Loss

ML Instruction Team, Fall 2022

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Classification Loss

■ Both the cross-entropy and the Kullback–Leibler (KL) divergence measures the distance between two probability distributions *P* and *Q*.

$$H(P,Q) = -\sum_{x} P(x) \log Q(x)$$

$$KL(P \mid Q) = \sum_{x} P(x) \log \frac{P(x)}{Q(x)} = H(P,Q) - H(P)$$

- In the above formula, H(P) = H(P, P) is the entropy of the distribution P, which is a constant term.
- Hence, it turns out that the minimization of KL divergence is equivalent to the minimization of cross-entropy.



Classification Loss

Logarithmic loss indicates how close a distribution of prediction probability comes to the real probability distribution of the data in binary classification.

$$H(p,q) = -\frac{1}{m} \sum_{i=1}^{m} y_i \log(p(y_i)) + (1 - y_i) \log(1 - p(y_i))$$

where $y_i \in \{0, 1\}$

Cross-entropy loss indicates how close a distribution of prediction probability comes to the real probability distribution of the data in multilabel classification.

$$H(p,q) = -\frac{1}{m} \sum_{i=1}^{m} \sum_{j=1}^{k} y_j^{(i)} \log(p(y_j^{(i)}))$$

where $y_j^{(i)}$ and $p(y_j^{(i)})$ is respectively the true and predicted probability of the class *i*-th of the sample *j*-th.



Classification Loss

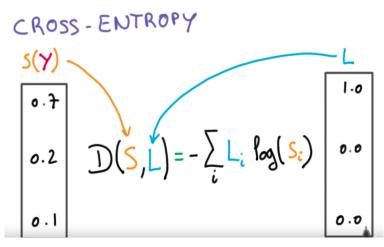


Figure: Cross Entropy Evaluation, Source

Regression Loss

$$MSE(y, \hat{y}) = \frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2$$

$$MAE(y, \hat{y}) = \frac{1}{m} \sum_{i=1}^{m} |(y_i - \hat{y}_i)|$$

$$MAPE(y, \hat{y}) = \frac{1}{m} \sum_{i=1}^{m} |\frac{(y_i - \hat{y}_i)}{y_i}|$$

$$Logcosh(y, \hat{y}) = \frac{1}{m} \sum_{i=1}^{m} \cosh(y_i - \hat{y}_i)$$

Regression Loss

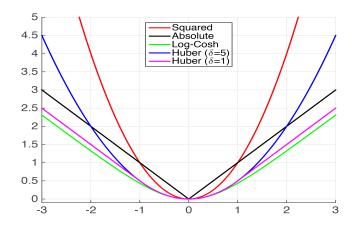


Figure: Various Regression Losses, Source

Thank You!

Any Question?