

(1)

The Conditional distribution

we have multivariate normal vector $\underline{X} \sim N(\underline{\mu}, \underline{\Sigma})$. Consider Partitioning $\underline{\mu}$ and $\underline{X}$ into:

$$\underline{X} = \begin{pmatrix} \underline{X}^{(1)} \\ \underline{X}^{(2)} \end{pmatrix}, \quad \underline{\mu} = \begin{pmatrix} \underline{\mu}^{(1)} \\ \underline{\mu}^{(2)} \end{pmatrix}$$

With similar partition of $\underline{\Sigma}$ into:

$$\underline{\Sigma} = \begin{bmatrix} \underline{\Sigma}_{11} & \underline{\Sigma}_{12} \\ \underline{\Sigma}_{21} & \underline{\Sigma}_{22} \end{bmatrix}$$

$\underline{\Sigma}_{11}$: var-cov matrix of $\underline{X}^{(1)}$

$\underline{\Sigma}_{22}$: var-cov matrix of $\underline{X}^{(2)}$

$\underline{\Sigma}_{12}$: Covariance between $\underline{X}^{(1)}$ of $\underline{X}^{(2)}$

There are two cases:-

Case (1) : $\underline{X}^{(1)}$ and $\underline{X}^{(2)}$ are independent

$$\underline{\Sigma}_{12} = \underline{\Sigma}_{21} = 0$$

$$P(\underline{X}^{(1)}, \underline{X}^{(2)}) = f(\underline{X}^{(1)}) \cdot f(\underline{X}^{(2)})$$

(2)

$$-\frac{1}{2} (\underline{x}^{(1)} - \underline{\mu}^{(1)})' \underline{\Sigma}_{11}^{-1} (\underline{x}^{(1)} - \underline{\mu}^{(1)})$$

$$= \frac{1}{(2\pi)^{p/2} |\underline{\Sigma}_{11}|^{1/2}} e$$

$$\frac{1}{(2\pi)^{p/2} |\underline{\Sigma}_{22}|^{1/2}} e$$

$$-\frac{1}{2} (\underline{x}^{(2)} - \underline{\mu}^{(2)})' \underline{\Sigma}_{22}^{-1} (\underline{x}^{(2)} - \underline{\mu}^{(2)})$$

$$\therefore P(\underline{x}^{(1)} | \underline{x}^{(2)} = \underline{x}^{(2)}) = \frac{P(\underline{x}^{(1)}, \underline{x}^{(2)})}{P(\underline{x}^{(2)} = \underline{x}^{(2)})} = P(\underline{x}^{(1)})$$

$$= \frac{1}{(2\pi)^{p/2} |\underline{\Sigma}_{11}|^{1/2}} e^{-\frac{1}{2} (\underline{x}^{(1)} - \underline{\mu}^{(1)})' \underline{\Sigma}_{11}^{-1} (\underline{x}^{(1)} - \underline{\mu}^{(1)})}$$

$$\therefore (\underline{x}^{(1)} | \underline{x}^{(2)} = \underline{x}^{(2)}) \sim N(\underline{\mu}^{(1)}, \underline{\Sigma}_{11})$$

Case (2): $(\underline{x}^{(1)})$ & $(\underline{x}^{(2)})$ are Correlated. We have the following Theorem:-

Theorem:

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Let the Components of $\underline{x}$ be divided into two groups Composing subvectors $\underline{x}^{(1)}$ and $\underline{x}^{(2)}$. Suppose the mean $\underline{\mu}$ is similarly divided into $\underline{\mu}^{(1)}$ & $\underline{\mu}^{(2)}$, and suppose the covariance matrix $\underline{\Sigma}$ of $\underline{x}$ is divided into $\underline{\Sigma}_{11}$, $\underline{\Sigma}_{12}$ and $\underline{\Sigma}_{22}$, if the distribution of $\underline{x}$ is multivariate Normal dist. then the Conditional distribution

(3)

of $X^{(1)}$ given $X^{(2)} = x^{(2)}$ is multivariate normal with mean $\mu^{(1)} + \Sigma_{12} \Sigma_{22}^{-1} (x^{(2)} - \mu^{(2)})$ and

covariance matrix $\Sigma_{11.2} = \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21}$

Proof.

Therefore we make the following linear transformation ^{دپ-ٽران}

• which generates the independence.

$$Y^{(1)} = X^{(1)} - \Sigma_{12} \Sigma_{22}^{-1} X^{(2)} \Rightarrow E(Y^{(1)}) = \mu^{(1)} - \Sigma_{12} \Sigma_{22}^{-1} \mu^{(2)} = 0^{(1)}$$

$$Y^{(2)} = X^{(2)} \Rightarrow E(Y^{(2)}) = \mu^{(2)} = 0^{(2)}$$

Since $Y^{(1)}$, $Y^{(2)}$ are independent then

$$f(Y^{(1)}, Y^{(2)}) = f(Y^{(1)}) f(Y^{(2)})$$

$$\therefore f(Y^{(1)}, Y^{(2)}) = \frac{1}{(2\pi)^{p/2} |\Sigma_{11.2}|^{1/2}} e^{-\frac{1}{2} [Y^{(1)} - 0^{(1)}]' \Sigma_{11.2}^{-1} [Y^{(1)} - 0^{(1)}]}$$

$$\times \frac{1}{(2\pi)^{\frac{p-q}{2}} |\Sigma_{22}|^{1/2}} e^{-\frac{1}{2} [Y^{(2)} - 0^{(2)}]' \Sigma_{22}^{-1} [Y^{(2)} - 0^{(2)}]}$$

To find $f(X^{(1)} | X^{(2)} = x^{(2)})$, first we must find

$$f(X^{(1)}, X^{(2)})$$

(4)

The joint dist. of $X^{(1)}, X^{(2)}$ can be found by

The transformation technique as follows:

$$f(\underline{x}) = f(\underline{x}^{(1)}, \underline{x}^{(2)}) = f(\underline{y}^{(1)}, \underline{y}^{(2)}) \cdot |J|$$

$$|J| = \begin{vmatrix} \frac{\partial \underline{y}^{(1)}}{\partial \underline{x}^{(1)}} & \frac{\partial \underline{y}^{(1)}}{\partial \underline{x}^{(2)}} \\ \frac{\partial \underline{y}^{(2)}}{\partial \underline{x}^{(1)}} & \frac{\partial \underline{y}^{(2)}}{\partial \underline{x}^{(2)}} \end{vmatrix} = \begin{vmatrix} I_{q \times q} & \Sigma_{12} \Sigma_{22}^{-1} \\ 0 & I_{(p-q)(p-q)} \end{vmatrix}$$

$$= |I_{q \times q}| |I_{(p-q)(p-q)}| = 1$$

$$\therefore f(\underline{x}^{(1)}, \underline{x}^{(2)}) = f(\underline{y}^{(1)}, \underline{y}^{(2)})$$

Since $\underline{y}^{(1)}$ & $\underline{y}^{(2)}$ are independent (given)

$$\therefore f(\underline{x}^{(1)}, \underline{x}^{(2)}) = f(\underline{y}^{(1)}) \cdot f(\underline{y}^{(2)})$$

Substitute the $\underline{y}^{(1)}$ & $\underline{y}^{(2)}$ values into the above equation we get:

$$\therefore f(\underline{x}^{(1)}, \underline{x}^{(2)}) = \left\{ \frac{1}{(2\pi)^{q/2} |\Sigma_{11}|^{1/2}} \exp \left[-\frac{1}{2} (\underline{x}^{(1)} - \Sigma_{12} \Sigma_{22}^{-1} \underline{x}^{(2)} - \underline{v}^{(1)})' \Sigma_{11}^{-1} (\underline{x}^{(1)} - \Sigma_{12} \Sigma_{22}^{-1} \underline{x}^{(2)} - \underline{v}^{(1)}) \right] \right\} * \left\{ \frac{1}{(2\pi)^{(p-q)/2} |\Sigma_{22}|^{1/2}} \exp \left[-\frac{1}{2} (\underline{x}^{(2)} - \underline{v}^{(2)})' \Sigma_{22}^{-1} (\underline{x}^{(2)} - \underline{v}^{(2)}) \right] \right\}$$

(5)

whereas: $\eta^{(1)} = \mu^{(1)} - \Sigma_{12} \Sigma_{22}^{-1} \mu^{(2)}$

$$\eta^{(2)} = \mu^{(2)}$$

$$\begin{aligned} \therefore L(\underline{X}^{(1)}, \underline{X}^{(2)}) &= \left\{ \frac{1}{(2\pi)^{9/2} |\Sigma_{11.2}|^{1/2}} \exp \left\{ -\frac{1}{2} [\underline{X}^{(1)} - \Sigma_{12} \Sigma_{22}^{-1} \underline{X}^{(2)}] \right. \right. \\ &\quad \left. \left. - (\mu^{(1)} - \Sigma_{12} \Sigma_{22}^{-1} \mu^{(2)})' \Sigma_{11.2}^{-1} [\underline{X}^{(1)} - \Sigma_{12} \Sigma_{22}^{-1} \underline{X}^{(2)} - (\mu^{(1)} - \Sigma_{12} \Sigma_{22}^{-1} \mu^{(2)})] \right\} \right. \\ &\quad \left. \times \left\{ \frac{1}{(2\pi)^{p/2} |\Sigma_{22}|^{1/2}} \exp \left\{ -\frac{1}{2} (\underline{X}^{(2)} - \mu^{(2)})' \Sigma_{22}^{-1} (\underline{X}^{(2)} - \mu^{(2)}) \right\} \right\} \right. \\ &= \left\{ \frac{1}{(2\pi)^{9/2} |\Sigma_{11.2}|^{1/2}} \exp \left\{ -\frac{1}{2} \left[\underline{X}^{(1)} - [\mu^{(1)} + \Sigma_{12} \Sigma_{22}^{-1} (\underline{X}^{(2)} - \mu^{(2)})] \right]' \Sigma_{11.2}^{-1} \right. \right. \\ &\quad \left. \left. [\underline{X}^{(1)} - [\mu^{(1)} + \Sigma_{12} \Sigma_{22}^{-1} (\underline{X}^{(2)} - \mu^{(2)})]] \right\} \right\} * \\ &\quad \left\{ \frac{1}{(2\pi)^{p/2} |\Sigma_{22}|^{1/2}} \exp \left\{ -\frac{1}{2} (\underline{X}^{(2)} - \mu^{(2)})' \Sigma_{22}^{-1} (\underline{X}^{(2)} - \mu^{(2)}) \right\} \right\} \end{aligned}$$

The conditional dist. of $(\underline{X}^{(1)} | \underline{X}^{(2)} = \underline{x}^{(2)})$ may be defined as:-

$$L(\underline{X}^{(1)} | \underline{X}^{(2)} = \underline{x}^{(2)}) = \frac{L(\underline{X}^{(1)}, \underline{x}^{(2)})}{L(\underline{x}^{(2)})}$$

$$\therefore L(\underline{X}^{(1)} | \underline{X}^{(2)} = \underline{x}^{(2)}) = \frac{1}{(2\pi)^{9/2} |\Sigma_{11.2}|^{1/2}} \exp \left\{ -\frac{1}{2} \left[\underline{x}^{(1)} - [\mu^{(1)} + \Sigma_{12} \Sigma_{22}^{-1} (\underline{x}^{(2)} - \mu^{(2)})] \right]' \Sigma_{11.2}^{-1} \right.$$

$$\left. \left[\underline{x}^{(1)} - [\mu^{(1)} + \Sigma_{12} \Sigma_{22}^{-1} (\underline{x}^{(2)} - \mu^{(2)})] \right] \right\}$$