

# Data Science and Artificial Intelligence

## Machine Learning



**Classification**

**Lecture No. 3**

**By- SIDDHARTH SABHARWAL SIR**

**GATE WALLAH**



# Recap of Previous Lecture



Topic

linear classification

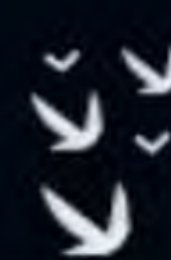
Topic

Topic

Topic

Topic

# Topics to be Covered



Topic

Linear Classification

Topic

Problem

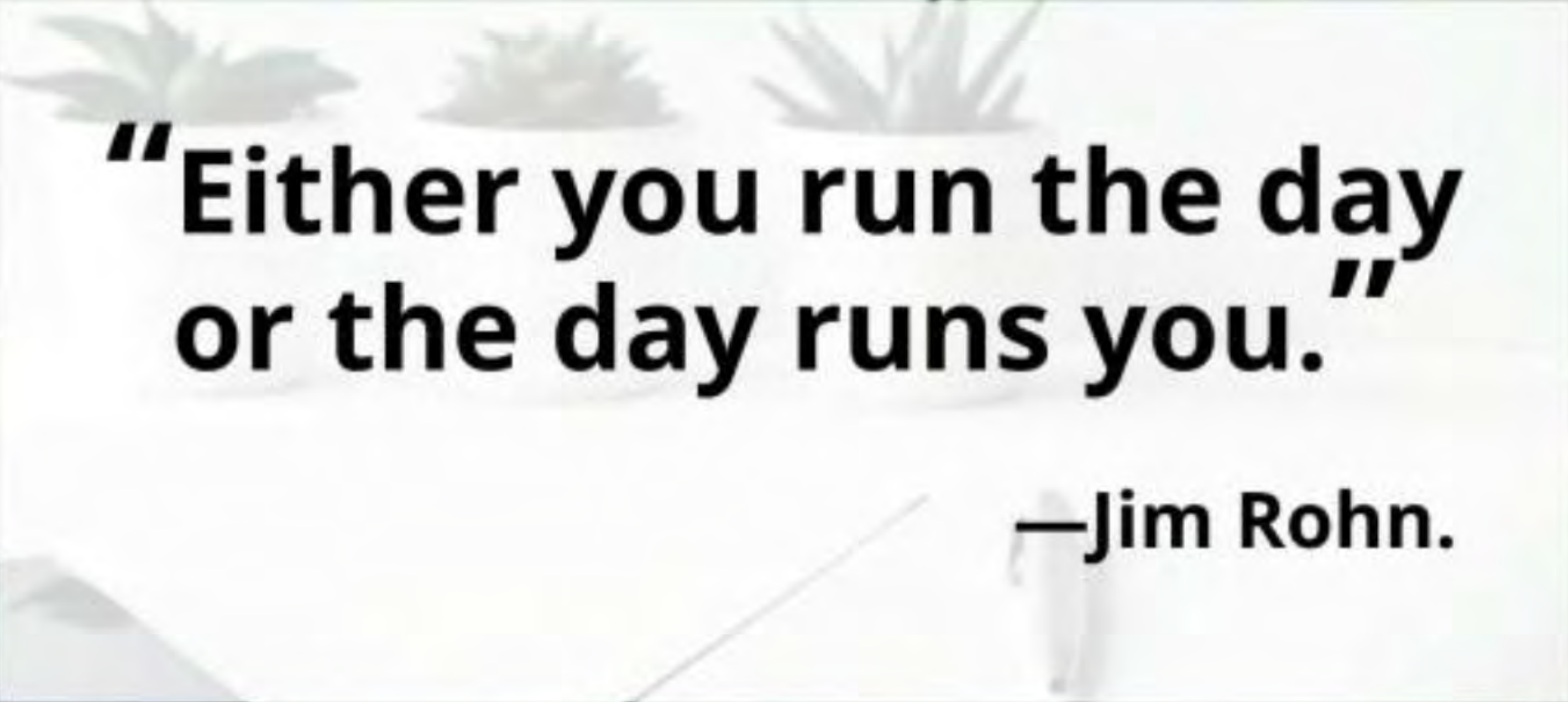
Topic

Logistic Regression

Topic

Topic





**"Either you run the day  
or the day runs you."**

**—Jim Rohn.**



## Linear Classification : The Loss function

+1  
\* \* \*  
\* \* \*

o o  
o o  
o o  
o o

loss  $f(x, n) \Rightarrow$

$$\max \sum_{i=1}^N (y_i x_i \beta)$$

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_D \end{bmatrix}$$

$$x_i^0 = [1, x_i^1, x_i^2, \dots]$$





## Linear Classification : The Problem

↳ (outlier) Class 1

So to max  $\sum y_i x_i \beta$

- line will get shifted

Line shifted

Class -1

$x_i \beta$

Outlier Class +1



Linear classifier eq

$$\Rightarrow \max \sum_{i=1}^N y_i x_i \beta = L$$

$$\hookrightarrow \sum_{i=1}^N y_i (\beta_0 + x_i^1 \beta_1 + x_i^2 \beta_2 + \dots) = L$$

$$\frac{\partial L}{\partial \beta_0} = 0$$

$$\frac{\partial L}{\partial \beta_1} = 0$$

- we will not get any Result
- Like we get in LR, RR



How algorithm Find  $\beta$

only for  
thinking

• not for exam

let take 2D data

$x^1$	$x^2$	$y_i$
a	b	1
c	d	1
e	f	-1
g	h	-1
i	j	1

$y_i(x_i\beta)$  shd be +ve

$$\beta_1 a + \beta_2 b + \beta_0 > 0$$

$$\beta_1 c + \beta_2 d + \beta_0 > 0$$

$$\beta_1 e + \beta_2 f + \beta_0 < 0$$

$$\beta_1 g + \beta_2 h + \beta_0 < 0$$



- The algo create all Planes and find region Common to all
- So from any point in the Common Region we can take  $\beta_1, \beta_0, \beta_2 \Rightarrow$  Classifier

Illustration



# Linear Classification

You are given a trained Logistic Regression model with the following numerical weight vector and bias:

weight vector ( $w$ ):  $[0.8, -1.2]$

Bias ( $b$ ):  $-0.5$

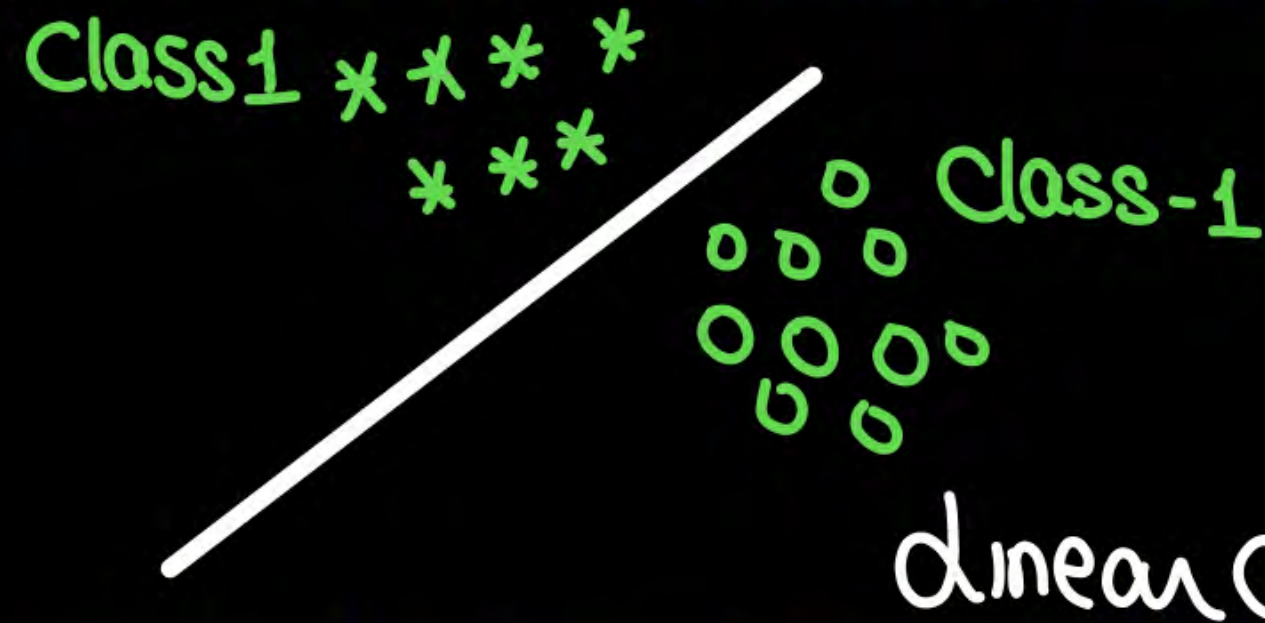
You need to classify four points (A, B, C, D) using this model. The data points and their respective feature vectors are as follows:

Point A:  $(3, 5)$

Point B:  $(-2, 4)$

Point C:  $(1, -1)$

Point D:  $(-4, -3)$



Which points will be classified as Class 1 (positive class) using this Logistic Regression model?



So class 1  $\Rightarrow$

positive class

$$(x_i \beta) > 0$$

$$\left( \beta_0 + \beta_1 x_i^1 + \beta_2 x_i^2 \right)$$

$$-0.5 + 0.8x_i^1 - 1.2x_i^2$$

$x^1 \ x^2$

$(3, 5)$

$$\rightarrow -4.1 \Rightarrow \text{Class -1}$$

$(-2, 4)$

$$\rightarrow -11 \Rightarrow \text{Class -1}$$

$(1, -1)$

$$\rightarrow -0.9 \Rightarrow \text{Class -1}$$

$(-4, -3)$

$$\rightarrow -0.1 \Rightarrow \text{Class -1}$$

So Concept

$$x_i \Rightarrow \beta_0 + \beta_1 x_i^1 + \beta_2 x_i^2 \dots$$

+ve  $\rightarrow$  class 1

-ve  $\rightarrow$  class -1





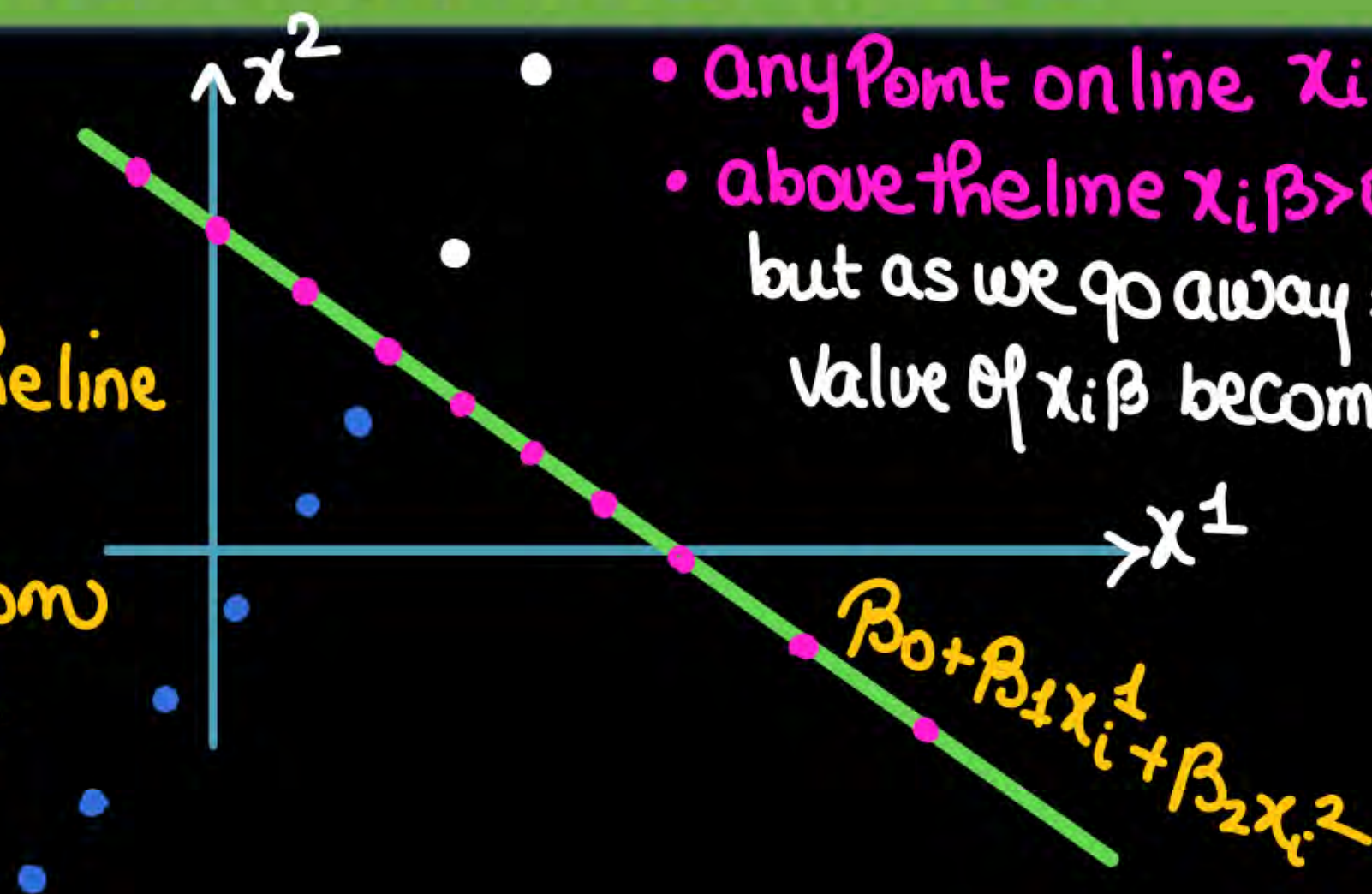


## Linear Classification

- Distance of a point from a line ...

Geometry  $\Rightarrow$

- Similarly below the line  $x_i \beta \Rightarrow$  -ve but as we go away from line  $x_i \beta$  become more -ve.



- any point on line  $x_i \beta = 0$
- above the line  $x_i \beta > 0$   
but as we go away from line  
value of  $x_i \beta$  become highly +ve



- Outlier effect the Classifier becuz of huge value of  $x_i \beta$

• Cost fcn  $\Rightarrow \max \sum_{i=1}^N y_i x_i \beta$



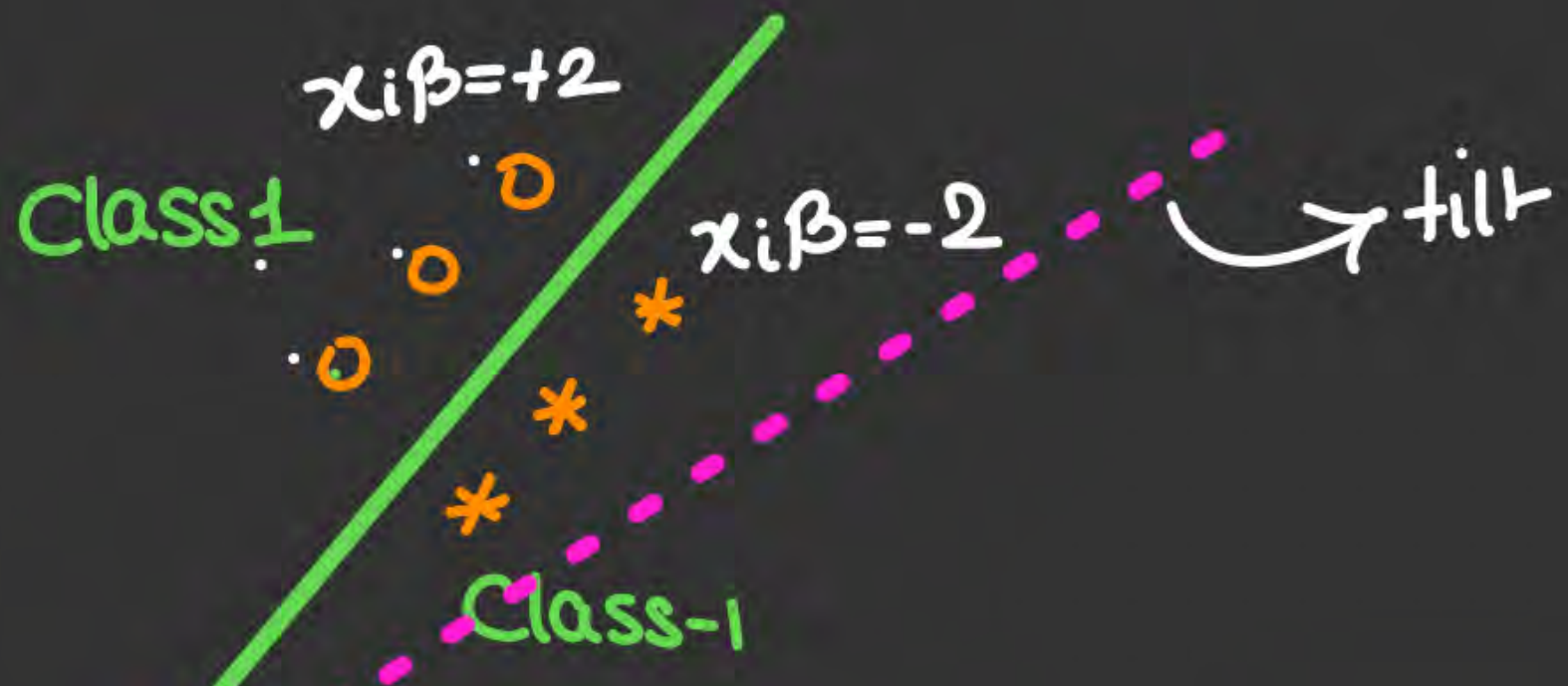
- generally all points are close

- $x_i \beta$  is small

- But outlier have large  $x_i \beta$ , so classifier tilt's to reduce  $x_i \beta$  for outlier







$$\sum y_i x_i \beta$$

$$\Rightarrow 2 \times 1 + 2 \times 1 + 2 \times 1$$

$$- 2 \times -1 + -2 \times -1 + -2 \times -1$$

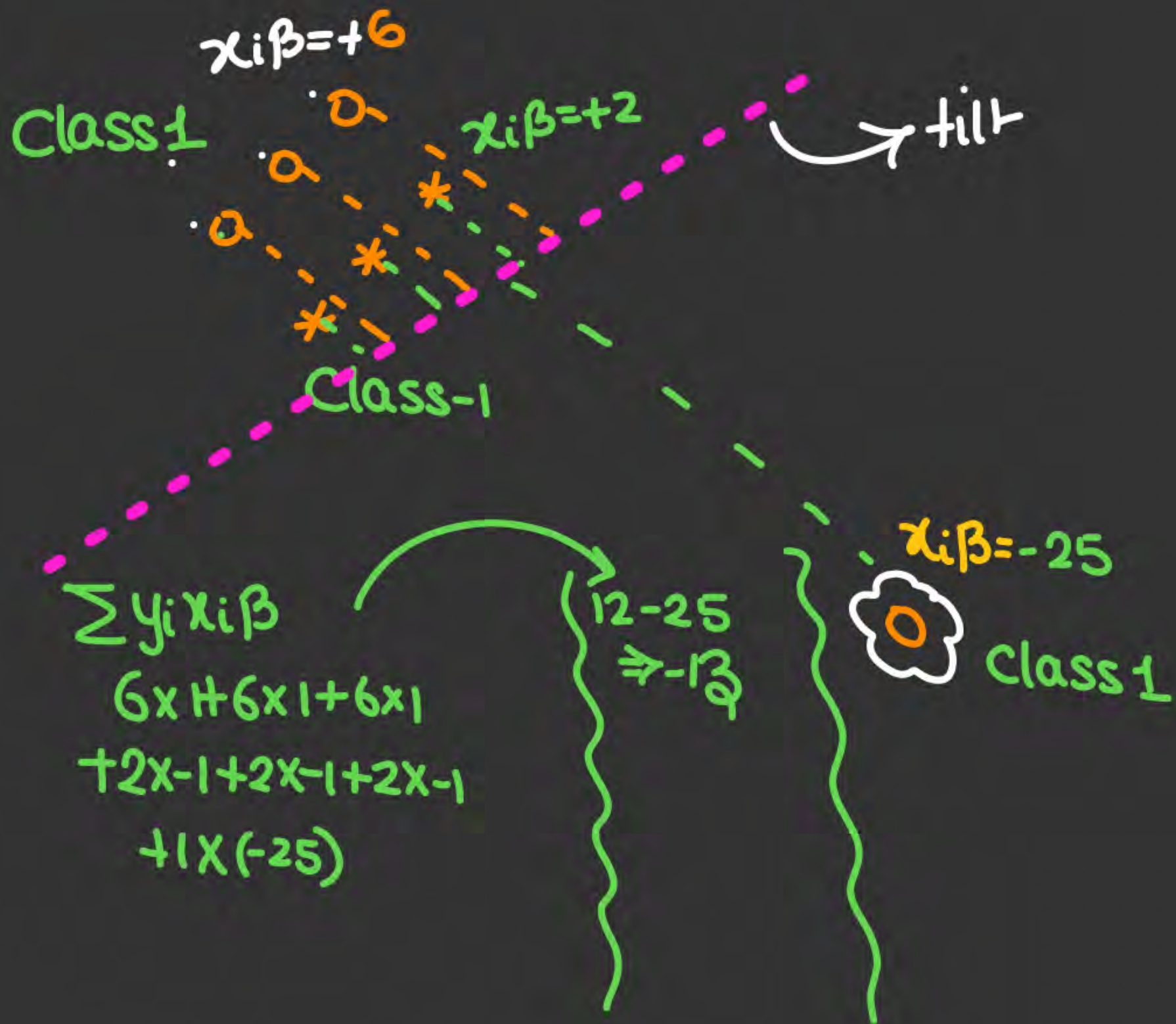
$$\Rightarrow (12)$$

$$12 - 50 = -38$$

$$x_i \beta = -50$$



Class 1





Why  $\max \sum_{i=1}^N y_i x_i \beta$

Classifier

class 1  $\rightarrow$  oopar  $\Rightarrow x_i \beta > 0$

Class -1  $\rightarrow$  neeche  $\Rightarrow x_i \beta < 0$

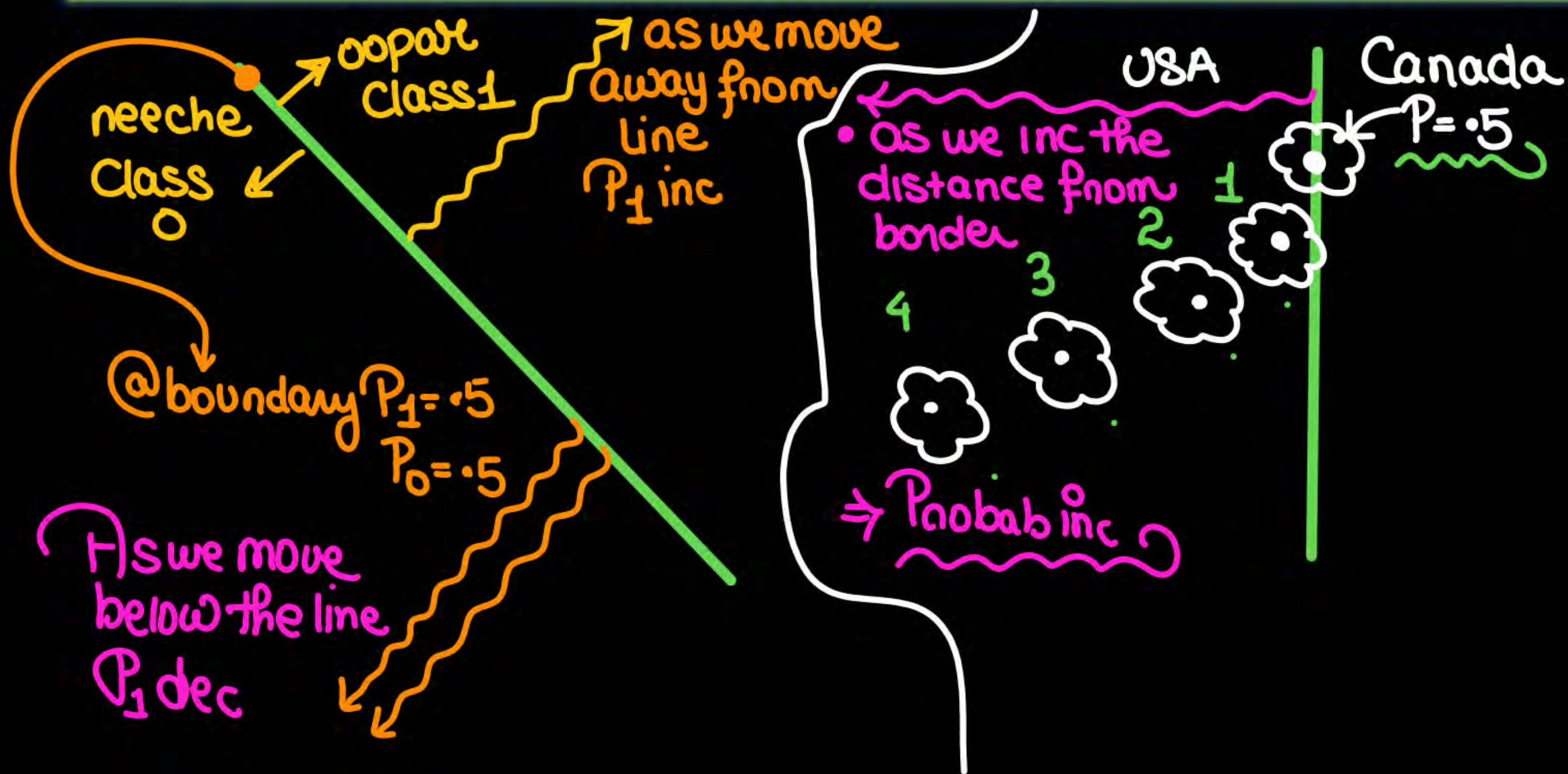
$\Rightarrow \underline{y_i x_i \beta}$  Shd be +ve for good classifier

So Best classifier  $\sum_{i=1}^N y_i x_i \beta \rightarrow \max$



# Linear Classification

- How can distance decide the probability of a point being class 1/0





Classifier

$x_i \beta$  more and more +ve  
 $P_1$  inc and  $P_1 = 1$

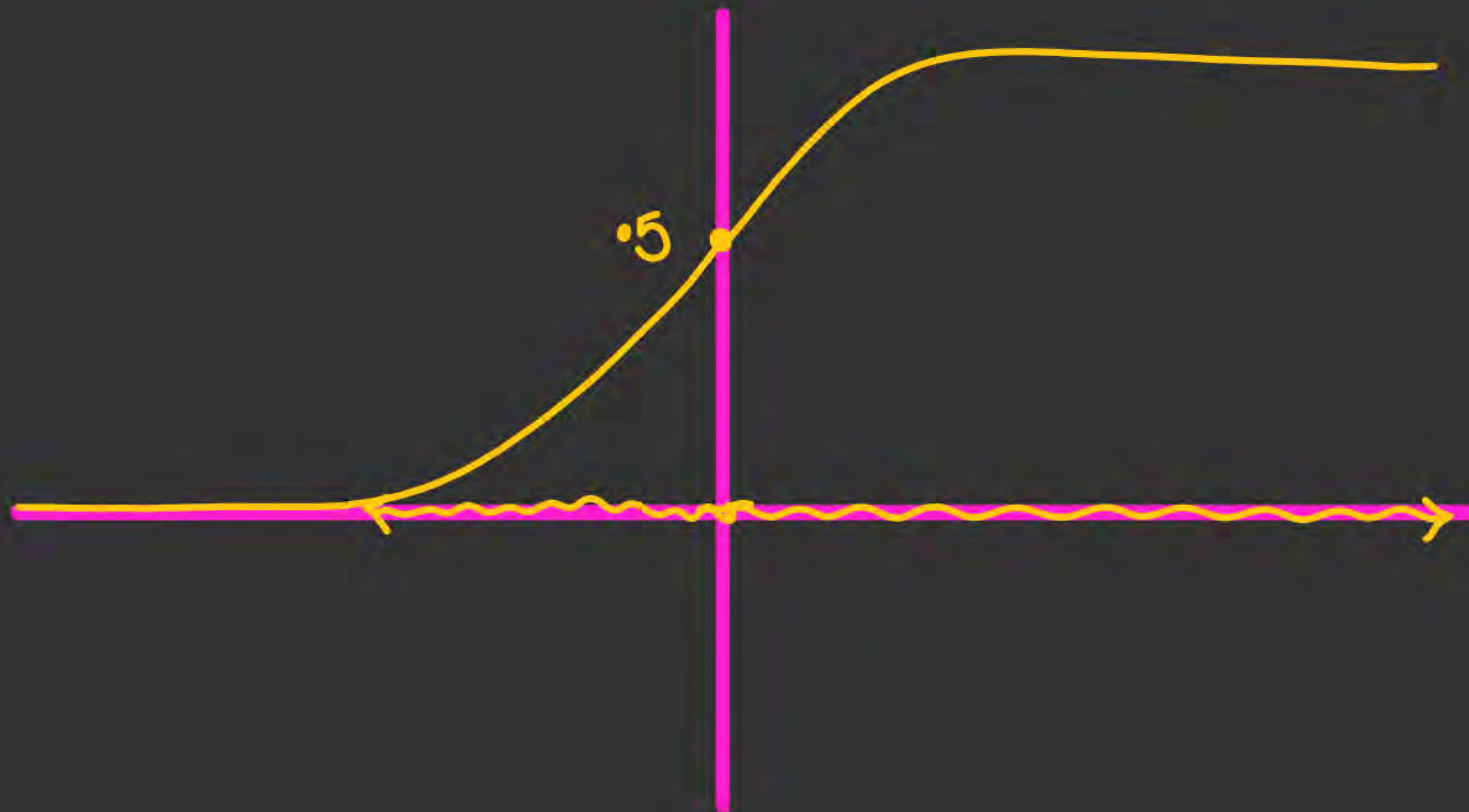
on the  
line  $P_1 = 0.5$   
 $P_0 = 0.5$

- as  $x_i \beta$  become  
-ve then  $P_1$   
dec

$x_i \beta = 0$

- Now we Relate  
 $x_i \beta$  with Probab  
that  $x_i$  belong to  
Class 1

$$P_0 + P_1 = 1$$







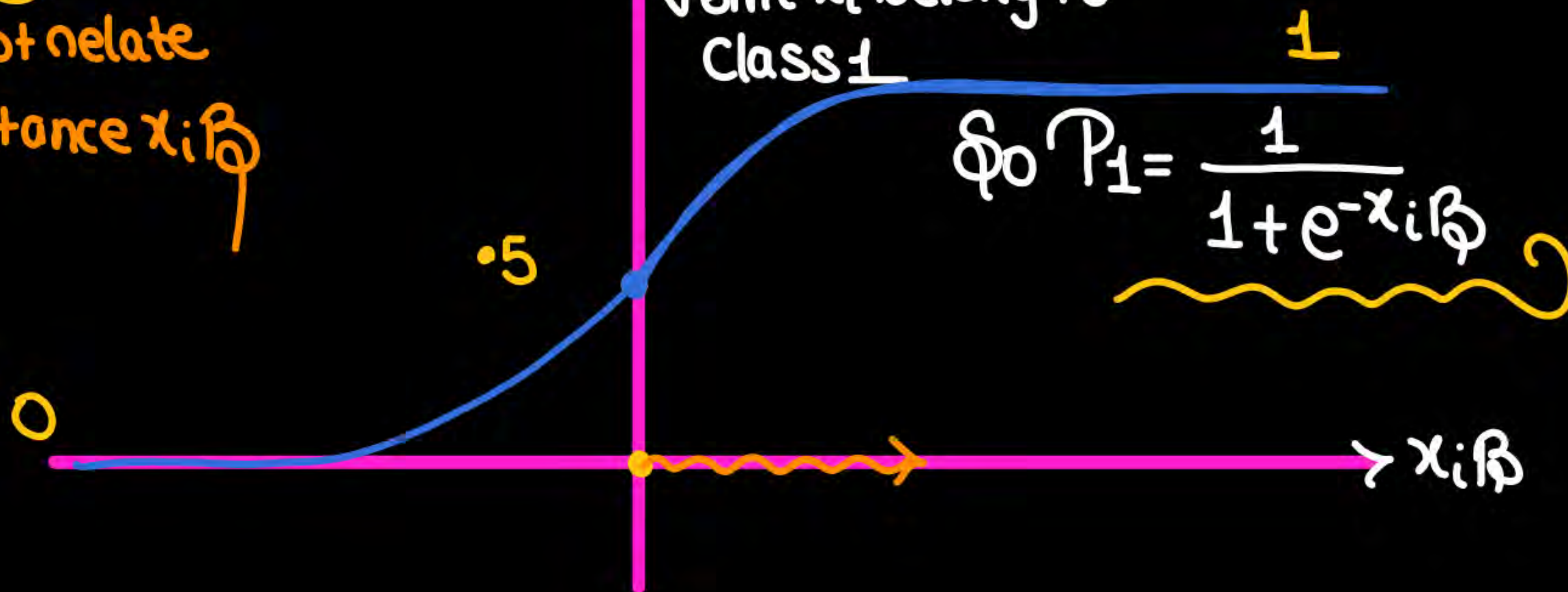
## Linear Classification

### Linear Classification

Probability

- So this plot relate  $P_1$  to distance  $x_i \beta$

- Probability that Point  $x_i$  belong to Class 1



So  $P_1 \Rightarrow \frac{1}{1+e^{-x_i \beta}}$  → Sigmoid function

$$x_i \beta = \infty \Rightarrow P_1 = \frac{1}{1+e^{-\infty}} = \frac{1}{1} = 1$$

$$x_i \beta = 0 \Rightarrow P_1 = \frac{1}{1+e^{-0}} = \frac{1}{1+1} = \frac{1}{2}$$

$$x_i \beta = -\infty \Rightarrow P_1 = \frac{1}{1+e^{\infty}} = \frac{1}{\infty} = 0$$

What will be

$$P_0 \Rightarrow 1 - P_1$$

$$\Rightarrow 1 - \frac{1}{1+e^{-x_i \beta}}$$

$$P_0 \Rightarrow \frac{e^{-x_i \beta}}{1+e^{-x_i \beta}}$$

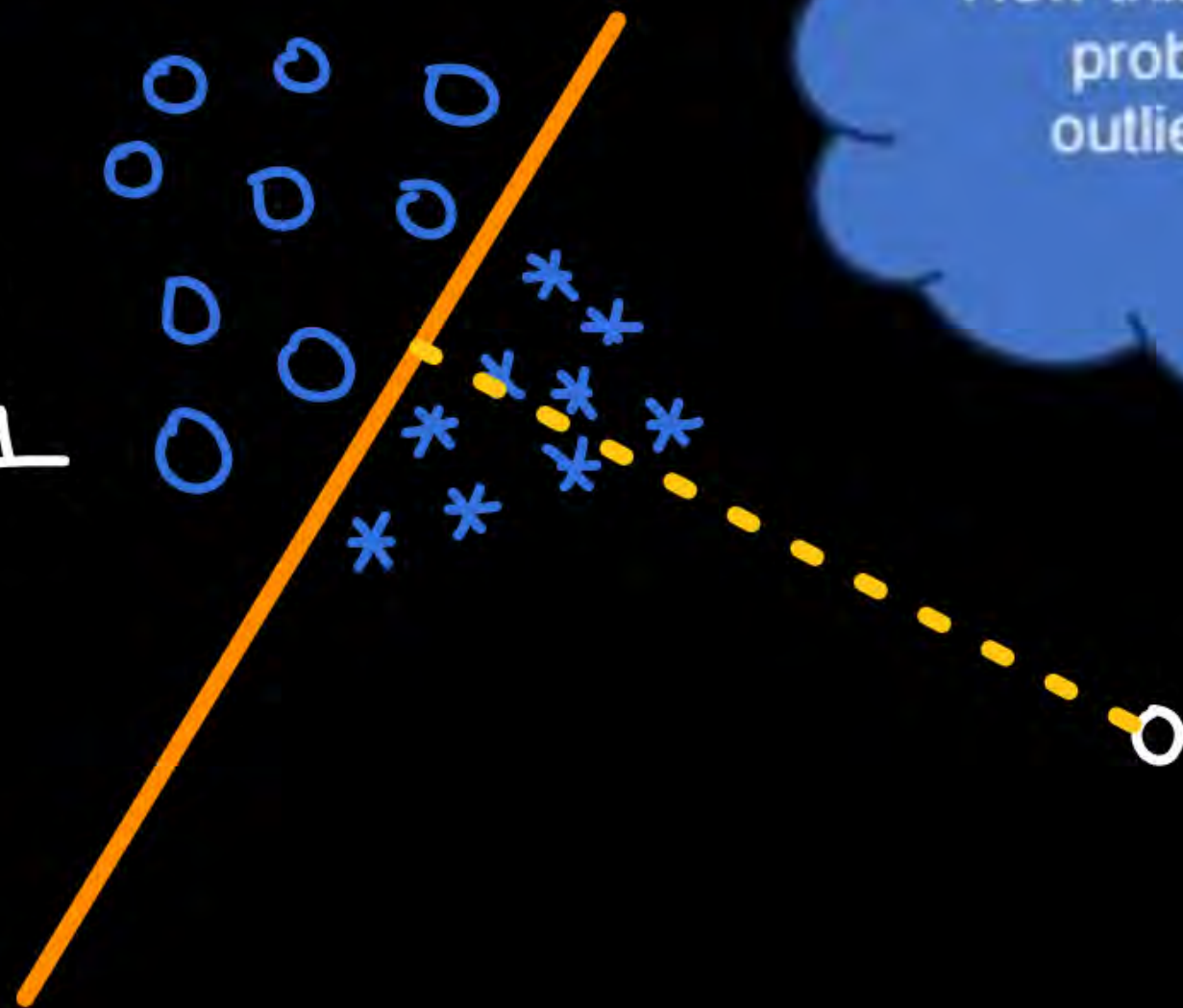




## Linear Classification

So we convert distance  $x_i \beta_0$  into Probability

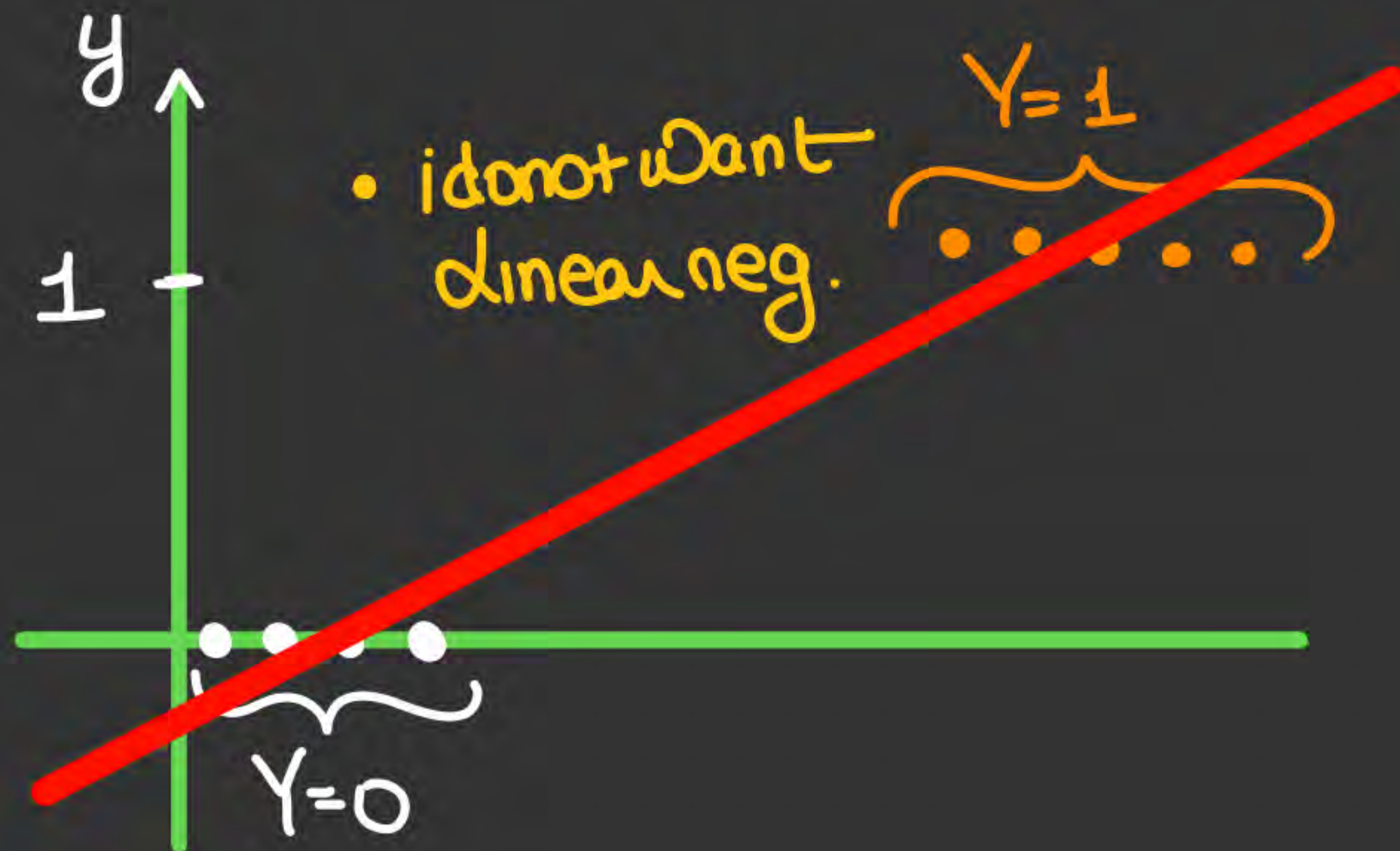
- So in this case the outlier which have large  $x_i \beta_0$ , the  $P_1$  will always be b/w 0 to 1 Only.



How this solve the problem of outliers...??

Feel the  
logistic  
Regression

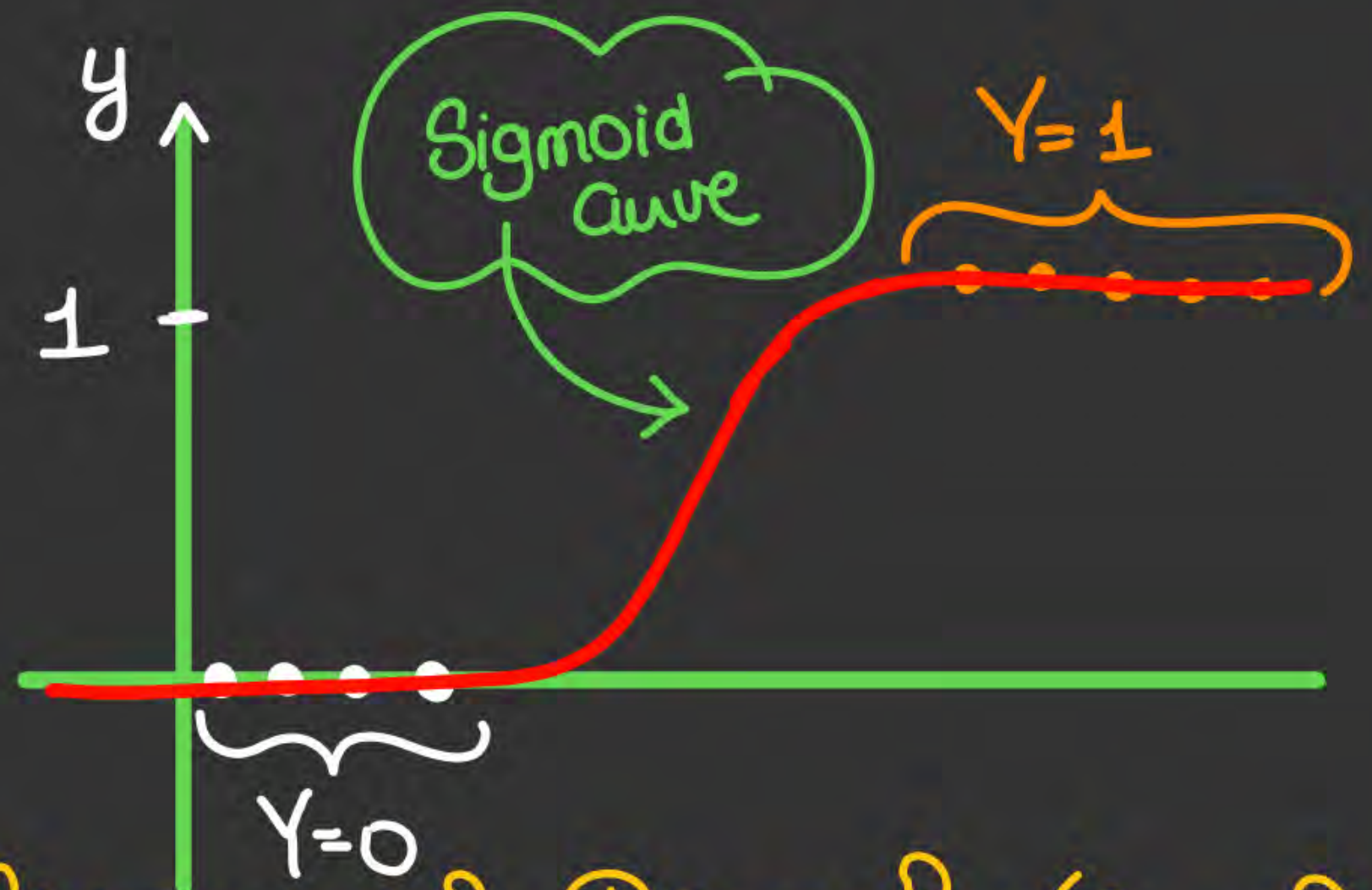
data	Y
→ data1	1
→ data2	1
⋮	0
→ data7	1





Feel the  
logistic  
Regression

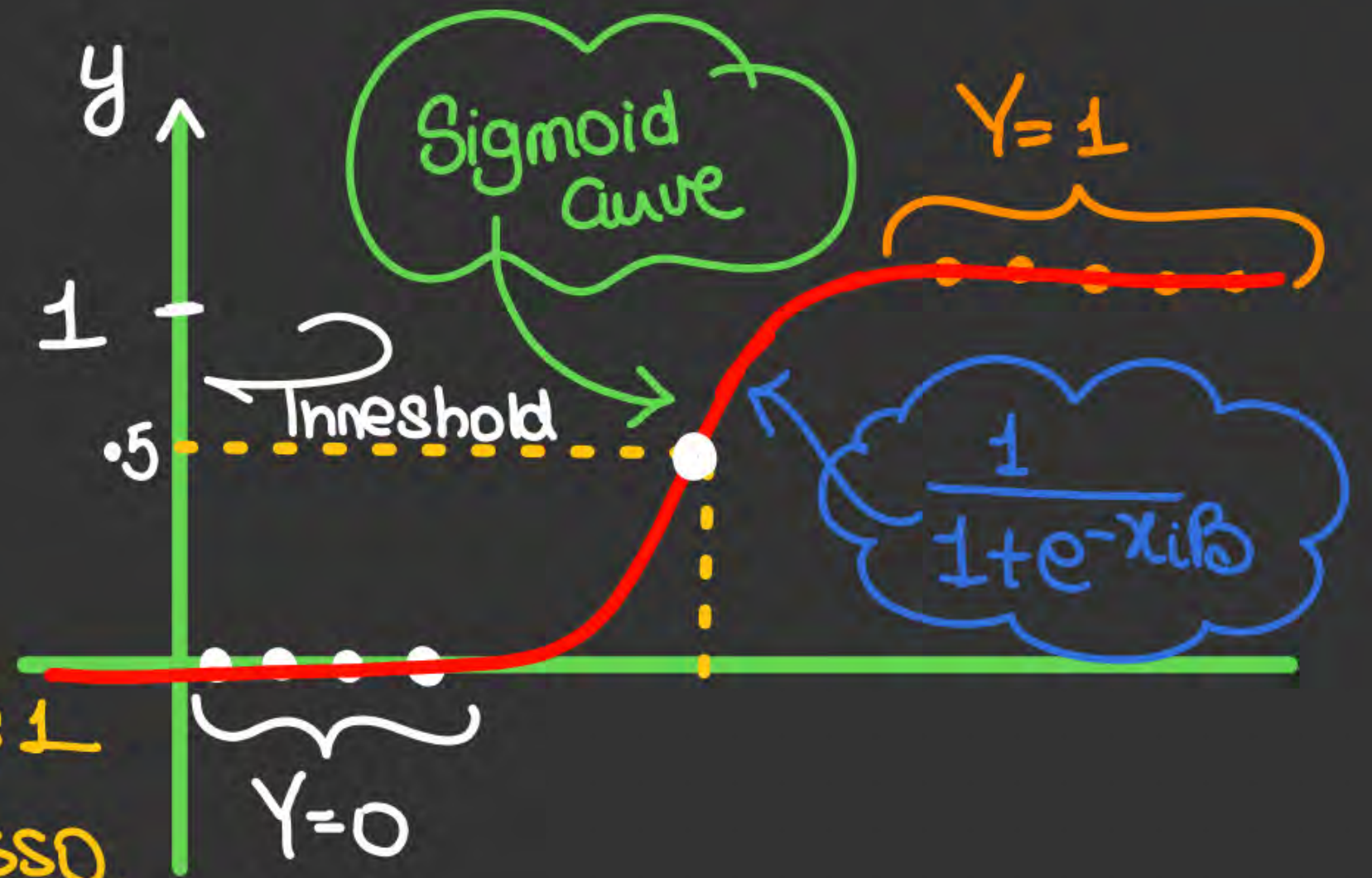
data	Y
→ data 1	1
→ data 2	1
⋮	0
	0
	0
→ data 7	1



- So we are doing Regression (Curve fitting)
- 'S' type Curve fitted on data.



Basic Rule to  
decide the  
Class of a new point  
So for any new point  
find  $Y \Rightarrow$  if  $Y > 0.5 \rightsquigarrow$  Class 1  
 $Y < 0.5 \rightsquigarrow$  Class 0.





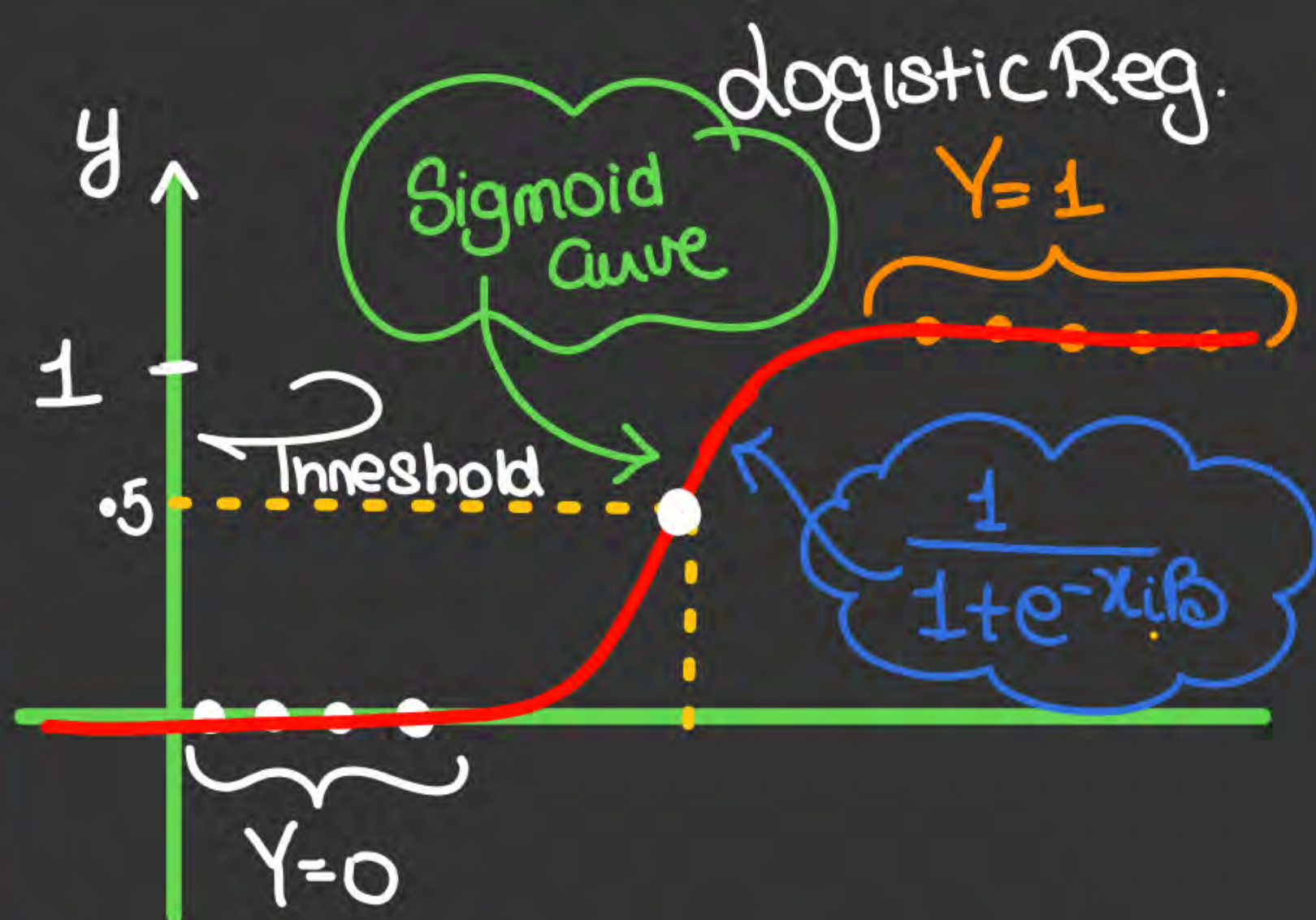
Linear classifier

\* \* \*

o o o

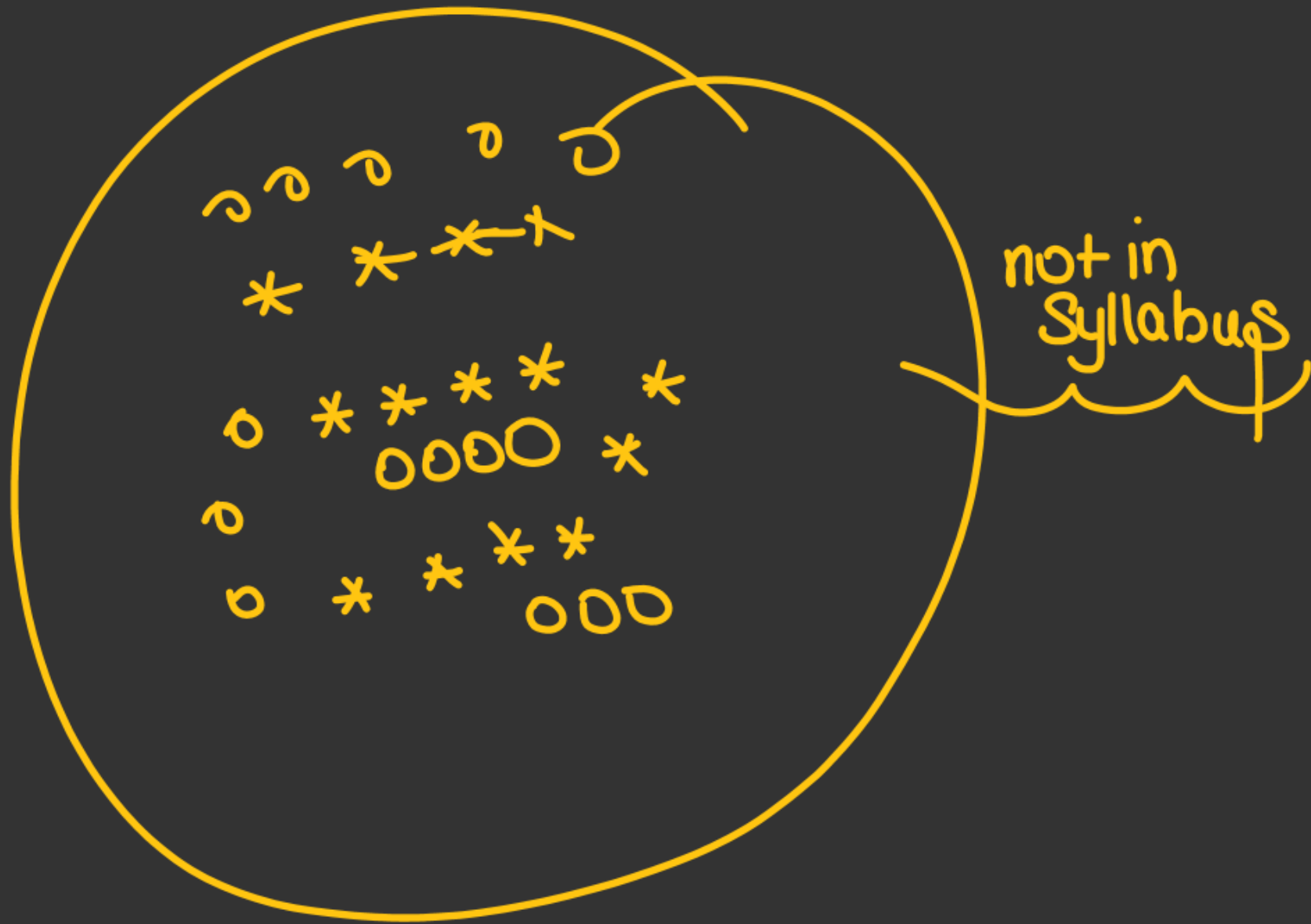
$x_i \beta > 0 \rightarrow \text{class 1}$   
 $x_i \beta < 0 \rightarrow \text{class 0}$

Cost fcn  $\max \sum_{i=1}^N y_i x_i \beta$



- $x_i \beta > 0, Y > 0.5 \Rightarrow \text{class 1}$   
 $x_i \beta < 0, Y < 0.5 \Rightarrow \text{class 0}$

Cost fcn ----







- **Logistic Regression**

- **Logistic Regression**

Let us have a data with some classes 1 and 0, these are the Y values of the input.  
In logistic Regression we actually try to fit a S curve on the data.

done

The Sigmoid  
Function...



- Logistic Regression

- Logistic Regression

Now we have the concept of the threshold, how to find the best coefficients ?

- ↓
- generally threshold = 0.5
  - But it can be changed.
- $Y = \frac{1}{1 + e^{-x_i \beta_0}} > 0.5 \Rightarrow \text{Class 1}$   
 $Y = \frac{1}{1 + e^{-x_i \beta_0}} < 0.5 \Rightarrow \text{Class 0}$

we have to find  $\beta$ 's





- **Logistic Regression**

- **Logistic Regression**

The concept of threshold

done

What is logit or log of odds

- $$\text{Odds} \Rightarrow \frac{\text{Probab of Success}}{\text{Probab of failure}}$$

- In our Case 
$$\text{Odds} = \frac{P_1}{P_0}$$
$$= \frac{P}{1-P}$$

- Probab of win  $\Rightarrow 0.8$

- Probab of losing  $\Rightarrow 0.2$

What is odds against

winning  $\Rightarrow \frac{P_{\text{losing}}}{P_{\text{win}}}$   
 $\Rightarrow 0.2/0.8$

Odds of winning  $\Rightarrow P_{\text{win}}/P_{\text{lose}}$





- Logistic Regression

- Logistic Regression

What is Logit ?

$$\begin{aligned} & \log_e \text{odds} \\ & \left\{ \log_e \frac{p}{1-p} \right\} \Rightarrow \left\{ \log_e \frac{1/1+e^{-x_i\beta}}{1-\frac{1}{1+e^{-x_i\beta}}} \right\} \end{aligned}$$

$$\Rightarrow \log_e \frac{1}{e^{1+e^{-x_i\beta}} - 1}$$

$$\Rightarrow \log_e \frac{1}{e^{-x_i\beta}}$$

$$\Rightarrow \log_e e^{+x_i\beta} \Rightarrow x_i\beta$$

Odds of winning =  $P_{\text{win}} / P_{\text{lose}}$   
Odds of losing =  $\frac{P_{\text{lose}}}{P_{\text{win}}}$



- Logistic Regression

- Logistic Regression

In logistic Reg

$$\begin{aligned}\log_{\text{odds}} &\Rightarrow x_i \beta \\ &\Rightarrow (\beta_0 + \beta_1 x_i^1 + \beta_2 x_i^2 \dots)\end{aligned}$$

Importance of  
Logit ??





- **Logistic Regression**

- **Logistic Regression**

The pattern of  
Questions on this

...



## Linear Classification



$40/70 \Rightarrow \text{Success}$   $\{30/40\} \Rightarrow \text{Fail}$

## Logistic Regression

7) Consider the data collected from 410 customers in a restaurant. It is observed that 40 of the 70 customers tipped the server who was wearing a black shirt and 130 of the 340 customers tipped the server who was wearing a different color. Compute the logit or log-odds of tipping a server wearing a black shirt.

- ☐ 0.2877
- ☐ 0.1249
- ☐ -0.7677
- ☐ -1.7677

410 Customers  $\Rightarrow$  40 out of 70 Customers tip Server with black shirt  
130 " " 340 " " " White shirt

loge odds of tipping the server wearing black shirt.  
 $\Downarrow$   
 $\log_e \left[ \frac{40/70}{30/70} \right] \Rightarrow \log_e (4/3) \Rightarrow 0.287.$



Q 1D data,

$$\text{if } x=1 \quad \log \text{ odd} \Rightarrow 0.45$$

$$\text{if } x=5 \quad \log \text{ odd} \Rightarrow 0.75$$

find  $\beta_1, \beta_0$  for logistic Reg  $\Rightarrow \frac{1}{1+e^{-x_i \beta}}$   
 $\hookrightarrow (\beta_0 + \beta_1 x_i)$

V. Imp in logistic Reg.

$$\log \text{ odd} = \beta_1 x^1 + \beta_0$$

$$0.45 = \beta_1 \times 1 + \beta_0$$

$$0.75 = 5\beta_1 + \beta_0$$

$$\beta_1 = 3/40, \beta_0 = 3/8.$$



## Logistic Regression

8) In continuation with question 7, let  $x = 1$  if the server is wearing black shirt and  $x = 0$  for servers wearing other colored shirts. We know that there are 270 observations with  $x = 1$  and 340 observations with  $x = 0$ . The response variable is also an indicator variable given by  $y = 1$  if the customer left a tip and  $y = 0$  if the customer did not leave a tip. Use this data to fit a logistic regression model to compute the log-odds of leaving a tip depending on the color of the server's shirt..

P.W

☐  $-0.4797 + 0.1249x$

☐  $0.2877 + 0.1249x$

☐  $0.1249 + 0.4317x$

☐  $-0.4797 + 0.7674x$





### Logistic Regression

What type of dependent variable is suitable for logistic regression?

- A) Continuous variable
- B) Categorical variable with multiple categories
- C) Binary or dichotomous variable
- D) Ordinal variable



### Logistic Regression

In logistic regression, what is the role of the logistic function (sigmoid function)?

- A) It transforms the independent variables.
- B) It models the relationship between the dependent and independent variables.
- C) It converts the log-odds into probabilities.
- D) It calculates the likelihood of the data.





### Logistic Regression

Which term represents the natural logarithm of the odds of an event occurring in logistic regression?

- A) Odds ratio
- B) Probability
- C) Log-odds or logit
- D) Coefficient



### Logistic Regression

What is the likelihood function used for in logistic regression?

- A) To estimate the coefficients of the model.
- B) To calculate the odds ratio.
- C) To find the best threshold for classification.
- D) To assess the fit of the model by maximizing the likelihood of the observed outcomes.





### Logistic Regression

1. What kind of algorithm is logistic regression?

- a) Cost function minimization
- b) Ranking
- c) Regression
- d) Classification



### Logistic Regression

6. Probability of an event occurring is 0.9. What is odds ratio?

- a) 0.9:1
- b) 9:1
- c) 1:9
- d) 1:0.9



#Q. The following table gives the binary labels ( $y^{(i)}$ ) for four points  $(x_1^{(i)}, x_2^{(i)})$  where  $i = 1, 2, 3, 4$ . Among the given options, which set of parameter values  $\beta_0, \beta_1, \beta_2$  of a standard logistic regression model  $p(x_i) = \frac{1}{1+e^{-(\beta_0+\beta_1x+\beta_2x)}}$  results in the highest likelihood for this data?

- (a)  $\beta_0 = 0.5, \beta_1 = 1.0, \beta_2 = 2.0$
- (b)  $\beta_0 = -0.5, \beta_1 = -1.0, \beta_2 = 2.0$
- (c)  $\beta_0 = 0.5, \beta_1 = 1.0, \beta_2 = -2.0$
- (d)  $\beta_0 = -0.5, \beta_1 = 1.0, \beta_2 = 2.0$

$x_1$	$x_2$	$y$
0.4	-0.2	1
0.6	-0.5	1
-0.3	0.8	0
-0.7	0.5	0



## Linear Classification



### Logistic Regression

- The Loss function





## Linear Classification



### Logistic Regression

- **The Loss function**

**How can we  
use log into  
this function**



## Linear Classification



### Logistic Regression

- Extending the case for more than 2 classes... (not imp)





## 2 mins Summary



Topic

Topic

Topic

Topic

Topic

**THANK - YOU**