Evaluating Classification model Performance

1 Confusion Matrix

DEFINITION

A confusion matrix is a table that is often used to describe the performance of a classification model on a set of test data for which the true values are known

Example

n=165	Predicted: NO	Predicted: YES	
Actual: NO	TN = 50	FP = 10	60
Actual: YES	FN = 5	TP = 100	105
	55	110	

Total no. of Patient : 165

Cancer - Binary prediction (Yes / No)

ACTUAL

Cancer Yes – 105 Patient | Cancer No– 60 Patient

OUR MODEL PREDICTED

Cancer Yes – 110 Patient | Cancer No– 55 Patient

Parameter

n=165	Predicted: NO	Predicted: YES
Actual: NO	TN = 50	FP = 10
Actual: YES	FN = 5	TP = 100

- True positives (TP): These are cases in which we predicted yes (they have the cancer), and they have the cancer
- True negatives (TN): We predicted no, and they don't have the cancer
- False positives (FP)/Type I error: We predicted yes, but they don't actually have the cancer
- False negatives (FN)/Type II error: We predicted no, but they actually have the cancer

Evaluation

n=165	Predicted: NO	Predicted: YES	
Actual: NO	TN = 50	FP = 10	60
Actual: YES	FN = 5	TP = 100	105
	55	110	

- Accuracy: Overall correct
  - **(TP+TN)/total = (100+50)/165 = 0.91**
- Misclassification Rate: Overall wrong | Error Rate
  - **(FP+FN)/total = (10+5)/165 = 0.09**
- Sensitivity or Recall: True Positive Rate
  - **TP/actual yes = 100/105 = 0.95**
- False Positive Rate: **FP/actual no = 10/60 = 0.17**
- Specificity: True Negative Rate
  - **TN/actual no = 50/60 = 0.83**
- Precision: **TP/predicted yes = 100/110 = 0.91**
- Prevalence: **actual yes/total = 105/165 = 0.64**

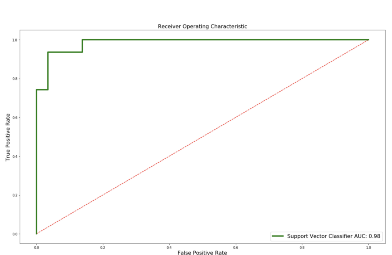
2 Accuracy Paradox

- Accuracy is defined as the freedom from mistake or error
- Accuracy is not a reliable metric to determine a model performance for imbalanced data
- That's why it's called a Paradox because, intuitively, you'd expect a Model with a higher Accuracy to have been the best Model but Accuracy Paradox tells us that this, sometimes, isn't the case

SOLUTION

F1 Score 2*((precision*recall)/(precision+recall))

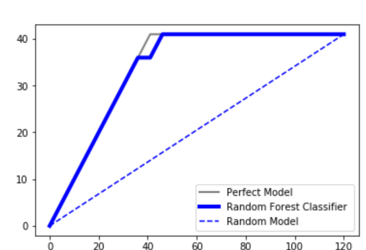
3 Receiver Operating Characteristic (ROC) Curve



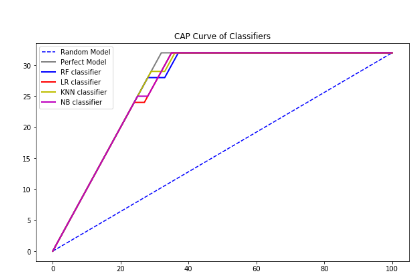
- True Positive Rate (TPR) is plot against False Positive Rate (FPR) for the probabilities of the classifier predictions. Then, the area under the plot is calculated
- Area Under the Curve (AUC) is the measure of the ability of a classifier to distinguish between classes and is used as a summary of the ROC curve
- The higher the AUC, the better the performance of the model at distinguishing between the positive and negative classes
- $sensitivity = \frac{count\ TP}{count\ TP + count\ FN}$ $specificity = \frac{count\ TN}{count\ TN + count\ FP}$

  Eqn, 1

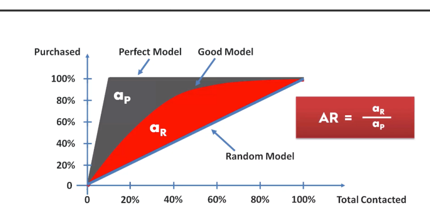
4 Cumulative Accuracy Profile (CAP) Curve



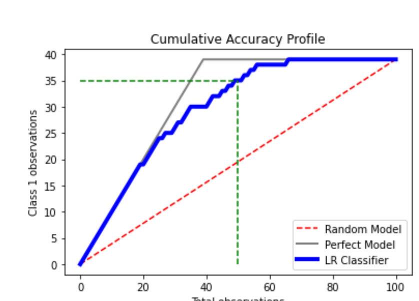
- It tries to analyse how to effectively identify all data points of a given class using minimum number of tries
- It helps us to understand and conclude about the robustness of the classification model



Method



CAP Analysis using Area Under Curve



CAP Analysis using Plot

Difference B/W ROC & CAP Curve - Easy Formula

	Gains	ROC
X axis:	$\frac{count\ TP + count\ FP}{count\ all\ observations}$	$\frac{count\ FP}{count\ TN + count\ FP}$
Y axis:	$\frac{count\ TP}{count\ TP + count\ FN}$	$\frac{count\ TP}{count\ TP + count\ FN}$

Curve Graph