Addis Ababa Science and Technology University

Department of Software Engineering

Introduction to Machine Learning

Individual Assignment

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1. Error measurement metrics

1.1. Mean Squared Error

Mean squared error is another popular error evaluation statistic in machine learning. (MSE). MSE determines the average of the squared deviations between the actual and expected values..A lower MSE score indicates that the model's predictions are closer to the truth. The steps required to compute the MSE are to find the difference between the anticipated and actual value, square the differences, add them all up, and divide the result by the number of samples in your datasets. Mean squared error (MSE) is frequently employed in machine learning algorithms like neural networks, logistic regression, and linear regression. The following is the MSE calculation formula:

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

1.2. Mean absolute error

Mean Absolute Error (MAE) is used to calculate the average difference between the actual values and the anticipated values. MAE shows how closely the model's predictions match the actual values. A common evaluation metric in machine learning regression algorithms is mean absolute error. The target variable's expected and actual values are compared, and the average absolute difference between them is calculated. It is highly useful in dealing with outliers because it is not strongly influenced by extreme values. It is incorporated into algorithms like gradient boosting, decision trees, random forests, and linear regression.

As its name suggests, the MAE score is calculated as the average of the absolute error values. Absolute or *abs()* is a mathematical function that simply makes a number positive. Therefore, the difference between an expected and predicted value may be positive or negative and is forced to be positive when calculating the MAE.

The MAE can be calculated as follows:

MAE = 1 / N * sum for i to N abs(y_i – yhat_i)

Where *y_i* is the i'th expected value in the dataset, *yhat_i* is the predicted value and *abs()* is the absolute function.

MAE in algorithms such as linear regression, decision tree, random forest and gradient boosting.

1.3. Root Mean Squared Error(RMSE)

The mean squared error has been extended to include RMSE. The square root of the error is determined, which is significant since it means that the units of the RMSE and the goal value that is being forecasted are the same. The evaluation metric known as root mean squared error is frequently employed in supervised learning algorithms such as neural networks, decision trees, random forests, and linear regression. It is employed to calculate the discrepancy between actual and anticipated values. The better the model fits the data, the lower the RMSE number.The following is the formula for computing RMSE:

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(y_j - \breve{y}_j)^2}$$

1.4. Mean absolute percentage error(MAPE)

A machine learning algorithm's accuracy on a certain dataset is determined by the statistical metric MAPE. The error defined by the model evaluation can be thought of as a loss function. In MAPE. This method can be used in a variety of machine learning algorithms including linear regression, decision trees, random forests, and neural networks the accuracy is expressed as a ratio with the following formula:

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

1.5. R-squared

The most used measure for regression models is R-squared (R2). R2 estimates the percentage of the output variable's fluctuation that can be accounted for by the input variables.A high R-squared number (near to 1) denotes a regression line that adequately fits the data, whereas a low R-squared value (closer to 0) denotes a line that does not adequately match the data. R-squared is frequently used in linear regression models to assess the model's goodness of fit. The formula for calculating R^2 is as follows:

$$R^2 = 1 - (SSres / SStot)$$

2. Performance measurement metrics

2.1. F1-Score

F1-score, often known as F-score, is a metric used to assess the precision of a model on a dataset. It is applied to the assessment of binary categorization schemes.It is a measurement used to assess a classification whose harmonic mean of recall and precision is used. It is a metric used in statistics to assess how accurate a test or model is. The formula for F1-score

$$\textit{F - measure} = \frac{2*\text{Recall}*\text{Precision}}{\text{Recall} + \text{Precision}}$$

2.2. Accuracy

accuracy calculates the proportion of cases in the datasets that were correctly categorized. The most fundamental method of model evaluation is accuracy, although this method frequently fails to accurately assess a model's performance. The formula for accuracy:

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

2.3. Precision

Precision is a crucial performance metric in machine learning. It calculates the ratio of actual positive results to all anticipated positive results. The entire number of the model's positive predictions is known as predicted positives, whereas the amount of the model's exact positive predictions is known as true positives. Precision is typically used to assess a model's ability to correctly forecast instances of positivity in binary classification problems. Even though it doesn't take into account false positives or false negatives, accuracy might not be a good enough standard to use in isolation to evaluate model performance.

2.4. Recall

A machine learning parameter called recall measures the proportion of genuine positive samples that the model correctly recognizes. Thus, recall measures a model's ability to identify all relevant instances, whether they are positive or negative.

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

2.5. Confusion matrix

A performance metric called the confusion matrix is used in machine learning to evaluate the accuracy of a classification algorithm. To summarize the classification results of a model, it is a table that compares the predicted and actual values of a set of data.

The confusion matrix contains true positive (TP), true negative (TN), false positive (FP), and false negative measurements. (FN). True positive cases are those that can be reliably predicted as being positive. (TP). True negative cases are those that are as anticipated to be negative. (TN). False positives (FP) are instances where a predicted positive outcome turned out to be negative. False negatives (FN) are situations in which a negative outcome was predicted but ended up being a positive one.