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# A sparse-group lasso variant for whole-genome regression models in half sibs

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# Background

“phenotype = genotype + environment”



Predict future  
performance  
of animals

- Estimate genotypic effects
- “ $p > n$ ”
- Selection and shrinkage approach



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# Objectives

Develop a statistical approach that jointly allows to:

- ① **Exploit relationships among predictors**
- ② **Achieve high-precision estimation of breeding values**
- ③ **Identify causative regions on the genome**



# Whole-genome regression model

- Model equation:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$$

$\mathbf{y}$  phenotype vector

$\mathbf{X}$  marker-genotype matrix

$\boldsymbol{\beta}$  vector of additive-genetic effects

$\mathbf{e}$  vector of i.i.d. residuals

- Optimization problem ( $n$ -invariant formulation):

$$\hat{\boldsymbol{\beta}} = \arg \min_{\boldsymbol{\beta}} \left\{ \frac{1}{2n} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 + \text{penalty} \right\}$$

# Valnialtet g eñf ñhreñ a regression model

$$\hat{\beta} = \arg \min_{\beta} \left\{ \frac{1}{2n} \|y - X\beta\|_2^2 + \text{penalty} \right\}$$

	Name	Penalty term
1	lasso (Tibshirani, 1996)	$\lambda \ \beta\ _1$
2	group lasso (Yuan and Lin, 2007)	$\lambda \sum_l \sqrt{p_l} \ \beta^{(l)}\ _2$
3	sparse-group lasso (Simon et al., 2013)	$\alpha \lambda \ \beta\ _1 + (1 - \alpha) \lambda \sum_l \sqrt{p_l} \ \beta^{(l)}\ _2$
4	modified sparse-group lasso	$\hat{\beta} = \arg \min_{\beta} \left\{ \frac{1}{2n} \ y - X\beta\ _2^2 + \text{penalty} \right\}$ <p style="color: #C8A23E; margin-left: 20px;"><math>\alpha \lambda \ \beta\ _1 + (1 - \alpha) \lambda \sum_l \sqrt{p_l} g_\varepsilon(\ X^{(l)}\beta^{(l)}\ _2)</math></p> <p style="color: #C8A23E; margin-left: 20px;"><math>g_\varepsilon \dots \text{Moreau envelope}</math></p>

# Variable selection and lasso implementation

$$\hat{\beta} = \arg \min_{\beta} \left\{ \frac{1}{2n} \|y - X\beta\|_2^2 + \text{penalty} \right\}$$

- Name: ~~Iterative algorithm: Proximal gradient descent~~
- Penalty term:  ~~$\lambda \sum_l \sqrt{p_l} \|\beta^{(l)}\|_2$~~
- ① lasso  
(Tibshirani, 1996)
- ② Stepsize for each iteration: Backtracking line search  
group lasso  
(Yuan and Lin, 2007)
- Optimal value for  $\lambda$ : Warm starts  
 $\lambda \sum_l \sqrt{p_l} \|\beta^{(l)}\|_2$
- Moreau envelope to circumvent potential troublesome sparse-group lasso  
(Simoni et al., 2013)
- ③ implementation:  

$$\alpha \lambda \|\beta\|_1 + (1 - \alpha) \lambda \sum_l \sqrt{p_l} \|\beta^{(l)}\|_2$$
- ④ modified sparse-group lasso  

$$g_\varepsilon(z) := \begin{cases} \alpha \frac{\|z\|_1}{\|z\|_2} + (1 - \alpha) \frac{\|z\|_2}{\|z\|_2} \sum_l \sqrt{p_l} g_\varepsilon(\|X^{(l)}\beta^{(l)}\|_2) & \text{if } \|z\|_2 > \varepsilon \\ \frac{\|z\|_2^2}{2\varepsilon} + \frac{\varepsilon}{2} & \text{if } \|z\|_2 \leq \varepsilon \end{cases}$$

Moreau envelope

# Simulated data

- 1000 individuals
  - ✓ 10 families
  - ✓ 100 half sibs per family
- 466 SNPs
  - ✓ 2 chromosomes
  - ✓ 233 SNPs per chromosome

- 3 different numbers of QTLs
  - ✓ 1, 3, or 9 groups per chromosome

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{e}$$

- 3 traits with different heritabilities  $h^2 \in \{0.1, 0.3, 0.5\}$

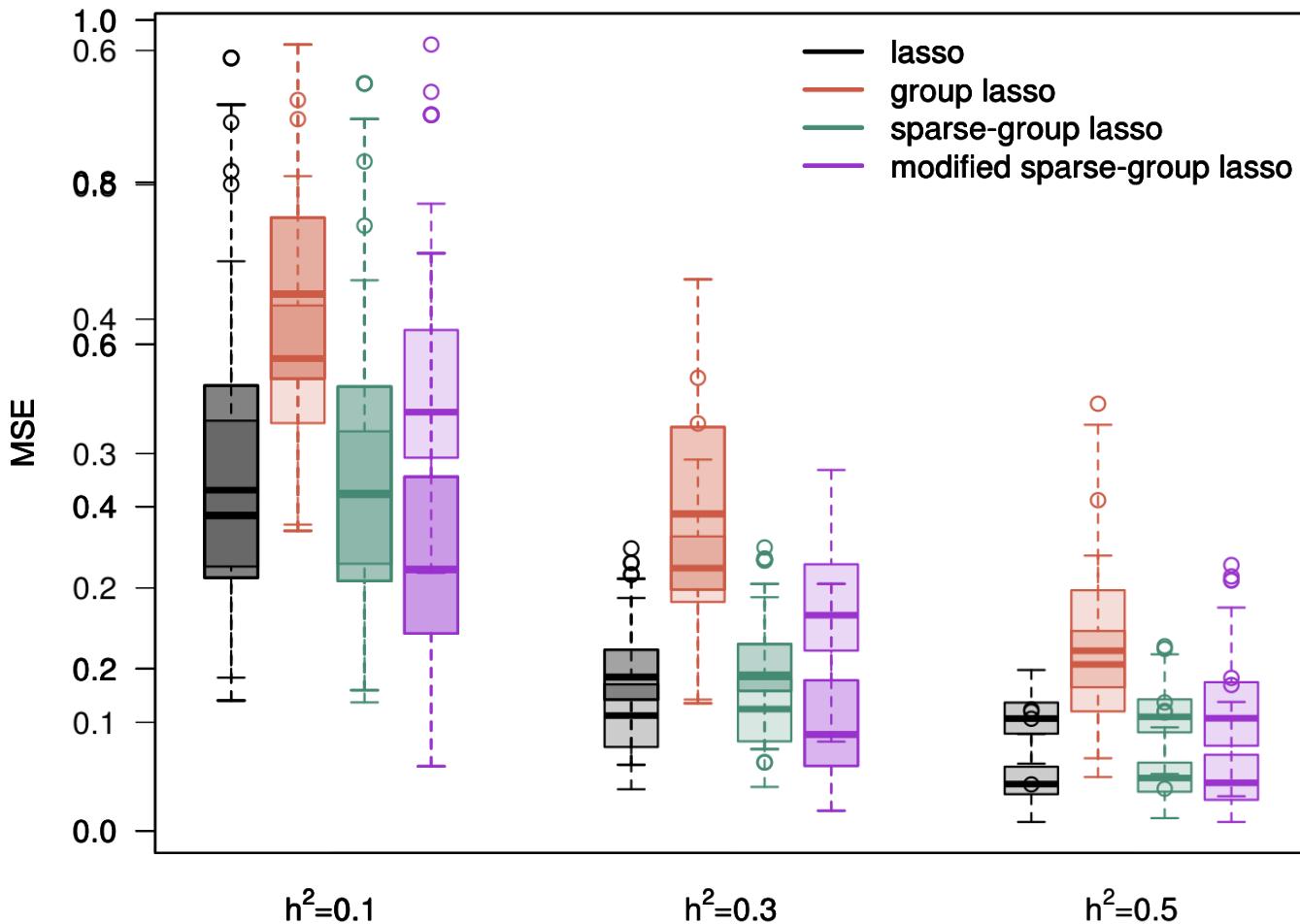
For statistical evaluation: 100 experiments in total

# Evaluation criteria

- ① Accuracy of estimation of variance components  
(additive-genetic and residual variance)
- ② Accuracy of prediction of breeding values (BVs)  
(correlation between true and predicted BVs)
- ③ Sensitivity and specificity of QTL detection
- ④ Mean squared errors:  $MSE(\hat{\beta})$



# Mean squared errors



- 3 groups of QTLs per chromosome
- $\alpha = 0.9$

# Discussion and outlook

## 1 Similarity measures within the grouping:

- Population-wide linkage disequilibrium
- Theoretical correlation (Wittenburg et al., 2016)

## 2 Modified sparse-group lasso:

- Choose  $\varepsilon$  for  $g_\varepsilon \left( \|X^{(l)}\beta^{(l)}\|_2 \right)$
- $\|X^{(l)}\beta^{(l)}\|_2 \rightarrow \sqrt{\langle \beta^{(l)}, P^{(l)}\beta^{(l)} \rangle_2}$   
( $P$ ... precision matrix)



# Summary

With respect to the MSE and compared to the lasso:

- ① Modified sparse-group lasso: severe improvements if 1 group of QTLs per chromosome
- ② Sparse-group lasso: no or small improvements if 3 or more groups of QTLs per chromosome
- ③ Group lasso: no improvements

**Thank you very much for your attention.**



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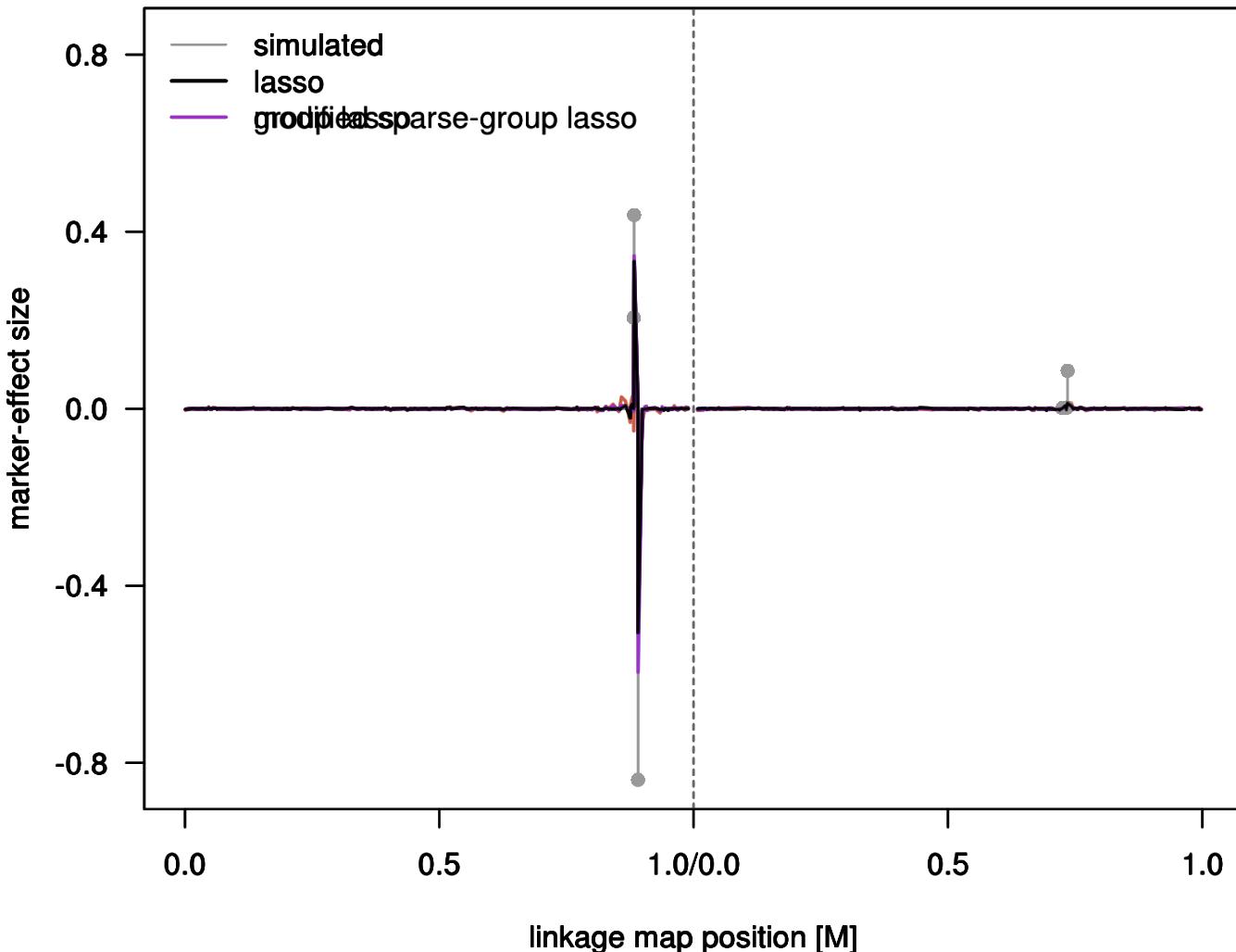
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# Average marker-effect estimation



- 1 group of QTLs per chromosome
- $h^2 = 0.3$
- $\alpha = 0.9$