LOG - LOSS →

Log loss is also a kind of a model evaluation metrics. For a model to perform better, we want the value of log-loss to be as low as possible. Lower the value of log loss, better the model performance will be. The formula for log loss is given by

$$\text{log loss} = \frac{1}{N}\sum_{i=1}^{n} -\left(y_i \log(p_i) - (1-y_i)\log(1-p_i)\right)$$

Here y_i = actual value

p_i = probablity of predicted value to be 1.

$(1-p_i)$ = probablity of predicted value to be 0.

Or, we can also calculate the log loss in terms of corrected probablities.

$$\text{Log loss} = \frac{1}{N}\sum_{i=1}^{n} -\left(\log(\text{corrected probablities})\right)$$

Now, we also need to understand that what are the corrected probablities. Let us Assume that y is the predicted values and p_i are prediction probablities for y to be 1. So lets first of all lets have a look at the table for the same.

y	Predicted Prob (p_i)	Corrected Probab.
1	0.94	0.94
1	0.90	0.90
1	0.78	0.78
0	0.51	0.49
0	0.47	0.53
1	0.83	0.83
1	0.89	0.81
0	0.10	0.90

As you can see from the table that the predicted probabilities are the probability of y=1. wherever the P_i are high, the predicted values are 1. when the value of P_i is below the cutoff, then the y=0. But, the corrected probability is the actual probability of the predicted values. So, it is same for y=1 ; but when y=0, the corrected probability is equal to $(1-P_i)$ as we can see from the table.

So, when we have calculated the corrected probabilities, then the log loss is given by

$$\text{log loss} = \frac{1}{N} \sum_{i=1}^{n} -(\log(\text{corrected probability}))$$

So, now if we get similar predictions from different models, then we can compare their performance using log loss. Lower the value of log loss, better the model performance.