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CONDITIONS FOR OPTIMALITY AND VALIDITY OF SIMPLE LEAST SQUARES THEORY

BY SUJIT KUMAR MITRA AND C. RADHAKRISHNA RAO

Indian Statistical Institute

1. Notation and introduction. A matrix is denoted by a bold face letter such as $\mathbf{A}$, $\mathbf{X}$, $\mathbf{\Sigma}$ etc. For a matrix $\mathbf{X}$ of order $n \times m$

$R(\mathbf{X})$ represents the rank of $\mathbf{X}$.

$\mathfrak{M}(\mathbf{X})$ represents the linear space generated by the columns of $\mathbf{X}$.

$\mathbf{X}^-$ represents a g-inverse as defined by Rao (1962, 1966, 1967b).

$\mathbf{P}_X = \mathbf{X}(\mathbf{X}'\mathbf{X})^-\mathbf{X}'$ is the projection operator which projects arbitrary n-vectors onto $\mathfrak{M}(\mathbf{X})$.

$\mathbf{X}^\perp$ denotes a matrix of maximum rank such that $\mathbf{X}'\mathbf{X}^\perp = \mathbf{0}$.

$\mathbf{I}$ denotes an identity matrix. The order of $\mathbf{I}$ will usually not be explicitly mentioned but can always be determined from the context.

Consider the Gauss-Markoff model $(\mathbf{Y}, \mathbf{X}\boldsymbol{\beta}, \mathbf{\Sigma})$ where $\mathbf{Y}$ is a vector of observations, $E(\mathbf{Y}) = \mathbf{X}\boldsymbol{\beta}$ and $D(\mathbf{Y}) = \mathbf{\Sigma}$, $\mathbf{X}$ being a given matrix of order $n \times m$ and $\boldsymbol{\beta}$ a vector of unknown parameters. In the context of the discussion in the present paper, the model will be simply referred to as $(\mathbf{X}, \mathbf{\Sigma})$. The best linear unbiased estimator (BLUE) of an estimable parametric function $\mathbf{p}'\boldsymbol{\beta}$, where $\mathbf{p}$ is a vector, under the model $(\mathbf{X}, \mathbf{\Sigma})$ is a linear function $\mathbf{L}'\mathbf{Y}$ such that $E(\mathbf{L}'\mathbf{Y}) = \mathbf{p}'\boldsymbol{\beta}$ and $\mathbf{L}'\mathbf{\Sigma}\mathbf{L}$ is a minimum. It is well known that a BLUE under $(\mathbf{X}, \mathbf{\Sigma})$ can be obtained by the general method of least squares (see Rao, 1965, page 188 and Mitra and Rao, 1968).

The BLUE of $\mathbf{p}'\beta$ under $(\mathbf{X}_0, \mathbf{\Sigma}_0)$ is said to be $(\mathbf{X}, \mathbf{\Sigma})$ optimal if it is also the BLUE of $\mathbf{p}'\boldsymbol{\beta}$ under the model $(\mathbf{X}, \mathbf{\Sigma})$. The object of the present paper is to characterize the set of $(\mathbf{X}, \mathbf{\Sigma})$ such that for every estimable parametric function the BLUE under a given model $(\mathbf{X}_0, \sigma^2\mathbf{I})$ is $(\mathbf{X}, \mathbf{\Sigma})$-optimal. Further, the classes of $\mathbf{\Sigma}$ for which different statistical methods based on $(\mathbf{X}, \sigma^2\mathbf{I})$ remain valid have been obtained.

In previous papers Rao (1967a, 1968)[1] gave the necessary and sufficient contions for BLUE under $(\mathbf{X}, \mathbf{\Sigma}_0)$ to be $(\mathbf{X}, \mathbf{\Sigma})$-optimal, in which case the investigation was confined to the characterization of $\mathbf{\Sigma}$ only. Similar results, but not providing an exact representation of $\mathbf{\Sigma}$, were also obtained by Zyskind (1967), Watson (1967) and Kruskal (1968) in the special case of $\mathbf{\Sigma}_0 = \sigma^2\mathbf{I}$.

2. The main results.

LEMMA 2.1. *If for every estimable parametric function the* BLUE *under* $(\mathbf{X}_0, \sigma^2\mathbf{I})$ *is* $(\mathbf{X}, \sigma^2\mathbf{I})$*-optimal, it is necessary and sufficient that* $\mathbf{X}$ *is of the form*

$$\mathbf{X} = \mathbf{X}_0 + (\mathbf{I} - \mathbf{P}_{X_0})\mathbf{A}, \tag{2.1}$$

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[1] The results were first given in a lecture at the Fifth Berkeley Symposium in 1965.

where $\mathbf{A}$ *is any matrix such that*

$$\mathfrak{M}(\mathbf{A}') \cap \mathfrak{M}(\mathbf{X}_0') = \{\mathbf{0}\}, \tag{2.2}$$

a set consisting exclusively of the null vector, or equivalently

$$\mathbf{X} = \mathbf{X}_0 + (\mathbf{I} - \mathbf{P}_{X_0})\mathbf{F}[\mathbf{I} + (\mathbf{I} - \mathbf{P}_{X_0'})\mathbf{D}]^{\perp'}, \tag{2.3}$$

where $\mathbf{D}$ *and* $\mathbf{F}$ *are arbitrary.*

We note that from standard results in the Gauss-Markoff theory (see Rao, 1965, page 178) it suffices to investigate conditions under which the elements of the vector $\mathbf{X}_0'\mathbf{Y}$ have the same expectations and minimum variance under the models $(\mathbf{X}_0, \sigma^2\mathbf{I})$ and $(\mathbf{X}, \sigma^2\mathbf{I})$.

Sufficiency of (2.1) *and* (2.2). Let $\mathbf{X}$ be of the form given in (2.1) and (2.2). Then

$$E(\mathbf{X}_0'\mathbf{Y} \mid \mathbf{X}, \sigma^2\mathbf{I}) = \mathbf{X}_0'\mathbf{X}\boldsymbol{\beta} = \mathbf{X}_0'\mathbf{X}_0\boldsymbol{\beta} = E(\mathbf{X}_0'\mathbf{Y} \mid \mathbf{X}_0, \sigma^2\mathbf{I}),$$

since $\mathbf{I} - \mathbf{P}_{X_0}$ is symmetric and $(\mathbf{I} - \mathbf{P}_{X_0})\mathbf{X}_0 = \mathbf{0}$.

Let $\mathbf{Z} = \mathbf{X}^{\perp}$, in which case $E(\mathbf{Z}'\mathbf{Y} \mid \mathbf{X}, \sigma^2\mathbf{I}) = \mathbf{0}$. By definition $\mathbf{X}'\mathbf{Z} = \mathbf{0} = \mathbf{X}_0'\mathbf{Z} + \mathbf{A}'(\mathbf{I} - \mathbf{P}_{X_0})\mathbf{Z}$, i.e., $\mathbf{X}_0'\mathbf{Z} = -\mathbf{A}'(\mathbf{I} - \mathbf{P}_{X_0})\mathbf{Z}$, which is a contradiction in view of (2.2) unless $\mathbf{X}_0'\mathbf{Z} = \mathbf{0}$. Hence by Lemma (i), page 257 in Rao, 1965, sufficiency is established.

Necessity of (2.1) *and* (2.2). Let a BLUE under $(\mathbf{X}_0, \sigma^2\mathbf{I})$ be $(\mathbf{X}, \sigma^2\mathbf{I})$ optimal. Necessity of (2.1) is obvious for expectations of $\mathbf{X}_0'\mathbf{Y}$ to be the same under the two models. Now suppose that $\mathfrak{M}(\mathbf{A}'(\mathbf{I} - \mathbf{P}_{X_0})) \cap \mathfrak{M}(\mathbf{X}_0')$ contains a vector $\boldsymbol{\alpha} \neq \mathbf{0}$, in which case $\boldsymbol{\alpha} = \mathbf{A}'(\mathbf{I} - \mathbf{P}_{X_0})\boldsymbol{\mu} = \mathbf{X}_0'\mathbf{X}_0\boldsymbol{\lambda}$ for some vectors $\boldsymbol{\mu}$ and $\boldsymbol{\lambda}$. Let $\mathbf{z} = \mathbf{X}_0\boldsymbol{\lambda} - (\mathbf{I} - \mathbf{P}_{X_0})\boldsymbol{\mu}$. Check that $\mathbf{X}'\mathbf{z} = \mathbf{0}$ and observe that $\mathbf{X}_0'\mathbf{z} = \mathbf{X}_0'\mathbf{X}_0\boldsymbol{\lambda} = \boldsymbol{\alpha} \neq \mathbf{0}$. This shows that at least some elements of $\mathbf{X}_0'\mathbf{Y}$ are correlated with $\mathbf{z}'\mathbf{Y}$ which is a contradiction. Hence $\mathfrak{M}(\mathbf{A}'(\mathbf{I} - \mathbf{P}_{X_0})) \cap \mathfrak{M}(\mathbf{X}_0') = \{\mathbf{0}\}$. Necessity of (2.2) follows from the fact that, without loss of generality, one may take $\mathbf{A}$ to be $(\mathbf{I} - \mathbf{P}_{X_0})\mathbf{A}$.

Necessity and sufficiency of (2.3). Using the condition of unbiasedness

$$E(\mathbf{X}_0'\mathbf{Y} \mid \mathbf{X}_0, \sigma^2\mathbf{I}) = E(\mathbf{X}_0'\mathbf{Y} \mid \mathbf{X}, \sigma^2\mathbf{I}) \Rightarrow \mathbf{X} = \mathbf{X}_0 + (\mathbf{I} - \mathbf{P}_{X_0})\mathbf{G}.$$

Let $\mathbf{Z} = \mathbf{X}^{\perp}$ and C stand for covariance. Since $\mathbf{X}_0'\mathbf{Y}$ are BLUE's under $(\mathbf{X}, \sigma^2\mathbf{I})$,

$$C(\mathbf{Z}'\mathbf{Y}, \mathbf{X}_0'\mathbf{Y} \mid \mathbf{X}, \sigma^2\mathbf{I}) = \mathbf{0} \Rightarrow \mathbf{X}_0 = \mathbf{X}\mathbf{H} \quad \text{for some} \quad \mathbf{H}.$$

Multiplying both sides of $\mathbf{X} = \mathbf{X}_0 + \mathbf{X}_0^{\perp}\mathbf{G}$ by $\mathbf{H}$ and writing $\mathbf{X}_0 = \mathbf{X}\mathbf{H}$ we obtain

$$\mathbf{X}_0 = \mathbf{X}_0\mathbf{H} + \mathbf{X}_0^{\perp}\mathbf{G}\mathbf{H} \Rightarrow \mathbf{X}_0 = \mathbf{X}_0\mathbf{H} \quad \text{and} \quad \mathbf{G}\mathbf{H} = \mathbf{0}.$$

Observe that $\mathbf{X}_0 = \mathbf{X}_0\mathbf{H} \Rightarrow \mathbf{H} = \mathbf{I} + (\mathbf{I} - \mathbf{P}_{X_0'})\mathbf{D}$ for some $\mathbf{D}$ and since $\mathbf{G}\mathbf{H} = \mathbf{0}$,

$$\mathbf{G} = \mathbf{F}(\mathbf{H}^{\perp})' = \mathbf{F}[\mathbf{I} + (\mathbf{I} - \mathbf{P}_{X_0'})\mathbf{D}]^{\perp'}.$$

Hence

$$\mathbf{X} = \mathbf{X}_0 + (\mathbf{I} - \mathbf{P}_{X_0})\mathbf{F}[\mathbf{I} + (\mathbf{I} - \mathbf{P}_{X_0'})\mathbf{D}]^{\perp'},$$

where $\mathbf{F}$ and $\mathbf{D}$ are arbitrary.

COROLLARY 1. *A sufficient condition that for every estimable function the* BLUE *under* $(\mathbf{X}_0, \sigma^2\mathbf{I})$ *is* $(\mathbf{X}, \sigma^2\mathbf{I})$*-optimal is*

$$\mathbf{X} = \mathbf{X}_0 + [\mathbf{I} - \mathbf{X}_0(\mathbf{X}_0'\mathbf{X}_0)^-\mathbf{X}_0']\mathbf{B}[\mathbf{I} - \mathbf{X}_0'\mathbf{X}_0(\mathbf{X}_0'\mathbf{X})^-], \tag{2.4}$$

where $\mathbf{B}$ *is arbitrary.*

COROLLARY 2. *If* $R(\mathbf{X}_0)$ *is equal to the number of columns in* $\mathbf{X}_0$, *then the conditions of Lemma* 2.1 *reduce to* $\mathbf{X} = \mathbf{X}_0$.

PROOF.

$$E(\mathbf{X}_0'\mathbf{Y} \mid \mathbf{X}, \sigma^2\mathbf{I}) = \mathbf{X}_0'\mathbf{X}_0\boldsymbol{\beta} \Rightarrow \mathbf{X} = \mathbf{X}_0 + \mathbf{X}_0^{\perp}\mathbf{G}, \tag{2.5}$$

for some $\mathbf{G}$. Since $\mathbf{X}_0'\mathbf{Y}$ are BLUE's under $(\mathbf{X}, \sigma^2\mathbf{I})$,

$$C(\mathbf{X}_0'\mathbf{Y}, \mathbf{Z}'\mathbf{Y}) = \mathbf{0} \Rightarrow \mathbf{X}_0'\mathbf{Z} = \mathbf{0} \Rightarrow \mathbf{X}_0 = \mathbf{X}\mathbf{D}, \tag{2.6}$$

for some $\mathbf{D}$. From (2.5) and (2.6),

$$\mathbf{X}\mathbf{D} = \mathbf{X}_0\mathbf{D} + \mathbf{X}_0^{\perp}\mathbf{G}\mathbf{D} = \mathbf{X}_0.$$

Multiplying by $\mathbf{X}_0'$,

$$\mathbf{X}_0'\mathbf{X}_0 = \mathbf{X}_0'\mathbf{X}_0\mathbf{D} \Rightarrow \mathbf{D} = \mathbf{I},$$

since $\mathbf{X}_0'\mathbf{X}_0$ is non-singular. Then $\mathbf{X}_0 = \mathbf{X}$ from (2.6).

LEMMA 2.2. *For the* BLUE *under* $(\mathbf{X}_0, \sigma^2\mathbf{I})$ *to be* $(\mathbf{X}, \boldsymbol{\Sigma})$*-optimal for every estimable parametric function, it is necessary and sufficient that*

$$\mathbf{X} = \mathbf{X}_0 + \mathbf{Z}_0\mathbf{G}, \tag{2.7}$$

$$\boldsymbol{\Sigma} = \mathbf{X}_0\mathbf{A}\mathbf{X}_0' + \mathbf{Z}_0\mathbf{B}\mathbf{Z}_0' + \mathbf{X}_0\mathbf{A}'\mathbf{G}'\mathbf{Z}_0' + \mathbf{Z}_0\mathbf{G}\mathbf{A}\mathbf{X}_0', \tag{2.8}$$

where $\mathbf{A}$, $\mathbf{B}$, $\mathbf{G}$ *are arbitrary except that* $\boldsymbol{\Sigma}$ *is non-negative definite and* $\mathbf{Z}_0$ *is written for* $\mathbf{X}_0^{\perp}$.

PROOF OF NECESSITY. As in Lemma 2.1, we consider the functions $\mathbf{X}_0'\mathbf{Y}$. The condition that $E(\mathbf{X}_0'\mathbf{Y})$ is the same for $(\mathbf{X}_0, \sigma^2\mathbf{I})$ and $(\mathbf{X}, \boldsymbol{\Sigma})$ implies that

$$\mathbf{X} = \mathbf{X}_0 + \mathbf{Z}_0\mathbf{G}, \tag{2.9}$$

for some $\mathbf{G}$. If $\mathbf{X}_0'\mathbf{Y}$ is optimal for $(\mathbf{X}, \boldsymbol{\Sigma})$, then

$$C(\mathbf{X}_0'\mathbf{Y}, \mathbf{Z}'\mathbf{Y} \mid \mathbf{X}, \boldsymbol{\Sigma}) = \mathbf{X}_0'\boldsymbol{\Sigma}\mathbf{Z} = \mathbf{0},$$

where $\mathbf{Z} = \mathbf{X}^{\perp}$. We write

$$\boldsymbol{\Sigma} = \mathbf{X}_0\boldsymbol{\Sigma}_1\mathbf{X}_0' + \mathbf{Z}_0\boldsymbol{\Sigma}_2\mathbf{Z}_0' + \mathbf{X}_0\boldsymbol{\Sigma}_3\mathbf{Z}_0' + \mathbf{Z}_0\boldsymbol{\Sigma}_3'\mathbf{X}_0', \tag{2.10}$$

where $\boldsymbol{\Sigma}_1$ and $\boldsymbol{\Sigma}_2$ are symmetrical, as in Rao (1968, equation 2.8). Then

$$\mathbf{X}_0'\boldsymbol{\Sigma}\mathbf{Z} = \mathbf{X}_0'(\mathbf{X}_0\boldsymbol{\Sigma}_1\mathbf{X}_0' + \mathbf{X}_0\boldsymbol{\Sigma}_3\mathbf{Z}_0')\mathbf{Z} = \mathbf{0} \Rightarrow \mathbf{X}_0\boldsymbol{\Sigma}_1\mathbf{X}_0'\mathbf{X}_0 + \mathbf{Z}_0\boldsymbol{\Sigma}_3'\mathbf{X}_0'\mathbf{X}_0$$

$$= \mathbf{X}\mathbf{M} = \mathbf{X}_0\mathbf{M} + \mathbf{Z}_0\mathbf{G}\mathbf{M} \Rightarrow \mathbf{X}_0\boldsymbol{\Sigma}_1\mathbf{X}_0'\mathbf{X}_0 = \mathbf{X}_0\mathbf{M}, \quad \mathbf{X}_0\boldsymbol{\Sigma}_1\mathbf{X}_0' = \mathbf{X}_0\mathbf{M}(\mathbf{X}_0'\mathbf{X}_0)^-\mathbf{X}_0',$$

$$\mathbf{Z}_0\boldsymbol{\Sigma}_3'\mathbf{X}_0'\mathbf{X}_0 = \mathbf{Z}_0\mathbf{G}\mathbf{M}, \quad \mathbf{Z}_0\boldsymbol{\Sigma}_3'\mathbf{X}_0' = \mathbf{Z}_0\mathbf{G}\mathbf{M}(\mathbf{X}_0'\mathbf{X}_0)^-\mathbf{X}_0'.$$

Writing $\mathbf{A} = \mathbf{M}(\mathbf{X}_0'\mathbf{X}_0)^-$, $\mathbf{B} = \boldsymbol{\Sigma}_2$, $\boldsymbol{\Sigma}$ can be written in the form (2.8).

NOTE 1. In Corollary 2 to Lemma 2.1, it was noted that $\mathbf{X} = \mathbf{X}_0$ when the rank of $\mathbf{X}_0$ is full and $\mathbf{\Sigma}$ is restricted to the form $\sigma^2\mathbf{I}$. This result need not be true, when a general $\mathbf{\Sigma}$, as in (2.10), is considered.

NOTE 2. Lemma 2.2 asserts that, when $\mathbf{X}$ and $\mathbf{\Sigma}$ are as in (2.7, 2.8), a BLUE of an estimable parametric function under $(\mathbf{X}_0, \sigma^2\mathbf{I})$ is also a BLUE under $(\mathbf{X}, \mathbf{\Sigma})$. But this does not imply that the minimum variances attained in the two models are the same. To compare the variances let us first compute the dispersion matrices of $\mathbf{X}_0'\mathbf{Y}$ under the two models.

$$D(\mathbf{X}_0'\mathbf{Y} \mid \mathbf{X}_0, \sigma^2\mathbf{I}) = \sigma^2\mathbf{X}_0'\mathbf{X}_0,$$

$$D(\mathbf{X}_0'\mathbf{Y} \mid \mathbf{X}, \mathbf{\Sigma} \text{ as in } 2.8) = \mathbf{X}_0'\mathbf{X}_0\mathbf{A}\mathbf{X}_0'\mathbf{X}_0.$$

If the variances of a BLUE are to be equal, a necessary and sufficient condition is

$$\sigma^2\mathbf{X}_0'\mathbf{X}_0 = \mathbf{X}_0'\mathbf{X}_0\mathbf{A}\mathbf{X}_0'\mathbf{X}_0, \tag{2.11}$$

or $\mathbf{A} = \sigma^2(\mathbf{X}_0'\mathbf{X}_0)^-$, while $\mathbf{B}$ and $\mathbf{G}$ in (2.8) can be arbitrary.

LEMMA 2.3. *Let $\mathbf{P}$ be a matrix of order $m \times k$ such that $\mathfrak{M}(\mathbf{P}) \subset \mathfrak{M}(\mathbf{X}_0')$ and $R(\mathbf{P}) = k$. A necessary and sufficient condition for $\mathbf{L}'\mathbf{Y} = \mathbf{P}'(\mathbf{X}_0'\mathbf{X}_0)^-\mathbf{X}_0'\mathbf{Y}$ to be the* BLUEs *for $\mathbf{P}'\boldsymbol{\beta}$ under $(\mathbf{X}, \sigma^2\mathbf{I})$ is that*

$$\mathbf{X} = \mathbf{X}_0 + [\mathbf{I} - (\mathbf{L}\mathbf{L}^-)'][\mathbf{C}\mathbf{B}^- + \mathbf{D}(\mathbf{I} - \mathbf{B}\mathbf{B}^-)], \tag{2.12}$$

where $\mathbf{B} = (\mathbf{P}^-)'\mathbf{L}'\mathbf{L}$, $\mathbf{C} = \mathbf{L} - \mathbf{X}_0\mathbf{B}$ and $\mathbf{D}$ an arbitrary matrix of order $n \times m$.

PROOF OF SUFFICIENCY. The sufficiency part follows from the fact that $\mathbf{L}'\mathbf{X} = \mathbf{L}'\mathbf{X}_0 = \mathbf{P}'$ and $\mathbf{X}\mathbf{B} = \mathbf{X}_0\mathbf{B} + [\mathbf{I} - (\mathbf{L}\mathbf{L}^-)']\mathbf{C} = \mathbf{X}_0\mathbf{B} + \mathbf{C} = \mathbf{L}$ since $R(\mathbf{P}) = k \Rightarrow R(\mathbf{L}) = k \Rightarrow R(\mathbf{B}) = k \Rightarrow \mathbf{B}^-\mathbf{B} = \mathbf{I}$, and $\mathbf{L}'\mathbf{C} = \mathbf{L}'\mathbf{L} - \mathbf{L}'\mathbf{X}_0\mathbf{B} = \mathbf{L}'\mathbf{L} - \mathbf{P}'\mathbf{B} = \mathbf{0}$.

PROOF OF NECESSITY. To establish the necessity part note that $E(\mathbf{L}'\mathbf{Y} \mid \mathbf{Y}, \mathbf{X}\boldsymbol{\beta}, \sigma^2\mathbf{I}) = \mathbf{P}'\boldsymbol{\beta} = \mathbf{L}'(\mathbf{X} - \mathbf{X}_0) = \mathbf{0} \Rightarrow \mathbf{X} = \mathbf{X}_0 + [\mathbf{I} - (\mathbf{L}\mathbf{L}^-)']\mathbf{G}$. Further, the fact that $\mathbf{L}'\mathbf{Y}$ is BLUE for $\mathbf{P}'\boldsymbol{\beta}$ under $(\mathbf{Y}, \mathbf{X}\boldsymbol{\beta}, \sigma^2\mathbf{I}) \Rightarrow \mathbf{L} = \mathbf{X}\mathbf{B}$ for some $\mathbf{B} \Rightarrow \mathbf{L}'\mathbf{L} = \mathbf{L}'\mathbf{X}\mathbf{B} = \mathbf{P}'\mathbf{B} \Rightarrow \mathbf{B} = (\mathbf{P}^-)'\mathbf{L}'\mathbf{L}$. The rest of the lemma follows from the general solution $(\mathbf{G})$ of the equation $\mathbf{A}\mathbf{G}\mathbf{B} = \mathbf{C}$, given in Theorem 2d of Rao (1967b) substituting $\mathbf{A} = \mathbf{I} - (\mathbf{L}\mathbf{L}^-)'$.

LEMMA 2.4. *Let us consider two alternative models $(\mathbf{X}, \sigma^2\mathbf{I})$ and $(\mathbf{X}, \mathbf{\Sigma})$ where $\mathbf{\Sigma}$ has the general representation $\mathbf{\Sigma} = \mathbf{X}\mathbf{\Sigma}_1\mathbf{X}' + \mathbf{Z}\mathbf{\Sigma}_2\mathbf{Z}' + \mathbf{X}\mathbf{\Sigma}_2\mathbf{Z}' + \mathbf{Z}\mathbf{\Sigma}_3'\mathbf{X}'$. Then the following are true.*

(a) $D(\mathbf{X}'\mathbf{Y} \mid \sigma^2\mathbf{I}) = D(\mathbf{X}'\mathbf{Y} \mid \mathbf{\Sigma}) \Rightarrow \mathbf{\Sigma}_1 = \sigma^2(\mathbf{X}'\mathbf{X})^-$.

(b) *Let $R_0^2 = \min_\beta (\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})'(\mathbf{Y} - \mathbf{X}\boldsymbol{\beta}) = \mathbf{Y}'(\mathbf{I} - \mathbf{P}_X)\mathbf{Y}$. Then* $E[\mathbf{Y}'(\mathbf{I} - \mathbf{P}_X)\mathbf{Y} \mid \sigma^2\mathbf{I}] = E[\mathbf{Y}'(\mathbf{I} - \mathbf{P}_X)\mathbf{Y} \mid \mathbf{\Sigma}] \Rightarrow \text{trace } \mathbf{Z}\mathbf{\Sigma}_2\mathbf{Z}' = (n - r)\sigma^2$ *where r is the rank of $\mathbf{X}$ and n is the number of elements in $\mathbf{Y}$.*

(c) *Let $\mathbf{Y}$ have a multivariate normal distribution. Then the distribution R_0^2/σ^2 under $(\mathbf{X}, \mathbf{\Sigma})$ is χ^2 on $(n - r)$ degrees of freedom iff $(\mathbf{Z}\mathbf{\Sigma}_2\mathbf{Z}')/\sigma^2 = (\mathbf{I} - \mathbf{P}_X)$. If further $\mathbf{X}'\mathbf{Y}$ and R_0^2 are to be independently distributed, then $\mathbf{X}\mathbf{\Sigma}_3\mathbf{Z}' = \mathbf{Z}\mathbf{\Sigma}_3'\mathbf{X}' = \mathbf{0}$.*

PROOF. The result (a) is easily established. To prove (b), we observe that

$$E[\mathbf{Y}'(\mathbf{I}-\mathbf{P}_X)\mathbf{Y}\mid\mathbf{\Sigma}] = \text{trace}\,[(\mathbf{I}-\mathbf{P}_X)\mathbf{\Sigma}] = \text{trace}\,(\mathbf{Z\Sigma}_2\mathbf{Z}' + \mathbf{Z\Sigma}_3\mathbf{X}') = \text{trace}\,\mathbf{Z\Sigma}_2\mathbf{Z}'. \tag{2.13}$$

Since $E(\mathbf{Y}'(\mathbf{I}-\mathbf{P}_X)\mathbf{Y}\mid\sigma^2\mathbf{I}) = (n-r)\sigma^2$, the result (b) is established.

The necessary and sufficient condition for $\mathbf{Y}'(\mathbf{I}-\mathbf{P}_X)\mathbf{Y}/\sigma^2$ to have a χ^2-distribution is (using the condition on page 443 of Rao, 1965)

$$\begin{aligned}\mathbf{\Sigma}(\mathbf{I}-\mathbf{P}_X)\mathbf{\Sigma}(\mathbf{I}-\mathbf{P}_X)\mathbf{\Sigma} &= \sigma^2\mathbf{\Sigma}(\mathbf{I}-\mathbf{P}_X)\mathbf{\Sigma}\\ &\Leftrightarrow (\mathbf{Z\Sigma}_2\mathbf{Z}' + \mathbf{X\Sigma}_3\mathbf{Z}')(\mathbf{Z\Sigma}_2\mathbf{Z}')(\mathbf{Z\Sigma}_2\mathbf{Z}' + \mathbf{Z\Sigma}_3{}'\mathbf{X}')\\ &= \sigma^2(\mathbf{Z\Sigma}_2\mathbf{Z}' + \mathbf{X\Sigma}_3\mathbf{Z}')(\mathbf{Z\Sigma}_2\mathbf{Z}' + \mathbf{Z\Sigma}_3{}'\mathbf{X}')\\ &\Leftrightarrow \mathbf{Z}'\mathbf{Z\Sigma}_2\mathbf{Z}'\mathbf{Z\Sigma}_2\mathbf{Z}'\mathbf{Z\Sigma}_2\mathbf{Z}'\mathbf{Z} = \sigma^2\mathbf{Z}'\mathbf{Z\Sigma}_2\mathbf{Z}'\mathbf{Z\Sigma}_2\mathbf{Z}'\mathbf{Z}\\ &\Leftrightarrow (\mathbf{Z\Sigma}_2\mathbf{Z}')(\mathbf{Z\Sigma}_2\mathbf{Z}')(\mathbf{Z\Sigma}_2\mathbf{Z}') = \sigma^2(\mathbf{Z\Sigma}_2\mathbf{Z}')(\mathbf{Z\Sigma}_2\mathbf{Z}')\\ &\Leftrightarrow (\mathbf{Z\Sigma}_2\mathbf{Z}')/\sigma^2 \text{ is idempotent.}\end{aligned} \tag{2.14}$$

The df of χ^2 is (see page 443 Rao, 1965)

$$\text{trace}\,(\mathbf{I}-\mathbf{P}_X)\mathbf{\Sigma}/\sigma^2 = \text{trace}\,(\mathbf{Z\Sigma}_2\mathbf{Z}' + \mathbf{Z\Sigma}_3\mathbf{X}')/\sigma^2 = \text{trace}\,\mathbf{Z\Sigma}_2\mathbf{Z}'/\sigma^2. \tag{2.15}$$

If trace $\mathbf{Z\Sigma}_2\mathbf{Z}' = (n-r)\sigma^2$, then we should have

$$\mathbf{Z\Sigma}_2\mathbf{Z}' = \sigma^2(\mathbf{I}-\mathbf{P}_X). \tag{2.16}$$

If $\mathbf{Z}'\mathbf{Y}$ and $\mathbf{Y}'(\mathbf{I}-\mathbf{P}_X)\mathbf{Y}$ are to be independently distributed, then $\mathbf{X}'\mathbf{\Sigma}(\mathbf{I}-\mathbf{P}_X) = \mathbf{0} \Rightarrow \mathbf{X\Sigma}_3\mathbf{Z}' = \mathbf{Z\Sigma}_3{}'\mathbf{X}' = \mathbf{0}$. Thus (c) is proved.

The following table gives the necessary and sufficient conditions on $\mathbf{\Sigma}$ for different procedures in the simple least squares theory (i.e. assuming $\mathbf{\Sigma} = \sigma^2\mathbf{I}$) to be optimal or valid.

Property	Representation of $\mathbf{\Sigma}$
(i) Every SLSE is BLUE	$\mathbf{X\Sigma}_1\mathbf{X}' + \mathbf{Z\Sigma}_2\mathbf{Z}'$
(ii) Expression for variance of a SLSE remains the same	$\sigma^2\mathbf{P}_X + \mathbf{Z\Sigma}_2\mathbf{Z}' + \mathbf{X\Sigma}_3\mathbf{Z}' + \mathbf{Z\Sigma}_3{}'\mathbf{X}'$
(iii) R_0^2/σ^2 is a χ^2 on $(n-r)$ df	$\mathbf{X\Sigma}_1\mathbf{X}' + \sigma^2(\mathbf{I}-\mathbf{P}_X) + \mathbf{X\Sigma}_3\mathbf{Z}' + \mathbf{Z\Sigma}_3{}'\mathbf{X}'$
(iv) Every SLSE and R_0^2 are independently distributed	$\mathbf{X\Sigma}_1\mathbf{X}' + \mathbf{Z\Sigma}_2\mathbf{Z}'$
(v) In addition to (iv), R_0^2/σ^2 is a χ^2 on $(n-r)$ df	$\mathbf{X\Sigma}_1\mathbf{X}' + \sigma^2(\mathbf{I}-\mathbf{P}_X)$
(vi) In addition to (v), (ii) is satisfied	$\sigma^2\mathbf{I}$
(vii) In addition to (v), the variance of a particular SLSE, say that of $\mathbf{p}'\boldsymbol{\beta}$ is the same	$\sigma^2\mathbf{I} + \mathbf{XAX}'$ where $\mathbf{p}'\mathbf{Ap} = 0$

From the table we observe that while some of the procedures based on simple least squares theory are valid for a wider class of $\mathbf{\Sigma}$, for the full battery of procedures on estimation and testing to be applicable (case vi), it is necessary that $\mathbf{\Sigma} = \sigma^2\mathbf{I}$. Case (vii) shows that if the procedures are to be valid for particular parametric functions, then $\mathbf{\Sigma}$ can belong to a wider class. A well known example which falls in this category is the treatment of two way classification (mixed model) discussed in Rao (1965, page 216).

3. Tests of linear hypotheses when (2.1) **holds.** Consider a parametric function $\mathbf{p}'\boldsymbol{\beta}$ which is estimable under the model $(\mathbf{Y}, \mathbf{X}_0\boldsymbol{\beta}, \sigma^2\mathbf{I})$. It is clear that if the true model $(\mathbf{Y}, \mathbf{X}\boldsymbol{\beta}, \sigma^2\mathbf{I})$ satisfies the conditions of Lemma 2.1, the expression for the BLUE of $\mathbf{p}'\boldsymbol{\beta}$ and for its variance as well remain unchanged in either case. Notice, however, that if R_0^2 denotes the residual sum of squares obtained under $(\mathbf{Y}, \mathbf{X}_0\boldsymbol{\beta}, \sigma^2\mathbf{I})$

$$
\begin{aligned}
E[\mathbf{R}_0^2 \mid \mathbf{X}\boldsymbol{\beta}, \sigma^2\mathbf{I}] &= E[\operatorname{tr} \mathbf{Y}'(\mathbf{I} - \mathbf{P}_{X_0})\mathbf{Y} \mid \mathbf{X}\boldsymbol{\beta}, \sigma^2\mathbf{I}] \\
&= E[\operatorname{tr} (\mathbf{I} - \mathbf{P}_{X_0})\mathbf{Y}\mathbf{Y}' \mid \mathbf{X}\boldsymbol{\beta}, \sigma^2\mathbf{I}] \\
&= \operatorname{tr} (\mathbf{I} - \mathbf{P}_{X_0})(\sigma^2\mathbf{I} + \mathbf{X}\boldsymbol{\beta}\boldsymbol{\beta}'\mathbf{X}') \qquad (3.1) \\
&= (n - r)\sigma^2 + \boldsymbol{\beta}'\mathbf{X}'(\mathbf{I} - \mathbf{P}_{X_0})\mathbf{X}\boldsymbol{\beta} \\
&= (n - r)\sigma^2 + \boldsymbol{\beta}'\mathbf{A}'(\mathbf{I} - \mathbf{P}_{X_0})\mathbf{A}\boldsymbol{\beta}
\end{aligned}
$$

which is equal to $(n - r)\sigma^2$ if and only if $(\mathbf{I} - \mathbf{P}_{X_0})\mathbf{A}\boldsymbol{\beta} = \mathbf{0}$ that is $\mathbf{X}\boldsymbol{\beta} = \mathbf{X}_0\boldsymbol{\beta}$.

This shows that if the two models are distinct (a) $R_0^2/(n - r)$ overestimates σ^2 and (b) R_0^2/σ^2 is distributed as noncentral chi-square on $(n - r)$ df, with the noncentrality parameter $\lambda = \boldsymbol{\beta}'\mathbf{A}'(\mathbf{I} - \mathbf{P}_{X_0})\mathbf{A}\boldsymbol{\beta}/\sigma^2$, independently of the BLUE $\mathbf{p}'\hat{\boldsymbol{\beta}}$. Hence

$$(\mathbf{p}'\hat{\boldsymbol{\beta}} - \mathbf{p}'\boldsymbol{\beta})/[\mathbf{p}'(\mathbf{X}_0'\mathbf{X}_0)^-\mathbf{p}R_0^2/(n - r)]^{\frac{1}{2}}$$

is distributed as the ratio of a standard normal variable and an independent root mean (noncentral) chi-square on $(n - r)$ df. Also the usual F-statistic, computed for testing several linear hypotheses on unknown parameters, is, in the null case, distributed as the ratio of a (central) mean chi-square and an independent mean (noncentral) chi-square on $(n - r)$ df. For various values of the noncentrality parameter λ, the following table gives the true level attained by the F-test under the model $(\mathbf{X}, \sigma^2\mathbf{I})$ when 1 per cent and 5 per cent critical values under the model $(\mathbf{X}_0, \sigma^2\mathbf{I})$ are used.

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TABLE 1

Table showing the actual level attained by the variance ratio test by using the tabulated critical value for 1% level of significance

n_1 = df for numerator; n_2 = df for denominator

n_1	$\lambda = 1$	$\lambda = 2$	$\lambda = 3$	$\lambda = 4$	$\lambda = 5$	$\lambda = 6$
			$\alpha = 1\%, n_2 = 10$			
1	.0076	.0058	.0045	.0034	.0026	.0020
2	.0074	.0055	.0041	.0030	.0022	.0016
3	.0073	.0053	.0038	.0028	.0020	.0015
4	.0072	.0052	.0037	.0027	.0019	.0014
5	.0071	.0051	.0036	.0026	.0018	.0013
			$\alpha = 1\%, n_2 = 20$			
1	.0085	.0073	.0062	.0053	.0046	.0039
2	.0083	.0069	.0058	.0048	.0040	.0033
3	.0082	.0067	.0055	.0045	.0037	.0030
4	.0081	.0065	.0053	.0043	.0034	.0028
5	.0080	.0064	.0051	.0041	.0033	.0026
			$\alpha = 1\%, n_2 = 30$			
1	.0089	.0080	.0072	.0064	.0058	.0052
2	.0088	.0077	.0067	.0059	.0052	.0045
3	.0086	.0075	.0065	.0056	.0048	.0042
4	.0086	.0073	.0063	.0053	.0046	.0039
5	.0085	.0072	.0061	.0052	.0044	.0037
			$\alpha = 1\%, n_2 = 40$			
1	.0092	.0084	.0077	.0071	.0065	.0060
2	.0090	.0081	.0073	.0066	.0060	.0054
3	.0089	.0080	.0071	.0063	.0056	.0050
4	.0088	.0078	.0069	.0061	.0054	.0048
5	.0088	.0077	.0068	.0059	.0052	.0046
			$\alpha = 5\%, n_2 = 10$			
1	.0414	.0343	.0285	.0236	.0196	.0163
2	.0399	.0319	.0254	.0203	.0162	.0129
3	.0391	.0305	.0239	.0186	.0145	.0113
4	.0385	.0297	.0228	.0176	.0135	.0104
5	.0381	.0291	.0221	.0168	.0128	.0097
			$\alpha = 5\%, n_2 = 20$			
1	.0451	.0406	.0367	.0331	.0299	.0270
2	.0439	.0386	.0339	.0298	.0262	.0230
3	.0432	.0374	.0323	.0279	.0241	.0208
4	.0427	.0365	.0311	.0265	.0226	.0193
5	.0423	.0358	.0302	.0255	.0215	.0182

TABLE 1—*Continued*

n_1	$\lambda = 1$	$\lambda = 2$	$\lambda = 3$	$\lambda = 4$	$\lambda = 5$	$\lambda = 6$
			$\alpha = 5\%, n_2 = 30$			
1	.0466	.0433	.0404	.0376	.0350	.0327
2	.0457	.0417	.0381	.0348	.0318	.0291
3	.0451	.0407	.0367	.0331	.0298	.0269
4	.0447	.0399	.0356	.0318	.0284	.0253
5	.0443	.0393	.0348	.0308	.0273	.0241
			$\alpha = 5\%, n_2 = 40$			
1	.0473	.0448	.0425	.0402	.0381	.0361
2	.0466	.0435	.0406	.0379	.0353	.0329
3	.0462	.0426	.0394	.0363	.0335	.0309
4	.0458	.0420	.0384	.0352	.0322	.0295
5	.0455	.0414	.0377	.0343	.0311	.0283

REFERENCES

[1] KRUSKAL, W. (1968). When are the Gauss-Markoff and least squares estimators identical? A coordinate free approach. *Ann. Math. Statist.* **39** 70–75.

[2] MITRA, S. K. and RAO, C. RADHAKRISHNA (1968). Some results in estimation and tests of linear hypotheses under the Gauss-Markoff model. *Sankhyā, Ser. A* **30** 281–290.

[3] RAO, C. RADHAKRISHNA (1962). A note on a generalized inverse of a matrix with applications to problems in mathematical statistics. *J. Roy. Statist. Soc. Ser. B* **24** 152–158.

[4] RAO, C. RADHAKRISHNA (1965). *Linear Statistical Inference and its Applications*. Wiley, New York.

[5] RAO, C. RADHAKRISHNA (1966). Generalized inverse for matrices and its application in mathematical statistics. *Research Papers in Statistics* (Festchrift for J. Neyman). 263–280. Wiley, New York.

[6] RAO, C. RADHAKRISHNA (1967a). Least squares theory using an estimated dispersion matrix and its application to measurement of signals. *Proc. Fifth Berkeley Symp. Math. Statist. Prob.* **1** 355–372 Univ. of California Press.

[7] RAO, C. RADHAKRISHNA (1967b). Calculus of generalized inverse of matrices, Part I: General theory. *Sankhyā Ser. A* **29** 317–342.

[8] RAO, C. RADKHAKRISHNA (1968). A note on a previous lemma in the theory of least squares and some further results. *Sankhyā Ser. A* **30** 245–252.

[9] WATSON, G. S. (1967). Linear least squares regression. *Ann. Math. Statist.* **38** 1679–1699.

[10] ZYSKIND, G. (1967). On canonical forms, negative covariance matrices and best and simple least squares linear estimator in linear models. *Ann. Math. Statist.* **38** 1092–1110.