

OHP Picture 1

Recap 2023-11-03

- Goal: Prediction of breeding values

$$y_{ij} = \mu + \text{herd}_j + e_{ij} \quad \left. \right\} \text{linear fixed effect model}$$

i: Tier

j: Herd

Insert data

$$\begin{aligned} y_{12,1} &= \mu + \text{herd}_1 + e_{12,1} \\ y_{26,1} &= \mu + \text{herd}_1 + e_{12,1} \end{aligned}$$

i=12

j=1

- Why mixed linear model and not fixed linear model?

$$y_{ij} = \mu + \text{herd}_j + u_i + e_{ij}$$

if herd_j and u_i both fix \Rightarrow fixed linear model

herd_j: fix

u_i: random $\left. \right\} \text{mixed linear model}$

OHP Picture 2

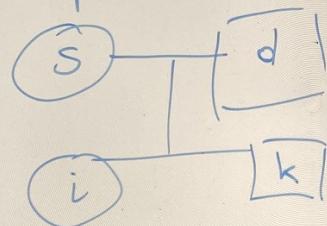
Breeding Values

$$y_{ij} = \mu + \text{herd}_j + u_i + e_{ij}$$

• Observation: weight of animal i in herd j

• u_i must be random, because $\text{cov}(u_i, u_k) \neq 0$
if animals i and k are relatives

• Example: animals i and k are full-sibs :



For animal k: $y_{kL} = \mu + \text{herd}_e + u_j + e_{ke}$

$\text{cov}(u_i, u_k) \neq 0$, because of decomposition of breeding values

$$\begin{aligned} u_i &= \frac{1}{2} u_s + \frac{1}{2} u_d + m_i \\ u_k &= \frac{1}{2} u_s + \frac{1}{2} u_d + m_k \end{aligned} \quad \left\{ \text{cov}(u_i, u_k) \neq 0 \right.$$

$$\begin{aligned} \text{cov}(u_i, u_k) &= \text{cov}\left(\left[\frac{1}{2} u_s + \frac{1}{2} u_d + m_i\right], \left[\frac{1}{2} u_s + \frac{1}{2} u_d + m_k\right]\right) \\ &= \frac{1}{4} \text{var}(u_s) + \frac{1}{4} \text{var}(u_d) = \frac{1}{2} \sigma_u^2 \end{aligned}$$

provided s and d not related

OHP Picture 3

(3)

□ Reason 2 why u_i is random :

- For fixed discrete effects, e.g. herd or breed, the factor level can be assigned to every record
- Breeding Value u_i is a sum of very many single locus breeding values

$$\begin{array}{c} | \bar{G}_i) \quad H_i \quad K_i \\ \hline | G_j | \quad H_j \quad K_j \\ \downarrow \\ BV_j + BV + BU + - - - = u_i \end{array}$$

too many genotypes
⇒ u_i random

OHP Picture 4

(4)

□ Regression

$$y_i = \mu + b \cdot \text{breast_circumference}_i + e_i$$

herd
 u_i

□ Mixed-linear Model

$$\underline{y_{ij} = \mu + \text{herd}_j + u_i + e_{ij}}$$

- Dataset

$$\begin{cases} y_{12,1} = \mu + \text{herd}_1 + u_{12} + e_{12,1} \\ y_{13,1} = \mu + \text{herd}_1 + u_{13} + e_{13,1} \\ \vdots \end{cases}$$
- Matrix-vector notation:
 - define vector $y = \begin{bmatrix} 2.61 \\ 2.31 \\ \vdots \\ 3.16 \end{bmatrix}$
 - define vector $\beta = \begin{bmatrix} \text{herd}_1 \\ \text{herd}_2 \end{bmatrix}$

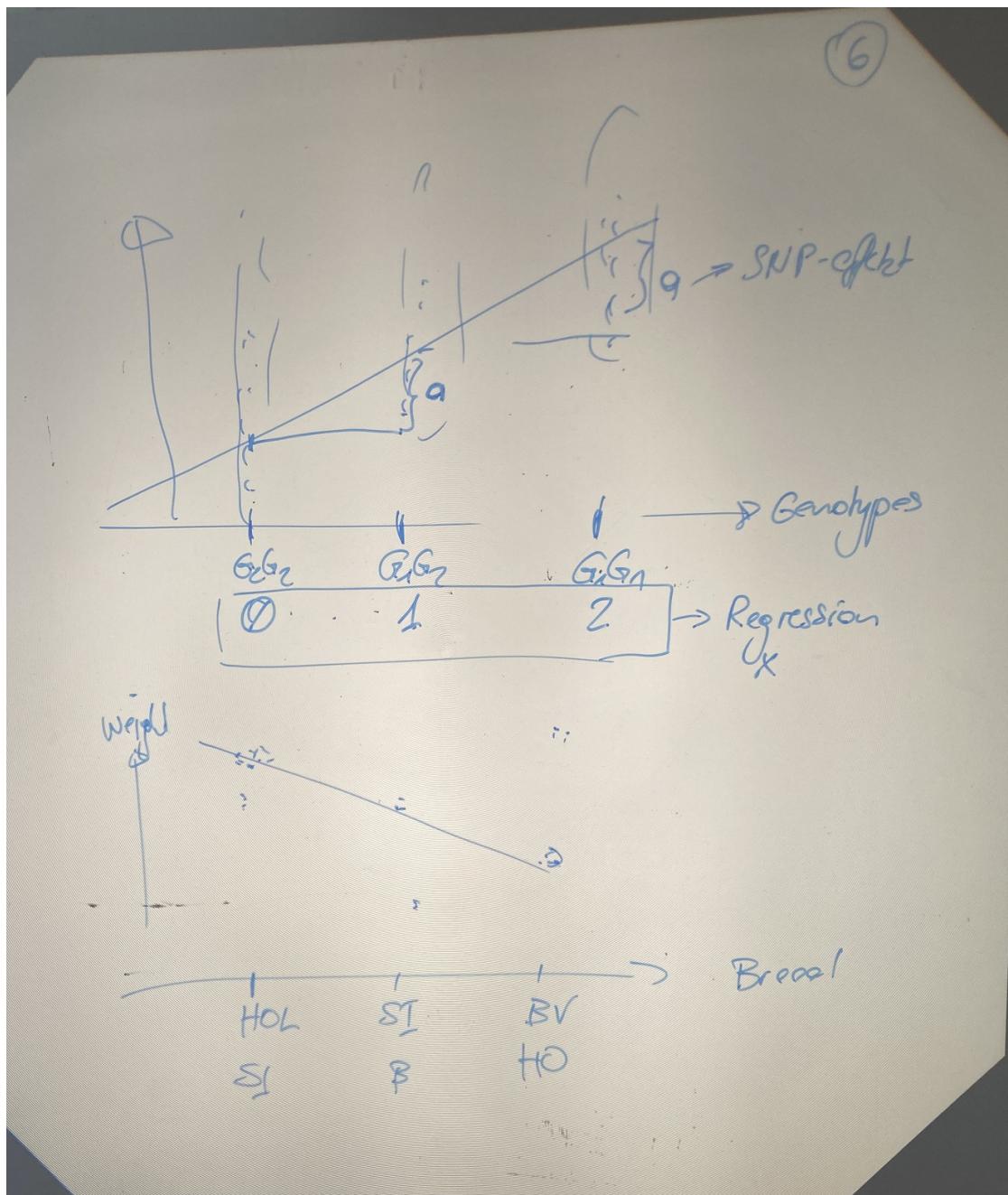
OHP Picture 5

(5)

- Vector y : observations
- Vector $\beta = \begin{bmatrix} \text{herd}_1 \\ \text{herd}_2 \end{bmatrix}$
- Vector $u = \begin{bmatrix} u_1 \\ \vdots \\ u_q \end{bmatrix}$
- Vector $e = \begin{bmatrix} e_1 \\ \vdots \\ e_N \end{bmatrix}$
- Matrices X and Z : design matrices
- Model: $y = X\beta + Zu + e$

$$\rightarrow \begin{bmatrix} y \\ 2.61 \\ 2.31 \\ \vdots \\ 3.16 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 \end{bmatrix} \cdot \begin{bmatrix} \text{herd}_1 \\ \text{herd}_2 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ e_3 \\ e_4 \\ e_5 \end{bmatrix}$$

OHP Picture 6



OHP Picture 7

Two types of linear mixed effect models

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- (1) Sire-model \Rightarrow only sires get breeding values
- (2) Animal-model \Rightarrow all animals get breeding values
(in pedigree)

$$\text{Model: } y = X\beta + Zu + e$$

Sire Model: u - vector of sire-breeding values

where $u = \begin{bmatrix} S_1 \\ S_2 \\ S_3 \end{bmatrix}$ with sires 1, 2 and 3

- alternative notation: $y = X\beta + Zs + e$

$$\rightarrow \begin{bmatrix} y \\ 2.61 \\ 2.31 \\ \vdots \\ 3.76 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ \vdots & \\ 0 & 1 \end{bmatrix} \beta + \begin{bmatrix} \text{head}_1 \\ \text{head}_2 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} S_1 \\ S_2 \\ S_3 \end{bmatrix} + \begin{bmatrix} e \\ e_{21} \\ e_{22} \\ \vdots \\ e_{27} \end{bmatrix}$$

OHP Picture 8

(8)

Animal Model: $y = X\beta + Z_u + e$

$$\Rightarrow \begin{bmatrix} y \\ \vdots \end{bmatrix} = \begin{pmatrix} X\beta \\ \vdots \end{pmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_{27} \end{bmatrix}$$

$\begin{bmatrix} X\beta \\ \vdots \end{bmatrix} = \begin{pmatrix} 1 & 0 \\ 1 & 0 \\ \vdots & \vdots \end{pmatrix} \begin{bmatrix} \text{head}_1 \\ \text{head}_2 \end{bmatrix} + \begin{bmatrix} 0 & 0 \end{pmatrix} \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_{27} \end{bmatrix}$

- BLUP Method to get predictions for unknown breeding values u and estimates of fixed effects (β)
- Model: y : known ; X, β : known
 $\beta, u, (e)$: unknown
- Goal: use model and data to get estimates $\hat{\beta}$ for β and predictions \hat{u} for u
- Solution based on BLUP and on model assumptions

OHP Picture 9

Model Assumptions: (must be specified for mixed model) (9)

- Expected values
 - vector u of breeding values, defined as deviations $\Rightarrow E(u) = \emptyset \Leftrightarrow E(\begin{pmatrix} u \\ e \end{pmatrix}) = \begin{pmatrix} \emptyset \\ \emptyset \end{pmatrix}$
 - vector e of residuals defined as deviations $\Rightarrow E(e) = \emptyset$
$$\Rightarrow E(y) = E[X\beta + Zu + e]$$

$$= E(X\beta) + E(Zu) + \underbrace{E(e)}_{\emptyset}$$

$$= X\beta + Z \cdot \underbrace{E(u)}_{\emptyset}$$

$$= X\beta$$
- Abbreviations:

$$E\begin{bmatrix} y \\ u \\ e \end{bmatrix} = \begin{bmatrix} X\beta \\ \emptyset \\ \emptyset \end{bmatrix}$$
- Variance: $\text{var}(u) = G$; $\text{var}(e) = R$; $\text{var}(y) = V$
 where G and R are known variance-covariance matrices.
 $\text{cov}(u, e) = \emptyset$

OHP Picture 10

(10)

- $\text{var}(u)$: variance-covariance matrix

$$G = \text{var}(u) = \begin{bmatrix} \text{var}(u_1) & \text{cov}(u_1, u_2) & \text{cov}(u_1, u_3) & \dots \\ \text{cov}(u_2, u_1) & \text{var}(u_2) & \text{cov}(u_2, u_3) & \dots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

where $u = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_{27} \end{bmatrix}$

- $\text{var}(e) = R = \begin{bmatrix} \text{var}(e_1) & \text{cov}(e_1, e_2) & \dots \\ \text{cov}(e_2, e_1) & \text{var}(e_2) & \dots \end{bmatrix}$

$\text{var}(e_1) = \text{var}(e_2) = \dots = \bar{e}^2$

$\text{cov}(e_1, e_2) = \text{cov}(e_1, e_3) = \dots = \emptyset$

$\Rightarrow R = \begin{bmatrix} \bar{e}^2 & \emptyset & \dots & \emptyset \\ \emptyset & \bar{e}^2 & \dots & \emptyset \\ \vdots & \vdots & \ddots & \vdots \end{bmatrix} = I \cdot \bar{e}^2$

OHP Picture 11

$$\begin{aligned}
 \text{cov}(y, u) &= \text{cov}(X\beta + Zu + e, u^\top) \\
 &= \underbrace{\text{cov}(X\beta, u^\top)}_{=0} + \text{cov}(Zu, u^\top) + \underbrace{\text{cov}(e, u^\top)}_{=0} \\
 &= \underbrace{\text{cov}(Zu, u^\top)}_{=0} = \underbrace{\sum \text{cov}(u, u^\top)}_{\text{var}(u)} = \prod G
 \end{aligned}$$

$$\begin{aligned}
 \text{cov}(y, e^\top) &= \text{cov}(X\beta + Zu + e, e^\top) \\
 &= \text{cov}(X\beta, e^\top) + \text{cov}(Zu, e^\top) + \text{cov}(e, e^\top) \\
 &= 0 + \underbrace{2\text{cov}(u, e^\top)}_{=0} + \text{var}(e) \\
 &= R
 \end{aligned}$$

$$\text{var} \begin{bmatrix} y \\ u \\ e \end{bmatrix} = \begin{bmatrix} V & ZG & R \\ GZ & G & \emptyset \\ R & \emptyset & R \end{bmatrix}, \quad V = ZG^\top + R$$

OHP Picture 12

(13)

- * Using properties of BLUP:
- solutions for \hat{u} and $\hat{\beta}$:
$$\hat{u} = G Z^T V^{-1} (y - X \hat{\beta})$$

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

* Practical Problem: Large data sets (10^7 Mio records)

V^{-1} : cannot be computed $(6 \cdot 10^7$ Mio)

□ Same solutions from system of equations:

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

- $R = I / \sigma^2 \Rightarrow R^{-1} = I \cdot \frac{1}{\sigma^2}$