

* Relation between zero covariance and independence.

$$X \& Y : \text{ind} \Rightarrow \text{Cov}(X, Y) = 0_{p \times q}$$

(*)

성립조건
: 정규분포!

$$\begin{pmatrix} X \\ Y \end{pmatrix} \sim N_{p+q} \left(\begin{pmatrix} \mu_x \\ \mu_y \end{pmatrix}, \begin{pmatrix} \Sigma_{xx} & \Sigma_{xy} \\ \Sigma_{yx} & \Sigma_{yy} \end{pmatrix} \right)$$

* 독립인지 확인하는 방법! $X, Y : \text{independent} \Leftrightarrow \text{Cov}(X, Y) = \Sigma_{XY} = 0$

① $f_{XY}(x, y) = f_X(x) \cdot f_Y(y) \quad \checkmark$

② $mgf_{XY}(s, t) = mgf_X(s) \cdot mgf_Y(t)$

← 인지 확인해 보자.

$$f_{XY}(x, y) = \frac{1}{12\pi|\Sigma|^{\frac{1}{2}}} \exp \left(-\frac{1}{2} \begin{pmatrix} x - \mu_x \\ y - \mu_y \end{pmatrix}^T \begin{pmatrix} \Sigma_{xx}^{-1} & 0 \\ 0 & \Sigma_{yy}^{-1} \end{pmatrix} \begin{pmatrix} x - \mu_x \\ y - \mu_y \end{pmatrix} \right)$$

서로
무관한
변수

$$= \frac{1}{12\pi|\Sigma|^{\frac{1}{2}}} \exp \left(-\frac{1}{2} (x - \mu_x)^T \Sigma_{xx}^{-1} (x - \mu_x) - \frac{1}{2} (y - \mu_y)^T \Sigma_{yy}^{-1} (y - \mu_y) \right)$$

x와
y로
분리

$$\begin{pmatrix} (x - \mu_x)^T & (y - \mu_y)^T \end{pmatrix} \begin{pmatrix} \Sigma_{xx}^{-1} & 0 \\ 0 & \Sigma_{yy}^{-1} \end{pmatrix} \begin{pmatrix} x - \mu_x \\ y - \mu_y \end{pmatrix} = \begin{pmatrix} (x - \mu_x)^T \Sigma_{xx}^{-1} & (y - \mu_y)^T \Sigma_{yy}^{-1} \end{pmatrix} \begin{pmatrix} x - \mu_x \\ y - \mu_y \end{pmatrix}$$

$$= (x - \mu_x)^T \Sigma_{xx}^{-1} (x - \mu_x) + (y - \mu_y)^T \Sigma_{yy}^{-1} (y - \mu_y)$$

* The conditional distributions of the components of X :

$$X = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} \sim N \left(\begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} \right)$$

Then, the conditional distribution of X_1 given $X_2 = x_2$ is $X_1 | X_2 = x_2$:

$$\begin{pmatrix} I_p & -\Sigma_{12}\Sigma_{22}^{-1} \\ 0 & I_q \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} = \begin{pmatrix} X_1 - \Sigma_{12}\Sigma_{22}^{-1}X_2 \\ \text{ind. } X_2 \end{pmatrix} \sim N \left(\begin{pmatrix} \mu_1 - \Sigma_{12}\Sigma_{22}^{-1}\mu_2 \\ \mu_2 \end{pmatrix}, \begin{pmatrix} 0 \\ \Sigma_{22} \end{pmatrix} \right)$$

← transpose

$$\textcircled{*} \begin{pmatrix} I_p & -\Sigma_{12}\Sigma_{22}^{-1} \\ 0 & I_q \end{pmatrix} \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} \begin{pmatrix} I & 0 \\ -\Sigma_{22}^{-1}\Sigma_{21} & I \end{pmatrix}$$

$$= \begin{pmatrix} \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21} & 0 \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} \begin{pmatrix} I & 0 \\ -\Sigma_{22}^{-1}\Sigma_{21} & I \end{pmatrix} = \begin{pmatrix} \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21} & 0 \\ 0 & \Sigma_{22} \end{pmatrix}$$

$$X_1 - \Sigma_{12}\Sigma_{22}^{-1}X_2, X_2 : \text{ind} \Rightarrow X_1 - \Sigma_{12}\Sigma_{22}^{-1}X_2 | X_2 = x_2 = X_1 - \Sigma_{12}\Sigma_{22}^{-1}x_2$$

$$X_1 - \Sigma_{12}\Sigma_{22}^{-1}X_2 + \Sigma_{12}\Sigma_{22}^{-1}x_2 | X_2 = x_2 \sim N(\mu_1 - \Sigma_{12}\Sigma_{22}^{-1}\mu_2 + \Sigma_{12}\Sigma_{22}^{-1}x_2, \Sigma_{11.2}) \sim N(\mu_1 - \Sigma_{12}\Sigma_{22}^{-1}\mu_2, \Sigma_{11.2})$$

$$\Rightarrow X_1 | X_2 = x_2 \sim N(\mu_1 + \Sigma_{12}\Sigma_{22}^{-1}(x_2 - \mu_2), \Sigma_{11.2})$$