

Insights into fine-mapping causal variants of complex traits from diverse populations

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SuSiE on meta-analysis

- Original model:

$$\mathbf{y} = \mathbf{X}\mathbf{b} + \mathbf{e}$$

$$\mathbf{e} \sim N_n(0, \sigma^2 \mathbf{I}_n)$$

$$\mathbf{b} = \sum_{l=1}^L \mathbf{b}_l$$

$$\mathbf{b}_l = \gamma_l \mathbf{b}_l$$

$$\gamma_l \sim \text{Mult}(1, \boldsymbol{\pi})$$

$$\mathbf{b}_l \sim N_1(0, \sigma_{0l}^2).$$

- Sufficient summary statistics for SuSiE:

$$\hat{\beta}, \text{SE}(\hat{\beta}), R = \mathbf{X}^T \mathbf{X} / n, \text{Var}(\mathbf{y}), \text{ and } n$$

OR

$$\mathbf{X}^T \mathbf{X}, \mathbf{X}^T \mathbf{y}, \mathbf{y}^T \mathbf{y}, \text{ and } n$$

Inverse-variance weighted fixed-effect meta-analysis

For jth SNP:

$$\langle \hat{\beta}_j \rangle = \frac{\sum_i \hat{\beta}_{ij} / \text{Var}(\hat{\beta}_{ij})}{\sum_i 1 / \text{Var}(\hat{\beta}_{ij})}, \quad \langle \text{SE}(\hat{\beta}_j) \rangle = \sqrt{\frac{1}{\sum_i 1 / \text{Var}(\hat{\beta}_{ij})}}$$

Setup:

$$X = \begin{matrix} \text{SNP } m_1 = 1 \\ \left(\begin{matrix} X_1 \\ X_2 \end{matrix} \right) \begin{matrix} \text{Pop1 } n_1 \\ \text{Pop2 } n_2 \end{matrix} \end{matrix} \quad \text{If SNP is Pop1-specific, then } X_2 = 0$$

Then:

$$\hat{\beta} = (X^T X)^{-1} X^T y = \left((X_1^T X_2^T) \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} \right)^{-1} (X_1^T X_2^T) \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \frac{X_1^T y_1 + X_2^T y_2}{X_1^T X_1 + X_2^T X_2}$$

$$\text{Var}(\hat{\beta}) = \sigma^2 (X^T X)^{-1} = \sigma^2 (X_1^T X_1 + X_2^T X_2)^{-1}$$

Weighted average of LD matrix?

Setup:

$$X = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} = \begin{pmatrix} A & B \\ C & D \end{pmatrix} \begin{matrix} \text{SNP1 } m_1 & \text{SNP2 } m_2 \\ \text{Pop1 } n_1 \\ \text{Pop2 } n_2 \end{matrix}$$

If SNP2 is Pop1-specific,
then $D = 0$

Given,

$$X_1^T X_1 = \begin{pmatrix} A^T \\ B^T \end{pmatrix} \begin{pmatrix} A & B \end{pmatrix} = \begin{pmatrix} A^T A & A^T B \\ B^T A & B^T B \end{pmatrix}, R_1 = \frac{X_1^T X_1}{n_1}$$

$$X_2^T X_2 = \begin{pmatrix} C^T \\ D^T \end{pmatrix} \begin{pmatrix} C & D \end{pmatrix} = \begin{pmatrix} C^T C & 0 \\ 0 & 0 \end{pmatrix}, R_2 = \frac{X_2^T X_2}{n_2}$$

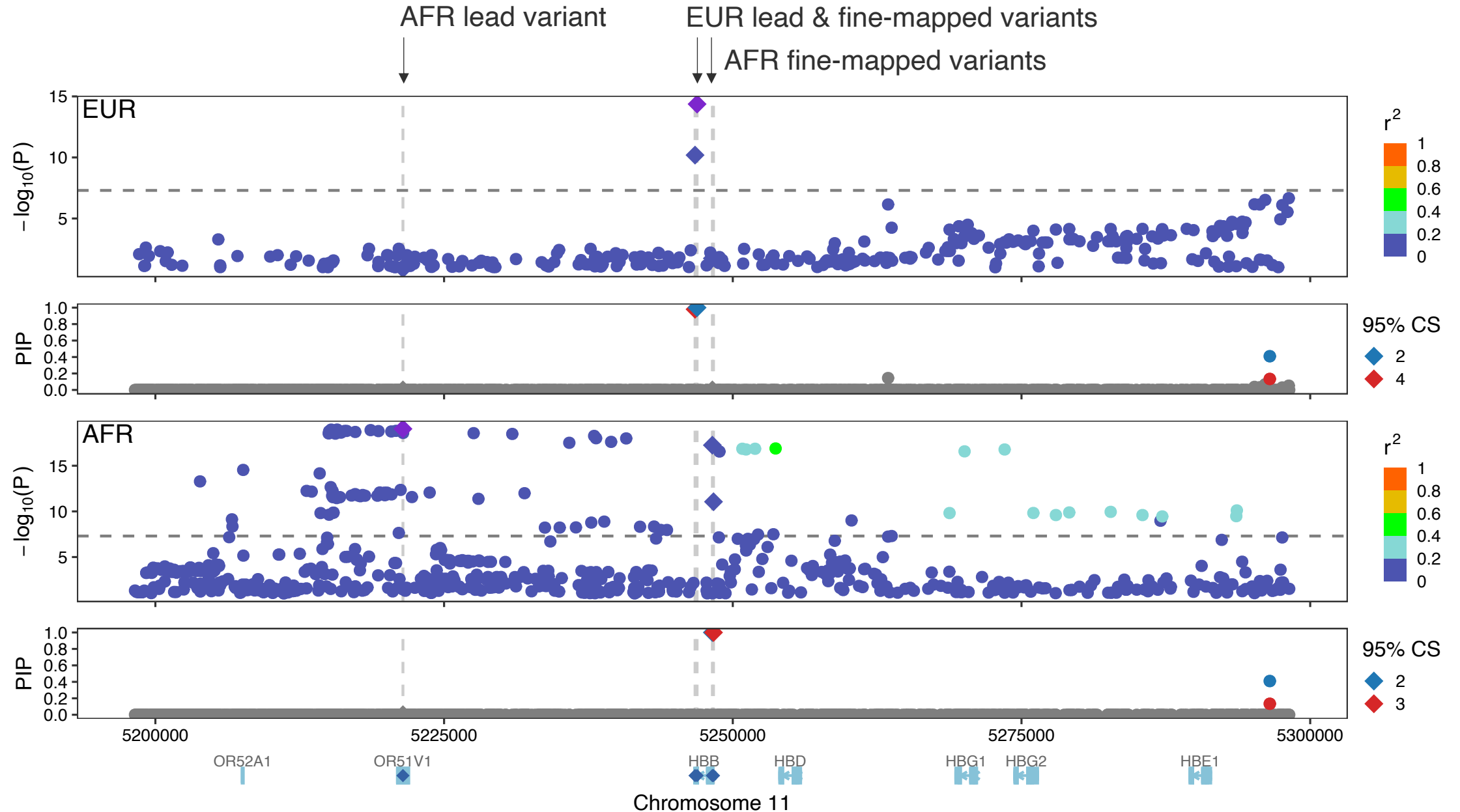
Then

$$X^T X = \begin{pmatrix} A^T & C^T \\ B^T & D^T \end{pmatrix} \begin{pmatrix} A & B \\ C & D \end{pmatrix} = \begin{pmatrix} A^T A + C^T C & A^T B + C^T D \\ B^T A + D^T C & B^T B + D^T D \end{pmatrix} = \begin{pmatrix} A^T A + C^T C & A^T B \\ B^T A & B^T B \end{pmatrix},$$

Thus:

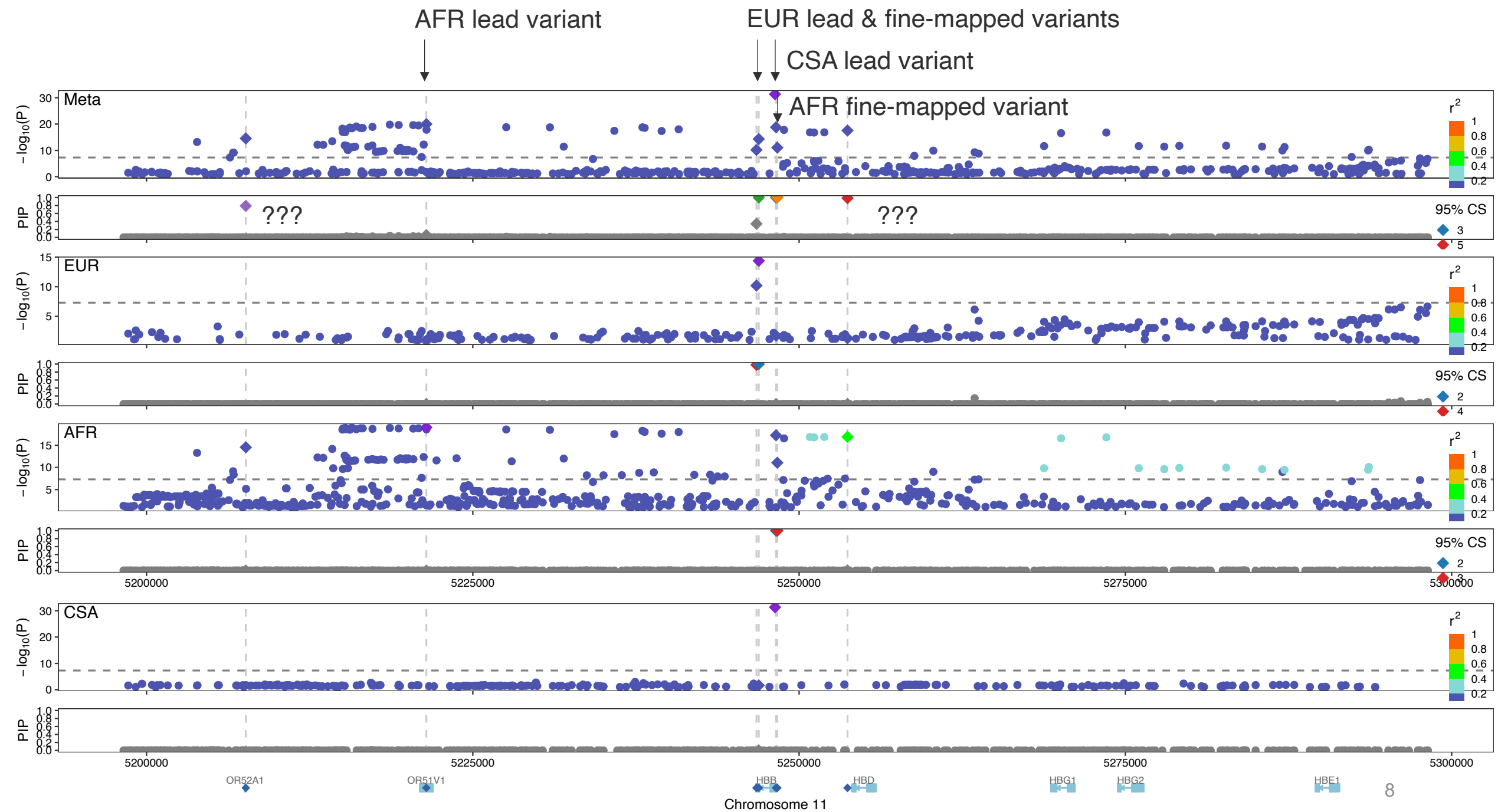
$$R = \frac{X^T X}{n} = \frac{X_1^T X_1 + X_2^T X_2}{n_1 + n_2} = \frac{n_1 R_1 + n_2 R_2}{n_1 + n_2}$$

HBB locus of mean corpuscular volume (MCV) GWAS



HBB, a known pathogenic gene for sickle cell disease





What breaks meta-analysis fine-mapping?

- Heterogeneity (assumption: true β is same across cohorts)
 - True heterogeneity
 - Environment (model: $y_k = X_k\beta + \varepsilon_k$ where $\varepsilon_k \sim N(0, \sigma^2 I)$)
 - Technical artifacts
 - E.g., phenotyping/genotyping/imputation error leads to systematic heterogeneity
- Missing causal variants
 - I think population-specific variants are fine... but...?