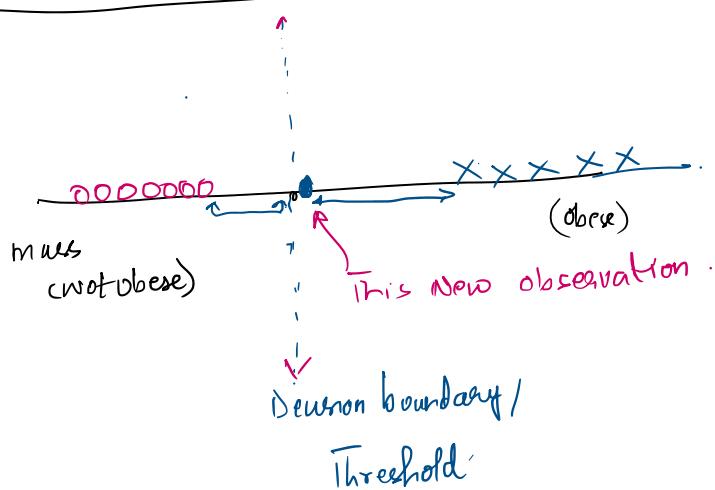


SVM [Support Vector Machine]

Consider \rightarrow



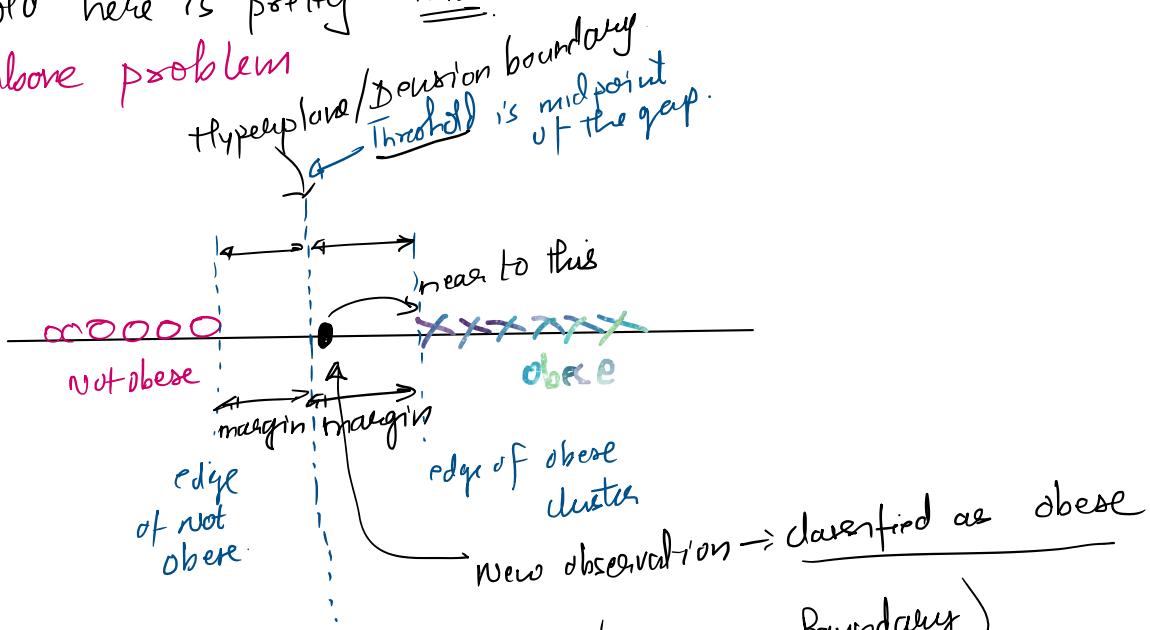
- * Here the new observation will be classified as obese. Even though the new observation is more near to Not obese as compared to obese.

* The threshold here is pretty large.

To Solve the above problem

Consider \rightarrow

We will consider threshold at mid-point of the gap between the edges of clusters



Here the margin is gap betn threshold (Decision Boundary) and the edge of the cluster

\rightarrow then the margin is Maximum

\rightarrow Known as Maximum Margin Classifier

\rightarrow Here in above Case there is No Misclassification

→ Also there are no Outliers

Consider → Here we have outliers in NOT obese (one)

* If we consider Margin as the edge of the cluster considering the Outlier.

* Here the new observation will be classified as not obese, even though it is near to obese.

* Here the Maximum Margin Classifier is very sensitive to outlier.

* Here even though we have outlier, however all the given data points are correctly classified → low Bias

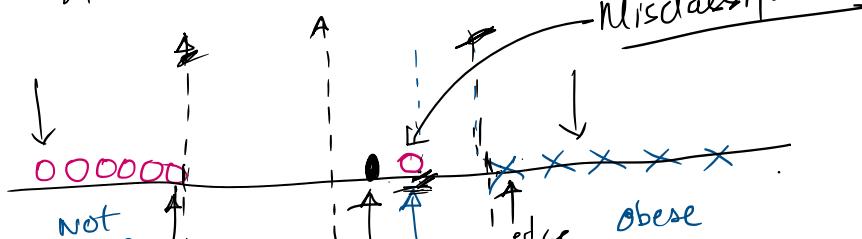
* But for the new observation if incorrectly classified ⇒ high Variance

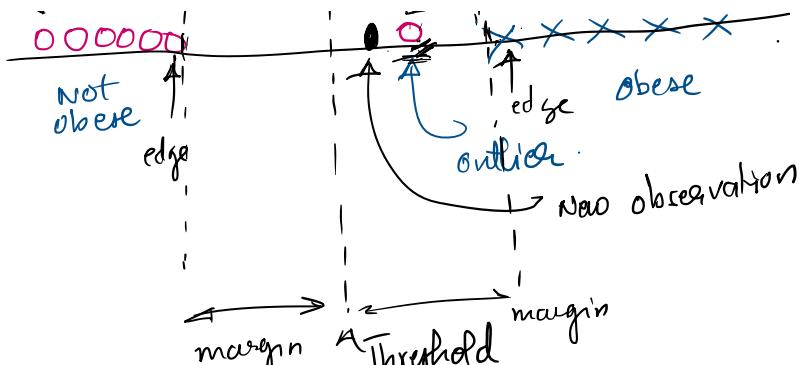
Note > With Hard Margin →

- Misclassification not allowed
- All data points correctly classified ⇒ low Bias
- New observation incorrectly classified ⇒ high Variance

Now: We can do better (To make the threshold Incentive to outlier)

→ For this to happen we must allow Misclassification.





Soft Margin

* Here since while considering edge of cluster, we have allowed misclassification, so the margin now known as soft margin

Note With Soft Margin :-

→ Misclassification is Allowed

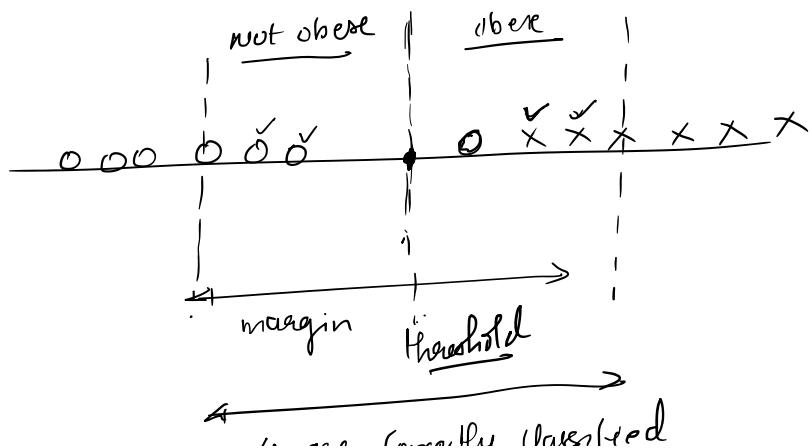
→ All given data points are not correctly classified (outliers). → High Bias

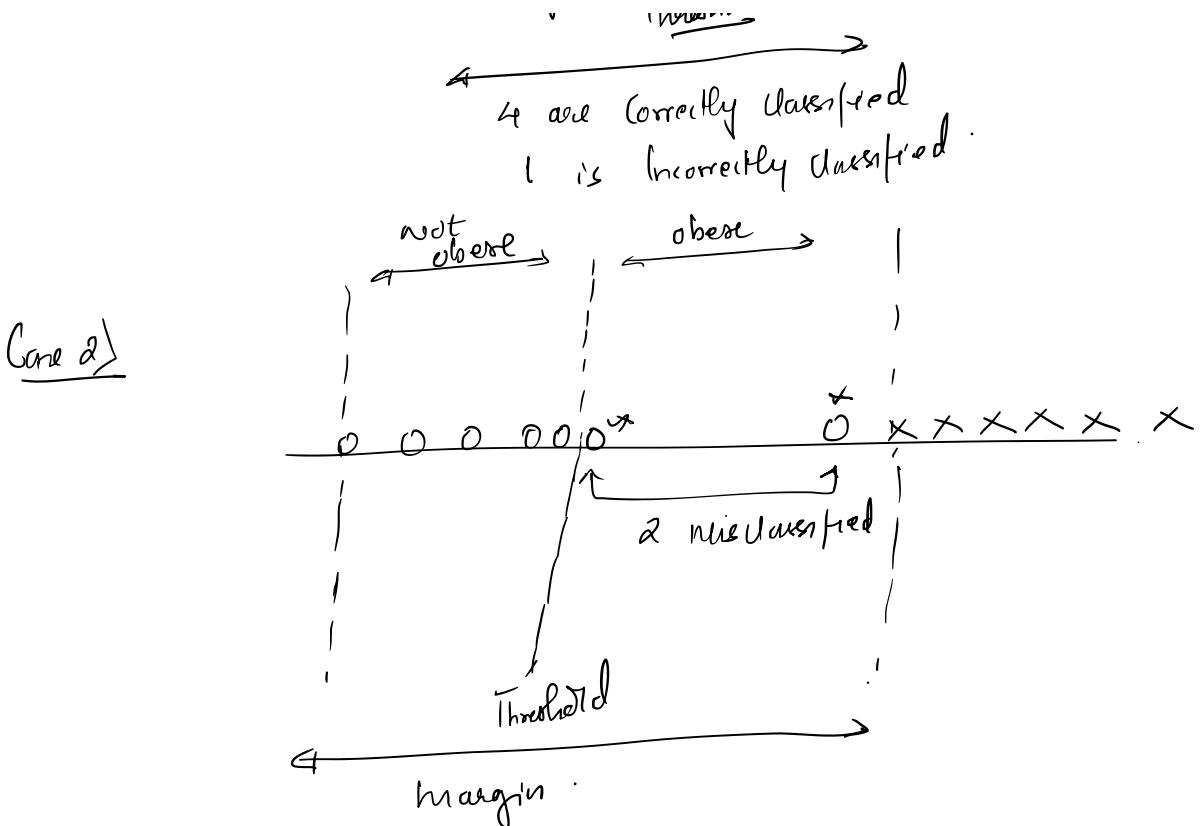
→ New observations are correctly classified \Rightarrow Low Variance

Soft Margin :- When Misclassification is allowed then the distance b/w threshold and given observation is known as Soft Margin -

* For above case we can have many soft margins.

Consider Case I :-





- * We will determine which soft margin is better by observing how many misclassification each soft margin allows.

Imp.
When we use soft margin to determine the location of threshold, then we are using "Soft Margin Classifier"
Also known as "Support Vector Classifier"

- * Support Vector Classifier \rightarrow Main Aim is to create a Decision Boundary with allowed misclassification
 \rightarrow It allows small amount of Overlapping

But if the Dataset is as follows \rightarrow

- * Here there is very high level of overlapping
... at some

* Here there is very high level of overfitting

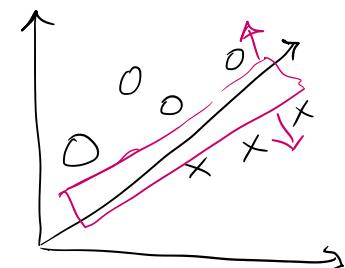
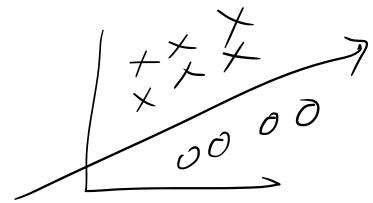
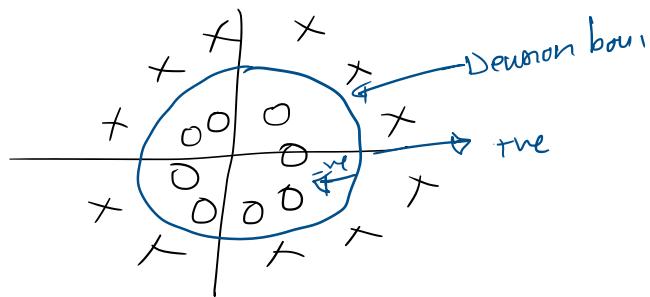
<u>not obse</u>	<u>obse</u>	<u>not obse</u>
0 0 0 0 0	X X X X X	0 0 0 0 0

Marks

* Here we cannot have linear separator.

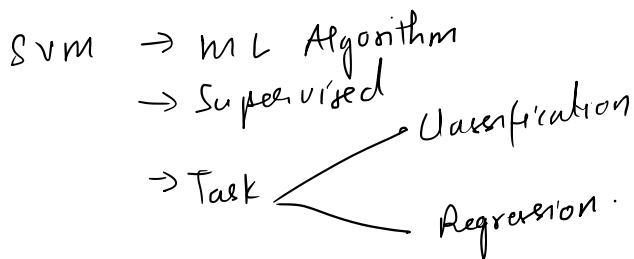
Also \rightarrow [For 1-D data Decision Boundary is a point
For 2-D Data " " is a line
For 3-D Data " " is a plane]

Also



Here also Linear Decision Boundary Not Possible.

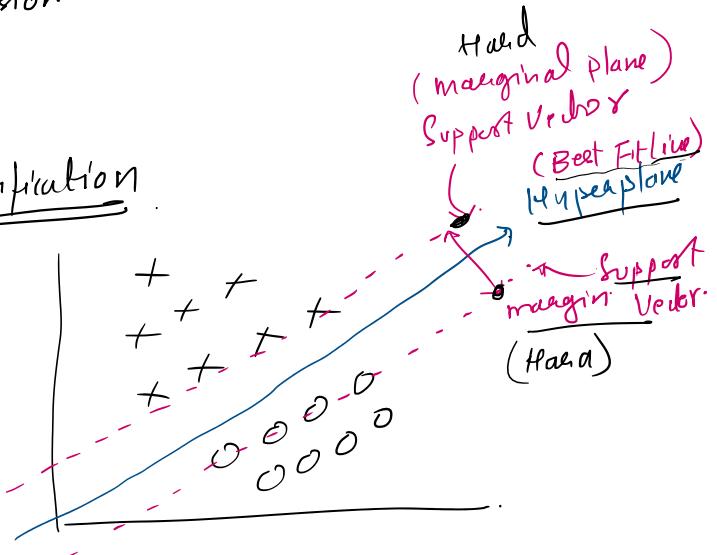
Note



* Support Vector Classifier for Classification.

* Consider Binary Classification →

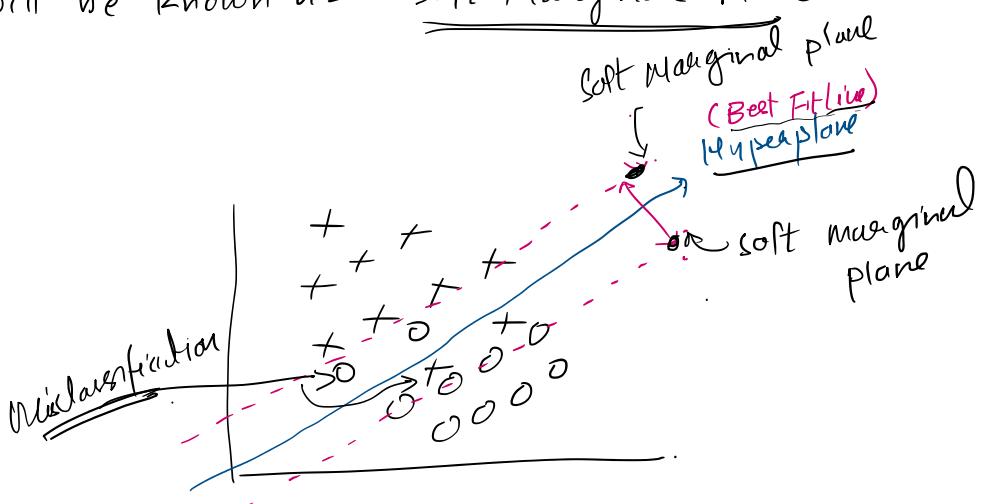
Aim →
Create a Hyperplane and
Marginal plane such that
the Margin is Maximum →



* If we get perfect Marginal plane & Hyperplane [No Misclassification]
Then we can linearly separate the Data points.

This Margin will be known as Hard Marginal Plane

* If there are Misclassification allowed then the plane will be known as "Soft Marginal Plane"



Note Consider Hyperplane \rightarrow Here 2-D Data
hyperplane will be line.

$$\text{Eq: } y = mx + c$$

$$\text{or } y = \theta_0 x_0 + \theta_1$$

$$\text{or } y = \underline{\theta_1 x_1 + b}$$

For multilinear regression \Rightarrow Many features $x_1 x_2 x_3 \dots x_n$
Each feature will have weight $w_1 w_2 w_3 \dots w_n$

$$y = \underline{w_1 x_1 + w_2 x_2 + w_3 x_3 + \dots + w_n x_n} + b.$$

$$y = \underline{\underline{w^T X}} + b$$

\uparrow $t_{\text{predicted}}$

actual value

$$w^T = [w_1 \ w_2 \ \dots \ w_n]$$

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

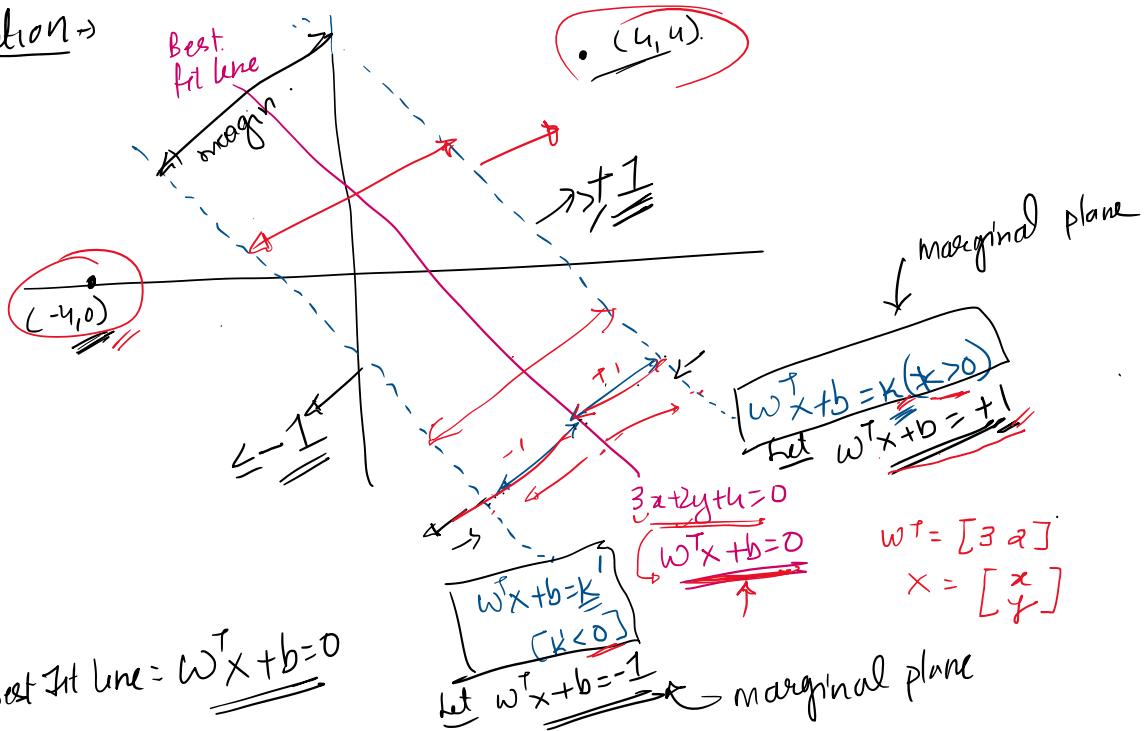
Consider \Rightarrow

Sum For Classification \rightarrow
 (consider)

$$\text{Eq}^1 \Rightarrow 3x + 2y + b = 0$$

put $(-1, 0) = 3(-1) + 2(0) + b < 0$

$$(1, 1) = 3(1) + 2(1) + b \\ = 2b > 0$$



Our Aim is to draw two Marginal planes (+ve & -ve side)
 and need to ensure the distance (Margin) is maximum.

* We want to find distance bet^n the Marginal Planes.

lets find difference:

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

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

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

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

Here w = slope (coefficient) \nwarrow magnitude
 direction \nearrow Vector.

In convert w^T into Vector ie $\vec{w^T}$

To convert w^T into Vector ie \vec{w}^T

divide by $\|w\|$

\therefore

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

difference
(margin)

value

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

\therefore To Maximize the Margin \rightarrow

$$\checkmark \text{Maximize } (w, b) = \frac{2}{\|w\|}$$

Constraints \rightarrow

y_i Actual / observed

$$+1$$

-1

when $w^T x + b \geq 1$
(point lies outside of $w^T x + b = 1$)

↓ predicted

when $w^T x + b \leq -1$
(point lies below of $w^T x + b = -1$)

The Constraints are for Correctly Classified Data point

\therefore Final Constraints for S.V Classifier.

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

↑ observed (actual)

↑ Predicted value

For correctly classified Data point

\therefore To Maximize $= \frac{2}{\|w\|}$, Subjected to

$$\boxed{y_i * (w^T x + b) \geq 1}$$

$$y_i = +1$$

$$w^T x + b \geq +1$$

~~To Maximize~~ = $\frac{\alpha}{\|w\|}$, subject to \leq

(Also can be written as)

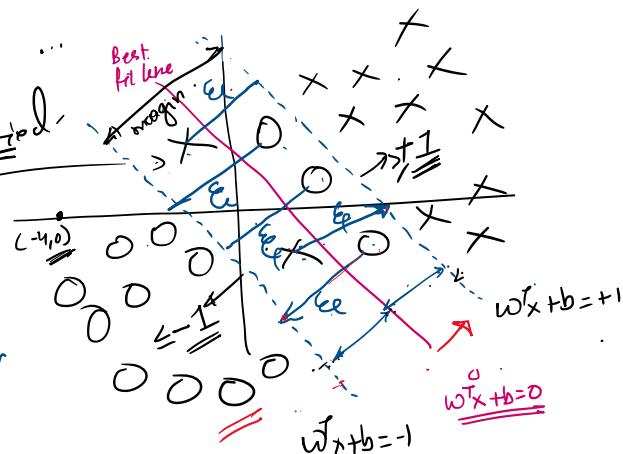
* ~~To Minimize~~ = $\frac{\|w\|}{\alpha}$, subjected to $y_i * (w^T x + b) \geq 1$
only for ~~Correctly Classified Data points.~~

here we have not considered for Misclassification
But in real world there will be always Misclassification.

To Consider for Misclassification we have to use
"Hyper parameters"

We allow Misclassification

Now we will use Misclassified
two Hyperparameters



$\epsilon \Rightarrow$ Margin \Rightarrow distance betⁿ the Misclassified point and correct Marginal plane

$C_i \Rightarrow$ No of Allowed Misclassified

Now Final Cost F^n (For All data points) [Correctly & Incorrectly Classified]

* Objective \rightarrow

$$\text{To Minimize}_{(w,b)} \frac{\|w\|}{\alpha} + C_i \sum_{i=1}^{C_i} \epsilon_i$$

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

for Hyperparameters

ii. Labeled Cost F^n for SVC used for Classification

~~Non-
Identified~~ Misclassification
The label cost F^n for SVC used for classification
[For Allowed Misclassification].