

# INFERENCES ABOUT THE MEAN VECTOR

**Reference:** Johnson & Wichern (2007) *Applied Multivariate Statistical Analysis* Chapter 5.

## 1 Hypotheses Testing for $\mu$

**Problem:**

Given a random sample  $\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_n$  from a  $p$  variate normal (or approximately normal) population with mean  $\mu$  and covariance matrix  $\Sigma$  where  $\Sigma$  is unknown. Examine whether  $\mu$  is significantly different from a given value,  $\mu_0$  at a specified level of significance, say  $\alpha$ .

**Note:** Since  $\mathbf{X}_j \sim N_p(\mu, \Sigma)$ , sample mean  $\bar{\mathbf{X}}_n \sim N_p(\mu, \frac{1}{n}\Sigma)$ .

**Hypotheses:**  $H_0 : \mu = \mu_0$  against  $H_1 : \mu \neq \mu_0$ .

**Test Statistic:**  $T^2 = n(\bar{\mathbf{X}}_n - \mu_0)^T \mathcal{S}_n^{-1}(\bar{\mathbf{X}}_n - \mu_0)$ .

Note that  $T^2$  has a Hotelling's  $T^2$  distribution and hence,  $\frac{n-p}{p(n-1)}T^2$  has a  $F$ -distribution with  $p$  and  $n-p$  degrees of freedom.

**Decision:** Reject  $H_0$  if

$$\frac{n-p}{p(n-1)}T^2 > F_{p,n-p}(\alpha)$$

where  $F_{p,n-p}(\alpha)$  is the upper  $100\alpha$  percentile of the  $F_{p,n-p}$  distribution.

## 2 Confidence Region for $\boldsymbol{\mu}$

Since the distribution of  $\frac{n-p}{p(n-1)}T^2$  is  $F_{p,n-p}$ ,

$$\mathcal{P} \left[ \frac{n-p}{p(n-1)}T^2 > F_{p,n-p}(\alpha) \right] = \alpha.$$

Hence,  $\mathcal{P} \left[ T^2 \leq \frac{p(n-1)}{n-p}F_{p,n-p}(\alpha) \right] = 1 - \alpha$  and

$$\mathcal{P} \left[ n(\bar{\mathbf{X}}_n - \boldsymbol{\mu})^T \mathcal{S}_n^{-1} (\bar{\mathbf{X}}_n - \boldsymbol{\mu}) \leq \frac{p(n-1)}{n-p}F_{p,n-p}(\alpha) \right] = 1 - \alpha$$

Thus  $\bar{\mathbf{X}}_n$  will be within  $\left[ \frac{p(n-1)}{n-p}F_{p,n-p}(\alpha) \right]^{1/2}$  of  $\boldsymbol{\mu}$  with probability  $1 - \alpha$  provided distance is defined in terms of  $(\mathcal{S}_n/n)^{1/2}$ . Therefore, a  $100(1 - \alpha)\%$  confidence region for  $\boldsymbol{\mu}$  is

$$n(\bar{\mathbf{X}}_n - \boldsymbol{\mu})^T \mathcal{S}_n^{-1} (\bar{\mathbf{X}}_n - \boldsymbol{\mu}) \leq \frac{p(n-1)}{n-p}F_{p,n-p}(\alpha).$$

If  $\bar{\mathbf{x}}_n$  is the sample average of the observed values, then

$$n(\bar{\mathbf{x}}_n - \boldsymbol{\mu})^T \mathcal{S}_n^{-1} (\bar{\mathbf{x}}_n - \boldsymbol{\mu}) \leq \frac{p(n-1)}{n-p}F_{p,n-p}(\alpha).$$

This is an ellipsoid with center at  $\bar{\mathbf{x}}_n$ . The axes and relative lengths are given by eigenvectors  $\mathbf{e}_i$  and eigenvalues  $\lambda_i$  of  $\mathcal{S}_n$ .

Let  $c^2 = \frac{p(n-1)}{n-p}F_{p,n-p}(\alpha)$  then length of the axis along  $\mathbf{e}_i$  is  $2\sqrt{\frac{\lambda_i}{n}}c$ . That is the axes of the  $p$ -variate confidence ellipsoid are

$$\bar{\mathbf{x}}_n \pm 2\sqrt{\frac{\lambda_i}{n}}c \mathbf{e}_i \quad \text{for } i = 1, 2, \dots, p.$$

### 3 Simultaneous Confidence Interval ( $T^2$ - Interval)

Let  $\mathbf{a}$  be a  $p \times 1$  constant vector, then for ever  $\mathbf{a}$

$$\mathbf{a}^T \bar{\mathbf{X}}_n \pm \sqrt{\frac{p(n-1)}{n-p} F_{p,n-p}(\alpha)} \frac{\mathbf{a}^T \mathbf{S}_n \mathbf{a}}{n}$$

is a  $100(1 - \alpha)\%$  confidence interval for  $\mathbf{a}^T \boldsymbol{\mu}$ .

The successive choices of  $\mathbf{a}^T = (1, 0, \dots, 0)$ ,  $\mathbf{a}^T = (0, 1, \dots, 0)$ , and so on through  $\mathbf{a}^T = (0, 0, \dots, 1)$  gives the confidence interval for  $\mu_1, \mu_2, \dots, \mu_p$  respectively.

$$\begin{aligned} \bar{X}_{1n} &\pm \sqrt{\frac{p(n-1)}{n-p} F_{p,n-p}(\alpha)} \sqrt{\frac{S_{11}}{n}}, \\ \bar{X}_{2n} &\pm \sqrt{\frac{p(n-1)}{n-p} F_{p,n-p}(\alpha)} \sqrt{\frac{S_{22}}{n}}, \\ &\vdots \\ \bar{X}_{pn} &\pm \sqrt{\frac{p(n-1)}{n-p} F_{p,n-p}(\alpha)} \sqrt{\frac{S_{pp}}{n}}. \end{aligned}$$

where  $\bar{\mathbf{X}}_n^T = (\bar{X}_{1n}, \bar{X}_{2n}, \dots, \bar{X}_{pn})$ . Thus confidence interval for  $\mu_i$ , ( $i = 1, 2, \dots, p$ ) is given by

$$\left( \bar{X}_{in} - \sqrt{\frac{p(n-1)}{n-p} F_{p,n-p}(\alpha)} \sqrt{\frac{S_{ii}}{n}}, \quad \bar{X}_{in} + \sqrt{\frac{p(n-1)}{n-p} F_{p,n-p}(\alpha)} \sqrt{\frac{S_{ii}}{n}} \right).$$

Further taking  $\mathbf{a}^T = (0, 0, \dots, a_i, 0, \dots, 0, a_k, 0, \dots, 0)$  with  $a_i = -a_k = 1$ , we can obtain a  $(1 - \alpha)\%$  confidence interval for  $\mu_i - \mu_k$  as follows:

$$\begin{aligned} &\left( (\bar{X}_{in} - \bar{X}_{kn}) - \sqrt{\frac{p(n-1)}{n-p} F_{p,n-p}(\alpha)} \sqrt{\frac{S_{ii} - 2S_{ik} + S_{kk}}{n}}, \right. \\ &\quad \left. (\bar{X}_{in} - \bar{X}_{kn}) + \sqrt{\frac{p(n-1)}{n-p} F_{p,n-p}(\alpha)} \sqrt{\frac{S_{ii} - 2S_{ik} + S_{kk}}{n}} \right). \end{aligned}$$

**Note:** Since  $\frac{p(n-1)}{n-p} F_{p,n-p} = T^2$ , the above confidence intervals are called  $T^2$  intervals.

## 4 Bonferroni Intervals

Bonferroni confidence intervals can be computed for any number  $m(\leq p)$  of individuals means. The length of a Bonferroni interval is shorter than the length of the corresponding  $T^2$  interval and they are equal only if  $m = p = 1$ .

For any  $m(\leq p)$ ,  $100(1 - \alpha)\%$  Bonferroni intervals for  $\mu_i$  ( $i = 1, 2, \dots, m$ ) are given by

$$\left( \bar{X}_{in} - t_{n-1} \left( \frac{\alpha}{2m} \right) \sqrt{\frac{S_{ii}}{n}}, \quad \bar{X}_{in} + t_{n-1} \left( \frac{\alpha}{2m} \right) \sqrt{\frac{S_{ii}}{n}} \right).$$

**Note:**

Length of Bonferroni interval =  $2t_{n-1} \left( \frac{\alpha}{2m} \right) \sqrt{\frac{S_{ii}}{n}}$  and

Length of  $T^2$  interval =  $2\sqrt{\frac{p(n-1)}{n-p} F_{p,n-p}(\alpha)} \sqrt{\frac{S_{ii}}{n}}$ .

Thus, the ratio

$$\frac{\text{Length of Bonferroni interval}}{\text{Length of } T^2 \text{ interval}} = \frac{t_{n-1} \left( \frac{\alpha}{2m} \right)}{\sqrt{\frac{p(n-1)}{n-p} F_{p,n-p}(\alpha)}}$$

This does not depend on random quantities,  $\bar{\mathbf{X}}_n$  and  $\mathcal{S}_n$  and using numerical computation we can show that this ratio is less than 1 for all  $m \leq p$  and  $p > 1$ .

## 5 Large sample Theory

When the sample size is large, test of hypotheses and confidence intervals for  $\boldsymbol{\mu}$  can be constructed without the normality assumption on the population.

Consider a random sample  $\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_n$  from a  $p$ -variate population (not necessarily normal) with mean  $\boldsymbol{\mu}$  and positive definite covariance matrix  $\Sigma$ . Further,  $n$  is large relative to  $p$ .

It can be proved that distribution of  $T^2$ , for this case, is approximately chi-square with  $p$  degrees of freedom. That is,

$$n (\bar{\mathbf{X}}_n - \boldsymbol{\mu})^T \mathcal{S}_n^{-1} (\bar{\mathbf{X}}_n - \boldsymbol{\mu}) \approx \chi_p^2.$$

Note that when  $n$  is large relative to  $p$

- (a)  $\mathcal{S}_n \approx \Sigma$  (using law of large numbers)
- (b) and hence, the distribution of  $T^2$  is approximately  $\chi_p^2$ .
- (c) Further, it can be proved that, as  $n \rightarrow \infty$

$$\frac{p(n-p)}{n-p} F_{p,n-p} \rightarrow \chi_p^2$$

## 6 Hypotheses Testing for $\mu$

Consider the hypotheses:

$$H_0 : \mu = \mu_0 \quad \text{against} \quad H_1 : \mu \neq \mu_0.$$

Since  $n$  is large relative to  $p$ , test statistic

$$T^2 = n (\bar{\mathbf{X}}_n - \mu_0)^T \mathcal{S}_n^{-1} (\bar{\mathbf{X}}_n - \mu_0) \approx \chi_p^2.$$

Hence reject  $H_0$  if  $T^2 > \chi_p^2(\alpha)$  where  $\chi_p^2(\alpha)$  is the upper  $100\alpha$  percentile of the chi-square distribution with  $p$  degrees of freedom.

## 7 Confidence Region for $\mu$

A  $100(1 - \alpha)\%$  confidence interval for  $\mu$  is

$$n (\bar{\mathbf{X}}_n - \mu)^T \mathcal{S}_n^{-1} (\bar{\mathbf{X}}_n - \mu) \leq \chi_p^2(\alpha)$$

Note that this is an ellipsoid and the axes of the ellipsoid can calculate using the eigenvalues and eigenvectors of  $\mathcal{S}$ . See Week 4 Lecture Note for details.

## 8 Simultaneous Confidence Intervals

A  $100(1 - \alpha)\%$  confidence interval for  $\mu_i$  for  $i = 1, 2, \dots, p$  is given by

$$\left( \bar{X}_{in} - \sqrt{\chi_p^2(\alpha)} \sqrt{\frac{S_{ii}}{n}}, \quad \bar{X}_{in} + \sqrt{\chi_p^2(\alpha)} \sqrt{\frac{S_{ii}}{n}} \right).$$