

Hotelling's T^2

$$\underline{x} \sim N_d(\underline{\mu}, \Sigma), \quad W \sim W_d(m, \Sigma) \quad \text{independent}$$

$$\text{def: } T^2 = m(\underline{x} - \underline{\mu})^T W^{-1} (\underline{x} - \underline{\mu}) \sim T^2(d, m)$$

$$T^2(d, m) = \frac{md}{m-d+1} F(d, m-d+1) \quad \text{cf. th. 2.8}$$

$$\text{compare with } t \sim t(m) \Rightarrow t^2 \sim F(1, m)$$

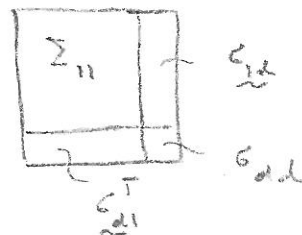
Lemma 2.5

$$\underline{u} = \begin{bmatrix} u_1 \\ \vdots \\ u_d \end{bmatrix} \sim N_d(\underline{\theta}, \Sigma); \quad \underline{u}^{(1)} = \begin{bmatrix} u_1 \\ \vdots \\ u_{d-1} \end{bmatrix}$$

$$u_d | \underline{u}^{(1)} \sim N(\beta_0 + \underline{\beta}^T \underline{u}^{(1)}, \frac{1}{\epsilon_{dd}}), \quad \text{where}$$

$$\epsilon^{jk} = (\Sigma^{-1})_{jk}$$

Proof:

Partition of Σ :

From th 2.1 (viii) follows

$$\begin{aligned} u_d | \underline{u}^{(1)} &\sim N(\theta_d + \epsilon_{1d}^T \Sigma_{11}^{-1} (\underline{u}^{(1)} - \underline{\theta}^{(1)}), \cdot) \\ &= N(\theta_d - \epsilon_{1d}^T \Sigma_{11}^{-1} \underline{\theta}^{(1)} + \epsilon_{1d}^T \Sigma_{11}^{-1} \underline{u}^{(1)}, \cdot) \\ &= N(\beta_0 + \underline{\beta}^T \underline{u}^{(1)}, \cdot) \end{aligned}$$

$$\text{Var}(u_d | \underline{u}^{(1)}) = \epsilon_{dd} - \epsilon_{d1}^T \Sigma_{11}^{-1} \epsilon_{1d}$$

Note that $\det \Sigma = \det \Sigma_{11} \det (\sigma_{dd} - \underline{\sigma}_{d1}^T \Sigma_{11}^{-1} \underline{\sigma}_{1d})$ cf. A3.2

$$= \det \Sigma_{11} (\sigma_{dd} - \underline{\sigma}_{d1}^T \Sigma_{11}^{-1} \underline{\sigma}_{1d})$$

$$\Rightarrow \text{Var}(u_d | \underline{u}_{11}^{(1)}) = \frac{\det \Sigma}{\det \Sigma_{11}}$$

Note also that

$$(\Sigma^{-1})_{dd} = \left(\frac{\text{adj} \Sigma}{\det \Sigma} \right)_{dd} = \frac{1}{\det \Sigma} (-1)^{d+d} \det \Sigma_{11} = \frac{\det \Sigma_{11}}{\det \Sigma}$$

Hence $\frac{\det \Sigma}{\det \Sigma_{11}} = \frac{1}{\sigma_{dd}} \Rightarrow \text{Var}(u_d | \underline{u}_{11}^{(1)}) = \frac{1}{\sigma_{dd}}$

Lemma 2.6

Linear normal model $\underline{y} = K\underline{x} + \underline{\varepsilon}$ with

K $m \times p$, $\text{rank } K = p$ and $\underline{\varepsilon} \sim N_m(\underline{0}, \sigma^2 I_m)$

$$Q = \underline{y}^T (I_m - P) \underline{y} \sim \sigma^2 \chi^2(m-p), \quad P = K(K^T K)^{-1} K^T$$

projection matrix

$$Q = \frac{1}{w_{dd}}, \quad \text{where } W = \begin{bmatrix} K^T \\ \underline{y}^T \end{bmatrix} \begin{bmatrix} K & \underline{y} \end{bmatrix}$$

Proof:

$$W = \begin{bmatrix} K^T K & K^T \underline{y} \\ \underline{y}^T K & \underline{y}^T \underline{y} \end{bmatrix} = \begin{bmatrix} W_{11} & \underline{w}_{1d} \\ \underline{w}_{d1}^T & w_{dd} \end{bmatrix}, \quad \begin{array}{l} W_{11} \text{ is not} \\ \text{stochastic} \\ \text{here} \end{array}$$

note that $\frac{1}{w_{dd}} = \frac{\det W}{\det W_{11}}$ cf. lemma 2.5

$$= \frac{\det W_{11} (w_{dd} - \underline{w}_{d1}^T W_{11}^{-1} \underline{w}_{1d})}{\det W_{11}} \quad \text{cf. A3.2}$$

$$= \underline{y}^T \underline{y} - \underline{y}^T K (K^T K)^{-1} K^T \underline{y}$$

$$= \underline{y}^T (I_m - K (K^T K)^{-1} K^T) \underline{y}$$

$$= \underline{y}^T (I_m - P) \underline{y} = Q$$

Lemma 2.7

$$W \sim W_d(m, \Sigma) \quad m \geq d$$

(i) $\frac{\epsilon^{d,d}}{w^{d,d}} \sim \chi^2(m-d+1)$ indep. of W_{11}

(ii) $\forall \underline{l} \neq \underline{0} : \frac{\underline{l}^T \Sigma^{-1} \underline{l}}{\underline{l}^T W^{-1} \underline{l}} \sim \chi^2(m-d+1)$

Proof:

ad (i) Let $W = \sum_{i=1}^m \underline{x}_i \underline{x}_i^T$, $\underline{x}_i \sim N_d(\underline{0}, \Sigma)$, $i=1, \dots, m$, independent
 $= X^T X$

From lemma 2.5 follows

$$\underline{x}_i | \underline{x}_i^{(1)} \sim N\left(\underline{0} + \underline{\beta}^T \underline{x}_i^{(1)}, \frac{1}{\epsilon^{d,d}}\right) \quad i=1, \dots, m$$

$$\Rightarrow \underline{x}^{(d)} | K \sim N_m\left(K \underline{\beta}, \frac{1}{\epsilon^{d,d}} I_m\right), \quad K^T = [\underline{x}_1^{(1)} \dots \underline{x}_m^{(1)}]$$

Lemma 2.6 with $\underline{y} := \underline{x}^{(d)}$ shows

$$\frac{1}{w^{d,d}} | K \sim \frac{1}{\epsilon^{d,d}} \chi^2(m-(d-1)) = \frac{1}{\epsilon^{d,d}} \chi^2(m-d+1)$$

The distribution does not depend on the elements of K

$$\Rightarrow \frac{1}{w^{d,d}} \sim \frac{1}{\epsilon^{d,d}} \chi^2(m-d+1) \text{ indep. of } K, \text{ cf. ex. 2.19}$$

$$\Rightarrow \frac{\epsilon^{d,d}}{w^{d,d}} \sim \chi^2(m-d+1) \text{ indep. of } W_{11} = K^T K$$

ad (ii) Take an orthogonal matrix L with last

row $\frac{1}{\|\underline{l}\|} \underline{l}^T$:

$$\frac{\underline{l}^T \Sigma^{-1} \underline{l}}{\underline{l}^T W^{-1} \underline{l}} = \frac{\left(\frac{1}{\|\underline{l}\|} \underline{l}^T\right) \Sigma^{-1} \left(\frac{1}{\|\underline{l}\|} \underline{l}\right)}{\left(\frac{1}{\|\underline{l}\|} \underline{l}^T\right) W^{-1} \left(\frac{1}{\|\underline{l}\|} \underline{l}\right)} = \frac{(L \Sigma^{-1} L^T)_{d,d}}{(L W^{-1} L^T)_{d,d}}$$

$$= \frac{((L\Sigma L^T)^{-1})_{dd}}{((LWL^T)^{-1})_{dd}} = \frac{(L\Sigma L^T)^{dd}}{(LWL^T)^{dd}} \sim \chi^2(m-d+1)$$

cf. th. 2.2 and lemma 2.7 (i)

(we have used that $L^T = L^{-1}$)

Theorem 2.8 $y \sim N_d(0, \Sigma)$, $W \sim W_d(m, \Sigma)$ independent

$$T^2 = m y^T W^{-1} y \sim \frac{md}{m-d+1} F(d, m-d+1)$$

(= $T^2(d, m)$)

Proof :

$$\frac{T^2}{m} = y^T W^{-1} y = \frac{z^T \Sigma^{-1} z}{\frac{z^T \Sigma^{-1} z}{y^T W^{-1} y}} = \frac{G}{H}$$

$H | y \sim \chi^2(m-d+1)$ cf. lemma 2.7 (ii)

the distribution does not depend on the elements of y

$\Rightarrow H \sim \chi^2(m-d+1)$ indep. of y

$G \sim \chi^2(d)$ cf. th. 2.1 (vi) indep. of H

$$\frac{\frac{G}{d}}{\frac{H}{m-d+1}} = \frac{m-d+1}{d} \frac{T^2}{m} \sim F(d, m-d+1)$$

$$\Leftrightarrow T^2 \sim \frac{md}{m-d+1} F(d, m-d+1) \Leftrightarrow T^2 \sim T^2(d, m)$$

Corollary $\underline{x} \sim N_d(\underline{\mu}, \frac{1}{\lambda} \Sigma)$, $W \sim W_d(m, \Sigma)$ indep.

$$T^2 = \lambda m (\underline{x} - \underline{\mu})^T W^{-1} (\underline{x} - \underline{\mu}) \sim T^2(d, m)$$

Proof : $\frac{T^2}{m} = \lambda (\underline{x} - \underline{\mu})^T W^{-1} (\underline{x} - \underline{\mu}) = y^T W^{-1} y$ where

$$y = \sqrt{\lambda} (\underline{x} - \underline{\mu}) \sim N_d(0, \Sigma) \Rightarrow T^2 \sim T^2(d, m)$$

Beta distribution

$h \sim \chi^2(m_h)$, $e \sim \chi^2(m_e)$ independent

$t = \frac{h}{e} \sim \frac{m_h}{m_e} F(m_h, m_e)$ type II beta distribution or inverse beta dist.

$f(t) = \frac{1}{B(\frac{m_h}{2}, \frac{m_e}{2})} \frac{t^{\frac{m_h}{2}-1}}{(1+t)^{\frac{m_h+m_e}{2}}}$, $0 < t < \infty$

$v = \frac{h}{e+h} = \frac{t}{1+t} \sim B(\frac{m_h}{2}, \frac{m_e}{2})$ (type I) beta dist.

$g(v) = \frac{1}{B(\frac{m_h}{2}, \frac{m_e}{2})} v^{\frac{m_h}{2}-1} (1-v)^{\frac{m_e}{2}-1}$, $0 < v < 1$

note that $1-v = \frac{e}{e+h} = \frac{1}{1+t} = (1+t)^{-1}$
 $B(\frac{m_h}{2}, \frac{m_e}{2})$ $B(\frac{m_e}{2}, \frac{m_h}{2})$ $\frac{m_h}{m_e} F(m_h, m_e)$

Multi dimensional beta distributions

$H \sim W_d(m_H, \Sigma)$, $m_H \geq d$
 $E \sim W_d(m_E, \Sigma)$, $m_E \geq d$ } independent

$T = E^{-\frac{1}{2}} H E^{-\frac{1}{2}}$, T sym.

$V = (E+H)^{-\frac{1}{2}} H (E+H)^{-\frac{1}{2}}$, V sym.

notation : $g(\underbrace{v_{11}, \dots, v_{dd}}_{\frac{d(d+1)}{2} \text{ variables}}) = g(V)$

Theorem 2.9 :

$g(V) = \frac{1}{B_d(\frac{m_H}{2}, \frac{m_E}{2})} (\det V)^{\frac{m_H-d-1}{2}} (\det(I_d-V))^{\frac{m_E-d-1}{2}}$,
 $0 < V < I_d$

proof:

$$f(H, E) = \frac{1}{c_H} (\det H)^{\frac{m_H - d - 1}{2}} \operatorname{etr}(-\frac{1}{2} \Sigma^{-1} H) \frac{1}{c_E} (\det E)^{\frac{m_E - d - 1}{2}} \operatorname{etr}(-\frac{1}{2} \Sigma^{-1} E)$$

$$= \frac{1}{c_H c_E} (\det H)^{\frac{m_H - d - 1}{2}} (\det E)^{\frac{m_E - d - 1}{2}} \operatorname{etr}(-\frac{1}{2} \Sigma^{-1} (E+H))$$

change of variables:

$$V = (E+H)^{-\frac{1}{2}} H (E+H)^{-\frac{1}{2}}$$

$$Z = E+H$$

$$\frac{\partial(H, E)}{\partial(V, Z)} = (\det Z)^{\frac{d+1}{2}} \quad \text{cf A 9.2}$$

$$h(V, Z) = \frac{1}{c_H c_E} (\det(Z^{\frac{1}{2}} V Z^{\frac{1}{2}}))^{\frac{m_H - d - 1}{2}} (\det(Z - Z^{\frac{1}{2}} V Z^{\frac{1}{2}}))^{\frac{m_E - d - 1}{2}} \operatorname{etr}(-\frac{1}{2} \Sigma^{-1} Z) (\det Z)^{\frac{d+1}{2}}$$

$$= \frac{1}{c_H c_E} (\det V)^{\frac{m_H - d - 1}{2}} (\det(I_d - V))^{\frac{m_E - d - 1}{2}} (\det Z)^{\frac{m_H + m_E - d - 1}{2}} \operatorname{etr}(-\frac{1}{2} \Sigma^{-1} Z)$$

$$g(V) = \int_{R^{\frac{d(d+1)}{2}}} h(V, Z) d\Omega_Z$$

$$= \frac{c_{H+E}}{c_H c_E} (\det V)^{\frac{m_H - d - 1}{2}} (\det(I_d - V))^{\frac{m_E - d - 1}{2}}$$

$$\int_{R^{\frac{d(d+1)}{2}}} \frac{1}{c_{H+E}} (\det Z)^{\frac{m_H + m_E - d - 1}{2}} \operatorname{etr}(-\frac{1}{2} \Sigma^{-1} Z) d\Omega_Z$$

$$= \frac{2^{\frac{(m_H + m_E)d}{2}} (\det \Sigma)^{\frac{m_H + m_E}{2}} \Gamma_d(\frac{m_H + m_E}{2})}{2^{\frac{m_H d}{2}} (\det \Sigma)^{\frac{m_H}{2}} \Gamma_d(\frac{m_H}{2}) 2^{\frac{m_E d}{2}} (\det \Sigma)^{\frac{m_E}{2}} \Gamma_d(\frac{m_E}{2})} (\det V)^{\frac{m_H - d - 1}{2}} (\det(I_d - V))^{\frac{m_E - d - 1}{2}} \cdot 1$$

$$= \frac{1}{B(\frac{m_H}{2}, \frac{m_E}{2})} (\det V)^{\frac{m_H - d - 1}{2}} (\det(I_d - V))^{\frac{m_E - d - 1}{2}}$$

$V > 0$ a.s. of A 5.7 } $\Rightarrow 0 < V < I_d$ a.s.
 $I_d - V > 0$ a.s. due to sym.

$f(T)$ depends on Σ

$T > 0$

Eigenvalues corresponding to V (and $I_d - V$)

$V > 0$ a.s. \Rightarrow eigenvalue $\theta > 0$ a.s. cf. A 5.1

$I_d - V > 0$ a.s. $\Rightarrow 1 - \theta > 0$ a.s. cf. A 1.2 (c) and A 5.1

hence $0 < \theta < 1$ a.s.

$$\begin{aligned} \det(V - \theta I_d) &= \det(E+H)^{-1} \det(H - \theta(E+H)) \\ &= \det(E+H)^{-1} \det((1-\theta)H - \theta E) \\ &= \det(E+H)^{-1} \det((1-\theta)E) \det(HE^{-1} - \frac{\theta}{1-\theta} I_d) \\ &= k \det(HE^{-1} - \varphi I_d), \quad \varphi = \frac{\theta}{1-\theta} \end{aligned}$$

$\varphi_1, \dots, \varphi_d$ are different with probability 1 (without proof)

$\Rightarrow \theta_1, \dots, \theta_d$ - - - - -

note that $\det V = \prod_j \theta_j$ and $\det(I_d - V) = \prod_j (1 - \theta_j)$,
 cf. A 1.2 (b) cf. A 1.2 (c)

Θ_{max} is often used as test statistic, critical values are tabled

Trace variables

Lawley - Hotelling :

$$\begin{aligned} T_1^2 &= m_E \operatorname{tr}(HE^{-1}) = m_E \sum_{j=1}^s \varphi_j = m_E \sum_{j=1}^s \frac{\theta_j}{1-\theta_j} \\ &= m_E U^{(s)}, \quad m_E \geq d, \quad s = \min(d, m_H) \end{aligned}$$

Pillai :

$$V^{(s)} = \operatorname{tr}(H(E+H)^{-1}) = \sum_{j=1}^s \theta_j, \quad m_E \geq d, \quad s = \min(d, m_H)$$

U distribution (Λ distribution)

$$U = \det(I_d - V) = \det(E+H)^{-1} \det E = \frac{\det E}{\det(E+H)}$$

also $U = \prod_{j=1}^s (1 - \theta_j)$, $s = \min(d, m_H)$

Def: $U \sim U(d, m_H, m_E)$, $m_E \geq d$

$$U(d, m_H, m_E) = U(m_H, d, m_E + m_H - d) \quad \text{cf. p. 37 top}$$

in particular

$$\frac{1 - U(1, m_H, m_E)}{U(1, m_H, m_E)} = \frac{m_H}{m_E} F(m_H, m_E)$$

$$\frac{1 - U(d, 1, m_E)}{U(d, 1, m_E)} = \frac{d}{m_E + 1 - d} F(d, m_E + 1 - d)$$

$$\frac{1 - (U(2, m_H, m_E))^{\frac{1}{2}}}{(U(2, m_H, m_E))^{\frac{1}{2}}} = \frac{m_H}{m_E - 1} F(2m_H, 2(m_E - 1))$$

$$\frac{1 - (U(d, 2, m_E))^{\frac{1}{2}}}{(U(d, 2, m_E))^{\frac{1}{2}}} = \frac{d}{m_E + 1 - d} F(2d, m_E + 1 - d)$$

When $m_H = 1$ we have

$$\text{rank}(H(E+H)^{-1}) = \text{rank } H = 1$$

$$\Rightarrow \det(H - \theta(E+H)) = 0 \text{ has one root } \theta$$

$$U^{(1)} = \frac{\theta}{1-\theta}, \quad V^{(1)} = \theta$$

$$U = 1 - \theta$$

$$\begin{aligned} T_1^2 &= m_E U^{(1)} = m_E \operatorname{tr}(HE^{-1}), \quad \text{let } H = \underline{x} \underline{x}^T \\ &= m_E \operatorname{tr}(\underline{x} \underline{x}^T E^{-1}) \\ &= m_E \operatorname{tr}(\underline{x}^T E^{-1} \underline{x}) = m_E \underline{x}^T E^{-1} \underline{x} \sim T^2(d, m_E) \end{aligned}$$

$\underline{x} \sim N_d(\underline{0}, \Sigma)$ indep. of E

$$m_E U^{(1)} \sim T^2(d, m_E) \Leftrightarrow U^{(1)} \sim \frac{d}{m_E - d + 1} F(d, m_E - d + 1)$$

alternative calculation:

$$\begin{aligned} U &= \frac{\det E}{\det(E+H)} = \frac{\det E}{\det(E + \underline{x} \underline{x}^T)} = \left(\det(I_d + E^{-1} \underline{x} \underline{x}^T) \right)^{-1} \\ &= \left(\det(I_d + \underline{x}^T E^{-1} \underline{x}) \right)^{-1} \quad \text{cf. hint to exercise 2.12 a (problems 4)} \\ &= \left(1 + \underline{x}^T E^{-1} \underline{x} \right)^{-1} = \left(1 + \frac{T^2}{m_E} \right)^{-1}, \quad T^2 \sim T^2(d, m_E) \\ \Rightarrow T^2 &= m_E \left(\frac{1}{U} - 1 \right) = m_E \frac{1-U}{U} = m_E \frac{\theta}{1-\theta} = m_E U^{(1)} = T_1^2 \end{aligned}$$

$$\left(U^{(1)} \right)^{-1} \sim \frac{m_E - d + 1}{d} F(m_E - d + 1, d) \Rightarrow$$

$$V^{(1)} = \frac{U^{(1)}}{U^{(1)} + 1} = \left(1 + \left(U^{(1)} \right)^{-1} \right)^{-1} \sim B\left(\frac{d}{2}, \frac{m_E - d + 1}{2} \right)$$

$$\text{also } V^{(1)} = \frac{T_1^2}{m_E + T_1^2}$$