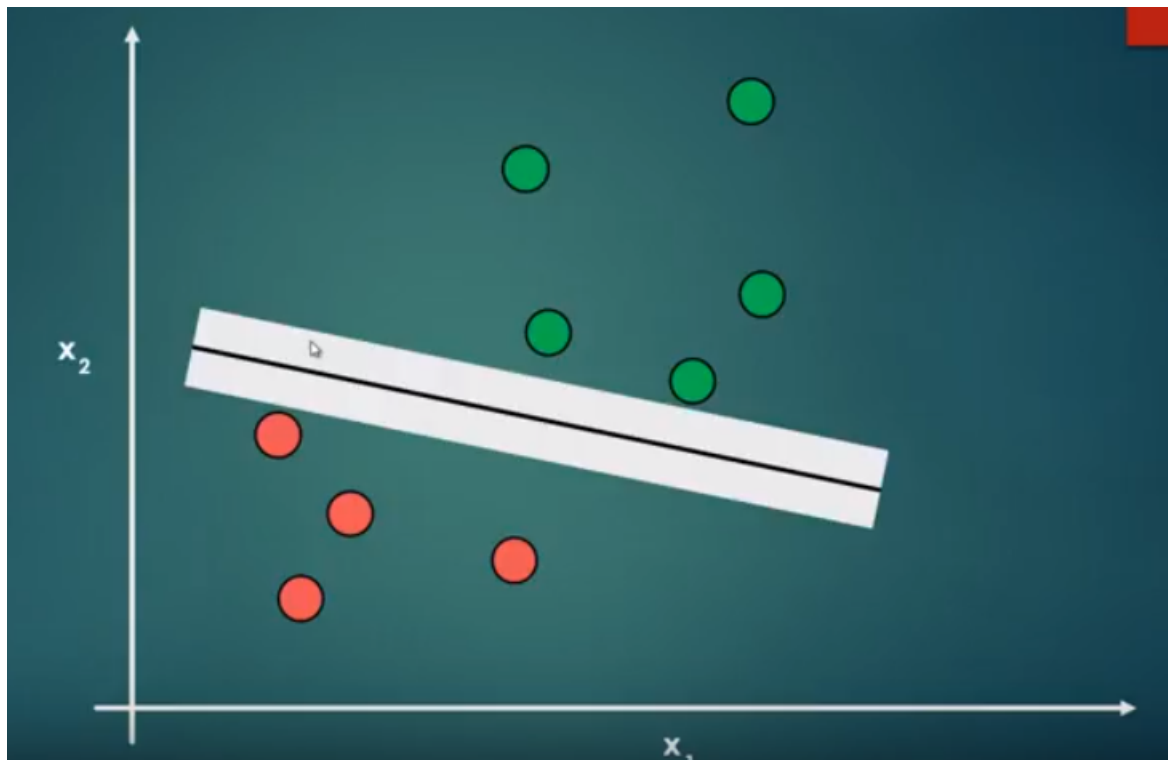
- Very popular and widely used supervised learning classification algorithm
- The great benefit: it can operate even in infinite dimension
- SVM finds a hyperplane or decision surface or (line) that leads to a homogeneous partition of data
- A good separation is achieved by the hyperplane that has largest distance to the nearest training data points of any class
- so we have to maximize the margin
- performs classification by finding the hyperplane that maximizes the margin between two classes



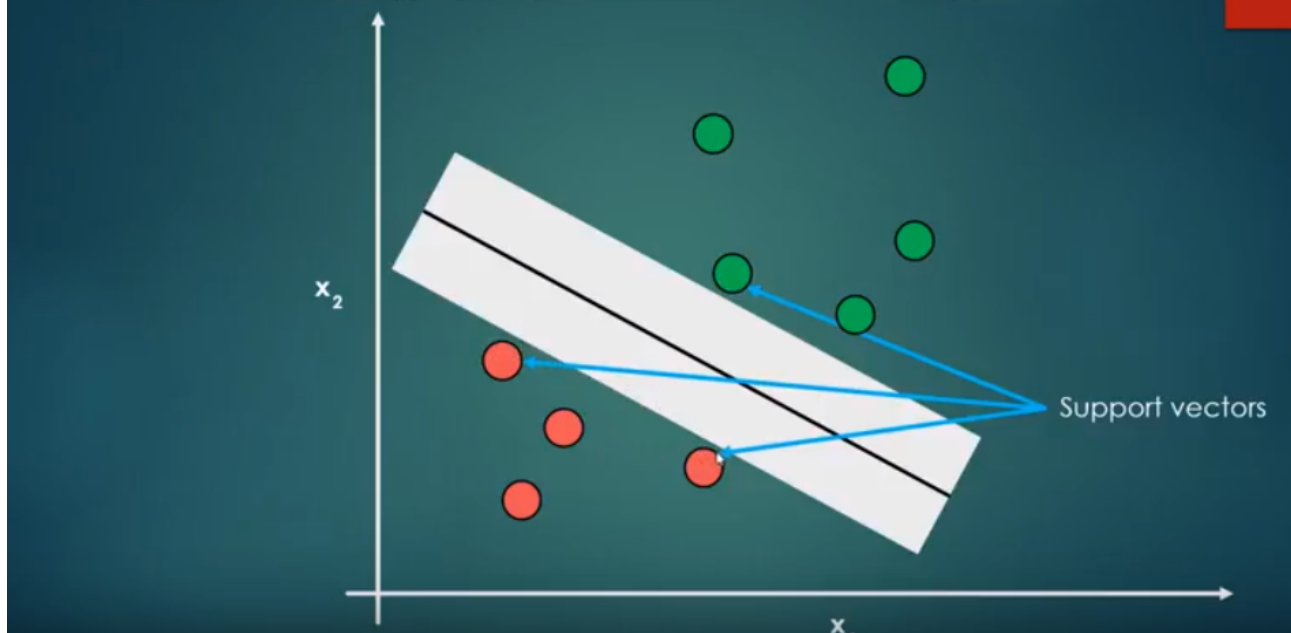
### Goal is:

classify the data points by finding the straight line ( or hyper-plane ) that differentiate the two classes with **maximum margin**

Hyperplane might be this...



**Support vectors:** the points from each class that are closest to the maximum margin hyperplane // each class have at least 1 support vector



## How to find hyperplane when problem is linearly separable

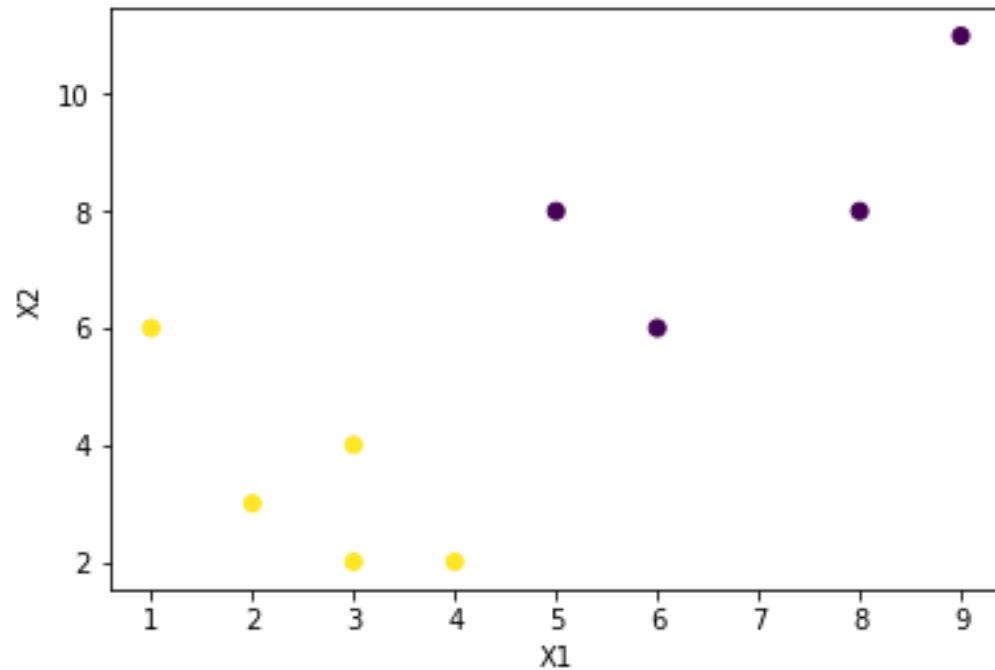
```
import numpy as np
import matplotlib.pyplot as plt

x1=[1,2,5,4,3,8,3,9,6]
x2 =[6,3,8,2,4,8,2,11,6]
y=[1,1,0,1,1,0,1,0,0]

plt.scatter(x1,x2,c=y)

plt.xlabel('X1')
plt.ylabel('X2')

plt.show()
```



Here a line easily separate these data points so hyperplane is a line

```
clf = SVC(C=1.0,kernel='linear')
```

and line:

$mX+b$

or

$wX+b$  here  $w$  or  $m$  is weight of feature  $x$

if we have 2 features then line:

$m_1X_1+m_2X_2+b$

or

$w_1X_1+w_2X_2+b$

similarly for  $n$  features

$m_1X_1+m_2X_2+\dots\dots\dots m_nX_n+ b$

or

$w_1X_1+w_2X_2+\dots\dots\dots +w_nX_n +b$

or

$$\vec{w} * \vec{x} + b$$

If we have 2 classes then

$$w * x + b \geq +1$$

testing data points to class 1

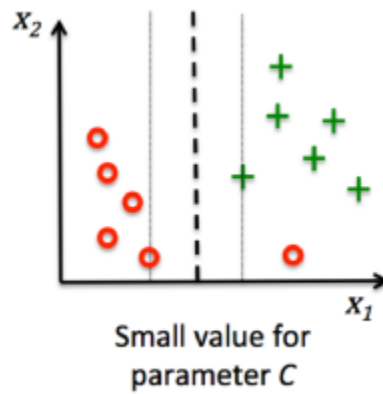
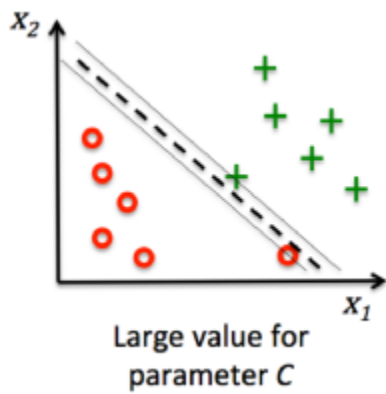
And,

$$w * x + b \leq -1$$

more precisely  $< -1$

testing data points to class 0

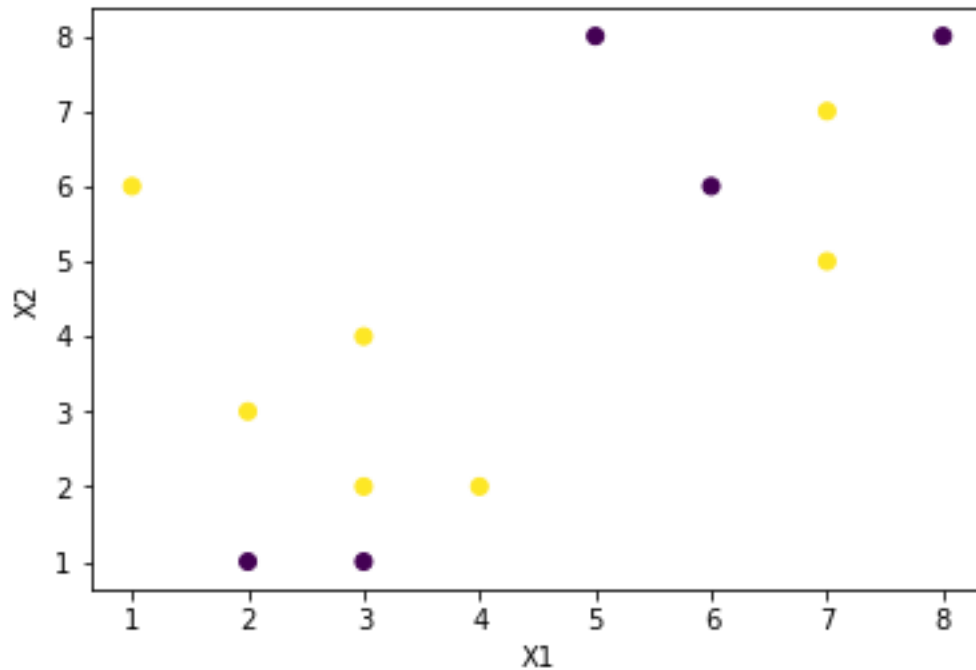
**Role of C parameter:**



- **Regularization: How much importance should you give individual data points as compared to better generalized model**
- **Regularization parameter  $c$** 
  - **Larger values of  $c$  = less regularization**
    - **Fit training data as well as possible, every data point important**
  - **Smaller values of  $c$  = more regularization**
    - **More tolerant to errors on individual data points**

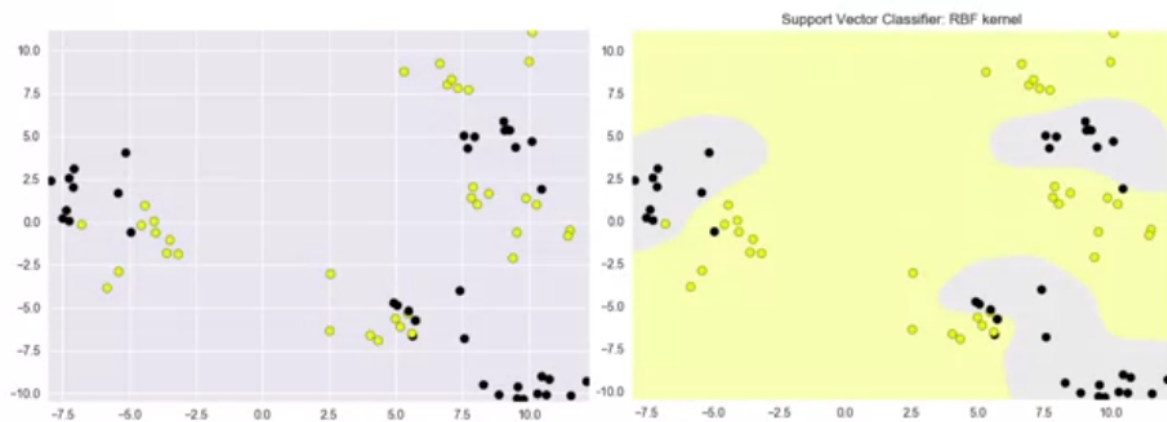
### **How to find hyperplane when problem is non-linearly separable**

```
import numpy as np
import matplotlib.pyplot as plt
x1=[1,2,5,4,3,8,3,2,6,3,7,7]
x2 =[6,3,8,2,4,8,2,1,6,1,7,5]
y=[1,1,0,1,1,0,1,0,0,0,1,1]
plt.scatter(x1,x2,c=y)
plt.xlabel('X1')
plt.ylabel('X2')
plt.show()
```



`clf = SVC(kernel='rbf') // (Radial basis function)`

## Applying the SVM with RBF kernel



In this case value of  $\gamma$  is given by:

$$\text{Exp}(-\gamma \cdot \text{sqrt}(\text{sqrt}(x1-x2))) + b$$

Now classification is done on the basis of

$\text{Exp}(-\gamma \sqrt{x_1 - x_2}) + b \geq 0$  class 1

And

$\text{Exp}(-\gamma \sqrt{x_1 - x_2}) + b < 0$  class 0

### Role of gamma parameter in RBF:

This shows that as gamma increases, the algorithm tries harder to avoid misclassifying training data, which leads to overfitting.

i.e.

higher value of gamma .....overfitting

lesser value of gamma.....underfitting



