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A STUDY OF  
THE DISTRIBUTIONS OF THE  $T^2$  & WILKS' STATISTICS

BY

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# A STUDY OF THE DISTRIBUTIONS OF $T^2$ AND WILKS' 'STATISTIC'S

## I. Introduction

Much work has been done by different authors in the case of the univariate analysis of variance and when the parent population is assumed to be normal, this study is almost complete. But in practice it appears necessary to measure the individual for a large number of correlated characters and thus the univariate theory needs to be appropriately generalised. The study of multivariate samples dates back to as early as the time of Pearson's investigations into the problem of racial likeness with the aid of a number of measurements on the skulls. Suppose there is a sample of skulls each of which is measured for certain p-characters which are supposed to be the discriminating characteristics of a race. It may be of interest to test the set of p sample means against a hypothetical set or the corresponding mean values calculated from another sample, which might have been taken at a different occasion, or different localities. The problem may be made more general by considering more than two such independent samples, the homogeneity of the mean values of which is the problem under question.

An instance of a different type of multivariate problem in economic studies may be posed somewhat like this:- Consider the demand for a particular commodity; the prices of alternate or complementary commodities, the population and income levels at the particular point of the time interval, besides the price of the commodity in question are responsible for variations that may be observed in the volume of demand. This leads to the study of the relation of one variate with a number of variates. One cannot overlook the presence of significant correlations within the set of these predicting or independent variates and thus the study of individual correlations of the single dependent variate with each of the independent variates separately does not seem to give an overall picture of the situation. The problem considered may be further generalised by considering a set of characters on the dependent side which the set of independent variates together effect and the variates within which by themselves may be correlated with each other.

When there is a single multivariate sample known to have emanated from a multivariate normal population with unknown covariance matrix, Hotelling's  $T^2$  (1) is the appropriate statistic to test the set of sample means against a set of p-values. When there are two samples ( $p$ -variate) known to have emanated from two multivariate normal populations having identical, but unspecified covariance matrix, then Mahalanobis or Studentized  $D^2$  statistics (2) is the appropriate statistic to test the hypothesis of equality of the two sets of means or the hypothesis of the identity of the populations from which the samples have emanated.

The quantity defined to measure the relationship of one variate with a set of auxiliary or independent variates is the multiple correlation coefficient ( $R^2$ ), and an overall test of the relation will thus be a test of significance of the sample multiple correlation coefficient.

When it comes to the problem of tests of significance, as in univariate case, one is confronted with the consideration of the two kinds of error (viz.)

(i) rejecting a hypothesis when it is true,  
and (ii) accepting the hypothesis when an alternative is true.  
While evaluating the two, there comes the need for the probability distributions of the test statistic and both when the hypothesis is true and false or the null and the non-null distributions of which always the former could be easily obtained. But to study the other important characters of the test, e.g., the unbiasedness, the non-null distribution will be required. The non-null distributions of  $T^2$  and  $D^2$  were first obtained in 1938 (2, 3). The non-null distributions of the multiple correlation coefficient when the set of independent variates is fixed either random or fixed, fix were first obtained in 1928 by Fisher (4), who called them the A and C-distributions respectively of the multiple correlation coefficient.

The multiple correlation coefficient when the set of independent variates follows a normal law, and when the dependent variate is an artificially constructed pseudo-variate taking fixed values, happens to be an algebraical derivative of  $T^2$  and  $D^2$  (5), and we shall denote this by  $R^2$  throughout this thesis. The similarity or the duality between the distributions of this  $R^2$  and C-distributions was later established and one of the most useful results that

followed is the derivation of the  $T^2$  and  $D^2$  distributions from the C-distribution. The distribution of this  $R^2$  which thus appears to be playing quite an important role in the multivariate theory was obtained by various authors from time to time (2, 3, 6, 7, 8 & 9). But it should however be noted that all the authors in attacking the problem whether through an analytic approach or through the concept of hyperspace geometry have been invariably assuming the invariance property of this multiple correlation coefficient under any linear transformation of the set of  $p$  variates, and employing the same property advantageously to simplify the otherwise unsolved problem. But to know if some interesting properties are covered under the simplicity effected by the above property, the distribution of  $R^2$  is derived without assuming the invariance property in this thesis.  $T^2$  and  $D^2$  distributions are then derived as particular cases of this distribution.

$D^2$  statistic, as already referred to, is appropriate only in the case of two  $p$ -variate samples to test the hypothesis of homogeneity of set of means under the assumption of identical covariance matrix and the problem of  $k$ -multivariate samples is not yet completely solved even under the assumption of identical but unspecified population covariance matrix. There have been two approaches suggested neither of which is fully investigated as yet. One of them is by the method of discriminant function leading to the study of the  $(k-1)$  canonical correlations, which are defined as the roots of a certain determinantal equation; the joint distribution of (null distribution) of these roots was obtained by Hsu and others (10, 11, 12) and the null distribution of the individual roots was later obtained by Roy and others (13, 14). One drawback from which this approach suffers, as already pointed out by Bartlett (15), is that the order of roots in the sample may not correspond to the order in the population. Another difficulty is the lack of knowledge as to which root or what particular functions of the roots provides the most powerful test; for though the nonnull distributions of the roots have been to some extent studied by Bartlett, Roy and others (16, 17, 18), these attempts hardly throw much light on the comparative power functions. The other approach is through the likelihood ratio method which gives the ratio of the within sample covariance

matrix to the total covariance matrix as the appropriate statistic to test the homogeneity of the means in the k-sample case. This approach was due to Wilks and others (19, 20, 21) and the criterion defined by him to measure the relation between two sets of variates, one set containing  $(k-1)$  variates and the other containing  $p$  variates, also reduces to the above likelihood ratio when the set of  $(k-1)$  variates is fixed and the other set follows a multivariate normal law. Another interesting property of this criterion, that makes this approach rather preferable, is its being a symmetric function of the above referred  $(k-1)$  roots. The null distribution of this statistic was partly studies by Wald and Brookner (22). The nonnull distribution of this statistic was not obtained before even for any value of  $k = 2$ . Anderson (9) has given the moments of the statistic for  $k = 3$  when the set of  $k-1=2$  variates is fixed and the other set follows a normal law; i.e., for the likelihood ratio appropriate to test the homogeneity of means for three multivariate samples. In the present paper the derivation of the nonnull distribution for  $k = 3$  will be given

- (i) when the set of  $(k-1)$  variates is fixed - the statistic is a generalisation of  $R^2$  and
- (ii) when the set of  $p$  variates if fixed - which thus gives the statistic relevant to what is called the general regression problem by Hsu (23).

One particular object of this study is to investigate if some sort of duality (as in the case of the distribution of  $R^2$  and Fisher's  $\chi^2$  distribution) exists between the above two nonnull distributions. In the case of the distribution of the canonical correlations, the duality has been shown by Bartlett (16) to hold only if the number of the population non-vanishing correlations is one or zero.

2. Distribution of the multiple correlation coefficient when the dependent variate is fixed and the set of independent variates follows a multivariate normal law.

Let  $[x_{i0}; \{x_{iu}\}]$  ( $u = 1, 2, \dots, p; i = 1, 2, \dots, N$ )

be a sample of size  $N$ ,  $x_0$  being the dependent variate and  $\{x_u\}$  the set of independent variates.

Given that i)  $\{x_{iu}\}$  follow a normal law

$$\text{ii)} E(x_{ir}) = m_r x_{i0}; r = 1, 2, \dots, p$$

and iii)  $|d_{rs}|$  is the covariance matrix of  $\{x_r\}$

then the probability of the sample is given by

$$\text{Const. } \exp -\frac{1}{2} \left[ \sum_{r,s=1}^p d_{rs} \left\{ \sum_{i=1}^N (x_{ir} - m_r x_{i0})(x_{is} - m_s x_{i0}) \right\} \right] \prod_{i=1}^N \prod_{r=1}^p \{dx_{ir}\} \quad (2.1)$$

$$\text{where } |d_{rs}| = |d_{rs}^{-1}|$$

under these conditions, the likelihood ratio  $\lambda$  appropriate to test the hypothesis  $H (m_1 = 0, \dots, m_p = 0)$  is then given by

$$(\lambda)^{\frac{2}{N}} = 1 - R^2 = \frac{\begin{vmatrix} v_{00} & v_{01} & \cdots & v_{0p} \\ v_{10} & v_{11} & \cdots & v_{1p} \\ \vdots & \vdots & \ddots & \vdots \\ v_{p0} & v_{p1} & \cdots & v_{pp} \end{vmatrix}}{\begin{vmatrix} v_{00} & v_{10} & \cdots & v_{p0} \\ v_{10} & v_{11} & \cdots & v_{1p} \\ v_{p0} & v_{p1} & \cdots & v_{pp} \end{vmatrix}} \quad (2.2)$$

$$\text{where } v_{rs} = \sum_{i=1}^N x_{ir} x_{is}.$$

$$\text{Writing } h^2 = \sum_{i=1}^N x_{i0}^2, \quad h^2 w_r = \sum_{i=1}^N x_{ir} x_{i0}$$

$$\text{and } a_{rs} = \sum_{i=1}^N (x_{ir} - w_r x_{i0})(x_{is} - w_s x_{i0})$$

$$v_{rs} = a_{rs} + h^2 w_r w_s \quad (2.3)$$

(2.2) can be rewritten as

$$1 - R^2 = \frac{|a_{rs}|}{|v_{rs}|} \quad (r, s = 1, 2, \dots, p)$$

$$\text{or } R^2 = 1 - \sum v_{rs}^2 w_r w_s \quad (2.4)$$

we will then proceed to derive the sampling distribution of  $\lambda$  or  $R^2$  for fixed  $x_0$  when

- i)  $H$  is true
- and ii)  $H$  is not true.

The distribution of  $[\{a_{rs}\}, \{w_r\}]$ ; ( $r, s = 1, 2, \dots, p$ ) derived from (2.1), is given by

$$\text{Const. } \exp -\frac{1}{2} \left[ \sum_{r,s=1}^p \alpha^{rs} \{a_{rs} + (w_r - m_r)(w_s - m_s)h^2\} \right] \cdot |a_{rs}|^{\frac{N-p-2}{2}} \prod_{r,s} \{da_{rs}\} \prod_r \{dw_r\}. \quad (2.5)$$

Writing  $\Delta^2 = \sum_{r,s=1}^p \alpha^{rs} m_r m_s$  and using (2.3), (2.5)

leads to the distribution of  $[\{v_{rs}\}, \{w_r\}]$  given by

$$\text{Const. } \exp -\frac{1}{2} \left[ \sum_{r,s} \alpha^{rs} v_{rs} + h^2 \Delta^2 + \sum_{r,s} \alpha^{rs} m_r w_s h^2 \right] \cdot |v_{rs}|^{\frac{N-p-2}{2}} \left( 1 - h^2 \sum r s v_{rs} w_r w_s \right)^{\frac{N-p-2}{2}} \prod_{r,s} \{dv_{rs}\} \prod_r \{dw_r\}. \quad (2.6)$$

Because  $\Delta^2$  is a +ve definite quadratic form in  $m_r$ 's,  $\Delta^2 = 0$  if and only if each  $m_r$  vanishes. Thus  $\Delta^2 = 0$  implies that  $H$  is true and vice versa. Thus when  $H$  is true, the distribution of  $R^2$  which is a quadratic in  $w_r$  of rank  $p$  follows immediately from (2.6) as

$$\frac{\Gamma(\frac{N-p}{2})}{\Gamma(\frac{N-p}{2}) \Gamma(\frac{p}{2})} (1 - R^2)^{\frac{N-p-2}{2}} (R^2)^{\frac{p}{2}-1} dR^2 \quad (2.7).$$

which is the well known Beta distribution.

## ii) Distribution when H is not true.

Without loss of generality  $\alpha^{rs} = 0$  for  $r \neq b$   
 $\alpha^{bb} = 1$

The former derivations involve the assumption of all the  $m$ 's except  $m_1$  vanishing. We will not assume any  $m$  to vanish so that

$$\Delta^2 = m_1^2 + m_2^2 + \dots + m_p^2$$

and so let us write  $m_{ri} = \Delta c_r$  (2.8)  
where  $c_1^2 + c_2^2 + \dots + c_p^2 = 1$

We then adopt the transformation  $\{w_r\}$  to  $\{b_r\}$

$$b_r = \frac{\begin{vmatrix} w_r & w_1 & w_2 & \dots & w_{r-1} \\ v_{1r} & v_{11} & v_{12} & \dots & v_{1, r-1} \\ \vdots & \vdots & \vdots & & \vdots \\ v_{r-1, r} & v_{r-11} & v_{r-12} & \dots & v_{r-1, r-1} \end{vmatrix}}{\begin{vmatrix} v_{11} & v_{12} & \dots & v_{1r} \\ v_{21} & v_{22} & \dots & v_{2r} \\ \vdots & \vdots & & \vdots \\ v_{rr} & v_{r2} & \dots & v_{rr} \end{vmatrix}} \quad (2.9)$$

and letting

$$x_r^2 = \frac{\begin{vmatrix} v_{11} & v_{12} & \dots & v_{1r} \\ v_{21} & v_{22} & \dots & v_{2r} \\ \vdots & \vdots & & \vdots \\ v_{rr} & v_{r2} & \dots & v_{rr} \end{vmatrix}}{\begin{vmatrix} v_{11} & v_{12} & \dots & v_{r-1, r} \\ v_{21} & v_{22} & \dots & v_{2, r-1} \\ \vdots & \vdots & & \vdots \\ v_{r-1, 1} & v_{r-1, 2} & \dots & v_{r-1, r-1} \end{vmatrix}}$$

the jacobian of the transformation is given by

$$\frac{\partial(w_1, w_2, \dots, w_p)}{\partial(b_1, b_2, \dots, b_p)} = (x_1^2 x_2^2 \dots x_p^2) = |v_{rs}|$$

We observe that under this transformation

$$R^2 = \sum_{r=1}^p b_r^2 x_r^2 \quad (2.10)$$

$$v_{rr} = x_r^2 + \sum_{u=r+1}^p z_{ru}^2$$

$$\text{and } h w_n = b_n x_n \cdot x_n + \sum_{u=1}^{n-1} b_u x_u \cdot z_{nu}$$

where  $z_{nu} = b_{nu} x_u$

The joint distribution of

$\{b_n x_n, z_{n,n-1}, \dots, z_{n,1}, x_n^2\} (n=1, 2, \dots, p)$

can then be derived from (2.6) with the use of

(2.8), (2.9) and (2.10) as

$$\text{Const. } e^{-\frac{h^2 \Delta^2}{2}} \left(1 - \sum b_n^2 x_n^2\right)^{\frac{N-h-2}{2}}$$

$$\prod_{n=1}^p \left[ \exp -\frac{1}{2} \left( x_n^2 + z_{n,n-1}^2 + \dots + z_{n,1}^2 + h \Delta c_n \sum_{u=1}^n b_u x_u z_{nu} \right) \right]$$

$$\prod_{n=1}^p (dx_n^2 dz_{n,n-1} \dots dz_{n,1} d\bar{b}_n x_n) \quad (2.11)$$

Setting the further transformation

$$b_p x_p = R \cos \theta_1 \cos \theta_2 \dots \cos \theta_{p-2} \cos \theta_{p-1}$$

$$b_{p-1} x_{p-1} = R \cos \theta_1 \cos \theta_2 \dots \cos \theta_{p-2} \sin \theta_{p-1}$$

$$\dots \dots \dots \dots \dots \dots$$

$$b_n x_n = R \cos \theta_1 \cos \theta_2 \dots \cos \theta_{n-1} \sin \theta_n$$

$$\dots \dots \dots \dots \dots \dots$$

$$b_2 x_2 = R \cos \theta_1 \sin \theta_2$$

$$b_1 x_1 = R \sin \theta_1 \quad (2.12)$$

The jacobian is given by

$$\frac{\partial (b_p x_p, b_{p-1} x_{p-1}, \dots, b_2 x_2, b_1 x_1)}{\partial (R, \theta_1, \theta_2, \dots, \theta_{p-2}, \theta_{p-1})}$$

$$= R^{\frac{p-1}{2}} \cos \theta_1^{\frac{p-2}{2}} \cos \theta_2^{\frac{p-3}{2}} \dots \cos \theta_{p-2}^{\frac{1}{2}} \quad (2.13)$$

Using (2.12) and (2.13), (2.11) leads then to

the joint distribution of

$$(R^2, \cos \theta_1, \dots, \cos \theta_{p-1}) \quad \left\{ \begin{array}{l} 0 \leq R^2 \leq 1 \\ 0 \leq \theta \leq \frac{\pi}{2} \\ 0 \leq x^2 \leq \infty \\ -\infty \leq z \leq \infty \end{array} \right.$$

$\left\{ \begin{array}{l} x_n, z_{n-1}, \dots, z_1 \end{array} \right\} (n=1, 2, \dots, p)$

Given as

which is given as

When we integrate out for

$$\{ x_n^2, x_{n+1}^2, \dots, x_m^2 \} \quad (n=1, 2, \dots, p)$$

and making use of the relation

$$\frac{1}{\sqrt{\pi}} \cdot - \frac{2^{2l_{ru}} \Gamma(l_{ru} + \frac{1}{2})}{\Gamma(2l_{ru} + 1)} = \frac{1}{\Gamma(l_{ru} + 1)}$$

we get at the joint distribution of

$$\begin{aligned}
 & -\frac{\hbar^2 \Delta^2}{e^2} \left( R^2, \cos \theta_1, \dots, \cos \theta_{p-1} \right) \quad \text{as} \\
 & \text{Const. } -\frac{\hbar^2 \Delta^2}{e^2} (R^2)^{\frac{p}{2}-1} (1-R^2)^{\frac{N-p-2}{2}} dR^2 \cos \theta_1 \dots \cos \theta_{p-1} \cos \theta_p \\
 & \times \prod_{n=1}^p \left\{ \sum_{l_{nn}=0}^{\infty} \left( \frac{\hbar^2 R^2 \Delta^2}{2} \right)^{l_{nn}} \frac{1}{l_{nn}!} (c_n^2)^{l_{nn}} (\cos \theta_1, \dots, \cos \theta_{n-1}, \sin \theta_n)^{l_{nn}} \right. \\
 & \quad \left. \frac{\Gamma(N-n + l_{nn})}{\Gamma(l_{nn} + \frac{1}{2})} \right. \\
 & \quad \left[ \prod_{u=1}^{n-1} \left( \sum_{l_{nu}=0}^{\infty} \left( \frac{\hbar^2 R^2 \Delta^2}{2} \right)^{l_{nu}} \frac{1}{l_{nu}!} (c_n^2)^{l_{nu}} (\cos \theta_1, \dots, \cos \theta_{u-1}, \sin \theta_u)^{l_{nu}} \right) \right]
 \end{aligned}$$

$$\text{Writing } \sum_{u=1}^{\pi} l_{ru} = l_{r.}, \quad \sum_{u=1}^p l_{ru} = l_{r.p}$$

$$\text{and } l = \sum_{r=1}^p l_{r.} = \sum_u l_{r.u} \quad (2.15) \text{ can be}$$

written as

$$\text{Const. } e^{-\frac{h^2 \Delta^2}{2}} (R^2)^{\frac{p}{2}-1} (1-R^2)^{\frac{N-p-2}{2}} dR^2$$

$$\sum_{l=0}^{\infty} \left[ \left( \frac{h^2 R^2 \Delta^2}{2} \right)^l \frac{1}{l!} \sum_{\substack{\sum_{r,u} l_{ru} = l \\ (c_1^2)^{l_1} (c_2^2)^{l_2} \dots (c_p^2)^{l_p}}} \left\{ \frac{e^l}{l_{11}! l_{21}! l_{22}! \dots l_{p1}! \dots l_{pp}!} \right. \right.$$

$$\left. \left. \prod_{r=1}^p \frac{\Gamma(\frac{N-r}{2} + l_{rr})}{\Gamma(l_{rr} + \frac{1}{2})} \right. \right.$$

$$(sin \theta_1)^{2l_{11}} (cos \theta_1)^{2(l-l_{11}-l_{1.}+l_{11})+p-2}$$

$$(sin \theta_u)^{2l_{uu}} (cos \theta_u)^{2(l-l_{1.} \dots -l_{u-1} - l_{1.} + l_{11})+p-u}$$

$$(sin \theta_{p-1})^{2l_{p-1}} (cos \theta_{p-1})^{2(l_{pp} - l_{1.} + l_{11})} \left. \right\}$$

$$d\theta_1 d\theta_2 \dots d\theta_{p-1} \quad (2.16)$$

The general term of the summation (under the curly brackets inside the square bracket) in (2.16) when integrated for  $\theta_1, \theta_2, \dots, \theta_{p-1}$  ( $0 \leq \theta \leq \frac{\pi}{2}$ ) gives

$$\frac{l!}{l_{11}! l_{21}! l_{22}! \dots l_{p1}! \dots l_{pp}!} (c_1^2)^{l_{11}} (c_2^2)^{l_{21}} \dots (c_p^2)^{l_{p1}}$$

$$\prod_{r=1}^p \left\{ \frac{\Gamma(\frac{N-r}{2} + l_{rr})}{\Gamma(l_{rr} + \frac{1}{2})} \right\} \prod_{u=1}^{p-1} \frac{\Gamma(\frac{2l_{uu}+1}{2}) \Gamma(z \frac{-l-l_{1.} \dots -l_{u-1} - l_{1.} + l_{11}}{2} + p-u)}{\Gamma(\frac{2l_{u+1}+1}{2}) \Gamma(z \frac{-l-l_{1.} \dots -l_{u-1} - l_{1.} + l_{11}}{2} + p-u+r)}$$

$$(2.17)$$

Noting that  $l_{1.} = l_{11}$ , and  $l_{.p} = l_{pp}$ , (2.17) will be written as

$$\begin{aligned}
 & \frac{l!}{l_{11}! l_{21}! \cdots l_{p1}!} (c_{12})^{l_{11}} \cdots (c_{p2})^{l_{p1}} \frac{1}{\Gamma(\frac{p}{2} + l)} \\
 & \cdot \frac{l_{11}!}{l_{11}!} \frac{l_{21}!}{l_{21}! l_{22}!} \cdots \frac{l_{uu}!}{l_{u1}! \cdots l_{uu}!} \cdots \frac{l_{pp}!}{l_{p1}! \cdots l_{pp}!} \\
 & \Gamma\left(\frac{2l_{11}+1}{2}\right) \Gamma\left(\frac{2l_{21}+1}{2}\right) \cdots \cdots \cdots \Gamma\left(\frac{2l_{p1}+1}{2}\right) \\
 & \frac{\Gamma\left(\frac{N-1}{2} + l_{11}\right) \Gamma\left(\frac{N-2}{2} + l_{21}\right) \cdots \cdots \cdots \Gamma\left(\frac{N+1-p}{2} + l_{p-1, p-1}\right) \Gamma\left(\frac{N-1}{2} + l_{pp}\right)}{\Gamma\left(\frac{1}{2} + l_{11}\right) \Gamma\left(\frac{1}{2} + l_{22}\right) \cdots \cdots \cdots \Gamma\left(\frac{1}{2} + l_{p-1, p-1}\right)}
 \end{aligned}$$

(2.18)

$$\begin{aligned}
 & \Gamma\left(\frac{N-2}{2}\right) \cdots \cdots \cdots \Gamma\left(\frac{N-p}{2}\right) \\
 & \times \left\{ \frac{\Gamma(l + \frac{N-1}{2})}{\Gamma(l + \frac{p}{2})} \frac{l!}{l_{11}! l_{21}! \cdots l_{p1}!} (c_{12})^{l_{11}} (c_{22})^{l_{21}} \cdots (c_{p2})^{l_{p1}} \right. \\
 & \left. \frac{l_{11}!}{l_{11}!} \frac{l_{21}!}{l_{21}! l_{22}!} \cdots \frac{l_{uu}!}{l_{u1}! \cdots l_{uu}!} \cdots \frac{l_{pp}!}{l_{p1}! \cdots l_{pp}!} \right. \\
 & \left. B\left(\frac{N-p}{2} + l_{p1}, l_{p-1} + \frac{1}{2}\right) B\left(\frac{N-1-p}{2} + l_{p1} + l_{p-1}, l_{p-2} + \frac{1}{2}\right) \cdots B\left(\frac{N-2}{2} + l_{p1} + l_{p-1}, l_{p-1} + \frac{1}{2}\right) \right. \\
 & \left. B\left(\frac{N-2}{2}, l_{11} + \frac{1}{2}\right) B\left(\frac{N-3}{2}, l_{22} + \frac{1}{2}\right) \cdots \cdots B\left(\frac{N-p}{2}, l_{p-1, p-1} + \frac{1}{2}\right) \right\}
 \end{aligned}$$

This expression is to be summed over all values of  $l_{uu}$  satisfying  $\sum_{u \leq n} l_{uu} = l$  for a fixed value of  $l$ .  
 The summation will be done in two stages. As a first step we will sum the latter portion of (2.19) (viz.)

$$\begin{aligned}
 & \frac{l_{11}!}{l_{11}!} \frac{l_{21}!}{l_{21}! l_{22}!} \cdots \frac{l_{uu}!}{l_{u1}! \cdots l_{uu}!} \cdots \frac{l_{pp}!}{l_{p1}! \cdots l_{pp}!} \\
 & B\left(\frac{N-p}{2} + l_{p1}, l_{p-1} + \frac{1}{2}\right) \cdots \cdots \cdots B\left(\frac{N-2}{2} + l_{p1} + \cdots + l_{p-2, p-1} + \frac{1}{2}, l_{p-1} + \frac{1}{2}\right) \\
 & B\left(\frac{N-2}{2}, l_{11} + \frac{1}{2}\right) \cdots \cdots \cdots B\left(\frac{N-p}{2}, l_{p-1, p-1} + \frac{1}{2}\right)
 \end{aligned}$$

(2.20)

The product of Beta functions in the numerator can be written as a constant multiplied by

$$\int_0^{\frac{\pi}{2}} \int_0^{\frac{\pi}{2}} \int_0^{\frac{\pi}{2}} \cdots \int_0^{\frac{\pi}{2}} \left\{ \begin{array}{l} (\sin^2 \lambda_1)^{l_1} (\cos^2 \lambda_1)^{\frac{N-3}{2} + l_{p+1} + \dots + l_{p+q}} d\lambda_1 \\ (\sin^2 \lambda_2)^{l_2} (\cos^2 \lambda_2)^{\frac{N-4}{2} + l_{p+1} + \dots + l_{p+q}} d\lambda_2 \\ \vdots \\ (\sin^2 \lambda_u)^{l_u} (\cos^2 \lambda_u)^{\frac{N-2u}{2} + l_{p+1} + \dots + l_{p+q}} d\lambda_u \\ (\sin^2 \lambda_{p+1})^{l_{p+1}} (\cos^2 \lambda_{p+1})^{\frac{N-1-p}{2} + l_p} d\lambda_{p+1} \end{array} \right\}$$

The integrand above can be split up as

We then consider a rearrangement of (2.20) where the expressions in the curly brackets of the successive components in (2.22) are to be combined with

$$\frac{e_p!}{e_{p1}! e_{p2}! \cdots e_{pp}!}, \frac{e_{p+1}!}{e_{p+1,1}! \cdots e_{p+1,p+1}!}, \dots \frac{e_u!}{e_{u1}! \cdots e_{uu}!}, \dots \frac{e_{2k}!}{e_{2k,1}! e_{2k,2}!}$$

respectively (2.23)

The expression in the curly bracket of the first component in (2.22) when combined with the appropriate factor, in (2.23), will be summed up

over all values of  $\ell_{p1}, \ell_{p2}, \dots, \ell_{pp}$  for a fixed value of  $\ell_p$ . (i.e)

$$\sum_{\substack{\ell_{p1} + \dots + \ell_{pp} \\ = \ell_p}} \left\{ \frac{\ell_p!}{\ell_{p1}! \dots \ell_{pp}!} \cdot (\sin^2 \lambda_1)^{\ell_{p1}} \cdots (\cos^2 \lambda_1 \cdots \cos^2 \lambda_{p-1})^{\ell_{pp}} \right\}$$

$$= (\sin^2 \lambda_1 + \cos^2 \lambda_1, \sin^2 \lambda_2 + \cdots + \cos^2 \lambda_1 \cdots \cos^2 \lambda_{p-1})^{\ell_p}$$

$$= 1$$

The remaining expression of the first component (viz)  $(\sin^2 \lambda_{p-1})^{\ell_{p-1} p-1} (\cos^2 \lambda_{p-1})^{\frac{N-1+p}{2}}$ , which and which alone now contains  $\lambda_{p-1}$ , will be integrated w.r.t.  $\lambda_{p-1}$  so that the net result of the first summation followed by the first integration is  $B(\ell_{p-1} p-1 + \frac{1}{2}, \frac{N-p}{2})$ ; and this Beta function cancels out with the last Beta function of the denominator of (2.20). Similarly carrying on similar summations each time followed by a similar integration with each of the successive components of (2.22) we arrive at the last component

(vi3)

$$\left[ \left\{ (\sin^2 \lambda_1)^{\ell_{21}} (\cos^2 \lambda_1)^{\ell_{22}} \right\} (\sin^2 \lambda_1)^{\ell_{11}} (\cos^2 \lambda_1)^{\frac{N-3}{2}} \right]$$

the expression in the curly brackets of which will be combined with the respective factor of (2.23).

(vi3).

$$\frac{\ell_{21}!}{\ell_{21}! \ell_{22}!} \quad \text{and summed over}$$

all values of  $\ell_{21}$  and  $\ell_{22}$  for fixed values of  $\ell_{21} + \ell_{22} = \ell_2$ . This summation resulting unity, will then be followed by the integration of the remaining expression in the component

$$(vi3) \quad (\sin^2 \lambda_1)^{\ell_{11}} (\cos^2 \lambda_1)^{\frac{N-3}{2}} \text{ w.r.t } \lambda_1$$

The result of this integration is a Beta function which will again cancel out with the <sup>first</sup> Beta function left in the denominator of (2.20).

Thus the sub summation of (2.16) finally reduces to the summation

$$\sum_{l_1 + l_2 + \dots + l_p = l} \frac{l!}{l_1! \dots l_p!} (c_{12})^{l_1} \dots (c_{pq})^{l_p} \frac{\Gamma(\frac{N-1}{2} + l)}{\Gamma(\frac{p}{2} + l)}$$

$$= \frac{\Gamma(\frac{N-1}{2} + l)}{\Gamma(\frac{p}{2} + l)} \quad \text{because of (2.8).}$$

Thus the distribution of  $R^2$  in (2.16) finally comes out as

$$\text{Const. } e^{-\frac{h^2 \Delta^2}{2}} (R^2)^{\frac{p}{2}-1} (1-R^2)^{\frac{N-p-2}{2}} dR^2$$

$$\sum_{l=0}^{\infty} \left\{ \frac{h^2 \Delta^2 R^2}{2} \right\}^l \frac{1}{l!} \frac{\Gamma(\frac{N-1}{2} + l)}{\Gamma(\frac{p}{2} + l)}$$

where the constant is given by  $\frac{1}{B(\frac{p}{2}, \frac{N-p-2}{2})} \Gamma(\frac{N-1}{2}) \Gamma(\frac{p}{2})$   
so the distribution written in the standard form

$$\frac{1}{B(\frac{p}{2}, \frac{N-p-2}{2})} e^{-\frac{h^2 \Delta^2}{2}} (R^2)^{\frac{p}{2}-1} (1-R^2)^{\frac{N-p-2}{2}} F_1\left(\frac{N-1}{2}, \frac{p}{2}; \frac{h^2 \Delta^2 R^2}{2}\right) \quad (2.24)$$

Derivation of the  $T^2$  distribution.

Let  $\{x_{in}\}_{i=1,2,\dots,N}^{n=1,2,\dots,p}$  be a sample of size  $N$  from a  $p$ -variate normal population. If  $\{\bar{x}_{in}\}$  denotes the set of sample means and

$$b_{rs} = \sum_{i=1}^N (x_{in} - \bar{x}_{in})(x_{is} - \bar{x}_{is}), \text{ then}$$

Hotelling's  $T^2$  is defined as

$$T^2 = N(N-1) \sum b_{rs} \bar{x}_{in} \bar{x}_{is} \quad (2.25)$$

Now in our problem setting

$x_{i0} = 1$  for any  $i$ , we observe that

$$h^2 = \sum_{i=1}^N x_{i0}^2 = N$$

$$h^2 w_n = \sum_{i=1}^N x_{i0} x_{in} = N \bar{x}_{in} \text{ or } w_n = \bar{x}_{in}$$

$$\text{and } a_{ns} = \sum_{i=1}^N (x_{in} - w_n x_{i0})(x_{is} - w_s x_{i0}) \\ = b_{ns} \quad (2.26)$$

From (2.4), (2.25) and (2.26) we have

$$\begin{aligned}
 1-R^2 &= \frac{|a_{rs}|}{|v_{rs}|} \\
 &= \frac{|a_{rs}|}{|a_{rs} + h^2 w_r w_s|} = \frac{1}{1 + h^2 \sum a_{rs} w_r w_s} \\
 &= 1 - \frac{1}{1 + \frac{T^2}{N-1}} \quad (2.27)
 \end{aligned}$$

Thus for the above transformation of  $R^2$  to  $T^2$ , we have

$$dR^2 = \frac{1}{N-1} \left( \frac{1}{1 + \frac{T^2}{N-1}} \right)^2 dT^2$$

$$\text{and } R^2 = \frac{T^2}{(N-1) + T^2}$$

and (2.24) leads to the distribution of  $T^2$  given by

$$\frac{1}{B\left(\frac{p}{2}, \frac{N-p}{2}\right)} e^{-\frac{N\Delta^2}{2}} \left\{ \frac{T^2}{(N-1) + T^2} \right\}^{\frac{p}{2}-1} \left\{ \frac{N-1}{N-1 + T^2} \right\}^{\frac{N-p}{2}} \left( \frac{N-1}{N-1 + T^2} \right)^2 dT^2$$

$$, F_1\left(\frac{N-1}{2}, \frac{p}{2}; \frac{N\Delta^2 T^2}{N-1 + T^2}\right) dT^2$$

$$\frac{1}{B\left(\frac{p}{2}, \frac{N-p}{2}\right)} e^{-\frac{N\Delta^2}{2}} \left( \frac{N-p}{N-1} \right)^{\frac{p}{2}-1} \left\{ \frac{(T^2)}{(N-1) + T^2} \right\}^{\frac{N}{2}} dT^2$$

$$, F_1\left(\frac{N-1}{2}, \frac{p}{2}; \frac{N\Delta^2 T^2}{N-1 + T^2}\right) \quad (2.28)$$

Derivation of the Distribution of the  $D^2$  statistic.

If all the variates ( $x_0, x_1, x_2, \dots, x_p$ ) were measured from the respective sample means  $\{\hat{x}_r\}$ , the power of  $|a_{rs}|$  in (2.5) will be  $\frac{N-p-3}{2}$  and this will be carried on to the end to the power of  $(1-R^2)$  in (2.24) and the distribution in this case will be

$$\frac{1}{B\left(\frac{p}{2}, \frac{N-p-1}{2}\right)} e^{-\frac{h^2 \Delta^2}{2}} \left(R^2\right)^{\frac{p}{2}-1} \left(1 - R^2\right)^{\frac{N-p-3}{2}} , F_1\left(\frac{N-1}{2}, \frac{p}{2}; \frac{h^2 \Delta^2 R^2}{2}\right) \quad (2.29)$$

Let  $\{x_{ir}\}$  ( $i=1, 2, \dots, n_1; r=1, 2, \dots, p$ ) and

$\{x_{ir}\}$  ( $i=n_1+1, \dots, n_1+n_2; r=1, 2, \dots, p$ ) be two

samples of sizes  $n_1$  and  $n_2$  respectively from two  
ivariate normal populations having identical  
but unspecified covariance matrix  $\Sigma$ . If

$\{\bar{x}_{ir}\}$  and  $\{\bar{x}'_{ir}\}$  where  $\bar{x}_{ir} = \frac{1}{n_1} \sum_{i=1}^{n_1} (x_{ir})$

and  $\bar{x}'_{ir} = \frac{1}{n_2} \sum_{i=n_1+1}^{n_1+n_2} (x_{ir})$ , be the two

sets of sample means and if

$$(n_1 + n_2) C_{rs} = \sum_{i=1}^{n_1} (x_{ir} - \bar{x}'_{ir}) (x_{is} - \bar{x}_s) \\ + \sum_{i=n_1+1}^{n_1+n_2} (x_{ir} - \bar{x}'_{ir}) (x_{is} - \bar{x}_s)$$

then the  $D^2$  statistic is defined by

$$P(D^2) = \sum_{r, s=1}^p C_{rs}^{-1} (\bar{x}_{ir} - \bar{x}'_{ir}) (\bar{x}_{is} - \bar{x}'_s)$$

where  $\|C_{rs}\|^{-1}$  is the matrix reciprocal to  
 $\|C_{rs}\|$ .

To consider this as a special case of  
the problem we have considered, let the  $n_1 + n_2 = N$   
sets of observations be looked upon as a single sample.  
All the variates  $\{x_{ir}\}$  are to be measured from  
the respective sample means  $\{\hat{x}_{ir}\}$  where

$$\hat{x}_{ir} = \frac{1}{N} \sum_{l=1}^N x_{il} = \frac{n_1 \bar{x}_{ir} + n_2 \bar{x}'_{ir}}{N} \text{ or the}$$

origin of measurement for the  $r$ th variate is taken  
at this point. In accordance with this general  
requirement let us set

$$x_{i0} = \frac{n_2}{N} \text{ for } i=1, 2, \dots, n_1$$

$$= -\frac{n_1}{N} \text{ for } i=n_1+1, \dots, (n_1+n_2)$$

$$\text{Then } f^2 = \frac{N}{N} \sum_{i=1}^N x_{i0}^2 = \frac{n_1 n_2}{N}$$

$$f^2 w_n = \sum_{i=1}^N x_{i0} x_{ir} = \frac{n_1 n_2}{N} (\bar{x}_{ir} - \bar{x}'_{ir})$$

$$\text{or. } w_n = (\bar{x}_{ir} - \bar{x}'_{ir})$$

$$\text{and } a_{rs} = \sum_{l=1}^N (x_{rl} - \bar{x}_r x_{l0}) (x_{ls} - \bar{x}_s x_{l0})$$

$$\begin{aligned} &= \sum_{l=1}^{n_1} \left\{ x_{rl} - \frac{n_2}{N} (\bar{x}_r - \bar{x}_{r1}) \right\} \left\{ x_{ls} - \frac{n_2}{N} (\bar{x}_s - \bar{x}_{s1}) \right\} \\ &+ \sum_{l=n_1+1}^{n_1+n_2} \left\{ x_{rl} + \frac{n_1}{N} (\bar{x}_r - \bar{x}_{r1}) \right\} \left\{ x_{ls} + \frac{n_1}{N} (\bar{x}_s - \bar{x}_{s1}) \right\} \\ &= N C_{rs} \quad \text{because of the origin of measurement} \end{aligned}$$

Thus we will have -

$$1 - R^2 = \frac{1}{1 + \frac{1}{n^2} \sum a_{rs}^2 w_r w_s}$$

$$= \frac{1}{1 + \frac{\bar{n} p D^2}{2N}} \quad \text{where } \frac{\bar{n}}{n} = \frac{1}{n_1} + \frac{1}{n_2}$$

$$\therefore dR^2 = \left( \frac{1}{1 + \frac{\bar{n} p D^2}{2N}} \right)^2 \frac{\bar{n} p}{2N} dD^2$$

$$R^2 = \frac{\bar{n} p D^2}{2N + \bar{n} p D^2} \quad \text{so that (2.29)}$$

leads to the distribution of  $D^2$  given by

$$\frac{1}{B(\frac{p}{2}, \frac{N-p-1}{2})} \left( \frac{\bar{n} p D^2}{2N + \bar{n} p D^2} \right)^{\frac{p}{2}-1} \left( \frac{2N}{2N + \bar{n} p D^2} \right)^{\frac{N-p-3}{2}} \frac{2N \bar{n} p}{(2N + \bar{n} p D^2)^2} dD^2$$

$$, F_1 \left( \frac{N-1}{2}, \frac{p}{2}; \frac{\bar{n}^2 \Delta^2 p D^2}{8N + 4\bar{n} p D^2} \right)$$

which reduces to can be rewritten as

$$\frac{\Gamma(\frac{N-1}{2})}{\Gamma(\frac{p}{2}) \Gamma(\frac{N-p-1}{2})} \left( \frac{\bar{n} p}{2N} \right)^{\frac{p}{2}} e^{-\frac{\bar{n} \Delta^2}{4}} (D^2)^{\frac{p}{2}-1} \left( 1 + \frac{p \bar{n} D^2}{2N} \right)^{-\frac{N-1}{2}} dD^2$$

$$, F_1 \left( \frac{N-1}{2}, \frac{p}{2}; \frac{\bar{n}^2 \Delta^2 p D^2}{8N + 4\bar{n} p D^2} \right) \quad (2.31)$$

Here  $\Delta^2 = \sum a_{rs}^2 (m_r - m'_r)(m_s - m'_s)$   
 and runs  $p \Delta^2 / p$  will be the population parameter  
 corresponding to  $D^2$  defined by (2.30); where  $m_r$   
 and  $m'_r$  have the meaning

$$E(x_{rl}) = m_r x_{l0} \quad l = 1 \text{ to } n_1$$

$$= m'_{r1} x_{l0} \quad l = n_1 + 1 \text{ to } n_1 + n_2$$

and Null

3. Non null distributions of the Wilks statistic

for  $\lambda_{\text{null}}$  when the set of  $k-1 (= p)$  variates is  
fixed and the other set follows a normal law.

Let  $\{x_{id}; x_{ir}\}$ , ( $i=1, 2, \dots, N$ ;  $d=0, 1$ ;  $r=2, 3, \dots, p+1$ ),

be a sample of size  $N$ ,  $x_0$  and  $x_1$  being the two dependent variates and  $\{x_r\}$  ( $r=2, 3, \dots, p+1$ ) being the set of  $p$  independent variates. The origin of measurement for each of the variate (both on the dependent and independent side) is taken at the respective sample mean. Given that

1)  $\{x_r\}$  follows a normal law

$$2) E(x_r) = \beta_r x_{1,0} + \delta_r x_0$$

where  $x_{1,0}$  is the residual  $= x_1 - b_{1,0} x_0$

and 3)  $|x_{rs}|$  is the covariance matrix of  $\{x_r\}$ ,  
then the probability of the sample is given by

$$\text{Const. } \exp^{-\frac{1}{2}} \left[ \sum_{r,s=2}^{p+1} \alpha \left\{ \sum_{i=1}^N (x_{ir} - \beta_r x_{1,0} - \delta_r x_0)^2 \right. \right. \\ \left. \left. (x_{is} - \beta_s x_{1,0} - \delta_s x_0) \right\} \right] \\ \times \prod_{i=1}^N \prod_{r=2}^{p+1} (dx_{ir}) \quad (3.1)$$

where  $|x^{rs}|$  is the matrix reciprocal to  $|x_{rs}|$ .

Under these conditions, the likelihood ratio  $\lambda$

appropriate to test the hypothesis  $H$  ( $\beta_2 = \beta_3 = \dots = \beta_{p+1} = 0$ ;  
 $\delta_2 = \delta_3 = \dots = \delta_{p+1} = 0$ )

is then given by

$$\lambda^{\frac{2}{N}} = 1 - W^2 = \frac{\begin{vmatrix} v_{00} & v_{01} & \cdots & v_{0,p+1} \\ v_{10} & v_{11} & \cdots & v_{1,p+1} \\ \vdots & \vdots & & \vdots \\ v_{p+1,0} & v_{p+1,1} & \cdots & v_{p+1,p+1} \end{vmatrix}}{\begin{vmatrix} v_{00} & v_{01} & & v_{2,p+1} \\ v_{10} & v_{11} & & v_{3,p+1} \\ v_{20} & v_{21} & \cdots & v_{3,p+1} \\ v_{p+1,0} & v_{p+1,1} & \cdots & v_{p+1,p+1} \end{vmatrix}} \quad (3.2)$$

where  $v_{rs} = \sum_{i=1}^N x_{ir} x_{is}$ . N

Writing  $\sum_{i=1}^N x_{i1.0}^2 = g^2$ ,  $\sum_{i=1}^N x_{i0}^2 = h^2$

$$g^2 c_r = \sum_{i=1}^N x_{ir} x_{i1.0}, h^2 d_r = \sum_{i=1}^N x_{ir} x_{i0} (r=2, \dots, p+1)$$

and  $a_{rs} = \sum_{i=1}^N (x_{ir} - c_r x_{i1.0} - d_r x_{i0})(x_{is} - c_s x_{i1.0} - d_s x_{i0})$   
 $(r, s = 2, 3, \dots, p+1)$  (3.3)

it can be seen that

$$\begin{aligned} v_{rs} &= a_{rs} + g^2 c_r c_s + h^2 d_r d_s \\ \text{and } 1-w^2 &= \frac{|a_{rs}|}{|v_{rs}|} \end{aligned} \quad \{ \quad (3.4)$$

We will now proceed to get the distribution of  $w^2$ , known as Wilks statistic, when H is not true, for fixed values of  $x_0$  &  $x_{1.0}$ . The distribution, when H is true can be deduced at that stage. The distribution of  $[ \{a_{rs}\}, \{c_r\} \text{ and } \{d_r\} ] (r=2, \dots, p+1)$  derived from (3.1) is given by

$$\begin{aligned} \text{Const. } \exp -\frac{1}{2} \left[ \sum_{r,s=2}^{p+1} \alpha \left\{ a_{rs} + g^2 (c_r - \bar{c}_r)(c_s - \bar{c}_s) \right. \right. \\ \left. \left. + h^2 (d_r - \bar{d}_r)(d_s - \bar{d}_s) \right\} \right] \\ |a_{rs}|^{\frac{N-p-4}{2}} \prod_{r,s} (d_{rs}) \cdot \prod_n (dc_n dd_n) \quad (3.5) \end{aligned}$$

In virtue of (3.4), (3.5) leads to the distribution of  $[ \{v_{rs}\}, \{c_r\}, \{d_r\} ]$  given by

$$\begin{aligned} \text{Const. } \exp -\frac{1}{2} \left[ g^2 \sum_{r,s=2}^{p+1} \bar{c}_r \bar{c}_s + h^2 \sum_{r,s=2}^{p+1} \bar{d}_r \bar{d}_s \right] \\ \times \exp -\frac{1}{2} \left[ \sum_{r,s=2}^{p+1} \alpha^{rs} \left\{ v_{rs} - 2g^2 c_r c_s - 2h^2 d_r d_s \right\} \right] \\ |v_{rs}|^{\frac{N-p-4}{2}} (1-w^2)^{\frac{N-p-4}{2}} \prod_{r,s} dv_{rs} \prod_n (dc_n dd_n) \end{aligned}$$

The distribution problem is enormously simplified if we make use of the property of invariance of the Wilks statistic for linear transformations of variates within sets. In fact this property is partly used already when we started the problem with  $x_{1.0}$  and  $x_0$  on the dependent side. Without loss of generality, we can further write (3.6)

- i)  $\alpha^{rs} = 0$  if  $r+s$  and ii) the variances of  $x_0$  and  $x_{1.0}$  are unity.
- $= 1$  if  $r=s$
- $\bar{c}_r = 0$  for  $r \neq 2$
- $\bar{d}_r = 0$  for  $r \neq 3$

$x_0$  and  $x_1$  being fixed the second assumption leads to  $g^2 = h^2 = N-1$  (3.7a)

using this invariance property (3.7), (3.6) reduces to

$$\begin{aligned}
 & \text{const. } \exp -\frac{1}{2} (g^2 \gamma_2^2 + h^2 \delta_3^2) \\
 & \times \exp -\frac{1}{2} \left[ \sum_{n=2}^{p+1} v_{nn} \right] (1-w^2)^{\frac{N-p-4}{2}} |v_{ns}|^{\frac{N-p-4}{2}} \prod_{n,s} dv_n \\
 & \times \exp (g^2 \gamma_2 c_2 + h^2 \delta_3 d_3) \prod_{n=2}^p (dc_n dd_n) \tag{3.8}
 \end{aligned}$$

We now change from

$$(c_2, c_3, \dots c_{p+1}; d_2, d_3, \dots d_{p+1})$$

to a new set of variables

$$(B_2, B_3, \dots B_{p+1}; b_2, b_3, \dots b_{p+1})$$

by the following transformations.

$$B_n = b_{1,n} (23 \dots n-1; 0)$$

$$g = \frac{\begin{vmatrix} c_n & c_{n-1} & \dots & c_2 \\ v_{nn} - h^2 d_n d_{n-1} & \dots & \dots & \dots \\ \vdots & & & \\ v_{nj} - h^2 d_i d_j & \dots & \dots & \dots \\ v_{n2} - h^2 d_n d_2 & & & \end{vmatrix}}{|v_{nj} - h^2 d_i d_j|^{\frac{n-1}{2}}} \tag{3.9}$$

and

$$b_n = b_{0,n} (23 \dots n-1)$$

$$h = \frac{\begin{vmatrix} d_n & d_{n-1} & \dots & d_2 \\ v_{n-1,n} & v_{n-2,n-1} & \dots & v_{1,2} \\ \vdots & & & \\ v_{2n} & v_{2n-1} & \dots & v_{22} \end{vmatrix}}{|v_{nj}|^{\frac{n}{2}}} \tag{3.10}$$

The above transformations in particular lead to

$$B_2 = \frac{g c_2}{v_{22} - h^2 d_2^2}$$

$$b_2 = \frac{h d_2}{v_{22}}$$

$$\text{and } b_3 = \frac{h (v_{22} d_3 - v_{32} d_2)}{(v_{33} v_{22} - v_{32}^2)} \quad (3.11)$$

and the Jacobian of the transformation

$$J = \frac{\partial (c_2, c_3, \dots, c_{p+1}, d_2, d_3, \dots, d_{p+1})}{\partial (B_2, B_3, \dots, B_{p+1}, b_2, b_3, \dots, b_{p+1})}$$

is given by

$$J = \left\{ |v_{ij}|_2^{p+1} \right\} \left\{ |v_{ij} - h^2 d_i d_j|_2^{p+1} \right\} \quad (3.12)$$

As usual defining

$$x_r^2 = \frac{|v_{ij}|_2^r}{|v_{ij}|_2^{r-1}} \quad \text{and} \quad x_{r,0}^2 = \frac{|v_{ij} - h^2 d_i d_j|_2^r}{|v_{ij} - h^2 d_i d_j|_2^{r-1}}$$

for  $r > 2$

$$\text{and } x_2^2 = v_{22} \quad \text{and} \quad x_{2,0}^2 = v_{22} - h^2 d_2^2 \quad (3.13)$$

we observe that

$$R_{0(23 \dots p+1)}^2 = \sum_{r=2}^{p+1} b_r^2 x_r^2$$

$$\text{and } R_{1(23 \dots p+1);0}^2 = \sum_{r=2}^{p+1} B_r^2 x_{r,0}^2 \quad (3.14)$$

where  $R_{0(23 \dots p+1)}$  is the multiple correlation coefficient of  $x_0$  with the set  $\{x_r\}$  and

$R_{1(23 \dots p+1);0}$  is the multiple correlation coefficient of the residual  $x_{1,0}$  with the set of residuals  $\{x_{r,0}\}$ . For simplicity we will write these two multiple correlation coefficients by  $R_0$  and  $R_1$  respectively. We also

observe that

$$1 - R_0^2 = \frac{|v_{ij} - h^2 d_i d_j|_2^{p+1}}{|v_{ij}|_2^{p+1}} = \frac{x_{2,0}^2 x_{3,0}^2 \dots x_{p+1,0}^2}{x_2^2 x_3^2 \dots x_{p+1}^2}$$

Using the new quantities defined in (3.13),

(3.11) can be rewritten as

$$g c_2 = (B_2 x_{2,0}) x_2 (1 - b_2^2 x_2^2)^{\frac{1}{2}}$$

$$h d_2 = b_2 x_2^2$$

$$\text{and } h d_3 = \frac{b_3 x_3^2 + b_2 x_2 z_{32}}{N} \quad (3.16)$$

$$\text{where } z_{32} = \frac{\sum_{r=1}^{p+1} x_{r3} x_{r2}}{x_2}$$

The jacobian  $J$  in (3.12) also can be rewritten with the use of (3.13), (3.14) and (3.15) as

$$\begin{aligned} J &= (1 - R_0^2)^{\frac{1}{2}} (x_2^2 \dots x_{p+1}^2)^{\frac{3}{2}} (x_{2,0}^2 \dots x_{p+1,0}^2)^{\frac{1}{2}} \\ &= \left( 1 - \sum_{n=2}^{p+1} b_n^2 x_n^2 \right)^{\frac{1}{2}} (x_2^2 \dots x_{p+1}^2)^{\frac{3}{2}} (x_{2,0}^2 \dots x_{p+1,0}^2)^{\frac{1}{2}} \end{aligned} \quad (3.17)$$

using the well known result

$$1 - W^2 = (1 - R_0^2)(1 - R_1^2) \quad (3.18)$$

$$= \left\{ 1 - \sum_{n=2}^{p+1} b_n^2 x_n^2 \right\} \left\{ 1 - \sum_{n=2}^{p+1} B_n^2 x_{n,0}^2 \right\}$$

we see that the portion in (3.8) relevant to the problem of the distribution of  $W^2$  is one which leads to the distribution of

$$x_2^2, x_3^2, z_{32}, \{b_n x_n\} \text{ and } \{B_n x_{n,0}\},$$

which with the use of (3.16), (3.17) and (3.18) can be written as

$$\text{Const. } \exp -\frac{1}{2} (g^2 z_2^2 + h^2 z_{32}^2)$$

$$\times \exp -\frac{1}{2} (x_2^2 + z_{32}^2 + x_2^2)$$

$$\times \exp \left\{ g z_2 (B_2 x_{2,0}) (1 - b_2^2 x_2^2)^{\frac{1}{2}} x_2 + h z_3 (x_3 \cdot b_3 x_3 + z_{32} b_2) \right.$$

$$\left. \left( 1 - \sum_{n=2}^{p+1} b_n^2 x_n^2 \right)^{\frac{N-p-3}{2}} \left( 1 - \sum_{n=2}^{p+1} B_n^2 x_{n,0}^2 \right)^{\frac{N-p-4}{2}} (x_2^2)^{\frac{N-3}{2}} (x_3^2)^{\frac{N-4}{2}} \right\}$$

$$d(x_2^2) d(x_3^2) d z_{32} \prod_{n=2}^{p+1} d(b_n x_n) \prod_{n=2}^{p+1} d(B_n x_{n,0}) \quad (3.19)$$

$$\text{Writing } H_0^2 = \sum_{n=4}^{p+1} b_n^2 x_n^2 \text{ and } H_1^2 = \sum_{n=3}^{p+1} B_n^2 x_{n,0}^2 \quad (3.20)$$

the distribution of

$$\{ H_0^2, H_1^2, b_2 x_2, b_3 x_3, B_2 x_{2,0}, x_2^2, x_3^2 \text{ & } z_{32}^2 \}$$

can be immediately derived from (3.19). as

$$\text{Const. } \exp -\frac{1}{2} (g^2 \gamma_2^2 + h^2 \delta_3^2)$$

$$\times \exp -\frac{1}{2} (x_3^2 + z_{32}^2 + x_2^2)$$

$$\times \exp [g \gamma_2 (B_2 x_{2,0}) (1 - b_2^2 x_2^2)^{\frac{1}{2}} x_2 + h \delta_3 (x_3 b_3 x_3 + z_{32} b_2 x_2)]$$

$$(1 - H_0^2 - b_2^2 x_2^2 - b_3^2 x_3^2)^{\frac{N-p-3}{2}} (1 - H_1^2 - B_2^2 x_{2,0}^2)^{\frac{N-p-4}{2}}$$

$$(H_0^2)^{\frac{p-2}{2}-1} (H_1^2)^{\frac{p-1}{2}-1} (x_2^2)^{\frac{N-3}{2}} (x_3^2)^{\frac{N-4}{2}}$$

$$d(x_3^2) d(x_2^2) dz_{32} dH_0^2 dH_1^2 d(b_2 x_2) d(b_3 x_3) d(B_2 x_{2,0})$$

(3.21)

Applying then the transformation

$$H_0 = R_0 \cos \theta_1, \cos \theta_2$$

$$b_3 x_3 = R_0 \cos \theta_1, \sin \theta_2$$

$$b_2 x_2 = R_0 \sin \theta_1$$

$$H_1 = R_1 \cos \theta_3 \quad (3.22)$$

$$B_2 x_{2,0} = R_2 \sin \theta_3$$

the jacobian of which is given by

$$\frac{\partial (H_0, H_1, B_2 x_{2,0}, b_2 x_2, b_3 x_3)}{\partial (R_0^2, R_1^2, \theta_1, \theta_2, \theta_3)}$$

$$= R_0 R_1 \cos \theta_1 \dots \quad (3.23)$$

the joint distribution of

$$(R_0^2, R_1^2, \theta_1, \theta_2, \theta_3, x_3^2, x_2^2, z_{32}^2) \text{ is given by}$$

$$\left( \begin{array}{l} 0 \leq R^2 \leq 1 \\ 0 \leq \theta \leq \frac{\pi}{2} \end{array} \right)$$

$$\text{Const. } \exp -\frac{1}{2} (g^2 \gamma_2^2 + h^2 \delta_3^2) \times \exp -\frac{1}{2} (x_3^2 + x_2^2 + z_{32}^2)$$

$$\sum_{l=0}^{\infty} \left( \frac{g^2 \gamma_2^2}{2l!} \right)^l (1 - R_0^2 \sin^2 \theta_1)^l (x_2^2 R_1^2 \sin^2 \theta_3)^l$$

$$\sum_{m=0}^{\infty} \left( \frac{h^2 \delta_3^2}{2m!} \right)^m (x_3^2 R_0^2 \cos^2 \theta_1, \sin^2 \theta_2)^m$$

$$\sum_{n=0}^{\infty} \left( \frac{h^2 \delta_3^2}{2n!} \right)^n (z_{32}^2 R_0^2 \sin^2 \theta_1)^n$$

$$(1 - R_1^2)^{\frac{N-p-4}{2}} (1 - R_0^2)^{\frac{N-p-3}{2}} (R_0 \cos \theta_1, \cos \theta_2)^{\frac{p-3}{2}} (R_1 \cos \theta_3)^{\frac{p-2}{2}} R_0 \cos \theta_1$$

Integration of (3.24) for  $(x_3^2, x_2^2, z_{32}, \theta_2, \text{and } \theta_3)$

leads to the joint distribution of  $(R_0^2, R_1^2 \text{ and } \theta_1)$   
as given by

$$\begin{aligned} & \text{Const. } \exp -\frac{1}{2} (g^2 \gamma_2^2 + h^2 \delta_3^2) \\ & (1-R_0^2)^{\frac{N-h-3}{2}} (1-R_1^2)^{\frac{N-h-4}{2}} (R_0^2 R_1^2)^{\frac{p-2}{2}} (\cos \theta_1) \\ & \sum_{l=0}^{\infty} \left( \frac{g^2 \gamma_2^2}{2} \right)^l \frac{1}{l!} \left\{ R_1^2 (1-R_0^2 \sin^2 \theta_1) \right\}^l \frac{\Gamma(\frac{N-1}{2} + l)}{\Gamma(\frac{p}{2} + l)} \\ & \sum_{m=0}^{\infty} \left( \frac{h^2 \delta_3^2}{2} \right)^m \frac{1}{m!} (R_0^2 \cos^2 \theta_1)^m \frac{\Gamma(\frac{N-2}{2} + m)}{\Gamma(\frac{N-1}{2} + m)} \\ & \sum_{n=0}^{\infty} \left( \frac{h^2 \delta_3^2}{2} \right)^n \frac{1}{n!} (R_0^2 \sin^2 \theta_1)^n \\ & dR_0^2 dR_1^2 d\theta_1, \end{aligned} \quad (3.25)$$

In (3.25) if we write the binomial expansion for  $(1-R_0^2 \sin^2 \theta_1)^l$  in the first series as

$$(1-R_0^2 \sin^2 \theta_1)^l = \sum_{l_1+l_2=l} \frac{l!}{l_1! l_2!} (\cos^2 \theta_1)^{l_1} \{8 \sin^2 \theta_1 (1-R_0^2)\}^{l_2}$$

and integrating for  $\theta_1$  ( $0 \leq \theta_1 \leq \frac{\pi}{2}$ ) we are led to the joint distribution of  $R_0^2$  and  $R_1^2$  as

$$\begin{aligned} & \text{Const. } \exp -\frac{1}{2} \left\{ (g^2 \gamma_2^2 + h^2 \delta_3^2) \right\} (1-R_0^2)^{\frac{N-h-3}{2}} (1-R_1^2)^{\frac{N-h-4}{2}} (R_0^2 R_1^2)^{\frac{p-2}{2}} \\ & \sum_{l_1, l_2, m, n} \left\{ \left( \frac{g^2 \gamma_2^2}{2} \right)^{l_1} \left( \frac{h^2 \delta_3^2}{2} \right)^{l_2} \frac{\Gamma(\frac{N-1}{2} + l_1 + l_2)}{\Gamma(\frac{p}{2} + l_1 + l_2)} \frac{\Gamma(\frac{N-2}{2} + m)}{\Gamma(\frac{p-1}{2} + m)} \frac{\Gamma(\frac{p-1}{2} + m + l_1)}{\Gamma(l_1 + m + l_1)} \frac{\Gamma(\frac{p-1}{2} + m + l_2)}{\Gamma(l_2 + m + l_2)} \right. \\ & \left. (R_0^2)^{l_1} (R_1^2)^{l_2} (1-R_0^2)^{l_1} \right\} \frac{1}{l_1! l_2! m! n!} dR_0^2 dR_1^2. \end{aligned} \quad (3.26)$$

We now transform  $R_0^2$  and  $R_1^2$  to a pair of new variables  $u$  and  $w^2$  where the latter is given by (3.18) and

$$u = \frac{R_0^2}{W^2} \quad \text{so that the limits of}$$

of  $u$  are 0 and 1 independent of  $W^2$ . Then the joint distribution of  $u$  &  $w^2$  can be immediately

derived from (3.26) as

$$\text{const. } \exp -\frac{1}{2} (g^2 J_2^2 + h^2 \delta_3^2)$$

$$\times (W^2)^{\frac{p-1}{2}} (1-W^2)^{\frac{N-p+4}{2}} \{ u(1-u)\}^{\frac{p-2}{2}}$$

$$\times \sum_{l_1, l_2, m, n}^{\ell_1 + \ell_2} \left\{ \left( \frac{g^2 J_2^2}{2} \right)^{m+n} \left( \frac{h^2 \delta_3^2}{2} \right)^{m+n} \frac{\Gamma(N/2 + l_1 + l_2) \Gamma(N/2 + m)}{\Gamma(p/2 + l_1 + l_2) \Gamma(p/2 + m)} B(p/2 + m + l_1 + l_2, N/2 + m + l_1 + l_2) \right. \\ \left. - \frac{(p-1+l_1)}{u^{m+n}} (1-u)^{m+n+l_1+l_2} (W^2)^{m+n+l_1+l_2} \right\} dW^2 du$$

(3.27)

Integrating (3.27) with respect to  $u$  ( $0 \leq u \leq 1$ )

and while doing so using the well known result

$$B(\beta, \gamma - \beta) = F_\beta(\alpha, \beta; \gamma, \gamma)$$

$$= \int_0^1 t^{\beta-1} (1-t)^{\gamma-\beta-1} (1-xt)^{-\alpha} dt \text{ for } |x| <$$

we get the distribution of  $W^2$  as given by

$$\text{const. } \exp -\frac{1}{2} \left\{ (g^2 J_2^2 + h^2 \delta_3^2) \right\} (W^2)^{\frac{p-1}{2}} (1-W^2)^{\frac{N-p+4}{2}}$$

$$\sum_{l_1, l_2, m, n}^{\ell_1 + \ell_2} \left\{ \left( \frac{g^2 J_2^2}{2} \right)^{m+n} \left( \frac{h^2 \delta_3^2}{2} \right)^{m+n} \frac{(W^2)^{m+n+l_1+l_2}}{l_1! l_2! m! n!} \right.$$

$$\left. \frac{\Gamma(N/2 + l_1 + l_2) \Gamma(N/2 + m)}{\Gamma(p/2 + m + l_1 + l_2 + n + 1/2)} \right.$$

$$\left. \frac{\Gamma(p + l_1 + l_2 + m + n)}{\Gamma(p/2 + m + n)} \right.$$

$$F\left(\frac{p-1}{2} + l_1, \frac{p}{2} + m + n; p + m + n + l_1 + l_2, W^2\right) \} d(W^2)$$

(3.28)

In view of (3.7), it can be easily seen that all the variates  $x_0, x_{1,0}, \{x_n\}$  correspond to Hotelling's canonical variates and that  $J_2^2$  and  $\delta_3^2$

are the two non vanishing of the two canonical correlations  $P_1^2$  and  $P_0^2$ . Then writing

$(N-1) P_0^2 = E^2$ ,  $(N-1) P_1^2 = F^2$ , the distribution can be written as

$$\text{Const. } \exp -\frac{1}{2} \left\{ E^2 + F^2 \right\} (W^2)^{\frac{p-1}{2}} (1-W^2)^{\frac{N-p-4}{2}} dW^2$$

$$\sum_{l_1, l_2, m, n} \left\{ \left( \frac{E^2}{2} \right)^{m+n} \left( \frac{F^2}{2} \right)^{l_1+l_2} \frac{(W^2)^{m+n+l_1+l_2}}{l_1! l_2! m! n!} \right.$$

$$\left. \frac{\Gamma(\frac{N-1}{2} + l_1 + l_2) \Gamma(\frac{N-2}{2} + m) \Gamma(\frac{p}{2} + m + n) B(\frac{p-1}{2} + m + l_1, l_2 + n + \frac{1}{2})}{\Gamma(p + l_1 + l_2 + m + n) \Gamma(\frac{p-1}{2} + m)} F\left(\frac{p-1}{2} + l_1, \frac{p}{2} + m + n; p + m + n + l_1 + l_2; W^2\right) \right\} \quad (3.29)$$

The expression for the constant <sup>say C</sup> in the above distribution is seen can be seen to be independent of  $E$  or  $F$  and as such it will be same as the constant of the distribution, deduced from (3.29) with  $E=F=0$  - (i.e) constant of the distribution when H is true, which will be deduced from above. Thus the distribution, when H is true is given

as  $\text{Const. } (W^2)^{\frac{p-1}{2}} (1-W^2)^{\frac{N-p-4}{2}}$

$$x \frac{\Gamma(\frac{N-1}{2}) \Gamma(\frac{N-2}{2}) \Gamma(\frac{p}{2})}{\Gamma(p)} F\left(\frac{p-1}{2}, \frac{p}{2}; p, W^2\right) dW^2 \quad (3.30)$$

The hypergeometric series in the above distribution is known to satisfy the differential equation

$$x(1-x) \frac{d^2y}{dx^2} + \left\{ p - \left(p + \frac{1}{2}\right)x \right\} \frac{dy}{dx} - \frac{p(p-1)}{4} y = 0$$

with  $x = W^2$ . By well known methods of solving this type of second order differential equations it will be seen that

$$y = (1 + \sqrt{1-x})^{-\frac{p-1}{2}} \text{ is a principal solution and so it will be seen that}$$

$$F\left(\frac{p-1}{2}, \frac{p}{2}; p, W^2\right) = \frac{2^{\frac{p-1}{2}}}{(1 + \sqrt{1-W^2})^{p-1}} \quad (3.31)$$

Using (3.31), the distribution given in (3.30).

leads to the distribution of  $L = (1-W^2)$ , as given by

$$\text{const. } K \cdot 2^{\frac{p}{2}} (1-\sqrt{L})^{p-1} (\sqrt{L})^{N-p-4} dL \text{ where } K \text{ is}$$

the product of the constant,  $C$  in (3.30) and the other constant terms of that expression. By integrating the above distribution with respect to  $\sqrt{L}$  between 0 & 1 and equating the integral to unity it is seen that

$$K \cdot 2^{\frac{p}{2}} = \frac{1}{2 B(N-p-2, p)} \text{ whence in virtue}$$

$$\text{of the relation } \Gamma(x + \frac{1}{2}) \Gamma(x+1) = \frac{\sqrt{\pi} \Gamma(2x+1)}{2^{2x}}$$

it is seen that  $C = \frac{2^{N-p-3}}{\pi \Gamma(N-p-2)}$

Thus the nonnull and null distributions of  $1-W^2 = L$  are respectively given by

$$\begin{aligned} & \frac{2^{N-p-3}}{\pi \Gamma(N-p-2)} e^{-\frac{1}{2}(E^2+F^2)} (1-L)^{p-1} L^{\frac{N-p-4}{2}} \\ & \sum_{l_1, l_2, m, n} \left\{ \left(\frac{E^2}{2}\right)^{m+n} \left(\frac{F^2}{2}\right)^{l_1+l_2} \frac{(1-L)^{m+n+l_1+l_2}}{l_1! l_2! m! n!} \right. \\ & \quad \frac{\Gamma(\frac{N-1}{2} + l_1 + l_2) \Gamma(\frac{N-2}{2} + m) \Gamma(\frac{p}{2} + m + n)}{\Gamma(p + l_1 + l_2 + m + n) \Gamma(\frac{p-1}{2} + m)} \\ & \quad \left. B\left(\frac{p-1}{2} + m + l_1, l_2 + n + \frac{1}{2}\right) F\left(\frac{N-1}{2} + l_1, \frac{N-2}{2} + m + n; p + m + n + l_1 + l_2, (1-L)\right) \right\} dL \end{aligned} \quad (3.32)$$

and

$$\frac{1}{2 B(N-p-2, p)} (1-\sqrt{L})^{p-1} (\sqrt{L})^{N-p-4} dL. \quad (3.33)$$

and Null

4. Nonnull distributions of the Wilks statistic relevant to the general regression problem with two variates in the dependent set and  $p$  variates in the predicting or independent set.

Let  $\{x_{i\alpha}; x_{ir}\}$  ( $i = 1, 2, \dots, N$ ;  $\alpha = 0, 1, r = 2, 3, \dots, p+1$ ) be a set of  $N$  observations on the dependent set  $\{x_\alpha\}$  and the independent set  $\{x_r\}$ , the latter taking a set of fixed values. The origin of measurement for each of the variates is taken at the respective mean. Given that

i)  $(x_0, x_1)$  follow a bivariate normal law with

$$\text{ii) } E(x_{1,0}) = \beta_{12} x_{2,0} + \beta_{13} x_{3,0} + \dots + \beta_{1,p+1} x_{p+1,0}$$

$$\text{and } E(x_0) = \beta_{02} x_2 + \beta_{03} x_3 + \dots + \beta_{0,p+1} x_{p+1}$$

where  $x_{1,0}$ ,  $\{x_{r,0}\}$  are the residuals

of  $x_1$ ,  $\{x_r\}$  respectively, after eliminating the portion due to regression on  $x_0$ .

iii)  $K_1^2$  &  $K_0^2$  are the two population variances defined by

$$K_1^2 = E(x_{1,0} - \sum \beta_{1,r} x_{r,0})^2 \quad (4.1)$$

$$K_0^2 = E(x_0 - \sum \beta_{0,r} x_r)^2$$

The hypothesis that  $\{x_\alpha\}$  is independent of  $\{x_r\}$  will mean in terms of the parameters that

$$H: \beta_{1,r} = 0; \beta_{0,r} = 0 \text{ for all } r = 2, 3, \dots, p+1.$$

The sample Wilks statistic  $W^2$  is the exp a function of the appropriate likelihood ratio  $\lambda$  and  $W^2$  is given as

$$\begin{aligned} \frac{\lambda}{N} = 1 - W^2 &= \frac{\left[ \sum_{l=1}^N \left\{ x_{l,0} - \sum_{r=2}^{p+1} b_{lr, (0,2,3,\dots,r-1)} x_{r,0} \right\}^2 \right]}{\sum_{l=1}^N x_{l,0}^2} \\ &= \frac{\sum_{l=1}^N \left\{ x_{l,0} - \sum_{r=2}^{p+1} b_{0r, (2,3,\dots,r-1)} x_{r,0} \right\}^2}{\sum_{l=1}^N x_{l,0}^2} \end{aligned} \quad (4.2)$$

$$\text{where } b_{1r \cdot (023 \dots r-1)} = \frac{\sum_{i=1}^N \{ x_{i1} x_{in \cdot (023 \dots r-1)} \}}{\sum_{i=1}^N \{ x_{in \cdot (023 \dots r-1)} \}^2}$$

$$\text{and } b_{0r \cdot (23 \dots r-1)} = \frac{\sum_{i=1}^N \{ x_{i0} x_{in \cdot (23 \dots r-1)} \}}{\sum_{i=1}^N \{ x_{in \cdot (23 \dots r-1)} \}^2} \quad (4.3)$$

with

$$x_{r \cdot (023 \dots r-1)} =$$

$$\frac{\begin{vmatrix} x_n & v_{n \cdot n-1} & \cdots & v_{n2} & v_{02} \\ x_{n-1} & v_{n-1 \cdot n-1} & \cdots & v_{n-2 \cdot 2} & v_{0 \cdot n-1} \\ \vdots & & & & \\ x_2 & v_{2 \cdot 1 \cdot 2} & \cdots & v_{22} & v_{02} \\ x_0 & v_{0 \cdot n-1} & \cdots & v_{02} & v_{00} \end{vmatrix}}{v_{n-1 \cdot n-1} v_{n-1 \cdot n-2} \cdots v_{n-1 \cdot 2} v_{n-1 \cdot 0}}$$

$$\frac{\begin{vmatrix} v_{n-2 \cdot n-1} & v_{n-2 \cdot n-2} & \cdots & v_{n-2 \cdot 2} & v_{n-2 \cdot 0} \\ v_{n-2 \cdot n-1} & v_{n-2 \cdot n-2} & \cdots & v_{n-2 \cdot 2} & v_{n-2 \cdot 0} \\ \vdots & & & & \\ v_{2 \cdot n-1} & v_{2 \cdot n-2} & \cdots & v_{22} & v_{20} \\ v_{0 \cdot n-1} & v_{0 \cdot n-2} & \cdots & v_{02} & v_{00} \end{vmatrix}}{v_{2 \cdot n-1} v_{2 \cdot n-2} \cdots v_{22} v_{20}}$$

and

$$x_{n \cdot (23 \dots r-1)} =$$

$$\frac{\begin{vmatrix} x_n & v_{n \cdot n-1} & \cdots & v_{n2} \\ x_{n-1} & v_{n-1 \cdot n-1} & \cdots & v_{n-2 \cdot 2} \\ \vdots & & & |v_{ij}|_{\frac{n}{2}}^{n-1} \end{vmatrix}}{|v_{ij}|_{\frac{n}{2}}^{n-1}}$$

(4.4)

$$\text{and } v_{ij} = \sum_{i=1}^N x_{in} x_{is},$$

(4.2) can be re-written as

$$1 - W^2 = \frac{\chi^2_{1 \cdot (023 \dots p+1)}}{\chi^2_{1 \cdot 0}} \times \frac{\chi^2_{0 \cdot (23 \dots p+1)}}{\chi^2_0} \quad (4.5)$$

where the definition of  $\chi^2$ 's is quite clear by comparing (4.5) with (4.2). We will derive the distribution of  $1 - W^2$  for fixed values of  $\{x_n\}$  when the hypothesis  $H$  being tested is not true - (i) the non-null distribution - from which the null distribution, (ii) the distribution when  $H$  is true can be immediately deduced.

$\chi^2_{1 \cdot 0}$  and  $\chi^2_0$  can be split up as

$$\sum_{i=1}^N x_{i1 \cdot 0}^2 = \chi^2_{1 \cdot 0} = \chi^2_{1 \cdot (023 \dots p+1)} + \sum_{n=2}^{p+1} z_{1r \cdot (02 \dots n-1)}^2$$

$$\text{and } \sum_{i=1}^N x_{i0}^2 = \chi^2_0 = \chi^2_{0 \cdot (23 \dots p+1)} + \sum_{n=2}^{p+1} z_{0r \cdot (23 \dots n-1)}^2$$

where  $z_{1r \cdot (02 \dots n-1)}$ , for simplicity  $z_{1r \cdot 0}$  is given by

$$z_{1r \cdot 0}^2 = b_{1r \cdot (023 \dots n-1)}^2 \sum_{i=1}^N x_{ir \cdot (023 \dots n-1)}^2$$

=  $b_{1r \cdot 0} \chi^2_{1 \cdot 0}$  say.

and  $\Sigma_{or} \cdot (23 \dots n-1)$ , for simplicity  $\Sigma_{or}$  is

$$\text{given by } \Sigma_{or}^2 = b_{on}^2 \cdot (23 \dots n-1) \sum_{r=1}^N x_{or}^2 \cdot (23 \dots n-1) \\ = b_{on}^2 x_n^2 \text{ (say).}$$

Thus introducing these quantities (4.5) can be rewritten as

$$1 - W^2 = \frac{x_{1 \cdot (023 \dots p+1)}^2}{x_{1 \cdot (023 \dots p+1)}^2 + \sum_{r=2}^{p+1} z_{1 \cdot r \cdot 0}^2} \times \frac{x_{0 \cdot (23 \dots p+1)}^2}{x_{0 \cdot (23 \dots p+1)}^2 + \sum_{r=2}^{p+1} z_{or}^2} \quad (4.6)$$

It can be easily seen that the two factors on the right hand side in (4.6) (viz)

$$\frac{x_{1 \cdot (023 \dots p+1)}^2}{x_{1 \cdot (023 \dots p+1)}^2 + \sum z_{1 \cdot r \cdot 0}^2}, \quad \frac{x_{0 \cdot (23 \dots p+1)}^2}{x_{0 \cdot (23 \dots p+1)}^2 + \sum z_{or}^2} \quad (4.7)$$

are  $(1 - R_1^2)$  and  $(1 - R_0^2)$  respectively, where  $R_1^2$  is the sample multiple correlation coefficient of the residual  $x_{1 \cdot 0}$  with the set of residuals  $\{x_{r \cdot 0}\}$  and  $R_0^2$  is the sample multiple correlation coefficient of  $x_0$  with the set  $\{x_{or}\}$ . It can be rightly pointed that the relation between the two sets of variates  $(x_0, x_1)$  and  $\{x_{r \cdot 0}\}$  is completely characterised by these two coefficients.

The portion relevant for the distribution problem of  $W^2$ , taken out from the total sample probability density, namely, the distribution, when H is not true, of

$x_{1 \cdot (023 \dots p+1)}^2, \{z_{1 \cdot r \cdot 0}\}, x_{0 \cdot (23 \dots p+1)}^2, \{z_{or}\}$  is given by

$$\begin{aligned} & \text{const.} \exp -\frac{1}{2k_2} \left[ x_{1 \cdot (023 \dots p+1)}^2 + \sum_{n=p+1}^N \left\{ z_{1 \cdot n \cdot 0} - x_{n \cdot 0} \sum_{u=p+1}^n \beta_{1u} b_{un} \right\}^2 \right] \\ & \times \left\{ x_{1 \cdot (023 \dots p+1)}^2 \right\}^{\frac{N-p-2}{2}} d x_{1 \cdot (023 \dots p+1)}^2 \prod \{dz_{1 \cdot r \cdot 0}\} \\ & \exp -\frac{1}{2k_0} \left[ x_{0 \cdot (23 \dots p+1)}^2 + \sum_{n=p+1}^N \left\{ z_{0 \cdot n} - x_{n \cdot 0} \sum_{u=p+1}^n \beta_{0u} b_{un} \right\}^2 \right] \\ & \times \left\{ x_{0 \cdot (23 \dots p+1)}^2 \right\}^{\frac{N-p-1}{2}} d(x_{0 \cdot (23 \dots p+1)}^2) \prod \{dz_{0 \cdot n}\} \end{aligned} \quad (4.8)$$

where

$$b_{ur}(02 \dots n-1) = \sum_{i=1}^N x_{iu} x_{ir} (02 \dots n-1)$$

$$= 1, \text{ if } u = r$$

$$b_{ur}(23 \dots n-1) = \sum_{i=1}^N x_{iu} x_{ir} (23 \dots n-1)$$

$$= 1 \text{ if } u = r$$

The distribution problem is considerably simplified if we make use of the property of invariance of the Wilks statistic for linear transformations of variates within sets. In fact this property is already partly employed when we started the problem with  $x_{1,0}$  and  $x_0$  on the dependent side. Without loss of generality, we can further write

$$K_1^2 = K_0^2 = 1; \quad \beta_{1r} = 0 \quad \text{for } r = 3, 4, \dots, p+1, (\text{ie}) \beta_{12} \neq 0$$

$$\beta_{0r} = 0 \quad \text{for } r = 2, 3, \dots, p+1, \text{ or } \beta_{03} \neq 0$$

$$x^{rs} = 0 \quad \text{if } r \neq s$$

$= 1$  if  $r = s$  where  $\{x_{rs}\}$  is the covariance matrix of the independent set  $\{x_r\}$ ; the latter assumption leads to

$$b_{ur}(23 \dots n-1) = 0 \quad \text{or} \quad z_{ur} = 0 \quad \text{for } u > r$$

$(r = 2, 3, \dots, p+1)$

$x_2^2 = N-1, x_3^2 = N-2$  etc for the independent set  $\{x_{rn}\}$  is considered to be fixed. (4.9)

Noting that the first part (portion containing  $\chi^2_{1,(023 \dots p+1)}$ ,  $\{z_{1rn}\}$ ) in (4.8) leads to the distribution of  $R_1^2$  for fixed  $\{x_{rn}\}$  which under the first of assumptions in (4.9) can be written as

$$\text{Const. } e^{-\frac{\beta_{12}^2 x_{2,0}^2}{2R_1}} (1-R_1^2)^{\frac{N-p-4}{2}} (R_1^2)^{\frac{p-2}{2}}$$

$$, F_1 \left( \frac{N-2}{2}, \frac{1}{2}; \frac{\beta_{12}^2 x_{2,0}^2}{2} R_1^2 \right) dR_1$$

The desired distribution is to be thus derived from the product of (4.10) and the second part (portion containing  $\chi^2_{0,(23 \dots p+1)}$ ,  $\{z_{0n}\}$  in (4.8) reduced with the use of (4.9)). Since the distribution of  $(1-W^2)$  is to be derived for fixed values of  $\{x_{rn}\}$

and not  $\{x_{r,0}\}$ ,  $x_{2,0}^2$  coming in (4.10) is to be suitably expressed in terms of the quantities we will be integrating for in course of the derivation.

Writing,

$$x_{2,0}^2 = \frac{x_2^2}{x_{0,(23..p+1)}^2 + \sum_{n=2}^{p+1} z_{0,n}^2} \left\{ x_{0,(23..p+1)}^2 + \sum_{n=3}^{p+1} z_{0,n}^2 \right\}$$

$$= x_2^2 \left\{ 1 - \frac{z_{0,2}^2}{x_{0,(23..p+1)}^2 + \sum_{n=2}^{p+1} z_{0,n}^2} \right\}$$

and using the second assumption of (4.9) the above referred product (i.e.) the distribution of  $[R_1^2, x_{0,(23..p+1)}^2 (x_0^2 \text{ for simplicity}) \text{ and } \{z_{0,n}\}]$  for fixed  $\{x_r\}$ , restricting the variation of  $z_{0,3}, z_{0,2}$  to  $0 \leq z_{0,3} \leq \infty, 0 \leq z_{0,2} \leq \infty$ , can be written as

$$\begin{aligned} & \text{const.} \cdot \exp -\frac{1}{2} \left\{ \beta_{03}^2 x_3^2 + \beta_{12}^2 x_2^2 \right\} \\ & \times \exp -\frac{1}{2} \left\{ x_0^2 + \sum_{n=2}^{p+1} z_{0,n}^2 \right\} (R_1^2)^{\frac{N-1-4}{2}} (1-R_1^2)^{\frac{N-1-3}{2}} (x_0^2)^{\frac{N-1-3}{2}} \\ & \sum_{l=0}^{\infty} \frac{\Gamma(\frac{N-2}{2} + l)}{\Gamma(\frac{1}{2} + l) l!} \left\{ R_1^2 \beta_{12}^2 x_2^2 \left( 1 - \frac{z_{0,2}^2}{x_0^2 + \sum_{n=2}^{p+1} z_{0,n}^2} \right) \right\}^l \\ & \sum_{m=0}^{\infty} \frac{1}{m!} \left( \frac{\beta_{12}^2 x_2^2}{2} \frac{z_{0,2}^2}{x_0^2 + \sum_{n=2}^{p+1} z_{0,n}^2} \right)^m \\ & \sum_{n=0}^{\infty} \frac{1}{2n!} \left( \frac{\beta_{03}^2 x_3^2}{2} \frac{z_{0,3}^2}{x_0^2 + \sum_{n=2}^{p+1} z_{0,n}^2} \right)^n \\ & dx_0^2 dR_1^2 \prod_{n=2}^{p+1} \{dz_{0,n}\} \quad \dots \quad (4.11) \end{aligned}$$

Adopting the transformation

$$z_{0,2} = H \sin \theta,$$

$$z_{0,3} = H \sin \theta_2 \cos \theta,$$

.....

$$z_{0,u} = H \cos \theta_1 \cos \theta_2 \dots \cos \theta_{u-1} \sin \theta_u$$

.....

$$z_{0,p+1} = H \cos \theta_1 \cos \theta_2 \dots \cos \theta_{p-2} \cos \theta_{p-1}, \quad (4.12)$$

the jacobian of which is given by

$$\frac{\partial(z_{0,2}, z_{0,3}, \dots, z_{0,p+1})}{\partial(H, \theta_1, \theta_2, \dots, \theta_{p-1})} = H^{p-1} \cos \theta_1 \cos \theta_2 \dots \cos \theta_{p-2} \quad (4.13)$$

(4.11) leads to the joint distribution of

$\{R_1^2, X_0^2, H^2, \theta_1, \theta_2, \dots, \theta_{k-1}\}$  and this joint distribution, when all the immediately possible integrals (viz) those with respect to  $\theta_2, \theta_3, \dots, \theta_{k-1}$  are carried out, leads to the joint distribution of

$$(R_1^2, X_0^2, H^2 \& \theta_1) \text{ as } \begin{cases} 0 \leq R_1^2 \leq 1, 0 \leq H^2 \leq \infty \\ 0 \leq X_0^2 \leq \infty, 0 \leq \theta_1 \leq \frac{\pi}{2} \end{cases}$$

as const.  $\exp -\frac{1}{2} \left\{ \beta_{03}^2 X_0^2 + \beta_{12}^2 X_2^2 \right\}$

$$* \exp -\frac{1}{2} (X_0^2 + H^2) (R_1^2)^{\frac{k-2}{2}} (1-R_1^2)^{\frac{N-k-4}{2}} (H^2)^{\frac{k-2}{2}} (X_0^2)^{\frac{N-k}{2}} \cos^{\frac{k-2}{2}} \theta_1$$

$$\sum_{l=0}^{\infty} \frac{\Gamma(N-\frac{2}{2}+l)}{\Gamma(\frac{k}{2}+l) l!} \left\{ R_1^2 \beta_{12}^2 \frac{X_2^2}{2} \left( 1 - \frac{H^2 \sin^2 \theta_1}{X_0^2 + H^2} \right) \right\}^l$$

$$\sum_{m=0}^{\infty} \frac{1}{m!} \left\{ \frac{\beta_{03}^2 X_0^2}{2} \frac{H^2 \sin^2 \theta_1}{X_0^2 + H^2} \right\}^m$$

$$\sum_{n=0}^{\infty} \frac{1}{n!} \left( \frac{\beta_{03}^2 X_0^2}{2} \right)^n \left( \frac{H^2 \cos^2 \theta_1}{2} \right)^n \frac{1}{\Gamma(\frac{k-1}{2}+n)}$$

$$dR_1^2 dX_0^2 dH^2 d\theta_1 \quad \therefore (4.14)$$

Transforming  $(H^2, X_0^2)$  into  $(D^2, R_0^2)$  where

$$X_0^2 = D^2 (1 - R_0^2)$$

$H^2 = D^2 R_0^2$  where  $R_0^2$  is the multiple correlation coefficient of  $x_0$  with  $\{x_n\}$ , and integrating the transformed form with respect to  $D^2 \quad 0 \leq D^2 \leq \infty$ , the joint distribution of  $(R_1^2, R_0^2 \& \theta_1)$  is given by.

$$\text{const. } \exp -\frac{1}{2} \left\{ \beta_{03}^2 X_0^2 + \beta_{12}^2 X_2^2 \right\}$$

$$(R_0^2 R_1^2)^{\frac{k-2}{2}} (1-R_1^2)^{\frac{N-k-4}{2}} (1-R_0^2)^{\frac{N-k-3}{2}} \cos^{\frac{k-2}{2}} \theta_1$$

$$\sum_{l=0}^{\infty} \frac{\Gamma(N-\frac{2}{2}+l)}{\Gamma(\frac{k}{2}+l) l!} \left\{ R_1^2 \beta_{12}^2 \frac{X_2^2}{2} \left( 1 - R_0^2 \sin^2 \theta_1 \right)^l \right\}$$

$$\sum_{m=0}^{\infty} \frac{1}{m!} \left( \frac{\beta_{03}^2 X_0^2}{2} \right)^m (R_0^2 \sin^2 \theta_1)^m$$

$$\sum_{n=0}^{\infty} \frac{1}{n!} \left( \frac{\beta_{03}^2 X_0^2}{2} \right)^n \frac{\Gamma(N-\frac{1}{2}+n)}{\Gamma(\frac{k-1}{2}+n)} (R_0^2 \cos^2 \theta_1)^n$$

$$dR_0^2 dR_1^2 d\theta_1 \quad (4.15)$$

Setting  $\frac{1}{l!} (1 - R_0^2 \sin^2 \theta_1)^l = \sum_{l_1+l_2=l} \frac{(\cos^2 \theta_1)^{l_1} (1 - R_0^2 \sin^2 \theta_1)^{l_2}}{l_1! l_2!}$

as in (3.25), and integrating for  $\theta_1$  ( $0 \leq \theta_1 \leq \frac{\pi}{2}$ ) we get the joint distribution of  $(R_0^2, R_1^2)$  as

$$\text{const. } \exp \left\{ -\frac{1}{2} \left( \beta_{03}^2 X_3^2 + \beta_{12}^2 X_2^2 \right) \right\}$$

$$(1-R_1^2)^{\frac{N-\lambda-4}{2}} (1-R_0^2)^{\frac{N-\lambda-3}{2}} (R_0^2 R_1^2)^{\frac{\lambda-2}{2}}$$

$$\sum_{l_1, l_2} \left[ \frac{\Gamma(N-\frac{1}{2}+l_1+l_2)}{\Gamma(\frac{\lambda}{2}+l_1+l_2) l_1! l_2!} \left( \frac{R_1^2 \beta_{12}^2 X_2^2}{2} \right)^{l_1+l_2} (1-R_0^2)^{l_2} \right]$$

$$\sum_{m, n} \left\{ \frac{\Gamma(N-\frac{1}{2}+n)}{\Gamma(n+\frac{\lambda-1}{2})} \frac{B(l_1+n+\frac{\lambda-1}{2}, l_2+m+\frac{1}{2})}{m! n!} \right.$$

$$\left. \left( \frac{\beta_{12}^2 X_2^2}{2} \right)^m \left( \frac{\beta_{03}^2 X_3^2}{2} \right)^n (R_0^2)^{m+n} \right\} dR_0^2 dR_1^2 \quad (4.16)$$

Transforming  $R_0^2$  and  $R_1^2$  into  $(u, w^2)$ , where the latter is the Wilks statistic given as

$$1-w^2 = (1-R_0^2)(1-R_1^2)$$

$$\text{and } u = R_0^2 / w^2 \text{ so that}$$

$$\frac{\partial (R_0^2, R_1^2)}{\partial (w^2, u)} = \frac{-w^2}{1-uw^2} \text{ and the limits of}$$

$u$  are 0 and 1 independent of  $w^2$ . Then the joint distribution of  $u$  &  $w^2$  can then be immediately derived from (4.16) as

$$\text{const. } \exp \left\{ -\frac{1}{2} \left( \beta_{03}^2 X_3^2 + \beta_{12}^2 X_2^2 \right) \right\}$$

$$(w^2)^{\frac{\lambda-1}{2}} (1-w^2)^{\frac{N-\lambda-4}{2}} \left\{ u(1-u) \right\}^{\frac{\lambda-2}{2}} (1-uw^2)^{-\frac{\lambda-1}{2}}$$

$$\times \sum_{l_1, l_2} \left[ \frac{\Gamma(N-\frac{1}{2}+l_1+l_2)}{\Gamma(\frac{\lambda}{2}+l_1+l_2) l_1! l_2!} \left( \frac{\beta_{12}^2 X_2^2 w^2}{2} \right)^{l_1+l_2} (1-u)^{l_1+l_2} (1-uw^2)^{-l_1} \right]$$

$$\sum_{m, n} \left\{ \frac{\Gamma(N-\frac{1}{2}+n)}{\Gamma(\frac{\lambda-1}{2}+n)} \frac{B(l_1+n+\frac{\lambda-1}{2}, l_2+m+\frac{1}{2})}{m! n!} \right.$$

$$\left. \left( \frac{\beta_{12}^2 X_2^2}{2} \right)^m \left( \frac{\beta_{03}^2 X_3^2}{2} \right)^n (W^2 u)^{m+n} \right\} du dw \quad (4.17)$$

Integrating (4.17) with respect  $u$  by using the well known result

$$B(\alpha, \beta) F(\alpha, \beta; \gamma, x) = \int_0^1 t^{\alpha-1} (1-t)^{\beta-1} (1-xt)^{-\gamma} dt \text{ for } |x| \leq 1$$

we get to the distribution of  $W^2$  as given by

$$\text{Const. } \exp -\frac{1}{2} (\beta_{03}^2 x_3^2 + \beta_{12}^2 x_2^2) (W^2)^{\frac{p-1}{2}} (1-W^2)^{\frac{N-p-4}{2}}$$

$$\sum_{l_1, l_2, m, n} \left\{ \left( \frac{\beta_{12}^2 x_2^2}{2} \right)^{l_1 + l_2 + m} \left( \frac{\beta_{03}^2 x_3^2}{2} \right)^n \frac{(W^2)^{l_1 + l_2 + m + n}}{l_1! l_2! m! n!} \right.$$

$$\frac{\Gamma(N-\frac{2}{2}+l_1+l_2) \Gamma(N-\frac{1}{2}+n) \Gamma(\frac{p}{2}+m+n)}{\Gamma(n+\frac{p-1}{2}) \Gamma(p+l_1+l_2+m+n)} B(l_1+n+\frac{p-1}{2}, l_2+m+\frac{1}{2})$$

$$\left. F\left(\frac{p-1}{2}+l_1, \frac{p}{2}+m+n; p+l_1+l_2+m+n, W^2\right) \right\} dW^2 \quad (4.18)$$

As in the previous section, in view of (4.9)  
it can be easily seen that all the variates  
 $x_0, x_{1,0}, \{x_{ij}\}$  correspond to Hotelling's canonical variates and that  $\beta_{12}^2$  and  $\beta_{03}^2$  are the two non-vanishing of the two canonical correlations  $P_1^2$  and  $P_0^2$ . Then writing

$(N-1) P_0^2 = E^2$  and  $(N-1) P_1^2 = F^2$ , the distribution can be written as

$$C. \exp -\frac{1}{2} \{ E^2 + F^2 \} (W^2)^{\frac{p-1}{2}} (1-W^2)^{\frac{N-p-4}{2}}$$

$$\sum_{l_1, l_2, m, n} \left\{ \left( \frac{E^2}{2} \right)^n \left( \frac{F^2}{2} \right)^{l_1 + l_2 + m} \frac{(W^2)^{m+n+l_1+l_2}}{l_1! l_2! m! n!} \right.$$

$$\frac{\Gamma(N-\frac{2}{2}+l_1+l_2) \Gamma(N-\frac{1}{2}+n) \Gamma(\frac{p}{2}+m+n)}{\Gamma(n+\frac{p-1}{2}) \Gamma(p+l_1+l_2+m+n)} B(l_1+n+\frac{p-1}{2}, l_2+m+\frac{1}{2})$$

$$\left. F\left(\frac{p-1}{2}+l_1, \frac{p}{2}+m+n; p+l_1+l_2+m+n, W^2\right) \right\} dW^2 \quad (4.19)$$

Here onwards proceeding in a way exactly similar to that in the previous section, either while determining the constant C or while deducing and reducing the null distribution, we arrive at the nonnull and null distributions of  $1-W^2=L$ , the expressions for which are given by

$$\frac{\frac{N-h-3}{2}}{\pi \Gamma(N-h-2)} e^{-\frac{1}{2}(E^2+F^2)} (1-L)^{p-1} L^{\frac{N-h-4}{2}}$$

$$\sum_{l_1, l_2, m, n} \left\{ \left(\frac{E^2}{2}\right)^n \left(\frac{F^2}{2}\right)^m \frac{(1-L)^{m+l_1+l_2}}{m! n! l_1! l_2!} \right.$$

$$\frac{\Gamma(\frac{N-2}{2} + l_1 + l_2) \Gamma(\frac{N-1}{2} + n) \Gamma(\frac{p}{2} + m + n)}{\Gamma(n + \frac{p-1}{2}) \Gamma(p + l_1 + l_2 + m + n)}$$

$$B\left(\frac{N-1}{2} + n + l_1, l_2 + m + \frac{1}{2}\right)$$

$$F\left(\frac{N-1}{2} + l_1, \frac{N-1}{2} + m + n, p + l_1 + l_2 + m + n, 1-L\right) \} dL \quad (4.20)$$

and

$$\frac{1}{2B(N-h-2, p)} (1-\sqrt{L})^{p-1} (\sqrt{L})^{\frac{N-h-4}{2}} dL \quad (4.21)$$

respectively.

If we put  $E = F$ , it is seen that the nonnull distributions in both the cases, as given by (4.20) and (3.32) are of the same form. Thus there exists duality when both the nonvanishing correlations are equal, and not in the general case.

5. SUMMARY:- The nonnull distributions of Hotelling's  $T^2$  and Mahalanobis  $D^2$  statistics are obtained without assuming the invariance property through a completely analytic approach. The nonnull and null distributions of the Wilk's statistic with two variates in the dependent set and  $p$  variates in the independent set, when either of the sets is fixed, are derived. It is interesting indeed to find that there is no duality between the two general nonnull distributions as in the case of only one variate in the dependent set. However, it is shown that there exists duality when the two nonvanishing correlations are equal.

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