

What to do today?

Part I. Introduction and Preparation

Part II. Inference under Multivariate Normal Distribution (Chp 4-7)

II.1 Multivariate Normal Distribution (Chp 4)

II.2 Inferences on Mean Vector (Chp 5)

II.2.1 Introduction (Chp5.1-2a)

II.2.2 Hotelling's T^2 and Likelihood Ratio Test (Chp5.2b-3)

II.2.3 Confidence Regions and Simultaneous Comparisons of Component Means (Chp5.4)

II.2.4 Large Sample Inference on Population Mean (Chp5.5)

II.2.5 Some Related Topics* (Chp5.6-8)

II.3 Comparisons of Several Mean Vector (Chp 6)

II.4 Multivariate Linear Regression (Chp 7)

Part II.1.1 Multivariate Normal Distribution, Review

Multivariate normal distribution A p-dim r.v. \mathbf{X} has a *normal* distribution if its pdf

$$f(\mathbf{x}; \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{\sqrt{|2\pi\boldsymbol{\Sigma}|}} \exp \left\{ -\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right\}, \quad -\infty < \mathbf{x} < \infty,$$

where $\boldsymbol{\Sigma}$ is positive definite. Denote it by $\mathbf{X} \sim MN_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$.

Shape of Multivariate Normal Density If $\mathbf{X} \sim BN(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, its pdf

$f(\mathbf{x}; \boldsymbol{\mu}, \boldsymbol{\Sigma})$ is a constant for all $\mathbf{x} = (x_1, x_2)'$ satisfy

$(\mathbf{x} - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) = c^2$. (It defines an ellipse centered at

$\boldsymbol{\mu} = (\mu_1, \mu_2)'$, and with axes $\pm c\sqrt{\lambda_j} \mathbf{e}_j$.)

$(\mathbf{X} - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{X} - \boldsymbol{\mu}) \sim \chi_p^2$, the Chi-square distribution with degree of freedom p .

II.1.2 Estimation of μ and Σ , Review

Consider $\mathbf{X} \sim MN_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$: what are $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$?

Suppose $\mathbf{X}_1, \dots, \mathbf{X}_n$ are iid observations on \mathbf{X} , how to use the data to estimate $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$?

II.1.2A. By Method of Moments: The MME $\hat{\boldsymbol{\mu}} = \bar{\mathbf{X}} = \sum_{i=1}^n \mathbf{X}_i / n$, the sample mean, and $\hat{\boldsymbol{\Sigma}} = \frac{1}{n} \sum_{i=1}^n (\mathbf{X}_i - \bar{\mathbf{X}})(\mathbf{X}_i - \bar{\mathbf{X}})'$ $= \frac{n-1}{n} \mathbf{S}$.

II.1.2B. By Maximum Likelihood Estimation The MLE $\hat{\boldsymbol{\mu}} = \bar{\mathbf{X}}$ and $\hat{\boldsymbol{\Sigma}} = \frac{n-1}{n} \mathbf{S}$ are the same as the MME.

II.2.2 Hotelling's T^2 and Likelihood Ratio Test (Chp5.2b-3), Review

Suppose $\mathbf{X} \sim MN_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ with iid observations $\mathbf{X}_1, \dots, \mathbf{X}_n$

To test on $H_0 : \boldsymbol{\mu} = \boldsymbol{\mu}_0$ vs $H_1 : \text{otherwise}$ when $\boldsymbol{\Sigma}$ is known

- ▶ *Test statistic.* Note that $\mathbf{Z} = \sqrt{n}\boldsymbol{\Sigma}^{-1/2}(\bar{\mathbf{X}} - \boldsymbol{\mu}_0) \sim MN(\mathbf{0}, \mathbf{I})$ under H_0 . Consider to use

$$W = \mathbf{Z}'\mathbf{Z} = (\bar{\mathbf{X}} - \boldsymbol{\mu}_0)' \left(\frac{\boldsymbol{\Sigma}}{n} \right)^{-1} (\bar{\mathbf{X}} - \boldsymbol{\mu}_0) \sim \chi^2(p) \text{ under } H_0$$

- ▶ *Rejection region.* With pre-determined α , $\mathcal{R} = \{w : w > \chi_{\alpha}^2(p)\}$
- ▶ *Making decision.* Reject H_0 if $W_{obs} \in \mathcal{R}$; otherwise, accept H_0 .

Wald-test procedure.

Suppose $\mathbf{X} \sim MN_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ with iid observations $\mathbf{X}_1, \dots, \mathbf{X}_n$

To test on $H_0 : \boldsymbol{\mu} = \boldsymbol{\mu}_0$ vs $H_1 : \text{otherwise}$ when $\boldsymbol{\Sigma}$ is unknown

- ▶ *Test statistic.* Consider $\mathbf{T} = \sqrt{n}\mathbf{S}^{-1/2}(\bar{\mathbf{X}} - \boldsymbol{\mu}_0)$ and under H_0

$$W = \mathbf{T}'\mathbf{T} = (\bar{\mathbf{X}} - \boldsymbol{\mu}_0)' \left(\frac{\mathbf{S}}{n} \right)^{-1} (\bar{\mathbf{X}} - \boldsymbol{\mu}_0) \sim T^2(p, n-1)$$

- ▶ *Rejection region.* With pre-determined α ,
$$\mathcal{R} = \{w : w > T_{\alpha}^2(p, n-1)\}$$
- ▶ *Making decision.* Reject H_0 if $W_{obs} \in \mathcal{R}$; otherwise, accept H_0 .

Hotelling's T^2 -test procedure.

Suppose $\mathbf{X} \sim MN_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ with iid observations $\mathbf{X}_1, \dots, \mathbf{X}_n$

To test on $H_0 : \boldsymbol{\mu} = \boldsymbol{\mu}_0$ vs H_1 : otherwise when $\boldsymbol{\Sigma}$ is unknown by the likelihood ratio test

$$L(\boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{np/2} |\boldsymbol{\Sigma}|} \exp \left\{ -\frac{1}{2} \sum_{i=1}^n (\mathbf{x}_i - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{x}_i - \boldsymbol{\mu}) \right\}$$

- ▶ Test statistic.

$$\Lambda = \frac{L(\boldsymbol{\mu}_0, \hat{\boldsymbol{\Sigma}}_0)}{L(\hat{\boldsymbol{\mu}}, \hat{\boldsymbol{\Sigma}})} = \left(\frac{|\hat{\boldsymbol{\Sigma}}|}{|\hat{\boldsymbol{\Sigma}}_0|} \right)^{n/2}$$

$\Lambda^{2/n}$ is called Wilks's lambda and

$$\Lambda^{2/n} = \left(1 + \frac{T^2}{n-1} \right)^{-1}$$

under H_0 .

- ▶ Rejection region. With pre-determined α , $\mathcal{R} = \{\lambda : \lambda < c\}$ with c determined by $P_{H_0}(\Lambda < c) = \alpha$.
- ▶ Making decision. Reject H_0 if $\Lambda_{obs} \in \mathcal{R}$; otherwise, accept H_0 .

Likelihood ratio test procedure

Why not just perform multiple univariate t-tests?

Suppose $\mathbf{X} \sim MN_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ and we want to test

$$H_0 : \boldsymbol{\mu} = \boldsymbol{\mu}_0.$$

- ▶ A natural idea: test each component μ_j using a univariate *t*-test.
- ▶ Reject H_0 if *any* of the component-wise tests rejects.

A simulation example

- ▶ Generate repeated random samples from a multivariate normal distribution under $H_0 : \boldsymbol{\mu} = \boldsymbol{\mu}_0$.
- ▶ For each sample:
 - ▶ perform p separate univariate *t*-tests for μ_1, \dots, μ_p , and reject if any test rejects;
 - ▶ perform a single Hotelling's T^2 test for $\boldsymbol{\mu}$.
- ▶ Compare how often each procedure rejects H_0 .

II.2.3A Confidence Regions (Chp5.4)

Consider $\mathbf{X} \sim MN_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$: what are $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$?

Suppose $\mathbf{X}_1, \dots, \mathbf{X}_n$ are iid observations on \mathbf{X} , how to use the data to estimate $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$?

The $100(1 - \alpha)\%$ **confidence region** for $\boldsymbol{\mu}$ is

$$R(\mathbf{x}_1, \dots, \mathbf{x}_n) = \left\{ \boldsymbol{\mu} : \frac{(n-p)t^2}{(n-1)p} \leq F_{p,n-p}(\alpha) \right\}, \quad t^2 = (\bar{\mathbf{x}} - \boldsymbol{\mu})' \left(\frac{\mathbf{S}}{n} \right)^{-1} (\bar{\mathbf{x}} - \boldsymbol{\mu})$$

since

$$P\{R(\mathbf{x}_1, \dots, \mathbf{x}_n) \ni \text{the true } \boldsymbol{\mu}\} = 1 - \alpha$$

$$\iff P\left\{ (\bar{\mathbf{x}} - \boldsymbol{\mu})' \left(\frac{\mathbf{S}}{n} \right)^{-1} (\bar{\mathbf{x}} - \boldsymbol{\mu}) \leq \frac{(n-1)p}{(n-p)} F_{p,n-p}(\alpha) \right\} = 1 - \alpha.$$

Remarks.

- ▶ The $100(1 - \alpha)\%$ confidence region is the collection of μ_0 :
 $\{\mu_0 : "H_0 : \mu = \mu_0" \text{ cannot be rejected by } T^2\text{-test with type I error rate of } \alpha\}.$
- ▶ $R(\mathbf{x}_1, \dots, \mathbf{x}_n)$ is an ellipsoid centered at $\bar{\mathbf{x}}$, the axes of the confidence ellipsoid are

$$\pm \sqrt{\lambda_i} \sqrt{\frac{(n-1)p}{n-p} F_{p,n-p}(\alpha)} \mathbf{e}_i$$

with $(\lambda_i, \mathbf{e}_i)$ are the eigenvalues and eigenvectors of \mathbf{S}/n .

- ▶ To determine whether a given μ is in the region or not, compute the *squared generalized distance* between the value and $\bar{\mathbf{x}}$: $(\bar{\mathbf{x}} - \mu)' \left(\frac{\mathbf{S}}{n}\right)^{-1} (\bar{\mathbf{x}} - \mu)$ and then compare it with $\frac{(n-1)p}{(n-p)} F_{p,n-p}(\alpha)$.

Example. (Data of textbook p215, Table 5.1, Perspiration from 20 healthy females). Consider first two variables:

$$x_1 = (\text{Sweat rate}), \quad x_2 = (\text{Sodium})$$

II.2.3B Simultaneous Comparison of Component Means

Consider $\mathbf{X} \sim MN_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$. Suppose $\mathbf{X}_1, \dots, \mathbf{X}_n$ are iid observations on \mathbf{X} , how to use the data to estimate $\mathbf{a}' \boldsymbol{\mu}$?

Various $\mathbf{a}' \boldsymbol{\mu}$:

- ▶ $\mu_1 = \mathbf{a}' \boldsymbol{\mu}$ with $\mathbf{a}' = (1, 0, \dots, 0)$
- ▶ $\mu_1 - \mu_2 = \mathbf{a}' \boldsymbol{\mu}$ with $\mathbf{a}' = (1, -1, \dots, 0)$

Note that

$$Z = \mathbf{a}' \bar{\mathbf{X}} \sim N(\mathbf{a}' \boldsymbol{\mu}, \frac{1}{n} \mathbf{a}' \boldsymbol{\Sigma} \mathbf{a}), \quad s_Z^2 = \mathbf{a}' \mathbf{S} \mathbf{a}.$$

The t-statistic:

$$\frac{\mathbf{a}' \bar{\mathbf{X}} - \mathbf{a}' \boldsymbol{\mu}}{\sqrt{\mathbf{a}' \mathbf{S} \mathbf{a} / n}} \sim t_{n-1}$$

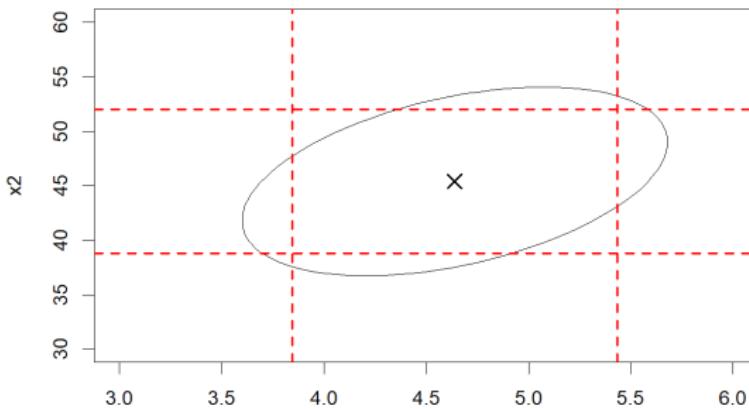
Thus, a $100(1 - \alpha)\%$ CI for $\mathbf{a}' \boldsymbol{\mu}$ is

$$\mathbf{a}' \bar{\mathbf{X}} \pm t_{n-1}(\alpha/2) \sqrt{\mathbf{a}' \mathbf{S} \mathbf{a} / n}.$$

Example. (cont'd) Consider $\mathbf{a}_1 = (1, 0)'$ and $\mathbf{a}_2 = (0, 1)'$. They CIs are

$$\bar{x}_1 \pm t_{20-1}(0.05/2) \sqrt{\frac{2.87}{20}} = (3.846, 5.434).$$

$$\bar{x}_2 \pm t_{20-1}(0.05/2) \sqrt{\frac{199.78}{20}} = (38.785, 52.015).$$



Why the confidence region and the two confidence intervals are different?

Denote the Cls by μ_1, μ_2 are (L_1, R_1) and (L_2, R_2) .

Let $A = \text{"}\mu_1 \in (L_1, R_1)\text{"}$ and $B = \text{"}\mu_2 \in (L_2, R_2)\text{"}$

- ▶ $P(A) = .95$ and $P(B) = .95$.

- ▶ $P(A \cap B) = ?$

If A and B are indpt,

$$P(A \cap B) = P(A)P(B) = (.95)^2 = .9025 < .95.$$

- ▶ In general, if $P(A) = 1 - \alpha$ and $P(B) = 1 - \alpha$.

$$P(A \cap B) = 1 - P(A^c \cup B^c) \geq 1 - [P(A^c) + P(B^c)] = 1 - 2\alpha$$

Correction?

How to construct $100(1 - \alpha)\%$ simultaneous confidence intervals for m quantities, $\mathbf{a}_1' \boldsymbol{\mu}, \dots, \mathbf{a}_m' \boldsymbol{\mu}$?

Bonferroni intervals

- ▶ For $\mathbf{a}_j' \boldsymbol{\mu}$,

$$\mathbf{a}_j' \bar{\mathbf{x}} \pm t_{n-1}(\alpha_j/2) \sqrt{\mathbf{a}_j' \mathbf{S} \mathbf{a}_j / n}$$

with $j = 1, \dots, m$ and to have $1 - (\alpha_1 + \dots + \alpha_m) = 1 - \alpha$

- ▶ Often to use $\alpha_j = \alpha/m$.
- ▶ Make sure overall confidence level $\geq 1 - \alpha$.

How to construct $100(1 - \alpha)\%$ simultaneous confidence intervals for m quantities, $\mathbf{a}_1' \boldsymbol{\mu}, \dots, \mathbf{a}_m' \boldsymbol{\mu}$?

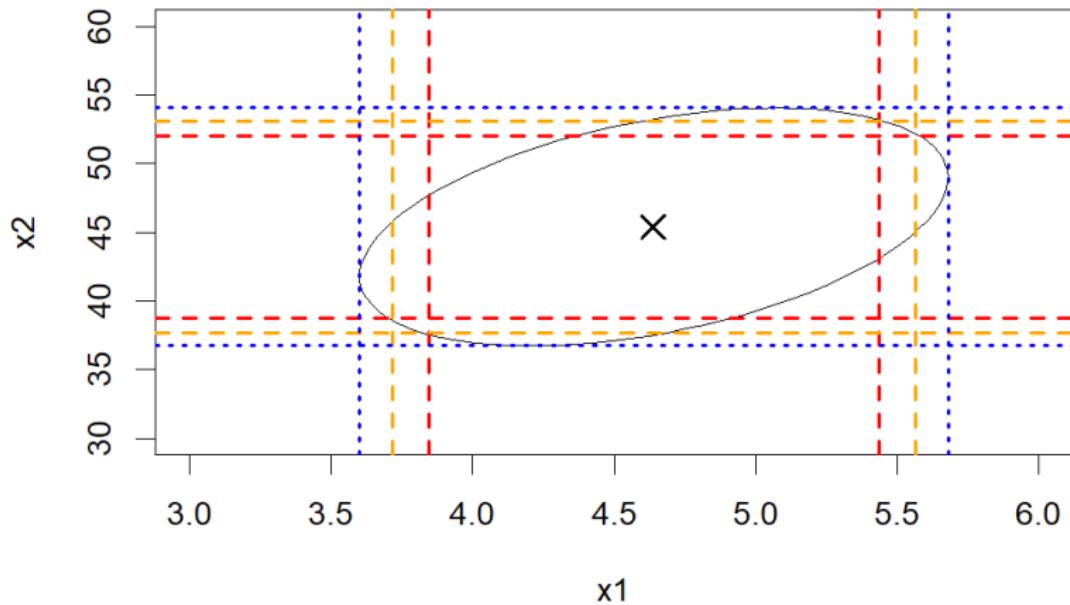
Simultaneous confidence intervals

- ▶ \implies for all \mathbf{a}

$$\mathbf{a}' \bar{\mathbf{x}} \pm \sqrt{\frac{(n-1)p}{n-p} F_{p,n-p}(\alpha)} \sqrt{\mathbf{a}' \mathbf{S} \mathbf{a} / n}$$

- ▶ Make sure even the worst-case direction has confidence level $\geq 1 - \alpha$.

Example. (cont'd)



II.2.4 Large Sample Inference on Population Mean (Chp5.5)

Consider iid p -dim r.v.s. $\mathbf{X}_1, \dots, \mathbf{X}_n$ with mean μ and variance Σ .

How to make inference about μ ?

- ▶ $\sqrt{n}\Sigma^{-1/2}(\bar{\mathbf{X}} - \mu) \rightarrow MN_p(\mathbf{0}, \mathbf{I})$ by CLT as $(n - p) \rightarrow \infty$.
Thus $n(\bar{\mathbf{X}} - \mu)' \Sigma^{-1} (\bar{\mathbf{X}} - \mu) \rightarrow \chi_p^2$ as $(n - p) \rightarrow \infty$.
- ▶ $n(\bar{\mathbf{X}} - \mu)' \mathbf{S}^{-1} (\bar{\mathbf{X}} - \mu) \rightarrow \chi_p^2$ as $(n - p) \rightarrow \infty$.

Hypothesis Testing $H_0 : \mu = \mu_0$ vs $H_1 : \mu \neq \mu_0$.

- ▶ Use the test statistic $T^2 = n(\bar{\mathbf{X}} - \mu_0)' \mathbf{S}^{-1} (\bar{\mathbf{X}} - \mu_0)$.
- ▶ Reject H_0 if $T^2 \geq \chi_p^2(\alpha)$. $\chi_p^2(\alpha)$ is the upper 100α -th percentile of χ_p^2 -distn.

Approximate confidence region. $T^2 = n(\bar{\mathbf{X}} - \mu)' \mathbf{S}^{-1} (\bar{\mathbf{X}} - \mu)$.

$$R(\mathbf{x}_1, \dots, \mathbf{x}_n) = \{\boldsymbol{\mu} : t^2 \leq \chi_p^2(\alpha)\}$$

II.2.5 Some Related Topics* (Chp 5.6-8)

- ▶ *Multivariate Quality Control Charts (Chp 5.6)*
system is under control or not?
 - ▶ extensions of univariate quality control charts
 - ▶ Ellipse Format Chart; T^2 -Chart; ...
- ▶ *Inference about Mean Vectors when Some Observations are Missing (Chp 5.7)*
 - ▶ prediction?
 - ▶ missing mechanism?
- ▶ *Dependence in Multivariate Observations*
 - ▶ time series
 - ▶ spatial correlated data
 - ▶ clustered data

What will we study next?

- ▶ *Part I. Introduction and Preparation*
- ▶ **Part II. Inference under Multivariate Normal Distribution (Chp 4-7)**
 - ▶ *II.1 Multivariate Normal Distribution (Chp 4)*
 - ▶ *II.2 Inferences on Mean Vector (Chp 5)*
 - ▶ **II.3 Comparisons of Several Mean Vector (Chp 6)**
 - ▶ *II.3.1 Introduction (Chp 6.1)*
 - ▶ **II.3.2 Comparing Mean Vectors from Two Populations (Chp 6.2-3)**
 - ▶ *II.3.3 Comparing Several Mean Vectors and Related (Chp 6.4-6)*
 - ▶ *II.3.3 Two-Way Multivariate Analysis of Variance (Chp 6.7)*
 - ▶ *II.4 Multivariate Linear Regression (Chp 7)*

Midterm 2 Papers Will be Returned on Thur Feb 7.