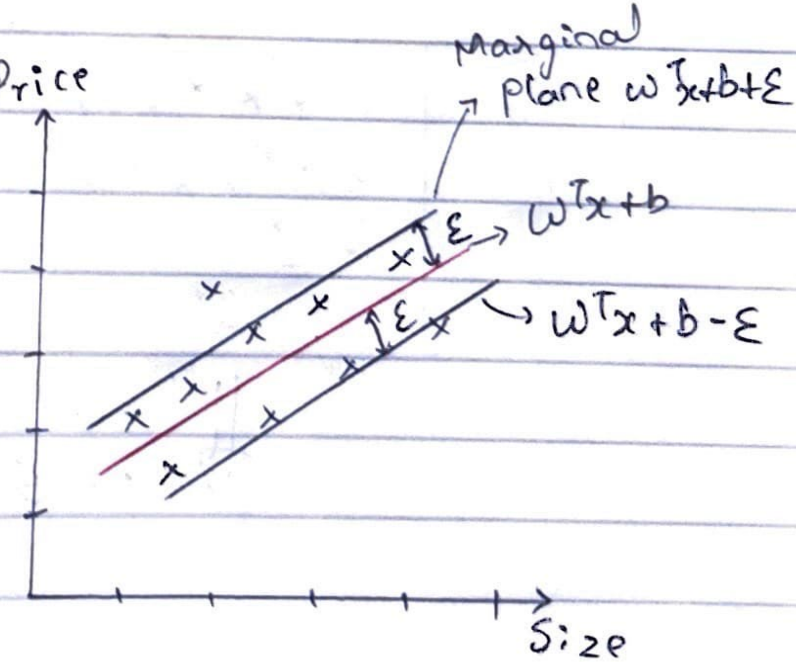
II Support vector regressor (SVR)

Best fit line → $w^T x + b$

Marginal planes → $w^T x + b + \varepsilon$

$w^T x + b - \varepsilon$



Cost function

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

Constraint

$\xi_i \rightarrow$ Summation of datapoint to marginal plane

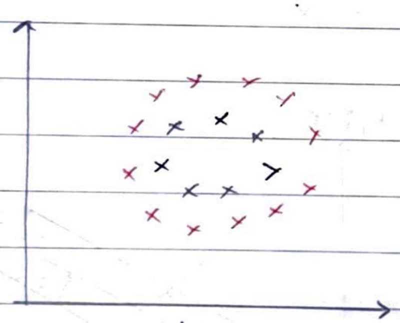
$|y_i - w^T x_i| \leq \varepsilon + \xi_i$

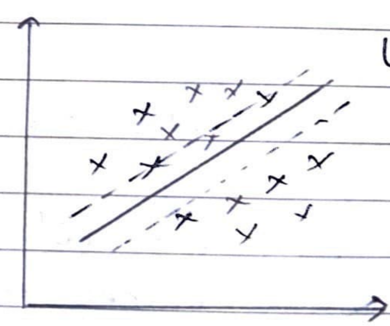
* The diff. b/w real & predicted data point should be less than ε

$\varepsilon \rightarrow$ Marginal error
$\xi_i \rightarrow$ Error above the margin

—— x —— x —— x ——

SVM Kernels



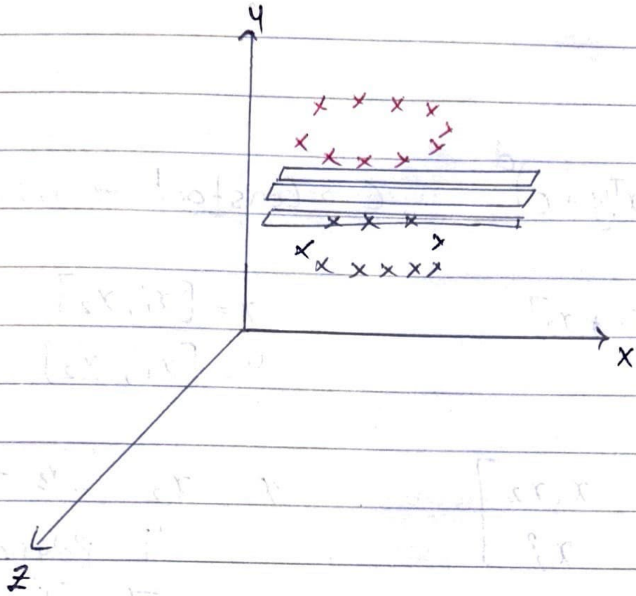


Linear SVC

$\Downarrow$

$\rightarrow$ SVM Kernels (transforms the datapoints
$\Downarrow$ Transforms (changing feature)

Mathematical formula
to make changes in features
2D $\rightarrow$ 3D
Two feature $\rightarrow$ 3 feature



Example :-

Dataset

	x	y
4	2	Yes
16	4	No
36	6	Yes
64	8	Yes

↓ ploting

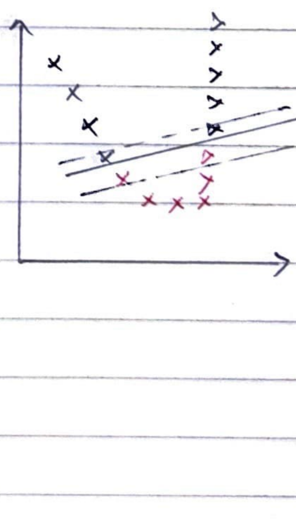
After Transformation

SVM Kernel

Transformation

Creating new feature

~~y = x~~ $Z = x^2$



Types of Kernel

1. Polynomial kernel
2. RBF kernel
3. Sigmoid Kernel

i) Polynomial kernel

$$f(x,y) = (x^T y + c)^d$$

$c \rightarrow$ Constant $\rightarrow 1, 2, 3$

$$= \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} * [x_1 \; x_2]$$

$x = [x_1, x_2]$

$y = [x_1, x_2]$

$$= \begin{bmatrix} x^2 & x_1 x_2 \\ x_1 x_2 & x_2^2 \end{bmatrix}$$

$x_1 \quad x_2 \quad y \rightarrow 2D$

$\Downarrow$ Polynomial Transformation

$x_1^2 \quad x_1 x_2 \quad x_2^2$