# On best affine unbiased covariance-preserving prediction of factor scores

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#### **Abstract**

This paper gives a generalization of results presented by ten Berge, Krijnen, Wansbeek & Shapiro. They examined procedures and results as proposed by Anderson & Rubin, McDonald, Green and Krijnen, Wansbeek & ten Berge. We shall consider the same matter, under weaker rank assumptions. We allow some moments, namely the variance  $\Omega$  of the observable scores vector and that of the unique factors,  $\Psi$ , to be singular. We require  $T'\Psi T>0$ , where  $T\Lambda T'$  is a Schur decomposition of  $\Omega$ . As usual the variance of the common factors,  $\Phi$ , and the loadings matrix A will have full column rank.

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## 1 Introduction

We consider the factor model  $y = \mu_y + Af + \varepsilon$ , where y is a  $p \times 1$  vector of observable random variables called «scores», f is an  $m \times 1$  vector of non-observable random variables called «common factors», A is a  $p \times m$  matrix of full column rank whose elements are called «factor loadings» and  $\varepsilon$  is a  $p \times 1$  vector of non-observable random variables called «unique factors». The usual moment definitions and assumptions are

$$E(\varepsilon) = 0$$
,  $E(f) = 0$ ,  $E(y) = \mu_y$ ,  $D(\varepsilon) = \Psi$ ,  $D(f) = \Phi$ ,  $C(f, \varepsilon) = 0$ .

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This yields the moment structure

$$\Omega = A\Phi A' + \Psi,$$

where  $\Omega = D(y)$  and  $\Psi$  can be singular,  $\Phi$  and A have full column rank. Notice that

$$\mathcal{M}(A) \subset \mathcal{M}(\Omega).$$
 (1.1)

The following additional assumption is made:

$$T'\Psi T>0.$$

It is inspired by the Schur decomposition  $\Omega = T\Lambda T'$ , with  $T'T = I_r$  and diagonal  $\Lambda > 0$ . Obviously  $p \ge r > m$ .

In two recent publications Krijnen, Wansbeek & ten Berge (1996) and ten Berge, Krijnen, Wansbeek & Shapiro (1999) studied the problem of best linear prediction of f given y, subject to the constraint  $E\hat{f}\hat{f}'=Eff'$ , where  $\hat{f}=B'y$  is their predictor function. Vectors f and g have a simultaneous distribution. The two expectations are taken with respect to this distribution.

The constraint  $E\hat{f}\hat{f}' = Eff'$  is mistakenly referred to as «correlation-preserving». We shall call it «covariance-preserving», although at face value only the RHS expression is a variance matrix. We shall use an affine predictor function  $\hat{f} = a + B'y$ . It will be shown that  $a + B'\mu_y = 0$ . Hence the predictor function will become  $\hat{f} = B'(y - \mu_y)$  which is linear and unbiased. Consequently the LHS expression will become a variance matrix.

In their article ten Berge *et al.* (1999) examine three prediction procedures, due to McDonald (1981) —who generalized a procedure proposed by Anderson & Rubin (1956)—, Green (1969) and Krijnen *et al.* (1996), respectively.

We shall consider the same three procedures. The second and third are based on the mean-squared-error matrix  $M = E(\hat{f} - f)(\hat{f} - f)'$ . Where Green minimizes its trace, tr M, Krijnen  $et\ al$ . minimize its determinant, |M|. McDonald uses a different though related criterion  $\operatorname{tr} \Psi^{-1} E(y - \mu_y - A\hat{f})(y - \mu_y - A\hat{f})'$  which he minimizes. Note that these authors assume  $\Psi > 0$ , hence  $\Omega > 0$ . ten Berge  $et\ al$ . conclude that McDonald's and Krijnen  $et\ al$ .'s solutions for B coincide.

In the present paper we shall again consider the above-mentioned procedures, under weaker rank assumptions. We shall show that the MSE matrix M is positive definite. Minimization of the trace and the determinant of M yields immediately  $a + B'\mu_y = 0$ . Minimization of McDonald's criterion function yields the same result. As mathematical methods we use a Kristof-type theorem and a matrix inequality developed by Zhang (1999). Finally we show that 1)  $\hat{f}_G$ , the Green predictor and  $\hat{f}_K$ , the Krijnen *et al.* predictor coincide when  $\Phi$  and  $A'\Omega^+A$  commute, 2)  $\hat{f}_M$ , the McDonald predictor and  $\hat{f}_K$  coincide when  $\Psi$  and  $A\Phi A'$  commute.

# 2 A Kristof-type theorem

Two of the three criterion functions can be seen to belong to the class  $\operatorname{tr} P'X$ , where P and X have dimension  $p \times m$ . The constant matrix P has rank q. The variable matrix X satisfies the constraint  $X'X = I_m$ . The aim is to maximize  $\operatorname{tr} P'X$  subject to  $X'X = I_m$ . Define then the Lagrangean function

$$\varphi(X) = \operatorname{tr} P'X - \frac{1}{2}\operatorname{tr} L(X'X - I_m),$$

where L is a *symmetric* matrix of multipliers. Symmetry of L is vital. It is justified, of course, by the symmetry of the constraint.

The differential of the function, namely

$$d\varphi = \operatorname{tr} P'dX - \operatorname{tr} LX'dX = \operatorname{tr} (P - XL)'dX$$

has to be zero. This yields the equations

$$P = XL \tag{2.1}$$

$$X'X = I_m \tag{2.2}$$

From these we obtain

$$P'P = L^2 (2.3)$$

$$P = X(P'P)^{\frac{1}{2}} \tag{2.4}$$

Which square root will be selected is still undecided. Consider equation (2.4). As

$$P(P'P)^{+\frac{1}{2}}(P'P)^{\frac{1}{2}} = P$$

it is consistent. The symbol «+» denotes the Moore-Penrose inverse. The symbols «+» and « $\frac{1}{2}$ » are interchangeable in  $(P'P)^{+\frac{1}{2}}$ . The general solution of (2.4) is

$$X_{\circ} = P(P'P)^{+\frac{1}{2}} + Q - Q(P'P)^{\frac{1}{2}}(P'P)^{+\frac{1}{2}}, \quad Q \text{ arbitrary}$$
 (2.5)

When we use the singular-value decomposition  $P = F_1 \Gamma_1^{\frac{1}{2}} G_1'$ , with  $F_1' F_1 = G_1' G_1 = I_q$  and (diagonal)  $\Gamma_1^{\frac{1}{2}} > 0$ , we can write the solution as

$$X_{\circ} = F_1 G_1' + Q (I_m - G_1 G_1')$$
 (2.6)

It follows from (2.5) that

$$\operatorname{tr} P' X_{\circ} = \operatorname{tr} (P' P)^{\frac{1}{2}}.$$
 (2.7)

As we look for a *maximum*, we have to take the *positive* definite square root  $(P'P)^{\frac{1}{2}}$ . The solution  $X_{\circ}$  is *not* unique, unless q = m. In that case it can be written as

$$X_{\circ} = P(P'P)^{-\frac{1}{2}} = F_1 G_1' \tag{2.8}$$

For the connaisseurs we shall examine the second differential

$$d^2\varphi = -\operatorname{tr}(dX)L(dX)' \tag{2.9}$$

When this expression is *negative* for all  $dX \neq 0$  satisfying  $(dX)'X_{\circ} + X'_{\circ}dX = 0$ , a maximum has been found. The choice  $L = (P'P)^{\frac{1}{2}} > 0$  guarantees this.

## 3 The Green procedure

As stated we use the MSE matrix  $M = E(\hat{f} - f)(\hat{f} - f)' = (a + B'\mu_y)(a + B'\mu_y)' + B'\Omega B + \Phi - B'A\Phi - \Phi A'B$ . Obviously  $a + B'\mu_y = 0$ , as we have to minimize trM. As a consequence  $E\hat{f}\hat{f}' = B'\Omega B$ . Imposition of the constraint  $E\hat{f}\hat{f}' = Eff'$  yields then  $M = 2\Phi - B'A\Phi - \Phi A'B$ . Green (1969) defines the problem:

$$\min_{B} \operatorname{tr} (2\Phi - B'A\Phi - \Phi A'B) \quad \text{subject to } B'\Omega B = \Phi.$$

We introduce  $C' = \Phi^{-\frac{1}{2}} B' \Omega^{\frac{1}{2}}$ . Clearly  $C'C = I_m$ . This yields the equivalent problem

$$\max_{C} \operatorname{tr} \Phi^{\frac{3}{2}} A' \Omega^{+\frac{1}{2}} C \quad \text{subject to } C'C = I_{m}$$

We used:  $A'\Omega^{+\frac{1}{2}}C\Phi^{\frac{1}{2}} = R'\Omega^{\frac{1}{2}}\Omega^{+\frac{1}{2}}\Omega^{\frac{1}{2}}B = R'\Omega^{\frac{1}{2}}B = A'B$ , with  $A = \Omega^{\frac{1}{2}}R$  due to (1.1). Application of the Kristof-type theorem gives the solution

$$C_G = \Omega^{+\frac{1}{2}} A \Phi^{\frac{3}{2}} \left( \Phi^{\frac{3}{2}} A' \Omega^+ A \Phi^{\frac{3}{2}} \right)^{-\frac{1}{2}},$$

from which follows the solution

$$B_G = \Omega^+ A \Phi^{\frac{3}{2}} \left( \Phi^{\frac{3}{2}} A' \Omega^+ A \Phi^{\frac{3}{2}} \right)^{-\frac{1}{2}} \Phi^{\frac{1}{2}} + \left( I_p - \Omega^{+\frac{1}{2}} \Omega^{\frac{1}{2}} \right) Q, \quad Q \text{ arbitrary.}$$

The arbitrary component disappears in the predictor expression  $B'_G(y - \mu_y)$ , because  $\left(I_p - \Omega^{\frac{1}{2}}\Omega^{+\frac{1}{2}}\right)\left(y - \mu_y\right) = 0$  with probability one (w. p. 1).

Hence we get as predictor

$$\hat{f}_G = \Phi^{\frac{1}{2}} \left( \Phi^{\frac{3}{2}} A' \Omega^+ A \Phi^{\frac{3}{2}} \right)^{-\frac{1}{2}} \Phi^{\frac{3}{2}} A' \Omega^+ \left( y - \mu_y \right).$$

The reader can verify that  $A'\Omega^+A > 0$ .

An alternative expression is

$$C_G = F_2 G_2'$$

where we have used the singular-value decomposition

$$\Omega^{+\frac{1}{2}}A\Phi^{\frac{3}{2}}=F_2\Gamma_2^{\frac{1}{2}}G_2',$$

with  $F_2'F_2 = G_2'G_2 = G_2G_2' = I_m$ . Use was made of the fact that  $\Omega^{+\frac{1}{2}}A$  has full column rank (m).

For nonsingular  $\Omega$  the solution becomes that given by ten Berge *et al.* (1999) in their presentation, namely between (6) and (7).

## 4 The McDonald procedure

This approach is based on the weighted-least-squares function

$$\operatorname{tr} \Psi^+ E \left( y - \mu_y - A \hat{f} \right) \left( y - \mu_y - A \hat{f} \right)'$$
.

Clearly

$$\begin{split} E\left(y-\mu_{y}-A\hat{f}\right)\left(y-\mu_{y}-A\hat{f}\right)' &= \left(I_{p}-AB'\right)\Omega\left(I_{p}-BA'\right) + \\ &+ A\left(a+B'\mu_{y}\right)\left(a+B'\mu_{y}\right)'A'. \end{split}$$

Again we find that  $a + B'\mu_{y} = 0$ , now having to minimize

$$\operatorname{tr} \Psi^+ E \left( y - \mu_y - A \hat{f} \right) \left( y - \mu_y - A \hat{f} \right)'$$
.

Notice that  $A'\Psi^+A > 0$ .

Imposition of the constraint  $E\hat{f}\hat{f}' = Eff'$  leads to the problem of minimizing

$$\operatorname{tr} \Psi^+ (I_p - AB') \Omega (I_p - BA')$$
 subject to  $B'\Omega B = \Phi$ .

Using  $C' = \Phi^{-\frac{1}{2}} B' \Omega^{\frac{1}{2}}$  we define the problem:

$$\max_{C} \operatorname{tr} \Phi^{\frac{1}{2}} A' \Psi^{+} \Omega^{\frac{1}{2}} C \quad \text{subject to } C'C = I_{m}.$$

Application of the Kristof-type theorem yields the solution

$$C_M = \Omega^{\frac{1}{2}} \Psi^+ A \Phi^{\frac{1}{2}} \left( \Phi^{\frac{1}{2}} A' \Psi^+ \Omega \Psi^+ A \Phi^{\frac{1}{2}} \right)^{-\frac{1}{2}},$$

from which follows the solution

$$B_{M} = \Omega^{+\frac{1}{2}} \Omega^{\frac{1}{2}} \Psi^{+} A \Phi^{\frac{1}{2}} \left( \Phi^{\frac{1}{2}} A' \Psi^{+} \Omega \Psi^{+} A \Phi^{\frac{1}{2}} \right)^{-\frac{1}{2}} \Phi^{\frac{1}{2}} + \left( I_{p} - \Omega^{+\frac{1}{2}} \Omega^{\frac{1}{2}} \right) Q, \quad Q \text{ arbitrary.}$$

Finally the predictor turns out to be

$$\hat{f}_{M} = \Phi^{\frac{1}{2}} \left( \Phi^{\frac{1}{2}} A' \Psi^{+} \Omega \Psi^{+} A \Phi^{\frac{1}{2}} \right)^{-\frac{1}{2}} \Phi^{\frac{1}{2}} A' \Psi^{+} \left( y - \mu_{y} \right).$$

Again we used

$$(I_p - \Omega^{\frac{1}{2}} \Omega^{+\frac{1}{2}})(y - \mu_y) = 0$$
 w.p.1.

The reader can verify that  $A'\Psi^+\Omega\Psi^+A > 0$ , using

$$A'\Psi^{+}\Omega\Psi^{+}A = A'\Psi^{+}(A\Phi A' + \Psi)\Psi^{+}A = A'\Psi^{+}A\Phi A'\Psi^{+}A + A'\Psi^{+}A.$$

An alternative expression is

$$C_M = F_3 G_3'$$

where

$$\Omega^{\frac{1}{2}}\Psi^{+}A\Phi^{\frac{1}{2}} = F_{3}\Gamma_{3}^{\frac{1}{2}}G_{3}',$$

with 
$$F_3'F_3 = G_3'G_3 = G_3G_3' = I_m$$
.

For nonsingular  $\Omega$  the solution becomes that given by ten Berge *et al.* (1999) in their presentation, namely between (4) and (5).

#### 5 The Krijnen et al. procedure

Like Green's this approach uses the MSE matrix M of  $\hat{f}$ . Instead of tr  $(2\Phi - B'A\Phi - \Phi A'B)$ , Krijnen *et al.* use  $|2\Phi - B'A\Phi - \Phi A'B|$  which has to be minimized. The first thing to do is to prove that  $2\Phi - B'A\Phi - \Phi A'B > 0$ .

We have

$$\begin{split} 2\Phi - B'A\Phi - \Phi A'B &= \Phi^{\frac{1}{2}} \left( 2I_m - \Phi^{-\frac{1}{2}}B'A\Phi^{\frac{1}{2}} - \Phi^{\frac{1}{2}}A'B\Phi^{-\frac{1}{2}} \right) \Phi \\ &= \Phi^{\frac{1}{2}} \left( 2I_m - \Phi^{-\frac{1}{2}}B'\Omega^{\frac{1}{2}}\Omega^{\frac{1}{2}}A\Phi^{\frac{1}{2}} - \Phi^{\frac{1}{2}}A'\Omega^{+\frac{1}{2}}\Omega^{\frac{1}{2}}B\Phi^{-\frac{1}{2}} \right) \Phi^{\frac{1}{2}} \\ &= \Phi^{\frac{1}{2}} \left( 2I_m - C'V - V'C \right) \Phi^{\frac{1}{2}} \\ &= \Phi^{\frac{1}{2}} \left[ (C - V)' (C - V) + (I_m - V'V) \right] \Phi^{\frac{1}{2}} \end{split}$$

where

$$V = \Omega^{+\frac{1}{2}} A \Phi^{\frac{1}{2}}$$
 and hence  $V'V = \Phi^{\frac{1}{2}} A' \Omega^{+} A \Phi^{\frac{1}{2}}$ .

We shall show that all eigenvalues of V'V are positive and less than unity. Pre-(post-) multiply the moment structure  $\Omega = A\Phi A' + \Psi$  by  $\Phi^{\frac{1}{2}}A'\Omega^{+}\left(\Omega^{+}A\Phi^{\frac{1}{2}}\right)$ . This leads to  $\Phi^{\frac{1}{2}}A'\Omega^{+}A\Phi^{\frac{1}{2}} = \left(\Phi^{\frac{1}{2}}A'\Omega^{+}A\Phi^{\frac{1}{2}}\right)^{2} + \Phi^{\frac{1}{2}}A'\Omega^{+}\Psi\Omega^{+}A\Phi^{\frac{1}{2}}$ , hence

$$\Phi^{\frac{1}{2}}A'\Omega^{+}A\Phi^{\frac{1}{2}} > \left(\Phi^{\frac{1}{2}}A'\Omega^{+}A\Phi^{\frac{1}{2}}\right)^{2}$$
,

as  $\Phi^{\frac{1}{2}}A'\Omega^+\Psi\Omega^+A\Phi^{\frac{1}{2}}>0$ , and  $\lambda_i>\lambda_i^2$  where  $\lambda_i$  is any eigenvalue of  $\Phi^{\frac{1}{2}}A'\Omega^+A\Phi^{\frac{1}{2}}$ . This proves the property. Hence  $I_m-V'V>0$ . As  $(C-V)'(C-V)\geqslant 0$  we have shown that  $2\Phi-B'A\Phi-\Phi A'B>0$ .

Hence  $|2\Phi - B'A\Phi - \Phi A'B| > 0$ . Consider then the positive definite matrix  $2I_m - C'V - V'C$ . We use (7.18) in Zhang (1999) which yields

$$C'V + V'C \leq 2U' \left(V'CC'V\right)^{\frac{1}{2}} U$$

where U is an orthogonal matrix.

As  $C'C = I_m$  we have  $CC' \le I_p$ . This in its turn leads to  $V'CC'V \le V'V$ . The latter inequality gives  $(V'CC'V)^{\frac{1}{2}} \le (V'V)^{\frac{1}{2}}$ . See Theorem 2.5.5 in Wang & Chow (1994).

Finally, we have

$$C'V + V'C \leqslant 2U' (V'V)^{\frac{1}{2}} U$$

or equivalently

$$2I_m - C'V - V'C \geqslant 2\left[I_m - U'\left(V'V\right)^{\frac{1}{2}}U\right].$$

From this we derive

$$|2I_m - C'V - V'C| \ge |2[I_m - U'(V'V)^{\frac{1}{2}}U]| = |2[I_m - (V'V)^{\frac{1}{2}}]|.$$

It is easy to see that  $C_K = V(V'V)^{-\frac{1}{2}}$  leads to the equality

$$|2I_m - C'_K V - V'C_K| = |2[I_m - (V'V)^{\frac{1}{2}}]|.$$

Hence  $C_K$  solves the problem. It is not clear whether the solution is unique. In fact,  $C_K$  also solves the related problem

$$\max_{C} \operatorname{tr} V'C \quad \text{subject to } C'C = I_m.$$

The (unique) solution is  $C_K$  by the Kristof-type theorem.

Application of Zhang's (7.18) yields

$$2 \operatorname{tr} V'C = \operatorname{tr} (C'V + V'C) \leq 2 \operatorname{tr} U' (V'V)^{\frac{1}{2}} U = 2 \operatorname{tr} (V'V)^{\frac{1}{2}},$$

which again has solution  $C_K$ . We then get the solution

$$B_K = \Omega^+ A \Phi^{\frac{1}{2}} \left( \Phi^{\frac{1}{2}} A' \Omega^+ A \Phi^{\frac{1}{2}} \right)^{-\frac{1}{2}} \Phi^{\frac{1}{2}} + \left( I_p - \Omega^{+\frac{1}{2}} \Omega^{\frac{1}{2}} \right) Q, \quad Q \text{ arbitrary.}$$

From this follows the unique predictor

$$\hat{f}_K = \Phi^{\frac{1}{2}} \left( \Phi^{\frac{1}{2}} A' \Omega^+ A \Phi^{\frac{1}{2}} \right)^{-\frac{1}{2}} \Phi^{\frac{1}{2}} A' \Omega^+ \left( y - \mu_y \right).$$

For nonsingular  $\Omega$  the solution  $C_K$  coincides with that given by ten Berge *et al.* (1999), namely in (9).

# 6 Equality of $\hat{f}_G$ and $\hat{f}_K$ when $\Phi$ and $A'\Omega^{\dagger}A$ commute

ten Berge *et al.* (1999) showed that  $C_G = C_K$  under their assumptions when  $\Phi$  and  $A'\Omega^{-1}A$  commute. We shall prove that  $\hat{f}_G = \hat{f}_K$  under our milder conditions.

When  $\Phi$  and  $A'\Omega^+A$  commute we have  $\Phi = SMS'$  and  $A'\Omega^+A = SNS'$ , where M and N are positive definite diagonal matrices and S is orthogonal. Hence

$$\Phi^{\frac{3}{2}} \left( \Phi^{\frac{3}{2}} A' \Omega^{+} A \Phi^{\frac{3}{2}} \right)^{-\frac{1}{2}} = S M^{\frac{3}{2}} S' \left( S M^{\frac{3}{2}} S' S N S' S M^{\frac{3}{2}} S' \right)^{-\frac{1}{2}}$$

$$= S M^{\frac{3}{2}} S' \left( S M^{3} N S' \right)^{-\frac{1}{2}} = S M^{\frac{3}{2}} S' S \left( M^{3} N \right)^{-\frac{1}{2}} S'$$

$$= S N^{-\frac{1}{2}} S' = (A' \Omega^{+} A)^{-\frac{1}{2}}.$$

Further  $\Phi^{\frac{1}{2}} \left( \Phi^{\frac{1}{2}} A' \Omega^{+} A \Phi^{\frac{1}{2}} \right)^{-\frac{1}{2}} = (A' \Omega^{+} A)^{-\frac{1}{2}}.$  This yields  $\hat{f}_{G} = \hat{f}_{K} = \Phi^{\frac{1}{2}} \left( A' \Omega^{+} A \right)^{-\frac{1}{2}} A' \Omega^{+} \left( y - \mu_{y} \right).$ 

# 7 Equality of $\hat{f}_M$ and $\hat{f}_K$ when $\Psi$ and $A\Phi A'$ commute

ten Berge *et al.* (1999) showed that  $C_M = C_K$  under their assumptions when  $\Psi$  is nonsingular. Essential is the expression

$$\Omega^{-1} = \Psi^{-1} - \Psi^{-1} A \Phi^{\frac{1}{2}} \left( I_m + \Phi^{\frac{1}{2}} A' \Psi^{-1} A \Phi^{\frac{1}{2}} \right)^{-1} \Phi^{\frac{1}{2}} A' \Psi^{-1}.$$

Under our assumptions  $I_m + \Phi^{\frac{1}{2}}A'\Psi^+A\Phi^{\frac{1}{2}}$  is nonsingular because  $A'\Psi^+A > 0$  which follows from  $T'\Psi T > 0$  and (1.1). When we additionally assume that  $\Psi$  and  $A\Phi A'$  commute we can establish the equality

$$\Omega^{+} = \Psi^{+} - \Psi^{+} A \Phi^{\frac{1}{2}} \left( I_{m} + \Phi^{\frac{1}{2}} A' \Psi^{+} A \Phi^{\frac{1}{2}} \right)^{-1} \Phi^{\frac{1}{2}} A' \Psi^{+}.$$

*Proof.* When  $\Psi$  and  $A\Phi A'$  commute we have  $\Psi = SMS'$  and  $A\Phi A' = SNS'$  where M and N are positive definite diagonal matrices and  $S'S = I_m$ . Further  $A\Phi^{\frac{1}{2}} = SN^{\frac{1}{2}}T'$ , with orthogonal T, a singular-value decomposition. Hence

$$\begin{split} \Psi^{+} &- \Psi^{+} A \Phi^{\frac{1}{2}} \left( I_{m} + \Phi^{\frac{1}{2}} A' \Psi^{+} A \Phi^{\frac{1}{2}} \right)^{-1} \Phi^{\frac{1}{2}} A' \Psi^{+} \\ &= S M^{-1} S' - S M^{-1} S' S N^{\frac{1}{2}} T' \left( I_{m} + T N^{\frac{1}{2}} S' S M^{-1} S' S N^{\frac{1}{2}} T' \right)^{-1} T N^{\frac{1}{2}} S' S M^{-1} S' \\ &= S M^{-1} S' - S M^{-1} N^{\frac{1}{2}} T' \left( I_{m} + T M^{-1} N T' \right)^{-1} T M^{-1} N^{\frac{1}{2}} S' \\ &= S M^{-1} S' - S M^{-1} N^{\frac{1}{2}} T' T \left( I_{m} + M^{-1} N \right)^{-1} T' T M^{-1} N^{\frac{1}{2}} S' \\ &= S M^{-1} S' - S M^{-1} N^{\frac{1}{2}} \left( I_{m} + M^{-1} N \right)^{-1} M^{-1} N^{\frac{1}{2}} S'. \end{split}$$

Further  $\Omega = A\Phi A' + \Psi = S(M+N)S'$ , and  $\Omega^+ = S(M+N)^{-1}S'$ . It is easy to see that

$$(M+N)^{-1} = M^{-1} - M^{-1}N^{\frac{1}{2}} (I_m + M^{-1}N)^{-1} M^{-1}N^{\frac{1}{2}}.$$

This yields the result.

Recall that

$$\hat{f}_{M} = \Phi^{\frac{1}{2}} \left( \Phi^{\frac{1}{2}} A' \Psi^{+} \Omega \Psi^{+} A \Phi^{\frac{1}{2}} \right)^{-\frac{1}{2}} \Phi^{\frac{1}{2}} A' \Psi^{+} (y - \mu_{y})$$

and

$$\hat{f}_K = \Phi^{\frac{1}{2}} \left( \Phi^{\frac{1}{2}} A' \Omega^+ A \Phi^{\frac{1}{2}} \right)^{-\frac{1}{2}} \Phi^{\frac{1}{2}} A' \Omega^+ (y - \mu_y).$$

Consider

$$\Phi^{\frac{1}{2}}A'\Omega^{+}A\Phi^{\frac{1}{2}} = \Phi^{\frac{1}{2}}A'\Psi^{+}A\Phi^{\frac{1}{2}} - \Phi^{\frac{1}{2}}A'\Psi^{+}A\Phi^{\frac{1}{2}} \left(I_{m} + \Phi^{\frac{1}{2}}A'\Psi^{+}A\Phi^{\frac{1}{2}}\right)^{-1} \times \Phi^{\frac{1}{2}}A'\Psi^{+}A\Phi^{\frac{1}{2}}$$

$$= \left(I_{m} + \Phi^{\frac{1}{2}}A'\Psi^{+}A\Phi^{\frac{1}{2}}\right)^{-1}\Phi^{\frac{1}{2}}A'\Psi^{+}A\Phi^{\frac{1}{2}}$$

$$= \left(I_{m} + E\right)^{-1}E,$$

$$\Phi^{\frac{1}{2}}A'\Psi^{+}\Omega\Psi^{+}A\Phi^{\frac{1}{2}} = \Phi^{\frac{1}{2}}A'\Psi^{+}A\Phi A'\Psi^{+}A\Phi^{\frac{1}{2}} + \Phi^{\frac{1}{2}}A'\Psi^{+}A\Phi^{\frac{1}{2}}$$

$$= \Phi^{\frac{1}{2}}A'\Psi^{+}A\Phi^{\frac{1}{2}} + \left(\Phi^{\frac{1}{2}}A'\Psi^{+}A\Phi^{\frac{1}{2}}\right)^{2}$$

$$= E + E^{2},$$

$$\Phi^{\frac{1}{2}}A'\Omega^{+} = \Phi^{\frac{1}{2}}A'\Psi^{+} - \Phi^{\frac{1}{2}}A'\Psi^{+}A\Phi^{\frac{1}{2}} \left(I_{m} + \Phi^{\frac{1}{2}}A'\Psi^{+}A\Phi^{\frac{1}{2}}\right)^{-1}\Phi^{\frac{1}{2}}A'\Psi^{+}$$

$$= \left(I_{m} + \Phi^{\frac{1}{2}}A'\Psi^{+}A\Phi^{\frac{1}{2}}\right)^{-1}\Phi^{\frac{1}{2}}A'\Psi^{+}$$

$$= \left(I_{m} + E\right)^{-1}\Phi^{\frac{1}{2}}A'\Psi^{+},$$

$$\hat{f}_{K} = \Phi^{\frac{1}{2}} \left[\left(I_{m} + E\right)^{-1}E\right]^{-\frac{1}{2}} \left(I_{m} + E\right)^{-1}\Phi^{\frac{1}{2}}A'\Psi^{+} \left(y - \mu_{y}\right),$$
arrly
$$I_{m} = \Phi^{\frac{1}{2}} \left(E + E^{2}\right)^{-\frac{1}{2}}\Phi^{\frac{1}{2}}A'\Psi^{+} \left(y - \mu_{y}\right).$$

Clearly

$$\left[ (I_m + E)^{-1} E \right]^{-\frac{1}{2}} (I_m + E)^{-1} = \left( E + E^2 \right)^{-\frac{1}{2}} \quad \text{as } E > 0.$$

This establishes the equality of  $\hat{f}_K$  and  $\hat{f}_M$ .

#### 8 Comments

- 1. ten Berge *et al.* (1999) claim that the McDonald method is undefined when  $\Psi$  is singular. This is unjustified. What matters is the nonsingularity of  $T'\Psi T$ . We make that assumption. It implies that  $A'\Psi^+A>0$  which we use several times.
- 2. Application of Zhang's result shows immediately that  $C_G$  and  $C_M$  yield the maximum. The Kristof-type theorem shows the *unicity* of the solutions.

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The author is grateful to Götz Trenkler for drawing his attention to Zhang's result (7.18) which was fruitfully applied in Section 5. The reasoning why  $B'\mu_y + a$  should be equal

to zero in all three procedures is due to Albert Satorra. This yields  $\hat{f} = B'(y - \mu_y)$ , an unbiased predictor.

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#### Resum

Es dóna una generalització dels resultats presentats per ten Berge, Krijnen, Wansbeek and Shapiro . Aquests autors examinen mètodes i resultats basats en Anderson i Rubin. Mc Donald, Green i Krijnen, Wansbeek i ten Berge. Considerarem el mateix plantejament però sota condicions de rang més dèbils. Així suposarem que alguns moments, com les matrius de covariàncies  $\Omega$  del vector de mesures observades dels factors comuns i  $\psi$  dels factors únics, siguin singulars. Imposem la condició  $T'\psi T>0$ , essent  $T\Lambda T'$  la descomposició de Schur de  $\Omega$ . Com és usual, suposem que tenen rang màxim per columnes les matrius de covariàncies  $\Phi$  dels factors comuns i la matriu A del model factorial.

MSC: 62H25, 15A24

Paraules clau: anàlisi factorial, mesures de factors, preservació de la covariància, teorema tipus Kristof