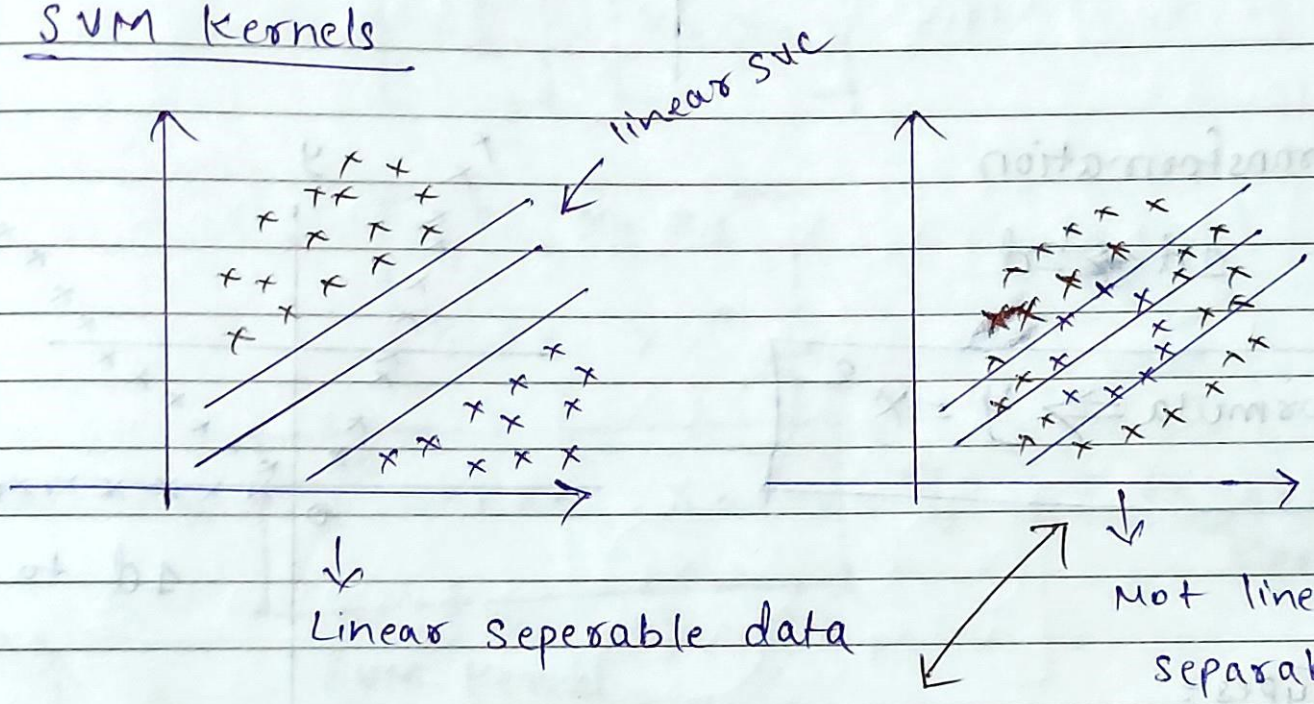
SVM Kernels and Roc Auc Curve

Agenda

1. SVM Kernels
2. Roc AUC Curve

SVM Kernels

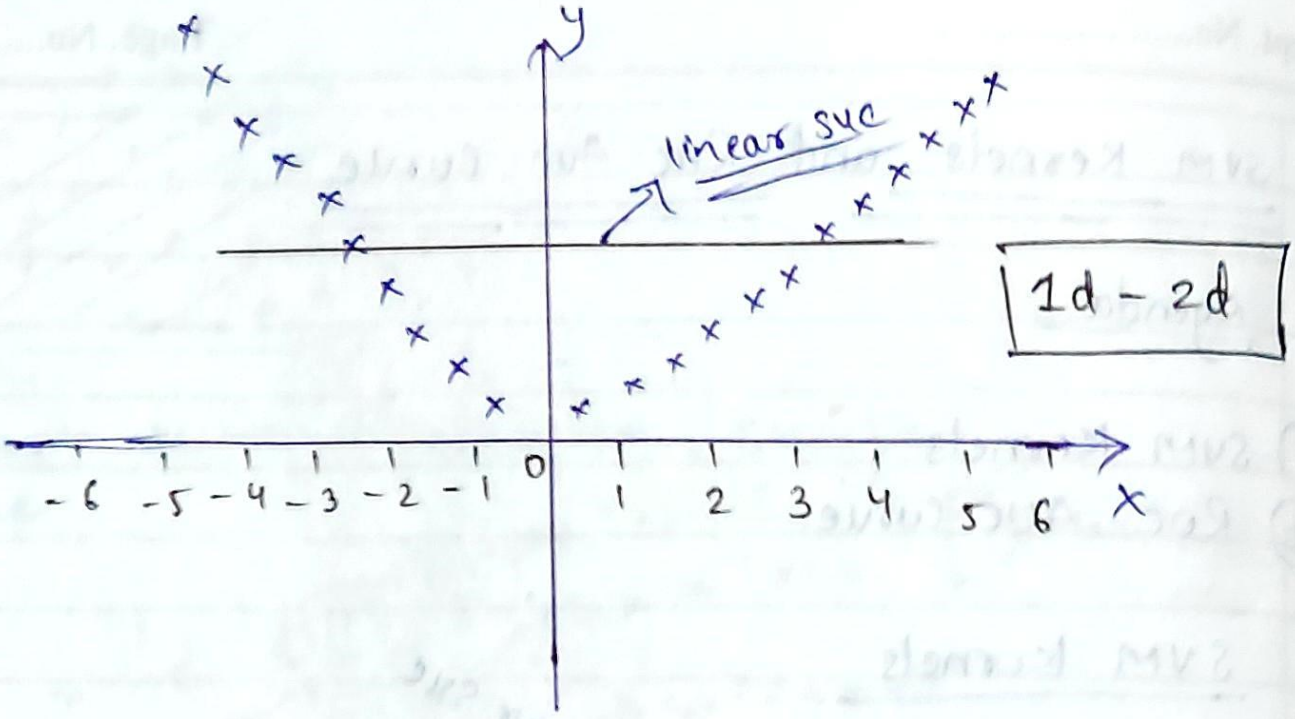


for Non-Linear Separable data we use SVM Kernel which increases dimension

SVM Kernel → Transformation → Increase the Dimension

↓

Mathematical formula

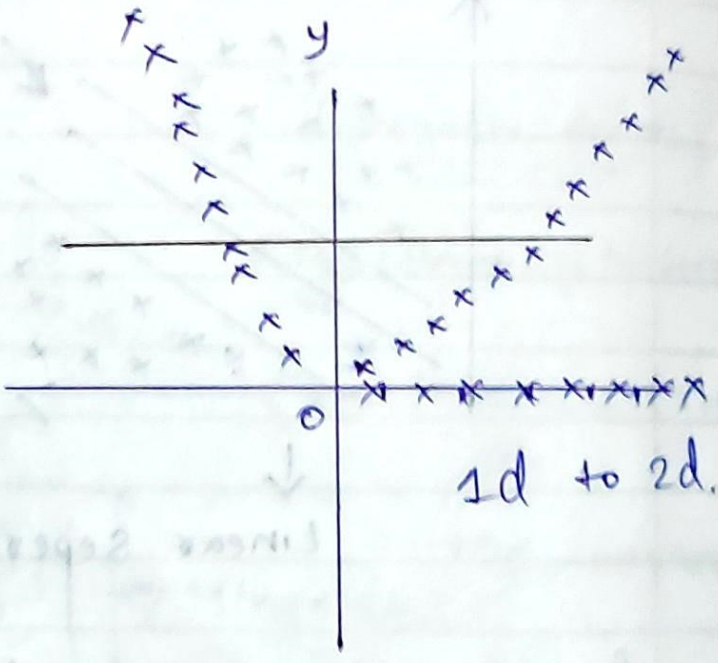


1d - 2d

Transformation

1d ↔ 2d

formula ⇒ $y = x^2$



1d to 2d.

Types :-

SVM Kernels

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

Date.....

Expt. No..... Page. No.....

(1) Polynomial Kernel

formula

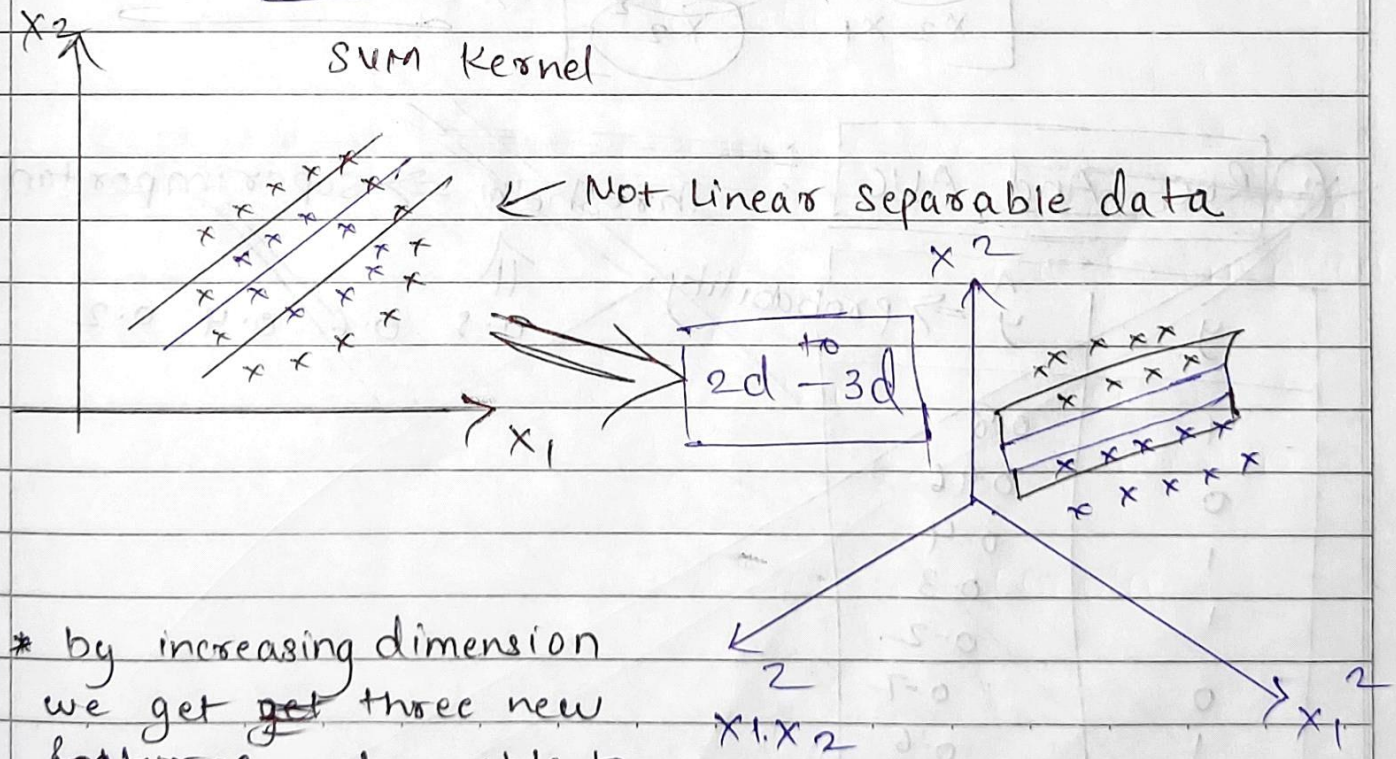
$$f(x_1, x_2) = (x_1^T \cdot x_2 + 1)^d$$

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \cdot \begin{bmatrix} x_1 & x_2 \end{bmatrix} \Rightarrow \text{Dot operation}$$

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

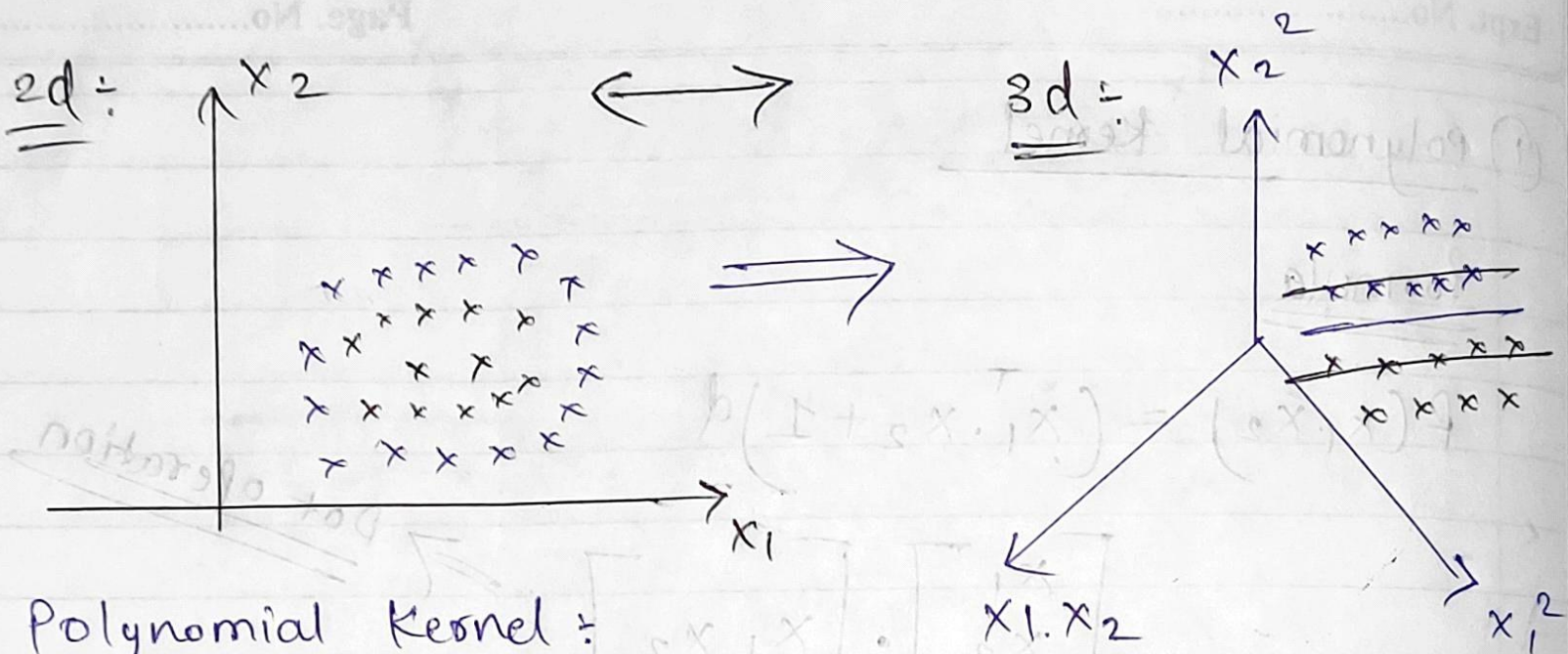
x_1 x_2 $\begin{bmatrix} x_1^2 & x_1 \cdot x_2 & x_2^2 \end{bmatrix}$ o/p $\Rightarrow$ Polynomial Kernel

SVM Kernel



* by increasing dimension we get ~~get~~ three new features, and we able to separate data

Teacher's Signature.....



Polynomial Kernel :

Formula :

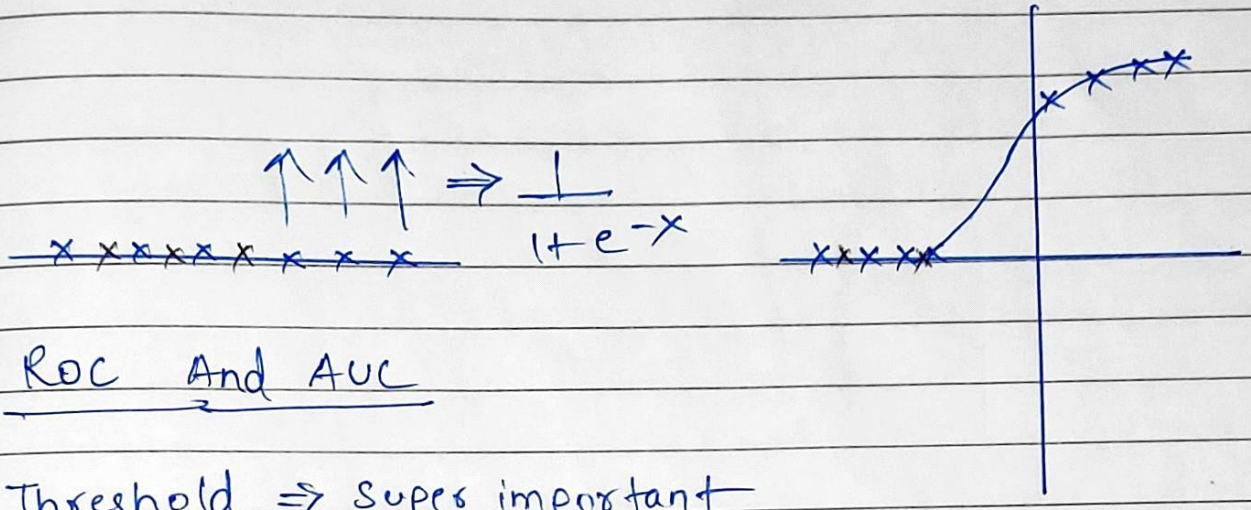
$$f(x_1 x_2) = (x_1^T \cdot x_2 + 1)^d$$

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \cdot \begin{bmatrix} x_1 & x_2 \end{bmatrix}$$

x_1	x_2	x_1^2	$x_1 \cdot x_2$	x_2^2	y
—	—	—	—	—	
—	—	—	—	—	
—	—	—	—	—	

$$\begin{bmatrix} x_1^2 & x_1 \cdot x_2 \\ x_2 \cdot x_1 & x_2^2 \end{bmatrix} \Rightarrow \text{3 new features.}$$

sigmoid Kernel :



① ROC And AUC

Threshold ⇒ super important

0.5 0.6 0.4 0.2

Actual O/P y	Probability $\hat{y}$	$\hat{y}(0)$	$\hat{y}(0.2)$	$\hat{y}(0.4)$
1	0.8	1	1	1
0	0.96	1	1	1
1	0.4	1	1	0
1	0.3	1	1	0
0	0.2	1	0	0
1	0.7	1	1	1

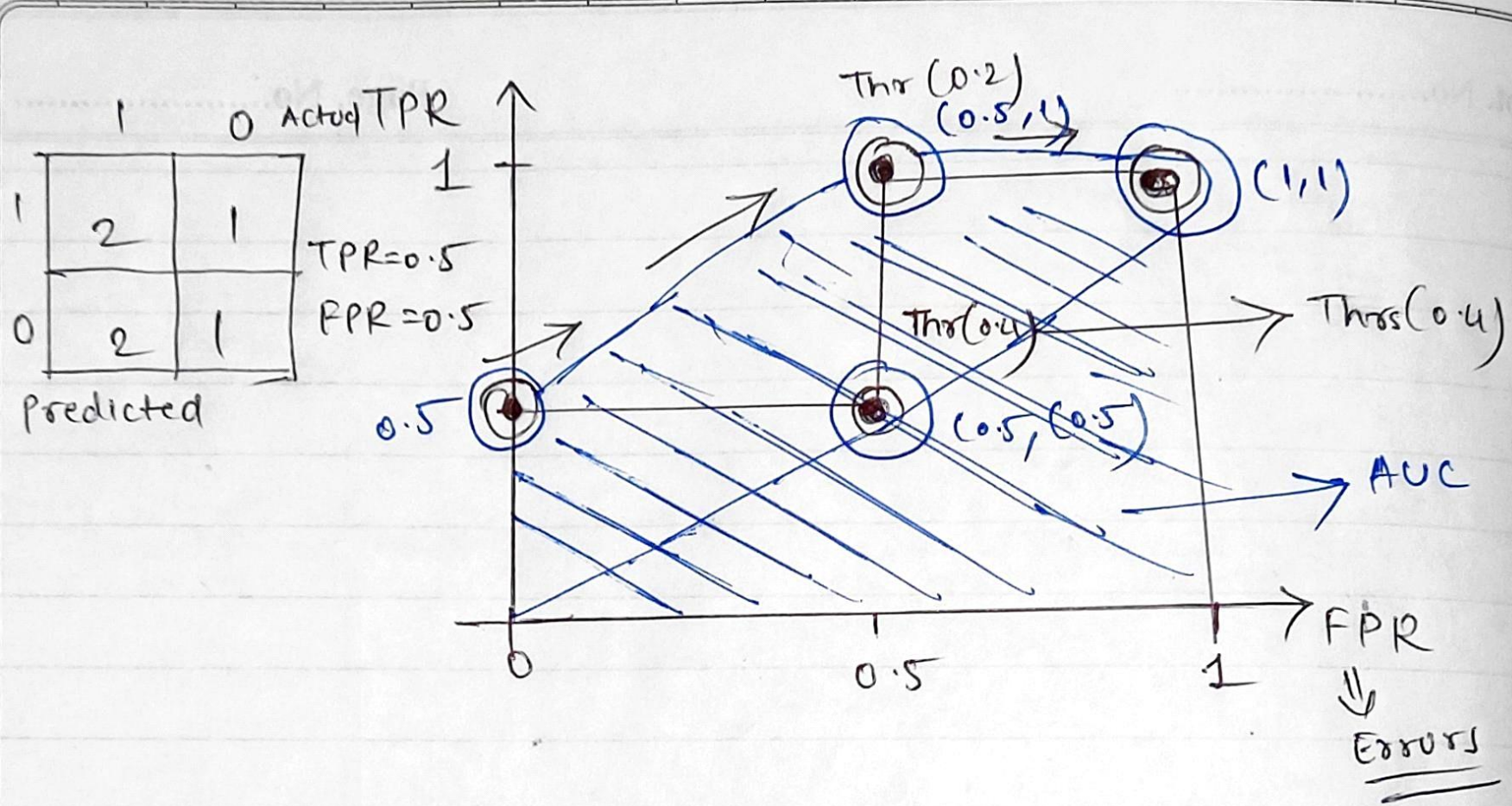
confusion matrix :

Predict \ Actual	1	0
1	4	1
0	0	1

$$TPR = \frac{TP}{TP + FN} = \frac{4}{4+0} = 1$$

$$FPR = \frac{FP}{FP + TN} = \frac{2}{2+0} = 1$$

TPR = 1
FPR = 1


1
0
Actual
1
0
2
1
TPR=0.5
FPR=0.5
Predicted
TPR
1
0.5
Thr (0.2)
(0.5, 1)
(1, 1)
Thr(0.4)
Thr(0.4)
(0.5, 0.5)
AUC
0
0.5
1
FPR
Errors