# On the Relationships Between Population Characteristics and QTL Mapping 

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## Outline of the talk

Models

- A model for the response.
- A model for pedigrees.
- A model for the population.


## Score statistics

- Association and linkage.
- The noncentrality parameter.

Population covariance

- The noncentrality parameter in the normal case.

■ The structure of the covariance and the resulting effect.

## Genetic model for the trait

The phenotype

- $Y=$ the response in a GLM regression.
- $\theta=h(\eta)=$ the natural parameter. $\eta(\beta)=$ a linear predictor.
- $\ell(\beta)=\sum_{i=1}^{n}\left[Y_{i} \theta_{i}-\psi\left(\theta_{i}\right)\right] / \phi=$ the conditional likelihood of the sample, given the predictors.

The genotype

- $Q=$ the genotype at the investigated locus.
- $G=$ the genetic background, independent of $Q$.
- $\eta_{i}=\beta Q_{i}+z_{i}+G_{i}$, for $z$ deterministic predictors.
- The genetic predictors are correlated.
- $Q$ and $G$ share the same correlation structure.


## A model for pedigrees

The pedigree graph

- A pedigree is composed of founders and non-founders.

■ Founder gametes $=$ Independence + Hardy-Weinberg.
■ Segregation to non-founders $=$ Mendel rules.

The sample

- The sample is a sub-collection of pedigree members.
- $Y$ and $Q$ are measured over the sample. Correlation tested.

■ $\mathbb{E}\left(Q_{i} \mid \nu\right)=\mathbb{E}\left(Q_{i}\right), \operatorname{Var}\left(Q_{i}\right)=V(0)$.

- $\operatorname{Cov}\left(Q_{i}, Q_{j} \mid \nu\right)=\hat{\Phi}_{i j} V(0)$.

■ $\hat{\Phi}_{i j}=$ identity by decent (IBD) between $i$ and $j$. $\nu=$ inheritance vector.

## A population model

A coalescent tree

- The gametes of the sample coalesce to the most recent common ancestor (MRCA).
- Mutations emerge as a Poisson process over the tree.
- A mutation $=$ an ergodic transformation of $Q$.

The sample

- The sample corresponds to the leaves of the tree.
- The marginal distributions of genotypes are fixed.
- $\operatorname{Cov}\left(Q_{i}, Q_{j} \mid \mu\right)=V\left(m_{i j}\right), V(m) \downarrow 0$.
- $m_{i j}=\#\{$ mutations $\}$ between $i$ and $j$ and their MRCA.


## A population-pedigree model

The graph

- The population model describes the production of the founders' gametes.
- The pedigree graph describes the inheritance of these gametes to the sample.

The sample genotypes
Conditional on the mutation process and the inheritance vector:

$$
\begin{aligned}
\mathbb{E}\left(Q_{i} \mid \nu, \mu\right) & =\mathbb{E}\left(Q_{i}\right), \\
\operatorname{Var}\left(Q_{i} \mid \nu, \mu\right) & =V(0) \\
\mathbb{C o v}\left(Q_{i}, Q_{j} \mid \nu, \mu\right) & =\hat{\Phi}_{i j} V(0)+\left[1-\hat{\Phi}_{i j}\right] V\left(m_{f(i), f(j)}\right) \\
& =\hat{\Phi}_{i j}\left[V(0)-V\left(m_{f(i), f(j)}\right)\right]+V\left(m_{f(i), f(j)}\right) .
\end{aligned}
$$

## The likelihood function

Joint log-likelihood

$$
\ell(\beta ; Y, Q)=\log \mathbb{E}\left[e^{\ell(\beta)} \mid Y, Q\right]
$$

Association (conditional on $Y$ )

$$
\ell(\beta ; Q \mid Y)=\log \mathbb{E}\left[e^{\ell(\beta)} \mid Y, Q\right]-\log \mathbb{E}\left[e^{\ell(\beta)} \mid Y\right]
$$

Linkage (conditional on $Y$ )

$$
\ell(\beta ; \nu \mid Y)=\log \mathbb{E}\left[e^{\ell(\beta)} \mid Y, \nu\right]-\log \mathbb{E}\left[e^{\ell(\beta)} \mid Y\right]
$$

( $\nu$ can be replaced by $\mu$ or by the pair $\nu, \mu$ ).

## Score statistic for association

- Score $=$ derivative of the log-likelihood, evaluated at $\beta=0$.
- If $\beta=0$ then $(Y, G)$ and $Q$ are independent.

■ Let $\epsilon_{i}=\epsilon\left(Y_{i}, z_{i}, G_{i}\right)=\left[Y_{i}-\psi^{\prime}\left(h\left(\eta_{i}(0)\right)\right] h^{\prime}\left(\eta_{i}(0)\right) / \phi\right.$.
Then

$$
\begin{aligned}
\dot{\ell}(0 ; Q \mid Y) & =\sum_{i=1}^{n} \mathbb{E}\left(\epsilon_{i} \mid Y\right)\left\{Q_{i}-\mathbb{E}\left(Q_{i}\right)\right\} \\
& =\langle\mathbb{E}(\epsilon \mid Y), Q-\mathbb{E}(Q)\rangle
\end{aligned}
$$

and

$$
\mathbb{V} \operatorname{ar}(\dot{\ell}(0 ; Q \mid Y))=\operatorname{tr}(\mathrm{AB})
$$

for $\mathrm{A}=\operatorname{Var}(\mathbb{E}[\epsilon \mid Y]), \mathrm{B}=\mathbb{V} \operatorname{ar}(Q)$.

## Score statistic for linkage

- $\dot{\ell}(0 ; \nu \mid Y) \equiv 0$, since $\mathbb{E}(Q \mid \nu)=\mathbb{E}(Q)$.
- The local behavior of the log-likelihood is determined by the second derivative:

$$
\begin{aligned}
\ddot{\ell}\left(\beta_{0} ; \nu \mid Y\right) & =2 \sum_{i=2}^{n} \sum_{j=1}^{i-1} \mathbb{E}\left[\epsilon_{i} \epsilon_{j} \mid Y\right]\left\{\mathbb{E}\left[Q_{i} Q_{j} \mid \nu\right]-\mathbb{E}\left[Q_{i} Q_{j}\right]\right\} \\
& =\left\langle\operatorname{vec}\left(\mathbb{E}\left[\epsilon \epsilon^{\prime} \mid Y\right]\right), \operatorname{vec}(\mathbb{V} \operatorname{ar}[Q \mid \nu]-\mathbb{V a r}[Q])\right\rangle
\end{aligned}
$$

- The same argument applies to the population and the population-pedigree model when $\nu$ is replaced by $\mu$ or by $\nu$ and $\mu$, respectively.


## Statistical power

The noncentrality parameter

- The noncentrality parameter $=$ expectation of the test statistic (squared).
- A major factor in the determination of the power.
- Local alternatives + score $\Rightarrow \mathrm{ncp} \propto \operatorname{Var}(\dot{\ell}(0 ; Q \mid Y)) / n$.

Normal response

- Assume normal family, regular linear regression.
- $\operatorname{Var}(G)=\sigma_{g}^{2} \cdot \operatorname{Var}(Q)=\sigma_{g}^{2} \mathrm{~B}$.
- $\operatorname{Var}(Y)=\Sigma=\sigma_{e}^{2} \mathrm{I}+\sigma_{g}^{2} \mathrm{~B}$.
- $\mathrm{A}=\operatorname{Var}(\mathbb{E}[\epsilon \mid Y])=\Sigma^{-1}$.


## Facts about matrices

Eigenvalues

- $\lambda_{i}, 1 \leq i \leq n$, eigenvalues of B .
- B non-negative definite $\Rightarrow \lambda_{i} \geq 0$.
- $\mathrm{B}, \Sigma$ share eigenvectors $\Rightarrow \operatorname{tr}(\mathrm{AB})=\sum_{i=1}^{n}\left\{\lambda_{i} /\left[\sigma_{e}^{2}+\sigma_{g}^{2} \lambda_{i}\right]\right\}$.
- If $\mathrm{B}_{1}, \mathrm{~B}_{2}$ non-negative definite $\Rightarrow$

$$
\lambda_{i}\left(\mathrm{~B}_{1}\right) \leq \lambda_{i}\left(\mathrm{~B}_{1}+\mathrm{B}_{2}\right) \leq \lambda_{i}\left(\mathrm{~B}_{1}\right)+\lambda_{1}\left(\mathrm{~B}_{2}\right)
$$

Rank-one modifications

- $\mathrm{B}=\mathrm{B}_{0}+b b^{\prime}, \Sigma=\Sigma_{0}+\sigma_{g}^{2} b b^{\prime}$.
- $\mathrm{A}=\Sigma^{-1}, \mathrm{~A}_{0}=\Sigma_{0}^{-1}$.
- $\operatorname{tr}(\mathrm{AB})=\operatorname{tr}\left(\mathrm{A}_{0} \mathrm{~B}_{0}\right)+\left[1-\sigma_{g}^{2} b^{\prime} \mathrm{A}_{0} \mathrm{~B}_{0} \mathrm{~A}_{0} b\right] /\left[1+\sigma_{g}^{2} b^{\prime} \mathrm{A}_{0} b\right]$.


## Population covariance structure

## Covariance

- $V_{i j}=\mathrm{E}\left[V\left(m_{i j}\right)\right]=$ covariance between $i$ and $j$.
- A decreasing function of the time to the MRCA of $i$ and $j$.
- $V_{i i}=V(0)=$ the variance.

A sum of rank-one matrices

- $i$ and $j$ coalesced by time $t, h$ has not $\Rightarrow V_{i h}=V_{j h}$.
- $\tau_{t}=$ time between consecutive coalescent events.
- $v_{t}=\mathrm{E}\left[V\left(m\left(2 \sum_{j=1}^{t-1} \tau_{j}\right)\right)\right]-\mathrm{E}\left[V\left(m\left(2 \sum_{j=1}^{t} \tau_{j}\right)\right)\right]$.
- $1_{t, k}=$ indicator of a coalescent set.

■ $\mathrm{B}=\mathrm{I} \cdot v_{T}+\sum_{t=2}^{T}\left\{v_{t-1}\left[\sum_{i=1}^{K_{t}}\left(1_{t, i}\right)\left(1_{t, i}\right)^{\prime}\right]\right\}$.

## The effect of population covariance

A bound on the trace

- $\epsilon>0$, given.
- $T(\epsilon) \Leftrightarrow \sum_{t=T(\epsilon)}^{T}\left\{v_{t} \max _{1 \leq i \leq K_{t}}\left(n_{t, i}\right)\right\} \leq \epsilon$.
$\Rightarrow \operatorname{tr}(\mathrm{AB}) \leq \operatorname{rank}\left(\sum_{t=2}^{T(\epsilon)}\left\{v_{t-1}\left[\sum_{i=1}^{K_{t}}\left(1_{t, i}\right)\left(1_{t, i}\right)^{\prime}\right]\right\}\right)+\epsilon n$
Corollary
- Assume $v_{t} \leq c \tau_{t}$, for all $t$.
- For the Kingman coalescent $T=n$ and $T(\epsilon)=c \sqrt{n \log n}$.
- ncp of population model is o(1).
- ncp of population-pedigree model $=\mathrm{ncp}$ pedigree model with IBD probabilities decreased by $1-\mathrm{E}\left[V\left(m_{f(i), f(j)}\right)\right] / V(0)$.

