

P1: We are given that Gaussian Vector (X_1, X_2, X_3) with zero mean and Cov matrix

$$\begin{bmatrix} 5 & 2 & 2 \\ 2 & 5 & 2 \\ 2 & 2 & 5 \end{bmatrix} \quad E[X_1] = E[X_2] = E[X_3] = 0$$

(a) $E[X_1 | X_2, X_3]$ directly from $f_{X_1 | X_2, X_3}(x_1 | x_2, x_3)$

$$\begin{aligned} f_{X_1 | X_2, X_3}(x_1 | x_2, x_3) &= \frac{1}{(\sqrt{2\pi})^3 \sqrt{\det(C)}} e^{-\frac{1}{2} [X_1 \ X_2 \ X_3] C^{-1} \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix}} \\ &= \frac{1}{(\sqrt{2\pi})^3 \sqrt{\det C_{2 \times 2}}} e^{-\frac{1}{2} [X_2 \ X_3] \cdot C_{2 \times 2}^{-1} \begin{bmatrix} X_2 \\ X_3 \end{bmatrix}} \\ &= \frac{1}{\sqrt{8\pi} \cdot \sqrt{\det(C)}} \cdot e^{-\frac{1}{2} (X_1 \ X_2 \ X_3) \cdot \frac{1}{21} \begin{bmatrix} 7 & -2 & -2 \\ -2 & 7 & -2 \\ -2 & -2 & 7 \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix}} \\ &= \frac{1}{\sqrt{4\pi} \sqrt{\det C_{2 \times 2}}} \cdot e^{-\frac{1}{2} (X_2 \ X_3) \cdot \frac{1}{21} \begin{bmatrix} 5 & -2 \\ -2 & 5 \end{bmatrix} \begin{bmatrix} X_2 \\ X_3 \end{bmatrix}} \\ &= \sqrt{\frac{7}{54\pi}} e^{-\frac{1}{2} (X_1 \ X_2 \ X_3) \cdot \frac{1}{21} \begin{bmatrix} 7 & -2 & -2 \\ -2 & 7 & -2 \\ -2 & -2 & 7 \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix} - \frac{1}{21} [X_2 \ X_3] \begin{bmatrix} 5 & -2 \\ -2 & 5 \end{bmatrix} \begin{bmatrix} X_2 \\ X_3 \end{bmatrix}} \\ &= \sqrt{\frac{7}{54\pi}} e^{-\frac{1}{2} \left(\frac{7}{21} (X_1 - \frac{2}{7}(X_2 + X_3))^2 \right)} \\ &= \frac{1}{\sqrt{2\pi}} \cdot \frac{1}{\sqrt{\frac{2}{7}}} \cdot e^{-\frac{1}{2} \left(\frac{1}{\sqrt{\frac{2}{7}}} \right)^2 (X_1 - \frac{2}{7}(X_2 + X_3))^2} \\ &= \frac{1}{\sqrt{2\pi}} \cdot \frac{1}{\sqrt{\frac{2}{7}}} \cdot e^{-\frac{1}{2} \left(\frac{1}{\sqrt{\frac{2}{7}}} \right)^2 (X_1 - \frac{2}{7}(X_2 + X_3))^2} \end{aligned}$$

Therefore, $f_{X_1 | X_2, X_3}$ is also Gaussian distribution with mean = $\frac{2}{7}(X_2 + X_3)$ and var = $\sqrt{\frac{2}{7}}$

$$\therefore E[X_1 | X_2, X_3] = \frac{2}{7}(X_2 + X_3)$$

1(b) The LMSE of x_1 from x_2 and x_3 .

from the formula:

$$E[x|Y] = E[x] + \text{Cov}(x, Y) \text{Var}(Y)^{-1} (Y - E[Y])$$

$$\therefore E[x_1 | x_2, x_3] = A \left(\begin{bmatrix} x_2 \\ x_3 \end{bmatrix} - \begin{bmatrix} E[x_2] \\ E[x_3] \end{bmatrix} \right) + m[x_1]$$

$$= A \begin{bmatrix} x_2 \\ x_3 \end{bmatrix}$$

$$= A \begin{bmatrix} x_2 \\ x_3 \end{bmatrix}$$

$$\Rightarrow A \cdot C_{x_2, x_3} = C_{x_1, x_2, x_3}$$

$$A \begin{bmatrix} 5 & 2 \\ 2 & 5 \end{bmatrix} = \begin{bmatrix} 2 & 2 \end{bmatrix}$$

$$A = \begin{bmatrix} 2 & 2 \end{bmatrix} \left(\begin{bmatrix} 5 & 2 \\ 2 & 5 \end{bmatrix} \right)^{-1}$$

$$A = \begin{bmatrix} \frac{2}{7} & \frac{2}{7} \end{bmatrix}$$

$$\text{Therefore, } E[x_1 | x_2, x_3] = \begin{bmatrix} \frac{2}{7} & \frac{2}{7} \end{bmatrix} \begin{bmatrix} x_2 \\ x_3 \end{bmatrix}$$

$$= \frac{2}{7}x_2 + \frac{2}{7}x_3$$

LMSE of x_1 which is the same as $E[x_1 | x_2, x_3]$

$$1(c) \text{Var}(x_1 | x_2, x_3) = E[(x_1 - g(x_2, x_3))^2]$$

$$= E[(x_1 - (\frac{2}{7}x_2 + \frac{2}{7}x_3))^2]$$

$$= E[x_1^2 - 2x_1(\frac{2}{7}x_2 + \frac{2}{7}x_3) + (\frac{2}{7}x_2 + \frac{2}{7}x_3)^2]$$

$$= E[x_1^2 - \frac{4}{7}x_1x_2 - \frac{4}{7}x_1x_3 + \frac{4}{49}x_2^2 + \frac{8}{49}x_2x_3 + \frac{4}{49}x_3^2]$$

$$= E[x_1^2] - \frac{4}{7}E[x_1x_2] - \frac{4}{7}E[x_1x_3] + \frac{4}{49}E[x_2^2] + \frac{8}{49}E[x_2x_3] + \frac{4}{49}E[x_3^2]$$

$$= \text{Var}(x_1^2) - \frac{4}{7}\text{Cov}(x_1, x_2) - \frac{4}{7}\text{Cov}(x_1, x_3) + \frac{4}{49}\text{Var}(x_2^2) + \frac{8}{49}\text{Cov}(x_2, x_3) + \frac{4}{49}\text{Var}(x_3^2)$$

$$= 5 - \frac{4}{7} \cdot 2 - \frac{4}{7} \cdot 2 + \frac{4}{49} \cdot 5 + \frac{8}{49} \cdot 2 + \frac{4}{49} \cdot 5$$

$$= \frac{27}{7}$$

P2,

We are given that $f_{XZ}(X, Z) = f_X(X) f_Y(Z-X)$, the joint PDF of X and Z , where $Z = X+Y$. And $X_1 \sim \exp(1)$ and $X_2 \sim \exp(1)$, $Y_1 = X_1$, $Y_2 = X_1 + X_2$

$$R(Y_1) = [0, \infty), R(Y_2) = [0, \infty)$$

$$f_{X_1}(X) = e^{-X_1} \quad f_{X_2}(X) = e^{-X_2}$$

Therefore, by formula

$$\begin{aligned} E[Y_1|Y_2] &= \int_0^\infty Y_1 \cdot f_{Y_1|Y_2}(Y_1|Y_2) \cdot dY_1 \\ &= \int_0^\infty Y_1 \cdot \frac{f_{Y_1, Y_2}(Y_1, Y_2)}{f_{Y_2}(Y_2)} \cdot dY_1 \end{aligned}$$

$$\begin{aligned} f_{Y_1, Y_2}(Y_1, Y_2) &= f_{X_1}(X_1) f_{X_2}(Y_2 - X_1) \quad \text{and} \quad f_{Y_2}(Y_2) = \int_0^{Y_2} f_{Y_1, Y_2}(Y_1, Y_2) \cdot dY_1 \\ &= f_{X_1}(X_1) f_{X_2}(X_2) \\ &= e^{-X_1} \cdot e^{-X_2} \\ &= e^{-(X_1 + X_2)} \\ &= Y_2 e^{-Y_2} \end{aligned}$$

Overall,

$$\begin{aligned} E[Y_1|Y_2] &= \int_0^\infty Y_1 \cdot f_{Y_1|Y_2}(Y_1|Y_2) \cdot dY_1 \\ &= \int_0^\infty Y_1 \cdot \frac{f_{Y_1, Y_2}(Y_1, Y_2)}{f_{Y_2}(Y_2)} \cdot dY_1 \\ &= \int_0^\infty Y_1 \cdot \frac{e^{-(X_1 + X_2)}}{Y_2 e^{-Y_2}} \cdot dY_1 \\ &= \int_0^{Y_2} Y_1 \cdot \frac{e^{-Y_2}}{Y_2 e^{-Y_2}} \cdot dY_1 \\ &= \int_0^{Y_2} Y_1 \cdot \frac{1}{Y_2} \cdot dY_1 \\ &= \left. \frac{1}{2} Y_1^2 \cdot \frac{1}{Y_2} \right|_0^{Y_2} \\ &= \frac{Y_2}{2} \end{aligned}$$

\therefore the MUSE estimate of Y_1 using Y_2 is $\frac{Y_2}{2}$

P3.

$$(a) f(x) = E[|x-a|]$$

$$f(x) = \int_{-\infty}^a -(x-a) f_x(x) \cdot dx + \int_a^{\infty} (x-a) f_x(x) \cdot dx$$

$$\begin{aligned} \Rightarrow f'(x) &= \int_{-\infty}^a f_x(x) \cdot dx + a f_x(a) - a f_x(a) - a f_x(a) - \int_a^{\infty} f_x(x) \cdot dx + a f_x(a) \\ &= \int_{-\infty}^a f_x(x) \cdot dx - \int_a^{\infty} f_x(x) \cdot dx \end{aligned}$$

$$\text{let } f'(x) = 0$$

$$\Rightarrow \int_{-\infty}^a f_x(x) \cdot dx - \int_a^{\infty} f_x(x) \cdot dx = 0$$

$$\Rightarrow \int_{-\infty}^a f_x(x) \cdot dx = \int_a^{\infty} f_x(x) \cdot dx$$

$$\Rightarrow F_x(x) \Big|_{-\infty}^a = F_x(x) \Big|_a^{\infty}$$

$$\Rightarrow F_x(a) - F_x(-\infty) = F_x(\infty) - F_x(a)$$

$$\Rightarrow 2F_x(a) = \underbrace{F_x(-\infty) + F_x(\infty)}_1$$

Since we are given that $F_x(a^*) = \frac{1}{2}$

$$\therefore F_x(a) = \frac{1}{2}$$

$$a = F_x^{-1}\left(\frac{1}{2}\right)$$

3(b)

$$\min_{g(\cdot)} E[X - g(Y)]$$

$$E[|x - g(y)|] = \int f_Y(y) \cdot dy \left(\int f_{X|Y}(x) \cdot dx |x - g(y)| \right)$$

Based on part (a)

$$\int_{-\infty}^{g(y)} f_{X|Y}(x|Y) \cdot dx = \int_{g(y)}^{\infty} f_{X|Y}(x|Y) \cdot dx$$

$$F_{X|Y}(g^*(Y)|Y) = \frac{1}{2}$$

P4

(a) X, Y and Z are three random variables with known var and cov

By the formula of LMSE,

$$g_{(X,Y)} = A \left(\begin{bmatrix} X \\ Y \end{bmatrix} - \begin{bmatrix} E[X] \\ E[Y] \end{bmatrix} \right) + E[Z]$$

$$A C_{XY} = C_{Z,XY}$$

$$A = C_{X,Y} \cdot C_{XY}^{-1}$$

We are given that X and Y are uncorrelated

$$\therefore \text{Cov}(X, Y) = 0$$

$$\therefore C_{XY} = \begin{bmatrix} \text{Var}(X) & 0 \\ 0 & \text{Var}(Y) \end{bmatrix}$$

And since $\text{Var}(X) > 0$ and $\text{Var}(Y) > 0$

$\therefore C_{XY}$ is invertible and

$$C_{XY}^{-1} = \begin{bmatrix} \frac{1}{\text{Var}(X)} & 0 \\ 0 & \frac{1}{\text{Var}(Y)} \end{bmatrix}$$

$$\therefore A = \begin{bmatrix} \text{Cov}(Z, X) & \text{Cov}(Z, Y) \end{bmatrix} \begin{bmatrix} \frac{1}{\text{Var}(X)} & 0 \\ 0 & \frac{1}{\text{Var}(Y)} \end{bmatrix}$$

$$= \left[\frac{\text{Cov}(Z, X)}{\text{Var}(X)}, \frac{\text{Cov}(Z, Y)}{\text{Var}(Y)} \right]$$

$$\therefore g_{(X,Y)} = \frac{\text{Cov}(Z, X)}{\text{Var}(X)} \cdot (X - E[X]) + \frac{\text{Cov}(Z, Y)}{\text{Var}(Y)} \cdot (Y - E[Y]) + E[Z]$$

b) In general case, X, Y are not uncorrelated
Thus,

$$C_{XY} = \begin{bmatrix} \text{Var}(X) & \text{Cov}(X, Y) \\ \text{Cov}(X, Y) & \text{Var}(Y) \end{bmatrix}$$

and $\det(C)$ is not 0 in general case, thus C_{XY}^{-1} exists.

$$\therefore g(X, Y) = [\text{Cov}(Z, X) \quad \text{Cov}(Z, Y)] \left(\begin{bmatrix} \text{Var}(X) & \text{Cov}(X, Y) \\ \text{Cov}(X, Y) & \text{Var}(Y) \end{bmatrix} \right)^{-1} \begin{bmatrix} X - E[X] \\ Y - E[Y] \end{bmatrix} + E[Z]$$

P5.

We are given that

$$\begin{pmatrix} 1 & 0.5 & 0.5 & 0 \\ 0.5 & 1 & 0.5 & 0.25 \\ 0.5 & 0.5 & 1 & 0.25 \\ 0 & 0.25 & 0.25 & 1 \end{pmatrix}$$

$$\text{and } E[Y_1] = E[Y_2] = E[Y_3] = E[X] = 0$$

$$\begin{aligned} \text{(a)} \quad \tilde{Y}_1 &= Y_1 - E[Y_1] = Y_1 \\ \tilde{Y}_2 &= Y_2 - E[Y_2] - \text{cov}(Y_2, \tilde{Y}_1) \text{Var}(\tilde{Y}_1)^{-1} \tilde{Y}_1 \\ &= Y_2 - \text{cov}(Y_2, Y_1) \text{Var}(Y_1)^{-1} Y_1 \\ &= Y_2 - \frac{1}{2} \cdot 1 \cdot Y_1 \\ &= Y_2 - \frac{1}{2} Y_1 \end{aligned}$$

$$\begin{aligned} \tilde{Y}_3 &= Y_3 - E[Y_3] - \sum_{k=1}^2 \text{cov}(Y_3, \tilde{Y}_k) \cdot \text{Var}(\tilde{Y}_k)^{-1} \tilde{Y}_k \\ &= Y_3 - \text{cov}(Y_3, \tilde{Y}_2) \cdot \text{Var}(\tilde{Y}_2)^{-1} \tilde{Y}_2 - \text{cov}(Y_3, \tilde{Y}_1) \text{Var}(\tilde{Y}_1)^{-1} \tilde{Y}_1 \\ &= Y_3 - \underline{\text{cov}(Y_3, (Y_2 - \frac{1}{2} Y_1))} \cdot \underline{\text{Var}(Y_2 - \frac{1}{2} Y_1)^{-1}} (Y_2 - \frac{1}{2} Y_1) - \underline{\text{cov}(Y_3, Y_1)} \text{Var}(Y_1)^{-1} Y_1 \end{aligned}$$

$$\begin{aligned} \text{cov}(Y_3, (Y_2 - \frac{1}{2} Y_1)) &= E[Y_3(Y_2 - \frac{1}{2} Y_1)] - E[Y_3] E[Y_2 - \frac{1}{2} Y_1] & \text{Var}(Y_2 - \frac{1}{2} Y_1) &= \text{Var}(Y_2) + \frac{1}{4} \text{Var}(Y_1) \\ &= E[Y_3 Y_2 - \frac{1}{2} Y_3 Y_1] & & - E[(Y_2 - E[Y_2])(Y_1 - E[Y_1])] \\ &= E[Y_3 Y_2] - \frac{1}{2} E[Y_3 Y_1] & & = 1 + \frac{1}{4} - \frac{1}{2} \\ &= \text{cov}(Y_3, Y_2) - \frac{1}{2} \text{cov}(Y_3, Y_1) & & = \frac{3}{4} \\ &= \frac{1}{2} - \frac{1}{2} \times \frac{1}{2} \\ &= \frac{1}{4} \end{aligned}$$

$$\begin{aligned} \therefore \tilde{Y}_3 &= Y_3 - \frac{1}{4} \cdot \frac{4}{3} \cdot (Y_2 - \frac{1}{2} Y_1) - \frac{1}{2} \cdot 1 \cdot Y_1 \\ &= Y_3 - \frac{1}{3} Y_2 - \frac{1}{3} Y_1 \end{aligned}$$

b) Compute the LMSE of X

$$\begin{aligned}\hat{E}[X | \hat{Y}_1, \hat{Y}_2, \tilde{Y}_3] &= E[X] + \sum_{i=1}^3 \hat{E}[X - E[X] | \hat{Y}_i] \\ &= \hat{E}[X | \hat{Y}_1] + \hat{E}[X | \hat{Y}_2] + \hat{E}[X | \tilde{Y}_3]\end{aligned}$$

Where $\hat{E}[X | \hat{Y}_1] = \hat{E}[X | Y_1]$

$$= \text{Cov}(X, Y_1) \text{Var}(Y_1)^{-1} Y_1$$

$$= 0.$$

$$\begin{aligned}\hat{E}[X | \hat{Y}_2] &= \text{Cov}(X, \hat{Y}_2) \text{Var}(\hat{Y}_2)^{-1} \tilde{Y}_2 \\ &= \text{Cov}(X, Y_2 - \frac{1}{2} Y_1) \cdot \text{Var}(Y_2 - \frac{1}{2} Y_1)^{-1} (Y_2 - \frac{1}{2} Y_1) \\ &= (\text{Cov}(X, Y_2) - \frac{1}{2} \text{Cov}(X, Y_1)) \left(\frac{3}{4}\right)^{-1} (Y_2 - \frac{1}{2} Y_1) \quad \text{By part (a)} \\ &= \frac{4}{3} \cdot \frac{4}{3} (Y_2 - \frac{1}{2} Y_1) \\ &= \frac{4}{3} (Y_2 - \frac{1}{2} Y_1)\end{aligned}$$

$$\hat{E}[X | \hat{Y}_3] = \text{Cov}(X, Y_3 - \frac{1}{3} Y_2 - \frac{1}{3} Y_1) \cdot \text{Var}(\hat{Y}_3)^{-1} \tilde{Y}_3$$

$$\begin{aligned}\text{Cov}(X, \hat{Y}_3) &= \text{Cov}(X, Y_3) - \frac{1}{3} \text{Cov}(X, Y_2) - \frac{1}{3} \text{Cov}(X, Y_1) \\ &= \frac{4}{3} - \frac{1}{3} \cdot \frac{4}{3} - \frac{1}{3} \cdot 0 = \frac{4}{9}\end{aligned}$$

$$\begin{aligned}\text{Var}(\hat{Y}_3) &= \text{Var}(Y_3 - \frac{1}{3} Y_2 - \frac{1}{3} Y_1) \\ &= \text{Var}(Y_3) + \frac{1}{9} \text{Var}(Y_2) + \frac{1}{9} \text{Var}(Y_1) - \frac{2}{3} \text{Cov}(Y_3, Y_2) - \frac{2}{3} \text{Cov}(Y_1, Y_3) + \frac{2}{9} \text{Cov}(Y_1, Y_2) \\ &= 1 + \frac{1}{9} \cdot 1 + \frac{1}{9} - \frac{2}{3} \cdot \frac{1}{2} - \frac{2}{3} \cdot \frac{1}{2} + \frac{2}{9} \cdot \frac{1}{2} \\ &= \frac{4}{9} - \frac{1}{3} - \frac{1}{3} + \frac{1}{9} \\ &= \frac{2}{9}\end{aligned}$$

$$\begin{aligned}\therefore \hat{E}[X | \hat{Y}_3] &= \frac{4}{9} \cdot \frac{3}{2} \cdot (Y_3 - \frac{1}{3} Y_2 - \frac{1}{3} Y_1) \\ &= \frac{2}{3} (Y_3)\end{aligned}$$

Overall,

$$\begin{aligned}\hat{E}[X | \hat{Y}_1, \hat{Y}_2, \hat{Y}_3] &= \frac{2}{3} (Y_2 - \frac{1}{2} Y_1) + \frac{4}{3} (Y_3 - \frac{1}{3} Y_2 - \frac{1}{3} Y_1) \\ &= \frac{2}{3} Y_2 - \frac{1}{3} Y_1 + \frac{4}{3} Y_3 - \frac{1}{3} Y_2 - \frac{1}{3} Y_1 \\ &= \frac{4}{3} Y_3 + \frac{1}{3} Y_2 - \frac{2}{3} Y_1\end{aligned}$$