

M7wl : linear mixed effects models (LME) 01.11.2018

Beaches: random intercept pr beach

Notation:

$$Y_i = \begin{bmatrix} Y_{i1} \\ Y_{i2} \\ \vdots \\ Y_{in_i} \end{bmatrix} \quad \begin{array}{l} Y_{ij} \text{ response for cluster } i \\ \text{for sample } j \\ j=1, \dots, n_i \end{array} \quad \begin{array}{l} \text{beach} \\ \downarrow \\ i=1, \dots, m \end{array}$$

(n_i x 1)

with covariates x_{i1}, \dots, x_{in_i}
 p x 1 x_{ij} element

$$X_i = \begin{bmatrix} x_{i1}^T \\ \vdots \\ x_{in_i}^T \end{bmatrix} \quad (n_i \times p)$$

Beaches: $m=9$
 $n_i=5$
 $p=2$

Random intercept model

$$Y_{ij} = \beta_0 + \beta_1 x_{ij} + \underbrace{\gamma_{0i}}_{\substack{\text{RV} \\ \text{deviation from the pop. intercept} \\ N(0, \tau_0^2)}} + \underbrace{\epsilon_{ij}}_{\substack{\text{RV} \\ \text{i.i.d. } N(0, \sigma^2) \\ \text{Variance Components}}}$$

β_0, β_1 population fixed effects
 γ_{0i} one covariate
 ϵ_{ij} one covariate

Q: What are the unknown parameters?

A: $\beta_0, \beta_1, \tau_0^2, \sigma^2$ Printout:

$$\begin{aligned} \hat{\beta}_0 &= 6.58 \\ \hat{\beta}_1 &= -2.57 \\ \hat{\tau}_0^2 &= 8.67 \\ \hat{\sigma}^2 &= 9.36 \end{aligned}$$

Correlation

WANT: $\text{Cov}(Y_i)$
 $n_i \times n_i$

$$Y_{ij} = \beta_0 + \beta_1 x_{ij} + \gamma_{0i} + \varepsilon_{ij} \sim N_1(\beta_0 + \beta_1 x_{ij}, \tau_0^2 + \sigma^2)$$

$N(0, \tau_0^2)$ $N(0, \sigma^2)$
 \downarrow \downarrow
 γ_{0i} ε_{ij}
 \uparrow \uparrow
 independent

$\text{Var}(Y_{ij}) = \tau_0^2 + \sigma^2$

$$\text{Cov}(Y_{ij}, Y_{ik}) = E \left[(Y_{ij} - \mu_{ij}) (Y_{ik} - \mu_{ik}) \right]$$

\uparrow \uparrow
 $\beta_0 + \beta_1 x_{ij}$ $\beta_0 + \beta_1 x_{ik}$

$$= E \left[(\cancel{\beta_0 + \beta_1 x_{ij}} + \gamma_{0i} + \varepsilon_{ij} - \cancel{\beta_0 + \beta_1 x_{ij}}) (\cancel{\beta_0 + \beta_1 x_{ik}} + \gamma_{0i} + \varepsilon_{ik} - \cancel{\beta_0 + \beta_1 x_{ik}}) \right]$$

$$= E \left[(\gamma_{0i} + \varepsilon_{ij}) (\gamma_{0i} + \varepsilon_{ik}) \right] = E \left[\gamma_{0i}^2 + \varepsilon_{ij} \cdot \gamma_{0i} + \gamma_{0i} \cdot \varepsilon_{ik} + \varepsilon_{ij} \cdot \varepsilon_{ik} \right]$$

$$= \underbrace{E(\gamma_{0i}^2)} + \underbrace{E(\varepsilon_{ij})}_{0} \cdot \underbrace{E(\gamma_{0i})}_{0} + \underbrace{E(\gamma_{0i})}_{0} \cdot \underbrace{E(\varepsilon_{ik})}_{0} + \underbrace{E(\varepsilon_{ij})}_{0} \cdot \underbrace{E(\varepsilon_{ik})}_{0} = \tau_0^2$$

$$\text{Var}(\gamma_{0i}) = E(\gamma_{0i}^2) - \underbrace{E(\gamma_{0i})^2}_0 = \tau_0^2$$

$$\text{Cov}(Y_i) = \text{Cov} \begin{bmatrix} Y_{i1} \\ Y_{i2} \\ \vdots \\ Y_{in_i} \end{bmatrix} = \begin{bmatrix} \sigma^2 + \tau_0^2 & \tau_0^2 & \dots & \tau_0^2 \\ \tau_0^2 & \sigma^2 + \tau_0^2 & & \\ \vdots & & \ddots & \\ \tau_0^2 & & & \sigma^2 + \tau_0^2 \end{bmatrix}$$

$$= \sigma^2 \cdot \mathbf{I}_{n_i \times n_i} + \tau_0^2 \cdot \mathbf{1}\mathbf{1}^T$$

compound symmetry
 $n_i \times n_i$ with 1s everywhere

$$\text{Corr}(Y_{ij}, Y_{ik}) = \frac{\tau_0^2}{\tau_0^2 + \sigma^2} \leftarrow \text{intra-class correlation ICC}$$

$\sqrt{\sigma^2 + \tau_0^2} \cdot \sqrt{\sigma^2 + \tau_0^2}$

Breches:

$$\hat{\sigma}_0^2 = 8.67 \leftarrow \text{between}$$

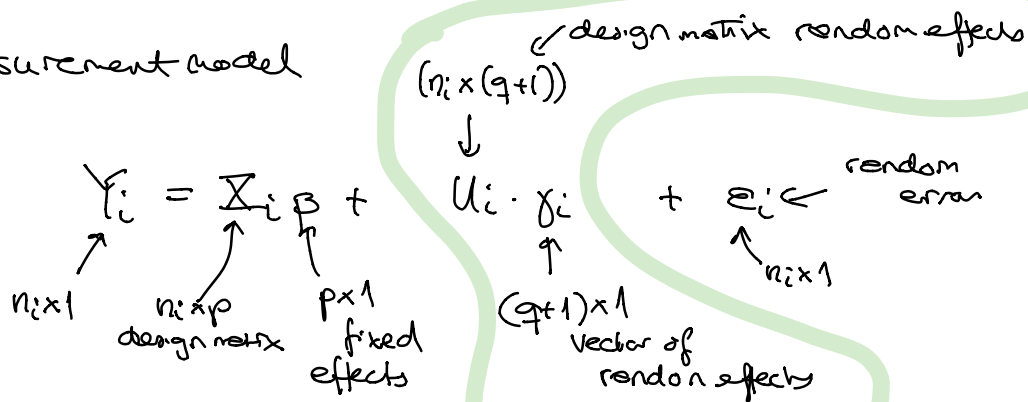
$$\hat{\sigma}^2 = 9.36 \leftarrow \text{within}$$

$$ICC = \frac{\hat{\sigma}_0^2}{\hat{\sigma}_0^2 + \hat{\sigma}^2} = \frac{8.67}{8.67 + 9.36} = \underline{\underline{0.48}}$$

↑
 $\text{Corr}(Y_{ij}, Y_{ik})$ two obs from the same
 beach

Linear mixed effects model

Measurement model



$$U_i = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \text{ if random intercept model } (q=0)$$

$$U_i = \begin{bmatrix} 1 & u_{i1} \\ 1 & \vdots \\ \vdots & \vdots \\ i & u_{in_i} \end{bmatrix}$$

\nwarrow NAP for beach i , $u_{ij} = x_{ij}$

Distributional assumptions

For cluster i $y_i \sim N_{(q+1)}(0, Q)$ and $\varepsilon_i \sim N(0, \sigma^2 I)$

random intercept $Q = \tau_0^2$
 1×1

random intercept and slope $Q = \begin{bmatrix} \tau_0^2 & \tau_{01} \\ \tau_{01} & \tau_1^2 \end{bmatrix}$
 2×2

Two views: conditional and marginal

$$Y_i = X_i \beta + U_i y_i + \varepsilon_i \quad y_i \sim N(0, Q), \quad \varepsilon_i \sim N(0, \sigma^2 I)$$

The conditional distr. of Y_i :

$$Y_i | y_i \sim N(X_i \beta + U_i y_i, \sigma^2 I)$$

The marginal distr. of Y_i :

$$Y_i = X_i \beta + \varepsilon_i^* \quad \text{where} \quad \varepsilon_i^* = U_i y_i + \varepsilon_i$$

$$\varepsilon_i^* \text{ is m.v.N with } E(\varepsilon_i^*) = U_i \cdot E(y_i) + E(\varepsilon_i) = 0$$

$$V_i = \text{Cov}(\varepsilon_i^*) = \text{Cov}(U_i y_i) + \text{Cov}(\varepsilon_i)$$

$$= U_i \underbrace{\text{Cov}(y_i)}_Q U_i^T + \sigma^2 I$$

$$= U_i Q U_i^T + \sigma^2 I$$

$$Y_i \text{ has } E(Y_i) = X_i \beta, \quad \text{Cov}(Y_i) = V_i$$

$$Y_i \sim N_{n_i} (X_i \beta, V_i)$$

Parameter estimation $\rightarrow \beta$ row

Global model $Y = X\beta + \epsilon^*$ $\epsilon^* \sim N(0, V)$

\uparrow
 $Uy + \epsilon$

See module page

A

$$\hat{\beta} = (X^T V^{-1} X)^{-1} X^T V^{-1} Y$$

$= \left(\sum_{i=1}^m X_i^T V_i^{-1} X_i \right)^{-1} \sum_{i=1}^m X_i V_i^{-1} Y_i$

Home work:
Find
 $E(\hat{\beta})$
 $Cov(\hat{\beta})$

$$\hat{\beta} \sim N(\beta, (X^T V^{-1} X)^{-1})$$