







Bias of dairy sheep evaluations using BLUP and SSGBLUP with metafounders and unknown parent groups.



- Evaluations are unbiased on average but with random variations across years: don't trust a single check of your evaluations
- With Unknown Parent Groups:
 - BLUP unbiased
 - Some SSGBLUP methods are biased

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(your speaker)





Why should I look at dairy sheep?

- Dairy sheep milk is a drop in an ocean of cow milk
- But we, dairy sheep geneticists, can do things that dairy cattle geneticists can not ©
 - Simpler selection schemes
 - No import/export of animals, no Interbull
 - Human-size data sets (in the few millions of records)
 - Can try things quickly
- Some of our results might be of interest for the whole community of dairy geneticists









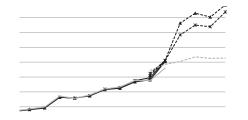
Manech Tete Rousse breeding program

- Progeny testing , Artificial Insemination (AI)
- Steady genetic progress $\sim 0.2\sigma_g/year$
- 35 years of pedigree and records
 - 60,000 records / year
 - 15,000 females / year
 - 200 elite (AI) males / year
- Genomic selection started in 2018
- We don't want overestimation of young animals' GEBVs (bias)
- All rams have very complete pedigrees, but
- 20% ewes have missing sires in pedigree due to Natural Mating
 - These unknown Natural Mating sires are actually offspring of AI rams
 - Use of Unknown Parent Groups in BLUP to model genetic trend
 - unclear how to include missing pedigrees in SSGBLUP



Objectives

- Do we have bias in genetic (genomic) evaluations?
- How to best model missing pedigrees?



- The time-honored method to check bias is time-point truncation (Mantysaari et al., 2010, Olson et al., 2011)
- We want to check bias across multiple truncation time points
 - we don't want to use DYDs as we have small progeny groups: method LR



- Should we use...
 - 13 Unknown Parent Groups (fixed)
- or
 - 13 Metafounders (random with relationships)





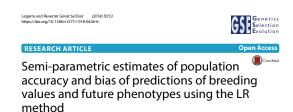


Data & records

- 2 M records of milk yield in the complete data set
- 500,000 animals in pedigree
- 3,000 genotyped AI males (all progeny-tested males since 2000)
 with the 50K Illumina ovine chip
- (SSG)BLUP evaluations for milk yield
 - animal model with repeated records and correction for heterogeneity of variances (Meuwissen et al., 1996)
- Software heterf90, blup90iod2 (Misztal et al.)

Method LR in a nutshell

- Define a "focal set" of "comparable" animals of interest
 - e.g. contemporary young males born in 2010 or young females born in 2008
- Define evaluations "partial data" (early) and "whole data" (late). From "partial" to "whole":
- Averages of EBVs should not change (i.e. some young animals will go up and some down)
- <u>Dispersion</u> of EBVs should increase by the right amount (more information -> more dispersion)
 - Slope (EBVs_whole ~ EBVs_partial) should be 1
- Corr(EBVs_whole,EBVs_partial) is a function of respective accuracies



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Behavior of the Linear Regression method to estimate bias and accuracies with correct and incorrect genetic evaluation models

Application of method LR

Evaluations with data until 2005, until 2006 and so on until 2017.

We compare *within-model*

- (G)EBVs at birth of a set (~200) of future AI males
- (G)EBVs of the same males in later evaluations (after having progeny).

For example for males born in 2005, 11 pairs of evaluations were compared

- 2005 vs 2007
- 2005 vs 2008
- ...
- 2005 vs 2017

The same for males born in 2006, 2007 ... 2015

- 2006 vs 2008
- ..
- 2015 vs 2017

Total of 66 comparisons that were then "averaged" using a pseudo-model

Bias

 $\widehat{\Delta}_p = \overline{\widehat{u}}_{partial} - \overline{\widehat{u}}_{whole}$ Expected value of 0 in absence of bias.

Slope of the regression EBV_w on EBV_p

$$\hat{b}_{p} = \frac{cov(\hat{u}_{partial}, \hat{u}_{whole})}{var(\hat{u}_{partial})}$$

With a value of 1 in unbiased procedure.

Models for UPG/metafounders

BLUP_MF (metafounders)

$$A^{[\Gamma]-1} = \begin{pmatrix} A_{anim,anim}^{[\Gamma]} & A_{anim,mf}^{[\Gamma]} \\ A_{mf,anim}^{[\Gamma]} & \Gamma \end{pmatrix}^{-1}$$

Legarra et al. 2015

2. BLUP_UPG

$$A^* = \begin{pmatrix} A_{anim,anim}^{-1} & -A_{anim,anim}^{-1}Q \\ -Q'A_{anim,anim}^{-1} & Q'A_{anim,anim}^{-1}Q \end{pmatrix}$$

Thompson 1979 Quaas 1988

ssGBLUP_EUPG ("exact"_UPG)

$$H^{(\text{exact})-1} = A^* + \begin{pmatrix} 0 & 0 & 0 \\ 0 & G^{-1} - A_{22}^{-1} & -(G^{-1} - A_{22}^{-1})Q_2 \\ 0 & -Q_2(G^{-1} - A_{22}^{-1}) & Q_2(G^{-1} - A_{22}^{-1})Q_2 \end{pmatrix}$$

Misztal et al. 2013 Matilainen et al 2018

4. ssGBLUP_MF (metafounders)

$$H^{[\Gamma]-1} = A^{[\Gamma]-1} + \begin{pmatrix} 0 & 0 & 0 \\ 0 & G_{05}^{-1} - A_{22}^{[\Gamma]-1} & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

Legarra et al. 2015

5. ssGBLUP_UPG

$$H^* = A^* + \begin{pmatrix} 0 & 0 & 0 \\ 0 & G^{-1} - A_{22}^{-1} & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

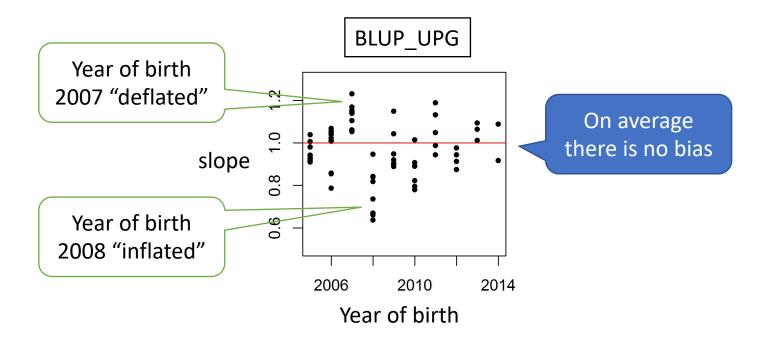
Default blupf90

^{*} Γ was computed by GLS from all genotypes

Results 1: more than one check

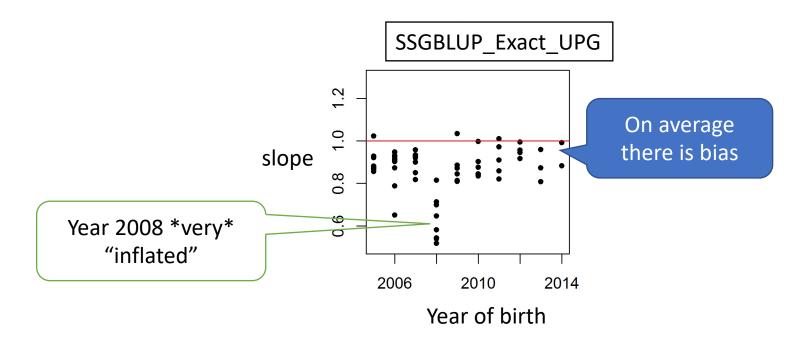
Use of method LR allows many, easy, systematic checks of bias

- High variability due to year of birth ("partial") and year of "whole" evaluation
- We should use several comparisons to decide the rightness of the model



Results 2: some methods are better

Some methods (SSGBLUP_Exact_UPG) look wrong even compared to themselves (they are incoherent from one year to the next ones)



Results 3: all methods together

Accuracies

Model	$ar{\hat{u}}_p - ar{\hat{u}}_w$ Bias	$\hat{u}_w \sim \hat{u}_p$ Slope	$\left(\frac{\widehat{acc_p}}{acc_w}\right)$	$\widehat{acc_p^2}$	$\left(\frac{\widehat{acc_p^2}}{acc_w^2}\right)$
BLUP-MF	0.21	0.99	0.56	0.22	0.33
BLUP-UPG	0.36	0.97	0.55	0.24	0.31
SSGBLUP-EUPG	0.39	0.87	0.62	NA	0.44
SSGBLUP-MF	0.20	0.98	0.67	0.33	0.46
SSGBLUP-UPG	0.27	0.95	0.65	NA	0.44

- There is some small bias in the genetic trend of $\sim 0.25\sigma_g$
- BLUPs are generally unbiased
- SSGBLUP more accurate than BLUP
- SSGBLUP is better with metafounders (less bias, more accurate)

^{*} All estimators have s.e. < 0.02

Conclusions

- Run more than one test !!!
- Method LR allows quick and automatic checks

- *In our data set*, no bias if we do things correctly
 - BLUP_UPG and BLUP_MF were unbiased
 - SSGBLUP_MF was unbiased
 - Good compatibility of marker and pedigree information while avoiding double counting

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Conclusions

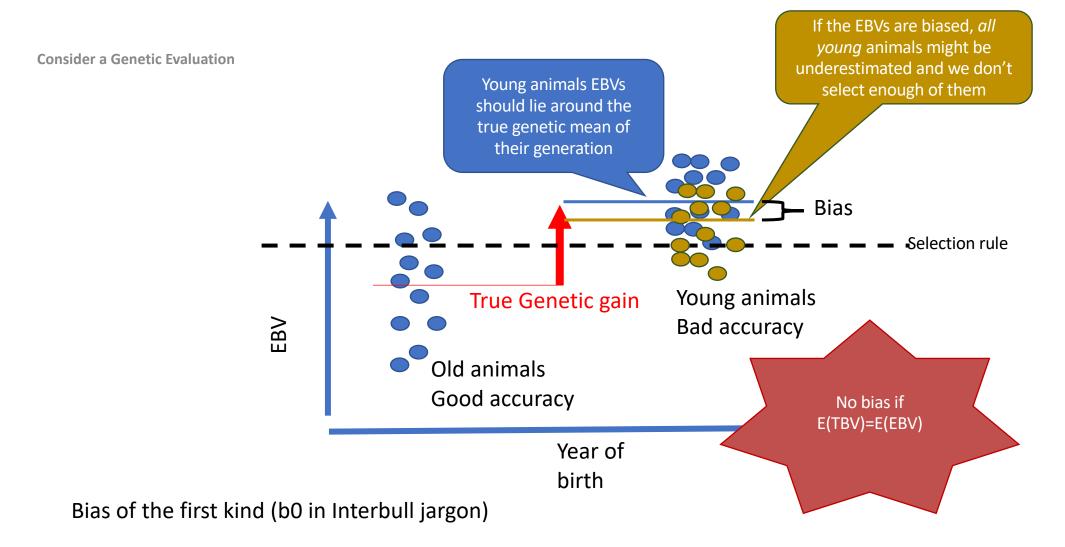
Thank you for your attention

- Run more than one test !!!
- Method LR allows quick and automatic checks

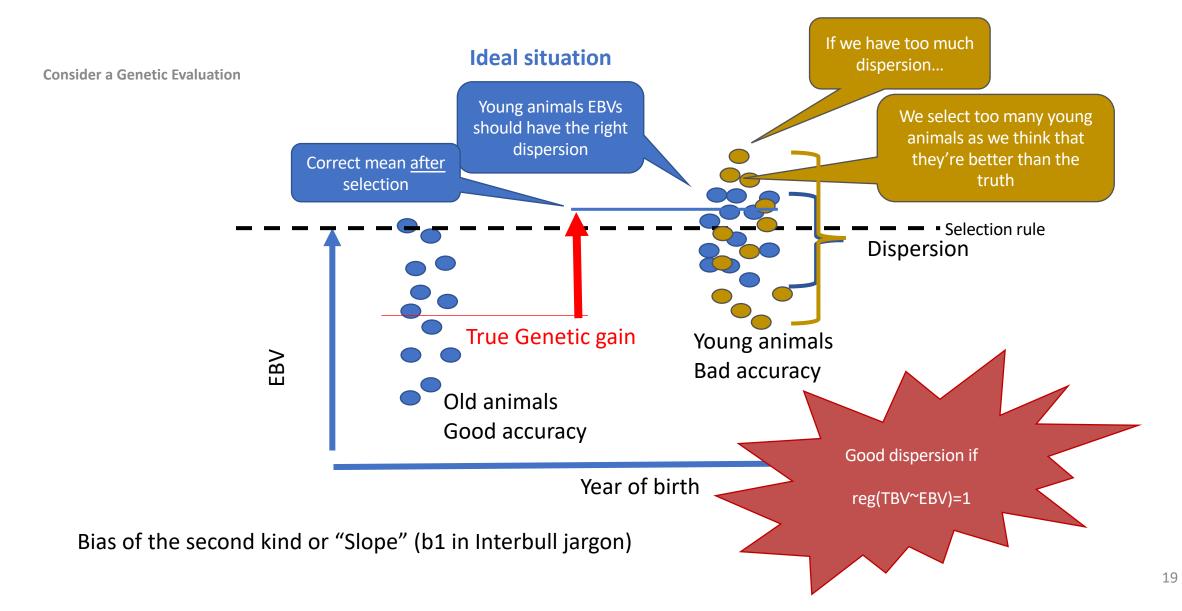
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Leftovers

Bias due to genetic trend



Bias due to dispersion (slope)



Checks for bias

- Traditional method
 - Compare DYDs after daughters with (G)EBVs before daughters
 - Not always possible:
 - Small data sets: RFI, methane emissions, small populations (sheep & goat but also small breeds)
 - Traits such as maternal ability in beef, carcass yield in pigs
 - Hard to make automatic
- Hence method LR:
 - comparison of old EBVs (\hat{u}_p) with new EBVs (\hat{u}_w) for a group of animals of interest





RESEARCH ARTICLE

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Semi-parametric estimates of population accuracy and bias of predictions of breeding values and future phenotypes using the LR method



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Behavior of the Linear Regression method to estimate bias and accuracies with correct and incorrect genetic evaluation models

Method LR in a nutshell

- We can use these ideas in reverse:
 - If the mean(EBV) does change there is a problem
 - If the dispersion does not hold to the theory there is a problem
 - either Henderson's theory was wrong (maybe) or our genetic evaluations are wrong (likely)
 - Also, average change indicates reliabilities