Loss Functions for Classification

Binary Cross Entropy / Log Loss

Binary Cross Entropy / Log Loss

ID	Actual	Predicted probabilities
ID6	1	0.94
ID1	1	0.90
ID7	1	0.78
ID8	0	0.56
ID2	0	0.51
ID3	1	0.47
ID4	1	0.32
ID5	0	0.10

Binary Cross Entropy / Log Loss

It is the negative average of the log of corrected predicted probabilities

Binary Cross Entropy / Log Loss

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ID6	1	0.94	0.94
ID1	1	0.90	0.90
ID7	1	0.78	0.78
ID8	0	**0.56**	**0.44**
ID2	0	**0.51**	**0.49**
ID3	1	0.47	0.47
ID4	1	0.32	0.32
ID5	0	**0.10**	**0.90**

Binary Cross Entropy / Log Loss

It is the negative average of the log of corrected predicted probabilities

$\log(p_i)$

Binary Cross Entropy / Log Loss

ID	Actual	Predicted probabilities	Corrected Probabilities	Log
ID6	1	0.94	0.94	-0.0268721464
ID1	1	0.90	0.90	-0.0457574906
ID7	1	0.78	0.78	-0.1079053973
ID8	0	0.56	0.44	-0.3565473235
ID2	0	0.51	0.49	-0.30980392
ID3	1	0.47	0.47	-0.3279021421
ID4	1	0.32	0.32	-0.4948500217
ID5	0	0.10	0.90	-0.0457574906

Binary Cross Entropy / Log Loss

It is the negative average of the log of corrected predicted probabilities

$$- \frac{1}{N} \sum_{i=1}^{N} (\log(p_i))$$

Binary Cross Entropy / Log Loss

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ID6	1	0.94	0.94	-0.0268721464
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Log Loss =0.2144

Binary Cross Entropy / Log Loss

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

Binary Cross Entropy / Log Loss

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

- p_i is probability of 1
- $1-p_i$ is probability of 0

Binary Cross Entropy / Log Loss

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

- p_i is probability of 1
- $1-p_i$ is probability of 0

Binary Cross Entropy / Log Loss

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

- p_i is probability of 1
- $1-p_i$ is probability of 0

Binary Cross Entropy / Log Loss

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

Binary Cross Entropy / Log Loss

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

$$\text{Log loss} = -\frac{1}{N}\sum_{i=1}^{N}\left(y_{i1} * \log(p_{i1}) + y_{i2} * \log(p_{i2})\right)$$

Binary Cross Entropy / Log Loss

$$\text{Log loss} = -\frac{1}{N}\sum_{i=1}^{N}(y_i * \log(p_i) + (1-y_i) * \log(1-p_i))$$

$$\boxed{\text{Log loss} = -\frac{1}{N}\sum_{i=1}^{N}(y_{i1} * \log(p_{i1}) + y_{i2} * \log(p_{i2}))}$$

- When the actual class is 1:
  - $y_{i1} = 1, y_{i2} = 0$
- When the actual class is 0:
  - $y_{i1} = 0, y_{i2} = 1$
- pi1 and pi2 : probability of first and second class

Categorical Cross Entropy

$$logloss = -\frac{1}{N}\sum_{i}^{N}\sum_{j}^{M} y_{ij}\log(p_{ij})$$

- N is the number of rows
- M is the number of classes

Thank You