AUC - ROC Curve

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What are Sensitivity/True Positive Rate, Specificity and False Positive Rate?

Sensitivity / True Positive Rate / Recall

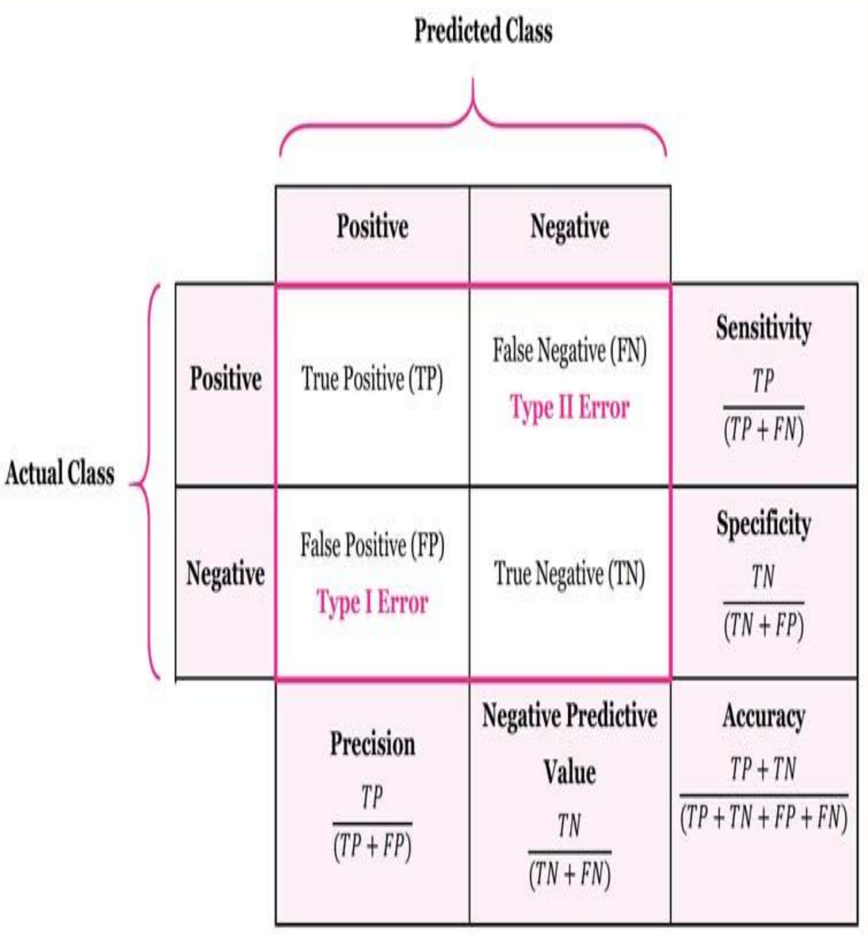
Sensitivity tells us **what proportion of the positive class got correctly classified**.

A test with a **higher sensitivity** has a **lower type II error rate**.

Specificity / True Negative Rate

Specificity tells us **what proportion of the negative class got correctly classified**.

A test with a **higher specificity** has a **lower type I error rate**.



False Positive Rate

FPR tells us **what proportion of the negative class got incorrectly classified by the classifier**.

A higher TNR and a lower FPR is desirable since we want to correctly classify the negative class.

FPR = 1 - Specificity

Metric	Formula and Description
True Positive Rates (TPR)	$TPR = TP / (TP + FN)$
False Positive Rates (FPR)	$FPR = FP / (FP + TN)$
Precision	$Precision = TP / (TP + FP)$
Recall	$Recall = TP / (TP + FN)$
F-Measure	$F\text{-}Measure = 2TP / (2TP + FP + FN)$
Accuracy	$Accuracy = (TP + TN) / (TP + TN + FP + FN)$

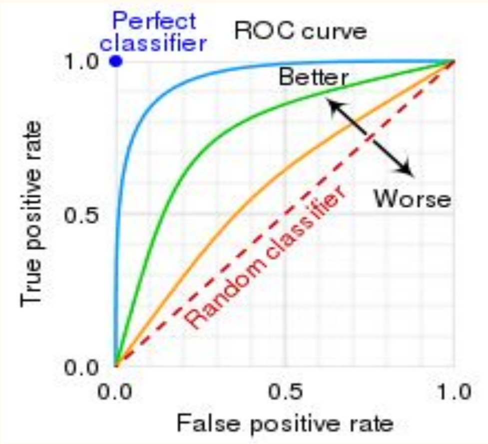
What is the AUC and ROC curve?

ROC

The **Receiver Operator Characteristic (ROC)** curve is an evaluation metric for **binary classification problems**. It is a graph showing the performance of a classification model at all classification thresholds. This curve plots two parameters:

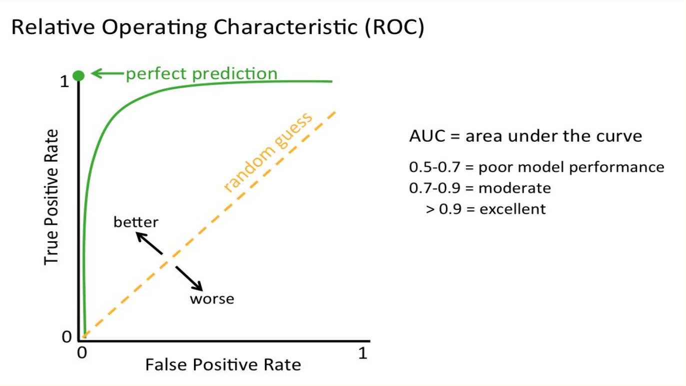
- True Positive Rate
- False Positive Rate

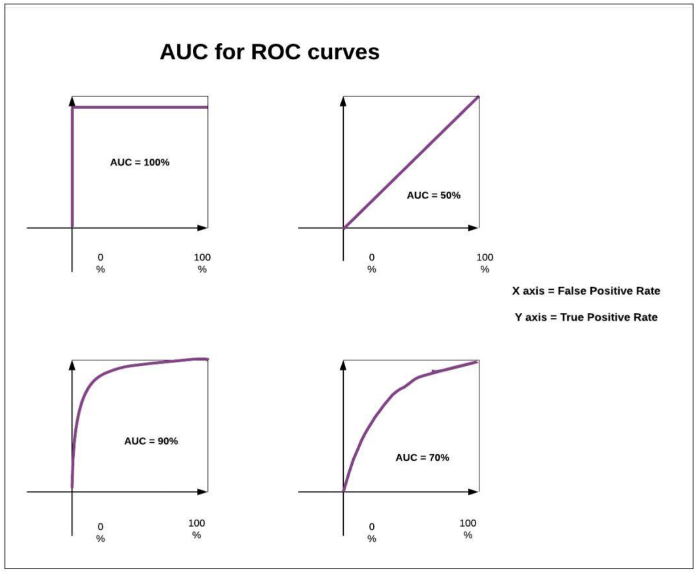
It is a probability curve that plots the **TPR against FPR at various threshold values**. Lowering the classification threshold classifies more items as positive, thus **increasing both False Positives and True Positives**.



AUC

AUC stands for **Area Under the Curve**. ROC can be quantified using AUC. **The way it is done is to see how much area has been covered by the ROC curve**. If we obtain a **perfect classifier**, then the **AUC score is 1.0**. If the classifier is **random in its guesses**, then the **AUC score is 0.5**. In the real world, we don't expect an AUC score of 1.0, but if the AUC score for the classifier is in the **range of 0.6 to 0.9**, then it is considered to be a **good classifier**.



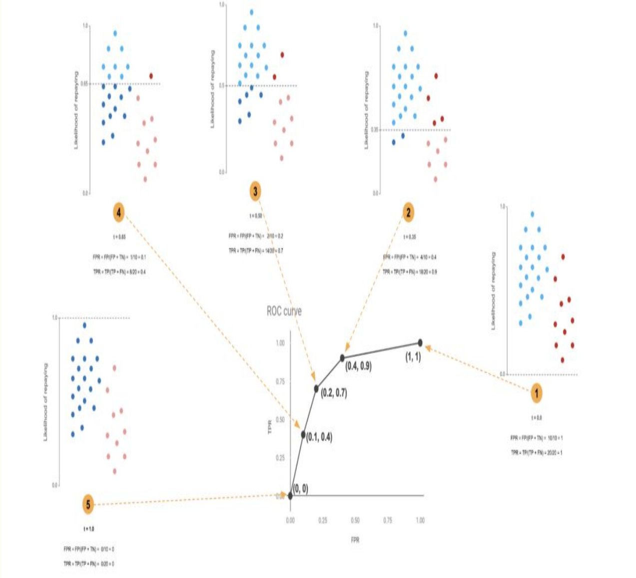


How does the AUC-ROC Curve works in Plot?

To plot the ROC curve, we need **to calculate the TPR and FPR for many different thresholds**. For each threshold, we plot the FPR value in the x-axis and the TPR value in the y-axis. We join the dots with a line. Each point of the ROC curve represents the FPR and TPR of a classification at a given cut-off. **The threshold at 1 leads to the first point at (0, 0) and the threshold at 0 leads to the last point at (1, 1)**.

The **area covered below the line** is called "**Area Under the Curve (AUC)**". This is used to evaluate the performance of a classification model. The higher the AUC, the better the model is at distinguishing between classes.

A high threshold value gives - high specificity and low sensitivity. A low threshold value gives - low specificity and high sensitivity.



When and Why to use AUC-ROC Curve?

WHEN

- You should use it **when you ultimately care about ranking predictions** and not necessarily about outputting well-calibrated probabilities.
- You **should not use it when your data is heavily imbalanced**. Because false positive rate for highly imbalanced datasets is pulled down due to a large number of true negatives.
- You should use it **when you care equally about positive and negative classes**.

WHY

- AUC is **scale-invariant**. It measures how well predictions are ranked, rather than their absolute values. AUC is **classification-threshold-invariant**.
- ROC curves are frequently used to **show in a graphical way the connection/trade-off between sensitivity and specificity for every possible cut-off for a test or a combination of tests**.


Thank you