Genomic Selection Algorithms

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Descriptive

Predictive

Prescriptive



$\mathsf{G}{\times}\mathsf{E}$ Interactions

Yield Prediction

Genomic Selection

Breeding cycle

Genomic selection

Optimizer and nature

Interactions between optimizer and nature

Optimizer vs. nature vs. simulator

Key messages

Optimizers

selection truncation truncation group group group short-term short-term long-term long

mating

time management

robust against prediction error

CGS conventional genomic selection

- GEBV (genomic estimated breeding value): Sum of additive genetic effects of all alleles [Meuwissen et al. 2001]
- Select individuals that have the highest GEBVs.
- Pros: Effective at achieving short-term genetic gains (verified by numerous experiments in plants and animals)
- Cons: Loss of long-term growth potential

example

- OHV (optimal haploid value): Best progeny from self pollination in the next generation [Daetwyler et al. 2015]
- Select individuals that have the highest OHVs.
- Pros: Emphasis on the potential of progeny (rather than achievement of the parents)
- Cons: Still a truncation selection

example

- OPV (optimal population value): Best progeny of selected parents after multiple generations [Goiffon et al. 2017]
- Select a group of parents that have the highest OPV.
- Pros: Proposed complementarity based selection rather than truncation selection
- Cons: Ignores time constraints

Publication

HIGHLIGHTED ARTICLE GENETICS | GENOMIC SELECTION

Improving Response in Genomic Selection with a Population-Based Selection Strategy: Optimal Population Value Selection

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Deep blue (1996)

Go vs. GS

States	Board positions, $\sim 3^{361}$	Population genotypes, $\sim 3^{4,000,000}$	
Actions	Adding one stone to the board, ≤ 361	Selection, mating, resource allocation, $\sim 200^{40}$	
Transition	Deterministic	Stochastic	
Reward	Win or loss	Genetic gain	

Publication

GENOMIC PREDICTION

Optimizing Selection and Mating in Genomic Selection with a Look-Ahead Approach: An Operations Research Framework

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look ahead trace back

trace back to candidate crosses

Differences between LATB and LAS

- ► LATB accounts for selection; LAS doesn't.
- LAS assumes accurate allele effects; LATB doesn't.
- LATB looks ahead one generation at a time;
 LAS looks directly at the final generation.

Publication

www.nature.com/scientificreports

Check for updates

scientific reports

OPEN The look ahead trace back optimizer for genomic selection under transparent and opaque simulators

Fatemeh Amini, Felipe Restrepo Franco, Guiping Hu & Lizhi Wang

Key messages

27/40

Nature vs. simulator

Transparent vs. opaque simulators

	Transparent	Opaque
G	G is the whole genome	G is a subset of the whole genome \overline{G}
β	eta is the truth	True additive and non-additive effects, θ , of the whole genome are unknown
Р	$P = G\beta + \epsilon$	$P = f(\overline{G} \theta) + \epsilon$

Q: How to make \overline{G} and $f(\cdot|\theta)$?

A: Arbitrarily. The purpose is not to predict how nature behaves but to reveal how the optimizer interacts with an opaque nature.

Four simulators

Simulator	Observed	Whole	Additive	Dominance
	Genome	Genome	Effects	Epistases
S1	1,000	1,000	known	none
S2	1,000	1,000	unknown	none
S3	1,000	100,000	unknown	none
S4	1,000	100,000	unknown	unknown

Additive effects used in simulators

Recombination frequencies used in simulators

Four optimizers

Optimizer	Prediction
PS	none
CGS	one β from ridge regression
LAS	one β from ridge regression
LATB	multiple β 's from ridge regression

Results: phenotypic response

Results: genetic diversity (minor allele frequency)

Look ahead selection for multiple traits

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Publication

GENETICS | GENOMIC PREDICTION

Multi-trait Genomic Selection Methods for Crop Improvement

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Take home message

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Thank you

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