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# Identification of cell-type-specific genetic regulation of gene expression for transcriptome-wide association studies

Qiurui Ma; Duo Zhang; Brandon Jew; Sriram Sankararaman

# **The Central Dogma**

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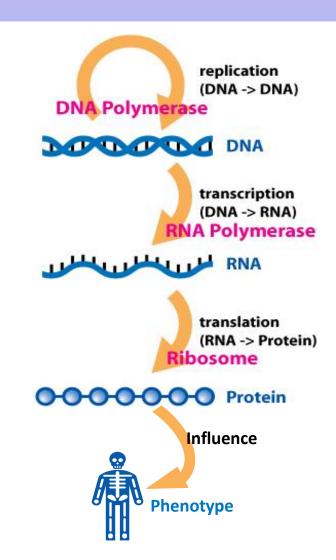
TCA-TWAS

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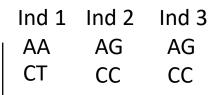
# **The Central Dogma**

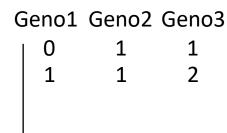
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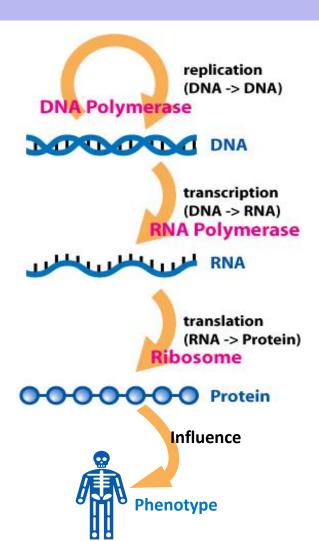
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**SNPs** 







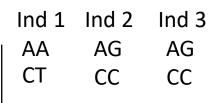
# **The Central Dogma**

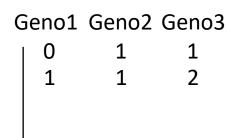
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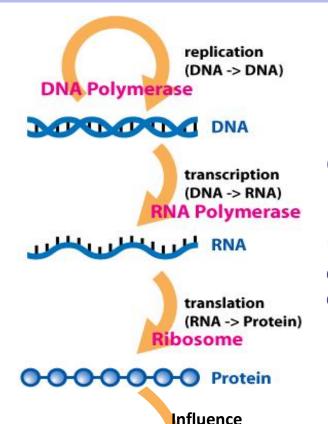
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**SNPs** 







**Phenotype** 

Gene
Expression
(GE):
cell 1, cell 2, cell 3, cell 4

Phenotype: Height, Skin Color

#### **Current Research: GWAS**

Linear

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replication (DNA -> DNA) **DNA Polymerase** transcription (DNA -> RNA) RNA Polymerase Regression of SNPs and translation (RNA -> Protein) phenotype Ribosome Protein Influence **Phenotype** 

#### **Current Research: TWAS**

Linear

Regression

phenotype

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replication (DNA -> DNA) **DNA Polymerase** DNA transcription (DNA -> RNA) RNA Polymerase of SNPs and translation (RNA -> Protein) Ribosome - Protein Influence **Phenotype** 

Linear Regression of SNPs and GE

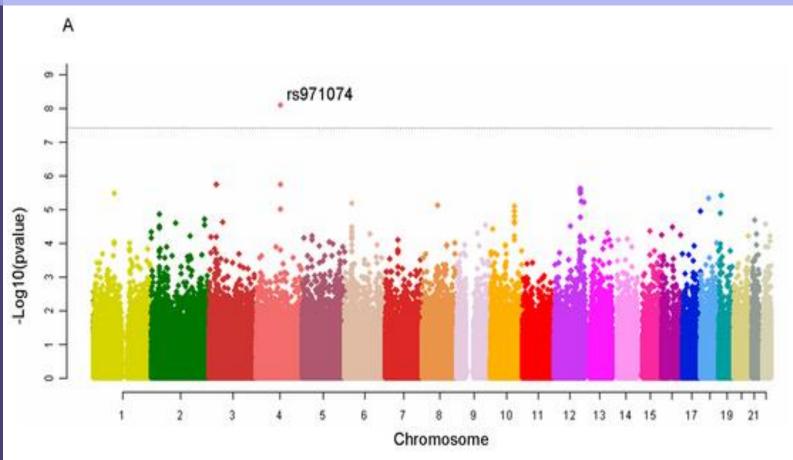
Linear Regression of GE and Phenotype

## **Current Research: Results**

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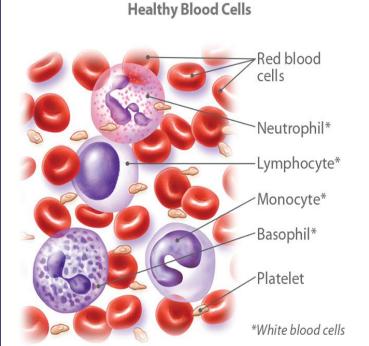
Manhattan Plot of UADT(Upper Aero-Digestive Tract)
Cancer GWAS Discovery Phase

# **Bulk & Cell-Specific GE**

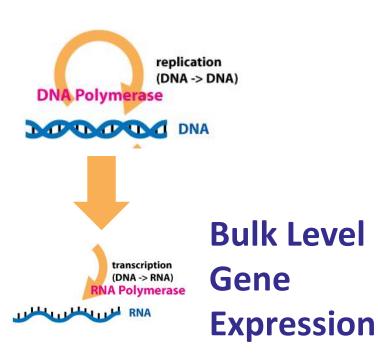
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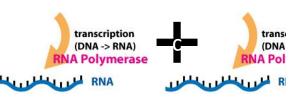
Background Model Experiment Conclusion

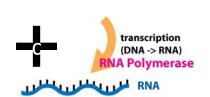


Weighted Cell-Type-**Specific Gene Expression** 









# **Challenges in Current Work**

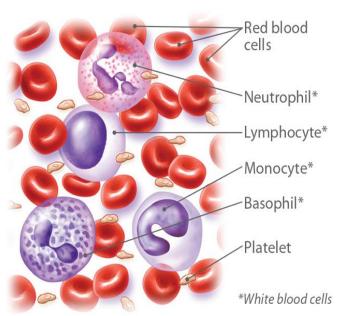
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#### **Healthy Blood Cells**



#### Methodological:

Unclear how SNPs affect phenotypes

- Missing cell type information
- Fail to tell causality from correlation

#### **Practical:**

Cell-Specific Biological Data being resource intensive, expensive to acquire

# **Challenges in Current Work**

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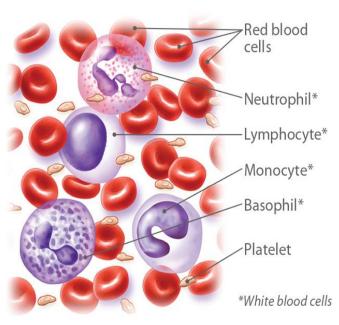
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#### **Healthy Blood Cells**



#### Methodological:

Unclear how SNPs affect phenotypes

- Missing cell type information
- Fail to tell causality from correlation

#### **Practical:**

Cell-Specific Biological Data being resource intensive, expensive to acquire

# Goal:

Impute cell-type specific gene expressions from SNPs and bulk level gene expressions to perform downstream TWAS

# **Train & Target Dataset**

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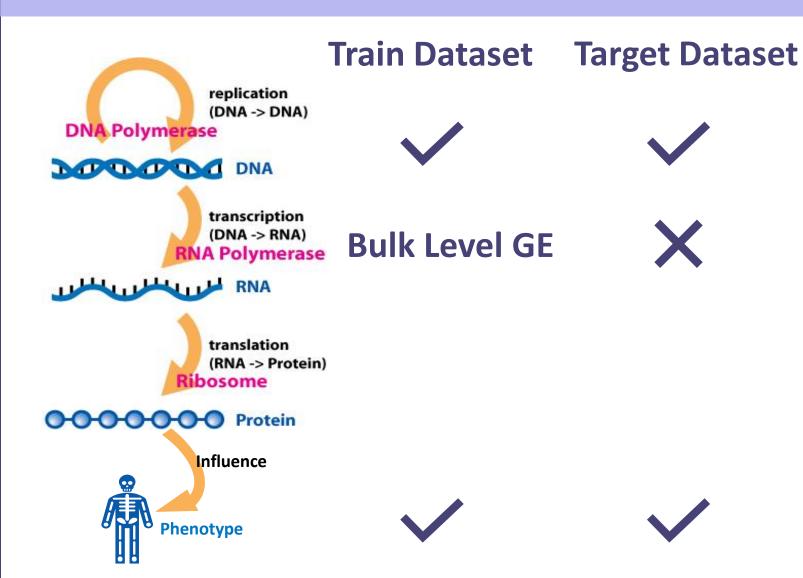
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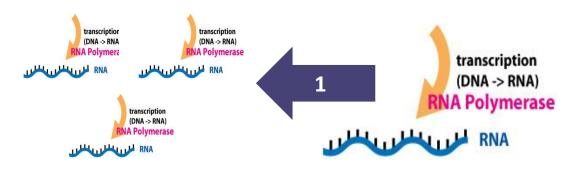
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Train Dataset
TCA
Deconvolution



Cell-Type-Specific Gene Expression Bulk Level Gene Expression

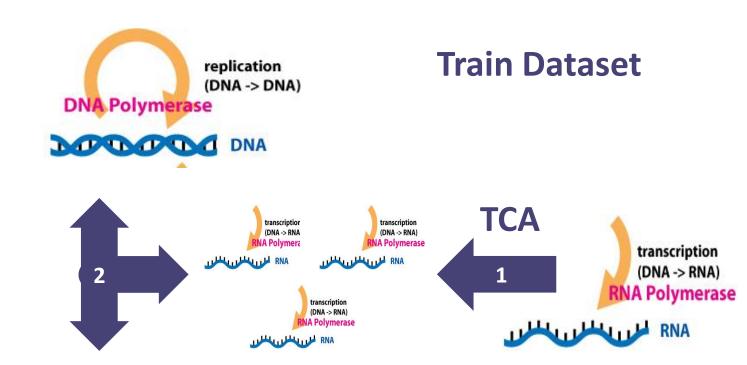
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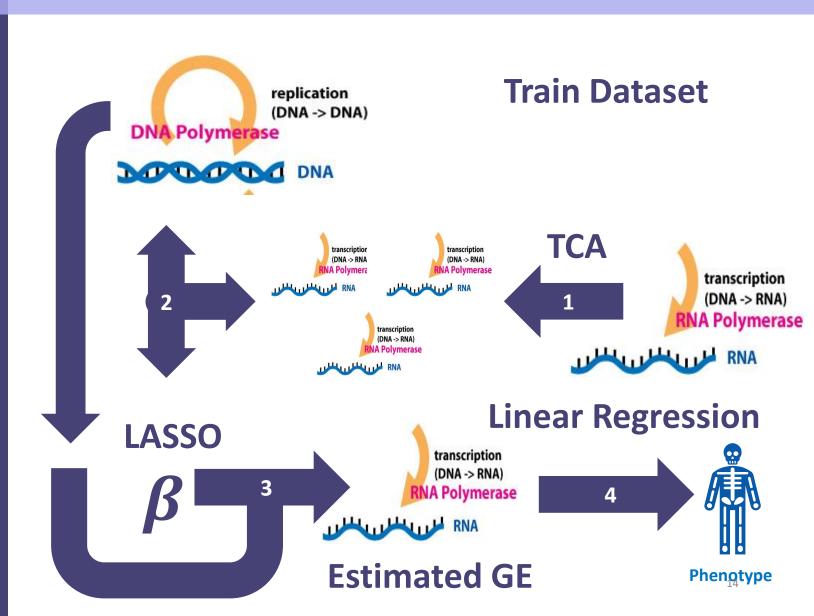
**B** Estimated effect size of SNPs on GE

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Background Model Experiment

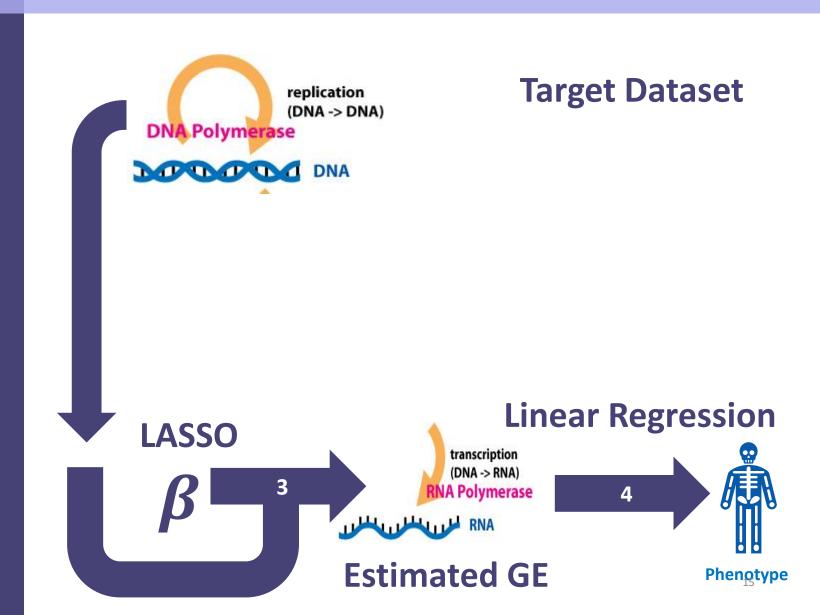
Conclusion



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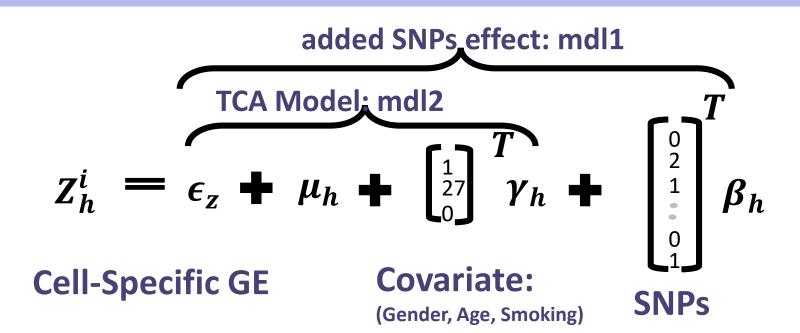
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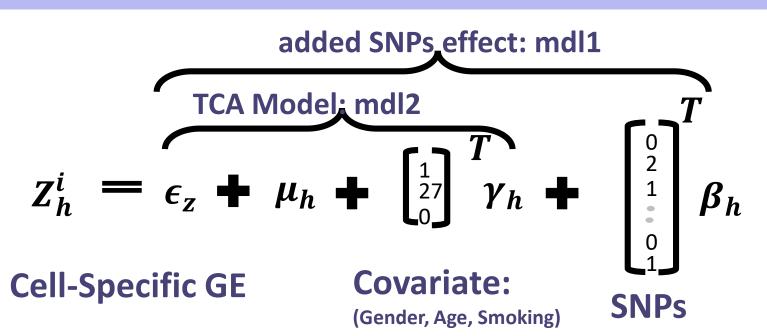


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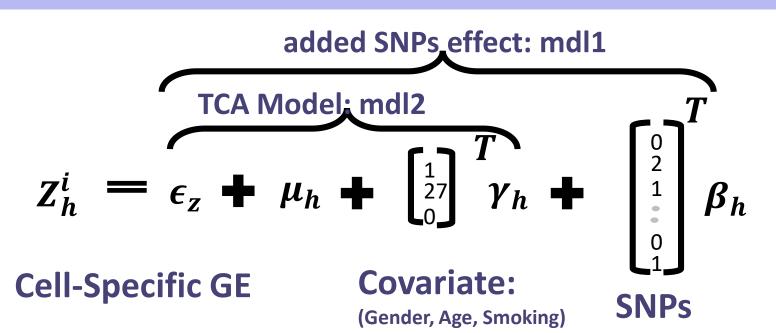
$$G_i = c_i^2 \delta + \sum_{h=1}^k w_{hi} z_{hi} + \epsilon_g$$

**Cell Type Weight Extra Information** 

Background Model

Experiment

Conclusion



$$G_i = c_i^2 \delta + \sum_{h=1}^k w_{hi} z_{hi} + \epsilon_g$$

**Cell Type Weight Extra Information** 

$$Pr(Z_h^i|G_i, w_i, \mu_h, \sigma_z, \sigma_g, \sigma_\delta)$$

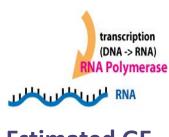
EM to infer parameters

Background Model

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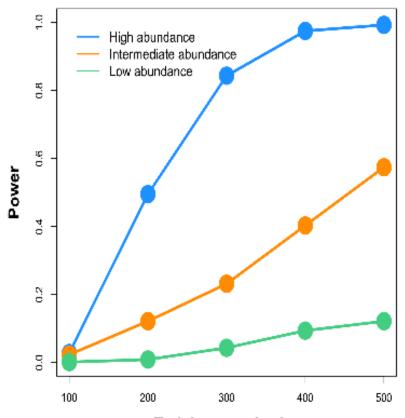
#### Is the prediction result of proposed model significant?



#### **Estimated GE**



#### Power of cell-specific expression imputation



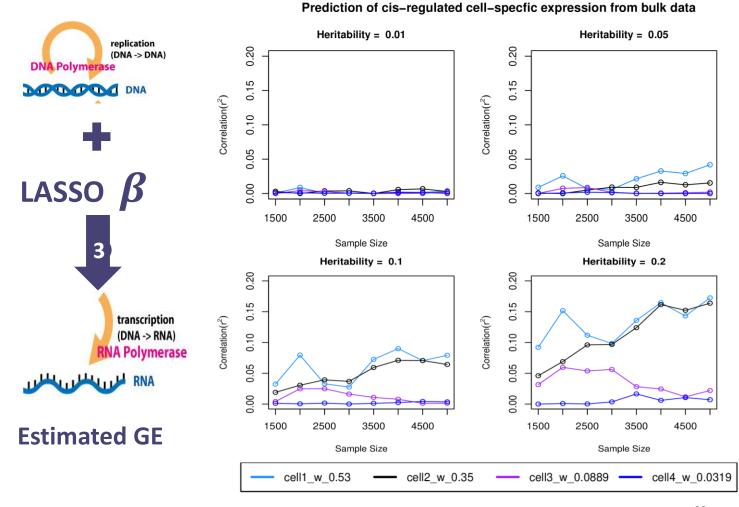
Training sample size

Power calculated as percentage of p value less than threshold Heritability 0.3, 1000 genes, 100000 sample size

Background Model Experiment

Conclusion

#### Is the model underfitting or overfitting?

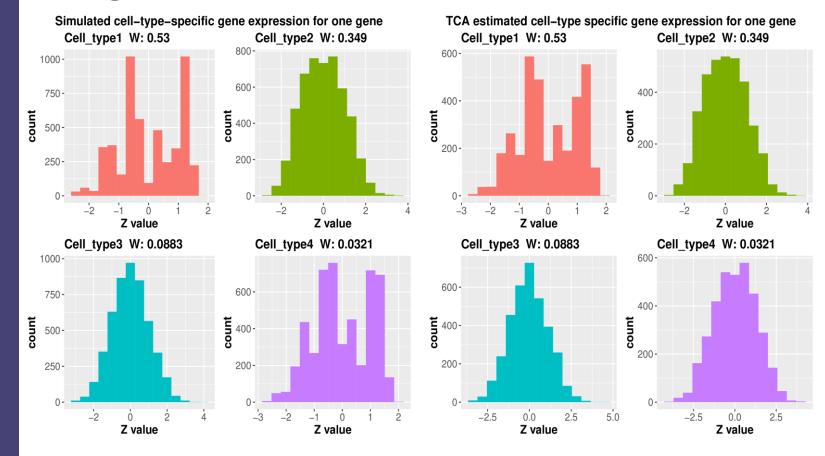


Heritability being theoretical upper bound for r^2

Background Model Experiment

Conclusion

# Could TCA recover the ground truth data distribution? Step 1



TCA recover abundant cell type distribution, but not the lesser ones

# **Simulated Data**

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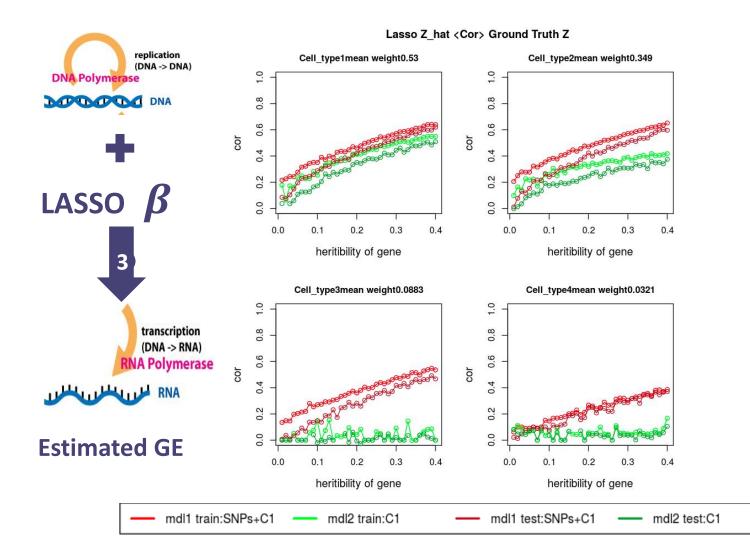
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#### Compare our modified TCA and the original TCA, which is better? Correlation of estimated SNPs effect size and the ground truth Cell\_type1 mean weight 0.53 Cell type2 mean weight 0.349 0.8 0.8 9.0 9.0 cor cor replication (DNA -> DNA) 0.4 0.4 DNA Polymerase 0.2 0.2 DNA 0.0 0.0 0.0 0.1 0.2 0.3 0.4 0.0 0.1 0.2 0.3 0.4 transcription heritibility of gene heritibility of gene (DNA -> RNA (DNA -> RNA) A Polymerase Cell\_type3 mean weight 0.0883 Cell\_type4 mean weight 0.0321 1.0 0.8 0.8 (DNA -> RNA) 9.0 9.0 co cor 0.4 0.4 0.2 0.2 LASSO B 0.0 0.2 0.3 0.4 0.0 0.1 0.2 0.3 0.4 heritibility of gene heritibility of gene TCA's beta\_hat mdl1:SNPs+C1 Lasso's beta hat mdl1:SNPs+C1 Lasso's beta hat mdl2:C1

Background Model Experiment

Conclusion

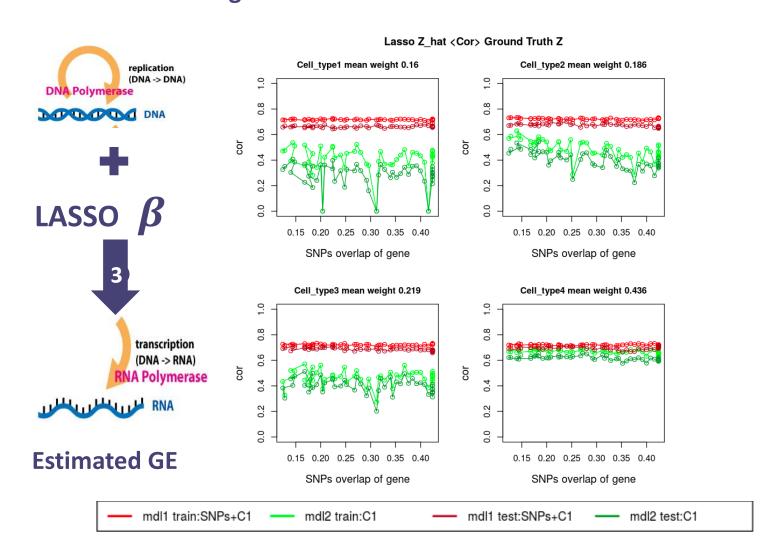
#### Compare our modified TCA and the original TCA, which is better?



Background Model Experiment

Conclusion

#### Can the model leverage other structural information inside data?



# **Dutch Dataset**

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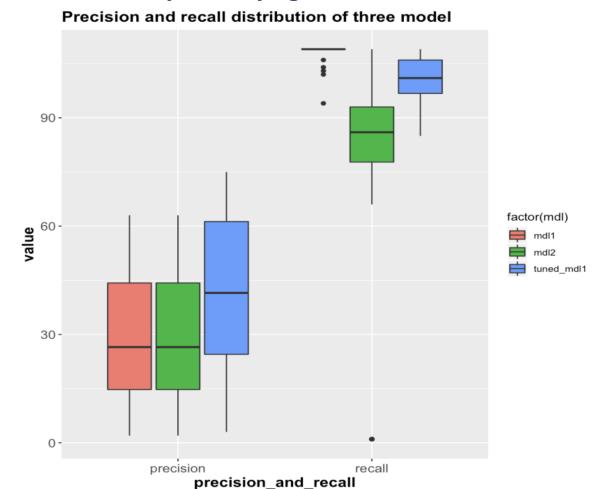
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Background Model

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#### Is the model's correctly identifying causal effects?



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## **Train Dataset: Dutch Dataset with GE**

- 5000 individuals, blood, 4 cell types
- 10201 Genes, 801501 SNPs, 10201 GE

Ancestry Pruning



LD Pruning



Missing Value Imputation



CIS-SNPs locating



**Pipeline** 

# **Target Dataset: UKBiobank Dataset without GE**

- 500,000 individuals
- SNPs, Phenotypes

## **Dutch Dataset**

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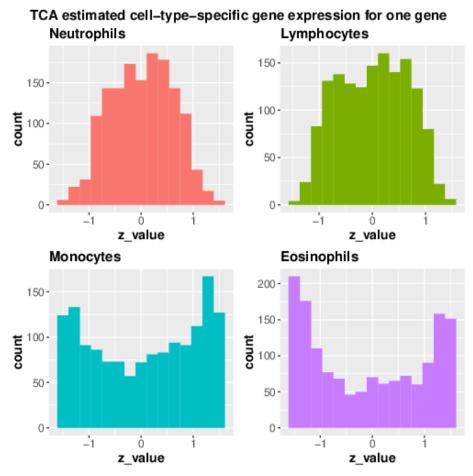
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#### Is the model's performance consistent between cell types?



TCA's estimation result fall short of normal distribution, which is the original assumption

#### **Dutch Dataset**

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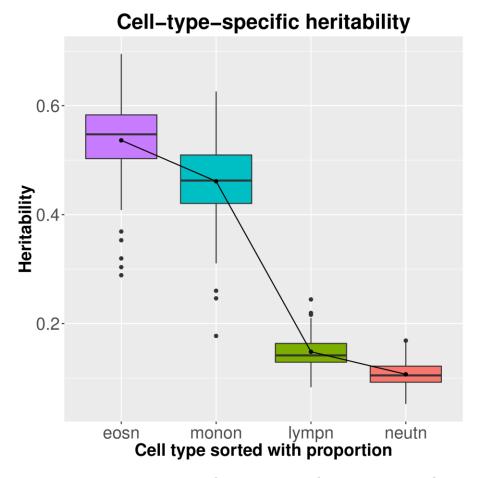
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Is the model's performance consistent between cell types?



Heritability calculated from LASSO's prediction for gene expression. Overfitting occurs for low cell types

Background Model Experiment

Conclusion

#### **Summary**

 Cell-type-specific GE can be imputed from SNPs in a relative low cost to conduct the downstream phenotype association study

# **Key Contribution**

- Incorporated genetic effects into TCA to deconvolute bulk level GE into cell-type specific ones
- Produced effect size estimators on Dutch Dataset to impute cell-type specific gene expressions on UKBiobank Dataset
- Functional R package on Cran for standard usage

#### **Future Work**

- Add sparsity constraints to TCA parameter estimates
- Utilize extra correlation structure to enhance TCA performance
- Consider batch effects when transferring effect size from train dataset to target dataset

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Q&A