Addis Ababa Science And Technology University
College of Mechanical And Electrical Engineering
Department of Software Engineering
Individual Assignment of Machine Learning

Name of Student: Bewuketu Lake
Id Number: ETS 0146/12

Section A

Submitted to: Mr. Tesfaye

Date of Submission: Apr 14 2023 G.C

1. Root Mean Squared Error (RMSE)

Root Mean Squared Error (RMSE) is a measurement metric used to evaluate a regression model's performance in machine learning. It measures the difference between predicted and actual values to determine how well the model fits the data.

RMSE is a deviation from the predicted response which is the distance between the actual and the predicted values. The deviation gives an idea of how much the predicted value varies from the actual value, which can be positive or negative. The RMSE is an extension of the Mean Squared Error (MSE) formula where the square root is taken of the average squared error.
The formula for RMSE is as follows:

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(d_i - p_i)^2}$$

Let's breakdown the above formula -

- **Σ -** It represents the "sum".
- **d_i-** It represents the predicted value for the i^{th}
- **p_i-** It represents the predicted value for the i^{th}
- **n -** It represents the sample size.

Interpretation of RMSE is relatively simple: the lower the RMSE value for a regression model, the better it is. It indicates how closely the model's predictions match the actual values. For example, if a model has an RMSE of 5, it means that the average difference between the predicted and actual values is equal to 5 units. Therefore, a smaller RMSE is better because it suggests that the model predictions are more accurate.

A value of 0 (almost never achieved in practice) would indicate a perfect fit to the data. In general, a lower RMSE is better than a higher one. However, comparisons across different types of data would be invalid because the measure is dependent on the scale of the numbers used.

2. Receiver Operating Characteristics Curve (ROC)

ROC or Receiver Operating Characteristic curve represents a probability graph to show the performance of a classification model at different threshold levels. The curve is plotted between two parameters, which are:

	Positive condition	Negative condition
Actual condition	True positive	False Positive
Actual condition	False negative	True Negative

- **True Positive Rate or TPR**
- **False Positive Rate or FPR**

In the curve, TPR is plotted on the Y-axis, whereas FPR is on the X-axis.
TPR or True Positive rate is a synonym for Recall, which can be calculated as:

$$TPR = \frac{TP}{TP + FN}$$

FPR or False Positive Rate can be calculated as:

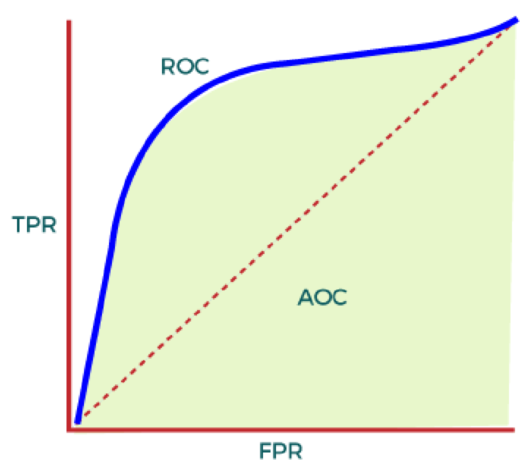
$$TPR = \frac{FP}{FP + TN}$$

Where as:

TP: True Positive **FP**: False Positive

TN: True Negative **FN**: False Negative

Now, to efficiently calculate the values at any threshold level, we need a method, which is AUC.AUC is known for **Area Under the ROC curve**. As its name suggests, AUC calculates the two-dimensional area under the entire ROC curve ranging from (0,0) to (1,1), as shown below image:



3. Mean directional accuracy (MDA)

Mean directional accuracy (MDA) is a popular evaluation metric used in machine learning algorithms to measure the accuracy of predicted values. It helps us understand the direction in which our predictions are biased in a specific dataset. This metric is important when we want to ensure that our prediction models are unbiased and provide sufficiently accurate results. For example, in trading or financial analytics, directional accuracy of market prediction models is especially critical as we want to make sure that we are making informed decisions based on reliable data.

MDA ranges from -1 to 1, where values close to 1 represent highly accurate models, and values close to -1 indicate highly inaccurate predictions. An MDA score of 0 indicates that the model's predictions are akin to random guesses. A high MDA indicates high predictive power and can be useful when examining multivariate series of different market indicators or with multiple predictive models.

Suppose we have a dataset with n observations and we make m predictions using our machine learning algorithm. We calculate the MDA score as the mean of the directional accuracy (DA) of m predicted values. The DA of each predicted value is calculated as follows:

If the predicted value is higher than the true value and the next observation has a higher value than the last observation, then DA = 1
If the predicted value is lower than the true value and the next observation has a lower value than the last observation, then DA = 1
If the predicted value's direction is not in the same direction as the next observation, then DA = 0

4. Precision

The precision metric is used to overcome the limitation of Accuracy. The precision determines the proportion of positive predictions that was actually correct. It can be calculated as the True Positive or predictions that are actually true to the total positive predictions (True Positive and False Positive).

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{(\boldsymbol{TP} + \boldsymbol{FP})}$$

5. F-Scores

F-score or F1 Score is a metric to evaluate a binary classification model on the basis of predictions that are made for the positive class. It is calculated with the help of Precision and Recall. It is a type of single score that represents both Precision and Recall. So, ***the F1 Score can be calculated as the harmonic mean of both precision and Recall, assigning equal weight to each of them.***

The formula for calculating the F1 score is given below:

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

As F-score makes use of both precision and recall, it should be used if both of them are important for evaluation, but one (precision or recall) is slightly more important to consider than the other. For example, when False negatives are comparatively more important than false positives, or vice versa.

6. R Squared Score

R squared error is also known as Coefficient of Determination, which is another popular metric used for Regression model evaluation. The R-squared metric enables us to compare our model with a constant baseline to determine the performance of the model. To select the constant baseline, we need to take the mean of the data and draw the line at the mean.

The R squared score will always be less than or equal to 1 without concerning if the values are too large or small.

$$R^2 = 1 - \frac{MSE(Model)}{MSE(Baseline)}$$

7. Mean squared logarithmic error (MSLE)

Mean squared logarithmic error (MSLE) is a loss function that is used to solve regression problems. MSLE is calculated as the average of the squared differences between the log-transformed actual and predicted values.

The formula to calculate the MSLE:

$$MSLE = \frac{1}{n}\sum_{i=1}^{n}(\log(y_i + 1) - \log(\hat{y}_i + 1))^2$$

- n - the number of data points.
- y - the actual value of the data point. Also known as true value.
- ŷ - the predicted value of the data point. This value is returned by model.

Let's say we have the following sets of numbers:

actual values of y	4	0	5	2
predicted values of ŷ	3.5	1	5	3

Here is example how MSLE can be calculated using these numbers:

$$MSLE = \frac{(\log(4+1) - \log(3.5+1))^2 + (\log(0+1) - \log(1+1))^2 +}{4} =$$

$$= \frac{+(\log(5+1) - \log(5+1))^2 + (\log(2+1) - \log(3+1))^2}{4} \approx 0.1436$$

Reference:

https://lindevs.com/calculate-mean-squared-logarithmic-error-using-tensorflow-2

https://www.javatpoint.com/machine-learning

https://en.wikipedia.org/wiki/Main_Page