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Discussion

Given two classifiers G_1 and G_2 and a dataset, we can associate to each its false positive and false negative rate on the dataset. For a finite dataset, these are two rational numbers. It is natural to prefer G_1 to G_2 if the former has a smaller false positive rate. Conversely, it is natural to prefer G_2 to G_1 if the former has a smaller false negative rate. Unfortunately, one may need to trade-off these two desiderata (see **Combined Orders**), since there is no total order. In other words, choosing between G_1 and G_2 is a multiobjective optimization problem.

Scalarization

Let \mathcal{G} be a set of classifiers and let $f : \mathcal{G} \rightarrow \mathbf{R}^2$ be defined so that $f_1(G)$ is the false negative rate of G on some dataset and $f_2(G)$ is the false positive rate of G on the same dataset. The κ -scalarized error metric (or *Neyman-Pearson metric* associated with $G \in \mathcal{G}$ is $\kappa f_1(G) + f_2(G)$. In the case that $\kappa > 1$, false negatives are given higher cost than false positives, and vice versa when $\kappa < 1$. For $\kappa = 1$, the scalarized error metric is the same as the overall error rate.

¹Future editions will include.

