MACHINE LEARNING

Metrics – Machine Learning

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Overview

- Used to determine the performance of a model.
- Classification and Regression has different sets of metrics.
- There are no metrics for Clustering as there is no Y label in this type of problems.

- Classification metrics are based on how many predictions are correct or incorrect.

- Regression metrics are based on how close is the predicted value from the actual value.

Regression

- MSPE
- MSAE
- R Square
- Adjusted R Square

Classification

- Precision-Recall
- ROC-AUC
- Accuracy
- Log-Loss

Unsupervised Models

- Rand Index
- Mutual Information

Others

- CV Error
- Heuristic methods to find K
- BLEU Score (NLP)

Classification

Classification Accuracy -:

- This is when we say accuracy.

$$\text{Classification Accuracy} = \frac{\text{No of correct predictions}}{\text{Total number of predictions made}}$$

- Works well if there are equal number of samples belonging to each class.
- Classification Accuracy is great, but gives us the false sense of achieving high accuracy, when the classes are imbalanced.

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Logarithmic loss :

- Works well for multi-class classification
- When working with Log Loss, the classifier must assign probability to each class for all the samples.
- This varies from 0 to infinity $[0, \infty)$
- Log loss nearer to 0 indicates higher accuracy.

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• Confusion Matrix :

TN	**FP**
FN	TP

n=165	**Predicted: NO**	**Predicted: YES**
Actual: NO	50	10
Actual: YES	5	100

True negative(TN) **Correct prediction**	**False Positive(FP)** **Incorrectly predicted as positive.**
False Negative(FN) **Incorrectly predicted as –ve**	True Positive(TP) Correct Prediction

There are 4 important terms :

- True Positives : The cases in which we predicted YES and the actual output was also YES.
- True Negatives : The cases in which we predicted NO and the actual output was NO.
- False Positives : The cases in which we predicted YES and the actual output was NO.
- False Negatives : The cases in which we predicted NO and the actual output was YES.

- Accuracy = $$\frac{\text{True Positive + True Negative}}{\text{Total number of samples}}$$

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

- Precision – Accuracy of positive predictions.

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Area Under the Curve (AUC) :

- Used for binary classification problem and quality check.

- Recall/Sensitivity/True Positive Rate =

$$\frac{\text{True positive}}{\text{False Negative + True Positive}}$$

- True Positive Rate is the fraction of relevant instances that have been retrieved over the total amount of relevant instances.

- False Positive Rate =

$$\frac{\text{False Positive}}{\text{False Positive + True Negative}}$$

- False Positive Rate is the proportion of all Negative data points that are mistakenly predicted as positive, w.r.t. all negative data points.

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- Area under the Curve (AUC) = Area under the curve of the plot False Positive rates vs True Positive rates at different points [0,1].

- The higher the value of our AUC curve, the better the performance of the model.

F1 Score :

- It is the harmonic mean between precision and recall.

$$F1 = 2 * \frac{1}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}}$$

- Very important measure for classification.

- F1 is usually more useful than accuracy, especially if you have an uneven class distribution.
- Accuracy works best if false positives and false negatives have similar cost.
- If the cost of false positives and false negatives are very different, it’s better to look at both Precision and Recall than the F1 score.