



## Why

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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  $\kappa$ -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 whtn  $\kappa < 1$ . For  $\kappa = 1$ , the scalarized error metric is the same as the overall error rate.

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<sup>1</sup>Future editions will include.



