

MAXIMUM CONDITIONAL ESTIMATES

Why

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

Definition

Denote by $g: \mathbf{R}^d \times \mathbf{R}^n \to \mathbf{R}$ the joint density for (x,y).\(^1\) Denote the conditional density for x given y by $g_{x|y}: \mathbf{R}^d \times \mathbf{R}^n \to \mathbf{R}$. In this setting, $g_{x|y}$ is called the *posterior density*, g_x is called the *prior density*, and $g_{y|x}$ is called the *likelihood density* and g_y is called the *marginal likelihood density*.

As usual (and assuming $g_y > 0$), the posterior is related to the likelihood, prior and marginal likelihood by

$$g_{x|y} \equiv \frac{g_x g_{y|x}}{g_y}.$$

A maximum conditional estimate for $x:\Omega\to \mathbf{R}^n$ 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. The maximum conditional estimate is natural, in part, because it also maximizes the joint density, since $g(\xi,\gamma)=g_y(\gamma)g_{x|y}(\xi,\gamma)$ for all $\xi\in \mathbf{R}^d$ and $\gamma\in \mathbf{R}^n$.

 $^{^1\}mathrm{Future}$ editions will comment on the existence of such a density.

