

Karhunen-Loève decomposition of Gaussian measures on Banach spaces

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- 5 Particular case of $C(K)$, K metric and compact.
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Motivation

The problem of representation of Gaussian elements in linear series is used in:

- 1 Simulation (e.g. truncated Karhunen-Loève series),
- 2 Approximation and Dimension reduction (e.g. PCA or POD),
- 3 Optimal quantization,
- 4 Bayesian inverse problems.

If the existence of an optimal basis is well known in Hilbert spaces...

- ... it's not always explicit (eigenvalue problem),
- ... it's not the case in Banach spaces.

What if we are interested in non-Hilbertian norms ?

Motivation

In the case of a continuous Gaussian process on $[0, 1]$ we may inject it in $L^2([0, 1], dx)$ and use Hilbertian geometry...

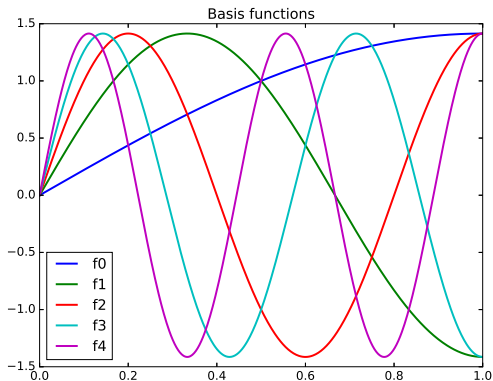


Figure: Karhunen-Loève basis of Brownian motion in $L^2([0, 1], dx)$.

or tackle the problem directly in $C([0, 1])$...

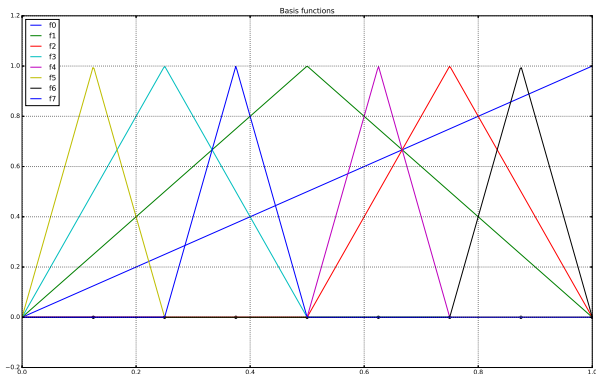


Figure: Brownian motion basis functions in $C([0, 1])$ (Paul Levy's construction).

...in the hope of better approximation w.r.t. supremum norm !

Karhunen-Loève decomposition in Hilbert spaces

Gaussian vector in Euclidian spaces

Consider the euclidian space \mathbb{R}^n with canonical inner product $\langle \cdot, \cdot \rangle$.

Gaussian random vector

Let $(\Omega, \mathcal{F}, \mathbb{P})$ a probability space and $X : (\Omega, \mathcal{F}, \mathbb{P}) \rightarrow (\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n))$ a measurable mapping, then X is a Gaussian vector if and only if $\forall y \in \mathbb{R}^n$, $\langle X, y \rangle$ is a Gaussian random variable.

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Covariance

Given a (centered) Gaussian random vector X , define the bilinear form:

$$\forall x, y \in \mathbb{R}^n, \text{Cov}(x, y) = \mathbb{E}[\langle X, x \rangle \langle X, y \rangle], \quad (1)$$

which uniquely defines $\Sigma : \mathbb{R}^n \rightarrow \mathbb{R}^n$ such that:

$$\forall x, y \in \mathbb{R}^n, \langle \Sigma x, y \rangle = \text{Cov}(x, y). \quad (2)$$

Considering the Gaussian vector X gives a fundamental structure:

- Gaussian space: $\text{Vect}(\langle X, e_k \rangle, k \in [1, n]) \subset L^2(\mathbb{P})$
- Cameron-Martin space $H_X = \text{Range}(\Sigma)$ equipped with $\langle \cdot, \cdot \rangle_X = \langle \Sigma^{-1} \cdot, \cdot \rangle$

Loève isometry

The following application:

$$\langle X, x \rangle \in L^2(\mathbb{P}) \rightarrow \Sigma x \in H_X \quad (3)$$

is an isometry.

Representation of Gaussian vectors in \mathbb{R}^n

- For any orthonormal basis (e_k) in \mathbb{R}^n , we can write:

$$X(\omega) = \sum_{k=1}^n \langle X(\omega), e_k \rangle e_k \text{ a.s.} \quad (4)$$

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- $\langle X(\omega), e_i \rangle, \langle X(\omega), e_j \rangle$ are independent if and only if $\text{Cov}(e_i, e_j) = \langle \Sigma e_i, e_j \rangle = \langle \Sigma e_i, \Sigma e_j \rangle_X = 0$.

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- For any orthonormal basis (x_k) in H_X :

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- The Spectral theorem (on covariance operator) exhibits a particular (Karhunen-Loève) basis (bi-orthogonal and $\Sigma h_k = \lambda_k h_k$):

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Note P^k the linear projector on the k -th biggest eigenvalues, then:

$$\forall k \leq n, \min_{\text{rank}(P)=k} \mathbb{E}[\|X - PX\|^2] = \mathbb{E}[\|X - P^k X\|^2] = \lambda_{k+1} + \dots + \lambda_{\dim(H_X)} \quad (7)$$

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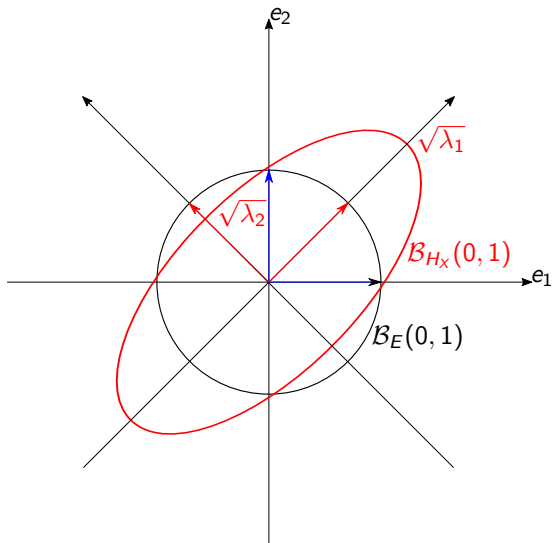


Figure: Karhunen-Loève basis in dimension 2.

Gaussian element in Hilbert spaces

Consider the (real) Hilbert space H with inner product $\langle \cdot, \cdot \rangle$.

Gaussian random element

Let $(\Omega, \mathcal{F}, \mathbb{P})$ a probability space and $X : (\Omega, \mathcal{F}, \mathbb{P}) \rightarrow (H, \mathcal{B}(H))$ a measurable mapping, then X is a Gaussian element if and only if $\forall y \in H$, $\langle X, y \rangle$ is a Gaussian random variable.

Covariance

Given a Gaussian random element X , define the bilinear form:

$$\forall x, y \in H, \text{Cov}(x, y) = \mathbb{E}[\langle X, x \rangle \langle X, y \rangle], \quad (8)$$

and the associated covariance operator $\mathcal{C} : H \rightarrow H$ such that:

$$\forall x, y \in H, \langle \mathcal{C}x, y \rangle = \text{Cov}(x, y). \quad (9)$$

Representation of Gaussian elements in Hilbert spaces

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- For any basis (x_k) in H_X and (ξ_k) i.i.d. $\mathcal{N}(0, 1)$:

$$X(\omega) \stackrel{d}{=} \sum_{k \geq 0} \xi_k(\omega) x_k \quad (11)$$

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- Spectral theorem applies and exhibits a (Karhunen-Loève) bi-orthogonal basis (h_k) : $X(\omega) = \sum_{k \geq 0} \sqrt{\lambda_k} \xi_k(\omega) h_k$ a.s.

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- Eckart-Young theorem is still valid (functional PCA, ...)

$$\forall k > 0, \min_{\text{rank}(P)=k} \mathbb{E}[\|X - PX\|_H^2] = \mathbb{E}[\|X - P^k X\|_H^2] = \sum_{i > k} \lambda_i \quad (12)$$

Karhunen-Loève decomposition in Banach spaces

Gaussian element in Banach spaces

Consider the (real) Banach space E with duality pairing $\langle \cdot, \cdot \rangle_{E, E^*}$.

Gaussian random element

Let $(\Omega, \mathcal{F}, \mathbb{P})$ a probability space and $X : (\Omega, \mathcal{F}, \mathbb{P}) \rightarrow (E, \mathcal{B}(E))$ a measurable mapping, then X is a Gaussian element if and only if $\forall f \in E^*$, $\langle X, f \rangle_{E, E^*}$ is a Gaussian random variable.

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Given a Gaussian random element X , define the bilinear form:

$$\forall f, g \in E^*, \text{Cov}(f, g) = \mathbb{E}[\langle X, f \rangle_{E, E^*} \langle X, g \rangle_{E, E^*}], \quad (13)$$

and the associated covariance operator $\mathcal{C} : E^* \rightarrow E$ (see Vakhania 1987 or Bogachev 1998) such that:

$$\forall f, g \in E^*, \langle \mathcal{C}f, g \rangle_{E, E^*} = \text{Cov}(f, g). \quad (14)$$

Representation of Gaussian elements in Banach spaces

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- We know that (Bogachev 1998, Vakhania 1991):
 - $\exists (x_k) \in \text{Range}(\mathcal{C})$ Hilbert basis in H_X ,
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- If the basis (x_k) is in $\text{Range}(\mathcal{C})$ with $x_k = \mathcal{C}x_k^*$, then:

$$X(\omega) = \sum_{k \geq 0} \langle X(\omega), x_k^* \rangle_{E, E^*} x_k \quad (16)$$

Factorization of covariance operators (Vakhania 1987, Bogachev 1998).

Let \mathcal{C} be the covariance operator of a Gaussian element, then:

$$\mathcal{C} = SS^*, \quad (17)$$

where $S : H \rightarrow E$ is a bounded operator and H a Hilbert space.

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Examples:

- In the Hilbert case, $S = \mathcal{C}^{\frac{1}{2}}$,
- $S : H_X \rightarrow E$ the inclusion map,
- $S : f \in \overline{E^*}^{L^2(\mathbb{P})} \rightarrow \mathbb{E}[f(X)X] \in E$ (S^* is the injection from E^* to L^2)

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(Luschgy and Pagès 2009)

Let $\mathcal{C} = SS^*$ with $S : H \rightarrow E$. Then for any basis (h_n) in H :

$$X \stackrel{d}{=} \sum_{k \geq 0} \xi_k S h_k, \quad (18)$$

where (ξ_k) are i.i.d. $\mathcal{N}(0, 1)$.

This methodology has been widely used:

- When $E = \mathcal{C}([0, 1])$, $S^* : f \in E^* \rightarrow L^2([0, 1], dx) \dots$

We will now give a different methodology, mimicking the Hilbert case, to construct a Hilbert basis in H_X . We will proceed as follows:

- 1 Find "directions" of maximum variance,
- 2 Choose a right notion of orthogonality to iterate,
- 3 Study the asymptotics.

Decomposition of the Cameron-Martin space

- 1 For any (Gaussian) covariance operator, $f \in E^* \rightarrow \text{Cov}(f, f) \in \mathbb{R}^+$
 - may be interpreted as a Rayleigh quotient,
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We will note $x_0^* = f_0$ and $x_n^* = f_n - \sum_{k=0}^{n-1} \langle x_k, f_n \rangle_{E, E^*} x_k^*$ such that $P_n = \sum_{k=0}^n x_k^* \otimes x_k$ (similar to Gram-Schmidt).

Properties of the decomposition

Few comments about the previous construction...

Properties

This construction gives the following properties:

- $X(\omega) = \sum_{k \geq 0} \langle X(\omega), x_k^* \rangle_{E, E^*} x_k$ a.s.
- $\mathcal{C} = SS^*$ with $S^* : f \in E^* \rightarrow \sum_{k \geq 0} \lambda_k \langle x_k, f \rangle_{E, E^*} x_k$
- Note $\mathcal{C}^n = \sum_{k=0}^n \lambda_k x_k \otimes x_k$ then $\|\mathcal{C} - \mathcal{C}^n\|_{\mathcal{L}(E^*, E)} = \lambda_{n+1}$.
- Recovers Karhunen-Loève basis in the Hilbert case.
- $(x_k, x_k^*) \subset E \times E^*$ is bi-orthogonal.
- $\overline{\text{Vect}(x_k, k \geq 0)}^E = \overline{H_X}^E$,
- $\forall k \in \mathbb{N}, \|f_k\|_{E^*} = \|x_k\|_E = 1$.

Remarks

- $\sum_{k \geq 0} \lambda_k$ need not be finite (not a nuclear representation of \mathcal{C}).
- Optimality seems out of reach (Rate optimality ?).

Particular case of $(\mathbb{R}^n, \|\cdot\|_\infty)$

Here, $E^* = (\mathbb{R}^n, \|\cdot\|_1)$ and $\forall(x, f) \in E \times E^*$, $\langle x, f \rangle_{E, E^*} = \sum_{i=1}^n x_i f_i$.

- Suppose a centered dataset $(y_i)_{i \in [1, p]} \in (\mathbb{R}^n)^p$,
- Form the usual covariance matrix $\Sigma \in \mathcal{M}_n(\mathbb{R})$,
- Find the direction of maximal variance $f_0 \in \mathbb{R}^n$:

$$\lambda_0 = f_0^T \Sigma f_0 = \max_{i \in [1, n]} \Sigma_{(i, i)} \text{ with } f_0 = (0, \dots, 0, 1, 0, \dots, 0) \quad (19)$$

- If $\lambda_0 > 0$ then $x_0 = \frac{\Sigma f_0}{\lambda_0}$.
- $\Sigma_1 = \Sigma - \lambda_0 x_0 x_0^T$
- Iterate.

Application in \mathbb{R}^n

- Residuals norm as $r_k = \frac{1}{n} \sum_{i=1}^n \|x_i - \sum_{j=0}^k \langle x_i, x_j^* \rangle_{E, E^*} x_j\|_\infty$,
- Projections norm as $p_k = \frac{1}{n} \sum_{i=1}^n \|\sum_{j=0}^k \langle x_i, x_j^* \rangle_{E, E^*} x_j\|_\infty$.

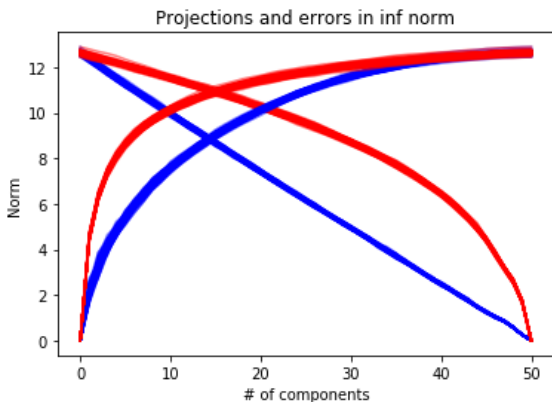


Figure: Residuals (decreasing) and projections (increasing) norm (blue for L2-PCA, red for Banach PCA)

Particular case of $C(K)$, K metric and compact.

Let X be a Gaussian element such that $X \in C(K)$ almost-surely and suppose that

$$k : (s, t) \in K^2 \rightarrow \langle C\delta_s, \delta_t \rangle_{E, E^*} = \text{Cov}(X_s, X_t) \in \mathbb{R} \quad (20)$$

is continuous. The Cameron-Martin space H_X coincides here with the Reproducing Kernel Hilbert space (RKHS). The previous decomposition becomes:

- 1 Set $n = 0$ and $k_n = k$,
- 2 Find $x_n \in K$ such that $k_n(x_n, x_n) = \max_{x \in K} k_n(x, x)$,
- 3 If $\lambda_n = k_n(x_n, x_n) > 0$ then $k_{n+1}(s, t) = k_n(s, t) - \frac{k_n(s, x_n)k_n(x_n, t)}{\lambda_n}$,
- 4 $n \leftarrow n + 1$.

Illustration on Brownian motion: Step 1

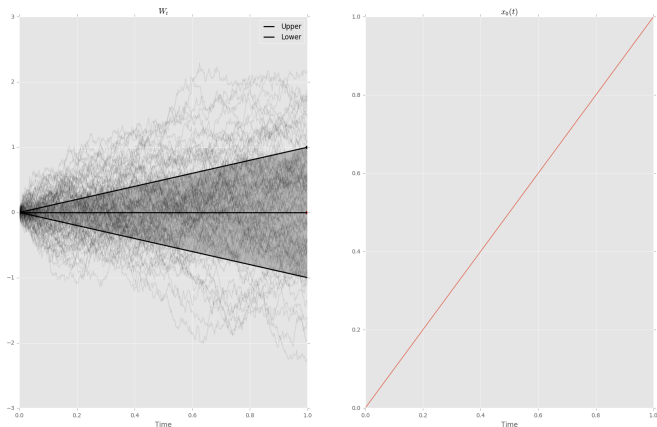


Figure: Left: Brownian motion samples and point-wise (symmetrized) variance. Right: First basis function $x_0(t) = t$ associated to $f_0 = \delta_1$.

Illustration on Brownian motion: Step 2

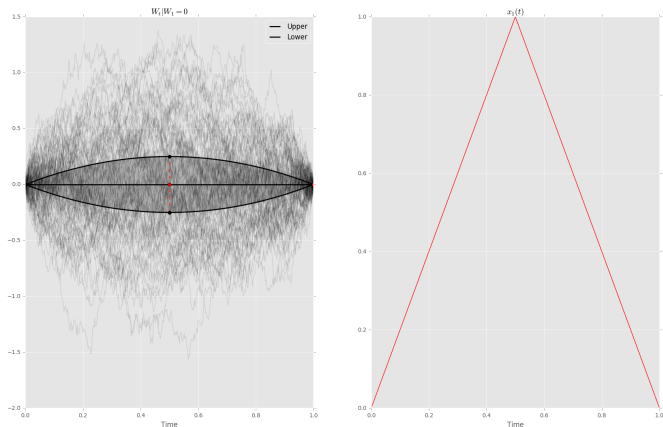


Figure: Left: Brownian bridge samples and point-wise (symmetrized) variance. Right: Second basis function $x_1(t) = \min(t, 0.5) - 0.5t$, associated to $f_1 = \delta_{\frac{1}{2}}$.

Illustration on Brownian motion: Step 3

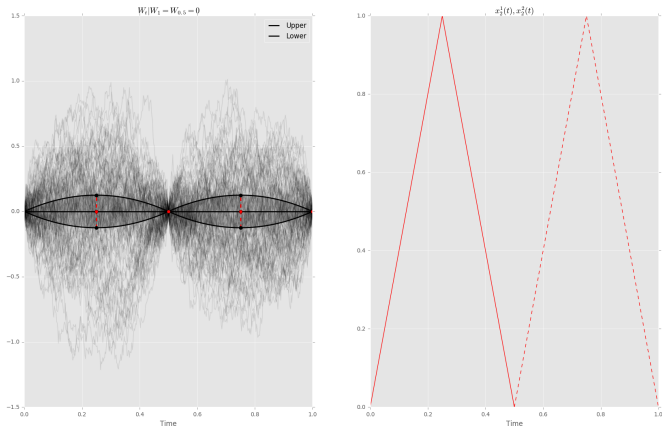


Figure: Left: Conditional Brownian motion samples and point-wise (symmetrized) variance. Right: Third and fourth basis functions.

A word on summability

The proposed decomposition need not be a nuclear representation of \mathcal{C} , that is $\sum_{k \geq 0} \lambda_k \in [0, +\infty]$. Indeed, the Brownian case shows us:

$$\sum_{k \geq 0} \lambda_k = 1 + \frac{1}{2} + 2 * \frac{1}{4} + 4 * \frac{1}{16} + 8 * \frac{1}{32} + \dots = +\infty \quad (21)$$

However, a simple transformation gives a nuclear representation in this case:

$$\tilde{f}_2^1 = \frac{f_2^1 - f_2^2}{2} \Rightarrow \text{Cov}(\tilde{f}_2^1, \tilde{f}_2^1) = \frac{\text{Cov}(f_2^1, f_2^1)}{2} = \frac{1}{8} \quad (22)$$

$$\tilde{f}_2^2 = \frac{f_2^1 + f_2^2}{2} \Rightarrow \text{Cov}(\tilde{f}_2^2, \tilde{f}_2^2) = \frac{\text{Cov}(f_2^2, f_2^2)}{2} = \frac{1}{8} \quad (23)$$

Doing similar transformations at each step gives:

$$\sum_{k \geq 0} \lambda_k = 1 + \frac{1}{2} + 2 * \frac{1}{8} + 4 * \frac{1}{64} + 8 * \frac{1}{256} + \dots = 2 \quad (24)$$

Remark that $\mathbb{E}[\|\sum_{k \geq n} \xi_k h_k\|^2] \leq \sum_{k \geq n} \lambda_k$, thus the approximation error is exponentially decreasing !

Conclusion and open questions






Conclusions

- New "practical" method to represent Gaussian elements, based on covariance operator.
- Numerical solution in the case of $E = C(K)$ (K metric and compact).
- Rediscovered Paul Levy's construction of Brownian motion.

Open question & future work

- Other properties of $(x_k, x_k^*) \in E \times E^*$?
- Rate optimality of finite dimensional approximations in $C(K)$?
- Multiplicity of decomposition elements ?
- Links with approximation numbers (ex: $I(X) = \mathbb{E}[\|X\|^2]^{\frac{1}{2}}$) approximation theory (s -numbers) ? Properties of Banach spaces ?
- Optimality for projection norm ? Dual problem ?
- Interpretation of $\sum_{k \geq 0} \lambda_k$ when it is finite ?
- Evolution of $\|x_k^*\|_{E^*}$?

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Appendix

Examples with different kernels

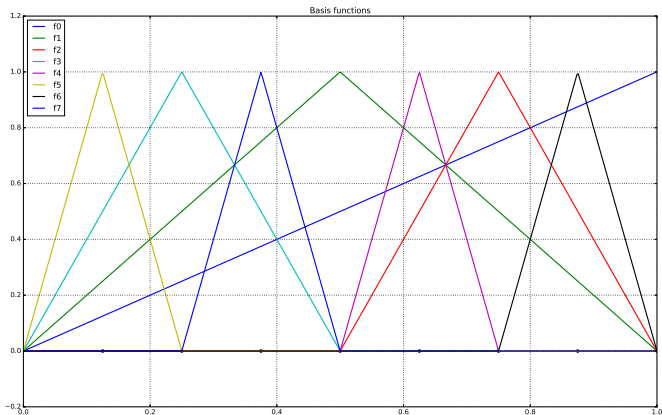


Figure: Wiener measure basis functions.

Examples with different kernels

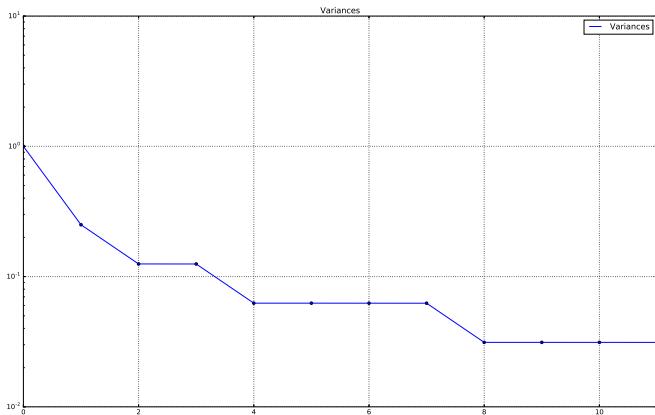


Figure: Wiener measure basis variances.

Examples with different kernels

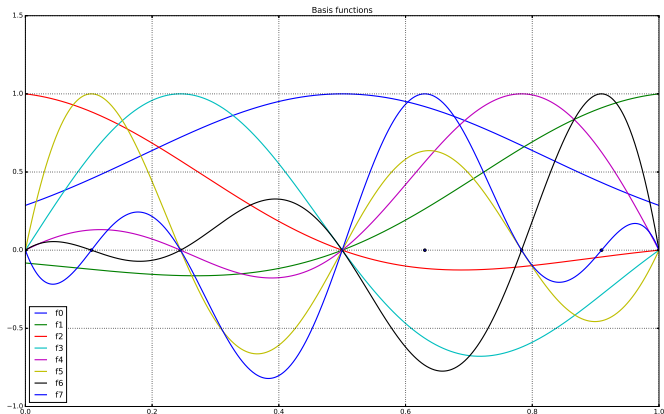


Figure: $k(s, t) = \exp\left(-\frac{(s-t)^2}{2}\right)$ basis functions.

Examples with different kernels

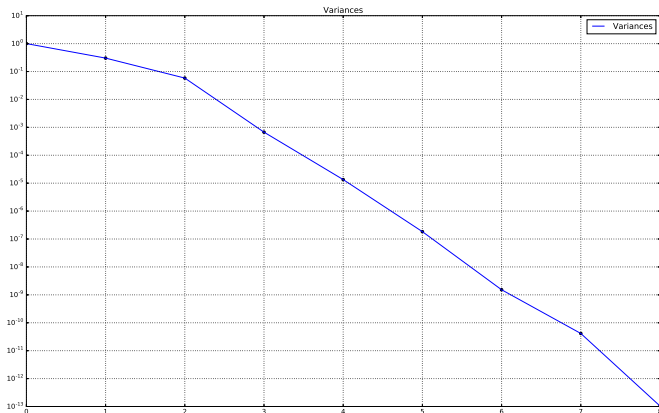


Figure: $k(s, t) = \exp\left(-\frac{(s-t)^2}{2}\right)$ basis variances.

Examples with different kernels

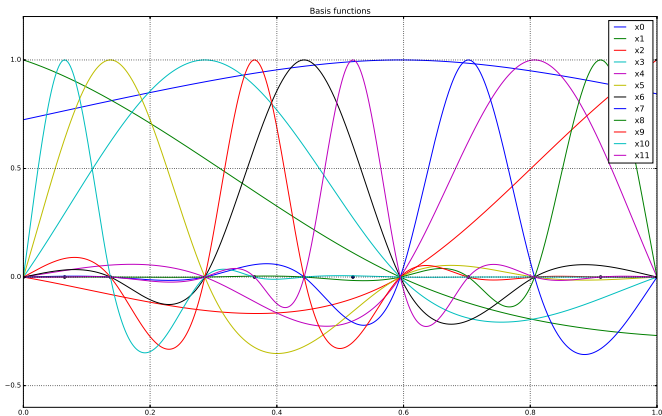


Figure: Matern 3/2 kernel basis functions.

Examples with different kernels

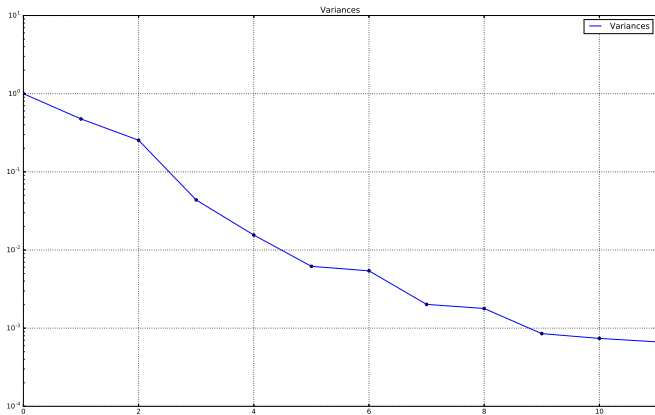


Figure: Matern 3/2 kernel basis variances.

Examples with different kernels

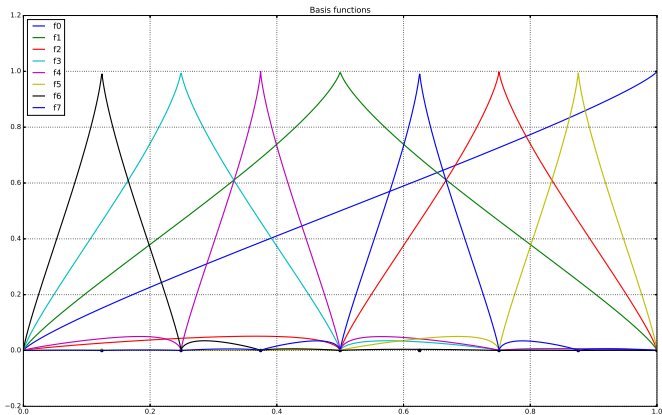


Figure: Fractional brownian motion ($H = 75\%$) basis functions.

Examples with different kernels

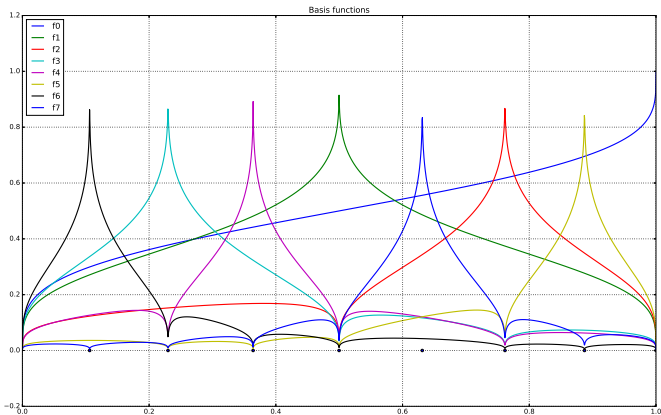


Figure: Fractional brownian motion ($H = 25\%$) basis functions.