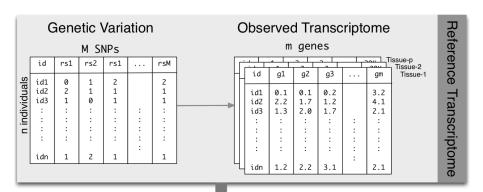
## Understanding the genetic architecture of gene expression

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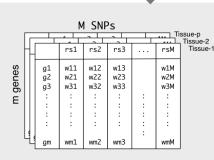
February 18, 2015

#### PrediXcan Step 1: Build and Test Predictors



#### PrediXcan Step 2: Build database of Best Predictors





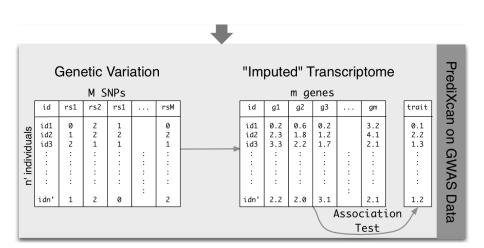
Additive model of gene expression trait trained in reference transcriptome datasets

$$T = \sum_{k} w_k X_k + \epsilon$$

$$GReX$$

Weights stored in PredictDB

# PrediXcan Step 3: Impute gene expression and test for association with phenotype



## Explore the Genetic Architecture of Transcriptome Regulation

Optimizing predictors for PrediXcan also tells us about the underlying genetic architecture of gene expression.

We can ask what proportion of genes have:

- cis vs. trans effects
- sparse vs. polygenic effects
- cross-tissue vs. tissue-specific effects

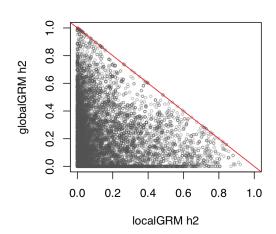
#### Primary cohort: DGN

- Battle et al. "Characterizing the genetic basis of transcriptome diversity through RNA-sequencing of 922 individuals." Genome Research 2014, 24(1):14-24
- Whole blood from Depression Genes and Networks study
- n = 922
- RNA-seq: "normalized gene-level expression data used for trans-eQTL analysis. The data was normalized using HCP (Hidden Covariates with Prior) where the parameters were optimized for detecting 'trans' trends"
- 600K genotypes: I have imputed to 1000 Genomes, but some earlier analyses were genotyped data only.

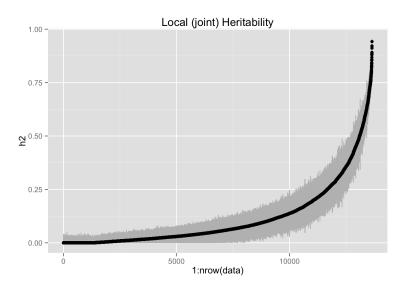
#### cis vs. trans effects

Estimate the heritability of gene expression in a joint analysis: localGRM (SNPs w/in 1Mb) + globalGRM (all SNPs)

#### **DGN-WB GCTA**

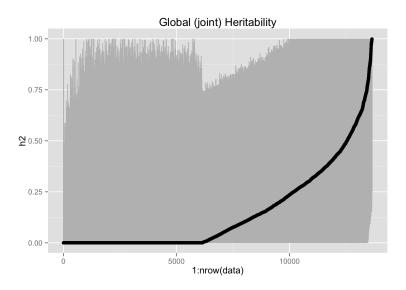


### Local (joint) sorted h<sup>2</sup> estimates with 95% CI from GCTA



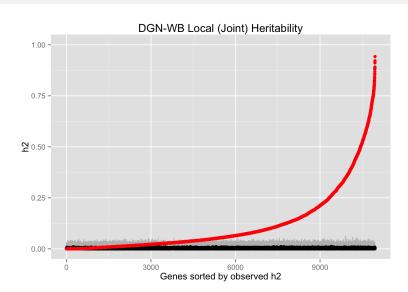
https://github.com/hwheeler01/cross-tissue/blob/master/analysis/sources/heritab\_analysis.html

### Global (joint) sorted h<sup>2</sup> estimates with 95% CI from GCTA

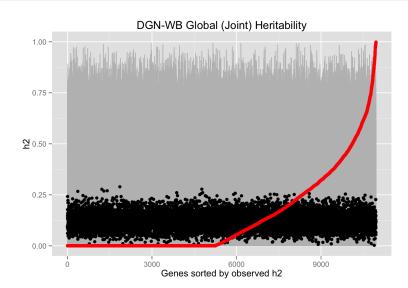


https://github.com/hwheeler01/cross-tissue/blob/master/analysis/sources/heritab\_analysis.html

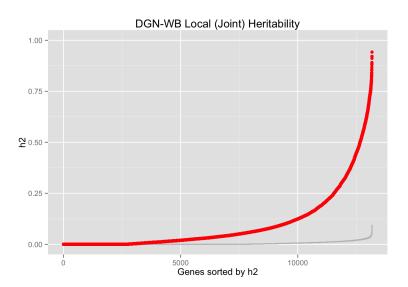
## 100 permutations to determine expected distribution of $h^2$ estimates



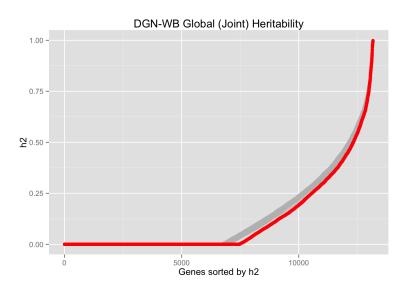
## 100 permutations to determine expected distribution of h<sup>2</sup> estimates



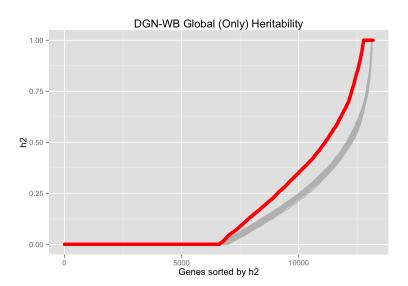
### Sort the h<sup>2</sup> from each permutation



#### Sort the h<sup>2</sup> from each permutation



### Sort the h<sup>2</sup> from each permutation



#### cis vs. trans effects

Try a larger sample to better caputure trans effects

#### Framingham Heart Study

- n = 5257
- exon expression array and genotype array

#### sparse vs. polygenic effects

glmnet solves the following problem

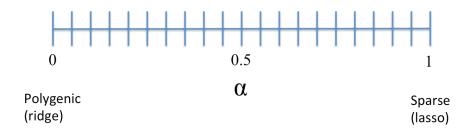
$$\min_{\beta_0,\beta} \frac{1}{N} \sum_{i=1}^{N} w_i I(y_i, \beta_0 + \beta^T x_i) + \lambda \left[ (1-\alpha) ||\beta||_2^2 / 2 + \alpha ||\beta||_1 \right],$$

over a grid of values of  $\lambda$  covering the entire range.

The elastic-net penalty is controlled by  $\alpha$ , and bridges the gap between lasso ( $\alpha=1$ , the default) and ridge ( $\alpha=0$ ). The tuning parameter  $\lambda$  controls the overall strength of the penalty.

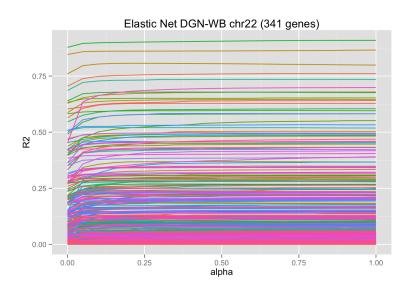
http://web.stanford.edu/~hastie/glmnet/glmnet\_alpha.html

#### sparse vs. polygenic effects



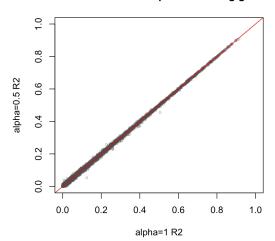
For each gene, determine  $\alpha$  with best 10-fold CV predictive performance using  $\emph{cis}$  SNPs.

### Predictive performance consistent across most alphas



## Predictive performance consistent between $\alpha{=}0.5$ and $\alpha{=}1$

#### E-N DGN-WB all 13K protein coding genes



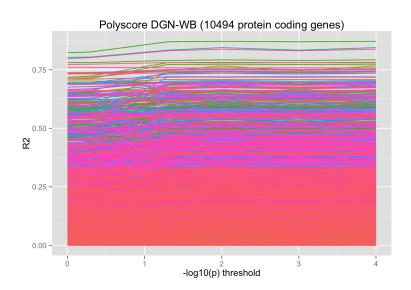
## Also tested Polyscore predictive performance using 10-fold CV

$$expression = \sum \hat{w} * gt$$

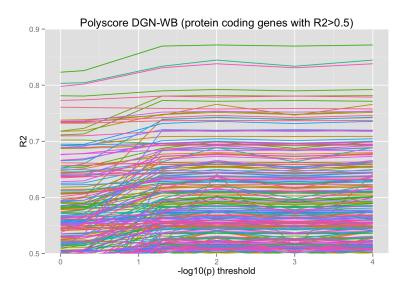
Single variant linear regression coefficients (w) at several P-value thresholds included in the additive model:

- P < 0.0001
- P < 0.001</li>
- P < 0.01</li>
- P < 0.05</li>
- P < 0.5</li>
- P < 1</li>

### Polyscore (cis SNPs only) predictive performance

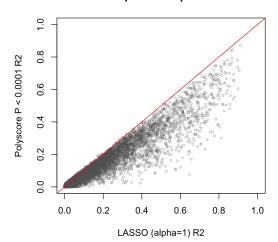


### Polyscore (cis SNPs only) predictive performance

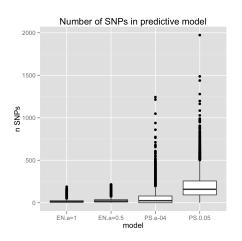


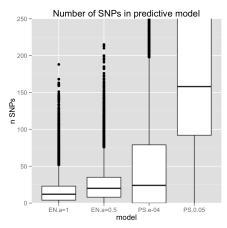
#### LASSO predicts gene expression better than Polyscore

#### **DGN-WB** predictive performance

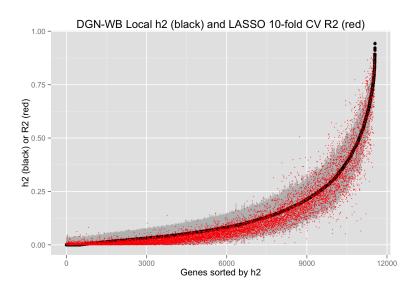


### For robustness, consider EN (alpha=0.5) for PrediXcan

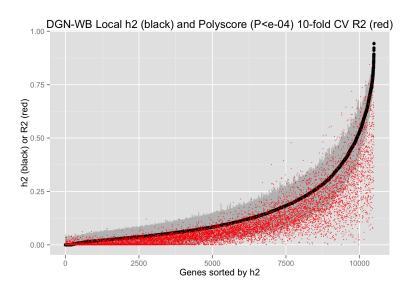




# LASSO predictive performance reaches (or exceeds?) local $h^2$ of most genes

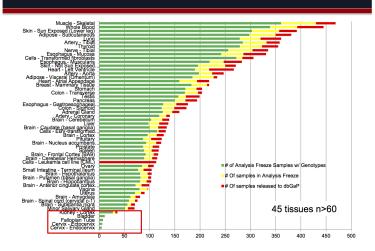


# Polyscore predictive performance does not reach local $h^2$ of many genes



#### cross-tissue vs. tissue-specific effects with GTEx

## RNA Seq Samples per tissue



#### Modeling cross-tissue expression

Linear mixed effect model using GTEx\_Data\_2014-06-13 release

- 8555 tissues across 544 subjects
- limited to ~17K protein coding genes

```
library(lme4)
fit <- lmer(expression ~ (1|SUBJID) + TISSUE
+ GENDER + PEERs)
#cross-tissue expression
fitranef <- ranef(fit)
#tissue-specific expression
fitresid <- resid(fit)
```

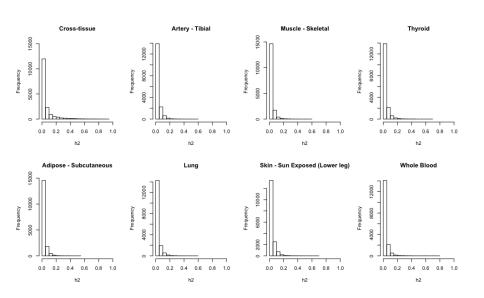
#### Estimating heritability with GCTA

Tested two genetic relationship matrix (GRM) models for each expressed gene

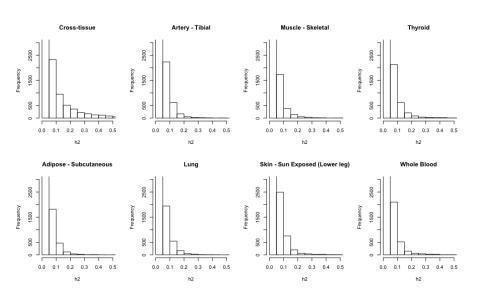
- localGRM (SNPs within 1 Mb of gene)
- localGRM + globalGRM (all SNPs)

First pass: estimated  $h^2$  of cross-tissue expression and tissue-specific expression in the 7 tissues with the most samples

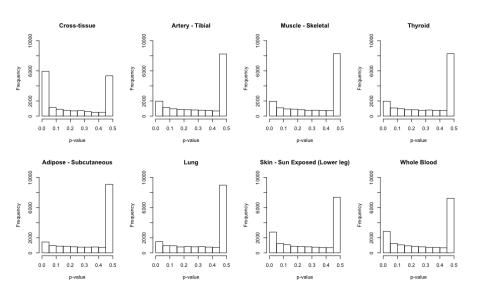
## GCTA heritability: localGRM h<sup>2</sup>



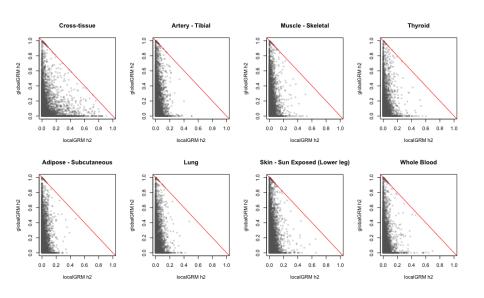
## GCTA heritability: localGRM h<sup>2</sup> **ZOOM**



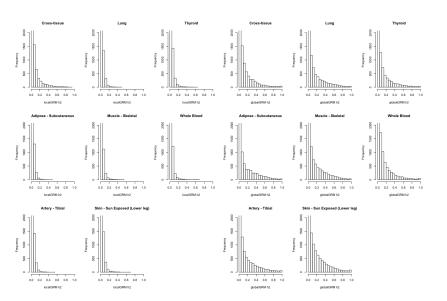
### GCTA heritability: localGRM p-values



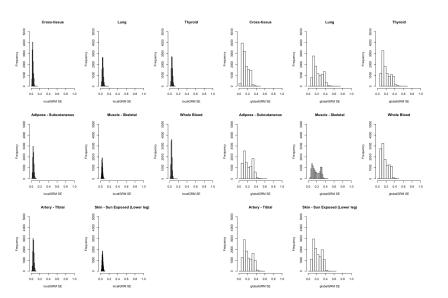
### GCTA joint heritability: localGRM + globalGRM h<sup>2</sup>



### GCTA joint heritability: localGRM + globalGRM h<sup>2</sup>



### GCTA joint heritability: localGRM + globalGRM SE



#### Summary

#### cis vs. trans effects

- *cis* effects are easily detected: 37% of DGN-WB genes have local  $h^2 > 0.1$ , 81% have local  $h^2 > 0.01$
- good estimates of trans h<sup>2</sup> will require larger n

#### sparse vs. polygenic effects

cis effects are mostly sparse (LASSO beats ridge and polyscore)

#### cross-tissue vs. tissue-specific effects

• GTEx cross-tissue local h<sup>2</sup> is greater than tissue-specific local h<sup>2</sup>