



Why

We want to estimate a random vector $x : \Omega \rightarrow \mathbf{R}^d$ from a random vector $y : \Omega \rightarrow \mathbf{R}^n$.

Definition

Denote by $g : \mathbf{R}^d \times \mathbf{R}^n \rightarrow \mathbf{R}$ the joint density for (x, y) .¹ Denote the conditional density for x given y by $g_{x|y} : \mathbf{R}^d \times \mathbf{R}^n \rightarrow \mathbf{R}$. A *maximum conditional estimate* for $x : \Omega \rightarrow \mathbf{R}^d$ given that y has taken the value $\gamma \in \mathbf{R}^n$ is a maximizer $\xi \in \mathbf{R}^d$ of $g_{x|y}(\xi, \gamma)$. It is also called the *maximum a posteriori estimate* or *MAP estimate*.

Also maximizes joint

Notice that since $g(\xi, \gamma) = g_y(\gamma)g_{x|y}(\xi, \gamma)$, the MAP estimate also maximizes the joint pdf.

Proposition 1. *The MAP estimate maximizes the joint pdf.*²

¹Future editions will comment on the existence of such a density.

²Future editions will include an account.

