

## Testing a Hypothesis about the Mean

- ▶ Consider as usual a random sample  $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N$  from  $N_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ .
- ▶ Recall: if  $\boldsymbol{\Sigma}$  is known, we can test the null hypothesis

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

with the size- $\alpha$  critical region

$$N(\bar{\mathbf{x}} - \boldsymbol{\mu}_0)' \boldsymbol{\Sigma}^{-1} (\bar{\mathbf{x}} - \boldsymbol{\mu}_0) > \chi_p^2(\alpha)$$

- ▶ If  $\boldsymbol{\Sigma}$  is unknown, the natural statistic to use is

$$T^2 = N(\bar{\mathbf{x}} - \boldsymbol{\mu}_0)' \mathbf{S}^{-1} (\bar{\mathbf{x}} - \boldsymbol{\mu}_0).$$

- ▶ We need to justify its use, and find its null distribution.

# Likelihood Ratio Test

- ▶ The likelihood function is

$$L(\boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{\left(\sqrt{\det 2\pi\boldsymbol{\Sigma}}\right)^N} \exp \left[ -\frac{1}{2} \sum_{\alpha=1}^N (\mathbf{x}_\alpha - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{x}_\alpha - \boldsymbol{\mu}) \right].$$

- ▶ The generalized likelihood ratio statistic is

$$\lambda = \frac{\max_{\boldsymbol{\Sigma}} L(\boldsymbol{\mu}_0, \boldsymbol{\Sigma})}{\max_{\boldsymbol{\mu}, \boldsymbol{\Sigma}} L(\boldsymbol{\mu}, \boldsymbol{\Sigma})}$$

- ▶ Write  $\hat{\Sigma}_\omega$  for the mle of  $\Sigma$  under  $H_0$ , when  $\mu = \mu_0$ , and  $\hat{\Sigma}_\Omega$  for the mle of  $\Sigma$  under the alternative hypothesis, when  $\mu$  is unconstrained.
- ▶ Then

$$\hat{\Sigma}_\omega = \frac{1}{N} \sum_{\alpha=1}^N (\mathbf{x}_\alpha - \mu_0) (\mathbf{x}_\alpha - \mu_0)'$$

and

$$L(\mu_0, \hat{\Sigma}_\omega) = \max_{\Sigma} L(\mu_0, \Sigma) = \frac{1}{\left(\sqrt{\det 2\pi \hat{\Sigma}_\omega}\right)^N} \times e^{-\frac{1}{2}pN}.$$

- ▶ Similarly

$$\hat{\Sigma}_\Omega = \frac{1}{N} \sum_{\alpha=1}^N (\mathbf{x}_\alpha - \bar{\mathbf{x}}) (\mathbf{x}_\alpha - \bar{\mathbf{x}})'$$

and

$$L(\bar{\mathbf{x}}, \hat{\Sigma}_\Omega) = \max_{\mu, \Sigma} L(\mu, \Sigma) = \frac{1}{\left(\sqrt{\det 2\pi \hat{\Sigma}_\Omega}\right)^N} \times e^{-\frac{1}{2}pN}.$$

- ▶ So the generalized likelihood ratio statistic is

$$\lambda = \frac{\left(\sqrt{\det 2\pi \hat{\Sigma}_{\Omega}}\right)^N}{\left(\sqrt{\det 2\pi \hat{\Sigma}_{\omega}}\right)^N}$$

$$= \left\{ \frac{\det \left[ \sum_{\alpha=1}^N (\mathbf{x}_{\alpha} - \bar{\mathbf{x}}) (\mathbf{x}_{\alpha} - \bar{\mathbf{x}})' \right]}{\det \left[ \sum_{\alpha=1}^N (\mathbf{x}_{\alpha} - \mu_0) (\mathbf{x}_{\alpha} - \mu_0)' \right]} \right\}^{\frac{1}{2}N}$$

► Now

$$\begin{aligned}
 \sum_{\alpha=1}^N (\mathbf{x}_\alpha - \boldsymbol{\mu}_0) (\mathbf{x}_\alpha - \boldsymbol{\mu}_0)' & \\
 &= \sum_{\alpha=1}^N (\mathbf{x}_\alpha - \bar{\mathbf{x}}) (\mathbf{x}_\alpha - \bar{\mathbf{x}})' + N(\bar{\mathbf{x}} - \boldsymbol{\mu}_0)(\bar{\mathbf{x}} - \boldsymbol{\mu}_0)' \\
 &= (N-1)\mathbf{S} + N(\bar{\mathbf{x}} - \boldsymbol{\mu}_0)(\bar{\mathbf{x}} - \boldsymbol{\mu}_0)'
 \end{aligned}$$

whence

$$\begin{aligned}
 \det \left[ \sum_{\alpha=1}^N (\mathbf{x}_\alpha - \boldsymbol{\mu}_0) (\mathbf{x}_\alpha - \boldsymbol{\mu}_0)' \right] & \\
 &= \det[(N-1)\mathbf{S}] \{1 + N(\bar{\mathbf{x}} - \boldsymbol{\mu}_0)'[(N-1)\mathbf{S}]^{-1}(\bar{\mathbf{x}} - \boldsymbol{\mu}_0)\}
 \end{aligned}$$

- ▶ So

$$\begin{aligned}\lambda^{\frac{2}{N}} &= \frac{1}{1 + N(\bar{\mathbf{x}} - \boldsymbol{\mu}_0)'[(N - 1)\mathbf{S}]^{-1}(\bar{\mathbf{x}} - \boldsymbol{\mu}_0)} \\ &= \frac{1}{1 + \frac{T^2}{N - 1}}\end{aligned}$$

- ▶ Since  $\lambda$  is a monotone function of  $T^2$ , they define equivalent tests.
- ▶ That is, the test based on  $T^2$ , known as *Hotelling's  $T^2$* , is equivalent to the generalized ratio test.

## Invariance

- ▶ If  $\mathbf{X} \sim N_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$  and  $\mathbf{X}^* = \mathbf{C}\mathbf{X}$  for a nonsingular  $\mathbf{C}$ , then  $\mathbf{X}^* \sim N_p(\boldsymbol{\mu}^*, \boldsymbol{\Sigma}^*)$ , where

$$\boldsymbol{\mu}^* = \mathbf{C}\boldsymbol{\mu}, \quad \boldsymbol{\Sigma}^* = \mathbf{C}\boldsymbol{\Sigma}\mathbf{C}'$$

- ▶ The null hypothesis  $H_0 : \boldsymbol{\mu} = \boldsymbol{\mu}_0$  is equivalent to the null hypothesis  $H_0^* : \boldsymbol{\mu}^* = \mathbf{C}\boldsymbol{\mu}_0$ .
- ▶ If  $T^2$  is the statistic for testing  $H_0$ , based on  $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N$ , and  $T^{*2}$  is the statistic for testing  $H_0^*$ , based on  $\mathbf{x}_1^*, \mathbf{x}_2^*, \dots, \mathbf{x}_N^*$ , then  $T^{*2} = T^2$ .
- ▶ That is, the statistic  $T^2$ , and the test based on it, are invariant to the mapping  $\mathbf{X} \mapsto \mathbf{X}^*, \boldsymbol{\mu} \mapsto \boldsymbol{\mu}^*$ .
- ▶ The test based on Hotelling's  $T^2$  is the *uniformly most powerful* test with this invariance property.

## Distribution of $T^2$

- ▶  $T^2$  may be written as  $\mathbf{Y}'\mathbf{S}^{-1}\mathbf{Y}$ , where  $\mathbf{Y} \sim N_p(\boldsymbol{\nu}, \boldsymbol{\Sigma})$ , and  $\mathbf{S}$  is of the form

$$n\mathbf{S} = \sum_{\alpha=1}^n \mathbf{z}_\alpha \mathbf{z}'_\alpha$$

where  $\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_n$  are iid  $N_p(\mathbf{0}, \boldsymbol{\Sigma})$ , independent of  $\mathbf{Y}$ .

- ▶ Without loss of generality, we can take  $\boldsymbol{\Sigma} = \mathbf{I}_p$  (see above, “Invariance”).
- ▶ Construct a  $p \times p$  orthogonal matrix  $\mathbf{Q}$  with first row  $\mathbf{Y}'/\sqrt{\mathbf{Y}'\mathbf{Y}}$ , and the remaining rows arbitrary.
- ▶ Then

$$\mathbf{Q}\mathbf{Y} = \begin{pmatrix} \sqrt{\mathbf{Y}'\mathbf{Y}} \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$



- ▶ Hence

$$\begin{aligned}
 T^2 &= \mathbf{Y}'\mathbf{S}^{-1}\mathbf{Y} \\
 &= (\mathbf{QY})'(\mathbf{QSQ}')^{-1}(\mathbf{QY}) \\
 &= (\mathbf{Y}'\mathbf{Y})(\mathbf{QSQ}')^{1,1}
 \end{aligned}$$

where  $\mathbf{A}^{i,j}$  denotes the  $(i,j)$  entry of  $\mathbf{A}^{-1}$ .

- ▶ Write

$$n\mathbf{QSQ}' = \mathbf{B} = \begin{pmatrix} b_{1,1} & \mathbf{b}'_{(1)} \\ \mathbf{b}_{(1)} & \mathbf{B}_{2,2} \end{pmatrix}$$

and note that

$$n\mathbf{QSQ}' = \mathbf{B} = \sum_{\alpha=1}^n (\mathbf{QZ}_{\alpha})(\mathbf{QZ}_{\alpha})'$$

- ▶  $\mathbf{Q}$  is random, but conditionally on  $\mathbf{Q}$ ,  $\mathbf{QZ}_\alpha$  has the same distribution as  $\mathbf{Z}_\alpha$ , so  $\mathbf{B}$  has the same distribution as  $n\mathbf{S}$ .
- ▶ Since this *conditional* distribution does not depend on  $\mathbf{Q}$ , it is also the *unconditional* distribution, and  $\mathbf{B}$  is independent of  $\mathbf{Q}$ , and hence of  $\mathbf{Y}$ .
- ▶ Also

$$\frac{1}{b^{1,1}} = b_{1,1} - \mathbf{b}'_{(1)} \mathbf{B}_{2,2}^{-1} \mathbf{b}_{(1)} = b_{1,1 \cdot 2, \dots, p}$$

a sample partial (or residual) variance, which is therefore distributed as  $\chi^2$  with  $n - (p - 1)$  degrees of freedom.

- ▶ So finally,

$$\frac{T^2}{n} = \frac{\mathbf{Y}'\mathbf{Y}}{b_{1,1,2,\dots,p}}$$

is the ratio of a (possibly non-central)  $\chi^2$  random variable with  $p$  degrees of freedom to an independent central  $\chi^2$  random variable with  $n - (p - 1)$  degrees of freedom.

- ▶ Consequently,

$$\frac{n - (p - 1)}{p} \times \frac{T^2}{n} = \frac{\mathbf{Y}'\mathbf{Y}/p}{b_{1,1,2,\dots,p}/[n - (p - 1)]}$$

has the  $F$  distribution with  $p$  and  $n - (p - 1)$  degrees of freedom.

- ▶ Under the null hypothesis  $\boldsymbol{\mu} = \boldsymbol{\mu}_0$ ,  $\boldsymbol{\nu} = \mathbf{0}$ , and the distribution is central.