

Confusion Matrix:

		Predicted	
		Negative	Positive
Actual	Negative	True Negative	False Positive
	Positive	False Negative	True Positive

Precision

Great! Now let us look at Precision first.

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

What do you notice for the denominator? The denominator is actually the Total Predicted Positive! So the formula becomes

		Predicted	
		Negative	Positive
Actual	Negative	True Negative	False Positive
	Positive	False Negative	True Positive

True Positive + False Positive = Total Predicted Positive

$$\begin{aligned}\text{Precision} &= \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \\ &= \frac{\text{True Positive}}{\text{Total Predicted Positive}}\end{aligned}$$

Immediately, you can see that Precision talks about how precise/accurate your model is out of those predicted positive, how many of them are actual positive.

Precision is a good measure to determine, when the costs of False Positive is high. For instance, email spam detection. In email spam detection, a false positive means that an email that is non-spam (actual negative) has been identified as spam (predicted spam). The email user might lose important emails if the precision is not high for the spam detection model.

Recall

Let us apply the same logic for Recall. Recall how Recall is calculated.

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

		Predicted	
		Negative	Positive
Actual	Negative	True Negative	False Positive
	Positive	False Negative	True Positive

$$\text{True Positive} + \text{False Negative} = \text{Actual Positive}$$

There you go! So, Recall calculates how many of the Actual Positives our model capture through labeling it as Positive (True Positive). Applying the same understanding, we know that Recall shall be the model metric we use to select our best model when there is a high cost associated with False Negative.

For instance, in fraud detection or sick patient detection. If a fraudulent transaction (Actual Positive) is predicted as non-fraudulent (Predicted Negative), the consequence can be very bad for the bank.

Similarly, in sick patient detection. If a sick patient (Actual Positive) goes through the test and predicted as not sick (Predicted Negative). The cost associated with False Negative will be extremely high if the sickness is contagious.

F1 Score

Now if you read a lot of other literature on Precision and Recall, you cannot avoid the other measure, F1 which is a function of Precision and Recall.

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

F1 Score is needed when you want to seek a balance between Precision and Recall

Type I and Type II errors

