

Basic Designs for Estimation of Genetic Parameters

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Heritability

Narrow vs. broad sense

Narrow sense: $h^2 = V_A/V_P$

Slope of midparent-offspring regression
(sexual reproduction)

Broad sense: $H^2 = V_G/V_P$

Slope of a parent - cloned offspring regression
(asexual reproduction)

When one refers to heritability, the default is narrow-sense, h^2

h^2 is the measure of (easily) usable genetic variation under sexual reproduction

Why h^2 instead of h ?

Blame Sewall Wright, who used h to denote the correlation between phenotype and breeding value. Hence, h^2 is the total fraction of phenotypic variance due to breeding values

$$r(A, P) = \frac{\sigma(A, P)}{\sigma_A \sigma_P} = \frac{\sigma_A^2}{\sigma_A \sigma_P} = \frac{\sigma_A}{\sigma_P} = h$$

Heritabilities are functions of populations

Heritability values only make sense in the context of the population for which it was measured.

Heritability measures the *standing genetic variation* of a population, A zero heritability DOES NOT imply that the trait is not genetically determined

Heritabilities are functions of the distribution of environmental values (i.e., the *universe* of E values)

Decreasing V_p increases h^2 .

Heritability values measured in one environment (or distribution of environments) may not be valid under another

Measures of heritability for lab-reared individuals may be very different from heritability in nature

Heritability and the prediction of breeding values

If P denotes an individual's phenotype, then best linear predictor of their breeding value A is

$$A = \frac{\sigma(P, A)}{\sigma_P^2} (P - \mu_p) + e = h^2(P - \mu_p) + e$$

The residual variance is also a function of h^2 :

$$\sigma_e^2 = (1 - h^2)\sigma_A^2$$

The larger the heritability, the tighter the distribution of true breeding values around the value $h^2(P - \mu_p)$ predicted by an individual's phenotype.

Heritability and population divergence

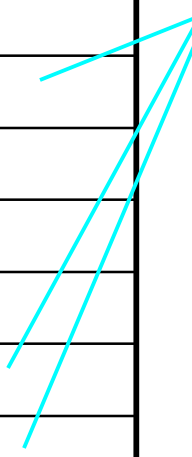
*Heritability is a **completely unreliable predictor** of long-term response*

Measuring heritability values in two populations that show a difference in their means provides no information on whether the underlying difference is genetic

Sample heritabilities

People		h^s
	Height	0.80
	Serum IG	0.45
Pigs		
	Back-fat	0.70
	Weight gain	0.30
	Litter size	0.05
Fruit Flies		
	Abdominal Bristles	0.50
	Body size	0.40
	Ovary size	0.3
	Egg production	0.20

Traits more closely associated with fitness tend to have lower heritabilities



Estimation: One-way ANOVA

Simple (balanced) full-sib design: N full-sib families, each with n offspring: One-way ANOVA model

Trait value in sib j from family i

Common Mean

Deviation of sib j from the family mean

$$z_{ij} = \mu + f_i + w_{ij}$$

The diagram illustrates the decomposition of a trait value z_{ij} into three components. The equation $z_{ij} = \mu + f_i + w_{ij}$ is centered. Three arrows point from descriptive text to the terms: one from 'Trait value in sib j from family i' to z_{ij} , one from 'Common Mean' to μ , and one from 'Deviation of sib j from the family mean' to w_{ij} . A fourth arrow points from a red text block below to the f_i term.

Effect for family i =
deviation of mean of i from
the common mean

Covariance between members of the same group equals the variance among (between) groups

$$\begin{aligned}\text{Cov}(\text{Full Sibs}) &= \sigma(z_{ij}, z_{ik}) \\ &= \sigma[(\mu + f_i + w_{ij}), (\mu + f_i + w_{ik})] \\ &= \sigma(f_i, f_i) + \sigma(f_i, w_{ik}) + \sigma(w_{ij}, f_i) + \sigma(w_{ij}, w_{ik}) \\ &= \sigma_f^2\end{aligned}$$

Hence, the variance among family effects equals the covariance between full sibs

$$\sigma_f^2 = \sigma_A^2/2 + \sigma_D^2/4 + \sigma_{E_c}^2$$

The within-family variance $\sigma_w^2 = \sigma_p^2 - \sigma_f^2$,

$$\begin{aligned}\sigma_{w(FS)}^2 &= \sigma_P^2 - (\sigma_A^2/2 + \sigma_D^2/4 + \sigma_{Ec}^2) \\ &= \sigma_A^2 + \sigma_D^2 + \sigma_E^2 - (\sigma_A^2/2 + \sigma_D^2/4 + \sigma_{Ec}^2) \\ &= (1/2)\sigma_A^2 + (3/4)\sigma_D^2 + \sigma_E^2 - \sigma_{Ec}^2\end{aligned}$$

One-way Anova: N families with n sibs, T = Nn

Factor	Degrees of freedom, df	Sums of Squares (SS)	Mean sum of squares (MS)	E[MS]
Among-family	N-1	$SS_F = n \sum_{i=1}^N (\bar{z}_i - \bar{z})^2$	$SS_f / (N-1)$	$\sigma_w^2 + n \sigma_f^2$
Within-family	T-N	$SS_W = \sum_{i=1}^N \sum_{j=1}^n (z_{ij} - \bar{z}_i)^2$	$SS_w / (T-N)$	σ_w^2

Estimating the variance components:

$$\text{Var}(f) = \frac{\text{MS}_f - \text{MS}_w}{n}$$

$$\text{Var}(w) = \text{MS}_w$$

$$\text{Var}(z) = \text{Var}(f) + \text{Var}(w)$$

Since $\sigma_f^2 = \sigma_A^2/2 + \sigma_D^2/4 + \sigma_{Ec}^2$

$2\text{Var}(f)$ is an upper bound for the additive variance

Assigning standard errors (= square root of Var)

Fun fact: Under normality, the (large-sample) variance for a mean-square is given by

$$\sigma^2(\text{MS}_x) \simeq \frac{2(\text{MS}_x)^2}{\text{df}_x + 2}$$

$$\text{Var}[\text{Var}(w(FS))] = \text{Var}(\text{MS}_w) \simeq \frac{2(\text{MS}_w)^2}{T - N + 2}$$

$$\begin{aligned} \text{Var}[\text{Var}(f)] &= \text{Var}\left[\frac{\text{MS}_f - \text{MS}_w}{n}\right] \\ &\simeq \frac{2}{n^2} \left(\frac{(\text{MS}_f)^2}{N + 1} + \frac{(\text{MS}_w)^2}{T - N + 2} \right) \end{aligned}$$

Estimating heritability

$$t_{\text{FS}} = \frac{\text{Var}(f)}{\text{Var}(z)} = \frac{1}{2}h^2 + \frac{\sigma_D^2/4 + \sigma_{E_c}^2}{\sigma_z^2}$$

Hence, $h^2 \leq 2 t_{\text{FS}}$

An approximate large-sample standard error for h^2 is given by

$$\text{SE}(h^2) \simeq 2(1 - t_{\text{FS}})[1 + (n - 1)t_{\text{FS}}] \sqrt{2/[Nn(n - 1)]}$$

Worked example

10 full-sib families, each with 5 offspring are measured

Factor	Df	SS	MS	EMS
Among-families	9	$SS_f = 405$	45	$\sigma^2_w + 5 \sigma^2_f$
Within-families	40	$SS_w = 800$	20	σ^2_w

$$\text{Var}(f) = \frac{MS_f - MS_w}{n} = \frac{45 - 20}{5} = 5 \longrightarrow V_A < 10$$

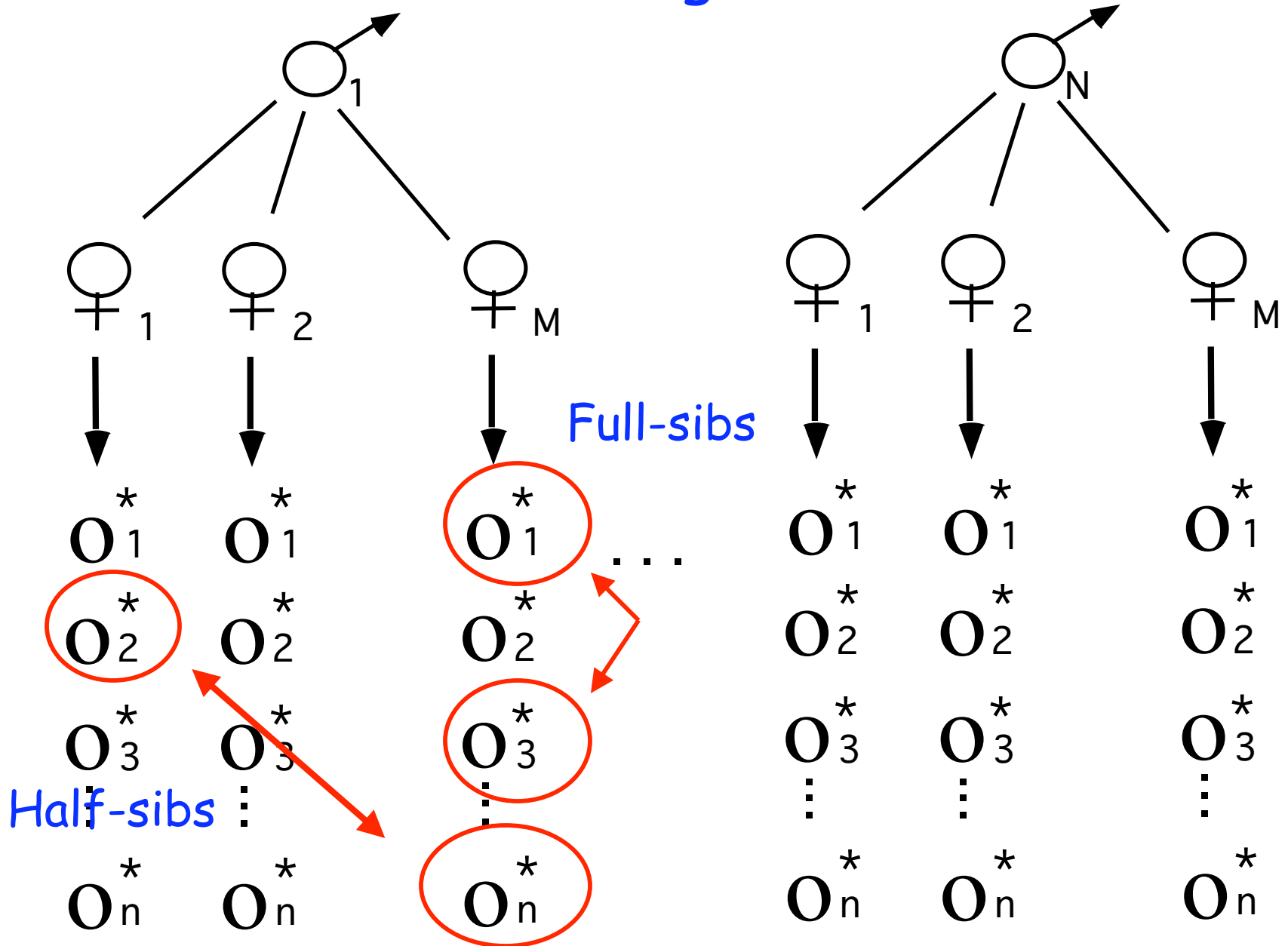
$$\text{Var}(w) = MS_w = 20$$

$$\text{Var}(z) = \text{Var}(f) + \text{Var}(w) = 25$$

$$h^2 < 2 (5/25) = 0.4$$

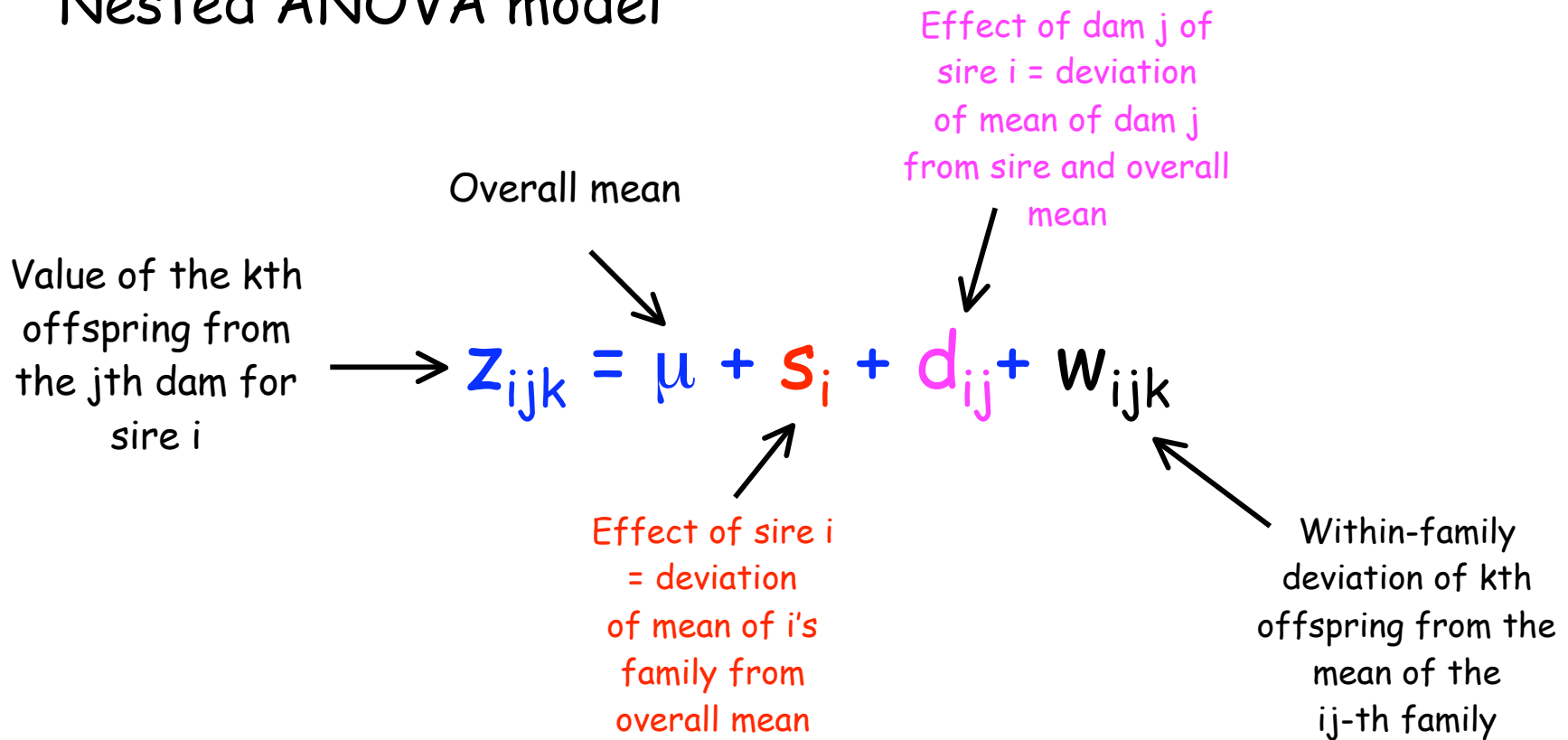
$$SE(h^2) \simeq 2(1 - 0.4)[1 + (5 - 1)0.4] \sqrt{2/[50(5 - 1)]} = 0.312$$

Full sib-half sib design: **Nested ANOVA**



Estimation: Nested ANOVA

Balanced full-sib / half-sib design: N males (**sires**) are crossed to M **dams** each of which has n offspring:
Nested ANOVA model



Nested ANOVA model:

$$Z_{ijk} = \mu + s_i + d_{ij} + w_{ijk}$$

σ^2_s = between-sire variance = variance in sire family means

σ^2_d = variance among dams within sires =
variance of dam means for the same sire

σ^2_w = within-family variance

$$\sigma^2_T = \sigma^2_s + \sigma^2_d + \sigma^2_w$$

Nested Anova: N sires crossed to M dams, each with n sibs, T = NMn

Factor	Df	SS	MS	EMS
Sires	N-1	$SS_s = Mn \sum_{i=1}^N \sum_{j=1}^{M_i} (\bar{z}_i - \bar{z})^2$	$SS_s / (N-1)$	$\sigma_w^2 + n\sigma_d^2 + Mn\sigma_s^2$
Dams(Sires)	N(M-1)	$SS_d = n \sum_{i=1}^N \sum_{j=1}^M (\bar{z}_{ij} - \bar{z}_i)^2$	$SS_d / (N[M-1])$	$\sigma_w^2 + n\sigma_d^2$
Sibs(Dams)	T-NM	$SS_w = \sum_{i=1}^N \sum_{j=1}^M \sum_{k=1}^n (z_{ijk} - \bar{z}_{ij})^2$	$SS_w / (T-NM)$	σ_w^2

Estimation of sire, dam, and family variances:

$$\text{Var}(s) = \frac{MS_s - MS_d}{Mn}$$

$$\text{Var}(d) = \frac{MS_d - MS_w}{n}$$

$$\text{Var}(e) = MS_w$$

Translating these into the desired variance components

- $\text{Var}(\text{Total}) = \text{Var}(\text{between FS families}) + \text{Var}(\text{Within FS})$

$$\longrightarrow \sigma_w^2 = \sigma_z^2 - \text{Cov}(\text{FS})$$

- $\text{Var}(\text{Sires}) = \text{Cov}(\text{Paternal half-sibs})$

$$\begin{aligned}\sigma_d^2 &= \sigma_z^2 - \sigma_s^2 - \sigma_w^2 \\ &= \sigma(\text{FS}) - \sigma(\text{PHS})\end{aligned}$$

Summarizing,

$$\sigma_s^2 = \sigma(\text{PHS})$$

$$\sigma_d^2 = \sigma_z^2 - \sigma_s^2 - \sigma_w^2$$

$$\sigma_w^2 = \sigma_z^2 - \sigma(\text{FS})$$

$$= \sigma(\text{FS}) - \sigma(\text{PHS})$$

Expressing these in terms of the genetic and environmental variances,

$$\sigma_s^2 \simeq \frac{\sigma_A^2}{4}$$

$$\sigma_d^2 \simeq \frac{\sigma_A^2}{4} + \frac{\sigma_D^2}{4} + \sigma_{E_c}^2$$

$$\sigma_w^2 \simeq \frac{\sigma_A^2}{2} + \frac{3\sigma_D^2}{4} + \sigma_{E_s}^2$$

Intraclass correlations and estimating heritability

$$t_{\text{PHS}} = \frac{\text{Cov}(\text{PHS})}{\text{Var}(z)} = \frac{\text{Var}(s)}{\text{Var}(z)} \longrightarrow 4t_{\text{PHS}} = h^2$$

$$t_{\text{FS}} = \frac{\text{Cov}(\text{FS})}{\text{Var}(z)} = \frac{\text{Var}(s) + \text{Var}(d)}{\text{Var}(z)} \longrightarrow h^2 \leq 2t_{\text{FS}}$$

Note that $4t_{\text{PHS}} = 2t_{\text{FS}}$ implies no dominance or shared family environmental effects

Worked Example:

N=10 sires, M = 3 dams, n = 10 sibs/dam

Factor	Df	SS	MS	EMS
Sires	9	4,230	470	$\sigma_w^2 + 10\sigma_d^2 + 30\sigma_s^2$
Dams(Sires)	20	3,400	170	$\sigma_w^2 + 10\sigma_d^2$
Within Dams	270	5,400	20	σ_w^2

$$\sigma_w^2 = MS_w = 20$$

$$\sigma_d^2 = \frac{MS_d - MS_w}{n} = \frac{170 - 20}{10} = 15$$

$$\sigma_s^2 = \frac{MS_s - MS_d}{Nn} = \frac{470 - 170}{30} = 10$$

$$\sigma_P^2 = \sigma_s^2 + \sigma_d^2 + \sigma_w^2 = 45$$

$$\begin{aligned} \sigma_d^2 = 15 &= (1/4)\sigma_A^2 + (1/4)\sigma_D^2 + \sigma_{E_c}^2 \\ &= 10 + (1/4)\sigma_D^2 + \sigma_{E_c}^2 \end{aligned}$$

$$\sigma_A^2 = 4\sigma_s^2 = 40$$

$$h^2 = \frac{\sigma_A^2}{\sigma_P^2} = \frac{40}{45} = 0.89$$

$$\sigma_D^2 + 4\sigma_{E_c}^2 = 20$$

Parent-offspring regression

Single parent - offspring regression

$$z_{o_i} = \mu + b_{o|p}(z_{p_i} - \mu) + e_i$$

The expected slope of this regression is:

$$E(b_{o|p}) = \frac{\sigma(z_o, z_p)}{\sigma^2(z_p)} \simeq \frac{(\sigma_A^2/2) + \sigma(E_o, E_p)}{\sigma_z^2} = \frac{h^2}{2} + \frac{\sigma(E_o, E_p)}{\sigma_z^2}$$

Residual error variance (spread around expected values)

$$\sigma_e^2 = \left(1 - \frac{h^2}{2}\right) \sigma_z^2$$

The expected slope of this regression is:

$$E(b_{o|p}) = \frac{\sigma(z_o, z_p)}{\sigma^2(z_p)} \simeq \frac{(\sigma_A^2/2) + \sigma(E_o, E_p)}{\sigma_z^2} = \frac{h^2}{2} + \frac{\sigma(E_o, E_p)}{\sigma_z^2}$$

Shared environmental values

To avoid this term, typically regressions are male-offspring, as female-offspring more likely to share environmental values

Midparent - offspring regression

$$z_{oi} = \mu + b_{o|MP} \left(\frac{z_{mi} + z_{fi}}{2} - \mu \right) + e_i$$

$$\begin{aligned} b_{o|MP} &= \frac{\text{Cov}[z_o, (z_m + z_f)/2]}{\text{Var}[(z_m + z_f)/2]} \\ &= \frac{[\text{Cov}(z_o, z_m) + \text{Cov}(z_o, z_f)]/2}{[\text{Var}(z) + \text{Var}(z)]/4} \\ &= \frac{2\text{Cov}(z_o, z_p)}{\text{Var}(z)} = 2b_{o|p} \end{aligned}$$

The expected slope of this regression is h^2

Residual error variance (spread around expected values)

$$\sigma_e^2 = \left(1 - \frac{h^2}{2} \right) \sigma_z^2$$

Standard errors

Single parent-offspring regression, N parents, each with n offspring

Squared regression slope

$$\text{Var}(b_{o|p}) \simeq \frac{n(t - b_{o|p}^2) + (1 - t)}{Nn}$$

Total number of offspring

Sib correlation

$$t = \begin{cases} t_{HS} = h^2/4 & \text{for half-sibs} \\ t_{FS} = h^2/2 + \frac{\sigma_D^2 + \sigma_{E_c}^2}{\sigma_z^2} & \text{for full sibs} \end{cases}$$

$$\text{Var}(h^2) = \text{Var}(2b_{o|p}) = 4\text{Var}(b_{o|p})$$

Midparent-offspring regression,
N sets of parents, each with n offspring

$$\text{Var}(h^2) = \text{Var}(b_{o|MP}) \simeq \frac{2[n(t_{FS} - b_{o|MP}^2/2) + (1 - t_{FS})]}{Nn}$$

- Midparent-offspring variance half that of single parent-offspring variance

$$\text{Var}(h^2) = \text{Var}(2b_{o|p}) = 4\text{Var}(b_{o|p})$$

Estimating Heritability in Natural Populations

Often, sibs are reared in a laboratory environment, making parent-offspring regressions and sib ANOVA problematic for estimating heritability

Let b' be the slope of the regression of the values of lab-raised offspring regressed in the trait values of their parents in the wild

A lower bound can be placed of heritability using parents from nature and their lab-reared offspring,

$$h_{min}^2 = (b'_{o|MP})^2 \frac{\text{Var}_n(z)}{\text{Var}_l(A)}$$

← Trait variance in nature

← Additive variance in lab

Why is this a lower bound?

Covariance between
breeding value in nature
and BV in lab



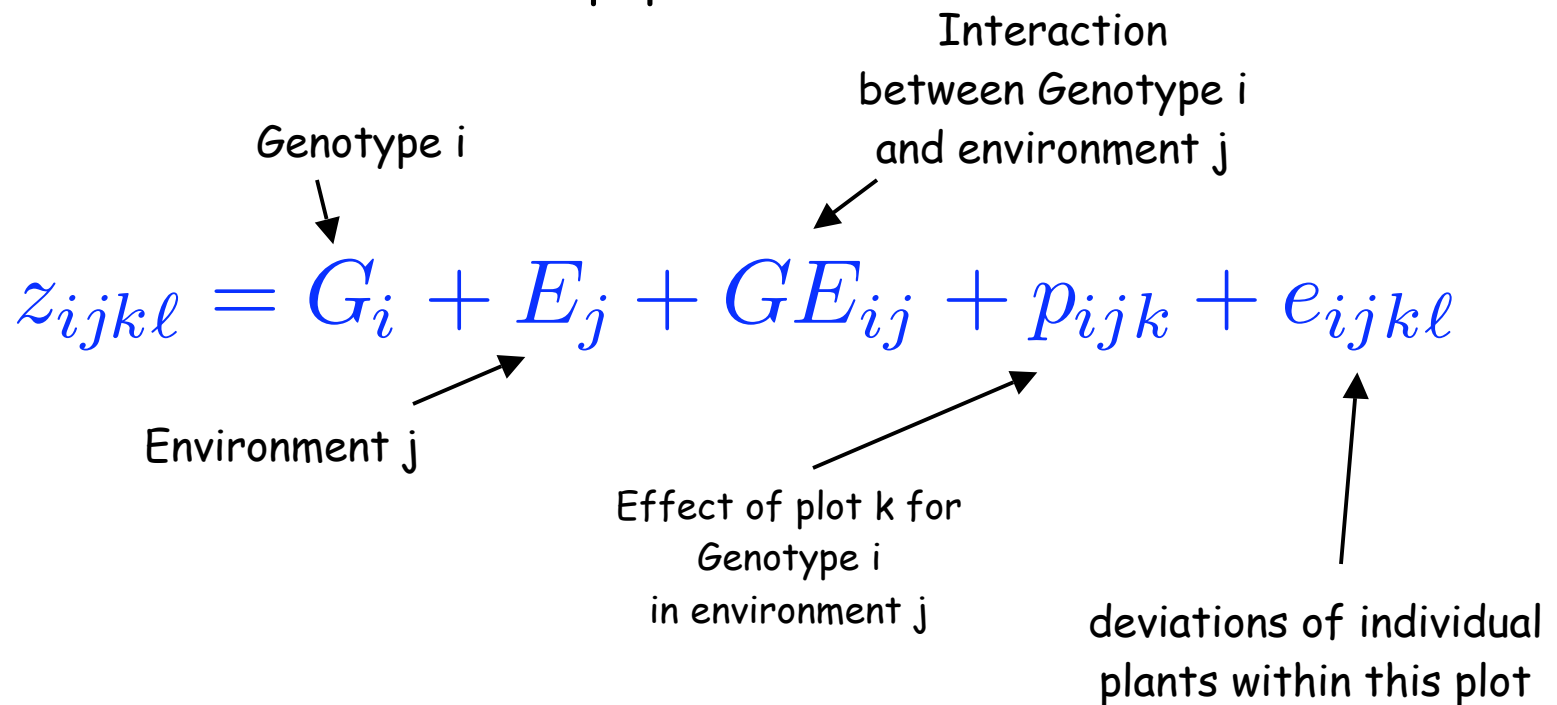
$$(b'_{o|MP})^2 \frac{\text{Var}_n(z)}{\text{Var}_l(A)} = \left[\frac{\text{Cov}_{l,n}(A)}{\text{Var}_n(z)} \right]^2 \frac{\text{Var}_n(z)}{\text{Var}_l(A)} = \boxed{\gamma^2 h_n^2}$$

where $\gamma = \frac{\text{Cov}_{l,n}(A)}{\sqrt{\text{Var}_n(A)\text{Var}_l(A)}}$

is the additive genetic covariance between
environments and hence $\gamma^2 \leq 1$

Defining H^2 for Plant Populations

Plant breeders often do not measure individual plants (especially with pure lines), but instead measure a **plot** or a **block** of individuals. This can result in inconsistent measures of H^2 even for otherwise identical populations



$$z_{ijkl} = G_i + E_j + GE_{ij} + p_{ijk} + e_{ijkl}$$

$$\sigma^2(z_i) = \sigma_G^2 + \sigma_E^2 + \frac{\sigma_{GE}^2}{e} + \frac{\sigma_p^2}{er} + \frac{\sigma_e^2}{ern}$$

e = number of environments

r = (replicates) number of plots/environment

n = number of individuals per plot

Hence, V_p , and hence H^2 , depends on our choice of e , r , and n