Receiver-operating characteristic curve

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1 What is a ROC curve?

Accuracy alone can be a misleading metric of how well a model performs. So the ROC curve checks how well a binary classification model works by separating the positive cases like people with a disease from the negative cases like people without the disease at different threshold level. It shows how good the model is at telling the difference between the two classes. It does this by plotting:

True Positive Rate (TPR): How often the model correctly predicts positive cases also known as Sensitivity or Recall.

False Positive Rate (FPR): how often the model incorrectly predicts a negative case as positive.

Specificity: measures the proportion of actual negatives that the model correctly identifies. It is calculated as 1 - FPR.

2 Building the ROC Curve

$$TPR = \frac{True \ Positives}{True \ Positives + False \ Negatives}$$
 (1)

$$FPR = \frac{False Positives}{False Positives + True Negatives}$$
 (2)

The ROC curve is drawn by calculating the true positive rate (TPR) and false positive rate (FPR) at every possible threshold (in practice, at selected intervals), then graphing TPR over FPR.

3 Interpreting the Curve and AUC

The area under the ROC curve (AUC) represents the probability that the model, if given a randomly chosen positive and negative example, will rank the positive higher than the negative. For example a model with AUC equaling to 1 means that there is a 100% chance that the model is gonna guess correctly and with an AUC equaling 0.5 means that the model can't distinguish between the positive and negative classes hence the results are basically random.

AUC is a useful measure for comparing the performance of two different models, as long as the dataset is roughly balanced. The model with greater area under the curve is generally the better one.

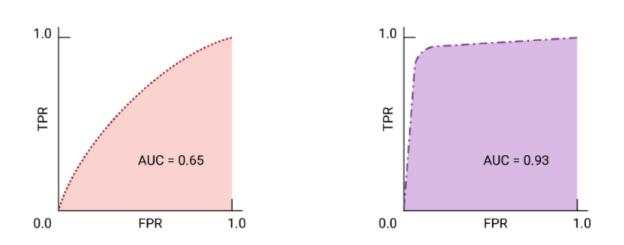


Figure 1: AUC of different graphs

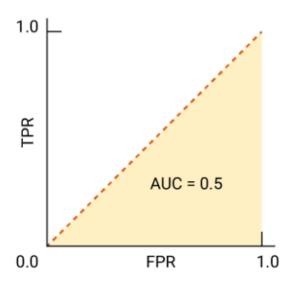


Figure 2: ROC and AUC of completely random guesses.