

CANONICAL VARIABLES AS OPTIMAL PREDICTORS

BY V. J. YOHAI AND M. S. GARCIA BEN

Universidad de Buenos Aires

Let $\mathbf{X} = (X_1, \dots, X_m)'$ and $\mathbf{Y} = (Y_1, \dots, Y_n)'$ be two random vectors. Given any random vector \mathbf{Z} , let \mathbf{Y}_Z^* be the best linear predictor of \mathbf{Y} based on \mathbf{Z} . Let p be any natural number smaller than m . We consider the problem of finding the p -dimensional random vector $\mathbf{Z} = (Z_1, \dots, Z_p)'$ where each component Z_i is a linear function of \mathbf{X} , which minimizes the determinant of $E(\mathbf{Y} - \mathbf{Y}_Z^*)(\mathbf{Y} - \mathbf{Y}_Z^*)'$. We show that Z_1, \dots, Z_p coincide with the first p canonical variables (except for a nonsingular linear transformation). We also show that the square of the $(p+1)$ th canonical correlation coefficient measures the relative improvement in the prediction of \mathbf{Y} when $p+1$ Z_i 's are used instead of p .

1. Introduction. Let $\mathbf{X} = (X_1, \dots, X_m)'$ and $\mathbf{Y} = (Y_1, \dots, Y_n)'$ be two random vectors and assume $m \leq n$. Assume also that $E(\mathbf{X}) = E(\mathbf{Y}) = \mathbf{0}$ and let

$$\begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}$$

be the covariance matrix of $(\mathbf{X}', \mathbf{Y}')'$, where Σ_{11} and Σ_{22} are nonsingular matrices.

Classically, the problem of canonical correlation consists of finding vectors $\mathbf{b}_1, \dots, \mathbf{b}_m$ in R^m and $\mathbf{c}_1, \dots, \mathbf{c}_n$ in R^n such that if $V_i = \mathbf{b}_i' \mathbf{X}$ and $W_i = \mathbf{c}_i' \mathbf{Y}$ then

(i) V_1, W_1 are the two linear functions of \mathbf{X} and \mathbf{Y} respectively, with variance 1, which have correlation coefficient with maximum absolute value.

(ii) for $i \leq m$, V_i is the linear function of \mathbf{X} with variance 1, uncorrelated with V_1, \dots, V_{i-1} , and W_i is the linear function of \mathbf{Y} with variance 1, uncorrelated with W_1, \dots, W_{i-1} , such that the pair (V_i, W_i) has a correlation coefficient with maximum absolute value.

(iii) for $i > m$, W_i has variance 1 and is uncorrelated with W_1, \dots, W_{i-1} .

For $1 \leq i \leq m$ the pair of variables (V_i, W_i) is called the i th pair of canonical variables and the absolute value of its correlation coefficient ρ_i is called the i th canonical correlation. Clearly $\rho_1^2 \geq \rho_2^2 \geq \dots \geq \rho_m^2$ is satisfied.

It is well known [Rao (1973, Section 8f)] that to solve this problem it suffices to find a $m \times m$ matrix \mathbf{B} and a $n \times n$ matrix \mathbf{C} such that

$$(1.1) \quad \mathbf{B}' \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} \mathbf{B} = \mathbf{R}_1$$

$$(1.2) \quad \mathbf{B}' \Sigma_{11} \mathbf{B} = \mathbf{I}_m$$

$$(1.3) \quad \mathbf{C}' \Sigma_{21} \Sigma_{11}^{-1} \Sigma_{12} \mathbf{C} = \mathbf{R}_2$$

$$(1.4) \quad \mathbf{C}' \Sigma_{22} \mathbf{C} = \mathbf{I}_n$$

Received August 1978; revised March 1979.

AMS 1970 subject classifications. Primary 62H20.

Key words and phrases. Canonical variables, canonical correlations, linear predictors.

where \mathbf{I}_m is the $m \times m$ identity matrix and where \mathbf{R}_1 and \mathbf{R}_2 are two diagonal matrices with decreasing elements in their diagonals. Then the vectors $\mathbf{b}_i(1 < i < m)$ and $\mathbf{c}_i(1 < i < n)$ which solve the problem of canonical correlation are given by the columns of \mathbf{B} and \mathbf{C} respectively. The i th diagonal element of \mathbf{R}_1 and \mathbf{R}_2 is ρ_i^2 if $1 < i < m$ and if $i > m$ the i th diagonal element of \mathbf{R}_2 is 0. The treatment of the case where $m > n$ is analogous.

The solution to the canonical correlation problem is unique (except for a change of sign in the \mathbf{b}_i 's or the \mathbf{c}_i 's) if and only if the numbers ρ_i^2 are all different.

In this approach to the canonical correlation problem, the vectors \mathbf{X} and \mathbf{Y} play symmetrical roles, but in many practical problems their roles differ. This happens for example when the components of \mathbf{X} are observable variables correlated to the components of \mathbf{Y} , while the components of \mathbf{Y} are not observable or have high cost of observation. In this case the researcher may be interested in using \mathbf{X} to predict \mathbf{Y} . If m is very large it would be useful to summarize the information contained in \mathbf{X} in a few variables Z_1, \dots, Z_p , linear functions of \mathbf{X} :

$$Z_i = \mathbf{a}_i' \mathbf{X},$$

choosing $\mathbf{a}_i, 1 < i < p$, such that the vector $\mathbf{Z} = (Z_1, \dots, Z_p)'$ be the best for linearly predicting the vector \mathbf{Y} . This may be formalized as follows: Let \mathbf{Y}_Z^* be the least square predictor of \mathbf{Y} based on \mathbf{Z} . Then \mathbf{Y}_Z^* is given by [Rao (1973, Section 4g)]:

$$(1.5) \quad \mathbf{Y}_Z^* = E(\mathbf{Y}\mathbf{Z}') E(\mathbf{Z}\mathbf{Z}')^{-1} \mathbf{Z}.$$

It is well known that \mathbf{Y}_Z^* is the best linear predictor of \mathbf{Y} based on \mathbf{Z} using either of the following criteria:

(i) it minimizes $E(\|\mathbf{Y} - \mathbf{Y}_Z^*\|^2)$,

and

(ii) it minimizes $|E(\mathbf{Y} - \mathbf{Y}_Z^*)(\mathbf{Y} - \mathbf{Y}_Z^*)'|$, among all predictors of the forms $\mathbf{Y}_Z^* = \mathbf{D}\mathbf{Z}$, where \mathbf{D} is any $n \times p$ matrix. ($| \cdot |$ indicates the matrix determinant and $\| \cdot \|$ the vector Euclidean norm).

Then we may define the best p -vector \mathbf{Z} for predicting \mathbf{Y} using two different criteria:

(a) the vector \mathbf{Z} which minimizes

$$(1.6) \quad E(\|\mathbf{Y} - \mathbf{Y}_Z^*\|^2)$$

or

(b) the vector \mathbf{Z} which minimizes

$$(1.7) \quad |E(\mathbf{Y} - \mathbf{Y}_Z^*)(\mathbf{Y} - \mathbf{Y}_Z^*)'|.$$

The problem of finding \mathbf{Z} which minimizes (1.6) is treated in Rao (1973, Chapter 8, Problem 2). The variables Z_1, \dots, Z_p which solve this problem are in general different from the first p canonical variables, being the same in the particular case that Σ_{22} is of the form $\lambda \mathbf{I}_n$ where λ is a scalar.

On the other hand, if the criterium for choosing \mathbf{Z} is to minimize (1.7), we will show that a solution is to choose $\mathbf{Z} = (V_1, \dots, V_p)'$ where V_1, \dots, V_p are the first canonical variables.

2. Proofs. We will prove the following theorem:

THEOREM. Consider the problem of choosing a $m \times p$ matrix \mathbf{A}^* such that $\mathbf{Z}^* = \mathbf{A}^* \mathbf{X}$ minimizes (1.7), among all the p -dimensional vectors $\mathbf{Z} = \mathbf{A}' \mathbf{X}$. Then

(i) The $m \times p$ matrix \mathbf{A}_0 given by the first p columns of the matrix \mathbf{B} satisfying (1.1) and (1.2) is a solution to this problem.

(ii) If $\rho_p^2 > \rho_{p+1}^2$ then every other solution \mathbf{A}^* is of the form $\mathbf{A}^* = \mathbf{A}_0 \mathbf{G}$ where \mathbf{G} is any nonsingular $p \times p$ matrix.

On the other hand with k equal eigenvalues $\rho_{q+1}^2 = \rho_{q+2}^2 = \dots = \rho_{q+k}^2$ and $q < p < q + k$ the $p - q$ last columns of \mathbf{A}_0 can be chosen as any set of $p - q$ orthogonal eigenvectors associated with the common eigenvalue, and in this framework every solution can be written in the form $\mathbf{A}^* = \mathbf{A}_0 \mathbf{G}$.

(iii) The minimum value of (1.7) is given by

$$|\Sigma_{22}| \prod_{i=1}^p (1 - \rho_i^2).$$

PROOF. Replacing in (1.7) \mathbf{Y}_Z^* by its expression (1.5), it turns out that (1.7) is equivalent to

$$(2.1) \quad |E(\mathbf{Y}\mathbf{Y}') - E(\mathbf{Y}\mathbf{Z}')E(\mathbf{Z}\mathbf{Z}')^{-1}E(\mathbf{Z}\mathbf{Y}')|.$$

Let us note that the best linear predictor of \mathbf{Y} based on \mathbf{Z} is the same as the best linear predictor of \mathbf{Y} based on $\mathbf{D}\mathbf{Z}$ for any $p \times p$ nonsingular matrix \mathbf{D} . \mathbf{D} may be always chosen such that the covariance matrix of $\mathbf{D}\mathbf{Z}$ be the identity. Then without loss of generality we may choose \mathbf{A}^* among the matrices \mathbf{A} such that:

$$(2.2) \quad E(\mathbf{Z}\mathbf{Z}') = \mathbf{A}'\Sigma_{11}\mathbf{A} = \mathbf{I}_p.$$

Replacing \mathbf{Z} by $\mathbf{A}'\mathbf{X}$ in (2.1) and using (2.2) the expression (1.7) to be minimized may be written

$$|\Sigma_{22} - \Sigma_{21}\mathbf{A}\mathbf{A}'\Sigma_{12}|$$

and this is equal to [Press (1972, Formula 2.4.2)]:

$$(2.3) \quad |\Sigma_{22}| |\mathbf{I}_p - \mathbf{A}'\Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}\mathbf{A}|.$$

Since the first factor does not depend on \mathbf{A} , the problem of minimizing (1.7) is reduced to finding a $m \times p$ matrix \mathbf{A} such that

$$(2.4) \quad |\mathbf{I}_p - \mathbf{A}'\Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}\mathbf{A}|$$

is minimized, subject to the restriction (2.2).

Let \mathbf{B} be a matrix satisfying (1.1) and (1.2) and put $\mathbf{H} = \mathbf{B}^{-1}\mathbf{A}$. Then replacing $\mathbf{A} = \mathbf{B}\mathbf{H}$ and using (1.1), (2.4) is equivalent to

$$(2.5) \quad |\mathbf{I}_p - \mathbf{H}'\mathbf{R}_1\mathbf{H}|.$$

Moreover by (2.2) and (1.2) the matrix \mathbf{H} satisfies

$$(2.6) \quad \mathbf{H}'\mathbf{H} = \mathbf{I}_p.$$

Given any $p \times p$ symmetric matrix \mathbf{A} we denote by $\lambda_i(\mathbf{A})$ the i th largest eigenvalue of \mathbf{A} . Then (2.5) is equivalent to

$$(2.7) \quad \prod_{i=1}^p (1 - \lambda_i(\mathbf{H}'\mathbf{R}_1\mathbf{H})).$$

According to Lemma 2.6 of Okamoto (1969) a $p \times m$ matrix \mathbf{H}^* minimizes (2.7) if and only if

$$(2.8) \quad \mathbf{H}^* = \mathbf{S}\mathbf{Q},$$

where \mathbf{Q} is any nonsingular $p \times p$ matrix, in particular we may take

$$\mathbf{Q} = \mathbf{I}_p$$

and \mathbf{S} is any $m \times p$ matrix whose columns are eigenvectors of \mathbf{R}_1 corresponding to the first p largest eigenvalues. Since \mathbf{R}_1 is diagonal with nondecreasing elements in its diagonal, the first p vectors of the canonical base on \mathbf{R}^P satisfy this property. Therefore \mathbf{H}^* may be taken equal to

$$\mathbf{H}_0 = \begin{pmatrix} \mathbf{I}_p \\ \mathbf{O} \end{pmatrix},$$

where \mathbf{O} denotes the $(m - p) \times p$ matrix with all its elements 0. Then $\mathbf{A}_0 = \mathbf{B}\mathbf{H}_0$ is a solution to the problem of minimizing (1.7), where the matrix \mathbf{A}_0 is formed by the first p columns of \mathbf{B} .

The proof of (iii) follows immediately replacing \mathbf{A} by \mathbf{A}_0 in (2.3) and using (1.1).

To prove (ii) it is enough to observe that given any other matrix \mathbf{A}^* such that $\mathbf{Z}^* = \mathbf{A}^{*'}\mathbf{X}$ minimizes (1.7), we may obtain a nonsingular matrix \mathbf{D} such that $\tilde{\mathbf{A}} = \mathbf{A}^*\mathbf{D}'$ satisfies (2.2). Denote $\mathbf{H}^* = \mathbf{B}^{-1}\tilde{\mathbf{A}}$. Then from (2.8) and the fact that $\rho_p^2 > \rho_{p+1}^2$ we have

$$\mathbf{H}^* = \begin{pmatrix} \mathbf{I}_p \\ \mathbf{O} \end{pmatrix}\mathbf{Q}$$

where \mathbf{Q} is a $p \times p$ nonsingular matrix. Then

$$\mathbf{A}^* = \mathbf{B} \begin{pmatrix} \mathbf{I}_p \\ \mathbf{O} \end{pmatrix} \mathbf{Q}\mathbf{D}'^{-1} = \mathbf{A}_0\mathbf{Q}\mathbf{D}'^{-1}$$

and denoting $\mathbf{G} = \mathbf{Q}\mathbf{D}'^{-1}$ we obtain (ii).

In the case where $\rho_{q+1}^2 = \rho_{q+2}^2 = \dots = \rho_{q+k}^2$ and $q < p < q + k$ the matrix of the $p - q$ last columns of \mathbf{A}_0 can be replaced by

$$(\mathbf{b}_{q+1}, \mathbf{b}_{q+2}, \dots, \mathbf{b}_{q+k})\mathbf{F}$$

where \mathbf{F} is a $k \times (p - q)$ matrix such that $\mathbf{F}'\mathbf{F} = \mathbf{I}_{p-q}$. After this change the solution $\mathbf{A}^* = \mathbf{A}_0\mathbf{G}$ depends on both \mathbf{F} and \mathbf{G} , and every solution which minimizes (2.4) can be written in this way.

REMARK. Point (iii) of the theorem yields an interpretation of the square of the $p + 1$ -canonical correlation ρ_{p+1} : it measures the relative improvement in the prediction of \mathbf{Y} when a $(p + 1)$ -dimensional vector \mathbf{Z} is used instead of a p -dimensional one. In effect from point (iii) of the above theorem we have that the determinant of the covariance matrix of the residual vector $\mathbf{Y} - \mathbf{Y}_Z^*$ when an optimal p -dimensional vector \mathbf{Z} is used is

$$|\Sigma_{22}| \prod_{i=1}^p (1 - \rho_i^2).$$

If a $(p + 1)$ -dimensional optimal vector \mathbf{Z} is used the determinant will be reduced to

$$|\Sigma_{22}| \prod_{i=1}^{p+1} (1 - \rho_i^2)$$

and then the relative reduction of the determinant is ρ_{p+1}^2 .

Acknowledgment. We are grateful to a referee for suggesting extensions of our original results to the case where some of the eigenvalues are equal.

REFERENCES

- [1] OKAMOTO, M. (1969). Optimality of principal components. In *Proc. Second Internat. Symp. Multivariate Anal.* (P. R. Krishnaiah, ed.), 673–685. Academic Press, New York.
- [2] PRESS, S. J. (1972). *Applied Multivariate Analysis*. Holt, Rinehart and Winston, U.S.A.
- [3] RAO, C. R. (1973). *Linear Statistical Inference and Its Applications*. Wiley, New York.

DEPARTAMENTO DE MATEMATICAS
FACULTAD DE CIENCIAS EXACTAS Y NATURALES
CIUDAD UNIVERSITARIA
PABELLON 1
1428 BUENOS AIRES
ARGENTINA