

# Stat 992: Lecture 11

## Karhunen-Loève Expansion.

Moo K. Chung `mchung@stat.wisc.edu`

February 13, 2004

1. *Orthogonal expansion for fields* Let  $\mathcal{G} = L^2(G(\Omega))$  be the space of zero mean Gaussian random fields in  $\Omega \subset \mathbb{R}^n$  with inner product

$$\langle X, Y \rangle = \mathbb{E} \int_{\Omega} X(x)Y(x) dx$$

with  $\|X\| < \infty$ . This is basically the integral of cross-covariance function between fields  $X$  and  $Y$ .  $\mathcal{G}$  can be shown to be a separable Hilbert space. This can be shown by finding countable orthonormal basis in  $\mathcal{G}$ . See *Random Fields and Their Geometry* by R.J. Adler and J.E. Taylor.

Let  $\psi_i$  be basis for  $L^2(\Omega)$  and  $Z_i$  be i.i.d.  $N(0, \sigma_i^2)$ . We will construct orthonormal expansion in the following fashion. Suppose for any  $X \in \mathcal{G}$ ,

$$X(x) = \sum_{i=0}^{\infty} Z_i \psi_i(x).$$

Note that  $\mathbb{E}X(x) = 0$  while the covariance function is

$$\begin{aligned} R(x, y) &= \mathbb{E} \sum_{i,j=0}^{\infty} Z_i \psi_i(x) Z_j \psi_j(y) \\ &= \sum_{i=0}^{\infty} \sigma_i^2 \psi_i(x) \psi_i(y). \end{aligned}$$

The covariance function of zero mean Gaussian field completely characterizes the field itself so we need to know if any covariance function can be expressed this way. Obviously  $R$  has to be symmetric to be expressible this way.

2. *Degenerate kernels.* We follow the argument of R. Courant and D. Hilbert (*Methods of Mathematical Physics, Vol I.* 1953). Suppose we fix  $y$ . Then from the Weierstrass's approximation theorem, for continuous function,  $R(x, \cdot) = \sum_{i=0}^{\infty} \alpha_i(x)$  for some basis functions  $\alpha_i$  uniformly. Now fix  $x$  and we

have

$$\begin{aligned} R(x, y) &= \sum_{i=0}^{\infty} \alpha_i(x) \sum_{j=0}^{\infty} \beta_j(y) \\ &= \sum_{i,j=0}^{\infty} \alpha_i(x) \beta_j(y) \end{aligned}$$

Again,  $\beta_j$  are basis functions. Courant and Hilbert termed such the kernel degenerate. For finite number of basis  $\alpha_1, \dots, \alpha_p$  and  $\beta_1, \dots, \beta_p$ , it can be representable as a linear combination of orthogonal basis  $\psi$  using the Gram-Schmidt orthogonalization. So we have

$$R(x, y) = \sum_{i,j=0}^{\infty} c_{ij} \psi_i(x) \psi_j(y).$$

Assume further that the kernel is symmetric then

$$\sum_{i,j=0}^p (c_{ij} - c_{ji}) \psi_i(x) \psi_j(y) = 0$$

for  $p \rightarrow \infty$ . Since  $\psi_i$  and  $\psi_j$  are independent,  $c_{ij} = c_{ji}$ . We can do a better job than this via Mercer's theorem (Read Riesz and Sz.-Nagy, 1956; Courant and Hilbert. 1953; Adler and Taylor, 2004).

3. *Mercer's theorem.* For continuous symmetric kernel  $R$ , define linear operator  $\mathcal{R} : L^2(\Omega) \rightarrow L^2(\Omega)$  as

$$\mathcal{R}f(x) = \int_{\Omega} R(x, y) f(y) dy.$$

This is a compact self-adjoint operator<sup>1</sup> which yields unique countable eigenvalues  $\lambda_i$  and orthonormal eigenfunctions  $\phi_i$  such that  $\mathcal{R}\phi_i =$

<sup>1</sup>  $R$  is compact if the closure of  $R(\text{close ball})$  is compact and it is self-adjoint if  $\langle \mathcal{R}f, g \rangle = \langle f, \mathcal{R}g \rangle$ . See J.B. Conway's *A Course in Functional Analysis*, 2nd edition (1990) for the discussion of compact operators on Hilbert space. S.C. Joshi's PhD thesis (1998) *Large Deformation Diffeomorphisms and Gaussian Random Fields for Statistical Characterization of Brain Sub-manifolds* for it's use in actual image analysis.

$\lambda_i \phi_i^2$  with  $\lambda_\infty = 0$ . We will order them such that  $\lambda_0 > \lambda_1 > \lambda_2 > \dots$ .

The compact self-adjoint operator  $\mathcal{R}$  has a spectral representation  $\mathcal{R}f = \sum_{i=0}^{\infty} \lambda_i \langle \phi_i, f \rangle \phi_i$ .<sup>3</sup> Mercer's theorem states that

$$R(s, t) = \sum_{i=0}^{\infty} \lambda_i \phi_i(x) \phi_i(y).$$

Hence identifying  $\lambda_i = \sigma_i^2$  and  $\phi_i = \psi_i$ , we have the desired orthonormal expansion and it is called the Karhunen-Loève expansion.

To prove the theorem, note that  $\phi_i(x)\phi_j(y)$  forms basis in  $\Omega \otimes \Omega$ . This is how you expand basis function in 1 dimension to higher dimension in Euclidean space. Assuming  $R(x, y) \in L^2(\Omega \otimes \Omega)$ ,

$$R(x, y) = \sum_{i,j=0}^{\infty} c_{ij} \phi_i(x) \phi_j(y).$$

Then

$$\begin{aligned} \int_{\Omega} R(x, y) \phi_k(y) dy &= \sum_{i,j=0}^{\infty} c_{ij} \int_{\Omega} \phi_k(y) \phi_i(x) \phi_j(y) dy \\ \lambda_k \phi_k(x) &= \sum_{i,j=0}^{\infty} c_{ij} \phi_i(x) \delta_{jk} = \sum_{i=0}^{\infty} d_i \phi_i(x) \end{aligned}$$

where  $d_i = \sum_{k=0}^{\infty} c_{ik}$ . Since they are linearly independent,  $c_j = \lambda_j$ .

**Problem 21.** Let  $X$  be a Brownian motion with covariance function given by  $R(x, y) = \min(x, y)$ . Find the eigenvalues and eigenfunctions. Based on this eigensystem, expand the Brownian motion via the Karhunen-Loève expansion. Based on the Karhunen-Loève expansion, simulate Brownian motion in MATLAB.

**Problem 22.** Without using the property of compact self-adjoint operator in Hilbert space, prove Mercer's theorem. Follow Riesz and Sz.-Nagy's classical derivation.

---

<sup>2</sup>This eigenequation is called a Fredholm equation of the first kind. Given covariance function, there is a numerical technique for estimating  $\lambda_i$  and  $\phi_i$  numerically.

<sup>3</sup>See Conway Theorem 7.6.