

Variance Heterogeneity in Genetic Mapping

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ABSTRACT

Robert Wallace Corty: Variance Heterogeneity in Genetic Mapping
(Under the direction of William Valdar)

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Dedication...

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QTL	quantitative trait locus
mQTL	mean-controlling quantitative trait loci
vQTL	variance-controlling quantitative trait loci
mvQTL	mean or variance controlling quantitative trait loci
LMM	Linear Mixed Model
GLS	Generalized Least Squares
SLM	Standard Linear Model
DGLM	Double Generalized Linear Model
AYO	Add Your Own in alphabetic order. . .

CHAPTER 1

Introduction

	accommodate variance hetero- geneity	detect variance heterogeneity	handle differen- tial relatedness
LM	no	no	no
DGLM	yes	yes	no
LMM	no	no	yes
wLMM	yes	no	yes

CHAPTER 2

Genetic Mapping in Experimental Crosses with the Double Generalized Linear Model

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CHAPTER 3

Genetic Mapping in Human Cohorts with the Double Generalized Linear Model

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CHAPTER 4

The Heteroscedastic Linear Mixed Model

Whereas the previous chapters have dealt with differential relatedness obliquely, either assuming its absence or using a heuristic to correct for it, this chapter addresses it directly. The linear mixed model (LMM) [posulates] an observed phenotype, y , as the sum of four unobserved, but estimated quantities: the population mean, μ , the fixed effect deviation, $X\beta$, the genomic value, a , and the residual deviation, e .

$$y = \mu + X\beta + a + e \quad (4.1)$$

with

$$a \sim N(0, K\tau^2), \quad (4.2)$$

and

$$e \sim N(0, D\sigma^2) \quad (4.3)$$

where X is a matrix of covariates, K is a known positive semi-definite genomic similarity matrix, and D is a known diagonal residual variance matrix. Of the estimated parameters, β and μ are unconstrained, τ^2 and σ^2 are constrained to be non-negative, and a and e are constrained by their hierarchical specification (Equations 4.2 and 4.3).

This model can be useful in genetic mapping because In the context of genetic mapping, the goal is to fit this model for many different values of X ... and compare to one with no genetic in X to do LRT. The default way to do so would be to use Henderson's method each time, but this is very slow. A recent development described a matrix math trick to make this process fast when $D = I$. I first summarize that trick and then go on to describe a further trick that allows for fast fitting for any diagonal D .

This model is equivalent to:

$$\mathbf{y} \sim N(\mathbf{X}\boldsymbol{\beta}, \boldsymbol{\Sigma}) \quad (4.4)$$

where

$$\boldsymbol{\Sigma} = \mathbf{K}\tau^2 + \mathbf{D}\sigma^2 \quad (4.5)$$

This model can be reparametrized by $h^2 = \frac{\tau^2}{\tau^2 + \sigma^2}$ and $\lambda = \tau^2 + \sigma^2$, such that, after defining $\mathbf{V} = \mathbf{K}h^2 + \mathbf{D}(1 - h^2)$, it reduces to a generalized least squares (GLS) model.

$$\boldsymbol{\Sigma} = \left(\mathbf{K} \frac{\tau^2}{\tau^2 + \sigma^2} + \mathbf{D} \frac{\sigma^2}{\tau^2 + \sigma^2} \right) (\tau^2 + \sigma^2) \quad (4.6)$$

$$= \mathbf{K}h^2 + \mathbf{D}(1 - h^2)\lambda \quad (4.7)$$

$$= \mathbf{V}\lambda \quad (4.8)$$

and thus

$$\mathbf{y} \sim N(\boldsymbol{\mu} + \mathbf{X}\boldsymbol{\beta}, \mathbf{V}\lambda) \quad (4.9)$$

There is a known, closed-form, maximum likelihood estimator of $\boldsymbol{\beta}$ for the GLS model.

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T \mathbf{V}^{-1} \mathbf{X})^{-1} \mathbf{X}^T \mathbf{V}^{-1} \mathbf{y} \quad (4.10)$$

We want to do LRT, so we need to estimate maximum likelihood values for beta, sigma, and tau. Many SNPs, so need to fit it fast.

Imagine we knew of a multiplier matrix, \mathbf{M} such that

$$\mathbf{M}^T \mathbf{M} = \mathbf{V}^{-1} \quad (4.11)$$

By now considering a new phenotype vector, $\mathbf{y}_m = \mathbf{M}\mathbf{y}$ and a new covariate matrix, $\mathbf{X}_m = \mathbf{M}\mathbf{X}$, we can make progress toward fast fitting of the real phenotype vector and covariate matrix.

The expectation and variance of \mathbf{y}_m are:

$$\mathbf{E}(\mathbf{y}_m) = \mathbf{E}(\mathbf{M}\mathbf{y}) \quad (4.12)$$

$$= \mathbf{M}\mathbf{E}(\mathbf{y}) \quad (4.13)$$

$$\text{Var}(\mathbf{y}_m) = \text{Var}(\mathbf{M}\mathbf{y}) \quad (4.14)$$

$$= \mathbf{M}\text{Var}(\mathbf{y})\mathbf{M}^T \quad (4.15)$$

Recalling that We are now considering a model of the form:

Note the similarity of their log likelihoods:

$$\ell(\boldsymbol{\beta}, \sigma^2; \mathbf{X}, \mathbf{y}, \mathbf{V}) = -\frac{n}{2} \log(2\pi) - \frac{1}{2} \log |\mathbf{V}\sigma^2| - \frac{1}{2\sigma^2} (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})^T \mathbf{V}^{-1} (\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) \quad (4.16)$$

$$= -\frac{n}{2} \log(2\pi) - \frac{1}{2} \log |\mathbf{V}| - \frac{n}{2} \log \sigma^2 - \frac{1}{2\sigma^2} (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})^T \mathbf{V}^{-1} (\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) \quad (4.17)$$

$$\ell(\boldsymbol{\beta}_m, \sigma_m^2; \mathbf{X}_m, \mathbf{y}_m) = \quad (4.18)$$

4.1 Maximum Likelihood Estimation for the Homoscedastic Model

[D = I] Kang proposed the following [cite EMMA].

4.2 Maximum Likelihood Estimation for the Heteroscedastic Model

Want to have a diagonal D, but not necessarily I.

$$\mathbf{M} = (\boldsymbol{\Lambda}_L + \delta \mathbf{I})^{-\frac{1}{2}} \mathbf{U}_L^T \mathbf{D}^{-\frac{1}{2}} \quad (4.19)$$

where

$$\mathbf{L} = \mathbf{D}^{-\frac{1}{2}} \mathbf{K} \mathbf{D}^{-\frac{1}{2}} \quad (4.20)$$

and

$$\mathbf{L} = \mathbf{U}_L \mathbf{\Lambda}_L \mathbf{U}_L^T \quad (4.21)$$

is its eigen decomposition

4.2.1 Validity

To be a valid multiplier matrix, \mathbf{M} must have the property:

$$\mathbf{M}^T \mathbf{M} = \mathbf{V}^{-1}$$

Proof. First, derive a useful form of \mathbf{V} .

$\mathbf{V} = \mathbf{K} + \delta \mathbf{D}$	definition
$= \mathbf{D}^{\frac{1}{2}} \mathbf{D}^{-\frac{1}{2}} (\mathbf{K} + \delta \mathbf{D})$	pre-multiply by $\mathbf{D}^{\frac{1}{2}} \mathbf{D}^{-\frac{1}{2}} = \mathbf{I}$
$= \mathbf{D}^{\frac{1}{2}} \mathbf{D}^{-\frac{1}{2}} (\mathbf{K} + \delta \mathbf{D}) \mathbf{D}^{-\frac{1}{2}} \mathbf{D}^{\frac{1}{2}}$	post-multiply by $\mathbf{D}^{-\frac{1}{2}} \mathbf{D}^{\frac{1}{2}} = \mathbf{I}$
$= \mathbf{D}^{\frac{1}{2}} (\mathbf{D}^{-\frac{1}{2}} \mathbf{K} \mathbf{D}^{-\frac{1}{2}} + \delta \mathbf{D}^{-\frac{1}{2}} \mathbf{D} \mathbf{D}^{-\frac{1}{2}}) \mathbf{D}^{\frac{1}{2}}$	distribute $\mathbf{D}^{-\frac{1}{2}}$ in
$= \mathbf{D}^{\frac{1}{2}} (\mathbf{D}^{-\frac{1}{2}} \mathbf{K} \mathbf{D}^{-\frac{1}{2}} + \delta \mathbf{I}) \mathbf{D}^{\frac{1}{2}}$	definition of root inverse
$= \mathbf{D}^{\frac{1}{2}} (\mathbf{L} + \delta \mathbf{I}) \mathbf{D}^{\frac{1}{2}}$	define: $\mathbf{L} = \mathbf{D}^{-\frac{1}{2}} \mathbf{K} \mathbf{D}^{-\frac{1}{2}}$
$= \mathbf{D}^{\frac{1}{2}} (\mathbf{U}_L \mathbf{\Lambda}_L \mathbf{U}_L^T + \delta \mathbf{I}) \mathbf{D}^{\frac{1}{2}}$	eigen decomposition of \mathbf{L}
$= \mathbf{D}^{\frac{1}{2}} (\mathbf{U}_L \mathbf{\Lambda}_L \mathbf{U}_L^T + \delta \mathbf{U}_L \mathbf{U}_L^T) \mathbf{D}^{\frac{1}{2}}$	property of eigen vectors
$= \mathbf{D}^{\frac{1}{2}} \mathbf{U}_L (\mathbf{\Lambda}_L + \delta \mathbf{I}) \mathbf{U}_L^T \mathbf{D}^{\frac{1}{2}}$	distributive property

and invert it

$\mathbf{V}^{-1} = \left(\mathbf{D}^{\frac{1}{2}} \mathbf{U}_L (\mathbf{\Lambda}_L + \delta \mathbf{I}) \mathbf{U}_L^T \mathbf{D}^{\frac{1}{2}} \right)^{-1}$	definition
$= \left(\mathbf{D}^{\frac{1}{2}} \right)^{-1} (\mathbf{U}_L (\mathbf{\Lambda}_L + \delta \mathbf{I}) \mathbf{U}_L^T)^{-1} \left(\mathbf{D}^{\frac{1}{2}} \right)^{-1}$	inverse of product
$= \mathbf{D}^{-\frac{1}{2}} (\mathbf{U}_L (\mathbf{\Lambda}_L + \delta \mathbf{I}) \mathbf{U}_L^T)^{-1} \mathbf{D}^{-\frac{1}{2}}$	inverse of diagonal matrix
$= \mathbf{D}^{-\frac{1}{2}} \mathbf{U}_L (\mathbf{\Lambda}_L + \delta \mathbf{I})^{-1} \mathbf{U}_L^T \mathbf{D}^{-\frac{1}{2}}$	inverse of eigen decomposition

and compare to $\mathbf{M}^T \mathbf{M}$

$$\begin{aligned}
\mathbf{M}^T \mathbf{M} &= \left((\boldsymbol{\Lambda}_{\mathbf{L}} + \delta \mathbf{I})^{-\frac{1}{2}} \mathbf{U}_{\mathbf{L}}^T \mathbf{D}^{-\frac{1}{2}} \right)^T \left((\boldsymbol{\Lambda}_{\mathbf{L}} + \delta \mathbf{I})^{-\frac{1}{2}} \mathbf{U}_{\mathbf{L}}^T \mathbf{D}^{-\frac{1}{2}} \right) && \text{definition} \\
&= \left(\mathbf{D}^{-\frac{1}{2}} \mathbf{U}_{\mathbf{L}} (\boldsymbol{\Lambda}_{\mathbf{L}} + \delta \mathbf{I})^{-\frac{1}{2}} \right) \left((\boldsymbol{\Lambda}_{\mathbf{L}} + \delta \mathbf{I})^{-\frac{1}{2}} \mathbf{U}_{\mathbf{L}}^T \mathbf{D}^{-\frac{1}{2}} \right) && \text{transpose of product} \\
&= \mathbf{D}^{-\frac{1}{2}} \mathbf{U}_{\mathbf{L}} \left((\boldsymbol{\Lambda}_{\mathbf{L}} + \delta \mathbf{I})^{-\frac{1}{2}} (\boldsymbol{\Lambda}_{\mathbf{L}} + \delta \mathbf{I})^{-\frac{1}{2}} \right) \mathbf{U}_{\mathbf{L}}^T \mathbf{D}^{-\frac{1}{2}} && \text{associative property} \\
&= \mathbf{D}^{-\frac{1}{2}} \mathbf{U}_{\mathbf{L}} (\boldsymbol{\Lambda}_{\mathbf{L}} + \delta \mathbf{I})^{-1} \mathbf{U}_{\mathbf{L}}^T \mathbf{D}^{-\frac{1}{2}} && \text{definition of root inverse}
\end{aligned}$$

□

4.3 Simulation Results

4.4 Software

CHAPTER 5

Conclusion and Future Directions

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