

# QTL mapping in humans

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# Biometrical preliminaries

Consider a single QTL with alleles  $a_1, a_2, \dots, a_n$   
at frequencies  $p_1, p_2, \dots, p_n$

Assume random mating and Hardy-Weinberg equilibrium

Let  $Y$  = an individual's phenotype;  $G$  = QTL genotype

Define  $\mu_{ij} \equiv E(Y \mid G = a_i a_j)$  ( $\mu_{ij} = \mu_{ji}$  for all  $i, j$ )

Write  $\mu_{ij} = \mu + \alpha_i + \alpha_j + \delta_{ij}$

where  $\mu = \sum_{ij} \mu_{ij} p_i p_j$

$\alpha_i = \sum_j (\mu_{ij} - \mu) p_j$  average effect of allele  $a_i$

$\delta_{ij} = \mu_{ij} - (\mu + \alpha_i + \alpha_j)$  "dominance deviation"

# Genetic variances

For  $I$ , a random variable taking values  $1, 2, \dots, n$ ,  
with probability  $p_1, p_2, \dots, p_n$

$$E(\alpha_I) = \sum_i \alpha_i p_i = 0$$

$$E(\delta_{Ij}) = \sum_i \delta_{ij} p_i = 0 \quad \text{for any } j$$

Let  $J$  have the same distribution as  $I$ , with  $I$  &  $J$  being independent.

$$\text{var}(\alpha_I + \alpha_J) = 2 \text{var}(\alpha_I) = 2 \sum_i \alpha_i^2 p_i \equiv \sigma_a^2 \quad \text{additive variance}$$

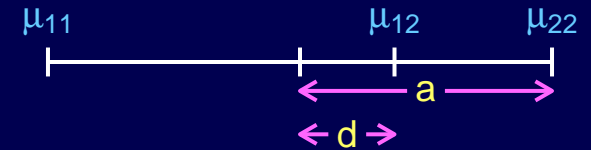
$$\text{var}(\delta_{IJ}) = \sum_{i,j} \delta_{ij}^2 p_i p_j \equiv \sigma_d^2 \quad \text{dominance variance}$$

Assume  $\text{var}(Y \mid G = a_i a_j) \equiv \sigma_e^2$

$$\text{Then } \text{var}(Y) = \sigma_a^2 + \sigma_d^2 + \sigma_e^2$$

# Special case

Diallelic QTL, equally frequent alleles



$$\mu = \frac{1}{4}\mu_{11} + \frac{1}{2}\mu_{12} + \frac{1}{4}\mu_{22}$$

$$\begin{aligned}\alpha_1 &= \frac{1}{2}(\mu_{11} - \mu) + \frac{1}{2}(\mu_{12} - \mu) \\ &= \frac{1}{2}\mu_{11} + \frac{1}{2}\mu_{12} - \mu \\ &= \dots = \frac{1}{4}(\mu_{11} - \mu_{22})\end{aligned}$$

$$\alpha_2 = -\alpha_1$$

$$\begin{aligned}\delta_{11} &= \mu_{11} - \mu - \alpha_1 - \alpha_2 \\ &= \dots = \frac{1}{2}\{(\mu_{11} + \mu_{22})/2 - \mu_{12}\}\end{aligned}$$

$$\delta_{22} = \delta_{11}$$

$$\delta_{12} = \delta_{21} = -\delta_{11}$$

# Kinship coefficient

Consider 2 individuals and a single autosomal locus.

Let  $I, J$  = random alleles chosen from each individual.

$$\Phi_{a,b} = \Pr(I \text{ \& } J \text{ are IBD})$$

For noninbred individuals,  $\Phi_{a,b} = \frac{1}{4}\pi_1 + \frac{1}{2}\pi_2$

Relationship	$\pi_0$	$\pi_1$	$\pi_2$	$\Phi$
MZ twins	0	0	1	1/2
Parent-offspring	0	1	0	1/4
Full sibs	1/4	1/2	1/4	1/4
Half sibs	1/2	1/2	0	1/8
Uncle-nephew	1/2	1/2	0	1/8
Grandparent-GC	1/2	1/2	0	1/8
Double 1st cousins	9/16	6/16	1/16	1/8
1st cousins	3/4	1/4	0	1/16
1st cousins once rem.	7/8	1/8	0	1/32
2nd cousins	15/16	1/16	0	1/64

# Inbreeding coefficient

$$f = \Phi_{\text{mom,dad}}$$

$$= \text{Pr}(\text{the individual's two alleles are IBD})$$

$$= 2\Phi_{a,a} - 1$$

# Genetic correlations

Let  $A, B$  be non-inbred individuals with phenotypes  $Y_A, Y_B$ .

$$\text{Let } X_i = Y_i - \mu$$

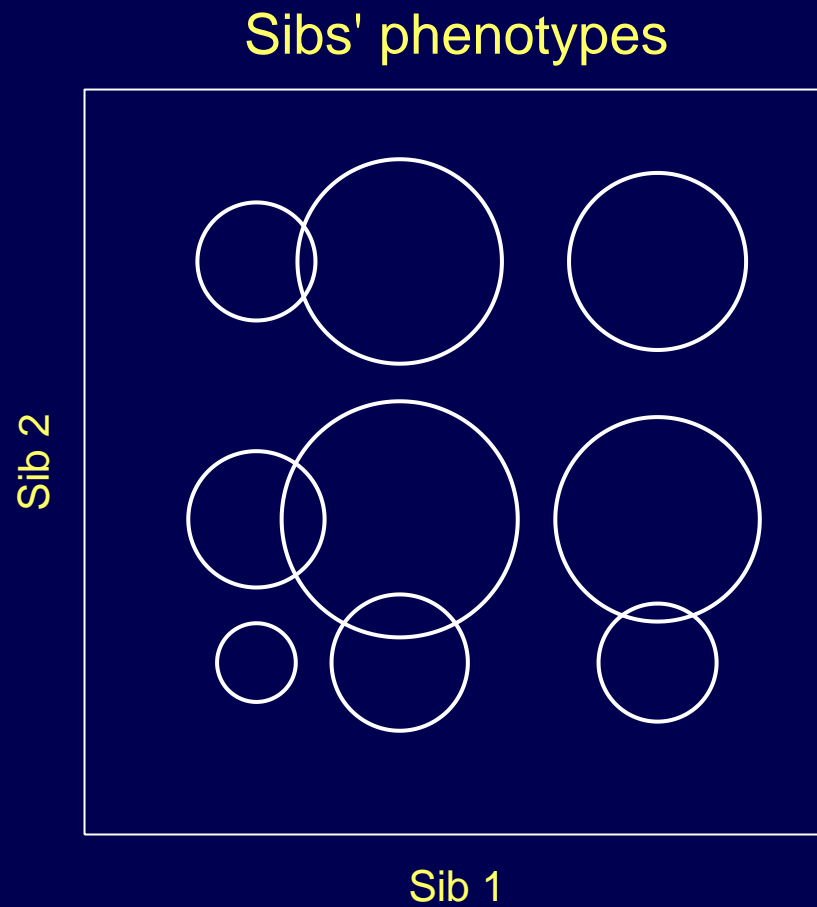
Assuming one QTL:

$$\begin{aligned} \text{cov}(Y_A, Y_B) &= E(X_A X_B) \\ &= \sum_k E(X_A X_B \mid k \text{ alleles IBD at QTL}) \pi_k \end{aligned}$$

$$\begin{cases} E(X_A X_B \mid 2 \text{ alleles IBD}) = \dots = \sigma_a^2 + \sigma_d^2 \\ E(X_A X_B \mid 1 \text{ alleles IBD}) = \dots = \frac{1}{2} \sigma_a^2 \\ E(X_A X_B \mid 0 \text{ alleles IBD}) = \dots = 0 \end{cases}$$

$$\begin{aligned} \text{Thus } \text{cov}(Y_A, Y_B) &= (\sigma_a^2 + \sigma_d^2) \pi_2 + \frac{1}{2} \sigma_a^2 \pi_1 \\ &= \left(\frac{1}{2}\pi_1 + \pi_2\right) \sigma_a^2 + \pi_2 \sigma_d^2 \\ &= 2 \Phi_{A,B} \sigma_a^2 + \pi_2 \sigma_d^2 \end{aligned}$$

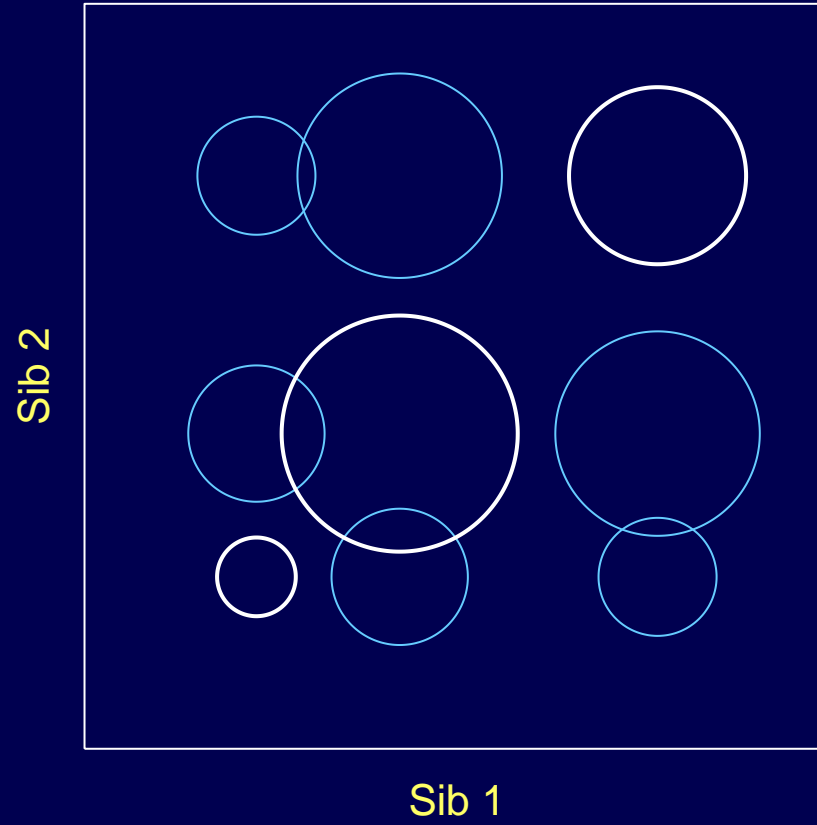
# Sibpair, diallelic QTL





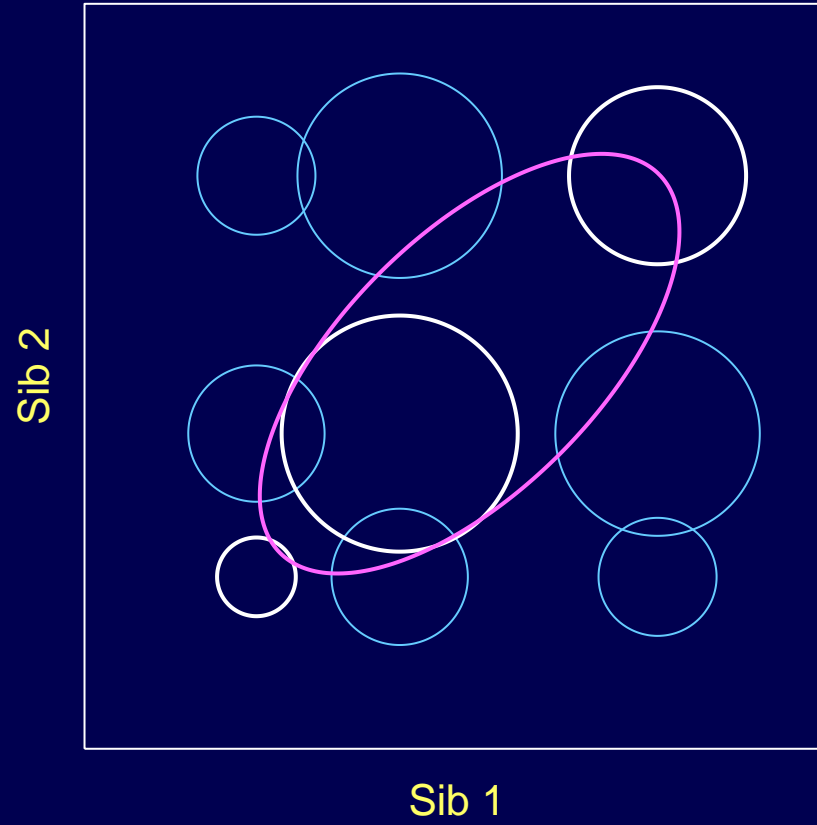
IBD=2

Sibs' phenotypes



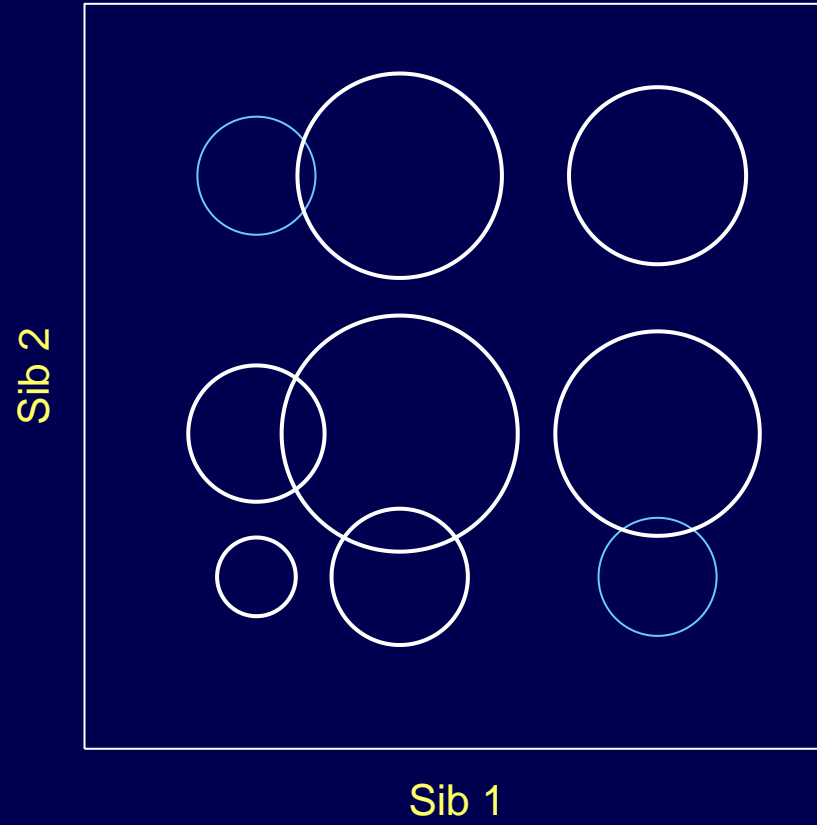
IBD=2

Sibs' phenotypes



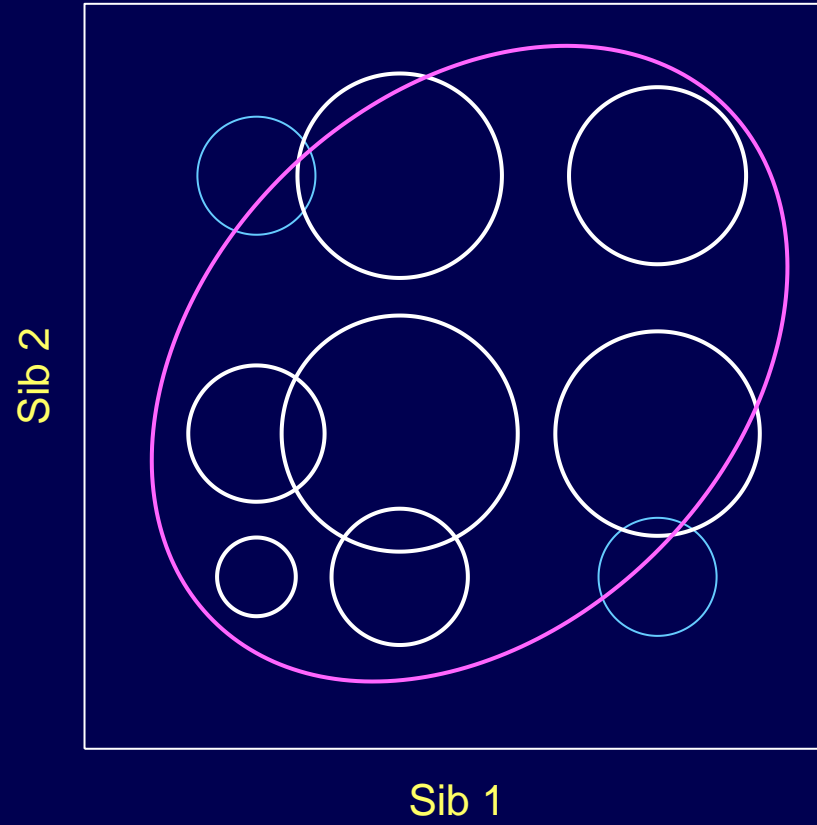
IBD = 1

Sibs' phenotypes



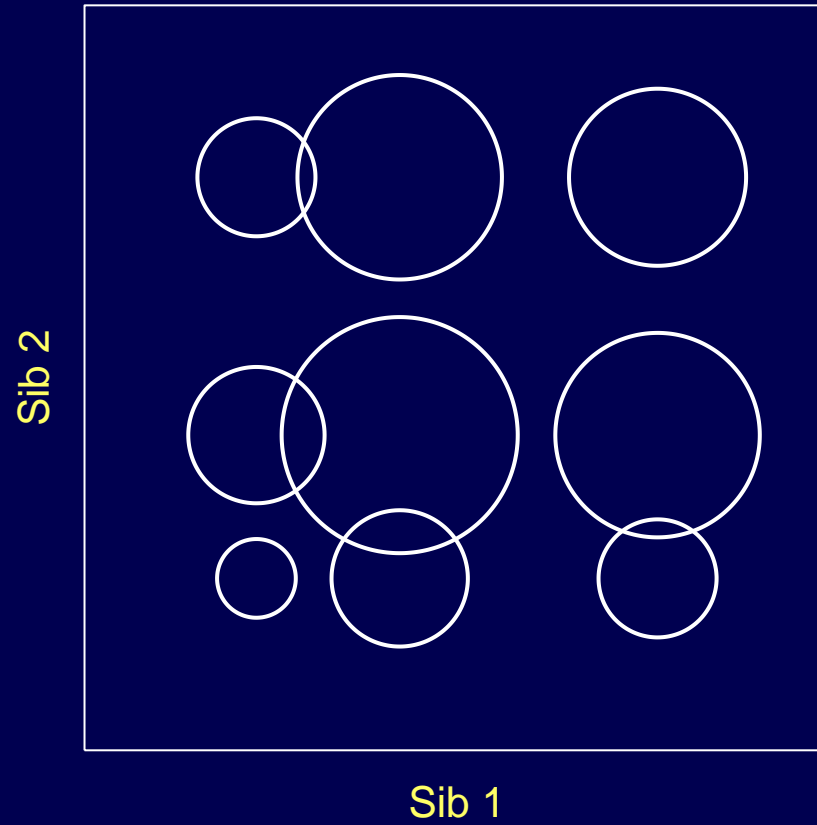
IBD = 1

Sibs' phenotypes



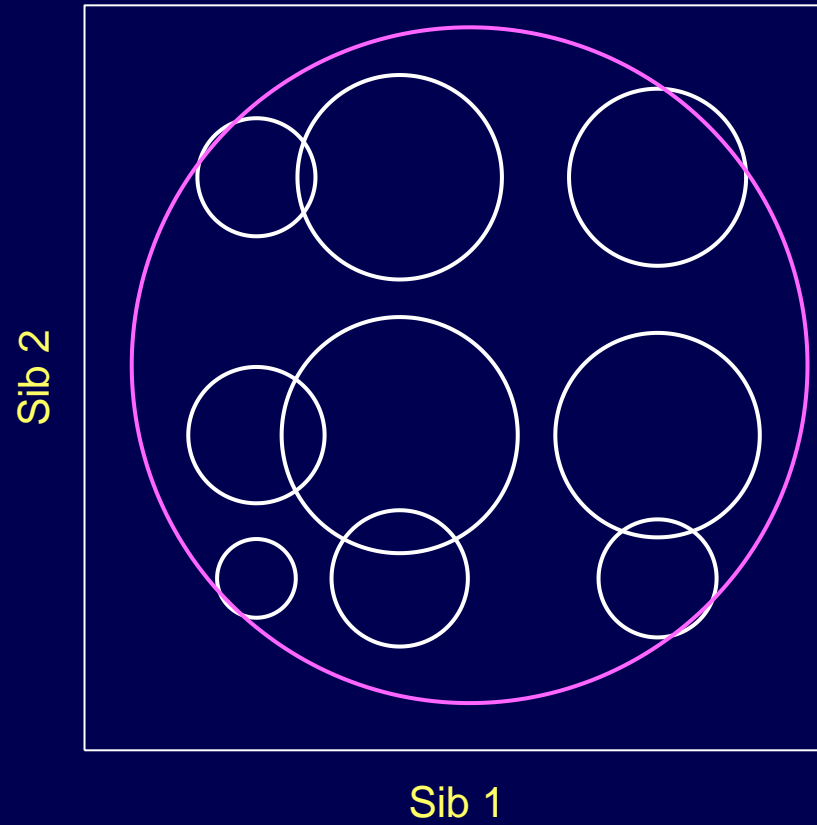
IBD = 0

Sibs' phenotypes



IBD = 0

Sibs' phenotypes



# A few more calculations...

Let  $K = \#$  alleles IBD at marker,  $V = \#$  alleles IBD at QTL

$r =$  recombination fraction between marker and QTL

$$\psi = r^2 + (1 - r)^2$$

For sib pairs,  $\Pr(V = v \mid K = k) =$

		v		
		0	1	2
k				
0		$(1 - \psi)^2$	$2 \psi (1 - \psi)$	$\psi^2$
1		$\psi (1 - \psi)$	$(1 - \psi)^2 + \psi^2$	$\psi (1 - \psi)$
2		$\psi^2$	$2 \psi (1 - \psi)$	$(1 - \psi)^2$

$$\text{cov}(Y_A, Y_B \mid K = k) = \sum_k \text{cov}(Y_A, Y_B \mid V = v) \Pr(V = v \mid K = k)$$

$$= \begin{cases} \psi (\sigma_a^2 + \psi \sigma_d^2) & \text{if } k = 0 \\ \frac{1}{2} \sigma_a^2 + \psi(1 - \psi)\sigma_d^2 & \text{if } k = 1 \\ (1 - \psi) [\sigma_a^2 + (1 - \psi)\sigma_d^2] & \text{if } k = 2 \end{cases}$$

# One more thing...

$$\begin{aligned} E \left[ (Y_A - Y_B)^2 \mid V = v \right] &= \text{var} [Y_A - Y_B \mid V = v] + \{E(Y_A - Y_B \mid V = v)\}^2 \\ &= \text{var}(Y_A \mid V = v) + \text{var}(Y_B \mid V = v) - 2 \text{cov}(Y_A, Y_B \mid V = v) \\ &= 2(\sigma_a^2 + \sigma_d^2 + \sigma_e^2) - k \sigma_a^2 + \delta_{k^2} (2 \sigma_d^2) \end{aligned}$$



# QTL mapping with sib pairs

## 1. Explicit diallelic model

$(Y_{i1}, Y_{i2})$  follows a mixture of 9 bivariate normals, parametrized by  $\mu_{11}, \mu_{12}, \mu_{22}, \sigma^2$

## 2. “Variance components”

$(Y_{i1}, Y_{i2}) \mid \# \text{ alleles IBD at QTL} = k$

follows a bivariate normal distribution, with mean  $(\mu, \mu)$  and variance matrix

$$V_k = \begin{pmatrix} v_{11} & v_{12}^k \\ v_{12}^k & v_{11} \end{pmatrix}$$

where  $v_{11} = \sigma_a^2 + \sigma_d^2 + \sigma_e^2$ ,

$$v_{12}^k = \begin{cases} 0 & \text{if } k = 0 \\ \frac{1}{2} \sigma_a^2 & \text{if } k = 1 \\ \sigma_a^2 + \sigma_d^2 & \text{if } k = 2 \end{cases}$$

# QTL mapping with sib pairs

## 2. “Variance components”

Method 2A: With incomplete data on  $k$ , treat as

mixture of 3 bivariate normal dist'ns, with wts  $\Pr(K=k \mid \text{marker data})$

Method 2B: With incomplete data on  $k$ , treat as

single bivariate normal, plugging in

$\hat{k} = E(k \mid \text{marker data})$  for  $k$  and

$\Pr(k = 2 \mid \text{marker data})$  for  $\delta_{k2}$

→ replace  $V_k$  with  $E(V_k \mid \text{marker data})$

# QTL mapping with sib pairs

## 3. Haseman-Elston regression

Consider only  $(Y_{i1} - Y_{i2})^2$

$$E \{ (Y_{i1} - Y_{i2})^2 \mid k \text{ alleles IBD at QTL} \} = \beta_0 - (\sigma_a^2) k + (2\sigma_d^2) \delta_{k2}$$

→ Regress  $(Y_1 - Y_2)^2$  on  $k$  (or on  $k$  and  $\delta_{k2}$ )

→ Incomplete info on  $k$ ? Plug in  $\hat{k}$

Assumes  $(Y_1 - Y_2)^2 \mid k \sim$  normal with constant variance

# Larger pedigrees

## 1. Variance components

phenotype = mean + add've QTL + “polygenes” + noise

$$\text{var}(Y) = \sigma_{Q_a}^2 + \sigma_{P_a}^2 + \sigma_e^2$$

$$\text{cov}(Y_i, Y_j \mid k \text{ alleles IBD at QTL}) = \frac{1}{2} k \sigma_{Q_a}^2 + 2 \Phi_{ij} \sigma_{P_a}^2$$

## 2. Explicit diallelic QTL model (via MCMC)

# Larger pedigrees

## 1. Variance components

phenotype = mean + add've QTL + “polygenes” + noise

$$\text{var}(Y) = \sigma_{Q_a}^2 + \sigma_{P_a}^2 + \sigma_e^2$$

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## 2. Explicit diallelic QTL model (via MCMC)

H-E robust to non-normality, but has low power

V-C powerful when the MVN model is correct, but is not robust

Other issues: selective sampling, treatment of covariates