



Why

What is the best linear regressor if we choose according to a squared loss function.

Definition

Let $X \in \mathbf{R}^{n \times d}$ and $y \in \mathbf{R}^d$. In other words, we have a paired dataset of records with inputs in \mathbf{R}^d (the rows of X) and outputs in \mathbf{R} (the elements of y).

A *least squares linear predictor* or *linear least squares predictor* is a linear transformation $f : \mathbf{R}^d \rightarrow \mathbf{R}$ (the field is \mathbf{R}) which minimizes

$$\frac{1}{n} \sum_{i=1}^n (f(x^i) - y_i)^2.$$

over the dataset of pairs $(x^1, y_1), \dots, (x^n, y_n) \in \mathbf{R}^d \times \mathbf{R}$ where $(x^i)^\top$ is the i th row of X for $i = 1, \dots, n$.

The set of linear functions from \mathbf{R}^d to \mathbf{R} is in one-to-one correspondence with \mathbf{R}^d . So we want to find $\theta \in \mathbf{R}^d$ to minimize

$$\frac{1}{n} \|X\theta - y\|^2.$$

Solution

Proposition 1. *There exists a unique linear least squares predictor and its parameters are given by $(X^\top X)^{-1} X^\top y$.¹*

¹Future editions will include an account.

