Credit Score Cards - Notes

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1 Sensitivity and Specificity

Sensitivity and specificity are statistical measures of performance of a binary classifier.

Sensitivity, also known as true positive rate, recall or probability of detection, measures the proportion of actual positives that are correctly identified (e.g., percentage of sick people who are correctly identified as sick).

Specificity, also called true negative rate, measures the proportion of actual negatives that are correctly identified (e.g., percentage of healthy people who are incorrectly identified as sick).

$$sensitivity = \frac{number\ of\ true\ positives}{number\ of\ true\ positives + number\ of\ false\ negatives} \tag{1}$$

$$specificity = \frac{number\ of\ true\ negatives}{number\ of\ true\ negatives + number\ of\ false\ positives} \tag{2}$$

A highly sensitive test rarely overlooks an actual positive; a highly specific test rarely registers a positive classification for anything that is not the target of testing.

Sensitivity therefore quantifies the avoidance of false negatives and specificity does the same for false positives. For any test, there is usually a trade-off between the measures. For instance, in airport security, since testing of passengers is for potential threads to safety, scanners might be set to trigger alarm on low-risk items like belt buckles (low specificity) in order to increase the probability of identifying dangerous objects. This trade-off could presented graphically using a receiver operating characteristic (ROC) curve.

1.1 Confusion matrix

Consider a group with P positive instances and N negative instances of some condition. Four possible outcomes can be formulated in a 2x2 confusion matrix.

		True condition				
	Total population	Condition positive	Condition negative	Prevalence $= \frac{\Sigma \text{ Condition positive}}{\Sigma \text{ Total population}}$	Accuracy (ACC) $= \frac{\Sigma \text{ True positive} + \Sigma \text{ True negative}}{\Sigma \text{ Total population}}$	
Predicted condition	Predicted condition positive	**True positive**	**False positive**, Type I error	Positive predictive value (PPV), Precision $= \frac{\Sigma \text{ True positive}}{\Sigma \text{ Predicted condition positive}}$	False discovery rate (FDR) $= \frac{\Sigma \text{ False positive}}{\Sigma \text{ Predicted condition positive}}$	
	Predicted condition negative	**False negative**, Type II error	**True negative**	False omission rate (FOR) $= \frac{\Sigma \text{ False negative}}{\Sigma \text{ Predicted condition negative}}$	Negative predictive value (NPV) $= \frac{\Sigma \text{ True negative}}{\Sigma \text{ Predicted condition negative}}$	
		True positive rate (TPR), Recall, Sensitivity, probability of detection, Power $= \frac{\Sigma \text{ True positive}}{\Sigma \text{ Condition positive}}$	False positive rate (FPR), Fall-out, probability of false alarm $= \frac{\Sigma \text{ False positive}}{\Sigma \text{ Condition negative}}$	Positive likelihood ratio (LR+) $= \frac{\text{TPR}}{\text{FPR}}$	Diagnostic odds ratio (DOR) $= \frac{\text{LR+}}{\text{LR−}}$	F_1 score $= 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$
		False negative rate (FNR), Miss rate $= \frac{\Sigma \text{ False negative}}{\Sigma \text{ Condition positive}}$	Specificity (SPC), Selectivity, True negative rate (TNR) $= \frac{\Sigma \text{ True negative}}{\Sigma \text{ Condition negative}}$	Negative likelihood ratio (LR−) $= \frac{\text{FNR}}{\text{TNR}}$		

Figure 1: Confusion matrix

2 Receiver operating characteristic

A receiver operating characteristic (ROC) curve is evaluates diagnostic ability of a binary classifier.

The ROC curve plots true positive rate (TPR) against false positive rate (FPR) for various levels of the binary threshold. In machine learning the true positive rate is also known as sensitivity, recall or probability of detection. The false positive rate is then known as probability of false alarm and could be calculated as $1 - \textit{specificity}$. If probability distributions of detection and false alarm are know, the ROC curve could be generated by plotting cumulative distribution function of detection probability in the y-axis versus cumulative distribution of the false-alarm probability on x-axis.