

Inference in Canonical Correlation Analysis

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Communicated by P. R. Krishnaiah

The asymptotic behavior, for large sample size, is given for the distribution of the canonical correlation coefficients. The result is used to examine the Bartlett-Lawley test that the residual population canonical correlation coefficients are zero. A marginal likelihood function for the population coefficients is obtained and the maximum marginal likelihood estimates are shown to provide a bias correction.

1. INTRODUCTION

Let r_1, \dots, r_p be the sample canonical correlation coefficients between variates y_1, \dots, y_p and x_1, \dots, x_q ($p \leq q$) calculated from a sample of size $N = n + 1$ observations from a $(p + q)$ -variate normal distribution. The exact joint density function of r_1^2, \dots, r_p^2 is (see Constantine [5], James [9])

$$\prod_{i=1}^p (1 - \rho_i^2)^{\frac{1}{2}n} {}_2F_1^{(p)}\left(\frac{1}{2}n, \frac{1}{2}n; \frac{1}{2}q; P^2, R^2\right) \times k_1 \prod_{i=1}^p (r_i^2)^{\frac{1}{2}(q-p-1)} (1 - r_i^2)^{\frac{1}{2}(n-q-p-1)} \prod_{i < j}^p (r_i^2 - r_j^2) \tag{1.1}$$

$$(1 > r_1^2 > r_2^2 > \dots > r_p^2 > 0),$$

Received November 30, 1976.

AMS 1970 subject classification: Primary 62H10.

Key words and phrases: canonical correlations, asymptotic distributions.

* Research supported in part by the National Science Foundation under Contract MCS75-01493.

† Research supported by the National Science Foundation under Contract MCS76-14876 and MCS78-18583.

where $1 \geq \rho_1 \geq \rho_2 \geq \dots \geq \rho_p \geq 0$ are the population canonical correlation coefficients, $R = \text{diag}(r_1, \dots, r_p)$, $P = \text{diag}(\rho_1, \dots, \rho_p)$,

$$k_1 = \Gamma_p(\frac{1}{2}n)\pi^{\frac{1}{2}p^2}/[\Gamma_p(\frac{1}{2}(n - q)) \Gamma_p(\frac{1}{2}q) \Gamma_p(\frac{1}{2}p)], \tag{1.2}$$

and ${}_2F_1^{(p)}$ is a hypergeometric function with the matrices P^2 and R^2 as arguments. The distribution of r_1^2, \dots, r_p^2 depends only on ρ_1, \dots, ρ_p and hence that part of the distribution involving ρ_1, \dots, ρ_p can be regarded as a marginal likelihood. From (1.1) we see that the marginal likelihood function is

$$\prod_{i=1}^p (1 - \rho_i^2)^{\frac{1}{2}n} {}_2F_1^{(p)}(\frac{1}{2}n, \frac{1}{2}n; \frac{1}{2}q; P^2, R^2). \tag{1.3}$$

In Section 2 we derive an asymptotic representation for the ${}_2F_1^{(p)}$ function, and hence for the distribution (1.1) and marginal likelihood (1.3), for large sample size n . This is done by expressing ${}_2F_1^{(p)}$ as a complicated multiple integral and using a multivariate extension of Laplace's method for integrals to obtain its asymptotic behavior. In Section 3 the asymptotic distribution is used to examine the Bartlett-Lawley test of the null hypothesis that the last $p - k$ population canonical correlation coefficients are zero. Maximum marginal likelihood estimates of certain transformed population coefficients are also obtained and are shown to provide a bias correction.

2. ASYMPTOTIC DISTRIBUTIONS

Before deriving the asymptotic behavior of the ${}_2F_1^{(p)}$ function in (1.1) we first note Hsu's extension [8] of Laplace's method for obtaining the asymptotic behavior of integrals. If the function $f(x) = f(x_1, \dots, x_m)$ has an absolute maximum at an interior point ξ of a domain \mathcal{S} in real m -dimensional space, then under suitable conditions, as $n \rightarrow \infty$

$$\int_{\mathcal{S}} f(x)^n \varphi(x) dx \sim (2\pi/n)^{\frac{1}{2}m} f(\xi)^n \varphi(\xi) \Delta(\xi)^{-\frac{1}{2}}, \tag{2.1}$$

where $a \sim b$ means that $\lim_{n \rightarrow \infty} a/b = 1$ and $\Delta(x) = \det(-\partial^2 \log f / \partial x_i \partial x_j)$.

We begin by looking at the ${}_2F_1$ function with one $k \times k$ matrix T^2 as argument (see [9]). Without loss of generality T can be assumed diagonal, $T = \text{diag}(t_1, \dots, t_k)$, and we will assume that the roots are distinct with $1 > t_1 > t_2 > \dots > t_k > 0$. The integrals involved in the subsequent development can be found in James [9] and Herz [7].

THEOREM 1. As $n \rightarrow \infty$

$${}_2F_1(\frac{1}{2}n, \frac{1}{2}n; \frac{1}{2}q; T^2) \sim c_1 \prod_{i=1}^k t_i^{\frac{1}{2}(k-q)} (1 - t_i)^{-n+\frac{1}{2}q} \prod_{i < j}^k (t_i + t_j)^{-\frac{1}{2}}, \quad (2.2)$$

where

$$c_1 = (\frac{1}{2}n)^{-\frac{1}{2}k(q-\frac{1}{2}k-\frac{1}{2})} \Gamma_k(\frac{1}{2}q) \pi^{-\frac{1}{2}k(k+1)} 2^{-k} [1 + O(n^{-1})].$$

Proof. The idea here is to express ${}_2F_1$ as a multiple integral to which Hsu's result (2.1) can be applied. We can write

$$\begin{aligned} {}_2F_1(\frac{1}{2}n, \frac{1}{2}n; \frac{1}{2}q; T^2) &= c_2 \int_{O(k)} \int_{D_U} \int_{O(k)} \int_{D_V} \int_{V(k,q)} \exp\{-\frac{1}{2}n \operatorname{tr}(U^2 + V^2)\} \\ &\quad \times |UV|^{n-k} \exp\{n \operatorname{tr}([TH_1UH_1'H_2VH_2' : O]Q_1)\} \\ &\quad \times \prod_{i < j}^k (u_i^2 - u_j^2)(v_i^2 - v_j^2)(dQ_1)(dV)(dH_2)(dU)(dH_1), \end{aligned} \quad (2.3)$$

where

$$c_2 = (\frac{1}{2}n)^{nk} 2^{-k} \pi^{\frac{1}{2}k(k-2q)} \Gamma_q(\frac{1}{2}q) [\Gamma_k(n/2)^2 \Gamma_{q-k}(\frac{1}{2}(q-k))],$$

$O(k)$ is the group of $k \times k$ orthogonal matrices, (dH_i) ($i = 1, 2$) is the unnormalized measure on $O(k)$, so that the volume of $O(k)$ is $2^k \pi^{(1/2)k^2} / \Gamma_k(\frac{1}{2}k)$, $U = \operatorname{diag}(u_1, \dots, u_k)$, $V = \operatorname{diag}(v_1, \dots, v_k)$, $D_u = \{(u_1, \dots, u_k); u_1 > u_2 > \dots > u_k > 0\}$, and $V(k, q)$ is the Stiefel manifold consisting of all $q \times k$ matrices Q_1 with orthonormal columns. The integral (2.3) is of the form $c_2 \int_{\mathcal{S}} f^n \phi$, where

$$f = \exp\{-\frac{1}{2} \operatorname{tr}(U^2 + V^2) + \operatorname{tr}([TH_1UH_1'H_2VH_2' : O]Q_1)\} |UV|$$

and

$$\phi = |UV|^{-k} \prod_{i < j}^k (u_i^2 - u_j^2)(v_i^2 - v_j^2).$$

It can be shown that f achieves its maximum value at the 2^{2k} points in \mathcal{S} of the form

$$H_1 = \begin{bmatrix} \pm 1 & & & 0 \\ & \pm 1 & & \\ & & \ddots & \\ 0 & & & \pm 1 \end{bmatrix}, \quad Q_1 = \begin{bmatrix} I_k \\ \cdots \\ 0 \end{bmatrix},$$

$$H_2 = \begin{bmatrix} \pm 1 & & & 0 \\ & \pm 1 & & \\ & & \ddots & \\ 0 & & & \pm 1 \end{bmatrix},$$

$$U = V = \text{diag}\{(1 - t_1)^{-\frac{1}{2}}, \dots, (1 - t_k)^{-\frac{1}{2}}\},$$

and the maximum value of f is

$$\hat{f} = e^{-k} \prod_{i=1}^k (1 - t_i)^{-1}. \tag{2.4}$$

At these maxima φ has the value

$$\hat{\varphi} = \prod_{i=1}^k (1 - t_i)^{2-k} \prod_{i < j}^k (t_i - t_j)^2 \tag{2.5}$$

and it can be shown that the Hessian is

$$\Delta = 2^{2k} \prod_{i=1}^k t_i^{q-k} (1 - t_i)^{4-2k-q} \prod_{i < j}^k (t_i - t_j)^4 (t_i + t_j). \tag{2.6}$$

The number of variables m in Hsu's result being integrated is $\frac{1}{2}k(k + 2q + 1)$. Substitution of (2.4), (2.5), and (2.6) in (2.1), together with an obvious simplification of c_2 , yields the theorem. As a check on some very tedious algebra it can be noted that when $k = 1$, (2.2) agrees with the known asymptotic behavior of the classical hypergeometric function (see Luke [13, Sect. 7.2]).

The asymptotic behavior of the two-matrix ${}_2F_1^{(p)}$ function follows from Theorem 1. Let $R = \text{diag}(r_1, \dots, r_p)$, where $1 > r_1 > \dots > r_p > 0$ and let P be a $p \times p$ diagonal matrix of the form

$$P = \begin{bmatrix} P_1 & 0 \\ 0 & 0 \end{bmatrix},$$

where $P_1 = \text{diag}(\rho_1, \dots, \rho_k)$ with $1 > \rho_1 > \dots > \rho_k > 0$. Then we have

THEOREM 2. As $n \rightarrow \infty$,

$${}_2F_1^{(p)}(\frac{1}{2}n, \frac{1}{2}n; \frac{1}{2}q; P^2, R^2) \sim c_3 \prod_{i=1}^k (1 - r_i \rho_i)^{-n + \frac{1}{2}(p+q-1)} (r_i \rho_i)^{\frac{1}{2}(p-q)} \times \prod_{i=1}^k \prod_{\substack{j=1 \\ i < j}}^p C_{ij}^{-\frac{1}{2}}, \tag{2.7}$$

where

$$c_3 = (\frac{1}{2}n)^{-(1/2)k(p+q-k-1)} \pi^{-(1/2)k(k+1)} \Gamma_k(\frac{1}{2}q) \Gamma_k(\frac{1}{2}p) 2^{-k} [1 + O(n^{-1})]$$

and

$$C_{ij} = (r_i^2 - r_j^2)(\rho_i^2 - \rho_j^2) \quad i = 1, \dots, k; \quad j = 1, \dots, p.$$

Proof. This follows from (2.1), (2.2), and the fact that

$${}_2F_1^{(p)}(\frac{1}{2}n, \frac{1}{2}n; \frac{1}{2}q; P^2, R^2) = \frac{\Gamma_k(\frac{1}{2}p)}{\pi^{\frac{1}{2}pk}} \int_{V(k,p)} {}_2F_1(\frac{1}{2}n, \frac{1}{2}n; \frac{1}{2}q; P_1 H_1 R^2 H_1' P_1)(dH_1). \tag{2.8}$$

Using (2.2) in (2.8) it follows that

$${}_2F_1^{(p)}(\frac{1}{2}n, \frac{1}{2}n; \frac{1}{2}q; P^2, R^2) \sim c_4 \int_{V(k,p)} \prod_{i=1}^k [\delta_i^{\frac{1}{2}(k-a)} (1 - \delta_i)^{-n + \frac{1}{2}q}] \prod_{i < j}^k (\delta_i + \delta_j)^{-\frac{1}{2}} (dH_1),$$

where $c_4 = c_1 \Gamma_k(\frac{1}{2}p) \pi^{-(1/2)pk}$ and $\delta_1 > \dots > \delta_k$ are the positive square roots of the latent roots of $P_1 H_1 R^2 H_1' P_1$. This integral is of the form $c_4 \int_{V(k,p)} f^n \phi$, where

$$f = \prod_{i=1}^k (1 - \delta_i)^{-1}$$

and

$$\phi = \prod_{i=1}^k \delta_i^{\frac{1}{2}(k-a)} (1 - \delta_i)^{\frac{1}{2}a} \prod_{i < j}^k (\delta_i + \delta_j)^{-\frac{1}{2}}.$$

It can be shown that f has 2^k maxima which are obtained when H_1 has the form

$$H_1 = \begin{bmatrix} \pm 1 & & 0 & \vdots \\ & \cdot & & \vdots \\ & & & 0 \\ 0 & & \pm 1 & \vdots \\ & & & \vdots \end{bmatrix} \begin{matrix} k \\ \\ p - k \end{matrix}$$

At these values for H_1 , $\delta_i = r_i \rho_i$ for $i = 1, \dots, k$, and the maximum value of f is

$$f = \prod_{i=1}^k (1 - r_i \rho_i)^{-1}.$$

The value of φ at these maxima is

$$\hat{\varphi} = \prod_{i=1}^k (r_i \rho_i)^{\frac{1}{2}(k-a)} (1 - r_i \rho_i)^{\frac{1}{2}a} \prod_{i < j}^k (r_i \rho_i + r_j \rho_j)^{-\frac{1}{2}},$$

and it can be shown that the Hessian is

$$\Delta = \prod_{i=1}^k (r_i \rho_i)^{k-p} (1 - r_i \rho_i)^{1-p} \prod_{i < j}^k \frac{(r_i^2 - r_j^2)(\rho_i^2 - \rho_j^2)}{(r_i \rho_i + r_j \rho_j)} \prod_{i=1}^k \prod_{j=k+1}^p [\rho_i^2 (r_i^2 - r_j^2)].$$

The theorem now follows from a straightforward application of (2.1).

Substitution of (2.7) in (1.1) gives an asymptotic representation for the distribution of r_1^2, \dots, r_p^2 under the assumption that the population canonical correlation coefficients satisfy

$$1 > \rho_1 > \dots > \rho_k > \rho_{k+1} = \dots = \rho_p = 0. \tag{2.9}$$

This is summarized in the following

THEOREM 3. *The asymptotic density function of r_1^2, \dots, r_p^2 for large n , when the population coefficients satisfy (2.9), is*

$$\begin{aligned} k_2 \prod_{i=1}^k (1 - r_i \rho_i)^{-n + \frac{1}{2}(p+q-1)} (r_i^2)^{\frac{1}{2}(q-p) - \frac{1}{2}} (1 - r_i^2)^{\frac{1}{2}(n-p-q-1)} \prod_{i < j}^k \left(\frac{r_i^2 - r_j^2}{\rho_i^2 - \rho_j^2} \right)^{\frac{1}{2}} \\ \times \prod_{i=1}^k \prod_{j=k+1}^p (r_i^2 - r_j^2)^{\frac{1}{2}} \\ \times \prod_{i=k+1}^p (r_i^2)^{\frac{1}{2}(q-p-1)} (1 - r_i^2)^{\frac{1}{2}(n-q-p-1)} \prod_{\substack{i < j \\ k+1}}^p (r_i^2 - r_j^2), \end{aligned} \tag{2.10}$$

where

$$\begin{aligned} k_2 = k_1 \left(\frac{1}{2}n\right)^{-\frac{1}{2}k(p+q-k-1)} \pi^{-\frac{1}{2}k(k+1)} \Gamma_k\left(\frac{1}{2}q\right) \Gamma_k\left(\frac{1}{2}p\right) 2^{-k} \\ \times \prod_{i=1}^k (1 - \rho_i^2)^{\frac{1}{2}n} \rho_i^{k - \frac{1}{2}(p+q)} [1 + O(n^{-1})] \end{aligned}$$

and k_1 is given by (1.2).

An alternative asymptotic result has been given by Chattopadhyay and Pillai [3] and Chattopadhyay, Pillai, and Li [4]; however the asymptotic behavior given by these authors involves a ${}_2F_1$ function with the matrix P^2R^2 as argument and appears to be incorrect. From Theorem 3 it is easy to obtain the following:

COROLLARY. *The asymptotic conditional density function of the $p - k$ smallest sample coefficients r_{k+1}^2, \dots, r_p^2 given the first k coefficient r_1^2, \dots, r_k^2 is proportional to*

$$\prod_{i=1}^k \prod_{j=k+1}^p (r_i^2 - r_j^2)^{\frac{1}{2}} \prod_{i=k+1}^p (r_i^2)^{\frac{1}{2}(q-p-1)} (1 - r_i^2)^{\frac{1}{2}(n-q-p-1)} \prod_{\substack{j=k+1 \\ i < j}}^p (r_i^2 - r_j^2). \tag{2.11}$$

From this we see that the largest k sample coefficients r_1^2, \dots, r_k^2 are asymptotically sufficient for $\rho_1^2, \dots, \rho_k^2$. This suggests the use of (2.11) as a basis for testing the null hypothesis that the smallest $p - k$ population coefficients are all zero; this approach will be followed in the next section.

3. TESTING AND ESTIMATION

We first investigate the Barlett-Lawley test of the null hypothesis $H_0: \rho_k^2 > \rho_{k+1}^2 = \dots = \rho_p^2 = 0$ against $H: \rho_{k+1}^2 \geq \dots \geq \rho_p^2 \geq 0$ and $\rho_k^2 > 0$ using the distribution (2.11) of r_{k+1}^2, \dots, r_p^2 given r_1^2, \dots, r_k^2 which does not depend on the nuisance parameters ρ_1, \dots, ρ_k . The approach given here is similar to that used by James [10] in another context.

The likelihood ratio statistic is

$$T_k = -\log \prod_{j=k+1}^p (1 - r_j^2)$$

and under H_0 Bartlett [1, 2] showed that $\{n - \frac{1}{2}(p + q + 1)\}T_k$ has an asymptotic χ^2 distribution with $(p - k)(q - k)$ degrees-of-freedom. Lawley [12] obtained a correction to Bartlett's multiplying factor which makes the moments equal to those of the asymptotic χ^2 distribution, apart from errors of order n^{-2} . Fujikoshi [6] has obtained an expansion for the asymptotic distribution of Lawley's statistic. This statistic involves the k largest population coefficients and since these will usually be unknown, Lawley suggested, somewhat tentatively, that they be replaced by the k largest sample coefficients. Here we attempt to provide some information about the accuracy of the approximation when this is done.

The appropriate multiplier of T_k can be obtained by finding its expected value. For notational convenience let E_c denote expectation taken with respect to the conditional distribution (2.11) of r_{k+1}^2, \dots, r_p^2 given r_1^2, \dots, r_k^2 and let E_N

denote expectation with respect to the null distribution obtained by ignoring the linkage factor

$$\prod_{i=1}^k \prod_{j=k+1}^p (r_i^2 - r_j^2)^{\frac{1}{2}}$$

in (2.11). In order to obtain $E_c(T_k)$ we first find $E_c(e^{-hT_k})$. This can obviously be done by finding

$$E_N \left[\left\{ \prod_{i=1}^k \prod_{j=k+1}^p \left(1 - \frac{r_j^2}{r_i^2} \right)^{\frac{1}{2}} \right\} e^{-hT_k} \right]. \tag{3.1}$$

Writing

$$\prod_{i=1}^k \prod_{j=k+1}^p \left(1 - \frac{r_j^2}{r_i^2} \right)^{\frac{1}{2}} = 1 - \frac{\alpha}{2} \sum_{j=k+1}^p r_j^2 + O_p(n^{-2}),$$

where

$$\alpha = \sum_{i=1}^k r_i^{-2},$$

and substituting this in (3.1) it is seen that we need the following:

LEMMA.

$$E_N \left(e^{-hT_k} \sum_{j=k+1}^p r_j^2 \right) = \frac{(p-k)(q-k)}{n-2k+2h} E_0(h), \tag{3.2}$$

where $E_0(h) = E_N(e^{-hT_k})$.

The proof of this follows easily from the fact that

$$\sum_{j=k+1}^p r_j^2 = \text{tr}(I - U),$$

where U is a $(p-k) \times (p-k)$ matrix having a multivariate Beta $\{\frac{1}{2}(n-q-k), \frac{1}{2}(q-k)\}$ distribution (see Kshirsagar [11, Chap. 8]). Using the lemma we can then show, from (3.1), that

$$E_c(e^{-hT_k}) = \theta(h)/\theta(0),$$

where $\theta(h) = E_0(h)f(h)$ with $f(h) = 1 - \alpha(p - k)(q - k)/[2(n - 2k + 2h)]$.
 Now

$$E_c(T_k) = -\frac{d}{dh} \left\{ \frac{\theta(h)}{\theta(0)} \right\}_{h=0}$$

$$= -E'_0(0) - \frac{\alpha(p - k)(q - k)}{(n - 2k)^2} + O(n^{-3}).$$

But $-E'_0(0) = E_N(T_k)$ and when H_0 is true we know that

$$[n - k - \frac{1}{2}(p + q + 1)]T_k$$

has an asymptotic χ^2 distribution with $(p - k)(q - k)$ degrees-of-freedom and the means agree to $O(n^{-2})$ so that

$$-E'_0(0) = (p - k)(q - k)/[n - k - \frac{1}{2}(p + q + 1)] + O(n^{-3}).$$

Hence it follows that

$$E_c(T_k) = (p - k)(q - k)/\{[n - k - \frac{1}{2}(p + q + 1) + \alpha] + O(n^{-1})\}.$$

Thus the appropriate multiplier of T_k is $n - k - \frac{1}{2}(p + q + 1) + \alpha$. Summarizing this, together with Lawley's result [12] we have the following theorem.

THEOREM 4. *The statistic*

$$L_k = \left\{ n - k - \frac{1}{2}(p + q + 1) + \sum_{i=1}^k r_i^{-2} \right\} T_k$$

has an asymptotic χ^2 distribution with $(p - k)(q - k)$ degrees-of-freedom and $E_c(L_k) = (p - k)(q - k) + O(n^{-2})$.

We now turn to the problem of estimating the parameters ξ_1, \dots, ξ_p defined via the familiar transformation

$$\xi_i = \tanh^{-1} \rho_i = \frac{1}{2} \log \frac{1 + \rho_i}{1 - \rho_i}.$$

Let $z_i = \tanh^{-1} r_i$ ($i = 1, \dots, p$), the usual maximum likelihood estimate of ξ_i , which has a bias term of order n^{-1} . We will show that the maximum marginal likelihood estimate of ξ_i provides a bias correction.

From (1.3) and (2.7) with $k = p$ we see that the asymptotic marginal log likelihood function is

$$\begin{aligned} \log L = & \frac{1}{2}n \sum_{i=1}^p \log(1 - \rho_i^2) + \left\{ \frac{1}{2}(p + q - 1) - n \right\} \sum_{i=1}^p \log(1 - r_i \rho_i) \\ & + \frac{1}{2}(p - q) \sum_{i=1}^p \log \rho_i - \frac{1}{2} \sum_{i < j}^p \log(\rho_i^2 - \rho_j^2) \end{aligned}$$

from which it follows easily that the maximum marginal likelihood estimate of ξ_i is

$$\hat{\xi}_i = z_i - \frac{1}{2nr_i} \left\{ p + q - 2 + r_i^2 + 2(1 - r_i^2) \sum_{j \neq i} \frac{r_j^2}{r_i^2 - r_j^2} \right\} + O(n^{-2}).$$

Using expressions for the mean and variance of r_i given by Lawley [12] it can readily be verified

$$E(\hat{\xi}_i) = \xi_i + O(n^{-2})$$

and

$$\text{Var}(\hat{\xi}_i) = 1/n + O(n^{-2})$$

so that these estimates stabilize the variance to order n^{-1} and also provide a correction for bias.

ACKNOWLEDGMENT

The authors would like to thank a referee for his useful comments.

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