



Why

Let $X = \{a, b\}$ and $Y = \{0, 1\}$. Define $f : X \rightarrow Y$ by $f \equiv 0$.

The dataset $(a, 0)$ is consistent with f . So are the datasets $((a, 0), (a, 0))$ and $((a, 0), (a, 0), (a, 0))$. Unfortunately, these datasets are “bad” in the sense that we do not see the value associated with b . Each dataset is consistent with the (functional) relations $\{(a, 0), (b, 0)\}$ and $\{(a, 0), (b, 1)\}$.

In other words, a dataset can be incomplete. In spite of this limitation, we want to discuss an inductor’s performance on consistent (but possibly incomplete) datasets.

We take two steps. First, we put a measure on the set of training sets and only consider high-measure subsets. Second, we consider inductors which perform well in some tolerance.

Definition

Let (X, \mathcal{X}) and (Y, \mathcal{Y}) be measurable spaces and R be a relation on $X \times Y$. Let $\mu : \mathcal{X} \times \mathcal{Y} \rightarrow [0, 1]$ be a probability measure so that $\mathcal{D} = (X \times Y, \mathcal{X} \times \mathcal{Y}, \mu)$ is a probability space.

If μ satisfies $\mu(B) = 0$ for all $B \subset C_{X \times Y}(R)$, then we call \mathcal{D} a *probabilistic dataset model* for R . In other words, μ gives zero measure to any set of points not in the relation.

If R is functional, then we call \mathcal{D} a *supervised probabilistic dataset model*. In this case, since there is a functional relation between X and Y , we call the marginal measure $\mu_X : \mathcal{X} \rightarrow$

$[0, 1]$ the *data-generating distribution* or *underlying distribution* since $\mu(A) = \mu_X(\{x \in X \mid (x, y) \in A\})$. In this case we call the (functional) relation R the *correct labeling function*. Many authors refer to a supervised probabilistic data model as the *statistical learning (theory) framework*.

Probable datasets

For datasets of size n , we use the product measure $((X \times Y)^n, (\mathcal{X} \times \mathcal{Y})^n, \mu^n)$. We interpret this measure as modeling independent and identically distributed elements of R .

For $\delta \in (0, 1)$, $\mathcal{S} \subset (X \times Y)^n$ is $1 - \delta$ -*probable* if $\mu^n(S) \geq 1 - \delta$. If δ is small, we interpret \mathcal{S} as a set of “reasonable” datasets. We call δ the *confidence parameter*.

