Loss Function is a measure of how well the algorithm performs.It shows the Error in the model and how much it differs from expected optimal output.

Difference between Cost Function and Loss Function

Cost Function is when a cost is associated with a decision.Total Aggregate of all the loss functions is the Cost Function.Loss Function is the loss per observation whereas Cost function is the loss for the entire dataset.

Types of Loss Functions-Classification and Regression Loss

A)Regression Loss:

1)Mean Absolute Error:(i=1 to n over SIGMA|Yi-Xi|)/n where,
Yi=Prediction,Xi=Actual Value and n=total observations

2)Mean Squared Error:1/n(i=1 to n over SIGMA(Yi-Y'i)^2) where,
n=total observations,Yi=actual observations,Y'i=Predicted Values

3)Huber loss is defined as: error ^{2}/2, if error < delta (ie, if it is a small error) delta * (|error| - delta/2), otherwise (|error| means the absolute value error)

B)Categorical Loss

1)Binary Cross Entropy

$$\text{Log Loss} = -\frac{1}{N}\sum_{i=1}^{N} y_i \log \hat{y}_i + (1-y_i)\log(1-\hat{y}_i)$$

- yi – actual values
- yihat – Neural Network prediction

2)Categorical Cross Entropy

$$\text{Loss} = -\sum_{j=1}^{K} y_j \log(\hat{y}_j)$$

where k is number of classes in the data

$$\text{Cost} = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{k}[y_{ij}\log(\hat{y}_{ij})]$$

where

- k is classes,
- y = actual value
- yhat – Neural Network prediction