# Additional Aspects of BLUP Peter von Rohr

\* Prediction of breeding values using linear mixed effects models

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mixed effects models.

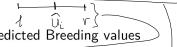
\* Examples: Sire model, animal model

\* Solutions for fixed effects estimates and for predicted breeding values can be obtained using Mixed Model equations.

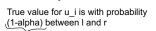
In MME, A^{-1} required ==> efficient computations shown

## **Aspects**

- Accurracy
  - Results from MME are estimates of fixed effects and predictions of breeding values
  - ▶ Need statement about quality of estimates and predictions
- Confidence Intervals



Decomposition of Predicted Breeding values



With estimates and predictions, there are always errors associated ==> quantify error

## Accurracy

fixed effects 
$$(\beta - \hat{\beta})$$
 where  $\beta$  breeding values  $\beta - \hat{\beta}$ 

- One property of BLUP was that variance of prediction error is minimal
- How can we measure the variance of the prediction error
- Fixed effects

$$f(x) = 0$$

► Random effects

MIN

$$var(u-\hat{u}) = var(u)-2*cov(u,\hat{u})+var(\hat{u}) = var(u)-var(\hat{u}) = PEV(\hat{u})$$

because with BLUP:  $cov(u, \hat{u}) = var(\hat{u})$ 

Aim: predicted breeding values should be as close as possible to the true breeding values ==> PEV ==> 0 In practise: Coefficient matrix of MME cannot be inverted, hence PEV are always approximation

PEV depends on inverse of coefficient matrix of MME

$$\begin{bmatrix} X^T R^{-1} X & X^T R^{-1} Z \\ Z^T R^{-1} X & Z^T R^{-1} Z + G^{-1} \end{bmatrix}^{-1} = \begin{bmatrix} C^{11} & C^{12} \\ C^{21} & C^{22} \end{bmatrix}$$

ightharpoonup For predicted breeding values  $\hat{u}$ 

$$PEV(\hat{u}) = var(u) - var(\hat{u}) = C^{22}$$

## Single Animal i

That 
$$V_{\text{CV}}(v_{i}) - V_{\text{CV}}(\hat{v}_{i}) = \underbrace{(C)_{ii}^{22}}_{\text{i-th diagonal elements}} V_{\text{CV}}(\hat{v}_{i})$$

where  $(C)_{ii}^{22}$  is the *i*-th diagonal of  $C^{22}$ 

► Accuracy measured by correlation

of the predicted breeding value for animal i 
$$r_{u_{i},\hat{u}_{i}} = \frac{cov(u_{i},\hat{u}_{i})}{\sqrt{var(u_{i})*var(\hat{u}_{i})}} = \sqrt{\frac{var(\hat{u}_{i})}{var(u_{i})}} \sqrt{\frac{var(\hat{u}_{i})}{var(u_{i})}}$$

$$PEV(\hat{u}_{i}) = (C)_{ii}^{22} = var(u_{i}) - var(\hat{u}_{i}) = var(u_{i}) - r_{u_{i},\hat{u}_{i}}^{2} var(u_{i})$$

$$(1 - \sqrt{2}) \vee 6 \vee (u_{i})$$

$$B_{i} = r_{u_{i},\hat{u}_{i}}^{2} = \frac{var(u_{i}) - (C)_{ii}^{22}}{var(u_{i})} = 1 - \underbrace{\frac{PEV(\hat{u}_{i})}{var(u_{i})}}_{Var(u_{i})} = 1 - \underbrace{\frac{(C)_{ii}^{22}}{var(u_{i})}}_{Var(u_{i})}$$

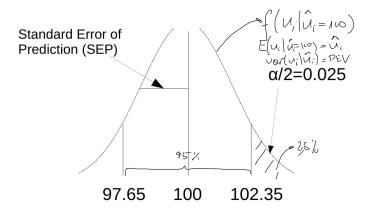
- $ightharpoonup B_i$  is large for small  $PEV(\hat{u}_i)$
- ▶ In the limit  $B_i \rightarrow 1$  for  $PEV(\hat{u}_i) \rightarrow 0$
- ▶ For  $PEV(\hat{u}_i) \rightarrow 0$  we must have  $var(\hat{u}_i) \rightarrow var(u_i)$
- ▶ Therefore, the closer  $var(\hat{u}_i)$  is to  $var(u_i)$ , the more accurate the predicted breeding value

## Confidence Intervals of $\hat{u}_i$

- ▶ Predicted breeding value  $(\hat{u}_i)$  is a function of the data (y)
- ▶ Hence  $\hat{u}_i$  is a random variable with a distribution

#### Distribution

#### SEP: Standard error of prediction



$$SEP(\hat{u}_i) = \sqrt{PEV(\hat{u}_i)} = \sqrt{(1 - \underbrace{r_{u_i,\hat{u}_i}^2}_{\Lambda_2}) * \underbrace{var(u_i)}_{\Lambda_2}}$$

#### Widths Of Confidence Intervals

Table 1: Widths of Confidence Intervals for Given Accuracies

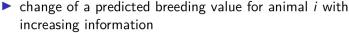
Accurracy	Interval Width	
→ 0.40	36.44	
0.50	33.26	e Ú,
0.60	29.75	(= 100)
0.70	25.76	( , )
0.80	21.04	
0.90	14.88	
0.95	10.52	→ 95 -105
0.99	4.70	_

with  $\hat{u}_i=100$ ,  $var(u_i)=144$  and lpha=0.05  $\Im$   $\Im$ 



Correlation  $r_{u_i,\hat{u}_i}$  for a single animal i

across conceptual repeated sampling



ightharpoonup related to standard error of prediction (SEP) ightarrow measure of risk of using i as parent

Accuracies also important for selection response

► correlation between true and predicted breeding values in

- selection candidates

  population accuracy
- characteristic of population not of single animal
- estimation with cross-validation

 $\rightarrow$  use correlation between predicted breeding values with whole and partial data

## Decomposition of Predicted Breeding Value

► Write MME as

$$M \cdot s = r$$

with

$$s = \left[ egin{array}{c} \hat{eta} \ \hat{u} \end{array} 
ight]$$

- $\triangleright$   $\hat{\beta}$  has length p
- $\hat{u}$  has length q

## Simplified Model

$$y_i = \mu + u_i + e_i$$

where  $y_i$  Observation for animal i  $u_i$  breeding value of animal i with a variance of  $(1+F_i)\sigma_u^2$   $e_i$  random residual effect with variance  $\sigma_e^2$   $\mu$  single fixed effect

#### Data

- all animals have an observation
- ▶ animal *i* has
  - parents s and d
  - ightharpoonup n progeny  $k_i$  (with  $j = 1, \ldots, n$ )
  - ightharpoonup n mates  $l_i$  (with  $j=1,\ldots,n$ ).
- ightharpoonup progeny  $k_j$  has parents i and  $l_j$ .

## Example

Animal	Sire	Dam	WWG
1	NA	NA	4.5
2	NA	NA	2.9
3	NA	NA	3.9
4	1	2	3.5
5	4	3	5.0

Variance components  $\sigma_e^2=40$  and  $\sigma_u^2=20$ .

## Model Components

$$X = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \ Z = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$X^TX = \begin{bmatrix} 5 \end{bmatrix}, X^TZ = \begin{bmatrix} 1 & 1 & 1 & 1 \end{bmatrix}$$

$$Z^T Z = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

## Right-hand Side

$$X^{T}y = \left[\sum_{j=1}^{n} y_{i}\right] = 19.8$$

$$\begin{bmatrix} y1 \end{bmatrix} \quad \begin{bmatrix} 4.5 \end{bmatrix}$$

$$Z^{T}y = \begin{bmatrix} y1 \\ y2 \\ y3 \\ y4 \\ y5 \end{bmatrix} = \begin{bmatrix} 4.5 \\ 2.9 \\ 3.9 \\ 3.5 \\ 5 \end{bmatrix}$$

#### $\Delta^{-1}$

## as(<dtTMatrix>, "dtCMatrix") is deprecated since Matrix

$$A^{-1} = \begin{bmatrix} 1.5 & 0.5 & 0 & -1 & 0 \\ 0.5 & 1.5 & 0 & -1 & 0 \\ 0 & 0 & 1.5 & 0.5 & -1 \\ -1 & -1 & 0.5 & 2.5 & -1 \\ 0 & 0 & -1 & -1 & 2 \end{bmatrix}$$

#### **MME**

$$\begin{bmatrix} X^T X & X^T Z \\ Z^T X & Z^T Z + A^{-1} * \lambda \end{bmatrix} \begin{bmatrix} \hat{\mu} \\ \hat{u} \end{bmatrix} = \begin{bmatrix} X^T y \\ Z^T y \end{bmatrix}$$

#### Insert Data

$$\begin{bmatrix} 5 & 1 & 1 & 1 & 1 & 1 \\ 1 & 4 & 1 & 0 & -2 & 0 \\ 1 & 1 & 4 & 0 & -2 & 0 \\ 1 & 0 & 0 & 4 & 1 & -2 \\ 1 & -2 & -2 & 1 & 6 & -2 \\ 1 & 0 & 0 & -2 & -2 & 5 \end{bmatrix} \begin{bmatrix} \mu \\ \hat{u}1 \\ \hat{u}2 \\ \hat{u}3 \\ \hat{u}4 \\ \hat{u}5 \end{bmatrix} = \begin{bmatrix} 19.8 \\ 4.5 \\ 2.9 \\ 3.9 \\ 3.5 \\ 5 \end{bmatrix}$$

#### Animal 4

- parents 1 and 2
- progeny 5
- ► mate 3
- inspection of second but last equation in MME where  $y_4$  and  $\hat{u}_4$  occur
- ▶ Remember from construction of  $A^{-1}$ , the variable  $d^{ii}$  can assume the following values

$$d^{ii} = \begin{cases} 2 & \text{both parents known} \\ \frac{4}{3} & \text{one parent known} \\ 1 & \text{both parents unknown} \end{cases}$$

## **Extract Equation**

$$y_4 = 3.5 = 1 * \hat{\mu} - 2 * \hat{u}_1 - 2 * \hat{u}_2 + 1 * \hat{u}_3 + 6 * \hat{u}_4 - 2 * \hat{u}_5$$

▶ Solving for û<sub>4</sub>

$$\hat{u}_4 = \frac{1}{6} \left[ y_4 - \hat{\mu} + 2 * (\hat{u}_1 + \hat{u}_2) - \hat{u}_3 + 2\hat{u}_5 \right]$$

- $ightharpoonup \hat{u}_4$  depends on
  - $\triangleright$  own performance record  $y_4$
  - ightharpoonup estimate of fixed effect  $\hat{\mu}$  environment
  - predicted breeding value of parents 1 and 2, mate 3 and progeny 5

### General Equation

$$\hat{u}_{i} = \frac{1}{1 + \alpha \delta^{(i)} + \frac{\alpha}{4} \sum_{j=1}^{n} \delta^{(k_{j})}} \left[ y_{i} - \hat{\mu} + \frac{\alpha}{2} \left\{ \delta^{(i)} (\hat{u}_{s} + \hat{u}_{d}) + \sum_{j=1}^{n} \delta^{(k_{j})} (\hat{u}_{k_{j}} - \frac{1}{2} \hat{u}_{l_{j}}) \right\} \right]$$

where  $\alpha$  ration between variance components  $\sigma_e^2/\sigma_u^2$   $\delta^{(j)}$  contribution for animal j to  $A^{-1}$