

Maximum likelihood estimation

$x_i \sim N_d(\mu, \Sigma)$, $i=1, \dots, n$, independent, $n-1 \geq d$

$$\begin{aligned} L(\mu, \Sigma) &= \prod_{i=1}^n (2\pi)^{-\frac{d}{2}} (\det \Sigma)^{-\frac{1}{2}} \exp\left(-\frac{1}{2} (x_i - \mu)^T \Sigma^{-1} (x_i - \mu)\right) \\ &= (2\pi)^{-\frac{nd}{2}} (\det \Sigma)^{-\frac{n}{2}} \exp\left(-\frac{1}{2} \sum_{i=1}^n (x_i - \mu)^T \Sigma^{-1} (x_i - \mu)\right) \end{aligned}$$

$$\ln L(\mu, \Sigma) = -\frac{nd}{2} \ln(2\pi) - \frac{n}{2} \ln \det \Sigma - \frac{1}{2} \sum_{i=1}^n (x_i - \mu)^T \Sigma^{-1} (x_i - \mu)$$

$$\begin{aligned} \sum_{i=1}^n (x_i - \mu)^T \Sigma^{-1} (x_i - \mu) &= \sum_{i=1}^n \text{tr}\left((x_i - \mu)^T \Sigma^{-1} (x_i - \mu)\right) \\ &= \sum_{i=1}^n \text{tr}\left(\Sigma^{-1} (x_i - \mu)(x_i - \mu)^T\right) \\ &= \text{tr}\left(\Sigma^{-1} \sum_{i=1}^n (x_i - \mu)(x_i - \mu)^T\right) \end{aligned}$$

$$\begin{aligned} \sum_{i=1}^n (x_i - \mu)(x_i - \mu)^T &= \sum_{i=1}^n (x_i - \bar{x} + \bar{x} - \mu)(x_i - \bar{x} + \bar{x} - \mu)^T \\ &= \sum_{i=1}^n (x_i - \bar{x})(x_i - \bar{x})^T + 0 + 0 + n(\bar{x} - \mu)(\bar{x} - \mu)^T \\ &= Q + n(\bar{x} - \mu)(\bar{x} - \mu)^T \end{aligned}$$

$$\begin{aligned} \sum_{i=1}^n (x_i - \mu)^T \Sigma^{-1} (x_i - \mu) &= \text{tr}\left(\Sigma^{-1} Q + n \Sigma^{-1} (\bar{x} - \mu)(\bar{x} - \mu)^T\right) \\ &= \text{tr}(\Sigma^{-1} Q) + n \text{tr}\left((\bar{x} - \mu)^T \Sigma^{-1} (\bar{x} - \mu)\right) \\ &\geq \text{tr}(\Sigma^{-1} Q) \end{aligned}$$

$$\ln L(\mu, \Sigma) \leq -\frac{nd}{2} \ln(2\pi) - \frac{n}{2} \ln \det \Sigma - \frac{1}{2} \text{tr}(\Sigma^{-1} Q)$$

equality for $\mu = \bar{x}$, thus $\hat{\mu} = \bar{x}$ for all $\Sigma > 0$

$$\ln L(\hat{\mu}, \Sigma) = -\frac{nd}{2} \ln(2\pi) - \frac{n}{2} \left(\ln \det \Sigma + \text{tr}\left(\Sigma^{-1} \frac{Q}{n}\right) \right)$$

Take $f(\Sigma) = \ln \det \Sigma + \text{tr}(\Sigma^{-1} A)$, $A > 0$

in the following we use A5.5, A5.4, A1.4, A5.7 and A5.1

$\Sigma^{-1}A$ and $\Sigma^{-\frac{1}{2}}A\Sigma^{-\frac{1}{2}}$ has the same eigenvalues λ_i

$$\Sigma^{-\frac{1}{2}}A\Sigma^{-\frac{1}{2}} > 0 \Rightarrow \lambda_i > 0, i=1, \dots, d$$

view the difference

$$f(\Sigma) - f(A) = \ln \det \Sigma + \text{tr}(\Sigma^{-1}A) - \ln \det A - \text{tr} I_d$$

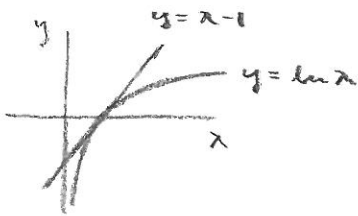
$$= -\ln \det(\Sigma^{-1}A) + \text{tr}(\Sigma^{-1}A) - d$$

$$= -\ln \prod_i \lambda_i + \sum_i \lambda_i - d \quad \text{cf. A1.2 (a), (c)}$$

$$= \sum_i (-\ln \lambda_i + \lambda_i - 1)$$

$$= \sum_i ((\lambda_i - 1) - \ln \lambda_i) \geq 0$$

equality for $\lambda_i = 1, i=1, \dots, d$, thus $\Sigma = A$
(see ** page 7)



$$\ln L(\hat{\mu}, \hat{\Sigma}) \leq -\frac{nd}{2} \ln(2\pi) - \frac{n}{2} (\ln \det \frac{Q}{n} + \text{tr} I_d)$$

equality for $\Sigma = \frac{Q}{n}$, thus $\hat{\Sigma} = \frac{Q}{n}$

$$\ln L(\hat{\mu}, \hat{\Sigma}) = -\frac{nd}{2} \ln(2\pi) - \frac{n}{2} \ln \det \hat{\Sigma} - \frac{nd}{2}$$

$$L(\hat{\mu}, \hat{\Sigma}) = (2\pi e)^{-\frac{nd}{2}} (\det \hat{\Sigma})^{-\frac{n}{2}}$$

Theorem 3.1

$$\left. \begin{aligned} (i) \quad & \bar{x} \sim N_d(\mu, \frac{\Sigma}{n}) \\ & Q \sim W_d(n-1, \Sigma) \end{aligned} \right\} \text{independent} \quad (Q = (n-1)S)$$

$$(ii) \quad T^2 = n(\bar{x} - \mu)^T S^{-1} (\bar{x} - \mu) \sim T^2(d, n-1)$$

Proof:

(i) Let $y_i = x_i - \mu$, hence $y_i \sim N_d(0, \Sigma)$, $i=1, \dots, n$
independent

$$\text{and } P = \frac{1}{n} \underset{\sim}{1}_n \underset{\sim}{1}_n^T$$

Now using corollary 3 to theorem 2.4 :

$$\left. \begin{aligned} \bar{y} &= Y^T \left(\frac{1}{n} \mathbf{1}_n \right) \sim N_d \left(\underline{\mu}, \frac{\Sigma}{n} \right) \\ Q &= Y^T (I_n - P) Y \sim W_d (n-1, \Sigma) \end{aligned} \right\} \text{independent}$$

as $\text{Var} \bar{y} = \frac{\Sigma}{n}$ cf. corollary to lemma 2.3 (ii)

$$\text{rank} (I_n - P) = n - \text{rank} P = n - 1$$

$$(I_n - P) \frac{1}{n} \mathbf{1}_n = \frac{1}{n} \mathbf{1}_n - \frac{1}{n} \mathbf{1}_n \mathbf{1}_n^T \frac{1}{n} \mathbf{1}_n = \underline{0}$$

Consequently

$$\left. \begin{aligned} \bar{x} &= \bar{y} + \underline{\mu} \sim N_d \left(\underline{\mu}, \frac{\Sigma}{n} \right) \\ Q &= X^T (I_n - P) X \sim W_d (n-1, \Sigma) \end{aligned} \right\} \text{independent}$$

as Q is unchanged, cf. formula (1.11)

$$\begin{aligned} (ii) \quad T^2 &= n (\bar{x} - \underline{\mu})^T S^{-1} (\bar{x} - \underline{\mu}) = n (\bar{x} - \underline{\mu})^T \left(\frac{Q}{n-1} \right)^{-1} (\bar{x} - \underline{\mu}) \\ &= n(n-1) (\bar{x} - \underline{\mu})^T Q^{-1} (\bar{x} - \underline{\mu}) \sim T^2(d, n-1) \end{aligned}$$

cf. corollary to theorem 2.8

Hotelling's T^2 test

When $H_0: \underline{\mu} = \underline{\mu}_0$ is true

$$\begin{aligned} T^2 &= n (\bar{x} - \underline{\mu}_0)^T S^{-1} (\bar{x} - \underline{\mu}_0) \sim T^2(d, n-1) \\ &= \frac{(n-1)d}{n-d} F(d, n-d) \end{aligned}$$

i.e. reject when $\frac{n-d}{(n-1)d} T^2_{\text{obs}} > F_{1-\alpha}(d, n-d)$

Technique: Find the Cholesky decomposition $Q = U^T U$, solve $U^T \underline{z} = \bar{x} - \underline{\mu}_0$ w.r.t \underline{z} ,

$$\begin{aligned}
 & \text{calculate } n(n-1) \underline{\bar{x}}^T \underline{\bar{x}} \\
 & = n(n-1) (\underline{\bar{x}} - \underline{\mu}_0)^T U^{-1} (U^T)^{-1} (\underline{\bar{x}} - \underline{\mu}_0) \\
 & = n(n-1) (\underline{\bar{x}} - \underline{\mu}_0)^T Q^{-1} (\underline{\bar{x}} - \underline{\mu}_0) \\
 & = n (\underline{\bar{x}} - \underline{\mu}_0)^T S^{-1} (\underline{\bar{x}} - \underline{\mu}_0) = T^2
 \end{aligned}$$

Example	Weight (kg)	Height (mm)	Weight (kg)	Height (mm)
	71.0	1629	59.5	1513
	56.5	1569	61.0	1653
	56.0	1561	57.0	1566
	61.0	1619	57.5	1580
	65.0	1566	74.0	1647
	62.0	1639	72.0	1620
	53.0	1494	62.5	1637
	53.0	1568	68.0	1528
	65.0	1540	63.4	1647
	57.0	1530	68.0	1605
	66.5	1622	69.0	1625
	59.1	1486	73.0	1615
	64.0	1578	64.0	1640
	69.5	1645	65.0	1610
	64.0	1648	71.0	1572
	56.5	1521	60.2	1534
	57.0	1547	55.0	1536
	55.0	1505	70.0	1630
	57.0	1473	87.0 ^b	1542 ^b
	58.0	1538		

EXAMPLE 3.1 In Table 3.1 we have bivariate observations on the weights and heights of 39 Peruvian Indians. Suppose we wish to test $H_0: \mu = (63.64, 1615.38)' = \mu_0$ (corresponding to 140 lb and 63 in., respectively). A plot of the data (Fig. 3.1) suggests that the last item is an outlier. Other plots (see Examples 4.3 and 4.6 in Section 4.3) also indicate that the normality assumption is tenable, though there is some suggestion of kurtosis. Ignoring the last item (i.e., $n = 38$), we write

$$\begin{aligned}
 \bar{x} &= \begin{pmatrix} 62.5316 \\ 1579.8900 \end{pmatrix}, & \bar{x} - \mu_0 &= \begin{pmatrix} -1.1084 \\ -35.4900 \end{pmatrix}, \\
 Q &= \begin{pmatrix} 1331.62 & 7304.83 \\ 7304.83 & 104118 \end{pmatrix}, & U &= \begin{pmatrix} 36.4914 & 200.179 \\ 0 & 253.073 \end{pmatrix}.
 \end{aligned}$$

Solving

$$\begin{pmatrix} 36.4914 & 0 \\ 200.179 & 253.073 \end{pmatrix} \begin{pmatrix} z_1 \\ z_2 \end{pmatrix} = \begin{pmatrix} -1.1084 \\ -35.4900 \end{pmatrix}$$

gives $z' = (-0.0303749, -0.116191)$. Hence

$$T_0^2 = n(n-1)z'z = 20.2798$$

and

$$F_0 = \frac{T_0^2}{n-1} \frac{n-d}{d} = \frac{20.2798}{37} \frac{36}{2} = 9.87.$$

Since $F_{2,30}^{0.001} = 8.77$, $F_0 > F_{2,30}^{0.001} > F_{2,36}^{0.001}$ and we reject H_0 at the 0.1% level of significance. If the outlier is included, $F_0 = 10.50$. □

Linear transformation of observations and hypothesis

$$\underline{z} = F \underline{x} + \underline{c} \quad E \underline{z} = F E \underline{x} + \underline{c} = F \underline{\mu} + \underline{c} = \underline{q}$$

$$H_0: \underline{q} = \underline{q}_0 = F \underline{\mu}_0 + \underline{c}$$

$$\begin{aligned} T_z^2 &= n (\bar{\underline{z}} - \underline{q}_0)^T S_z^{-1} (\bar{\underline{z}} - \underline{q}_0) \quad (\text{see * page 7}) \\ &= n (F \bar{\underline{x}} + \underline{c} - F \underline{\mu}_0 - \underline{c})^T (F S F^T)^{-1} (F \bar{\underline{x}} + \underline{c} - F \underline{\mu}_0 - \underline{c}) \\ &= n (\bar{\underline{x}} - \underline{\mu}_0)^T F^T (F^T)^{-1} S^{-1} F^{-1} F (\bar{\underline{x}} - \underline{\mu}_0) \\ &= n (\bar{\underline{x}} - \underline{\mu}_0)^T S^{-1} (\bar{\underline{x}} - \underline{\mu}_0) = T^2 \end{aligned}$$

Theorem 3.2 :

T^2 is equivalent to the likelihood ratio test statistic for $H_0: \underline{\mu} = \underline{\mu}_0$ versus $H_1: \underline{\mu} \neq \underline{\mu}_0$

Proof :

$$\begin{aligned} \ln L(\underline{\Sigma}) &= -\frac{nd}{2} \ln(2\pi) - \frac{n}{2} \ln \det \underline{\Sigma} - \frac{1}{2} \text{tr} \left(\underline{\Sigma}^{-1} \sum_{i=1}^n (\underline{x}_i - \underline{\mu}_0)(\underline{x}_i - \underline{\mu}_0)^T \right) \\ &= -\frac{nd}{2} \ln(2\pi) - \frac{n}{2} (\ln \det \underline{\Sigma} + \text{tr}(\underline{\Sigma}^{-1} \underline{Q}_0)) \\ &\leq -\frac{nd}{2} \ln(2\pi) - \frac{n}{2} (\ln \det \frac{\underline{Q}_0}{n} + \text{tr} \underline{I}_d) \end{aligned}$$

equality for $\underline{\Sigma} = \frac{\underline{Q}_0}{n}$, thus $\hat{\underline{\Sigma}}_0 = \frac{\underline{Q}_0}{n}$

$$\ln L(\hat{\underline{\Sigma}}_0) = -\frac{nd}{2} \ln(2\pi) - \frac{n}{2} \ln \det \hat{\underline{\Sigma}}_0 - \frac{nd}{2}$$

$$\Rightarrow L(\hat{\underline{\Sigma}}_0) = (2\pi e)^{-\frac{nd}{2}} (\det \hat{\underline{\Sigma}}_0)^{-\frac{n}{2}}$$

$$l = \frac{\sup_{\underline{\Sigma}} L(\underline{\Sigma})}{\sup_{\underline{\mu}, \underline{\Sigma}} L(\underline{\mu}, \underline{\Sigma})} = \frac{(2\pi e)^{-\frac{nd}{2}} (\det \hat{\underline{\Sigma}}_0)^{-\frac{n}{2}}}{(2\pi e)^{-\frac{nd}{2}} (\det \hat{\underline{\Sigma}})^{-\frac{n}{2}}} = \left(\frac{\det \hat{\underline{\Sigma}}}{\det \hat{\underline{\Sigma}}_0} \right)^{\frac{n}{2}}$$

$$l^{\frac{2}{n}} = \frac{\det Q}{\det Q_0} = \frac{\det Q}{\det (Q + n(\bar{\underline{x}} - \underline{\mu}_0)(\bar{\underline{x}} - \underline{\mu}_0)^T)}$$

$$\begin{aligned}
 \lambda^{\frac{2}{n}} &= \frac{1}{\det(\mathbb{I}_d + n Q^{-1}(\bar{\underline{x}} - \underline{\mu}_0)(\bar{\underline{x}} - \underline{\mu}_0)^T)} \\
 &= \frac{1}{\det(\mathbb{I}_1 + n(\bar{\underline{x}} - \underline{\mu}_0)^T Q^{-1}(\bar{\underline{x}} - \underline{\mu}_0))} \quad \text{cf. hint to ex. 2.12 a} \\
 &= \frac{1}{1 + n(\bar{\underline{x}} - \underline{\mu}_0)^T Q^{-1}(\bar{\underline{x}} - \underline{\mu}_0)} \\
 &= \frac{1}{1 + \frac{1}{n-1} T^2} \quad \Rightarrow \quad T^2 = (n-1) (\lambda^{-\frac{2}{n}} - 1)
 \end{aligned}$$

Note that small values of λ correspond to large values of T^2 .

Relation to the usual t-test :

$$\begin{aligned}
 T^2 &= n(\bar{\underline{x}} - \underline{\mu}_0)^T S^{-1}(\bar{\underline{x}} - \underline{\mu}_0) \\
 &= n \sup_{\underline{l}} \frac{(\underline{l}^T(\bar{\underline{x}} - \underline{\mu}_0))^2}{\underline{l}^T S \underline{l}} \quad \text{cf. A 7.6} \\
 &= \sup_{\underline{l}} \left(\frac{\sqrt{n}(\underline{l}^T \bar{\underline{x}} - \underline{l}^T \underline{\mu}_0)}{\sqrt{\underline{l}^T S \underline{l}}} \right)^2 \\
 &= \sup_{\underline{l}} t_{\underline{l}}^2, \quad \text{where } t_{\underline{l}} \sim t(n-1) \text{ is the}
 \end{aligned}$$

usual statistic for testing the hypothesis

$$H_{0l}: \underline{l}^T \underline{\mu} = \underline{l}^T \underline{\mu}_0 \quad ; \quad N(\underline{l}^T \underline{\mu}, \underline{l}^T \Sigma \underline{l})$$

U- Π -test variable

$$\text{Note that } H_0 = \bigcap_{\underline{l}} H_{0l} \text{ and } H_1 = \bigcup_{\underline{l}} H_{1l}$$

Acceptance area for H_0 is $\{X \mid t_x^2 \leq k\}$

$$k = (t_{1-\frac{\alpha}{2}}(n-1))^2$$

Acceptance area for H_0 :

$$\begin{aligned} \bigcap_x \{X \mid t_x^2 \leq k\} &= \{X \mid \sup_x t_x^2 \leq k\} \\ &= \{X \mid T^2 \leq k\} \end{aligned}$$

i.e. again Hotelling's T^2 as test statistic

$$\begin{aligned} * \quad Q_z &= \sum_{i=1}^n (\underline{z}_i - \bar{z})(\underline{z}_i - \bar{z})^T \\ &= \sum_{i=1}^n (F\underline{x}_i + \underline{c} - F\bar{x} - \underline{c})(F\underline{x}_i + \underline{c} - F\bar{x} - \underline{c})^T \\ &= \sum_{i=1}^n F(\underline{x}_i - \bar{x})(\underline{x}_i - \bar{x})^T F^T \\ &= F \left(\sum_{i=1}^n (\underline{x}_i - \bar{x})(\underline{x}_i - \bar{x})^T \right) F^T \\ &= FQF^T \end{aligned}$$

$$\Rightarrow S_2 = FSF^T$$

$$\begin{aligned} ** \quad \exists T \text{ (orthogonal)} : \quad & T^T(\Sigma^{-\frac{1}{2}} A \Sigma^{-\frac{1}{2}}) T = I_d \\ \Leftrightarrow & \Sigma^{-\frac{1}{2}} A \Sigma^{-\frac{1}{2}} = T I_d T^T = I_d \\ \Leftrightarrow & \Sigma^{-\frac{1}{2}} \Sigma^{-\frac{1}{2}} A \Sigma^{-\frac{1}{2}} \Sigma^{\frac{1}{2}} = \Sigma^{-\frac{1}{2}} I_d \Sigma^{\frac{1}{2}} \\ \Leftrightarrow & \Sigma^{-1} A = I_d \\ \Leftrightarrow & \Sigma = A \end{aligned}$$