# Fine-mapping causal tissues and genes at disease-associated loci

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#### Outline

- 1. Motivation for fine-mapping causal tissues and genes at disease loci
- 2. Methods
- 3. Simulations
- 4. Results: Tissue-gene fine-mapping for 45 UK Biobank diseases and complex traits with 38 GTEx tissues

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## Genetic predisposition for complex disease/trait acts through disease-relevant tissues/cell-types



#### **Evidence from genome-wide analyses:**

- Finucane et al, Nature Genetics 2018: Trait heritability enrichment around specifically expressed genes of specific GTEx tissues and cell types
- Ongen et al, Nature Genetics, 2017: Assess enrichment of tissue eQTLs colocalizing with GWAS signal
- Amariuta et al, Nature Genetics 2023: Trait heritability explained by genetically predicted tissue expression

#### Different loci from a single disease can be mediated by different tissues

Project goal: Fine-map the causal tissue and gene at each disease signal



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- Develop statistical model, TGFM (tissue-gene fine-mapping), to fine-map the causal tissue and gene at each genetic disease signal
  - Calculate causal probabilities for each (gene, tissue) pair and causal probabilities for each nonmediated variant
  - Based on integration of GWAS data and multi-tissue/cell type eQTL data

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TWAS calculates marginal association between predicted genetic gene expression and disease



Gusev et al. Nat. Genet. 2016 Wainberg et al. Nat Genet. 2019

### TWAS calculates marginal association between predicted genetic expression and disease

Step 1: Estimate predicted genetic gene expression using eQTL data



Disease Status

Gamazon et al. Nat. Genet. 2015 Gusev et al. Nat. Genet. 2016 Wainberg et al. Nat Genet. 2019

### TWAS calculates marginal association between predicted genetic expression and disease

Step 2: Associate predicted genetic gene expression with disease



## TWAS cannot distinguish causal from tagging gene-tissue pairs

- Analogous to variant LD obscuring causal from tagging variants using marginal GWAS associations
- A significant TWAS association for a gene-tissue pair can result from:
- 1. The gene-tissue pair having a causal effect on the disease
- 2. The gene-tissue pair does not have a causal effect on disease, but is correlated with another causal gene-tissue pair or causal non-mediated variant

Mancuso et al. Nat. Genet. 2019 Yao et al Nat. Genet 2020 Amariuta et al. Nat. Genet. 2023 Zhao et al. BioRxiv 2022

### TGFM (tissue gene fine-mapping) distinguishes causal from tagging gene-tissue pairs



#### Strober et al. medRxiv 2023

### TGFM (tissue gene fine-mapping) distinguishes causal from tagging gene-tissue pairs

Step 1: Estimate predicted genetic gene expression for each gene-tissue pair using eQTL data



Strober et al. medRxiv 2023

### TGFM (tissue gene fine-mapping) distinguishes causal from tagging gene-tissue pairs

Step 2: Identify gene-tissue pairs with non-zero effects on disease while accounting for other gene-tissue pairs and non-mediated genetic effects



#### Generative Model likelihood

$$Y = G \vec{\beta} + \sum_{g} \sum_{t} G \vec{\delta^{gt}} \alpha^{gt} + e$$
Non-mediated Gene-tissue mediated genetic effects mediated genetic effects

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$$Y = G \vec{\beta} + \sum_{g} \sum_{t} G \vec{\delta^{gt}} \alpha^{gt} + \epsilon$$
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$$\left[\vec{\beta},\vec{\alpha}\right] = ?$$

Generative Model likelihood

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Non-mediated Gene-tissue mediated genetic effects mediated genetic effects

SuSiE fine-mapping prior

$$\left[\vec{\beta},\vec{\alpha}\right] = \sum_{l} \gamma_{l} d_{l}$$

 $\gamma_l \sim Categorical(\pi)$ 

$$d_l \sim N(0, \sigma_l^2)$$

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 Posterior Inclusion Probabilities (PIPs): Probability each genetic element (non-mediated variant or gene-tissue pair) has non-zero effect on the disease/trait

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TGFM allow for multiple (*l*) causal genetic elements in a genomic region

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Non-mediated Gene-tissue mediated genetic effects mediated genetic effects

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 $\gamma_l \sim Categorical(\pi)$ 

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**TGFM improves fine-mapping power** by leveraging data from across the genome to learn tissue-specific prior probability ( $\pi$ ) of each genetic element being causal

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SuSiE fine-mapping prior

$$Y = G \vec{\beta} + \sum_{g} \sum_{t} G \vec{\delta^{gt}} \alpha^{gt} + \epsilon$$
Non-mediated Gene-tissue mediated genetic effects effects

$$\left[\vec{\beta},\vec{\alpha}\right] = \sum_{l} \gamma_{l} d_{l}$$

 $\gamma_l \sim Categorical(\pi)$ 

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**TGFM improves fine-mapping calibration** using a sampling approach to model uncertainty in predicted causal eQTL effect sizes ( $\delta^{gt}$ )

#### TGFM input data and output statistics



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\*We refer to variants, (genetic) genes, and (genetic) gene-tissue pairs as genetic elements\*

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TGFM gene-tissue pair fine-mapping FDR is well-calibrated in simulations



**FOCUS**: Mancuso et al. Nat. Genet. 2019 **coloc**: Giambartolomei et al. Plos Genet. 2014

TGFM well calibrated to fine-map multiple classes of genetic elements in simulations TGFM (Gene–Tissue) TGFM (Gene) **TGFM** (Variant) PIP >= 0.5PIP >= 0.90.6-0.6-0.4 0.4 FDR FDR 0.2 0.2 0.0 0.0 300 500 1000 300 500 1000 eQTL sample size eQTL sample size

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#### TGFM fine-maps genetic elements underlying 45 UK Biobank diseases and traits using 38 GTEx tissues



### TGFM applied to UK Biobank diseases/traits identifies disease genes and their tissue of action











## High TGFM PIP genes are strongly enriched within high PoPS genes

• PoPS (Weeks et al. Nat. Genet 2023) is trait-specific gene score based many gene features, such as cell-type specific expression



### Application of TGFM to fine-grained PBMC cell types (Perez et al. Science 2022)

- Generate pseudobulk in each pre-defined cell type
- 9 cell types:
  - B
  - NK: Natural Killer cells
  - Prolif: Proliferation cells
  - T4
  - T8
  - cDC: classical Dendritic cells
  - pDC: Plasmacytoid dentric cells
  - cM: classical Monocytes
  - ncM: non-classical Monocytes



## Fine-grained PBMC cell type help resolve the biological mechanism underlying disease loci



## TGFM identified 30 addition gene-PBMC cell type pairs at PIP > 0.5

• Primarily (23 of 30) for autoimmune and blood cell traits



#### Conclusions

- Develop new statistical method (TGFM) to jointly fine-map the causal gene and tissue at disease loci
- TGFM generates well-calibrated PIPs for gene-tissue pairs, genes, and non-mediated variants in simulations
- High PIP gene-tissue pairs often originate in disease relevant tissues and high PIP genes are enriched in independent gene sets
- TGFM applied to fine-grained cell types in single-cell eQTL data can help resolve the biological mechanism underlying disease loci

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