

Multivariate Statistical Analysis Mid Term 2008

Reference Solution

1. (6%)

Answer:

$$CI_{95} : \left(\bar{x} - t_{n-1}(0.025) \frac{s}{\sqrt{n}}, \bar{x} + t_{n-1}(0.025) \frac{s}{\sqrt{n}} \right)$$

$$\text{i.e., } \left(56 - t_{15}(0.025) \frac{15}{\sqrt{16}}, 56 + t_{15}(0.025) \frac{15}{\sqrt{16}} \right)$$

$$t_{15}(0.025) \approx 2.131$$

Thus, $CI_{95} : (48.01, 63.99)$, in cm.

2. (6%)

Answer:

In all samples of size 16 from all collegiate basketball players in Taiwan if they take *MagicPill*, 95% of the intervals determined by CI_{95} computed in the same way as in Problem 1 will include the actual average height jumped by all collegiate basketball players in Taiwan if they take *MagicPill*.

3. (6%)

Answer:

Power = 90% = $1 - \beta$. Thus the type II error $\beta = 0.1$

For critical value CV to achieve type I error $\alpha = 0.05$, and type II error $\beta = 0.1$,

$$\text{we have } \frac{CV - 50}{15/\sqrt{n}} = z(0.025) = 1.96 = z_{\alpha}, \quad \frac{56 - CV}{15/\sqrt{n}} = z(0.1) = 1.28 = z_{\beta}$$

$$\text{Thus, } n = \left(\frac{\sigma(z_{\alpha} + z_{\beta})}{\Delta} \right)^2 = \left(\frac{15 * (1.96 + 1.28)}{56 - 50} \right)^2 \approx 65.61. \quad \text{Take } n = 66.$$

4. (6%)

Answer:

The sample correlation coefficient $r_{ik} = \frac{s_{ik}}{\sqrt{s_{ii}} \sqrt{s_{kk}}}$ can be regarded as cosine of

the angle formed by the deviation vectors $\mathbf{d}_i = \mathbf{y}_i - \bar{x}_i \mathbf{1}$ and $\mathbf{d}_k = \mathbf{y}_k - \bar{x}_k \mathbf{1}$ in the n -space..

5. (4%)

Answer:

The generalized sample variance $|S| = (n-1)^{-p} (\text{volume})^2$, where *volume* is the volume generated in n -space by the p deviation vectors $\mathbf{d}_1 = \mathbf{y}_1 - \bar{x}_1 \mathbf{1}$, $\mathbf{d}_2 = \mathbf{y}_2 - \bar{x}_2 \mathbf{1}, \dots, \mathbf{d}_p = \mathbf{y}_p - \bar{x}_p \mathbf{1}$.

6. (6%)

Answer:

By spectral decomposition, $\Sigma = \lambda_1 \mathbf{e}_1 \mathbf{e}_1' + \lambda_2 \mathbf{e}_2 \mathbf{e}_2'$, and by Result 4.1 in Textbook, $\Sigma^{-1} = \frac{1}{\lambda_1} \mathbf{e}_1 \mathbf{e}_1' + \frac{1}{\lambda_2} \mathbf{e}_2 \mathbf{e}_2'$. Thus, the equation $(\mathbf{x} - \boldsymbol{\mu})' \Sigma^{-1} (\mathbf{x} - \boldsymbol{\mu}) = c^2$ can be

expressed as $(\mathbf{x} - \boldsymbol{\mu})' \left(\frac{1}{\lambda_1} \mathbf{e}_1 \mathbf{e}_1' + \frac{1}{\lambda_2} \mathbf{e}_2 \mathbf{e}_2' \right) (\mathbf{x} - \boldsymbol{\mu}) = c^2$, with $\mathbf{y} = [y_1 \quad y_2]' = \begin{bmatrix} \mathbf{e}_1' \\ \mathbf{e}_2' \end{bmatrix} (\mathbf{x} - \boldsymbol{\mu})$,

the ellipse equation may be written as

$$\frac{1}{\lambda_1} (\mathbf{e}_1' (\mathbf{x} - \boldsymbol{\mu}) \mathbf{e}_1)' (\mathbf{e}_1' (\mathbf{x} - \boldsymbol{\mu}) \mathbf{e}_1) + \frac{1}{\lambda_2} (\mathbf{e}_2' (\mathbf{x} - \boldsymbol{\mu}) \mathbf{e}_2)' (\mathbf{e}_2' (\mathbf{x} - \boldsymbol{\mu}) \mathbf{e}_2) = c^2, \quad \text{i.e.,}$$

$$\frac{y_1^2}{c^2 \lambda_1} + \frac{y_2^2}{c^2 \lambda_2} = 1.$$

7. (4%)

Answer:

$$\begin{bmatrix} 12 & 6 \\ 6 & 7 \end{bmatrix} \begin{bmatrix} 3/\sqrt{13} \\ 2/\sqrt{13} \end{bmatrix} = \begin{bmatrix} 48/\sqrt{13} \\ 32/\sqrt{13} \end{bmatrix} = 16 \begin{bmatrix} 3/\sqrt{13} \\ 2/\sqrt{13} \end{bmatrix}, \text{ i.e., } \begin{bmatrix} 12 & 6 \\ 6 & 7 \end{bmatrix} \mathbf{e}_1 = \lambda_1 \mathbf{e}_1$$

$$\begin{bmatrix} 12 & 6 \\ 6 & 7 \end{bmatrix} \begin{bmatrix} -2/\sqrt{13} \\ 3/\sqrt{13} \end{bmatrix} = \begin{bmatrix} -6/\sqrt{13} \\ 9/\sqrt{13} \end{bmatrix} = 3 \begin{bmatrix} -2/\sqrt{13} \\ 3/\sqrt{13} \end{bmatrix}, \text{ i.e., } \begin{bmatrix} 12 & 6 \\ 6 & 7 \end{bmatrix} \mathbf{e}_2 = \lambda_2 \mathbf{e}_2$$

8. . (6%)

Answer:

Based on Eq. (5-6) or (5-7),

$$\begin{aligned} T^2 &= n(\bar{\mathbf{x}} - \boldsymbol{\mu}_0)' \mathbf{S}^{-1} (\bar{\mathbf{x}} - \boldsymbol{\mu}_0) = 30 \begin{bmatrix} 0.5 & -0.5 \end{bmatrix} \frac{1}{48} \begin{bmatrix} 7 & -6 \\ -6 & 12 \end{bmatrix} \begin{bmatrix} 0.5 \\ -0.5 \end{bmatrix} \\ &= \frac{5}{8} \begin{bmatrix} 0.5 & -0.5 \end{bmatrix} \begin{bmatrix} 6.5 \\ -9 \end{bmatrix} = 7.75 \times \frac{5}{8} \approx 4.8438 \end{aligned}$$

$$\text{Critical value} = \frac{(n-1)p}{n-p} F_{p, n-p}(0.1) = \frac{29 \times 2}{28} F_{2, 28}(0.1) = \frac{58}{28} \times 2.50 = 5.17857$$

$T^2 < \text{critical value. } \therefore \text{ can not reject } H_0$

9. (6%)

Answer:

From Eq. (5-18),

$$n(\bar{\mathbf{x}} - \boldsymbol{\mu})' \mathbf{S}^{-1} (\bar{\mathbf{x}} - \boldsymbol{\mu}) \leq \frac{p(n-1)}{n-p} F_{p, n-p}(0.1) = 5.17857$$

$$(\bar{\mathbf{x}} - \boldsymbol{\mu})' \mathbf{S}^{-1} (\bar{\mathbf{x}} - \boldsymbol{\mu}) \leq \frac{5.17857}{30} = 0.172619$$

By Eq. (5-19), major axes $\sqrt{\lambda_i} \sqrt{\frac{p(n-1)}{n(n-p)} F_{p, n-p}(0.1)}$ and directions \mathbf{e}_i

namely, major axes $4\sqrt{0.172619} \approx 1.66$ and $\sqrt{3}\sqrt{0.172619} \approx 0.72$.

$$\text{directions } \frac{1}{\sqrt{13}} \begin{bmatrix} 3 \\ 2 \end{bmatrix} \approx \begin{bmatrix} 0.83 \\ 0.55 \end{bmatrix} \text{ and } \frac{1}{\sqrt{13}} \begin{bmatrix} -2 \\ 3 \end{bmatrix} \approx \begin{bmatrix} -0.55 \\ 0.83 \end{bmatrix}$$

10. (6%)

Answer: In all samples of size 30 drawn from the population, 90% of the Hotelling's T^2 confidence region determined in the same way as in Problem 7 will include the population mean vector $\boldsymbol{\mu}$.

11. (6%)

Answer:

Use Eq. (5.24),

$$\bar{x}_1 - \sqrt{\frac{p(n-1)}{n-p} F_{p,n-p}(0.1)} \sqrt{\frac{s_{11}}{n}} \leq \mu_1 \leq \bar{x}_1 + \sqrt{\frac{p(n-1)}{n-p} F_{p,n-p}(0.1)} \sqrt{\frac{s_{11}}{n}}$$

$$\bar{x}_2 - \sqrt{\frac{p(n-1)}{n-p} F_{p,n-p}(0.1)} \sqrt{\frac{s_{22}}{n}} \leq \mu_2 \leq \bar{x}_2 + \sqrt{\frac{p(n-1)}{n-p} F_{p,n-p}(0.1)} \sqrt{\frac{s_{22}}{n}}$$

$$\sqrt{\frac{p(n-1)}{n-p} F_{p,n-p}(0.1)} = \sqrt{5.17857} = 2.27565$$

$$-0.5 - \sqrt{5.17857} \sqrt{\frac{12}{30}} \leq \mu_1 \leq -0.5 + \sqrt{5.17857} \sqrt{\frac{12}{30}}, \quad \mu_1 \in (-1.94, 0.94)$$

$$0.5 - \sqrt{5.17857} \sqrt{\frac{7}{30}} \leq \mu_2 \leq 0.5 + \sqrt{5.17857} \sqrt{\frac{7}{30}}, \quad \mu_2 \in (-0.60, 1.60)$$

12. (6%)

Answer:

In all samples of size 30 drawn from the population, 90% of the simultaneous T^2 confidence intervals determined in the same way as in Problem 9 will include the population mean vector μ .

13. (6%)

Answer:

From Eq. (5-29),

$$\bar{x}_1 - t_{n-1}\left(\frac{0.1}{2p}\right) \sqrt{\frac{s_{11}}{n}} \leq \mu_1 \leq \bar{x}_1 + t_{n-1}\left(\frac{0.1}{2p}\right) \sqrt{\frac{s_{11}}{n}}$$

$$\bar{x}_2 - t_{n-1}\left(\frac{0.1}{2p}\right) \sqrt{\frac{s_{22}}{n}} \leq \mu_2 \leq \bar{x}_2 + t_{n-1}\left(\frac{0.1}{2p}\right) \sqrt{\frac{s_{22}}{n}}$$

$$t_{29}(0.025) = 2.045$$

$$-0.5 - 2.045 \sqrt{\frac{12}{30}} \leq \mu_1 \leq -0.5 + 2.045 \sqrt{\frac{12}{30}}, \quad \mu_1 \in (-1.79, 0.79)$$

$$0.5 - 2.045 \sqrt{\frac{7}{30}} \leq \mu_2 \leq 0.5 + 2.045 \sqrt{\frac{7}{30}}, \quad \mu_2 \in (-0.49, 1.49)$$

14. (6%)

Answer:

$$\text{Likelihood} = \prod_{j=1}^n \frac{1}{\sqrt{2\pi\sigma}} e^{-(x_j - \mu)^2 / (2\sigma^2)} = \frac{1}{(2\pi)^{n/2} \sigma^n} e^{-\sum_{j=1}^n (x_j - \mu)^2 / 2\sigma^2} = L(\mu, \sigma^2)$$

Since the μ and σ^2 which maximize $L(\mu, \sigma^2)$ are the same as those maximize,

$$l(\mu, \sigma^2) = \ln L(\mu, \sigma^2) = -\sum_{j=1}^n (x_j - \mu)^2 / 2\sigma^2 - \frac{n}{2} \ln 2\pi - \frac{n}{2} \ln \sigma^2, \text{ we set}$$

$$\frac{\partial l(\mu, \sigma^2)}{\partial \mu} = \frac{1}{\sigma^2} \sum_{j=1}^n (x_j - \mu) = 0, \quad \text{and} \quad \frac{\partial l(\mu, \sigma^2)}{\partial \sigma^2} = \frac{1}{2\sigma^4} \sum_{j=1}^n (x_j - \mu)^2 - \frac{n}{2} \frac{1}{\sigma^2} = 0.$$

From the first equation, we have the maximum likelihood estimate of μ :

$$\hat{\mu} = \frac{1}{n} \sum_{j=1}^n x_j = \bar{x}. \text{ Substitute it into the second equation, we obtain the maximum}$$

likelihood estimate of σ^2 : $\hat{\sigma}^2 = \frac{1}{n} \sum_{j=1}^n (x_j - \bar{x})^2$. The corresponding maximum

$$\text{likelihood is thus } \max_{\mu, \sigma^2} L(\mu, \sigma^2) = \frac{1}{(2\pi)^{n/2} \hat{\sigma}^n} e^{-n/2}$$

15. (6%)

Answer:

$$\text{Likelihood} = \prod_{j=1}^n \frac{1}{\sqrt{2\pi\sigma}} e^{-(x_j - \mu_0)^2 / (2\sigma^2)} = \frac{1}{(2\pi)^{n/2} \sigma^n} e^{-\sum_{j=1}^n (x_j - \mu_0)^2 / 2\sigma^2} = L(\sigma^2)$$

Since the σ^2 which maximize $L(\sigma^2)$ are the same as those maximize,

$$l(\sigma^2) = \ln L(\sigma^2) = -\sum_{j=1}^n (x_j - \mu_0)^2 / 2\sigma^2 - \frac{n}{2} \ln 2\pi - \frac{n}{2} \ln \sigma^2, \text{ we set}$$

$$\frac{\partial l(\sigma^2)}{\partial \sigma^2} = \frac{1}{2\sigma^4} \sum_{j=1}^n (x_j - \mu_0)^2 - \frac{n}{2} \frac{1}{\sigma^2} = 0. \text{ From this equation, we can obtain the}$$

maximum likelihood estimate of σ^2 : $\hat{\sigma}_0^2 = \frac{1}{n} \sum_{j=1}^n (x_j - \mu_0)^2$. The corresponding

$$\text{maximum likelihood is thus } \max_{\sigma^2} L(\sigma^2) = \frac{1}{(2\pi)^{n/2} \hat{\sigma}_0^n} e^{-n/2}$$

16. (6%)

Answer:

$$\Lambda = \frac{\max_{\sigma^2} L(\sigma^2)}{\max_{\mu, \sigma^2} L(\mu, \sigma^2)} = \left(\frac{\hat{\sigma}^2}{\hat{\sigma}_0^2} \right)^{n/2}. \quad \text{Thus, } \Lambda^{2/n} = \frac{\hat{\sigma}^2}{\hat{\sigma}_0^2} = \frac{\sum_{j=1}^n (x_j - \bar{x})^2}{\sum_{j=1}^n (x_j - \mu_0)^2}$$

$$\Lambda^{2/n} = \frac{\sum_{j=1}^n (x_j - \bar{x})^2}{\sum_{j=1}^n (x_j - \mu_0)^2} = \frac{\sum_{j=1}^n (x_j - \bar{x})^2}{\sum_{j=1}^n (x_j - \bar{x} + \bar{x} - \mu_0)^2}. \quad \text{Since}$$

$$\begin{aligned} \sum_{j=1}^n (x_j - \bar{x} + \bar{x} - \mu_0)^2 &= \sum_{j=1}^n [(x_j - \bar{x})^2 + 2(x_j - \bar{x})(\bar{x} - \mu_0) + (\bar{x} - \mu_0)^2] \\ &= \sum_{j=1}^n (x_j - \bar{x})^2 + 2(\bar{x} - \mu_0) \sum_{j=1}^n (x_j - \bar{x}) + \sum_{j=1}^n (\bar{x} - \mu_0)^2, \quad \text{, because} \\ &= \sum_{j=1}^n (x_j - \bar{x})^2 + n(\bar{x} - \mu_0)^2 \end{aligned}$$

$$\sum_{j=1}^n (x_j - \bar{x}) = \sum_{j=1}^n x_j - n\bar{x} = 0. \quad \text{Thus,}$$

$$\Lambda^{2/n} = \frac{1}{1 + \frac{n(\bar{x} - \mu_0)^2}{\sum_{j=1}^n (x_j - \bar{x})^2}} = \left(1 + \frac{n(\bar{x} - \mu_0)^2}{(n-1)s^2} \right)^{-1} = \left(1 + \frac{t^2}{n-1} \right)^{-1}, \quad t = \frac{\bar{x} - \mu_0}{s/\sqrt{n}}$$

17. (6%)

Answer:

Since $\Lambda = \frac{\max_{\sigma^2} L(\sigma^2)}{\max_{\mu, \sigma^2} L(\mu, \sigma^2)} \leq 1$, and if H_0 holds, Λ will be close to 1. Thus if

$\Lambda \leq c_\alpha$, we may reject H_0 at significance level α . From Problem 16, we have

$$\Lambda^{2/n} = \left(1 + \frac{t^2}{n-1} \right)^{-1}, \quad \text{i.e., } \left(1 + \frac{t^2}{n-1} \right)^{-1} \leq c_\alpha^{2/n}, \quad \text{or } 1 + \frac{t^2}{n-1} \geq c_\alpha^{-2/n}.$$

Thus, $t^2 \geq (n-1)(c_\alpha^{-2/n} - 1)$ is required to reject H_0 at significance level α . This

is achieved by choosing $\sqrt{(n-1)(c_\alpha^{-2/n} - 1)} = t_{n-1}\left(\frac{\alpha}{2}\right)$, or $c_\alpha = \left(1 + \frac{t_{n-1}^2(\alpha/2)}{n-1}\right)^{-n/2}$.