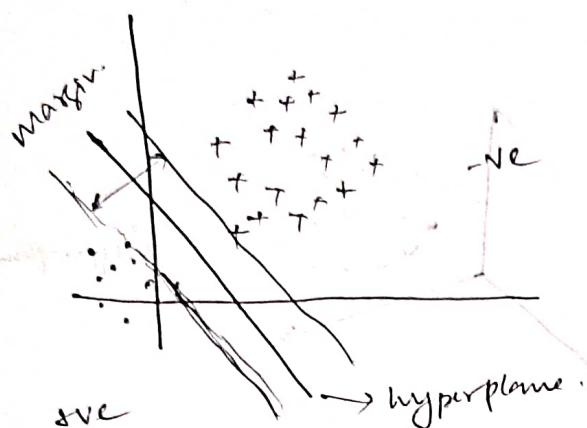


SVM

→ Basic steps:

1. Select 2 hyperplane (2D) which separates data with no points b/w them.
2. Maximise distance.
3. Average line will be decision boundary.



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

Let $b = 0$,
 $y = w^T x$

So this case,
 $w^T x + b \geq 1$ for $y_i = +1$
 i.e. positive region

& vice-versa.

$$\therefore y_i (w^T x_i + b_i) \geq 1$$

\therefore Optimization function = (w^*, b^*) for $\max \frac{2}{\|w\|}$

For this case

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

(grad. descent)

For this case:

$$(w^*, b^*) = \min \frac{\|w\|}{2}$$

$$+ c \sum_{i=1}^n \xi_i$$

Regularization (hyperparameter)

How many errors can model can consider

Summation of values of error

→ SVM Kernels for Non-linear cases.

Types of Kernels:-

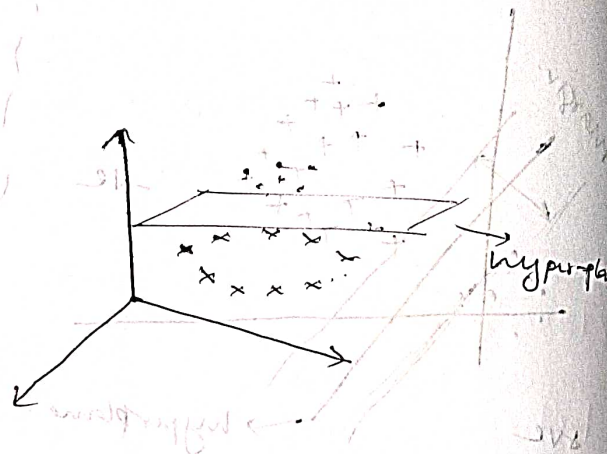
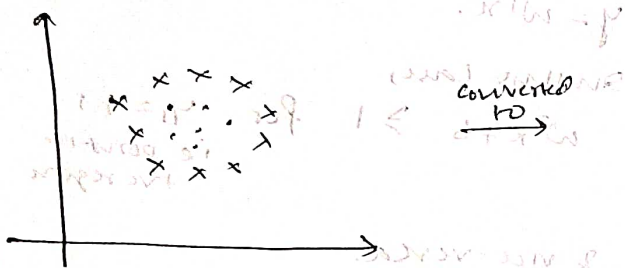
- i. Polynomial Kernels
- ii. RBF Kernels
- iii. SIGMOID Kernels.

MVC

SOME TERMS:

1. Hard Margin - No error
2. Soft Margin - Some errors

→ How does kernel work.

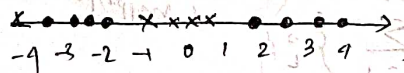


In this example 2d to 3d.

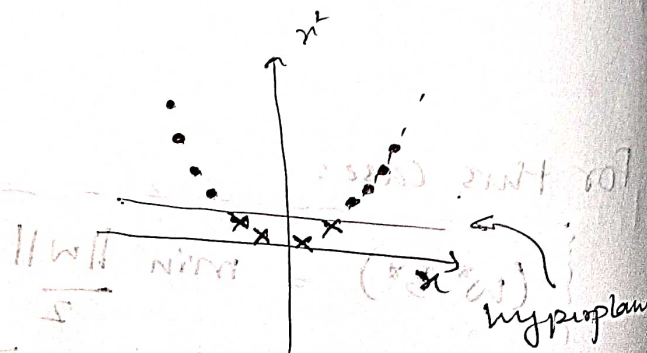
→ SVM kernel does some kind of transformation from lower to higher dimension.

Polynomial Kernel

1-D



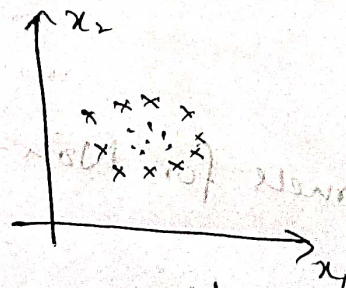
Squaring



Convert 1D to 2D

$$f(x_1, x_2) = (x_1^T \cdot x_2 + 1)^d$$

Vector operation



$$y = f(x_1, x_2),$$

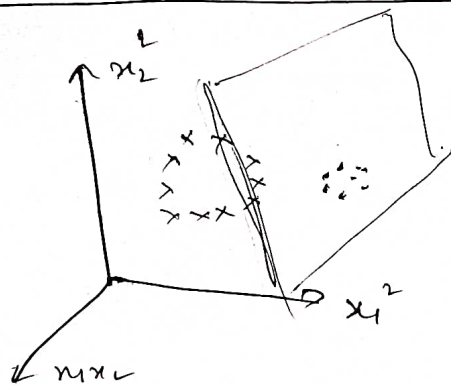
$$\therefore f(x_1, x_2) = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \cdot \begin{bmatrix} x_1 & x_2 \end{bmatrix} + 1$$

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

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

$\therefore x_1 \quad x_2 \quad y \quad x_1^2 \quad x_2^2 \quad x_1 x_2$ } Use all 5 to create hyperplane. 5 dimensions.

Using only $x_1^2, x_2^2, x_1 x_2$



Generalized

$$K(x_i, x_j) = (x_i x_j + 1)^d$$

RBF Kernel

$$K(x_i, x_j) = e^{-\gamma (\|x_i - x_j\|)^2}$$

Almost like ... seeing neighbourhood elements. Different from k-means.

Sigmoid Kernel

$$K(x, y) = \tanh(x^T y + c)$$

→ Hyper-Parameters to tune:

- (i) Regularization (C & errors)
- (ii) Gamma (γ) (Distance factor from neighbours etc.)
- (iii) Margin
- (iv) Kernel type

