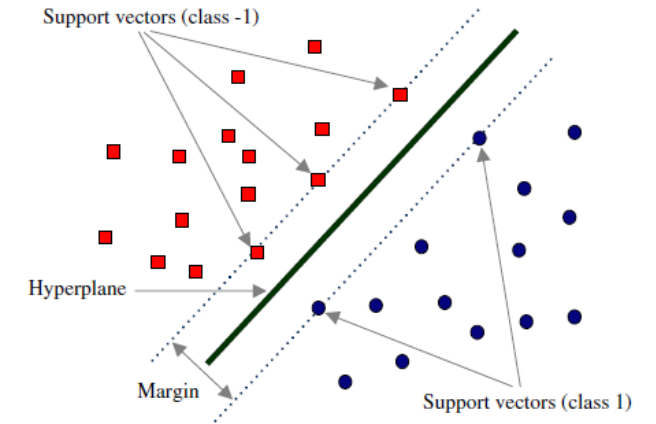
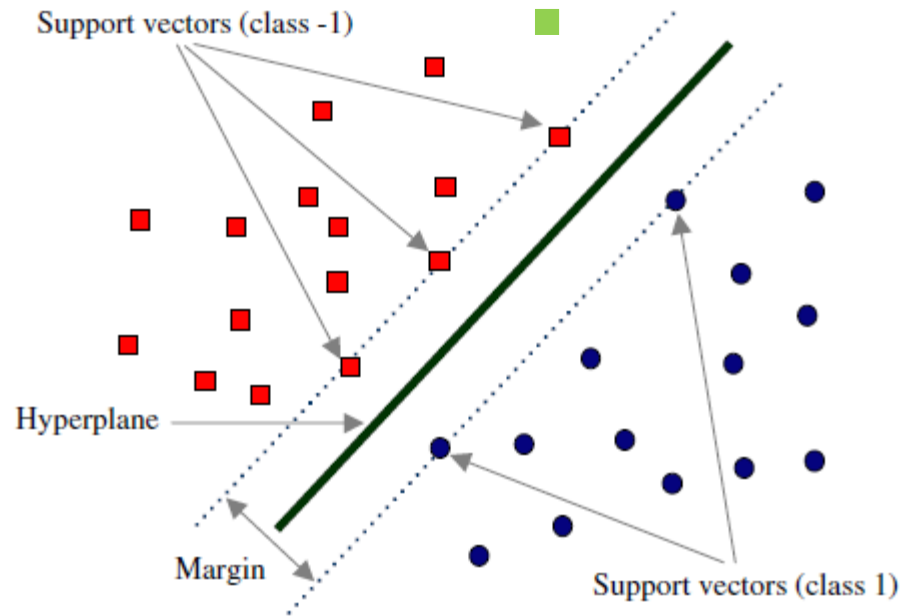


Siddhardhan

# Loss Function for Support Vector Machine Classifier



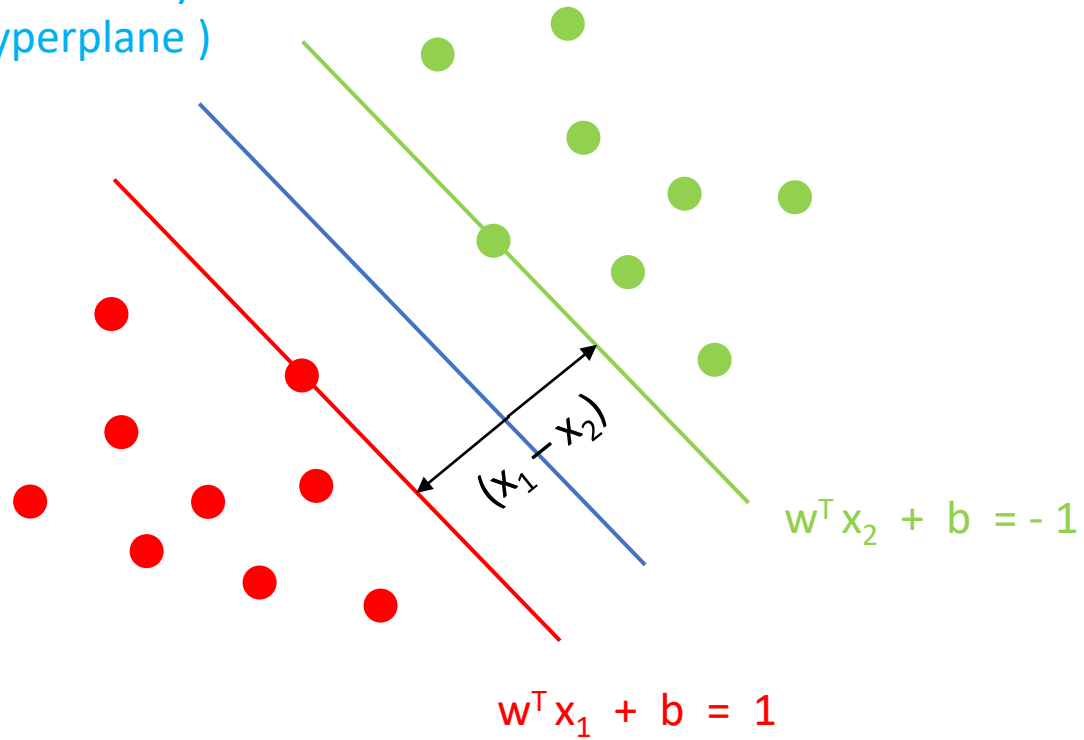
# Support Vector Machine Classifier



- Hyperplane
- Support Vectors
- Margin
- Linearly separable data

# Support Vector Machine Classifier

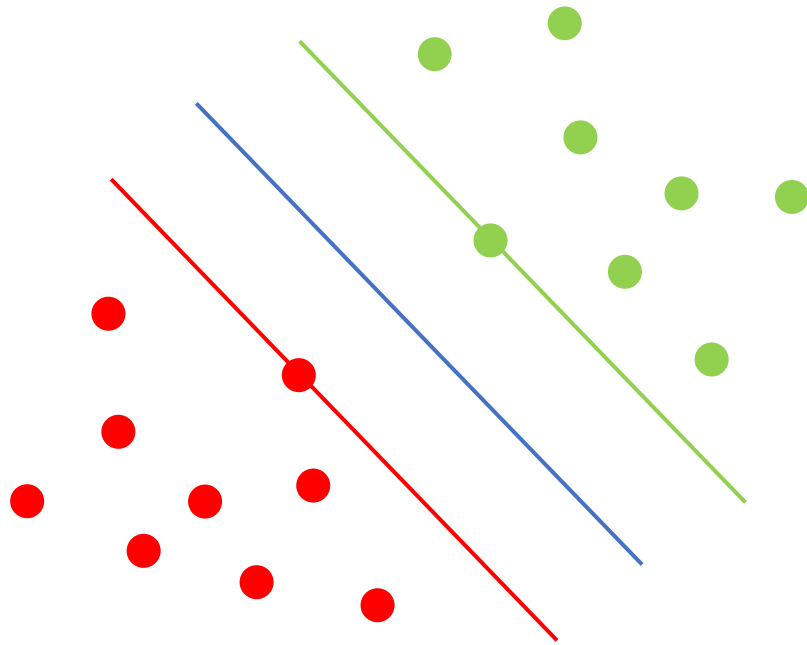
$w^T x + b = y$   
( Hyperplane )



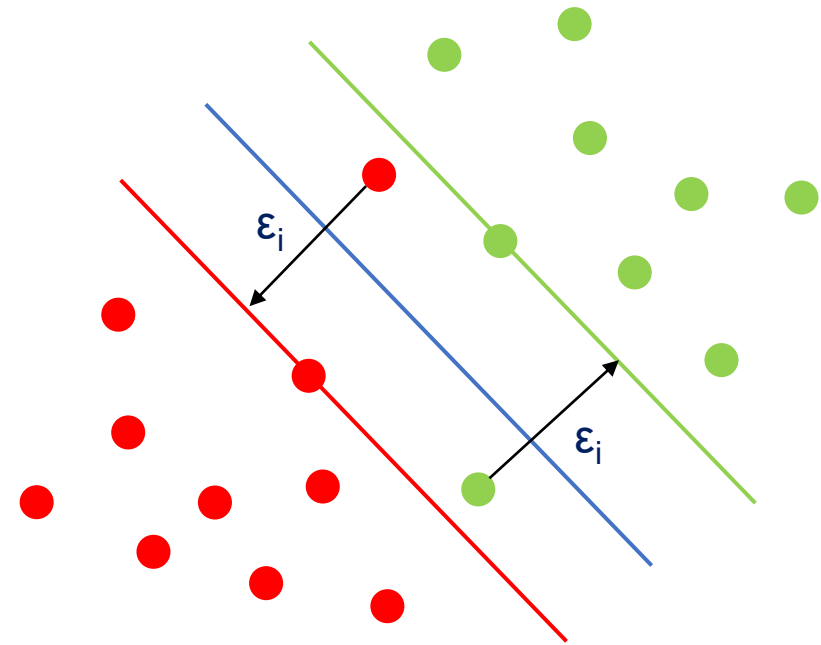
$$\max \left( \frac{2}{||w||} \right) \quad (\text{margin})$$

$$\hat{y}_i = \begin{cases} -1, & w^T x_1 + b \leq -1 \\ 1, & w^T x_1 + b \geq 1 \end{cases}$$

# Support Vector Machine Classifier



Hard Margin



Soft Margin

## Loss Function

Loss function measures how far an estimated value is from its true value.

It is helpful to determine which model performs better & which parameters are better.



$$\text{Loss} = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$

For Support Vector Machine Classifier “Hinge Loss” is used as the Loss Function.

# Hinge Loss

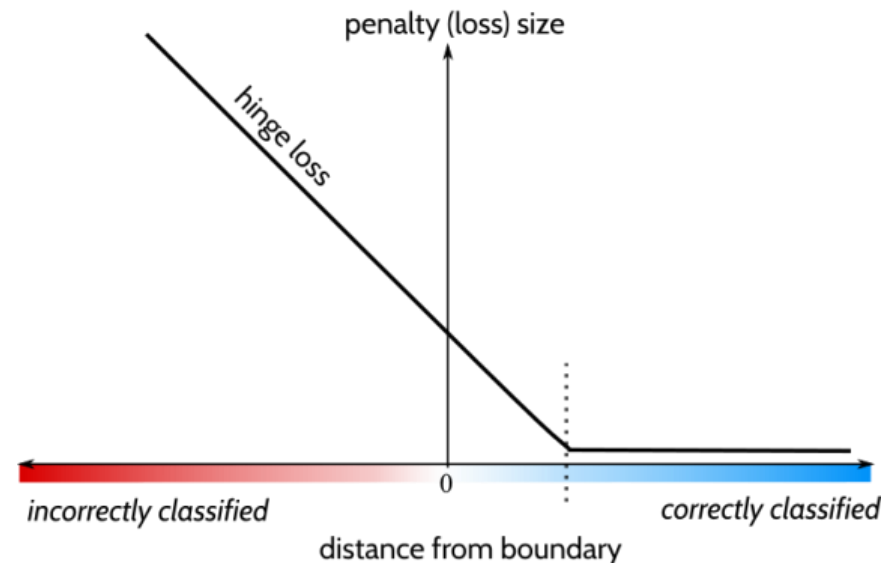
Hinge Loss is one of the types of Loss Function, mainly used for maximum margin classification models.

Hinge Loss incorporates a margin or distance from the classification boundary into the loss calculation. Even if new observations are classified correctly, they can incur a penalty if the margin from the decision boundary is not large enough.

$$L = \max(0, 1 - y_i (w^T x_i + b))$$

0 - for correct classification

1 - for wrong classification



## Hinge Loss

### **Misclassification :**

$$y_i = 1 \quad \hat{y}_i = -1$$

$$L = (1 - (1)(-1))$$

$$L = (1 + 1)$$

$$L = 2 \text{ (High loss Value)}$$

$$y_i = -1 \quad \hat{y}_i = 1$$

$$L = (1 - (-1)(1))$$

$$L = (1 + 1)$$

$$L = 2 \text{ (High loss Value)}$$

$$L = \max(0, 1 - y_i (w^T x_i + b))$$

0 - for correct classification

1 - for wrong classification

### **Correct classification :**

$$y_i = 1 \quad \hat{y}_i = 1$$

$$L = (0 - (1)(1))$$

$$L = (0 - 1)$$

$$L = -1 \text{ (Low loss Value)}$$

$$y_i = -1 \quad \hat{y}_i = -1$$

$$L = (0 - (-1)(-1))$$

$$L = (0 - 1)$$

$$L = -1 \text{ (Low loss Value)}$$