

#### Agenda



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AMP overview. Making AMP approach scalable and stable for the GWAS 2.inference task

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AMP overview. Making AMP approach scalable and stable for the GWAS inference task

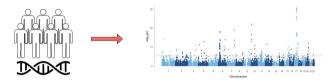


3. Comparison to the state-of-the-art methods (regenie, GMRM)

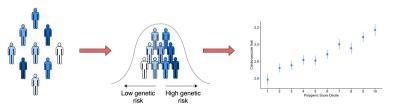


# 1. Genome-Wide Association Studies

Step 1: Genome-wide association studies in adult populations from the UK Biobank



Step 2: Whole genome polygenic risk scores



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Bayesian Linear Regression for the individual-level model:

$$y_i = \langle \textbf{X}(i,:), \beta \rangle + \epsilon_i \text{ for } i \in [N] = \{1, \dots, N\}$$

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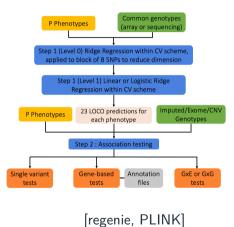
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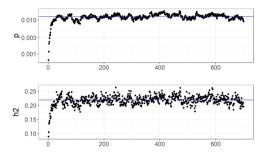
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$$\begin{split} y_i &= \langle \mathbf{X}(i,:), \beta \rangle + \epsilon_i \text{ for } i \in [N] = \{1, \dots, N\} \quad \text{ and } \\ \beta_j &\sim (1 - \pmb{\lambda}) \cdot \delta_0(\cdot) + \pmb{\lambda} \cdot \sum_{i=1}^L \pi_i \cdot \mathcal{N}(\cdot, 0, \sigma_i^2), \quad \epsilon_i \sim \mathcal{N}(0, \pmb{\gamma_\epsilon}^{-1}) \end{split}$$

Inference of Genetic Effects via Approximate Message Passing

#### **Prior Work**





[LDpred2, SBayesR, SBayesRC, GMRM]



 family of iterative algorithms that incorporate structural information about genetic signal



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- linear models [Kab03, BM12, BM11, DMM09, KMS+12], generalized linear models [BKM+19, MLKZ20, Ran11, SR14, SC19] and low-rank matrix estimation



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- linear models [Kab03, BM12, BM11, DMM09, KMS+12], generalized linear models [BKM+19, MLKZ20, Ran11, SR14, SC19] and low-rank matrix estimation
- achieves Bayes-optimal performance for some models [DM14, DJM13, BKM+19]



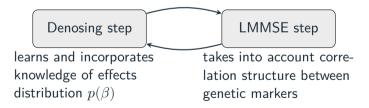
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1. Filtering the normalized genotype matrix for first-degree relatives to reduce the correlation between rows ( $\sim 400,000$  out of 460,000 participants from UK Biobank study)

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# genomic VAMP

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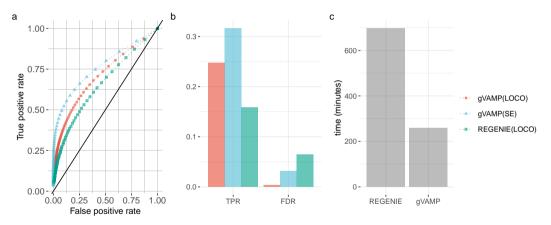
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- 8. data processing by using a lookup table + SIMD:

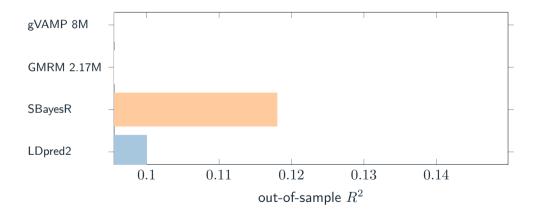
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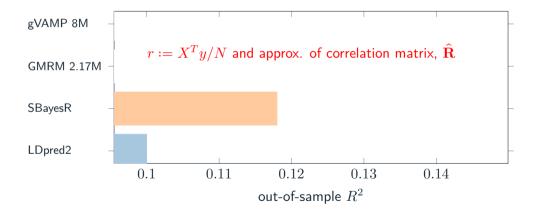
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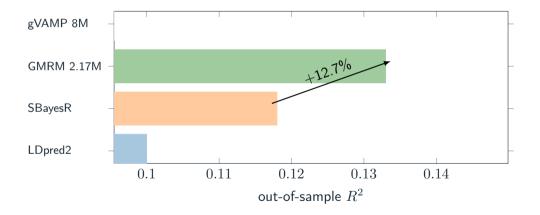


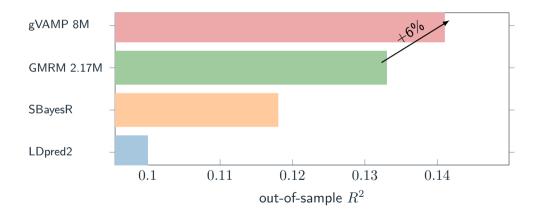
$$y^{(i)} := y - \mathbf{X}_{\backslash \mathsf{chr}(i)} \hat{\beta}_{\backslash \mathsf{chr}(i)} \sim \mathbf{X}(:,i)$$





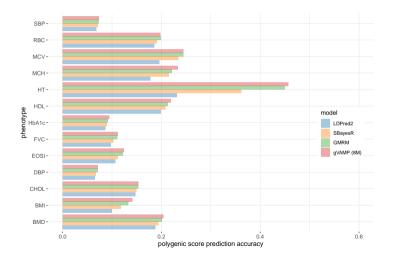






# **Prediction accuracy**

SBP: Systolic blood pressure RBC: Red blood cell count MCV: Mean corpuscular volume MCH: Mean corpuscular haemoglobin HT: Standing height HDL: High density lipoprotein HbA1c: Glycated haemoglobin FVC: Forced vital capacity EOSI: Eosinophill count DBP: Diastolic blood pressure CHOL: Cholesterol BMI: Body mass index BMD: Heel bone mineral density



Inference of Genetic Effects via Approximate Message Passing

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- 1. summary statistics & meta analysis models
  - access only to  $r:=X^Ty/N$  and an approximation of a correlation matrix, called  $\hat{\mathbf{R}}$
  - merging information from different databases/cohorts

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- 3. using gVAMP on WGS data (between 10 12M genetic variants)
- 4. low-complexity alternatives to VAMP?

#### gVAMP git repo: https://github.com/medical-genomics-group/gVAMP

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# The End

# Thanks for your attention!