



Why

We analyze the performance of inductors in a framework in which we assume the dataset comes as random samples some probability space.

Definition

Let \mathcal{X} be the domain set, or set of inputs and let \mathcal{Y} be the label set, or set of outs. Let $\mathcal{D} = (\mathcal{X}, \mathcal{A}, \mathbf{P})$ be a probability space. Let $f : \mathcal{X} \rightarrow \mathcal{Y}$.

Let a $(x_1, y_1), \dots, (x_n, y_n)$ of size n generated is by sampling x_i from \mathcal{D} and then labeling it with $y_i = f(x_i)$.¹ For this reason we call \mathcal{D} the *data-generating distribution* or *underlying distribution* and we call f the *correct labeling function*.

Measures of success

Let $A \in \mathcal{A}$, then the *error of a classifier* (or of a prediction rule) $h : \mathcal{X} \rightarrow \mathcal{Y}$ is

$$\mathbf{P}(\{x \in \mathcal{X}\} h(X) \neq f(x)).$$

In other words, the probability (w.r.t. the underling distribution) that the classifier h mislabels a point. Many authors associate an event $A \in \mathcal{A}$ with a function $\pi : \mathcal{X} \rightarrow \{0, 1\}$

¹Future editions will be more precise by what we mean by sampling. In other words, future editions will likely treat of these “samples” as random variables.

so that $A = \{x \in \mathcal{X} \mid \pi(x) = 1\}$ and it is common to write $\mathbf{P}[\pi(x)]$ for $\mathbf{P}(A)$.

The error is measured with respect to the distribution \mathcal{D} and correct labeling function f . Other names for the error of a classifier include the *generalization error*, the *risk* or the *true error* or *loss* of h .

Statistical learning theorem

Many authors refer to a data-generating distribution along with an input set, output set, correct labeling function, and set of predictors as the *statistical learning theory framework*.

