Population Structure in Genetic Association Studies

Biostatistics 666

Today's Lecture

- Impact of population structure on association tests
- Detecting population structure
 - Association between unlinked markers
 - QQ plots: a useful diagnostic
- Handling population structure
 - Family based analyses
 - The genomic control method
 - More explicit models of population structure

Sources of Association

- Causal association
 - Genetic marker alleles influence susceptibility
- Linkage disequilibrium
 - Genetic marker alleles associated with other nearby alleles that influence susceptibility
 - Population stratification
 - Genetic marker is unrelated to disease alleles



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useful
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Stratification vs Disequilibrium





Impact of Stratification at One Locus – Numerical Example

	<u>Sample</u>		
	Population 1	Population 2	Combined
Allele Frequencies			
p ₁	0.20	0.80	0.50
p ₂	0.80	0.20	0.50
Genotype Frequenci	<u>es</u>		
p ₁₁	0.04	0.64	0.34 (0.25 expected)
p ₁₂	0.32	0.32	0.32 (0.50 expected)
p ₂₂	0.64	0.04	0.34 (0.25 expected)

Notice the excess of homozygotes and deficit of heterozygotes.

Impact of Stratification at Two Loci – Numerical Example

Population A

	B ₁	B ₂
A ₁	160	160
A ₂	40	40

Chi² = 0.0

Population B

	B ₁	B ₂
A ₁	160	40
A ₂	160	40

Chi² = 0.0

Combined Population

	B ₁	B ₂
A ₁	320	200
A ₂	200	80

Chi² = 7.83

The Stratification Problem

- If phenotypes differ between populations
- And allele frequencies have drifted apart
- Unlinked markers exhibit association
- Not very useful for gene mapping!

Stratification

- Due to non-random mating
 - Eg. Mating based on proximity or culture
- Allele frequencies drift apart in each group
 - Eg. Allele frequency differences at many genes between African-Americans and Caucasians
- If disease prevalence also differs, association studies can produce misleading results
 - Eg. Glaucoma has prevalence of ~2% in elderly Caucasians, but ~8% in African-Americans

Possible solutions

• Collect a better matched sample

Identify population groupings

- Using self reported ethnicity or genetic markers
- Carry out association analysis within each group
- Account for inflated false-positive rate
- Use family based controls





Comparison of expected and observed p-values in a study of LDL cholesterol for all markers (**red**) and for markers in regions not known to impact LDL levels (**blue**).





In genomewide studies, most markers show no association with the trait and, therefore, very similar observed and expected p-values.







 Distinguish "true" association from population stratification

Trio Families

- Families with two genotyped parents
- One affected child
- Calculate distribution of child genotypes conditional on parental data
 - Focus on children with heterozygous parents

The Spielman TDT

- Traditional case-control
 - Compare allele frequencies in two samples
 - Cases and controls must be one population
- Heterozygous parents
 - Parental alleles are the study population
 - Population allele frequencies fixed
 - 50:50, independent of original
 - Check proportion of each allele transmitted to affected offspring

Basic TDT

- Is allele consistently transmitted from heterozygotes?
- Affirmative answer requires
 - Allele is associated
 - Allele is linked
 - Or we have a false-positive



The TDT statistic

	Transmitted 1	Transmitted 2
Not-Transmitted 1	а	b
Not-Transmitted 2	С	d

$$\frac{(b-c)^2}{b+c} \sim \chi_1^2$$

Caution: Parental genotypes crucial!

- It seems we can deduce transmitted allele...
- However, this leads to bias...
 - Why?



Caution: Parental genotypes crucial!

 Probability of inferring transmitted genotype depends on population allele frequencies

 Expected ratio of observed transmissions no longer 50/50.



The Sib-TDT

- Parents may be missing
 - eg. late onset conditions
- Compare alleles that differ between siblings
 - When sib genotypes differ, which allele is carried by affected sib?



The Sib-TDT statistic Affected has 1 Affected has 2 **Unaffected has 1** b а **Unaffected has 2** С C $\frac{(b-c)^2}{b+c} \sim \chi_1^2$

Further Extensions

- The TDT can be further extended to model genotype, rather than allele, distributions
 - Schaid (1999) Genet Epidemiol 16:250-260
- The TDT can be extended to accommodate different family structures

What if families are not available?

- Test null markers across genome
 - Markers that are unlikely to be associated
 - Markers that are outside genes
 - Markers in genes that are unlikely to be involved
- Initially, 50 markers suggested as minimum
- Now, typical to use 100,000 SNPs or more (from genomewide studies) as null

What if "null markers" reject null?

- Early suggestion:
 - Reject Association
 - Pritchard and Rosenberg (1999)
 Am J Hum Genet
 65:220-228
- What might be a better approach?



(Figure from Cardon and Bell, Nature Reviews Genetics, 2001)



Define Inflation Factor

Compute chi-squared for each marker

• Inflation factor λ

- Average observed chi-squared
- Median observed chi-squared / 0.456
- Should be >= 1
- Adjust statistic at candidate markers

• Replace χ^2_{biased} with $\chi^2_{\text{fair}} = \chi^2_{\text{biased}} / \lambda$

Questions

- When defining the inflation factor λ ...
- Why do we use a lower bound of 1?
- What might be the advantages of using the median rather than the mean?

Applying Genomic Control

- Simple and convenient approach...
 - Easily adapted to other test statistics, such as those for quantitative trait and haplotype tests
- Under the null, stratification always inflates evidence for association...
 - Is this also true under the alternative?
 - What might be the consequences?





association. If these large p-values were to deviate from expected, there is a problem! In this case, λ =1.02.

Structured Association

- Use unlinked markers to assign individuals to subpopulations then...
 - Test for association within each subpopulation
 - Test for association while conditioning on subpopulation



(Figure courtesy of Shaun Purcell and Pak Sham)

Some Attractive Features

- Allows for flexibility in association test
- Describing subpopulations can be useful
- Does not assume constant population differentiation across the genome

Simple Mixture Distribution

$$p(x|\boldsymbol{\pi}, \boldsymbol{\Phi}) = \pi_1 p(x|\phi_1) + ... + \pi_k p(x|\phi_2)$$

- p() are the probability functions
- *x* are the observed genotypes
- π are the mixture proportions for subpopulations
- ϕ are allele frequencies for each subpopulation
- *k* is the number of components

Maximum Likelihood Approach

 Find the parameters that maximize the likelihood for the entire sample

$$L = \prod_{j} p(x_{j} | \boldsymbol{\pi}, \boldsymbol{\Phi})$$
$$\ell = \sum_{j} \log p(x_{j} | \boldsymbol{\pi}, \boldsymbol{\Phi})$$

- Prior for the allele frequencies may also be included in the likelihood
- Likelihood can be maximized using a Gibbs sampler or E-M algorithm

Classifying Individuals

• Let Z_j be the population membership for individual *i* $Pr(Z_i = i | \pi, \Phi) = \pi_i$

$$\Pr(Z_j = i | x_j, \boldsymbol{\pi}, \boldsymbol{\Phi}) = \frac{\pi_i p(x_j | \phi_i)}{\sum_l \pi_l p(x_j | \phi_l)}$$

Results from the application of Bayes' theorem

Classification of Individuals Using Genetic Data



Genetic classification of individuals across several populations, as the number of modeled subpopulations (K) changes.

(from Rosenberg et al, Science, 2002)

Testing for Association

- Once individuals are classified, there is leeway in selecting association test:
 - Test within each subpopulation
 - Test within each subpopulation, combine results
 - Model effect of population membership
 - For example, using covariates in a regression model

Refinements to the Model

- Allowing for admixture within individuals
- Setting up a prior for allele frequencies that favors similar frequencies across populations
- Allowing for different tiers of population structure

Principal Components Analysis

- Model each genotype as quantitative variable
 - Number of copies of the minor allele
- Identify small number of principal components (PC)
 - Linear combinations of observed genotype scores
 - Selected to explain variation in genotype scores
 - Typically, one to ten PC are modeled
- Allow population structure to be visualized
- Can be used as covariates in association analysis

Principal Components For a Large Association Study



WTCCC, Nature, 2007

Principal Components vs. Structured Association

- Both use genotypes to find similar individuals
 - Both can be combined with genomic control analysis
- Tuning structured association methods
 - Select number of subpopulations
 - Fit model parameters
 - Minimize genomic control value
- Tuning principal component analysis
 - Decide how many PC to include as covariates
 - Computationally less demanding
 - Minimize genomic control value

References

- Genomic Control for Association Studies
 - Devlin and Roeder (1999) Biometrics 55:997-1004
 - Pritchard and Rosenberg (1999) Am J Hum Genet 65:220-228
- Methods for Inferring Population Structure
 - Pritchard, Stephens and Donnelly, 2000. *Genetics* **155**: 945-959
- Principal Components Analysis
 - Price et al (2006) Nature Genetics 38:904-909
- Transmission Disequilibrium Tests
 - Spielman et al (1993) *Am J Hum Genet* **52**:506-16 (trios)
 - Curtis (1997) Ann Hum Genet 61:319-33 (sibling pairs)