**Types of the cost function**

There are many cost functions in machine learning and each has its use cases depending on whether it is a regression problem or classification problem.

1. Regression cost Function
2. Binary Classification cost Functions
3. Multi-class Classification cost Functions

1. Regression cost Function:

Regression models deal with predicting a continuous value for example salary of an employee, price of a car, loan prediction, etc. A cost function used in the regression problem is called “Regression Cost Function”. They are calculated on the distance-based error as follows:

Error = y-y’

Where,

Y – Actual Input

Y’ – Predicted output

The most used Regression cost functions are below,

**1.1 Mean Error (ME)**

* In this cost function, the error for each training data is calculated and then the mean value of all these errors is derived.
* Calculating the mean of the errors is the simplest and most intuitive way possible.
* The errors can be both negative and positive. So they can cancel each other out during summation giving zero mean error for the model.
* Thus this is not a recommended cost function but it does lay the foundation for other cost functions of regression models.

**1.2 Mean Squared Error (MSE)**

* This improves the drawback we encountered in Mean Error above. Here a square of the difference between the actual and predicted value is calculated to avoid any possibility of negative error.
* It is measured as the average of the sum of squared differences between predictions and actual observations.

MSE = (sum of squared errors)/n

* It is also known as L2 loss.
* In MSE, since each error is squared, it helps to penalize even small deviations in prediction when compared to MAE. But if our dataset has outliers that contribute to larger prediction errors, then squaring this error further will magnify the error many times more and also lead to higher MSE error.
* Hence we can say that it is less robust to outliers

**1.3 Mean Absolute Error (MAE)**

* This cost function also addresses the shortcoming of mean error differently. Here an absolute difference between the actual and predicted value is calculated to avoid any possibility of negative error.
* So in this cost function, MAE is measured as the average of the sum of absolute differences between predictions and actual observations.

          MAE = (sum of absolute errors)/n

* It is also known as L1 Loss.
* It is robust to outliers thus it will give better results even when our dataset has noise or outliers.

2. Cost functions for Classification problems

Cost functions used in classification problems are different than what we use in the regression problem. A commonly used loss function for classification is the cross-entropy loss. Let us understand cross-entropy with a small example. Consider that we have a classification problem of 3 classes as follows.

Class(Orange,Apple,Tomato)

The machine learning model will give a probability distribution of these 3 classes as output for a given input data. The class with the highest probability is considered as a winner class for prediction.

Output = [P(Orange),P(Apple),P(Tomato)]

The actual probability distribution for each class is shown below.

*Orange = [1,0,0]*

*Apple = [0,1,0]*

Tomato = [0,0,1]

If during the training phase, the input class is Tomato, the predicted probability distribution should tend towards the actual probability distribution of Tomato. If the predicted probability distribution is not closer to the actual one, the model has to adjust its weight. This is where cross-entropy becomes a tool to calculate how much far the predicted probability distribution from the actual one is. In other words, Cross-entropy can be considered as a way to measure the distance between two probability distributions. The following image illustrates the intuition behind cross-entropy:

FIg 3: Intuition behind croos-entropy (credit – machinelearningknowledge.ai )

This was just an intuition behind cross-entropy. It has its origin in information theory. Now with this understanding of cross-entropy, let us now see the classification cost functions.

**2.1 Multi-class Classification cost Functions**

This cost function is used in the classification problems where there are multiple classes and input data belongs to only one class. Let us now understand how cross-entropy is calculated. Let us assume that the model gives the probability distribution as below for ‘n’ classes & for a particular input data D.

And the actual or target probability distribution of the data D is

Then cross-entropy for that particular data D is calculated as

Cross-entropy loss(y,p) = – yT log(p)

= -(y1log(p1) + y2log(p2) + ……ynlog(pn) )

Let us now define the cost function using the above example (Refer cross entropy image -Fig3),

p(Tomato) = [0.1, 0.3, 0.6]

y(Tomato) = [0, 0, 1]

Cross-Entropy(y,P) = – (0\*Log(0.1) + 0\*Log(0.3)+1\*Log(0.6)) = 0.51

The above formula just measures the cross-entropy for a single observation or input data. The error in classification for the complete model is given by categorical cross-entropy which is nothing but the mean of cross-entropy for all N training data.

Categorical Cross-Entropy = (Sum of Cross-Entropy for N data)/N

**2.2 Binary Cross Entropy Cost Function**

Binary cross-entropy is a special case of categorical cross-entropy when there is only one output that just assumes a binary value of 0 or 1 to denote negative and positive class respectively. For example-classification between cat & dog.

Let us assume that actual output is denoted by a single variable y, then cross-entropy for a particular data D is can be simplified as follows –

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Cross-entropy(D) = – y\*log(p) when y = 1

Cross-entropy(D) = – (1-y)\*log(1-p) when y = 0

      The error in binary classification for the complete model is given by binary cross-entropy which is nothing but the mean of cross-entropy for all N training data.

Binary Cross-Entropy = (Sum of Cross-Entropy for N data)/N