

**STOCHASTIC PROCESSES. SOLUTIONS TO HOME  
ASSIGNMENTS**

5. GAUSSIAN PROCESSES

**Problem 5.1**

First note that:

$$\begin{aligned} & -1/2(x - a - iK\lambda)^T K^{-1}(x - a - iK\lambda) = \\ & = -1/2(x - a)^T K^{-1}(x - a) + i\lambda^T(x - a) + 1/2\lambda^T K\lambda \end{aligned}$$

Using this fact:

$$\begin{aligned} \Phi(\lambda) & \triangleq \int_{\mathbb{R}^N} e^{i\lambda^T x} p(x) dx = \\ & = \int_{\mathbb{R}^N} \exp\{i\lambda^T x\} \frac{1}{\sqrt{\det(2\pi K)}} \exp\{-1/2(x - a)^T K^{-1}(x - a)\} dx = \\ & = \frac{1}{\sqrt{\det(2\pi K)}} \int_{\mathbb{R}^N} \exp\{-1/2(x - a - iK\lambda)^T K^{-1}(x - a - iK\lambda) + \\ & + i\lambda^T a - 1/2\lambda^T K\lambda\} dx = \exp\{i\lambda^T a - 1/2\lambda^T K\lambda\} \times \\ & \times \underbrace{\int_{\mathbb{R}^N} \frac{1}{\sqrt{\det(2\pi K)}} \exp\{-1/2(x - a - iK\lambda)^T K^{-1}(x - a - iK\lambda) dx\}}_{\triangleq 1} = \\ & = \exp\{i\lambda^T a - 1/2\lambda^T K\lambda\} \end{aligned}$$

**Problem 5.2**

Let  $\varphi(\lambda) = \mathbb{E}e^{i\lambda\xi} = \mathbb{E}e^{i\lambda\eta}$ . Set  $X = \xi + \eta$  and  $Y = \eta - \xi$ , then by independence of  $X$  and  $Y$ :

$$\mathbb{E}e^{isX+itY} = \mathbb{E}e^{isX}\mathbb{E}e^{itY} = \varphi^2(s)\varphi(t)\varphi(-t)$$

On the other hand:

$$\mathbb{E}e^{isX+itY} = \mathbb{E}e^{i(s+t)\eta+i(s-t)\xi} = \varphi(s+t)\varphi(s-t)$$

so that  $\varphi(\cdot)$  obeys an equation:

$$\varphi^2(s)\varphi(t)\varphi(-t) = \varphi(s+t)\varphi(s-t), \quad \forall s, t$$

Assuming  $\varphi(x)$  is smooth enough, differentiating twice w.r.t  $t$  and setting  $t = 0$ , the ODE for  $\varphi(s)$  is obtained:

$$2\varphi^2(s)[\varphi''(0)\varphi(0) - (\varphi'(0))^2] = 2[\varphi''(s)\varphi(s) - (\varphi'(s))^2]$$

Without loss of generality assume  $\mathbb{E}\xi = 0$  and  $\mathbb{E}\xi^2 = 1$ , then  $\varphi(0) = 1$ ,  $\varphi'(0) = 0$ ,  $\varphi''(0) = -1$  and the equation is obtained:

$$\begin{aligned} -\varphi^2(s) &= \varphi''(s)\varphi(s) - [\varphi'(s)]^2 \\ \varphi(0) &= 1 \\ \varphi'(0) &= 0 \end{aligned}$$

which implies that:

$$(\log \varphi(s))'' = -1 \implies \varphi(s) = e^{-s^2/2}$$

i.e.  $\xi$  and  $\eta$  are Gaussian.

### Problem 5.3

$$\begin{aligned} \varphi(s) &:= \mathbb{E}e^{is\eta} = \mathbb{E} \exp \left\{ is \frac{\xi_1 + \xi_2 \xi_3}{\sqrt{1 + \xi_3^2}} \right\} = \\ &= \mathbb{E} \mathbb{E} \left\{ \exp \left( \frac{is\xi_1}{\sqrt{1 + \xi_3^2}} \right) \middle| \xi_3 \right\} \mathbb{E} \left\{ \exp \left( \frac{is\xi_2 \xi_3}{\sqrt{1 + \xi_3^2}} \right) \middle| \xi_3 \right\} = \\ &= \mathbb{E} \exp \left( \frac{-0.5s^2}{1 + \xi_3^2} \right) \exp \left( \frac{-0.5s^2 \xi_3^2}{1 + \xi_3^2} \right) = e^{-s^2/2} \end{aligned}$$

which implies that  $\eta$  is Gaussian with zero mean and unit variance.

### Problem 5.4

By virtue of Cauchy-Schwarz inequality

$$\left[ \mathbb{E} \left( \frac{p'(\xi)}{p(\xi)} \xi \right) \right]^2 \leq \mathbb{E} \left( \frac{p'(\xi)}{p(\xi)} \right)^2 \mathbb{E}\xi^2 = I_\xi \mathbb{E}\xi^2$$

but

$$\begin{aligned} \mathbb{E} \left( \frac{p'(\xi)}{p(\xi)} \xi \right) &= \int_{-\infty}^{\infty} \frac{p'(x)}{p(x)} xp(x) dx = \int_{-\infty}^{\infty} p'(x) x dx = \\ &= p(x)x \Big|_{-\infty}^{\infty} - \int_{-\infty}^{\infty} p(x) dx = -1 \end{aligned}$$

So  $\mathbb{E}\xi^2 \geq 1/I_\xi$ . The equality is attained only if  $p'(x)/p(x) = Cx$  for some constant  $C$ . This implies that

$$p(x) \propto e^{Cx^2/2}$$

i.e.  $\xi$  is Gaussian.

**Problem 5.5**

Use the property of the characteristic function<sup>1</sup>:

$$\frac{\partial^4}{\partial \lambda_1 \partial \lambda_2 \partial \lambda_3 \partial \lambda_4} \varphi(\lambda) \Big|_{\lambda=0} = \mathbb{E} \xi_1 \xi_2 \xi_3 \xi_4$$

For Gaussian vector  $\xi$  (with zero mean):

$$\varphi(\lambda) = \mathbb{E} \exp\{i \lambda^* \xi\} = \exp\{-1/2 \lambda^* R \lambda\} = \exp\left\{-1/2 \sum_{i,j} \lambda_i R_{ij} \lambda_j\right\}$$

where  $R_{ij} = \mathbb{E} \xi_i \xi_j$ ,  $1 \leq i, j \leq 4$ .

$$\begin{aligned} \frac{\partial}{\partial \lambda_1} \varphi(\lambda) &= -\varphi(\lambda) \sum_i \lambda_i R_{1i} \\ \frac{\partial^2}{\partial \lambda_1 \partial \lambda_2} \varphi(\lambda) &= \varphi(\lambda) \sum_i \lambda_i R_{1i} \sum_\ell \lambda_\ell R_{2\ell} - \varphi(\lambda) R_{12} := A + B \end{aligned}$$

Clearly

$$\frac{\partial^2}{\partial \lambda_3 \partial \lambda_4} B = -R_{12} \varphi(\lambda) \sum_k \lambda_k R_{3k} \sum_m \lambda_m R_{4m} + \varphi(\lambda) R_{12} R_{34}$$

so that

$$\frac{\partial^2}{\partial \lambda_3 \partial \lambda_4} B(\lambda) \Big|_{\lambda=0} = R_{12} R_{34} \varphi(0) \quad (5.1)$$

Further,

$$\begin{aligned} \frac{\partial}{\partial \lambda_3} A(\lambda) &= -\varphi(\lambda) \sum_i \lambda_i R_{1i} \sum_j \lambda_j R_{2j} \sum_\ell \lambda_\ell R_{3\ell} + \\ &\quad + \varphi(\lambda) \left[ R_{13} \sum_j \lambda_j R_{2j} + R_{23} \sum_i \lambda_i R_{1i} \right] \\ \frac{\partial^2}{\partial \lambda_3 \lambda_4} A(\lambda) \Big|_{\lambda=0} &= \varphi(0) [R_{13} R_{24} + R_{23} R_{14}] \end{aligned} \quad (5.2)$$

Eq. (5.1) and (5.2) imply the desired formula.

---

<sup>1</sup>why is it correct?

**Problem 5.6**

- (1) Verify that  $g_n(x)$  is a probability density function, i.e. that  $g_n(x) \geq 0$  for all  $x \in \mathbb{R}^n$  and that  $\int_{\mathbb{R}^n} g_n(x) dx = 1$ . The function  $g_n(x)$  is non-negative if

$$\left| (x_k - a) \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left\{ -(x_k - a)^2 / (2\sigma^2) \right\} \right| \leq 1, \quad x_k \in \mathbb{R}, \quad k = 1, \dots, n$$

or equivalently if

$$|\varphi(y)| = \left| \frac{y}{\sqrt{2\pi\sigma^2}} e^{-y^2/2\sigma^2} \right| \leq 1, \quad y \in \mathbb{R}$$

The latter holds if  $\max_t |\varphi(t)| \leq 1$ . The maximum and the points where it is attained can be found explicitly:

$$\varphi'(y) = \frac{1}{\sqrt{2\pi\sigma^2}} \left\{ e^{-y^2/(2\sigma^2)} - \frac{y^2}{\sigma^2} e^{-y^2/(2\sigma^2)} \right\}$$

$$\varphi'(y) = 0 \implies y_{1,2} = \pm\sigma$$

and

$$|\varphi(\sigma)| = \frac{1}{\sqrt{2\pi}} e^{-1/2} < 1$$

This implies that  $g_n(x) > 0$  for all  $x$ .

Note that  $f(x) = 1/\sqrt{2\pi\sigma^2} \exp\{-1/2(x-a)^2/\sigma^2\}$  is symmetric around  $a$  so that

$$\int_{\mathbb{R}} (x-a) f^2(x) dx = 0$$

which implies  $\int_{\mathbb{R}^n} g_n(x) dx = 1$ .

- (2) Let  $\tilde{X}$  be a subvector of  $X$  with  $k$  components. Denote its pdf by  $\tilde{g}_k(x)$ ,  $k < n$ , i.e.

$$\tilde{g}_k(x) = \int_{\mathbb{R}^{n-k}} g_n(x_1, \dots, x_n) dx_{i_1} \dots dx_{i_{n-k}}$$

where  $\mathcal{J} := \{i_1, \dots, i_{n-k}\}$  are the indices of the components, which do not appear at  $\tilde{X}$ . It is not difficult to see that

$$\tilde{g}_k(x) = \prod_{j \notin \mathcal{J}} f(x_j)$$

i.e. the distribution of any subvector of  $X$  is Gaussian !

- (3) On the other hand,  $X$  is clearly not Gaussian. This leads to a conclusion: a vector is Gaussian only if *any* combination of its components is Gaussian.

**Problem 5.7**

- (1) Clearly  $\int_{\mathbb{R}^2} g(x, y) dx dy = c_1 + c_2 = 1$  and  $c_1 > 0, c_2 > 0 \implies g(x, y) > 0$ , so that  $g(x, y)$  is a prob. density.
- (2)

$$f(x) = \int_{\mathbb{R}} g(x, y) dy = c_1 \varphi(x) + c_2 \varphi(x) = \varphi(x)$$

where  $\varphi(x)$  denotes standard Gaussian density. Similarly  $f(y) = \varphi(y)$ .

- (3)  $\mathbb{E}XY = c_1 \rho_1 + c_2 \rho_2$ . Choose e.g.  $c_1 = |\rho_2|$  and  $c_2 = |\rho_1|$ . If  $\rho_1 \rho_2 < 0$ , then  $\mathbb{E}XY = 0$ . But  $X$  and  $Y$  are dependent, since  $g(x, y) \neq f(x)f(y)$ .
- (4) A pair of r.v. can be dependent, even if each one is Gaussian (separately) and they are uncorrelated. However, if in addition they are jointly Gaussian, their independence follows.

**Problem 5.8**

- (1) First prove the auxiliary result.

**Lemma 5.1.** *if  $\alpha$  and  $\beta$  are independent Gaussian random variables with zero mean and variances  $\sigma_\alpha^2$  and  $\sigma_\beta^2$ , then  $\gamma = \alpha\beta/\sqrt{\alpha^2 + \beta^2}$  is a Gaussian r.v. with zero mean and variance  $\sigma_\alpha^2 \sigma_\beta^2 / (\sigma_\alpha + \sigma_\beta)^2$ .*

*Proof.* (there are other elegant proofs!) Note that  $\gamma^{-2} = \alpha^{-2} + \beta^{-2}$ . Let  $\psi_\alpha(s) = \mathbb{E}(e^{is/\alpha^2})$ :

$$\begin{aligned} \psi_\alpha(s) &= \frac{1}{\sqrt{2\pi\sigma_\alpha^2}} \int_{-\infty}^{\infty} \exp\left\{-\frac{is}{x^2} - \frac{x^2}{2\sigma_\alpha^2}\right\} dx = \\ &= \frac{1}{\sqrt{\pi}} \int_{-\infty}^{\infty} \exp\left\{-\frac{is}{z^2 2\sigma_\alpha^2} - z^2\right\} dz = h\left(\sqrt{\frac{s}{2\sigma_\alpha^2}}\right) \end{aligned}$$

where

$$h(t) = \frac{1}{\sqrt{\pi}} \int_{-\infty}^{\infty} \exp\left\{-\frac{it^2}{z^2} - z^2\right\} dz$$

It is easily seen that  $h'(t) = -2\sqrt{i}h(t)$ , so  $h(t) = C \exp\{-2\sqrt{i}t\}$ . Since  $h(0) = 1$  we finally conclude that  $h(t) = \exp\{-2\sqrt{i}t\}$ .

Consequently  $\psi_\alpha(s) = \exp\{-2\sqrt{is/(2\sigma_\alpha^2)}\}$  and analogously  $\psi_\beta(s) = \exp\{-2\sqrt{is/(2\sigma_\beta^2)}\}$ . Then since  $\alpha$  and  $\beta$  are independent, we have:

$$\begin{aligned} \psi_\gamma(s) &\stackrel{\Delta}{=} \mathbb{E}\left(e^{is/\gamma^2}\right) = \psi_\beta(s)\psi_\alpha(s) = \exp\{-\sqrt{2is}(1/\sigma_\beta + 1/\sigma_\alpha)\} \quad (5.3) \\ &= \exp\left\{-\sqrt{2is}\left(\frac{\sigma_\beta\sigma_\alpha}{\sigma_\beta + \sigma_\alpha}\right)^{-1}\right\} \end{aligned}$$

Note that  $\gamma$  has a symmetric density (Why ?), so the distribution of  $\gamma$  is determined by the distribution of  $1/\gamma^2$ . The latter and (5.3) allow to conclude that  $\gamma$  is Gaussian.  $\square$

Assume that  $X_{n-1}$  is Gaussian, then clearly  $X_n$  is Gaussian, since  $\xi_n$  and  $X_{n-1}$  are independent. Since the initial condition is Gaussian, we conclude that  $X_n$  is a Gaussian r.v. for each  $n$ .

- (2) The process  $(X_n)_{n \geq 0}$  is *not* Gaussian. By contradiction, assume that  $[X_0, X_1]$  is a Gaussian vector. Then since  $\mathbb{E}X_1X_0 = 0$  they are independent and hence we expect that  $\mathbb{E}(X_1^2|X_0) = \mathbb{E}X_1^2$  is not a function of  $X_0$ . Let's prove that the latter does not hold:

$$\mathbb{E}(X_1^2|X_0) = \mathbb{E}\left(\frac{X_0^2\xi_1^2}{X_0^2 + \xi_1^2} \middle| X_0\right) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \frac{X_0^2 z^2}{X_0^2 + z^2} e^{-z^2/2} dz \triangleq H(X_0)$$

Obviously  $H(X_0) \neq \text{const}$ :  $H(0) = 0$  and  $H(1) \neq 0$ .

- (3)  $m_n = \mathbb{E}X_n \equiv 0$  and

$$V_n = \frac{V_{n-1}\sigma_\xi^2}{(\sqrt{V_{n-1}} + \sigma_\xi)^2}, \quad V_0 = 1$$

- (4) Show that  $\lim_{n \rightarrow \infty} V_n = 0$  and then  $X_n \rightarrow 0$  as  $n \rightarrow \infty$  in mean square sense and hence also in the mean and in probability. Let  $Q_n = 1/V_n$  then

$$Q_n = (\sigma_\xi^{-1} + \sqrt{Q_{n-1}})^2$$

Define an auxiliary sequence:

$$\tilde{Q}_n = \tilde{Q}_{n-1} + \sigma_\xi^{-2}, \quad \tilde{Q}_0 = Q_0$$

By induction we show that  $Q_n \geq \tilde{Q}_n$  for  $n \geq 0$ : assume that  $Q_{n-1} \geq \tilde{Q}_{n-1}$  then

$$Q_n = \sigma_\xi^{-2} + Q_{n-1} + 2\sigma_\xi^{-1}\sqrt{Q_{n-1}} \geq \sigma_\xi^{-2} + Q_{n-1} \geq \sigma_\xi^{-2} + \tilde{Q}_{n-1} = \tilde{Q}_n$$

Clearly  $\tilde{Q}_n \rightarrow \infty$ , which implies  $Q_n \rightarrow \infty$  as  $n \rightarrow \infty$ , and thus  $V_n \rightarrow 0$ .