# Estimation of subparameters by IPM method 

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#### Abstract

In this study, a general partitioned linear model $\mathcal{M}=\{y, X \beta, V\}=\left\{y, X_{1} \beta_{1}+X_{2} \beta_{2}, V\right\}$ is considered to determine the best linear unbiased estimators (BLUEs) of subparameters $X_{1} \beta_{1}$ and $X_{2} \beta_{2}$. Some results are given related to the BLUEs of subparameters by using the inverse partitioned matrix (IPM) method based on a generalized inverse of a symmetric block partitioned matrix which is obtained from the fundamental BLUE equation.


Keywords: BLUE, generalized inverse, general partitioned linear model

## IPM yöntemi ile alt parametrelerin tahmini

## ÖZ

Bu çalışmada, $X_{1} \beta_{1}$ ve $X_{2} \beta_{2}$ alt parametrelerinin en iyi lineer yansız tahmin edicilerini (BLUE' larını) belirlemek için bir $\mathcal{M}=\{y, X \beta, V\}=\left\{y, X_{1} \beta_{1}+X_{2} \beta_{2}, V\right\}$ genel parçalanmış lineer modeli ele alınmıştr. Temel BLUE denkleminden elde edilen simetrik blok parçalanmış matrisin bir genelleştirilmiş tersine dayanan parçalanmış matris tersi (IPM) yöntemi kullanılarak alt parametrelerin BLUE' ları ile ilgili bazı sonuçlar verilmiştir.

Anahtar Kelimeler: BLUE, genelleştirilmiş ters, genel parçalanmış lineer model

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## 1. INTRODUCTION

Consider the general partitioned linear model
$y=X \beta+\varepsilon=X_{1} \beta_{1}+X_{2} \beta_{2}+\varepsilon$,
where $y \in R^{n x 1}$ is an observable random vector, $X=\left(X_{1}: X_{2}\right) \in R^{n x p} \quad$ is a known matrix with $X_{1} \in R^{n x p_{1}}$ and $X_{2} \in R^{n x p_{2}}, \beta=\left(\beta_{1}^{\prime}: \beta_{2}^{\prime}\right) \in R^{p x 1}$ is a vector of unknown parameters with $\beta_{1} \in R^{p_{1} x 1}$ and $\beta_{2} \in R^{p_{2} x 1}, \varepsilon \in R^{n x 1}$ is a random error vector. Further, the expectation $E(y)=X \beta$ and the covariance matrix $\operatorname{Cov}(y)=V \in R^{n x n}$ is a known nonnegative definite matrix. We may denoted the model (1) as a triplet
$\mathcal{M}=\{y, X \beta, V\}=\left\{y, X_{1} \beta_{1}+X_{2} \beta_{2}, V\right\}$.
Partitioned linear models are used in the estimations of partial parameters in regression models as well as in the investigations of some submodels and reduced models associated with the original model. In this study, we consider the general partitioned linear model $\mathcal{M}$ and we deal with the best linear unbiased estimators (BLUEs) of subparameters under this model. Our main purpose is to obtain the BLUEs of subparameters $X_{1} \beta_{1}$ and $X_{2} \beta_{2}$ under $\mathcal{M}$ by using the inverse partitioned matrix (IPM) method which is introduced by Rao [1] for statistical inference in general linear models. We also investigate some consequences on the BLUEs of subparameters obtained by using IPM approach.

Under the linear models, BLUE has been investigated by many statisticians. Some valuable properties of BLUE have been obtained, e.g., [2-6]. By applying matrix rank method, some characterizations of BLUE have been given by Tian $[7,8]$. IPM method for the general linear model with linear restrictions has been considered by Baksalary [9].

## 2. PRELIMINARIES

The BLUE of $X \beta$ under $\mathcal{M}$, denoted as $B L U E(X \beta \mid \mathcal{M})$, is defined to be an unbiased linear estimator $G y$ such that its covariance matrix $\operatorname{Cov}(G y)$ is minimal, in the Löwner sense, among all covariance matrices $\operatorname{Cov}(F y)$ such that $F y$ is unbiased for $X \beta$. It is well-known, see, e.g., $[10,11]$, that
$G y=B L U E(X \beta \mid \mathcal{M})$ if and only if $G$ satisfies the fundamental BLUE equation
$G(X: V Q)=(X: 0)$,
where $Q=\mathrm{I}-P_{x}$ with $P_{x}$ is orthogonal projector onto the column space $C(X)$. Note that the equation (3) has a unique solution if and only if $\operatorname{rank}(X: V)=n$ and the observed value of $G y$ is unique with probability 1 if and only if $\mathcal{M}$ is consistent, i.e., $y \in C(X: V)=C(X: V Q)$ holds with probability 1 ; see [12]. In the study, it is assumed that the model $\mathcal{M}$ is consistent.

The corresponding condition for $A y$ to be BLUE of an estimable parametric function $K \beta$ is $A(X: V Q)=(K: 0)$. Recall that a parametric function $K \beta$ is estimable under $\mathcal{M}$ if and only if $C\left(K^{\prime}\right) \subseteq C\left(X^{\prime}\right)$ and in particular, $X_{1} \beta_{1}$ and $X_{2} \beta_{2}$ is estimable under $\mathcal{M}$ if and only if $C\left(X_{1}\right) \cap C\left(X_{2}\right)=\{0\} ;$ see [13,14].

The fundamental BLUE equation given in (3) equivalently expressed as follows. $G y=B L U E(X \beta \mid \mathcal{M})$ if and only if there exists a matrix $L \in R^{p \times n}$ such that $G$ is solution to,
$\left(\begin{array}{cc}V & X \\ X^{\prime} & 0\end{array}\right)\binom{G^{\prime}}{L}=\binom{0}{X^{\prime}}$, i.e, $Z\binom{G^{\prime}}{L}=\binom{0}{X^{\prime}}$.
Partitioned matrices and their generalized inverses play an important role in the concept of linear models. According to Rao [1], the problem of inference from a linear model can be completely solved when one has obtained an arbitrary generalized inverse of the partitioned matrix $Z$. This approach based on the numerical evaluation of an inverse of the partitioned matrix $Z$ is known as the IPM method, see [1-15].

Let the matrix $C=\left(\begin{array}{cc}C_{1} & C_{2} \\ C_{3} & -C_{4}\end{array}\right)$ be an arbitrary generalized inverse of $Z$, i.e., $C$ is any matrix satisfying the equation $Z C Z=Z$, where $C_{1} \in R^{n x n}$ and $C_{2} \in R^{n x p}$. Then one solution to the (consistent) equation (4) is
$\binom{G^{\prime}}{L}=\left(\begin{array}{cc}C_{1} & C_{2} \\ C_{3} & -C_{4}\end{array}\right)\binom{0}{X^{\prime}}=\binom{C_{2} X^{\prime}}{-C_{4} X^{\prime}}$.
Therefore, we see that $B L U E(X \beta \mid \mathcal{M})=X C_{2}^{\prime} y=X C_{3} y$, which is one representation for the BLUE of $X \beta$ under $\mathcal{M}$. If we let $C$ vary through all generalized inverses of $Z$ we obtain all solutions to (4) and thereby all representations $G y$ for the BLUE of $X \beta$ under $\mathcal{M}$. As further reference for submatrices $C_{i}, i=1,2,3,4$, and their statistical applications, see [16-23].

## 3. SOME RESULTS ON A GENERALIZED INVERSE OF $Z$

Some explicit algebraic expression for the submatrices of $C$ was obtained in [15, Theorem 2.3]. The purpose of this section is to extend this theorem to $3 x 3$ symmetric block partitioned matrix to obtain the BLUEs of subparameters and their properties.

Let $D \in\left\{Z^{-}\right\}$, expressed as

$$
D=\left(\begin{array}{ccc}
D_{0} & D_{1} & D_{2}  \tag{6}\\
E_{1} & -F_{1} & -F_{2} \\
E_{2} & -F_{3} & -F_{4}
\end{array}\right)=\left(\begin{array}{ccr}
V & X_{1} & X_{2} \\
X_{1}^{\prime} & 0 & 0 \\
X_{2}^{\prime} & 0 & 0
\end{array}\right)^{-}
$$

where $D_{0} \in R^{n x n}, D_{1} \in R^{n x p_{1}}, D_{2} \in R^{n x p_{2}}, E_{1}, E_{2}, F_{1}$, $F_{2}, F_{3}, F_{4}$ are conformable matrices and $\left\{Z^{-}\right\}$stands for the set of all generalized inverse of $Z$. In the following theorem, we collect some properties related to the submatrices of $D$ given in (6).

Theorem 1. Let $V, X_{1}, X_{2}, D_{0}, D_{1}, D_{2}, E_{1}, E_{2}$, $F_{1}, \quad F_{2}, \quad F_{3}, \quad F_{4}$ be defined as before and let $C\left(X_{1}\right) \cap C\left(X_{2}\right)=\{0\}$. Then the following hold:
(i) $\left(\begin{array}{ccr}V & X_{1} & X_{2} \\ X_{1}^{\prime} & 0 & 0 \\ X_{2}^{\prime} & 0 & 0\end{array}\right)^{-}=\left(\begin{array}{ccc}D_{0}^{\prime} & E_{1}^{\prime} & E_{2}^{\prime} \\ D_{1}^{\prime} & -F_{1}^{\prime} & -F_{3}^{\prime} \\ D_{2}^{\prime} & -F_{2}^{\prime} & -F_{4}^{\prime}\end{array}\right)$
is another choice of a generalized inverse.
(ii) $V D_{0} X_{1}+X_{1} E_{1} X_{1}+X_{2} E_{2} X_{1}=X_{1}, \quad X_{1}^{\prime} D_{0} X_{1}=0$, $X_{2}^{\prime} D_{0} X_{1}=0$.
(iii) $V D_{0} X_{2}+X_{1} E_{1} X_{2}+X_{2} E_{2} X_{2}=X_{2}, \quad X_{1}^{\prime} D_{0} X_{2}=0$, $X_{2}^{\prime} D_{0} X_{2}=0$.
(iv) $V D_{0} V+X_{1} E_{1} V+X_{2} E_{2} V=V, \quad X_{1}^{\prime} D_{0} V=0$, $X_{2}^{\prime} D_{0} V=0$.
(v) $V D_{1} X_{1}^{\prime}=X_{1} F_{1} X_{1}^{\prime}+X_{2} F_{3} X_{1}^{\prime}, \quad X_{1} D_{1}^{\prime} X_{1}=X_{1}$, $X_{1} D_{1}^{\prime} X_{2}=0$.
(vi) $V D_{2} X_{2}^{\prime}=X_{1} F_{2} X_{2}^{\prime}+X_{2} F_{4} X_{2}^{\prime}, \quad X_{2} D_{2}^{\prime} X_{2}=X_{2}$, $X_{2} D_{2}^{\prime} X_{1}=0$ 。

Proof: The result (i) is proved by taking transposes of either side of (6). We observe that the equations
$V a+X_{1} b+X_{2} c=X_{1} d, X_{1}^{\prime} a=0, X_{2}^{\prime} a=0$
are solvable for any $d$, in which case $a=D_{0} X_{1} d$, $b=E_{1} X_{1} d, c=E_{2} X_{1} d$ is a solution. Substituting this solution in (7) and omitting $d$, we have (ii). To prove (iii), we can write the equations
$V a+X_{1} b+X_{2} c=X_{2} d, X_{1}^{\prime} a=0, X_{2}^{\prime} a=0$
which are solvable for any $d$. Then $a=D_{0} X_{2} d$, $b=E_{1} X_{2} d, c=E_{2} X_{2} d$ is a solution. Substituting this solution in (8) and omitting $d$, we have (iii). To prove (iv), the equations which are solvable for any $d$

$$
\begin{equation*}
V a+X_{1} b+X_{2} c=V d, X_{1}^{\prime} a=0, X_{2}^{\prime} a=0 \tag{9}
\end{equation*}
$$

are considered. In this case, one solution is $a=D_{0} V d$, $b=E_{1} V d, c=E_{2} V d$. If we substitute this solution in (9) and omit $d$, we have (iv). In view of the assumption $C\left(X_{1}\right) \cap C\left(X_{2}\right)=\{0\}$, we can consider the equations
$V a+X_{1} b+X_{2} c=0, X_{1}^{\prime} a=X_{1}^{\prime} d_{1}, X_{2}^{\prime} a=0$
and
$V a+X_{1} b+X_{2} c=0, X_{1}^{\prime} a=0, X_{2}^{\prime} a=X_{2}^{\prime} d_{2}$
for the proof of (v) and (vi), respectively, see [18, Theorem 7.4.8]. In this case $a=D_{1} X_{1}^{\prime} d_{1}, b=-F_{1} X_{1}^{\prime} d_{1}$, $c=-F_{3} X_{1}^{\prime} d_{1}$ is a solution for (10) and $a=D_{2} X_{2}^{\prime} d_{2}$, $b=-F_{2} X_{2}^{\prime} d_{2}, \quad c=-F_{4} X_{2}^{\prime} d_{2}$ is a solution for (11). Substituting these solutions into corresponding equations and omitting $d_{1}$ and $d_{2}$, we obtain the required results.

## 4. IPM METHOD FOR SUBPARAMETERS

The fundamental BLUE equation given in (4) can be accordingly written for $A y$ being the BLUE of estimable $K \beta$, that is, $A y=B L U E(K \beta \mid \mathcal{M})$ if and only if there exists a matrix $L \in R^{p x n}$ such that $A$ is solution to
$Z\binom{A^{\prime}}{L}=\binom{0}{K^{\prime}}$.
Now, assumed that $X_{1} \beta_{1}$ and $X_{2} \beta_{2}$ are estimable under $\mathcal{M}$. If we take $K=\left(X_{1}: 0\right)$ and $K=\left(0: X_{2}\right)$, respectively, from equation (12), we get the BLUE equations of subparameters $X_{1} \beta_{1}$ and $X_{2} \beta_{2}$. There exist $L_{1} \in R^{p_{1} \times n}, L_{2} \in R^{p_{2} \times n}, L_{3} \in R^{p_{1} \times n}, L_{4} \in R^{p_{2} \times n}$ such that $G_{1}$ and $G_{2}$ are solution to following the equations, respectively,

$$
\begin{align*}
G_{1} y= & B L U E\left(X_{1} \beta_{1} \mid \mathcal{M}\right) \\
& \Leftrightarrow\left(\begin{array}{ccc}
V & X_{1} & X_{2} \\
X_{1}^{\prime} & 0 & 0 \\
X_{2}^{\prime} & 0 & 0
\end{array}\right)\left(\begin{array}{c}
G_{1}^{\prime} \\
L_{1} \\
L_{2}
\end{array}\right)=\left(\begin{array}{c}
0 \\
X_{1}^{\prime} \\
0
\end{array}\right) \tag{13}
\end{align*}
$$

and

$$
\begin{align*}
G_{2} y= & B L U E\left(X_{2} \beta_{2} \mid \mathcal{M}\right) \\
& \Leftrightarrow\left(\begin{array}{ccc}
V & X_{1} & X_{2} \\
X_{1}^{\prime} & 0 & 0 \\
X_{2}^{\prime} & 0 & 0
\end{array}\right)\left(\begin{array}{l}
G_{2}^{\prime} \\
L_{3} \\
L_{4}
\end{array}\right)=\left(\begin{array}{c}
0 \\
0 \\
X_{2}^{\prime}
\end{array}\right) . \tag{14}
\end{align*}
$$

Therefore, the following theorem can be given to determine the BLUE of subparameters by the IPM method.

Theorem 2. Consider the general partitioned linear model $\mathcal{M}$ and the matrix $D$ given in (6). Suppose that $C\left(X_{1}\right) \cap C\left(X_{2}\right)=\{0\}$. Then
$\operatorname{BLUE}\left(X_{1} \beta_{1} \mid \mathcal{M}\right)=X_{1} D_{1}^{\prime} y=X_{1} E_{1} y$
and
$\operatorname{BLUE}\left(X_{2} \beta_{2} \mid \mathcal{M}\right)=X_{2} D_{2}^{\prime} y=X_{2} E_{2} y$.
Proof: The general solution of the matrix equation given in (13) is

$$
\begin{aligned}
\left(\begin{array}{l}
G_{1} \\
L_{1} \\
L_{2}
\end{array}\right)= & \left(\begin{array}{ccc}
D_{0} & D_{1} & D_{2} \\
E_{1} & -F_{1} & -F_{2} \\
E_{2} & -F_{3} & -F_{4}
\end{array}\right)\left(\begin{array}{c}
0 \\
X_{1}^{\prime} \\
0
\end{array}\right) \\
& +\left[\mathrm{I}-\left(\begin{array}{ccc}
D_{0} & D_{1} & D_{2} \\
E_{1} & -F_{1} & -F_{2} \\
E_{2} & -F_{3} & -F_{4}
\end{array}\right)\left(\begin{array}{ccc}
V & X_{1} & X_{2} \\
X_{1}^{\prime} & 0 & 0 \\
X_{2}^{\prime} & 0 & 0
\end{array}\right)\right] U
\end{aligned}
$$

and thereby we get

$$
\begin{aligned}
G_{1} y= & X_{1} D_{1}^{\prime} y+U_{1}^{\prime}\left(\mathrm{I}-V D_{0}^{\prime}-X_{1} D_{1}^{\prime}-X_{2} D_{2}^{\prime}\right) y \\
& +U_{2}^{\prime}\left(-X_{1}^{\prime} D_{0}^{\prime}\right) y+U_{3}^{\prime}\left(-X_{2}^{\prime} D_{0}^{\prime}\right) y
\end{aligned}
$$

Here $y$ can be written as $y=X_{1} L_{1}+X_{2} L_{2}+V Q L_{3}$ for some $L_{1}, L_{2}$ and $L_{3}$ since the model $\mathcal{M}$ is assumed to be consistent. From Theorem 1, we see that
$U_{1}^{\prime}\left(\mathrm{I}-V D_{0}^{\prime}-X_{1} D_{1}^{\prime}-X_{2} D_{2}^{\prime}\right)\left(X_{1} L_{1}+X_{2} L_{2}+V Q L_{3}\right)=0$,
$U_{2}^{\prime}\left(-X_{1}^{\prime} D_{0}\right)\left(X_{1} L_{1}+X_{2} L_{2}+V Q L_{3}\right)=0$,
$U_{3}^{\prime}\left(-X_{2}^{\prime} D_{0}\right) y=U_{3}^{\prime}\left(-X_{2}^{\prime} D_{0}\right)\left(X_{1} L_{1}+X_{2} L_{2}+V Q L_{3}\right)=0$.

Moreover, according to Theorem 1 (i), we can replace $D_{1}^{\prime}$ by $E_{1}$. Therefore, $\operatorname{BLUE}\left(X_{1} \beta_{1} \mid \mathcal{M}\right)=X_{1} D_{1}^{\prime} y=X_{1} E_{1} y \quad$ is obtained. $\operatorname{BLUE}\left(X_{2} \beta_{2} \mid \mathcal{M}\right)=X_{2} D_{2}^{\prime} y=X_{2} E_{2} y$ is obtained by similar way

The following results are easily obtained from Theorem 1 (v) and (vi) under $\mathcal{M}$.
$E\left(B L U E\left(X_{1} \beta_{1} \mid \mathcal{M}\right)\right)=X_{1} \beta_{1}$
and
$E\left(\operatorname{BLUE}\left(X_{2} \beta_{2} \mid \mathcal{M}\right)\right)=X_{2} \beta_{2}$,
$\operatorname{Cov}\left(\operatorname{BLUE}\left(X_{1} \beta_{1} \mid \mathcal{M}\right)\right)=X_{1} F_{1} X_{1}^{\prime}$
and
$\operatorname{Cov}\left(\operatorname{BLUE}\left(X_{2} \beta_{2} \mid \mathcal{M}\right)\right)=X_{2} F_{4} X_{2}^{\prime}$,
$\operatorname{Cov}\left(\operatorname{BLUE}\left(X_{1} \beta_{1} \mid \mathcal{M}\right), \operatorname{BLUE}\left(X_{2} \beta_{2} \mid \mathcal{M}\right)\right)$
$=X_{1} F_{2} X_{2}^{\prime}=X_{1} F_{3}^{\prime} X_{2}^{\prime}$.
)

## 5. ADDITIVE DECOMPOSITION OF THE BLUES OF SUBPARAMETERS

The purpose of this section is to give some additive properties of BLUEs of subparameters under $\mathcal{M}$.

Theorem 3. Consider the model $\mathcal{M}$ and assume that $X_{1} \beta_{1}$ and $X_{2} \beta_{2}$ are estimable under $\mathcal{M}$. $\left\{\operatorname{BLUE}\left(X_{1} \beta_{1} \mid \mathcal{M}\right)+\operatorname{BLUE}\left(X_{2} \beta_{2} \mid \mathcal{M}\right)\right\} \quad$ is always BLUE for $X \beta$ under $\mathcal{M}$.

Proof: Let $\operatorname{BLUE}\left(X_{1} \beta_{1} \mid \mathcal{M}\right)$ and $\operatorname{BLUE}\left(X_{2} \beta_{2} \mid \mathcal{M}\right)$ be given as in (15). Then we can write

$$
\begin{aligned}
& B L U E\left(X_{1} \beta_{1} \mid \mathcal{M}\right)+B L U E\left(X_{2} \beta_{2} \mid \mathcal{M}\right) \\
& \quad=\left(X_{1} D_{1}^{\prime}+X_{2} D_{2}^{\prime}\right) y
\end{aligned}
$$

According to fundamental BLUE equation and from Theorem 1 (v) and (vi), we see that $\left(X_{1} D_{1}^{\prime}+X_{2} D_{2}^{\prime}\right)\left(X_{1}: X_{2}: V Q\right)=\left(X_{1}: X_{2}: 0\right)$ for all $y \in C(X: V Q)$. Therefore the required result is obtained.

The following results are easily obtained from Theorem 1 (iv) and (16)-(18).
$E\left(\operatorname{BLUE}\left(X_{1} \beta_{1} \mid \mathcal{M}\right)+\operatorname{BLUE}\left(X_{2} \beta_{2} \mid \mathcal{M}\right)\right)=X \beta$,
$\operatorname{Cov}\left(\operatorname{BLUE}\left(X_{1} \beta_{1} \mid \mathcal{M}\right)+\operatorname{BLUE}\left(X_{2} \beta_{2} \mid \mathcal{M}\right)\right)$
$=X_{1} F_{1} X_{1}^{\prime}+X_{2} F_{4} X_{2}^{\prime}+X_{1} F_{2} X_{2}^{\prime}+X_{2} F_{3} X_{1}^{\prime}$.

## REFERENCES

[1] C. R. Rao, "Unified theory of linear estimation", Sankhyā, Ser. A 33:371-394, 1971. [Corrigendum (1972), 34, p. 194 and p. 477.].
[2] M. Nurhanen and S. Puntanen, "Effect of deleting an observation on the equality of the OLSE and BLUE", Linear Algebra and its Applications, vol. 176, pp. 131-136, 1992.
[3] H. J. Werner and C. Yapar, "Some equalities for estimations of partial coefficients under a general linear regression model", Linear Algebra and its Applications, 237/238, 395-404, 1996.
[4] P. Bhimasankaram and R. Saharay, "On a partitioned linear model and some associated reduced models", Linear Algebra and its Applications, vol. 264, pp. 329-339, 1997.
[5] J. Gross and S. Puntanen, "Estimation under a general partitioned linear model", Linear Algebra and its Applications, vol. 321, pp. 131-144, 2000.
[6] B. Zhang, B. Liu and C. Lu, "A study of the equivalence of the BLUEs between a partitioned singular linear model and its reduced singular linear models", Acta Mathematica Sinica, English Series, vol. 20, no.3, pp.557-568, 2004.
[7] Y. Tian and S. Puntanen, "On the equivalence of estimations under a general linear model and its transformed models", Linear Algebra and its Applications, vol. 430, pp. 2622-2641, 2009.
[8] Y. Tian, "On properties of BLUEs under general linear regression models", Journal of Statistical Planning and Inference, vol. 143, pp. 771-782, 2013.
[9] J. K. Baksalary, and P. R. Pordzik, "Inverse-Partitioned-Matrix method for the general GaussMarkov model with linear restrictions", Journal of Statistical Planning and Inference, vol. 23, pp. 133143, 1989.
[10] C. R. Rao, Least squares theory using an estimated dispersion matrix and its application to measurement of signals. In: Le Cam, L. M., Neyman, J., eds. Proc. Fifth Berkeley Symposium on Mathematical Statistics and Probability: Berkeley, California, 1965/1966. Vol. 1. Univ. Of California Press, Berkeley, 355-372, 1967.
[11] G. Zyskind, "On canonical forms, non-negative covariance matrices and best and simple least squares linear estimators in linear models" The Annals of Mathematical Statistics, vol. 38, pp. 1092-1109, 1967.
[12] C. R. Rao, "Representations of best linear unbiased estimators in the Gauss-Markoff model with a singular dispersion matrix", Journal of Multivariate Analysis, vol. 3, pp. 276-292, 1973.
[13] I. S. Alalouf and G. P. H. Styan, "Characterizations of estimability in the general linear model" The Annals of Statistics, vol. 7, pp. 194-200, 1979.
[14] S. Puntanen, G.P.H. Styan and J. Isotalo, "Matrix tricks for linear statistical models", Our Personal Top Twenty, Springer, Heidelberg, 2011.
[15] C. R. Rao, "A note on the IPM method in the unified theory of linear estimation", Sankhyā, Ser.A., vol. 34, pp. 285-288, 1972.
[16] H. Drygas, "A note on the Inverse-PartitionedMatrix method in linear regression analysis", Linear Algebra and its Applications, vol. 67, pp. 275-277, 1985.
[17] F. J. Hall and C. D. Meyer, "Generalized inverses of the fundamental bordered matrix used in linear
estimation", Sankhyā, Ser. A., vol. 37, pp. 428438, 1975. [Corrigendum (1978), 40, p. 399.]
[18] D. A. Harville, "Matrix algebra from a statisticians perspective", Springer, New York, 1997.
[19] J. Isotalo, "Puntanen, S., Styan, G. P. H., A useful matrix decomposition and its statistical applications in linear regression", Commun. Statist. Theor. Meth., vol. 37, pp. 1436-1457, 2008.
[20] R. M. Pringle and A. A. Rayner, "Generalized Inverse Matrices with Applications to Statistics", Hafner Publishing Company, New York, 1971.
[21] C. R. Rao, "Some recent results in linear estimation", Sankhyā, Ser. B, vol. 34, pp. 369-378, 1972.
[22] C. R. Rao, "Linear Statistical Inference and its Applications", 2nd Ed., Wiley, New York, 1973.
[23] H. J. Werner, C. R. Rao's IPM method: a geometric approach. New Perspectives in Theoretical and Applied Statistics (M. L. Puri, J. P. Vilaplana \& W. Wertz, eds.). Wiley, New York, 367-382, 1987.


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