Evaluation of binary classifiers

MATH-412 - Statistical Machine Learning

Sensitivity, precision and co.

| | Predicted | | |
|--------|-----------|-----|-----|
| Actual | | "P" | "N" |
| | P | TP | FN |
| | N | FP | TN |

- sensitivity, true positive rate or recall $r_{TP} = \frac{|TP|}{|P|}$
- ullet specificity or true negative rate $r_{TN}=rac{|TN|}{|N|}$
- false positive rate (type I error) $\alpha = r_{FP} = \frac{|FP|}{|N|} = 1 r_{TN}$
- false negative rate (type II error) $\beta = r_{FN} = \frac{|FN|}{|P|} = 1 r_{TP}$
- precision $prec = \frac{|TP|}{|FP| + |TP|}$

Sensitivity, specificity, etc

| | P | N |
|---------------|-------------------|-------------------|
| | Sensitivity (TPR) | FPR |
| \widehat{P} | $\frac{TP}{P}$ | $rac{FP}{N}$ |
| | FNR | Specificity (TNR) |
| \widehat{N} | $\frac{FN}{P}$ | $\frac{TN}{N}$ |

TPR True Positive Rate FPR False Positive Rate FNR False Negative Rate NPR True Negative Rate

Precision, FDR, etc

| | P | N |
|---------------|-------------------------|-------------------------|
| | Precision (PPV) | FDR |
| \widehat{P} | $rac{TP}{\widehat{P}}$ | $rac{FP}{\widehat{P}}$ |
| | FOR | NPV |
| \widehat{N} | $rac{FN}{\widehat{N}}$ | $rac{TN}{\hat{N}}$ |

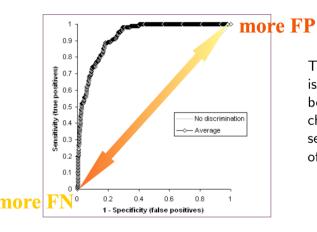
PPV Positive Predictive Value

FDR False Discovery Rate

FOR False Omission Rate

NPV Negative Predictive Value

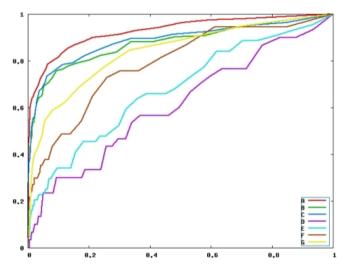
ROC curve



The Receiver Operating Characteristic is a representation of the trade-off between the Recall and the FPR as one changes the parameter controlling the sensitivity of the classifier, such as the offset *b*.

Evaluating ROC curves

Which one is the best ROC curve?



ROC curve and its convex hull

Convexity property of the ROC plot:

Given two points $\mathbf{e}_{\mathbf{r}}(\mathbf{e}_{\mathbf{r}}, \boldsymbol{\beta}_{\mathbf{r}})$ for elastifier f

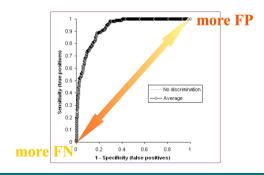
- (α_0, β_0) for classifier f_0
- (α_1, β_1) for classifier f_1 .

Consider the randomized classifier f_π which uses f_1 with probability π and f_0 with probability $1-\pi$. Then

$$(\alpha_{\pi}, \beta_{\pi}) = \pi(\alpha_1, \beta_1) + (1 - \pi)(\alpha_0, \beta_0).$$

Attainable points in the ROC plane form a convex set.

The ROC convex hull is the convex envelope of the attainable points, whose upper/left boundary forms a concave Pareto front.



Performance measures derived from the ROC

A number of performance measures can be obtained from the ROC curve. Let $\pi=\mathbb{P}(Y=1)$. It is estimated by $\widehat{\pi}=\frac{|P|}{|P|+|N|}$.

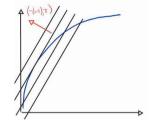


Misclassification error

$$\widehat{\mathcal{R}}_{\text{0-1}}^{\text{test}} = \widehat{\pi} \left(1 - r_{TP} \right) + \left(1 - \widehat{\pi} \right) r_{FP}$$

Cost

$$\widehat{\mathcal{R}}_{C_{+},C_{-}}^{\mathsf{test}} = \widehat{\pi} \, C_{+} \left(1 - r_{TP} \right) + \left(1 - \widehat{\pi} \right) C_{-} \, r_{FP}$$



- → For any cost, can change the threshold or other hyperparameter to minimize the cost.
 - Area under the curve (AUC)
 Actually corresponds to the Mann-Whitney-Wilcoxon U-statistic aka Wilcoxon signed rank test statistic on the score distribution to distinguish class 1 and class 0.
 - Truncated AUC

Precision - Recall curve

