# Affected Sibling Pairs 

Biostatistics 666

## Today ...

- Discussion of linkage analysis using affected sibling pairs
- Our exploration will include several components we have seen before:
- A simple disease model
- IBD sharing probabilities
- Maximum likelihood
- The E-M algorithm
- A Hidden Markov model
- Linkage analysis with sibling pairs using Risch's Maximum LOD Score (MLS)
- Distribution of IBD in affected sibling pairs and Holman's "Possible Triangle Constraint"


## Examplar Linkage Study

- Concannon et al (1998) Nature Genetics, 19:292-296
- Affected sibling pair study of type 1 diabetes
- Chronic disease affecting ~1 in 250 children
- 292 affected sibpairs for initial screen
- 467 affected sibpairs for follow-up
- Highest LOD score reaches 34.2 near HLA on chr. 6
- At this locus, chromosomes carried by affected sibs are identical in $73 \%$ of pairs.


## Examplar Linkage Study Results



Concannon et al (1998) Nature Genetics, 19:292-296

## Single Locus Disease Model

- Allele frequencies $p$ and (1-p)
- Penetrances $f_{11,} f_{12}, f_{22}$
- Useful in exploring behavior of linkage and association tests
- We used similar constructs to explore genetic association test power
- Simplification of reality, ignores other loci and the environment


## Using Penetrances

- Allele frequency $p$
- Genotype penetrances $f_{11}, f_{12}, f_{22}$
- Prevalence
- K =
- Probability of genotype given disease
- $P(G=i j \mid D)=$


## Pairs of Individuals

- A genetic model can predict probability of sampling different affected relative pairs
- We will first consider some simple cases:
- Unrelated individuals
- Parent-offspring pairs
- Monozygotic twins
- How much genetic material do these pairs share IBD?


## Unrelated Individuals

- Probability of affected pair of unrelateds

$$
\begin{aligned}
P(a \text { and } b \text { affected }) & =\mathrm{P}(a \text { affected }) \mathrm{P}(b \text { affected }) \\
& =\mathrm{P}(\text { affected })^{2} \\
& =\left[p^{2} f_{11}+2 p(1-p) f_{12}+(1-p)^{2} f_{22}\right]^{2} \\
& =K^{2}
\end{aligned}
$$

- For related individuals, probability that both affected is greater or equal


## Monozygotic Twins

- Probability of affected pair of identical twins

$$
\begin{aligned}
P(M Z \text { pair affected }) & =\sum_{G} P(G) P(a \text { affected } \mid G) P(b \text { affected } \mid G) \\
& =p^{2} f_{11}^{2}+2 p(1-p) f_{12}^{2}+(1-p)^{2} f_{22}^{2} \\
& =K_{M Z} K \\
& =\lambda_{M Z} K^{2}
\end{aligned}
$$

- $\mathrm{K}_{\mathrm{MZ}}$ is prevalence among MZ twins of an affected individual
- It is always greater than or equal to $K$
- $\lambda_{M Z}=K_{M Z} / K$ is the increase in risk for $M Z$ twins of an affected individual
- For any single locus disease model, it is always greater than 1


## Parent Offspring Pairs

- Probability of affected parent-offspring pair

$$
\begin{aligned}
P & =P(\text { parent and child affected }) \\
& =\sum_{G_{\mathrm{p}}} \sum_{G_{o}} P\left(G_{p}, G_{o}\right) f_{G_{p}} f_{G_{o}} \\
& =\sum_{i} \sum_{j} \sum_{k} P(i, j, k) f_{i j} f_{i k} \\
& =p^{3} f_{11}^{2}+(1-p)^{3} f_{22}^{2}+p(1-p) f_{12}^{2}+2 p^{2}(1-p) f_{11} f_{12}+2 p(1-p)^{2} f_{22} f_{12} \\
& =K_{o} K \\
& =\lambda_{o} K^{2}
\end{aligned}
$$

- $K_{\mathrm{o}}$ is the prevalence among offspring of an affected individual
- $\lambda_{\mathrm{o}}$ is the increase in risk for offspring of affected individuals, between 1 and $\lambda_{\mathrm{MZ}}$


## Point of Situation

- Probabilities of affected pairs for
- Unrelated Individuals
- Monozygotic Twins
- Parent-Offspring Pairs
- Prevalences $K_{M Z}$ and $K_{O}$ among twins and offspring of affected individuals
- Relative risks $\lambda_{\mathrm{MZ}}$ and $\lambda_{\mathrm{O}}$ summarizing changes in risk
- How to predict $K_{R}$ and $\lambda_{R}$ for other types of relatives?


## Recurrence Risks vs IBD

$$
\begin{aligned}
& \lambda_{I B D=2}=\lambda_{M Z}=\frac{P(\text { affected } \mid I B D=2 \text { with affected relative })}{P(\text { affected })} \\
& \lambda_{I B D=1}=\lambda_{O}=\frac{P(\text { affected } \mid I B D=1 \text { with affected relative })}{P(\text { affected })} \\
& \lambda_{I B D=0}=1=\frac{P(\text { affected } \mid I B D=0 \text { with affected relative })}{P(\text { affected })}
\end{aligned}
$$

## Affected Half-Siblings

- IBD sharing
- 0 alleles with probability 50\%
- 1 allele with probability 50\%
- This gives ...

$$
\begin{gathered}
\lambda_{H}=1 / 2 \lambda_{O}+1 / 2=1 / 2\left(\lambda_{O}+1\right) \\
K_{H}=1 / 2 K_{O}+1 / 2 K=1 / 2\left(K_{O}+K\right)
\end{gathered}
$$

## Affected Sibpairs

- IBD sharing ...
- 0 alleles with probability $25 \%$
- 1 alleles with probability $50 \%$
- 2 alleles with probability $25 \%$
- This gives ...

$$
\lambda_{S}=1 / 4 \lambda_{M Z}+1 / 2 \lambda_{O}+1 / 4=1 / 4\left(\lambda_{M Z}+2 \lambda_{O}+1\right)
$$

## What does this have to do with linkage analysis?

- For a single locus model...
- Siblings with IBD=0 are like unrelateds
- Siblings with IBD=1 are like parent offspring pairs
- Siblings with IBD=2 are like identical twins
- The genetic model parameters and the relative risks they imply allow us to calculate expected IBD probabilities at a disease locus ...
-... and compare these to null expectations where $z_{0}=1 / 4, z_{1}=1 / 2, z_{2}=1 / 4$

Expected IBD sharing among affected siblings... (at the disease locus!)

$$
\begin{aligned}
& \mathrm{z}_{0}=0.25 \frac{1}{\lambda_{s}} \\
& \mathrm{z}_{1}=0.50 \frac{\lambda_{o}}{\lambda_{s}} \\
& \mathrm{z}_{2}=0.25 \frac{\lambda_{\mathrm{MZ}}}{\lambda_{\mathrm{s}}}
\end{aligned}
$$

$1 \leq \lambda_{o} \leq \lambda_{s} \leq \lambda_{M Z}$ for any genetic model

## Possible Triangle



## Possible Triangle



## Intuition: Affected Sibpair Linkage Analyses

- Consider affected sibling pairs
- Consider one genetic marker at a time
- Are paired genotypes more similar than expected?



## Likelihood Based Linkage Test

- Depends on three parameters $\mathrm{z}_{0}, \mathrm{z}_{1}, \mathrm{z}_{2}$
- Probability of sharing 0,1 and 2 alleles IBD
- Null likelihood uses $z_{0}=1 / 4, z_{1}=1 / 2, z_{2}=1 / 4$
- Alternative likelihood uses MLE for $\mathrm{z}_{0}, \mathrm{z}_{1}, \mathrm{z}_{2}$
- Compare likelihoods with likelihood ratio test


# Potential Sib-Pair Likelihood 

Under the null hypothesis:

$$
L=(1 / 4)^{n_{\text {IBDO }}}(1 / 2)^{n_{\text {IBD1 }}}(1 / 4)^{n_{\text {IBD } 2}}
$$

Under the alternative hypothesis

$$
L=\left(\hat{z}_{0}\right)^{n_{I B D D}}\left(\hat{z}_{1}\right)^{n_{I B D 1}}\left(\hat{z}_{2}\right)^{n_{B B D 2}}
$$

## In real life...

- Markers are only partially informative
- IBD sharing is equivocal
- Uncertainty can only be partly reduced by examining relatives
- Need an alternative likelihood
- Should allow for partially informative data


## For A Single Family

$$
L_{i}=\sum_{j=0}^{2} P(I B D=j \mid A S P) P\left(\text { Genotypes }_{i} \mid I B D=j\right)=\sum_{j=0}^{2} z_{j} w_{i j}
$$

Risch (1990) defines

$$
w_{i j}=P\left(\text { Genotypes }_{i} \mid I B D=j\right)
$$

We only need proportionate $w_{i j}$

## Likelihood and LOD Score

$$
\begin{aligned}
& L\left(z_{0}, z_{1}, z_{2}\right)=\prod_{i} \sum_{j} z_{j} w_{i j} \\
& L O D=\log _{10} \prod_{i} \frac{\hat{z}_{0} w_{i 0}+\hat{z}_{1} w_{i 1}+\hat{z}_{2} w_{i 2}}{1 / 4 w_{i 0}+1 / 2 w_{i 1}+1 / 4 w_{i 2}}
\end{aligned}
$$

The MLS statistic is the LOD evaluated at the MLEs of $\mathrm{z}_{0}, \mathrm{z}_{1}, \mathrm{z}_{2}$

## w: P(Marker Genotype|IBD State)

| Relative |  | IBD |  |  |
| :---: | :---: | :---: | :---: | :---: |
| I | II | 0 | 1 | 2 |
| (a,b) | (c,d) | $4 \mathrm{pap}_{\mathrm{a}} \mathrm{Pb}_{\mathrm{c}} \mathrm{P}_{\mathrm{d}}$ | 0 | 0 |
| (a,a) | (b,c) | $2 \mathrm{pa}^{2} \mathrm{Pbp}_{\mathrm{c}}$ | 0 | 0 |
| (a,a) | (b,b) | $\mathrm{pa}^{2} \mathrm{p}_{\mathrm{b}}{ }^{2}$ | 0 | 0 |
| (a,b) | (a,c) | $4 \mathrm{pa}^{2} \mathrm{p}_{\mathrm{b}} \mathrm{P}_{\mathrm{c}}$ | $\mathrm{pap}_{\mathrm{a}} \mathrm{b}_{\mathrm{c}}$ | 0 |
| (a,a) | $(\mathrm{a}, \mathrm{b})$ | $2 \mathrm{pa}^{3}{ }^{3} \mathrm{pb}$ | $\mathrm{pa}^{2}{ }^{2} \mathrm{~Pb}$ | 0 |
| (a,b) | $(\mathrm{a}, \mathrm{b})$ | $4 \mathrm{pa}^{2} \mathrm{p}^{4}{ }^{2}$ | $\left(\mathrm{pap}_{\mathrm{a}}{ }^{2}+\mathrm{pa}^{2} \mathrm{~Pb}\right.$ ) | $2 \mathrm{pap}_{\mathrm{a}}$ |
| (a,a) | (a,a) | $\mathrm{Pa}^{4}$ | $\mathrm{Pa}^{3}$ | $\mathrm{pa}^{2}$ |
| Prior P | bility | 1/4 | 1/2 | 1/4 |

These probabilities apply to pair of individuals, when no other genotypes in the family are known.

## Example scoring for $\mathrm{w}_{\mathrm{ij}}$



In this case, relative weights depend on allele frequency.

## More examples for scoring: $\mathrm{w}_{\mathrm{ij}}$



In these cases, multiple weights are non-zero (but equal) for each family.

## How to maximize likelihood?

- If all families are informative
- Use sample proportions of IBD=0, 1, 2
- If some families are uninformative
- Use an E-M algorithm
- At each stage generate complete dataset with fractional counts
- Iterate until estimates of LOD and z parameters are stable


## Assigning Partial Counts in E-M

$$
\begin{aligned}
P(I B D & =j \mid \text { Genotypes })= \\
& =\frac{P(I B D=j \mid A S P) P(\text { Genotypes } \mid I B D=j)}{L_{i}} \\
& =\frac{P(I B D=j \mid A S P) P(\text { Genotypes } \mid I B D=j)}{\sum_{k=0}^{2} P(I B D=k \mid A S P) P(\text { Genotypes } \mid I B D=k)} \\
& =\frac{Z_{j} w_{i j}}{\sum_{k=0}^{2} z_{k} w_{i k}}
\end{aligned}
$$

## Example



Assume a bi-allelic marker where the two alleles have identical frequencies.

## Example of E-M Steps

| Parameters |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | ---: | :---: | ---: | ---: | ---: |
| $\mathbf{z 0}$ | z1 | z2 | IBD $=\mathbf{0}$ | IBD $=\mathbf{1}$ | IBD $=\mathbf{2}$ | IBD $=\mathbf{2}$ | LOD | LODi | LODu |
| 0.250 | 0.500 | 0.250 | 0.56 | 2.22 | 2.22 | 5 | 0.00 | 0.00 | 0.00 |
| 0.056 | 0.222 | 0.722 | 0.08 | 0.66 | 4.26 | 5 | 3.19 | 2.30 | 0.89 |
| 0.008 | 0.066 | 0.926 | 0.01 | 0.17 | 4.82 | 5 | 4.01 | 2.84 | 1.16 |
| 0.001 | 0.017 | 0.982 | 0.00 | 0.04 | 4.96 | 5 | 4.20 | 2.97 | 1.23 |
| 0.000 | 0.004 | 0.996 | 0.00 | 0.01 | 4.99 | 5 | 4.25 | 3.00 | 1.24 |
| 0.000 | 0.001 | 0.999 | 0.00 | 0.00 | 5.00 | 5 | 4.26 | 3.01 | 1.25 |
| 0.000 | 0.000 | 1.000 | 0.00 | 0.00 | 5.00 | 5 | 4.26 | 3.01 | 1.25 |

## Point of Situation ...

- Noted that affected siblings are more likely to share two alleles identical by descent
- Derived a likelihood based linkage test that compares sharing probabilities to null defaults
- Let's examine these probabilities in more detail ...


## Intuition: Possible Triangle Constraints

- Under the null
- True parameter values are ( $1 / 4,1 / 2,1 / 4$ )
- Estimates will wobble around this point
- Under the alternative
- True parameter values are within triangle
- Estimates will wobble around true point
- Holmans (1993) suggested we focus testing
 on searching for alternatives within the triangle
$\mathrm{Z}_{0}$
- These suggest a disease gene


## The possible triangle method

1. Estimate $z_{0}, z_{1}, z_{2}$ without restrictions
2. If estimate of $z_{1}>1 / 2$ then ...
a) Repeat estimation with $z_{1}=1 / 2$
b) If this gives $z_{0}>1 / 4$ then revert to null ( $M L S=0$ )
3. If estimates imply $2 z_{0}>z_{1}$ then ...
a) Repeat estimation with $z_{1}=2 z_{0}$
b) If this gives $z_{0}>1 / 4$ then revert to null ( $M L S=0$ )
4. Otherwise, leave estimates unchanged.

## Possible Triangle



## MLS Combined With Possible Triangle

- Under null, true $\mathbf{z}$ is a corner of the triangle
- Estimates will often lie outside triangle
- Restriction to the triangle decreases MLS
- MLS threshold for fixed type l error decreases
- Under alternative, true $\mathbf{z}$ is within triangle
- Estimates will lie outside triangle less often
- MLS decreases less
- Overall, power should be increased


## Example

- Type I error rate of 0.001
- LOD of 3.0 with unrestricted method
- Risch (1990)
- LOD of 2.3 with possible triangle constraint
- Holmans (1993)
- For some cases, almost doubles power


## Recommended Reading

- Holmans (1993)

Asymptotic Properties of
Affected-Sib-Pair Linkage Analysis
Am J Hum Genet 52:362-374

- Introduces possible triangle constraint
- Good review of MLS method


## Recommended Reading

- Risch (1990)
- Linkage Strategies for Genetically Complex Traits. III. The Effect of Marker Polymorphism on Analysis of Affected Relative Pairs
- Am J Hum Genet 46:242-253
- Introduces MLS method for linkage analysis
- Still, one of the best methods for analysis pair data
- Evaluates different sampling strategies
- Results were later corrected by Risch (1992)


## Intuition For Multipoint Analysis

- IBD changes infrequently along the chromosome
- Neighboring markers can help resolve ambiguities about IBD sharing
- In the Risch approach, they might ensure that only one w is effectively non-zero



## Ingredients for a multipoint model...



One ingredient will be the observed genotypes at each marker

## Ingredients for a multipoint model...



Another ingredient will be the possible IBD states at each marker ..

## Ingredients for a multipoint model...



The final ingredient connects IBD states along the chromosome ...

## The Likelihood of Marker Data

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

- General formulation, allows for any number of markers.
- Combined with Bayes' Theorem can estimate probability of each IBD state at any marker.
$P\left(X_{m} \mid I_{m}\right)$

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

$$
P\left(I_{m+1} \mid I_{m}\right)
$$

- Depends on recombination fraction $\theta$
- This is a measure of distance between two loci
- Probability grand-parental origin of alleles changes between loci

|  |  | IBD State at $\mathrm{m}+1$ |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  |  | 0 | 1 | 2 |
| IBD state | 0 | $(1-\psi)^{2}$ | $2 \psi(1-\psi)$ | $\psi^{2}$ |
| at marker | 1 | $\psi(1-\psi)$ | $(1-\psi)^{2}+\psi^{2}$ | $\psi(1-\psi)$ |
| m | 2 | $\psi^{2}$ | $2 \psi(1-\psi)$ | $(1-\psi)^{2}$ |

$$
\psi=2 \theta(1-\theta)
$$

## The Likelihood of Marker Data

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

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


## 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?


## 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


## 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

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

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


## Extending the MLS Method ...

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

- We just change the definition for the "weights" given to each configuration!


## Possible Further Extensions

- Modeling error
- What components might have to change?
- Modeling other types of relatives
- What components might have to change?
- Modeling larger pedigrees
- What components might have to change?

$$
p_{1}=0.5
$$

## Worked Example



$$
\begin{aligned}
& w_{0}=P(X \mid I B D=0)=p_{1}^{4}=1 / 16 \\
& w_{1}=P(X \mid I B D=1)=p_{1}^{3}=1 / 8 \\
& w_{2}=P(X \mid I B D=2)=p_{1}^{2}=1 / 4
\end{aligned}
$$

If $\mathrm{z}_{0}=0.25, \mathrm{z}_{1}=0.50, \mathrm{z}_{2}=0.25$, then

$$
\begin{aligned}
& P(X)=1 / 4 p_{1}^{4}+1 / 2 p_{1}^{3}+1 / 4 p_{1}^{2}=9 / 64 \\
& P(I B D=0 \mid X)=\frac{1 / 4 p_{1}^{4}}{P(X)}=1 / 9 \\
& P(I B D=1 \mid X)=\frac{1 / 2 p_{1}^{3}}{P(X)}=4 / 9 \\
& P(I B D=2 \mid X)=\frac{1 / 4 p_{1}^{2}}{P(X)}=4 / 9
\end{aligned}
$$

