ROC-AUC

What is Statistics?

- If we have to define statistics, we will simply say that statistics is a discipline of applied mathematics that deals with gathering, describing, analyzing, and inferring conclusions from numerical data.
- Differential and integral calculus, linear algebra, and probability theory are all used substantially in statistics' mathematical theories. Statisticians are particularly interested in learning how to make trustworthy inferences about big groups and general phenomena from the observable features of small samples that reflect just a tiny share of the big group or a small number of instances of a general occurrence.

ROC-AUC

- Classification performance metrics such as Log-Loss, Average Accuracy, AUC, metric used for evaluating the performance in classification models.
- capability of a model in distinguishing the classes.
  - The judging criteria being - Higher the AUC, better the model.
- graphical way the connection and trade-off between sensitivity and specificity
-

ROC

- ROC curve, also known as Receiver Operating Characteristics Curve,
- depicts the rate of true positives with respect to the rate of false positives.
- it is a comparison of two operating characteristics, the True Positive Rate and the False Positive Rate

You should know following

- TP/FP/FN/TN
- TPR/FPR
- Precision,Recall F1-score
- Sensitivity and specificity
-

DEfinitions

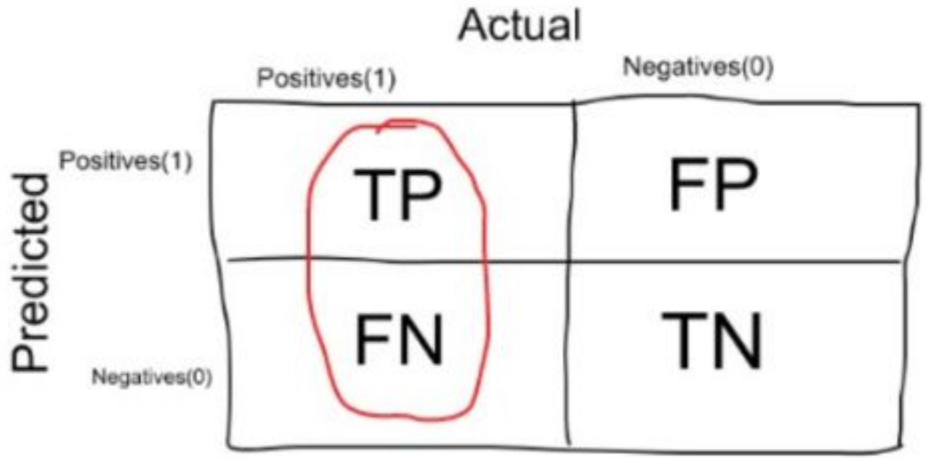
True Positive: Actual Positivity and Positivity Predicted

True Negative: Actual Negative and Negatively Predicted

Type I Error (False Positive): Although the situation is actually negative, it is anticipated to be positive.

False Negative :True Positive but anticipated as Negative (Type II Error): Actual Positive but anticipated as Negative.

Confusion Matrix



$$\text{Recall} = \frac{TP}{TP + FN}$$

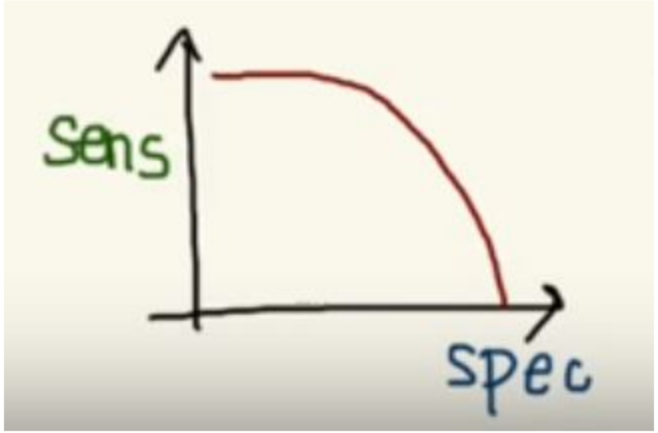
Predicted \ Actual	Positives(1)	Negatives(0)
Positives(1)	TP	FP
Negatives(0)	FN	TN

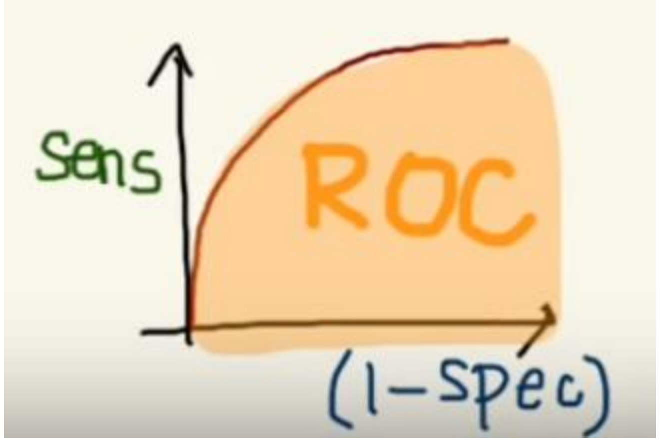
$$\text{Specificity} = \frac{TN}{TN + FP}$$

Tradeoff

As **Sensitivity** ⬇️ **Specificity** ⬆️

As **Specificity** ⬇️ **Sensitivity** ⬆️




Sens
ROC
(1-Spec)

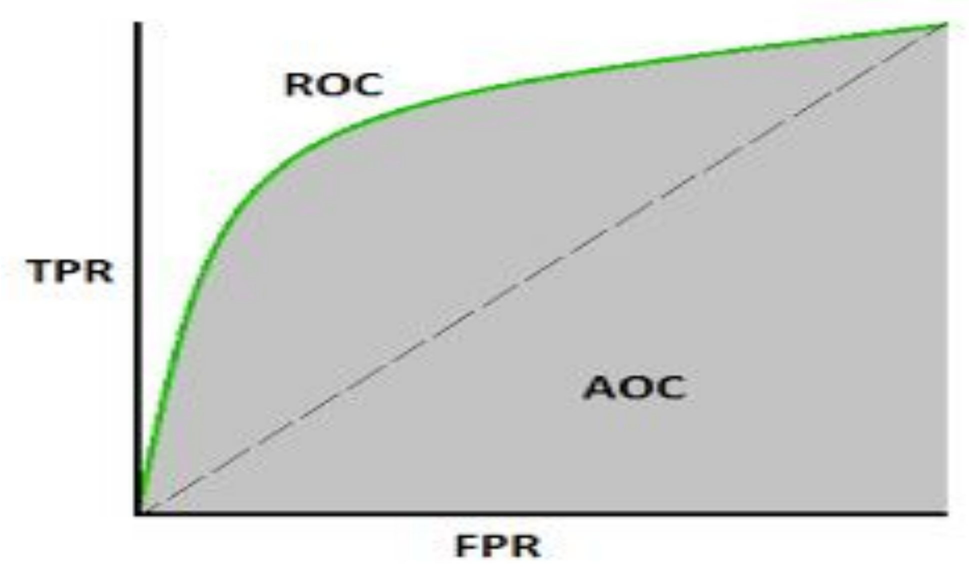
$$\text{True Positive Rate (TPR)} = \frac{TP}{P} = \frac{TP}{TP + FN}$$

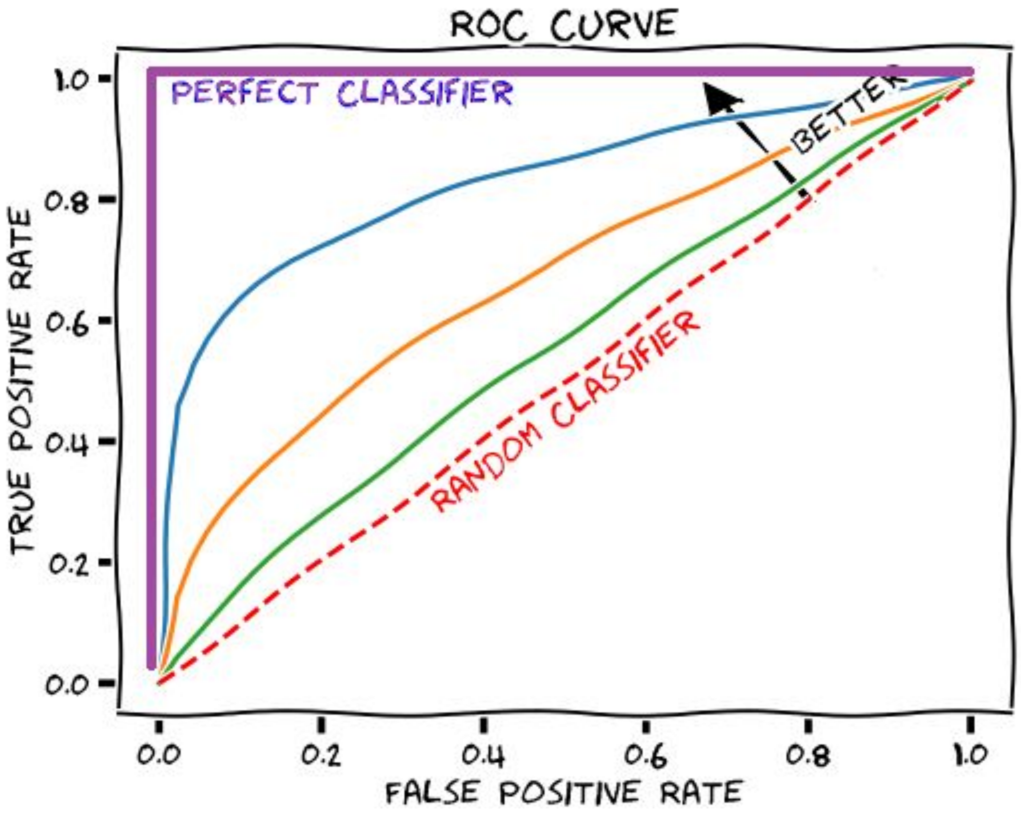
also called sensitivity/recall/hit rate

$$\text{False Positive Rate (FPR)} = \frac{FP}{N} = \frac{FP}{FP + TN}$$

also called fall out

ROC-AUC curve





ROC CURVE
PERFECT CLASSIFIER
BETTER
RANDOM CLASSIFIER
TRUE POSITIVE RATE
FALSE POSITIVE RATE
0.0
0.2
0.4
0.6
0.8
1.0

ROC

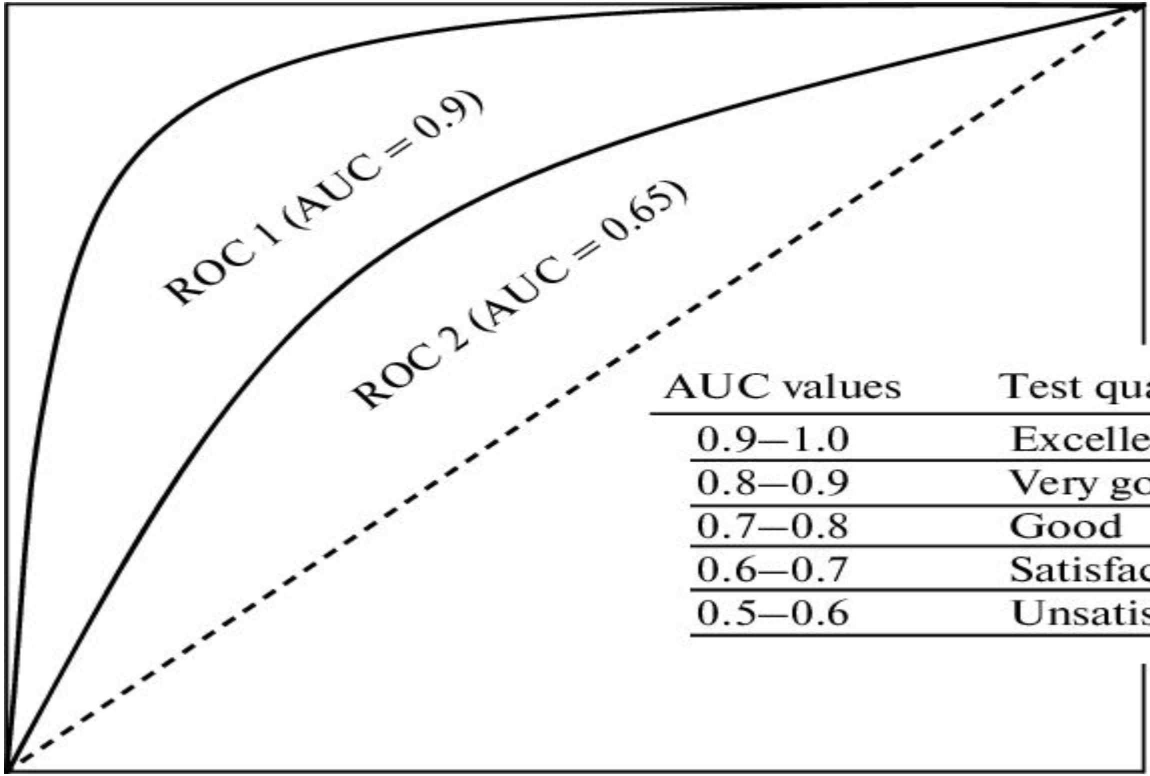
ROC curve can be used to select a threshold for a classifier, which maximizes the true positives and in turn minimizes the false positives.

ROC Curves help determine the exact trade-off between the true positive rate and false-positive rate for a model using different measures of probability thresholds.

AUC

- Area Under Curve or AUC is one of the most widely used metrics for model evaluation
- It is generally used for binary classification problems.
- AUC measures the entire two-dimensional area present underneath the entire ROC curve. AUC of a classifier is equal to the probability that the classifier will rank a randomly chosen positive example higher than that of a randomly chosen negative example.
- The Area Under the Curve provides the ability for a classifier to distinguish between classes and is used as a summary of the ROC curve.
- The higher the AUC, it is assumed that the better the performance of the model at distinguishing between the positive and negative classes.

AUC



AUC values	Test quality
0.9–1.0	Excellent
0.8–0.9	Very good
0.7–0.8	Good
0.6–0.7	Satisfactory
0.5–0.6	Unsatisfactory

interpretation of AUC-ROC curve

An excellent model poses an AUC near to the 1 which tells that it has a good measure of separability. A poor model will have an AUC near 0 which describes that it has the worst measure of separability. In fact, it means it is reciprocating the result and predicting 0s as 1s and 1s as 0s. When an AUC is 0.5, it means the model has no class separation capacity present whatsoever.

Higher the AUC, better the model.