



Why

We want an estimator for the parameters of a linear function, given observations of the function with additive noise.

Definition

Let $(\Omega, \mathcal{A}, \mathbf{P})$ be a probability space. Let $x : \Omega \rightarrow \mathbf{R}^d$. Define $g : \Omega \rightarrow (\mathbf{R}^d \rightarrow \mathbf{R})$ by $g(\omega)(a) = a^\top x(\omega)$, for $a \in \mathbf{R}^d$. In other words, for each outcome $\omega \in \Omega$, $g_\omega : \mathbf{R}^d \rightarrow \mathbf{R}$ is a linear function with parameters $x(\omega)$. g_ω is the function of interest.

Let $a^1, \dots, a^n \in \mathbf{R}^d$ a dataset with data matrix $A \in \mathbf{R}^{n \times d}$. Let $e : \Omega \rightarrow \mathbf{R}^n$ independent of x , and define $y : \Omega \rightarrow \mathbf{R}^n$ by

$$y = Ax + e.$$

In other words, $y_i = x^\top a^i + e_i$.

We call (x, A, e) a *probabilistic linear model*. Other terms include *linear model*, *statistical linear model*, *linear regression model*, *bayesian linear regression*, and *bayesian analysis of the linear model*.¹ We call x the parameters, A a *design*, e the *error* or *noise* vector, and y the *observation* vector.

One may want an estimator for the parameters x in terms of y or one may be modeling the function g and want to predict $g(a)$ for $a \in A$ not in the dataset.

¹The word bayesian is in reference to treating the object of interest— x —as a random variable.

Mean and variance

Proposition 1. $\mathbf{E}(y) = A \mathbf{E}(x) + \mathbf{E}(w)$ ²

Proposition 2. $\mathbf{cov}((x, y)) = A \mathbf{cov}(x) A^\top + \mathbf{cov} e$ ³

²By linearity. Full account in future editions.

³Full account in future editions.

