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Convergence in Distribution of Multiply-indexed Arrays, with Applications in MANOVA

Zbieżność według rozkładu wielowskaźnikowych tablic z zastosowaniami w MANOVA

Сходимость по распределению мультииндексных таблиц с приложениями в MANOVA

1. Introduction. The importance of convergence in distribution in statistical inference arises as follows. The data y_1, \dots, y_n arising from n performances of a given random process ϵ is used to calculate various quantities of interest, $W_n = (W_{1n}, \dots, W_{kn})'$ say, which are then used to construct significance, confidence intervals etc. These require the evaluation of probabilities of the form $P(W_n \in A)$, for given sets $A \in R^k$. If the distribution of W_n is intractable, an approximation to $P(W_n \in A)$ is available when the sample size n is large in the case when the sequence $\{W_n\}$ converges in distribution to a variate W with known distribution for then ([2], Theorem 2.1)

$$\lim_{n \rightarrow \infty} P(W_n \in A) = P(W \in A)$$

for all sets A of practical interest.

Consider now the situation in e.g. MANOVA. There are now several (k say) independent random processes $\epsilon_1, \dots, \epsilon_k$, the data arises from n_i performances of ϵ_i , $i = 1, \dots, k$, and leads to quantities of interest of the form W_{n_1, \dots, n_k} . An approximation to $P(W_{n_1, \dots, n_k} \in A)$ when all the sample sizes n_1, \dots, n_k are large may then be important in practice for similar reasons. Such approximations are provided by the type of convergence in distribution of multiply-indexed arrays $\{W_{n_1, \dots, n_k}\}$ of random vectors that is defined below.

2. Multiply-indexed arrays. We discuss in some detail only the case $k = 2$, since the treatment when $k > 2$ presents no additional difficulties.

2. 1 Definition and notation. We call a set of real numbers $\{a_{n_1, n_2}; n_1 \geq 1, n_2 \geq 1\}$ a doubly-indexed array. It may be conveniently pictured in table form –

n_2	1	2	3	...
1	a_{11}	a_{12}	a_{13}	...
2	a_{21}	a_{22}	a_{23}	...
3	a_{31}	a_{32}	a_{33}	...
⋮	⋮	⋮	⋮	⋮

In view of later use in MANOVA, it will be convenient to write $N = \text{diag}(n_1, n_2)$, $a_{n_1, n_2} = \{a_N\}$, and the array a_N .

Further, if $N_1 = \text{diag}(n_{11}, n_{12})$, $N_2 = \text{diag}(n_{21}, n_{22})$, we shall write $N_1 > N_2$ if $n_{11} > n_{21}$ and $n_{12} > n_{22}$, with a similar meaning for $N_1 \geq N_2$.

Finally by ' N is arbitrarily large' we shall mean that n_1 and n_2 are both arbitrarily large.

2.2 Limit points. We say that α (finite) is a limit point of $\{a_N\}$ if for arbitrary $\epsilon > 0$ and $n > 0$, $\exists N \geq nI$ such that $|a_N - \alpha| < \epsilon$.

There is the usual extension to infinite limit points. (There will be similar extension below, which in general will not be mentioned explicitly.)

We show now, by a standard argument, that every array $\{a_N\}$ has a limit point.

In the case when $\{a_N\}$ is bounded, $a_N \in J_0 = [a, b] \forall N$ say, construct a sequence $\{J_n\}$ of closed intervals by repeated subdivision of J_0 , viz., for $n = 1, 2, \dots$, J_n is the left half of J_{n-1} if this half contains terms a_N with N arbitrarily large, and otherwise J_n

is the right half. Then $\{J_n\}$ defines the point $\alpha = \bigcap_1 J_n$. This point α is a limit point of

$\{a_N\}$, since $\forall n J_n$ contains α and terms a_N with N arbitrarily large. Moreover, $\alpha = \liminf a_N$, since for arbitrary $\epsilon > 0$, $\exists n_0$ such that $a_N > \alpha - \epsilon \forall N \geq n_0I$.

If $\{a_N\}$ is not bounded, a similar argument shows that a_N has a limit point, which now may be infinite.

2.3 Subarrays. Let S be a subset of diagonal matrices N that contains matrices that are arbitrarily large. We call $\{a_N, N \in S\}$ a subarray of $\{a_N\}$.

Limit points of subarrays are defined in the obvious way, and it follows, as in 2.2, that every subarray has a limit point.

2.4 Convergence. We say that $\{a_N\}$ converges to α (finite), and write $\lim_{N \rightarrow \infty} a_N = \alpha$,

if for arbitrary $\epsilon > 0$, $\exists n_0$ such that $|a_N - \alpha| < \epsilon \forall N \geq n_0I$.

Similarly, we say that the subarray $\{a_N, N \in S\}$ converges to α (finite) if for arbitrary $\epsilon > 0$, $\exists n_0$ such that $|a_N - \alpha| < \epsilon \forall N \in S$ such that $N \geq n_0I$.

The usual results then follow. As an example, we prove that if α is a limit point of $\{a_N\}$ then there exists a subarray that converges to α .

In the case when α is finite, let $\{\epsilon_i\}$ be a null sequence of positive terms, and construct a set $S = \{N_i\}$ as follows.

Choose $N_1 > I$ such that $|a_{N_1} - \alpha| < \epsilon_1$, then successively choose $N_{i+1} > N_i$ such that $|a_{N_{i+1}} - \alpha| < \epsilon_{i+1}$, $i = 1, 2, \dots$, (such N_i always exist, from 2.2).

For given $\epsilon > 0$, $\exists j$ such that $\epsilon_i < \epsilon \forall i \geq j$. Then $|a_{N_i} - \alpha| < \epsilon \forall i \geq j$.

Writing $n_0 = \min(n_{j_1}, n_{j_2})$, where $N_j = \text{diag}(n_{j_1}, n_{j_2})$, then $S \cap \{N, N \geq n_0 I\} = \{N_i, i \geq j\}$, whence $|a_N - \alpha| < \epsilon \forall N \in S$ such that $N \geq n_0 I$ and the subarray $\{a_N, N \in S\}$ converges to α .

There is a similar result for limit points of subarrays.

We mention one further result, viz., that if $\{a_N\}$ converges to α , then every subarray of $\{a_N\}$ converges to α . And there is the corresponding result for convergent subarrays.

2.5 Lim inf and lim sup. The following treatment is parallel to Feller's treatment of lim inf and lim sup ([4], IV. 1), and uses his \cap, \cup notation.

We first introduce a sequential ordering of the terms of $\{a_N\}$ with $N \geq nI$, viz.

$$a_{nn}, a_{n+1n}, a_{nn+1}, a_{n+2n}, a_{n+1n+1}, a_{nn+2}, a_{n+3n}, \dots$$

Next, consider the sequence $\{w_n\}$, where

$$w_n = a_{nn} \cap a_{n+1n} \cap a_{nn+1} \cap a_{n+2n} \cap \dots = \bigcap_{N \geq nI} a_N$$

Clearly $w_n \uparrow$, whence $\{w_n\}$ convergence to a limit, α say. Thus, in the case when α is finite, for arbitrary

$$\epsilon > 0, \exists n_0 \text{ such that } \alpha - \epsilon < w_n \leq \alpha \forall n \geq n_0 \tag{1}$$

We now show that for arbitrary $\epsilon > 0$,

$$\exists n_1 \text{ such that } a_N > \alpha - \epsilon \forall N \geq n_1 I, \text{ and} \tag{i}$$

$$\exists N \text{ arbitrarily large such that } a_N < \alpha + \epsilon, \tag{ii}$$

from which it follows that $\alpha = \lim \inf a_N$. Firstly, since by definition $w_{n_0} \leq a_N \forall N \geq n_0 I$, then, from (1), (i) holds with $n_1 = n_0$. Next, suppose that (ii) does not hold. Then $\exists \epsilon_1 > 0$ and n_2 such that $a_N \geq \alpha + \epsilon_1 \forall N \geq n_2 I$. But then $w_n \geq w_{n_2} \geq \alpha + \epsilon_1 \forall n \geq n_2$, which contradicts (1).

There is a similar treatment for $\lim \sup a_N$.

2.6 Fatou's lemma and the dominated convergence theorem. We consider now an array $\{f_N(x)\}$ of functions $f: R^I \rightarrow R^1$. Then, from 2.5, for each x

$$w_n(x) = \bigcap_{N \geq nI} f_N(x)$$

defines an increasing sequence $\{w_n(x)\}$ that converges to $\lim \inf f_N(x)$.

Fatou's lemma. ([4], IV. 2) Suppose that $\{f_N(x)\}$ is an array of non-negative functions, and that $F(x)$ is a distribution function (d.f.).

If f_N is integrable for all N , i.e. if

$$E[f_N] = \int_{\mathbb{R}^2} f_N(x) dF(x) < \infty \quad \forall N$$

then

$$E[\liminf f_N] \leq \liminf E[f_N].$$

Proof. Define a sequence of functions $\{f_n\}$ as follows. For each $n \geq 1$, choose N_n such that $N_n \geq nl$, and define

$$f_n = f_{N_n} \quad (2)$$

By definition of w_n , $w_n \leq f_n \quad \forall n$, whence $E(w_n) \leq E(f_n) \quad \forall n$, and so

$$\liminf E(w_n) \leq \liminf E(f_n). \quad (3)$$

Since $w_n \uparrow$, $\lim w_n = \liminf f_N$, and w_n is integrable for all n , then, by the monotone convergence theorem ([4], IV. 2), $\{E(w_n)\}$ converges, and $\lim E(w_n) = E(\lim w_n)$.

It follows then, using (3), that

$$E(\liminf f_n) \leq \liminf E(f_n). \quad (4)$$

Since (4) holds for all sequences $\{f_n\}$ satisfying (2), it is enough to show that there exists such a sequence for which $\liminf E(f_n) = \liminf E(f_N)$. To show this, consider the array $\{E(f_N)\}$, and write $\alpha = \liminf E(f_N)$. By 2.4, there exists a subarray $\{E(f_N), N \in S\}$ that converges to α . Consider now the corresponding subarray $\{f_N, N \in S\}$, and construct from it a sequence $\{f_n\}$ as follows. Choose any element N_1 of S and define $f_1 = f_{N_1}$; then for $n = 1, 2, \dots$, choose an element N_{n+1} of S such that $N_{n+1} > N_n$ and define $f_{n+1} = f_{N_{n+1}}$. Then

(i) $N_n \geq nl \quad \forall n$, so that $\{f_n\}$ satisfies (2).

(ii) Since $\{E(f_n)\} = \{E(f_N), N \in S_1\}$, where $S_1 = \{N_i\} \subset S$, and, by 2.4, the subarray $\{E(f_N), N \in S_1\}$ converges to α , then $\lim_{n \rightarrow \infty} E(f_n) = \alpha$ and $\liminf E(f_n) = \liminf E(f_N)$, as required.

The following theorem then follows from Fatou's lemma in the standard way (see e.g. [4], IV. 2).

Dominated convergence theorem. If $\{f_N(x)\}$ is an array such that f_N is integrable $\forall N$, and that $\lim_{N \rightarrow \infty} f_N(x) = f(x)$ pointwise, and that there exists an integrable function u

such that $|f_N(x)| < u(x) \quad \forall x$, then

$$\lim_{N \rightarrow \infty} E(f_N) = E(f).$$

2.7 Helly's theorem. Helly's theorem ([4], VIII. 6) may be generalized to arrays $\{F_N(x)\}$ of d.f. The proof is essentially the same as the proof in Feller, and depends on the following lemma.

Lemma. If $\{f_N(x)\}$ is a given array of bounded functions ($R^k \rightarrow R^l$) and $\{a_i\}$ is a given sequence of points in R^k , then there exists a subarray $\{f_N, N \in S\}$ that converges at all points a_i .

Proof. (c.f. [4], VIII. 6). By 2.2, the bounded array $\{f_N(a_i)\}$ has a limit point, and hence contains a convergent subarray $\{f_N(a_1), N \in S_1\}$. Proceeding in this way, the bounded subarray $\{f_N(a_2), N \in S_1\}$ has a limit point, and hence contains a convergent subarray $\{f_N(a_2), N \in S_2\}$. Continuing this procedure, we generate a sequence of sets $S_1 \supset S_2 \supset \dots \supset S_n \supset \dots$ such that for each $i = 1, 2, \dots, \{f_N(a_i), N \in S_i\}$ is a convergent subarray.

For each $n \geq 1$ we now choose an element $N_n \in S_n$ such that $N_n \geq nl$, and define $S = \{N_n\}$. Then the subarray $f_N, N \in S$ has the required property. For consider $\{f_N(a_i), N \in S\}$. Since $N_n \in S_n \subset S_i \forall n \geq i$, then apart from a finite number of terms, $\{f_N(a_i), N \in S\}$ is a subarray of $\{f_N(a_i), N \in S_i\}$ which we know converges.

Thus $\{f_N(a_i), N \in S\}$ converges for $i = 1, 2, \dots$

The generalizations of these results when $k > 2$ are now used to develop a theory of convergence in distribution for multiply-indexed arrays.

3. Convergence in distribution for multiply-indexed arrays. Let $\{W_N\}$ be a k -fold multiply-indexed array of $l \times l$ vector variates and W an $l \times l$ vector variate. We denote the corresponding d.f. by $\{F_N(x)\}$ and $F(x)$, the corre-characteristic functions (c.f.) by $\{\zeta_N(t)\}$ and $\zeta(t)$, and write

$$E_N(f) = \int_{R^l} f(x) dF_N(x)$$

and

$$E(f) = \int_{R^l} f(x) dF(x).$$

Definition. We say that $\{W_N\}$ converges in distribution to W , and write $W_N \xrightarrow{D} W$, iff $\lim_{N \rightarrow \infty} F_N(x) = F(x) \forall$ continuity points x of F .

Theorem 1. $W_N \xrightarrow{D} W$ if and only if either

(i) $\lim_{N \rightarrow \infty} P(W_N \in I) = P(W \in I)$ for all bounded open 'rectangles' I such that $P(W \in \partial I) = 0$,

or (ii) $\lim_{N \rightarrow \infty} P(W_N \in A) = P(W \in A)$ for all Borel sets A such that $P(W \in \partial A) = 0$,

or (iii) $\lim_{N \rightarrow \infty} E_N(f) = E(f)$ for all bounded and continuous functions $f: R^l \rightarrow R^1$,

or (iv) $\lim_{N \rightarrow \infty} \zeta_N(t) = \zeta(t) \forall t$.

Moreover, if $W_N \xrightarrow{D} W$, then the convergence in (iv) is uniform for all t in any bounded domain of R^l .

Proof. The proof of (ii) and (iii) depends only on the content of 2.1 – 2.4 and follows step for step the corresponding proof of Bilingsley ([2], §2). The fact that (i) \Rightarrow (iii) similarly follows the proof of the theorem in [4], VIII. 1. The fourth part (a continuity theorem for c.f.) depends also on 2.6 – 2.7, and can be proved in the same way as the corresponding 'ordinary' theorem, as e.g. in [4], XV. 3 or in [3], Chapter 11.

In the case when \underline{W} has a singular distribution concentrated at the single point $\underline{\alpha}$, we say that $\{\underline{W}_N\}$ converges in probability to $\underline{\alpha}$, and we shall write $\underline{W}_N \xrightarrow{D} \underline{\alpha}$, as well as the standard $\underline{W}_N \xrightarrow{P} \underline{\alpha}$.

All the standard results for convergence in distribution of sequences of vector variates have their obvious counterparts in the theory of convergence in distribution of multiply-indexed arrays. We recall in particular two results. The first states that, if $\underline{W}_{1N} \xrightarrow{D} \underline{W}_1$ and $\underline{W}_{2N} \xrightarrow{D} \underline{\alpha}_2$, then writing $\underline{W}_N = (\underline{W}'_{1N}, \underline{W}'_{2N})'$, $\underline{W}_N \xrightarrow{D} \underline{W} = (\underline{W}'_1, \underline{W}'_2)'$, where $P(\underline{W}_2 = \underline{\alpha}_2) = 1$, i.e. the limiting joint distribution is singular, and concentrated on the hyperplane $\underline{W}_2 = \underline{\alpha}_2$. In such a case, we shall write

$$\begin{pmatrix} \underline{W}_{1N} \\ \underline{W}_{2N} \end{pmatrix} \xrightarrow{D} \begin{pmatrix} \underline{W}_1 \\ \underline{\alpha}_2 \end{pmatrix}$$

The second result, which has widespread application, we state as a theorem.

Theorem 2.

$$\underline{W}_N \xrightarrow{D} \underline{W} = \phi(\underline{W}_N) \xrightarrow{D} \phi(\underline{W})$$

for every Borel-measurable function $\phi: R^q \rightarrow R^q$ such that $P(\underline{W} \in D_\phi) = 0$, where

$$D_\phi = \{x; \phi(x) \text{ is discontinuous}\}.$$

The proof again follows step for step the corresponding proof in Billingsley ([2], Corollary 3 of theorem 3.3).

4. Some asymptotic results in MANOVA. As an application of §3, we now derive some asymptotic results in MANOVA, on the assumption of a common non-singular covariance matrix Σ .

4.1 MANOVA notation. We suppose that the data is obtained from n_i performances of the random process \mathfrak{E}_i , $i = 1, \dots, k$, where $\mathfrak{E}_1, \dots, \mathfrak{E}_k$ are independent processes. For \mathfrak{E}_i , we denote the $p \times 1$ variate by \underline{y}_i and its mean by $\underline{\mu}_i$. We denote the corresponding $n_i \times p$ data matrix by Y_i , and the sample mean and covariance matrix by \bar{y}_i and $S_{(i)}$. We write

$$\begin{aligned} \sum_1^k n_i &= n, & N &= \text{diag}(n_1, \dots, n_k), \\ M_{k \times p} &= \begin{pmatrix} \underline{\mu}'_1 \\ \vdots \\ \underline{\mu}'_k \end{pmatrix} = (\mu_{ij}), & \bar{Y}_{N \times p} &= \begin{pmatrix} \underline{y}'_1 \\ \vdots \\ \underline{y}'_k \end{pmatrix} = (y_{ij}), \\ y_{i \times p} &= \begin{pmatrix} \underline{y}'_{i1} \\ \vdots \\ \underline{y}'_{in_i} \end{pmatrix}, & Y_{n \times p} &= \begin{pmatrix} Y_1 \\ \vdots \\ Y_k \end{pmatrix}, \end{aligned}$$

$$\text{and } S_{p \times p} = \frac{1}{n-k} \sum_i (n_i - 1) S_{(i)} = \frac{1}{n-k} \sum_{i=1}^k \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_i) (y_{ij} - \bar{y}_i)'$$

The above assumptions, which we shall call the model G , can be summed up as follows:

G : The rows of Y are independent vector variates, and
 $E(Y) = XM, \text{Var}(Y) = \Sigma \otimes I_n$, where

$$X = \begin{pmatrix} I_1 & 0 & \dots & 0 \\ 0 & I_2 & \dots & 0 \\ \vdots & \vdots & \dots & \vdots \\ 0 & 0 & \dots & I_k \end{pmatrix}$$

$n \times k$

Note that

$$X'X = N, X'Y = N\bar{Y}_N \text{ and } r(X) = k \tag{6}$$

and further, that each column of $E(Y) \subset \mathcal{R}(X) \subset R^n$, that $P = X(X'X)^{-1} X' = XN^{-1} X'$ is the orthogonal projector matrix (o.p. matrix) onto $\mathcal{R}(X)$, and that $(n-k)S = Y'(I-P)Y$.

We now consider the usual kind of MANOVA hypothesis H , viz.

$$H: M = X_1 B_1$$

where X_1 is a known $k \times r$ matrix of rank r . (7)

When H is true, $E(Y) = XX_1 B_1 = X_0 B_1$ where $X_0 = XX_1$ has rank r , each column of $E(Y) \subset \mathcal{R}(X_0) \subset \mathcal{R}(X)$, the o.p. matrix onto $\mathcal{R}(X_0)$ is

$$P_0 = XX_1 (X_1' N X_1)^{-1} X_1' X'$$

and

$$S_0 = \frac{1}{n-r} Y'(I-P_0)Y$$

is an unbiased estimate of Σ .

The MANOVA table for testing H is then

Source	SSP	DF	MSSP
H vs. G	$Y'(P-P_0)Y = S_1$	$k-r$	S_1
Within class	$Y'(I-P)Y = S$	$n-k$	S
Total	$Y'(I-P_0)Y = S_0$	$n-r$	S_0

4.2 A central limit theorem.

Theorem 3. On G , $N^{1/2}(\bar{Y}_N - M) \xrightarrow{D} W \sim N(0, \Sigma \otimes I_k)$.

Proof. Writing

$$T_{k \times p} = \begin{pmatrix} t'_1 \\ \vdots \\ t'_k \end{pmatrix}$$

the c.f. $\zeta_N(T)$ of $W_N = N^{1/2}(\bar{Y}_N - M)$ is

$$\begin{aligned} \zeta_N(T) &= E[\exp(i \text{Tr}(T'W_N))] = E\left[\prod_{j=1}^k (\exp(i t'_j(\bar{y}_j - \mu_j) \sqrt{n_j}))\right] = \\ &= \prod_{j=1}^k E[\exp(i t'_j(\bar{y}_j - \mu_j) \sqrt{n_j})] = \prod_{j=1}^k \phi_{n_j}^{(j)}(t_j) \end{aligned}$$

since $\bar{y}_1, \dots, \bar{y}_k$ are independent where

$$\phi_{n_j}^{(j)}(t_j) = E[\exp(i t'_j(\bar{y}_j - \mu_j) \sqrt{n_j})], \quad j = 1, \dots, k.$$

But it is known from the ordinary multivariate central limit theorem that, for given t_j ,

$$\lim_{n_j \rightarrow \infty} \phi_{n_j}^{(j)}(t_j) = \exp(-0.5 t'_j \Sigma_j t_j), \quad j = 1, \dots, k$$

Thus, for given T ,

$$\lim_{N \rightarrow \infty} \zeta_N(T) = \prod_{j=1}^k \exp(-0.5 t'_j \Sigma_j t_j) = \exp(-0.5 \text{Tr}(T \Sigma T')) = E[\exp(i \text{Tr}(T'W))],$$

and the theorem follows from theorem 1.

4.3 The asymptotic distribution of S_1 . Suppose that A is a $p \times p$ symmetric matrix. By \underline{A} we shall mean the $p(p+1)/2 \times 1$ vector

$$A = (a_{11}, \dots, a_{1p}, a_{22}, \dots, a_{2p}, \dots, a_{pp}).$$

Theorem 4. When H is true, $S_1 \xrightarrow{D} \underline{V}$, where $V = U'U$ and $U \sim N(0, \Sigma \otimes I_{k-r})$.
 $(k-r) \times p$

Proof. When H is true, the columns of XM lie in $\mathcal{R}(X_0) \subset \mathcal{R}(X)$, so that $(P - P_0)XM = 0$. Thus

$$S_1 = Y'(P - P_0)Y = (Y - XM)'(P - P_0)(Y - XM) = W'_N(I - P_N)W_N,$$

where, from (6) and the definitions of P and P_0 ,

$$P_N = N^{1/2} X_1 (X_1' N X_1)^{-1} X_1' N^{1/2},$$

$$k \times k$$

the o.p. matrix onto the r -dimensional subspace Ω_N of R^k , where $\Omega_N = \mathcal{R}(N^{1/2} X_1)$.

Now let H_N be a matrix whose columns are an orthonormal basis of Ω_N . Then
 $k \times (k-r)$

$$H'_N H_N = I_{k-r}, \quad H_N H'_N = I - P_N, \text{ and}$$

$$S_1 = U'_N U_N \tag{8}$$

where $U_N = H'_N W_N$.

We now show that $U_N \xrightarrow{D} U \sim N(0, \Sigma \otimes I_{k-r})$, from which the theorem follows by a simple application of theorem 2. From Theorems 3 and 1

$$\zeta_N(T) = \exp(-0.5 Tr(T \Sigma T')) + f_N(T) \tag{9}$$

where $\lim_{N \rightarrow \infty} f_N(T) = 0$ uniformly for T in any bounded domain $A \subset R^{kp}$.

Consider now the c.f. $\phi_N(T_1)$ of U_N , where T_1 is $(k-r) \times p$.

$$\begin{aligned} \phi_N(T_1) &= E[\exp(i Tr(T'_1 U_N))] = \zeta_N(H_N T_1), \text{ using (8)} \\ &= \exp(-0.5 Tr(H_N T_1 \Sigma T'_1 H'_N)) + f_N(H_N T_1) = \exp(-0.5 Tr(T_1 \Sigma T'_1)) + f_N(H_N T_1) \end{aligned}$$

since $H'_N H_N = I_{k-r}$.

For fixed T_1 , choose in (9) $A = \{T; Tr(T' T) \leq Tr(T'_1 T_1)\}$. Since $Tr((H_N T_1)'(H_N T_1)) = Tr(T'_1 T_1) \forall N$, then, from (9) $\lim_{N \rightarrow \infty} f_N(H_N T_1) = 0$, and the result follows by an

application of Theorem 1.

Theorem 5. On $G, \underline{\Sigma} \xrightarrow{D} \underline{\Sigma}$.

Proof. We write $\nu_j = n_j - l, j = l, \dots, k$ and $\nu = n - k$, so that

$$S = \sum_{j=1}^k (\nu_j/\nu) S_{(j)}.$$

It is well-known that for each $j \underline{\Sigma}_{(j)} \xrightarrow{D} \underline{\Sigma}$ as $n_j \rightarrow \infty$. Thus, writing

$$\phi_{n_j}^{(j)}(t_j) = E[\exp(i t'_j \underline{\Sigma}_{(j)})] = \exp(i t'_j \underline{\Sigma}) + f_{n_j}^{(j)}(t_j),$$

then $\lim_{n_j \rightarrow \infty} f_{n_j}^{(j)}(t_j) = 0$ uniformly for t_j in any bounded domain.

Now write $g_{n_j}^{(j)}(t) = \exp(-i t'_j \underline{\Sigma}) f_{n_j}^{(j)}(t), j = l, \dots, k$.

Then

$$\phi_{n_j}^{(j)}(t) = (1 + g_{n_j}^{(j)}(t)) \exp(i t'_j \underline{\Sigma})$$

and, since $|\exp(i t'_j \underline{\Sigma})| = 1$, then, given $\epsilon_1 > 0, k > 0, \exists n_{0j}$ such that $|g_{n_j}^{(j)}(t)| < \epsilon_1 \forall n_j \geq n_{0j}$ and

$$\forall t \in A = \{t; t'_j t \leq k\}. \tag{10}$$

Consider now the c.f. $\zeta_N(t)$ of S , viz.

$$\zeta_N(t) = E\left[\prod_{j=1}^k \exp(i t' (v_j/\nu) S_{n_j})\right] = \prod_{j=1}^k \phi_{n_j}^{(j)}(v_j t/\nu),$$

since S_1, \dots, S_k are independent. Thus (all logs being principal-valued)

$$\log \zeta_N(t) = (i t' \Sigma) \sum_j (v_j/\nu) + \sum_j \log(1 + g_{n_j}^{(j)}(v_j t/\nu)) + (2C_N \pi) i,$$

where C_N is integer depending on N .

Since $\Sigma(v_j/\nu) = 1$, the theorem will follow by showing that, for fixed t ,

$$\lim_{N \rightarrow \infty} \sum_j \log(1 + g_{n_j}^{(j)}(v_j t/\nu)) = 0.$$

Using the fact that

$$|\log(1 + z)| < 2|z| \text{ if } |z| < 0.5,$$

then

$$|\sum_j \log(1 + g_{n_j}^{(j)}(v_j t/\nu))| < 2 \sum_j |g_{n_j}^{(j)}(v_j t/\nu)|$$

provided that

$$|g_{n_j}^{(j)}(v_j t/\nu)| < 0.5, \quad j = 1, \dots, k.$$

For arbitrary $\epsilon > 0$, choose now $\epsilon_1 = \epsilon/2k$ and $k = \lfloor t' t \rfloor$ in (10), and write $n_0 = \max(n_{01}, \dots, n_{0k})$. Since $v_j t/\nu \in A \forall N$, it then follows from (10) that

$$2 \sum_j |g_{n_j}^{(j)}(v_j t/\nu)| < \epsilon \forall N \geq n_0$$

and hence that

$$\lim_{N \rightarrow \infty} \sum_j \log(1 + g_{n_j}^{(j)}(v_j t/\nu)) = 0.$$

4.4 The eigen-values of $S_1 S^{-1}$. We now consider the asymptotic distribution of the

e. values of $S_1 S^{-1}$ when H is true. Since Theorem 5 $\Rightarrow |S| \xrightarrow{D} |\Sigma| > 0$, it follows that the possible lack of definition of S^{-1} has no effect on the asymptotic distribution. Furthermore, since

$$r(S_1) \leq \rho = \min(p, k - r) \forall N,$$

with equality almost always when n is large, only the ρ largest e. values $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_\rho$ are of interest.

Theorem 6. When H is true, $\underline{\lambda}_N \xrightarrow{D} L$, where $\underline{\lambda}_N = (\lambda_1, \dots, \lambda_\rho)'$, $L = (L_1, \dots, L_\rho)'$, $L_1 \geq L_2 \geq \dots \geq L_\rho$ are the largest e. values of $Z'Z$, and $Z \sim N(0, I_{p(k-r)})$.

Proof. From theorem 4 and 5

$$\begin{pmatrix} \underline{S}_1 \\ S \end{pmatrix} \xrightarrow{D} \begin{pmatrix} Y \\ \Sigma \end{pmatrix} \text{ when } H \text{ is true.}$$

Since $\underline{\lambda}_N = \phi(\underline{S}_1, \underline{S})$, where ϕ is Borel-measurable and continuous when $\underline{S} = \underline{\Sigma}$, it follows from Theorem 2 that $\underline{\lambda}_N \xrightarrow{D} \phi(\underline{V}, \underline{\Sigma})$, i.e. the vector of the ρ largest e. values of $V\Sigma^{-1} = U'U\Sigma^{-1}$, where from Theorem 1.4,

$$U \sim N(0, \Sigma \otimes I_{k-r}).$$

Write now $\Sigma^{-1} = A^2$, where A is symmetric. Since $V\Sigma^{-1} = A^{-1}(AU'UA)A = A^{-1}(Z'Z)A$, where $Z = UA \sim N(0, I_{p(k-r)})$, then $V\Sigma^{-1}$ and $Z'Z$ have the same e. values, and the result follows.

This theorem allows us to write down the asymptotic distribution when H is true of some statistics commonly used in practice for testing H , viz. Hotelling's T_0^2 , Pillai's $V^{(p)}$, and the statistic U , which is essentially the Normal theory likelihood-ratio statistic, where

$$T_0^2 = Tr(S_1 S^{-1}) = \sum_i \lambda_i, \quad V^{(p)} = \frac{n-k}{n-r} Tr(S_1 S_0^{-1}) = \sum_i \frac{\lambda_i}{1 + (\lambda_i/n - k)}$$

$$\text{and } U^{-1} = \prod_i \left(1 + \frac{\lambda_i}{n-k}\right)$$

see e.g. [1], Ch. 8).

Theorem 7. When H is true, T_0^2 , $V^{(p)}$ and $(n-k)(U^{-1} - I)$ each converges in distribution to

$$Tr(Z'Z) \sim \chi_{p(k-r)}^2.$$

Proof. It follows immediately from Theorem 2 that

$$T_0^2 = \sum_i \lambda_i \xrightarrow{D} \sum_i L_i = Tr(Z'Z) \sim \chi_{p(k-r)}^2$$

and similarly that

$$V^{(p)} \xrightarrow{D} \sum_i L_i / (1 + 0.L_i) = Tr(Z'Z).$$

Finally,

$$(n-k)(U^{-1} - I) = \sum_i \lambda_i + (n-k)^{-1} \sum_{i \neq j} \lambda_i \lambda_j + \dots + \frac{1}{(n-k)^{p-1}} \prod_i \lambda_i \\ \xrightarrow{D} \sum_i L_i + 0. \sum_{i \neq j} L_i L_j + \dots + 0. \prod L_i = Tr(Z'Z).$$

(It can also be shown somewhat similarly that

$$-n \log U \xrightarrow{D} \chi_{p(k-r)}^2.)$$

4.5 Estimation of B_1 . If H is not rejected, the estimation of B_1 will often be of importance. We consider the asymptotic distribution of \hat{B}_N when H is true, where $\hat{B}_N = (X_0'X_0)^{-1} X_0'Y$ is the matrix of minimum variance unbiased linear estimates of B_1 when H is true. Since $E(\hat{B}_N) = (X_0'X_0)^{-1} X_0'X_0 B_1 = B_1$ and

$$\text{Var}(\hat{B}_N) = (I_p \otimes (X'_0 X_0)^{-1} X'_0) (\Sigma \otimes I_n) (I_p \otimes X_0 (X'_0 X_0)^{-1}) = \Sigma \otimes (X'_1 N X_1)^{-1},$$

it might be expected that \hat{B}_N is asymptotically $N(B_1, \Sigma \otimes (X'_1 N X_1)^{-1})$, in the sense that, if C_N and A are respectively $r \times r$ and $p \times p$ symmetric matrices such that

$$C_N^2 = X'_1 N X_1, \quad A^2 = \Sigma^{-1} \quad (11)$$

then $C_N(\hat{B}_N - B_1)A \xrightarrow{D} Z_1 \sim N(0, I_{pr})$.

To prove this, note first that when H is true $E(Y) = XM = X_0 B_1$, so that, using (6) and the notation of Theorem 3,

$$\hat{B}_N - B_1 = (X'_0 X_0)^{-1} X'_0 (Y - XM) = (X'_1 N X_1)^{-1} X'_0 N^{1/2} W_N$$

and $C_N(\hat{B}_N - B_1)A = C_N (X'_1 N X_1)^{-1} X'_1 N^{1/2} W_N A = D_N W_N A$,

where

$$D_N = C_N (X'_1 N X_1)^{-1} X'_1 N^{1/2}.$$

The c.f. $\phi_N(T_1)$ of $C_N(\hat{B}_N - B_1)A$ is

$$\begin{aligned} \phi_N(T_1) &= E[\exp(i \text{Tr}(T'_1 D_N W_N A))] = \zeta_N(D'_N T_1 A) = \\ &= \exp(-0.5 \text{Tr}(D'_N T_1 A \Sigma A T'_1 D_N)) + f_N(D'_N T_1 A), \end{aligned}$$

from (9),

$$= \exp(-0.5 \text{Tr}(T'_1 T_1)) + f_N(D'_N T_1 A),$$

since, from (11) $A \Sigma A = I_p$ and $D_N D'_N = C_N (X'_1 N X_1)^{-1} C_N = I_r$.

To show that $\lim_{N \rightarrow \infty} f_N(D'_N T_1 A) = 0$ for fixed T_1 , note first that

$$\text{Tr}((D'_N T_1 A)' (D'_N T_1 A)) = \text{Tr}(T'_1 T_1 \Sigma^{-1}) \quad \forall N.$$

The result then follows from (9) by choosing

$$A = \left\{ T; \text{Tr}(T' T) \leq \text{Tr}(T'_1 T_1 \Sigma^{-1}) \right\}.$$

Of more interest in practice is the result obtained by replacing Σ by S (or S_0 , which is readily seen to converge in probability to Σ when H is true). If we write $A = \phi_2(\Sigma)$ and define

$$A_N = \phi_2(S), \quad (12)$$

it follows immediately from Theorem 2 that $A_N \xrightarrow{D} A$ and that

$$C_N(\hat{B}_N - B_1)A_N = (C_N(\hat{B}_N - B_1)A)A^{-1}A_N \xrightarrow{D} Z_1 A^{-1}A = Z_1,$$

which proves the following result.

Theorem 8. When H is true

$$\hat{B}_N \xrightarrow{L} N(B_1, S \otimes (X'_1 N X_1)^{-1}),$$

in the sense that

$$C_N (\hat{B}_N - B_1) A_N \xrightarrow{D} N(0, I_{pr}),$$

where C_N and A_N are defined in (11) and (12).

REFERENCES

- [1] Anderson, T. W. (1958), *An Introduction to Multivariate Statistical Analysis*, John Wiley, New York.
- [2] Billingsley, P. (1971), *Weak Convergence of Measures: Applications in Probability*, Regional Conference Series in Applied Mathematics, 5. SIAM, Philadelphia.
- [3] Breiman, L. (1968), *Probability*, Addison-Wesley, Reading, Mass.
- [4] Feller, W. (1966), *An Introduction to Probability Theory and its Applications*, vol. II, John Wiley, New York.

STRESZCZENIE

W pracy prezentuje się uogólnienie zbieżności według rozkładu na wielowskaźnikowe tablice wektorów losowych. Rozważania te wykorzystuje się w analizie zbieżności według rozkładu statystyki T_0^2 -Hotellinga i innych statystyk (w przypadku rozkładu różnego od normalnego) wykorzystywanych w MANOVA.

РЕЗЮМЕ

В работе представляются обобщение сходимости по распределению на мультииндексные таблицы случайных векторов. Эти исследования используются в анализе сходимости по распределению статистики T_0^2 -Хотеллинга и других статистик (в случае распределения разного от нормального) использованных в MANOVA.

