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Recap: 2023-10-27

□ Own performance record

Animal	y_i (Weight)
1	y_1
?	y_2
⋮	⋮
N	y_N

$$\mu = \frac{1}{N} \sum_{i=1}^N y_i$$

Regression Method

$$\hat{u}_i = h^2 (y_i - \mu)$$

$$h^2 = \frac{\sigma_u^2}{\sigma_p^2}, \quad \mu = E[y_i]$$

population mean

σ_u^2 : genetic (additive) variance; $\text{var}(u) = \sigma_u^2$
 σ_p^2 : phenotypic variance; $\text{var}(y_i) = \sigma_p^2$
 h^2 : heritability

→ how easy to select for a given trait
 traits with high h^2 are easier to select for.

□ Repeated Observations

$$\hat{u}_i = \frac{nh^2}{1+(n-1)t} (\bar{y}_i - \mu)$$

repeatability

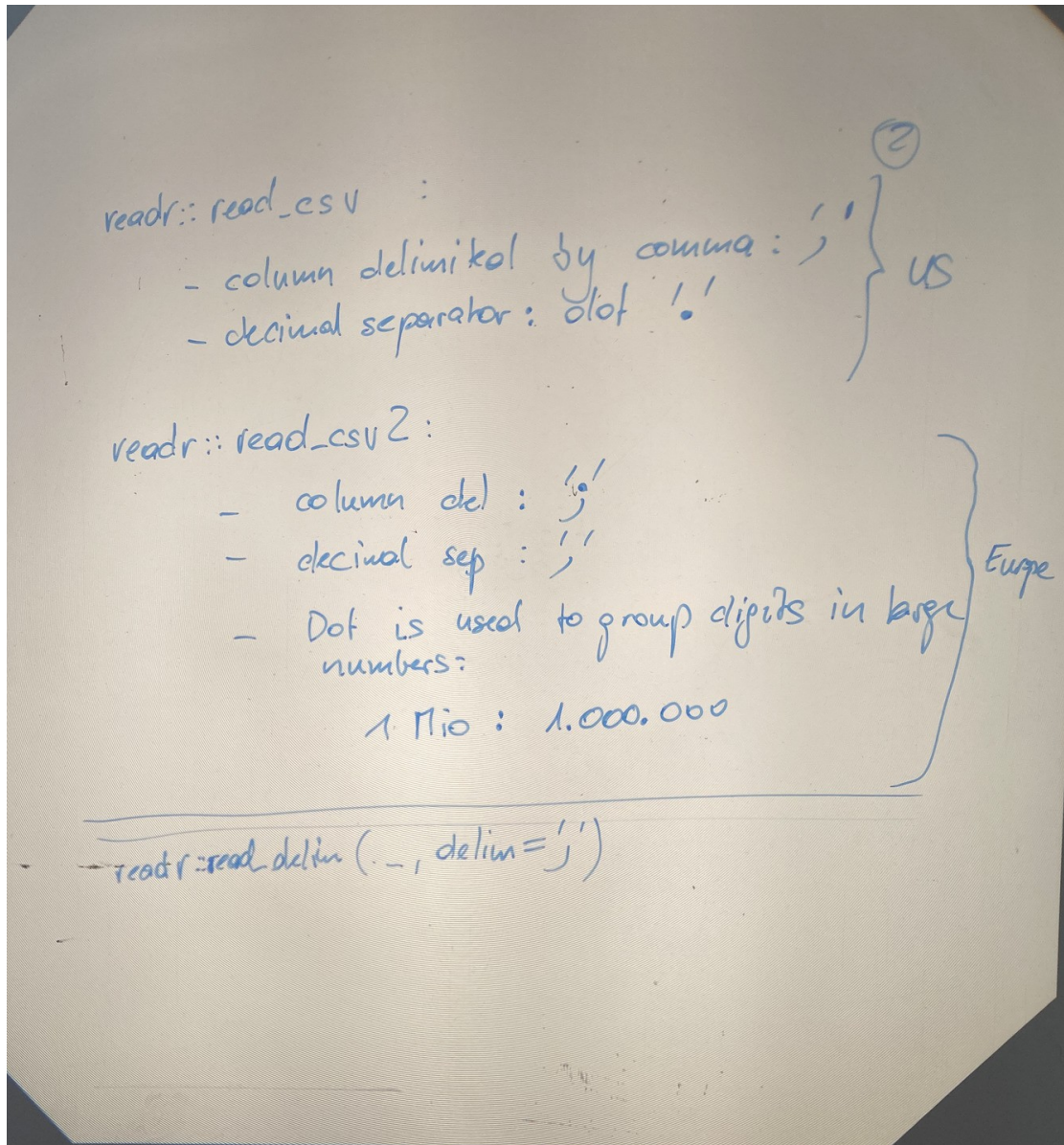
*average over repeated observations for animal i
 → each animal has n observations*

□ Progeny Records: For parent animal i with offspring records

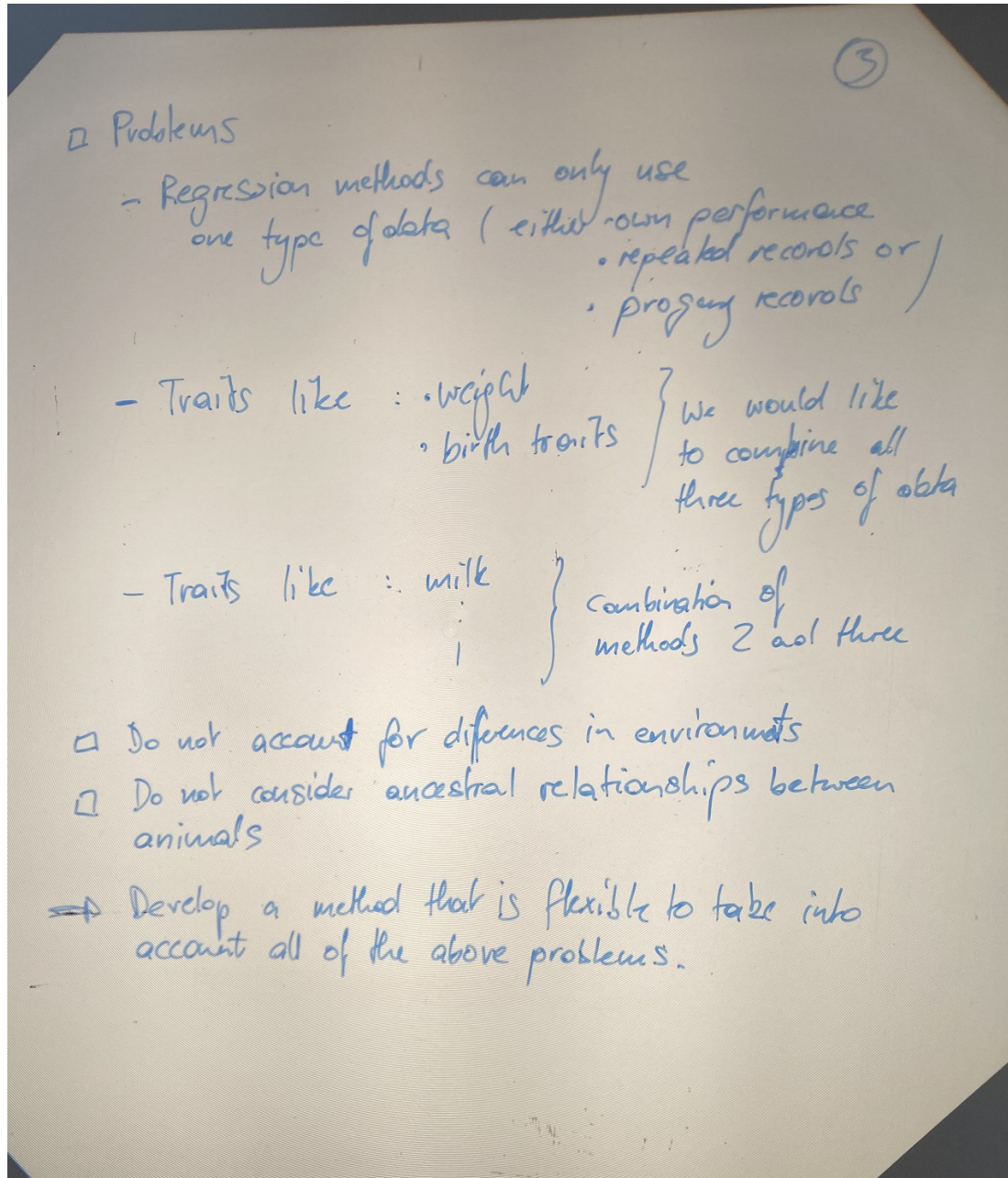
$$\hat{u}_i = \frac{2n}{n+k} (\bar{y}_i - \mu)$$

average of observations from progeny of animal i

OHP Picture 2



OHP Picture 3



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General Principle

Goal: Predicted breeding value for animal i

$$\hat{u}_i = \underbrace{(y_i)}_{\text{phenotypic record}} - \underbrace{\mu}_{\text{suitable correction for non-genetic factors that influence } y} \cdot \underbrace{b}_{\text{weighting factor}}$$

• Combine information from different sources can be done by aggregating them into index (I)

$$\hat{u}_i = I = b_1 \cdot y_1^* + b_2 \cdot y_2^* + \dots + b_k \cdot y_k^* = b^T y^*$$

with $b^T = [b_1 \ b_2 \ b_3 \ \dots \ b_k]$ } unknown

$y^{*T} = [y_1^* \ y_2^* \ y_3^* \ \dots \ y_k^*]$ } known

y_{je}^* is $(y_{je} - \mu)$ which is y_{je} corrected for non genetic factors

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Given that u_i is expressed by index I
with

$\hat{u}_i = I = b^T y^*$, we have to determine the vector b such that \hat{u}_i comes "as close as possible" to the true value of u_i .

□ "As close as possible" is quantified by $\text{var}(u_i - \hat{u}_i)$ where $(u_i - \hat{u}_i)$ is called prediction error and its variance is known as prediction error variance (PEV)

$\text{PEV} = \text{var}(u_i - \hat{u}_i) \rightarrow \text{minimal}$

$\Rightarrow \text{PEV} = \text{var}(u_i - \hat{u}_i) = \text{var}(u_i - I) = \text{var}(u_i - b^T y^*)$

$= \text{var}(u_i) + \text{var}(b^T y^*) - 2 \text{cov}(u_i, b^T y^*)$

$= \sigma_u^2 + b^T \text{var}(y^*) b - 2 b^T \text{cov}(u_i, y^*)$

$= \sigma_u^2 + b^T P b - 2 b^T G$

with $P = \text{var}(y^*)$ variance-covariance matrix of observations
 $G = \text{cov}(u_i, y^*)$

OHP Picture 6

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□ Finding the minimum of PEV is done by setting $\frac{\partial PEV}{\partial b} = 0$ and the vector b that satisfies this condition is the desired solution.

$$PEV = \sigma_u^2 + b^T P b - 2 b^T G$$

$$\frac{\partial PEV}{\partial b} = 0 + 2 P b - 2 G = 0$$

$$\Rightarrow 2 P b = 2 G$$

$$b = P^{-1} G$$

Problem with combining different sources of information to get \hat{u}_i is solved by index method.

Index Method
 \Downarrow
 Aggregate genotype (H)
 (Gesamtzucht wert)

$$H = v \cdot u$$

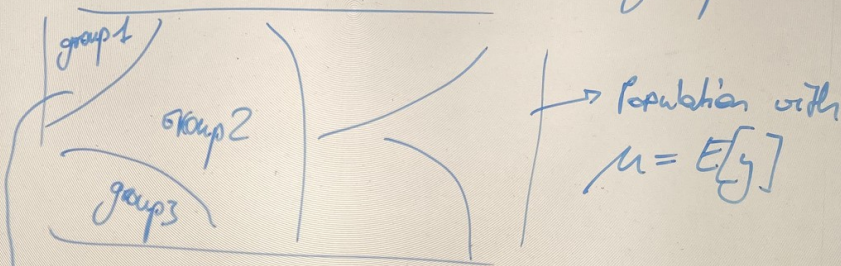
Find $I = b^T u^*$ such that $\text{var}(H - I) \rightarrow \text{minimized}$

$$\rightarrow \hat{u}_i = I = b^T y^* = P^{-1} G y^*$$

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Problem II: Correction of observations

- How to get from $y_i \rightarrow y_i^*$?
- So far correction was done by population mean μ . For observations from different time points and different environments the correction by a single value is not appropriate.
- First solution: Divide population into comparison groups



$\mu_1 = E[y_{in\ group 1}] \Rightarrow \hat{u}_{11} = b(y_{11} - \mu_1)$

Cattle "Leistungspunkte": groups were formed according to herds.

Pigs: Index on testing station. (1990 ies) } Bias

Solution to

- combining information from different sources
- correcting for non-genetic factors

is the BLUP method.

□ Linear Mixed Effect Model (LME)

$$y_{ijk} = \underbrace{\mu + \beta_i}_{\text{fixed effects}} + \underbrace{u_i}_{\text{random breeding value}} + \underbrace{e_{ijk}}_{\text{random residual}}$$

observation

fixed effects
used as corrections
for non-genetic factors

random residual

random breeding value

as opposed to linear fixed effect models

$$y_{ij} = \underbrace{\mu + \beta_j}_{\text{fixed}} + \underbrace{e_{ij}}_{\text{random residual}}$$

$$\text{LME: } y_{ijk} = \mu + \beta_j + u_i + e_{ijk} \quad (9)$$

- With BLUP:
- estimate fixed effect (BLUE) and random effect at the same time from same data
 - \hat{u}_i as conditional expectation of u given y :

$$\hat{u}_i = E(u_i | y)$$

Properties of \hat{u}_i :

Best Linear predictor: $\text{var}(u_i - \hat{u}_i) \rightarrow \text{minimal}$

Linear in observations

Unbiased: $E(\hat{u}) = E(u)$

P: Prediction (used for estimates of random effects.)

Schätzung

For fixed effects, the method is called BLUE \rightarrow estimate

□ Use of LME lets us account for ancestral relationships between animals. (10)

Because with fixed effect model:

$$y_{ijk} = \mu + \beta_j + u_i + e_{ijk}$$

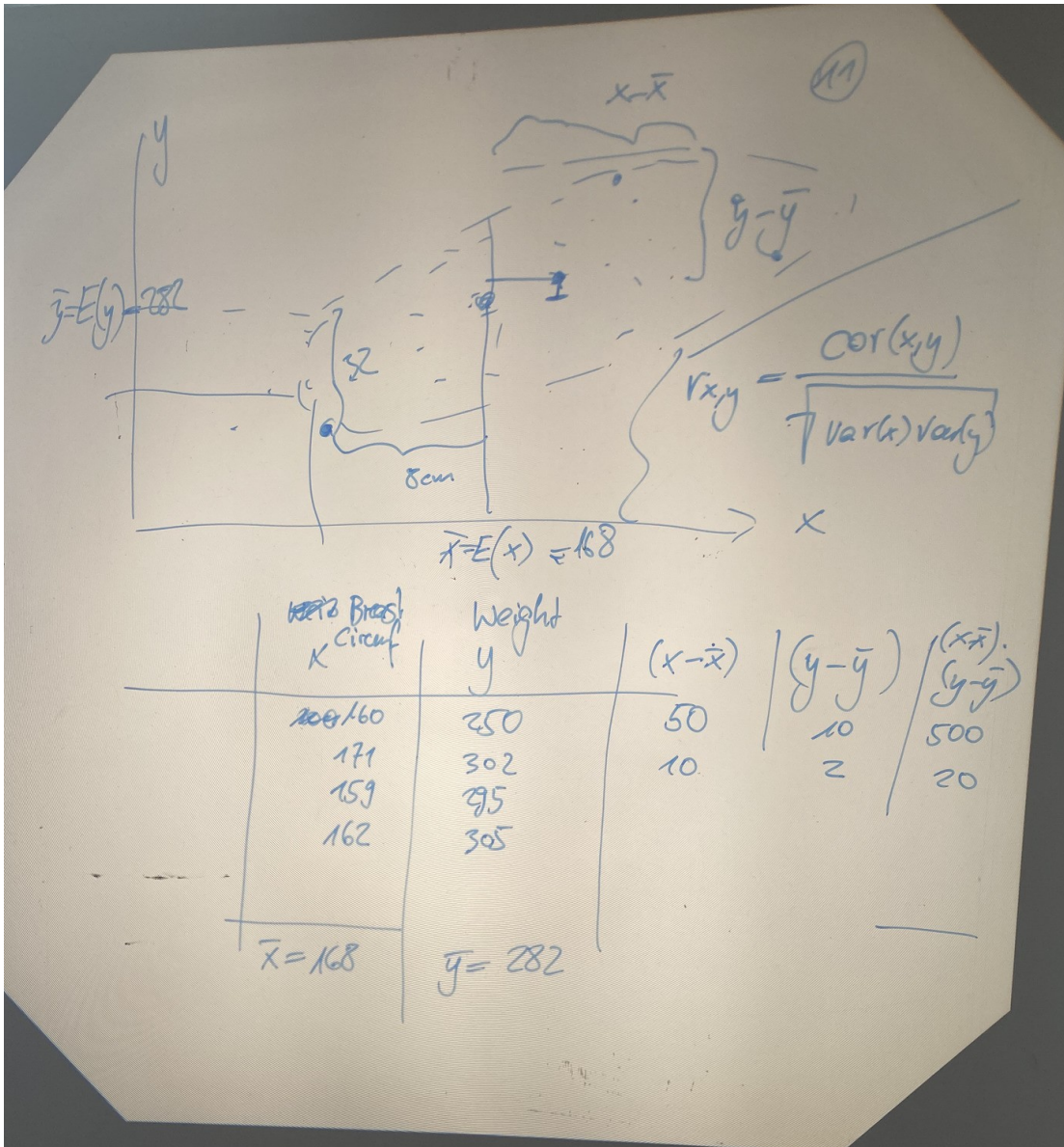
breeding value as fixed effect, there is no possibility to account for ancestral relationship. Ancestral relationship means that for animals i and j which are related, the $\text{cov}(u_i, u_j) \neq 0$

Example: Animals 26 and 27 are full sibs
 $\Rightarrow \text{cov}(u_{26}, u_{27}) \neq 0$

$$\text{cov}(x, y) = \sum_x \sum_y (x - E(x))(y - E(y)) f(x) f(y) \text{ discrete random variables}$$

$$\text{cov}(x, y) = \iint (x - E(x))(y - E(y)) \cdot f(x) \cdot f(y)$$

OHP Picture 11



OHP Picture 12

(12)

□ $\text{cov}(u_{26}, u_{27})$

$$u_{26} = \frac{1}{2} u_3 + \frac{1}{2} u_{11} + w_{26}$$

$$u_{27} = \frac{1}{2} u_3 + \frac{1}{2} u_{11} + w_{27}$$

$$\text{cov}(u_{26}, u_{27}) = \text{cov}\left(\frac{1}{2} u_3 + \frac{1}{2} u_{11} + w_{26}, \frac{1}{2} u_3 + \frac{1}{2} u_{11} + w_{27}\right)$$

$$= \text{cov}\left(\frac{1}{2} u_3, \frac{1}{2} u_3\right) + \text{cov}\left(\frac{1}{2} u_3, \frac{1}{2} u_{11}\right) + \text{cov}\left(\frac{1}{2} u_3, w_{27}\right)$$

$$+ \text{cov}\left(\frac{1}{2} u_{11}, \frac{1}{2} u_3\right) + \text{cov}\left(\frac{1}{2} u_{11}, \frac{1}{2} u_{11}\right) + \text{cov}\left(\frac{1}{2} u_{11}, w_{27}\right)$$

$$+ \text{cov}(w_{26}, \dots)$$

$$= \text{cov}\left(\frac{1}{2} u_3, \frac{1}{2} u_3\right) + \text{cov}\left(\frac{1}{2} u_{11}, \frac{1}{2} u_{11}\right)$$

$$= \frac{1}{4} \text{cov}(u_3, u_3) + \frac{1}{4} \text{cov}(u_{11}, u_{11})$$

$$= \frac{1}{4} \sigma_u^2 + \frac{1}{4} \sigma_u^2 = \frac{1}{2} \sigma_u^2$$

□ LME in Matrix-Vector Notation (13)

Instead of writing the model for each observation:

$$y_{ijk} = \mu + \beta_j + u_i + e_{ijk}$$

we group all observations into vector y

$$y = \begin{bmatrix} y_{12} \\ y_{13} \\ \vdots \\ y_{27} \end{bmatrix} = \begin{bmatrix} 2.61 \\ 2.51 \\ \vdots \\ 3.16 \end{bmatrix}$$

Group all fixed effects into vector β

$$\beta = \begin{bmatrix} \mu \\ \text{herd} \end{bmatrix}$$

Group all breeding values into vector u

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

; vector of random residuals

$$e = \begin{bmatrix} e_{12} \\ e_{13} \\ \vdots \\ e_{27} \end{bmatrix}$$

Matrices X and Z are design matrices.

OHP Picture 14

