**Evaluation Techniques for Regression Models**

**Reading Task 25**

Evaluation Metrics for regression are essential for assessing the performance of regression models specifically. These metrics help in measuring how well a regression model is able to predict continuous outcomes. Common regression evaluation metrics for regression include Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R-squared (Coefficient of Determination), and Mean Absolute Percentage Error (MAPE).

## **Regression:**

Regression is a type of Machine learning and supervised model which helps in finding the relationship between independent and dependent variables.

## **Why We Require Evaluation Metrics?**

## It is necessary to obtain the accuracy on training data, but it is also important It is necessary to obtain the accuracy on training data, but it is also important to get a genuine and approximate result on unseen data otherwise Model is of no use.So to build and deploy a generalized model we require to Evaluate the model on different metrics which helps us to better optimize the performance, fine-tune it, and obtain a better result.

## **Mean Absolute Error (MAE):**

MAE is a very simple metric which calculates the absolute difference between actual and predicted values let’s take an example you have input data and output data and use Linear Regression, which draws a best-fit line.

Now you have to find the MAE of your model which is basically a mistake made by the model known as an error. Now find the difference between the actual value and predicted value that is an absolute error but we have to find the mean absolute of the complete dataset so, sum all the errors and divide them by a total number of observations and this is MAE. And we aim to get a minimum MAE because this is a loss.

## **Mean Squared Error(MSE):**

MSE is a most used and very simple metric with a little bit of change in mean absolute error. Mean squared error states that finding the squared difference between actual and predicted value.

**Advantages of MSE:**

The graph of MSE is differentiable, so you can easily use it as a loss function.

**Disadvantages of MSE:**

The value you get after calculating MSE is a squared unit of output. If you have outliers in the dataset then it penalizes the outliers most and the calculated MSE is bigger.

## **Root Mean Squared Error (RMSE):**

## As RMSE is clear by the name itself, that it is a simple square root of mean squared error.

#### **Advantages of RMSE**

* The output value you get is in the same unit as the required output variable which makes interpretation of loss easy

#### **Disadvantages of RMSE**

* It is not that robust to outliers as compared to MAE.**Root Mean Squared Log Error (RMSLE):**Taking the log of the RMSE metric slows down the scale of error. The metric is very helpful when you are developing a model without calling the inputs. In that case, the output will vary on a large scale.

To perform RMSLE we have to use the NumPy log function over RMSE:

print("RMSE",np.log(np.sqrt(mean\_squared\_error(y\_test,y\_pred)))

## R Squared (R2)

## R2 score is a metric that tells the performance of your model, not the loss in an absolute sense that how many wells did your model perform

## The normal case is when the R2 score is between zero and one like 0.8 which means your model is capable to explain 80 per cent of the variance of data.

## from sklearn.metrics import r2\_score r2 = r2\_score(y\_test,y\_pred) print(r2)

## **Adjusted R Squared**

## The disadvantage of the R2 score is while adding new features in data the R2 score starts increasing or remains constant but it never decreases because It assumes that while adding more data variance of data increases.

But the problem is when we add an irrelevant feature in the dataset then at that time R2 sometimes starts increasing which is incorrect.

Now as K increases by adding some features so the denominator will decrease, n-1 will remain constant. R2 score will remain constant or will increase slightly so the complete answer will increase and when we subtract this from one then the resultant score will decrease. so this is the case when we add an irrelevant feature in the dataset.

And if we add a relevant feature then the R2 score will increase and 1-R2 will decrease heavily and the denominator will also decrease so the complete term decreases, and on subtracting from one the score increases.

n=40  
k=2  
adj\_r2\_score = 1 - ((1-r2)\*(n-1)/(n-k-1))  
print(adj\_r2\_score)

## Conclusion:

## Evaluating metrics for regression models using appropriate metrics is crucial for assessing their performance and making informed decisions. By understanding and utilizing metrics like MAE, MSE, RMSE, R-squared, and others, data scientists can quantify the accuracy, goodness of fit, and overall effectiveness of their models. Ultimately, these regression evaluation metrics serve as valuable tools for model selection, optimization, and deployment in real-world regression problems.