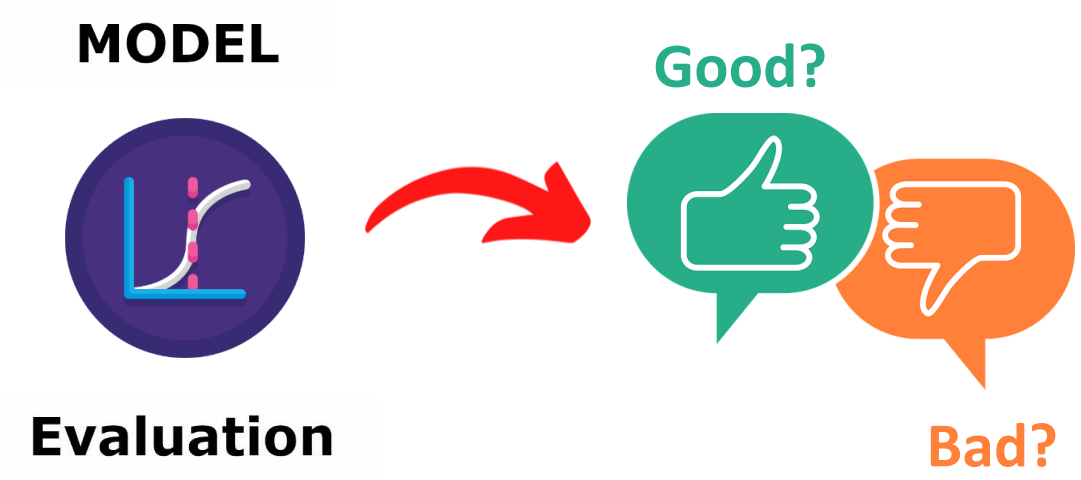
Siddhardhan

Precision, Recall, & F1 Score



Accuracy Score

In Classification, **Accuracy Score** is the ratio of **number of correct predictions** to the **total number of input data points**.

$$\text{Accuracy Score} = \frac{\text{Number of correct predictions}}{\text{Total Number of data points}} \times 100\ \%$$

Number of correct predictions = 128

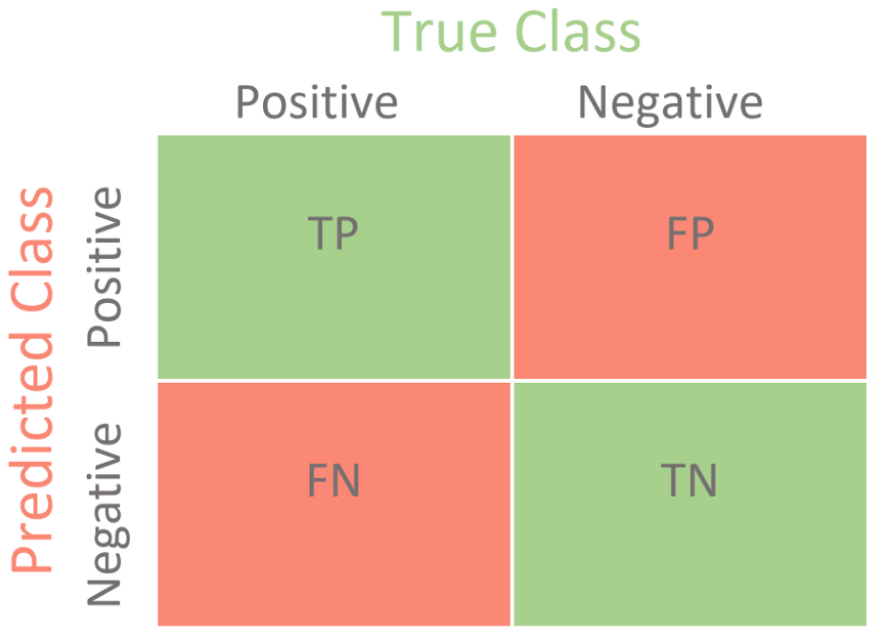
Total Number of data points = 150

Accuracy Score = 85.3 %

```
from sklearn.metrics import accuracy_score
```

Confusion Matrix

Confusion Matrix is a matrix used for evaluating the performance of a Classification Model. It gives more information than the accuracy score.



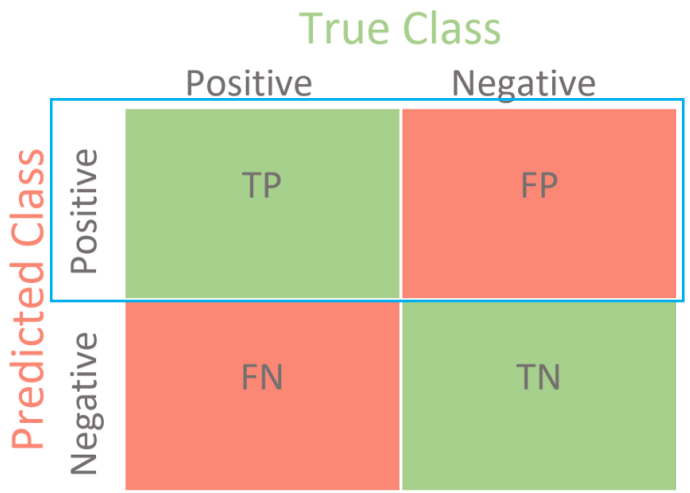
TP + TN = Correct Predictions

FP + FN = Wrong Predictions

sklearn.metrics.confusion_matrix

Precision

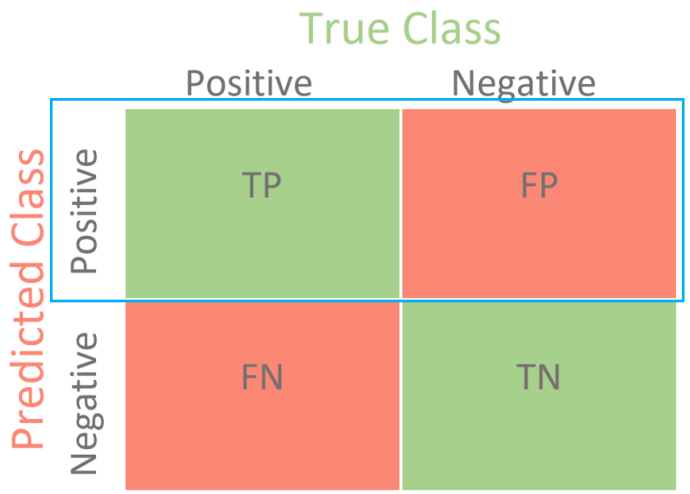
$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad \Rightarrow \quad \text{Precision} = \frac{\text{True Positive}}{\text{Total Predicted Positive}}$$



Precision is the ratio of number of **True Positive** to the **total number of Predicted Positive**. It measures, out of the total predicted positive, how many are actually positive.

Precision

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \textbf{False Positive}} \quad \Rightarrow \quad \text{Precision} = \frac{\text{True Positive}}{\text{Total Predicted Positive}}$$



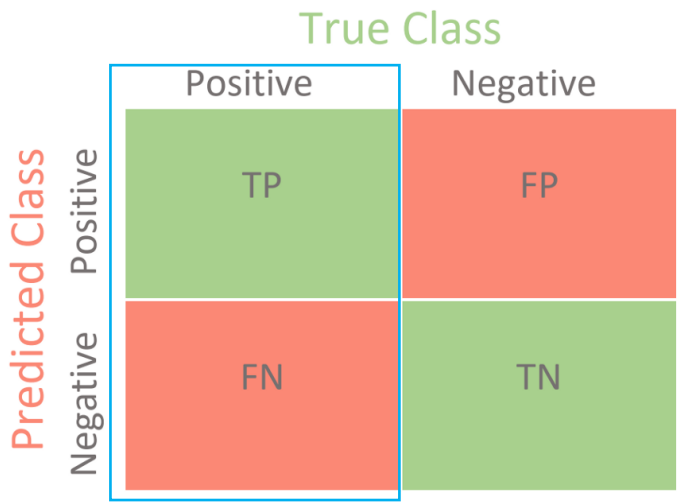
Precision is the ratio of number of **True Positive** to the **total number of Predicted Positive**. It measures, out of the total predicted positive, how many are actually positive.

Precision measures the error caused by **False Positives**. Hence it is a good evaluation metric when **False Positive** predictions are critical.

Example: Face Authentication

Recall

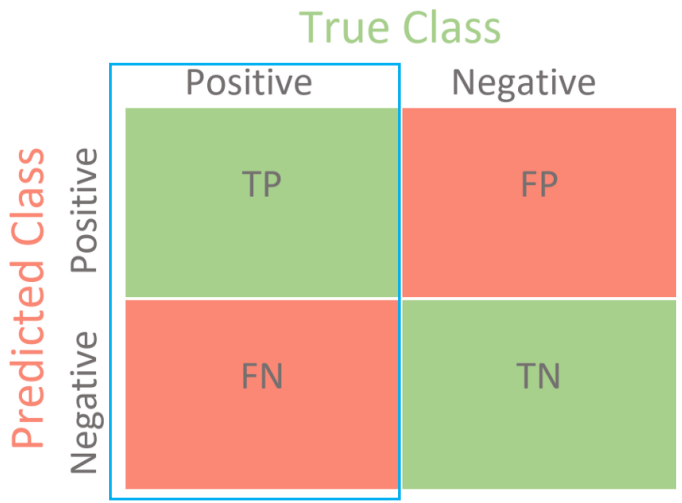
$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad \Rightarrow \quad \text{Recall} = \frac{\text{True Positive}}{\text{Total Actual Positive}}$$



Recall is the ratio of number of **True Positive** to the **total number of Actual Positive**. It measures, out of the total actual positive, how many are predicted as True Positive.

Recall

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \textbf{False Negative}} \quad \Rightarrow \quad \text{Recall} = \frac{\text{True Positive}}{\text{Total Actual Positive}}$$



Recall is the ratio of number of **True Positive** to the **total number of Actual Positive**. It measures, out of the total actual positive, how many are predicted as True Positive.

Recall measures the error caused by **False Negatives**. Hence it is a good evaluation metric when **False Negative** predictions are critical.

Example: Cancer Diagnosis

F1 Score

F1 Score is an important evaluation metric for binary classification that combines Precision & Recall. F1 Score is the **harmonic mean** of Precision & Recall.

This is a very useful metric when a dataset has imbalanced classes.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Precision, Recall & F1 Score

Example:

Actual \ Predicted	Positive	Negative
Positive	TP = 50	FN = 10
Negative	FP = 5	TN = 20

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} = \frac{50}{50 + 5}$$

Precision = 0.91

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} = \frac{50}{50 + 10}$$

Recall = 0.83

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = 2 \times \frac{0.91 \times 0.83}{0.91 + 0.83}$$

F1 Score = 0.87