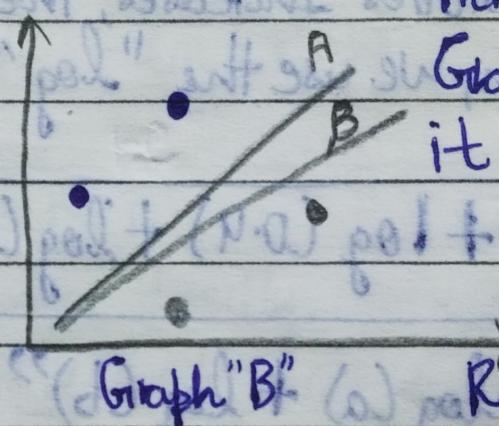
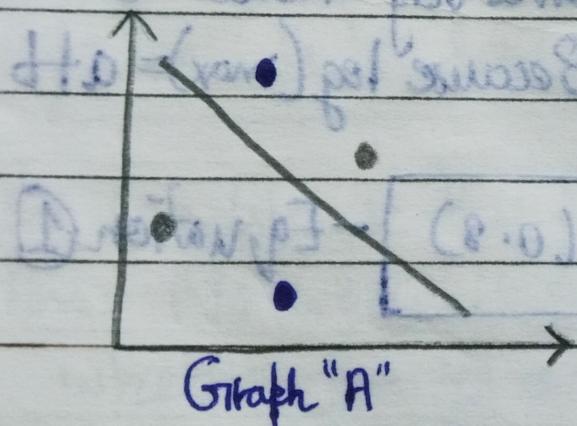


- Loss Function It tells how good [Accurate] our Classification Line is...

Q What is Loss Function?

Ans Loss Function is used to get the errors which we get while are making regression and these errors have a Quantitative Value. The minimum of that Quantitative Value Coordinates are the exact Values.



Loss Function

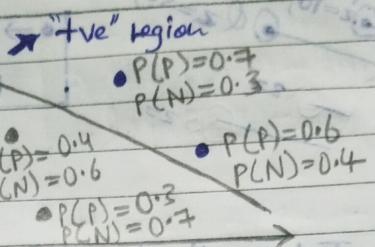
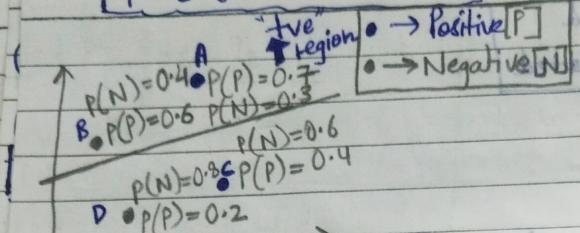
From Graph "A" and "B",
Graph "B" is better because it is accurately classified

But 'A' and 'B' which Regression line is better.
It is difficult to answer. For this we use Loss Function.

Spiral

Maximum Likelihood

$$\hat{Y} = \sigma(z) \text{ where } z = \sum k_i x_i$$



Q What is Maximum Likelihood says?

A Maximum Likelihood says that to decide, which model is best due to the following:-

① Firstly calculate all the Probabilities of all the points.

② Multiply [×] all the Probabilities and then compare.

③ Compare and whose Product is Greater is better model.

Note:- Take that Probability to which the points actually belongs to. $\rightarrow P(P) = 0.3$

S Calculating the Model 1 Maximum Likelihood :-

$$\text{Model 1} \Rightarrow 0.7 * 0.4 * 0.4 * 0.3 \\ \Rightarrow 0.0896$$

• Calculating the Model 2 Maximum Likelihood:

$$\text{Model 2} \Rightarrow 0.7 * 0.6 * 0.6 * 0.7$$

$$\Rightarrow 0.1764$$

There is one problem while calculating the Maximum Likelihood is that, as the points or Probabilities Increases, the value becomes very small. So to solve this problem, we use the "log" concept." Because $\log(ab) = a + b$

Using log.

$$\text{Model 1} = \log(0.7) + \log(0.4) + \log(0.4) + \log(0.3) \quad - \text{Equation 1}$$

"Because $\log(ab) = \log(a) + \log(b)$ "

"A" Note

Date.....

According to the Equation of log, it leads to 1 problem. Whenever, in calculates the equation ① Answer will be in the range between $(0 \rightarrow 1)$. But, as per the log, the value between $[0 \rightarrow 1]$ is negative.

$$\log(0 \rightarrow 1) \Rightarrow \text{Negative..}$$

To Solve this Problem, we can change the Equation ①, we can write it as:-

$$\boxed{\text{Model 1} = -\log(0.7) - \log(0.4) - \log(0.4) - \log(0.8)} \quad \text{Cross Entropy...}$$

This is the Correct Equation ① which helps in Calculating the Maximum Likelihood.

Q: What is the Cross Entropy?

Ans: Gross Entropy is defined as the Subtraction of Negative log of Maximum Likelihood, is known as Cross Entropy...

Q: Now, we use to calculate the Cross Entropy to Compare the Models?

Ans: Yes, we have to Calculate the Cross Entropy, not the Maximum Likelihood but, then How to Compare.

- In Cross Entropy we have to get the Minimum Entropy because the Minimum Entropy has the highest value.

For example:- $\log(0.1) > \log(0.9)$

$\rightarrow 1 > \Rightarrow 0.04$

\therefore therefore Selects the Minimum Entropy...

$$\boxed{-\log(\hat{Y}_1) - \log(\hat{Y}_2) - \log(\hat{Y}_3) - \log(\hat{Y}_4)} \quad \text{Formula}$$

Q: Can We use this formula directly?

Ans: No we can't use this Formula directly because we have to check whether the \hat{Y}_i is the Probability of Positive come or Negative. But we only want those Probabilities, the data point's color probability.

Date.....

Modifying the Formula as: $\Sigma_i Y_i \log(Y_i) - (1-Y_i) \log(1-Y_i)$

From ①, ②, ③, ④ Subtraction
 $\rightarrow \log(0.7) - \log(0.4)$
 $\rightarrow -\log(0.4) - \log(0.8)$

For First Point [A].

$Y_i = 1$ was SW (written, pd \rightarrow to expand) we
i.e., $\rightarrow -Y_i \log(Y_i) - (1-Y_i) \log(1-Y_i)$

$\Rightarrow -Y_1 \log(Y_1)$
 $\Rightarrow -\log(0.7)$

Hence we done.....
Same as the Gross Entropy....

For Second Point [B]

$Y_i = 0$

i.e., $\rightarrow -Y_i \log(Y_i) + (1-Y_i) \log(1-Y_i)$
 $\Rightarrow -\log(1-Y_i)$
 $\Rightarrow -\log(1-0.6)$
 $\Rightarrow -\log(0.4)$

For Third Point [D]

$Y_i = 0$

i.e., $\rightarrow Y_i \log(Y_i) - (1-Y_i) \log(1-Y_i)$
 $\Rightarrow -(1-0) \log(1-Y_i)$
 $\Rightarrow -\log(1-Y_i)$
 $\Rightarrow -\log(1-0.12)$
 $\Rightarrow -\log(0.88)$

For Fourth Point [C]

$Y_i = 1$ was SW standard which changed with SW & PD was off SW
i.e., $\rightarrow -Y_i \log(Y_i) + (1-Y_i) \log(1-Y_i)$
 $\Rightarrow -\log(Y_i)$
 $\Rightarrow -\log(0.4)$

Date

$$L = \sum_{i=1}^n -Y_i \log(\hat{Y}_i) - (1-Y_i) \log(1-\hat{Y}_i)$$

↳ Log Loss Error

↳ Binary Cross Entropy ...

"Minimum Value ..."

$$L = -\frac{1}{n} \sum_{i=1}^n Y_i \log(\hat{Y}_i) + (1-Y_i) \log(1-\hat{Y}_i)$$

↳ Average Loss Function OR Binary Cross Entropy ..