

CLASSIFIER ERRORS

Why

How should we compare two classifiers?

Definitions

Let a^1, \ldots, a^n in A be a dataset of inputs and b^1, \ldots, b^n in B be a dataset of labels. Let $G: A \to B$ be a classifier.

For each i = 1, ..., n, the classifier associates a prediction $G(a^i)$ with a_i The prediction $G(a^i)$ is correct if $G^(a^i) = b^i$ and incorrect (wrong, error) if $G(a^i) \neq b^i$. The error rate is the proportion of the dataset for which the classifier's prediction is an error. In other words, $1/n |\{i \mid G(a^i) \neq b^i\}|$.

Given two classifiers, we may be interested in the one with a lower error rate. Or given that these two are the results of different inductors applied on a shared dataset, we can use a different separate dataset to *validate* these.

Boolean case

In the case that $B = \{-1, 1\}$, we call the class -1 negative and the class +1 positive. Similarly, we call an example (a^i, b^i) a negative example if $b^i = -1$ and a positive example if $b^i = 1$.

We call the result of G on a^i a true positive if $b^i = 1$ and $G(a^i) = 1$, a true negative if $b^i = -1$ and $G(b^i) = -1$, a false negative (or type II error, read "type two error") if $b^i = 1$ and $G(a^i) = -1$ and a false positive (or type I error, read "type one error") if $b^i = -1$ and $G(a^i) = 1$.

The false positive rate (false negative rate) of a classifier on a dataset is the proportion of dataset elements for which it predicts a false positive (false negative).

The true positive rate (or sensitivity, recall) of the classifier G on the dataset is the proportion of positive examples which G labels positive. The true negative rate (or specificity, selectivity) is the proportion of negative examples which G labels negative.

On the other hand, the false alarm rate is the proportion of negative examples which G (incorrectly) labels positive. The precision (or positive predictive value) of G is the proportion of all examples which the classifier labels positive whose label is positive.

