

Chapter 23

Sire Model, Single Records

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A simple sire model is one in which sires, possibly related, are mated to a random sample of unrelated dams, no dam has more than one progeny with a record, and each progeny produces one record. A scalar model for this is

$$y_{ij} = \mathbf{x}'_{ij}\boldsymbol{\beta} + s_i + \mathbf{z}'_i\mathbf{u} + \mathbf{e}_{ij}. \quad (1)$$

$\boldsymbol{\beta}$ represents fixed effects with \mathbf{x}_{ij} relating the j^{th} progeny of the i^{th} sire to these effects.

s_i represents the sire effect on the progeny record.

\mathbf{u} represents other random factors with \mathbf{z}_{ij} relating these to the ij^{th} progeny record.

\mathbf{e}_{ij} is a random “error”.

The vector representation is

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}_s\mathbf{s} + \mathbf{Z}\mathbf{u} + \mathbf{e}. \quad (2)$$

$Var(\mathbf{s}) = \mathbf{A}\sigma_s^2$, where \mathbf{A} is the numerator relationship of the sires, and σ_s^2 is the sire variance in the “base” population. If the sires comprise a random sample from this population $\sigma_s^2 = \frac{1}{4}$ additive genetic variance. Some columns of \mathbf{Z}_s will be null if \mathbf{s} contains sires with no progeny, as will usually be the case if the simple method for computation of \mathbf{A}^{-1} requiring base population animals, is used.

$$\begin{aligned} Var(\mathbf{u}) &= \mathbf{G}, Cov(\mathbf{s}, \mathbf{u}') = \mathbf{0}. \\ Var(\mathbf{e}) &= \mathbf{R}, \text{ usually } = \mathbf{I}\sigma_e^2. \\ Cov(\mathbf{s}, \mathbf{e}') &= \mathbf{0}, Cov(\mathbf{u}, \mathbf{e}') = \mathbf{0}. \end{aligned}$$

If sires and dams are truly random,

$$\begin{aligned} \mathbf{I}\sigma_e^2 &= .75\mathbf{I} \text{ (additive genetic variance)} \\ &+ \mathbf{I} \text{ (environmental variance)}. \end{aligned}$$

With this model the mixed model equations are

$$\begin{pmatrix} \mathbf{X}'\mathbf{R}^{-1}\mathbf{X} & \mathbf{X}'\mathbf{R}^{-1}\mathbf{Z}_s & \mathbf{X}'\mathbf{R}^{-1}\mathbf{Z} \\ \mathbf{Z}'_s\mathbf{R}^{-1}\mathbf{X} & \mathbf{Z}'_s\mathbf{R}^{-1}\mathbf{Z}_s + \mathbf{A}^{-1}\sigma_s^{-2} & \mathbf{Z}'_s\mathbf{R}^{-1}\mathbf{Z} \\ \mathbf{Z}'\mathbf{R}^{-1}\mathbf{X} & \mathbf{Z}'\mathbf{R}^{-1}\mathbf{Z}_s & \mathbf{Z}'\mathbf{R}^{-1}\mathbf{Z} + \mathbf{G}^{-1} \end{pmatrix} \begin{pmatrix} \boldsymbol{\beta}^o \\ \hat{\mathbf{s}} \\ \hat{\mathbf{u}} \end{pmatrix} = \begin{pmatrix} \mathbf{X}'\mathbf{R}^{-1}\mathbf{y} \\ \mathbf{Z}'_s\mathbf{R}^{-1}\mathbf{y} \\ \mathbf{Z}'\mathbf{R}^{-1}\mathbf{y} \end{pmatrix}. \quad (3)$$

If $\mathbf{R} = \mathbf{I}\sigma_e^2$, (23.3) simplifies to (23.4)

$$\begin{pmatrix} \mathbf{X}'\mathbf{X} & \mathbf{X}'\mathbf{Z}_s & \mathbf{X}'\mathbf{Z} \\ \mathbf{Z}'_s\mathbf{X} & \mathbf{Z}'_s\mathbf{Z}_s + \mathbf{A}^{-1}\sigma_e^2/\sigma_s^2 & \mathbf{Z}'_s\mathbf{Z} \\ \mathbf{Z}'\mathbf{X} & \mathbf{Z}'\mathbf{Z}_s & \mathbf{Z}'\mathbf{Z} + \sigma_e^2\mathbf{G}^{-1} \end{pmatrix} \begin{pmatrix} \boldsymbol{\beta}^o \\ \hat{\mathbf{s}} \\ \hat{\mathbf{u}} \end{pmatrix} = \begin{pmatrix} \mathbf{X}'\mathbf{y} \\ \mathbf{Z}'_s\mathbf{y} \\ \mathbf{Z}'\mathbf{y} \end{pmatrix}. \quad (4)$$

We illustrate this model with the following data.

	n_{ij}				y_{ij}			
	Herds				Herds			
Sires	1	2	3	4	1	2	3	4
1	3	5	0	0	25	34	–	–
2	0	8	4	0	–	74	31	–
3	4	2	6	8	23	11	43	73

The model assumed is

$$\begin{aligned} y_{ijk} &= s_i + h_j + e_{ijk}. \\ \text{Var}(\mathbf{s}) &= \mathbf{A}\sigma_e^2/12, \\ \text{Var}(\mathbf{e}) &= \mathbf{I}\sigma_e^2. \end{aligned}$$

$$\mathbf{A} = \begin{pmatrix} 1.0 & .5 & .5 \\ & 1.0 & .25 \\ & & 1.0 \end{pmatrix}.$$

\mathbf{h} is fixed.

The ordinary LS equations are

$$\begin{pmatrix} 8 & 0 & 0 & 3 & 5 & 0 & 0 \\ & 12 & 0 & 0 & 8 & 4 & 0 \\ & & 20 & 4 & 2 & 6 & 8 \\ & & & 7 & 0 & 0 & 0 \\ & & & & 15 & 0 & 0 \\ & & & & & 10 & 0 \\ & & & & & & 8 \end{pmatrix} \begin{pmatrix} \hat{\mathbf{s}} \\ \hat{\mathbf{h}} \end{pmatrix} = \begin{pmatrix} 59 \\ 105 \\ 150 \\ 48 \\ 119 \\ 74 \\ 73 \end{pmatrix}. \quad (5)$$

The mixed model equations are

$$\begin{pmatrix} 28 & -8 & -8 & 3 & 5 & 0 & 0 \\ & 28 & 0 & 0 & 8 & 4 & 0 \\ & & 36 & 4 & 2 & 6 & 8 \\ & & & 7 & 0 & 0 & 0 \\ & & & & 15 & 0 & 0 \\ & & & & & 10 & 0 \\ & & & & & & 8 \end{pmatrix} \begin{pmatrix} \hat{s} \\ \hat{\mathbf{h}} \end{pmatrix} = \begin{pmatrix} 59 \\ 105 \\ 150 \\ 48 \\ 119 \\ 74 \\ 73 \end{pmatrix}. \quad (6)$$

The inverse of the matrix of (23.6) is

$$\begin{pmatrix} .0764 & .0436 & .0432 & -.0574 & -.0545 & -.0434 & -.0432 \\ .0436 & .0712 & .0320 & -.0370 & -.0568 & -.0477 & -.0320 \\ .0432 & .0320 & .0714 & -.0593 & -.0410 & -.0556 & -.0714 \\ -.0574 & -.0370 & -.0593 & .2014 & .0468 & .0504 & .0593 \\ -.0545 & -.0568 & -.0410 & .0468 & .1206 & .0473 & .0410 \\ -.0434 & -.0477 & -.0556 & .0504 & .0473 & .1524 & .0556 \\ -.0432 & -.0320 & -.0714 & .0593 & .0410 & .0556 & .1964 \end{pmatrix}. \quad (7)$$

The solution is

$$\begin{aligned} \hat{s}' &= (-.036661, .453353, -.435022), \\ \hat{\mathbf{h}}' &= (7.121439, 7.761769, 7.479672, 9.560022). \end{aligned}$$

Let us estimate σ_e^2 from the residual mean square using OLS reduction, and σ_e^2 by MIVQUE type computations. A solution to the OLS equations is

$$[10.14097, 11.51238, 9.12500, -2.70328, -2.80359, -2.67995, 0]$$

This gives a reduction in SS of 2514.166.

$$\mathbf{y}'\mathbf{y} = 2922.$$

Then $\hat{\sigma}_e^2 = (2922 - 2514.166)/(40-6) = 11.995$. MIVQUE requires computation of $\hat{s}'\mathbf{A}^{-1}\hat{s}$ and equating to its expectation.

$$\begin{aligned} \mathbf{A}^{-1} &= \frac{1}{3} \begin{pmatrix} 5 & -2 & -2 \\ -2 & 4 & 0 \\ -2 & 0 & 4 \end{pmatrix}. \\ \hat{s}'\mathbf{A}^{-1}\hat{s} &= .529500. \end{aligned}$$

Var (RHS of mixed model equations) = [Matrix (23.5)] σ_e^2 +

$$\begin{pmatrix} 8 & 0 & 0 \\ 0 & 12 & 0 \\ 0 & 0 & 20 \\ 3 & 0 & 4 \\ 5 & 8 & 2 \\ 0 & 4 & 6 \\ 0 & 0 & 8 \end{pmatrix} \mathbf{A} \begin{pmatrix} 8 & 0 & 0 & 3 & 5 & 0 & 0 \\ 0 & 12 & 0 & 0 & 8 & 4 & 0 \\ 0 & 0 & 20 & 4 & 2 & 6 & 8 \end{pmatrix} \sigma_s^2.$$

The second term of this is

$$\begin{pmatrix} 64 & 48 & 80 & 40 & 80 & 40 & 32 \\ & 144 & 60 & 30 & 132 & 66 & 24 \\ & & 400 & 110 & 130 & 140 & 160 \\ & & & 37 & 56 & 43 & 44 \\ & & & & 151 & 83 & 5 \\ & & & & & 64 & 56 \\ & & & & & & 64 \end{pmatrix} \sigma_s^2. \quad (8)$$

$$\text{Var}(\hat{\mathbf{s}}) = \mathbf{C}_s [\text{matrix (23.8)}] \mathbf{C}'_s \sigma_s^2 + \mathbf{C}_s [\text{matrix (23.5)}] \mathbf{C}'_s \sigma_e^2,$$

where $\mathbf{C}_s =$ first 3 rows of (23.7).

$$\begin{aligned} \text{Var}(\hat{\mathbf{s}}) = & \begin{pmatrix} .005492 & -.001451 & -.001295 \\ & .007677 & -.006952 \\ & & .007599 \end{pmatrix} \sigma_e^2 \\ & + \begin{pmatrix} .017338 & -.005622 & -.003047 \\ & .053481 & -.050670 \\ & & .052193 \end{pmatrix} \sigma_s^2. \end{aligned} \quad (9)$$

Then $E(\hat{\mathbf{s}}' \mathbf{A}^{-1} \hat{\mathbf{s}}) = \text{tr}(\mathbf{A}^{-1} [\text{matrix (23.9)}]) = .033184 \sigma_e^2 + .181355 \sigma_s^2$. With these results we solve for $\hat{\sigma}_s^2$ and this is .7249 using estimated $\hat{\sigma}_e^2$ as 11.995. This is an approximate MIVQUE solution because $\hat{\sigma}_e^2$ was computed from the residual of ordinary least squares reduction rather than by MIVQUE.