

~~Sample Size and Power Estimation for QTL~~ ~~Experiment~~ in Plant and Animal Breeding

What is “selection”?

Idea: Reproduction is a relay race. We want the baton of *good traits* to pass to the next generation.

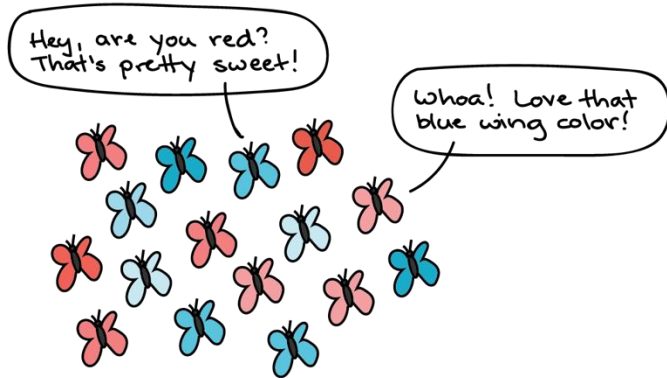
- **Selection** = choose the best individuals to be parents so useful traits become more common.
- **Natural selection:** the environment “scores” survival and reproduction.
- **Artificial selection:** people (breeders) “score” and choose the parents.

Traditional ways to select

- **Phenotypic selection:** “pick what you can see.”
- **Progeny testing:** “judge by the children.”
- **Backcross breeding:** “move a good gene into a good variety.”

We'll look at each and why they can be slow or imprecise.

Phenotypic selection



* Butterflies do not actually talk! Cartoon for cute illustration purposes only 😊

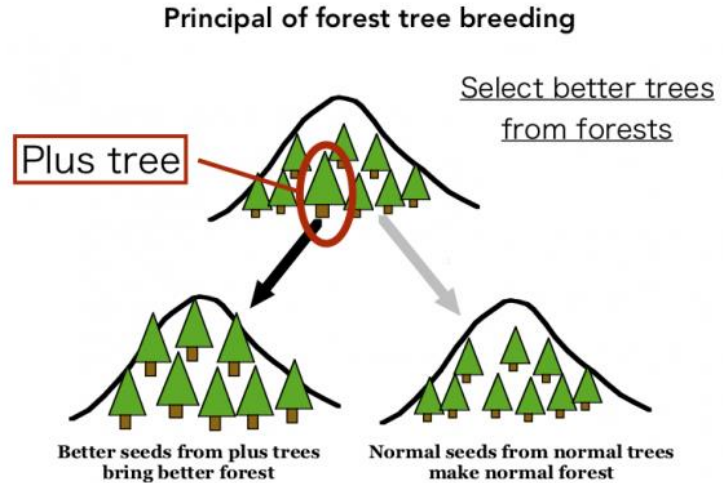
How it works - Choose plants/animals with better appearance or performance.

Limitations - Need many locations & seasons to separate genetics from weather and soil.

Progeny testing

How it works - Some traits can't be judged in the parent. Therefore, we look at offspring performance.

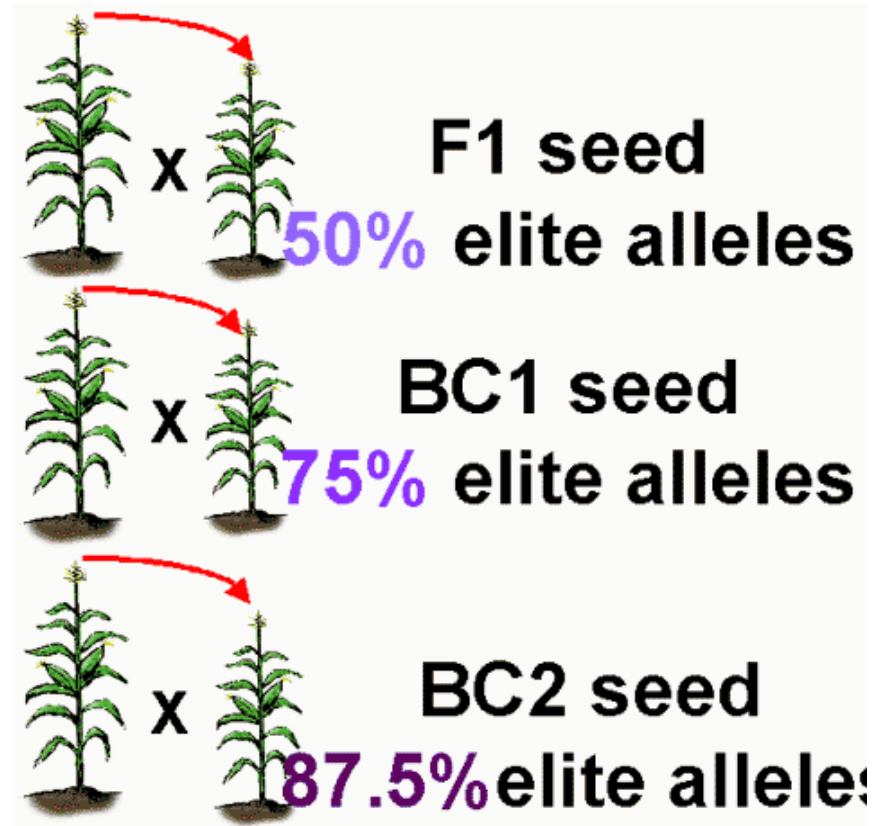
Limitations - Slow, expensive, resource-hungry.



Backcross breeding

How it works - Bring a useful gene from a donor into an elite variety you already like.

Limitations - 6–8 backcross generations



Why traditional methods are often inefficient

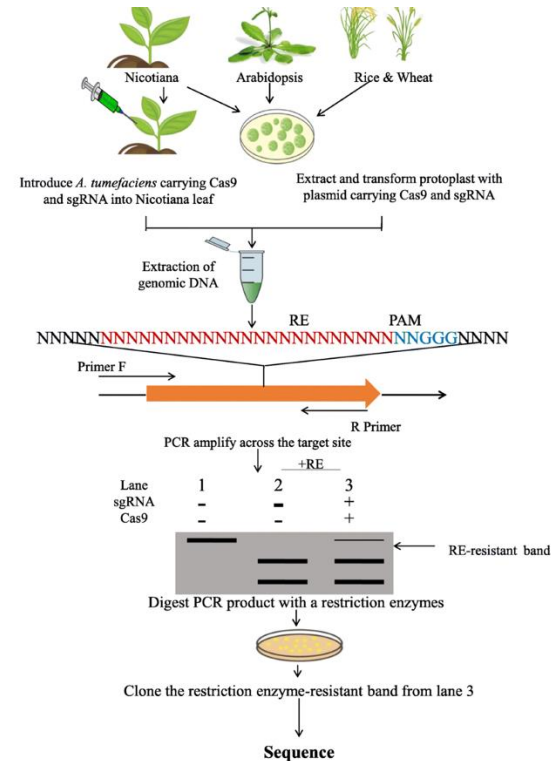
- Environment gets in the way
- Time and money
- Late or hard-to-measure traits
- Low-heritability traits
- Linkage drag

So we need faster, more precise tools !

Marker-assisted selection

Core idea - Don't wait for traits to show up. Look at **markers** !

If a marker sits very close to a useful gene/QTL and is rarely separated by reshuffling, seeing the marker \approx having the useful piece.






Why MAS helps?

- Earlier screening
- More stable than visible performance
- Stack multiple good genes
- Cheaper for certain traits

Connect phenotype and genotype

- How the letters make the colour in this one-gene example:
- BB: the flower is purple.
- Bb: the flower is purple too, because B is dominant—one copy is enough to give purple and it masks b.
- bb: the flower is white, because there's no B to make it purple.
- So, the genotype sets the instructions, and the phenotype is the outcome.

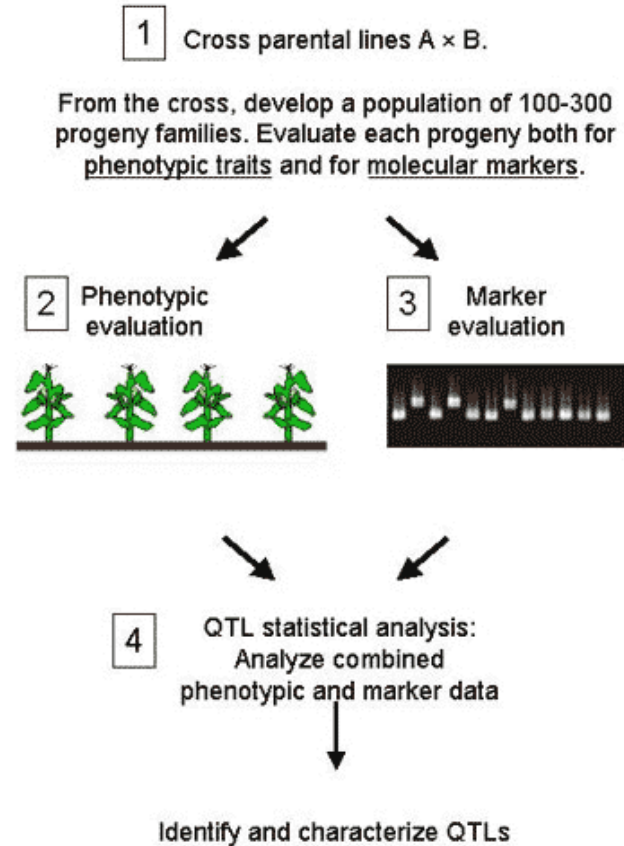
Genotype vs Phenotype	
GENOTYPE	PHENOTYPE
The genotype is an organism's genetic information.	The phenotype is the set of observable physical traits.
BB homozygous dominant	purple 
Bb heterozygous	purple 
bb homozygous recessive	white 

sciencenotes.org

(<https://sciencenotes.org/genotype-vs-phenotype-definitions-and-examples/>)

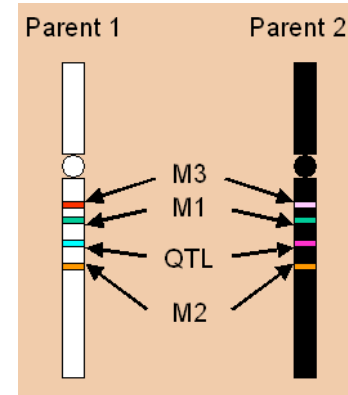
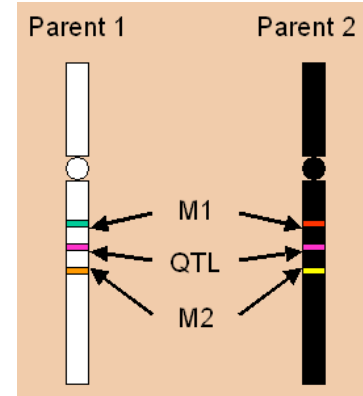
What is a QTL?

A QTL (Quantitative Trait Locus) is not a single precise gene address. It's more like a neighbourhood—a stretch of DNA statistically linked with variation in a quantitative trait.

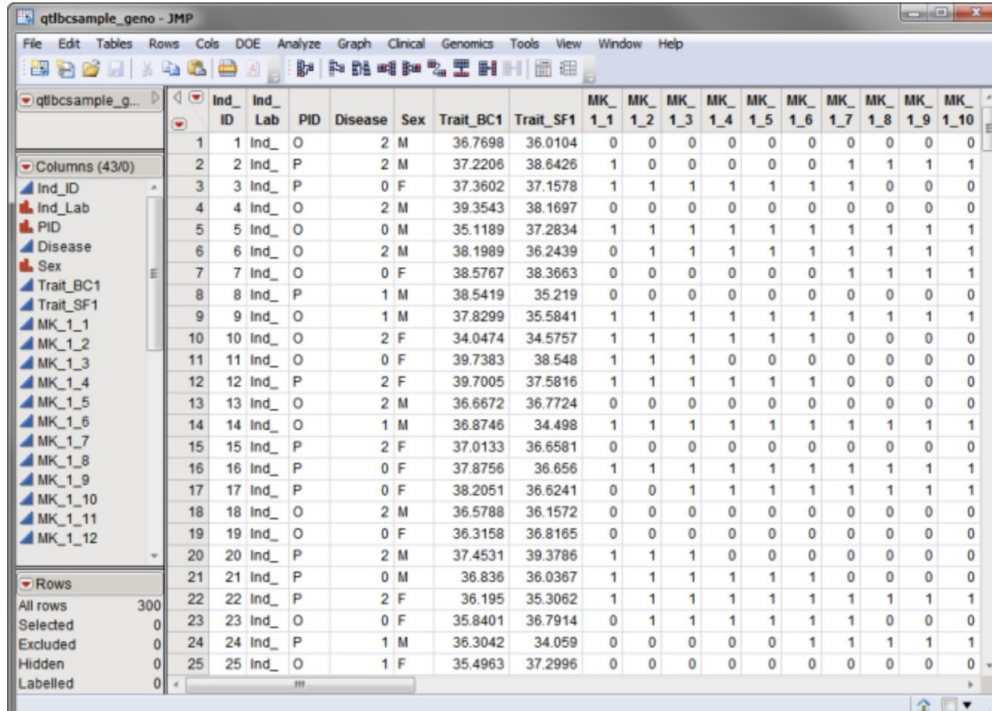


How to find QTL

- From the first figure, the QTL cannot be detected because the QTL is not polymorphic.
- From the second figure, the QTL is different, therefore, it can be detected. Besides, we can continue screening additional markers in the vicinity to find one that was polymorphic, as shown by M3



Data structure of QTL



Ind_ID	Ind_Lab	PID	Disease	Sex	Trait_BC1	Trait_SF1	MK_1_1	MK_1_2	MK_1_3	MK_1_4	MK_1_5	MK_1_6	MK_1_7	MK_1_8	MK_1_9	MK_1_10
1	1 Ind_	O	2	M	36.7698	36.0104	0	0	0	0	0	0	0	0	0	0
2	2 Ind_	P	2	M	37.2206	38.6426	1	0	0	0	0	0	1	1	1	1
3	3 Ind_	P	0	F	37.3602	37.1578	1	1	1	1	1	1	1	0	0	0
4	4 Ind_	O	2	M	39.3543	38.1697	0	0	0	0	0	0	0	0	0	0
5	5 Ind_	O	0	M	35.1189	37.2834	1	1	1	1	1	1	1	1	1	1
6	6 Ind_	O	2	M	38.1989	36.2439	0	1	1	1	1	1	1	1	1	1
7	7 Ind_	O	0	F	38.5767	38.3663	0	0	0	0	0	0	1	1	1	1
8	8 Ind_	P	1	M	38.5419	35.219	0	0	0	0	0	0	0	0	0	0
9	9 Ind_	O	1	M	37.8299	35.5841	1	1	1	1	1	1	1	1	1	1
10	10 Ind_	O	2	F	34.0474	34.5757	1	1	1	1	1	1	0	0	0	0
11	11 Ind_	O	0	F	39.7383	38.548	1	1	1	0	0	0	0	0	0	0
12	12 Ind_	P	2	F	39.7005	37.5816	1	1	1	1	1	1	0	0	0	0
13	13 Ind_	O	2	M	36.6672	36.7724	0	0	0	0	0	0	0	0	0	0
14	14 Ind_	O	1	M	36.8746	34.498	1	1	1	1	1	1	1	1	1	1
15	15 Ind_	P	2	F	37.0133	36.6581	0	0	0	0	0	0	0	0	0	0
16	16 Ind_	P	0	F	37.8756	36.656	1	1	1	1	1	1	1	1	1	1
17	17 Ind_	P	0	F	38.2051	36.6241	0	0	1	1	1	1	1	1	1	1
18	18 Ind_	O	2	M	36.5788	36.1572	0	0	0	0	0	0	0	0	0	0
19	19 Ind_	O	0	F	36.3158	36.8165	0	0	0	0	0	0	0	0	0	0
20	20 Ind_	P	2	M	37.4531	39.3786	1	1	1	0	0	0	0	0	0	0
21	21 Ind_	P	0	M	36.836	36.0367	1	1	1	1	1	1	0	0	0	0
22	22 Ind_	P	2	F	36.195	35.3062	1	1	1	1	1	1	1	1	1	1
23	23 Ind_	O	0	F	35.8401	36.7914	0	1	1	1	1	1	1	0	0	0
24	24 Ind_	P	1	M	36.3042	34.059	0	0	0	0	0	1	1	1	1	1
25	25 Ind_	O	1	F	35.4963	37.2996	0	0	0	0	0	0	0	0	0	0

Datasets often encode these two classes as 0/1 to simplify regression and plotting. A common convention is $g = 0$ for AA and $g = 1$ for AB.

Backcross & Intercross



Back cross

Parent: $TT \times tt$

F₁: Tt

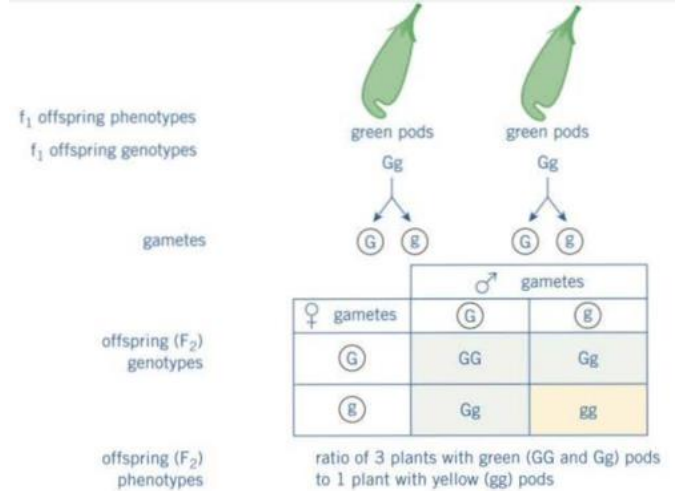
F₂: $Tt \times tt$ (Dominant backcross) or $Tt \times Tt$ (Recessive backcross)

F₁ crossed with any of the parent

Backcross: The target locus is known, markers are well defined, and the aim is to rapidly **import and retain** the recipient parent background.

Advantages: fast controllable genetic background.

Disadvantages: not suitable for accumulating many small-effect loci.



▲ Figure 2 F₁ intercross between pea plants that are heterozygous for green pods

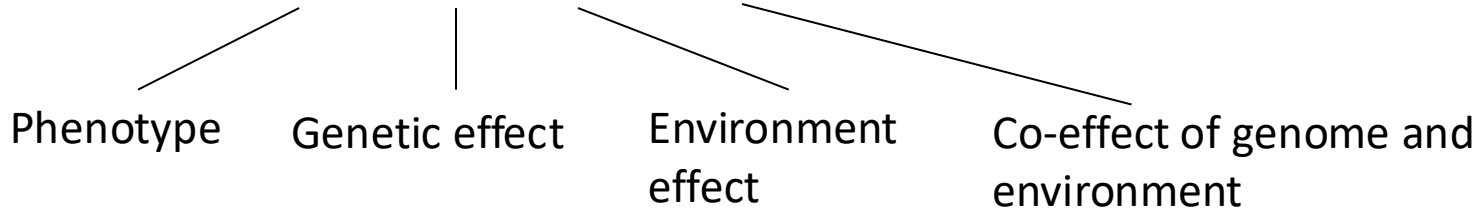
Inter-cross: The trait is controlled by multiple loci and requires accumulating/recombining **favourable** alleles.

Advantages: advance improvement at multiple loci simultaneously.

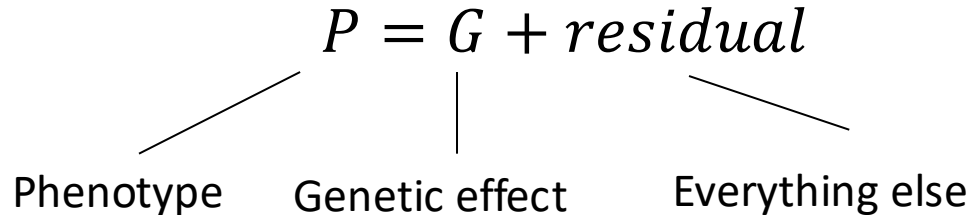
Disadvantages: longer breeding cycle; more demanding in terms of population size and marker design.

Phenotype factor decomposition

- Full model: $P = G + E + G \times E + residual$

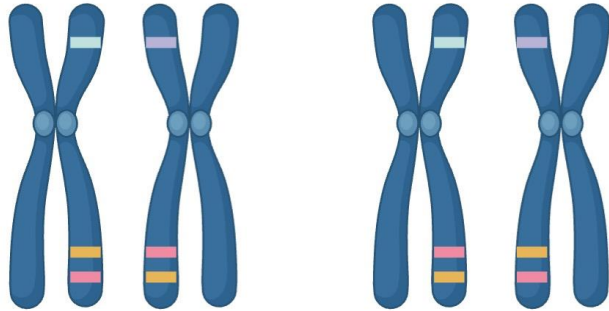


- Simplified model:



Linkage & Recombination frequency

- Linkage = two loci on the same chromosome tend to be inherited together because crossovers between them are infrequent.

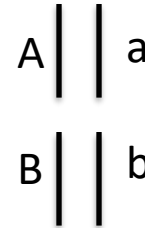
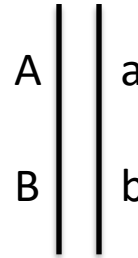


Recombination:

$$r = \Pr(\text{recombinant gamete})$$

Unlinked: $r = 0.5$

Tight linkage $r \approx 0$



AB Ab aB ab

$$r = 0.5$$

Single Marker Model in Backcross

- In a backcross population, each autosomal locus has only two genotypes AA AB. $G_i \in \{0,1\}$, $0 = AA, 1 = AB$.
- Work with the two group means $\mu_{AA}, \mu_{AB}, \Delta = \mu_{AB} - \mu_{AA}$

$$y_i = \mu + \beta G_i + \varepsilon_i ,$$

where $\beta = \mu_{AB} - \mu_{AA}$

P AA × BB

F1 AB × AA

F2 AA or AB

Classical one-way ANOVA (genotype as the factor)

- ~~ANOVA~~
- $H_0: \mu_{AA} = \mu_{AB}$
- Classical one-way ANOVA
- The between-group sum of squares $SS_B = \sum_j n_j (\bar{y}_j - \bar{y})^2$
- The within-group sum of squares $SS_W = \sum_j \sum_{i \in j} (y_{ij} - \bar{y}_j)^2$

$$F = \frac{SS_B / (k - 1)}{SS_W / (n - k)} \quad \text{💬}$$

with $k = 2$.

Mixture Distribution

- Let the left and right flanking markers be M_1, M_2 , and the candidate QTL position be Q .
- $r_{12} = \text{Recomb}(M_1, M_2)$, $r_{1Q} = \text{Recomb}(M_1, Q)$,
 $r_{2Q} = \text{Recomb}(M_2, Q)$.

- (1) Left = AA, Right = AA

$$\Pr(Q = AA) = \frac{(1 - r_{1Q})(1 - r_{2Q})}{1 - r_{12}},$$

$$\Pr(Q = AB) = \frac{r_{1Q}r_{2Q}}{1 - r_{12}}$$

$$Q = AA: \text{"no recomb left"} + \text{"no recomb right"} = (1 - r_{1Q})(1 - r_{2Q})$$

- (2) Left = AA, Right = AB

$$\Pr(Q = AA) = \frac{(1 - r_{1Q})r_{2Q}}{r_{12}},$$

$$\Pr(Q = AB) = \frac{r_{1Q}(1 - r_{2Q})}{r_{12}}$$

- (3) Left = AB, Right = AA

$$\Pr(Q = AA) = \frac{r_{1Q}(1 - r_{2Q})}{r_{12}},$$

$$\Pr(Q = AB) = \frac{(1 - r_{1Q})r_{2Q}}{r_{12}}$$

If the flanks are **different** (AA,AB or AB,AA), there was an **odd** number of crossovers; the event probability is r_{12}

- (4) Left = AB, Right = AB

$$\Pr(Q = AA) = \frac{r_{1Q}r_{2Q}}{1 - r_{12}},$$

$$\Pr(Q = AB) = \frac{(1 - r_{1Q})(1 - r_{2Q})}{1 - r_{12}}$$

If the two flanking marker genotypes are the same (AA,AA or AB,AB), then there must be an even number of crossovers between M_1, M_2 .

The probability of that conditioning event is $1 - r_{12}$.

Multiple markers model

- Goal: consider multiple markers simultaneously for a continuous trait, rather than analysing one marker at a time.

$$y_i = \mu + \sum_{j=1}^p x_{ij}\beta_j + \varepsilon_i, \quad \varepsilon_i \sim N(0, \sigma^2)$$

Phenotype of the i – th individual

The effect size of marker β_j

The numeric coding of marker j for individual i

Limitation in Multiple Marker Model

- **High dimensionality:** The number of markers p is often comparable to, or even much larger than, the sample size n ($p \gg n$);
- **Collinearity:** linkage disequilibrium (LD) makes columns highly correlated.
- As a result, plain OLS is unstable or even not identifiable.

Strategies for Multiple Marker Model

- **1、Stepwise selection**

simple but unstable under high dimension; ignores model uncertainty.

- **2、Bayesian shrinkage**

$$\beta_j \mid \sigma^2, \lambda_j \sim \mathcal{N}\left(0, \frac{\sigma^2}{\lambda_j}\right), \quad \lambda_j \sim \text{Gamma}(\alpha, \theta)$$

Marker-specific Gaussian shrinkage.

Large $\lambda_j \rightarrow$ strong shrinkage ($\beta_j \approx 0$)

Small $\lambda_j \rightarrow$ large effects

- 3、 Penalized regression-Elastic Net

$$\min_{\beta} \|y - Z\beta\|^2 + \lambda_1 \sum_{j=1}^p |\beta_j| + \lambda_2 \sum_{j=1}^p \beta_j^2$$

Ridge($\lambda_2 > 0, \lambda_1 = 0$): shrinks coefficients; no variable selection; robust under strong LD.

Lasso ($\lambda_1 > 0, \lambda_2 = 0$) : can shrink some β_j exactly to 0, but tends to pick one of several highly correlated markers.

Elastic net: combines both; good for *groups* of correlated markers.