## Additional Aspects of BLUP

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#### Aspects

Recap: BLUP Animal Model, means that we use a linear mixed effect model with the breeding values of all animals in the pedigree as additional random effect. Solutions for fixed effects and for predicted breeding values are obtained by Mixed Model Equations (MME)

#### 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

#### Accurracy

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

By definition of a fixed effect, the true value of the fixed effect, does not have any variance. This means var(\beta) = 0

$$var(eta - \hat{eta}) = var(\hat{eta})$$

► Random effects The true value of a random effect (e.g. the breeding value u) is expected to show a certain variation (for u, var(u) = A \* \sigma\_u^2). This means, the predicted breeding values, they are expected to have a variation that should as close as possible to the variance of the true breeding values.

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

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

**PEV: Prediction error variance** 

PEV



For real-world datasets, PEV can not be computed exactly, but it has to be approximated.

## Single Animal *i*

$$PEV(\hat{u}_i) = (C)_{ii}^{22}$$

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

Accuracy measured by correlation

Reliability (Bestimmtheitsmass) is the square of the accuracy

$$r_{u_i,\hat{u}_i} = \frac{cov(u_i,\hat{u}_i)}{\sqrt{var(u_i)*var(\hat{u}_i)}} = \sqrt{\frac{var(\hat{u}_i)}{var(u_i)}}$$



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

<del>Accuracy</del> B<sub>i</sub>

#### Reliability

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

- ▶  $B_i$  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(û<sub>i</sub>) is to var(u<sub>i</sub>), the more accurate the predicted breeding value

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

Predicted breeding value (û<sub>i</sub>) is a function of the data (y)
 Hence û<sub>i</sub> is a random variable with a distribution

#### Distribution



## Widths Of Confidence Intervals

Breeding values are predicted on different sources of information: Calf first has a parental average: B is around 0.2 - 0.3

Table 1: Widths of Confidence Intervals for Given Accuracies

With own performance records, then B depends on the heritability B is 0.3-0.4 For animals with progeny, B starts to grow above 0.6	Accurracy	Interval Width	The advantage of genomic selection is that already for a young animal, B values of around 0.4 to 0.5 can be reached
	0.40	36.44	
	0.50	33.26	
	0.60	29.75	
	0.70	25.76	
	0.80	21.04	
	0.90	14.88	
	0.95	10.52	
	0.99	4.70	

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

## Decomposition of Predicted Breeding Value



#### 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 n* progeny k<sub>j</sub> (with j = 1,..., n) *n* mates l<sub>j</sub> (with j = 1,..., n).
progeny k<sub>j</sub> has parents *i* and l<sub>j</sub>.

## 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

$$X = \begin{bmatrix} 1\\1\\1\\1\\1 \end{bmatrix}, Z = \begin{bmatrix} 1 & 0 & 0 & 0 & 0\\0 & 1 & 0 & 0 & 0\\0 & 0 & 1 & 0 & 0\\0 & 0 & 0 & 1 & 0\\0 & 0 & 0 & 0 & 1 \end{bmatrix}$$
$$X^{T}X = \begin{bmatrix} 5 \end{bmatrix}, X^{T}Z = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$
$$Z^{T}Z = \begin{bmatrix} 1 & 0 & 0 & 0 & 0\\0 & 1 & 0 & 0 & 0\\0 & 0 & 1 & 0 & 0\\0 & 0 & 0 & 1 & 0\\0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

## Right-hand Side

$$X^{T}y = \begin{bmatrix} \sum_{j=1}^{n} y_{j} \\ y_{j} \\ y_{j} \\ y_{j} \\ y_{j} \\ y_{j} \\ y_{j} \end{bmatrix} = \begin{bmatrix} 4.5 \\ 2.9 \\ 3.9 \\ 3.5 \\ 5 \end{bmatrix}$$

 $A^{-1}$ 

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

#### MME



#### Insert Data



# 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<sup>-1</sup>, the variable d<sup>ii</sup> 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



#### 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  $A^{-1}$