

# Data Science & AI



## Machine Learning



Unsupervised Learning

Lecture No.- 01



By- Krish Naik Sir

# Recap of Previous Lecture



Topic

Random Forest Classifier

Topic

KNN

K-means

Topic

Topic

Topic

# Topics to be Covered



Topic

SVM

Topic

PCA

Topic

Topic

Topic

# Machine Learning

① SVM (SVC and SVR) ✓

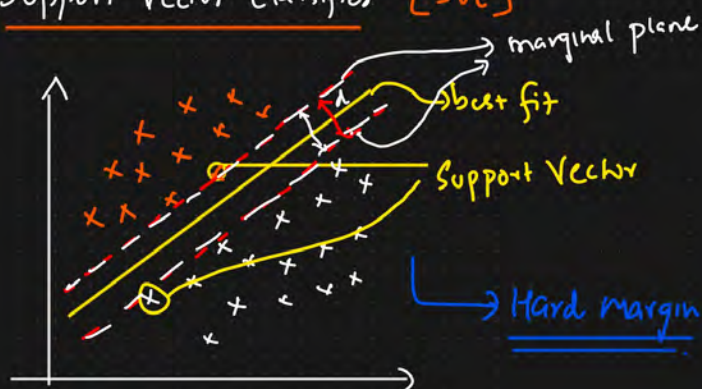
② PCA [Curse of dimensionality, Dimensionality Reduction] ✓✓

## ① Support Vector Machines

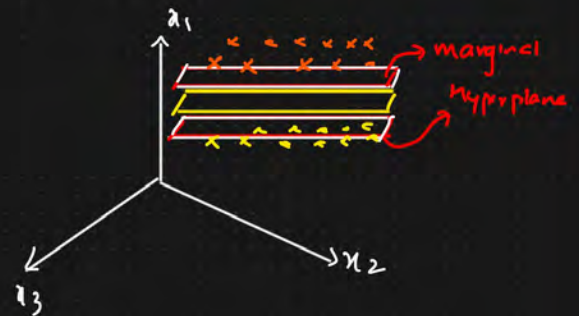
① Support Vector Classifier [SVC]  $\Rightarrow$  Classification.

② Support Vector Regressor [SVR]  $\Rightarrow$  Regression.

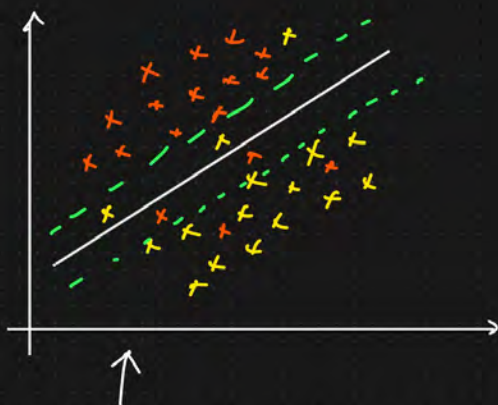
### i) Support Vector Classifier [SVC]



$d =$  marginal plane distance



### Soft Margin And Hard Margin In SVC



Soft Margins : Some data points are Misclassified.



# Support Vector Machine Intuition

## Equation of a straight line

$$y = mx + c \Leftrightarrow ax + by + c = 0$$

$$h(x) = \theta_0 + \theta_1 x_1$$

$$by = -ax - c$$

$$y = \left[ \frac{-a}{b} \right] x - \left[ \frac{c}{b} \right]$$

$\hookrightarrow m$        $\downarrow c$

$$y = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3$$

$$y = b + [w_1 x_1 + w_2 x_2 + w_3 x_3]$$

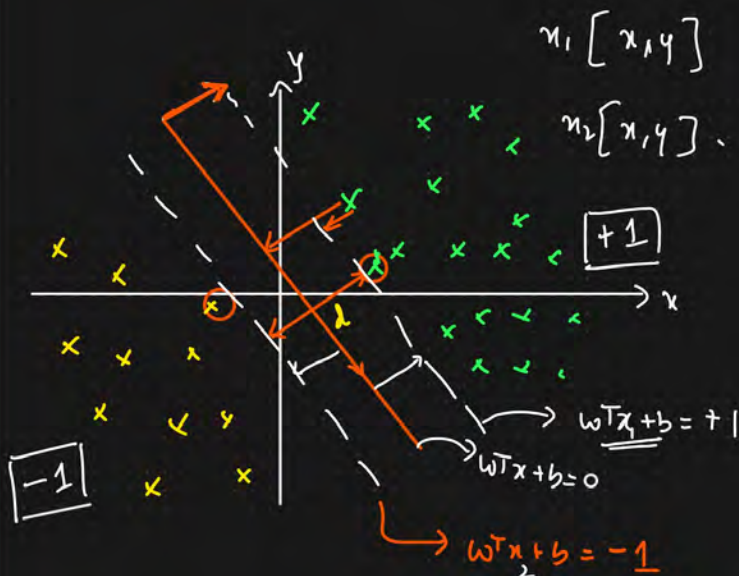
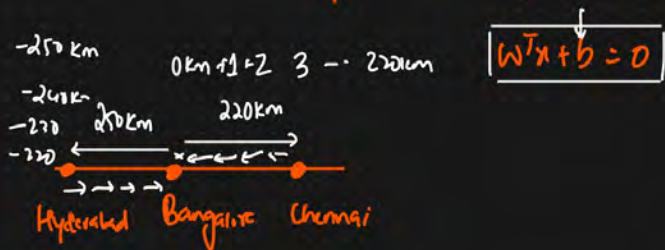
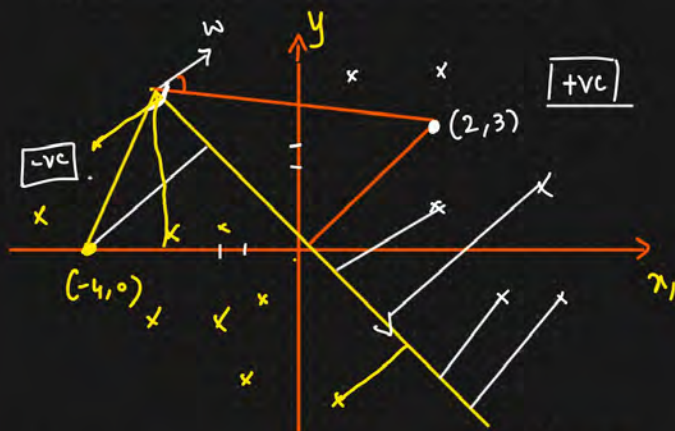
$$w = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} \quad x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

$$w^T \cdot x = [w_1 \ w_2 \ w_3] \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

$$y = w^T x + b$$

$$w^T x + b = +K$$

$$w^T x + b = -K$$



$$w^T x_1 + b = +1$$

$$w^T x_2 + b = -1$$

(-)      (-)      (+)

$$\frac{w^T (x_1 - x_2)}{\|w\|} = \frac{2}{\|w\|} \Rightarrow \text{Distance between marginal planes.}$$

## Cost fn

Maximize  
 $w, b$

$$\frac{2}{\|w\|}$$

$\Rightarrow$  Distance between Marginal planes.

Constraint such that

$$y_i \begin{cases} +1 & \text{if } w^T x + b \geq 1 \\ -1 & \text{if } w^T x + b \leq -1. \end{cases}$$

For all correct classified data points

$$y_i * [w^T x + b] \geq 1.$$

## Modified Cost fn

maximize  
 $w, b$

$$\frac{2}{\|w\|}$$

$$\Rightarrow \left\{ \begin{array}{l} \text{Minimize} \\ w, b \end{array} \frac{\|w\|}{2} \right\}$$

Constraint such that

$$y_i \begin{cases} +1 & \text{if } w^T x + b \geq 1 \\ -1 & \text{if } w^T x + b \leq -1. \end{cases}$$

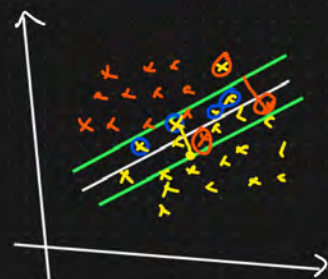
$\Rightarrow$  Hard Margin

## Cost fn of SVC [Soft Margin]

$$\text{Cost fn} = \min_{w, b} \frac{\|w\|}{2} + \left[ C_i \sum_{i=1}^n \xi_i \right] \Rightarrow \text{Hinge Loss}$$

$$\text{Hyperparameter} = \{ C_i \rightarrow \}$$

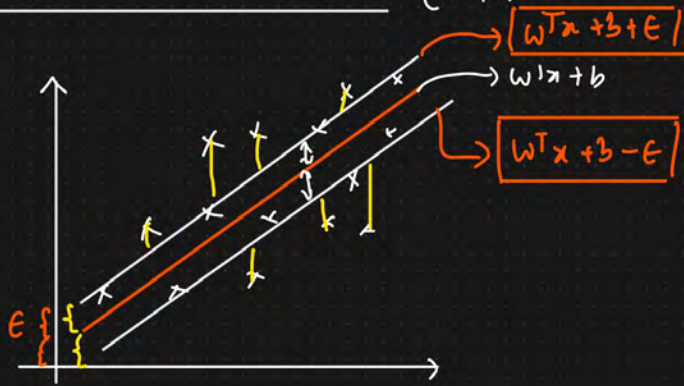
$\downarrow$   
 $\{ \text{Summation of the distance of incorrect data points from marginal plane} \}$





↓  
 { How many datapoints we  
 can consider for  
 misclassification }.

## ④ Support Vector Regressor (SVR)



Cost fn

$$\min_{w, b} \frac{\|w\|}{2} + \boxed{C \sum_{i=1}^n \zeta_i} \Rightarrow \text{Hinge Loss}$$

Constraint

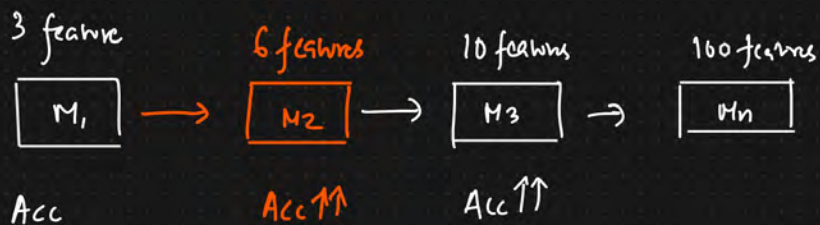
$$\boxed{|y_i - w^T x_i| \leq \epsilon + \zeta_i} \Rightarrow \text{Minimize Error}$$

$\epsilon \Rightarrow$  Marginal Error

$\zeta_i \Rightarrow$  Error above the Margin.

# Principal Component Analysis [PCA] [Dimensionality Reduction]

## ① Curse of Dimensionality



## Reduce the Dimensions

### ① Feature Selection

$\downarrow$   
Imp features

### ② Dimensionality Reduction (PCA)

$\downarrow$   
Feature Extraction

$\downarrow$

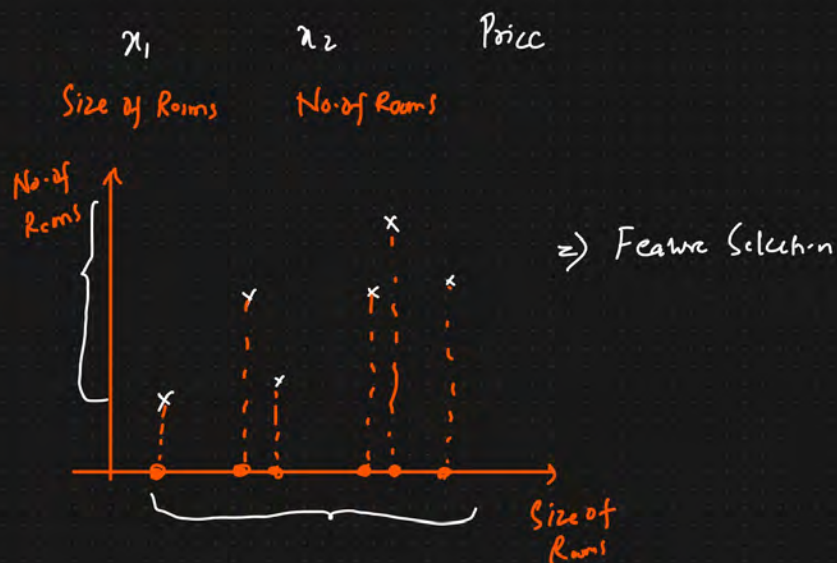
PCA

$\downarrow$

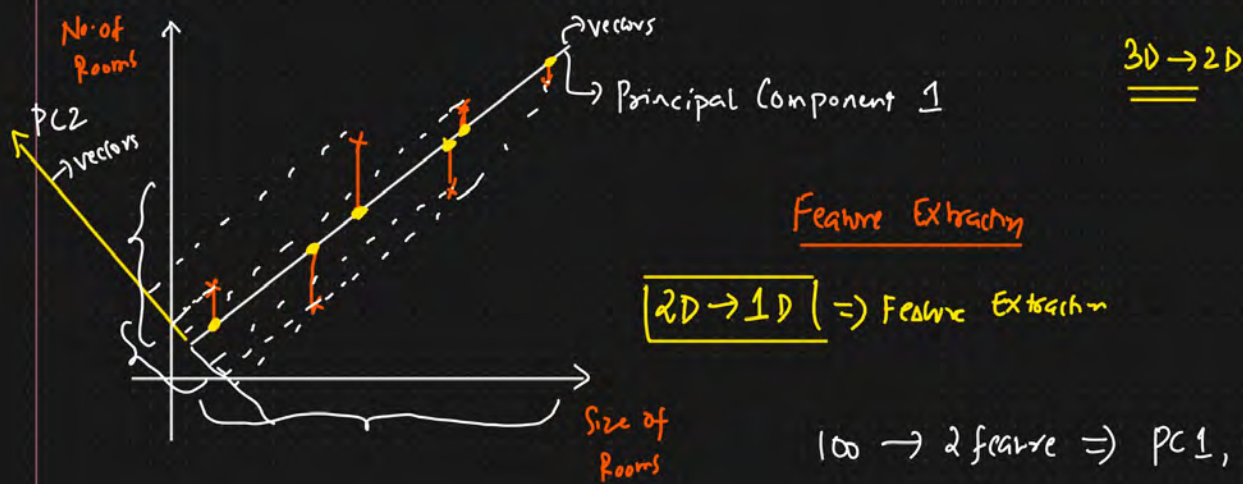
Eigen Values And Vectors

[100 features]  $\downarrow$  [20 features]  $\Rightarrow$  Variance Information Captured

## PCA Geometric Intuition





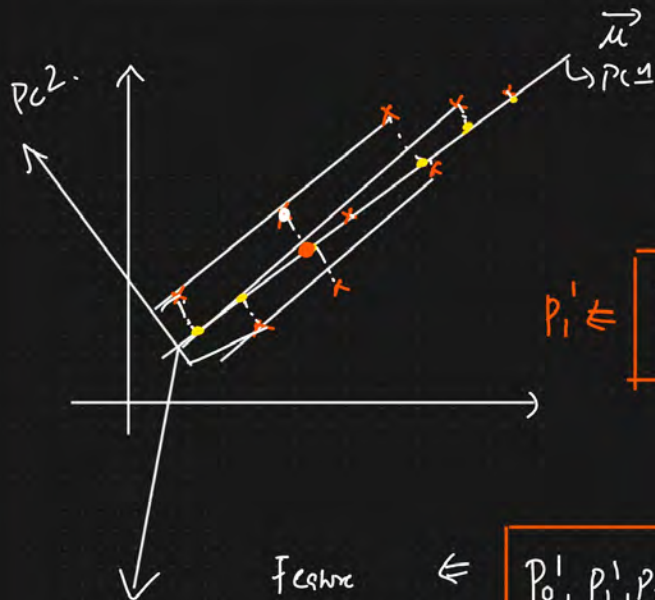


100  $\rightarrow$  2 feature  $\Rightarrow$  PC1, PC2

100  $\rightarrow$  3 features  $\Rightarrow$  PC1, PC2, PC3.

$\Rightarrow$  PC1.

Mathematical Intuition behind PCA Algorithms



① Projection

② Optimization  $\rightarrow$  Max Variance

$$P_1' \in \boxed{\text{Proj}_{P_1} \mu = P_1 \cdot \mu} = \begin{bmatrix} x_1 & y_1 \end{bmatrix} \begin{bmatrix} x_2 \\ y_2 \end{bmatrix}$$

$\Leftarrow x_1 x_2 + y_1 y_2 \Rightarrow$  Scalar Value.

Feature Extracted  $\Leftarrow \boxed{P_0', P_1', P_2', P_3', P_4' \dots P_n'}$

$\Downarrow$   
Scalar value

$\Downarrow$   
Max Variance

Q)  $\rightarrow$  How to find the vectors?

# Eigen Value Decomposition $\Rightarrow$ Eigen values And Eigen Vector

① Covariance Matrix between Features.  $\text{Cov}(f_1, f_2)$

100  $\rightarrow$  50

② Eigen values and Eigen vector will be computed

$\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5$

Using the Covariance Matrix =  $\boxed{A \cdot v = \lambda \cdot v}$

$\downarrow$                        $\downarrow$   
Covariance      Eigen value  
Matrix

③ Eigen Vector  $\rightarrow$  Eigen Values  $\rightarrow$  Capture the Maximum Variance

$\text{Cov}(x, y)$

$A =$

	x	y
x	$\text{Var}(x)$	$\text{Cov}(x, y)$
y	$\text{Cov}(x, y)$	$\text{Var}(y)$

$$\boxed{A \cdot v = \lambda \cdot v}$$

$$\begin{array}{cc} \lambda_1 & \lambda_2 \\ \downarrow & \downarrow \\ p_{c1} & p_{c2} \end{array}$$

3D  $\rightarrow$  2D

$$\boxed{\lambda_1, \lambda_2} \Rightarrow \text{Eigen values}$$

# THANK - YOU