

Estimating Variance Components

- Many ways to do it
 - ANOVA
 - Regression (developed for estimating h²!)
- For large unbalanced data sets with complex pedigrees: Linear Mixed Models
 - Fixed
 - Experimental/population specific effects
 - Random
 - Variables randomly sampled, e.g., individuals randomly sampled from a population

The "Animal Model"

- y = Xβ + Za + e
 y = (nx1) vector of phenotypic measures
 β = (px1) vector of fixed effect regression coefficients (FIXED)
 X = (nxp) design matrix relating y to β (FIXED)
 a = (qx1) vector of additive effects (q = number of individuals in the pedigree) (RANDOM)
 Z = (nxq) design matrix relating y to a (RANDOM)
 e = (nx1) vector of errors
- Assume

```
Var(e) = I\sigma_e^2 (errors are independent)

Var(a) = A\sigma_a^2 (var of a depends on relationship matrix A)

cov(a,e) = 0

\alpha = \sigma_e^2/\sigma_a^2 is known (!!!!) (need a starting point)
```

$$\begin{bmatrix} X'X & X'Z \\ Z'X & Z'Z+A^{-1}\alpha \end{bmatrix} \begin{bmatrix} \beta \\ a \end{bmatrix} = \begin{bmatrix} X'y \\ Z'y \end{bmatrix}$$

```
y = (nx1) vector of phenotypic measures = KNOWN
β = (px1) vector of fixed effect regression coefficients (FIXED) = UNKNOWN
X = (nxp) design matrix relating y to β (FIXED) = KNOWN
a = (qx1) vector of additive effects (q = number of individuals in the pedigree)
(RANDOM) = UNKNOWN
Z = (nxq) design matrix relating y to a (RANDOM) = KNOWN
A relationship matrix = KNOWN = (q x q) matrix where q = number of
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A relationship matrix = KNOWN = (q x q) matrix where q = number of individuals in the pedigree $\alpha = \sigma_e^2/\sigma_a^2 = \text{ESTIMATED}$

$$\begin{bmatrix} X'X & X'Z \\ Z'X & Z'Z+A^{-1}\alpha \end{bmatrix} \begin{bmatrix} \beta \\ a \end{bmatrix} = \begin{bmatrix} X'y \\ Z'y \end{bmatrix}$$
 SO

$$\begin{bmatrix} \beta \\ a \end{bmatrix} = \begin{bmatrix} X'X & X'Z \\ Z'X & Z'Z+A^{-1}\alpha \end{bmatrix}^{-1} \begin{bmatrix} X'y \\ Z'y \end{bmatrix}$$

Ex: Data and System of Linear Equations

id	Sire	Dam	Herd	Ptype
1	-	-	1	78
2	-	-	2	83
3	_	_	2	70
4	2	1	1	86
5	2	3	2	77

```
78 = \text{herd}_1 + \text{animal}_1 + \text{error}_1

83 = \text{herd}_2 + \text{animal}_2 + \text{error}_2

70 = \text{herd}_2 + \text{animal}_3 + \text{error}_3

86 = \text{herd}_1 + \text{animal}_4 + \text{error}_4

77 = \text{herd}_2 + \text{animal}_5 + \text{error}_5
```

Ex: Data and Knowns

id	Sire	Dam	Herd	Ptype
1	-	-	1	78
2	-	-	2	83
3	-	-	2	70
4	2	1	1	86
5	2	3	2	77

$$y = \begin{bmatrix} 78 \\ 83 \\ 70 \\ 86 \\ 77 \end{bmatrix} \times = \begin{bmatrix} 10 \\ 01 \\ 10 \\ 01 \end{bmatrix} = \begin{bmatrix} 10000 \\ 01000 \\ 00010 \\ 00001 \end{bmatrix}$$
 Note: $Z = I$

Ex: Data and Unknowns

id	Sire	Dam	Herd	Ptype
1	-	_	1	78
2	-	_	2	83
3	-	_	2	70
4	2	1	1	86
5	2	3	2	77

$$a_{1}$$

$$a_{2}$$

$$a = a_{3}$$

$$a_{4}$$

$$a_{5}$$

$$a_{6}$$

$$a_{7}$$

Assume $h^2 = .33$, so $\alpha = \sigma_e^2 / \sigma_a^2 = 2.0$

Example: Data and "A" Matrix

id	Sire		Dam		Herd		Ptype
1	_		_		1		78
2	_		_		2		83
3	_		_		2		70
4	2		1		1		86
5	2		3		2		77
		1	2	3	4	<u>5</u>	
	1	1					
	2	0	1				
A =	3	0	0	1			
	4	1/2	1/2	0	1		
	5	0	1/2	1/2	1/4	1	

$$\begin{bmatrix} X'X & X'Z \\ Z'X & Z'Z+A^{-1}\alpha \end{bmatrix} \begin{bmatrix} \beta \\ a \end{bmatrix} = \begin{bmatrix} X'y \\ Z'y \end{bmatrix}$$

SO

$$\begin{bmatrix} \beta \\ a \end{bmatrix} = \begin{bmatrix} X'X & X'Z \\ Z'X & Z'Z+A^{-1}\alpha \end{bmatrix}^{-1} \begin{bmatrix} X'y \\ Z'y \end{bmatrix}$$

$$\begin{bmatrix}
10010 \\
01101
\end{bmatrix}
\begin{bmatrix}
10 \\
01
\end{bmatrix} = \begin{bmatrix}
20 \\
01
\end{bmatrix}
\begin{bmatrix}
10
\end{bmatrix}$$

$$\begin{bmatrix} \beta \\ a \end{bmatrix} = \begin{bmatrix} X'X & X'Z \\ Z'X & Z'Z+A^{-1}\alpha \end{bmatrix} \begin{bmatrix} X'y \\ Z'y \end{bmatrix}$$

X'Z =
 10010
 10000

 01101
 01000

 00100

$$\begin{bmatrix} \beta \\ a \end{bmatrix} = \begin{bmatrix} X'X & X'Z \\ Z'X & Z'Z+A^{-1}\alpha \end{bmatrix}^{1} \begin{bmatrix} X'y \\ Z'y \end{bmatrix}$$

Z'X = IX =

$$\begin{bmatrix} \beta \\ a \end{bmatrix} = \begin{bmatrix} X'X & X'Z \\ Z'X & Z'Z+A^{-1}\alpha \end{bmatrix}^{1} \begin{bmatrix} X'y \\ Z'y \end{bmatrix}$$

$$Z'Z+A^{-1}\alpha =$$

$$\begin{bmatrix}
1.5 & 0.5 & 0 & -1 & 0 \\
0.1 & 0 & 0 & 0 \\
0.5 & 2 & 0.5 & -1 & -1 \\
0.5 & 2 & 0.5 & -1 & -1
\end{bmatrix} = \begin{bmatrix}
4.10 - 20 \\
1.5 & 1 - 2 - 2
\end{bmatrix} \\
0.5 & 1.5 & 0 & -1 & 0
\end{bmatrix} = \begin{bmatrix}
0.140 - 20 \\
0.5 & 2 & 0.5 & -1 & -1
\end{bmatrix} = \begin{bmatrix}
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0.140$$

$$\begin{bmatrix} \beta \\ a \end{bmatrix} = \begin{bmatrix} X'X & X'Z \\ Z'X & Z'Z+A^{-1}\alpha \end{bmatrix}^{1} \begin{bmatrix} X'y \\ Z'y \end{bmatrix}$$

X'y =

10010

 78

 83
 161

 70
 233

 86
 77

$$\begin{bmatrix} \beta \\ a \end{bmatrix} = \begin{bmatrix} X'X & X'Z \\ Z'X & Z'Z+A^{-1}\alpha \end{bmatrix}^{1} \begin{bmatrix} X'y \\ Z'y \end{bmatrix}$$

```
Z'y = Iy = [78]
83
70
86
77
```

Ex: Solving the Mixed Model Equation

$$\begin{bmatrix} \beta \\ a \end{bmatrix} = \begin{bmatrix} X'X & X'Z \\ Z'X & Z'Z+A^{-1}\alpha \end{bmatrix} \begin{bmatrix} X'y \\ Z'y \end{bmatrix}$$

$[h_1]$	[2011000]	[161]	
h ₂	0300111	233	
a ₁	10410-20	78	
a ₂ =	10151-2-2	83	<u>(</u>
a ₃	0 1 0 1 4 0 -2	70	
a ₄	0 1 -2 -2 0 5 0	86	
$\begin{bmatrix} a_5 \end{bmatrix}$	0 1 0 -2 -2 0 5	77	

Ex: Solutions

$$h_1 = 79.17$$

$$h_2 = 77.77$$

$$a_1 = 0.53$$

$$a_2 = 2.13$$

$$a_3 = -2.66$$

$$a_{1} = 2.71$$

$$a_4 = 2.71$$
 $a_5 = -0.37$

Additional Effects

- More fixed effects: Just increases the length of Beta = very easy
- More random effects: each one adds a new term consisting of a vector of random effects times a design matrix
 - Example: add maternal environmental effects

"Animal Model" with Maternal Effects

```
    y = Xβ + Za + Wm + e

   y = (nx1) vector of phenotypic measures
   \beta = (px1) vector of fixed effect regression
        coefficients (FIXED)
   X = (nxp) design matrix relating y to \beta (FIXED)
   a = (qx1) vector of additive effects (q = number
        of individuals in the pedigree) (RANDOM)
   Z = (nxq) design matrix relating y to a (RANDOM)
   m = (fx1) vector of maternal effects (f = number of dams
         in pedigree) (RANDOM)
   W = (nxf) design matrix relating y to m (RANDOM)
   e = (nx1) vector of errors

 Solve for β and a and m

  Assume
   Var(\mathbf{e}) = I\sigma_{\mathbf{e}}^2 (errors are independent)
   Var(a) = A\sigma_a^2 (var of a depends on relationship matrix A)
   Var(\mathbf{m}) = I \sigma_m^2 (maternal effects are independent)
   cov(a,m) and cov (e,m) are both 0 (a, m, e independent of each other)
   \sigma_e^2/\sigma_a^2 and \sigma_e^2/\sigma_m^2 are known (need starting points)
```

$$\begin{bmatrix} X'X & X'Z & X'W \\ Z'X & Z'Z + A^{-1}\alpha_a & Z'W \end{bmatrix} = \begin{bmatrix} \beta & X'y \\ a & Z'y \\ W'X & W'Z & W'W + I\alpha_m \end{bmatrix}$$

y = (nx1) vector of phenotypic measures = KNOWN

 β = (px1) vector of fixed effect regression coefficients (FIXED) = UNKNOWN

X = (nxp) design matrix relating y to β (FIXED) = KNOWN

a = (qx1) vector of additive effects (q = number of individuals in the pedigree)(RANDOM) = UNKNOWN

Z = (nxq) design matrix relating y to a (RANDOM) = KNOWN

A relationship matrix = KNOWN

m = (fx1) vector of maternal effects (f = number of dams in pedigree) (RANDOM)

W = (nxf) design matrix relating **y** to **m** (RANDOM)

I = identity matrix

$$\alpha_a = \sigma_e^2/\sigma_a^2 = \text{ESTIMATED}; \alpha_m = \sigma_e^2/\sigma_m^2 = \text{ESTIMATED}$$

Likelihood Approach

• Likelihood = $Pr(y|\mu, \sigma^2)$ = conditional probability of the data (y) given the parameters:

$$μ = Xβ$$

$$σ2 = Z(Aσa2)Z' + Iσe2$$
genetic variance + error variance

Iterations:

$$(\sigma_e^2/\sigma_a^2)_{sv} -> a_i -> (\sigma_e^2/\sigma_a^2)_i$$

 $(\sigma_e^2/\sigma_a^2)_i -> a_j -> (\sigma_e^2/\sigma_a^2)_j$
 $(\sigma_e^2/\sigma_a^2)_i -> a_k -> (\sigma_e^2/\sigma_a^2)_k$

Rinse & Repeat until parameters stabilize

Bayesian Approach

- $Pr(\mu, \sigma^2|y)$ = conditional probability of the parameters given the data
 - Yay! More intuitive than Likelihood
- Except that it is proportional to:

 $Pr(y|\mu, \sigma^2)Pr(\mu, \sigma^2)$

(Likelihood)(Prior belief in possible parameter values)

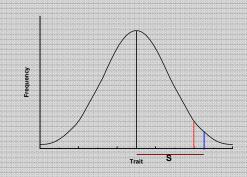
- Produces a posterior distribution =
 probabilistic distribution associating each
 value of a parameter to a probability
- Need iterative process to solve: MCMC

Markov Chain Monte Carlo

- Algorithm based on the proposal of a new value for a parameter, as a function of the value of the other parameters, at each iterative step.
- Saving the value of the parameter at each iteration, we ultimately get a series of values, which is the posterior distribution of interest, i.e., a posterior probability distribution for each parameter.

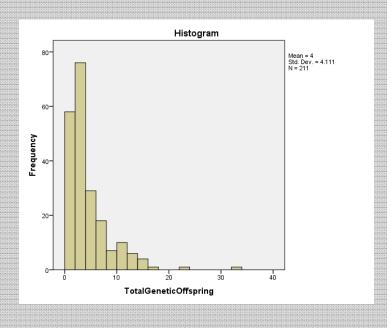
Non-Gaussian Traits

 For a continuous trait, if family relationships in the population are known, and assuming many loci of small effect, the phenotypic variance can be partitioned:



$$-V_P = V_G + V_E$$

 But what if the trait of interest is not continuous or is non-Gaussian? How can we estimate variance components?



Generalized Linear Mixed Model (GLMM)

- Combination of Generalized Linear Models and Linear Mixed Models
- Can handle non-Gaussian traits
 - Requires use of a link function (e.g., probability density function for binary outcomes) otherwise still...
- An "Animal Model"
 - y = Xβ + Za + e
- Requires Bayesian approaches

