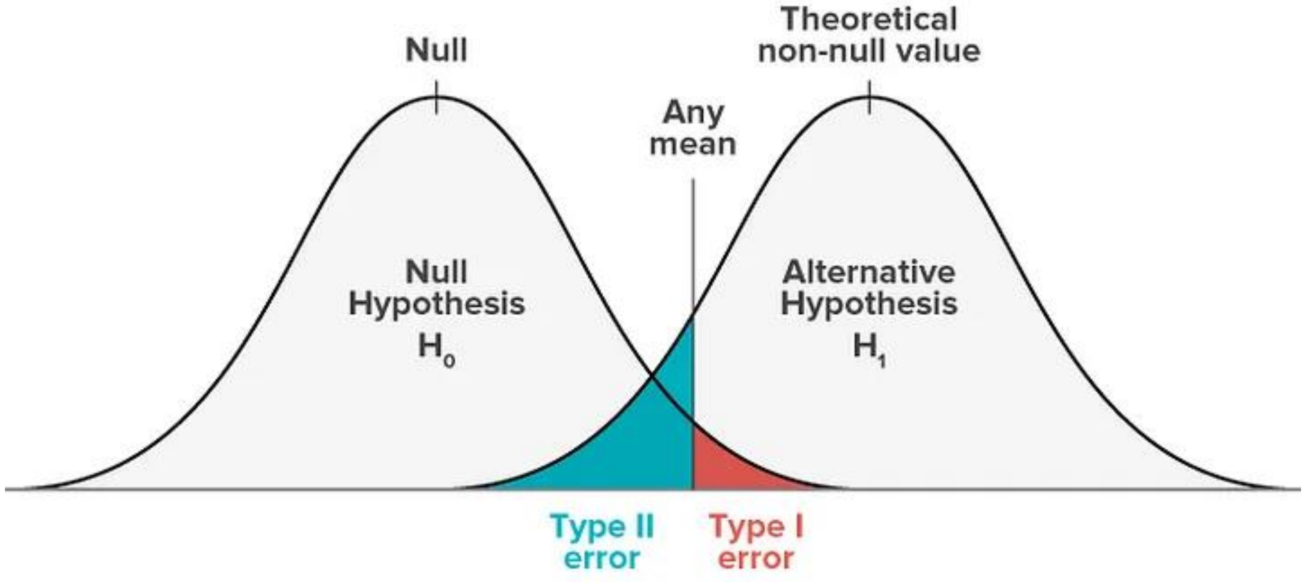
Performance Metrics

Dr. Mrunal Rane

Type I and Type II Errors

type-I error: **null hypothesis** is **rejected** which should not be in actual.

type-II error: although alternate hypothesis is true, you are **failing to reject null** hypothesis.



1. Confusion and Classification Matrix

		Predicted Class: Positive	Predicted Class: Negative	
Actual Class	Positive	True Positive (TP)	False Negative (FN) Type II Error	Sensitivity $\frac{TP}{(TP+FN)}$
	Negative	False Positive (FP) Type I Error	True Negative (TN)	Specificity $\frac{TN}{(TN+FP)}$
		Precision $\frac{TP}{(TP+FP)}$	Negative Predictive Value $\frac{TN}{(TN+FN)}$	Accuracy $\frac{TP+TN}{(TP+TN+FP+FN)}$

4. Recall or Sensitivity (True Positive Rate)

It measures the ratio of positive instances that are correctly detected by the classifier. Recall helps you to answer the question **"What proportion of actual positives is correctly classified?"**

2. Accuracy

Accuracy measures the fraction of total observations that are correctly classified. It is a ratio of the number of total correct classifications to the total number of observations.

3. Precision

Precision measures the accuracy of the positive prediction i.e. it measures the ratio of positive class out of the total predicted positively by a classifier. Precision helps you to answer the question ***"How precisely a classifier will predict the positive class?"***

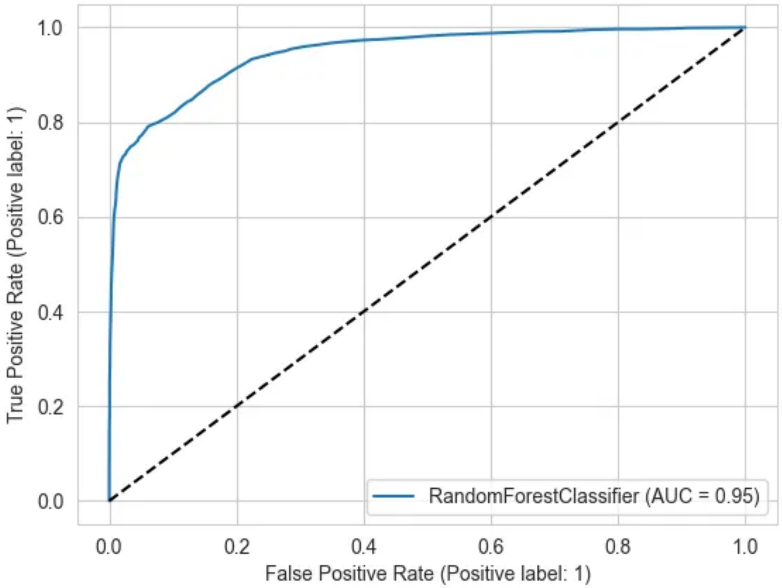
5. F1-Score:

- F1-score is a metric to evaluate the binary classification based on a prediction of the positive class.
- It measures the test accuracy.
- F1-score is the harmonic mean of the precision

$$F1 - score = 2 * \frac{precision * recall}{precision + recall}$$

6. Receiver operating characteristic curve (ROC curve):

$$TPR = \frac{TP}{TP + FN}$$



$$FPR = \frac{FP}{FP + TN}$$

Example

	Predicted No	Predicted Yes
Actual No	45	5
Actual Yes	5	95

- Accuracy
- Precision
- Recall
- F1-Score

	Predicted No	Predicted Yes
Actual No	TN = 45	FP = 5
Actual Yes	FN = 5	TP = 95