

Introduction to QTL mapping in model organisms

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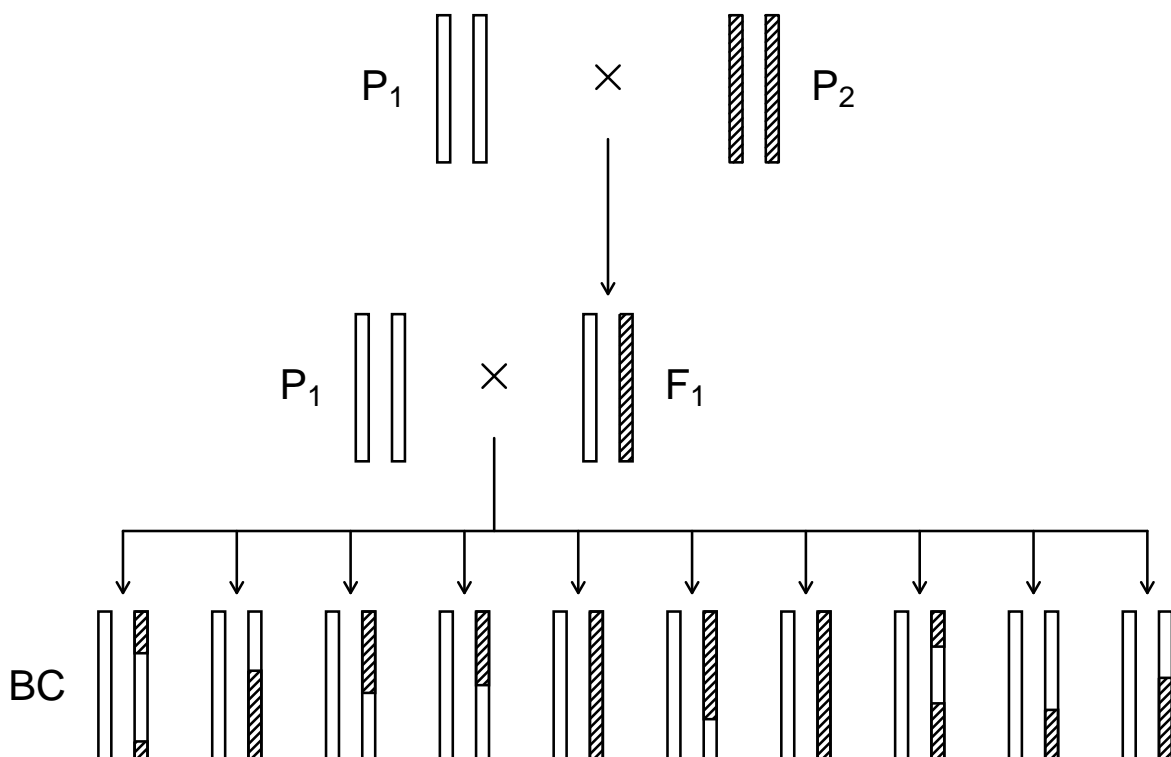
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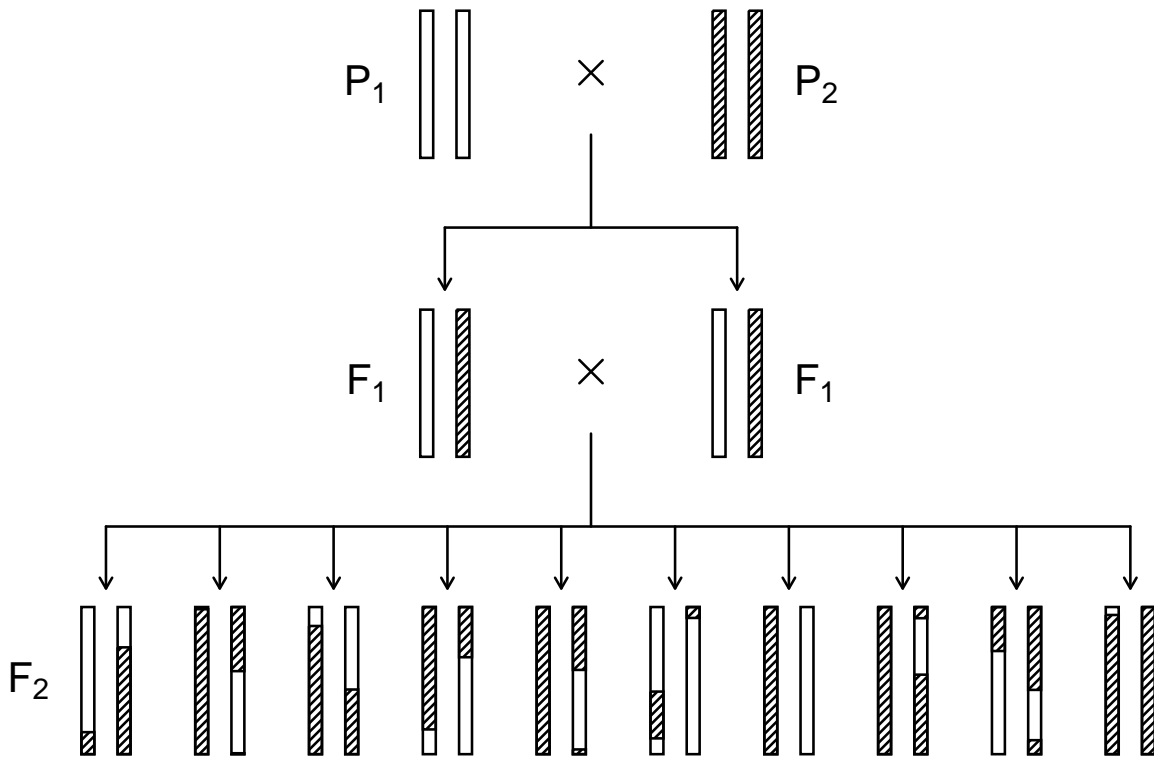
[→ Teaching → Miscellaneous lectures]



Backcross

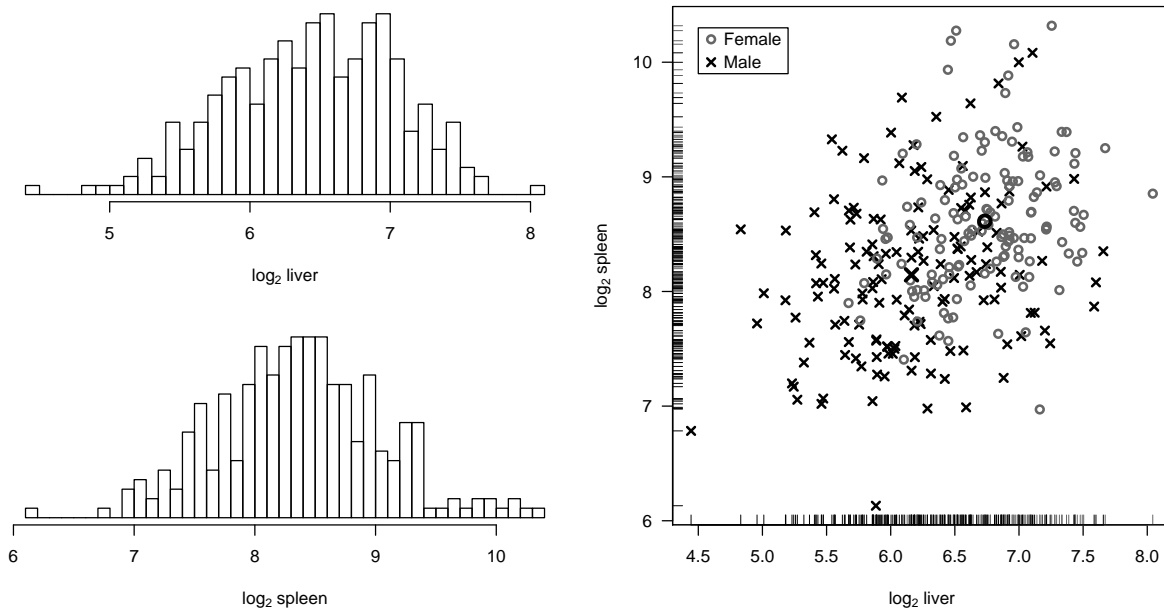


Intercross



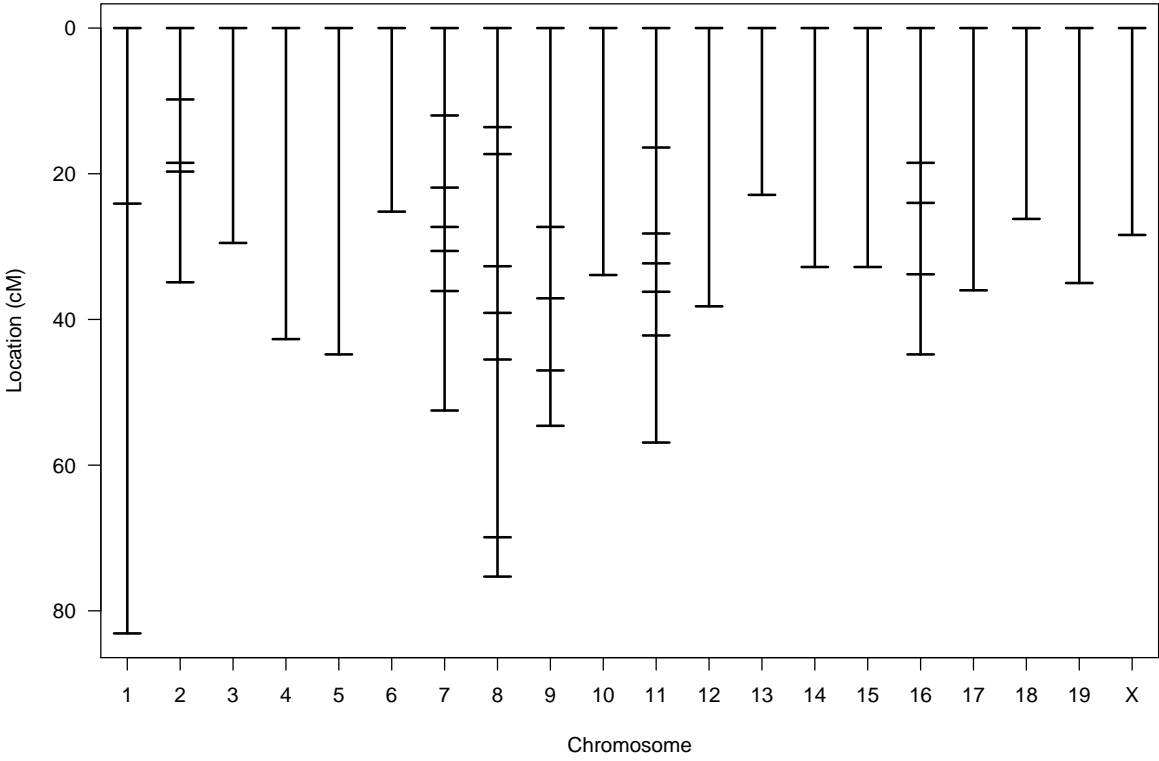
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Phenotype data



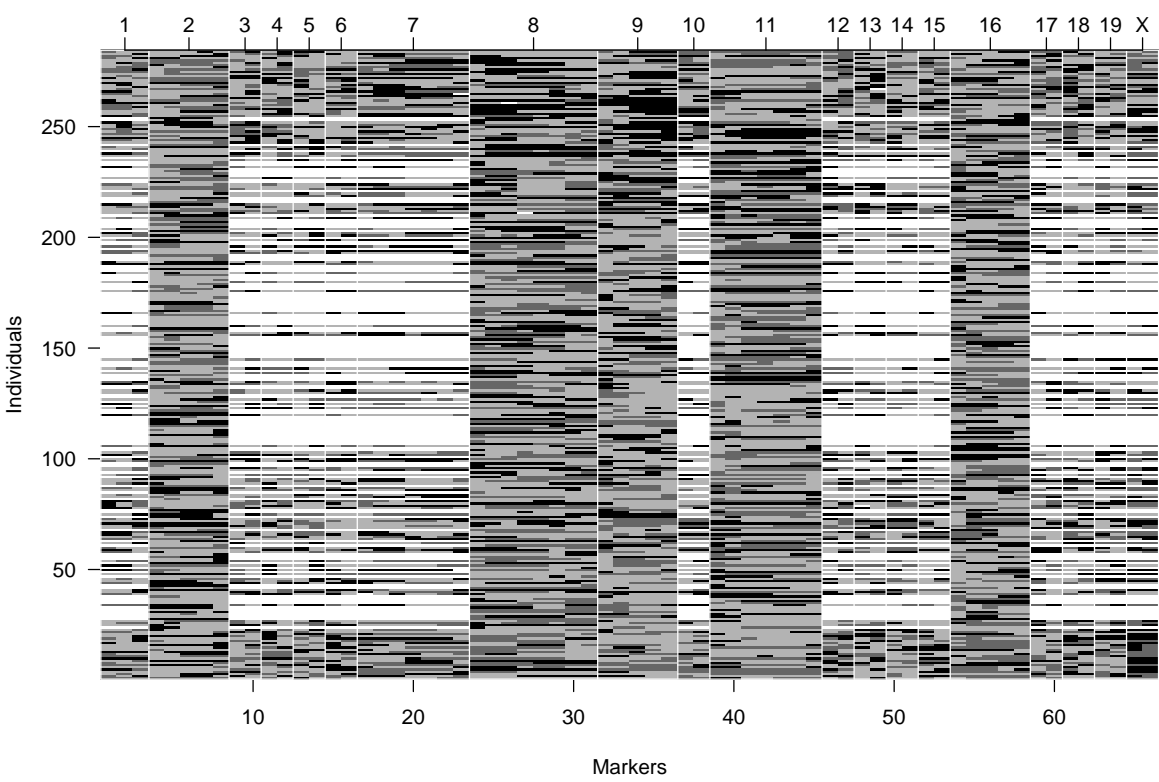
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Genetic map



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Genotype data



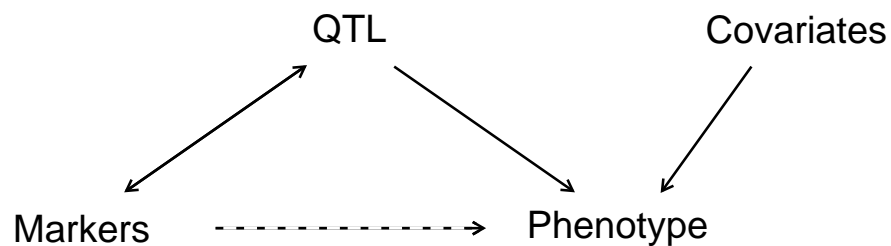
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Goals

- Identify quantitative trait loci (QTL)
(and interactions among QTL)
- Interval estimates of QTL location
- Estimated QTL effects

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Statistical structure



The missing data problem:

Markers \longleftrightarrow QTL

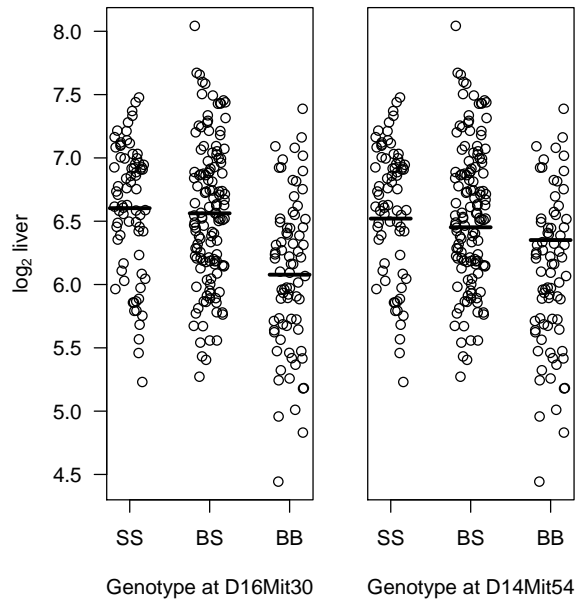
The model selection problem:

QTL, covariates \longrightarrow phenotype

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ANOVA at marker loci

- Also known as marker regression.
- Split mice into groups according to genotype at a marker.
- Do a t-test / ANOVA.
- Repeat for each marker.



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ANOVA at marker loci

Advantages

- Simple.
- Easily incorporates covariates.
- Easily extended to more complex models.
- Doesn't require a genetic map.

Disadvantages

- Must exclude individuals with missing genotype data.
- Imperfect information about QTL location.
- Suffers in low density scans.
- Only considers one QTL at a time.

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Interval mapping

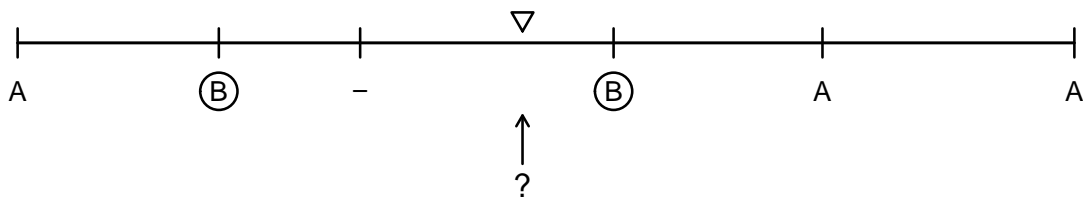
Lander & Botstein (1989)

- Assume a single QTL model.
- Each position in the genome, one at a time, is posited as the putative QTL.
- Let $q = 1/0$ if the (unobserved) QTL genotype is BB/AB.
(Or 2/1/0 if the QTL genotype is BB/AB/AA in an intercross.)
Assume $y|q \sim N(\mu_q, \sigma)$
- Given genotypes at linked markers, $y \sim$ mixture of normal dist'ns with mixing proportions $\Pr(q | \text{marker data})$:

		QTL genotype	
M ₁	M ₂	BB	AB
BB	BB	$(1 - r_L)(1 - r_R)/(1 - r)$	$r_L r_R/(1 - r)$
BB	AB	$(1 - r_L)r_R/r$	$r_L(1 - r_R)/r$
AB	BB	$r_L(1 - r_R)/r$	$(1 - r_L)r_R/r$
AB	AB	$r_L r_R/(1 - r)$	$(1 - r_L)(1 - r_R)/(1 - r)$

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Genotype probabilities



Calculate $\Pr(q | \text{marker data})$, assuming

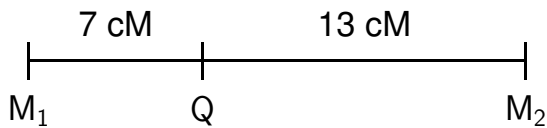
- No crossover interference
- No genotyping errors

Or use the hidden Markov model (HMM) technology

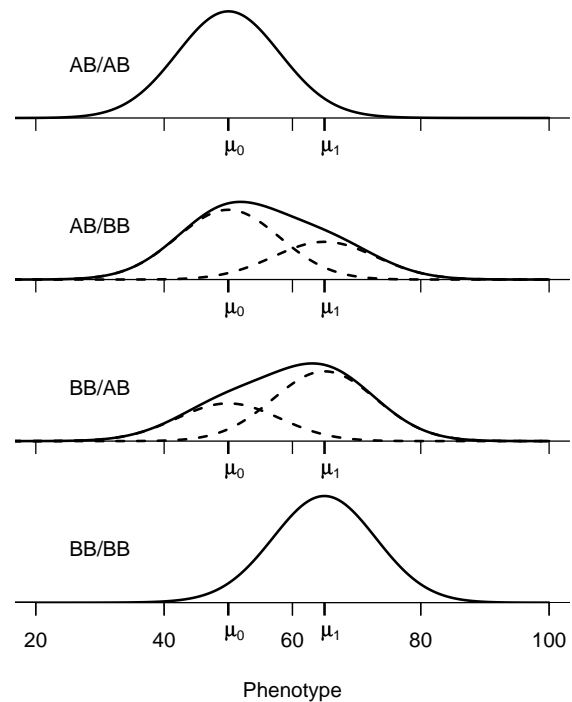
- To allow for genotyping errors
- To incorporate dominant markers
- (Still assume no crossover interference.)

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The normal mixtures



- Two markers separated by 20 cM, with the QTL closer to the left marker.
- The figure at right shows the distributions of the phenotype conditional on the genotypes at the two markers.
- The dashed curves correspond to the components of the mixtures.



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Interval mapping

Let $p_{ij} = \Pr(q_i = j | \text{marker data})$

$$y_i | q_i \sim N(\mu_{q_i}, \sigma^2)$$

$$\Pr(y_i | \text{marker data}, \mu_0, \mu_1, \sigma) = \sum_j p_{ij} f(y_i; \mu_j, \sigma)$$

$$\text{where } f(y; \mu, \sigma) = \exp[-(y - \mu)^2 / (2\sigma^2)] / \sqrt{2\pi\sigma^2}$$

$$\text{Log likelihood: } l(\mu_0, \mu_1, \sigma) = \sum_i \log \Pr(y_i | \text{marker data}, \mu_0, \mu_1, \sigma)$$

Maximum likelihood estimates (MLEs) of μ_0, μ_1, σ :

values for which $l(\mu_0, \mu_1, \sigma)$ is maximized.

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EM algorithm

Dempster et al. (1977)

E step:

$$\begin{aligned}\text{Let } w_{ij}^{(k)} &= \Pr(q_i = j | y_i, \text{ marker data}, \hat{\mu}_0^{(k-1)}, \hat{\mu}_1^{(k-1)}, \hat{\sigma}^{(k-1)}) \\ &= \frac{p_{ij} f(y_i; \hat{\mu}_j^{(k-1)}, \hat{\sigma}^{(k-1)})}{\sum_j p_{ij} f(y_i; \hat{\mu}_j^{(k-1)}, \hat{\sigma}^{(k-1)})}\end{aligned}$$

M step:

$$\begin{aligned}\text{Let } \hat{\mu}_j^{(k)} &= \sum_i y_i w_{ij}^{(k)} / \sum_i w_{ij}^{(k)} \\ \hat{\sigma}^{(k)} &= \sqrt{\sum_i \sum_j w_{ij}^{(k)} (y_i - \hat{\mu}_j^{(k)})^2 / n}\end{aligned}$$

The algorithm:

Start with $w_{ij}^{(1)} = p_{ij}$; iterate the E & M steps until convergence.

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LOD scores

The LOD score is a measure of the strength of evidence for the presence of a QTL at a particular location.

$\text{LOD}(\lambda) = \log_{10}$ likelihood ratio comparing the hypothesis of a QTL at position λ versus that of no QTL

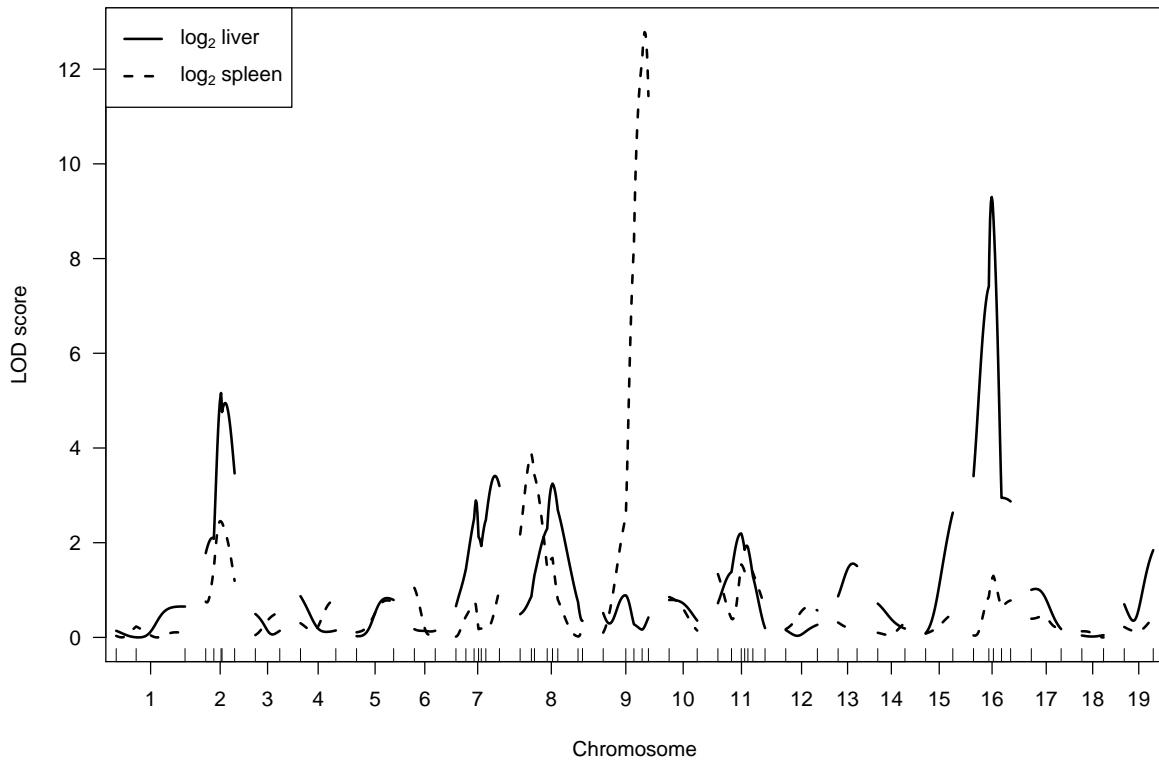
$$= \log_{10} \left\{ \frac{\Pr(y | \text{QTL at } \lambda, \hat{\mu}_{0\lambda}, \hat{\mu}_{1\lambda}, \hat{\sigma}_\lambda)}{\Pr(y | \text{no QTL}, \hat{\mu}, \hat{\sigma})} \right\}$$

$\hat{\mu}_{0\lambda}, \hat{\mu}_{1\lambda}, \hat{\sigma}_\lambda$ are the MLEs, assuming a single QTL at position λ .

No QTL model: The phenotypes are independent and identically distributed (iid) $N(\mu, \sigma^2)$.

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LOD curves



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Interval mapping

Advantages

- Takes proper account of missing data.
- Allows examination of positions between markers.
- Gives improved estimates of QTL effects.
- Provides pretty graphs.

Disadvantages

- Increased computation time.
- Requires specialized software.
- Difficult to generalize.
- Only considers one QTL at a time.

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LOD thresholds

Large LOD scores indicate evidence for the presence of a QTL

Question: How large is large?

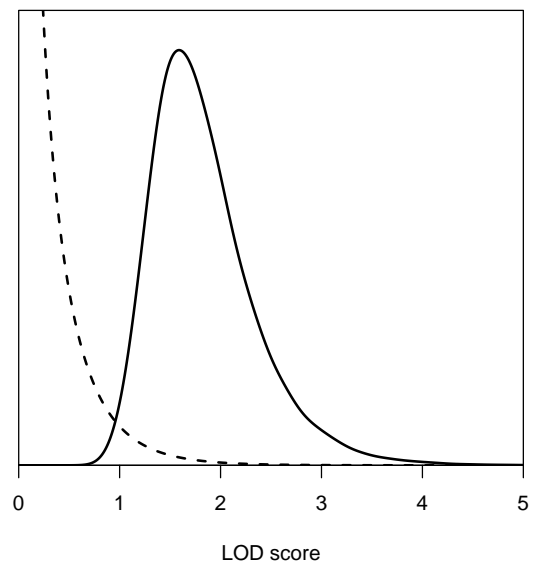
LOD threshold = 95 %ile of distr'n of max LOD, genome-wide, if there are no QTLs anywhere

- Derivation:
- Analytical calculations (L & B 1989)
 - Simulations (L & B 1989)
 - Permutation tests (Churchill & Doerge 1994)

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Null distribution of the LOD score

- Null distribution derived by computer simulation of backcross with genome of typical size.
- Dashed curve: distribution of LOD score at any one point.
- Solid curve: distribution of maximum LOD score, genome-wide.



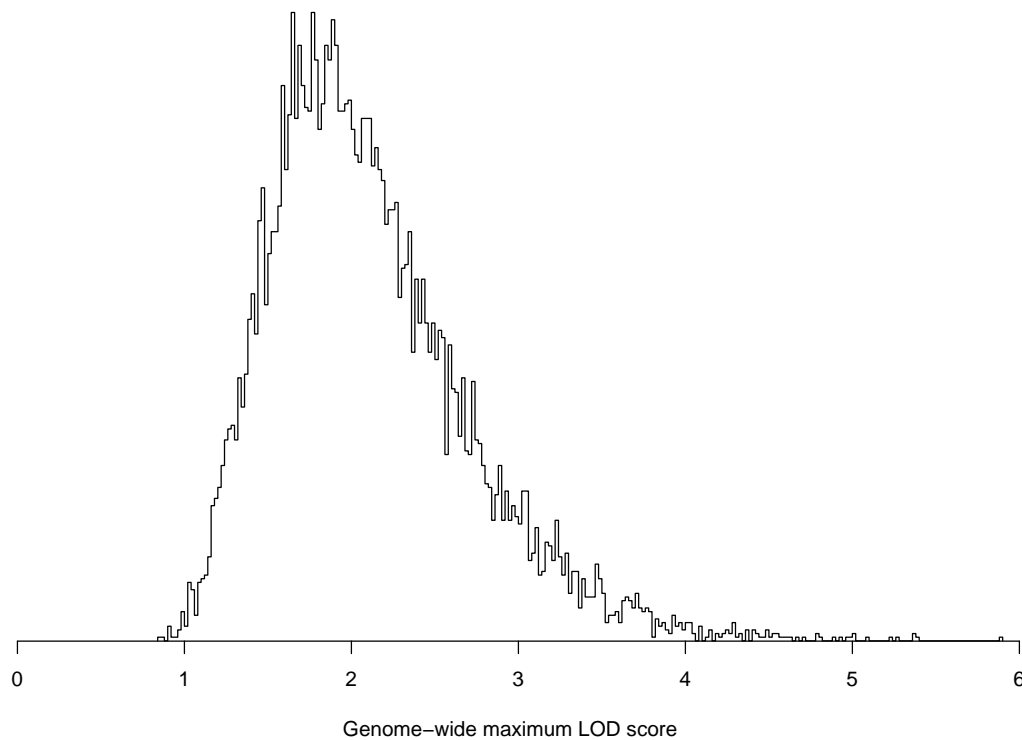
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Permutation test



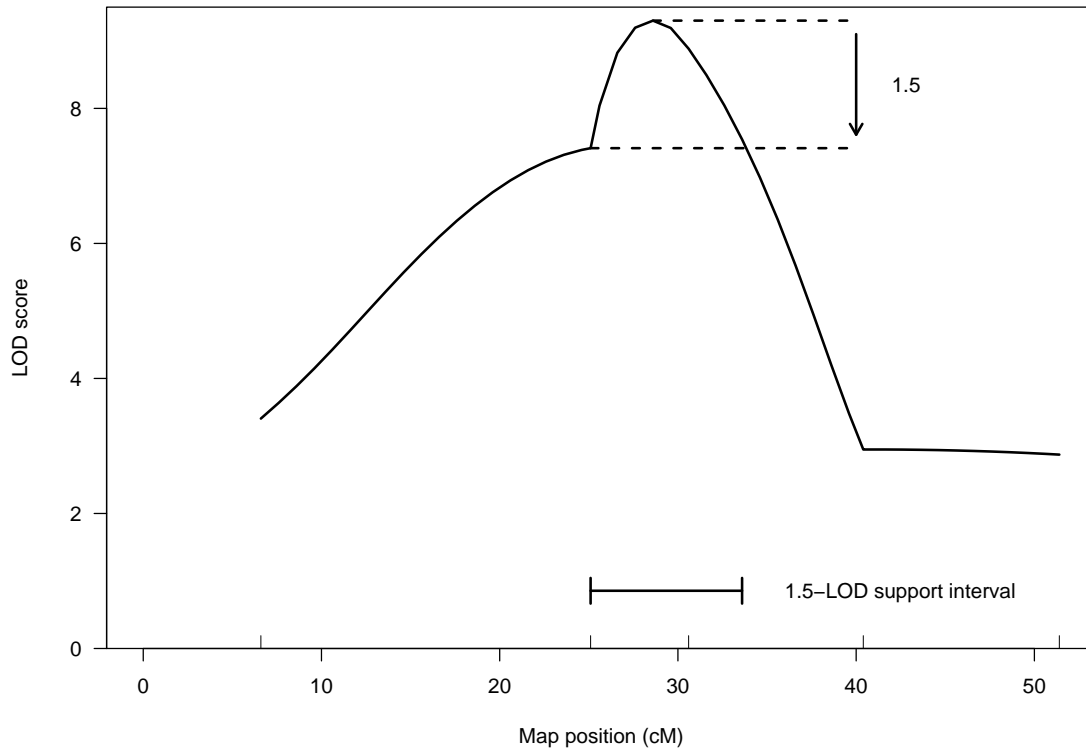
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Permutation results



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LOD support intervals



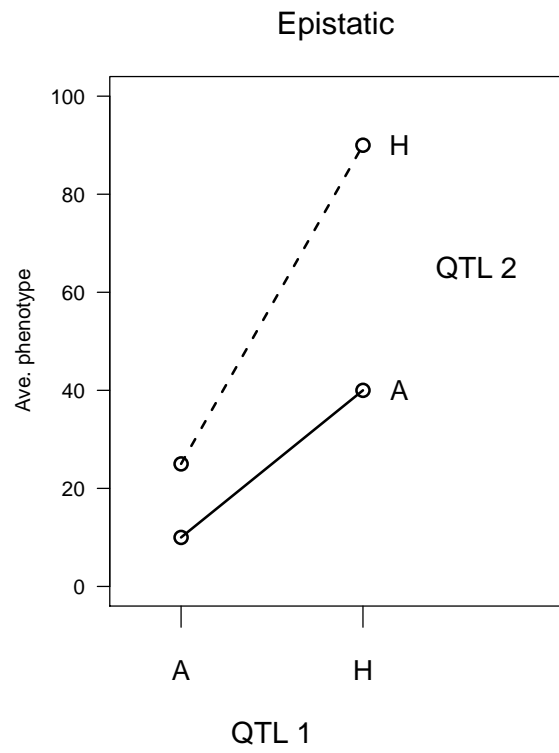
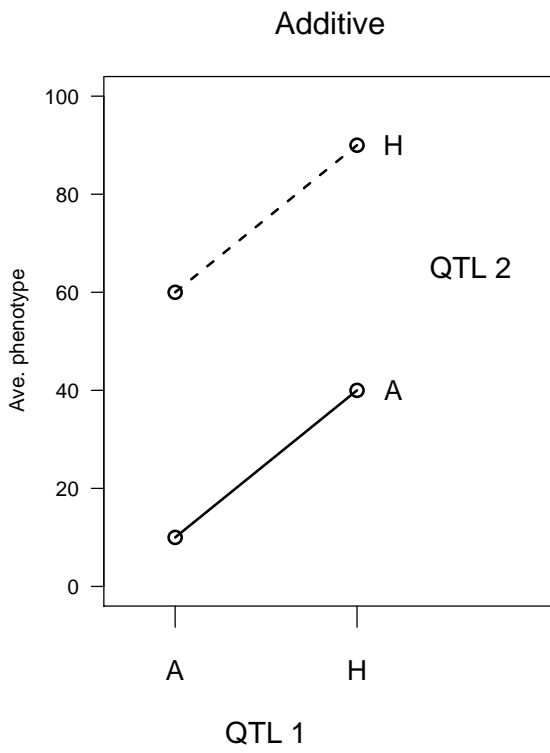
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Modelling multiple QTL

- Reduce residual variation \implies increased power
- Separate linked QTL
- Identify interactions among QTL

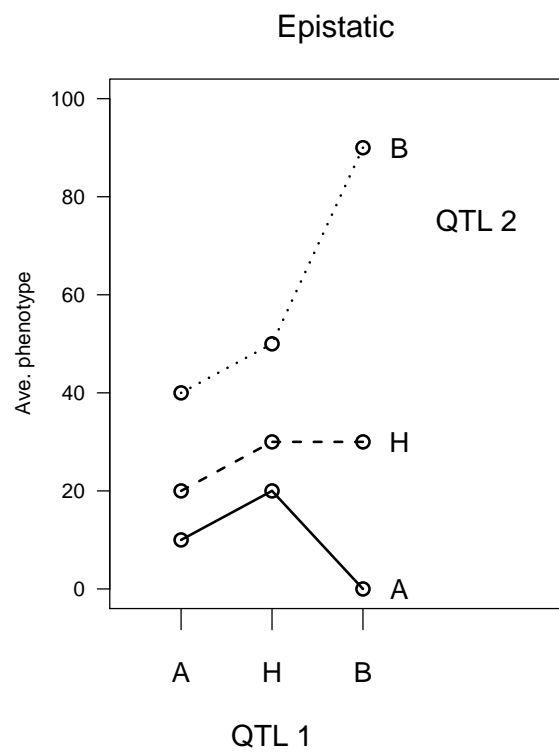
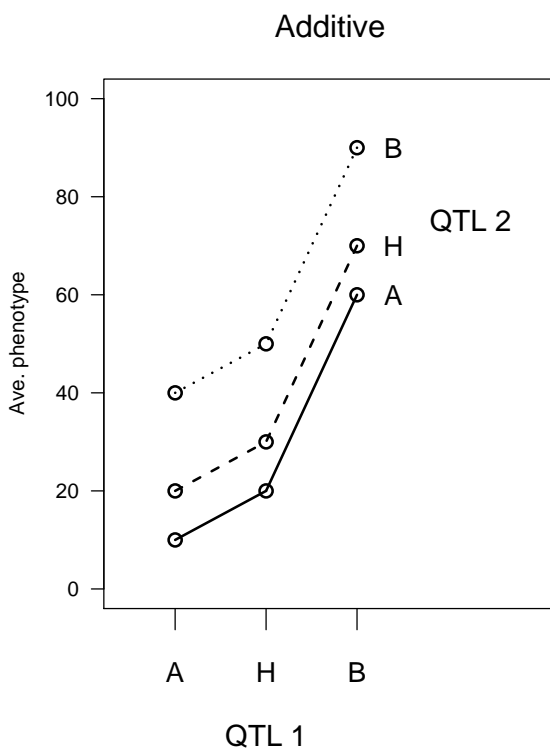
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Epistasis in BC



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Epistasis in F₂



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