

Kaizô I. Beltrão and Djalma G.C. Pessoa, Instituto de Matemática Pura e Aplicada

1. Introduction

In this paper some estimators of treatment effects and of strata variances are analyzed, under the framework of General Balance (G.B.) introduced by Nelder (1965 a,b). We deal with the case where  $T$ , the treatment space, is balanced with respect to all strata in the block structure.

Under (G.B.) the data covariance matrix is determined by the block structure and the strata variances  $\{\xi_\alpha\}$ . Assuming  $\{\xi_\alpha\}$  known, the overall BLUE of the treatment effects (or contrasts of it) uses information from all effective strata. It is computed by combining the BLUE in each stratum, the latter not depending on  $\{\xi_\alpha\}$ , with weights proportional to the inverse of the  $\{\xi_\alpha\}$ . Alternative estimators of treatment effects can be obtained by plugging in the expression of the overall BLUE different estimators of  $\{\xi_\alpha\}$ .

In Section 2 we present the needed notation and in Section 3 we describe several estimators of  $\{\xi_\alpha\}$ , the strata variances. The following estimators are considered: the straightforward one using only the stratum residuals; Yates estimator; Nelder's estimator; and a "leave-one-stratum-out" estimator. In Section 4 we derive the distribution of some of those estimators, in the case of two effective strata (e.g., BIB, Youden Squares) and under normality assumptions for the data. In Section 5 we report the results of a Monte-Carlo simulation comparing the estimators in a BIB design.

2. Notations and Basic Notions

Assume we have a random vector of observations  $y = (y_i)_{i \in I}$ , taking values in a vector space  $D = R^1$  and indexed by a set  $I$  with cardinality  $|I| = n$ . Consider in  $D$  the usual Euclidean norm.

The models to be considered are linear,  $\tau = EY \varepsilon T$ , where  $T \subseteq D$  is a linear subspace of  $D$ . Following Nelder (1965) we consider an orthogonal block structure given by a partition  $D = \bigoplus S_\alpha$ , or equivalently by the decomposition  $I = \bigcup S_\alpha$ , where  $S_\alpha$  is, for each  $\alpha$ , the orthogonal projection on  $S_\alpha$  and  $\{S_\alpha\}$  satisfy  $S_\alpha = S_\alpha^2$ ,  $\Psi_\alpha$  and  $S_\alpha S_\beta = S_\beta S_\alpha = 0$  if  $\alpha \neq \beta$ .

The dispersion matrix of  $Y$  will be assumed to have the form  $DY = V = \sum \xi_\alpha S_\alpha$ , where  $\xi_\alpha \geq 0$  for all  $\alpha$ . Situations where the above model arises are described in Houtman and Speed (1983), from whom we borrow the notation and terminology used here. Moreover we call strata the subspaces  $\{S_\alpha\}$  and, since  $DS_\alpha y = \xi_\alpha S_\alpha y$ , we call  $\{\xi_\alpha\}$  strata variances. In order to relate  $T$  and  $\{\xi_\alpha\}$  we consider the property of General Balance (G.B.).

Definition. A design with block structure  $\{S_\alpha\}$  is generally balanced (G.B.) with respect to the partition  $T = \bigoplus T_\beta$  if there exists  $\{\lambda_{\alpha\beta}\}$  such that for all  $\alpha$   $TS_\alpha T = \sum \lambda_{\alpha\beta} T_\beta$ , where  $T$  is the projection on to  $T$  and for each  $\beta$ ,  $T_\beta$  is the orthogonal projection on  $T_\beta$ . In particular in

this paper, we deal with the case where the whole space  $T$  is a eigenspace of  $TS_\alpha T$ , i.e.,  $TS_\alpha T = \lambda_\alpha T$ ,  $\forall \alpha$ .

If a design satisfies the G. B. property and the  $\{\xi_\alpha\}$  are known (up to a constant) it is very simple to get the BLUE of  $\tau$  and of contrasts  $\langle t, \tau \rangle$ ,  $\langle t, l \rangle = 0$ ,  $t \in T$ , by simply combining their BLUEs in different strata. The reduced data  $S_\alpha y$  to the stratum  $S_\alpha$  satisfies

$$ES_\alpha Y = S_\alpha \tau \varepsilon S_\alpha T \text{ and } DS_\alpha Y = \xi_\alpha S_\alpha,$$

and the usual least-squares analysis can be used ( $S_\alpha$  is the identity in  $S_\alpha$ ). The least-squares estimator  $\hat{\tau}_\alpha$  of  $\tau$  within the stratum  $S_\alpha$  satisfies the normal equation

$$TS_\alpha T \hat{\tau} = TS_\alpha y$$

and is given by  $\hat{\tau}_\alpha = \lambda_\alpha^{-1} TS_\alpha y$ .

Under (G.B.) the overall BLUE of  $\tau$  is as follows

$$\hat{\tau} = Uy = \sum \omega_\alpha \hat{\tau}_\alpha$$

where  $\omega_\alpha = \xi_\alpha^{-1} \lambda_\alpha / \sum (\xi_\alpha^{-1} \lambda_\alpha)$  is the weight for the  $\alpha$  stratum. The BLUE of a contrast  $\langle t, \tau \rangle$ ,  $t \in T$  and  $\langle t, l \rangle = 0$ , is then

$$\begin{aligned} \langle t, \hat{\tau} \rangle &= \sum \omega_\alpha \lambda_\alpha^{-1} \langle t, TS_\alpha Y \rangle \\ &= \sum \omega_\alpha \langle t, \hat{\tau}_\alpha \rangle. \end{aligned}$$

Now, observe that  $\text{cov}(\langle t, TS_\alpha Y \rangle, \langle t, TS_{\alpha'} Y \rangle) = 0$  if  $\alpha \neq \alpha'$  and  $\text{var}(\langle t, \tau_\alpha \rangle) = \lambda_\alpha^{-1} \xi_\alpha \|t\|^2$ , therefore the overall BLUE of  $\langle t, \tau \rangle$ , in the G.B. case, is a combination of the BLUEs of  $\langle t, \tau \rangle$  in each stratum, with weight proportional to the inverse of its variance.

In order to compute the appropriate weights we need to estimate the  $\{\xi_\alpha\}$ . The ANOVA table within the stratum  $\alpha$  allows, in some cases, an easy way of estimating  $\xi_\alpha$  (see Table I).

3. Estimators of Strata Variances

In this section we present different estimators of  $\{\xi_\alpha\}$ . They are all obtained by equating the expected value of a residual squared norm to its observed value. Consider first the simplest estimator, using the residual sum of squares within each stratum, when  $d_\alpha = \dim S_\alpha - \dim T \neq 0$ . This estimate is defined as

$$\hat{\xi}_{\alpha, S} = \frac{\|S_\alpha Y\|^2 - \frac{1}{\lambda_\alpha} \|TS_\alpha Y\|^2}{\dim S_\alpha - \dim T}$$

and is not feasible for several commonly used designs such as the symmetric BIBD and some types of lattices where  $d_\alpha = 0$ . Yates (1939) proposed for the BIBD design an estimator for the interblock variance based upon the interblock sum of squares eliminating the treatment. This estimator can be extended to

the multistrata case considering the sum of squares for a given stratum  $S = S_\gamma$  eliminating  $T$ , denoted by  $SS_{S/T}$  and given by

$$SS_{S/T} = SS_{T/S} + SS_S - SS_T \quad (1)$$

$$= || \sum_{\alpha \neq \gamma} \frac{1}{\lambda_\alpha} S_\alpha TS_\alpha y ||^2 + || S_\gamma y ||^2 - || Ty ||^2$$

with expectation

$$E(SS_{S/T}) = \xi_\gamma (\dim S_\gamma - \lambda_\gamma \dim T) + \sum_{\alpha \neq \gamma} \xi_\alpha (1 - \lambda_\alpha) \dim T. \quad (2)$$

If we have unbiased estimators for all the  $\{\xi_\alpha\}$  but one, say  $\xi_\gamma$ , with  $d_\gamma = 0$ , we can define from (2) an unbiased estimator of  $\xi_\gamma$

$$\hat{\xi}_{\gamma, Y} = \frac{SS_{S/T} - [\sum_{\alpha \neq \gamma} \hat{\xi}_\alpha (1 - \lambda_\alpha)] \dim T}{\dim S_\gamma - \lambda_\gamma \dim T} \quad (3)$$

where  $\hat{\xi}_\alpha$  is an unbiased estimator of  $\xi_\alpha$ . If  $d_\alpha = 0$  in more than one stratum, we can write a linear system of equations similar to (3) and get explicit estimators for all the  $\hat{\xi}_\alpha$ 's with  $d_\alpha = 0$ .

In the first estimator described, the number of degrees of freedom (d.f.) left to estimate  $\xi_\alpha$  within  $S_\alpha$  is  $d_\alpha = \dim S_\alpha - \dim T$ . In Yates' estimator we use  $\dim S - \lambda_\gamma \dim T$  d.f. by subtracting only a fraction of the d.f. of the sum of squares due to treatments. Nelder's approach (1968) instead subtracts from  $\dim S_\gamma$  the fraction  $\omega_\alpha \dim T$  of the d.f. due to  $T$ , corresponding to the amount of information on  $T$  in  $S_\alpha$ . For this, he uses the "actual" residual in  $S_\alpha$  which is  $S_\alpha(I-U)y$ .

The residual norm squared considered is then  $|| S_\alpha(I-U)y ||^2$ , with expectation

$$E || S_\alpha(I-U)y ||^2 = d'_\alpha \xi_\alpha \quad (4)$$

where

$$d'_\alpha = d_\alpha + (1 - \omega_\alpha) \dim T$$

$$= \dim S_\alpha - \omega_\alpha \dim T$$

since  $\omega_\alpha$  depends on  $\xi_\alpha$ , the equation

$$|| S_\alpha(I-U)y ||^2 = d'_\alpha \xi_\alpha \quad (5)$$

can be solved only iteratively. It is worth noticing that equation (5) defines the likelihood equation for  $\xi_\alpha$  based upon  $|| (I-T)y ||^2$  under the assumption that  $Y$  has a multivariate normal distribution (for details see Patterson and Thompson (1971)).

Another iterative estimator for the variance of the  $\gamma$  stratum can be obtained using the information on  $\tau$  from all but the  $\gamma$  stratum, and which we call the leave-one-out stratum estimator. The BLUE of  $\tau$  based upon  $(I-S_\gamma)y$ , with known  $\{\xi_\alpha\}$ ,  $\alpha \neq \gamma$ , is

$$\hat{\tau}_\gamma = Q_\gamma y = \Sigma \omega'_\alpha (1/\lambda_\alpha) TS_\alpha y$$

where  $\omega'_\alpha = (\lambda_\alpha/\xi_\alpha)/\Sigma(\lambda_\alpha/\xi_\alpha) \forall \alpha$  with all the summations defined for  $\alpha \neq \gamma$ .

In this case, the residual under consideration is  $S_\gamma(I-Q_\gamma)y$ , with the expected squared norm

$$E || S_\gamma(I-Q_\gamma)y ||^2 = \xi_\gamma [\dim S_\gamma + \omega'_\gamma \dim T].$$

The estimator can be computed by iteratively solving

$$|| S_\gamma(I-Q_\gamma)y ||^2 = \xi_\gamma (\dim S_\gamma + \omega'_\gamma \dim T). \quad (6)$$

Since to estimate  $\xi_\gamma$  we use the BLUE of  $\tau$ , computed by excluding the information in  $S_\gamma$ , the "leave-one-out stratum estimator" will work better when estimating the  $\xi_\gamma$  with greater value.

#### 4. Variances of Estimators of $\xi_\alpha$ Two Strata Case.

In this section we assume that  $Y$  has a multivariate normal distribution with mean vector  $\tau = 0$  and dispersion matrix  $V = \Sigma \xi_\alpha S_\alpha$ .

To get the distribution of the variance strata estimators we apply the following theorem (see Box (1954)).

**Theorem.** If  $Y$  has multivariate normal distribution with mean vector  $\tau = 0$  and dispersion matrix  $V$ , the real quadratic form  $Q = YMY$  is distributed as a linear combination of independent Chi-squares with one d.f.  $(\chi(1)^2)$  and weights given by the eigenvalues of  $VM$ .

Using the above theorem it is immediate to show that  $\xi_{\alpha, S}$  as defined by equation (1) is distributed as a  $\xi_\alpha/d\chi(d)^2$ , which has expectation  $\xi_\alpha$  and variance  $2\xi_\alpha^2/d$ , (with  $d = d_\alpha$ ). Using the regular within stratum estimator for  $\xi_2$ , Yates interblock variance estimator is

$$\hat{\xi}_{1, Y} = \frac{SS_{S/T} - (1 - \lambda_2) \dim T \hat{\xi}_{2, Y}}{\dim S_1 - \lambda_1 \dim T}$$

It is easy to check that  $SS_{S/T}$  and  $\hat{\xi}_{2, S}$  are independent and  $SS_{S/T}$  is distributed as

$$\frac{(\xi_1 \lambda_2 + \xi_2 \lambda_1)}{\dim S_1 - \lambda_1 \dim T} \chi^2(\dim T)$$

$$+ \frac{\xi_1}{\dim S_1 - \lambda_1 \dim T} \chi^2(d_1),$$

and from this we can compute the variance of  $\hat{\xi}_{1, Y}$ .

Considering that Nelder's estimator is defined as a solution of (5), which can only be solved iteratively, its variance would be hard to compute. It is possible however to get the distribution of the actual residual  $|| S_\alpha(I-U)y ||^2$  and this is

$$\xi_\alpha [\chi^2(d_\alpha) + (1 - \omega_\alpha) \chi^2(\dim T)], \quad (7)$$

which could be used to approximate the distribution of  $\xi_{\alpha, N}$ . Nelder (1968) checked empirically, through a Monte-Carlo study the approximation of this distribution by  $\xi_{\alpha} \chi_{d'}^2/d'$  which is actually a first moment approximation to (7) (where  $d' = d_{\alpha}$ ).

The leave-one-stratum-out estimators when only two effective strata exist have closed forms

$$\hat{\xi}_{1, L} = \frac{\|S_1(y - \hat{\tau}_1)\|^2 \dim S_2 - \|S_2(y - \hat{\tau}_2)\|^2 \frac{\lambda_1}{\lambda_2} \dim T}{\dim S_1 \dim S_1 - \dim^2 T}$$

and

$$\hat{\xi}_{2, L} = \frac{\|S_2(y - \hat{\tau}_2)\|^2 \dim S_1 - \|S_1(y - \hat{\tau}_1)\|^2 \frac{\lambda_2}{\lambda_1} \dim T}{\dim S_1 \dim S_2 - \dim T}$$

It is straightforward to check that  $((\xi_1/\lambda_1)S_1 - (\xi_2/\lambda_2)S_2)T$ ,  $T$ ,  $(S_1 - (1/\lambda_1)S_1T)D$  are the common eigenspaces (with eigenvalue 0 for  $T$ ) and that the numerators are distributed, respectively, as:

$$\begin{aligned} & (\xi_1 + \frac{\lambda_1}{\lambda_2} \xi_2) d_2 \chi^2(\dim T) \\ & + \xi_1 \dim S_2 \chi^2(d_1) - t \frac{\lambda_1}{\lambda_2} \xi_2 \chi^2(d_2) \end{aligned}$$

and

$$\begin{aligned} & (\xi_2 + \frac{\lambda_2}{\lambda_1} \xi_1) d_1 \chi^2(\dim T) \\ & + \xi_2 \dim S_1 \chi^2(d_2) - t \frac{\lambda_2}{\lambda_1} \xi_1 \chi^2(d_1) \end{aligned}$$

## 5. Empirical Study of Estimators of $\xi_1$ and $\xi_2$

The performance of the estimators discussed above was assessed by a Monte-Carlo study. The BIBD exemplified by Cochran and Cox (1957) and used by Nelder (1968) was the design chosen for the simulation. It is a BIBD with 15 blocks of two plots each, 6 treatments with 5 replications and efficiency factor  $\lambda = 3/5$ . One thousand pseudomultinormal vectors of dimension 30 were generated by using IMSL subroutine GGNSM for three different  $\xi_2/\xi_1$  ratios. For each one of these 1000 vectors all the competing estimators were computed. For Nelder's iterative estimator, a 50 iterations limit and a tolerance of  $10^{-4}$  were adopted as the stopping rule. Typical numbers of iterations until convergence were around 3 to 5, few of them being over 10 (less than 5%). Table II displays a summary of the results obtained. The values (1,1), (3,1) and (5,1) were used for the pair  $(\xi_1, \xi_2)$ , where  $\xi_1$  is the inter-block and  $\xi_2$  the intra-block variance. In this table, the first value in each cell is the average of the respective estimator in all runs followed by its variance. The value in parenthesis is the computed theoretical variance of the estimator, whenever it had a closed form. For Nelder's estimator the corresponding figures are what the authors believe to be a lower bound for

the variances. The estimators empirical averages were, as expected, always close to its true value. The empirical median bias was 1% and in 20 out of 24 cases had absolute value less than 2%. In most cells the differences between theoretical and empirical variance is of the order of two decimals points. The within stratum estimator of  $\xi_2$  seems to do not worse than any other and is easy to compute. The leave-one-out, as expected, does the worse for the  $\xi_1/\xi_2$  ratios considered. The within stratum estimator of  $\xi_1$  did not perform well as indicated both by theoretical and empirical variances and the others presented similar performances. From the theoretical variances computed, the leave-one-out does slight better than Yates' for estimating  $\xi_1$ . These considerations suggest, for the design studied, that one should use either Yates estimator or a combination of within stratum to estimate  $\xi_2$  and leave-one-out to estimate  $\xi_1$ . If we rearrange the same five replications of six treatments in a 6/5 block structure (instead of the 15/2), we will get a symmetric BIB. In this case (symmetric BIB) the within stratum estimator for  $\xi_1$  is not defined ( $\dim S_1 = \dim T$ ) and it is easy to see that all the other estimators considered are exactly the same.

The exact variance of  $\hat{\xi}_2$  in the symmetric BIB is

$$\frac{2\xi_1^2}{\dim T} + 2\left[\left(\frac{\lambda_1 \xi_2}{\lambda_2}\right)^2 \left(\frac{1}{d_2} + \frac{1}{\dim T}\right) + \frac{2\xi_1 \xi_2 \lambda_1}{\lambda_2 \dim T}\right]$$

The "lower bound" suggested for the variance of Nelder's estimator is the leading term of this expression. For the 6/5 block structure considered and for  $\xi_1 = 1$ , the remaining terms amount to only  $.0009 \xi_2^2 + .0333 \xi_2$ .

## 6. References

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Table I. ANOVA table within stratum  $\alpha$

Source	d.f.	SS	E(MS)
Treatment	$\dim T$	$\lambda_\alpha^{-1}   TS_\alpha y  ^2$	$\xi_\alpha + \frac{\lambda_\alpha}{\dim T}   \tau  ^2$
Residual	$d_\alpha - \dim S_\alpha - \dim T$	$  S_\alpha y  ^2 - \lambda_\alpha^{-1}   TS_\alpha y  ^2$	$\xi_\alpha$ (if $d_\alpha > 0$ )
Total	$\dim S_\alpha$	$  S_\alpha y  ^2$	

Table II

		Within Stratum		Yates		Nelder		Leave-One-Out	
		$\xi_1$	$\xi_2$	$\xi_1$	$\xi_2$	$\xi_1$	$\xi_2$	$\xi_1$	$\xi_2$
$\xi_1 = 1$	$\hat{\mu}$	.998	1.023	1.019	1.026	1.015	1.036	1.021	1.057
	$\hat{\sigma}^2$	.227	.204	.250	.204	.231	.201	.261	.327
	$\hat{\sigma}^2$	(.222)	(.200)	(.206)	(.200)	(.150)	(.150)	(.206)	(.295)
$\xi_1 = 2$	$\hat{\mu}$	3.008	.977	3.036	.977	3.038	.983	3.038	1.018
	$\hat{\sigma}^2$	1.934	.183	1.405	.183	1.420	.195	1.404	1.099
	$\hat{\sigma}^2$	(2.000)	(.200)	(1.472)	(.200)	(1.297)	(.171)	(1.464)	(1.097)
$\xi_1 = 5$	$\hat{\mu}$	5.015	.977	5.052	.977	5.060	.982	5.055	1.031
	$\hat{\sigma}^2$	5.342	.184	3.719	.184	3.701	.199	3.691	2.569
	$\hat{\sigma}^2$	(5.555)	(.200)	(3.939)	(.200)	(3.584)	(.180)	(3.903)	(2.497)