

A MULTIVARIATE EXTENSION OF THE GAUSS-MARKOV THEOREM¹⁾

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1. Summary

In this note we present the best linear unbiased estimates for multivariate populations, which may not necessarily be normal.

2. The multivariate extension

Consider the usual multivariate linear model

$$(1) \quad \text{Exp}(Y) = \underset{n \times p}{A} \underset{n \times m}{\xi} \underset{m \times p}{\xi},$$

where $n \geq m$ and where

$$(2) \quad Y = (\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_p) = \begin{bmatrix} y_{11}, y_{12}, \dots, y_{1p} \\ \vdots \\ y_{n1}, y_{n2}, \dots, y_{np} \end{bmatrix} \\ = \begin{bmatrix} \mathbf{y}^{(1)} \\ \vdots \\ \mathbf{y}^{(n)} \end{bmatrix}, \text{ say}$$

is a matrix of np observations; A is a known matrix and

$$(3) \quad \xi = \begin{bmatrix} \xi_{11} & \xi_{12} & \dots & \xi_{1p} \\ \vdots & \vdots & \dots & \vdots \\ \xi_{m1} & \xi_{m2} & \dots & \xi_{mp} \end{bmatrix} = (\xi_1, \xi_2, \dots, \xi_p), \text{ say}$$

is a matrix of unknown parameters. We further assume that the vectors $\mathbf{y}_{(r)}$ ($r=1, 2, \dots, n$) are all uncorrelated and that for $r=1, 2, \dots, n$

$$(4) \quad \text{Var}(\mathbf{y}_{(r)}) = \Sigma = (\sigma_{jj'}), \text{ say},$$

where the dispersion matrix Σ is also unknown. The model (1) for the

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j th variable reduces to

$$(5) \quad \begin{aligned} \text{Exp}(\mathbf{y}_j) &= A\boldsymbol{\xi}_j \\ \text{Var}(\mathbf{y}_{jr}) &= \sigma_{jj}, \quad j=1, 2, \dots, p, \quad r=1, 2, \dots, n. \end{aligned}$$

If we consider just the j th variable and ignore the rest, we can obtain from (5), the best linear unbiased estimate $\mathbf{c}'_j \hat{\boldsymbol{\xi}}_j$ of $\mathbf{c}'_j \boldsymbol{\xi}_j$, where \mathbf{c}_j is any $m \times 1$ vector such that $\mathbf{c}'_j \boldsymbol{\xi}_j$ is estimable. Let

$$(6) \quad \theta = \sum_{j=1}^p \mathbf{c}'_j \boldsymbol{\xi}_j$$

be a linear function of all the mp unknown parameters, such that for each j , $\mathbf{c}'_j \boldsymbol{\xi}_j$ is estimable. Let

$$(7) \quad u = \sum_{j=1}^p \mathbf{c}'_j \hat{\boldsymbol{\xi}}_j.$$

Then we show that u is the best linear unbiased estimate of θ .

THEOREM. *Let*

$$z = \mathbf{b}'_1 \mathbf{y}_1 + \dots + \mathbf{b}'_p \mathbf{y}_p$$

be any other linear unbiased estimate of θ . Then, provided that the space of the $mp \times 1$ vector

$$(\xi_{11}, \xi_{12}, \dots, \xi_{1p}, \xi_{21}, \dots, \xi_{mp})$$

contains at least mp linearly independent points, we must have

$$\text{Var}(z) > \text{Var}(u),$$

whatever the population dispersion matrix Σ may be. (Notice that no assumption of normality is involved.)

PROOF. Suppose

$$(8) \quad u = \mathbf{d}'_1 \mathbf{y}_1 + \dots + \mathbf{d}'_p \mathbf{y}_p.$$

Since

$$\text{Exp}(z) = \text{Exp}(u) = \theta,$$

we have

$$\text{Exp}(z - u) = 0,$$

or

$$(\mathbf{b}'_1 - \mathbf{d}'_1)A\boldsymbol{\xi}_1 + \dots + (\mathbf{b}'_p - \mathbf{d}'_p)A\boldsymbol{\xi}_p = 0,$$

for all $\xi_1, \xi_2, \dots, \xi_p$. This however implies

$$(9) \quad (\mathbf{b}'_j - \mathbf{d}'_j)A = \mathbf{0}_{1m}, \quad j=1, 2, \dots, p,$$

where $\mathbf{0}_{1m}$ is a $1 \times m$ matrix. Also since \mathbf{b}_j and \mathbf{d}_j are free of the observations Y , we have

$$(10) \quad \begin{aligned} \text{Var}(u) &= \text{Var}(\mathbf{d}'_1 \mathbf{y}_1 + \dots + \mathbf{d}'_p \mathbf{y}_p) \\ &= n \sum_{j=1}^p (\mathbf{d}'_j \mathbf{d}_j) \sigma_{jj} + n \sum_{j \neq j'}^p (\mathbf{d}'_j \mathbf{d}_{j'}) \sigma_{jj'}, \end{aligned}$$

and similarly

$$\text{Var}(z) = n \sum_{j=1}^p (\mathbf{b}'_j \mathbf{b}_j) \sigma_{jj} + n \sum_{j \neq j'}^p (\mathbf{b}'_j \mathbf{b}_{j'}) \sigma_{jj'}.$$

Let A be of rank r and let \bar{W} be the vector space of rank $n-r$, which is orthogonal to the columns of A . Let $\theta_1, \theta_2, \dots, \theta_{n-r}$ be an orthogonal basis of \bar{W} . Then from (9), there exist constants $\mu_{j1}, \mu_{j2}, \dots, \mu_{j, n-r}$ ($j=1, 2, \dots, p$) such that

$$(11) \quad \mathbf{b}_j = \mathbf{d}_j + \mu_{j1} \theta_1 + \mu_{j2} \theta_2 + \dots + \mu_{j, n-r} \theta_{n-r}, \quad j=1, 2, \dots, p.$$

Let W be the vector space of rank r (orthogonal to \bar{W}) generated by the columns of A . Then since $\mathbf{c}'_j \xi_j$ is estimable as an univariate problem for the j th variable, it follows that

$$\text{Rank}(A) = \text{Rank} \begin{pmatrix} A \\ \mathbf{c}'_j \end{pmatrix}, \quad j=1, 2, \dots, p,$$

and hence that $\mathbf{d}_j \in W$, for all j .

Hence we have from (11)

$$\begin{aligned} \mathbf{b}'_j \mathbf{b}_j &= \mathbf{d}'_j \mathbf{d}_j + \mu_{j1}^2 + \mu_{j2}^2 + \dots + \mu_{j, n-r}^2 \\ \mathbf{b}'_j \mathbf{b}_{j'} &= \mathbf{d}'_j \mathbf{d}_{j'} + \mu_{j1} \mu_{j', 1} + \dots + \mu_{j, n-r} \mu_{j', n-r}. \end{aligned}$$

Therefore we get

$$\begin{aligned} \text{Var}(z) - \text{Var}(u) &= n \sum_{j=1}^p \left(\sum_{s=1}^{n-r} \mu_{js}^2 \right) \sigma_{jj} + n \sum_{j \neq j'}^p \left(\sum_{s=1}^{n-r} \mu_{js} \mu_{j's} \right) \sigma_{jj'} \\ &= n \sum_{s=1}^{n-r} \left[\sum_{j=1}^p \mu_{js}^2 \sigma_{jj} + \sum_{j \neq j'}^p \mu_{js} \mu_{j's} \sigma_{jj'} \right] \\ &= n \sum_{s=1}^n [\boldsymbol{\mu}'_s \boldsymbol{\Sigma} \boldsymbol{\mu}_s], \quad \text{where } \boldsymbol{\mu}'_s = (\mu_{1s}, \mu_{2s}, \dots, \mu_{ps}). \end{aligned}$$

But since $\boldsymbol{\Sigma}$ is positive definite,

$$\mu_s' \Sigma \mu_s > 0, \text{ unless } \mu_s = 0_{1p} \text{ (zero vector).}$$

Since however z is different from u , we must have $\mu_s \neq 0_{1p}$, for some s . Hence

$$\text{Var}(z) > \text{Var}(u),$$

which proves the theorem.

3. Acknowledgment

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