

# Gene mapping in mice

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# Goal

- Identify genes that contribute to common human diseases.



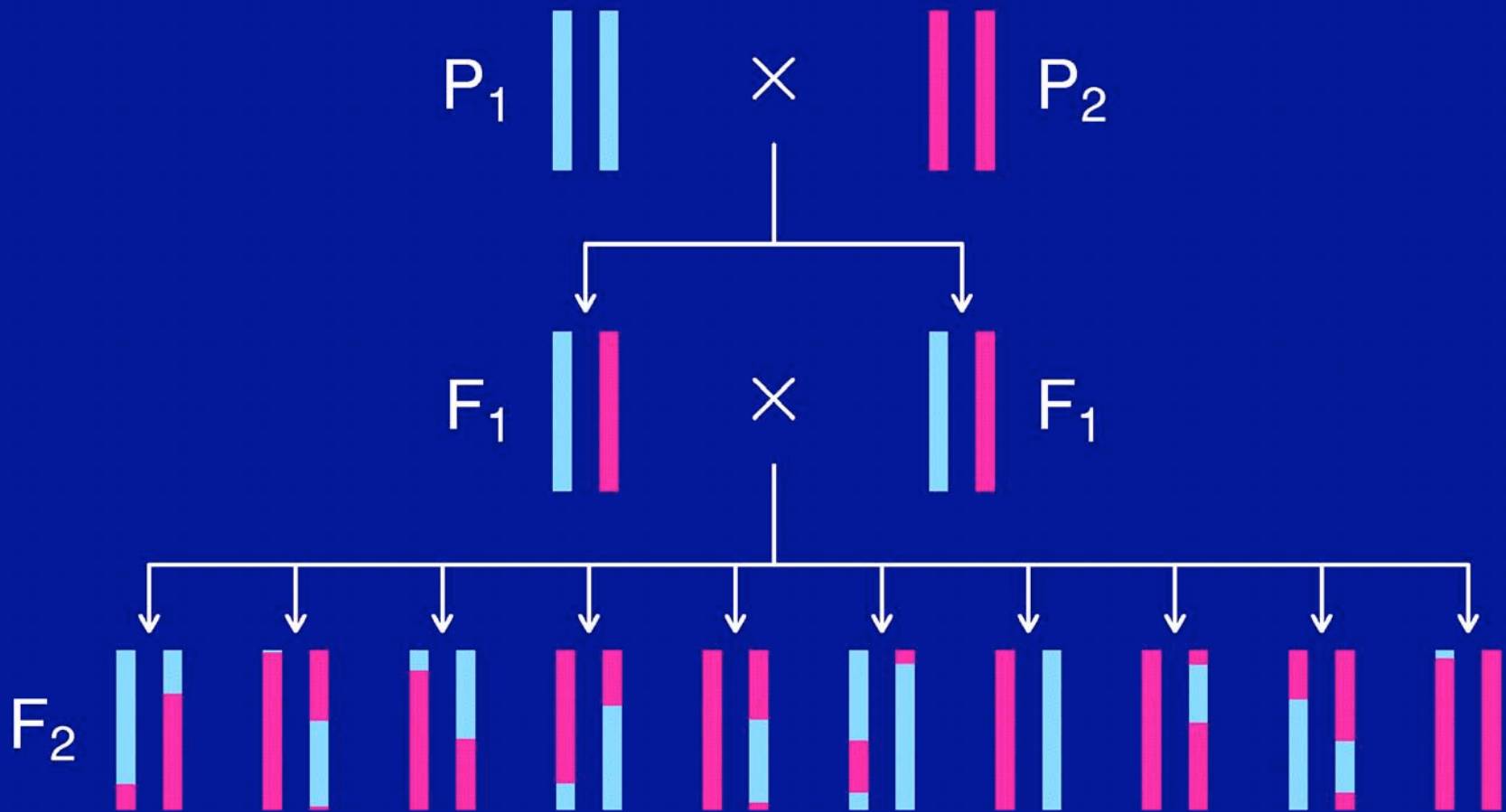
# Advantages of the mouse

- Small and cheap
- Inbred lines
- Large, controlled crosses
- Experimental interventions
- Knock-outs and knock-ins

# The mouse as a model

- Same genes?
  - The genes involved in a phenotype in the mouse may also be involved in similar phenotypes in the human.
- Similar complexity?
  - The complexity of the etiology underlying a mouse phenotype provides some indication of the complexity of similar human phenotypes.
- Transfer of statistical methods.
  - The statistical methods developed for gene mapping in the mouse serve as a basis for similar methods applicable in direct human studies.

# The intercross

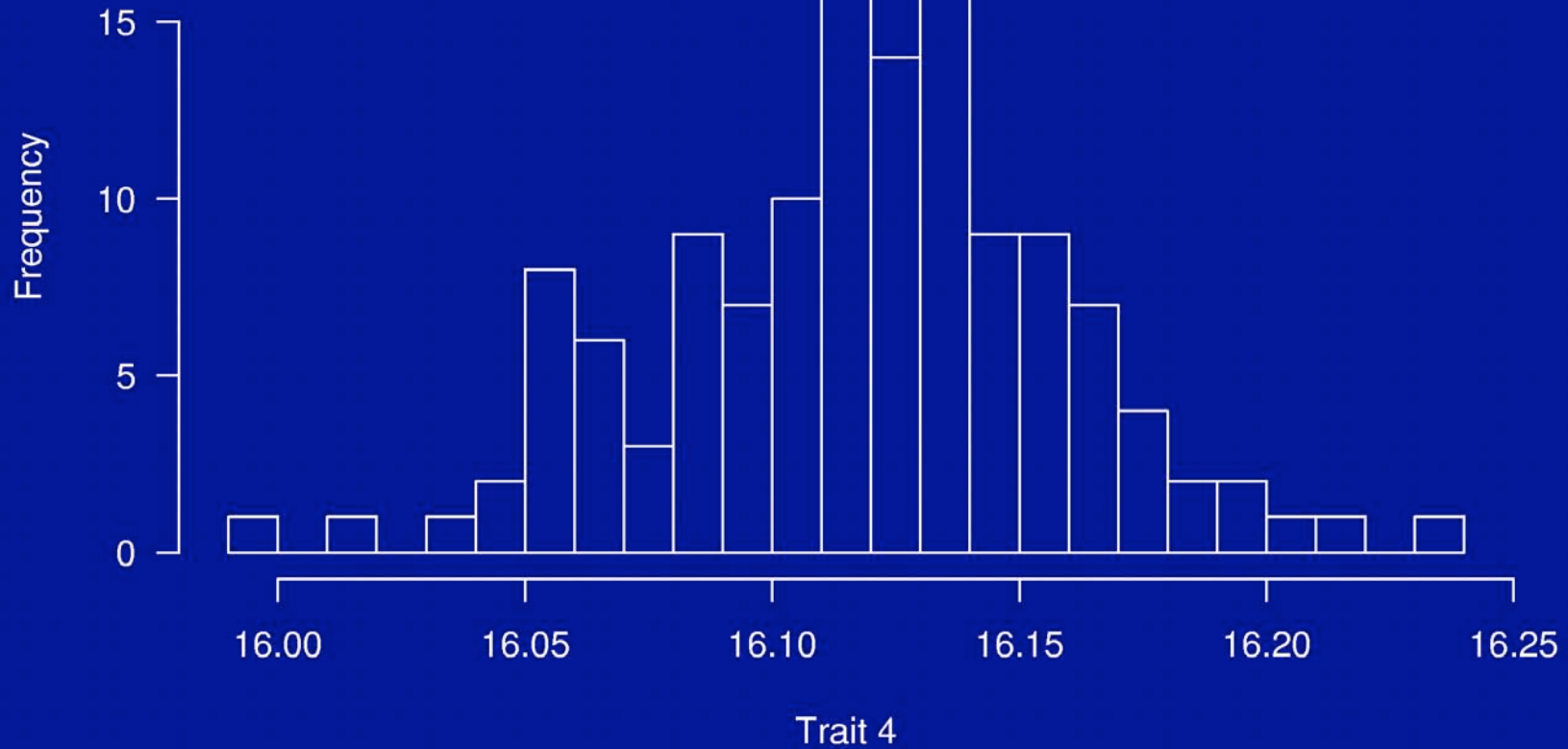


# The data

- Phenotypes,  $y_i$
- Genotypes,  $x_{ij} = AA/AB/BB$ , at genetic markers
- A genetic map, giving the locations of the markers.

# Phenotypes

133 females  
(NOD  $\times$  B6)  $\times$  (NOD  $\times$  B6)





# NOD



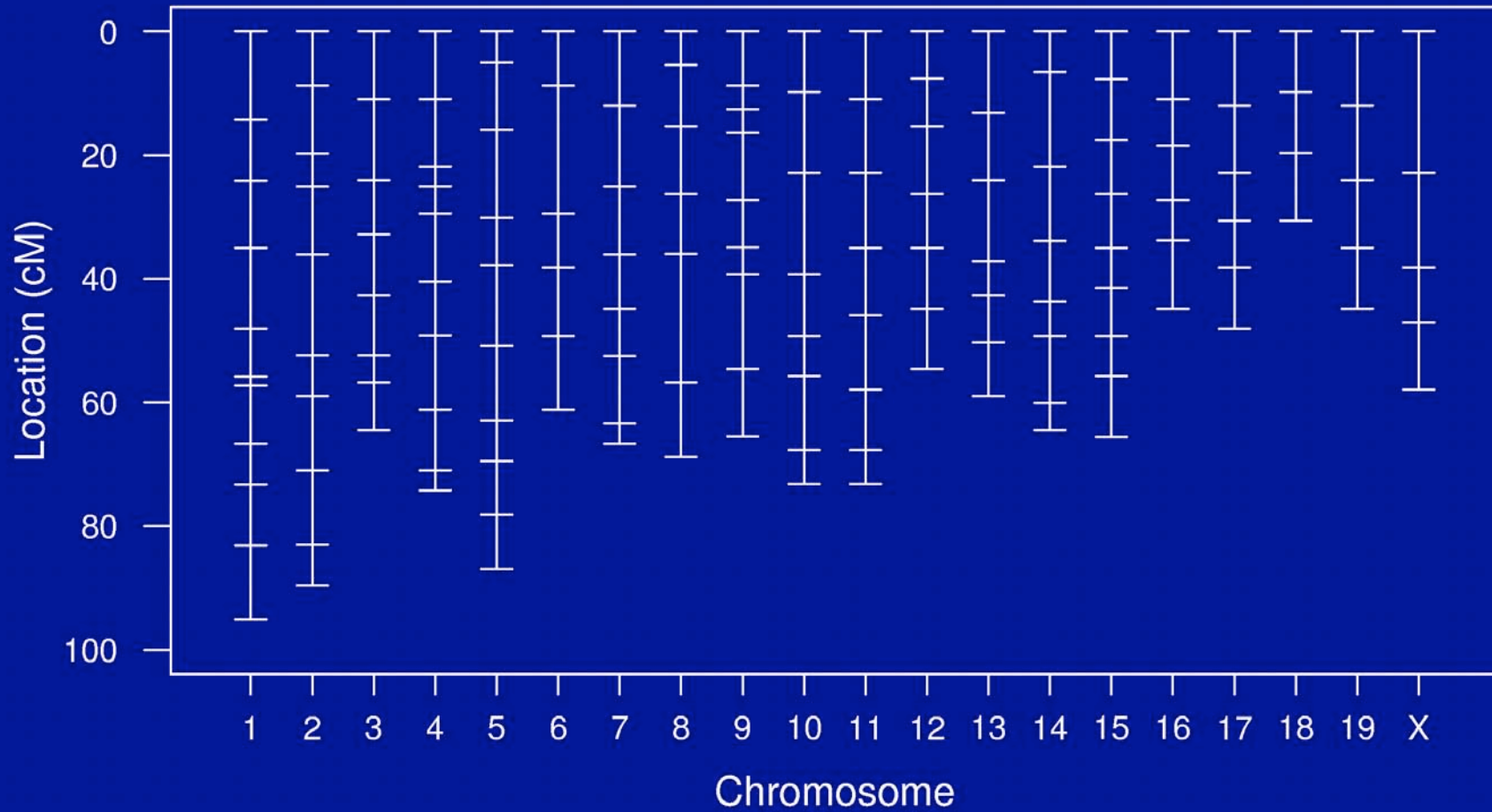
C57BL/6



# Agouti coat

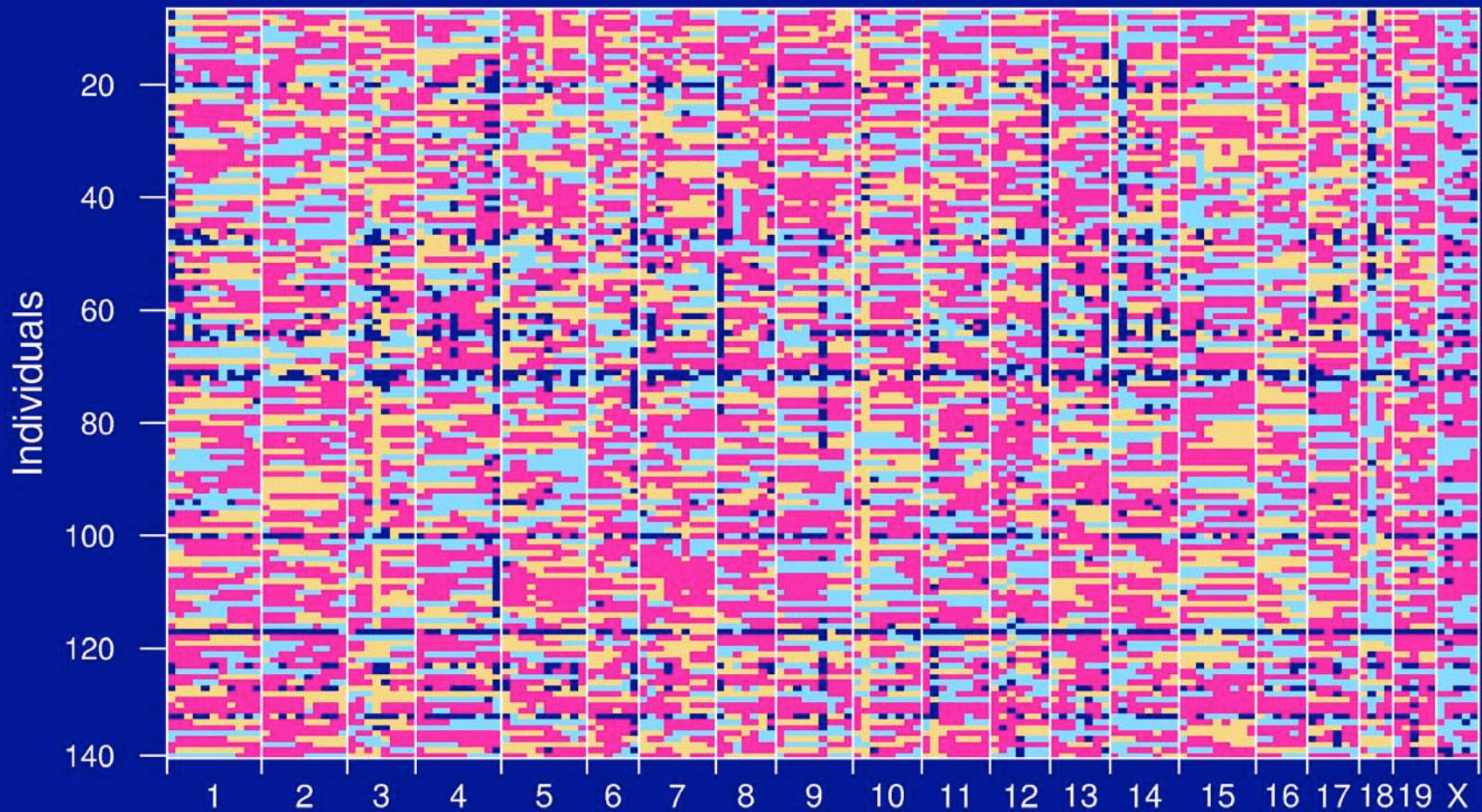


# Genetic map





# Genotype data



# Goals

- Identify genomic regions (QTLs) that contribute to variation in the trait.
- Obtain interval estimates of the QTL locations.
- Estimate the effects of the QTLs.

# Models: recombination

- No crossover interference
  - Locations of breakpoints according to a Poisson process.
  - Genotypes along chromosome follow a Markov chain.
- Clearly wrong, but super convenient.

# Models: gen $\square$ phe

Phenotype =  $y$ , whole-genome genotype =  $g$

Imagine that  $p$  sites are all that matter.

$$E(y | g) = \mu(g_1, \dots, g_p) \quad SD(y | g) = \sigma(g_1, \dots, g_p)$$

Simplifying assumptions:

- $SD(y | g) = \sigma$ , independent of  $g$
- $y | g \sim \text{normal}(\mu(g_1, \dots, g_p), \sigma)$
- $\mu(g_1, \dots, g_p) = \mu + \sum \alpha_j 1\{g_j = AB\} + \beta_j 1\{g_j = BB\}$

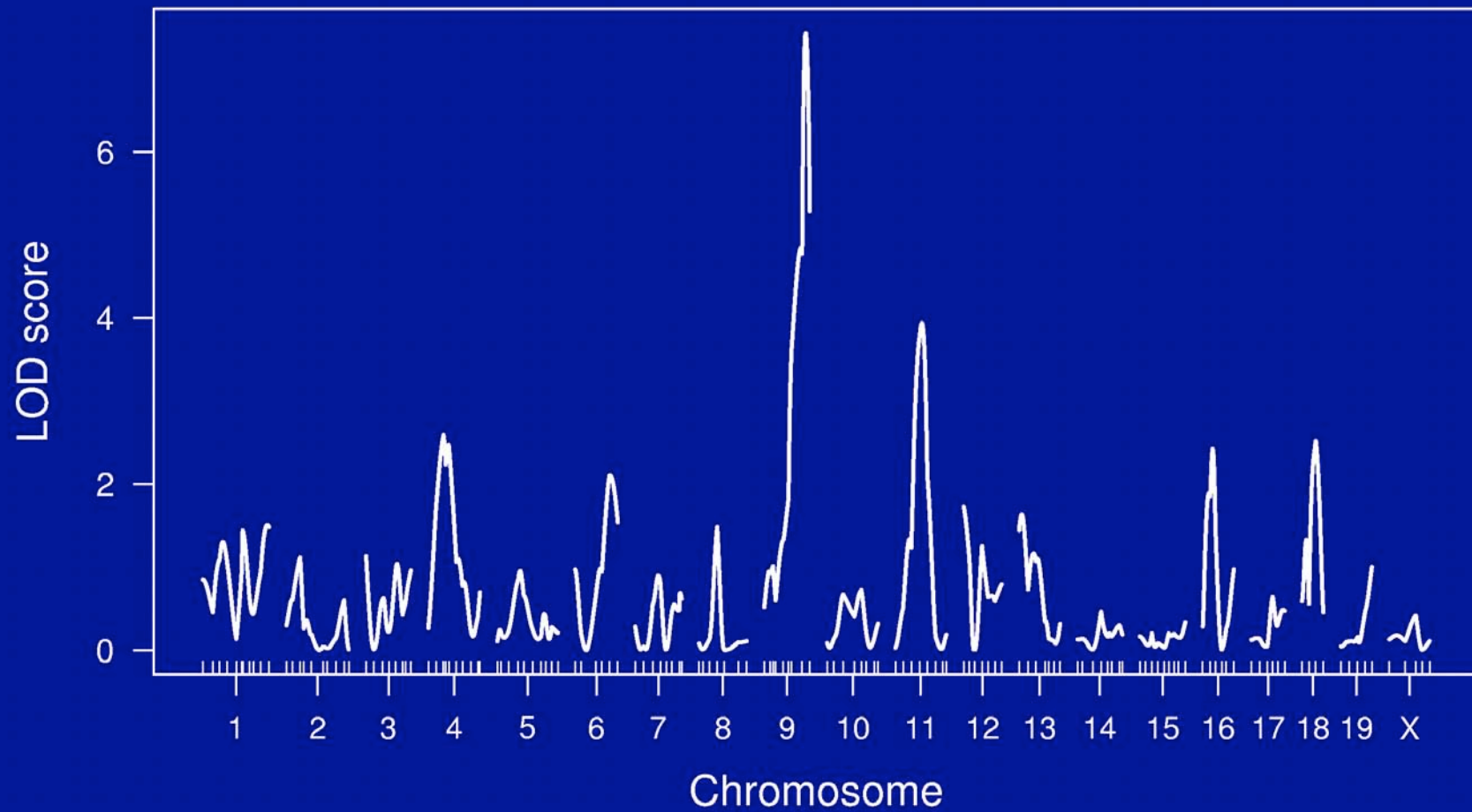


# Interval mapping

## Lander and Botstein 1989

- Imagine that there is a single QTL, at position  $z$ .
- Let  $q_i$  = genotype of mouse  $i$  at the QTL, and assume
$$y_i | q_i \sim \text{normal}(\mu(q_i), \sigma^2)$$
- We won't know  $q_i$ , but we can calculate
$$p_{ig} = \Pr(q_i = g | \text{marker data})$$
- $y_i$ , given the marker data, follows a **mixture** of normal distributions with known mixing proportions (the  $p_{ig}$ ).
- Use an EM algorithm to get MLEs of  $\mu = (\mu_{AA}, \mu_{AB}, \mu_{BB}, \sigma^2)$ .
- Measure the evidence for a QTL via the **LOD score**, which is the  $\log_{10}$  likelihood ratio comparing the hypothesis of a single QTL at position  $z$  to the hypothesis of no QTL anywhere.

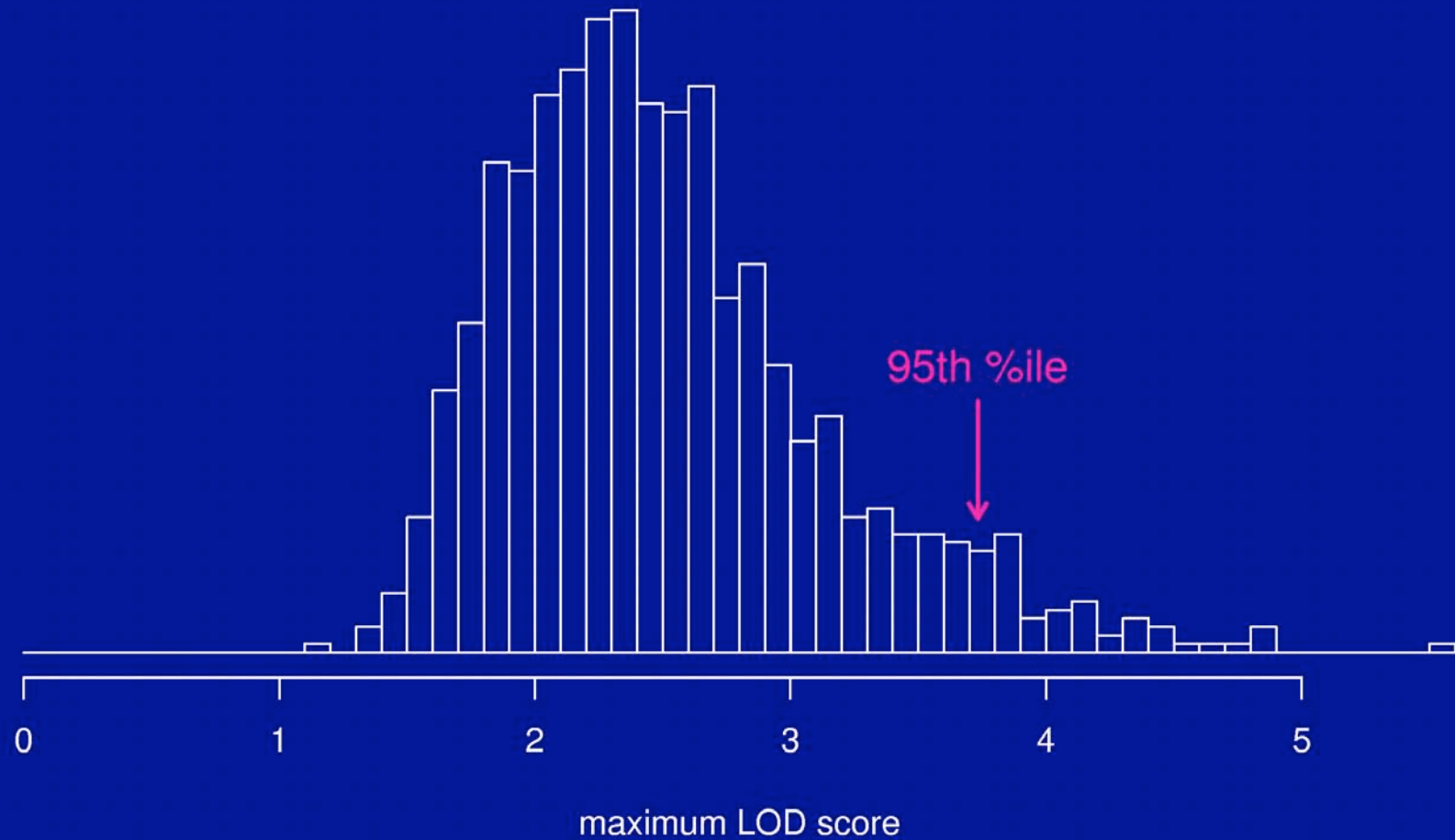
# LOD curves



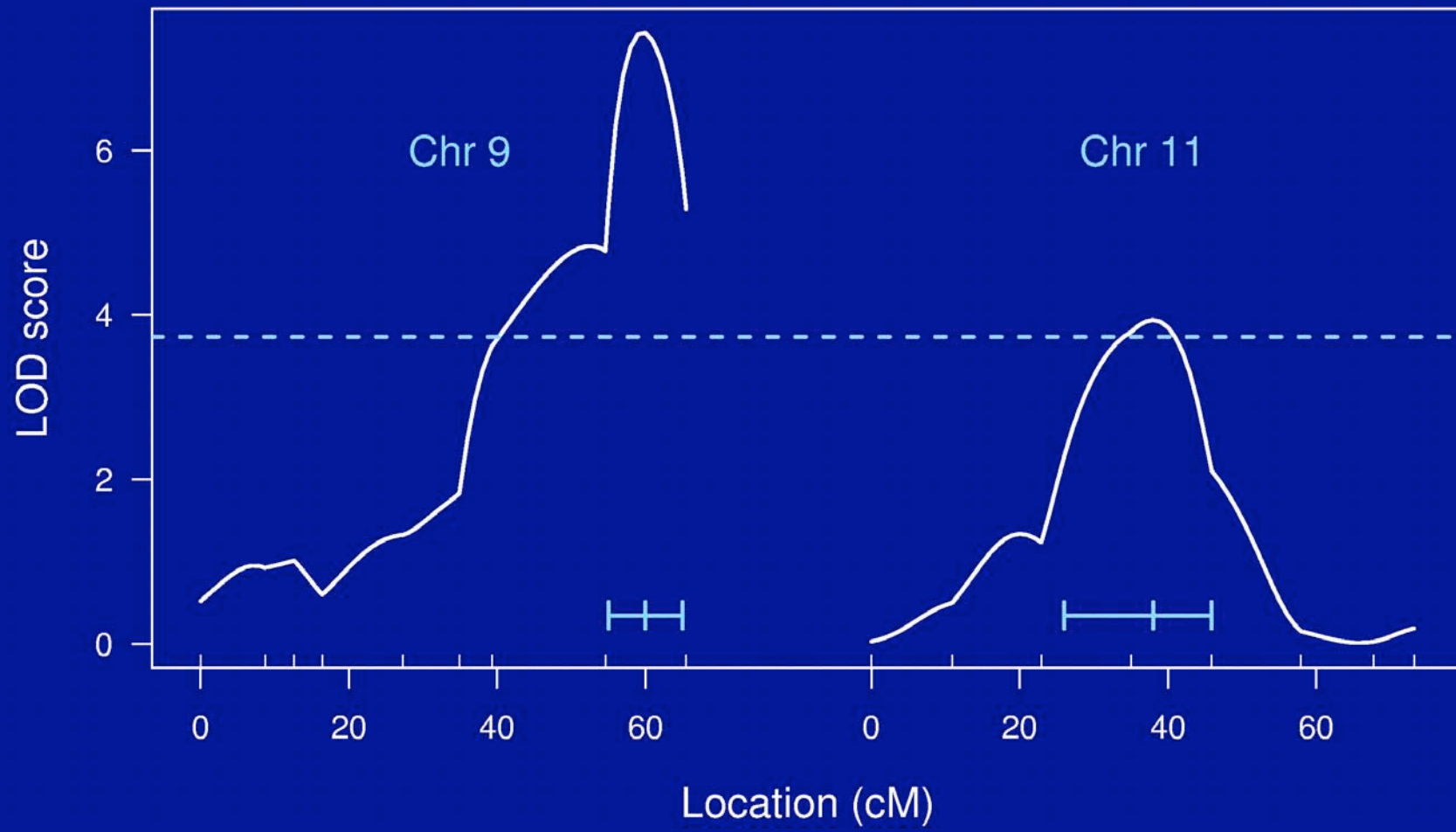
# LOD thresholds

- To account for the genome-wide search, compare the observed LOD scores to the distribution of the maximum LOD score, genome-wide, that would be obtained if there were no QTL anywhere.
- The 95th percentile of this distribution is used as a significance threshold.
- Such a threshold may be estimated via permutations (Churchill and Doerge 1994).

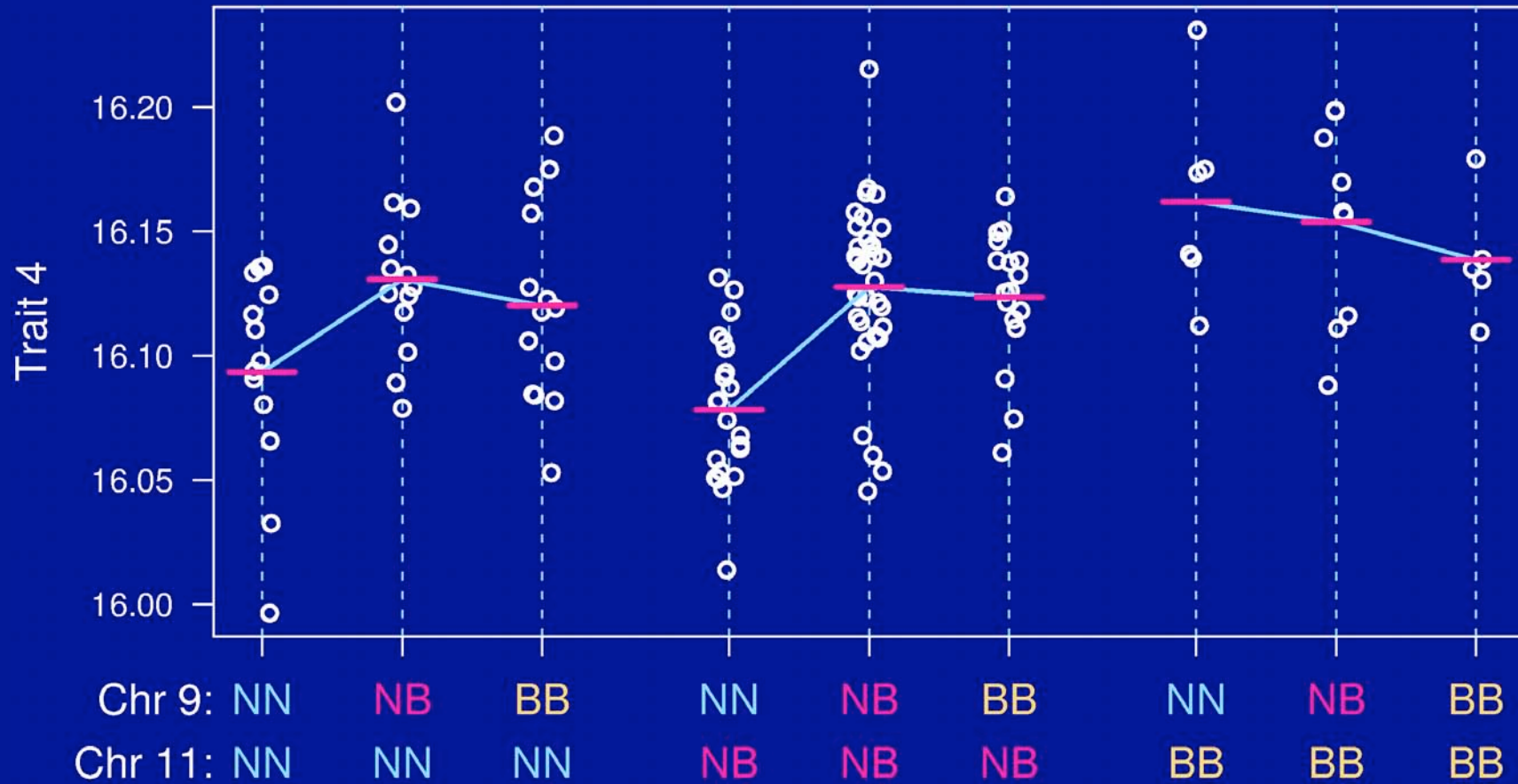
# Permutation distribution



# Chr 9 and 11



# Epistasis



# Going after multiple QTLs

- Greater ability to detect QTLs.
- Separate linked QTLs.
- Learn about interactions between QTLs (epistasis).

# Model selection

- Choose a class of models.
  - Additive; pairwise interactions; regression trees
- Fit a model (allow for missing genotype data).
  - Linear regression; ML via EM; Bayes via MCMC
- Search model space.
  - Forward/backward/stepwise selection; MCMC;
- Compare models.
  - $BIC_p(\beta) = \log L(\beta) + (p/2) |\beta| \log n$

Miss important loci  $\square$  include extraneous loci.



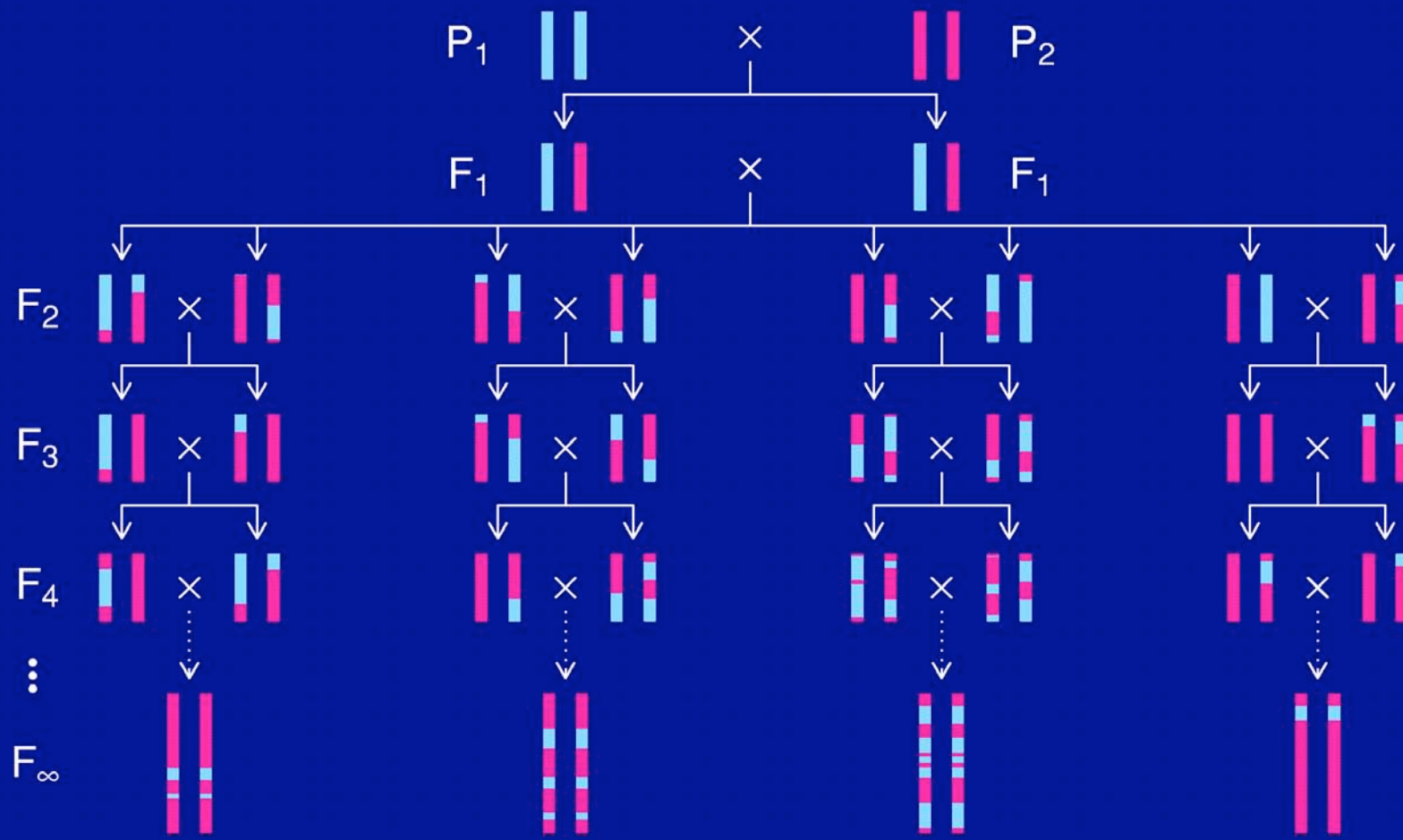
# Special features

- Relationship among the covariates.
- Missing covariate information.
- Identify the key players vs. minimize prediction error.

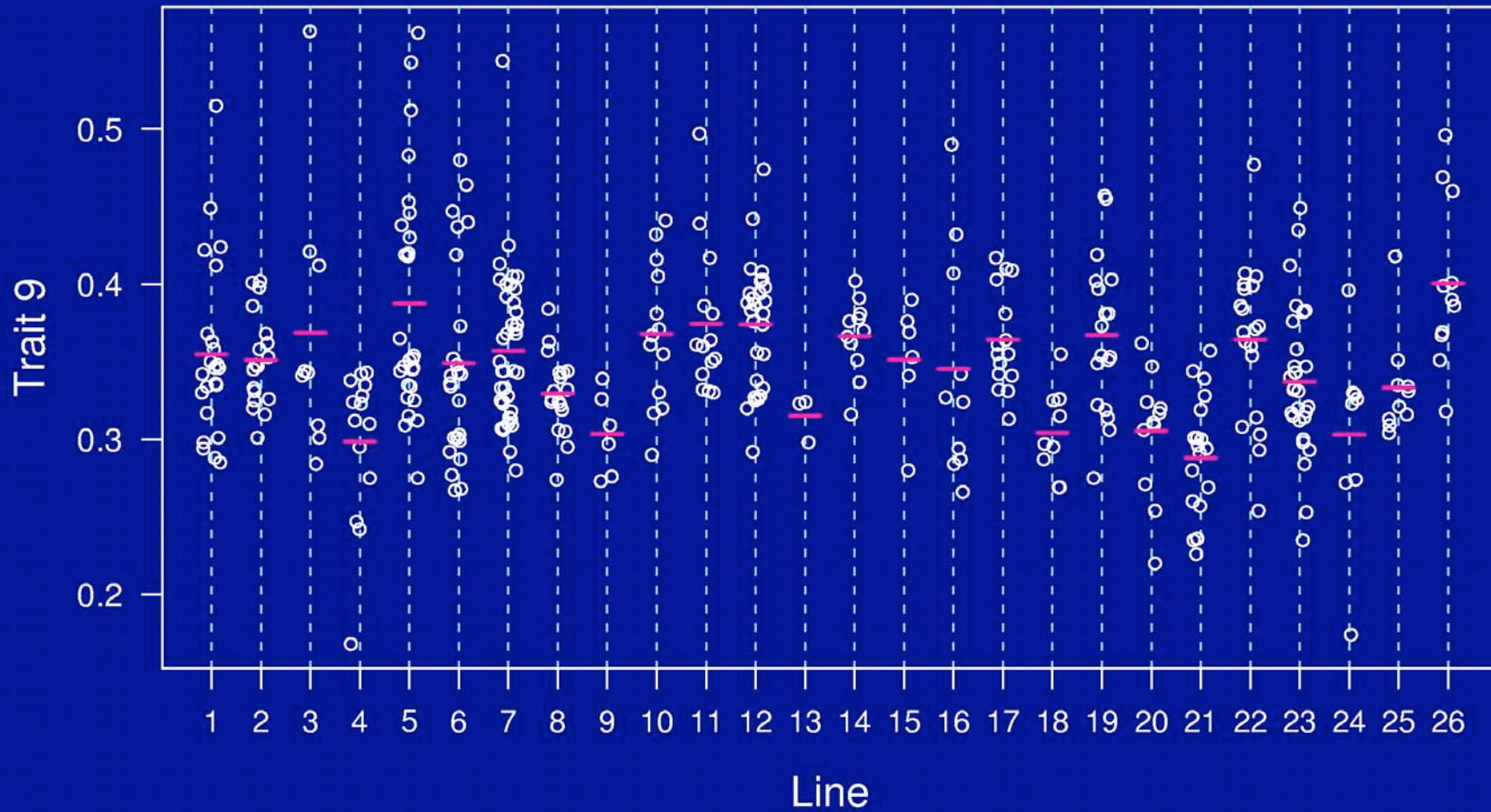
# Opportunities for improvements

- Each individual is unique.
  - Must genotype each mouse.
  - Unable to obtain multiple invasive phenotypes (e.g., in multiple environmental conditions) on the same genotype.
- Relatively low mapping precision.
- Design a set of inbred mouse strains.
  - Genotype once.
  - Study multiple phenotypes on the same genotype.

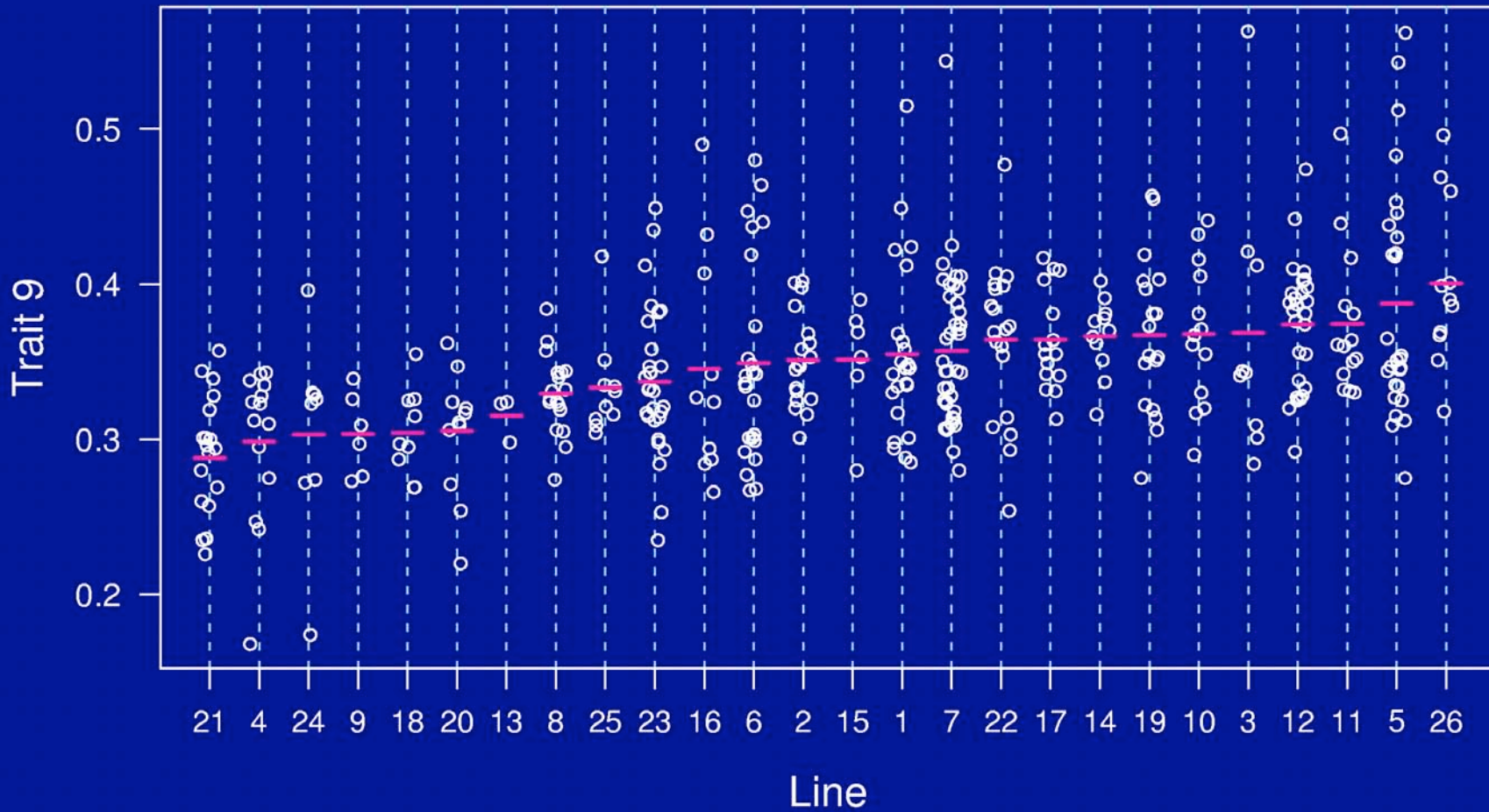
# Recombinant inbred lines



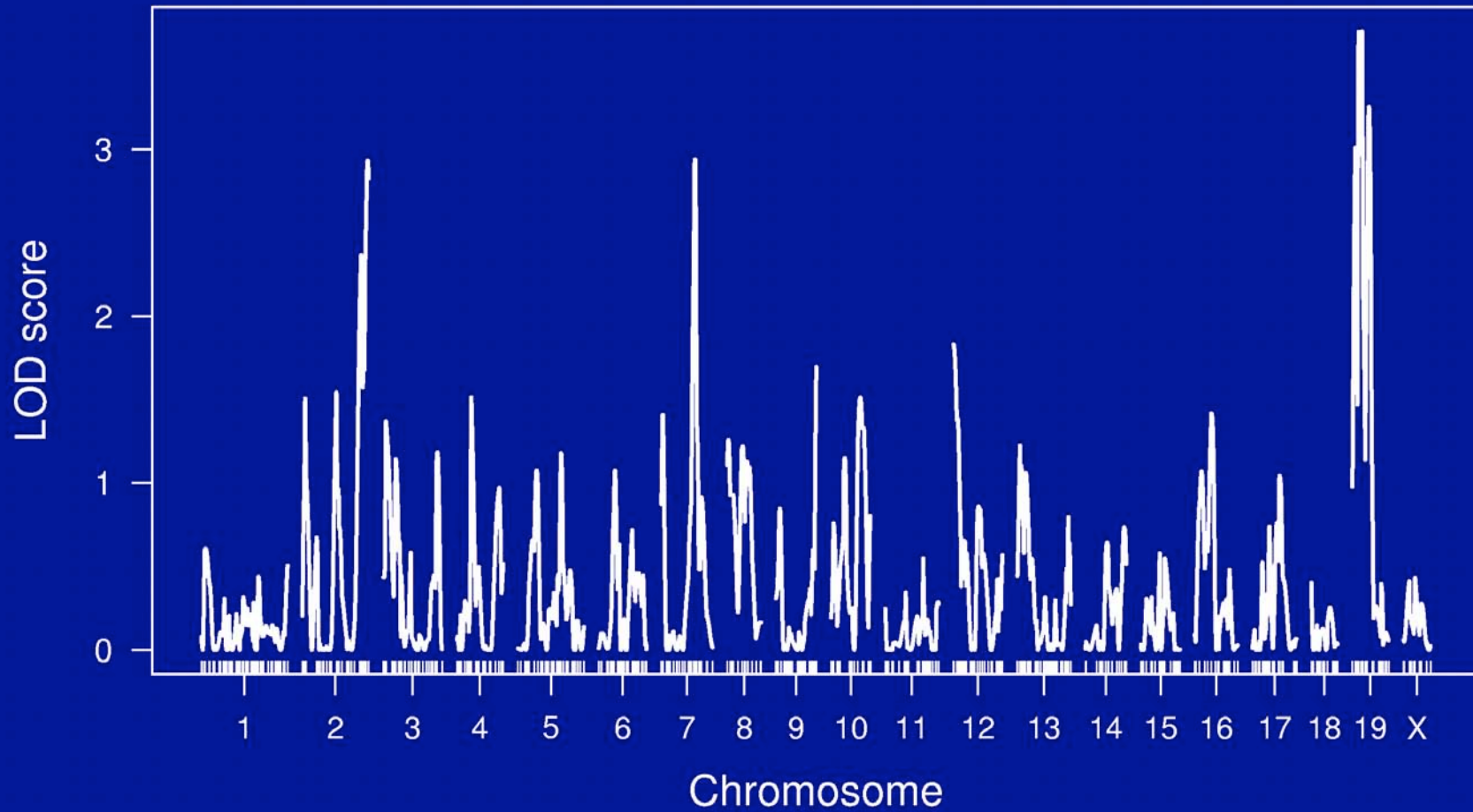
# AXB/BXA panel



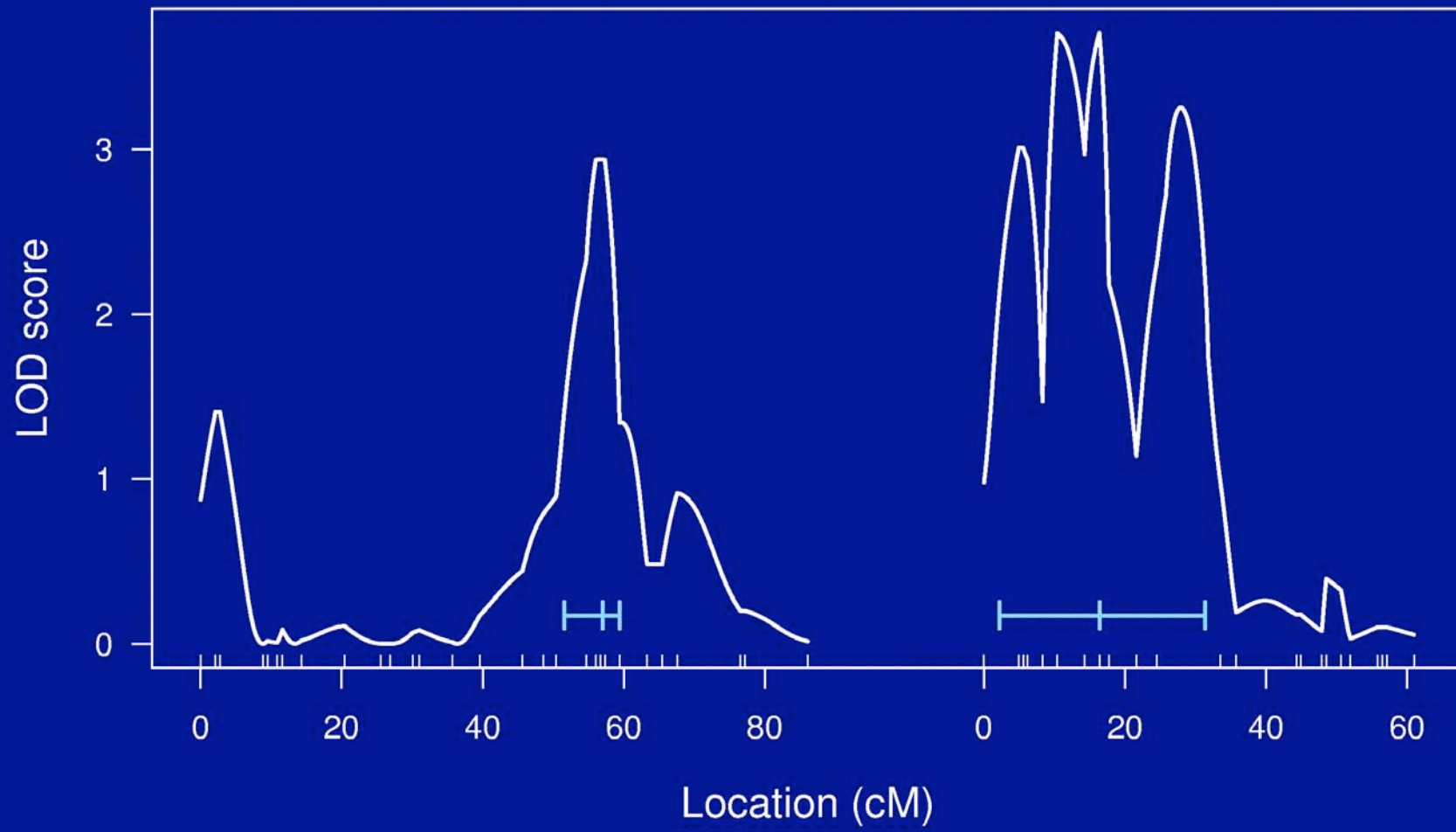
# AXB/BXA panel



# LOD curves

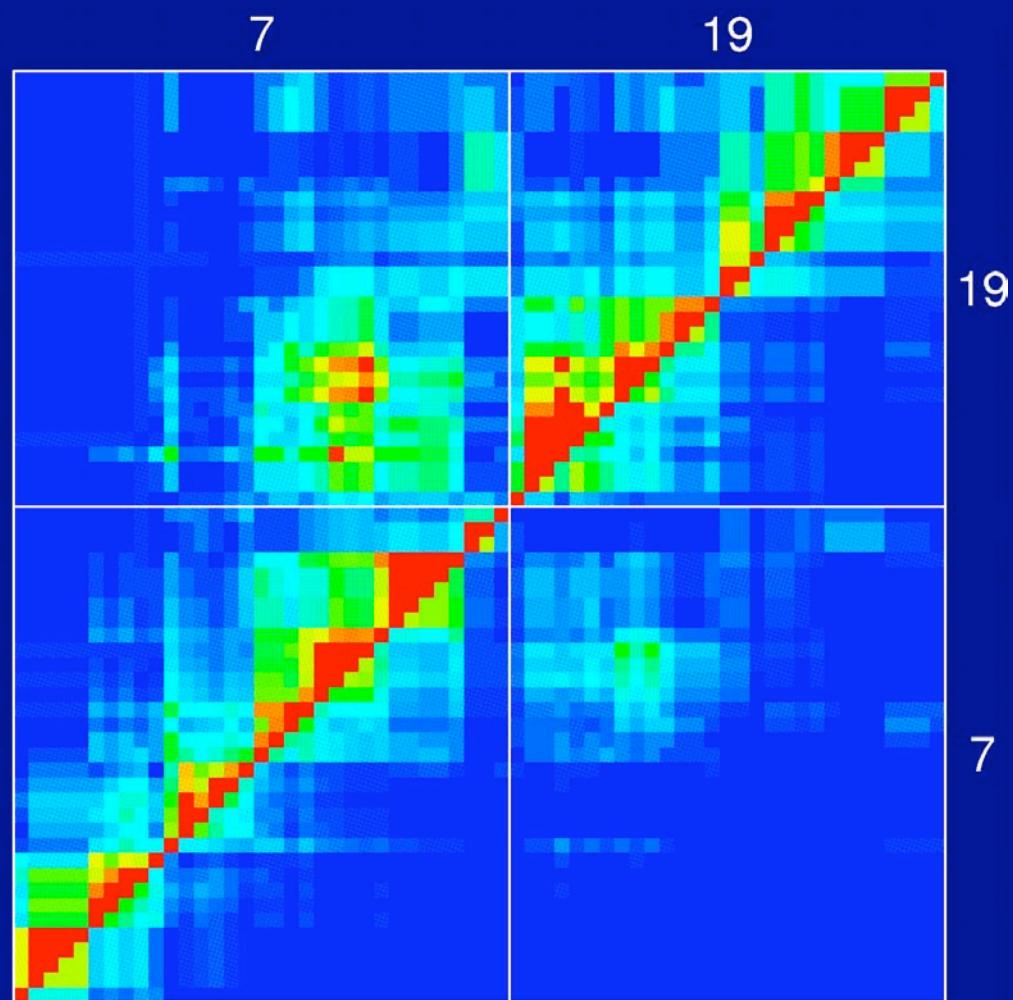


# Chr 7 and 19





# Recombination fractions





# RI lines

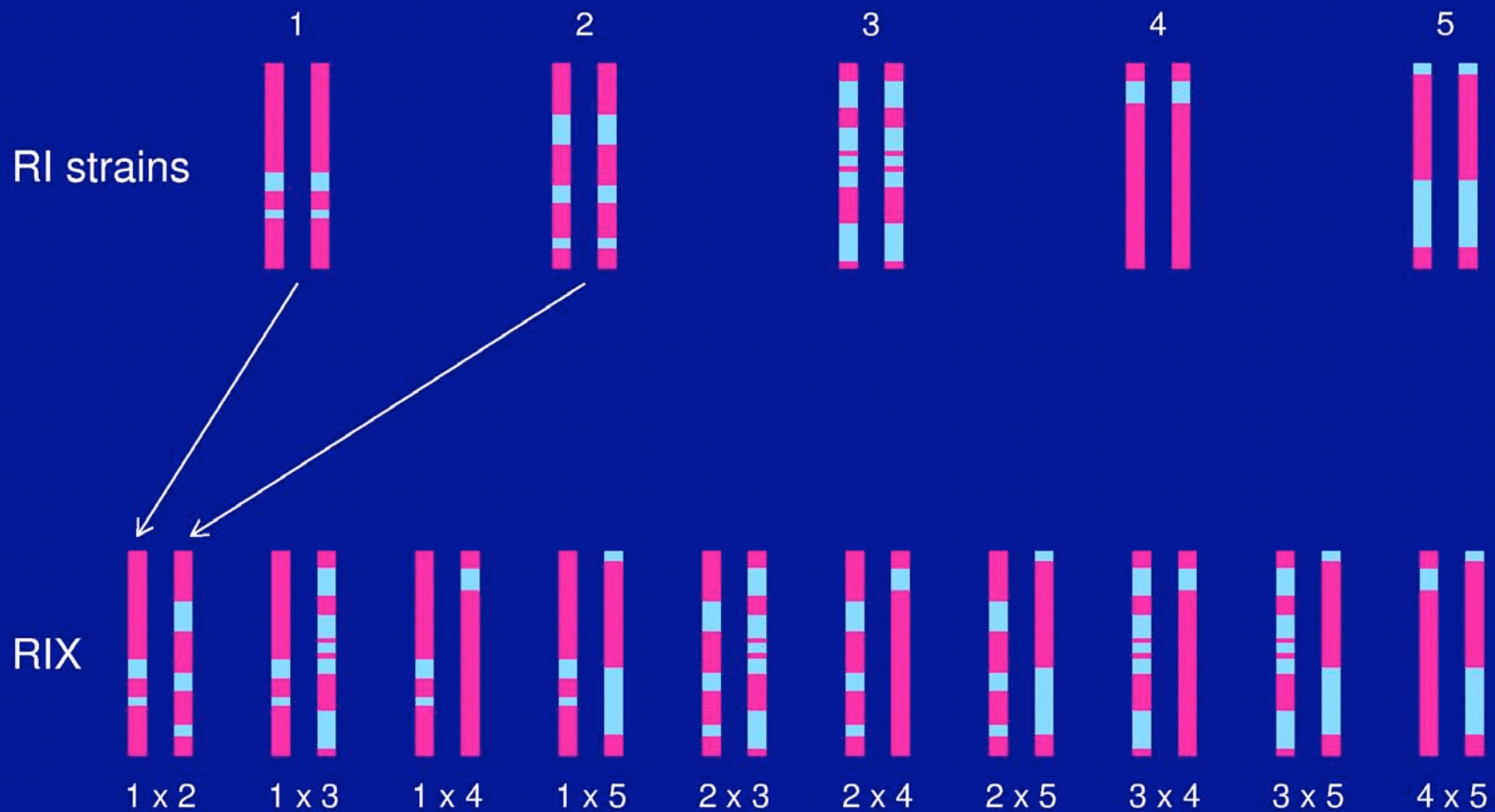
## Advantages

- Each strain is a eternal resource.
  - Only need to genotype once.
  - Reduce individual variation by phenotyping multiple individuals from each strain.
  - Study multiple phenotypes on the same genotype.
- Greater mapping precision.

## Disadvantages

- Time and expense.
- Available panels are generally too small (10-30 lines).
- Can learn only about 2 particular alleles.
- All individuals homozygous.

# The RIX design



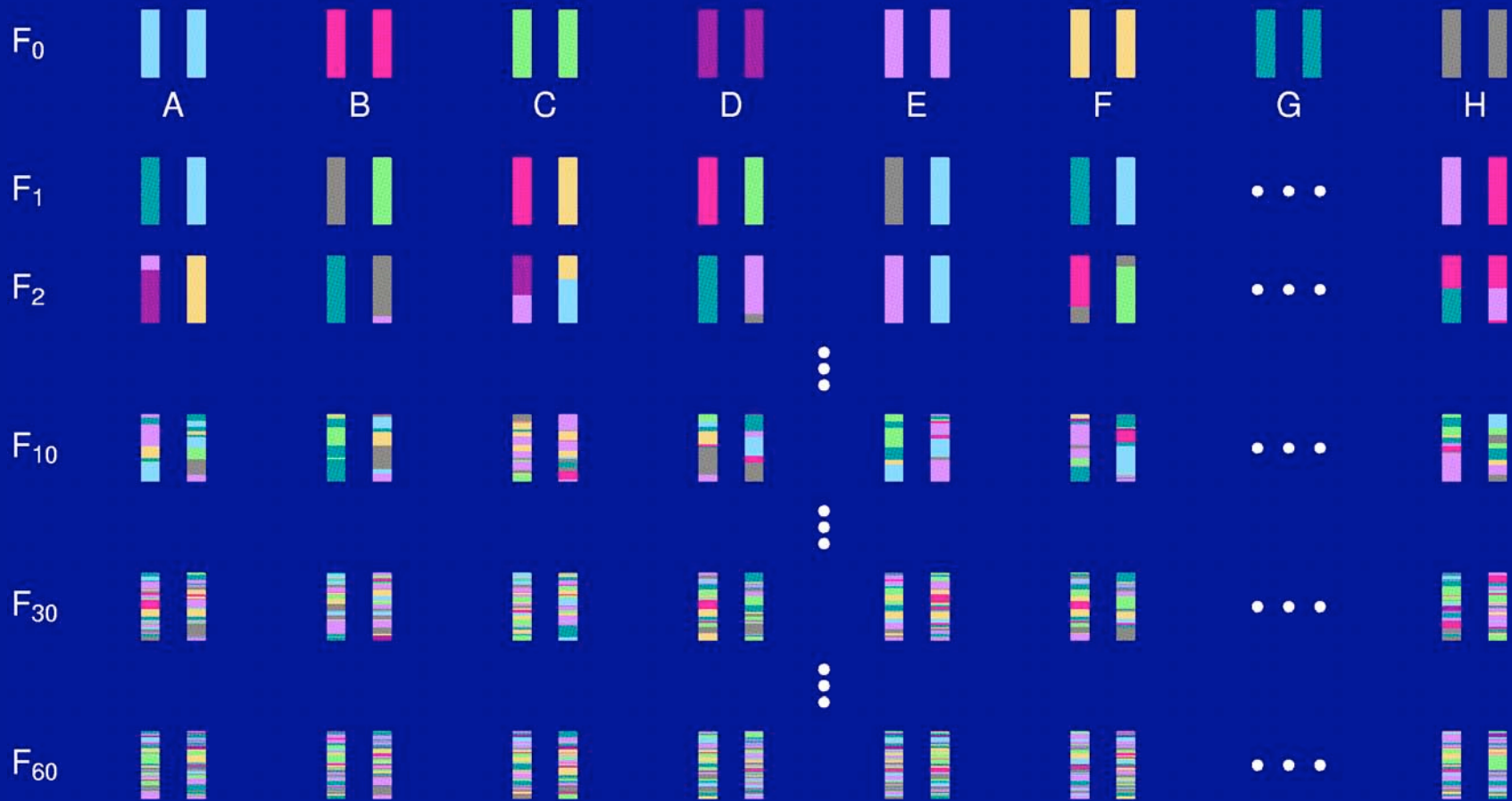
# Heterogeneous stock

McClearn et al. (1970)

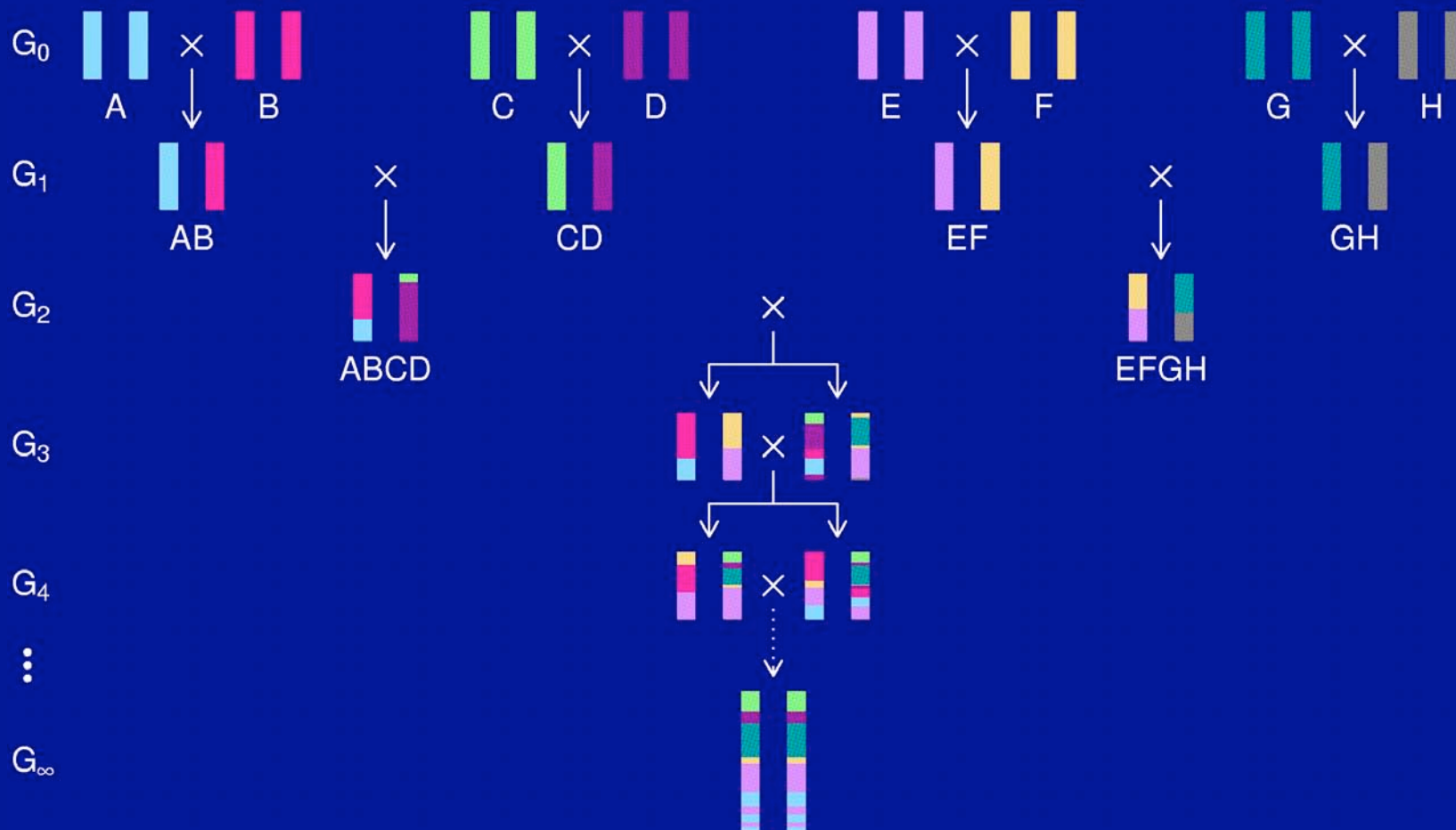
Mott et al. (2000); Mott and Flint (2002)

- Start with 8 inbred strains.
- Randomly breed 40 pairs.
- Repeat the random breeding of 40 pairs for each of ~60 generations (30 years).
- The genealogy (and protocol) is not completely known.

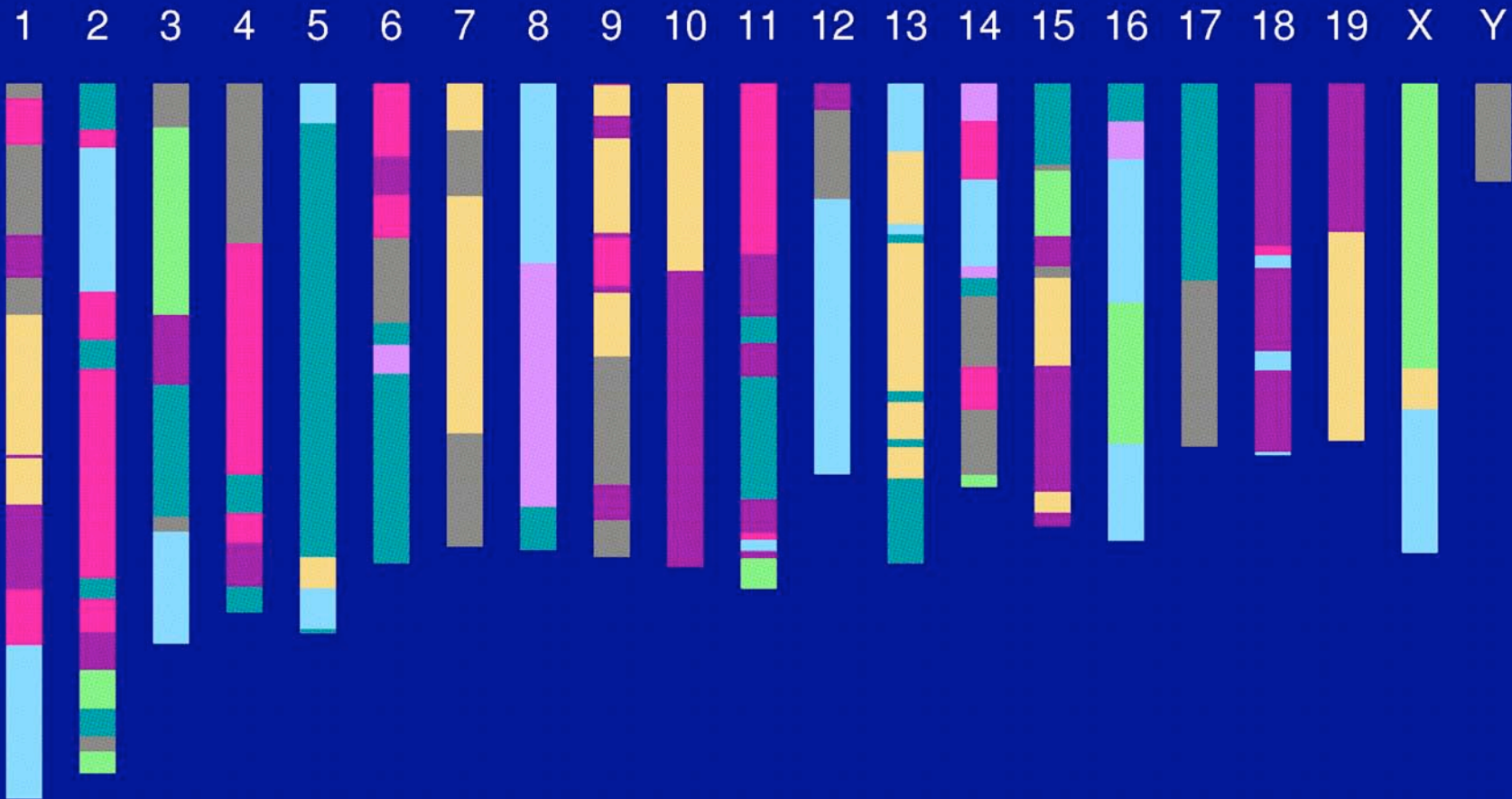
# Heterogeneous stock



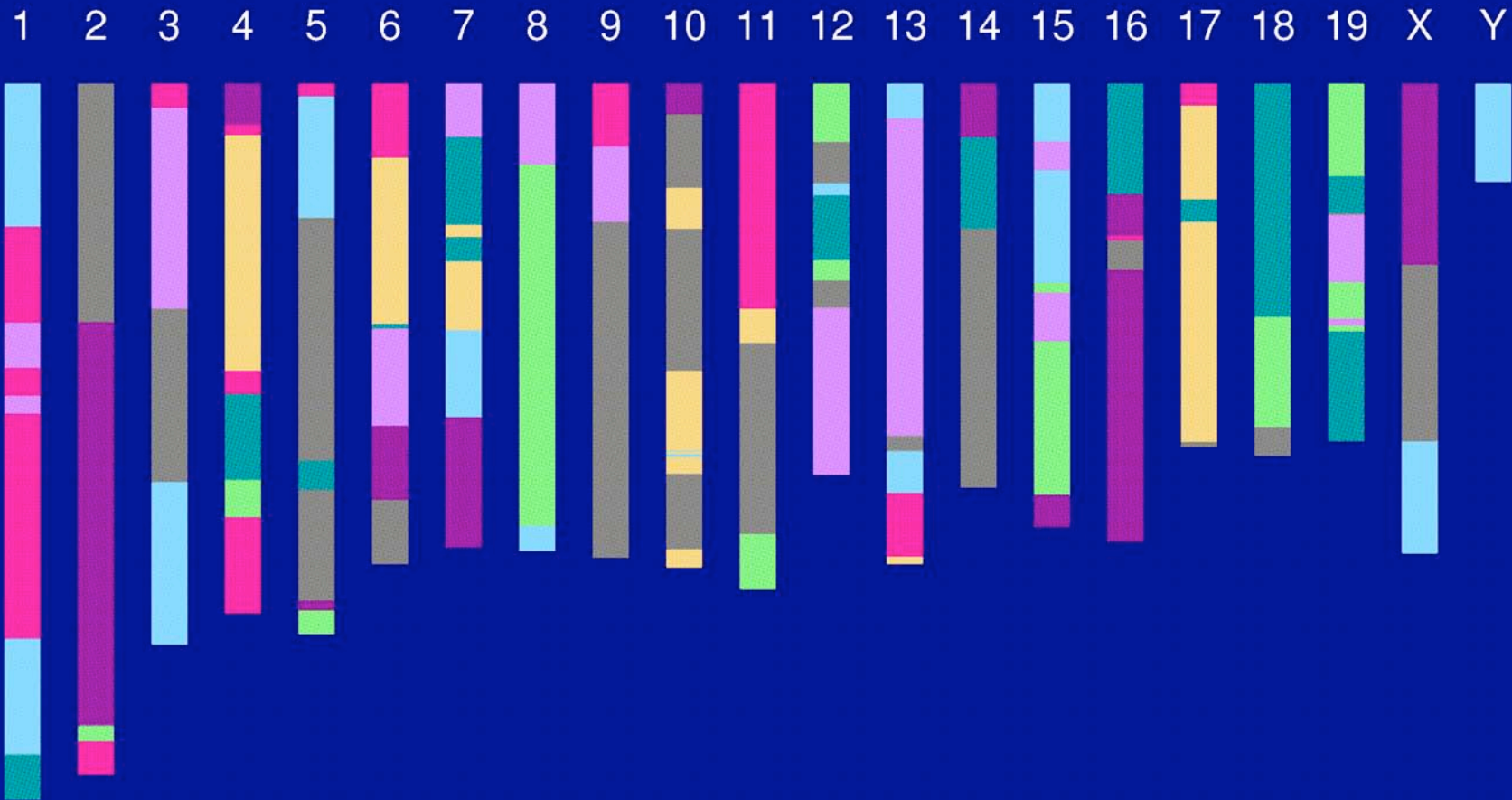
# The “Collaborative Cross”



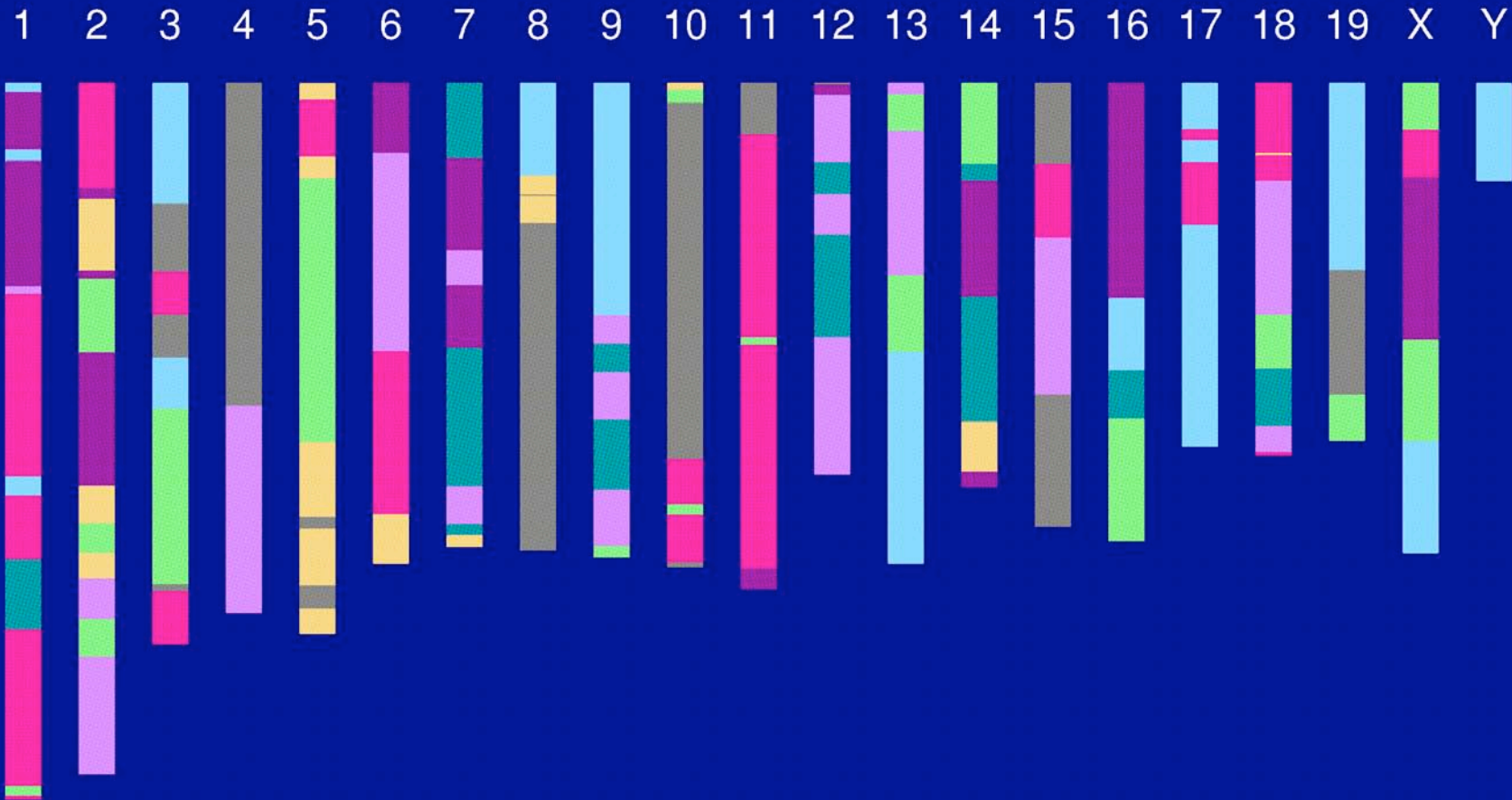
# Genome of an 8-way RI



# Genome of an 8-way RI

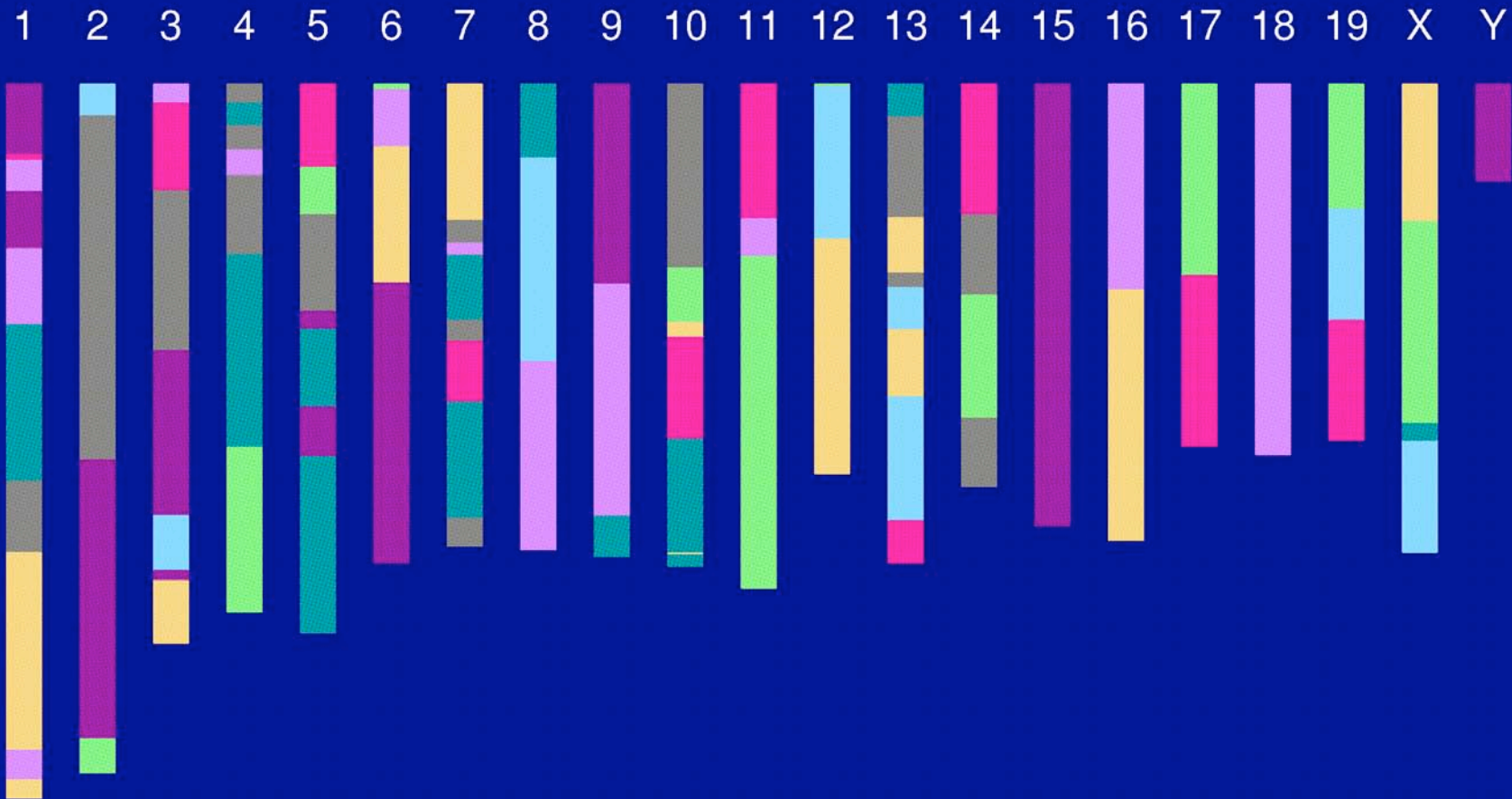


# Genome of an 8-way RI

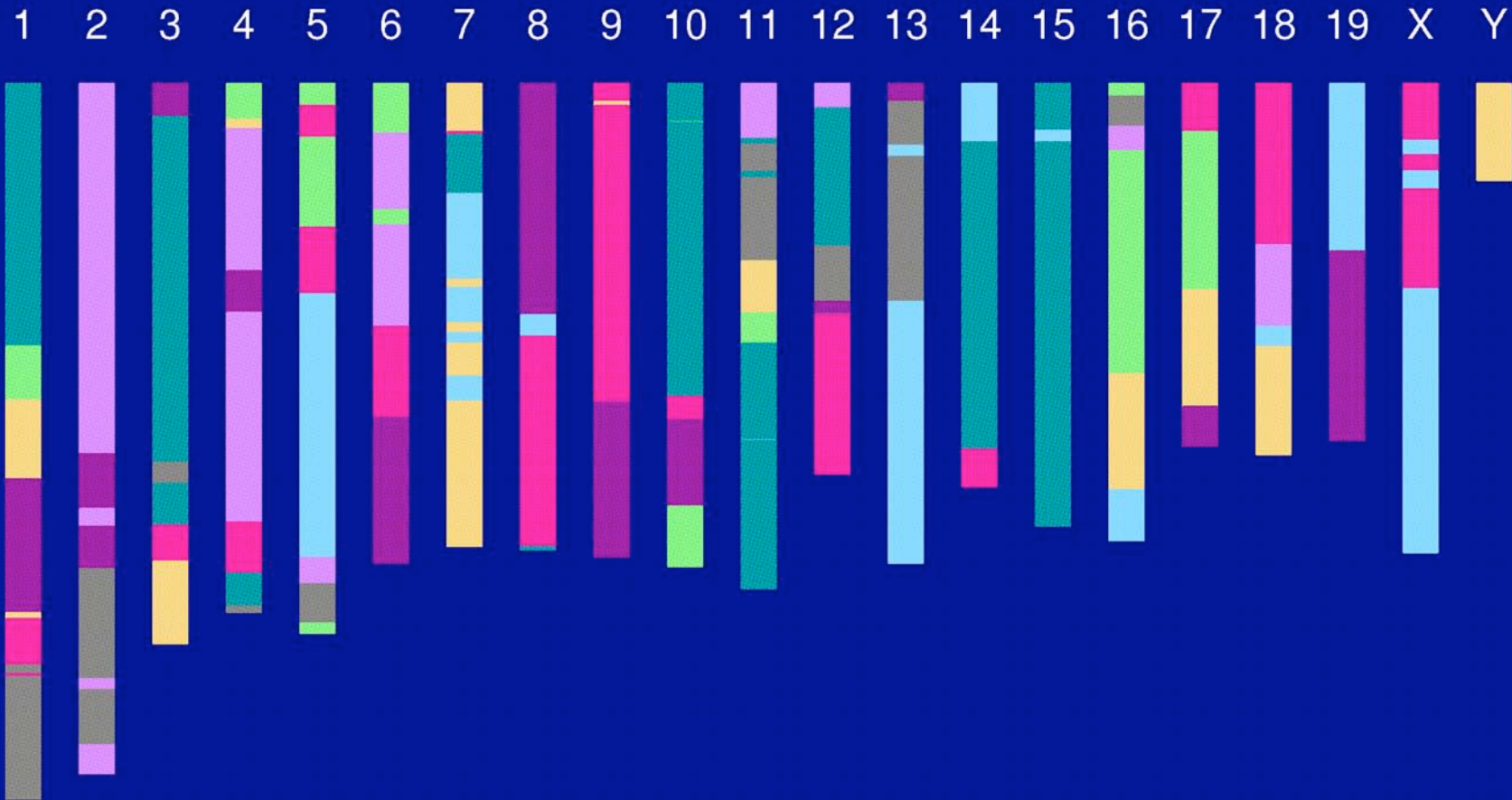




# Genome of an 8-way RI



# Genome of an 8-way RI



# The “Collaborative Cross”

## Advantages

- Great mapping precision.
- Eternal resource.
  - Genotype only once.
  - Study multiple invasive phenotypes on the same genotype.

## Barriers

- Advantages not widely appreciated.
  - Ask one question at a time, or Ask many questions at once?
- Time.
- Expense.
- Requires large-scale collaboration.

# To be worked out

- Breakpoint process along an 8-way RI chromosome.
- Reconstruction of genotypes given multipoint marker data.
- Single-QTL analyses.
  - Mixed models, with random effects for strains and genotypes/alleles.
- Power and precision (relative to an intercross).

# Acknowledgments

- Terry Speed, Univ. of California, Berkeley and WEHI
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