Metrics to Evaluate your Machine Learning Algorithm

Evaluating your machine learning algorithm is an essential part of any project. Your model may give you satisfying results when evaluated using a metric ***say accuracy score*** but may give poor results when evaluated against other metrics such as ***logarithmic loss*** or any other such metric. Most of the times we use classification accuracy to measure the performance of our model, however it is not enough to truly judge our model. In this post, we will cover different types of evaluation metrics available.

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Classification Accuracy

Classification Accuracy is what we usually mean when we use the term accuracy. It is the ratio of number of correct predictions to the total number of input samples.

$$Accuracy = \frac{Number\ of\ Correct\ predictions}{Total\ number\ of\ predictions\ made}$$

It works well only if there are equal number of samples belonging to each class.

For example, consider that there are 98% samples of class A and 2% samples of class B in our training set. Then our model can easily get **98% training accuracy** by simply predicting every training sample belonging to class A.

When the same model is tested on a test set with 60% samples of class A and 40% samples of class B, then the **test accuracy would drop down to 60%.** Classification Accuracy is great, but gives us the false sense of achieving high accuracy.

The real problem arises, when the cost of misclassification of the minor class samples are very high. If we deal with a rare but fatal disease, the cost of failing to diagnose the disease of a sick person is much higher than the cost of sending a healthy person to more tests.

Logarithmic Loss

Logarithmic Loss or Log Loss, works by penalizing the false classifications. It works well for multi-class classification. When working with Log Loss, the classifier must assign probability to each class for all the samples. Suppose there are N samples belonging to M classes, then the Log Loss is calculated as below:

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

where:

y_ij, indicates whether sample i belongs to class j or not

p_ij, indicates the probability of sample i belonging to class j

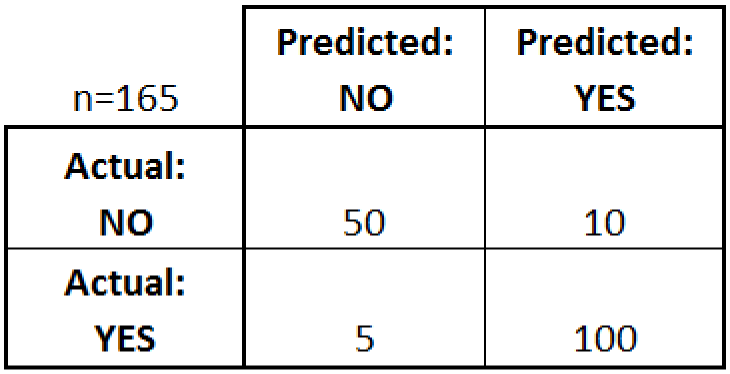
Log Loss has no upper bound and it exists on the range [0, ∞). Log Loss nearer to 0 indicates higher accuracy, whereas if the Log Loss is away from 0 then it indicates lower accuracy.

In general, minimizing Log Loss gives greater accuracy for the classifier.

Confusion Matrix

Confusion Matrix as the name suggests gives us a matrix as output and describes the complete performance of the model.

Lets assume we have a binary classification problem. We have some samples belonging to two classes: YES or NO. Also, we have our own classifier which predicts a class for a given input sample. On testing our model on 165 samples, we get the following result.



n=165	**Predicted: NO**	**Predicted: YES**
Actual: NO	50	10
Actual: YES	5	100

Confusion Matrix

There are 4 important terms:

- **True Positives**: The cases in which we predicted YES and the actual output was also YES.
- **True Negatives**: The cases in which we predicted NO and the actual output was NO.
- **False Positives**: The cases in which we predicted YES and the actual output was NO.
- **False Negatives**: The cases in which we predicted NO and the actual output was YES.

Accuracy for the matrix can be calculated by taking average of the values lying across the **“main diagonal”** i.e

$$Accuracy = \frac{TruePositive + TrueNegative}{TotalSample}$$
$$\therefore Accuracy = \frac{100 + 50}{165} = 0.91$$

Confusion Matrix forms the basis for the other types of metrics.

Area Under Curve

Area Under Curve (AUC) is one of the most widely used metrics for evaluation. It is used for binary classification problem. *AUC* of a classifier is equal to the probability that the classifier will rank a randomly chosen positive example higher than a randomly chosen negative example. Before defining *AUC*, let us understand two basic terms:

- **True Positive Rate (Sensitivity)**: True Positive Rate is defined as *TP/ (FN+TP)*. True Positive Rate corresponds to the proportion of positive data points that are correctly considered as positive, with respect to all positive data points.

$$TruePositiveRate = \frac{TruePositive}{FalseNegative + TruePositive}$$

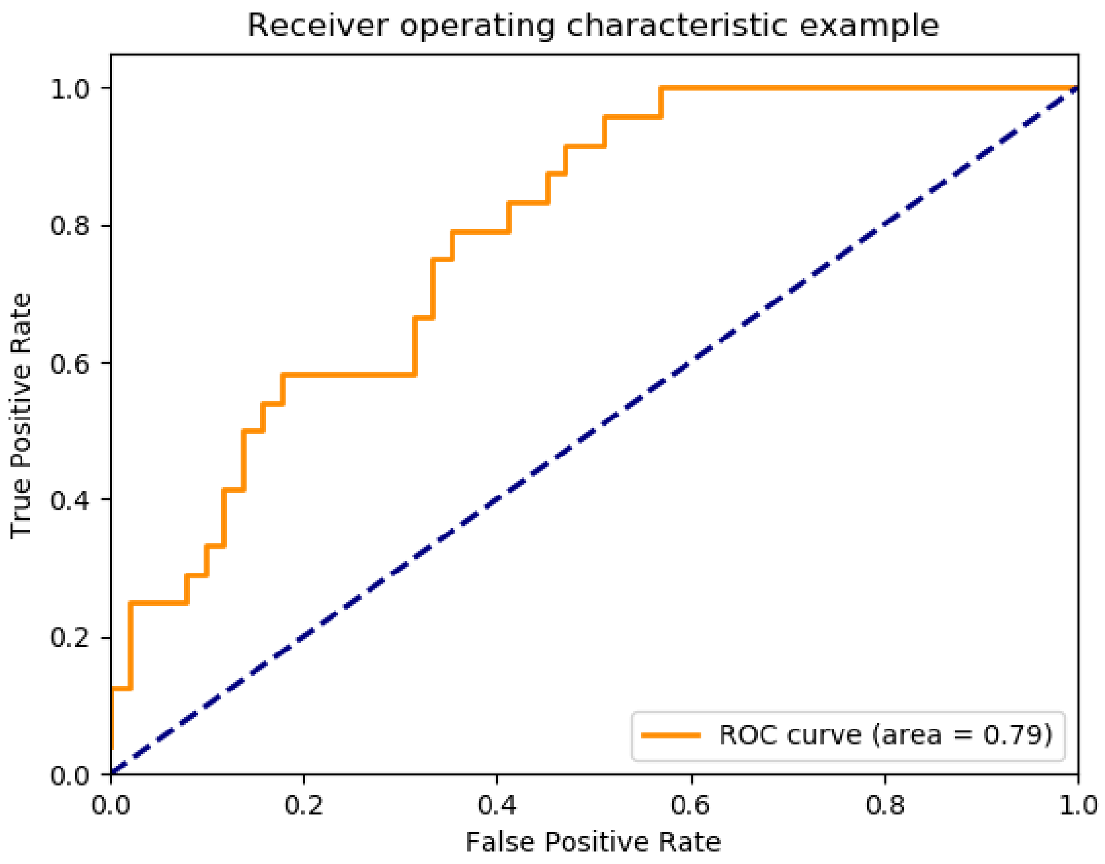
- **True Negative Rate (Specificity)**: True Negative Rate is defined as *TN / (FP+TN)*. False Positive Rate corresponds to the proportion of negative data points that are correctly considered as negative, with respect to all negative data points.

$$TrueNegativeRate = \frac{TrueNegative}{TrueNegative + FalsePositive}$$

- **False Positive Rate:** False Positive Rate is defined as *FP / (FP+TN)*. False Positive Rate corresponds to the proportion of negative data points that are mistakenly considered as positive, with respect to all negative data points.

$$FalsePositiveRate = \frac{FalsePositive}{TrueNegative + FalsePositive}$$

False Positive Rate and *True Positive Rate* both have values in the range **[0, 1]**. *FPR* and *TPR* both are computed at varying threshold values such as (0.00, 0.02, 0.04, …., 1.00) and a graph is drawn. *AUC* is the area under the curve of plot *False Positive Rate vs True Positive Rate* at different points in **[0, 1]**.



As evident, *AUC* has a range of [0, 1]. The greater the value, the better is the performance of our model.

F1 Score

F1 Score is used to measure a test's accuracy

F1 Score is the Harmonic Mean between precision and recall. The range for F1 Score is [0, 1]. It tells you how precise your classifier is (how many instances it classifies correctly), as well as how robust it is (it does not miss a significant number of instances).

High precision but lower recall, gives you an extremely accurate, but it then misses a large number of instances that are difficult to classify. The greater the F1 Score, the better is the performance of our model. Mathematically, it can be expressed as:

$$F1 = 2 * \frac{1}{\frac{1}{precision} + \frac{1}{recall}}$$

F1 Score

F1 Score tries to find the balance between precision and recall.

- **Precision:** It is the number of correct positive results divided by the number of positive results predicted by the classifier.

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives}$$

Precision

- **Recall:** It is the number of correct positive results divided by the number of ***all*** relevant samples (all samples that should have been identified as positive).

$$Precision = \frac{TruePositives}{TruePositives + FalseNegatives}$$

Recall

Mean Absolute Error

Mean Absolute Error is the average of the difference between the Original Values and the Predicted Values. It gives us the measure of how far the predictions were from the actual output. However, they don’t give us any idea of the direction of the error i.e., whether we are under predicting the data or over predicting the data. Mathematically, it is represented as:

$$MeanAbsoluteError = \frac{1}{N}\sum_{j=1}^{N}|y_j - \hat{y}_j|$$

Mean Squared Error

Mean Squared Error (MSE) is quite similar to Mean Absolute Error, the only difference being that MSE takes the average of the **square** of the difference between the original values and the predicted values. The advantage of MSE being that it is easier to compute the gradient, whereas Mean Absolute Error requires complicated linear programming tools to compute the gradient. As, we take square of the error, the effect of larger errors become more pronounced than smaller error, hence the model can now focus more on the larger errors.

$$MeanSquaredError = \frac{1}{N}\sum_{j=1}^{N}(y_j - \hat{y}_j)^2$$

Mean Squared Error