



Why

Are there conditions under which every empirical error minimizer does not overfit? One route is to ask whether there are situations in which good performance on empirical risk implies (or makes it highly likely to achieve) good performance on the underlying distribution.

In other words, we want to connect performance on the training dataset with performance on the underlying model distribution.

Discussion

Let $((\Omega, \mathcal{A}, \mathbf{P}), \{x_i : \Omega \rightarrow \mathcal{X}\}_{i=1}^n, f : \mathcal{X} \rightarrow \mathcal{Y})$ be probabilistic data-generation model with training set $S : \Omega \rightarrow (\mathcal{X} \times \mathcal{Y})^n$.

Since the empirical error minimization algorithm selects a hypothesis on the basis on the training set S , and this dataset is random, it can happen that the dataset does not “reflect well” the underlying distribution. For this reason, we will speak probabilistically about whether the error of an empirical error minimizer is large. Let $((\Omega, \mathcal{A}, \mathbf{P}), \{x_i : \Omega \rightarrow \mathcal{X}\}_{i=1}^n, f : \mathcal{X} \rightarrow \mathcal{Y})$ be probabilistic data-generation model with training set $S : \Omega \rightarrow (\mathcal{X} \times \mathcal{Y})^n$.

Moreover, there is always some nonzero probability that we will not see a particular input in \mathcal{X} and so we can not hope to achieve zero generalizaion error.

Definition

For these reasons, let $\delta, \varepsilon \in (0, 1)$.

Let $(\Omega, \mathcal{A}, \mathbf{P})$ be a probability space. Let $(\mathcal{D}, f : \mathcal{X} \rightarrow \mathcal{Y})$ be a probabilistic data-generation model.

