

Genomic selection strategies and their potential to maintain rare alleles and de-novo mutations

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Motivation

Rare alleles and de-novo mutations have...

- low correlation with phenotypes at the population level
- usually weak linkage with SNP markers



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Led to think that

- genomic selection may not use favorable rare alleles effectively
- could loose rare alleles at a higher rate than pedigree selection



Compared mass selection, pedigree selection and genomic selection

Mulder et al., (2019) Genetics Wientjes et al., (2022) GSE

Wientjes et al., (2023) Genetics

4



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Some conclusions about genomic selection:

• inclusion of own phenotypes is a main factor in the conservation of rare alleles

Mulder et al., (2019) Genetics Wientjes et al., (2022) GSE Wientjes et al., (2023) Genetics 5



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Compared mass selection, pedigree selection and genomic selection

Some conclusions about genomic selection:

- inclusion of own phenotypes is a main factor in the conservation of rare alleles
- doesn't have to be worse than pedigree selection at this
- but is much more prone, specifically, to hitch-hiking than pedigree selection

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Assessment of different genomic selection strategies

Not *if* genomic selection but *how* genomic selection may be implemented



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Selection Strategies:

Truncation selection (TS) ------ \rightarrow Maximize average EBVs from selected candidates

Optimal contributions (OCS) ---- \rightarrow with a constraint on the candidates' coancestry Meuwissen et al., (2020) Frontiers

Alleles re-weighting (ARW) -----→with favorable rare alleles up-weighted in EBVsLiu et al., (2015) GSE(2 versions: *fixed* and *moving* time horizon)

Constrained allele loss (CAL) -----with a constraint on the reduction in frequencynovel strategyof rare favourable alleles

*plus Random selection (RS) for reference

9



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11



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12



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The Simulation

The Population: 50 discrete generations 1000 individuals

100 sires + 100 dams selected

selected without own phenotypes
using marker effects learnt from
the 3 prior generations

Genome:

20k SNP marker panel

- MAFs 0.5 to 0.1
- neutral loci

2k starting causal loci mutations rate 3.8x10⁻⁵(loci.ind)⁻¹

Simulation approach from Wientjes, et al. 2022



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The Traits

Additive Normally distributed additive effects, with a common variance.

Dominant Includes dominance effects, with a small positive bias for heterozygotes.

Epistatic Includes pairwise interactions, with connectivity pattern taken from a yeast study.



Yeast study in Costanzo et al., 2016



Evolution of total genetic value



Evolution of additive genetic variance

Genetic gain vs. genetic variance

Alternative strategies compared with truncation selection (Additive)



Genetic gain vs. genetic variance

Alternative strategies compared with truncation selection (Additive)



Genetic gain vs. genetic variance

Alternative strategies compared with truncation selection (Additive)



22

Genetic gain vs. genetic variance

Alternative strategies compared with truncation selection (Additive)



ARW strategies allow effective trade-off between increased genetic gain and conservation of genetic variance

Genetic gain vs. genetic variance

Alternative strategies compared with truncation selection (Epistatic)



Considering traits with non-additive effects improves the assessments of OCS and ARWm for genetic gain

Selection of de-novo mutations

Contribution of DNMs to TBVs



Selection of de-novo mutations



Selection of de-novo mutations



No strategy outperforms truncation selection on these metrics

All selection strategies are applying pressure on the mutations

Selection of de-novo mutations



Considering traits with non-additive effects, selection of DNMs becomes more challenging

CAL selection has the lowest and OCS the highest contribution of DNMs to TBVs



For the fully additive trait

- Truncation selection starts with higher gains,
 - Saturates earlier and gain is surpassed by a reweighting strategy.
- Allelic reweighting is an effective strategy for long term selection,
 - Even if working with markers rather than causal loci.
- No strategy is significantly more effective at keeping favourable de-novo mutations segregating,
 - Although they are all slowly purging the deleterious mutational load.



For the trait with epistasis

- Allelic reweighting remains an effective strategy for long term selection,
 - Even while favorable alleles change through generations.
- Optimal contribution outperforms truncation's long term genetic gain,
 - Which didn't happen for the fully additive trait.
- Purging deleterious mutations becomes more challenging for all the selection criteria explored,
 - Possibly due to a combination of lower narrow-sense heritability and changes in which rare alleles are estimated to be favorable.







6	
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Thank you for your attention

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Extra Slides

Truncation selection (TS)

Maximizes average EBVs from selected candidates without any consideration of diversity management

We estimated SNP effects (β) with the phenotypes of the 3 previous generations (by means of a SNPBLUP model)

And selected the 100 top sires and 100 top dams for: GEBVs = $X\beta$

Optimal contribution selection (OCS)

Maximize average EBVs from selected candidates with a constraint on the candidates' coancestry

Maximize $\mathbf{g} = \mathbf{c}' \mathbf{X} \boldsymbol{\beta}$ $K_t \ge \frac{1}{2} \mathbf{c}' \mathbf{G} \mathbf{c}$ $\mathbf{Q} \mathbf{c} = [\frac{1}{2} \frac{1}{2}]'$ $\mathbf{c} \ge 0$ where $K_t = K_{t-1} + (1-K_{t-1})/(2Ne)$, using Ne=60

From Meuwissen, et al. (2020) "Management of genetic diversity in the era of genomics."



wGEBVs = $XW\beta$

(years to horizon; dotted line: 5 years, solid line: 20 years)





Allele re-weighting (ARW)

Included two variants of this strategy, using different definitions for the time horizons:

- ARWf (fixed): using the full length of the simulation of 50 generations, as the time horizon.
- ARWm (moving): using a moving horizon, always 5 generations ahead.



Constrained allele loss (CAL)

Maximize average EBVs from selected candidates with a constraint on the loss of rare (favourable) alleles.

(logarithm with offset log(1/n + x))

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Maximize \mathbf{g} = \mathbf{c}' \mathbf{X} \mathbf{\beta}

\mathbf{L} \ge \mathbf{c}' \mathbf{X} \mathbf{\alpha}

\mathbf{Q} \mathbf{c} = [\frac{1}{2} \frac{1}{2}]'

\mathbf{c} \ge 0
```

where $\alpha_j = -\log(1/n * (1 + (J'X)_j))$ [if $\beta_j \ge 0$], L = 1.10*1/n*(J'X α), and J is an n-length vector of ones.

Genetic gain vs. genetic variance

Genetic improvement vs. reduction in genetic variance

Results

