

OHP Picture 1

Recap 2023-11-03

□ Goal: Prediction of breeding values

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

i : Tier

j : Herd

Insert data

$$\begin{aligned} y_{12,1} &= \mu + \text{herd}_1 + e_{12,1} \\ [2,6,1 &= \mu + \text{herd}_1 + e_{12,1}] \\ i &= 12 \\ j &= 1 \end{aligned}$$

□ Why mixed linear model and not fixed linear model?

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

herd_j : fix
 u_i : random } mixed linear model

If herd_j and u_i both
fix \Rightarrow fixed linear
model

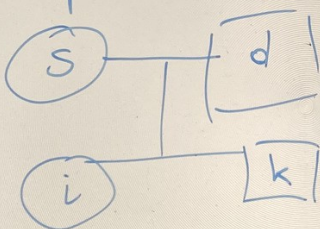
OHP Picture 2

□ Breeding Values

$$y_{ij} = \mu + herd_j + u_i + e_{ij}$$

- Observation: weight of animal i in herd j
- u_i must be random, because $cov(u_i, u_k) \neq 0$ if animals i and k are related

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



For animal k : $y_{k\ell} = \mu + herd_\ell + u_k + e_{k\ell}$
 $cov(u_i, u_k) \neq 0$, because of decomposition of breeding values

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

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

provided s and d not related.

OHP Picture 3

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□ 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

G_i	H_i	K_i
G_j	H_j	K_j

$BV_j + BV + BU + \dots = u_i$

} too many genotypes
=> u_i random

OHP Picture 4

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□ Regression

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

↑
herd
 u_i

□ Mixed-linear Model

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

- 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

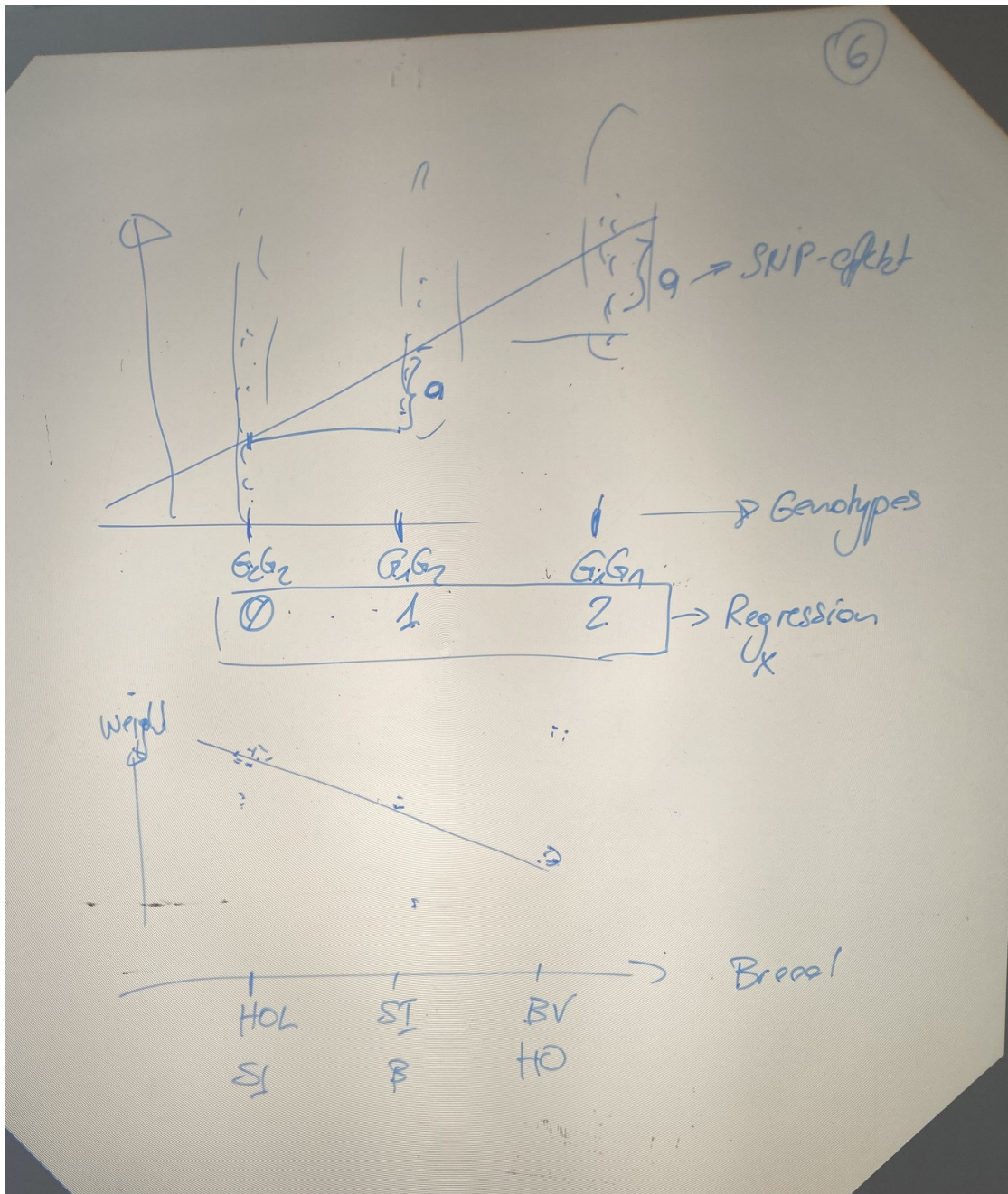
⑤

- 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 : $y = X\beta + Zu + e$

$$\begin{array}{c} \rightarrow \\ \rightarrow \end{array} \begin{array}{c} y \\ \begin{bmatrix} 2.61 \\ 2.31 \\ \vdots \\ 3.16 \end{bmatrix} \end{array} = \begin{array}{c} \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \\ \text{herd}_1 \end{array} \begin{array}{c} \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \\ \text{herd}_2 \end{array} \cdot \begin{array}{c} \beta \\ \begin{bmatrix} \text{herd}_1 \\ \text{herd}_2 \end{bmatrix} \end{array} + \begin{array}{c} Z \\ \begin{bmatrix} \\ \\ \\ \\ \\ \\ \\ \\ \\ \end{bmatrix} \end{array} \begin{array}{c} u \\ \begin{bmatrix} \\ \\ \\ \\ \\ \\ \\ \\ \\ \end{bmatrix} \end{array} + \begin{array}{c} e \\ \begin{bmatrix} \\ \\ \\ \\ \\ \\ \\ \\ \\ \end{bmatrix} \end{array}
 \end{array}$$

OHP Picture 6



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

• Expected values

▷ vector u of breeding values, defined as deviations $\Rightarrow E(u) = 0 \Rightarrow E\begin{pmatrix} u_1 \\ \vdots \\ u_n \end{pmatrix} = \begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix}$

▷ vector e of residuals defined as deviations $\Rightarrow E(e) = 0$

$$\begin{aligned} \Rightarrow E(y) &= E(X\beta + Zu + e) \\ &= E(X\beta) + E(Zu) + E(e) \\ &= X\beta + Z \cdot \underbrace{E(u)}_0 \quad \underbrace{0} \\ &= X\beta \end{aligned}$$

• Abbreviation:

$$E \begin{bmatrix} y \\ u \\ e \end{bmatrix} = \begin{bmatrix} X\beta \\ 0 \\ 0 \end{bmatrix}$$

• Variance: $\text{var}(u) = G$; $\text{var}(e) = R$; $\text{var}(y) = V$
 when G and R are known variance-covariance matrices.

$$\text{cov}(u, e) = 0$$

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

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

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

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

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

$\text{cov}(e_1, e_2) = \text{cov}(e_1, e_3) = \dots = 0$

$\Rightarrow R = \begin{bmatrix} \sigma_e^2 & 0 & 0 & \dots & 0 \\ 0 & \sigma_e^2 & & & \\ \vdots & & \ddots & & \\ 0 & & & \sigma_e^2 & \\ \vdots & & & & \ddots \end{bmatrix} = I \cdot \sigma_e^2$

OHP Picture 11

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$$\begin{aligned}
 \text{cov}(y, u) &= \text{cov}(X\beta + Zu + e, u^T) \\
 &= \underbrace{\text{cov}(X\beta, u^T)}_{\text{fix} = 0} + \text{cov}(Zu, u^T) + \underbrace{\text{cov}(e, u^T)}_{=0} \\
 &= \text{cov}(Zu, u^T) = Z \underbrace{\text{cov}(u, u^T)}_{\text{var}(u)} = ZG \\
 \text{cov}(y, e^T) &= \text{cov}(X\beta + Zu + e, e^T) \\
 &= \text{cov}(X\beta, e^T) + \text{cov}(Zu, e^T) + \text{cov}(e, e^T) \\
 &= 0 + Z \underbrace{\text{cov}(u, e^T)}_{=0} + \text{var}(e) \\
 &= R \\
 \text{var} \begin{bmatrix} y \\ u \\ e \end{bmatrix} &= \begin{bmatrix} V & ZG & R \\ GZ & G & 0 \\ R & 0 & R \end{bmatrix} ; \quad V = ZGZ^T + R
 \end{aligned}$$

