

Detecting single QTL

Search for one QTL at fixed cM intervals across the genome

- + Estimate additive (and possibly dominance) effects of QTL at every putative QTL location
- + Identified QTL may be used as cofactors in consecutive analyses to remove background noise - often called Multiple QTL Mapping or **Composite interval mapping**

Detecting multiple QTL

II) Likelihood based Multiple QTL Method (Kao et al 1999)

- + Identification of regions with indications of QTL activity
- + Searches for multiple interacting QTL at fixed cM intervals in these regions

> Model selection

- + Yet not solved how to chose the significance threshold for these analyses
- + Very time consuming analysis, **Many combinations possible**
randomization testing intractable

Detecting multiple QTL

Carlborg, O., Andersson, L. and Kinghorn, B.P. 2000. The use of a genetic algorithm for simultaneous mapping of multiple interacting quantitative trait loci. *Genetics*. In Press

A simultaneous search for multiple interacting QTL has higher power to detect QTL and estimates parameters better

Simultaneous mapping of multiple QTL can be used in practice if a better search algorithm is used

The genetic algorithms are good for QTL mapping since they are:

- + Robust
- + Easy to implement
- + Computationally efficient

Models of dominance and epistasis

Dominance:
$$\begin{pmatrix} II \\ Ii \\ ii \end{pmatrix} = \begin{pmatrix} \mu + A_i \\ \mu + D_i \\ \mu - A_i \end{pmatrix}$$

Use genetic markers for known QTL (I, i).

Use coefficients of expression for genome-wide effects

Epistasis (2-locus):

$$\begin{pmatrix} II JJ & II Jj & II jj \\ Ii JJ & Ii Jj & Ii jj \\ ii JJ & ii Jj & ii jj \end{pmatrix} = \begin{pmatrix} \mu + A_i + A_j + AA_{ij} & \mu + A_i + D_j + AD_{ij} & \mu + A_i - A_j - AA_{ij} \\ \mu + D_i + A_j + AD_{ji} & \mu + D_i + D_j + DD_{ij} & \mu + D_i - A_j - AD_{ji} \\ \mu - A_i + A_j - AA_{ij} & \mu - A_i + D_j - AD_{ij} & \mu - A_i - A_j + AA_{ij} \end{pmatrix}$$

... many parameters to estimate!

Detecting multiple QTL – epistatic models

Reasons for using an epistatic model when mapping multiple QTL:

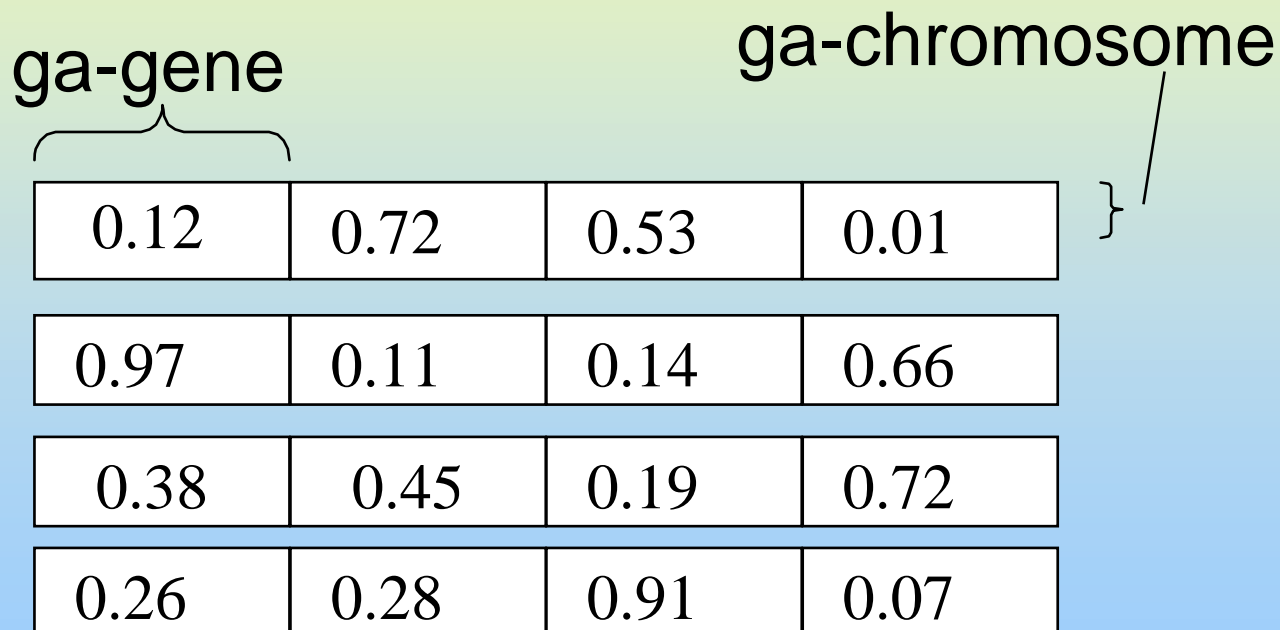
- Higher power to detect interacting QTL
- Better estimates of QTL effects

Classical epistatic interactions are e.g.

- + Complementary epistasis (9:7)
- + Dominant epistasis (12:3:1)
- + Duplicate epistasis (15:1)
- + Recessive epistasis (9:3:4)
- + Inhibitory epistasis (13:3)

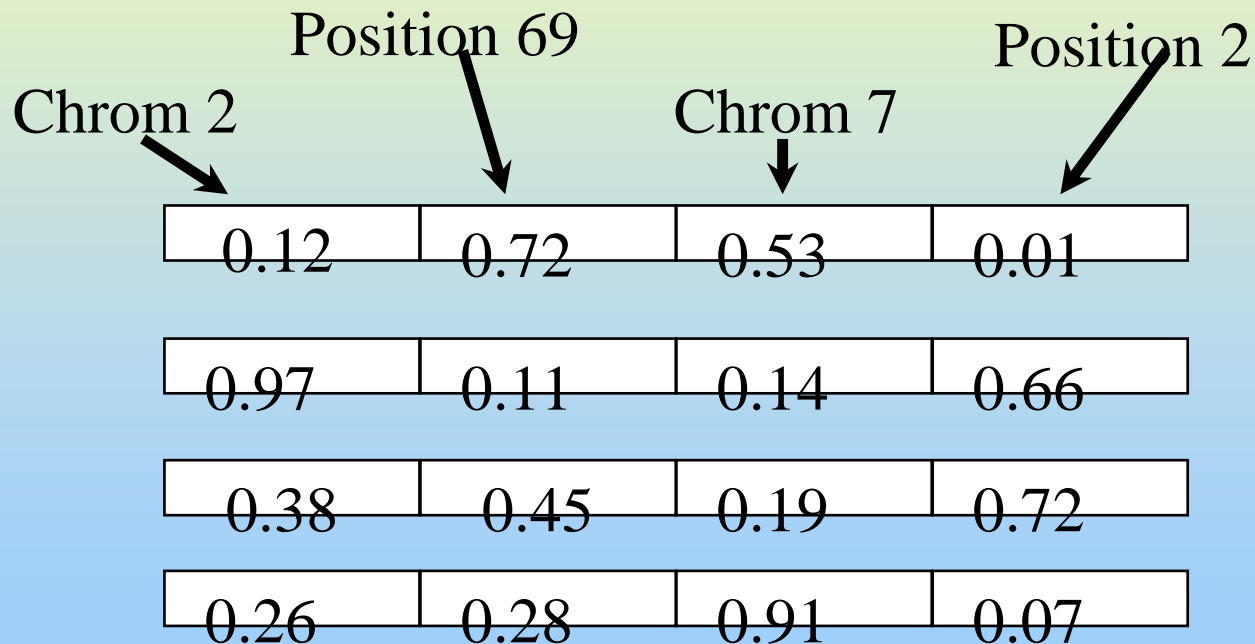
Implementation of genetic algorithm:

1) Generate a population of ga-chromosomes



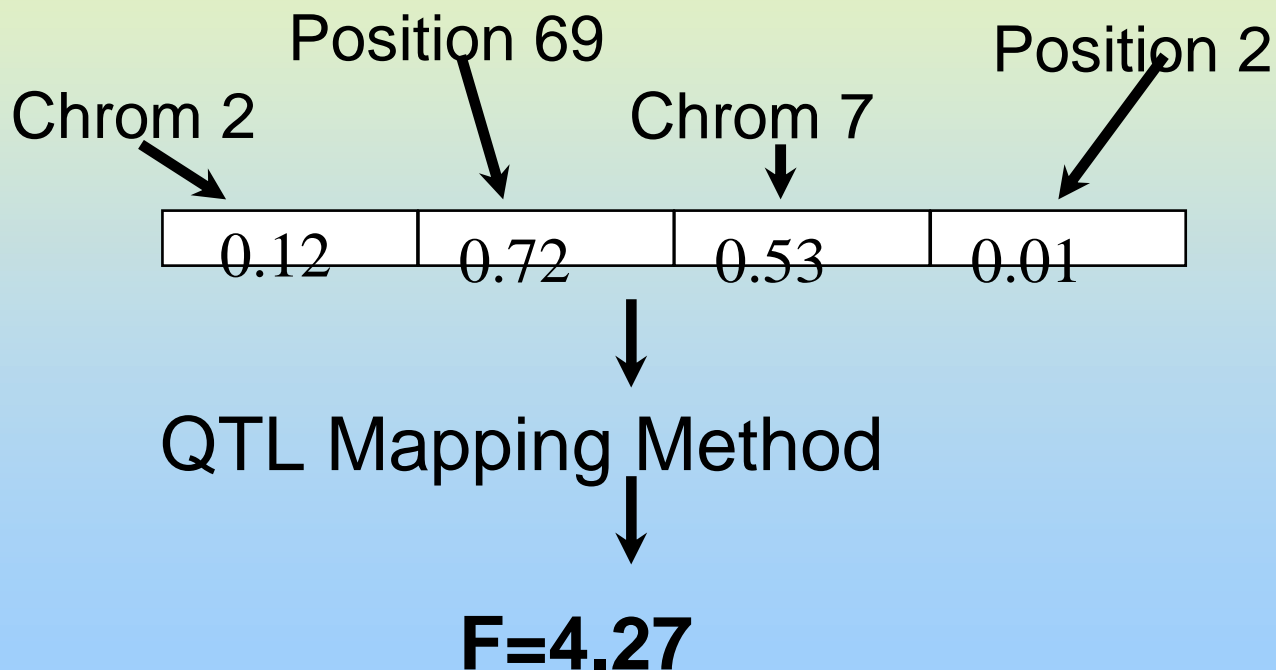
Implementation in QTL mapping:

2) Translate coded values to QTL positions



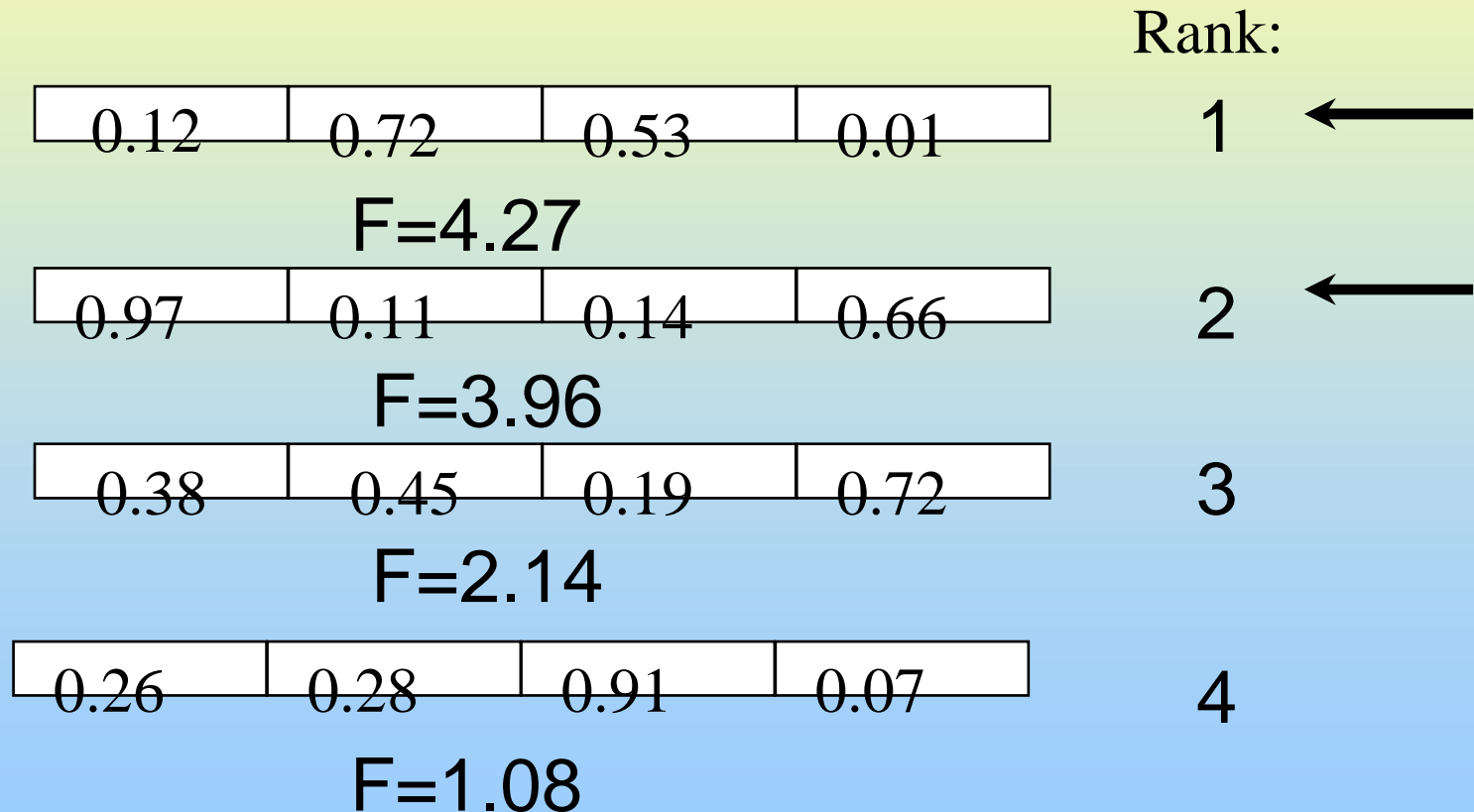
Implementation in QTL mapping:

3) Evaluate statistical fit for each ga-chromosome



Implementation in QTL mapping:

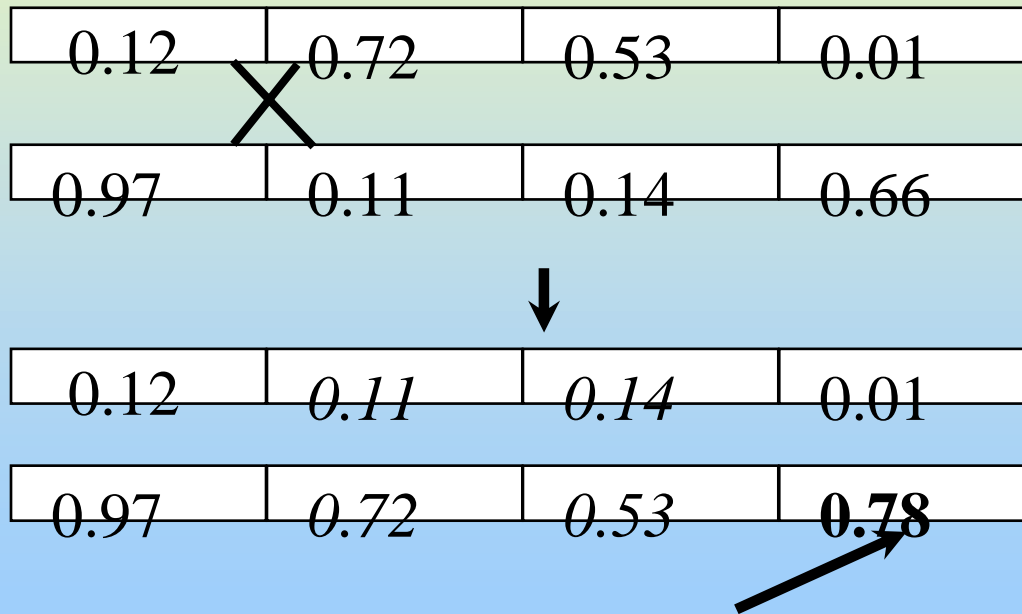
4) Select good ga-chromosomes



Implementation in QTL mapping:

5) Generation of new ga-chromosomes (Breeding)

Recombination



Mutation

Gain in computing speed ...

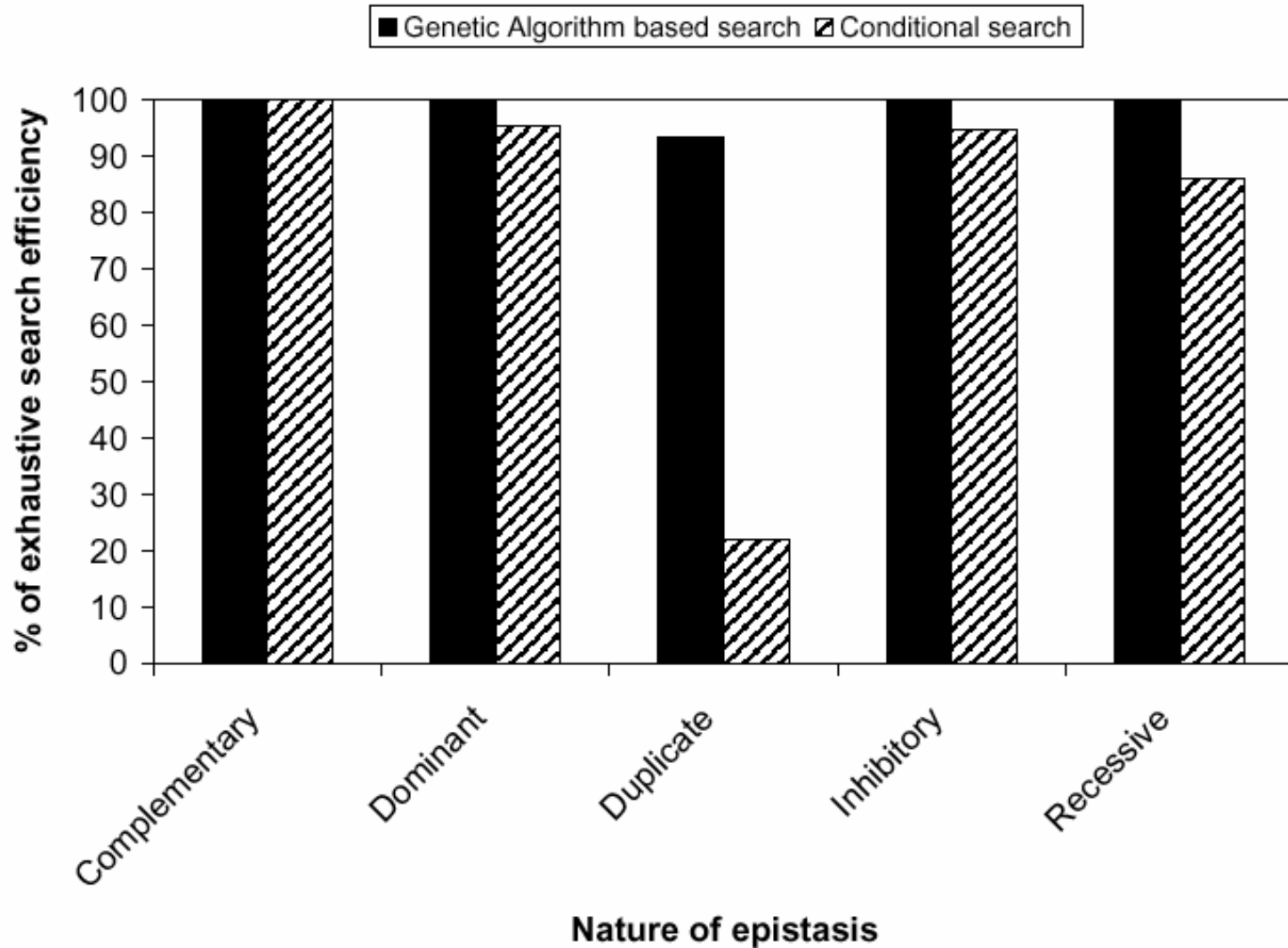
Genetic algorithm versus exhaustive search

In a genome size of 2000 cM:

- + For 2 QTL improvement by factor 120
- + For 3 QTL improvement by factor 65,000
- + For 4 QTL improvement by factor 1.7×10^7

Plus: GA method has finer resolution

Results from genome scan

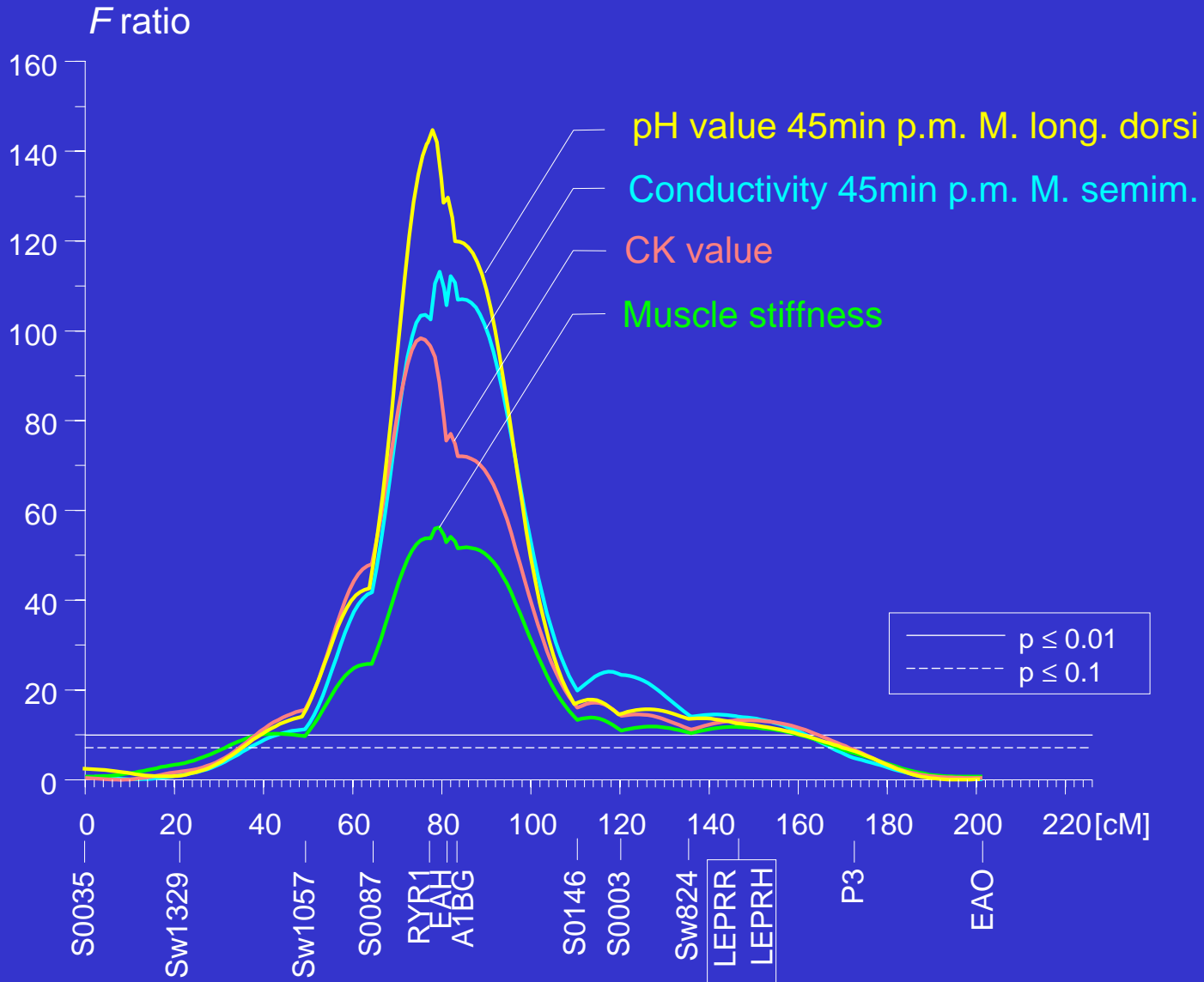


Multiple trait

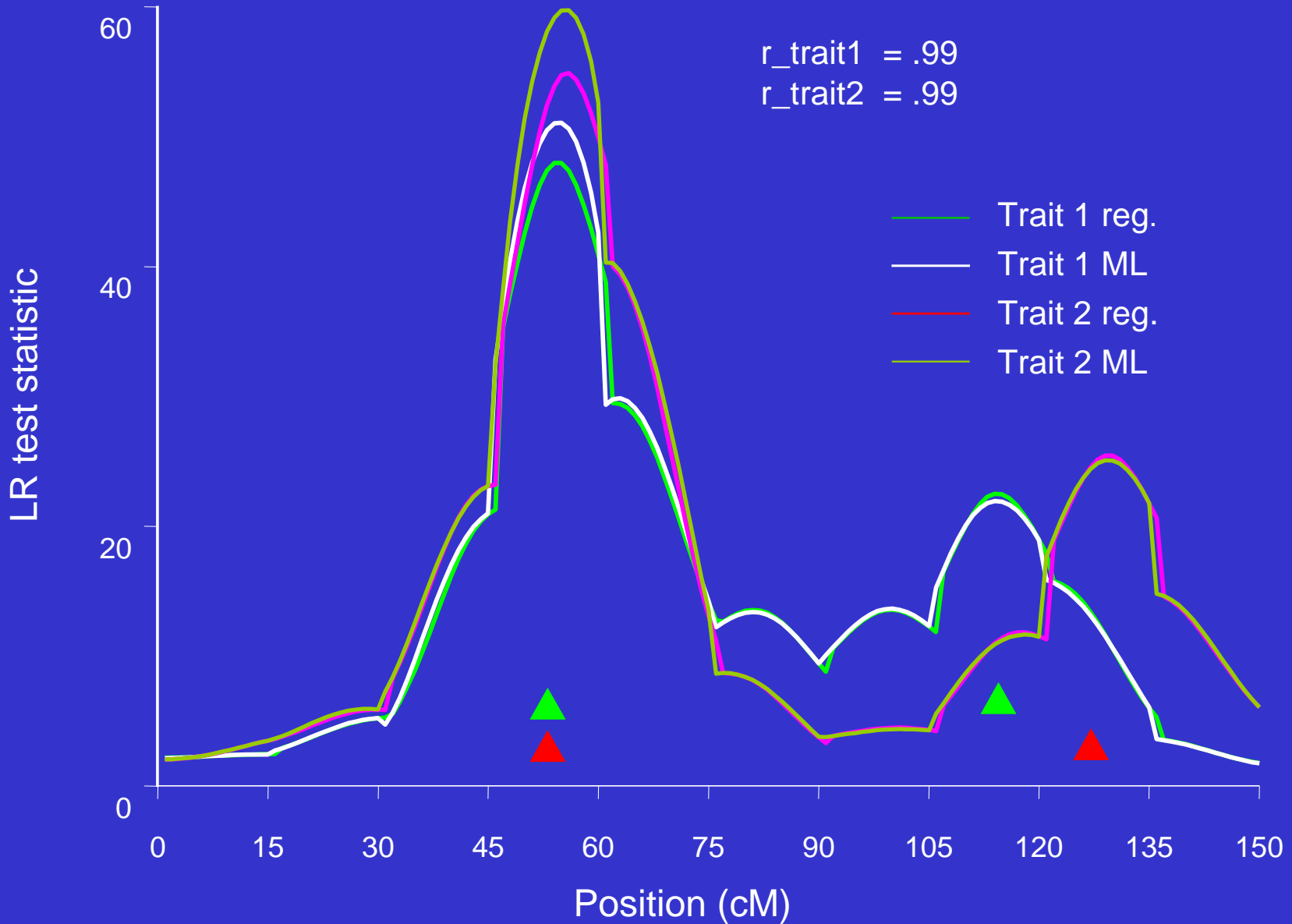
- Increased power from using multiple traits
- testing models regarding genetic correlation
 - pleiotropy or close linkage

QTL Map of Chromosome 6 in Family WxP Stress Reaction and Meat Quality Traits

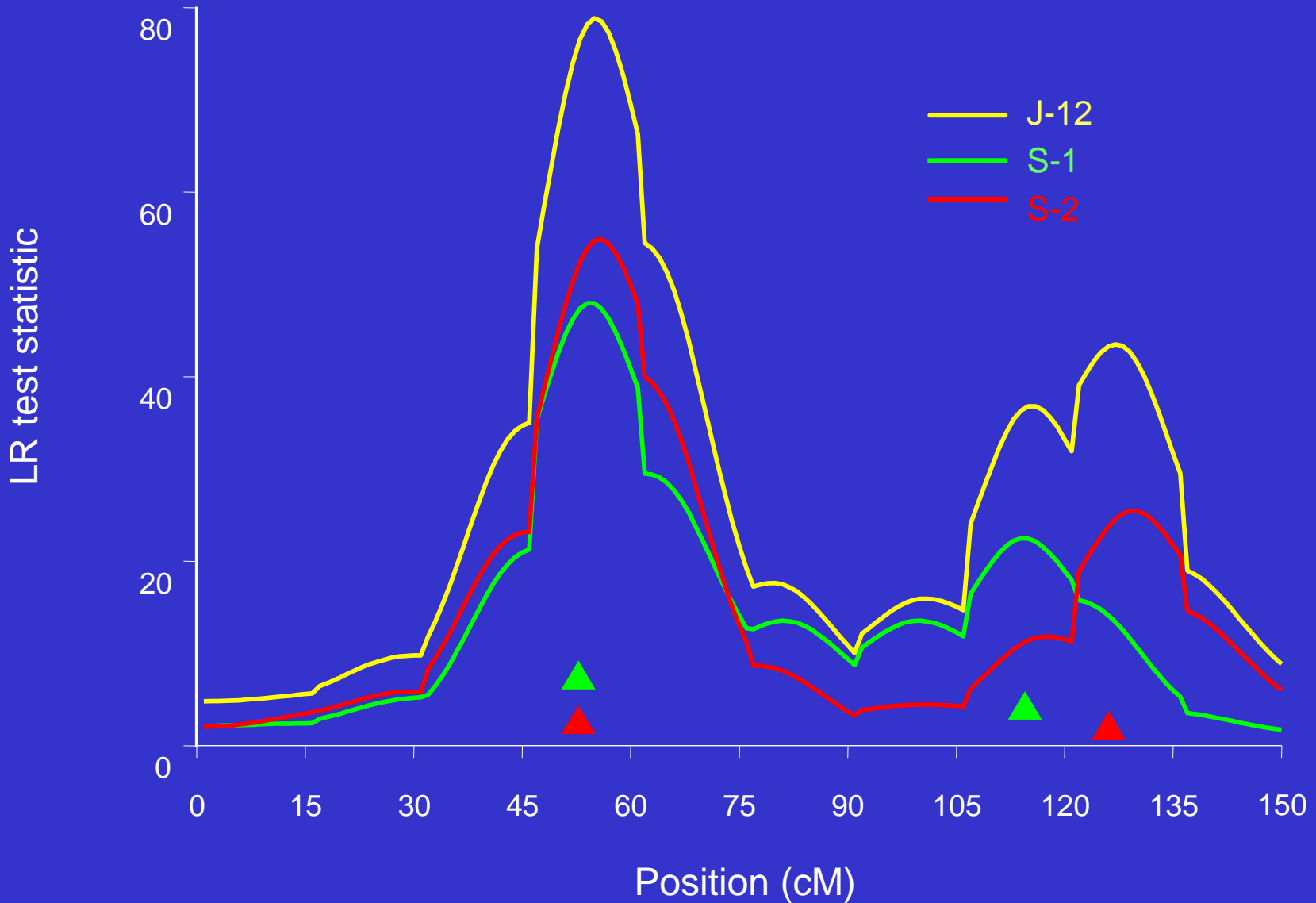
F ratio testing the hypothesis of a single QTL at a given position on the chromosome



ML and regression for single traits (CIM)



Joint mapping vs. separate mapping using regression (CIM)



Properties of the joint analysis

a) $r = 0$

if traits uncorrelated

$$LR_j \approx LR_{S1} + LR_{S2}$$

i.e. increased power

b) $\beta_2 = 0$

if only one trait affected

$$LR_j \approx LR_{S1}/(1-r)^2 \geq LR_{S1}$$

increased power

c)

$$LR_j \geq \text{maximum}[LR_{S1}, LR_{S2}]$$

d) $r \beta_1 \beta_2 < 0$ (i.e r and $\beta_1 \beta_2$ have different signs)

$$LR_j > LR_{S1} + LR_{S2}$$

Testing for linked TL vs pleiotropic QTL

H_0 : position 1 = position 2

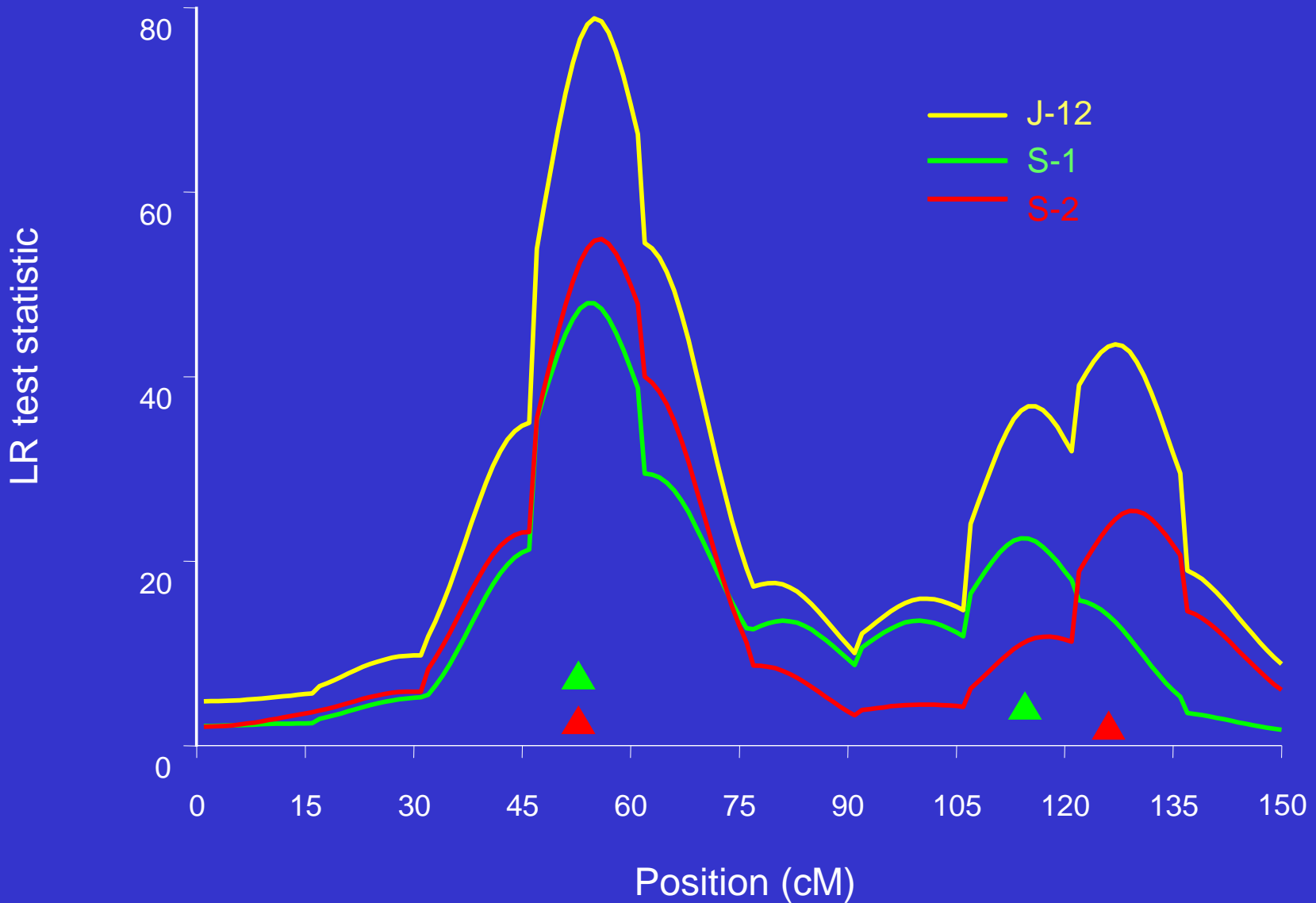
H_1 : position 1 \neq position 2

Testing different genetic models

Existence of epistasis

QTL affecting single traits vs. QTL affecting multiple traits

Joint mapping vs. separate mapping using regression (CIM)



Approximate LR test statistic using regression

Single trait analysis:

$$LR \approx n \log_e \left[\frac{RSS_{reduced}}{RSS_{full}} \right]$$

Multiple trait analysis:

$$LR \approx n \log_e \frac{|\Sigma_{reduced}|}{|\Sigma_{full}|}$$

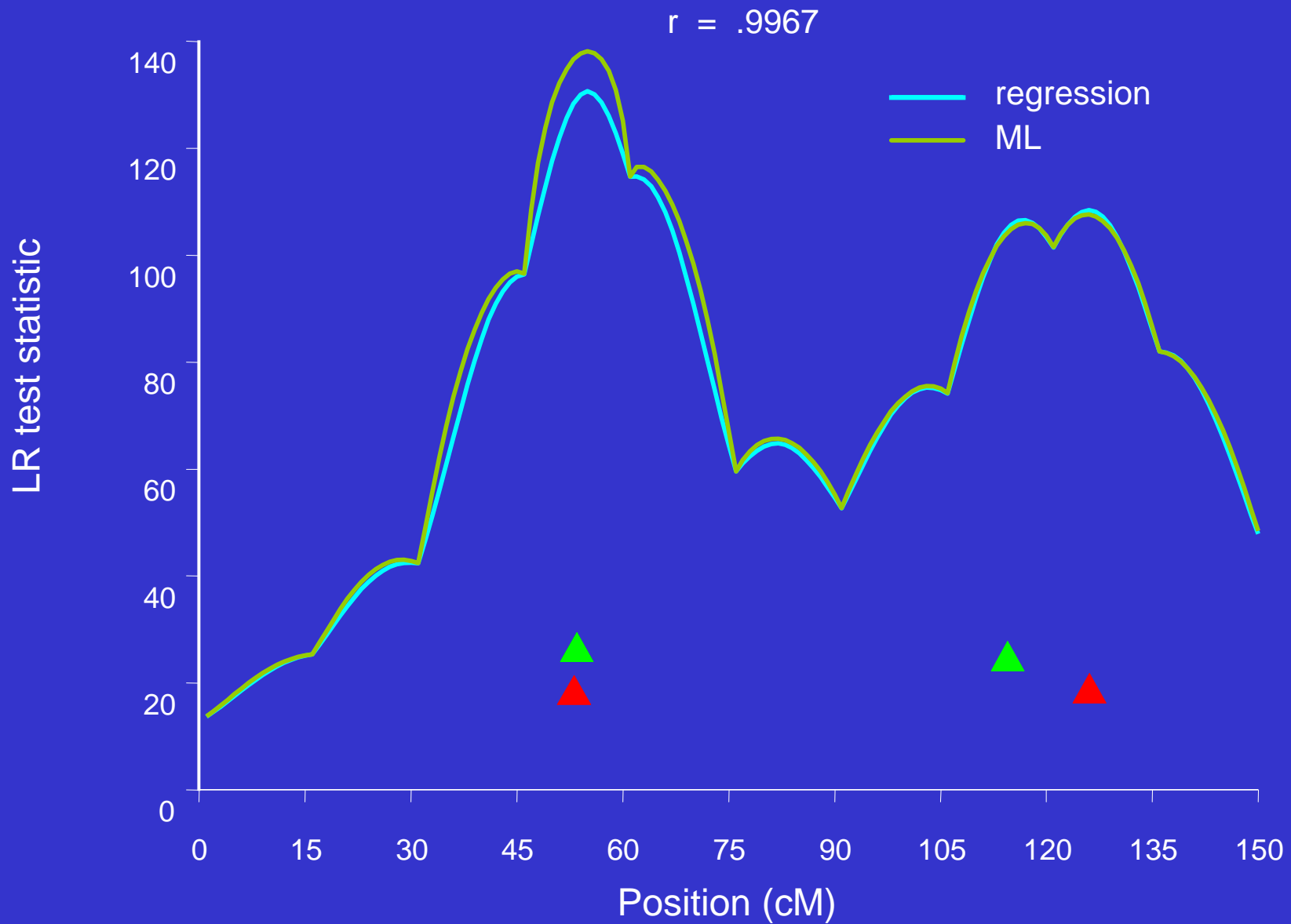
Test pleiotropy *vs.* close linkage

$$|\Sigma| = \begin{vmatrix} RSS_{11} & RSP_{12} \\ RSP_{12} & RSS_{22} \end{vmatrix}$$

$$H_0 = p(1) = p(2)$$

$$H_1 = p(1) \neq p(2)$$

Joint mapping on 2 traits by ML and regression (IM)



Multiple trait analysis using logistic regression

Henshall and Goddard, 1999

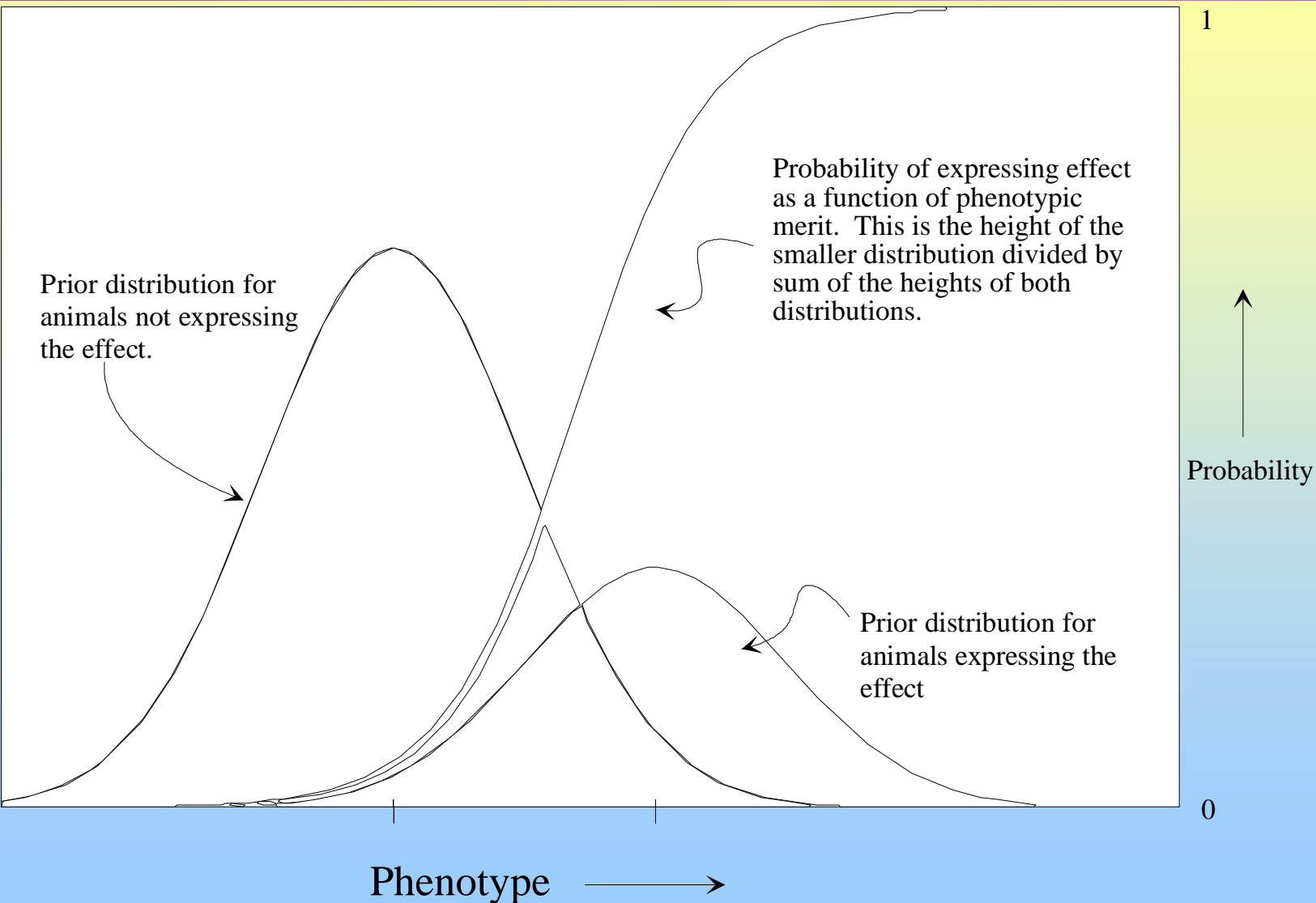
- Regress QTL genotype on phenotype rather than the other way around.

$Y = \text{Phenotype} + e$

Y- Binomial

- Just as simple as regression but more ML properties
- Method accounts for selection in phenotypes
 - (think of selective genotyping)

Regression method: Genotype probabilities ...



Multiple trait

- Increased power from using multiple traits
- testing models regarding genetic correlation
 - pleiotropy or close linkage