Performance Parameters of a Neural Network

The performance of a binary classification neural network model is measured through following measures

- Accuracy
- Specificity
- Sensitivity
- Precision
- F1 Score

In order to define these parameters completely one need to understand the following terms when it comes to predictions of a model separating Signal class labeled as 1 from Background class labeled as 0.These are as follows:

1. **True Positive (TP)**

   The number of labels predicted as Signal that are in reality Signal .In simple terms number of correct prediction of Signal class.

2. **True Negative(TN)**

   The number of labels predicted as Background by the model that are actually Background i.e. number of correct prediction of Background labels

3. **False Positive(FP)**

   The number of labels predicted as Signal that are in reality Background .In other words, number of incorrect prediction of Background class as Signal class.

4. **False Negative(FN)**

   The number of labels predicted as background that were in reality Signal i.e. number of incorrect predictions of Signal as Background class.

In order to visualize these terms in order of importance for a binary classification model as a 2x2 matrix ,they can be arranged as follows where a bigger valued diagonal ensures a better predicting model.

True Positive	**False Positive**
False Negative	**True Negative**

The Parameters could be defined as follows:

Accuracy

It is ratio of number of data points for which the model predicts the correct output to the total number of data points in the dataset .It is often employed as a suitable metric for evaluating the performance of a binary classification model when the number of data points belonging to both classes i.e. Background and Signal are equal .Incase when both classes don’t have an equal proportion in the dataset, it is not a reliable metric and other performance metrics are preferred.

It is formularized in terms of above mentioned defined terms as

$$\textbf{Accuracy} = \frac{\mathbf{TP+TN}}{\mathbf{TP+FP+FN+TN}}$$

Precision

It is the ratio of total number of correctly predicted Signal class by the model over the number of data points whose output is predicted as Signal including also the Background label which are falsely predicted as Signal by the model .Its formula is given by:

$$\text{Precision} = \frac{\mathbf{TP}}{\mathbf{TP+FP}}$$

It quantifies how accurate is the model in predicting the Signal class correctly .

Recall

The ratio of correctly predicted positive labels i.e. Signal class to the total number of positive labels in the dataset is called recall- .It is calculated as

$$\text{Recall} = \frac{\mathbf{TP}}{\mathbf{TP+FN}}$$

It is a measure of how accurately the model predicts the Signal class given the total number of data points belonging to the Signal class in the dataset. Recall is also referred to as Sensitivity.

Specificity

It is the ratio of correctly predicted negative labels by the model i.e. data points belonging to Background class to total number of negative labels in the data. It is calculated as

$$\text{Specificity} = \frac{\mathbf{TN}}{\mathbf{TN+FP}}$$

F1 Score

F1 score also known as F-measure is the harmonic mean of Precision and Recall. It is given by:

$$\text{F1 Score} = \frac{2*(\text{Recall} * \text{Precision})}{\text{Recall} + \text{Precision}}$$

F1 score is preferred over Accuracy when the dataset has not equal number of data points for both the classes i.e. an imbalanced dataset .Given Perfect Precision and Recall, the highest possible value for F1 score is 1 and similarly minimum F1 score is 0.

Loss Function

In order to define Binary Cross Entropy Loss Function, we need to look at what is a loss function. A loss function is a metric that enables us to optimize our model performance by comparing the model predictions to original labels .An optimized model will have a smaller loss function since the distance between the prediction and original label would be less .A machine learning model's performance is quantified with performance metrics like F1 score and in training the model, we are opting to optimize such metrics and cost function would give us a direction where we need to tune in model's learning parameters .In mathematical connotation

$$\text{Loss} = \text{abs}(Y\hat{} - Y)$$

Here Y^ is predicted output and Y is the actual output.

Binary Cross Entropy Loss

A neural network defines a probability distribution by way of cross entropy between the correct output and model predictions as P(yi|xi,theta) .In that case our Binary Cross Entropy loss function is given by

It is written as

$$\text{J (theta)} = -\sum_{i=1}^{n} \mathrm{yi}\log(\mathrm{pi}) + (1-\mathrm{yi})\log(1-\mathrm{pi}))$$

Given that we have only two classes i.e. Signal (labeled as 1) and Background (labeled as 0), pi is the i-indexed data point prediction probability when yi = 1 and hence (1-pi) is the probability when yi =0.As observed from the formula given yi=1 ,the second part of the formula is cancelled out and a large value of -log(pi) would be beneficial in terms of optimizing our performance parameters because in that case our error would be minimum and is only possible when the predicted probability for the example is close to 1 just like the original label .Similarly with yi=0 ,one second part remains and we want log(1-pi) to be maximum given the negative sign in order to optimize our model which is possible when pi is close to zero closely mimicking the original label.