Accuracy measures the performance of classifier on basis of it performance on negative and positive class

CLASSIFICATION METRICS VII

Accuracy

- Accuracy indicates the overall predictions performance of the classifier.
- Equation 7 represents the formula of computing accuracy.

$$\text{Accuracy} = \frac{TP+TN}{N} \tag{7}$$

Using Confusion matrix in Figure 54,

$$\text{Accuracy} = \frac{71+62}{71+7+10+62} = \frac{133}{150} = 88.6\%$$

		Actual	
		Positive (1)	Negative (0)
Predicted	Positive (1)	71	7
	Negative (0)	10	62

Figure 54: Confusion Matrix Example

- Classification models with high accuracy are preferred. However, accuracy measure should only be used when the class distribution in the data set is nearly equal.
- In case of class imbalance, accuracy is not a good criteria to evaluate the performance of the classifier.

- **Precision is performance matrixes that judges how many true predictions were made by positive class.**
- **Recall is performance matrixes that calculates out of the total positive how many positive classes are predicted by model.**

CLASSIFICATION METRICS VIII

Precision

- Precision is the true predictions out of total prediction made by the model (including positive and negative).
- Precision can be measured for each individual class present in the data set.
- For the positive class, precision is the number of correct positive results divided by the number of positive results predicted by the classifier, refer 8.

$$\text{Precision (positive class)} = \frac{TP}{TP + FP} \qquad (8)$$

- Precision for negative class is the number of correct negative results divided by the number of negative results predicted by the classifier, refer 9.

$$\text{Precision (negative class)} = \frac{TN}{TN + FN} \qquad (9)$$

- For Confusion matrix in Figure 55,

$$\text{Precision (positive class)} = \frac{71}{71 + 7} = 91.02\%$$

$$\text{Precision (negative class)} = \frac{62}{62 + 10} = 86.11\%$$

		Actual	
		Positive (1)	Negative (0)
Predicted	Positive (1)	71	7
	Negative (0)	10	62

Figure 55: Confusion Matrix Example

CLASSIFICATION METRICS IX

Recall

- Recall is the true predictions out of actual positive or negative class present in the data set.
- Recall can also be measured for each individual class present in the data set.
- For positive class (also known as sensitivity), it is the ratio of true positives to the actual positive samples present, refer Equation 10.

$$\text{Recall (positive class)} = \frac{TP}{TP+FN} \quad (10)$$

- In case of negative class (also known as specificity), it is the ratio of true negatives to the actual negative samples present, refer Equation 11.

$$\text{Recall (negative class)} = \frac{TN}{TN+FP} \quad (11)$$

		Actual	
		Positive (1)	Negative (0)
Predicted	Positive (1)	71	7
	Negative (0)	10	62

Figure 56: Confusion Matrix Example

- For Confusion matrix in Figure 56,

$$\text{Recall (positive class)} = \frac{71}{71+10} = 87.6\%$$

$$\text{Recall (negative class)} = \frac{62}{62+7} = 89.85\%$$

- Use Precision when positive class is important.
- Use Recall when most of the positive class has to be predicted.

CLASSIFICATION METRICS X

Precision and Recall

- Precision and recall are very important measures to access the quality of classifier on bases of the classes present in the data set.
- A good classifier should give high precision and high recall. However, it also depends upon the application to fix the important measure between precision and recall.
- For example, in the problem of predicting email as "ham" or "spam", suppose the concern is good recall, *i.e.*, we only worry about classification results where, classifier is able to find maximum samples belonging to a particular class correctly.

Predicted

30	30
10	30

Classifier 1

38	50
2	10

Classifier 2

$$\text{Precision(positive class)} = \frac{30}{60} = 91.02\%$$

$$\text{Precision(negative class)} = \frac{62}{62+10} = 86.11\%$$

$$\text{Recall(positive class)} = \frac{71}{71+10} = 87.6\%$$

$$\text{Recall (negative class)} = \frac{62}{62+7} = 89.85\%$$

Figure 57: Confusion matrixes by two different classifiers

F1 Score is needed when you want to seek a balance between Precision and Recall as it takes both Precision and Recall into consideration.

CLASSIFICATION METRICS XI

F1-score

- F1-score is the weighted average of Precision and Recall.
- It is particularly important when it is hard to figure out what model to select on the basis of precision and recall.
- F1 score selects a model based on a balance between precision and recall. It is measured using Equation 12,

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (12)$$

CLASSIFICATION METRICS XII

F1-score Example

Consider confusion matrixes in Figure 58 produced by two different models. Using F1-score, we need to find the better model with a balance of precision and recall.

Predicted \ Actual	Positive (1)	Negative (0)
Positive (1)	60	1
Negative (0)	2	61

Predicted \ Actual	Positive (1)	Negative (0)
Positive (1)	38	27
Negative (0)	17	42

Figure 58: Confusion matrixes by two different classifiers

Using Equation 12, the F1-score of classifier 1 on positive class is as in Equation13.

$$F1-score\ (\text{classifier } 1) = 2 \times \frac{0.92 \times 0.98}{0.92 + 0.98} = 0.94 \qquad (13)$$

F1-score on classifier 2 is computed using Equation 14.

$$F1-score\ (\text{classifier } 1) = 2 \times \frac{0.58 \times 0.69}{0.58 + 0.69} = 0.62 \qquad (14)$$

Based on F1-score, classifier 1 is better than classifier 2.