# The effect of missing information on gene mapping 

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## Topics

- Admixture mapping.
- The statistic and its non-centrality parameter.
- The effect of reconstruction.
- Other effects.


## Admixture mapping

- Population based (characteristics of experimental genetics): Co-segregation of

Phenotypes $=$ disease status, and

Founder origin $=$ detected by molecular markers.

- Affected only: Scanning for discrepancies from expected background levels.
- A case-random design: Scanning for discrepancies between cases and random controls.



## A random gamete



$$
\begin{aligned}
& P\left(X_{t}=1\right)=p \\
& P\left(X_{t}=0\right)=1-p
\end{aligned}
$$

## A random gamete

Denote:

$$
\begin{aligned}
X_{t} & =\text { The population source of locus } t(0 \text { or } 1) . \\
p & =\mathbb{P}\left(X_{t}=1\right), \text { for a random gamete. } \\
D, d & =\text { Two alleles of a gene linked to } t
\end{aligned}
$$

Then

$$
\begin{aligned}
p & =\overbrace{\frac{p \mathbb{P}\left(D \mid X_{t}=1\right)}{p \mathbb{P}\left(D \mid X_{t}=1\right)+(1-p) \mathbb{P}\left(D \mid X_{t}=0\right)}}^{(1)} \times \mathbb{P}(D) \\
& +\overbrace{\frac{p \mathbb{P}\left(d \mid X_{t}=1\right)}{p \mathbb{P}\left(d \mid X_{t}=1\right)+(1-p) \mathbb{P}\left(d \mid X_{t}=0\right)}}^{(2)} \times \mathbb{P}(d)
\end{aligned}
$$

## A susceptibility gene

- Terms (1) and (2) are determined by:

1. $p \Rightarrow$ History of admixture, and
2. $\mathbb{P}\left(D \mid X_{t}=i\right) \Rightarrow$ Characteristics of the founders.

- $\mathbb{P}(D)=1-\mathbb{P}(d) \Rightarrow$ The penetrance associated with the gene and the selected sampling.
- Hardy-Weinberg + multiplicative GRR $\Rightarrow$ Binomial distribution of $D$ alleles among cases and controls.


## Distribution of $X_{t}$ at a QTL

Among cases:

- $X_{t} \sim B\left(p_{\theta}, 2\right)$, where
- $\theta=\log \left(\left[p_{\theta}(1-p)\right] /\left[\left(1-p_{\theta}\right) p\right]\right)$,
- and:

$$
\frac{p_{\theta}-p}{p(1-p)}=\frac{\mathbb{P}_{\theta}(D)-\mathbb{P}(D)}{\mathbb{P}(D)(1-\mathbb{P}(D))} \times[\mathbb{P}(D \mid 1)-\mathbb{P}(D \mid 0)]
$$

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## The test statistic

- For a sample of $n$ affected: $S_{t}=\sum_{i=1}^{n} X_{i t} \sim B\left(2 n, p_{\theta}\right)$.
- Reject $\theta=0$ for a given locus $t$ if $\left|Z_{t}\right|$ is large. ( $Z_{t}=$ standardized version of $S_{t}$.)
- Consider all $t$ over the entire length of the genome.
- Significance is discounted by multiple testing.


## The non-centrality parameter

- Assume a QTL at $t$.
- Let $\xi=\mathbb{E}_{\theta}\left(Z_{t}\right)$ be the non-centrality parameter.
- Then:

$$
\begin{aligned}
\xi & =\mathbb{E}\left(Z_{t} e^{\theta S_{t}-2 n \psi(\theta)}\right) \\
& \approx \theta \mathbb{E}\left(Z_{t}\left(S_{t}-2 n \dot{\psi}(0)\right)\right) \\
& =\theta\left\{2 n(p(1-p)\}^{1 / 2}\right.
\end{aligned}
$$

Genotypes and the reconstruction of $X_{t}$

- Unfortunately, $X_{t}$ cannot be observed directly.
- Instead, one observes molecular markers.
- The distribution of markers may depends on the state of $X_{t}$.
- Consequently, one may reconstruct the state from the genotypic information.


## Genotypes



## A hidden markov model

- $X=\left\{X_{t}\right\}=$ Population origin within an individual.
- Assumed to be a stationary, reversible and continuous markov process. ( $Q=\left(q_{i j}\right)=$ transition rates.)
- Hardy-Weinberg $\Rightarrow X_{t}=X_{t}^{F}+X_{t}^{M}$, independent.
- $G=$ The genotypic information for the individual.
- If the components of $G$ are conditionally independent given $X \Rightarrow(X, G)=\mathrm{HMM}$.


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## The reconstructed scanning process

- Assume $Q_{i}$ and the conditional distributions of $G_{i}$ are known.
- $\hat{X}_{i t}=\mathbb{E}\left(X_{i t} \mid G_{i}\right)=$ the reconstructed process.
- $\mathbb{E}\left(\widehat{X}_{i t}\right)=\mathbb{E}\left(\widehat{X}_{i t}\right)=2 p$ and $\sigma_{i}^{2}=\operatorname{Var}\left(\widehat{X}_{i t}\right)$.
- $\hat{Z}_{t}=$ Scanning statistic $=\frac{\sum_{i=1}^{n}\left(\hat{X}_{i t}-2 p\right)}{\sqrt{\sum_{i=1}^{n} \sigma_{i}^{2}}}$.

The non-centrality of the reconstructed statistic

- For a QTL at $t$ :

$$
\begin{aligned}
\mathbb{E}\left(\widehat{Z}_{t}\right) & =\mathbb{E}\left(\widehat{Z}_{t} e^{\theta S_{t}-2 n \psi(\theta)}\right) \\
& \approx \theta \mathbb{E}\left(\widehat{Z}_{t}\left(S_{t}-2 n \dot{\psi}(0)\right)\right) \\
& =\xi \times \frac{\operatorname{Cov}\left(\hat{Z}_{t}, S_{t}\right)}{\left\{2 n(p(1-p)\}^{1 / 2}\right.} \\
& =\xi \times\left\{\frac{1}{n} \sum_{i=1}^{n} \frac{\sigma_{i}^{2}}{2 p(1-p)}\right\}^{1 / 2}
\end{aligned}
$$

- Note that $\sigma_{i}^{2}<2 p(1-p)$.

The reduction in non-centrality


## A basic equation

- $\mathbb{P}\left(X_{t}=i \mid G\right)=\frac{\mathbb{P}\left(X_{t}=i, G\right)}{\mathbb{P}(G)}$ : Incomplete likelihood ratio.
- From the likelihood ratio identity:

$$
\begin{aligned}
\mathbb{E}\left[\mathbb{P}\left(X_{t}=j \mid G\right) \cdot \mathbb{P}\left(X_{t}=i \mid G\right)\right] & =\mathbb{E}\left[\mathbb{P}\left(X_{t}=j \mid G\right) ; X_{t}=i\right] \\
& =\pi_{i} \mathbb{E}\left[\mathbb{P}\left(X_{t}=j \mid G\right) \mid X_{t}=i\right] .
\end{aligned}
$$

- $\pi_{i}=\mathbb{P}\left(X_{t}=i\right)$ : The stationary probability.

An asymptotic approximation of $\sigma^{2}$

- Let $j \neq i$ and consider $\widehat{\pi}_{j}=\mathbb{P}\left(X_{t}=j \mid G\right)$.
- Assume transition rates are low: $q_{i j} \rightarrow 0$.
- $G$ is relatively informative in $[t-r, t+r]$.
- $\widehat{\pi}_{j}$ small, but non-negligible, only when

1. $\left\{X_{t-r}=i, X_{t}=i, X_{t+r}=j\right\}$ or
2. $\left\{X_{t-r}=j, X_{t}=i, X_{t+r}=i\right\}$.

## An asymptotic approximation of $\sigma^{2}$ (cont.)

It follows that:

$$
\mathbb{E}\left(\widehat{\pi}_{j} \widehat{\pi}_{i}\right) \approx 2 \pi_{i} q_{i j} \mathbb{E}\left[\frac{R_{r}^{-} R_{r}^{+}}{R_{r}^{-}+R_{r}^{+}}\right]
$$

where

$$
\begin{aligned}
R_{r}^{-} & =\int_{0}^{r} e^{\ell(i, j,-s)-\ell(i, j, 0)} d s \\
R_{r}^{+} & =\int_{0}^{r} e^{\ell(i, j, s)-\ell(i, j, 0)} d s \text { and } \\
\ell(i, j, u) & =\text { conditional log-likelihoods of } G .
\end{aligned}
$$

## Analytical expressions

- Assume $\ell(i, j, u)-\ell(i, j, 0) \approx$ a Brownian motion.
- Then $1 / R_{\infty} \sim \operatorname{Gamma}\left(-2 \mu / \sigma^{2}, \sigma^{2} / 2\right)$.
- If $-\mu=\sigma^{2} / 2$ then

$$
\begin{aligned}
\mathbb{E}\left[\frac{R_{r}^{-} R_{r}^{+}}{R_{r}^{-}+R_{r}^{+}}\right] & \approx H\left(\mu_{i j}, \mu_{j i}\right) \\
& = \begin{cases}-\frac{\mu_{i j} \mu_{j i}}{\mu_{i j}-\mu_{i j}} \log \left(\mu_{i j} / \mu_{j i}\right), & \text { if } \mu_{i j} \neq \mu_{j i} \\
-\mu_{i j}, & \text { if } \mu_{i j}=\mu_{j i}\end{cases}
\end{aligned}
$$

## Analytical expressions (cont.)

For admixture mapping

- $\Delta=$ Distance between markers.
- $\mu_{i j}=\mathbb{E}\left[\left.\log \left\{\frac{\mathbb{P}\left(G_{t} \mid X_{t}=j\right.}{\mathbb{P}\left(G_{t} \mid X_{t}=i\right)}\right\} \right\rvert\, X_{t}=i\right] / \Delta$.
- $H_{i j}=H\left(\mu_{i j}, \mu_{j i}\right)$.
- $\hat{\sigma}^{2} \approx 2 p(1-p)-2\left\{(1-p)^{2} q_{01} H_{01}+p^{2} q_{21} H_{21}\right\}$.

The fit of the analytical approximation


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## Other effects:

- Covariance structure and significance level.
- Estimation of unknown parameters - both global or local.
- Robustness to modeling assumptions - Markov process, Brownian process.
- Statistic which involves sums of dependent components.

Thank you!

