

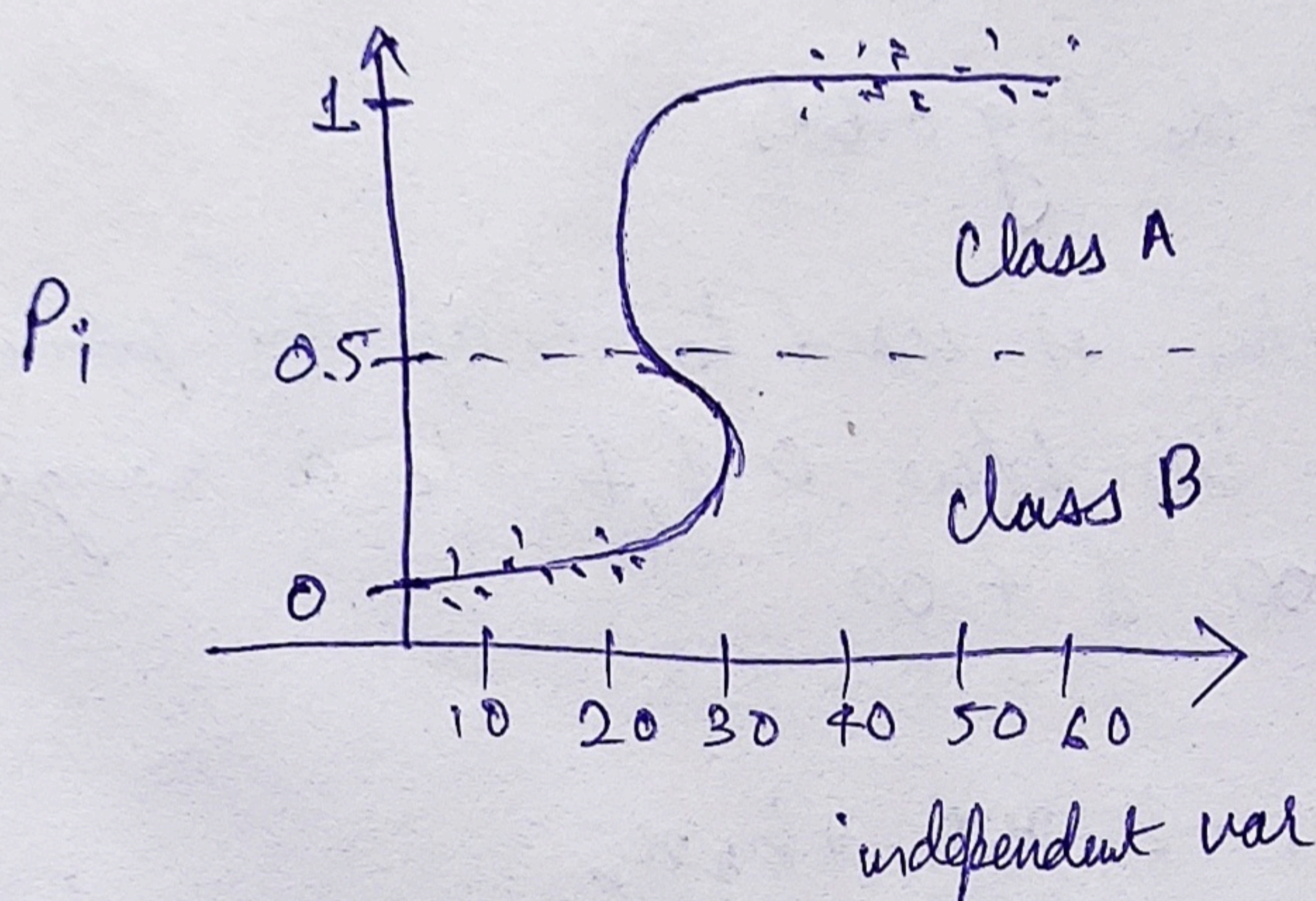
# Logistic Regression

- # used in categorical dataset. (yes/no, true/false, true/false)
- # fraud detection, disease diagnosis, Emergency detection, spam/no spam

$$\text{Sigmoid fn} = y = \frac{1}{1 + e^{-x}} \rightarrow \text{independent variable}$$

↘ 2.718

- # Sigmoid fn is trying to convert the independent var. into a expression of probability that ranges b/w 0 & 1 w.r.t dependent var.



$$\frac{1}{1 + e^{-x}} = \frac{1}{1 + e^{-mx + c}}$$

$m$  = give stretching  
 $c$  = gives the moment of the sigmoid up or down

- # To calculate the error we use the log loss fn.

$$\left[ -\frac{1}{n} \sum_{i=1}^n y_i \log(P_i) + (1 - y_i) \log(1 - P_i) \right]$$

↘ Goes to gradient descent for calculation

↓  
goal is to minimize this to a large -ve number



## Logistic Model

# Features  $x_1, x_2, \dots, x_n$

#  $y =$  binary output

#  $p = P(y=1)$  (Probability of  $y=1$ )

$$\ln \left( \frac{p}{1-p} \right) = b_0 + b_1 x_1 + b_2 x_2 + \dots + b_n x_n$$

#  $b_0, b_1, b_2, \dots$  parameter of weight that will be estimated by training

#  $\frac{p}{1-p}$  = the odds

#  $\ln \left( \frac{p}{1-p} \right)$  = the log odds

→ This is used to map the ~~prob~~ probability that lies b/w 0 & 1 to a range b/w  $-\infty$  &  $+\infty$

$$\frac{p}{1-p} = e^{b_0 + b_1 x_1 + b_2 x_2 + \dots + b_n x_n}$$

$$\Rightarrow p = \frac{e^{b_0 + b_1 x_1 + b_2 x_2 + \dots + b_n x_n}}{1 + e^{b_0 + b_1 x_1 + b_2 x_2 + \dots + b_n x_n}}$$

$$\Rightarrow p = \frac{1}{1 + e^{-(b_0 x_0 + b_1 x_1 + \dots + b_n x_n)}}$$

$$\parallel S(x) = \frac{1}{1 + e^{-x}}$$

## Loss fn:-

# used to calculate error in the predicted value

# The L2 loss fn:-

$$L = \sum_{i=1}^n (y_i - \bar{y}_i)^2$$

Our goal is to minimize the entire loss using ~~for~~ gradient descent algorithm.



## Gradient Descent Algorithm for Logistic Reg:-

$$\bar{y}_i = p = \frac{1}{1 + e^{-(b_0 + b_1 x_i)}} = \frac{1}{1 + e^{-b_0 - b_1 x_i}}$$

① Initially  $b_0 = 0$ ,  $b_1 = 0$ ,  $L = 0.001$

② Calculate partial derivatives:-

$$D_{b_0} = -2 \sum_{i=1}^n (y_i - \bar{y}_i) \times \bar{y}_i \times (1 - \bar{y}_i)$$

$$D_{b_1} = -2 \sum_{i=1}^n (y_i - \bar{y}_i) \times \bar{y}_i \times (1 - \bar{y}_i) \times x_i$$

③ update  $b_0$  &  $b_1$

$$b_0 = b_0 - L \times D_{b_0}$$

$$b_1 = b_1 - L \times D_{b_1}$$

④ Repeat until loss is 0