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Multivariate Analysis.

$$\underline{x} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}, \underline{\mu} = E(\underline{x}) = \begin{bmatrix} E(x_1) \\ E(x_2) \\ \vdots \\ E(x_n) \end{bmatrix}, E|x_i| < \infty \quad \forall i = 1, 2, \dots, n.$$

$$Y = ((Y_{ij}))_{m \times n}, \quad E(Y) = ((E Y_{ij}))_{m \times n}.$$

$$D(\underline{x}) = ((\text{cov}(x_i, x_j)))_{n \times n}.$$

$$= ((E[(x_i - E(x_i))(x_j - E(x_j))]))_{n \times n}.$$

$$= ((E(x_i x_j) - E(x_i) E(x_j)))_{n \times n}.$$

$$= ((E(x_i x_j) - \mu_i \mu_j))_{n \times n}.$$

$$= E[(\underline{x} - \underline{\mu})(\underline{x} - \underline{\mu})^T] = \sum_x$$

(1) $E(\underline{x} + \underline{b}) = E(\underline{x}) + \underline{b} = \underline{\mu} + \underline{b}$.

(2) $D(\underline{x} + \underline{b}) = D(\underline{x})$.

(3) $\text{cov}(\underline{x} + \underline{b}, \underline{y} + \underline{c}) = \text{cov}(\underline{x}, \underline{y}) = \Gamma_{xy}$.

$\underline{b}, \underline{c}$ are constant vectors.

$$\Gamma_{xy} = ((\text{cov}(x_i, y_j)))_{p \times n}.$$

(1) $E(A\underline{x}) = A E(\underline{x}) = A \underline{\mu}$.

If $A = \underline{\gamma}^T$ then $E(A\underline{x}) = E\left(\sum_{i=1}^n \gamma_i x_i\right) = \sum_{i=1}^n \gamma_i E(x_i) = \sum_{i=1}^n \gamma_i \mu_i$

$$\underline{\mu}^T \underline{\mu} = E(\underline{x}^T \underline{x}) = E\left(\sum_{i=1}^n x_i^2\right) = \sum_{i=1}^n E(x_i^2) = \sum_{i=1}^n \mu_i^2$$

(2) $\text{cov}(\underline{v}, \underline{y}) = \Gamma \Rightarrow \text{cov}(A\underline{v}, B\underline{v}) = A \Gamma B^T$.

\Rightarrow If $\underline{v} = \underline{y} = \underline{x} \Rightarrow \text{cov}(A\underline{x}, B\underline{x}) = A \sum B^T$.

$\Rightarrow \underline{\gamma}^T = A = B \Rightarrow \text{cov}(\underline{\gamma}^T \underline{x}, \underline{\gamma}^T \underline{x}) = \text{var}(\underline{\gamma}^T \underline{x}) = D(\underline{\gamma}^T \underline{x})$.

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\underline{x} is a random vector.

$D(\underline{x}) = \Sigma$. Then $D(\underline{x}) = \Sigma$ is a p.s.d matrix.

Consider $\underline{z}^T \neq \underline{o}^T$ then.

$$D(\underline{z}^T \underline{x}) = V(\underline{z}^T \underline{x}) \geq 0 \quad \forall \underline{z}^T \neq \underline{o}^T.$$

$$\Rightarrow \underline{z}^T \Sigma \underline{z} \geq 0 \quad \forall \underline{z}^T \neq \underline{o}^T.$$

$\Rightarrow \Sigma$ is a p.s.d or n.n.d matrix.

Also, Σ is a symmetric matrix. $\Sigma = \Sigma^T$.

Th. Let $E(\underline{x}) = \underline{\mu}$, $D(\underline{x}) = \Sigma$.

then. $P((\underline{x} - \underline{\mu}) \in \ell(\Sigma)) = 1$

To prove this it is enough to show that

if $\underline{z} \in (\ell(\Sigma))^{\perp}$ then $\underline{z}^T (\underline{x} - \underline{\mu}) = 0$.

If $\underline{z} \in (\ell(\Sigma))^{\perp}$.

$$\Leftrightarrow \underline{z}^T \Sigma = \underline{o}^T.$$

$$\Rightarrow \underline{z}^T \Sigma \underline{z} = \underline{o}^T \underline{z}.$$

$$\Rightarrow \underline{z}^T \Sigma \underline{z} = 0$$

$$\Rightarrow D(\underline{z}^T \underline{x}) = 0.$$

$$\Rightarrow D(\underline{z}^T (\underline{x} - \underline{\mu})) = 0.$$

$$\left| \begin{array}{l} \text{① } D(\underline{z}^T (\underline{x} - \underline{\mu})) = 0. \\ \text{② } E(\underline{z}^T (\underline{x} - \underline{\mu})) = 0 \end{array} \right. \Rightarrow P(\underline{z}^T (\underline{x} - \underline{\mu}) = 0) = 1.$$

$\therefore \underline{z}$ is orthogonal to $(\underline{x} - \underline{\mu})$.

$$\Rightarrow P((\underline{x} - \underline{\mu}) \in \ell(\Sigma)) = 1.$$

$$E(\underline{x}^T A \underline{x}) = \text{tr}(A\Sigma) + \underline{\mu}^T A \underline{\mu}$$

$$E(\underline{x}) = \underline{\mu}, \\ D(\underline{x}) = \Sigma.$$

Special case.

- If $\underline{x} \sim N(\underline{\mu}, \Sigma)$

$$E(\underline{x}^T \underline{x}) = E(\underline{x}^T I_n \underline{x}) = \text{tr}(I_n \Sigma) + \underline{\mu}^T \underline{\mu}$$

$$= \text{tr}(\Sigma) + \underline{\mu}^T \underline{\mu}. \quad \text{Non-centered } \chi^2.$$

- If $\underline{x} \sim N(\underline{\mu}, I_n)$, $\underline{x}^T \underline{x} \sim \chi_{n, \text{nct}}^2$, $nct = \underline{\mu}^T \underline{\mu}$.

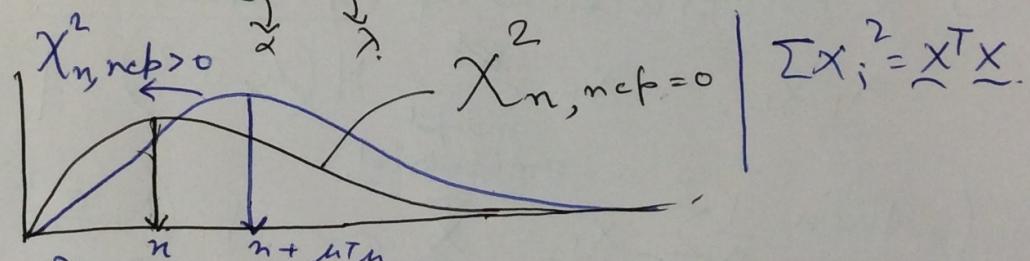
$$E(\underline{x}^T \underline{x}) = n + \underline{\mu}^T \underline{\mu} = n + \sum_{i=1}^n \mu_i^2 = E(\sum x_i^2) = \sum_{i=1}^n (1 + \mu_i^2)$$

- If $\underline{x} \sim N(\underline{\mu}, I_n)$, $\Rightarrow x_1, x_2, \dots, x_n$ iid $N(0, 1)$.

$$E(\underline{x}^T \underline{x}) = n + 0 = n = E(\chi_n^2)$$

If $\underline{x} \sim N(\underline{\mu}, I_n)$ then $\underline{x}^T \underline{x} \sim \chi_n^2$ (central χ^2).

$$\chi_n^2 = G\left(\frac{n}{2}, \frac{1}{2}\right). \quad E(G(\lambda, \alpha)) = \frac{\alpha}{\lambda}.$$



$$E(\chi_{n, \text{nct}=\underline{\mu}^T \underline{\mu}}^2) = n + \underline{\mu}^T \underline{\mu}.$$

$$E(\chi_{n, \text{nct}=0}^2) = n + 0.$$

$$E(\underline{x}^T A \underline{x}) = \text{tr}(A\Sigma) + \underline{\mu}^T A \underline{\mu}$$

Proof: $E(\underline{x}^T A \underline{x}) = E[\text{tr}(\underline{x}^T A \underline{x})]$

$$= E[\text{tr}(A \underline{x} \underline{x}^T)] = \text{tr}[A E(\underline{x} \underline{x}^T)]$$

$$= \text{tr}[A (\Sigma + \underline{\mu} \underline{\mu}^T)]$$

$$= \text{tr}[A\Sigma + A \underline{\mu} \underline{\mu}^T]$$

$$= \text{tr}(A\Sigma) + \text{tr}(A \underline{\mu} \underline{\mu}^T)$$

$$= \text{tr}(A\Sigma) + \underline{\mu}^T A \underline{\mu}.$$

$$\text{tr}(AB) = \text{tr}(BA).$$

$$E(\underline{x}) = \underline{\mu}$$

$$D(\underline{x}) = \Sigma.$$

~~$$E(\underline{x} \underline{x}^T) = \Sigma + \underline{\mu} \underline{\mu}^T$$~~

$$\text{tr}(A+B) = \text{tr}(A) + \text{tr}(B)$$

$$D(x) = \Sigma = E(\underline{x} \underline{x}^T) - \underline{\mu} \underline{\mu}^T$$

• If $\underline{X} \sim N(\underline{\mu}, I_n)$. Then. $\underline{X}^T A \underline{X}$ follows a Chi-squared.⁽⁴⁾
distribution. iff. A is an idempotent matrix.

• If A_1 & A_2 are square symmetric idempotent
matrices. and $\underline{Q} = A_1 - A_2$ is p.s.d.

✓ Then. $\underline{X}^T Q \underline{X}$ and ~~$\underline{X}^T A_2 \underline{X}$~~ are
independantly distributed.

* Let $\underline{X} \sim N(\underline{\mu}, I_n)$. A is symmetric and
if $C A = 0$ matrix. then. $\underline{X}^T A \underline{X}$ and $C \underline{X}$ are
independantly distributed.

④ Construction of T-statistic.

$x_1, x_2, \dots, x_n \stackrel{\text{iid}}{\sim} N(\mu, \sigma^2) \quad [\text{iid}]$

{ then $\frac{1}{n} \sum_{i=1}^n x_i = \bar{x} \sim N\left(\mu, \frac{\sigma^2}{n}\right)$ }
 $\sum_{i=1}^n (x_i - \bar{x})^2 = S^2 \sim \sigma^2 \chi_{n-1}^2$ independent.

$$\Rightarrow \text{Define. } T = \frac{(\bar{x} - \mu) / (\sigma / \sqrt{n})}{\sqrt{\frac{S^2}{\sigma^2(n-1)}}} \approx = \frac{\sqrt{n}(\bar{x} - \mu)}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 / (n-1)}}.$$

$$T \sim t_{n-1}, \text{ and } T^2 \sim F_{1, (n-1)}.$$

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$$\bar{x} = \frac{1}{n} \underline{1}^T \underline{x} = \left(\frac{1}{n} \underline{1} \cdots \frac{1}{n} \underline{1} \right) \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = \underline{1}^T \underline{x}.$$

where $\underline{1}^T = \left(\frac{1}{n}, \frac{1}{n}, \dots, \frac{1}{n} \right)$.

$$\underline{x} \sim N \left(\underline{\mu}, I_n \sigma^2 \right) \text{ where } \underline{\mu} = n \cdot \underline{1} = \begin{pmatrix} n \\ n \\ \vdots \\ n \end{pmatrix}$$

$$\Rightarrow \underline{1}^T \underline{x} \sim N \left(\underline{1}^T \underline{\mu}, \underline{1}^T \Sigma \underline{1} \right) \equiv N \left(\mu, \frac{\sigma^2}{n} \right)$$

$$S^2 = \sum_{i=1}^n (x_i - \bar{x})^2 = \underline{x}^T (I_n - \frac{1}{n} \underline{1} \underline{1}^T) \underline{x}.$$

$$A = \left(I_n - \frac{1}{n} \underline{1} \underline{1}^T \right) \text{ hence } A^T = A, \begin{array}{l} \text{Symmetric} \\ \text{Idempotent} \end{array} \quad A^2 = A.$$

$$\underline{y} = \frac{\underline{x}}{\sigma} \sim N \left(\frac{\underline{\mu}}{\sigma}, I_n \right)$$

$$S^2 = \underline{x}^T A \underline{x}.$$

$$= \sigma^2 \left(\frac{\underline{x}^T}{\sigma} \right) A \left(\frac{\underline{x}}{\sigma} \right)^T = \sigma^2 \underline{y}^T A \underline{y}$$

$$S^2 \sim \sigma^2 \chi^2_{\text{rank}(A)}, \left(\frac{\underline{\mu}}{\sigma} \right)^T A \left(\frac{\underline{\mu}}{\sigma} \right).$$

Note $\text{rank}(A) = \text{trace}(A) = n-1$

$$\frac{1}{\sigma^2} (\underline{y}^T A \underline{y}) = \mu \cdot \left[\underline{1}^T \left(I_n - \frac{1}{n} \underline{1} \underline{1}^T \right) \underline{1} \right] \cdot \mu = \mu^2 \cdot 0 = 0.$$

$$\Rightarrow S^2 \sim \sigma^2 \chi^2_{n-1}.$$

$$\begin{aligned} \underline{1}^T A &= \frac{1}{n} \underline{1}^T \left(I_n - \frac{1}{n} \underline{1} \underline{1}^T \right) & \bar{x} = \underline{1}^T \underline{x}, \quad S^2 = \underline{x}^T A \underline{x} \\ &= \frac{1}{n} \left(\underline{1}^T - \frac{1}{n} (\underline{1}^T \underline{1}) \underline{1}^T \right) \\ &= \frac{1}{n} (\underline{1}^T - \underline{1}^T) = \underline{0}^T. \end{aligned} \quad \begin{cases} A^T = A, \\ A^2 = A, \end{cases}$$

\bar{x} and S^2 are independently distributed.

$$\bar{x} \sim N \left(\mu, \frac{\sigma^2}{n} \right) \Rightarrow \sqrt{n} \left(\frac{\bar{x} - \mu}{\sigma} \right) \sim N(0, 1). \quad \text{indepant.}$$

and. $\frac{S^2}{\sigma^2} \sim \chi^2_{n-1}$