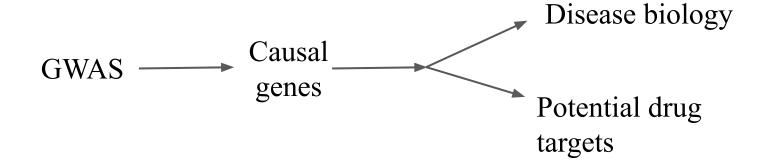
Leveraging co-expression between genes to identify gene sets that are enriched for disease heritability

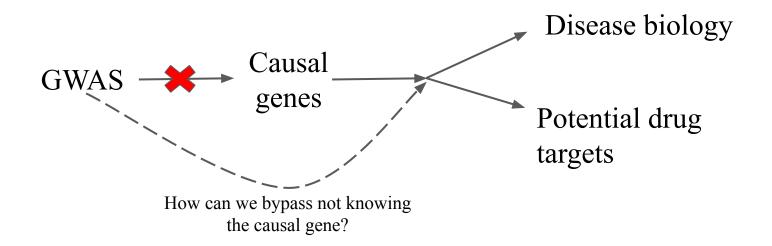
Katie Siewert

Post-doc, group of Alkes Price Harvard T.H. Chan School of Public Health 5/13/2020

Learning from GWAS

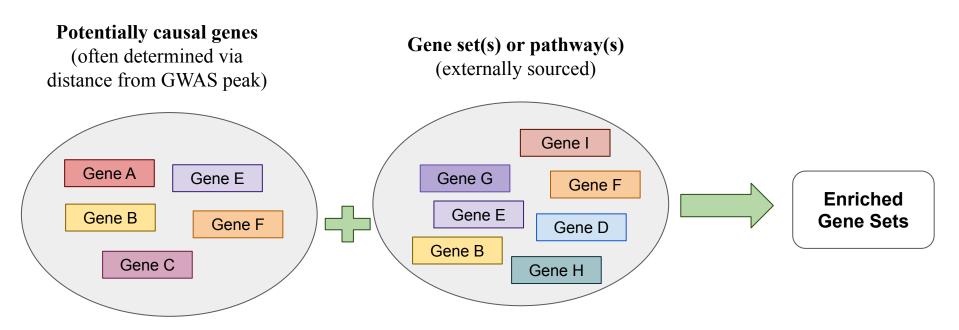


Learning from GWAS



Causal genes are often unknown.

Gene set analysis



Example Methods: DEPICT (Pers 2015), MAGMA (de Leeuw 2015), S-LDSC (Kim 2019)

Gene set analysis: Loss of power

- Nearest gene is causal in only ~50% of cases (Gamazon 2018)
 - \circ Causes noise in gene set analysis \Rightarrow Reduces power

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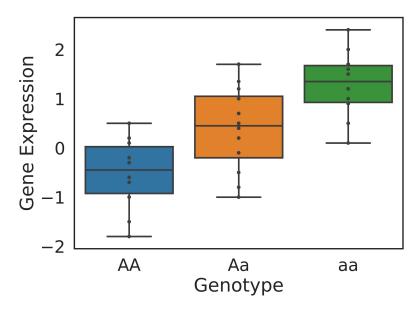
Can we do better than nearest gene approaches?

Outline

- Background
 - o eQTLs, TWAS and gene co-expression
- Our approach for gene set enrichment: Gene Co-expression Score Regression (GCSC)
- Results
 - Simulations
 - Enriched gene sets

eQTLs: SNPs associated with a gene's expression

- eQTLs identified by measuring gene expression levels in genotyped individuals
 - e.g. the GTEx project

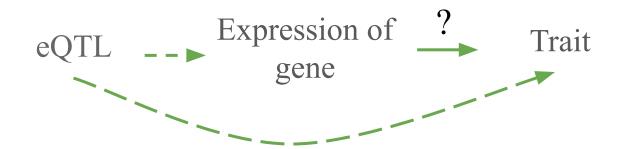


eQTLs: SNPs associated with a gene's expression



• eQTLs can inform causal genes at GWAS loci

eQTLs: SNPs associated with a gene's expression



- eQTLs can inform causal genes at GWAS loci
- However, not proof of causality
 - eQTL could also be regulating other genes, maybe in other tissues or conditions

TWAS: Transcriptome-wide association study

Tests for association between genetically predicted gene expression & disease

Step 1) Make gene model

- Input: Assayed gene expression & genotypes in same individuals
- Learn: Predictive model of gene expression (weighted combo of SNPs)

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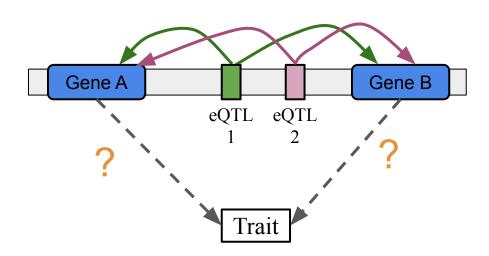
Step 2) Test for association

- Input: eQTL weights in gene model & GWAS z-scores
- ullet Tests: Correlation between eQTL weights for a gene and Z_{GWAS}

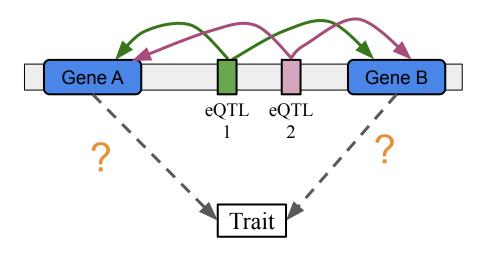
TWAS pools information across eQTLs

- By pooling info from all eQTLs in a gene model, TWAS looks for consistency in magnitude & direction of effect.
- Result: stronger evidence for gene⇒trait association than looking at a single eQTL

Co-expression can cause multiple association in TWAS



Co-expression can cause multiple association in TWAS



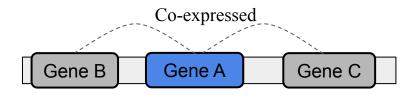
Correlation in predicted gene expression can be caused by:

- Shared causal eQTL(s)
- Causal eQTL(s) in LD
- Errors in gene model

Co-expression increases TWAS associations

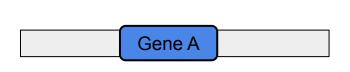


Significant χ^2_{TWAS} only if gene A is causal

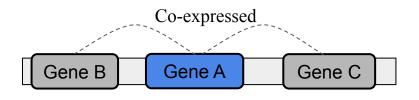


Significant χ^2_{TWAS} if A, B or C is causal

Co-expression increases TWAS associations



Significant χ^2_{TWAS} only if gene A is causal



Significant χ^2_{TWAS} if A, B or C is causal

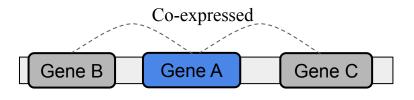
The more genes that a gene is co-expressed with, the more likely its expression is correlated with a causal gene's expression

 \rightarrow Increases $E[\chi^2_{TWAS}]$

Co-expression increases TWAS associations



Significant χ^2_{TWAS} only if gene A is causal



Significant χ^2_{TWAS} if A, B or C is causal

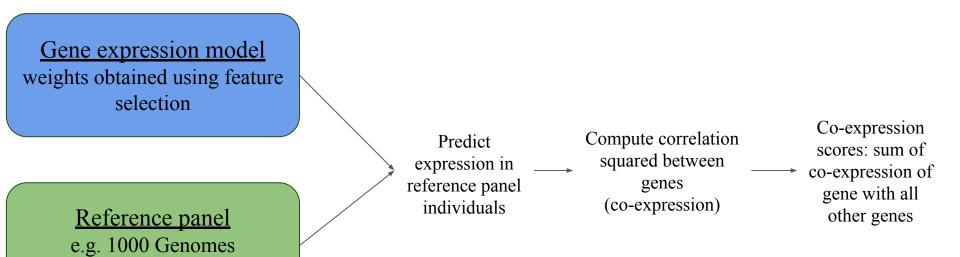
Can't simply compare the TWAS χ^2 of genes in a set to other genes

- Co-expression adds noise and confounds

Goal: Develop method to quantify heritability enrichment in gene sets using gene expression

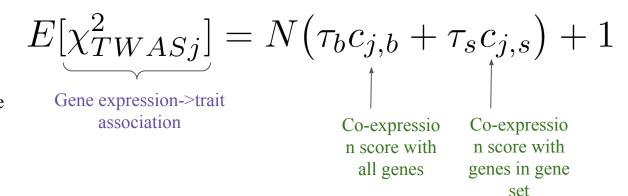
- 1. eQTLs allow us to more accurately map SNPs to genes
- 2. TWAS allows us to pool information across eQTLs, looking for directional consistency
- 3. Is not confounded by co-expression

Co-expression can be calculated using models for gene expression and a reference panel



Gene Co-expression Score Regression regresses on co-expression to estimate heritability

GCSC Regression equation



Terms we calculate ahead of time:

Gene Co-expression Score Regression regresses on co-expression to estimate heritability

GCSC Regression equation

Terms we estimate using GCSC:

Heritability explained by Additional heritability predicted gene expression explained by genes in the gene set

> n score with all genes

n score with

genes in gene set

$$E[\chi^2_{TWASj}] = N(\tau_b c_{j,b} + \tau_s c_{j,s}) + 1$$

Gene expression->trait association

GWAS

Sample Size

Recore with

Gene expressio

Recore with

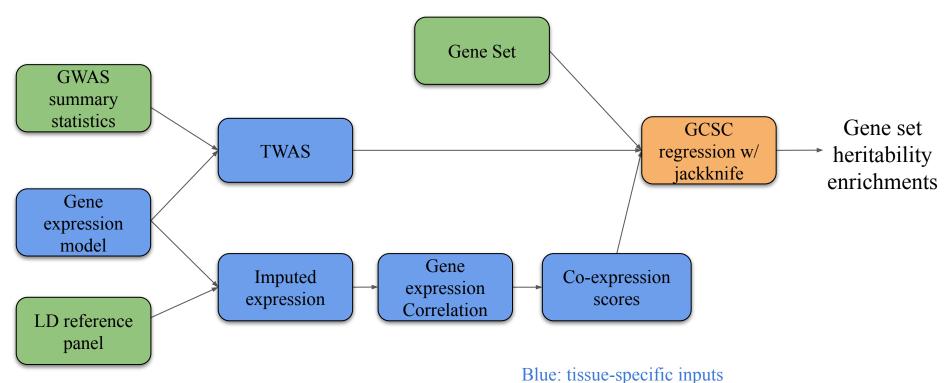
Terms we calculate ahead of time:

Gene Co-expression Score Regression is analogous to stratified LD score regression

• Stratified LD score regression: GWAS χ^2 are regressed against LD scores for an annotation to estimate heritability explained by the annotation

• GCSC regression: TWAS χ^2 are regressed against co-expression scores for a gene set to estimate heritability explained by predicted expression of genes in a set

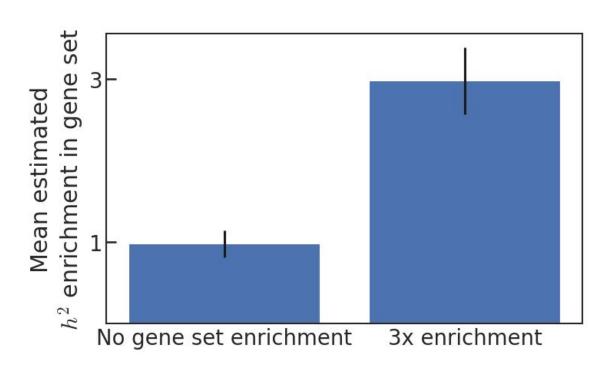
GCSC pipeline



Green: not related to tissue

Can perform tissue-specific, or combined tissue GCSC

GCSC simulation results



Error bars denote +- 2 s.e.

Appropriate standard errors also verified

Gene sets enriched for heritability using all tissue GCSC

- Tested 59 gene sets, results are meta-analyzed across 44 independent traits
- Significant (after Bonferroni) enrichments include:
 - LoF constraint genes: ExAC pLI genes (1.2x enrichment P:7.5e-34)
 - Olfactory receptors (0.13x, 1.3e-33)
 - Top decile of genes with most LD-independent SNPs (0.68x, 7.8e-22)
 - Essential genes (1.14x, 6.5e-19)
 - High Enhancer domain score genes (1.13x, 8.4e-14)
 - High protein-protein closeness centrality genes (1.1x, 1.3e-11)
 - Haploinsufficient genes (1.4x, 1.5e-8)
 - o eQTL deficient genes (0.82x, 1.1e-7)
 - Educational and developmental disorder genes (1.1x, 5.2e-4)

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Compare to s-LDSC approaches using:

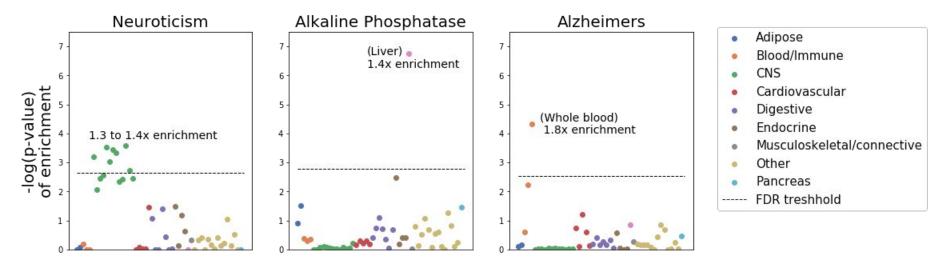
- fine-mapped eQTLs (Hormozdiari 2018 NG): p-value 4.9e-17
- eQTL effect sizes (Yao et al 2020 bioRXiv): p-value 2.3e-25

GCSC finds enrichment of gene specifically expressed in blood and immune cell types in Alzheimer's

Tested for enrichment of heritability explained in 44 traits for specifically expressed genes in 53 tissues -Found 118 significantly enriched trait/tissue combinations

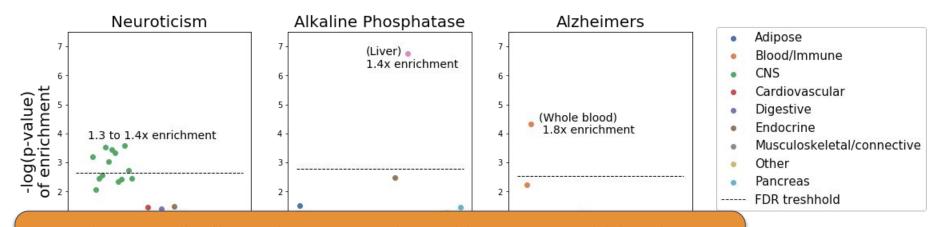
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Corroborates findings that expression of immune and blood genes play role in Alzheimer's (Gjoneska 2015 Nature, Sims 2017 NG)

Gene sets from Finucane 2018 NG

Conclusions

GCSC (Gene Co-expression Score Regression) for gene set enrichment

• Uses TWAS to detect sets of genes whose expression is enriched for trait heritability

• Found large number of heritability enrichments, including specifically expressed genes

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Sasha Gusev

Price group





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Thank you!