Using Stepwise Regression to Find Independent eQTLs

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Introduction

- Matrix eQTL reports many eQTLs, but not all of them are independent (i.e. two eQTLs may not explain much more variance in gene expression than just one of them)
- We can use stepwise regression methods to find independent eQTLs
- Final model: $GE = \beta_0 + \beta_1 \times SNP_1 + \beta_2 \times SNP_2 + ... + \beta_n \times SNP_n$

Methods

• Current model: $GE = \beta_0$

SNP _i	p-value of SNP _i in G	$\beta_0 + \beta_1 \times SNP_i$
rs1	0.03	
rs2	0.045	
rs3	5.4*10 ⁻⁵⁴	
rs4	0.01	

Methods

• Current model: $GE = \beta_0 + \beta_1 \times rs3$

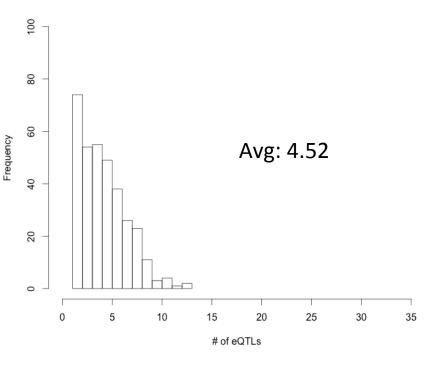
SNP _i	p-value of SNP _i in $GE = \beta_0 + \beta_1 \times rs3 + \beta_2 \times SNP_i$
rs1	0.4
rs2	0.08
rs3	
rs4	0.1

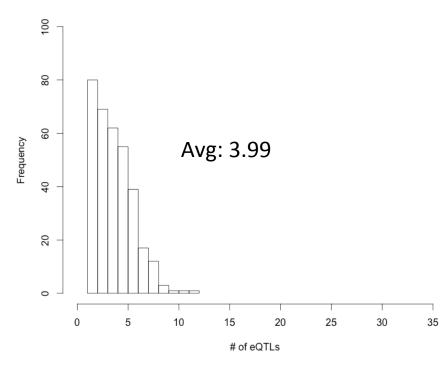
Final model: $GE = \beta_0 + \beta_1 \times rs3$

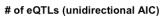
Methods

- We don't have to select by p-value; we can also select using AIC (Akaike information criterion)
- ♦ We can also remove SNPs from the model if they become insignificant upon adding another SNP, or if the AIC would decrease from removing it
- Gives a total of 4 sub-methods of performing stepwise regression

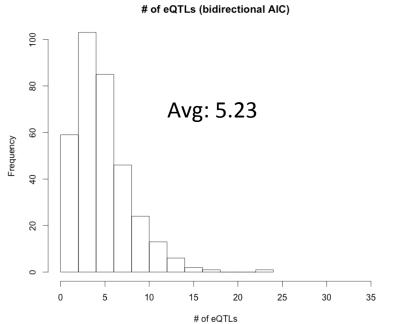
Results

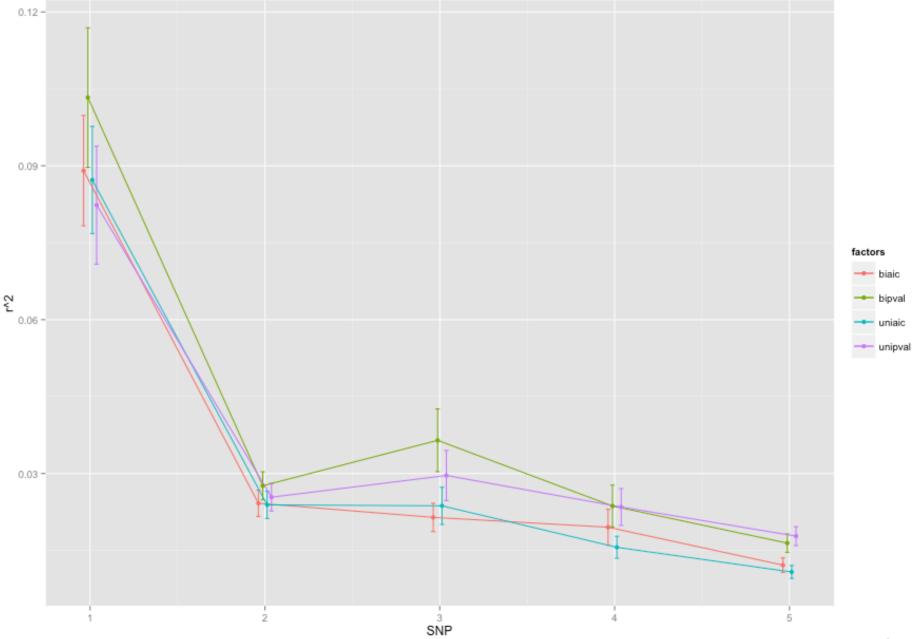




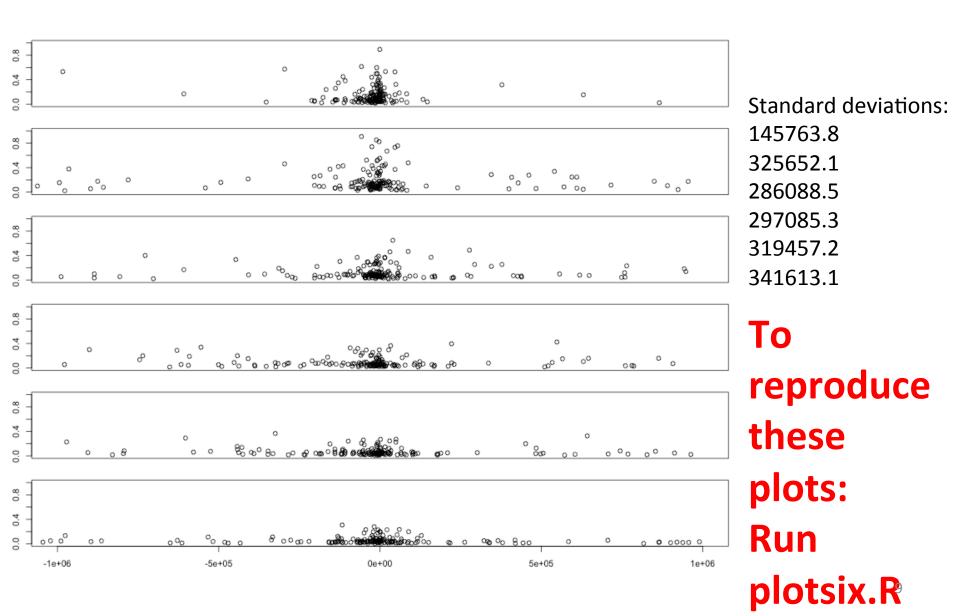


Avg: 5.53 Frequency # of eQTLs

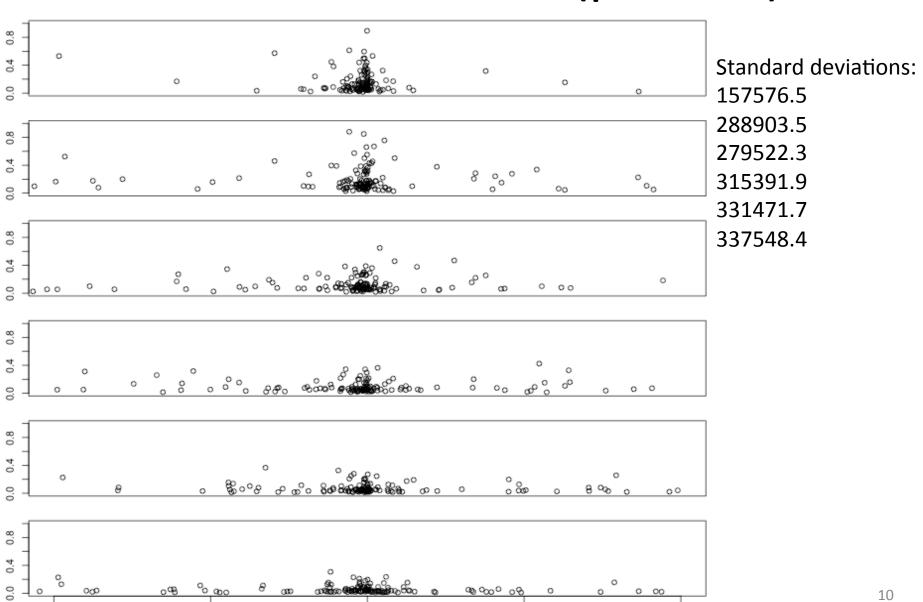




Unidirectional FSR (p-value)



Bidirectional FSR (p-value)



5e+05

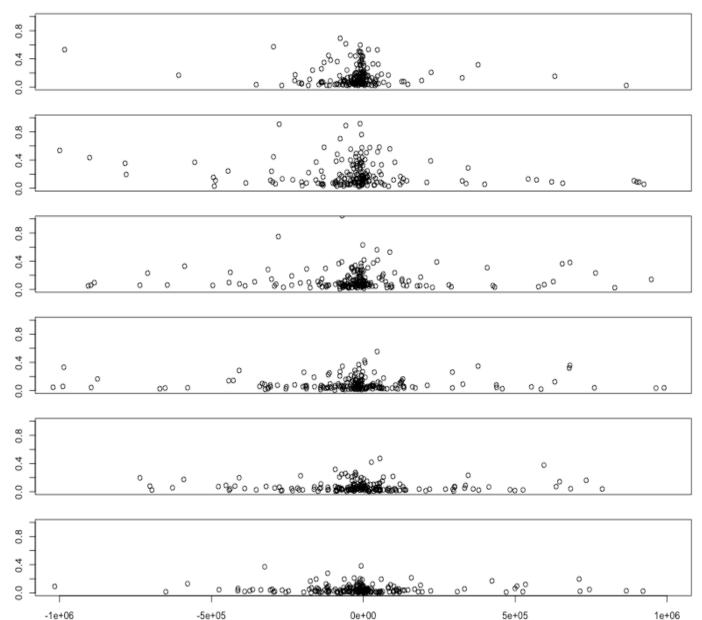
1e+06

-1e+06

-5e+05

0e+00

Unidirectional FSR (AIC)



Standard deviations:

143157.4

258628.3

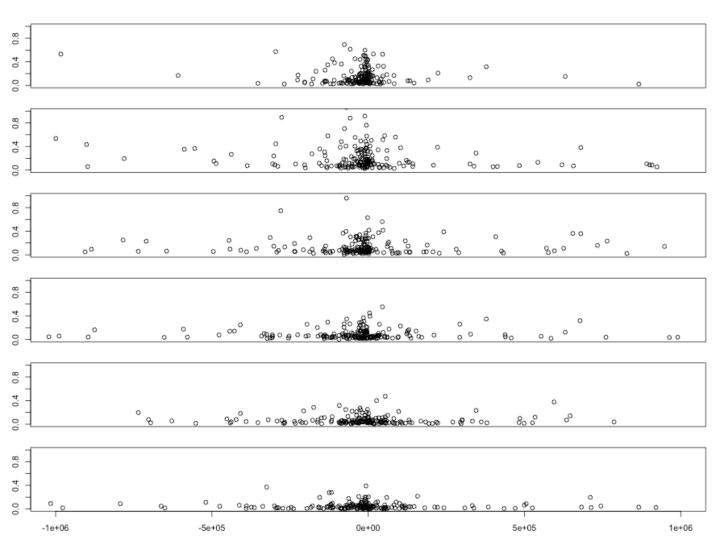
251230.1

272980.8

232340.1

227413.1

Bidirectional FSR (AIC)



Standard deviations:

144710.1

271350.3

260022.4

262815.4

225550.9

257592.3

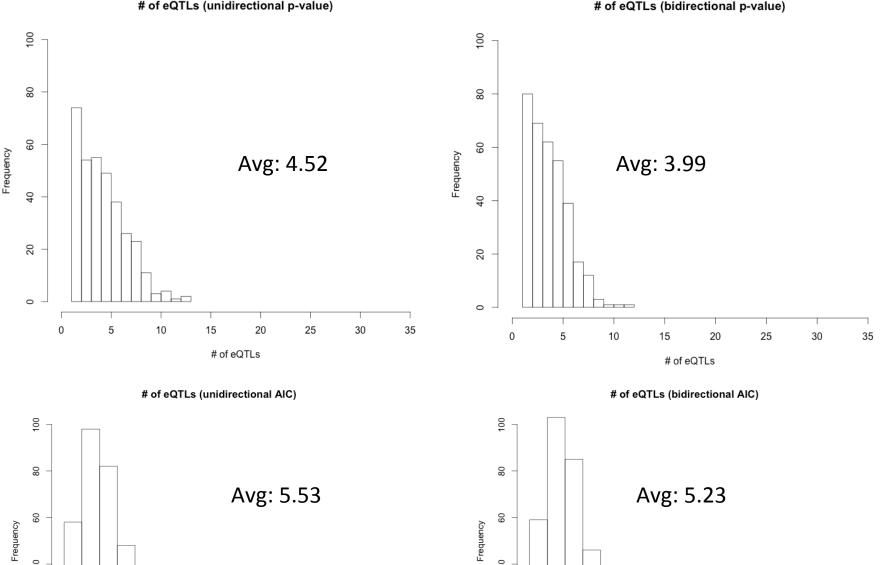
Collinearity / Linear Dependence

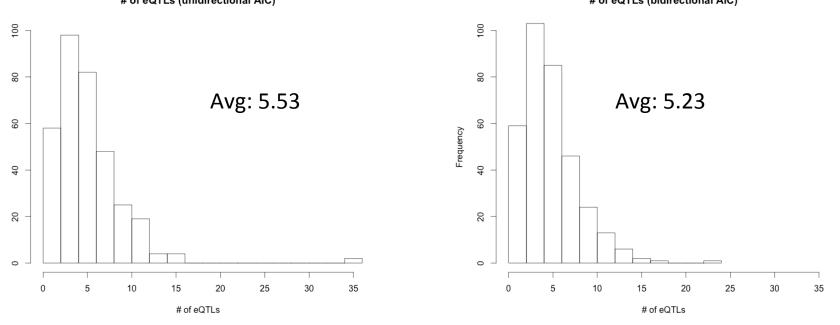
The Problem

- If 2 SNPs are perfectly collinear, or multiple SNPs are linearly dependent, it's not clear how to include them into the model.
- ♦ My scripts get rid of these collinear/linearly dependent SNPs, but they do not make an informed decision about which SNPs to keep in the model.

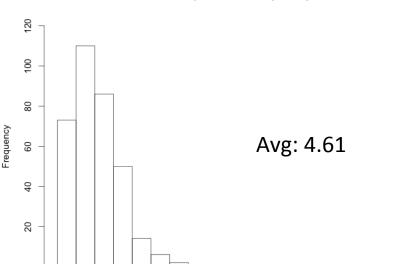
Possible Solutions

- ♦ Keep the best SNP reported by Matrix eQTL
- ♦ Assign weights to SNPs based on biological factors (e.g. distance from TSS, conservation score, DNASE I HS, etc...)



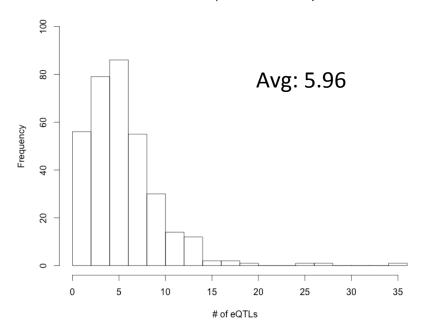




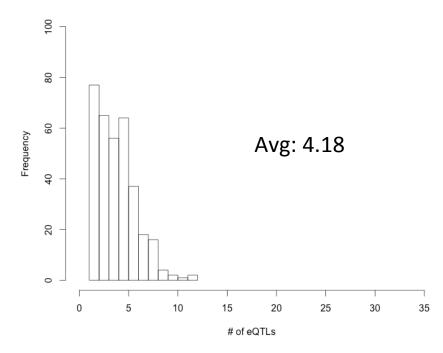


of eQTLs (unidirectional AIC)

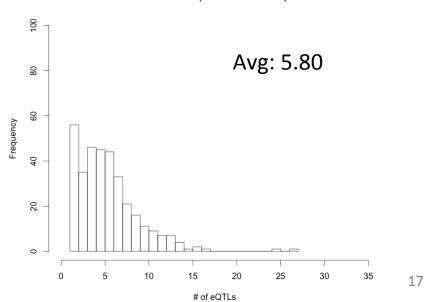
of eQTLs

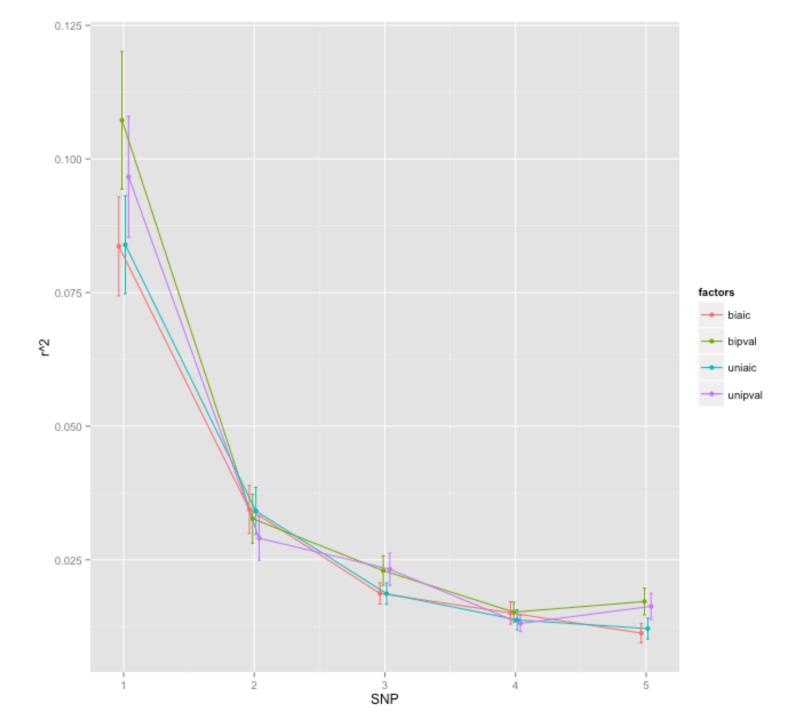


of eQTLs (bidirectional pvalue)



of eQTLs (bidirectional AIC)





Cross-validation

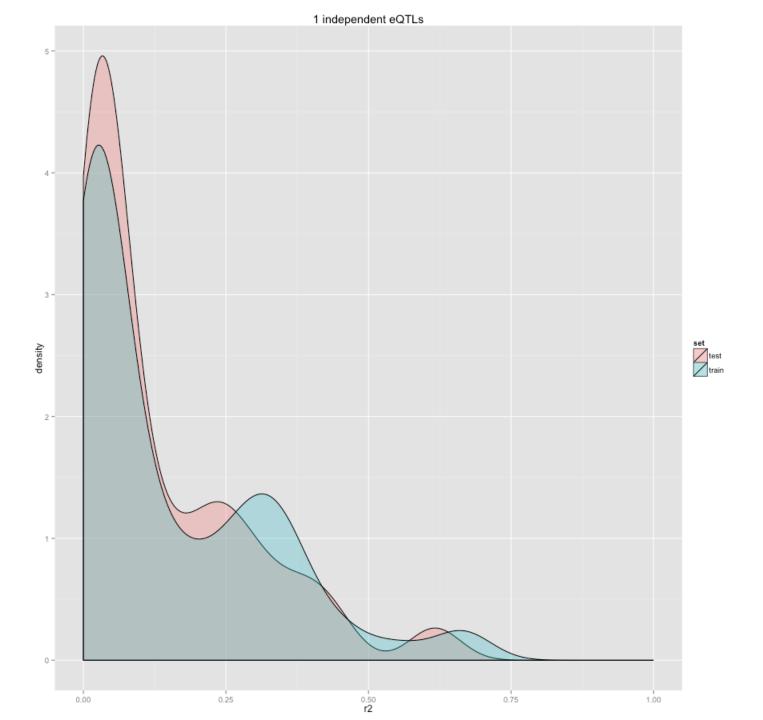
lack Average r^2 across all genes for the four methods:

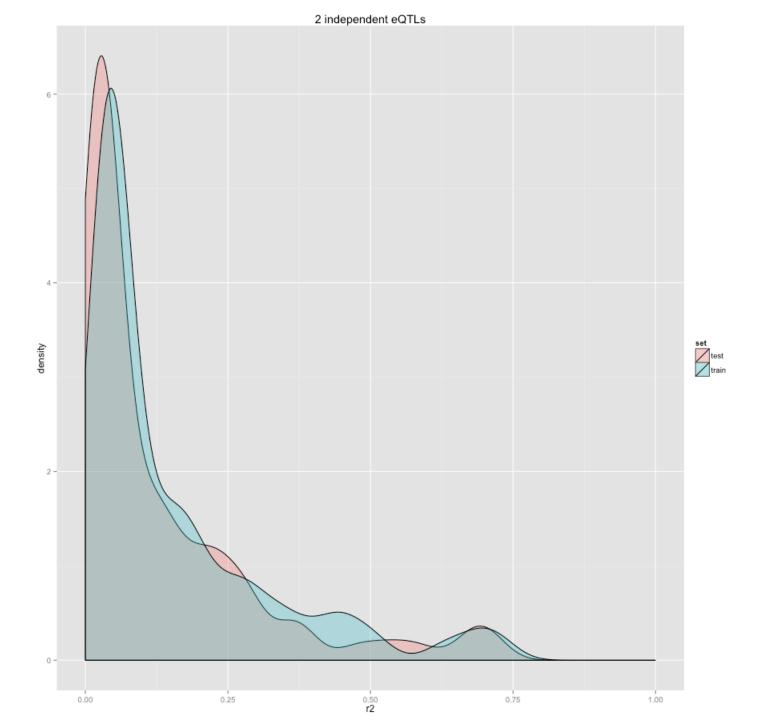
Method	Avg r ² for training set	Avg r ² for testing set
p-value unidirectional	0.174	0.115
p-value bidirectional	0.172	0.114
AIC unidirectional	0.228	0.065
AIC bidirectional	0.227	0.064

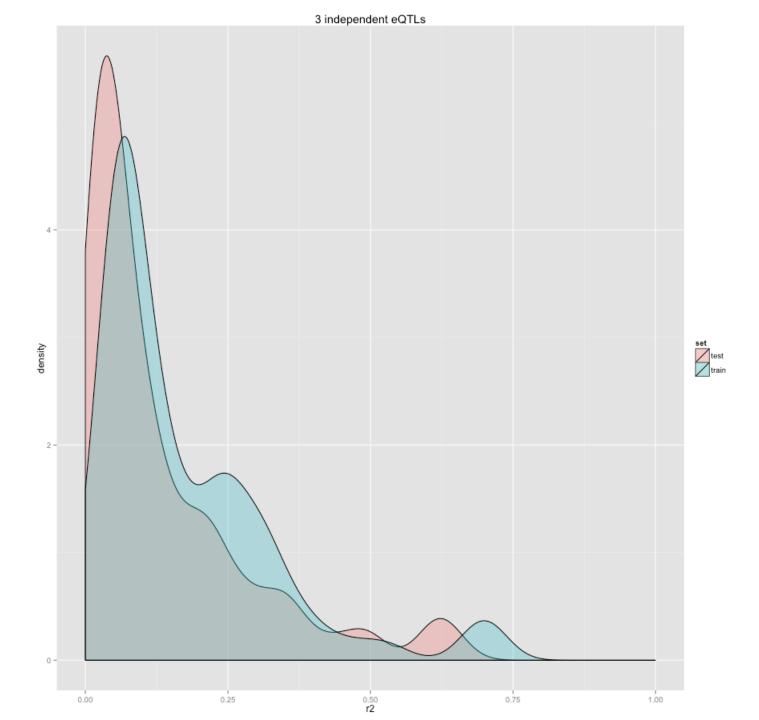
Cross-validation

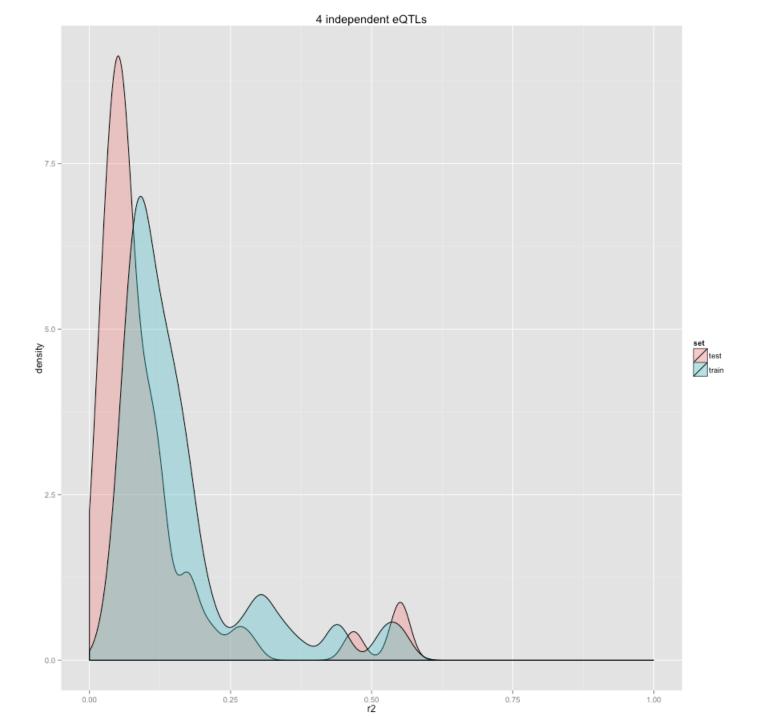
♦ Average r² across all genes for the four methods when all four methods are forced to take the same # of SNPs in the model:

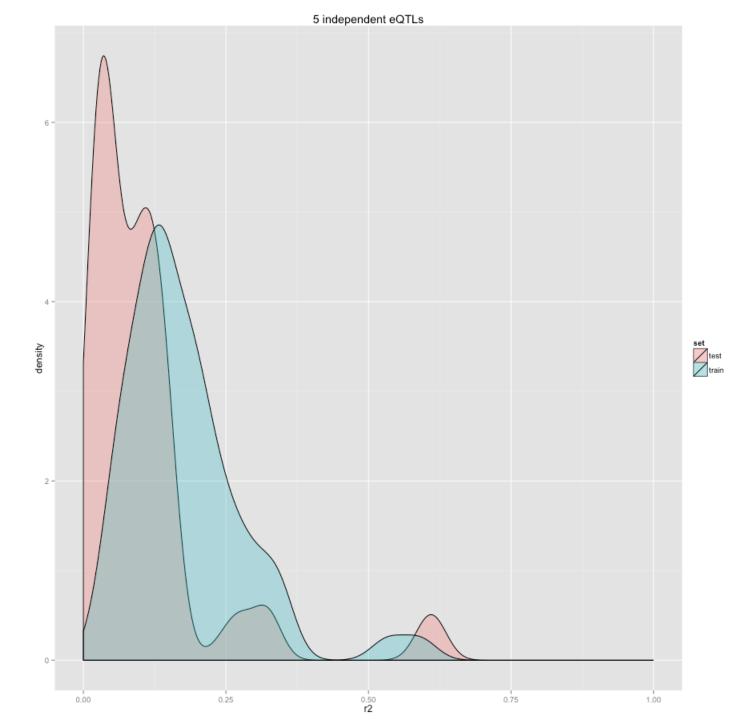
Method	Avg r ² for training set	Avg r ² for testing set
p-value unidirectional	0.171	0.118
p-value bidirectional	0.172	0.118
AIC unidirectional	0.156	0.114
AIC bidirectional	0.157	0.114

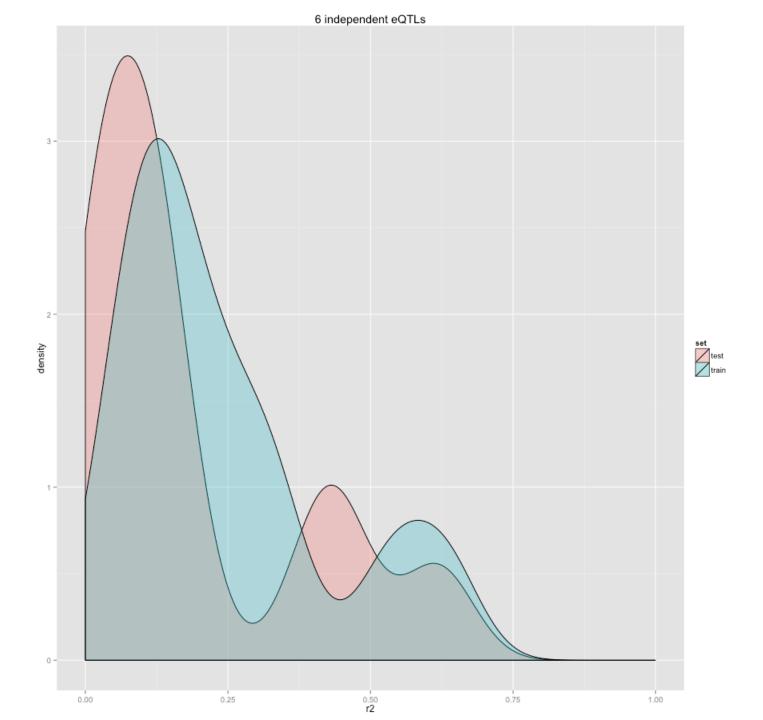


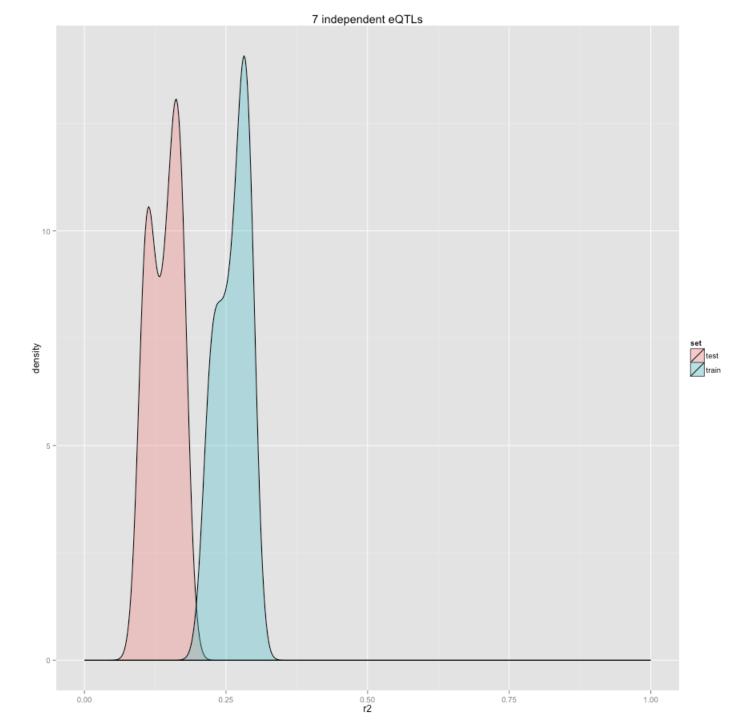


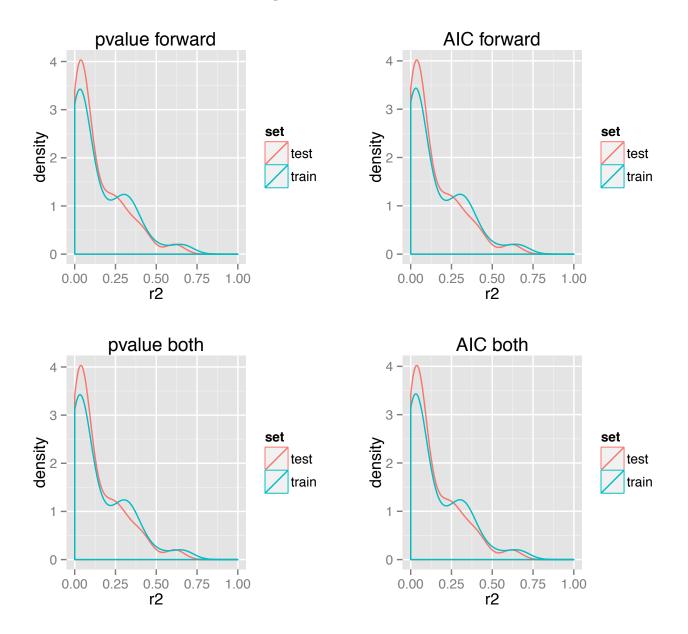


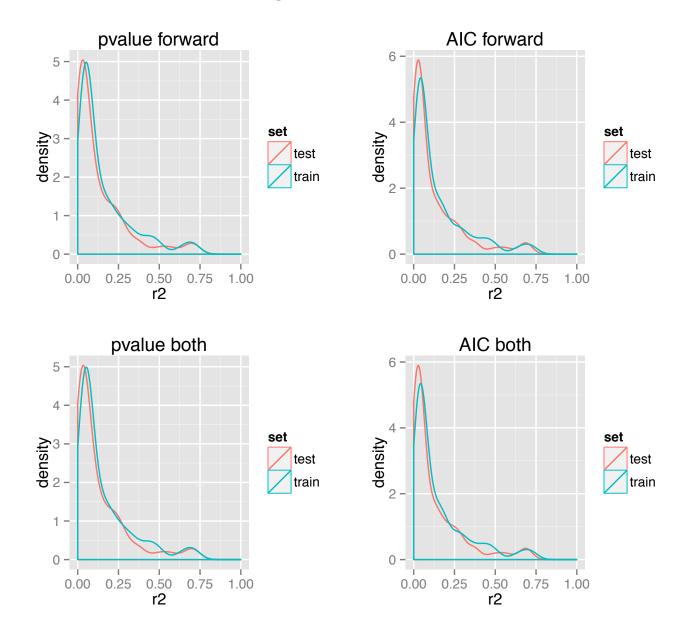


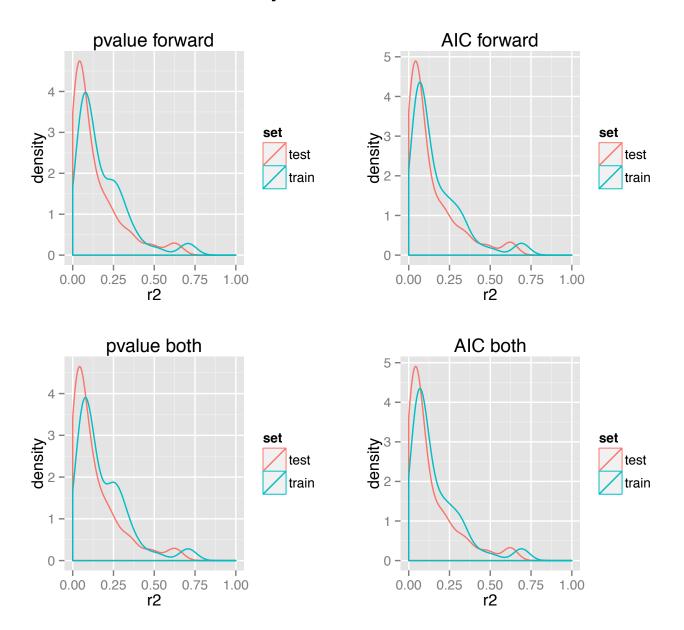


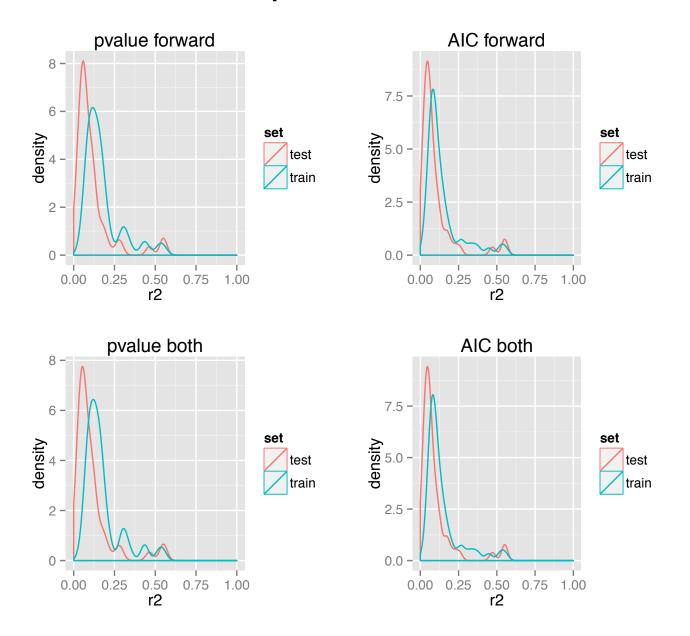


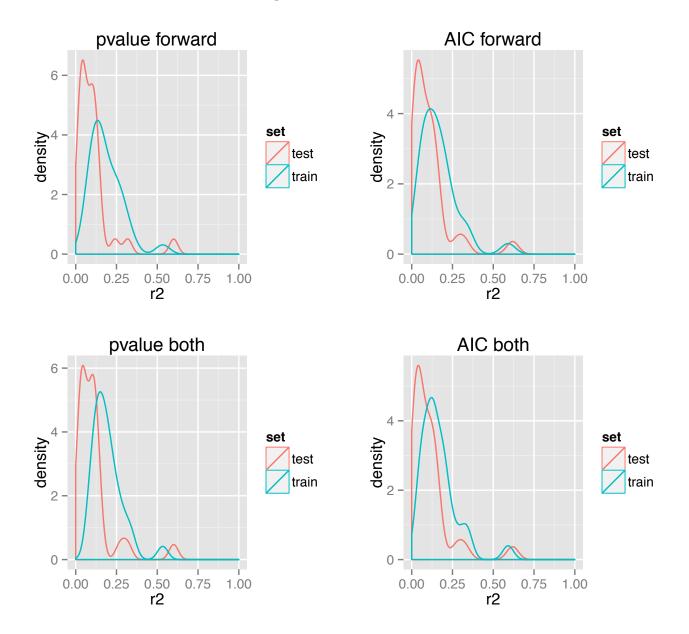


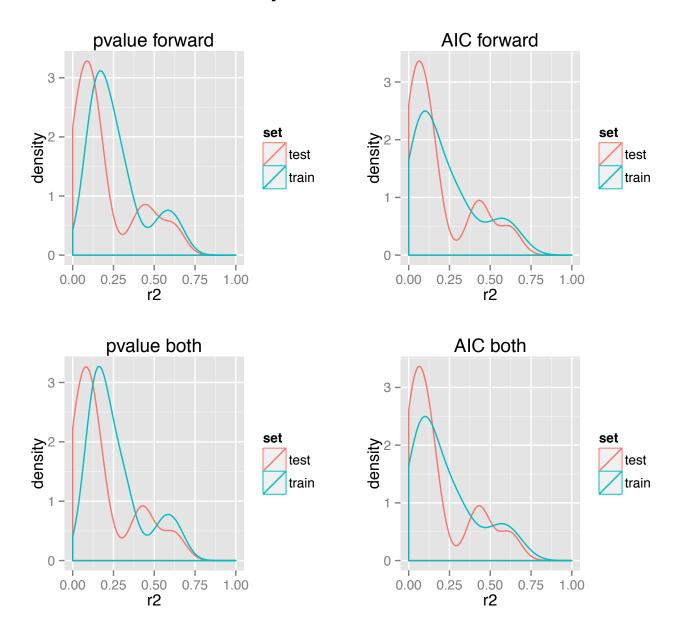


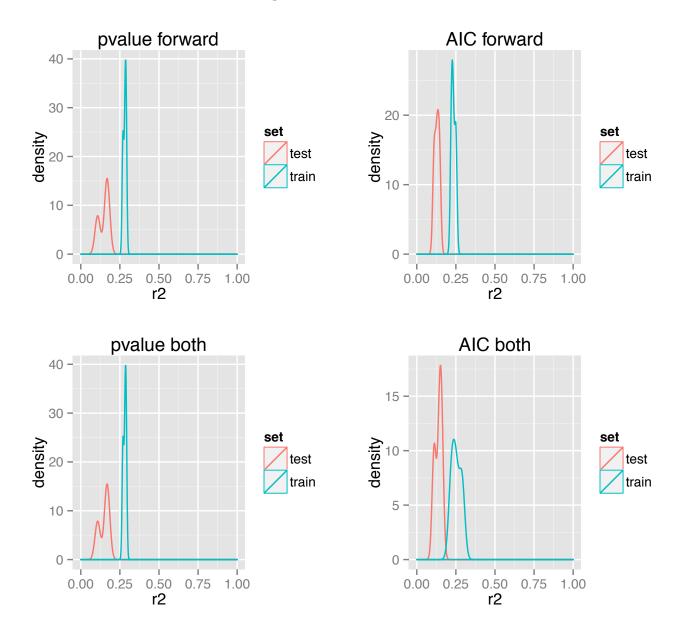












Future Directions/Questions

- ♦ Is effect size or p-value the best criterion by which to order SNPs?
- ♦ Improve the collinear/linearly dependent SNP problem
- The SNPs studied here were cis-eQTLs; do their corresponding trans-eQTLs influence the same transcriptional network?

Future Directions/Questions

▲ LASSO???

