

Test for blockwise independence / b blocks

$$\underline{x}_i \sim N_d(\underline{\mu}, \Sigma), \quad i = 1, \dots, n, \quad \text{independent}, \quad n-1 \geq d$$

Partition :

$$\underline{x}_i = \begin{bmatrix} \underline{x}_{i1} \\ \underline{x}_{i2} \\ \vdots \\ \underline{x}_{ib} \end{bmatrix}, \quad \underline{\mu} = \begin{bmatrix} \underline{\mu}_1 \\ \underline{\mu}_2 \\ \vdots \\ \underline{\mu}_b \end{bmatrix}, \quad \Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} & \dots & \Sigma_{1b} \\ \Sigma_{21} & \Sigma_{22} & \dots & \Sigma_{2b} \\ \vdots & \vdots & \ddots & \vdots \\ \Sigma_{b1} & \Sigma_{b2} & \dots & \Sigma_{bb} \end{bmatrix}$$

$$\underline{x}_{ir} \quad d_r\text{-dim}, \quad \Sigma_{rr} \quad d_r \times d_r, \quad r = 1, \dots, b, \quad \sum_r d_r = d$$

$$H_0: \underline{x}_{i1}, \underline{x}_{i2}, \dots, \underline{x}_{ib} \text{ independent} \quad (\Leftrightarrow) \quad \Sigma_{ir} = 0, \quad i \neq r$$

cf. th. 2.1 (iv)

By calculations analogous to the case of two blocks we find

$$\Lambda = L^{\frac{2}{n}} = \frac{\det Q}{\det Q_{11} \det Q_{22} \dots \det Q_{bb}}$$

but the distribution of Λ can not be specified exactly

$$\begin{aligned} \text{No. of parameters in } \underline{\mu} \text{ and } \Sigma &: d + \left(\frac{d^2 - d}{2} + d \right) = d + \frac{d^2 + d}{2} \\ &= d + \frac{1}{2} d(d+1) = \frac{1}{2} d(d+3) \end{aligned}$$

$$\begin{aligned} - & \quad - \quad , \quad H_0 \text{ true} : \frac{1}{2} \sum_{r=1}^b d_r (d_r + 3) \\ & = \frac{1}{2} \sum_r d_r^2 + \frac{3}{2} d \end{aligned}$$

$-2 \ln L \sim \chi^2(v)$ approximately when H_0 is true

$$\begin{aligned} v &= \frac{1}{2} d(d+3) - \frac{1}{2} \left(\sum_r d_r^2 + 3d \right) \\ &= \frac{1}{2} \left(d^2 - \sum_r d_r^2 \right) \end{aligned}$$

Thus $-n \ln \Lambda \sim \chi^2 \left(\frac{1}{2} (d^2 - \sum_r d_r^2) \right)$ approx. when H_0 is true

A better approximation can be found in the book p. 91

Nagaos test statistic

$$L_b = \frac{1}{2}(n-1) \operatorname{tr} (Q Q_{(b)}^{-1} - I_d)^2, \text{ where}$$

$$Q_{(b)} = \Gamma \begin{bmatrix} Q_{11} & & \\ & Q_{22} & \\ & & \dots \\ & & & Q_{bb} \end{bmatrix}$$

Test for diagonal variance matrix

$$H_{01}: \Sigma = \Gamma \begin{bmatrix} \sigma_1^2 & & \\ & \sigma_2^2 & \\ & & \dots \\ & & & \sigma_d^2 \end{bmatrix} \text{ (blockwise indep., } d_r = 1)$$

$$\text{Let } b = d, \quad \tilde{x}_{ir} = x_{ir}, \quad Q_{rr} = q_{rr} = \sum_i (x_{ir} - \bar{x}_{.r})^2$$

$$\Lambda_1 = \frac{\det Q}{q_{11} q_{22} \dots q_{dd}}, \quad -n \ln \Lambda_1 \sim \chi^2 \left(\frac{1}{2} d(d-1) \right) \text{ app.}$$

when H_{01} is true

Empirical correlation coefficient between x_{ij} and x_{ik}

$$r_{jh} = \frac{q_{jh}}{\sqrt{q_{jj}} \sqrt{q_{hh}}}, \text{ choose } R = \{r_{jh}\} \text{ symm., i.e.}$$

$$R = \begin{bmatrix} \frac{1}{\sqrt{q_{11}}} & & \\ & \dots & \\ & & \frac{1}{\sqrt{q_{dd}}} \end{bmatrix} Q \begin{bmatrix} \frac{1}{\sqrt{q_{11}}} & & \\ & \dots & \\ & & \frac{1}{\sqrt{q_{dd}}} \end{bmatrix}$$

$$\Lambda_1 = \det R$$

A special case:

$$H_{02}: \Sigma = \sigma^2 I_d, \quad \sigma^2 \text{ unknown parameter}$$

$$\Lambda_2 = \frac{\det Q}{\left(\operatorname{tr} \frac{Q}{d} \right)^d} \text{ cf. exercise 3.8}$$

H_{02} is equivalent to a test for all eigenvalues of Σ equal

$$\lambda_1 = \dots = \lambda_d \Leftrightarrow \left(\prod_i \lambda_i \right)^{\frac{1}{d}} = \frac{1}{d} \sum_j \lambda_j \Leftrightarrow \frac{(\det \Sigma)^{\frac{1}{d}}}{\frac{1}{d} \operatorname{tr} \Sigma} = 1$$

↑ d.f. r. 6

Determine a test statistic by exchanging Σ with $\hat{\Sigma}$, hence

$$\text{reject when } \frac{(\det \hat{\Sigma})^{\frac{1}{d}}}{\operatorname{tr} \frac{\hat{\Sigma}}{d}} = \frac{(\det Q)^{\frac{1}{d}}}{\operatorname{tr} \frac{Q}{d}} = \Lambda_2^{\frac{1}{d}} \ll 1$$

H_{02} is called the spherical hypothesis, as the

ellipse $(\underline{x} - \underline{\mu})^T \Sigma^{-1} (\underline{x} - \underline{\mu}) = c^2$ is reduced

to $(\underline{x} - \underline{\mu})^T (\underline{x} - \underline{\mu}) = \sigma^2 c^2$ when H_{02} is true

$$H_{03}: \Sigma = I_d$$

$$L_3 = \left(\frac{e}{n} \right)^{\frac{nd}{2}} (\det Q)^{\frac{n}{2}} \exp \left(-\frac{1}{2} \operatorname{tr} Q \right) \quad \text{cf. ex. 3.9}$$

When H_{03} is true $-2 \ln L_3 \sim \chi^2(\nu)$ approximately,

$$\nu = \frac{1}{2} d(d+1) - d = \frac{1}{2} d(d+1)$$

$H_{02}^1: \Sigma = \sigma^2 \Sigma_0$ and $H_{03}^1: \Sigma = \Sigma_0$, Σ_0 known, is

reduced to H_{02} and H_{03} respectively by the trans-

formation $y_i = \Sigma_0^{-\frac{1}{2}} \underline{x}_i$, as

$$\operatorname{Var} y_i = \Sigma_0^{-\frac{1}{2}} \sigma^2 \Sigma_0 \Sigma_0^{-\frac{1}{2}} = \sigma^2 I_d$$

$H_{04}: \underline{\mu} = \underline{\mu}_0, \Sigma = \Sigma_0$ is referred to ex. 3.10

Test for equal diagonal blocks under the assumption that all covariance blocks are equal

Σ is partitioned in b^2 $d_0 \times d_0$ blocks, $b d_0 = d$

Given: $\Sigma_{rs} = \Sigma_1$, $r \neq s$ ($\Rightarrow \Sigma_1$ symmetric)

H_{05} : $\Sigma_{rr} = \Sigma_0$, $r = 1, \dots, b$

Let $\bar{\underline{x}}_i = \frac{1}{b} (\underline{x}_{i1} + \underline{x}_{i2} + \dots + \underline{x}_{ib})$

$$\text{and } \underline{y}_i = \begin{bmatrix} y_{i1} \\ y_{i2} \\ \vdots \\ y_{ib} \end{bmatrix} = \begin{bmatrix} \bar{\underline{x}}_i \\ \underline{x}_{i2} - \bar{\underline{x}}_i \\ \vdots \\ \underline{x}_{ib} - \bar{\underline{x}}_i \end{bmatrix} = C \underline{x}_i$$

C is non-singular, cf. ex. 3.11

$\underline{y}_i \sim N_d(C \underline{\mu}, C \Sigma C^T)$ cf. theorem 2.1 (i)

$$\begin{aligned} \text{Cov}(y_{ir}, y_{is}) &= \text{Cov}(\underline{x}_{ir} - \bar{\underline{x}}_i, \bar{\underline{x}}_i), \quad r = 2, \dots, b \\ &= \text{Cov}(\underline{x}_{ir}, \bar{\underline{x}}_i) - \text{Var} \bar{\underline{x}}_i \\ &= \frac{1}{b} \sum_s \text{Cov}(\underline{x}_{ir}, \underline{x}_{is}) - \frac{1}{b^2} \sum_q \sum_s \text{Cov}(\underline{x}_{iq}, \underline{x}_{is}) \\ &= \frac{1}{b} ((b-1)\Sigma_1 + \Sigma_0) - \frac{1}{b^2} (b(b-1)\Sigma_1 + b\Sigma_0) \\ &= 0 \quad (d_0 \times d_0) \end{aligned}$$

$$\text{Let } \underline{y}_{i2}^* = \begin{bmatrix} y_{i2} \\ \vdots \\ y_{ib} \end{bmatrix} \Rightarrow \underline{y}_i = \begin{bmatrix} y_{i1} \\ \underline{y}_{i2}^* \end{bmatrix} \quad \begin{array}{l} d_0\text{-dim.} \\ (b-1)d_0\text{-dim.} \end{array}$$

$$\text{Cov}(\underline{y}_{i1}, \underline{y}_{i2}^*) = 0 \quad ((b-1)d_0 \times d_0)$$

H_{05} is equivalent with testing for independence between \underline{y}_{i1} and \underline{y}_{i2}^* (blockwise indep. / 2 blocks)

In the case $b=2$ the presumption becomes

$$\Sigma_{12} = \Sigma_{21} (= \Sigma_1)$$

Test for equal variances and equal correlations

$$H_{06}: \Sigma = \sigma^2 \begin{bmatrix} 1 & \rho & \dots & \rho \\ \rho & 1 & & \rho \\ \vdots & \vdots & \ddots & \vdots \\ \rho & \rho & & 1 \end{bmatrix}$$

Maximum likelihood estimates:

$$\left. \begin{aligned} \hat{\sigma}^2 &= \frac{1}{d} \sum_j s_{jj}^* \\ \hat{\sigma}_{\rho}^2 &= \frac{1}{d(d-1)} \sum_j \sum_{k \neq j} s_{jk}^* \end{aligned} \right\} \text{where } S^* = \frac{Q}{n}, \quad \text{cf. exercise 3.12}$$

The likelihood ratio test statistic

$$l_0^{\frac{2}{n}} = \frac{\det S^*}{(\hat{\sigma}^2)^d (1 - \hat{\rho})^{d-1} (1 + (d-1)\hat{\rho})} \quad \text{cf. ex. 3.13}$$

$$-2 \ln l_0 \sim \chi^2 \left(\frac{1}{2} d(d+1) - 2 \right) \quad \text{app. when } H_0 \text{ is true}$$

↑ cf. page 95 bottom

Establishing $(\prod_j \lambda_j)^{\frac{1}{d}} \leq \frac{1}{d} \sum_j \lambda_j$:

Jensen's inequality: $\varphi\left(\int_{\Omega} f d\mu\right) \leq \int_{\Omega} (\varphi \circ f) d\mu$, φ convex

The stochastic equivalent: $\varphi(EX) \leq E[\varphi \circ X]$, φ convex

Consider a discrete stoch. var. X uniformly distributed on $\{x_1, \dots, x_d\}$

i.e. $P(X=x_j) = \frac{1}{d}$, $j=1, \dots, d$.

$$EX = \sum_j x_j \frac{1}{d} = \frac{1}{d} \sum_j x_j$$

Applied to the convex function \exp we get

$$E[\exp X] = \sum_j e^{x_j} \frac{1}{d} = \frac{1}{d} \sum_j e^{x_j}$$

$$\exp(EX) = e^{\frac{1}{d} \sum_j x_j} = \left(\prod_j e^{x_j}\right)^{\frac{1}{d}}$$

Jensen's inequality: $(\prod_j e^{x_j})^{\frac{1}{d}} \leq \frac{1}{d} \sum_j e^{x_j}$

With $e^{x_j} = \lambda_j$: $(\prod_j \lambda_j)^{\frac{1}{d}} \leq \frac{1}{d} \sum_j \lambda_j$

Note that the equality sign is valid when $\lambda_1 = \dots = \lambda_d (= \lambda)$

Two sets of observations

Test of equal variance matrix

$$\left. \begin{aligned} \underline{x}_i &\sim N_d(\underline{\mu}_1, \Sigma_1), \quad i=1, \dots, n_1 \\ \underline{w}_j &\sim N_d(\underline{\mu}_2, \Sigma_2), \quad j=1, \dots, n_2 \end{aligned} \right\} \text{all independent}$$

$$\begin{aligned} L(\hat{\underline{\mu}}_1, \hat{\underline{\mu}}_2, \hat{\Sigma}_1, \hat{\Sigma}_2) &= L_1(\hat{\underline{\mu}}_1, \hat{\Sigma}_1) L_2(\hat{\underline{\mu}}_2, \hat{\Sigma}_2), \quad \hat{\underline{\mu}}_1 = \bar{\underline{x}}, \quad \hat{\underline{\mu}}_2 = \bar{\underline{w}} \\ &= (2\pi e)^{-\frac{n_1 d}{2}} (\det \hat{\Sigma}_1)^{-\frac{n_1}{2}} (2\pi e)^{-\frac{n_2 d}{2}} (\det \hat{\Sigma}_2)^{-\frac{n_2}{2}} \\ &= (2\pi e)^{-\frac{nd}{2}} (\det \hat{\Sigma}_1)^{-\frac{n_1}{2}} (\det \hat{\Sigma}_2)^{-\frac{n_2}{2}}, \quad n = n_1 + n_2 \end{aligned}$$

$$H_0: \Sigma_1 = \Sigma_2 (= \Sigma), \quad H_1: \Sigma_1 \neq \Sigma_2$$

When H_0 is true:

$$\begin{aligned} \ln L(\hat{\underline{\mu}}_1, \hat{\underline{\mu}}_2, \Sigma) &= \ln L_1(\hat{\underline{\mu}}_1, \Sigma) + \ln L_2(\hat{\underline{\mu}}_2, \Sigma), \quad \hat{\underline{\mu}}_1 = \bar{\underline{x}}, \quad \hat{\underline{\mu}}_2 = \bar{\underline{w}} \\ &= -\frac{n_1 d}{2} \ln(2\pi) - \frac{1}{2} (n_1 \ln(\det \Sigma) + \text{tr}(\Sigma^{-1} Q_1)) \\ &\quad - \frac{n_2 d}{2} \ln(2\pi) - \frac{1}{2} (n_2 \ln(\det \Sigma) + \text{tr}(\Sigma^{-1} Q_2)) \\ &= -\frac{nd}{2} \ln(2\pi) - \frac{1}{2} (n \ln(\det \Sigma) + \text{tr}(\Sigma^{-1} Q)), \\ &\hspace{15em} Q = Q_1 + Q_2 \end{aligned}$$

$$\hat{\Sigma} = \frac{Q}{n} \quad \text{cf. formula (3.5) page 61}$$

$$L(\hat{\underline{\mu}}_1, \hat{\underline{\mu}}_2, \hat{\Sigma}) = (2\pi e)^{-\frac{nd}{2}} (\det \hat{\Sigma})^{-\frac{n}{2}}$$

$$\begin{aligned} l &= \frac{(2\pi e)^{-\frac{n_1 d}{2}} (\det \hat{\Sigma}_1)^{-\frac{n_1}{2}}}{(2\pi e)^{-\frac{nd}{2}} (\det \hat{\Sigma}_1)^{-\frac{n_1}{2}} (\det \hat{\Sigma}_2)^{-\frac{n_2}{2}}} = \frac{(\det \hat{\Sigma}_1)^{\frac{n_1}{2}} (\det \hat{\Sigma}_2)^{\frac{n_2}{2}}}{(\det \hat{\Sigma})^{\frac{n}{2}}} \\ &= \frac{n^{\frac{nd}{2}}}{n_1^{\frac{n_1 d}{2}} n_2^{\frac{n_2 d}{2}}} \frac{(\det Q_1)^{\frac{n_1}{2}} (\det Q_2)^{\frac{n_2}{2}}}{(\det(Q_1 + Q_2))^{\frac{n}{2}}} \end{aligned}$$

$$\begin{aligned} -2 \ln l &\sim \chi^2(v) \quad \text{app.}, \quad v = 2 \frac{1}{2} d(d+3) - (\frac{1}{2} d(d+3) + d) \\ &= \frac{1}{2} d(d+1) \end{aligned}$$

$$\forall \underline{l} : \left. \begin{aligned} \underline{l}^T Q_1 \underline{l} &\sim \underline{l}^T \Sigma_1 \underline{l} \chi^2(m_1-1) \\ \underline{l}^T Q_2 \underline{l} &\sim \underline{l}^T \Sigma_2 \underline{l} \chi^2(m_2-1) \end{aligned} \right\} \text{ independent}$$

$$H_{02} : \underline{l}^T \Sigma_1 \underline{l} = \underline{l}^T \Sigma_2 \underline{l} \quad , \quad \bigcap_{\underline{l}} H_{02} = H_0$$

$$H_{02} \text{ true} : \frac{\frac{\underline{l}^T Q_1 \underline{l}}{(m_1-1) \underline{l}^T \Sigma_1 \underline{l}}}{\frac{\underline{l}^T Q_2 \underline{l}}{(m_2-1) \underline{l}^T \Sigma_2 \underline{l}}} = \frac{\underline{l}^T S_1 \underline{l}}{\underline{l}^T S_2 \underline{l}} \sim F(m_1-1, m_2-1)$$

Acceptance area for H_0 :

$$\begin{aligned} & \bigcap_{\underline{l}} \left\{ (V, W) : F_{\alpha_1} < \frac{\underline{l}^T S_1 \underline{l}}{\underline{l}^T S_2 \underline{l}} < F_{1-\alpha_2} \right\}, \quad \alpha_1 + \alpha_2 = \alpha \\ & = \bigcap_{\underline{l}} \left\{ (V, W) : \frac{m_1-1}{m_2-1} F_{\alpha_1} < \frac{\underline{l}^T Q_1 \underline{l}}{\underline{l}^T Q_2 \underline{l}} < \frac{m_1-1}{m_2-1} F_{1-\alpha_2} \right\} \\ & = \left\{ (V, W) : \frac{m_1-1}{m_2-1} F_{\alpha_1} \leq \varphi_{\min} \leq \varphi_{\max} \leq \frac{m_1-1}{m_2-1} F_{1-\alpha_2} \right\}, \\ & \quad \text{where } \varphi \text{ is eigenvalues for } Q_1 Q_2^{-1}, \text{ cf. A7.5} \\ & = \left\{ (V, W) : c_1 \leq \Theta_{\min} \leq \Theta_{\max} \leq c_2 \right\}, \\ & \quad \text{where } \Theta \text{ is eigenvalues for } Q_1 (Q_1 + Q_2)^{-1}, \quad \Theta = \frac{\varphi}{1+\varphi} \end{aligned}$$

Critical area for H_0 :

$$\left\{ (V, W) : \Theta_{\min} < c_1 \vee \Theta_{\max} > c_2 \right\}$$

The choice of c_1 and c_2 which gives maximum test strength is not known