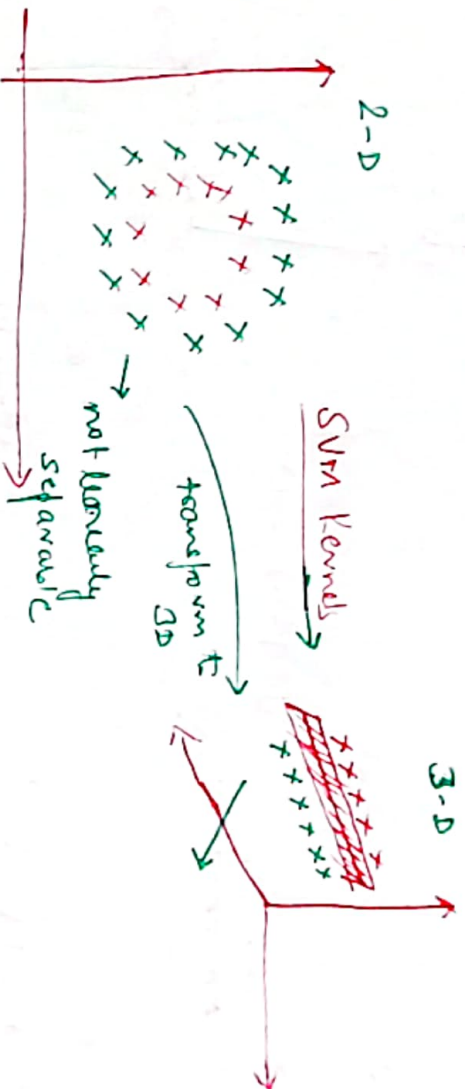
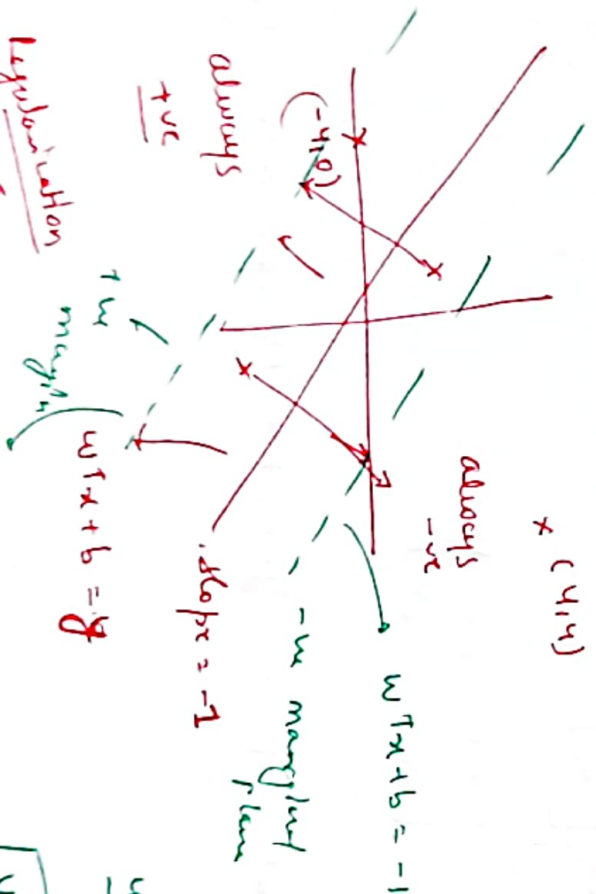


→ SVM classifier.

- Eff
- we should maximise $D_2 \uparrow$.
 - support vectors are the ones that touch the m_1 & m_2 .



SVM maths intuition



$$w^T (x_2 - x_1) = 2$$

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

now can use GD & other min

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

maximise this

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

$$y_i \cdot x (w^T x + b) \geq 1$$

min $\frac{\|w\|}{2} + C_i \sum_{i=1}^n \xi_i$ value of the error.

How many error my model can

if this not the case this is a mis classification.

SVM Kernels

- Polynomial Kernels

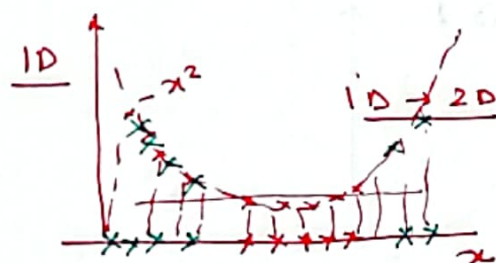
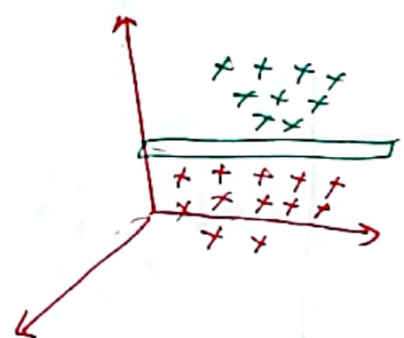
- RBF Kernels
- Sigmoid Kernels

Some kind of transformation from lower dimension to higher dimensions.

[Soft margin - $C > 1$
hard margin



↓ SVM Kernel
3D



$$y = f(x) = x^2$$

Polynomial Kernel:

$$f(x_1, x_2) = (x_1^T x_2 + 1)^d \quad d \rightarrow \text{dimension}$$

$$x_1 \mid x_2 \mid y_0 \mid x_1^2 \mid x_2^2 \mid x_1 x_2 \mid \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \begin{bmatrix} x_1 & x_2 \end{bmatrix}$$

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

what to use polynomial, rbf or sigmoid? \rightarrow hyperparameter tuning.

KNN Limitations:-

- ① Cannot be used efficiently with huge data sets.
- ② Outliers impact this algorithm hugely. sensitive to outliers.
- ③ sensitive to missing values.

SVM Regression

$$w^T x + b + \epsilon = 0$$

$$w^T x + b = 0$$

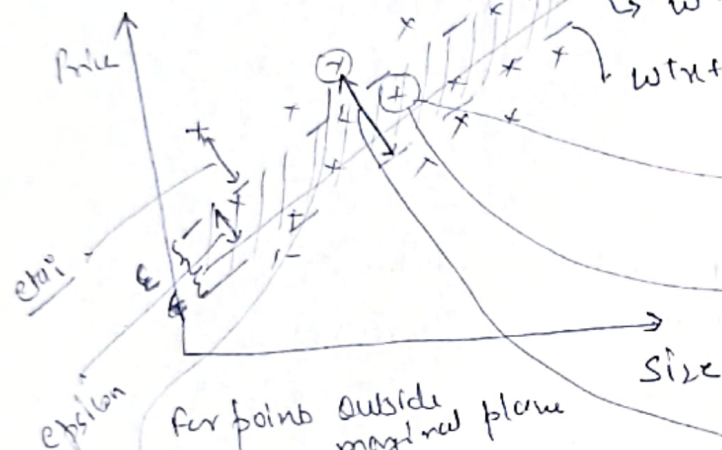
$$w^T x + b - \epsilon = 0$$

① Fit a line like a linear regression to the data

② find a marginal plane

for points inside marginal plane

$$\text{lost fn} = \min_{(w, b)} \frac{\|w\|}{2}$$



for points outside marginal plane

min (w, b)

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

how many points we can adjust outside the marginal plane

constraint

$$|y_i - \frac{w^T x_i}{g}| \leq \epsilon \text{ (epsilon)}$$

It is a good predⁿ

distance b/w the point & marginal plane

C, ξ

hyper parameters / hinge loss.



constraint

$$|y_i - w^T x_i| \leq \epsilon + |\xi_i| \text{ (eta)} /$$