

Gaussian processes

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- A(second order)stochastic process is a measurable application $(t, \omega) \in \mathcal{T} \times \Omega \rightarrow X_t(\omega)$ such that $X_t \in L^2$.
- \mathcal{T} is the time set which can be discrete $\mathcal{T} = \mathbb{N}$ or $\mathcal{T} = \mathbb{Z}$ or continuous $\mathcal{T} = [a, b], \mathcal{T} = \mathbb{R}^+, \mathcal{T} = \mathbb{R}$.
- When T is many-dimensional as in images or in multi-sensor fusion or in fluid mechanics, the right term is random field
- We shall consider that time set \mathcal{T} is continuous.
- Mean-square continuity of the process is the continuity of $t \in \mathcal{T} \rightarrow X_t \in L^2$. Hereafter, continuity is meaning "mean square continuity".
- In that case,

$$t \in \mathcal{T} \rightarrow m(t) = E(X_t)$$

and

$$(s, t) \in \mathcal{T} \times \mathcal{T} \rightarrow k(s, t) = Cov(X_s, X_t)$$

are continuous.

- A Gaussian vector \mathbf{X} is a random vector such that the vector subspace of L^2 generated by its components (X_1, \dots, X_n) is a set of Gaussian random variables.
- The law of a Gaussian vector is completely determined by its expectation \mathbf{m} and its covariance matrix Γ . More precisely, its characteristic function is

$$\phi_X(\mathbf{u}) = \exp[i(\mathbf{m}|\mathbf{u}) - \frac{1}{2}(\mathbf{u}|\Gamma\mathbf{u})]$$

- If \mathbf{X} is a Gaussian vector with law $\mathcal{N}(\mathbf{m}, \Gamma)$ then $A\mathbf{X} + \mathbf{b}$ is a Gaussian vector with law $\mathcal{N}(A\mathbf{m} + \mathbf{b}, A\Gamma\tilde{A})$
- When Γ is invertible, \mathbf{X} has the following probability density

$$x \rightarrow \frac{1}{\sqrt{(2\pi)^n |\Gamma|}} \exp\left[-\frac{1}{2}(\mathbf{X} - \mathbf{m}|\Gamma^{-1}(\mathbf{X} - \mathbf{m}))\right]$$

Definition

A Gaussian process is a stochastic process such that for any $(t_1, \dots, t_n) \in \mathcal{T}^n$ and any $(\alpha_1, \dots, \alpha^n) \in \mathbb{R}$ the random variable $\sum_{k=1}^n \alpha_k X_{t_k}$ is Gaussian.

The law of $(X_{t_1}, \dots, X_{t_n})$ is defined by the mean function $t \rightarrow m(t)$ and the covariance kernel $(s, t) \rightarrow k(s, t)$ of the process since

$$\mathbb{E} \begin{bmatrix} X_{t_1} \\ \dots \\ X_{t_n} \end{bmatrix} = \begin{bmatrix} m(t_1) \\ \dots \\ m(t_n) \end{bmatrix}$$
$$\text{Cov} \begin{bmatrix} X_{t_1} \\ \dots \\ X_{t_n} \end{bmatrix} = \begin{bmatrix} k(t_1, t_1) & k(t_1, t_2) & \dots & k(t_1, t_n) \\ k(t_2, t_1) & k(t_2, t_2) & \dots & k(t_2, t_n) \\ \dots & \dots & \dots & \dots \\ k(t_{n-1}, t_1) & k(t_{n-1}, t_2) & \dots & k(t_{n-1}, t_n) \\ k(t_n, t_1) & k(t_n, t_2) & \dots & k(t_n, t_n) \end{bmatrix}$$

Definition

Let (X_t) be a Gaussian process. The mapping $t \rightarrow X_t \in L^2$ is continuous if the covariance kernel is continuous since

$$\|X_s - X_t\|^2 = k(s, s) + k(t, t) - 2\operatorname{Re}\{k(s, t)\}$$

The continuity of the process allows to compute in the Hilbert space L^2 . Notably, if $\mu \in \mathcal{M}([a, b])$, we can define

$$Z = \int_a^b X_t d\mu(t) = \lim_{\Delta t \rightarrow 0} \sum_{k=0}^{\frac{b-a}{\Delta t}} X_{a+k\Delta t} \mu([a + k\Delta t, a + (k+1)\Delta t])$$

Definition

A stochastic process with $\mathcal{T} = \mathbb{R}$ is said stationary if any finite dimensional law is invariant by time shift, i.e.

$$\forall (t_1, \dots, t_n, t) \in \mathbb{R}^{n+1}, (X_{t_1}, \dots, X_{t_n}) \sim (X_{t_1-t}, \dots, X_{t_n-t})$$

Proposition

A Gaussian process is stationary if and only if its mean function is constant and his covariance kernel is of the form

$$k(t, s) = c(t - s)$$

Application: finite filtering by moving average (MAn)

Proposition

Consider a stochastic process (X_t) and a finite set of times and weights $((\alpha_1, t_1), \dots, (\alpha_n, t_n)) \in (\mathbb{R} \times \mathcal{T})^n$. The stochastic process (Y_t) defined by $Y_t = X_t - \alpha_1 X_{t-t_1} \dots \alpha_n X_{t-t_n}$ is called moving average process of order n (MAn). The stochastic process (Y_t) is Gaussian -resp. continuous, stationary- as soon as (X_t) is Gaussian, - stationary, continuous.

It is easy to compute the mean function and the covariance kernel of (Y_t) (left to exercise)

Basic example: Brownian motion alias Wiener process

Proposition

The Wiener process $t \in \mathbb{R}^+ \rightarrow W_t$ is the stationary independent increase Gaussian process with mean function $m(t) = 0$ and covariance kernel $k(s, t) = \min(s, t)$

Proposition

The Wiener process is continuous (in quadratic mean sense)

More advanced theory shows that we can build a probability space where almost all the trajectories of the Wiener process are continuous

Exercises on the Wiener process as limit of discrete random walks

Exercise

We consider the discrete time process with stationary independent increase $X(n\epsilon) \sim \mathcal{N}(0, n\epsilon^2)$. Show that when $\epsilon \rightarrow 0$ it converges towards the Wiener process.

Exercise

Let (Y_N) a sequence of independent identically distributed binary variables such that $P(Y_n = 1) = 1 - P(Y_n = -1) = p$. Let $X(n\epsilon) = \epsilon(Y_1 + \dots + Y_n)$.

- ① If $p = 0.5$, show that its limit in law is the Wiener process.
- ② What about the general case $0 < p < 1$?

Proposition

Let $\{X_n\}$ a sequence of Gaussian random variables that converges in L^2 towards X . Then X is Gaussian too.

Proof We have $E(X_n) \rightarrow E(X)$ and $Var(X_n) \rightarrow Var(X)$. So

$$\begin{aligned}\phi_X(u) &= \lim \phi_{X_n}(u) = \lim \exp(jE(X_n)u - \frac{Var(X_n)u^2}{2}) \\ &= \exp(jE(X)u - \frac{Var(X)u^2}{2})\end{aligned}$$

Definition

Let $t \in \mathcal{T} \rightarrow X_t \in L^2$ a Gaussian process, then the associate Gaussian space is the Hilbert sub-space $\mathcal{H}_X \subset L^2$ generated by the Gaussian variables X_t .

It's clear that all the elements of \mathcal{H}_X are Gaussian random variables.