Multipoint Analysis for Sibling Pairs

Biostatistics 666 Lecture 18

Previously ...

Linkage analysis with pairs of individuals

"Non-parametric" IBS Methods

"Maximum Likelihood" IBD Based Method

Possible Triangle Constraint

ASP Methods Covered So Far ...

Increasing degrees of sophistication and complexity

 In each case, only a single marker is evaluated...

IBS Based Linkage Test

$$\chi_{2df}^{2} = \sum_{i} \frac{\left[N_{IBS=i} - E(N_{IBS=i})\right]^{2}}{E(N_{IBS=i})}$$

$$LOD = \frac{\chi^2}{2\ln 10}$$

- Expect counts calculated using:
 - Allele frequencies for marker
 - Relationship for affected individuals

Likelihood for a Single ASP

$$L_{i} = \sum_{j=0}^{2} P(IBD = j \mid ASP)P(Genotypes \mid IBD = j) = \sum_{j=0}^{2} z_{j}w_{ij}$$

Risch (1990) defines

$$w_{ij} = P(Genotypes_i \mid IBD = j)$$

We only need proportionate w_{ii}

MLS Linkage Test

$$L(z_0, z_1, z_2) = \prod_i \sum_j z_j w_{ij}$$

$$LOD = \log_{10} \prod_{i} \frac{z_0 w_{i0} + z_1 w_{i1} + z_2 w_{i2}}{\frac{1}{4} w_{i0} + \frac{1}{2} w_{i1} + \frac{1}{4} w_{i2}}$$

The MLS statistic is the LOD evaluated at the MLEs of z_0, z_1, z_2

Possible Triangle Constraint

- For any genetic model, we expect ASPs to be more similar than unselected pairs of siblings.
- More precisely, Holmans (1993) showed that for any genetic model
 - $Z_2 \ge \frac{1}{4}$
 - $z_1 \le \frac{1}{2}$ and $z_1 \ge 2 z_0$
 - $z_0 \le \frac{1}{4}$

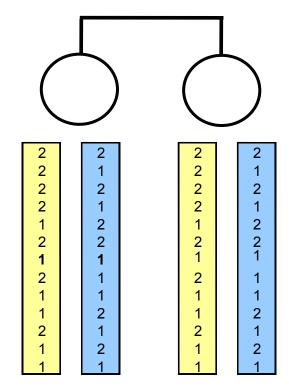
Further Improvements ...

 All these methods lose information when a marker is uninformative in a particular family...

 Today, we will see how to use neighboring markers to extract more information about IBD.

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, effectively, only one w is non-zero



Today ...

- Framework for multipoint calculations
 - First, likelihood of genotypes for series of markers
 - Discuss application to the MLS linkage test
 - Later, we will use it for useful applications such as error detection and relationship inference
- Refresher on IBD probabilities
- Using a Markov Chain to speed analyses

Ingredients



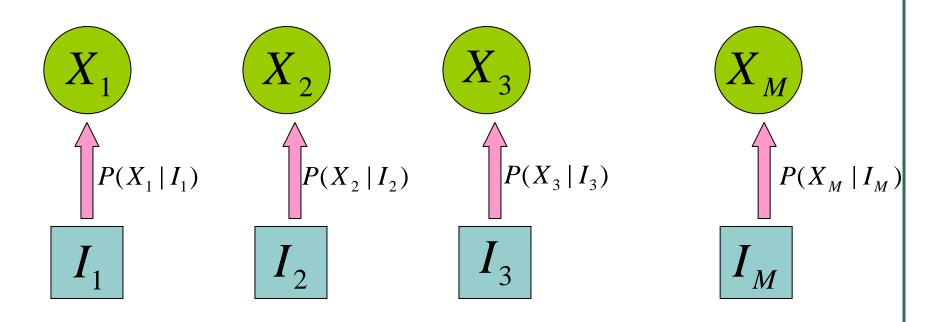






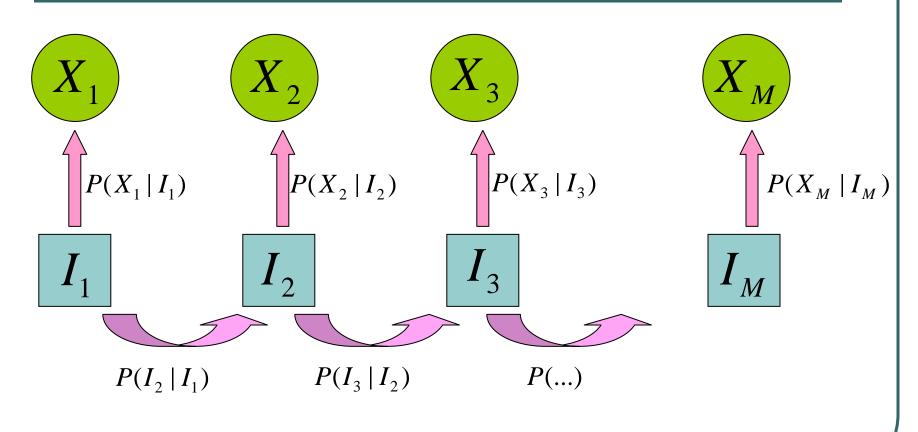
One ingredient will be the observed genotypes at each marker ...

Ingredients



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

Ingredients



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

The Likelihood of Marker Data

$$L = \sum_{I_1} \sum_{I_2} ... \sum_{I_M} P(I_1) \prod_{i=2}^{M} P(I_i \mid I_{i-1}) \prod_{i=1}^{M} P(X_i \mid I_i)$$

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

The Ingredients ...

 Probability of observed genotypes at each marker conditional on IBD state

 Probability of changes in IBD state along chromosome

Hidden Markov Model

 $P(I_1)$

Prior Probability of IBD States

IBD Probabilities

Number of alleles identical by descent

- For sibling pairs, must be:
 - 0
 - 1
 - 2

Not always determined by marker data

 $P(X_i \mid I_i)$

Probability of Observed Genotypes, Given IBD State

$P(X_m | I_m)$

		IBD				
Sib	CoSib	0	1	2		
(a,b)	(c,d)	$4p_ap_bp_cp_d$	0	0		
(a,a)	(b,c)	$2p_a^2p_bp_c$	0	0		
(a,a)	(b,b)	$p_a^2 p_b^2$	0	0		
(a,b)	(a,c)	$4p_a^2p_bp_c$	$p_a p_b p_c$	0		
(a,a)	(a,b)	$2p_a^3p_b$	$p_a^2 p_b$	0		
(a,b)	(a,b)	$4p_a^2p_b^2$	$(p_a p_b^2 + p_a^2 p_b)$	$2p_ap_b$		
(a,a)	(a,a)	p_a^{4}	$p_a{}^3$	$p_a^{\ 2}$		
Prior Probability		1/4	1/2	1/4		

Note: Assuming unordered genotypes

Question: What to do about missing data?

 What happens when some genotype data is unavailable?

$$P(I_{i+1} | I_i)$$

Model for Transitions in IBD Along Chromosome

$$P(I_{m+1} | I_m)$$

- Depends on recombination fraction θ
 - This is a measure of distance between two loci
 - Probability grand-parental origin of alleles changes between loci
- Naturally, leads to probability of change in IBD:

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

$$P(I_{m+1} | I_m)$$

		IBD State at m + 1		
		0	1	2
IBD state	0	$(1-\psi)^2$	2ψ(1-ψ)	ψ^2
at marker	1	$\psi(1-\psi)$	$(1-\psi)^2 + \psi^2$	$\psi(1-\psi)$
m	2	ψ^2	$2\psi(1-\psi)$	$(1-\psi)^2$

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

 $P(I_{1})$ $P(X_{i}|I_{i})$ $P(I_{i+1}|I_{i})$

All the Ingredients!

Example

- Consider two loci separated by $\theta = 0.1$
- Each loci has two alleles, each with frequency .50
- If two siblings have the following genotypes:

Sib1 Sib2

Marker A: 1/1 2/2

Marker B: 1/1 1/1

- What is the probability of IBD=2 at marker B when...
 - You consider marker B alone?
 - You consider both markers simultaneously?

The Likelihood of Marker Data

$$L = \sum_{I_1} \sum_{I_2} ... \sum_{I_M} P(I_1) \prod_{i=2}^{M} P(I_i \mid I_{i-1}) \prod_{i=1}^{M} P(X_i \mid I_i)$$

- 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

A Markov Rearrangement ...

$$LEFT_{1}(j) = P(IBD = j)P(X_{1} | I_{1} = j)$$

$$LEFT_{i+1}(j) = \sum_{k=0,1,2} LEFT_{i}(k)P(I_{i+1} = j | I_{i} = k)P(X_{i+1} | I_{i+1} = j)$$

$$L = \sum_{k=0,1,2} LEFT_{last}(k)$$

- Using this arrangement, we calculate the likelihood by:
 - Evaluating LEFT function at the first position
 - Evaluating LEFT function along chromosome
 - Each time, re-using results from the previous position only
 - Required effort increases linearly with number of markers
 - Final summation gives overall likelihood

Improvements ...

 The previous arrangement, quickly gives the likelihood for any number of markers

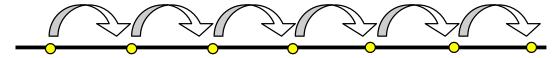
 A more flexible arrangement would allow us to quickly calculate conditional IBD probabilities along chromosome...

A More Flexible Arrangement...

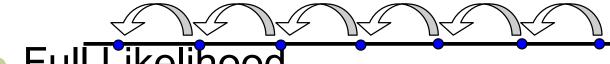
Single Marker



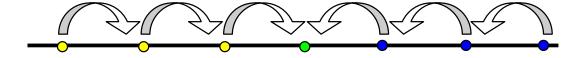
Left Conditional



Right Conditional



Full Likelihood



The Likelihood of Marker Data

$$L = \sum_{I_{j}} P(I_{j})P(X_{j} | I_{j})P(X_{1}...X_{j-1} | I_{j})P(X_{j+1}...X_{M} | I_{j})$$

$$= \sum_{I_{j}} P(I_{j})P(X_{j} | I_{j})L_{j}(I_{j})R_{j}(I_{j})$$

- A different arrangement of the same likelihood
- The nested summations are now hidden inside the L_j and R_j functions...

Left-Chain Probabilities

$$L_{m}(I_{m}) = P(X_{1},...,X_{m-1} | I_{m})$$

$$= \sum_{I_{m-1}} L_{m-1}(I_{m-1})P(X_{m-1} | I_{m-1})P(I_{m-1} | I_{m})$$

$$L_{1}(I_{1}) = 1$$

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

Right-Chain Probabilities

$$\begin{split} R_{m}(I_{m}) &= P(X_{m+1}, ..., X_{M} \mid I_{m}) \\ &= \sum_{I_{m+1}} R_{m+1}(I_{m+1}) P(X_{m+1} \mid I_{m+1}) P(I_{m+1} \mid I_{m}) \\ R_{M}(I_{M}) &= 1 \end{split}$$

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

Extending the MLS Method ...

$$w_{j} = P(X_{j} | I_{j})P(X_{1}...X_{j-1} | I_{j})P(X_{j+1}...X_{M} | I_{j})$$

$$= P(X_{j} | I_{j})L_{j}(I_{j})R_{j}(I_{j})$$

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

Some Extensions We'll Discuss

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

Today

 Efficient computational framework for multipoint analysis of sibling pairs