## Relationship Checking

Biostatistics 666

## Last Lecture

- Multipoint analysis
- Combining information across multiple markers for linkage analysis in sib pairs
- Markov Chain framework allows efficient computation


## Ingredients of Multipoint Analysis



## The Likelihood of Marker Data

$L=\sum_{I_{1}} \sum_{I_{2}} \cdots \sum_{I_{M}} P\left(I_{1}\right) \prod_{i=2}^{M} P\left(I_{i} \mid I_{i-1}\right) \prod_{i=1}^{M} P\left(X_{i} \mid I_{i}\right)$

- General, but slow unless there are only a few markers.
- Combined with Bayes' Theorem can estimate probability of each IBD state at any marker.


## Last Lecture's Example

- Consider two loci separated by $\theta=0.1$
- Each loci has two alleles, each with frequency . 50
- If two siblings are homozygous for the first allele at both loci, what is the probability that IBD $=2$ at the first locus?


## Solution

| $\mathrm{I}_{1}$ | $\mathrm{I}_{2}$ | $\mathrm{P}\left(\mathrm{I}_{1}\right)$ | $\mathrm{P}\left(\mathrm{I}_{2} \mid \mathrm{I}_{1}\right)$ | $\mathrm{P}\left(\mathrm{X}_{1} \mid \mathrm{I}_{1}\right)$ | $\mathrm{P}\left(\mathrm{X}_{2} \mid \mathrm{I}_{2}\right)$ |  |
| :--- | :--- | ---: | ---: | ---: | ---: | ---: |
| 0 | 0 | 0.25 | 0.67 | 0.0625 | 0.0625 | $\mathbf{0 . 0 0 0 6 6}$ |
| 0 | 1 | 0.25 | 0.30 | 0.0625 | 0.125 | $\mathbf{0 . 0 0 0 5 8}$ |
| 0 | 2 | 0.25 | 0.03 | 0.0625 | 0.25 | $\mathbf{0 . 0 0 0 1 3}$ |
| 1 | 0 | 0.50 | 0.15 | 0.125 | 0.0625 | $\mathbf{0 . 0 0 0 5 8}$ |
| 1 | 1 | 0.50 | 0.70 | 0.125 | 0.125 | $\mathbf{0 . 0 0 5 5 1}$ |
| 1 | 2 | 0.50 | 0.15 | 0.125 | 0.25 | $\mathbf{0 . 0 0 2 3 1}$ |
| 2 | 0 | 0.25 | 0.03 | 0.25 | 0.0625 | $\mathbf{0}$ |
| 2 | 1 | 0.25 | 0.30 | 0.25 | 0.125 | $\mathbf{0 . 0 0 0 1 3}$ |
| 2 | 2 | 0.25 | 0.67 | 0.25 | 0.25 | $\mathbf{0 . 0 1 0 5 1}$ |

## Solution

- Taking into account all available genotype data...
- $P\left(I_{1}=2\right)=0.57$
- $P\left(I_{1}=1\right)=0.37$
$-P\left(I_{1}=0\right)=0.06$
- Considering only one marker, the corresponding probabilities would be $0.44,0.44$ and 0.11 .


## The Likelihood of Marker Data

$L=\sum_{I_{1}} \sum_{I_{2}} \cdots \sum_{I_{M}} P\left(I_{1}\right) \prod_{i=2}^{M} P\left(I_{i} \mid I_{i-1}\right) \prod_{i=1}^{M} P\left(X_{i} \mid I_{i}\right)$

- General, but slow unless there are only a few markers.
- How do we speed things up?


## A Markov Model

- Re-organize the computation slightly, to avoid evaluating nested sum directly
- Three components:
- Probability considering a single location
- Probability including left flanking markers
- Probability including right flanking markers
- Scale of computation increases linearly with number of markers


## The Likelihood of Marker Data

$$
\begin{aligned}
L & =\sum_{I_{j}} P\left(I_{j}\right) P\left(X_{j} \mid I_{j}\right) P\left(X_{1} \ldots X_{j-1} \mid I_{j}\right) P\left(X_{j+1} \ldots X_{M} \mid I_{j}\right) \\
& =\sum_{I_{j}} P\left(I_{j}\right) P\left(X_{j} \mid I_{j}\right) L_{j}\left(I_{j}\right) R_{j}\left(I_{j}\right)
\end{aligned}
$$

- A different arrangement of the same likelihood
- The nested summations are now hidden inside the $L_{j}$ and $R_{j}$ functions...


## Left-Chain Probabilities

$$
\begin{aligned}
L_{m}\left(I_{m}\right) & =P\left(X_{1}, \ldots, X_{m-1} \mid I_{m}\right) \\
& =\sum_{I_{m-1}} L_{m-1}\left(I_{m-1}\right) P\left(X_{m-1} \mid I_{m-1}\right) P\left(I_{m-1} \mid I_{m}\right) \\
L_{1}\left(I_{1}\right) & =1
\end{aligned}
$$

- Proceed one marker at a time.
- Computation cost increases linearly with number of markers.


## Right-Chain Probabilities

$$
\begin{aligned}
R_{m}\left(I_{m}\right) & =P\left(X_{m+1}, \ldots, X_{M} \mid I_{m}\right) \\
& =\sum_{I_{m+1}} R_{m+1}\left(I_{m+1}\right) P\left(X_{m+1} \mid I_{m+1}\right) P\left(I_{m+1} \mid I_{m}\right)
\end{aligned}
$$

$$
R_{M}\left(I_{M}\right)=1
$$

- Proceed one marker at a time.
- Computation cost increases linearly with number of markers.


## Pictorial Representation

- Single Marker

- Left Conditional

- Right Conditional
- FullLikelihood



## Today's Lecture

- Verifying Genetic Relationships
- Multipoint Analysis for Different Relatives
- Relationship changes transition probabilities
- Relationship changes potential IBD states
- Approaches for Relationship Checking


## Results

Our analysis of the pedigree structures by means of the genotypes generated as part of the genome scan highlighted that, in each of the ethnic groups, there were individuals identified as males that were likely to be females (and vice versa), half siblings labeled as full siblings, and pedigree members that showed no relationship to their supposed pedigree. Given that not all of the parents were available for study, it was difficult to distinguish between parental errors and blood- or DNAsample mixups. In summary, $24.4 \%$ of the families contained pedigree errors and $2.8 \%$ of the families contained errors in which an individual appeared to be unrelated to the rest of the members of the pedigree and were possibly blood-sample mixups. The percentages were consistent across all ethnic groups. In total, 212 individuals were removed from the pedigrees to eliminate these errors.

## Genomewide Search for Type 2 Diabetes Susceptibility Genes in Four American Populations

[^0]
## Verifying relationships is crucial

- Genetic analyses require relationships to be specified
- Misspecified relationships lead to tests of inappropriate size
- Inflated Type I error
- Decreased power


## Strategy:

- Information we have:
- X - observed genotypes at each marker
${ }^{-} p$ - allele frequencies at each marker
- $\theta$ - recombination fraction between consecutive markers
- $P(X \mid R)$ for each possible relationship $R$
- unrelated, half-sib, sib-pairs, MZ twins


## Likelihood

- Sum over IBD states at each location

$$
L=\sum_{I_{1}} \cdots \sum_{I_{m}} P\left(I_{1}\right) \prod_{i=2}^{m} P\left(I_{i} \mid I_{i-1}\right) \prod_{i=1}^{m} P\left(X_{i} \mid I_{i}\right)
$$

Different relationships imply

- Different $P\left(I_{1}\right)$
- Different $P\left(I_{i} \mid I_{i-1}\right)$


## Notation

- $R$

Hypothesized Relationship

- $I_{k}=\left(I_{k m}, I_{k f}\right) \quad$ Allele sharing at locus $k$
${ }^{-} X_{k}$
Genotype pair at locus $k$
$\alpha_{k}(j \mid R)=P\left(X_{1}, X_{2}, \ldots, X_{k-1}, I_{k}=j \mid R\right)$
- Joint probability of data at first $k$-1 markers and IBD vector $I_{k}=j$ at marker $k$


## Details on I

- For convenience, separate IBD=1 into maternal and paternal sharing states
- Possible inheritance patterns
- $(0,0)$ - no sharing
- $(1,0)$ - share maternal allele
${ }^{\circ}(0,1)$ - share paternal allele
- $(1,1)$ - share both alleles


## Algorithm for Likelihood Calculation

$$
\begin{aligned}
& \alpha_{1}(j \mid R)=P\left(I_{1}=j \mid R\right) \\
& \alpha_{k+1}(j \mid R)=\sum_{i} \alpha_{k}(i \mid R) P\left(X_{k} \mid I_{k}=i\right) t_{k}(i, j) \\
& L=\sum_{j} \alpha_{M}(j \mid R) P\left(X_{M} \mid I_{M}=j\right)
\end{aligned}
$$

## Relationship between I and R

- Probability of $\mathrm{I}_{1}=(0,0),(1,0),(0,1)$ and $(1,1)$ :
- MZ Twins
- Unrelated
(0, 0, 0, 1)
?
- Parent-Offspring
- Full sibs
- Maternal half sibs
- Paternal half sibs


## ?

$(1 / 4,1 / 4,1 / 4,1 / 4)$
$(1 / 2,1 / 2,0,0)$
?

## $P\left(X_{m} \mid I_{m}\right)$

| Sib | CoSib | IBD |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  |  | $(0,0)$ | $(0,1)$ or $(1,0)$ | $(1,1)$ |
| (a,b) | (c,d) | $4 \mathrm{pap}_{\mathrm{a}} \mathrm{P}_{2} \mathrm{P}_{\mathrm{c}} \mathrm{P}_{\mathrm{d}}$ | 0 | 0 |
| (a,a) | (b,c) | $2 \mathrm{pa}^{2} \mathrm{p}_{5} \mathrm{p}_{\mathrm{c}}$ | 0 | 0 |
| (a,a) | (b,b) | $\mathrm{pa}^{2} \mathrm{p}_{\mathrm{b}}{ }^{2}$ | 0 | 0 |
| (a,b) | (a,c) | $4 \mathrm{pa}^{2}{ }^{2} \mathrm{p}_{\mathrm{b}} \mathrm{P}_{\mathrm{c}}$ | $\mathrm{Pa}_{\mathrm{a}} \mathrm{Pb}_{\mathrm{b}} \mathrm{P}_{\mathrm{c}}$ | 0 |
| (a,a) | (a,b) | $2 \mathrm{pa}_{3}{ }^{3} \mathrm{~Pb}_{\text {b }}$ | $\mathrm{Pa}^{2} \mathrm{~Pb}$ | 0 |
| (a,b) | (a,b) | $4 \mathrm{pa}^{2} \mathrm{pb}_{4}{ }^{2}$ | $\left(\mathrm{papb}^{2}+\mathrm{pa}^{2}{ }^{2} \mathrm{~Pb}\right)$ | $2 \mathrm{pap}_{\mathrm{a}} \mathrm{P}_{\mathrm{b}}$ |
| (a,a) | (a,a) | $\mathrm{Pa}^{4}$ | $\mathrm{pa}^{3}$ | $\mathrm{pa}^{2}$ |

Note: Assuming unordered genotypes

## Transition Matrix $P\left(I_{i} \mid I_{i-1}\right)$ (Full Sibs)

$$
\begin{aligned}
& (0,0) \\
& (1,0) \\
& (0,1) \\
& (1,1)
\end{aligned}\left[\begin{array}{cccc}
(0,0) & (1,0) & (0,1) & (1,1) \\
(1-\psi)^{2} & (1-\psi) \psi) \psi(1-\psi) & \psi^{2} \\
(1-\psi) \psi & (1-\psi)^{2} & \psi^{2} & \psi(1-\psi) \\
(1-\psi) \psi & \psi^{2} & (1-\psi)^{2} & (1-\psi) \psi \\
(1-\psi) \psi & (1-\psi) \psi & (1-\psi)^{2}
\end{array}\right], \begin{array}{r}
r(i, j)=\left|i_{1}-j_{1}\right|+\left|i_{2}-j_{2}\right| \\
\psi=2 \theta(1-\theta)
\end{array}
$$

## Transition Matrix $P\left(I_{i} \mid I_{i-1}\right)$ (Maternal Half Sibs)

$$
\begin{aligned}
& (0,0) \\
& (1,0) \\
& (0,1) \\
& (1,1)
\end{aligned}\left[\begin{array}{cccc}
(0,0) & (1,0) & (0,1) & (1,1) \\
\psi & \psi & 0 & 0 \\
(1-\psi) & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0
\end{array}\right] .
$$

## Transition Matrix $P\left(I_{i} \mid I_{i-1}\right)$ (Paternal Half Sibs)

$$
\begin{aligned}
& (0,0) \\
& (1,0) \\
& (0,1) \\
& (1,1)
\end{aligned}\left[\begin{array}{cccc}
(0,0) & (1,0) & (0,1) & (1,1) \\
(1-\psi) & 0 & \psi & 0 \\
0 & 0 & 0 & 0 \\
\psi & 0 & (1-\psi) & 0 \\
0 & 0 & 0 & 0
\end{array}\right] \quad \begin{aligned}
& r(i, j)=\left|i_{2}-j_{2}\right| \\
& \psi=2 \theta(1-\theta) \\
& t(i, j)=\psi^{r(i, j)}(1-\psi)^{1-r(i, j)}
\end{aligned}
$$

## Transition Matrix $P\left(I_{i} \mid I_{i-1}\right)$ (Unrelated)

$\left.\begin{array}{c} \\ (0,0) \\ (1,0) \\ (0,1) \\ (1,1)\end{array} \begin{array}{cccc}(0,0) & (1,0) & (0,1) & (1,1) \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0\end{array}\right]$

## Transition Matrix $P\left(I_{i} \mid I_{i-1}\right)$ (MZ twins)

$(0,0)$
$(1,0)$
$(0,1)$
$(1,1)$
$(0,0)$
$(1,0)$
$(0,1)$
$(1,1)$
$\left[\begin{array}{l}0 \\ 0 \\ 0 \\ 0\end{array}\right.$
0
0
07

## Example I

- Consider genotypes for one marker
- Let $\mathrm{X}=(1 / 1,1 / 1)$
- Assume $\mathrm{p}_{1}=.5$
- Calculate $\mathrm{P}(\mathrm{X} \mid \mathrm{R})$ for each relationship
- MZ twin, Full Sibs, Half-Sibs, Unrelated
- How do results change with $p_{1}$ ?


## Example II

- Consider genotypes for 2 markers
- $X_{1}=(1 / 1,2 / 2)$
- $X_{2}=(1 / 1,2 / 2)$
- Assume $p_{1}=p_{2}=1 / 2$
- Assume
- $\theta=0.0528, \psi=0.10$
- $\theta=0.5000, \psi=0.50$
- Calculate $\mathrm{P}(\mathrm{X} \mid \mathrm{R})$ for each relationship


## Simulations ( $\theta=.1, M=50$ )

Inferred R
True R Full Sibs Half Sibs Unrelated

| Full Sibs | .914 | .085 | .001 |
| :--- | ---: | ---: | ---: |
| Half Sibs | .044 | .872 | .081 |
| Unrelated | $<.001$ | .059 | .941 |

## Simulations ( $\theta=.2, \mathrm{M}=50$ )

## Inferred R

| True R | Full Sibs | Half Sibs | Unrelated |
| :--- | ---: | :---: | :---: |
| Full Sibs | .948 | .052 | $<.001$ |
| Half Sibs | .038 | .899 | .064 |
| Unrelated | $<.001$ | .062 | .938 |

## Simulations ( $\theta=.1, \mathrm{M}=400$ )

## Inferred R

True R Full Sibs Half Sibs Unrelated
Full Sibs
1.000
<. 001
<. 001
Half Sibs
<. 001
1.000
<. 001
Unrelated
<. 001
<. 001
1.000

## Bayesian Approach

- Given some prior information on the expected frequency of each relative pair...
- Alternative to simply maximizing $P(X \mid R=r)$

$$
P(R=r \mid X)=\frac{\operatorname{Prior}(R) P(X \mid R=r)}{\sum_{R} \operatorname{Prior}(R) P(X \mid R)}
$$

## More distant relationships



Figure 1 Autosomal transition probabilities for grandparent-grandchild (GG), half-sib (HS), and avuncular (AV) pairs. $P\left(I_{k+1}=1 \mid I_{k}=\right.$ $0)=P\left(I_{k+1}=0 \mid I_{k}=1\right)$ is shown. Note that $P\left(I_{k+1}=0 \mid I_{k}=0\right)=1-P\left(I_{k+1}=1 \mid I_{k}=0\right)$ and $P\left(I_{k+1}=1 \mid I_{k}=1\right)=1-P\left(I_{k+1}=0 \mid I_{k}=1\right)$.

## Problem

- Consider some genome scan data
- 380 microsatellite markers
- Consider some pair of individuals
- Observed Sharing
- Identical for 379/380 genotype pairs
- $L(X \mid R=M Z$ Twins $)=0$
- $\mathrm{L}(\mathrm{X} \mid \mathrm{R}=$ Any other $)>0$


## Solution: Allow for Genotyping Errors

- Even a few errors can lead to misclassification
- If likelihood formulation ignores errors
- Need to update likelihood to allow errors
- $\varepsilon$ - error rate parameter models difference between true genotypes $G$ and observed genotypes $X$

$$
\begin{aligned}
& P\left(X_{i} \mid I_{i}\right) \\
& \quad=\sum_{G_{i}} P\left(X_{i} \mid G_{i}, \varepsilon\right) P\left(G_{i} \mid I_{i}\right) \\
& \quad=(1-\varepsilon)^{2} P\left(G_{i} \mid I_{i}\right)+\left[1-(1-\varepsilon)^{2}\right] P\left(X_{i 1}\right) P\left(X_{i 2}\right)
\end{aligned}
$$

## Conclusions

- Likelihood approach provides reliable manner to infer relationships
- Can incorporate multiple linked markers
- Some distant relationships can only be discerned by likelihood approach


## Alternative Strategy I: Mendelian Inconsistencies

- Verify that observed genotypes are compatible with Mendelian segregation
- Common checks:
- Does each putative offspring get one allele from each parent?
- Is the set of genotypes in a putative sibship compatible?


## Mendelian Checks

- If many markers exhibit incompatibilities, there may be a pedigree problem.
- Requires informative markers and relatively complete pedigrees
- With only a sibling pair, any genotype pair fits
- With bi-allelic markers, all genotypes fit any sibship
- Does not pinpoint source of error or suggest correct relationship


## Alternative Strategy II: Allele Sharing Methods

- Summarize IBS sharing across all available markers
- Compare observed values for each pair to expected values
- Expectations derived by examining other pairs with the same putative relationship


## IBS Sharing Scores

- $S_{k}$ - IBS score $(0,1,2)$ for marker $k$

$$
\bar{S}=\frac{\sum_{k} S_{k}}{n_{\text {markers }}}
$$

$$
s^{2}=\frac{\sum_{k}\left(S_{k}-\bar{S}\right)^{2}}{n_{\text {markers }}-1}
$$

## Could construct a Z-score

- Comparing observed IBS score to expected values within class of relatives

$$
Z=\frac{\bar{S}-E(\bar{S} \mid R)}{\sqrt{\operatorname{Var}(\bar{S} \mid R)}}
$$

## Example...

- ~800 marker genome scan
- Calculated IBS for each set of putative relationships...
- Unrelated pairs
- Sibling pairs
- Parent-offspring pairs


## Putative Unrelated Pairs

IBS for Putative Unrelated Pairs


## Parent-Offspring Pairs

IBS for Putative Parent Offspring Pairs


## Putative Sibling Pairs

IBS for Putative Sib Pairs


## Problem Individuals Are Outliers

IBS for Putative Sib Pairs


Circled pairs are likely misclassified

## Additional Information in Variance of IBS Sharing



## Additional Information in Variance of IBS Sharing


(V Parent-Offspring

| Load...... |
| :---: |
| Print... |
| Options... |
| About... |
| Quit |

## Problems with IBS Scores

- Inefficient
- Ignore information on allele frequencies
- Ignore correlations between neighboring markers
- ... not too bad if large amounts of data available
- Cannot distinguish some types of relatives


## Recommended Reading

- Boehnke and Cox (1997) Am J Hum Genet 61:423-429
- Optional
- Broman and Weber (1998), AJHG 63:1563-4
${ }^{-}$McPeek and Sun (2000), AJHG 66:1076-94
- Epstein et al. (2000), AJHG 67:1219-31


[^0]:    Margaret Gelder Ehm, ${ }^{1}$ Maha C. Karnoub, ${ }^{1}$ Hakan Sakul, ${ }^{2, *}$ Kirby Gottschalk, Donald C. Holt, ${ }^{1}$ James L. Weber, ${ }^{3}$ David Vaske, ${ }^{3,+}$ David Briley, ${ }^{1}$ Linda Briley, ${ }^{1}$ Jan Kopf, ${ }^{1}$ Patrick McMillen, ${ }^{1}$ Quan Nguyen, ${ }^{1}$ Melanie Reisman, ${ }^{1}$ Eric H. Lai, ${ }^{1}$ Geoff Joslyn, ${ }^{2,4}$ Nancy S. Shepherd, ${ }^{\text { }}$ Callum Bell, ${ }^{2,5}$ Michael J. Wagner, ${ }^{1}$ Daniel K. Burns, ${ }^{1}$ and the American Diabetes Association GENNID Study Group

