

Best Linear Unbiased Prediction and Related Inference in the Mixed Model

In the usual mixed model

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\mathbf{u} + \boldsymbol{\epsilon}$$

with

$$\mathbb{E} \begin{pmatrix} \mathbf{u} \\ \boldsymbol{\epsilon} \end{pmatrix} = \mathbf{0} \text{ and } \text{Var} \begin{pmatrix} \mathbf{u} \\ \boldsymbol{\epsilon} \end{pmatrix} = \begin{pmatrix} \mathbf{G} & \mathbf{0} \\ \mathbf{0} & \mathbf{R} \end{pmatrix}$$

and using the notation

$$\mathbf{V} = \mathbf{Z}\mathbf{G}\mathbf{Z}' + \mathbf{R}$$

we consider problems of prediction related to the random effects contained in \mathbf{u} . Under the MVN assumption

$$\mathbb{E}[\mathbf{u}|\mathbf{Y}] = \mathbf{G}\mathbf{Z}'\mathbf{V}^{-1}(\mathbf{Y} - \mathbf{X}\boldsymbol{\beta}) \quad (1)$$

which, obviously, depends on the fixed effect vector $\boldsymbol{\beta}$. (For what it is worth,

$$\text{Var} \begin{pmatrix} \mathbf{u} \\ \mathbf{Y} \end{pmatrix} = \begin{pmatrix} \mathbf{G} & \mathbf{G}\mathbf{Z}' \\ \mathbf{Z}\mathbf{G} & \mathbf{Z}\mathbf{G}\mathbf{Z}' + \mathbf{R} \end{pmatrix}$$

and the $\mathbf{G}\mathbf{Z}'$ appearing in (1) is the covariance between \mathbf{u} and \mathbf{Y} .) Something that is close to the conditional mean (1), but that does not depend on fixed effects is

$$\hat{\mathbf{u}} = \mathbf{G}\mathbf{Z}'\mathbf{V}^{-1}(\mathbf{Y} - \hat{\mathbf{Y}}^*) \quad (2)$$

where $\hat{\mathbf{Y}}^*$ is the generalized least squares (best linear unbiased) estimate of the mean of \mathbf{Y} ,

$$\hat{\mathbf{Y}}^* = \mathbf{X}(\mathbf{X}'\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}'\mathbf{V}^{-1}\mathbf{Y}$$

The predictor (2) turns out to be the Best Linear Unbiased Predictor of \mathbf{u} , and if we temporarily abbreviate

$$\mathbf{B} = \mathbf{X}(\mathbf{X}'\mathbf{V}^{-1}\mathbf{X})^{-1}\mathbf{X}'\mathbf{V}^{-1} \text{ and } \mathbf{P} = \mathbf{V}^{-1}(\mathbf{I} - \mathbf{B}) \quad (3)$$

this can be written as

$$\hat{\mathbf{u}} = \mathbf{G}\mathbf{Z}'\mathbf{V}^{-1}(\mathbf{Y} - \mathbf{B}\mathbf{Y}) = \mathbf{G}\mathbf{Z}'\mathbf{V}^{-1}(\mathbf{I} - \mathbf{B})\mathbf{Y} = \mathbf{G}\mathbf{Z}'\mathbf{P}\mathbf{Y} \quad (4)$$

We consider here predictions based on $\hat{\mathbf{u}}$ and the problems of quoting appropriate “precision” measures for them.

To begin with the \mathbf{u} vector itself, $\hat{\mathbf{u}}$ is an obvious approximation and a precision of prediction should be related to the variability in the difference

$$\mathbf{u} - \hat{\mathbf{u}} = \mathbf{u} - \mathbf{B}\mathbf{Y} = \mathbf{u} - \mathbf{B}(\mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\mathbf{u} + \boldsymbol{\epsilon}) = \mathbf{u} - \mathbf{B}\mathbf{X}\boldsymbol{\beta} - \mathbf{B}\mathbf{Z}\mathbf{u} - \mathbf{B}\boldsymbol{\epsilon}$$

This random vector has mean $\mathbf{0}$ and covariance matrix

$$\text{Var}(\mathbf{u} - \hat{\mathbf{u}}) = (\mathbf{I} - \mathbf{B}\mathbf{Z})\mathbf{G}(\mathbf{I} - \mathbf{B}\mathbf{Z})' + \mathbf{B}\mathbf{R}\mathbf{B}' = \mathbf{G} - \mathbf{G}\mathbf{Z}'\mathbf{P}\mathbf{Z}\mathbf{G} \quad (5)$$

(This last inequality is not obvious to me, but is what McCulloch and Searle promise on page 170 of their book.)

Now $\hat{\mathbf{u}}$ in (4) is not available unless one knows the covariance matrices \mathbf{G} and \mathbf{V} . If one has estimated variance components and hence has estimates of \mathbf{G} and \mathbf{V} (and for that matter, \mathbf{R} , \mathbf{B} , and \mathbf{P}) the approximate BLUP

$$\hat{\mathbf{u}} = \hat{\mathbf{G}}\mathbf{Z}'\hat{\mathbf{P}}\mathbf{Y}$$

may be used. A way of making a crude approximation to a measure of precision of the approximate BLUP (as a predictor \mathbf{u}) is to plug estimates into the relationship (5) to produce

$$\text{Var}(\widehat{\mathbf{u}} - \hat{\mathbf{u}}) = \hat{\mathbf{G}} - \hat{\mathbf{G}}\mathbf{Z}'\hat{\mathbf{P}}\mathbf{Z}\hat{\mathbf{G}}$$

Consider now the prediction of a quantity

$$l = \mathbf{c}'\boldsymbol{\beta} + \mathbf{s}'\mathbf{u}$$

for an estimable $\mathbf{c}'\boldsymbol{\beta}$ (estimability has nothing to do with the covariance structure of \mathbf{Y} and so “estimability” means here what it always does). As it turns out, if $\mathbf{c}' = \mathbf{a}'\mathbf{X}$, the BLUP of l is

$$\hat{l} = \mathbf{a}'\hat{\mathbf{Y}}^* + \mathbf{s}'\hat{\mathbf{u}} = \mathbf{a}'\mathbf{B}\mathbf{Y} + \mathbf{s}'\hat{\mathbf{G}}\mathbf{Z}'\hat{\mathbf{P}}\mathbf{Y} = (\mathbf{a}'\mathbf{B} + \mathbf{s}'\hat{\mathbf{G}}\mathbf{Z}'\hat{\mathbf{P}})\mathbf{Y} \quad (6)$$

To quantify the precision of this as a predictor of l we must consider the random variable

$$\hat{l} - l$$

The variance of this is the unpleasant (but not impossible) quantity

$$\text{Var}(\hat{l} - l) = \mathbf{a}'\mathbf{X}(\mathbf{X}'\mathbf{V}^{-1}\mathbf{X})^{-}\mathbf{X}'\mathbf{a} + \mathbf{s}'\hat{\mathbf{G}}\mathbf{Z}'\hat{\mathbf{P}}\mathbf{Z}\hat{\mathbf{G}}\mathbf{s} - 2\mathbf{a}'\mathbf{B}\mathbf{Z}\hat{\mathbf{G}}\mathbf{s} \quad (7)$$

(This variance is from page 256 of McCulloch and Searle.)

Now \hat{l} of (6) is not available unless one knows covariance matrices. But with estimates of variance components and corresponding matrices, what is available as an approximation to \hat{l} is

$$\widehat{\hat{l}} = (\mathbf{a}'\hat{\mathbf{B}} + \mathbf{s}'\hat{\mathbf{G}}\mathbf{Z}'\hat{\mathbf{P}})\mathbf{Y}$$

A way of making a crude approximation to a measure of precision of the approximate BLUP (as a predictor of l) is to plug estimates into the relationship (7) to produce

$$\text{Var}(\widehat{\hat{l}} - l) = \mathbf{a}'\mathbf{X}(\mathbf{X}'\widehat{\mathbf{V}}^{-1}\mathbf{X})^{-}\mathbf{X}'\mathbf{a} + \mathbf{s}'\hat{\mathbf{G}}\mathbf{Z}'\hat{\mathbf{P}}\mathbf{Z}\hat{\mathbf{G}}\mathbf{s} - 2\mathbf{a}'\hat{\mathbf{B}}\mathbf{Z}\hat{\mathbf{G}}\mathbf{s}$$