

$$H_0: C\beta = m$$

$$H_a: C\beta \neq m$$

$$L(\beta, \sigma^2 | y, X) = \left(\frac{1}{2\pi\sigma^2} \right)^{n/2} \exp \left[-\frac{1}{2\sigma^2} (y - X\beta)' (y - X\beta) \right]$$

$$\mathcal{H} = \{ (\beta, \sigma^2), -\infty < \beta_j < \infty, j=0,1,2,\dots,k, \sigma^2 > 0 \}$$

$$\mathcal{H}_0 = \{ (\beta, \sigma^2) \in \mathcal{H} \mid C\beta = m \}$$

$$= \frac{\sup_{(\beta, \sigma^2) \in \mathcal{H}_0} L(\beta, \sigma^2 | y, X)}{\sup_{(\beta, \sigma^2) \in \mathcal{H}} L(\beta, \sigma^2 | y, X)}$$

$$\sup_{(\beta, \sigma^2) \in \mathcal{H}} L(\beta, \sigma^2 | y, X) = L(\hat{\beta}, \hat{\sigma}_{mv}^2 | y, X) =$$

$$\hat{\beta} = (X'X)^{-1} X'y \quad \hat{\sigma}_{mv}^2 = \frac{(y - X\hat{\beta})' (y - X\hat{\beta})}{n}$$

$$= (2\pi)^{-n/2} (\hat{\sigma}_{mv}^2)^{-n/2} e^{-n/2}$$

Cálculo de $\sup_{(\beta, \sigma^2) \in \mathcal{H}_0} L(\beta, \sigma^2 | y, X)$

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Cálculo de $\sup_{(\beta, \sigma^2) \in \mathcal{H}_0} L(\beta, \sigma^2 | y, X)$

$$\log L(\beta, \sigma^2 | y, X) =$$

$$= -\frac{n}{2} \left[\log(2\pi) + \log \sigma^2 \right] - \frac{1}{2\sigma^2} (y - X\beta)' (y - X\beta)$$

$$l = \log L - \lambda' (C\beta - m)$$

$$\frac{\partial l}{\partial \beta} = -\frac{1}{2\sigma^2} (2X'X\beta - 2X'y) - C'\lambda = 0$$

$$\frac{\partial l}{\partial \sigma^2} = -\frac{n}{2\sigma^2} + \frac{1}{2\sigma^4} (y - X\beta)' (y - X\beta) = 0$$

$$\frac{\partial l}{\partial \lambda} = -(C\beta - m) = 0$$

$$\rightarrow \frac{-n\sigma^2 + (y - X\beta)' (y - X\beta)}{2\sigma^4} = 0$$

$$\hat{\sigma}_0^2 = \frac{(y - X\hat{\beta}_0)' (y - X\hat{\beta}_0)}{n} \quad \text{estimador de máxima verossimilhança de } \sigma^2 \text{ sob } H_0 \text{ (ou em } \mathcal{H}_0)$$

$$\hat{\beta}_0 \text{ estimador de máxima verossimilhança de } \beta \text{ sob } H_0 \text{ (ou em } \mathcal{H}_0).$$

$$\frac{\partial \ell}{\partial \underline{\beta}} = 0 \Rightarrow \frac{1}{2\hat{\sigma}_0^2} (2X'X\underline{\beta} - 2X'\underline{y}) + C'\underline{\lambda} = 0$$

$$X'X \hat{\underline{\beta}}_0 = X'\underline{y} - C'\underline{\lambda} \hat{\sigma}_0^2$$

$$\begin{aligned} \hat{\underline{\beta}}_0 &= (X'X)^{-1} X'\underline{y} - (X'X)^{-1} C'\underline{\lambda} \hat{\sigma}_0^2 \\ &= \hat{\underline{\beta}} - (X'X)^{-1} C'\underline{\lambda} \hat{\sigma}_0^2 \end{aligned}$$

$$\frac{\partial \ell}{\partial \underline{\lambda}} = 0 \Rightarrow C\hat{\underline{\beta}}_0 = \underline{m}$$

$\times C$
 $C\hat{\underline{\beta}} - C(X'X)^{-1}C'\underline{\lambda} \hat{\sigma}_0^2 = \underline{m}$

$$\underline{\lambda} = \frac{[C(X'X)^{-1}C']^{-1} (C\hat{\underline{\beta}} - \underline{m})}{\hat{\sigma}_0^2}$$

$$\therefore \hat{\underline{\beta}}_0 = \hat{\underline{\beta}} - (X'X)^{-1} C' [C(X'X)^{-1}C']^{-1} (C\hat{\underline{\beta}} - \underline{m})$$

Ols:

$\hat{\sigma}_0^2$ e $\hat{\underline{\beta}}_0$ são os estimadores de máxima verossimilhança de σ^2 e $\underline{\beta}$ sob $H_0: C\underline{\beta} = \underline{m}$.

Coincidem com os estimadores de máxima verossimilhança no modelo reduzido sob H_0 .

$$\sup_{\theta \in \Theta_0} L(\beta, \sigma^2 | y, X) = L(\hat{\beta}_0, \hat{\sigma}_0^2 | y, X) =$$

$$= (2\pi)^{-n/2} (\hat{\sigma}_0^2)^{-n/2} e^{-n/2}$$

$$\Lambda = \left(\frac{\hat{\sigma}_{mv}^2}{\hat{\sigma}_0^2} \right)^{n/2}$$

$$RC: \Lambda = \left(\frac{\hat{\sigma}_{mv}^2}{\hat{\sigma}_0^2} \right)^{n/2} \leq \lambda_0$$

Usar a estatística $W = (\Lambda^{-2/n} - 1) \frac{n-k-1}{p}$ facilidade de obter a distribuição

— W é uma função monótona de Λ

$$- \Lambda \leq \lambda_0 \Leftrightarrow \Lambda^{-1} \geq \lambda_0^{-1} \Leftrightarrow \Lambda^{-2/n} \geq \lambda_0^{-2/n}$$

$$(\Lambda^{-2/n} - 1) \frac{n-k-1}{p} \geq (\lambda_0^{-2/n} - 1) \frac{n-k-1}{p} \Leftrightarrow$$

$$\Leftrightarrow W \geq w \quad \text{forma da região crítica}$$

$$W = \left(\frac{\hat{\sigma}_0^2}{\hat{\sigma}_{mv}^2} - 1 \right) \frac{n-k-1}{p} = \frac{\hat{\sigma}_0^2 - \hat{\sigma}_{mv}^2}{\hat{\sigma}_{mv}^2} \frac{n-k-1}{p} *$$

$$\hat{\sigma}_0^2 = \frac{(\underline{y} - X\hat{\beta}_0)'(\underline{y} - X\hat{\beta}_0)}{n}$$

$$\hat{\beta}_0 = \hat{\beta} - \underbrace{(X'X)^{-1}C'[C(X'X)^{-1}C']^{-1}}_{\substack{H \\ \sim (k+1) \times 1}} (C\hat{\beta} - \underline{m})$$

$$= \hat{\beta} - \underline{H}$$

$$\hat{\sigma}_0^2 = \frac{1}{n} \left[(\underline{y} - X\hat{\beta} + X\underline{H})'(\underline{y} - X\hat{\beta} + X\underline{H}) \right] =$$

$$= \frac{1}{n} \left\{ (\underline{y} - X\hat{\beta})'(\underline{y} - X\hat{\beta}) + (\underline{y} - X\hat{\beta})'X\underline{H} + \underline{H}'X'(\underline{y} - X\hat{\beta}) + \underline{H}'X'X\underline{H} \right\}$$

$$\underline{H}'X'(\underline{y} - X\hat{\beta}) = \underline{H}'(X'\underline{y} - X'X\hat{\beta}) = \underline{H}'(X'\underline{y} - X'\underline{y}) = 0$$

$$(\underline{y} - X\hat{\beta})'X\underline{H} = [\underline{H}'X'(\underline{y} - X\hat{\beta})]' = 0$$

$$= \hat{\sigma}^2 + \frac{\underline{H}'X'X\underline{H}}{n} = \hat{\sigma}^2 + \frac{1}{n} (C\hat{\beta} - \underline{m})'[C(X'X)^{-1}C']^{-1}C(X'X)^{-1}(X'X)$$

$$\begin{aligned}
 & (X'X)^{-1}C'[C(X'X)^{-1}C']^{-1}(C\hat{\beta} - \underline{m}) = \\
 & = \hat{\sigma}_{mv}^2 + \frac{1}{n} (C\hat{\beta} - \underline{m})'[C(X'X)^{-1}C']^{-1}(C\hat{\beta} - \underline{m})
 \end{aligned}$$

Substituindo em *

$$W = \frac{(C\hat{\beta} - \underline{m})'[C(X'X)^{-1}C']^{-1}(C\hat{\beta} - \underline{m})}{n \hat{\sigma}_{mv}^2} \quad \frac{n-k-1}{p}$$

$$= \frac{(C\hat{\beta} - \underline{m})'[C(X'X)^{-1}C']^{-1}(C\hat{\beta} - \underline{m})}{p \frac{(\underline{y} - X\hat{\beta})'(\underline{y} - X\hat{\beta})}{n-k-1}} =$$

$$= \frac{(C\hat{\beta} - \underline{m})'[C(X'X)^{-1}C']^{-1}(C\hat{\beta} - \underline{m})}{p \text{ MSE}} \quad \text{estatística de teste}$$

↳ do Modelo Completo $\underline{y} = X\beta + \underline{\epsilon}$

Distribuição de W

$$\frac{(C\hat{\beta} - \underline{m})' [C(X'X)^{-1}C']^{-1} (C\hat{\beta} - \underline{m})}{\sigma^2}$$

$$\hat{\beta} \sim N_{k+1}(\beta, (X'X)^{-1}\sigma^2)$$

$$C\hat{\beta} \sim N_p(C\beta, C(X'X)^{-1}C'\sigma^2)$$

$$(C\hat{\beta} - \underline{m}) \sim N_p(C\beta - \underline{m}, C(X'X)^{-1}C'\sigma^2)$$

$$A\hat{Z} = \frac{[C(X'X)^{-1}C']^{-1}}{\sigma^2} C(X'X)^{-1}C'\sigma^2 = I \quad (A\hat{Z} \text{ é idempotente})$$

$$\lambda = \frac{1}{2} (C\beta - \underline{m})' \frac{[C(X'X)^{-1}C']^{-1}}{\sigma^2} (C\beta - \underline{m})$$

$$\therefore \frac{(C\hat{\beta} - \underline{m})' [C(X'X)^{-1}C']^{-1} (C\hat{\beta} - \underline{m})}{\sigma^2} \sim \chi^2_{p, \lambda}$$

$\hat{\beta}$ e SSE são independentes $\Rightarrow$

$$W \sim F_{p, n-k-1, \lambda}$$

Sob H_0 $C\beta = \underline{m}$ $\lambda = 0$ e $W \sim F_{p, n-k-1}$ Central

O teste da razão de verossimilhança generalizada rejeita H_0 para $W \geq w$.

Tomar w tal $P(F_{p, n-k-1} \geq w) = \alpha$.

Obs:

$$1) W = \frac{\hat{\sigma}_0^2 - \hat{\sigma}_{mv}^2}{\hat{\sigma}_{mv}^2} \frac{n-k-1}{p}$$

$\hat{\sigma}_{mv}^2$ - estimador de max. veross. de σ^2 no modelo original

$\hat{\sigma}_0^2$ - estimador de max. veross. de σ^2 no modelo reduzido sob H_0 (ambos têm denominador n)

$\therefore W$ pode ser escrita como

$$W = \frac{SSE_R - SSE_C}{SSE_C} \frac{n-k-1}{p}$$

onde

SSE_C - soma de quadrados dos resíduos do modelo completo (modelo original) $= (\mathbf{y} - \mathbf{X}\hat{\beta})'(\mathbf{y} - \mathbf{X}\hat{\beta})$

SSE_n - soma de quadrados de resíduos do modelo reduzido sob $H_0 = (Y - X\hat{\beta}_0)'(Y - X\hat{\beta}_0) =$
 $= (Y - X\hat{\beta})'(Y - X\hat{\beta}) + (C\hat{\beta} - \underline{m})'[C(X'X)^{-1}C']^{-1}(C\hat{\beta} - \underline{m})$

$$SSE_n - SSE_c = (C\hat{\beta} - \underline{m})'[C(X'X)^{-1}C']^{-1}(C\hat{\beta} - \underline{m}) > 0$$

pois $C(X'X)^{-1}C'$ é positiva definida

Resultados

i) $X_{n \times p}$ $r(X) = p \Rightarrow X'X$ é positiva definida

ii) Se A é positiva definida então $r(CAC') = r(C)$

$\Rightarrow [C(X'X)^{-1}C']$ é inversível

iii) Se A é p.d. $n \times n$ e C é $p \times n$ com $r(C) = p$

então CAC' é positiva definida $\Rightarrow C(X'X)^{-1}C'$ é positiva definida ver pag 386

(Não escrever $SSE_n - SSE_c = SSR_c - SSR_n$, pois isto pode não valer. $SST = SSR_c + SSE_c$

$$SST = SSR_n + SSE_n$$

$$\Rightarrow SSE_n - SSE_c = SSR_c - SSR_n$$

Em alguns casos (raros), a redução sob H_0 altera a variável resposta e as somas de quadrados totais não são as mesmas)

$$E_X: Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon$$

$$H_0: \beta_1 = \beta_2 + 4$$

$$\text{Sob } H_0 \quad Y = \beta_0 + (\beta_2 + 4)x_1 + \beta_2 x_2 + \epsilon$$

$$Y - 4x_1 = \beta_0 + \beta_2(x_1 + x_2) + \epsilon$$

$$2) \text{Var}(C\hat{\beta}_2 - m) = \text{Var}(C\hat{\beta}_2) = C(X'X)^{-1}C'\sigma^2$$

$$\widehat{\text{Var}}(C\hat{\beta}_2) = C(X'X)^{-1}C' \text{MSE}$$

3) Para cada valor de λ (parâmetro de não centralidade da distribuição de W), o poder do teste é

$$\pi(\lambda) = \int_{w_\alpha}^{\infty} F(p, n-k-1, \lambda) dw$$

onde $F(p, n-k-1, \lambda)$ - densidade da $F_{p, n-k-1, \lambda}$

e w_α tal que $P(F_{p, n-k-1} \geq w_\alpha) = \alpha$,

α - nível de significância do teste.

$$4) \hat{\beta}_0 = \hat{\beta} - (X'X)^{-1}C'[C(X'X)^{-1}C']^{-1}(C\hat{\beta} - \underline{m})$$

est. max. veross. de β sob $H_0: C\beta = \underline{m}$

é também o estimador de mínimos quadrados de β sob H_0 . [minimiza $(Y - X\hat{\beta}_0)'(Y - X\hat{\beta}_0)$

sujeito à condição $C\hat{\beta}_0 = \underline{m}$]

5) A estatística W para testar $H_0: C\beta = \underline{m}$ contra $H_a: C\beta \neq \underline{m}$ fica inalterada se testarmos

$H_0: QC\beta = Q\underline{m}$ contra $H_a: QC\beta \neq Q\underline{m}$,

onde Q é uma matriz $p \times p$ não singular.

$$C - p \times (k+1)$$

$$C\beta = \underline{m} \Leftrightarrow$$

$$QC - p \times (k+1)$$

$$QC\beta = Q\underline{m}$$

$$W_1 = \frac{(QC\hat{\beta} - Q\underline{m})'[QC(X'X)^{-1}C'Q']^{-1}(QC\hat{\beta} - Q\underline{m})}{p \text{ MSE}}$$

$$= \frac{(C\hat{\beta} - \underline{m})'Q'Q^{-1}[C(X'X)^{-1}C']^{-1}Q^{-1}Q(C\hat{\beta} - \underline{m})}{p \text{ MSE}} =$$

$$= \frac{(C\hat{\beta} - \underline{m})' [C(X'X)^{-1}C']^{-1} (C\hat{\beta} - \underline{m})}{pMSE}$$

No exemplo 4, $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \epsilon$

$$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 \Leftrightarrow C\beta = \underline{m}$$

$$C = \begin{bmatrix} 0 & 1 & -1 & 0 & 0 \\ 0 & 1 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 & -1 \end{bmatrix}_{3 \times 5} \quad \underline{m} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \quad \begin{aligned} \beta_1 - \beta_2 &= 0 \\ \beta_1 - \beta_3 &= 0 \\ \beta_1 - \beta_4 &= 0 \end{aligned}$$

H_0 pode ser escrita alternativamente como

$$H_0: C_1 \beta = \underline{m}_1$$

$$C_1 = \begin{bmatrix} 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 1 & -1 \end{bmatrix} \quad \underline{m}_1 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \quad \begin{aligned} \beta_1 - \beta_2 &= 0 \\ \beta_2 - \beta_3 &= 0 \\ \beta_3 - \beta_4 &= 0 \end{aligned}$$

$$\text{Temos que } C_1 = \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix}}_{Q} C \quad C_1 = QC$$

$$|Q| = \begin{vmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 0 & -1 & 1 \end{vmatrix} = 1 \quad Q_{3 \times 3} \text{ n\~ao singular } \therefore$$

$$QC\beta = Q\underline{m}$$

W_1 para testar $H_0: C_1\beta = \underline{m}_1$ coincide com W que testa $H_0: C\beta = \underline{m}$. Os graus de liberdade s\~ao os mesmos $\Rightarrow$ as conclus\~oes s\~ao as mesmas.