



Why

We use a normal random function model to make a regressor.

Definition

Let $F : \Omega \rightarrow (A \rightarrow \mathbf{R})$ be a normal random function with mean function $m : A \rightarrow \mathbf{R}$ and covariance function $k : A \times A \rightarrow \mathbf{R}$ over the probability space $(\Omega, \mathcal{A}, \mathbf{P})$. Let the family of random variables (or stochastic process) of F be $f : A \rightarrow (\Omega \rightarrow \mathbf{R})$.

Let e be a normal random vector with mean zero and covariance Σ_e . We call e the *error vector* or *noise vector*. Let $a^1, \dots, a^n \in A$. We sometimes call the sequence a^1, \dots, a^n the *design*. Define $y : \Omega \rightarrow \mathbf{R}^d$ by

$$y_i = f(a^i) + e_i$$

We call y the *observation vector* or *observation random vector*.

Let $b^1, \dots, b^m \in A$. Define $z : \Omega \rightarrow \mathbf{R}^d$ by $z_i = f(b^i)$ for $i = 1, \dots, m$. So z_i is the random variable corresponding to the family at index $b^i \in A$. Then (y, z) is normal. We call the conditional density of z given y the *predictive density* for b given a .

Proposition 1. Define $m_a \in \mathbf{R}^n$ by $(m(a^1), \dots, m(a^n))^\top$ and

define m_b by $(m(b^1), \dots, m(b^m))^\top$.¹ Define $\Sigma_a \in \mathbf{R}^{n \times n}$ by

$$\begin{pmatrix} k(a^1, a^1) & \cdots & k(a^1, a^n) \\ \vdots & \ddots & \vdots \\ k(a^n, a^1) & \cdots & k(a^n, a^n) \end{pmatrix}$$

and define $\Sigma_{ba} \in \mathbf{R}^{m \times n}$ by

$$\begin{pmatrix} k(b^1, a^1) & \cdots & k(b^1, a^n) \\ \vdots & \ddots & \vdots \\ k(b^m, a^1) & \cdots & k(b^m, a^n) \end{pmatrix}.$$

The predictive density $g_{z|y}(\cdot, \gamma) : \mathbf{R}^m \rightarrow \mathbf{R}$ of $b \in A$ for design a^1, \dots, a^n is normal with mean.

$$m_b + K_{ba} (K_a + \Sigma_e)^{-1} (\gamma - m_a)$$

and covariance

$$\Sigma_b - \Sigma_{ba} (\Sigma_a + \Sigma_e)^{-1} \Sigma_{ab}.$$

Regressor

Ultimately, we want a regressor $h : A \rightarrow \mathbf{R}$. We maximize the the predictive density. The *normal random function predictor* or *gaussian process predictor* for dataset $(a^1, \gamma_1), \dots, (a^n, \gamma_n)$ in $A \times \mathbf{R}$ is $h : A \rightarrow \mathbf{R}$ defined by

$$h(x) = m(x) + \left(k(x, a^1) \cdots k(x, a^n) \right) (\Sigma_a + \Sigma_e)^{-1} (\gamma - m_a).$$

¹Future editions will fix the re-use of the symbol m .

The process of using a normal random function predictor is often called *Gaussian process regression*. The upside is that a gaussian process predictor interpolates the data, is smooth, and the so-called variance increases with the distance from the data.²

²This last piece is true for certain covariance kernels and will be clarified in future editions.

