Evaluation Metrics

Evaluation metrics are quantitative measure used to assess the performance and effectiveness of a statistical or machine learning model. These metrics provide insights into how well the model is performing and help in comparing different models or algorithms.

Evaluation metrics compare actual value/output (y) and predictive value ($\hat{y}$) to give scalar value. On the basis of scalar value you can predict how the model is behaving.

Regression Evaluation Metrics -

Note - y - actual/original value
$\hat{y}$ - predicted value

1) Sum of absolute error - Difference between Predicted and original values.

$$SAE = \sum_{i=1}^{N} |(y_i - \hat{y}_i|$$

2. Mean Absolute Error (MAE) - It is the average distance between Predicted and original values.

$$MAE = \frac{1}{N} \sum_{i=1}^{N} \left| y_i - \hat{y}_i \right|$$

3. Sum of squared Errors (SSE) - It is similar to sum of absolute error but the difference is it take the square between predicted and original values.

$$SSE = \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$

4. Mean squared Error (MSE) - It is similar to mean absolute error but the difference is it takes the square of the average of between predicted and original values.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$

Note - Range for above 4 models is $[0, \infty]$
"0" means ideal model.

5. r^2-score | r squared | coefficient of Determination-

$$R_2\ score = 1 - \left[\frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \right]$$

y_i = Actual / original value

$\hat{y}_i$ = Predicted value

$\bar{y}$ = Average of actual value

Note - Range for R2 score model is $(-\infty, 1)$
"1" means ideal model.