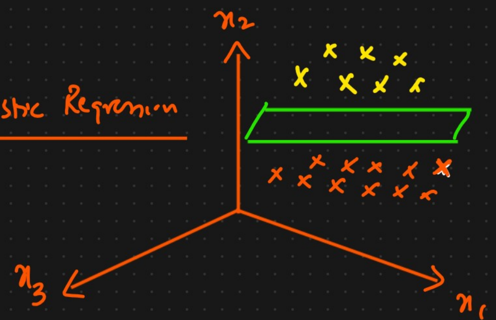
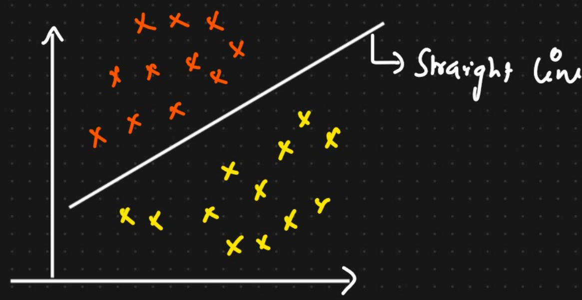
Support Vector Machines ML Algorithms.

① SVC (Support Vector Classifier)

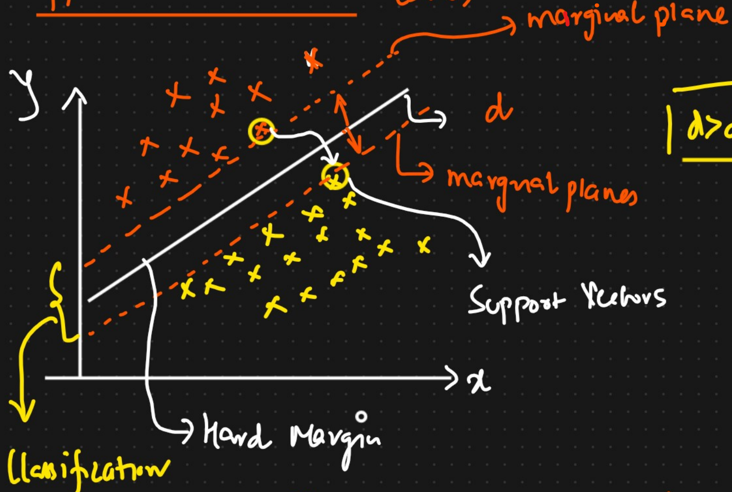
② SVR (Support Vector Regressor)

Logistic Regression

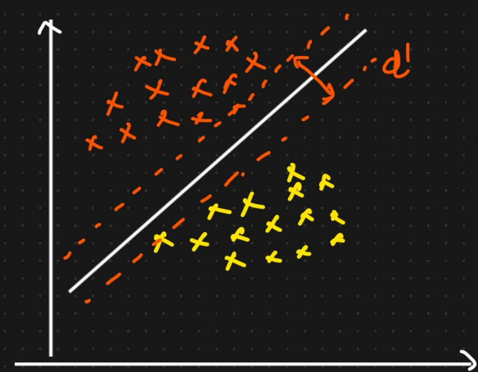


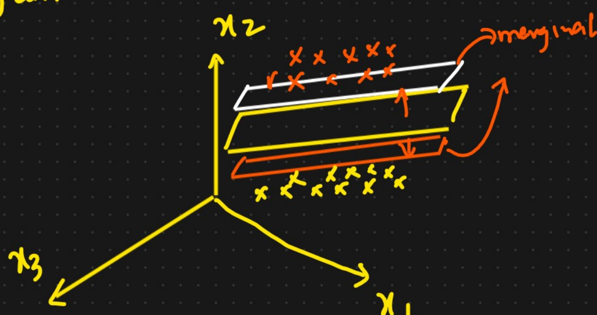


① Support Vector Machine (SVC)



$\boxed{d > d'}$





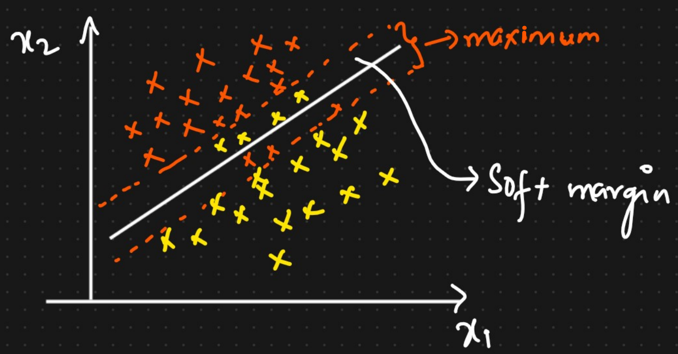
Soft Margin :-

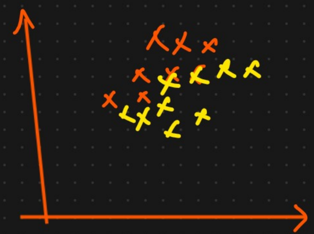
- We get some errors bcoz in real life, there are some overlapping points.
- And not clearly separated.

Hard Margin :-

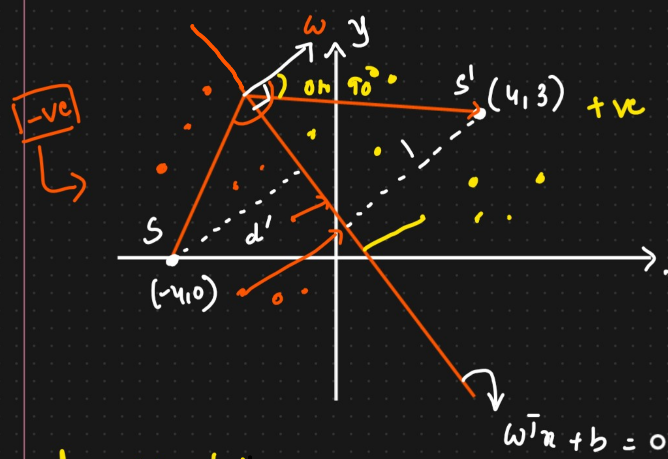
- Don't get any error. Points are clearly
- separated.

Soft Margin And Hard Margin In SVM





⊛ Support Vector Machines (SVC) Maths Intuition



$ax + by + c = 0$

$\Downarrow$

$w_1 x_1 + w_2 x_2 + b = 0$

$\boxed{w^T x + b = 0}$ W→Perpendicular to the line

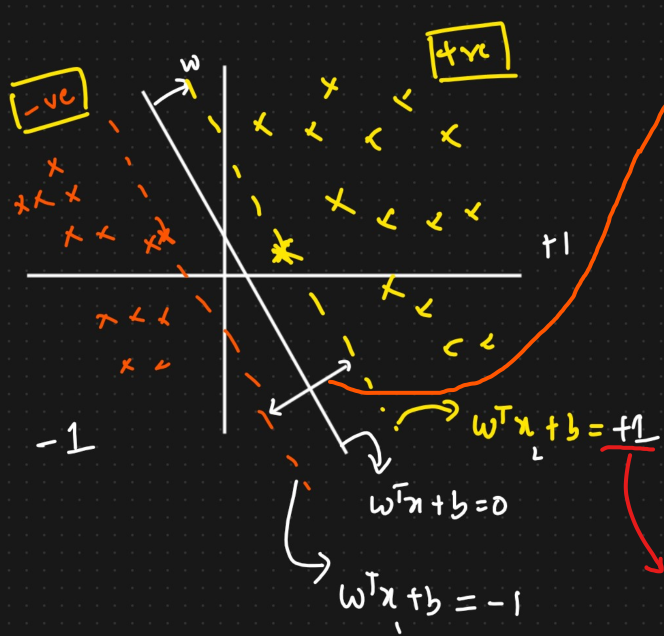
$\Downarrow$

$b = 0$

$\boxed{w^T x = 0}$

d= -ve below plane

d= +ve above plane



Our aim is to maximize this distance.

$w^T x_1 + \cancel{b} = 1$

$w^T x_2 \cancel{+ b} = -1$

(-) (-) (+)

$$\frac{w^T (x_1 - x_2)}{\|w\|} = \frac{+2}{\|w\|}$$

Unit vector {Magnitude of the vector is 1}

Bcoz after this in right direction value will be +ve.

Cost function

$$\underset{w,b}{\text{Maximize}} \quad \frac{2}{\|w\|}$$ ⇒ Distance between marginal plane

⇗ correctly classified point

Constraint such that $y_i \begin{cases} +1 & w^Tx+b \geq 1 \\ -1 & w^Tx+b \leq -1 \end{cases}$

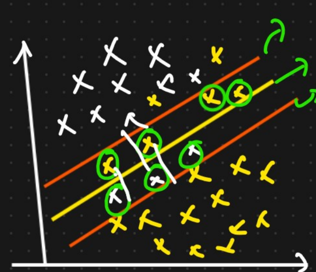
For all correct points

↑ predicted points

Constraint ⟶ $\boxed{y_i * (w^Tx+b) \geq 1}$

$\boxed{C_i = 6}$ ✓

$$\underset{w,b}{\text{Maximize}} \quad \frac{2}{\|w\|} \Rightarrow \boxed{\underset{(w,b)}{\text{Min}} \quad \frac{\|w\|}{2}}$$



- Soft Margin SVM Optimization

Cost function of SVM (SVC)

hyperparameter

$$\underset{w,b}{\text{Min}} \quad \frac{\|w\|}{2} + \boxed{C_i \sum_{i=1}^{n} \xi_i} \Rightarrow \boxed{\text{Hinge Loss}}$$

Hinge Loss is a loss function utilized within machine learning to train classifiers that optimize to increase the margin between data points and the decision boundary.

{How many points we want to avoid misclassification}

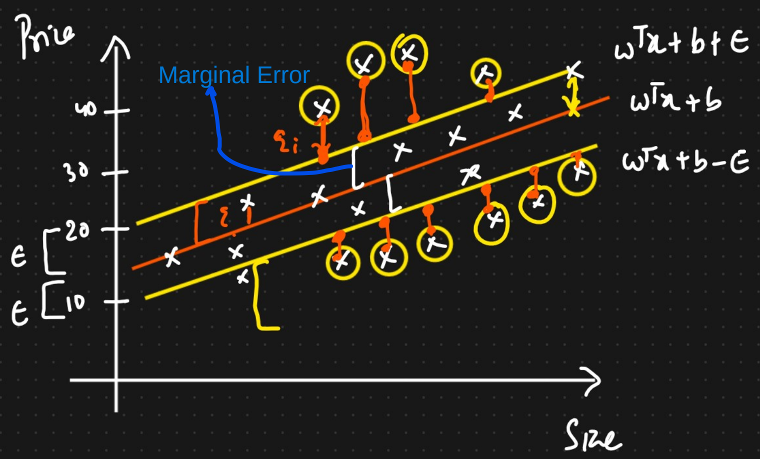
{Summation of the distance of the incorrect data points from the marginal plane}

⇓

Soft margin

Support Vector Regression

ϵ : Marginal Error



- Our main aim should be basically create best fit line along with marginal plane in such that distance b/w predicted point & real point, if I do the summation, it should be less.

Cost function

$$\min_{w,b} \frac{\|w\|}{2} + \boxed{C \sum_{i=1}^{n} \xi_i}$$

Hyperparameter

→ Hinge Loss

Relationship
C ↑↑
Loss function ↓

Constraint :

Truth point

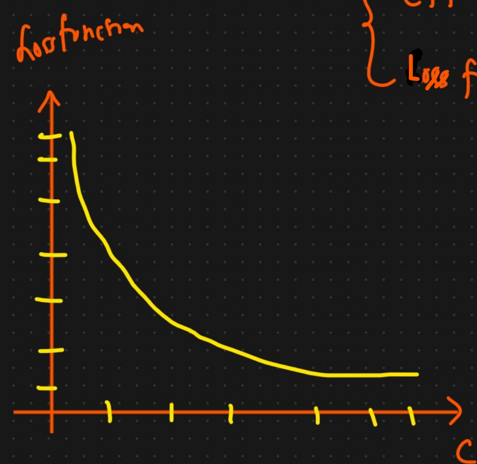
Predicted point

$$|y_i - w_i x_i| \leq \epsilon + \xi_i$$

That means model is performing well.

⇓

kind of loss function



ϵ → margin Error (Data points In b/w the marginal plane)

ξ_i → Error above the margin

(Data points above the marginal plane)