



Sequential Evaluation of Longitudinal Conformation Data in Dairy Cows

(or How to Deal with Massive Multi-Trait Longitudinal Data)

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www.robustmilk.eu





Introduction



- Why still trying to improve "traditional genetic evaluations"?
 - We have genomic evaluation !!!
- However genomic evaluations also need accurate models to describe phenotypic records!
 - Two step approach:
 - Genetic evaluations \Rightarrow first step \Rightarrow prediction equations
 - One step approach as basic model
 - Genetic evaluations ⇒ genomic evaluations (GBLUP)



Introduction



- Which issues still need work in genetic evaluation?
 - First *r* complexity of models
 - But also ↗ computing resources
- However still potentially some bottlenecks
 - In this study massive multiple-trait (MT) random regression models (RRM) for longitudinal traits:
 - Type data (as announced)
 - Extended to milk composition data (7FP RobustMilk)





- Complex models
 - Modified to simpler "equivalent" ones
- A type of generic longitudinal model

 $\mathbf{y} = \mathbf{H}\mathbf{h} + f[\mathbf{\Phi},\mathbf{t}] + \mathbf{e}$

- where:
 - h = time-independent effects
 - H = incidence matrix of h
 - Φ = "time-dependent" effects
 - t = time
 - $f[\Phi,t]$ = function linking y and Φ depending on t





Please note:

- If $f[\Phi,t]$ time-dependent, Φ is not !

 $\Phi = Xb + Zu + \epsilon$

- Where:
 - b fixed effects, u random effects, ϵ residual effects
 - X and Z being incidence matrices
- Final model needs to be rewritten as:

 $\mathbf{y} = \mathbf{H}\mathbf{h} + f[\mathbf{X}\mathbf{b} + \mathbf{Z}\mathbf{u} + \boldsymbol{\varepsilon}, \mathbf{t}] + \mathbf{e}$





- Models for longitudinal data ⇒ complex
 - Time-dependent covariance structures
 - Often multi-trait (MT) models
- However very useful
 - Many traits, highly correlated, some missing
 - Two examples: type traits, milk composition data
- Idea: rewriting model in two stages
 - First stage estimating Φ from y
 - Then modeling Φ which has become timeindependent





- First stage: $y_{ij} = H_{ij}h_{ij} + f[\Phi_{ij}, t_{ij}] + e_{ij}$
 - For every animal i having records along a given longitudinal time gradient j, this allows the estimation of a specific Φ_{ii}
 - Φ often called meta-data (meta-traits)
 - These models could remain single-trait (ST)
 - E.g., could be typically any type of regression coefficients per cow x lactation





• Second stage : $\Phi = Xb + Zu + \varepsilon$

- Where estimates from first stage Φ and/or a function of these are modeled
- These models typically multi-trait (MT) using the meta-data (meta-traits) as input
- MT necessary to recover links across meta-traits







Sounds exotic ?









- Sounds exotic ?
- However very simple US example
 - Stage 1: Best Prediction (BP)
 - Stage 2: Current USDA Animal Model (AM)
- Interesting example because shows different hidden issues
 - Will be used to give additional theoretical background



Hidden Issues



- Complete equivalence
 - Need complete BLUP and BLUE properties
 - Similarly to
 Modified Contemporary Comparison <> Mixed Models
 - \Rightarrow Iterative solving required
 - Updating estimation of meta-traits in Stage 1 using results from Stage 2
 - For a two step RRM shown by Gengler et al. (2000*)
 - Can be considered as difference between BP + AM and full test-day model
 - even if persistency or lactation differences included in BP

^{*} Gengler N., Tijani A., and G R Wiggans. 2000. Use of sequential estimation of regressions and effects on regressions to solve large multitrait test-day models. J Dairy Sci 83: 369



Hidden Issues



Distribution of meta-traits

- Meta-traits: estimates
- Two consequences
 - Loss of variance as meta-trait being an estimate
 - Uneven weights as differences in information used to estimate (reliability of estimates different)
- ⇒ Expansion of meta-traits required to recover variance
 - E.g., expansion of $BP \Rightarrow AM$
- ⇒ Weighting of meta-traits required to adjust for uneven weights
 - E.g., lactation weights \Rightarrow AM



Example: Type



- Type data from the routine performance recording in Walloon part of Belgium (01/2010)
 - 102,875 records from first parity
 - 30,378 records from second or later parities
 - 117,013 classified Holstein cows
 - Repeated records 16,240
 - With repetitions within and across lactations
- Request from the field
 - Better use of available longitudinal data along age at classification
- Use of this strategy to do (co)variance estimation



Type Model



Modification of current model

- Introduction of additional maturity effect
 - If lact = 1 \Rightarrow regression variable = 0 (LACT1)
 - If lact > 1 ⇒ regression variable = 1 (LACT2+)

Random regression model

- 33 traits \Rightarrow 66 random regressions (RR)
- 2145 parameters per (co)variance matrix
 - Genetic and Non-genetic (stage 2)
 - Residual (stage 1) \Rightarrow simplified to single traits (ST)
- Current results
 - Without expansion and weightings
 - Using Multiple Diagonalization (CT) EM-REML



Type Results



- h² dropped
 - On average 0.02, largest drop 0.06
 - h² drop showed lost of overall variance ⇒ need expansion
- Relative differences in phenotypic (genetic) correlations for LACT1 and LACT2+
 - Based on Frobenius Norm ratios:
 - LACT1: 0.34 (0.42), LACT2+: 0.33 (0.42)
- Very high genetic correlations LACT1, LACT2+
 - Always > 0.99

gembloux ^{•••}Milk Composition Data



Better example

agro

- Large number of traits
 - Potentially > 30
- Highly correlated
- Only recent data
 - Interest to include Indicator traits (e.g., fat, protein), as recorded since +30 year
- Here results from an ongoing feasibility study by Catherine Bastin



Example: Milk Composition Université

- Data
 - 162,021 test-day records
 - 44,885 cows
 - 1029 herds
 - Traits (all known to reduce need to weight):
 - Milk, fat and protein yields, saturated (SAT) and monounsaturated (MONO) fatty acids content in milk

Model

- Same basic model as presented by Soyeurt et al. (2010)
- Stage 1
 - Meta-trait was defined as phenotypic animal effects
 - Regression coefficients expanded by dividing them by REL
- Stage 2
 - CT-EM-REML, no weighting of meta-traits

305 d Results

Université

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(average h² on diagonal, genetic correlations above, phenotypic below)

| | Milk (kg) | Fat (kg) | Protein (kg) | SAT (%) | MONO (%) |
|--------------|----------------------------|----------|--------------|---------|----------|
| | MT-RRM estimates | | | | |
| Milk (kg) | 0.24 | 0.57 | 0.83 | -0.42 | -0.41 |
| Fat (kg) | 0.56 | 0.22 | 0.70 | 0.50 | 0.38 |
| Protein (kg) | 0.69 | 0.59 | 0.18 | -0.11 | -0.11 |
| SAT (%) | -0.24 | 0.24 | -0.08 | 0.44 | 0.80 |
| MONO (%) | -0.19 | 0.13 | -0.09 | 0.42 | 0.23 |
| | Two stage method estimates | | | | |
| Milk (kg) | 0.19 | 0.60 | 0.86 | -0.51 | -0.47 |
| Fat (kg) | 0.59 | 0.14 | 0.74 | 0.36 | 0.24 |
| Protein (kg) | 0.72 | 0.61 | 0.13 | -0.22 | -0.16 |
| SAT (%) | -0.23 | 0.21 | -0.10 | 0.33 | 0.71 |
| MONO (%) | -0.47 | 0.09 | -0.11 | 0.32 | 0.15 |



Conclusions



- Type traits
 - Based on the current results, limited interest
- Milk composition traits
 - Close estimates for correlations across traits
 - Still a certain lost of relative genetic variability
 - For the given situation
 - Hugh number of traits, MT
 - Random regression models RRM
 - Best solution
- Some methodological improvement under development



Conclusions



Proposed method showed large potential

- In these studies for VC estimation
- Also very interesting for improved solving of mixed model equations (better convergence)
- Easy to go further
 - More traits
 - Rank reduction
 - Sequential and iterative solving (updating), could be asynchronous (not same moment)
 - Herd-level for Stage 1
 - Population level for Stage 2





Questions?