

Accounting for trait-specific genomic and residual polygenic covariances in multivariate single-step genomic evaluation

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Introduction

- GBLUP: SNP markers available rarely explain all genetic variation
- Fit **R**esidual **P**oly**G**enic (RPG) effects
 - explicitly: augment model by RPG
 - double no. of equations for genetic effects (BV model)
 - slower convergence for iterative solution schemes
 - implicitly: weighted average of GRM & NRM for genotyped animals

$$\lambda \mathbf{G} + (1 - \lambda) \mathbf{A}_{22} \quad \text{with} \quad 0 \leq \lambda \leq 1$$

- Univariate: $\lambda = \text{Var}_{SNP} / (\text{Var}_{SNP} + \text{Var}_{RPG})$
- Multivariate: Single λ implies $\text{Cov}_{SNP} \propto \text{Cov}_{RPG}$
- Questions
 - How best to account for different λ for traits in MV analysis?
 - How much might we gain doing so?

Objectives

1. Show computing strategy for MV ssGBLUP with trait specific λ_i
 - avoid fitting separate RPG
 - exploit 'canonical transformation'
2. Use simulation to evaluate effects on accuracy & bias of EBVs

Model

- Breeding value model for t traits:

$$\mathbf{y} = \underbrace{\mathbf{X}\mathbf{b}}_{\text{Fixed}} + \underbrace{\mathbf{Z}\mathbf{u}}_{\text{Genetic}} + \mathbf{e} \quad \text{with} \quad \mathbf{u} = \underbrace{\mathbf{g}}_{\text{SNP}} + \underbrace{\mathbf{a}}_{\text{RPG}}$$

$$\Sigma_U = \Sigma_G + \Sigma_A$$

- Order \mathbf{u} : traits within animals; partition $\mathbf{u} = \begin{bmatrix} \mathbf{u}_1 \\ \mathbf{u}_2 \end{bmatrix}$
Non-genot.
Genotyped; n_2
- Coefficient matrix in MME for ssGBLUP

$$\underbrace{\begin{bmatrix} \mathbf{X}'\mathbf{R}^{-1}\mathbf{X} & \mathbf{X}'\mathbf{R}^{-1}\mathbf{Z} \\ \mathbf{Z}'\mathbf{R}^{-1}\mathbf{X} & \mathbf{Z}'\mathbf{R}^{-1}\mathbf{Z} \end{bmatrix}}_{\text{'Data' part}} + \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \underbrace{\mathbf{A}^{-1} \otimes \Sigma_U^{-1}}_{\text{NRM part}} + \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \underbrace{\Delta - \mathbf{A}_{22}^{-1} \otimes \Sigma_U^{-1}}_{\text{'add-on' from } \mathbf{H}^{-1}} \end{bmatrix} \end{bmatrix}$$

Calculating Δ

- For $\Sigma_G \propto \Sigma_A$
$$\Delta = \left(\lambda \mathbf{G} + (1 - \lambda) \mathbf{A}_{22} \right)^{-1} \otimes \Sigma_U^{-1} \quad \longrightarrow \text{need inverse of size } n_2 \times n_2$$
- Otherwise: Δ not separable \longrightarrow need inverse of size $tn_2 \times tn_2$
$$\Delta = \left(\mathbf{G} \otimes \Sigma_G + \mathbf{A}_{22} \otimes \Sigma_A \right)^{-1}$$

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$$\Delta = \left(\mathbf{G} \otimes \Sigma_G + \mathbf{A}_{22} \otimes \Sigma_A \right)^{-1}$$

- Use 'canonical transformation': $\mathbf{Q}\Sigma_G\mathbf{Q}' = \mathbf{I}$ and $\mathbf{Q}\Sigma_A\mathbf{Q}' = \mathbf{D}$
Simultaneously diagonalise both Σ

$$\Delta = \left[\mathbf{I} \otimes \mathbf{Q}' \right] \left(\mathbf{G} \otimes \mathbf{I} + \mathbf{A}_{22} \otimes \mathbf{D} \right)^{-1} \left[\mathbf{I} \otimes \mathbf{Q} \right]$$

Reorder \mathbf{u}_2 : Animals within traits \rightarrow need t inverses of size $n_2 \times n_2$

$$\Delta = \left[\mathbf{Q}' \otimes \mathbf{I} \right] \underbrace{\left(\mathbf{I} \otimes \mathbf{G} + \mathbf{D} \otimes \mathbf{A}_{22} \right)^{-1}}_{\text{Diagonal blocks for traits}} \left[\mathbf{Q} \otimes \mathbf{I} \right]$$

Efficient calculation of inverse matrices

- Use **Woodbury matrix identity** to compute t inverses

Mäntysaari et al. (2017)

For $\mathbf{G} = \mathbf{M}\mathbf{M}'/s$ with \mathbf{M} : matrix of centred marker counts

$$\left(\mathbf{G} + d_k \mathbf{A}_{22}\right)^{-1} = \frac{1}{d_k} \left[\mathbf{A}_{22}^{-1} - \mathbf{A}_{22}^{-1} \mathbf{M} (s d_k \mathbf{I} + \mathbf{M}' \mathbf{A}_{22}^{-1} \mathbf{M})^{-1} \mathbf{M}' \mathbf{A}_{22}^{-1} \right]$$

For $\mathbf{M}' \mathbf{A}_{22}^{-1} \mathbf{M} = \mathbf{E}\mathbf{T}\mathbf{E}'$ ← Eigen-decomposition

$$\left(\mathbf{G} + d_k \mathbf{A}_{22}\right)^{-1} = \frac{1}{d_k} \left[\mathbf{A}_{22}^{-1} - \mathbf{A}_{22}^{-1} \mathbf{M} \underbrace{\left(s d_k \mathbf{I} + \mathbf{T} \right)^{-1}}_{\text{Diagonal}} \mathbf{E}' \mathbf{M}' \mathbf{A}_{22}^{-1} \right]$$

⇒ Need **single eigen-decomp.** of matrix of size $m \times m$ (m : no. of markers)

Mäntysaari, E. A., Evans, R. D., and Strandén, I. (2017). Efficient single-step genomic evaluation for a multibreed beef cattle population having many genotyped animals. *J. Anim. Sci.*, 95(11):4728-4737.

Simulation

Data

- 21,000 animals; 8 gen.s
- 3 traits: $\lambda_i \approx 0.90, 0.85, 0.20$
- All $r_G = 0.7, r_E = 0.3$
- Randomly select 10, 30, 40, 50% of genotypes for animals in gen.s 5 to 8
- Omit records in gen. 8
- 30 replicates

REML analyses

FULL Estimate Σ_G and Σ_A

ONE Estimate Σ_U and single λ

FX0.5 Estimate Σ_U for $\lambda = 0.5$

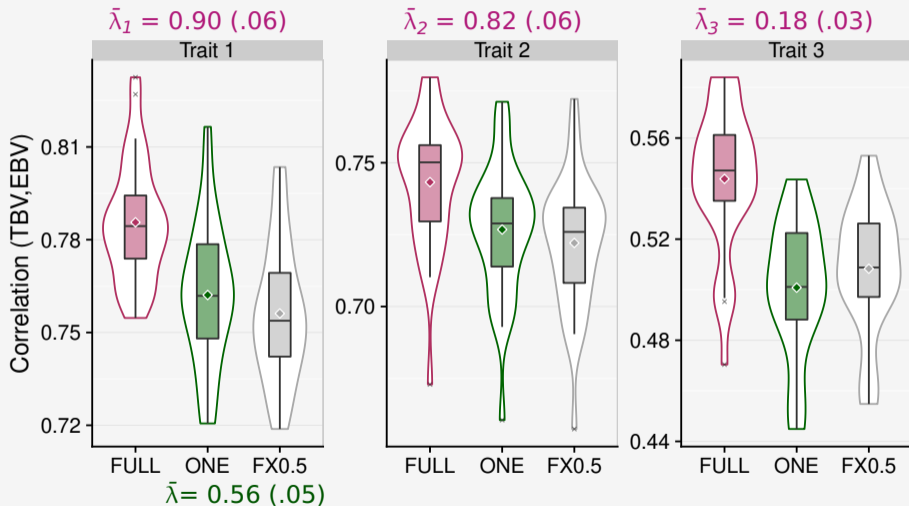
Summary statistics

Distribution over replicates

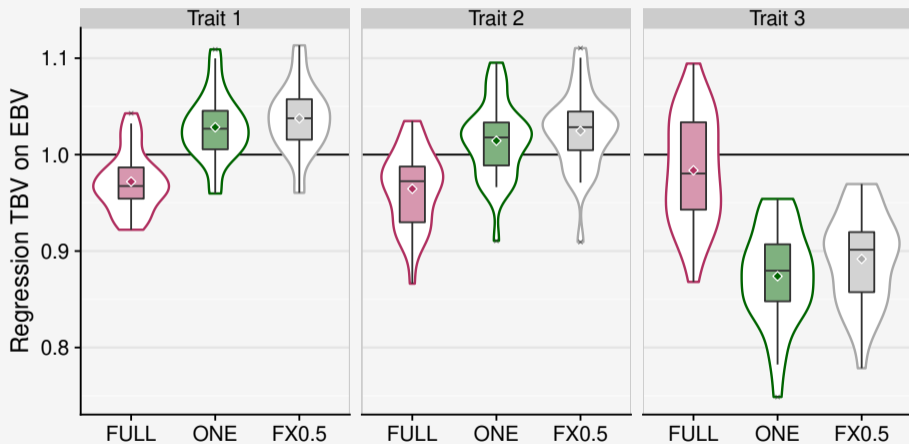
- Correlation TBV and EBV
- Regression of TBV on EBV

for genotyped animals in gen. 8

Accuracy of predicted BV

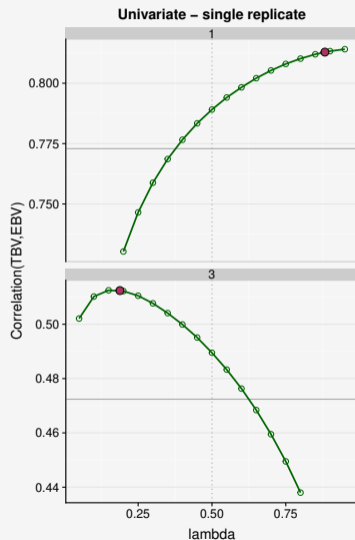


Dispersion of predicted BV



Comments

- Modest gains in accuracy for FULL
 - in spite of wide range in true λ_j
- Reasons?
 - Small simulation
 - Sampling errors in $\hat{\Sigma}_G$ and $\hat{\Sigma}_A$
 - EBVs insensitive against choices of λ_j deviating from 'optimal' values
 - reported in literature for univariate analyses
 - seems to hold for MV fitting single, 'average' λ



Conclusions

- Modelling trait-specific genetic covariances in ssGBLUP feasible
- Canonical transformation
 - Efficient calculation of matrix inverse
 - Avoid splitting EBVs into genomic & RPG parts
 - Substantially better convergence rates in iterative solution schemes (not shown)
- In practice
 - Trade-off potential gains vs. computational demands
 - Limited gains → evaluate carefully

