

# Gaussian Processes.

$$① f_{\mathbf{x}}(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right), \quad \mathbf{x} \sim N(\mu, \sigma^2).$$

$$② f_{\mathbf{x}}(x) = \frac{1}{(2\pi)^{\frac{n}{2}} (\det \Sigma)^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(\mathbf{x}-\mu)^T \Sigma^{-1}(\mathbf{x}-\mu)\right), \quad \mathbf{x} \sim N(\mu, \Sigma)$$

$$\Phi_{\mathbf{x}}(\omega) = \exp(j\omega^T \mu - \frac{1}{2}\omega^T \Sigma \omega)$$

(1) Linearity.  $\mathbf{x} \in \mathbb{R}^n$ .  $\mathbf{x} \sim N(\mu, \Sigma)$ .  $A \in \mathbb{R}^{m \times n}$ .  $\mathbf{y} = A\mathbf{x} \in \mathbb{R}^m$

$$\mathbf{y} \sim N(A\mu, A\Sigma A^T).$$

$$\begin{aligned} \Phi_{\mathbf{y}}(\omega) &= E(\exp(j\omega^T \mathbf{y})) = E(\exp(j\omega^T A \mathbf{x})) \\ &= E(\exp(j(A^T \omega)^T \mathbf{x})) = \Phi_{\mathbf{x}}(\tilde{\omega}) \Big|_{\tilde{\omega} = A^T \omega}. \end{aligned}$$

Linear Invariance.

$$= \exp(j\tilde{\omega}^T \mu - \frac{1}{2}\tilde{\omega}^T \Sigma \tilde{\omega}) \Big|_{\tilde{\omega} = A^T \omega} = \exp(j\omega^T A\mu - \frac{1}{2}\omega^T A\Sigma A^T \omega)$$

②. Marginal Distribution  $\mathbf{x} \in \mathbb{R}^n$ .  $\mathbf{x} \sim N(\mu, \Sigma)$ .  $\mathbf{x} = (x_1, \dots, x_n)^T$

$$\hat{\mathbf{x}} = (x_{n_1}, x_{n_2}, \dots, x_{n_k}), \quad \{n_1, \dots, n_k\} \subseteq \{1, \dots, n\}$$

$$= \frac{1}{2} (P(\bar{x}_1 \leq y) + P(\bar{x}_1 \geq -y)) = \frac{1}{2} (F_{\bar{x}_1}(y) + 1 - F_{\bar{x}_1}(-y))$$

$$f_{Y_2}(y) = \frac{d}{dy} F_{Y_2}(y) = \frac{1}{2} (f_{\bar{x}_1}(y) + f_{\bar{x}_1}(-y)) = f_{\bar{x}_1}(y)$$

$$F_{Y_2}(y) = \frac{1}{2} (P(|\bar{x}_2| \leq y) + P(|\bar{x}_2| \geq -y))$$

$$= \begin{cases} \frac{1}{2} (P(-y \leq \bar{x}_2 \leq y) + 1), & y \geq 0 \\ \frac{1}{2} (0 + P(\bar{x}_2 \geq -y \text{ or } \bar{x}_2 \leq y)), & y < 0 \end{cases}$$

$$\tilde{\mathbf{x}} = \begin{pmatrix} \bar{x}_{n_1} \\ \vdots \\ \bar{x}_{n_k} \end{pmatrix} = \mathbf{A} \begin{pmatrix} \bar{x}_1 \\ \vdots \\ \bar{x}_n \end{pmatrix} \sim N(\mathbf{A}\mu, \mathbf{A}\Sigma\mathbf{A}^T)$$

Marginal Gaussian  $\Rightarrow$  Joint Gaussian.

①.  $\bar{x}_1, \bar{x}_2$  independent.  $\bar{x}_1, \bar{x}_2 \sim N(0, 1)$ ,  $Y_1 = \bar{x}_1$ ,  $Y_2 = \bar{x}_1 \text{sgn}(\bar{x}_2)$

$$F_{Y_2}(y) = P(Y_2 \leq y) = P(\bar{x}_1 \text{sgn}(\bar{x}_2) \leq y) = P(\bar{x}_1 \leq y | \bar{x}_2 \geq 0) P(\bar{x}_2 \geq 0) + P(-\bar{x}_1 \leq y | \bar{x}_2 \leq 0) P(\bar{x}_2 \leq 0) = \frac{1}{2} (P(\bar{x}_1 \leq y) + P(-\bar{x}_1 \leq y)).$$



$$\int_{-\infty}^{+\infty} \exp(j\omega x) dx = 2\pi \delta(\omega).$$

$$= \frac{1}{2\pi} \exp\left(-\frac{x^2+y^2}{2}\right) (1 + \sin x \sin y)$$

$$(x, y) dx = \int_{-\infty}^{+\infty} g(x, y) dy = 0. \quad \left[ \int_{-\infty}^{+\infty} \sin x dx \neq 0 \right]$$

$$\int_{-\infty}^{+\infty} h(x) dx = \lim_{\substack{T_1 \rightarrow \infty \\ T_2 \rightarrow -\infty}} \int_{T_2}^{T_1} h(x) dx$$

$$\int_{-\infty}^{+\infty} h(x) dx = \lim_{T \rightarrow \infty} \int_{-T}^T h(x) dx$$

$$\begin{aligned} \int_{-\infty}^{+\infty} \sin x dx &= \frac{1}{2j} \int_{-\infty}^{+\infty} (\exp(jx) - \exp(-jx)) dx \\ &= \frac{\pi}{j} (\delta(1) + \delta(-1)) = 0. \end{aligned}$$

Cauchy P.V.  
(Principal Value)

$$\bar{x}_1 \sim N, \bar{x}_2 \sim N, \dots, \bar{x}_n \sim N.$$

Independent.

$$\bar{x}_k \sim N(\mu_k, \sigma_k^2).$$

$$\Downarrow \\ \Sigma = \text{diag}!$$

$$f_{\bar{x}_1, \dots, \bar{x}_n}(x_1, \dots, x_n) = \prod_{k=1}^n f_{\bar{x}_k}(x_k) = \prod_{k=1}^n \left( \frac{1}{\sqrt{2\pi}\sigma_k} \exp\left(-\frac{(x_k - \mu_k)^2}{2\sigma_k^2}\right) \right)$$

$$= \frac{1}{(2\pi)^{\frac{n}{2}} \prod_{k=1}^n \sigma_k} \exp\left(-\frac{1}{2} \sum_{k=1}^n \frac{(x_k - \mu_k)^2}{\sigma_k^2}\right) = \frac{1}{(2\pi)^{\frac{n}{2}} (\prod_{k=1}^n \sigma_k^2)^{\frac{1}{2}}} \exp\left(-\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu)\right)$$

$$\mu = (\mu_1, \dots, \mu_n)^T, \quad \Sigma = \text{diag}(\sigma_1^2, \dots, \sigma_n^2).$$

$$\begin{aligned}
 &= \frac{1}{2} (P(\bar{x}_1 \leq y) + P(\bar{x}_1 \geq -y)) = \frac{1}{2} (F_{\bar{x}_1}(y) + 1 - F_{\bar{x}_1}(-y)) \\
 f_{Y_2}(y) &= \frac{d}{dy} F_{Y_2}(y) = \frac{1}{2} (f_{\bar{x}_1}(y) + f_{\bar{x}_1}(-y)) = f_{\bar{x}_1}(y) \\
 F_{Y_2}(y) &= \frac{1}{2} (P(|\bar{x}_2| \leq y) + P(|\bar{x}_2| \geq -y)) \\
 &= \begin{cases} \frac{1}{2} (P(-y \leq \bar{x}_2 \leq y) + 1), & y \geq 0 \\ \frac{1}{2} (0 + P(\bar{x}_2 \geq -y \text{ or } \bar{x}_2 \leq y)), & y < 0 \end{cases} \\
 &\quad \frac{1}{2} (F_{\bar{x}_2}(y) - F_{\bar{x}_2}(-y) + 1) \quad \frac{1}{2} (F_{\bar{x}_2}(y) + 1 - F_{\bar{x}_2}(-y))
 \end{aligned}$$

$$\begin{aligned}
 &\bar{x} \in \mathbb{R}^n, \quad \bar{x} \sim N \iff \forall \alpha \in \mathbb{R}^n, \quad \alpha^T \bar{x} \sim N. \\
 &"\Rightarrow" \text{ Trivial! } E(\exp(j\alpha^T \bar{x})) = \Phi_Y(1) \boxed{\exp(j\alpha^T \mu - \frac{1}{2} \alpha^T \Sigma_{\bar{x}} \alpha)} \\
 &"\Leftarrow". \quad \Phi_{\bar{x}}(\omega) = E(\exp(j\omega^T \bar{x})) = \Phi_{\omega^T \bar{x}}(1) = \exp(j\mu_{\omega^T \bar{x}} - \frac{1}{2} \sigma_{\omega^T \bar{x}}^2) \\
 &\mu_{\omega^T \bar{x}} = E(\omega^T \bar{x}) = \omega^T E(\bar{x}) = \omega^T \mu. \\
 &\sigma_{\omega^T \bar{x}}^2 = E((\omega^T \bar{x} - \omega^T \mu)^2) = E(\omega^T (\bar{x} - \mu))^2 = E(\omega^T (\bar{x} - \mu)(\bar{x} - \mu)^T \omega) \\
 &\quad = \omega^T E((\bar{x} - \mu)(\bar{x} - \mu)^T) \omega = \omega^T \Sigma_{\bar{x}} \omega.
 \end{aligned}$$



$$\text{i.i.d. } \bar{x}_1, \dots, \bar{x}_n, \quad \bar{x} = \frac{1}{n} \sum_{k=1}^n \bar{x}_k, \quad \hat{\sigma}^2 = \frac{1}{n-1} \sum_{k=1}^n (\bar{x}_k - \bar{x})^2$$

$$E(\hat{\sigma}^2) = E\left(\sum_{k=1}^n (\bar{x}_k - \bar{x})^2\right) = E\left(\sum_{k=1}^n \bar{x}_k^2 + n(\bar{x})^2 - 2\sum_{k=1}^n \bar{x}_k \bar{x}\right)$$

$$= E\left(\sum_{k=1}^n \bar{x}_k^2 + n(\bar{x})^2 - 2n(\bar{x})^2\right) = E\left(\sum_{k=1}^n \bar{x}_k^2 - n(\bar{x})^2\right)$$

$$E(n(\bar{x})^2) = E\left(\frac{1}{n} \left(\sum_{k=1}^n \bar{x}_k\right)^2\right) = \frac{1}{n} E\left(\sum_{k=1}^n \bar{x}_k^2 + \sum_{i \neq j} \bar{x}_i \bar{x}_j\right) \quad E(\bar{x}_i \bar{x}_j) = E\bar{x}_i E\bar{x}_j$$

$$= \frac{1}{n} (n E\bar{x}_1^2 + n(n-1)(E\bar{x}_1)^2)$$

$$E\left(\sum_{k=1}^n \bar{x}_k^2 - n(\bar{x})^2\right) = n E\bar{x}_1^2 - \bar{x}_1^2 + (n-1)(E\bar{x}_1)^2$$

$$= (n-1)(E\bar{x}_1^2 - (E\bar{x}_1)^2) = (n-1) \text{Var}(\bar{x}_1)$$

$$E(\hat{\sigma}^2) = \frac{1}{n-1} E\left(\sum_{k=1}^n \bar{x}_k^2 - n(\bar{x})^2\right)$$

$$\bar{x}_1, \dots, \bar{x}_n \text{ i.i.d. } N(\mu, \sigma^2) \quad (n-1) \text{Var}(\bar{x}_1) = \text{Var}(\bar{x}_1)$$



ind.  $\bar{x}_1, \dots, \bar{x}_n$ .

$$\bar{x} = \frac{1}{n} \sum_{k=1}^n \bar{x}_k$$

$$\hat{\sigma}^2 = \frac{1}{n-1} \sum_{k=1}^n (\bar{x}_k - \bar{x})^2$$

$$\textcircled{1} \quad Y_1^2 + \dots + Y_n^2 = \bar{x}_1^2 + \dots + \bar{x}_n^2 = \sum_{k=1}^n (\bar{x}_k - \bar{x})^2 + n(\bar{x})^2$$

$$\sum_{k=1}^n (\bar{x}_k - \bar{x})^2 = \sum_{k=1}^n \bar{x}_k^2 - n(\bar{x})^2$$

$$= (n-1)\hat{\sigma}^2 + n(\bar{x})^2$$

$$\textcircled{2} \quad Y_1 = \frac{1}{\sqrt{n}} \sum_{k=1}^n \bar{x}_k = \sqrt{n} \bar{x} \Rightarrow Y_1^2 = \frac{\text{Chi-Square}}{\chi^2(n-1)} \quad \chi^2(n-1)$$

$$\Rightarrow Y_1^2 = n(\bar{x})^2, \quad \underline{Y_2^2 + \dots + Y_n^2} = (n-1) \cdot \hat{\sigma}^2 \quad \chi^2(1)$$

$$E\left(\sum_{k=1}^n \bar{x}_k^2 - n(\bar{x})^2\right) = n E\bar{x}_1^2 - (E\bar{x}_1^2 + (n-1)(E\bar{x}_1)^2)$$

$$= (n-1)(E\bar{x}_1^2 - (E\bar{x}_1)^2) = (n-1) \text{Var}(\bar{x}_1)$$

$$E(\hat{\sigma}^2) = \frac{1}{n-1} E\left(\sum_{k=1}^n \bar{x}_k^2 - n(\bar{x})^2\right) = \frac{1}{n-1} \cdot (n-1) \text{Var}(\bar{x}_1) = \text{Var}(\bar{x}_1)$$

$\bar{x}_1, \dots, \bar{x}_n$  ind.  $N(\mu, \sigma^2)$

$\bar{x} \quad \hat{\sigma}^2$  independent (Cochran)

$$BB^T = I, \quad \begin{pmatrix} \frac{1}{\sqrt{n}} & \frac{1}{\sqrt{n}} & \dots & \frac{1}{\sqrt{n}} \\ & \times & & \end{pmatrix} = B, \quad Y = B\bar{x}, \quad \bar{x} = (\bar{x}_1, \dots, \bar{x}_n)^T$$

Moment.  $X \sim N(0, \sigma^2)$ .

$$E(X^n) = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{+\infty} x^n \exp\left(-\frac{x^2}{2\sigma^2}\right) dx = I_n.$$

$$= \frac{1}{\sqrt{2\pi}\sigma} (-\sigma^2) \int_{-\infty}^{+\infty} x^{n-1} d\exp\left(-\frac{x^2}{2\sigma^2}\right) = \frac{1}{\sqrt{2\pi}\sigma} (-\sigma^2) \left(-\int_{-\infty}^{+\infty} \exp\left(-\frac{x^2}{2\sigma^2}\right) dx\right)^{n-1}.$$

$$(n-1)!! = (n-1)\sigma^2 \cdot \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{+\infty} x^{n-2} \exp\left(-\frac{x^2}{2\sigma^2}\right) dx = (n-1)\sigma^2 I_{n-2}$$

$$I_n = (n-1)\sigma^2 I_{n-2} = (n-1)(n-3)\sigma^4 I_{n-4} = \dots = \begin{cases} 0 & n=2k-1 \\ \frac{(2k-1)!!}{\sqrt{2\pi}\sigma} \sigma^{2k} & n=2k \end{cases}$$

$$E(X_1 X_2 X_3 X_4). \quad (X_1, \dots, X_4) \sim N. \quad E(X_1) = \dots = E(X_4) = 0.$$

$$= E(X_1 X_2) E(X_3 X_4) + E(X_1 X_3) E(X_2 X_4) + E(X_1 X_4) E(X_2 X_3)$$

$$E(X_1 X_2 X_3) = 0.$$

$$E(X_1 X_2 X_3 X_4 X_5 X_6) = \sum_{i < j} E(X_i X_j) E(X_k X_l) E(X_m X_n) \quad \text{if } \rightarrow 2n. \quad (2n-1)!!$$