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**Identifying Genetic Variants Associated with Disease: Case-Control
Association Testing with Related Individuals**

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Joint work with Catherine Bourgain and Tim Thornton

Case-control association testing: some preliminaries

- We consider a complex trait or disease (e.g. asthma, alcoholism), which we treat as binary (affected/unaffected).
- **Complex** trait: may be influenced by multiple genetic and non-genetic factors
- Goal: identify some of the genetic risk factors related to the trait.

Terminology

- A person who has the disease may be called an **affected** or a **case**.
- **Control** could be someone who does not have the disease or someone whose disease status is unknown (these types are treated differently in the analysis).

Terminology (continued)

- **SNP** (single nucleotide polymorphism) — site in genome with single base-pair change that distinguishes some individuals from others in same population, e.g. AAGGCTAA vs. ATGGCTAA
- The two different variants at a SNP are called **alleles**.
- **Genotype** is the pair of alleles of an individual at a SNP. Typically observe only number of copies of each allele held by individual, e.g. i copies of allele A, which is equivalent to $2-i$ copies of allele T, $i = 0, 1, 2$.

Case-control association testing

- For a given marker, compare the allele or genotype distributions of cases and controls.
- Null hypothesis is that there is no difference between case and control allele/genotype distributions at the given marker.
- E.g. consider classical χ^2 test for association with a biallelic marker, equivalent to test for independence in 2×2 table

	Case	Control
Allele 0	C_{00}	C_{01}
Allele 1	C_{10}	C_{11}

- This χ^2 test is valid when alleles are independent within and between individuals under the null hypothesis

Use of related individuals in case-control testing: how it arises, why it can be desirable

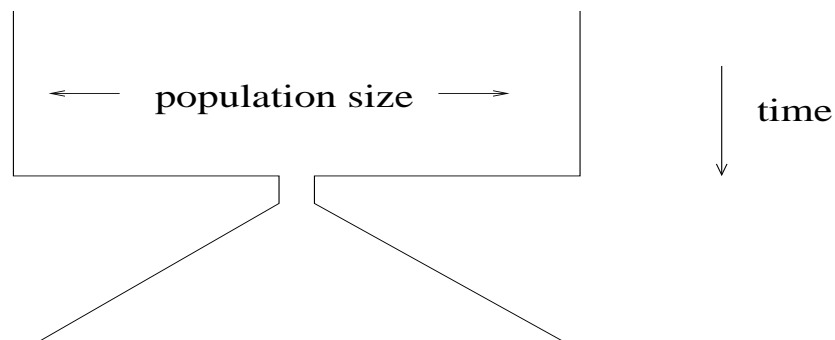
- Families sampled for a linkage study may be included in an association study.
 - **Linkage** is co-inheritance of trait with allele or genotype within a family.
 - Linkage analysis of families with multiple affected individuals may be used for coarse mapping of genetic variants.
 - Then population-based association used for finer-scale mapping.
- Sampling individuals from families with multiple affecteds may increase power to detect association with complex traits because of enrichment for genetic cases.
 - Complex diseases such as breast cancer and heart disease have both genetic and non-genetic causes.
 - Cases from families with multiple affecteds are more likely to have predisposing genetic variants.

Use of related individuals in case-control testing: how it arises, why it can be desirable (cont.)

- Use of unaffected relatives of cases as controls can provide some measure of protection against potential problems of population substructure.
 - Frequency of disease may differ across sub-populations, frequency of allele or genotype may differ as well.
 - Sub-population may be a hidden covariate contributing to false detection of association.
 - Using related cases and controls makes this problem less likely.
- Founder populations, in which most or all individuals are related, can be particularly valuable for genetic studies.

Complex trait mapping in founder populations

- **Founder population:** a population in which a recent bottleneck has resulted in a large number of individuals all descended from a small number of founders



- Founder populations may be particularly useful for complex trait mapping because of
 - reduced genetic heterogeneity due to small number of founders
 - in some cases, reduced environmental heterogeneity
 - linkage disequilibrium may exist over greater distances \Rightarrow less dense map required to detect association

Statistical issues that arise with use of related individuals in case-control testing

- When some individuals in the samples are related, it creates dependence among the observations.
- Both case-control status and allele/genotype run in families
- Type I error:
 - application of standard methods can result in a dramatic increase in false detections (Newman et al. 2001; Bourgain et al. 2003).
- Power:
 - information on relatedness can be used to increase power
 - explicitly taking into account the fact that there is an enrichment for predisposing variants in affecteds with affected relatives can also increase power

- We develop quasi-likelihood (QL) methods for case-control association testing of genetic traits with related individuals. Properties include:
 - uses only first and second moments
 - applicable to any sample of related individuals
 - Type I error is corrected for the dependence
 - weights depending on case-control status and relationships of individuals are used to optimize power (maximize non-centrality parameter) within a linear class of statistics
 - allows us to leave unspecified some parts of the model of which we are ignorant \implies retains a major part of the appeal of the original case-control association test
 - computationally feasible, even in large complex inbred pedigrees with multiple inbreeding loops

- More generally, QL inference methods can be used to extend other types of classical population genetic inference to founder populations, e.g.
 - allele frequency estimation
 - Armitage test for case-control association
 - Hardy-Weinberg equilibrium test

- Agenda for remainder of talk:
 - General QL approach
 - 3 approaches for case-control association testing in related individuals:
 - * correct the variance of the standard χ^2 statistic: $W_{\chi^2_{corr}}$
 - * QL approach under a simple model for case-control differences: W_{QLS}
 - * Improvement of power by more detailed consideration of properties of a genetic trait: M_{QLS}
 - Simulations and an example

Quasi-likelihood (QL) estimation

- Wedderburn (1974), Godambe (1960), Jarrett (1973), McCullagh and Nelder (1989), Heyde (1997)
- Let $X_{n \times 1}$ be random with $E(X) = \mu_{n \times 1}$ and $\text{Var}(X) = V_{n \times n}$, where
 - μ is a known, twice differentiable function of unknown parameter $\theta_{m \times 1}$,
 - V is a known differentiable function of θ (or sometimes known only up to unknown scale factor σ^2 not depending on θ), V invertible.
- Let $U(\theta) = D^T V^{-1}(X - \mu)$, where $D_{ij} = \partial \mu_i / \partial \theta_j$
- $U(\theta)$ is QL score function.
- QL estimator (QLE) $\hat{\theta}$ of θ is a solution of $U(\theta) = 0$.
- Matrix $i_\theta = D^T V^{-1} D = \text{Cov}(U(\theta)) = -E(\partial U / \partial \theta)$ plays similar role to Fisher information.
- Under regularity conditions, $i_\theta^{-1/2}(\hat{\theta} - \theta)$ is asymptotically $N(0, I)$, where $(i_\theta^{-1/2})^T i_\theta^{-1/2} = I$.

QL estimation: a few more details

- In special case when both of the following hold:
 1. $\mu = D\theta$, where D is known, i.e. μ is a linear function of θ and
 2. $V = Ks(\theta)$, where K is a known invertible matrix and s is a possibly unknown scalar that may depend on θ ,

then the QL estimator for θ is same as generalized regression estimator $(D^T K^{-1} D)^{-1} (D^T K^{-1} X)$.

- However, for some of the problems we are interested in, both 1 and 2 fail to hold.
- More generally, $\hat{\theta}$ is not linear in X and can be obtained by Newton-Raphson with Fisher scoring:

$$\hat{\theta}_{j+1} = \hat{\theta}_j + (\hat{D}_j^T \hat{V}_j^{-1} \hat{D}_j)^{-1} \hat{D}_j^T \hat{V}_j^{-1} (X - \hat{\mu}_j),$$

where $\hat{D}_j = D|_{\theta=\hat{\theta}_j}$, $\hat{V}_j = V|_{\theta=\hat{\theta}_j}$.

- QL estimating equation is of linear type
 $H(\theta)^T(X - \mu(\theta)) = 0$, where H and μ do not depend on X . QLE is asymptotically optimal among estimators obtained as solutions of linear estimating equations (under regularity conditions).

QL score test

- Simple null hypothesis
 - Suppose want to test null hypothesis $H_0 : \theta = \theta_0$ vs. alternative $H_A : \theta \neq \theta_0$.
 - Let ρ be the dimension of θ .
 - By analogy with usual likelihood score test, consider

$$W = U(\theta_0)^T i_{\theta_0}^{-1} U(\theta_0)$$

assuming i_{θ_0} invertible.

- Compare to a χ_{ρ}^2 distribution asymptotically

QL Score test: composite null hypothesis

- Set $\theta = (r, a)$ and consider testing null hypothesis $H_0 : r = r_0$ vs. alternative $H_A : r \neq r_0$.
- Let ρ be the dimension of r .
- Let

$$U(r, a) = \begin{pmatrix} U_r(r, a) \\ U_a(r, a) \end{pmatrix} = \begin{pmatrix} D_r^T V^{-1}(X - \mu) \\ D_a^T V^{-1}(X - \mu) \end{pmatrix},$$

where $D_r = \partial\mu/\partial r$ and $D_a = \partial\mu/\partial a$.

- By analogy with usual likelihood score statistic for composite null, consider

$$W = U_r^T(r_0, \hat{a}_0) i^{rr}(r_0, \hat{a}_0) U_r(r_0, \hat{a}_0),$$

where

- $i^{rr}(\theta)$ is the (r, r) th entry of i_θ^{-1}
- \hat{a}_0 is the QLE of the nuisance parameter a when $r = r_0$, i.e. $a = \hat{a}_0$ is solution of $U_a(r_0, a) = 0$.

- Compare to a χ_ρ^2 distribution asymptotically

Some terminology and notation

- **IBD:** identical by descent; a set of alleles is IBD if the alleles are inherited copies of the same ancestral allele
- **HBD:** homozygous by descent; an individual is said to be HBD at a locus if that individual's two alleles are IBD. This occurs when individuals are inbred.
- **kinship coefficient:** ϕ_{ij} is the probability that a randomly chosen pair of alleles, one each from individuals i and j are IBD at a given locus, conditional on the genealogy connecting i and j
 - For example, the kinship coefficient for siblings or for parent-offspring is .25, for first cousins it is .0625
- **inbreeding coefficient:** h_i is the probability that individual i is HBD at a given locus, conditional on the genealogy connecting i 's parents; $h_i = \phi_{mf}$, where m and f are the parents of i

Case-control association testing with relatives

Approach 1: Correct the variance of the standard χ^2 statistic

- For simplicity, consider a biallelic locus. All results generalize to multiple alleles.
- Let $X_j = \frac{1}{2}$ (the number of alleles (0, 1, or 2) of type 1 held by individual j), $j = 1, \dots, n$
- Let D_r be case indicator vector with $D_{rj} = 1$ if j is a case, 0 if j is a control.
- The standard Pearson's χ^2 statistic for the test of allelic association can be written

$$W_{\chi^2} = \frac{n[\sum_{j \in \text{cases}} (X_j - \bar{X})]^2}{\frac{1}{2}\bar{X}(1 - \bar{X})n_{\text{case}}n_{\text{con}}},$$

where $n_{\text{case}} = \mathbf{1}^T D_r$, and $n_{\text{con}} = n - n_{\text{case}}$.

- This statistic has the form $W = S^T [\widehat{\text{Var}}_o(S)]^{-1} S$, where $S = V^T X$ is linear in X .

- Standard χ^2 statistic has the form $W = S^T [\widehat{\text{Var}}_o(S)]^{-1} S$, where $S = V^T X$.
- Thus, $\text{Var}_o(S) = V^T \text{Var}_o(X) V$
- With unrelated outbred individuals, $\text{Var}_o(X) = \frac{1}{2}a(1-a)I_{n \times n}$, where $a = E(X)$ is the allele frequency under the null hypothesis. Can approximate a by \bar{X} under the null.
- With related and possibly inbred individuals, $\text{Var}_o(X) = \frac{1}{2}a(1-a)L$, where $L_{ij} = 1 + h_i$ if $i = j$ and $2\phi_{ij}$ if $i \neq j$, with h_i and ϕ_{ij} denoting inbreeding and kinship coeffs, respectively.
- Then the corrected χ^2 statistic is $W_{\chi^2_{corr}} = W_{\chi^2} \gamma$, where

$$\gamma = \frac{n_{case}n_{con}}{n(D_r^T L D_r - 2\frac{n_{case}}{n} \mathbf{1}^T L D_r + (\frac{n_{case}}{n})^2 \mathbf{1}^T L \mathbf{1})}$$
- Compare to χ^2_1 distribution under the null hypothesis of no association between the locus and the trait.

Case-control association testing with relatives Approach 2: QL approach under simple model

- The corrected χ^2 test works reasonably well, but can we increase power with minimal additional effort?
- Let $\mu = E(X)$, and consider the simple model: $\mu_i = a + r$ if i is a case, a if i is a control (constrain $0 < a < 1$, $0 < a + r < 1$)
- Null hypothesis is $H_0 : r = 0$ vs. alternative $H_A : r \neq 0$
- We have $\text{Var}_o(X) = \frac{1}{2}a(1 - a)L$
- $D_r = \partial\mu/\partial r$ has $D_{rj} = 1$ if j is a case and 0 if j is a control
- $D_a = \partial\mu/\partial a = \mathbf{1}_{n \times 1}$
- Then we obtain QL score statistic $W_{QLS} =$

$$\frac{[D_r^T L^{-1}(X - \hat{a}_0 \mathbf{1})]^2}{\hat{a}_0(1 - \hat{a}_0)[D_r^T L^{-1} D_r - (D_r^T L^{-1} \mathbf{1})^2 (\mathbf{1}^T L^{-1} \mathbf{1})^{-1}]}$$

where $\hat{a}_0 = (\mathbf{1}^T L^{-1} \mathbf{1})^{-1} \mathbf{1}^T L^{-1} X$.

Case-control association testing with relatives Approach 2: QL approach under simple model (cont.)

- Both $W_{\chi^2_{corr}}$ and W_{QLS} are of the form $W = S^T [\widehat{\text{Var}}_o(S)]^{-1} S$, where $S = V^T X$ is linear in X . Call this class of statistics \mathcal{W} .
- When the assumed model holds, i.e. $\mu_i = a + r$ if i is a case, a if i is a control, then W_{QLS} is optimal in the sense that it maximizes the non-centrality parameter.
- Thus, W_{QLS} should be more powerful than $W_{\chi^2_{corr}}$ under the assumed model.
- E.g., to compare the allele frequency in, say, Swedes vs. Han Chinese, with related individuals in the samples, W_{QLS} is much more powerful.
- Difficulty: our simple model does not take into account the fact that in complex diseases, cases with affected relatives are more likely to have a predisposing genetic variant than are cases without affected relatives.
- As a result, W_{QLS} can do worse than $W_{\chi^2_{corr}}$ for complex trait mapping, because it downweights related cases compared to cases with no relatives in the sample.

Case-control association testing with relatives

Approach 3: QL approach with better model

- Initial model (frequency $a + r$ in cases and a in controls, i.e. $\mu = a + rD_r$) was too simple to work well.
- We obtain slightly less simple model as follows:
 - Consider a two-allele trait model specified by an allele frequency a and penetrance parameters p_0 , $p_1 = p_0 + \epsilon_1$, and $p_2 = p_0 + \epsilon_2$, where $p_i = P\{\text{affected} \mid \text{have } i \text{ copies of allele}\}$.
 - Let $\nu_j = E(X_j | D_r)$, calculated under the two-allele model.
 - Let $\nu = E(X_j | D_{rj} = 1)$.
 - Let
$$\tilde{D}_r = \lim_{\epsilon_1, \epsilon_2 \rightarrow 0} \frac{\nu_j - a}{\nu - a}.$$
 - Our model is $\mu = a + r\tilde{D}_r$.
 - Intuitively: $r \approx \nu - a$, where ν is frequency in cases (unconditional on affection statuses of relatives) and a is population frequency.

Case-control association testing with relatives Approach 3: QL approach with better model (cont.)

- Model $\mu = a + r\tilde{D}_r$, where $\tilde{D}_r = \lim_{\epsilon_1, \epsilon_2 \rightarrow 0} \frac{\nu_j - a}{\nu - a}$.
- \tilde{D}_r turns out to have a simple form: $\tilde{D}_{rj} = L\delta$
- Here, L is the matrix defined before with $L_{ij} = 1 + h_i$ if $i = j$ and $2\phi_{ij}$ if $i \neq j$, with h_i and ϕ_{ij} denoting inbreeding and kinship coeffs, respectively.
- δ is the vector with j th entry = 1 if j is affected, $-K_p/(1 - K_p)$ if j is unaffected, and 0 if j 's status is unknown (e.g. population-based control).
- K_p is the population prevalence of the trait; in practice, an estimate of K_p can be used, if available, or an arbitrary number could be used.
- The M_{QLS} is the QL score statistic based on this model:

$$M_{QLS} = \frac{[\delta^T (X - \hat{a}_0 \mathbf{1})]^2}{\hat{a}_0(1 - \hat{a}_0)[\delta^T L\delta - (\delta^T \mathbf{1})^2 (\mathbf{1}^T L^{-1} \mathbf{1})^{-1}]}$$
 where $\hat{a}_0 = (\mathbf{1}^T L^{-1} \mathbf{1})^{-1} \mathbf{1}^T L^{-1} X$.

Case-control association testing with relatives Approach 3: QL approach with better model (cont.)

- We do not believe the simple model.
- Nonetheless, the resulting statistic captures the property that in complex diseases, cases with affected relatives are more likely to carry a genetic variant predisposing to the trait than are cases without affected relatives.
- Misspecification of the population prevalence K_p has no effect on validity of the test.
- We use simulation studies to assess
 - power of the method for multilocus trait models (i.e. 2-allele model does not hold).
 - power when K_p is drastically misspecified

Simulations to assess power and Type I error

- 60 extended outbred pedigrees, each with 16 individuals in 3 generations, ascertained for multiple affecteds.
- 20 pedigrees with 4 affecteds each, 20 with 5, and 20 with 6
- Each individual from pedigree is included in study if at least half of his first-degree relatives are affected
- Control sample includes 200 unrelated unaffecteds in addition to the unaffected relatives in the pedigrees
- Models
 - Model I: 2 unlinked causal SNPs with epistasis; 2 penetrance params.
 - Model II: 2 unlinked causal SNPs with epistasis; 4 penetrance parameters
 - Model III: 3 unlinked causal SNPs with epistasis; 2 penetrance parameters

Power to Detect Association (at .05 level, based on 5,000 simulated replicates)

Model	Estimated Power		
	$W_{\chi^2_{corr}}$	W_{QLS}	M_{QLS}
I-a	0.57	0.42	0.85
I-b	0.78	0.60	0.98
I-c	0.77	0.66	0.90
II-a	0.65	0.55	0.75
III-a	0.57	0.51	0.77
III-b	0.85	0.74	0.94

- Type I error verified at nominal level for each test.
- In each simulation
 - Use of the M_{QLS} drastically increases power.
 - More than 1 causal locus is involved in true model.
 - Assumptions used to derive M_{QLS} are false.
- M_{QLS} captures property that cases with affected relatives are enriched for predisposing variants.
- M_{QLS} seems to have high power under complex trait models.

Robustness of M_{QLS} to misspecification of K_p

Power of M_{QLS}

Assumed K_p	Multiple of True K_p	Estimated Power (s.e.)
0.039	1/2	0.78 (.006)
0.078	1	0.77 (.006)
0.156	2	0.79 (.006)
0.312	4	0.68 (.007)
0.390	5	0.46 (.007)

- Model has 3 unlinked causal SNPs with epistasis.
- True K_p is .078
- When assumed K_p is within a factor of 2 of true K_p , there is no change in power in this case.
- Power of M_{QLS} appears to be fairly robust to misspecification of K_p .

Example: Testing for Association With Alcoholism, Using Genome Screen Data

- Genetic Analysis Workshop (GAW) 14 data from Collaborative Study for the Genetics of Alcoholism (COGA)
- 143 pedigrees each with at least 3 affecteds
- 506 cases and 202 controls
- 10,081 autosomal SNPs analyzed
- In the M_{QLS} , set $K_p = .05$, an estimate from the National Institute on Alcohol Abuse and Alcoholism (NIAAA).
- Binary phenotype (Affected with ALDX1 or “pure unaffected”).

Most significant SNPs in COGA Data Set (p-value < 5.0e-5 by at least 1 test)

chr	pos.	n_{ca}	n_{co}	p	p-value		
					$W_{\chi^2_{corr}}$	W_{QLS}	M_{QLS}
16	59.8	383	137	0.85	1.0e-4	1.2e-4	<u>2.5e-7</u>
6	153.7	397	144	0.85	1.6e-2	3.3e-1	<u>9.2e-6</u>
3	158.2	350	142	0.82	1.1e-2	7.2e-3	<u>2.3e-5</u>
7	123.7	419	159	0.84	1.8e-3	<u>2.7e-5</u>	3.7e-2
18	104.7	266	111	0.62	3.3e-1	8.3e-1	<u>4.1e-5</u>
18	95.8	394	143	0.67	8.7e-3	6.3e-3	<u>4.6e-5</u>
1	188.1	477	183	0.92	3.1e-2	3.7e-2	<u>4.9e-5</u>

Markers are tsc1750530, tsc1288916, tsc0175005, tsc0043946, tsc0046696, tsc0054146, and tsc0275539, respectively.

- SNP on chromosome 16 is genome-wide significant (p-value .008) after Bonferroni correction for 10,081 SNPs and 3 tests per SNP: $2.5e-7 \times 10,081 \times 3 = 7.6e-3$
- The most significant results are generally obtained with M_{QLS} .

Summary

- The QL framework provides a way to extend standard testing and estimation methods to the situation when sampled individuals are related.
- First moments under null and alternative and 2nd moments under null are required for our testing methods.
- Methods are very fast, even in complex inbred pedigrees.
- We currently use QL methods for a number of genetic problems when samples contain related individuals:
 - allele frequency estimation
 - Hardy-Weinberg testing
 - case-control association testing
 - * allelic tests (← discussed today)
 - * genotypic tests (analogue of Armitage trend test)
- For case-control association testing, use of modified QLS greatly improves power

Extensions

- Analyze quantitative traits
- Incorporate covariates
- Extension to haplotype analysis when complete haplotype information is not available

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Former Ph.D. student: Timothy Thornton (U.C. Berkeley)

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