

# Modelos Matemáticos e Aplicações

Modelos lineares mistos

Linear mixed models

Elsa Gonçalves  
ISA/UL

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# Linear Mixed Models

## Summary:

1. Motivation: some typical examples involving mixed models
2. The general linear mixed model: description and properties; estimation of covariance parameters; estimation of fixed effects and prediction of random effects; hypothesis tests for covariance parameters, fixed and random effects; model selection (model comparison via likelihood ratio tests and via information criteria); validation of model assumptions
3. Some particular cases and applications: exercises

# Fitting linear mixed models

## *Packages usually used*

- Library **nlme**,  (<http://www.R-project.org>)
- Library **lme4**,  (<http://www.R-project.org>)
- **Proc mixed** do SAS (*SAS Institute, Inc.*)
- Library **ASREML-R**,  (*VSN International*) (mainly focused on animal and plant breeding)
- Library **rrBLUP**,  (<http://www.R-project.org>)  
(focused on genomic selection)

# Bibliography

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# What is a mixed model?

- Models in which the only effects are fixed effects are called fixed effects models.
- **Models that contain both fixed and random effects are called mixed models.**
- A special case of a mixed model is when there are no fixed effects (except a general mean common to all observations,  $\mu$ ), that is, a model having only random effects. It is called a **random model**.

# What are random effects?

When the levels of the factor have been selected at random from a population of possible levels and we want to obtain information about the parameters of the distribution of those levels.

The main goals of the analysis of random effects models are:

- Estimate covariance parameters
- Test hypotheses about the parameters or functions of the parameters
- Calculate predictors (BLUP) of the realized values of the random effects
- Compare treatment means

# Motivation

**Some typical examples involving mixed models**

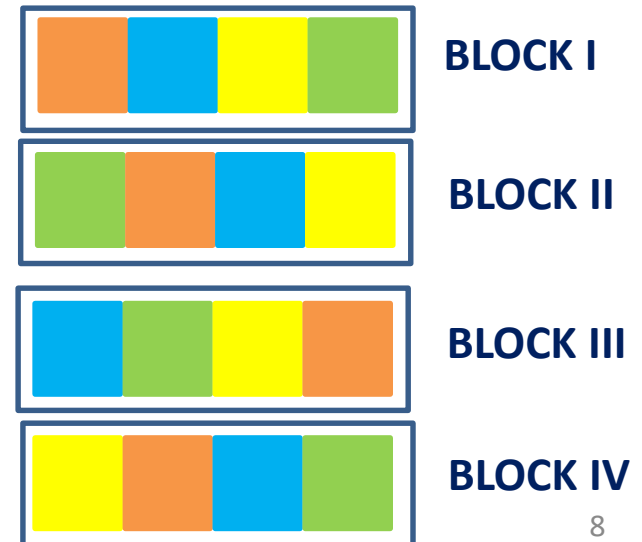
# The Randomized Complete Block design (RCB)

The randomized block design is just the beginning with mixed models.

Blocking is a research technique that is used to reduce the effects of variation among experimental units. The units can be people, plants, animals, etc..

- The RCB is the standard design for agricultural experiments.
- The field is divided into units to account for any variation in the field (by accounting for spatial effects). Blocks are groups of units that are formed so that units within the blocks are as nearly homogeneous as possible.
- The levels of the factor being investigated, called treatments, are randomly assigned to units within the blocks (each treatment once per block).
- The number of blocks is the number of replications.
- Any treatment can be adjacent to any other treatment, but not to the same treatment within the block.

**Example:** each row represents a block. There are 4 blocks (I-IV) and 4 treatments (different colors)





# The Randomized Complete Block (RCB) design

- Usually, the primary objectives are to estimate and compare treatment means. In most cases, the treatment effects are considered fixed because the treatments in the experiment are the only ones to which inference is to be made.
- Block effects are usually considered random because the blocks in the experiment constitute only a small subset of the larger set of blocks over which inferences about treatment means are to be made.

The model for data from a randomized blocks design usually contains a fixed effects factor and random effects for blocks, making it a mixed model

## RCB repeated at more than one location

- Blocks are laid out at more than one location. Treatments are assigned at random to those blocks.
  - Treatments are assigned at random within blocks, each treatment once per block.
  - The number of blocks is the number of replications.
  - Any treatment can be adjacent to any other treatment, but not to the same treatment within the block.
- Usually, the treatment effects are considered fixed.
- Usually, location effects are considered random because the locations constitute only a small subset of the larger set of locations over which inferences about treatment means are to be made.
- Block effects nested within location are usually considered random.

The model for data from this type of design contains a fixed effects factor and random effects factors,

it is a mixed model

**Example:** there are 4 treatments (different colors), 4 locations and 4 blocks per location

Location I



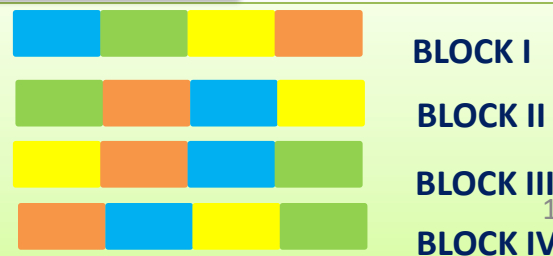
Location II



Location III



Location IV



# The split-plot design

- The split plot design has an agricultural heritage, with the whole plots usually being large areas of land and the subplots being smaller areas of land within the large areas.

Example: several varieties of a crop could be planted in different fields (whole plots), one variety to a field. Then each field could be divided into several subplots, and each subplot could be treated with a different type of fertilizer..

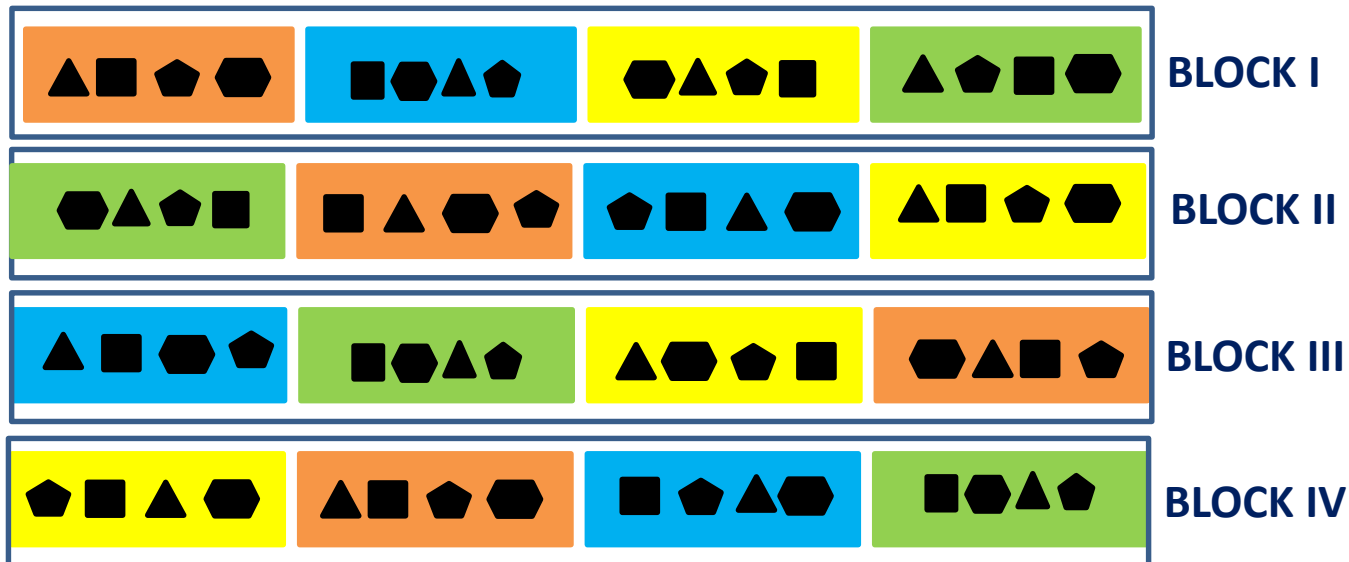
- Despite its agricultural basis, the split-plot design is useful in many other scientific areas.

## The split-plot design on a RCB

- Main treatments (levels of factor A) are assigned at random within blocks, each treatment once per block; they are divided further into additional independent units (subplots) to which another set of treatments (levels of factor B) are randomly assigned.
- The number of blocks is the number of replications.
- Any main treatment can be adjacent to any other treatment, but not to the same treatment within the block.

### Example:

Different colors represent different main treatments; each row represents a block. There are 4 blocks (I-IV) each of 4 main treatments (colors) divided into 4 further sub-plot treatments (symbols).



## The split-plot design on a RCB

- The effects of factor A, the effects of factor B and interaction  $A*B$  are considered fixed.
- Block effects are considered random effects.
- The effects of interaction Block\*Factor A (whole plot error) and Block\*Factor B are assumed random effects

The model for data from this type of design contains fixed and random effects,  
it is a mixed model

- ❑ Random models (a particular case of mixed model) and mixed models are historically applied in plant and animal breeding. In this context, the objectives are focused on the covariance parameters estimates and on the predictors of random effects.
- ❑ Other numerous experimental designs produce data for which mixed models are appropriate. Some examples are nested designs, designs belonging to the family of incomplete block designs, repeated measures designs, etc..

# The Linear Mixed Model

In matrix formulation, the linear mixed model can be written as (the bold will be used for matrix notation):

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\mathbf{u} + \mathbf{e}$$

$\mathbf{Y}_{(n \times 1)}$  is the vector of observations

$\boldsymbol{\beta}_{(p \times 1)}$  is the **vector of fixed effects**

$\mathbf{X}_{(n \times p)}$  is the model matrix for fixed effects

$\mathbf{u}_{(q \times 1)}$  is the **vector of random effects**

$\mathbf{Z}_{(n \times q)}$  is the model matrix for random effects

$\mathbf{e}_{(n \times 1)}$  is a vector random errors

The predictors can be factors or numeric variables.

**Example:** model with one fixed effects factor and one random effects factor (when  $X$  and  $Z$  are incidence matrices)

$$\begin{bmatrix} y_{11} \\ y_{12} \\ \vdots \\ y_{1q} \\ y_{21} \\ y_{22} \\ \vdots \\ y_{2q} \\ \vdots \\ y_{p1} \\ y_{p2} \\ \vdots \\ y_{pq} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & \cdots & 0 \\ 1 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & 0 & \cdots & 0 \\ 1 & 0 & 1 & \cdots & 0 \\ 1 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & 0 & \cdots & 1 \\ 1 & 0 & 0 & \cdots & 1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & 0 & \cdots & 1 \end{bmatrix} \begin{bmatrix} \mu \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \\ 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_q \end{bmatrix} + \begin{bmatrix} e_{11} \\ e_{12} \\ \vdots \\ e_{1q} \\ e_{21} \\ e_{22} \\ \vdots \\ e_{2q} \\ \vdots \\ e_{p1} \\ e_{p2} \\ \vdots \\ e_{pq} \end{bmatrix}$$

When  $X$  is a singular matrix, the procedure is similar to the already described for ANOVA with fixed effects



# Linear mixed model

$$Y = X\beta + Zu + e$$

- The vectors  $\mathbf{u}$  and  $\mathbf{e}$  are assumed mutually independent with multivariate normal distribution with vector of mean values  $\mathbf{0}_{(n \times 1)}$  and covariance matrices  $\mathbf{G}$  and  $\mathbf{R}$ , respectively:

$$\text{cov}[\mathbf{u}, \mathbf{e}] = \mathbf{0}$$

$$\mathbf{u} \sim \mathcal{N}_q(\mathbf{0}, \mathbf{G})$$

$$\mathbf{e} \sim \mathcal{N}_n(\mathbf{0}, \mathbf{R})$$

where  $\mathbf{G}_{(q \times q)}$  and  $\mathbf{R}_{(n \times n)}$  are symmetric and positive-definite matrices

□ As a consequence,

$$E[\mathbf{Y}] = \mathbf{X}\boldsymbol{\beta}$$

$$\text{var}[\mathbf{Y}] = \mathbf{ZGZ}^T + \mathbf{R} = \mathbf{V},$$

where  $\mathbf{Z}^T$  is the transpose of  $\mathbf{Z}$ .

$$\text{cov}[\mathbf{Y}, \mathbf{u}] = \mathbf{ZG}$$

□ The distribution of  $\mathbf{Y}$  is multivariate normal with mean value  $\mathbf{X}\boldsymbol{\beta}$  and variance-covariance matrix  $\mathbf{V}$ , symmetric and positive-definite,

$$\mathbf{Y} \cap \mathcal{N}_n(\mathbf{X}\boldsymbol{\beta}, \mathbf{V}).$$

# There are many variants for linear mixed models

- **In the classical linear mixed model is assumed that:**

- The elements of the vector  $\mathbf{u}$  are independent and identically distributed random variables (i.i.d.), that is, the covariance matrix is  $\mathbf{G} = \sigma_u^2 \mathbf{I}_q$ , where  $\mathbf{I}_q$  is the identity matrix  $q \times q$  ;

- The elements of the vector  $\mathbf{e}$  are i.i.d. random variables, that is, the covariance matrix is  $\mathbf{R} = \sigma_e^2 \mathbf{I}_n$ , where  $\mathbf{I}_n$  is the identity matrix  $n \times n$ .

- **A particular case is the traditional random model:**

It means that  $\mathbf{X} = \mathbf{1}_n, \boldsymbol{\beta} = \mu, \mathbf{G} = \sigma_u^2 \mathbf{I}_q, \mathbf{R} = \sigma_e^2 \mathbf{I}_n$

## Example: the particular case of ANOVA with one factor with random effects, balanced

$$Y_{ij} = \mu + u_i + e_{ij}$$

for  $i = 1, \dots, a, j = 1, \dots, b$ .

$Y_{ij}$  is the  $j$ th observation in the  $i$ th level of factor  $A$ ;

$\mu$  is a general mean (population);

$u_i$  is the effect of the level  $i$  of the factor  $A$ ;

$e_{ij}$  is the random error associated to the observation  $Y_{ij}$ .

**In the traditional random model it is assumed:**

- $u_i \cap \mathcal{N}(0, \sigma^2_u), \forall i$
- $e_{ij} \cap \mathcal{N}(0, \sigma^2_e), \forall ij$
- $E(Y_{ij}) = \mu$
- $\text{cov}(e_{ij}, e_{i'j'}) = 0$ , except for  $i = i'$  e  $j = j'$
- $\text{cov}(u_i, u_{i'}) = 0, \forall i \neq i'$
- $\text{cov}(u_i, e_{i'j'}) = 0, \forall i, i' \text{ e } j'$

- Although  $u_i$  and  $e_{ij}$  are uncorrelated, the  $Y_{ij}$ s are not. In the same random effect the observations are correlated (a difference from the fixed effects model):

$$\text{cov}(Y_{ij}, Y_{ij'}) = \text{cov}(\mu + u_i + e_{ij}, \mu + u_i + e_{ij'}) = \sigma^2_u, \text{ for } j \neq j'$$

$$\text{cov}(Y_{ij}, Y_{i'j'}) = 0, \text{ for } i \neq i'$$

- As a consequence,

$$\text{var}(Y_{ij}) = \text{var}(\mu + u_i + e_{ij}) = \sigma^2_u + \sigma^2_e$$

$$\text{var}(\bar{Y}_i) = \sigma^2_u + \frac{\sigma^2_e}{b}$$

In this context arises the concept of Intraclass Correlation:

$$\text{corr}(y_{ij}, y_{ij'}) = \frac{\sigma^2_u}{\sqrt{\sigma^2_u + \sigma^2_e} \sqrt{\sigma^2_u + \sigma^2_e}}$$

# Many other situations can arise according to:

## ➤ $X\beta$

- one or more factors of fixed effects (including interactions, nested factors, etc.)

## ➤ $Zu$

- one or more factors of random effects (including interactions, nested factors, etc.)

## ➤ **The structure of the covariance matrices $G$ and $R$**

As mentioned above, in the traditional linear model the **covariance matrices  $G$  and  $R$  are defined as  $G = \sigma_u^2 I_q$  and  $R = \sigma_e^2 I_n$** , respectively:

$$\mathbf{G}_{(q \times q)} = \begin{bmatrix} \sigma_u^2 & 0 & \cdots & 0 \\ 0 & \sigma_u^2 & \cdots & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & \cdots & \sigma_u^2 \end{bmatrix} \quad \mathbf{R}_{(n \times n)} = \begin{bmatrix} \sigma_e^2 & 0 & \cdots & 0 \\ 0 & \sigma_e^2 & \cdots & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & \cdots & \sigma_e^2 \end{bmatrix}$$

But modeling the covariance structure is arguably the most powerful and important single feature of mixed models, and what sets it apart from conventional linear models. This extends beyond covariance structure to include correlation among observations.



## ➤ $ZU$ and matrix $G$

For example, frequently:

□ vector  $\mathbf{u}$  consists in  $k$  sub-vectors, that is,

$$\mathbf{u} = (\mathbf{u}_1^T, \dots, \mathbf{u}_k^T)^T$$

where  $\mathbf{u}_i$  is a vector  $q_i \times 1$ , thus  $q = \sum_{i=1}^k q_i$ .

The model matrix associated to vector  $\mathbf{u}$  is:

$$\mathbf{Z} = [\mathbf{Z}_1 \ \mathbf{Z}_2 \ \dots \ \mathbf{Z}_k].$$

□ Generalizing for  $k$  sub-vectors of random effects,

$$\mathbf{Zu} = [\mathbf{Z}_1 \ \mathbf{Z}_2 \ \dots \ \mathbf{Z}_k] \begin{bmatrix} \mathbf{u}_1 \\ \mathbf{u}_2 \\ \vdots \\ \mathbf{u}_k \end{bmatrix} = \sum_{i=1}^k \mathbf{Z}_i \mathbf{u}_i$$

In the simplest case,

□ each sub-vector of random effects, represented by  $\mathbf{u}_i$ , has the properties:

$$E[\mathbf{u}_i] = 0 \quad \text{var}[\mathbf{u}_i] = \sigma_{u_i}^2 \mathbf{I}_{q_i} = \mathbf{G}_i,$$

□ vectors  $\mathbf{u}_i$  e  $\mathbf{u}_{i'}$ , are assumed mutually independent,

$$\text{cov}[\mathbf{u}_i, \mathbf{u}_{i'}] = 0, \text{ for } i \neq i',$$

and, consequently,

$$\text{var}[\mathbf{u}] = \bigoplus_{i=1}^k \mathbf{G}_i = \mathbf{G},$$

that is,  $\mathbf{G}$  is the direct sum of matrices  $\mathbf{G}_i$ .

$$\mathbf{G}_{(q \times q)} \begin{bmatrix} \mathbf{G}_1 & 0 & \cdots & 0 & 0 \\ 0 & \mathbf{G}_2 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & \mathbf{G}_{k-1} & 0 \\ 0 & 0 & \cdots & 0 & \mathbf{G}_k \end{bmatrix}$$

## Some other common covariance structures

- Unstructured (the most complex)

$$\begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} & \sigma_{14} \\ \sigma_{12} & \sigma_2^2 & \sigma_{23} & \sigma_{24} \\ \sigma_{13} & \sigma_{23} & \sigma_3^2 & \sigma_{34} \\ \sigma_{14} & \sigma_{24} & \sigma_{34} & \sigma_4^2 \end{bmatrix}$$

- Compound symmetry

$$\begin{bmatrix} \sigma^2 + \sigma_1^2 & \sigma_1^2 & \sigma_1^2 & \sigma_1^2 \\ \sigma_1^2 & \sigma^2 + \sigma_1^2 & \sigma_1^2 & \sigma_1^2 \\ \sigma_1^2 & \sigma_1^2 & \sigma^2 + \sigma_1^2 & \sigma_1^2 \\ \sigma_1^2 & \sigma_1^2 & \sigma_1^2 & \sigma^2 + \sigma_1^2 \end{bmatrix}$$

- Autoregressive

$$\begin{bmatrix} \sigma^2 & \sigma^2 \rho & \sigma^2 \rho^2 & \sigma^2 \rho^3 \\ \sigma^2 \rho & \sigma^2 & \sigma^2 \rho & \sigma^2 \rho^2 \\ \sigma^2 \rho^2 & \sigma^2 \rho & \sigma^2 & \sigma^2 \rho \\ \sigma^2 \rho^3 & \sigma^2 \rho^2 & \sigma^2 \rho & \sigma^2 \end{bmatrix}$$


- Toeplitz

$$\begin{bmatrix} \sigma^2 & \sigma_1 & \sigma_2 & \sigma_3 \\ \sigma_1 & \sigma^2 & \sigma_1 & \sigma_2 \\ \sigma_2 & \sigma_1 & \sigma^2 & \sigma_1 \\ \sigma_3 & \sigma_2 & \sigma_1 & \sigma^2 \end{bmatrix}$$

...

✓ Depending on the context, there are numerous structures for covariance matrices **G** and **R**. Some frequently used are inspired in time series and spatial analysis.

# The linear mixed model in

The linear mixed model can be fitted in  using functions **lme** (*library nlme*), **lmer** (*library lme4*), **varComp** (*library varComp*).

For example:

```
> library(nlme)
```

```
lme(fixed, ..., random, correlation, method, control, ....)
```

```
lme(response~fixed effects, random=~random effects...)
```

## Example 1: fitting the classical random model (one random effects factor, $G=\sigma_u^2 I_q$ , $R=\sigma_e^2 I_n$ )

### library(nlme)

There is a single fixed effect, the intercept

Indicates that there is a single random effect for each group and the grouping is given by the variable clone

```
> arlme1<-lme(rend~1, random=~1|clone, data=arinto)
```

```
> arlme1
```

Linear mixed-effects model fit by REML

Data: arinto

Log-restricted-likelihood: -714.2113

Fixed: rend ~ 1

(Intercept)

1.389713

Random effects:

Formula: ~1 | clone

(Intercept) Residual

StdDev: 0.3288653 0.4273398

## Example 2: fitting a classical linear mixed model (one factor of fixed effects, one factor of random effects factor, $G=\sigma_u^2 I_q$ , $R=\sigma_e^2 I_n$ )

### library(nlme)

- `> terrenolme1<-lme(rend~variedade, random=~1 | terreno, data=terrenos)`
  - Fixed effect
  - random effect
- `> terrenolme1`
- Linear mixed-effects model fit by REML
- Data: terrenos
- Log-restricted-likelihood: -21.71354
- Fixed: rend ~ variedade
- (Intercept) variedadeB variedadeC variedadeD
- 1.55600000 -0.02384615 -0.38907692 -0.37784615
  
- Random effects:
- Formula: ~1 | terreno
- (Intercept) Residual
- StdDev: 0.1604919 0.3123811
  
- Number of Observations: 52
- Number of Groups: 13

## Example 2: fitting a classical linear mixed model (one factor of fixed effects, one factor of random effects factor, $G=\sigma_u^2 I_q$ , $R=\sigma_e^2 I_n$ )

**library(lme4)**

Fixed effect      random effect  
↓                    ↓

```
> terrenoslmer1<-lmer(rend~ variedade + (1 | terreno), data = terrenos)
```

terrenoslmer1

Linear mixed model fit by REML ['lmerMod']

Formula: rend ~ variedade + (1 | terreno)

Data: terrenos

REML criterion at convergence: 43.4271

Random effects:

Groups	Name	Std.Dev.
--------	------	----------

terreno	(Intercept)	0.1605
---------	-------------	--------

Residual		0.3124
----------	--	--------

Number of obs: 52, groups: terreno, 13

Fixed Effects:

(Intercept)	variedadeB	variedadeC	variedadeD
-------------	------------	------------	------------

1.55600	-0.02385	-0.38908	-0.37785
---------	----------	----------	----------



## Example 3: fitting a random model with

$$G = \bigoplus_{i=1}^k G_i, G_i = \sigma_{u_i}^2 \mathbf{I}_{q_i}, R = \sigma_e^2 \mathbf{I}_n$$

### Library(nlme)

```
> arlme2<-lme(rend~1, random=list(clone=pdDiag(~regiao-1)), data=arinto)
```

```
> arlme2
```

Linear mixed-effects model fit by REML

Data: arinto

Log-restricted-likelihood: -712.0479

Fixed: rend ~ 1

(Intercept)

1.414257

Random effects:

Formula: ~regiao - 1 | clone

Structure: Diagonal

regiaoBairrada regiaoLafoes regiaoOeste regiaoVverdes Residual

StdDev: 0.3319987 0.3038772 0.4048056 0.272041 0.4273398

Number of Observations: 988

Number of Groups: 247

# Methods for estimating covariance parameters

## Variance component estimation in linear mixed models mainly use three approaches:

### ❑ restricted (or residual) maximum likelihood (REML)

It is the method of estimation currently most used (by default, it is the estimation method used in all packages). The restricted maximum likelihood method in the context of linear mixed models was introduced by Patterson e Thompson (1971)<sup>1</sup>.

### ❑ maximum likelihood (ML)

ML is sometimes discouraged, because the variance component estimates are biased downward.

### ❑ procedures based on expected mean squares from the analysis of variance (ANOVA)

It is the classical approach, well applied for simple models with balanced data and when  $\mathbf{G}$  and  $\mathbf{R}$  are diagonal matrices (some examples will be studied in the applications section).

<sup>1</sup> Patterson, H.D., Thompson, R. (1971) - Recovery of inter-block information when block sizes are unequal. *Biometrika* **58**:545-554.

## Some considerations about REML/ML/ANOVA estimators

- For unbalanced data each of ML and REML are to be preferred over procedures based on expected mean squares from the analysis of variance (ANOVA).
- REML and ML have the same merits of being based on the maximum likelihood principle that is known to have useful properties of consistency and asymptotic normality of the estimators and the asymptotic sampling dispersion matrix of the estimators is also known.
- For balanced data REML solutions are identical to ANOVA estimators.
- For complex models, ML and REML are computationally intensive.
- REML and ML estimators are based on assuming normality of the data, but in many circumstances that assumption is unlikely to be seriously wrong. Therefore, the asymptotic variance-covariance properties are valid only in the large-sample sense.

## Some considerations about REML/ML/ANOVA estimators

- ML provides estimators of fixed effects, whereas REML, of itself, does not.
- ML variance component estimates are biased downward. REML estimators are based on taking into account the degrees of freedom for the fixed effects in the model (losing 1 degree of freedom for each). For this reason, REML estimators for covariance parameters are unbiased for balanced data. The use of REML method instead of ML is particularly important when the rank of matrix  $\mathbf{X}$  is large in relation to the sample size.
- REML estimators do not seem to be as sensitive to outliers in the data as are ML estimators.

# Restricted (or residual) maximum likelihood (REML) method

General model  $Y = X\beta + Zu + e$ , with  $Y \sim \mathcal{N}_n(X\beta, V)$ ,

- Estimation of the covariance parameters included in matrix  $V$ :

$$V(\boldsymbol{\varphi}) = \mathbf{ZG}(\boldsymbol{\nu})\mathbf{Z}^T + \mathbf{R}(\boldsymbol{\phi}),$$

$\boldsymbol{\nu}$  is the vector of parameters included in matrix  $\mathbf{G}$ ,  $\boldsymbol{\phi}$  is the vector of parameters included in matrix  $\mathbf{R}$ ,  $\boldsymbol{\varphi} = (\boldsymbol{\nu}^T, \boldsymbol{\phi}^T)^T$ .

The likelihood function is

$$L(\boldsymbol{\beta}, \boldsymbol{\varphi} | \mathbf{y}) = \frac{1}{(2\pi)^{\frac{n}{2}} |\mathbf{V}|^{1/2}} \exp\left(-\frac{1}{2} (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})^T \mathbf{V}^{-1} (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})\right),$$

where  $\mathbf{V}^{-1} = \mathbf{R}^{-1} - \mathbf{R}^{-1}\mathbf{Z}(\mathbf{Z}^T\mathbf{R}^{-1}\mathbf{Z} + \mathbf{G}^{-1})^{-1}\mathbf{Z}^T\mathbf{R}^{-1}$ ,  $|\mathbf{V}| = |\mathbf{R}|^{-1} |\mathbf{I}_n + \mathbf{R}^{-1}\mathbf{ZGZ}^T|$

Thus the log-likelihood is

$$l(\boldsymbol{\beta}, \boldsymbol{\varphi} | \mathbf{y}) = -\frac{1}{2} n \ln 2\pi - \frac{1}{2} \ln |\mathbf{V}| - \frac{1}{2} (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})^T \mathbf{V}^{-1} (\mathbf{y} - \mathbf{X}\boldsymbol{\beta}).$$

The fundamental idea of REML is to maximize the likelihood after accounting for the model's fixed effects. Instead of maximizing the likelihood of  $Y \sim \mathcal{N}_n(\mathbf{X}\boldsymbol{\beta}, \mathbf{V})$ , maximize the likelihood of  $\mathbf{K}^T \mathbf{Y}$  where  $\mathbf{K}$  is any matrix such that  $E[\mathbf{K}^T \mathbf{Y}] = \mathbf{0}$  and hence  $\mathbf{K}^T \mathbf{Y} \sim \mathcal{N}_n(\mathbf{0}, \mathbf{K}^T \mathbf{V} \mathbf{K})$ . This removes the fixed effects from the estimation of  $\boldsymbol{\varphi}$ .

Let

$$\mathbf{K}^T \mathbf{Y} = \mathbf{K}^T \mathbf{X} \boldsymbol{\beta} + \mathbf{K}^T \mathbf{Z} \mathbf{u} + \mathbf{K}^T \mathbf{e}.$$

$\mathbf{K}^T$  is a matrix  $(n - r_X) \times n$  (where  $r_X$  is the rank of matrix  $\mathbf{X}$ ), such that  $E[\mathbf{K}^T \mathbf{Y}] = \mathbf{0}$  (that is,  $\mathbf{K}^T \mathbf{X} \boldsymbol{\beta} = \mathbf{0}$ ).  $\mathbf{K}$  is also called a matrix of error contrasts (hence the alternative name of residual maximum likelihood method).

The transformed model is

$$\mathbf{K}^T \mathbf{Y} = \mathbf{K}^T \mathbf{Z} \mathbf{u} + \mathbf{K}^T \mathbf{e}$$

with  $\mathbf{K}^T \mathbf{Y} \cap \mathcal{N}_n(\mathbf{0}, \mathbf{K}^T \mathbf{V} \mathbf{K})$

- The likelihood function of this model is called the restricted likelihood function and is given by:

$$L_R(\boldsymbol{\varphi} | \mathbf{y}) = \frac{1}{(2\pi)^{\frac{1}{2}(n-r_X)} |\mathbf{K}^T \mathbf{V} \mathbf{K}|^{1/2}} \exp\left(-\frac{1}{2} (\mathbf{K}^T \mathbf{y})^T (\mathbf{K}^T \mathbf{V} \mathbf{K})^{-1} (\mathbf{K}^T \mathbf{y})\right)$$



And the REML log - likelihood is

$$l_R(\boldsymbol{\varphi}|\mathbf{y}) = -\frac{1}{2}(n - r_X) \log 2\pi - \frac{1}{2} \log |\mathbf{K}^T \mathbf{V} \mathbf{K}| - \frac{1}{2} \mathbf{y}^T \mathbf{K} (\mathbf{K}^T \mathbf{V} \mathbf{K})^{-1} \mathbf{K}^T \mathbf{y}.$$

Denoting

$$\mathbf{K} (\mathbf{K}^T \mathbf{V} \mathbf{K})^{-1} \mathbf{K}^T = \mathbf{P},$$

$$l_R = -\frac{1}{2}(n - r_X) \log 2\pi - \frac{1}{2} \log |\mathbf{K}^T \mathbf{V} \mathbf{K}| - \frac{1}{2} \mathbf{y}^T \mathbf{P} \mathbf{y}.$$

Note: since  $\mathbf{K}^T$  has full row rank  $n - r_X$  and  $\mathbf{K}^T \mathbf{X} = \mathbf{0}$ , can be shown that

$$\mathbf{K} (\mathbf{K}^T \mathbf{V} \mathbf{K})^{-1} \mathbf{K}^T = \mathbf{P} \text{ where } \mathbf{P} = \mathbf{V}^{-1} - \mathbf{V}^{-1} \mathbf{X} (\mathbf{X}^T \mathbf{V}^{-1} \mathbf{X})^{-1} \mathbf{X}^T \mathbf{V}^{-1}$$

To maximize  $l_R$  we differentiate with respect to  $\varphi_i$  and equate to zero and solve the resulting equations.

$$\frac{\partial l_R(\boldsymbol{\varphi}|\mathbf{y})}{\partial \varphi_i} = 0.$$

Differentiate with respect to  $\varphi_i$ ,

$$\frac{\partial l_R}{\partial \varphi_i} = -\frac{1}{2} (\text{tr}(\mathbf{P}\dot{V}_i) - \mathbf{y}^T \mathbf{P}\dot{V}_i \mathbf{P}\mathbf{y}),$$

where  $\dot{V}_i$  is the derivative of  $V$  with respect to  $\varphi_i$ . Equating to zero, we obtain

$$\text{tr}(\mathbf{P}\dot{V}_i) = \mathbf{y}^T \mathbf{P}\dot{V}_i \mathbf{P}\mathbf{y}.$$

Completing the maximization demands checking second derivatives and also demands checking the likelihood function on the boundary of the parameter space, since the maximization must be confined to the parameter space.

REML estimation proceeds iteratively. We implement REML using *Newton-Raphson* or Fisher scoring algorithms (among others).

The Hessian and information matrices derived from REML log-likelihood are:

### Hessian (*ijth* element)

$$\frac{\partial \nabla l_R(\varphi_i)}{\partial \varphi_j} = \frac{1}{2} \text{tr}(\mathbf{P}\dot{\mathbf{V}}_j \mathbf{P}\dot{\mathbf{V}}_i) - \frac{1}{2} \text{tr}(\mathbf{P}\ddot{\mathbf{V}}_{ij}) + \frac{1}{2} \mathbf{y}^T \mathbf{P}\ddot{\mathbf{V}}_{ij} \mathbf{P}\mathbf{y} - \mathbf{y}^T \mathbf{P}\dot{\mathbf{V}}_i \mathbf{P}\dot{\mathbf{V}}_j \mathbf{P}\mathbf{y},$$

where  $\nabla l_R$  is the gradient vector of  $l_R$  and  $\ddot{\mathbf{V}}_{ij} = \frac{\partial^2 \mathbf{V}}{\partial \varphi_i \partial \varphi_j}$ .

### Information matrix (*ijth* element):

$$I_e(\varphi_i, \varphi_j) = E \left[ - \frac{\partial^2 l_R}{\partial \varphi_i \partial \varphi_j} \right]$$

It can be proved that  $I_e(\varphi_i, \varphi_j) = \frac{1}{2} \text{tr}(\mathbf{P}\dot{\mathbf{V}}_i \mathbf{P}\dot{\mathbf{V}}_j)$ .

## Properties of REML estimators

The REML estimator of  $\hat{\boldsymbol{\varphi}}$  is consistent and, under regularity conditions, is asymptotic normal with vector of mean values  $\boldsymbol{\varphi}$  and asymptotic covariance matrix  $[\mathbf{I}_e(\boldsymbol{\varphi})]^{-1}$ , where  $\mathbf{I}_e$  is the information matrix (expected information matrix):

$$\hat{\boldsymbol{\varphi}} \stackrel{a}{\sim} \mathcal{N}(\boldsymbol{\varphi}, [\mathbf{I}_e(\boldsymbol{\varphi})]^{-1}).$$

## Maximum likelihood (ML) method

The process for obtaining the ML estimators is identical, but is based on the log-likelihood, therefore,

$$\frac{\partial l}{\partial \boldsymbol{\beta}} = \mathbf{X}^T \mathbf{V}^{-1} \mathbf{y} - \mathbf{X}^T \mathbf{V}^{-1} \mathbf{X} \boldsymbol{\beta}$$

$$\frac{\partial l_R}{\partial \varphi_i} = -\frac{1}{2} \left( \text{tr}(\mathbf{V}^{-1} \dot{\mathbf{V}}_i) - (\mathbf{y} - \mathbf{X} \boldsymbol{\beta})^T \mathbf{V}^{-1} \dot{\mathbf{V}}_i \mathbf{V}^{-1} (\mathbf{y} - \mathbf{X} \boldsymbol{\beta}) \right)$$

where  $\dot{\mathbf{V}}_i$  is the derivative of  $\mathbf{V}$  with respect to  $\varphi_i$ .

Equating to zero it is shown that the ML equations are:

$$\mathbf{X}^T \mathbf{V}^{-1} \mathbf{X} \boldsymbol{\beta} = \mathbf{X}^T \mathbf{V}^{-1} \mathbf{y}$$

$$\text{tr}(\mathbf{V}^{-1} \dot{\mathbf{V}}_i) = (\mathbf{y} - \mathbf{X} \boldsymbol{\beta})^T \mathbf{V}^{-1} \dot{\mathbf{V}}_i \mathbf{V}^{-1} (\mathbf{y} - \mathbf{X} \boldsymbol{\beta})$$

## REML estimation

```
> terrenoslmer1<-lmer(rend~ variedad + (1 | terreno), data = terrenos)
```

```
> summary(terrenoslmer1)
```

Linear mixed model fit by REML ['lmerMod']

Formula: rend ~ variedad + (1 | terreno)

Data: terrenos

REML criterion at convergence: 43.4

Scaled residuals:

Min	1Q	Median	3Q	Max
-1.91520	-0.72001	0.03862	0.54535	2.82304

Random effects:

Groups	Name	Variance	Std.Dev.
terreno	(Intercept)	<b>0.02576</b>	0.1605
	Residual	<b>0.09758</b>	0.3124

Number of obs: 52, groups: terreno, 13

...

## ML estimation

```
> terrenoslmer1ML<-update(terrenoslmer1, REML=FALSE)
```

```
> summary(terrenoslmer1ML)
```

Linear mixed model fit by maximum likelihood ['lmerMod']

Formula: rend ~ variedad + (1 | terreno)

Data: terrenos

Scaled residuals:

Min	1Q	Median	3Q	Max
-1.9934	-0.7494	0.0402	0.5676	2.9383

Random effects:

Groups	Name	Variance	Std.Dev.
terreno	(Intercept)	<b>0.02378</b>	0.1542
	Residual	<b>0.09008</b>	0.3001

Number of obs: 52, groups: terreno, 13

## REML estimation

```
> terrenolme1<-lme(rend~variedade,
random=~1|terreno, data=terrenos)
```

```
> summary(terrenolme1)
```

Linear mixed-effects model fit by REML

Data: terrenos

AIC	BIC	logLik
55.42708	66.65429	-21.71354

Random effects:

Formula: ~1 | terreno

(Intercept)	Residual
-------------	----------

StdDev: 0.1604919	0.3123811
-------------------	-----------

....

```
> VarCorr(terrenolme1)
```

	Variance	StdDev
(Intercept)	0.02575765	0.1604919
Residual	0.09758196	0.3123811

## ML estimation

```
> terrenolme1ML<-update(terrenolme1,
method="ML")
```

```
> summary(terrenolme1ML)
```

Linear mixed-effects model fit by maximum likelihood

Data: terrenos

AIC	BIC	logLik
43.76901	55.47647	-15.8845

Random effects:

Formula: ~1 | terreno

(Intercept)	Residual
-------------	----------

StdDev: 0.1541963	0.3001259
-------------------	-----------

....

```
> VarCorr(arlme2ML)
```

	Variance	StdDev
(Intercept)	0.02377651	0.1541963
Residual	0.09007553	0.3001259

In 

## Estimated covariance (asymptotic) matrix for REML estimators

$$\widehat{\text{var}}(\hat{\boldsymbol{\phi}})$$

```
> vcov(terrenosvarcomp1, "varComp")
```

	<b>terreno</b>	<b>error</b>
<b>terreno</b>	<b>0.0004522882</b>	<b>-0.0001322531</b>
<b>error</b>	<b>-0.0001322531</b>	<b>0.0005290124</b>



# Estimating fixed effects and predicting random effects: the mixed model equations

- The estimators of fixed effects and predictors of random effects are obtained through *mixed model equations* (Henderson, 1975<sup>4</sup>).

<sup>4</sup>Henderson, C.R. (1975) - Best linear unbiased estimation and prediction under a selection model. *Biometrics* **31**:423 - 447.

The joint density of  $\mathbf{u}$  and  $\mathbf{Y}$  is

$$f(\mathbf{Y}, \mathbf{u}) = f(\mathbf{Y}|\mathbf{u})f(\mathbf{u}) = \frac{\exp\left(-\frac{1}{2}\left((\mathbf{Y} - \mathbf{X}\boldsymbol{\beta} - \mathbf{Z}\mathbf{u})^T \mathbf{R}^{-1}(\mathbf{Y} - \mathbf{X}\boldsymbol{\beta} - \mathbf{Z}\mathbf{u}) + \mathbf{u}^T \mathbf{G}^{-1}\mathbf{u}\right)\right)}{(2\pi)^{(n+q)/2} |\mathbf{R}|^{1/2} |\mathbf{G}|^{1/2}}$$

The mixed models equations are derived by maximizing  $\ln f(\mathbf{Y}, \mathbf{u})$  with respect to  $\boldsymbol{\beta}$  and  $\mathbf{u}$ :

$$\begin{aligned} \ln f(\mathbf{Y}, \mathbf{u}) &= -\frac{1}{2}(n+q)\log(2\pi) - \frac{1}{2}(\ln|\mathbf{R}| + \ln|\mathbf{G}|) \\ &\quad - \frac{1}{2}\left(\mathbf{Y}^T \mathbf{R}^{-1} \mathbf{y} - 2\mathbf{Y}^T \mathbf{R}^{-1} \mathbf{X}\boldsymbol{\beta} - 2\mathbf{Y}^T \mathbf{R}^{-1} \mathbf{Z}\mathbf{u} + 2\boldsymbol{\beta}^T \mathbf{X}^T \mathbf{R}^{-1} \mathbf{Z}\mathbf{u} + \boldsymbol{\beta}^T \mathbf{X}^T \mathbf{R}^{-1} \mathbf{X}\boldsymbol{\beta} + \mathbf{u}^T \mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z}\mathbf{u}\right) \end{aligned}$$

Equating to zero:

$$\frac{\partial \ln f(\mathbf{Y}, \mathbf{u})}{\partial \boldsymbol{\beta}} = \mathbf{0} \Leftrightarrow \mathbf{X}^T \mathbf{R}^{-1} \mathbf{Y} - \mathbf{X}^T \mathbf{R}^{-1} \mathbf{X}\boldsymbol{\beta} - \mathbf{X}^T \mathbf{R}^{-1} \mathbf{Z}\mathbf{u} = \mathbf{0}$$

$$\frac{\partial \ln f(\mathbf{Y}, \mathbf{u})}{\partial \mathbf{u}} = \mathbf{0} \Leftrightarrow \mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Y} - \mathbf{Z}^T \mathbf{R}^{-1} \mathbf{X}\boldsymbol{\beta} - \mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z}\mathbf{u} - \mathbf{G}^{-1} \mathbf{u} = \mathbf{0}.$$

Which results in

$$\begin{bmatrix} X^T R^{-1} X \beta + X^T R^{-1} Z u \\ Z^T R^{-1} X \beta + (Z^T R^{-1} Z + G^{-1}) u \end{bmatrix} = \begin{bmatrix} X^T R^{-1} y \\ Z^T R^{-1} y \end{bmatrix},$$

and, consequently, the mixed models equations are defined as:

$$\begin{bmatrix} X^T R^{-1} X & X^T R^{-1} Z \\ Z^T R^{-1} X & (Z^T R^{-1} Z + G^{-1}) \end{bmatrix} \begin{bmatrix} \beta \\ u \end{bmatrix} = \begin{bmatrix} X^T R^{-1} y \\ Z^T R^{-1} y \end{bmatrix}.$$

- *The estimator of fixed effects ( $\hat{\beta}$ ) and the predictor of random effects ( $\tilde{u}$ ) are:*

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

$$\tilde{u} = G Z^T V^{-1} (Y - X \hat{\beta}).$$

Proof in next slides, additional information

## Additional information

### Proof

Para chegar às soluções das equações do modelo misto, podemos começar por verificar, a partir da

segunda equação de 
$$\begin{bmatrix} X^T R^{-1} X & X^T R^{-1} Z \\ Z^T R^{-1} X & (Z^T R^{-1} Z + G^{-1}) \end{bmatrix} \begin{bmatrix} \beta \\ u \end{bmatrix} = \begin{bmatrix} X^T R^{-1} Y \\ Z^T R^{-1} Y \end{bmatrix}$$
 que

$$u = (Z^T R^{-1} Z + G^{-1})^{-1} Z^T R^{-1} (Y - X\beta),$$

e substituindo este resultado na primeira equação,

$$X^T R^{-1} X\beta + X^T R^{-1} Z (Z^T R^{-1} Z + G^{-1})^{-1} Z^T R^{-1} (y - X\beta) = X^T R^{-1} Y,$$

logo,

$$X^T R^{-1} Y - X^T R^{-1} X\beta - X^T R^{-1} Z (Z^T R^{-1} Z + G^{-1})^{-1} Z^T R^{-1} (Y - X\beta) = 0.$$

Depois de algum rearranjo da expressão anterior, chega-se a

$$X^T \left( R^{-1} - R^{-1} Z (Z^T R^{-1} Z + G^{-1})^{-1} Z^T R^{-1} \right) X\beta = X^T \left( R^{-1} - R^{-1} Z (Z^T R^{-1} Z + \right.$$

## Additional information

### Proof (cont.)

Voltando novamente a  $\mathbf{u}$ , verifica-se que

$$\begin{aligned}\tilde{\mathbf{u}} &= (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} \mathbf{Z}^T \mathbf{R}^{-1} \mathbf{V} \mathbf{V}^{-1} (\mathbf{Y} - \mathbf{X} \hat{\boldsymbol{\beta}}) \\ &= (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} \mathbf{Z}^T \mathbf{R}^{-1} (\mathbf{Z} \mathbf{G} \mathbf{Z}^T + \mathbf{R}) \mathbf{V}^{-1} (\mathbf{Y} - \mathbf{X} \hat{\boldsymbol{\beta}}) \\ &= (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} \mathbf{G} \mathbf{Z}^T + \mathbf{Z}^T) \mathbf{V}^{-1} (\mathbf{Y} - \mathbf{X} \hat{\boldsymbol{\beta}}) \\ &= (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1}) \mathbf{G} \mathbf{Z}^T \mathbf{V}^{-1} (\mathbf{Y} - \mathbf{X} \hat{\boldsymbol{\beta}}),\end{aligned}$$

isto é,

$$\tilde{\mathbf{u}} = \mathbf{G} \mathbf{Z}^T \mathbf{V}^{-1} (\mathbf{Y} - \mathbf{X} \hat{\boldsymbol{\beta}}).$$

- Vector  $\hat{\boldsymbol{\beta}}$  has multivariate normal distribution with vector of mean values  $\boldsymbol{\beta}$  and covariance matrix  $(\mathbf{X}^T \mathbf{V}^{-1} \mathbf{X})^{-1}$

$$\hat{\boldsymbol{\beta}} \cap \mathcal{N}(\boldsymbol{\beta}, (\mathbf{X}^T \mathbf{V}^{-1} \mathbf{X})^{-1})$$

- Vector  $\tilde{\mathbf{u}}$  has multivariate normal distribution with vector of mean values zero and covariance matrix  $\mathbf{GZ}^T \mathbf{PZG}$ ,

$$\tilde{\mathbf{u}} \cap \mathcal{N}(\mathbf{0}, \mathbf{GZ}^T \mathbf{PZG})$$

Exercise: prove the previous results.

- When matrices  $\mathbf{G}$  e  $\mathbf{R}$  are known,  $\hat{\boldsymbol{\beta}}$  is the best linear unbiased estimator (BLUE) of  $\boldsymbol{\beta}$ , and  $\tilde{\mathbf{u}}$  is the best linear unbiased predictor (BLUP) of  $\mathbf{u}$ .
- However, in general, matrices  $\mathbf{G}$  e  $\mathbf{R}$  are unknown, and only their estimates are available,  $\hat{\mathbf{G}}$  e  $\hat{\mathbf{R}}$ . In this case, we have the empirical best linear unbiased estimator (EBLUE) and the empirical best linear unbiased predictor (EBLUP):

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

and

$$\tilde{\mathbf{u}}_{EBLUP} = \hat{\mathbf{G}} \mathbf{Z}^T \hat{\mathbf{V}} (\mathbf{Y} - \mathbf{X} \hat{\boldsymbol{\beta}}_{EBLUE}).$$

Example: for a random model with one factor of random effects, balanced (factor with  $a$  levels,  $b$  observations per level), the empirical best linear unbiased predictor of  $u_i$  (for the level  $i$ ) is:

$$EBLUP(u_i) = \frac{b\hat{\sigma}_u^2}{b\hat{\sigma}_u^2 + \hat{\sigma}_e^2} (\bar{Y}_{i.} - \bar{Y}_{..})$$



Given the mixed model equations:

$$\begin{bmatrix} \boldsymbol{\beta} \\ \mathbf{u} \end{bmatrix} = \begin{bmatrix} \mathbf{X}^T \mathbf{R}^{-1} \mathbf{X} & \mathbf{X}^T \mathbf{R}^{-1} \mathbf{Z} \\ \mathbf{Z}^T \mathbf{R}^{-1} \mathbf{X} & \mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1} \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{X}^T \mathbf{R}^{-1} \mathbf{y} \\ \mathbf{Z}^T \mathbf{R}^{-1} \mathbf{y} \end{bmatrix},$$

denote by  $\mathbf{C}$  the matrix:

$$\begin{bmatrix} \mathbf{X}^T \mathbf{R}^{-1} \mathbf{X} & \mathbf{X}^T \mathbf{R}^{-1} \mathbf{Z} \\ \mathbf{Z}^T \mathbf{R}^{-1} \mathbf{X} & \mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1} \end{bmatrix}^{-1} = \mathbf{C}.$$

The elements of matrix  $\mathbf{C}$ :

$$\mathbf{C}_{11} = (\mathbf{X}^T \mathbf{V}^{-1} \mathbf{X})^{-1},$$

$$\mathbf{C}_{21} = -\mathbf{G} \mathbf{Z}^T \mathbf{V}^{-1} \mathbf{X} \mathbf{C}_{11},$$

$$\mathbf{C}_{22} = (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} - \mathbf{C}_{21} \mathbf{X}^T \mathbf{V}^{-1} \mathbf{Z} \mathbf{G} = \mathbf{G} - \mathbf{G} \mathbf{Z}^T \mathbf{P} \mathbf{Z} \mathbf{G}$$

$$\mathbf{C}_{12} = \mathbf{C}_{21}^T.$$

The matrix  $\mathbf{C}$  is the covariance matrix of  $(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}, \tilde{\mathbf{u}} - \mathbf{u})$ ,

$$\mathbf{C} = \begin{bmatrix} \text{var}[\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}] & \text{cov}[\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}, \tilde{\mathbf{u}} - \mathbf{u}] \\ \text{cov}[\tilde{\mathbf{u}} - \mathbf{u}, \hat{\boldsymbol{\beta}} - \boldsymbol{\beta}] & \text{var}[\tilde{\mathbf{u}} - \mathbf{u}] \end{bmatrix}.$$

$\text{var}[\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}] = \text{var}[\hat{\boldsymbol{\beta}}]$ , is the covariance matrix of the fixed effects estimators

$\text{var}[\tilde{\mathbf{u}} - \mathbf{u}]$ , is the prediction variance matrix of the random effects

**Proof (additional information):** Segundo a teoria de matrizes, a inversa da matriz não singular subdividida em

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$$

assumindo que todas as inversas necessárias existem, é

$$A^{-1} = \begin{bmatrix} T & -TA_{22}A_{22}^{-1} \\ -A_{22}^{-1}A_{21}T & A_{22}^{-1} + A_{22}^{-1}A_{21}TA_{12}A_{22}^{-1} \end{bmatrix}$$

onde  $T = (A_{11} - A_{12}A_{22}^{-1}A_{21})^{-1}$

Aplicando ao nosso caso, chega-se a

$$\begin{aligned} C_{11} &= \left( (X^T R^{-1} X) - (X^T R^{-1} Z)(Z^T R^{-1} Z + G^{-1})^{-1}(Z^T R^{-1} X) \right)^{-1} \\ &= \left( X^T \left( R^{-1} - R^{-1} Z (Z^T R^{-1} Z + G^{-1})^{-1} Z^T R^{-1} \right) X \right)^{-1}, \end{aligned}$$

e, atendendo a que  $V^{-1} = R^{-1} - R^{-1} Z (Z^T R^{-1} Z + G^{-1})^{-1} Z^T R^{-1}$ ,  $C_{11} = (X^T V^{-1} X)^{-1}$ .

$$\begin{aligned} C_{21} &= -(Z^T R^{-1} Z + G^{-1})^{-1} (Z^T R^{-1} X) (X^T V^{-1} X)^{-1} \\ &= -(Z^T R^{-1} Z + G^{-1})^{-1} (Z^T R^{-1} V V^{-1} X) (X^T V^{-1} X)^{-1} \\ &= -(Z^T R^{-1} Z + G^{-1})^{-1} (Z^T R^{-1} V) V^{-1} X (X^T V^{-1} X)^{-1} \\ &= -(Z^T R^{-1} Z + G^{-1})^{-1} (Z^T R^{-1} (Z G Z^T + R)) V^{-1} X (X^T V^{-1} X)^{-1} \\ &= -(Z^T R^{-1} Z + G^{-1})^{-1} (Z^T R^{-1} Z G Z^T + Z^T R^{-1} R) V^{-1} X (X^T V^{-1} X)^{-1} \\ &= -(Z^T R^{-1} Z + G^{-1})^{-1} (Z^T R^{-1} Z G Z^T + G^{-1} G Z^T) V^{-1} X (X^T V^{-1} X)^{-1} \\ &= -(Z^T R^{-1} Z + G^{-1})^{-1} (Z^T R^{-1} Z + G^{-1}) G Z^T V^{-1} X (X^T V^{-1} X)^{-1} = -G Z^T V^{-1} X C_{11}. \end{aligned}$$

## *Proof (additional information) (cont.)*

Finally,

$$\begin{aligned} C_{22} &= (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} - \left( -(\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{X}) (\mathbf{X}^T \mathbf{V}^{-1} \mathbf{X})^{-1} \right) (\mathbf{X}^T \mathbf{R}^{-1} \mathbf{Z}) (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} \\ &= (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} - C_{21} (\mathbf{X}^T \mathbf{V}^{-1} \mathbf{V} \mathbf{R}^{-1} \mathbf{Z}) (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} \\ &= (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} - C_{21} (\mathbf{X}^T \mathbf{V}^{-1} (\mathbf{Z} \mathbf{G} \mathbf{Z}^T + \mathbf{R}) \mathbf{R}^{-1} \mathbf{Z}) (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} \\ &= (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} - C_{21} \mathbf{X}^T \mathbf{V}^{-1} (\mathbf{Z} \mathbf{G} \mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{R} \mathbf{R}^{-1} \mathbf{Z}) (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} \\ &= (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} - C_{21} \mathbf{X}^T \mathbf{V}^{-1} (\mathbf{Z} \mathbf{G} \mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{Z} \mathbf{G} \mathbf{G}^{-1}) (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} \\ &= (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} - C_{21} \mathbf{X}^T \mathbf{V}^{-1} \mathbf{Z} \mathbf{G} (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1}) (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} \\ &= (\mathbf{Z}^T \mathbf{R}^{-1} \mathbf{Z} + \mathbf{G}^{-1})^{-1} - C_{21} \mathbf{X}^T \mathbf{V}^{-1} \mathbf{Z} \mathbf{G}. \end{aligned}$$

## *Proof (additional information)*

A matriz  $\mathbf{C}_{11}$ , corresponde à matriz de covariâncias dos estimadores  $\hat{\boldsymbol{\beta}}$ , já que

$$\text{Var}[\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}] = \text{Var}[\hat{\boldsymbol{\beta}}].$$

A matriz  $\mathbf{C}_{12}$ , corresponde à matriz de covariâncias entre os erros de estimação e de predição, uma vez que

$$\text{Cov}[\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}, \tilde{\mathbf{u}} - \mathbf{u}] = \mathbf{E}[\hat{\boldsymbol{\beta}}\tilde{\mathbf{u}}^T] - \mathbf{E}[\hat{\boldsymbol{\beta}}\mathbf{u}^T]$$

Mas,

$$\begin{aligned}\mathbf{E}[\mathbf{y}\mathbf{y}^T] &= \mathbf{V} + \mathbf{X}\boldsymbol{\beta}\boldsymbol{\beta}^T\mathbf{X}^T, \\ &= (\mathbf{X}^T\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{V}^{-1}\mathbf{E}[\mathbf{y}\mathbf{y}^T]\mathbf{P}\mathbf{Z}\mathbf{G},\end{aligned}$$

e sendo

$$\mathbf{E}[\hat{\boldsymbol{\beta}}\tilde{\mathbf{u}}^T] = \mathbf{E}[(\mathbf{X}^T\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{V}^{-1}\mathbf{y}\mathbf{y}^T\mathbf{P}\mathbf{Z}\mathbf{G}]$$

então,

$$\begin{aligned}\mathbf{E}[\hat{\boldsymbol{\beta}}\tilde{\mathbf{u}}^T] &= (\mathbf{X}^T\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{V}^{-1}(\mathbf{V} + \mathbf{X}\boldsymbol{\beta}\boldsymbol{\beta}^T\mathbf{X}^T)\mathbf{P}\mathbf{Z}\mathbf{G} \\ &= (\mathbf{X}^T\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{P}\mathbf{Z}\mathbf{G} + (\mathbf{X}^T\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{V}^{-1}\mathbf{X}\boldsymbol{\beta}\boldsymbol{\beta}^T\mathbf{X}^T\mathbf{P}\mathbf{Z}\mathbf{G} \\ &= \mathbf{0},\end{aligned}$$

porque  $\mathbf{X}^T\mathbf{P} = \mathbf{0}$  ( $\mathbf{P}\mathbf{X} = \mathbf{V}^{-1}\mathbf{X} - \mathbf{V}^{-1}\mathbf{X}(\mathbf{X}^T\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{V}^{-1}\mathbf{X} = \mathbf{0}$ ).

### ***Proof (additional information)***

Por outro lado,

$$\begin{aligned} E[\widehat{\beta}u^T] &= E[(X^T V^{-1} X)^{-1} X^T V^{-1} y u^T] \\ &= (X^T V^{-1} X)^{-1} X^T V^{-1} E[y u^T] \\ &= (X^T V^{-1} X)^{-1} X^T V^{-1} Z G \\ &= C_{11} X^T V^{-1} Z G, \end{aligned}$$

consequentemente,

$$\text{Cov}[\widehat{\beta} - \beta, \tilde{u} - u] = -C_{11} X^T V^{-1} Z G,$$

isto é,

$$\text{Cov}[\widehat{\beta} - \beta, \tilde{u} - u] = C_{12}.$$

Relativamente a  $C_{22}$

$$\begin{aligned} \text{Var}[\tilde{u} - u] &= G - GZ^T P Z G \\ &= G - GZ^T (V^{-1} - V^{-1} X (X^T V^{-1} X)^{-1} X^T V^{-1}) Z G \\ &= G - GZ^T V^{-1} Z G - GZ^T V^{-1} X (X^T V^{-1} X)^{-1} X^T V^{-1} Z G, \end{aligned}$$

**Proof (additional information)**

mas, tendo em conta que

$$GZ^T V^{-1} X (X^T V^{-1} X)^{-1} X^T V^{-1} Z G = C_{21} X^T V^{-1} Z G,$$

resta provar que

$$G - GZ^T V^{-1} Z G = (Z^T R^{-1} Z + G^{-1})^{-1}.$$

Sabendo-se que

$$GZ^T V^{-1} = (Z^T R^{-1} Z + G^{-1})^{-1} Z^T R^{-1},$$

então

$$\begin{aligned} G - (Z^T R^{-1} Z + G^{-1})^{-1} Z^T R^{-1} Z G - (Z^T R^{-1} Z + G^{-1})^{-1} &= \\ = G - (Z^T R^{-1} Z + G^{-1})^{-1} (Z^T R^{-1} Z G + I_q) &= \\ = G - (Z^T R^{-1} Z + G^{-1})^{-1} (Z^T R^{-1} Z + G^{-1}) G &= \\ = G - G = \mathbf{0}, & \end{aligned}$$

logo,

$$\text{Var}[\tilde{u} - u] = (Z^T R^{-1} Z + G^{-1})^{-1} - C_{21} X^T V^{-1} Z G = C_{22}.$$

# The residuals

In the linear mixed model ,  $Y = X\beta + Zu + e$ , with  $Y \sim \mathcal{N}_n(X\beta, V)$

- The conditional residuals that measure deviations from the conditional mean are defined as :

$$\tilde{e} = Y - X\hat{\beta} - Z\tilde{u}.$$

Alternatively, it is common appear in the form:

$$\tilde{e} = RPY,$$

with  $P = V^{-1} - V^{-1}X(X^TV^{-1}X)^{-1}X^TV^{-1}$  and  $V - ZGZ^T = R$ .

Proof in next slide (additional information)

Vector  $\tilde{e}$  has multivariate normal distribution with vector of mean values  $\mathbf{0}_{(n \times 1)}$  and covariance matrix  $RPR$ ,

$$\tilde{e} \sim \mathcal{N}_n(\mathbf{0}, RPR),$$

with  $P = V^{-1} - V^{-1}X(X^TV^{-1}X)^{-1}X^TV^{-1}$  and  $V - ZGZ^T = R$ .



➤ Proof:  $\tilde{\mathbf{e}} = \mathbf{R}\mathbf{P}\mathbf{Y}$  (additional information)

With the results obtained for  $\hat{\boldsymbol{\beta}}$  e  $\tilde{\mathbf{u}}$

$$\begin{aligned}\tilde{\mathbf{e}} &= \mathbf{Y} - \mathbf{X}(\mathbf{X}^T\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{V}^{-1}\mathbf{Y} - \mathbf{Z}\mathbf{G}\mathbf{Z}^T\mathbf{P}\mathbf{Y} \\ &= \left(\mathbf{I}_n - \mathbf{X}(\mathbf{X}^T\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{V}^{-1} - \mathbf{Z}\mathbf{G}\mathbf{Z}^T\mathbf{P}\right)\mathbf{Y} \\ &= \left(\mathbf{V}\left(\mathbf{V}^{-1} - \mathbf{V}^{-1}\mathbf{X}(\mathbf{X}^T\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{V}^{-1}\right) - \mathbf{Z}\mathbf{G}\mathbf{Z}^T\mathbf{P}\right)\mathbf{Y}.\end{aligned}$$

Using the result  $\mathbf{P} = \mathbf{V}^{-1} - \mathbf{V}^{-1}\mathbf{X}(\mathbf{X}^T\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{V}^{-1}$ ,

$$\begin{aligned}\tilde{\mathbf{e}} &= \mathbf{V}\mathbf{P}\mathbf{Y} - \mathbf{Z}\mathbf{G}\mathbf{Z}^T\mathbf{P}\mathbf{Y} \\ &= (\mathbf{V} - \mathbf{Z}\mathbf{G}\mathbf{Z}^T)\mathbf{P}\mathbf{Y},\end{aligned}$$

but  $\mathbf{V} - \mathbf{Z}\mathbf{G}\mathbf{Z}^T = \mathbf{R}$ , therefore,  $\tilde{\mathbf{e}} = \mathbf{R}\mathbf{P}\mathbf{Y}$

❑ **The empirical best linear unbiased estimator (EBLUE) of fixed effects**

> `fixed.effects(terrenolme1)`

```
(Intercept)  variedadeB variedadeC variedadeD  
1.55600000 -0.02384615 -0.38907692 -0.37784615
```

❑ **The empirical best linear unbiased predicted (EBLUP) of random effects**

> `ranef(terrenolme1)`

```
(Intercept)  
I 0.042982693  
II 0.123871539  
III -0.009659254  
IV -0.047150592  
IX -0.165530776  
V 0.208483839  
VI 0.056207377  
VII 0.010883945  
VIII 0.023081469  
X -0.211881368  
XI 0.032325909  
XII -0.122903638  
XIII 0.059288857
```

> fitted(terrenolme1)

I	II	III	IV	V	VI	VII	VIII
1.5989827	1.6798715	1.5463407	1.5088494	1.7644838	1.6122074	1.5668839	1.5790815
IX	X	XI	XII	XIII	I	II	III
1.3904692	1.3441186	1.5883259	1.4330964	1.6152889	1.5751365	1.6560254	1.5224946

...

> predict(terrenolme1)

I	II	III	IV	V	VI	VII	VIII
1.5989827	1.6798715	1.5463407	1.5088494	1.7644838	1.6122074	1.5668839	1.5790815
IX	X	XI	XII	XIII	I	II	III
1.3904692	1.3441186	1.5883259	1.4330964	1.6152889	1.5751365	1.6560254	1.5224946

...

> resid(terrenolme1) (conditional residuals)

I	II	III	IV	V	VI
0.201017307	0.029128461	-0.269340746	0.166150592	0.049516161	0.283792623
VII	VIII	IX	X	XI	XII
-0.488883945	0.160918531	-0.190469224	0.155881368	0.343674091	-0.264096362

...

## Estimated covariance (asymptotic) matrix for estimators $\hat{\beta}$

$$\widehat{\text{var}}(\hat{\beta}) = (\mathbf{X}^T \hat{\mathbf{V}}^{-1} \mathbf{X})^{-1}$$

### > `vcov(terrenolme1)`

```
      (Intercept)  variedadeB  variedadeC  variedadeD
(Intercept)  0.009487662 -0.007506305 -0.007506305 -0.007506305
variedadeB  -0.007506305  0.015012610  0.007506305  0.007506305
variedadeC  -0.007506305  0.007506305  0.015012610  0.007506305
variedadeD  -0.007506305  0.007506305  0.007506305  0.015012610
```

**Tests of Hypotheses for covariance parameters, fixed and random effects**

**Model selection (model comparison via likelihood ratio tests and via information criteria)**

# Tests of Hypotheses for covariance parameters

- Inference concerning covariance parameters of a linear mixed model usually relies on approximate distributions for the RE(ML) estimators derived from asymptotic results. In the current context of mixed models, the most important formal test for covariance components is **the likelihood ratio test (the most used is the REML likelihood ratio test )**.

# Likelihood ratio tests for covariance components

- **Hypotheses:**  $H_0: \varphi_i = 0$  (*reduced model*) vs  $H_1: \varphi_i \neq 0$  (*full model*)  
(  $H_0: \varphi_i = 0$  vs  $H_1: \varphi_i > 0$  , if  $\varphi_i$  is a variance component)
- **The REML likelihood ratio statistic :**

$$\Lambda = 2(l_{R_1} - l_{R_0}) \sim \chi^2_\nu$$

being  $l_{R_1}$  the REML log-likelihood of the more general model (full model) and  $l_{R_0}$  the REML log-likelihood of the reduced model (that is, the REML log-likelihood under the null hypothesis). Under regularity conditions and under the null hypothesis, the likelihood ratio statistic, has an approximate  $\chi^2_\nu$  distribution with the degrees of freedom ( $\nu$ ) equal to the difference in the number of parameters between the two models.


- The REML likelihood ratio test is only valid if the fixed effects are the same for both model.
- **Significance level:**  $\alpha$
- **Rejection region:** upper (right-hand) tail

$$\text{Reject } H_0 \text{ if } \Lambda_{calc} > \chi^2_{\alpha(\nu)}$$

For ML likelihood ratio test the procedure is similar, using the log-likelihood instead of REML log-likelihood.

## Likelihood ratio tests for covariance parameters

- The REML likelihood ratio test is implicitly two-sided, and must be adjusted when the test involves an hypothesis with the parameter on the boundary of the parameter space. When we test a variance component, under the null hypothesis the parameter falls on the boundary of the parameter space. Theoretically it can be shown that for a single variance component, the asymptotic distribution of the REMLRT is a mixture of  $\chi^2$  variates, where the mixing probabilities are 0.5, one with 0 degrees of freedom and the other with one degree of freedom. As a consequence we can perform the likelihood ratio test as if the standard conditions apply, and divide the resulting p-value by two.
- The distribution of the REMLRT for the test involving more complex situations (for example, test that  $k$  variance components are zero), involves a mixture of  $\chi^2$  variates from 0 to  $k$  degrees of freedom (Self and Liang, 1987; Stram and Lee, 1994; Verbeke and Molenberghs, 2003, etc.).

In  the library '**RLRsim**' is dedicated to the simulation of the empirical distribution of the REML likelihood statistic when variance components testing is involved. The library '**lme4**' also has this functionality.



## Likelihood ratio tests for covariance parameters

- The naïve approach to using a  $\chi^2$  distribution with degrees of freedom determined by the difference in the number of parameters in the models is currently implemented by several packages. However, one should be aware that the p-values obtained may be conservative (that is, the reported p-value may be greater than the true p-value for the test).

## Performing a REML likelihood ratio test for a variance component

```
> TerrenosH1<-varComp(rend~variedade, random=~terreno, data=terrenos)
```

```
> logLik(TerrenosH1)
```

```
'log Lik.' -202.4013 (df=2)
```

```
> TerrenosH0<-varComp(rend~variedade, data=terrenos)
```

```
> logLik(TerrenosH0)
```

```
'log Lik.' -203.6992 (df=1)
```

```
> 2*( logLik(TerrenosH1)-logLik(TerrenosH0))
```

```
'log Lik.' 2.595781
```

```
> 1-pchisq(2.595781,1)
```

```
[1] 0.1071486
```

```
> (1-pchisq(2.595781,1))/2
```

```
[1] 0.0535743
```

## Some considerations

1. For its historical importance, we will also study tests concerning variance components in balanced designs, with  $\mathbf{G}$  and  $\mathbf{R}$  diagonal matrices, derived from the usual analysis of variance in the applications section (for example: random model with one random effects factor; linear mixed model with one factor of fixed effects, one factor of random effects, without interaction and with interaction; models with several random effects factors; analysis of split plot experiments).

2. For random or complex mixed models there are no exact statistical tests for certain model effects (the numerator and denominator of the F statistics are linear combinations of mean squares). In these cases, approximate F tests are performed. One of the classic methods most used for this approach is the method of Satterthwaite (1941). However, other methods are implemented in more complex mixed models frequently reported in the literature and commonly used in several packages, for example, the methods of Giesbrecht and Burns (1985) and Kenward and Roger (1997 (additional information in the applications section)).

### 3. A note about Wald statistic

One common statistic is the Wald Z, which is computed as the parameter estimate divided by its estimated asymptotic standard error computed from the inverse of the second derivative matrix of the log-likelihood with respect to covariance parameters. The Wald Z test is valid for large samples, but it can be unreliable for small data sets and for parameters such as variance components that are known to have a bounded sampling distribution.

**Not recommended for variance components**

# Tests of hypotheses for fixed (and random effects)

## Tests of hypotheses for linear combinations of the effects of the mixed model ( $L^T \begin{bmatrix} \beta \\ u \end{bmatrix}$ ), being $L$ a non random vector

- **Hypotheses:**  $H_0: L^T \begin{bmatrix} \beta \\ u \end{bmatrix} = \mathbf{0}$  vs.  $H_1: L^T \begin{bmatrix} \beta \\ u \end{bmatrix} \neq \mathbf{0}$

- **Test statistic:**  $T = \frac{L^T \begin{bmatrix} \hat{\beta} \\ \hat{u} \end{bmatrix}}{\sqrt{(L^T \hat{\mathbf{C}} L)}} \sim t_{v_2}$ , under  $H_0$

Under the assumed normality of  $\mathbf{u}$  and  $\mathbf{e}$ ,  $T$  has an exact  $t$ -distribution only for data exhibiting certain types of balance and for some special unbalanced cases. In general, it is only approximately  $t$ -distributed, and its degrees of freedom must be estimated (for example, using *Satterthwaite approximation*). This not happen only for particular cases for data exhibiting certain types of balance and for some special unbalanced cases with the elements of the vectors  $\mathbf{u}$  e  $\mathbf{e}$  being *i.i.d.* random variables. In these cases,  $v_2 = n - r(\mathbf{W})$ , where  $r(\mathbf{W})$  is the rank of the matrix  $\mathbf{W}$  which contains the columns of matrices  $\mathbf{X}$  and  $\mathbf{Z}$ .

$\sqrt{(L^T \hat{\mathbf{C}} L)}$  is a scalar, is the standard error of the estimator of the parameter being tested, matrix  $\mathbf{C}$  was defined in slides 59 and 60.

# Tests of hypotheses for linear combinations of the effects of the mixed model ( $L^T \begin{bmatrix} \beta \\ u \end{bmatrix}$ ), being $L$ a non random vector (cont.)

- Significance level:  $\alpha$
- Rejection region: two-tailed

$$\text{Reject } H_0 \text{ if } |T_{calc}| > t_{\alpha/2}(v_2)$$

The current procedure is mainly focused on the test of hypotheses for the fixed effects of the model . In this case  $\hat{C} = (X^T \hat{V}^{-1} X)^{-1}$ .



It follows from previous slides that a confidence interval  $(1 - \alpha) \times 100\%$  for  $L^T \begin{bmatrix} \beta \\ u \end{bmatrix}$  is given as:

$$\left[ L^T \begin{bmatrix} \hat{\beta} \\ \hat{u} \end{bmatrix} - t_{\alpha/2, v_2} \sqrt{L^T \hat{C} L}, L^T \begin{bmatrix} \hat{\beta} \\ \hat{u} \end{bmatrix} + t_{\alpha/2, v_2} \sqrt{L^T \hat{C} L} \right]$$

## Tests of hypotheses for linear combinations of the effects of the mixed model ( $L^T \begin{bmatrix} \beta \\ u \end{bmatrix}$ ), when $L$ is a matrix (rank of $L$ greater than 1)

- **Hypotheses:**  $H_0: L^T \begin{bmatrix} \beta \\ u \end{bmatrix} = \mathbf{0}$  vs.  $H_1: \text{not all } L^T \begin{bmatrix} \beta \\ u \end{bmatrix} = \mathbf{0}$

- **Test statistic:**  $F = \frac{\begin{bmatrix} \hat{\beta} \\ \tilde{u} \end{bmatrix}^T L(L^T \hat{C} L)^{-1} L^T \begin{bmatrix} \hat{\beta} \\ \tilde{u} \end{bmatrix}}{\text{rank}(L)} \sim \mathcal{F}_{v_1, v_2}$ , sob  $H_0$

F in general has an approximate F-distribution, with  $v_1 = \text{rank}(L)$  and  $v_2$  must be estimated (for example, using *Satterthwaite approximation*). This not happen only for particular cases for data exhibiting certain types of balance and for some special unbalanced cases with the elements of the vectors  $u$  e  $e$  being *i.i.d.* random variables. In these cases,  $v_2 = n - r(\mathbf{W})$ , where  $r(\mathbf{W})$  is the rank of the matrix  $\mathbf{W}$  which contains the columns of matrices  $\mathbf{X}$  and  $\mathbf{Z}$ .

Tests of hypotheses for linear combinations of the effects of the mixed model ( $L^T \begin{bmatrix} \beta \\ u \end{bmatrix}$ ), when  $L$  is a matrix (rank of  $L$  greater than 1)  
(cont.)

- Significance level :  $\alpha$
- Rejection region: upper (right-hand) tail

Reject  $H_0$  if  $F_{calc} > f_{\alpha}(v_1, v_2)$

No 

**> summary(arlme2)**

Linear mixed-effects model fit by REML

Data: arinto

AIC	BIC	logLik
1152.537	1181.887	-570.2686

Random effects:

Formula: ~1 | clone

(Intercept) Residual

StdDev: 0.3512633 0.3488315

Fixed effects: rend ~ bloco

	Value	Std.Error	DF	t-value	p-value
(Intercept)	1.3938704	0.03149894	738	44.25134	0.0000
blocoB3	-0.3075385	0.03138934	738	-9.79754	0.0000
blocoB4	-0.0085951	0.03138934	738	-0.27382	0.7843
blocoB5	0.2995020	0.03138934	738	9.54152	0.0000

**> anova(arlme2)**

	numDF	denDF	F-value	p-value
(Intercept)	1	738	3101.4982	<.0001
bloco	3	738	124.6915	<.0001

```
> intervals(arlme2)
```

Approximate 95% confidence intervals

Fixed effects:

	lower	est.	upper
(Intercept)	1.33203224	1.393870445	1.4557087
blocoB3	-0.36916150	-0.307538462	-0.2459154
blocoB4	-0.07021818	-0.008595142	0.0530279
blocoB5	0.23787898	0.299502024	0.3611251

```
attr("label")
```

```
[1] "Fixed effects:"
```

Random Effects:

Level: clone

	lower	est.	upper
sd((Intercept))	0.3144	0.3512633	0.3924488

# Model selection

- Model comparison via likelihood ratio tests
  - REML and ML likelihood ratio tests can be used to compare nested models. One model is said to be nested within another model if it represents a special case of the other model.
  - The REML likelihood ratio tests should only be used for models with same fixed-effects specification.

(procedure already described in slide 71)

# Model selection

- **Model comparison via information criteria**
- Information criteria provide an alternative to formal testing. The two most widely used information criteria are the AIC (Akaike information criterion) and BIC (Bayesian information criterion). There are others, for example: sample corrected version of AIC, AICC; Information criterion of Hannan-Quinn, HQIC; etc..
- Both the AIC and BIC contain two terms that measure the fit of the model and the complexity of the model.
- With REML, AIC and BIC criteria can only be used for comparing models with same fixed-effects specification (with equal  $X\beta$ )
- They can be used to compare nested models and non-nested models

**Akaike information criterion ( $AIC_R$ )** is defined as:

$$AIC_R = -2l_R + 2n_{par} ,$$

$l_R$  is the REML log-likelihood of the model and  $n_{par}$  is the number of covariance parameters in the model.

- AIC is calculated for each model. The model with the smallest value is chosen as the preferred model.
- Penalizes model complexity (models with a higher number of parameters).

**Note:** For ML estimation method, REML log-likelihood is replaced by log-likelihood and  $n_{par}$  is the number of parameters in the model (thus, includes fixed effects).



**Bayesian information criterion** ( $BIC_R$ ) is defined as,

$$BIC_R = -2l_R + n_{par} \ln(n - r_X),$$

$l_R$  is the REML log-likelihood of the model and  $n_{par}$  is the number of covariance parameters in the model,  $n$  is the number of observations and  $r_X$  is the rank of matrix  $\mathbf{X}$ .

- BIC is calculated for each model. The model with the smallest value is chosen as the preferred model.
- Penalizes model complexity (models with a higher number of parameters).
- The number of observations is also taken into account.

**Note:** For ML estimation method, the REML log-likelihood is replaced by log-likelihood,  $n_{par}$  is the number of parameters in the model (thus, includes fixed effects) and  $\ln(n - r_X)$  is replaced by  $\ln(n)$ .

```
> siria.lme1 <- lme(rend ~ subpop + bloco, data = siria, random = list(clone = pdIdent(~subpop - 1)))
```

```
> summary(siria.lme1)
```

Linear mixed-effects model fit by REML

Data: siria

AIC	BIC	logLik
2163.291	2207.831	-1072.646

Random effects:

Formula: ~subpop - 1 | clone

Structure: Multiple of an Identity

subpopALE	subpopALG	subpopPINHEL	Residual
StdDev: 0.4550345	0.4550345	0.4550345	0.5784932

```
> siria.lme2 <- lme(rend ~ subpop + bloco, data = siria, random = list(clone = pdDiag(~subpop - 1)))
```

```
> summary(siria.lme2)
```

Linear mixed-effects model fit by REML

Data: siria

AIC	BIC	logLik
2153.235	2207.673	-1065.618

Random effects:

Formula: ~subpop - 1 | clone

Structure: Diagonal

subpopALE	subpopALG	subpopPINHEL	Residual
StdDev: 0.245502	0.4622154	0.5355529	0.5784956

```
> anova(siria.lme1, siria.lme2)
```

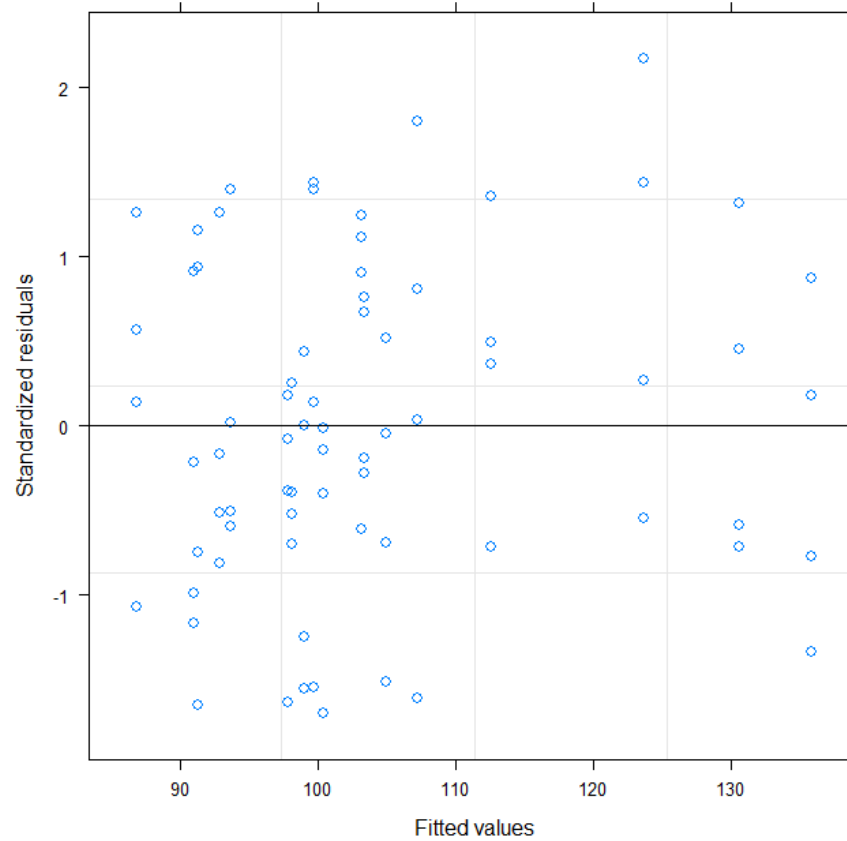
	Model	df	AIC	BIC	logLik	Test	L.Ratio	p-value
siria.lme1	1	9	2163.291	2207.831	-1072.646			
siria.lme2	2	11	2153.235	2207.673	-1065.618	1 vs 2	14.05585	9e-04

# Validation of the model assumptions

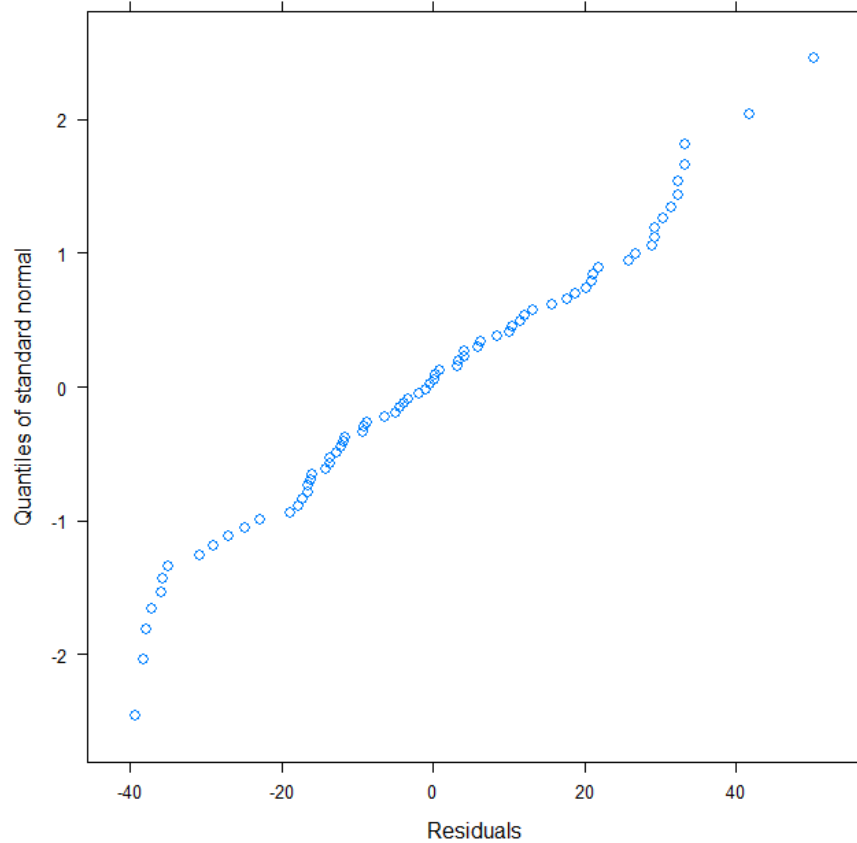
- ❑ As in classical linear model, validation of model assumptions is made essentially using graphic tools.
- ❑ One key assumption is the normality. Now it is necessary to validate this hypothesis in the residuals (by tools already mentioned in the linear model) and in the predictors of random effects (using the same diagnostic tools).
- ❑ In the classical linear mixed model, the homogeneity of variances is validated using diagnostic plots. In certain contexts, when this assumption fails, the usual technique is to fit a new linear mixed model that assumes heterogeneous variances. Both models are compared using a formal test (Likelihood ratio test) or by AIC and BIC criteria.
- ❑ In the classical linear mixed model, the classical assumption of independence can also be validated by graphic tools. In certain contexts, the semivariogram of the residuals (a tool of spatial analysis) is used for validation of this assumption. When this assumption fails, the usual technique is to fit a new linear mixed model with covariance matrices which include correlation among observations.

In 

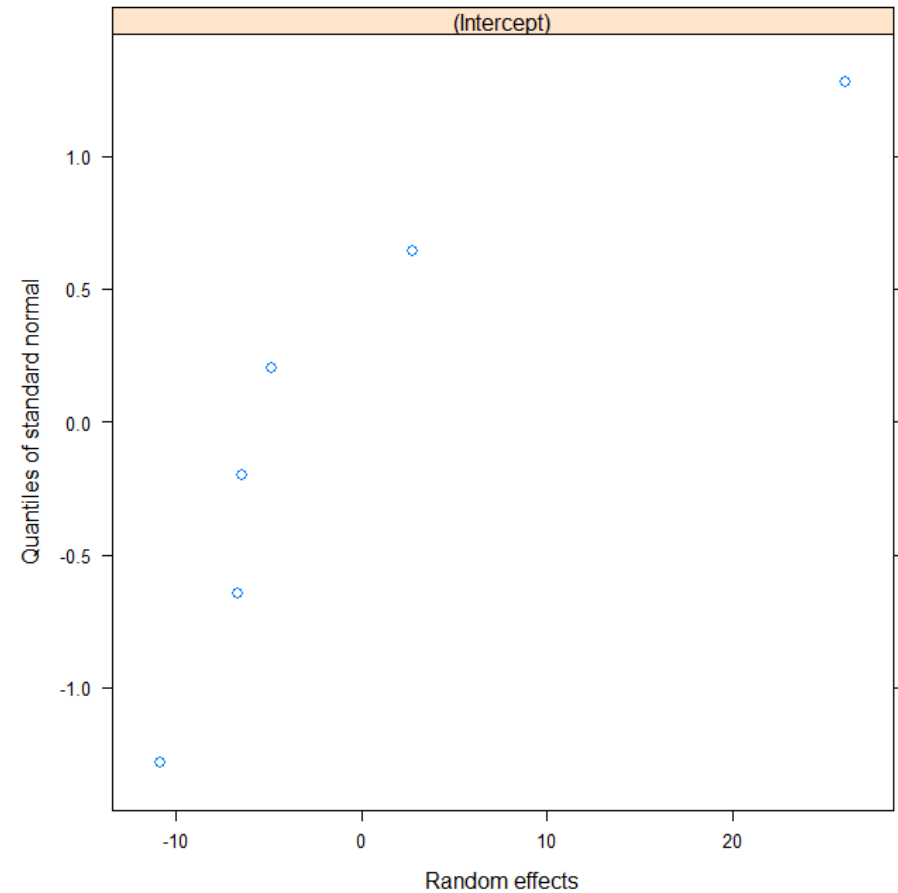
```
> oats.lme1<-lme(yield~Variety, data=oats,random=~1 | Blocks)  
> plot(oats.lme1)
```



```
>qqnorm(oats.lme1, ~resid(.))
```



```
>qqnorm(oats.lme1, ~ranef(.))
```



❑ Cook's Distance can be studied using package *"influence.ME"* (requires to fit the model with the function *lmer* of the package *lme4*).