

ON THE PREDICTION OF A FUNCTIONAL OF GAUSSIAN
RANDOM PROCESS

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Let $\{\xi(t), t \in T\}$ be a real Gaussian process (centered at the expectation: $E\xi(t) = 0$) and let η be a integrable functional measurable with respect to σ -field $F(T)$ generated by $\{\xi(t), t \in T\}$. It is well-known that the conditional expectation $\hat{\xi}(t) = E(\xi(t) | F(S))$, $S \subset T$, coincides with the projection of $\xi(t)$ on the Hilbert space $H^1(S)$ spanned on $\{\xi(t), t \in S\}$.

THEOREM. The functional $\hat{\eta} = E(\eta | F(S))$ is measurable with respect to σ -field $F_{\hat{\xi}}$ generated by $\{\hat{\xi}(t), t \in T\}$.

P r o o f. The conditional distribution (given $F(S)$) of η is determined by the family of the conditional distributions of the vectors $(\xi(t_1), \dots, \xi(t_n))$, $t_1, \dots, t_n \in T$. The conditional distribution of $(\xi(t_1), \dots, \xi(t_n))$ is Gaussian, so it is determined by the mean vector $(\xi(t_1), \dots, \xi(t_n))$ and the covariance matrix

$$B = \|b(t_i, t_j)\|, \quad i, j = 1, \dots, n,$$
$$b(t_i, t_j) = E((\xi(t_i) - \hat{\xi}(t_i))(\xi(t_j) - \hat{\xi}(t_j)) | F(S)).$$

But $\xi(t) - \hat{\xi}(t)$ is independent (for Gaussian process) of $F(S)$. So $b(t_i, t_j)$ is the constant $E((\xi(t_i) - \hat{\xi}(t_i))(\xi(t_j) - \hat{\xi}(t_j)))$. In this way the conditional distribution of η depends only of $\hat{\xi}(t)$, $t \in T$, and its conditional expectation $\hat{\eta}$ depends only of $\hat{\xi}(t)$, $t \in T$.

Theorem is closely related to [2], pp.73-78, but puts in evidence the evaluation of $\hat{\eta}$ by $\{\hat{\xi}(t)\}$.

Example 1. Let $H^n(S)$ be the linear closure of all polynomials of the variables $\xi(t)$, $t \in S$, the degree not greater than n . It is shown in [2] that $\eta \in H^n(T)$ implies $\hat{\eta} \in H^n(S)$. We precise this result showing that $\hat{\eta}$ belongs to the linear closure of all polynomials of the variables $\hat{\xi}(t)$, $t \in T$, the degree not greater than n . For this it is enough to see that

$$\begin{aligned} & E(\xi(t_1) \dots \xi(t_n) | F(S)) \text{ is a polynomial of} \\ & \hat{\xi}(t_1), \dots, \hat{\xi}(t_n) \text{ of the degree } n: \\ & E(\xi(t_1) \dots \xi(t_n) | F(S)) = \\ & = \frac{1}{(2\pi)^{n/2} (\det B)^{1/2}} \int \dots \int x_1 \dots x_n \exp\{-\frac{1}{2} \sum_{i,j} B_{ij} (x_i - \\ & - \hat{\xi}(t_i))(x_j - \hat{\xi}(t_j))\} dx_1 \dots dx_n = \frac{1}{(2\pi)^{n/2} (\det B)^{1/2}} \int \dots \\ & \dots \int \prod_{k=1}^n (u_k + \hat{\xi}(t_k)) \exp\{-\frac{1}{2} \sum_{i,j} B_{ij} u_i u_j\} du_1 \dots du_n = \\ & = P_n(\hat{\xi}(t_1), \dots, \hat{\xi}(t_n)) \cdot (B_{ij} \text{ is the cofactor of } b(t_i, t_j)) . \end{aligned}$$

Observe that

$$\frac{\partial}{\partial x_k} P_n(x_1, \dots, x_k, \dots, x_n) = P_{n-1}(x_1, \dots, x_{k-1}, x_{k+1}, \dots, x_n).$$

APPLICATION TO THE PREDICTION

Let $T = [t_0, \infty)$, $S = [t_0, s]$, $t_0 < s$. Then for fixed $t, t > s$, $\hat{\xi}(s, t) = E(\xi(t) | F_S)$, (we put $F(S) = F_S$), is the best (in the sense of the minimal variance) prediction of $\xi(t)$ by $\{\xi(u), u \in [t_0, s]\}$. $\hat{\xi}(s, t)$ coincides, for Gaussian process, with the best linear prediction which is widely elaborated for stationary process $\{\xi(t), -\infty < t < \infty\}$. In the terms of predication problem Theorem says

that the prediction $\hat{\eta}$ of an integrable functional η of $\{\xi(u), u \in [s, \infty)\}$ by $\{\xi(u), u \in [t_0, s]\}$ is the functional of $\{\hat{\xi}(s, u), u \in [s, \infty)\}$

Example 2. Prediction of the time over a level by Gaussian process. Supposing the continuity of $\{\xi(t), t \geq 0\}$ the functional $\eta = \int_s^t I(\xi(u) > c) du$, ($I(\cdot)$ is the indicator function), is the time over the level c by the process $\{\xi(u)\}$ during the time $[s, t]$. The prediction of η by $\{\xi(u), u \leq s\}$ is

$$\hat{\eta} = E(\eta | F_s) = \int_s^t P(\xi(u) > c | F_s) du = \int_s^t [1 - \Phi(\frac{c - \hat{\xi}(s, u)}{\sqrt{b(u, u)}})] du,$$

where $\Phi(\cdot)$ is the distribution function of a standard Gaussian variable.

Example 3. The problem of the prediction of the process $\{\zeta(t), t \geq 0\}$, $\zeta(t) = f(\xi(t))$, where $f(\cdot)$ is a non-random function, is posed in [1]. In the case $f(x) = x^2$ and the differentiable process $\{\xi(t), t \geq 0\}$ for which

$$\hat{\xi}(s, t) = \sum_{j=0}^{N-1} a_j(s, t) \xi^{(j)}(s),$$

(such process belongs to so called N -tuple Markov processes), the explicit formula for $\hat{\zeta}(s, t)$ in the terms of $\zeta(s), \dots, \zeta^{(N-1)}(s)$ is given.

But generally, because the conditional distribution of $\xi(t)$ given F_s is Gaussian with the parameters $\hat{\xi}(s, t)$ and $b(t, t)$, we have simple

$$\begin{aligned} \hat{\zeta}(s, t) = E(f(\xi(t)) | F_s) &= \frac{1}{\sqrt{2\pi b(t, t)}} \int f(x) \exp\{-\frac{1}{2} \frac{(x - \hat{\xi}(t, s))^2}{b(t, t)}\} dx = \\ &= g(\hat{\xi}(t, s)). \end{aligned}$$

For instance, if $\{\xi(t)\}$ is as in [1] and $f^{-1}(\cdot)$ is the differentiable function, we find $\hat{\zeta}(s, t)$ in terms of $\zeta(s), \dots, \zeta^{(N-1)}(s)$.

REFERENCES

- [1] Hida, T. and Kallianpur, G.: *The square of a Gaussian Markov process and non-linear prediction*, *J. of Mult. An.* 5, 1975, pp. 451-461.
- [2] Розанов, Ю.А.: Марковские случайные поля, М., 1981.

REZIME

O PREDVIDJANJU FUNKCIONALA GAUSOVOG
SLUČAJNOG PROCESA

Pokazuje se da je predviđanje funkcionala Gausovog procesa $\{\xi(t), t \in T\}$ funkcional od linearnog predviđanja $\{\hat{\xi}(s,t), t \in T\}$.