

Lecture 08

$$\begin{bmatrix} X_i \\ Y_i \end{bmatrix} \stackrel{iid}{\sim} N_2 \left(\begin{bmatrix} \mu_1 & \mu_2 \\ \mu_2 & \mu_1 \end{bmatrix}, \begin{bmatrix} \sigma_1^2 & \rho_{12} \sigma_1 \sigma_2 \\ \rho_{12} \sigma_1 \sigma_2 & \sigma_2^2 \end{bmatrix} \right) \quad \text{Corr}(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X) \cdot \text{Var}(Y)}}$$

$1 \leq i \leq n$

$$R_n = \frac{S_{n,XY}}{S_{n,X} \cdot S_{n,Y}}, \quad S_{n,X} = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})^2, \quad S_{n,Y} = \frac{1}{n} \sum_{i=1}^n (Y_i - \bar{Y})^2$$

$$S_{n,XY} = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})$$

- ① $R_n \xrightarrow{P} \rho$
- ② $\sqrt{n}(R_n - \rho) \Rightarrow N(0, \tau^2)$
- ③ τ^2 ?

Know:

$$S_{n,X}^2 = \overline{X_n^2} - (\overline{X_n})^2$$

$$S_{n,Y}^2 = \overline{Y_n^2} - (\overline{Y_n})^2$$

$$S_{n,XY} = (\overline{XY})_n - (\overline{X}_n)(\overline{Y}_n)$$

$$\sqrt{n} \left\{ \begin{bmatrix} \overline{X}_n \\ \overline{Y}_n \\ \overline{X_n^2} \\ \overline{Y_n^2} \\ (\overline{XY})_n \end{bmatrix} - \begin{bmatrix} \mathbb{E}(X_i) \\ \mathbb{E}(Y_i) \\ \mathbb{E}(X_i^2) \\ \mathbb{E}(Y_i^2) \\ \mathbb{E}(XY_i) \end{bmatrix} \right\} \xrightarrow{5 \times 5} N_5(0, \Sigma)$$

$$\Sigma = \begin{bmatrix} \text{Var}(X_1) & \text{Cov}(X_1, Y_1) & \text{Cov}(X_1, X_1^2) & \text{Cov}(X_1, Y_1^2) & \text{Cov}(X_1, XY_1) \\ \text{Var}(Y_1) & \text{Cov}(Y_1, X_1) & \text{Cov}(Y_1, X_1^2) & \text{Cov}(Y_1, Y_1^2) & \text{Cov}(Y_1, XY_1) \\ \text{Var}(X_1^2) & \text{Cov}(X_1^2, Y_1) & \text{Cov}(X_1^2, X_1^2) & \text{Cov}(X_1^2, Y_1^2) & \text{Cov}(X_1^2, XY_1) \\ \text{Var}(Y_1^2) & \text{Cov}(Y_1^2, X_1) & \text{Cov}(Y_1^2, X_1^2) & \text{Cov}(Y_1^2, Y_1^2) & \text{Cov}(Y_1^2, XY_1) \\ \text{Var}(XY_1) & & & & \text{Var}(XY_1) \end{bmatrix}$$

Work on the special case $\mu_1 = \mu_2 = 0, \sigma_1^2 = \sigma_2^2 = 1$, $X_i \rightarrow \frac{X_i - \mu_1}{\sigma_1}, Y_i \rightarrow \frac{Y_i - \mu_2}{\sigma_2}$

$$\begin{pmatrix} X \\ Y \end{pmatrix} \sim N_2 \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right)$$

* First consider the mean vector:

$$\begin{bmatrix} \mathbb{E}(X_1) \\ \mathbb{E}(Y_1) \\ \mathbb{E}(X_1^2) \\ \mathbb{E}(Y_1^2) \\ \mathbb{E}(X_1 Y_1) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \\ \rho \end{bmatrix}$$

* Then consider the covariance matrix

$$\text{Var}(X^2) = \mathbb{E}(X^4) - \mathbb{E}^2(X^2) = 3 - 1 = 2 = \text{Var}(Y^2)$$

$$\text{Cov}(x, X^2) = \mathbb{E}(X^3) - \mathbb{E}(X) \mathbb{E}(X^2) = 0$$

$$\rightarrow \text{Let } U = Y - \rho X \sim N(0, 1 - \rho^2)$$

$$\mathbb{E}(U) = \mathbb{E}(Y - \rho X) = 0,$$

$$\text{Var}(U) = \text{Var}(Y - \rho X) = \text{Var}(Y) + \rho^2 \text{Var}(X) - 2\rho \text{Cov}(X, Y) = 1 + \rho^2 - 2\rho^2 = 1 - \rho^2.$$

$$\rightarrow \text{Cov}(x, U) = \text{Cov}(x, Y - \rho X) = \text{Cov}(x, Y) - \rho \text{Cov}(x, X) = \rho - \rho \cdot 1 = 0.$$

$$\begin{bmatrix} x \\ u \end{bmatrix} = \begin{bmatrix} x \\ Y - \rho X \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ -\rho & 1 \end{bmatrix} \begin{bmatrix} x \\ Y \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 - \rho^2 \end{bmatrix}\right) \quad x \text{ unu}$$

$$\rightarrow \text{Cov}(x, Y^2) = \mathbb{E}(XY^2) - \mathbb{E}(X) \cdot \mathbb{E}(Y^2) = \mathbb{E}(XY^2)$$

$$\text{Cov}(Y, X^2) = \mathbb{E}(X^2 Y) - \mathbb{E}(X^2) \cdot \mathbb{E}(Y) = \mathbb{E}(X^2 Y) = \mathbb{E}(X^2(\rho X + U)) = \cancel{\rho} \mathbb{E}(X^3) + \mathbb{E}(X^2) \cdot \mathbb{E}(U) = 0.$$

$$\text{Cov}(x, XY) = \mathbb{E}(X^2 Y) - \mathbb{E}(X) \cdot \mathbb{E}(XY) = 0$$

$$\text{Cov}(X^2, XY) = \mathbb{E}(X^3 Y) - \cancel{\mathbb{E}(X^2)} \cdot \cancel{\mathbb{E}(XY)} = \mathbb{E}(X^3(\rho X + U)) - \cancel{\rho} = \cancel{\rho} \mathbb{E}(X^4) + \mathbb{E}(X^3) \cancel{\mathbb{E}(U)} - \cancel{\rho} = 2\rho$$

$$\text{Cov}(X^2, Y^2) = \mathbb{E}(X^2 Y^2) - \mathbb{E}(X^2) \cdot \mathbb{E}(Y^2) = \mathbb{E}(X^2(\rho X + U)^2) - 1$$

$$= \mathbb{E}(X^2(\rho^2 X^2 + 2\rho UX + U^2)) - 1 = \rho^2 \mathbb{E}(X^4) + 2\rho \mathbb{E}(U) \mathbb{E}(X^3) + \mathbb{E}(U^2) \mathbb{E}(X^2) - 1$$

$$= 3\rho^2 + (1 - \rho^2) - 1 = 2\rho^2$$

$$\text{Var}(XY) = \mathbb{E}(XY^2) - \mathbb{E}(XY) = 2\rho^2 + 1 - \rho^2 = \rho^2 + 1$$

$$\Sigma = \begin{bmatrix} \cancel{\text{Var}(X_1)}^1 & \cancel{\text{Cov}(X_1, Y_1)}^{\rho} & \cancel{\text{Cov}(X_1, X_1^2)}^0 & \cancel{\text{Cov}(X_1, Y_1^2)}^0 & \cancel{\text{Cov}(X_1, XY_1)}^0 \\ \cancel{\text{Var}(Y_1)}^1 & \cancel{\text{Cov}(Y_1, Y_1)}^0 & \cancel{\text{Cov}(Y_1, X_1^2)}^0 & \cancel{\text{Cov}(Y_1, Y_1^2)}^0 & \cancel{\text{Cov}(Y_1, XY_1)}^0 \\ \cancel{\text{Var}(X_1^2)}^2 & \cancel{\text{Cov}(X_1^2, Y_1)}^{2\rho} & \cancel{\text{Cov}(X_1^2, X_1^2)}^2 & \cancel{\text{Cov}(X_1^2, Y_1^2)}^{2\rho} & \cancel{\text{Cov}(X_1^2, XY_1)}^{2\rho} \\ \cancel{\text{Var}(Y_1^2)}^2 & \cancel{\text{Cov}(Y_1^2, Y_1)}^{2\rho} & \cancel{\text{Cov}(Y_1^2, X_1^2)}^{2\rho} & \cancel{\text{Cov}(Y_1^2, Y_1^2)}^2 & \cancel{\text{Cov}(Y_1^2, XY_1)}^{2\rho} \\ \cancel{\text{Var}(XY_1)}^{\rho^2+1} & \cancel{\text{Cov}(XY_1, Y_1)}^0 & \cancel{\text{Cov}(XY_1, X_1^2)}^0 & \cancel{\text{Cov}(XY_1, Y_1^2)}^0 & \cancel{\text{Cov}(XY_1, XY_1)}^0 \end{bmatrix}$$

$$= \begin{bmatrix} 1 & \rho & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 2 & 2\rho^2 & 2\rho^2 & 2\rho & 2\rho \\ 2 & 2\rho & 2\rho & \rho^2+1 & 0 \end{bmatrix}$$

As a result,

$$\sqrt{n} \left\{ \begin{bmatrix} \bar{X} \\ \bar{Y} \\ \bar{X^2} \\ \bar{Y^2} \\ \bar{XY} \end{bmatrix} - \mu \right\} \Rightarrow N_5(0, \Sigma) \quad R_n = \frac{\bar{XY} - \bar{X} \cdot \bar{Y}}{\sqrt{(\bar{X^2} - \bar{X}^2)(\bar{Y^2} - \bar{Y}^2)}} \\ = g(\bar{X}, \bar{Y}, \bar{X^2}, \bar{Y^2}, \bar{XY})$$

$$T_n \xrightarrow{P} \mu.$$

$$\text{where } g(a, b, c, d, e) = \frac{e - ab}{\sqrt{(c-a^2)(d-b^2)}}$$

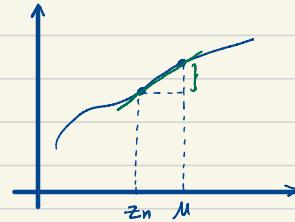
By CMT, we have $g(T_n) \xrightarrow{P} g(\mu)$

* The Delta theorem:

$$\text{Assume } \sqrt{n}(z_n - \mu) \Rightarrow N(0, \Sigma)$$

function $g(z)$ is smooth, then

$$\sqrt{n}(g(z_n) - g(\mu)) \Rightarrow N(0, \underbrace{\dot{g}(\mu)^T \Sigma \dot{g}(\mu)}_{\tau^2})$$



$$\sqrt{n}\{g(z_n) - g(\mu)\} = \dot{g}(\tilde{z}_n) \times \{\sqrt{n}(z_n - \mu)\} \Rightarrow N(0, \sigma^2 \dot{g}(\mu)^2) \quad g(z_n) - g(\mu) = \dot{g}(\tilde{z}_n)(z_n - \mu) \\ z_n \xrightarrow{P} \mu, \Rightarrow \tilde{z}_n \xrightarrow{P} \mu, \Rightarrow \dot{g}(\tilde{z}_n) \xrightarrow{P} \dot{g}(\mu) \quad \tilde{z}_n \in (z_n, \mu)$$

* Slutsky's theorem:

$$\text{If } Y_n \Rightarrow Y, X_n \xrightarrow{P} a, V_n \xrightarrow{P} b$$

$$\text{then } X_n + V_n Y_n \Rightarrow a + bY$$

Since $\sqrt{n}(T_n - \mu) \Rightarrow N_5(0, \Sigma)$

$$\text{then } \sqrt{n}(R_n - \rho) = \sqrt{n}(g(T_n) - g(\mu)) \Rightarrow N_5(0, \underbrace{\dot{g}(\mu)^T \Sigma \dot{g}(\mu)}_{\tau^2})$$