

$$1. F_X(x_2) - F_X(x_1) = \int_{x_1}^{x_2} f_X(x) dx$$

$$\because f_X(x) \geq 0, x_1 \leq x_2 \therefore \int_{x_1}^{x_2} f_X(x) dx \geq 0 \quad \text{Q.E.D.}$$

$$2. F_X(x_i) \triangleq \int_{-\infty}^{x_i} f_X(x) dx$$

$$P(x_1 \leq X < x_2) = \int_{x_1}^{x_2} f_X(x) dx = F_X(x_2) - F_X(x_1)$$

$$\Delta x \triangleq x_2 - x_1.$$

$$\lim_{\Delta x \rightarrow 0} \frac{F_X(x_1 + \Delta x) - F_X(x_1)}{\Delta x} = f_X(x_1) \quad \text{Q.E.D.}$$

$$3. F_X(x|A) = \frac{P(X \leq x | A)}{P(A)}$$

$$= \frac{P(A | X \leq x) P(X \leq x)}{P(A)}$$

$$= \frac{P(A | X \leq x) F_X(x)}{P(A)}$$

Bayes' theorem

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$

Q.E.D.

$$4. X, Y \text{ independent} \Leftrightarrow f_{XY}(x, y) = f_X(x) f_Y(y)$$

$$X, Y \text{ uncorrelated} \Leftrightarrow E[XY] = E[X] E[Y]$$

$$E[XY] = \iint xy f_{XY}(x, y) dx dy$$

$$= \iint xy f_X(x) f_Y(y) dx dy$$

$$= \int x f_X(x) dx \int y f_Y(y) dy = E[X] E[Y] \quad \text{Q.E.D.}$$

$$\begin{aligned}
5. \operatorname{Cov}(X, Y) &= E[(X - \mu_X)(Y - \mu_Y)] \\
&= E[XY - \mu_X Y - \mu_Y X + \mu_X \mu_Y] \\
&= E[XY] - \mu_X E[Y] - \mu_Y E[X] + \mu_X \mu_Y \\
&= E[XY] - \mu_X \mu_Y
\end{aligned}$$

$$\begin{aligned}
\operatorname{Cov}(X, Y) = 0 &\Rightarrow E[XY] = E[X]E[Y] \\
&\Rightarrow X, Y \text{ uncorrelated. Q.E.D.}
\end{aligned}$$

$$6. f_X(x) = 1, \quad x \in (0, 1).$$

$$\textcircled{1} F_Y(y) = P(Y \leq y) = P(g(X) \leq y) = P(X \leq g^{-1}(y))$$

$$\begin{aligned}
g(x) &= -\ln x \\
g^{-1}(y) &= e^{-y}
\end{aligned}$$

$$P(X \leq e^{-y}) = \int_{-\infty}^{e^{-y}} f_X(x) dx = \int_0^{e^{-y}} 1 dx, \quad e^{-y} \in (0, 1)$$

$$f_Y(y) = \frac{dF_Y(y)}{dy} = e^{-y}, \quad y \in (0, \infty)$$

$$\textcircled{2} f_Y(y) = \sum_i \frac{1}{|g'(x_i)|} f_X(x_i), \text{ where } x_i \text{'s are the solutions to } y = g(x).$$

$y = -\ln x$  has a single solution  $x = e^{-y}$  when  $y \in (0, \infty)$

$$\therefore f_Y(y) = \frac{1}{1 - \frac{1}{x}} = e^{-y}, \quad y \in (0, \infty).$$

$$7. f_X(x; \frac{1}{\lambda}) = \frac{1}{\lambda} e^{-\frac{x}{\lambda}}, x \geq 0$$

$y = \sqrt{x}$  has a single solution  $x = y^2$  when  $y \geq 0$ .

$$\begin{aligned} f_Y(y) &= \sum_i \frac{1}{|g'(x_i)|} f_X(x_i) = \frac{1}{|\frac{1}{2\sqrt{y}}|} \frac{1}{\lambda} e^{-\frac{x}{\lambda}} \\ &= \frac{2y}{\lambda} e^{-\frac{y^2}{\lambda}}, y \geq 0. \end{aligned}$$

This is a Rayleigh distribution. Q.E.D.

$$\begin{aligned} 8. \sigma^2 &\triangleq \int_{-\infty}^{+\infty} (x-\eta)^2 f_X(x) dx \\ &\geq \int_{|x-\eta| \geq \varepsilon\sigma} (x-\eta)^2 f_X(x) dx \\ &\geq \int_{|x-\eta| \geq \varepsilon\sigma} (\varepsilon\sigma)^2 f_X(x) dx \\ &= (\varepsilon\sigma)^2 P(|x-\eta| \geq \varepsilon\sigma) \end{aligned}$$

$$\therefore \frac{1}{\varepsilon^2} \geq P(|x-\eta| \geq \varepsilon\sigma) \quad \text{Q.E.D.}$$

$$9. P(X=k) = \frac{\lambda^k e^{-\lambda}}{k!}, E[X] = \lambda, \sigma^2 = \lambda.$$

$$(a) \text{ Let } \varepsilon = \sqrt{\lambda}$$

$$P(|X - \lambda| \geq \lambda) \leq \frac{1}{\lambda}$$

$$\therefore P(|X - \lambda| < \lambda) > 1 - \frac{1}{\lambda}$$

$$\therefore P(0 < X < 2\lambda) > \frac{\lambda-1}{\lambda} \quad \text{Q.E.D.}$$

Chebyshev's inequality

$$P(|X - \eta| \geq \varepsilon \sigma) \leq \frac{1}{\varepsilon^2}$$

$$(b) E[X(X-1)] = \sum_{k=0}^{\infty} k(k-1) \frac{\lambda^k e^{-\lambda}}{k!}$$

$$= e^{-\lambda} \sum_{k=2}^{\infty} k(k-1) \frac{\lambda^k e^{-\lambda}}{k!}$$

$$= e^{-\lambda} \cdot \lambda^2 \left( \sum_{k=2}^{\infty} \frac{\lambda^{k-2}}{(k-2)!} \right) = e^{-\lambda}$$

Taylor series  
Q.E.D.

$$(c) E[X(X-1)(X-2)] = e^{-\lambda} \cdot \lambda^3 \sum_{k=3}^{\infty} \frac{\lambda^{k-3}}{(k-3)!} = \lambda^3$$

Q.E.D.

(10)  $Y = |X|$  is called "folded normal distribution".

If  $\sigma^2 = 0$ , then  $Y$  is called "half-normal distribution".

$$E[X] = \int_{-\infty}^0 x f(x) dx + \int_0^{+\infty} x f(x) dx$$

$$E[|X|] = \int_{-\infty}^0 -x f(x) dx + \int_0^{+\infty} x f(x) dx$$

$$\begin{aligned}\therefore \frac{E[X + |X|]}{2} &= \int_0^{+\infty} x f(x) dx = \frac{1}{\sqrt{2\pi}\sigma} \int_0^{+\infty} x e^{-\frac{(x-\eta)^2}{2\sigma^2}} dx \\ &= \frac{1}{\sqrt{2\pi}\sigma} \int_0^{+\infty} (x-\eta) e^{-\frac{(x-\eta)^2}{2\sigma^2}} dx + \frac{1}{\sqrt{2\pi}\sigma} \int_0^{+\infty} \eta e^{-\frac{(x-\eta)^2}{2\sigma^2}} dx \\ &= \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{\eta^2}{2\sigma^2}} + \eta G\left(\frac{\eta}{\sigma}\right)\end{aligned}$$

$$\therefore E[|X|] = \sqrt{\frac{2}{\pi}} \sigma e^{-\frac{\eta^2}{2\sigma^2}} + 2\eta G\left(\frac{\eta}{\sigma}\right) - \eta. \quad \text{Q.E.D.}$$

11. (a)  $F_Z(z) = P(Z \leq z) = \iint_{\sqrt{x^2+y^2} \leq z} \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} dx dy$

$$= \int_0^{2\pi} \int_0^z \frac{1}{2\pi\sigma^2} e^{-\frac{r^2}{2\sigma^2}} r dr d\theta = 1 - e^{-\frac{z^2}{2\sigma^2}}$$

$\therefore f_Z(z) = \frac{dF_Z(z)}{dz} = \frac{z}{\sigma^2} e^{-\frac{z^2}{2\sigma^2}}, z \geq 0.$

(b)  $F_Z(z) = \int_0^{2\pi} \int_0^z \frac{1}{2\pi\sigma^2} e^{-\frac{r^2}{2\sigma^2}} r dr d\theta = 1 - e^{-\frac{z^2}{2\sigma^2}}$

$\therefore f_Z(z) = \frac{1}{\sigma^2} e^{-\frac{z^2}{2\sigma^2}}, z \geq 0.$

(c) Linear combination of independent Gaussian r.v.s are still Gaussian!

$U = X - Y \sim \mathcal{N}(0, 2\sigma^2).$

$$12. P(A)P(B)P(C) = 0.125. \quad P(ABC) = 0.25$$

$\therefore A, B, C$  are not independent.

$$P(A)P(B) = 0.25 = P(AB)$$

$$P(B)P(C) = 0.25 = P(BC)$$

$$P(C)P(A) = 0.25 = P(CA)$$

$\therefore A, B, C$  are independent in pairs.

$$13. f_{\theta}(\theta) = \frac{1}{2\pi}, \quad \theta \in [0, 2\pi)$$

$$\begin{aligned} E[n(t)] &= \int_{-\infty}^{+\infty} A \cos(2\pi f_c t + \theta) f_{\theta}(\theta) d\theta \\ &= \frac{A}{2\pi} \int_0^{2\pi} \cos(2\pi f_c t + \theta) d\theta = 0. \end{aligned}$$

$$\begin{aligned} E[n^2(t)] &= \frac{A^2}{2\pi} \int_0^{2\pi} \cos^2(2\pi f_c t + \theta) d\theta \\ &= \frac{A^2}{2\pi} \int_0^{2\pi} \frac{1}{2} (1 + \cos(4\pi f_c t + 2\theta)) d\theta \\ &= \frac{A^2}{2} \end{aligned} \quad \cos^2 \theta = \frac{1}{2} (1 + \cos 2\theta)$$

$$\cos a \cos b = \frac{1}{2} [\cos(a-b) + \cos(a+b)]$$

14. WSS:  $\begin{cases} \mu_X(t) = \mu_X \\ R_X(t, t+\tau) = R_X(\tau) \end{cases}$

n-th order SSS:  $\forall c,$

$$f_X(x_1 \dots x_n; t_1 \dots t_n) = f_X(x_1 \dots x_n; t_1+c \dots t_n+c)$$

WSS input  $\times$  LTI response  $\Rightarrow$  WSS output.

$$R_Y(\tau) = E[Y(t+\tau)Y(t)]$$

$$= E[X(t+\tau) \cos(2\pi f_c(t+\tau) + \theta) X(t) \cos(2\pi f_c t + \theta)]$$

$$\underbrace{X(t), \theta}_{\text{independent}} E[X(t+\tau)X(t)] E[\cos(2\pi f_c(t+\tau) + \theta) \cos(2\pi f_c t + \theta)]$$

$$= R_X(\tau) \frac{1}{2} E[\cos(2\pi f_c \tau) + \cos(2\pi f_c(2t+\tau) + 2\theta)]$$

$$= \frac{1}{2} R_X(\tau) \cos(2\pi f_c \tau)$$

$$S_Y(f) = \int_{-\infty}^{+\infty} R_Y(\tau) e^{-j2\pi f \tau} d\tau$$

$$= \frac{1}{2} \int_{-\infty}^{+\infty} R_X(\tau) \frac{e^{j2\pi f_c \tau} + e^{-j2\pi f_c \tau}}{2} e^{-j2\pi f \tau} d\tau$$

$$= \frac{1}{4} [S_X(f-f_c) + S_X(f+f_c)].$$



15.  $\Leftarrow$ : 1st order:

$$E[V(t)] = E[X] \cos(2\pi f_c t) - E[Y] \sin(2\pi f_c t) = 0$$

irrelevant to  $t$ .

2nd order: let  $E[X^2] = E[Y^2] \triangleq \sigma^2$ .

$$\begin{aligned} E[V(t+\tau)V(t)] &= E[X^2] \cos(2\pi f_c(t+\tau)) \cos(2\pi f_c t) \\ &\quad - E[XY] \left\{ \cos(2\pi f_c(t+\tau)) \sin(2\pi f_c t) \right. \\ &\quad \left. + \cos(2\pi f_c t) \sin(2\pi f_c(t+\tau)) \right\} \\ &\quad + E[Y^2] \sin(2\pi f_c(t+\tau)) \sin(2\pi f_c t) \end{aligned}$$

$$= \sigma^2 \cdot \frac{1}{2} [\cos(2\pi f_c \tau) + \cos(2\pi f_c(2t+\tau)) \\ + \cos(2\pi f_c \tau) - \cos(2\pi f_c(2t+\tau))]$$

$$= \sigma^2 \cos(2\pi f_c \tau) \quad \text{only depends on } \tau, \text{ not } t.$$

$\Rightarrow$ : 1st order:

$$E[V(t)] = E[X] \cos(2\pi f_c t) - E[Y] \sin(2\pi f_c t)$$

has to be constant  $\Rightarrow E[X] = E[Y] = 0$

2nd order:

$$\begin{aligned} E[V(t+\tau)V(t)] &= \frac{1}{2} \left\{ [E[X^2] + E[Y^2]] \cos(2\pi f_c \tau) \right. \\ &\quad \left. + [E[X^2] - E[Y^2]] \cos(2\pi f_c(2t+\tau)) \right. \\ &\quad \left. - 2E[XY] \sin(2\pi f_c(2t+\tau)) \right\} \end{aligned}$$

has to be irrelevant of  $t$ .

$$\Rightarrow E[X^2] = E[Y^2], \quad E[XY] = 0. \quad \text{Q.E.D.}$$

$$16. E[(X(t+L) \pm X(t))^2] \geq 0$$

$$\therefore E[X^2(t+L)] \pm 2E[X(t+L)X(t)] + E[X^2(t)] \geq 0$$

$\therefore X(t)$  is WSS

$$\therefore R_X(0) \pm R_X(L) \geq 0. \quad \text{Q.E.D.}$$

17. Gaussian input  $\times$  LTI response  $\Rightarrow$  Gaussian output  
To prove  $Y(t)$ ,  $Z(t)$  uncorrelated is sufficient.

$$R_{YZ}(t, u) = E[Y(t)Z(u)]$$

$$= E\left[\int_{-\infty}^{+\infty} h_1(\tau_1) X(t-\tau_1) d\tau_1 \int_{-\infty}^{+\infty} h_2(\tau_2) X(u-\tau_2) d\tau_2\right]$$

$$= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} h_1(\tau_1) h_2(\tau_2) E[X(t-\tau_1)X(u-\tau_2)] d\tau_1 d\tau_2$$

$$= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} h_1(\tau_1) h_2(\tau_2) R_X(t-\tau_1, u-\tau_2) d\tau_1 d\tau_2$$

$$\xrightarrow[\text{XSS}]{\tau = t-u} \int_{-\infty}^{+\infty} h_2(\tau_2) \int_{-\infty}^{+\infty} h_1(\tau_1) R_X(\tau - \tau_1 + \tau_2) d\tau_1 d\tau_2$$

$$\triangleq \int_{-\infty}^{+\infty} h_2(\tau_2) g(\tau + \tau_2) d\tau_2 = h_2(-\tau) * g(\tau)$$

$$= h_2(-\tau) * h_1(\tau) * R_X(\tau)$$

$$\therefore S_{YZ}(f) = H_1(f) H_2^*(f) S_X(f)$$

If  $H_1(f)$  and  $H_2(f)$  do not overlap, then  $R_{YZ}(t, u) = 0$ ,

and  $Y(t)$  and  $Z(t)$  are uncorrelated.