

ABOUT TEST CRITERIA IN MULTIVARIATE ANALYSIS

JOSÉ A. DÍAZ-GARCÍA AND FRANCISCO J. CARO-LOPERA

ABSTRACT. The exact distribution of a certain criterion announced as new by Olson (1974), but really defined by Wilks (1932), is studied. Tables of that criterion are computed for a sort of particular parameters. Some errors in two of the criteria obtained by Wilks (1932) are detected and corrected. The moments and the exact distribution of Dempster's test criterion are found. At the end, an example of the literature determines all the criteria and their tests.

1. INTRODUCTION

Consider the general multivariate linear model

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} \quad (1.1)$$

where: $\mathbf{Y} \in \Re^{n \times p}$ is the matrix of the observed values; $\boldsymbol{\beta} \in \Re^{q \times p}$ is the parameter matrix; $\mathbf{X} \in \Re^{n \times q}$ is the design matrix or the regression matrix of rank $r \leq q$; $\boldsymbol{\epsilon} \in \Re^{n \times p}$ is the error matrix which has a matrix variate normal distribution, specifically $\boldsymbol{\epsilon} \sim \mathcal{N}_{n \times p}(\mathbf{0}, \mathbf{I}_n \otimes \boldsymbol{\Sigma})$, see Muirhead (1982, p.430); \otimes denotes the Kronecker product; and $\boldsymbol{\Sigma} \in \Re^{p \times p}$, $\boldsymbol{\Sigma} > \mathbf{0}$. For this model, we want to test the hypothesis

$$H_0 : \mathbf{C}\boldsymbol{\beta}\mathbf{M} = \mathbf{0} \text{ versus } H_a : \mathbf{C}\boldsymbol{\beta}\mathbf{M} \neq \mathbf{0} \quad (1.2)$$

where $\mathbf{C} \in \Re^{\nu_H \times q}$ of rank $\nu_H \leq r$ and $\mathbf{M} \in \Re^{p \times g}$ of rank $g \leq p$. As in the univariate case, the matrix \mathbf{C} concerns to the hypothesis among the elements of the parameter matrix columns, while the matrix \mathbf{M} allows hypothesis among the different response parameters. The matrix \mathbf{M} plays a role in profile analysis, for example; in ordinary hypothesis test it is taken to be the identity matrix, $\mathbf{M} = \mathbf{I}_p$.

Let \mathbf{S}_H be the matrix of sums of squares and sums of products due to the hypothesis and let \mathbf{S}_E be the matrix of sums of squares and sums of products due to the error. Both are defined like this

$$\begin{aligned} \mathbf{S}_H &= (\mathbf{C}\tilde{\boldsymbol{\beta}}\mathbf{M})'(\mathbf{C}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{C}')^{-1}(\mathbf{C}\tilde{\boldsymbol{\beta}}\mathbf{M}) \\ \mathbf{S}_E &= \mathbf{M}'\mathbf{Y}'(\mathbf{I}_n - \mathbf{X}\mathbf{X}^{-1})\mathbf{Y}\mathbf{M}, \end{aligned} \quad (1.3)$$

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respectively; where $\tilde{\beta} = \mathbf{X}^{-}\mathbf{Y}$ and \mathbf{X}^{-} is any generalised inverse of \mathbf{X} such that $\mathbf{X} = \mathbf{XX}^{-}\mathbf{X}$. Besides, under the null hypothesis, \mathbf{S}_H has a g -dimensional Wishart distribution with ν_H degrees of freedom and parameter matrix $\mathbf{M}'\boldsymbol{\Sigma}\mathbf{M}$, i.e. $\mathbf{S}_H \sim \mathcal{W}_g(\nu_H, \mathbf{M}'\boldsymbol{\Sigma}\mathbf{M})$; similarly \mathbf{S}_E has a g -dimensional Wishart distribution with ν_E degrees of freedom and parameter matrix $\mathbf{M}'\boldsymbol{\Sigma}\mathbf{M}$, i.e. $\mathbf{S}_E \sim \mathcal{W}_g(\nu_E, \mathbf{M}'\boldsymbol{\Sigma}\mathbf{M})$; specifically, ν_H and ν_E denote the degrees of freedom of the hypothesis and the error, respectively. All the results given below are true for $\mathbf{M} \neq \mathbf{I}_p$, just compute \mathbf{S}_H and \mathbf{S}_E from (1.3) and replace p by g . Now, let $\lambda_1, \dots, \lambda_s$ be the $s = \min(\nu_H, g)$ non null eigenvalues of the matrix $\mathbf{S}_H\mathbf{S}_E^{-1}$ such that $0 < \lambda_s < \dots < \lambda_1 < \infty$ and let $\theta_1, \dots, \theta_s$ be the s non null eigenvalues of the matrix $\mathbf{S}_H(\mathbf{S}_H + \mathbf{S}_E)^{-1}$ with $0 < \theta_s < \dots < \theta_1 < 1$; here we note $\lambda_i = \theta_i/(1 - \theta_i)$ and $\theta_i = \lambda_i/(1 + \lambda_i)$, $i = 1, \dots, s$. Various authors have proposed a number of different criteria for testing the hypothesis (1.2). But it is known, see for example Kres (1983), that all the tests can be expressed in terms of the eigenvalues λ' s or θ' s. In our experience, a reason for which many of these test statistics are not used is due to lack and/or inaccessibility of tables for the respective critical values.

In this work the three test statistics proposed by Wilks (1932) are studied after correcting some errors in the published density functions. We emphasize that two of those statistics were proposed as new by Roy *et al.* (1971) (U -statistic) and Olson (1974) (V -statistic). Besides we show how to obtain the critical values for the U -statistic by starting from the tables of Wilks' Λ statistic. The density of the V -statistic is derived by three different methods and the tables for the critical points are constructed for several values of the parameters. The exact distribution of another test criterion proposed by Pillai (1955) is found. The moments and the exact distribution for the Dempster statistic are given. At the end, this work solves a problem in the literature by computing all the published test statistics studied, also we propose a way for finding the critical values for the remaining test criteria; special emphasis is given around some practical considerations that should be taken into account when the approximations are used.

2. WILKS' CRITERIA

Unfortunately, there is not homogeneity in the symbol of the test statistics; moreover, some of them were renamed creating more confusion. For example, the well known statistic of Wilks is often represented by W , but in the literature it is also defined as Wilks' Λ . However, Anderson (1982, p. 299) denoted it by U , but Wilks (1932) named another statistics with that symbol. In order to avoid any confusion in notation we return to the original notation of Wilks (1932) and we define the three criteria in this way:

$$\begin{aligned} \Lambda &= W &= \frac{|\mathbf{S}_E|}{|\mathbf{S}_E + \mathbf{S}_H|} &= \prod_{i=1}^s \frac{1}{1 + \lambda_i} \\ &= \prod_{i=1}^s (1 - \theta_i) && \text{Wilks (1932, p. 485)} \end{aligned}$$

$$\begin{aligned}
U &= \frac{|\mathbf{S}_H|}{|\mathbf{S}_E + \mathbf{S}_H|} = \prod_{i=1}^s \frac{\lambda_i}{1 + \lambda_i} \\
&= \prod_{i=1}^s \theta_i \quad \text{Wilks (1932, p. 482)} \\
V &= \frac{|\mathbf{S}_H|}{|\mathbf{S}_E|} = \prod_{i=1}^s \lambda_i \\
&= \prod_{i=1}^s \frac{\theta_i}{(1 - \theta_i)} \quad \text{Wilks (1932, p. 486).}
\end{aligned}$$

Curiously the U -statistic was proposed as a new statistic in the literature by Roy *et al.* (1971, last paragraph p. 72) with the same original notation of Wilks (1932). Similarly, the third statistic was proposed as new by Olson (1974); here we used that notation.

Moreover, Wilks (1932) proposed integral expressions for the densities of the three statistics, but even when the general expression for the W and the U statistics are correct (Wilks (1932, eq. (5), p. 475)), the density for W (Wilks (1932, eq. (35), p. 486)) is wrong. Maybe this fact explains the inconsistencies of some particular expressions for the densities of W published by Wilks (1935), such as it is corroborated by Consul (1966) when the results are compared with the results obtained by Anderson (1982, p. 308). The correct density function of W in Wilks (1932) is obtained by replacing $(p - 2)/2$ by $(p - 3)/2$ in the exponent of the term $(v_1 v_2 \cdots v_{n-1})$. Now, by using our notation

Wilks' notation	Our notation
N	$v_H + v_E + 1$
p	$v_H + 1$
n	p

where $v_E = N - p$, note the distribution of U can be found as a function of the distribution of W (and vice versa), just changing the rules of v_H and v_E . This is, by making the transformation

$$(v_H, v_E) \rightarrow (v_E, v_H).$$

Observe that in Wilks' notation the density of U can be obtained from the density of W by making the transformation

$$(N - p, p - 1) \rightarrow (p - 1, N - p);$$

here, the above-mentioned error in the density of W is detected again. This equivalency can be easily seen by replacing particular values of v_H and v_E in the densities of U and W (the densities were derived by Hsu (1940) from the joint density of the eigenvalues of the θ 's). For proving the equivalency, let us denote the density of $\Theta = (\theta_1, \dots, \theta_s)'$ by $p(\Theta; s, m, h)$, where

$$m = \frac{|v_H - p| - 1}{2} \text{ and } h = \frac{v_E - p - 1}{2},$$

see Díaz-García and Gutiérrez-Jáimez (1997), Nanda (1948), Pillai (1955) or Rencher (1995, p. 165). See also Srivastava and Khatri (1979, Theorem 3.6.2, p. 93), (but first note some minor errors appear there: the exponent of π must be $p^2/2$ instead of $p/2$ and the exponent of the l_i should be $(n_2 - p - 1)/2$ in place of $(n_2 - p - 1)$).

Now, it is known that $W \sim$ Wilks' Λ . If $\Theta^* = ((1 - \theta_1), \dots, (1 - \theta_s))' = (\theta_1^*, \dots, \theta_s^*)'$, the distribution of Θ^* is the same as that of Θ , by interchanging m and h , see Nanda (1948, Section 5). Then,

$$\Lambda^* = \prod_{i=1}^s \theta_i^* \sim \text{Wilks' } \Lambda, \quad \text{with } m \text{ and } h \text{ interchanged,}$$

but note $\Lambda^* = U$. Therefore,

$$U \sim \text{Wilks' } \Lambda, \quad \text{with } m \text{ and } h \text{ interchanged.}$$

But $v_E > p$ and $v_H \geq p$, then the interchange of m and h is equivalent to the interchange of v_H and v_E .

In summary,

Theorem 1. *The distribution of U -statistic, can be obtained from the distribution of the Λ -statistic, by interchanging v_H and v_E ; this is*

$$U_{v_H, v_E} \stackrel{d}{=} \Lambda_{v_E, v_H},$$

where $\stackrel{d}{=}$ denotes identically distributed and the statistics U and Λ were denoted with subindexes to indicate the interchange between the parameters v_E and v_H .

Note that, in general, all the distributions of the test statistics and the tabulation of the correspondent critical values were derived by assuming that $p \leq v_H$; however, if $p > v_H$, the associated densities and their respective critical values can be obtained by making the following transformations in the parameters, see Muirhead (1982, eq. (7), p. 455), Srivastava and Khatri (1979, p. 96) or Rencher (1995, p. 167),

$$(p, v_H, v_E) \rightarrow (v_H, p, v_E + v_H - p). \quad (2.1)$$

3. THIRD WILKS' STATISTIC, V -STATISTIC

Wilks' V -statistic have been rarely used, maybe because its exact and asymptotic distributions have not been derived, and of course, no tables of its critical values have been constructed, except the Table H in Olson (1973) where the critical values were obtained via Monte Carlo. Recently that statistic have been used in the context of sensitivity analysis in regression, see Díaz-García *et al.* (2007). In fact, Wilks never found its particular distribution; but the k -moments were derived and a suggestion for determining its distribution was given starting from the general equations (13) and (16) of Wilks (1932); however the equation (16) contains two errors.

The right density function of the V -statistic is (in our notation)

$$\begin{aligned} f_V(v) &= \frac{\pi^{p(p-1)/2} \prod_{i=1}^p [\Gamma((v_H + v_E)/2 - i + 1)]}{\Gamma_p[v_H/2] \Gamma_p[v_E/2]} v^{(v_H-p-1)/2} (1+v)^{-(\frac{v_H+v_E}{2}-p+1)} \\ &\times \int_0^1 \dots \int_0^1 \left\{ 1 - \frac{\prod_{i=1}^{p-1} (1-r_i)}{1+v} - \left[1 - \prod_{i=1}^{p-1} (1-r_i) - \frac{\prod_{i=1}^{p-1} r_i}{1+v} \right] \right\}^{-\left(\frac{v_H+v_E}{2}-p+1\right)} \\ &\times \prod_{i=1}^{p-1} [r_i(1-r_i)]^{(v_H+v_E)/2-(p+i)/2} dr_1 dr_2 \dots dr_{(p-1)}, \quad v > 0. \end{aligned}$$

Also we have that

$$\frac{1 - \prod_{i=1}^{p-1} (1 - r_i) - \frac{\prod_{i=1}^{p-1} r_i}{1+v}}{1 - \frac{\prod_{i=1}^{p-1} (1 - r_i)}{1+v}} < 1$$

and

$$\frac{\prod_{i=1}^{p-1} (1 - r_i)}{1 + v} < 1$$

for $r_i \in [0, 1]$ and $v > 0$. This allows us to expand in a double series of powers the term between the braces and later to integrate it term by term.

- For $p = 1$ we get

$$f_V(v) = \frac{\Gamma[\frac{\nu_H+\nu_E}{2}]}{\Gamma[\frac{\nu_H}{2}]\Gamma[\frac{\nu_E}{2}]} v^{\frac{\nu_H-2}{2}} (1+v)^{-\frac{\nu_H+\nu_E}{2}}, \quad v > 0.$$

- For $p = 2$ we have

$$f_V(v) = k_2 v^{\frac{\nu_H-3}{2}} \int_0^1 [(1-r_1)v + r_1]^{-\frac{\nu_H+\nu_E-2}{2}} [r_1(1-r_1)]^{\frac{\nu_H+\nu_E-3}{2}} dr_1, \quad v > 0,$$

$$k_2 = \frac{\Gamma[\frac{\nu_H+\nu_E}{2}]\Gamma[\frac{\nu_H+\nu_E-2}{2}]}{\Gamma[\frac{\nu_H}{2}]\Gamma[\frac{\nu_H-1}{2}]\Gamma[\frac{\nu_E}{2}]\Gamma[\frac{\nu_E-1}{2}]}.$$

- For $p = 3$ we obtain

$$\begin{aligned} f_V(v) &= k_3 v^{\frac{\nu_H-4}{2}} \int_0^1 \int_0^1 [(1-r_1)(1-r_2)v + r_1 r_2]^{-\frac{\nu_H+\nu_E-4}{2}} [r_1(1-r_1)]^{\frac{\nu_H+\nu_E-4}{2}} \\ &\times [r_2(1-r_2)]^{\frac{\nu_H+\nu_E-5}{2}} dr_1 dr_2, \quad v > 0, \end{aligned}$$

$$k_3 = \frac{\Gamma[\frac{\nu_H+\nu_E}{2}]\Gamma[\frac{\nu_H+\nu_E-2}{2}]\Gamma[\frac{\nu_H+\nu_E-4}{2}]}{\Gamma[\frac{\nu_H}{2}]\Gamma[\frac{\nu_H-1}{2}]\Gamma[\frac{\nu_H-2}{2}]\Gamma[\frac{\nu_E}{2}]\Gamma[\frac{\nu_E-1}{2}]\Gamma[\frac{\nu_E-2}{2}]}.$$

- For $p = 4$ we get

$$\begin{aligned} f_V(v) &= k_4 v^{\frac{\nu_H-5}{2}} \int_0^1 \int_0^1 \int_0^1 [(1-r_1)(1-r_2)(1-r_3)v + r_1 r_2 r_3]^{-\frac{\nu_H+\nu_E-6}{2}} \\ &\times [r_1(1-r_1)]^{\frac{\nu_H+\nu_E-5}{2}} [r_2(1-r_2)]^{\frac{\nu_H+\nu_E-6}{2}} [r_3(1-r_3)]^{\frac{\nu_H+\nu_E-7}{2}} dr_1 dr_2, \quad v > 0, \end{aligned}$$

$$k_4 = \frac{\Gamma[\frac{\nu_H+\nu_E}{2}]\Gamma[\frac{\nu_H+\nu_E-2}{2}]\Gamma[\frac{\nu_H+\nu_E-4}{2}]\Gamma[\frac{\nu_H+\nu_E-6}{2}]}{\Gamma[\frac{\nu_H}{2}]\Gamma[\frac{\nu_H-1}{2}]\Gamma[\frac{\nu_H-2}{2}]\Gamma[\frac{\nu_H-3}{2}]\Gamma[\frac{\nu_E}{2}]\Gamma[\frac{\nu_E-1}{2}]\Gamma[\frac{\nu_E-2}{2}]\Gamma[\frac{\nu_E-3}{2}]}.$$

Observe that for $p = 1$, the distribution of V is a constant times an F-distribution; so, we can use the tables of F in order to find the critical values of V . Tables for $p = 2, 3$ and several values of ν_H and ν_E are tabulated in the Appendix A.

Alternatively, the exact distribution of the V -statistic can be determined via the approach of Hsu (1940), i.e. by the joint distribution of the λ 's. In particular a simplified expression for $p = 2$ can be obtained as follows: from Muirhead (1982, pp. 451 and 454-455) we have that

$$f_{\lambda_1, \lambda_2}(\lambda_1, \lambda_2) = k (\lambda_1 \lambda_2)^{(\nu_H-3)/2} [(1 + \lambda_1)(1 + \lambda_2)]^{-(\nu_H+\nu_E)/2} (\lambda_1 - \lambda_2),$$

where

$$k = \frac{\pi \Gamma_2[(\nu_H + \nu_E)/2]}{\Gamma_2[\nu_H/2] \Gamma_2[\nu_E/2]},$$

if we define $V = \lambda_1 \lambda_2$ and $R = (1 + \lambda_1)(1 + \lambda_2)$, then $dV dr = (\lambda_1 - \lambda_2) d\lambda_1 d\lambda_2$. Thus

$$f_{V,R}(v, r) = k v^{(\nu_H-3)/2} r^{-(\nu_H+\nu_E)/2},$$

by integrating with respect to R and ranging from $(1 + \sqrt{v})^2$ to ∞ we get the density function

$$f_V(v) = k_2^* v^{(\nu_H-3)/2} (1 + \sqrt{v})^{-(\nu_H+\nu_E-2)}, \quad v > 0,$$

with

$$k_2^* = \frac{2k}{(\nu_H + \nu_E - 2)} = \frac{2 \sqrt{\pi} \Gamma[(\nu_H + \nu_E)/2] \Gamma[(\nu_H + \nu_E - 1)/2]}{(\nu_H + \nu_E - 2) \Gamma[\nu_H/2] \Gamma[(\nu_H - 1)/2] \Gamma[\nu_E/2] \Gamma[(\nu_E - 1)/2]}.$$

A third approach for deriving the distribution of the V -statistic is proposed by Consul (1966). It is based on the Mellin transform which we define as follows:

If $M(s)$ is analytic in the strip $\sigma_0 < \Re(s) < \sigma_1$, and if it tends to zero uniformly with increasing $\Im(s)$ for any real value c between a and b , with its integral along such a line converging absolutely, then if

$$f(x) = \frac{1}{2\pi i} \int_{c-i\infty}^{c+i\infty} M(s) x^{-s} ds.$$

we have that

$$M(s) = \int_0^\infty f(x) x^{s-1} dx$$

Conversely, suppose $f(x)$ is piecewise continuous on the positive real numbers, taking a value halfway between the limit values at any jump discontinuities, and suppose the integral

$$M(s) = \int_0^\infty f(x) x^{s-1} dx$$

is absolutely convergent when $\sigma_0 < \Re(s) < \sigma_1$. Then f is recoverable via the inverse Mellin transform from its Mellin transform M .

From Wilks (1932, p. 486) (in our notation),

$$E(V^h) = \frac{\Gamma_p[\nu_H/2 + h] \Gamma_p[\nu_E/2 + h]}{\Gamma_p[\nu_H/2] \Gamma_p[\nu_E/2]}.$$

Then the exact density function of V is

$$f_V(v) = \frac{1}{\Gamma_p[\nu_H/2]\Gamma_p[\nu_E/2]} \frac{1}{2\pi i} \int_{c-i\infty}^{c+i\infty} v^{-h-1} \Gamma_p[\nu_H/2+h] \Gamma_p[\nu_E/2+h] dh.$$

Putting $h + (\nu_E + 1 - p)/2 = t$, we obtain

$$f_V(v) = \frac{v^{(\nu_E-1-p)/2}}{\Gamma_p[\nu_H/2]\Gamma_p[\nu_E/2]} \frac{1}{2\pi i} \int_{c'-i\infty}^{c'+i\infty} v^{-t} \Gamma_p[t - (\nu_E - \nu_H + 1 - p)/2] \Gamma_p[t + (1 - p)/2] dt,$$

where $c' = c + (\nu_E + 1 - p)/2$.

4. EXACT DISTRIBUTION OF NEW PILLAI CRITERION, $W^{(s)}$

Pillai (1955) proposed another test criterion and its approximated distribution, apart from the other three criteria exposed in that work. The new criterion is defined like this

$$W^{(s)} = 1 - V^{(s)}/s = \frac{s - \sum_{i=1}^s \theta_i}{s} = \frac{\sum_{i=1}^s (1 - \theta_i)}{s}$$

where

$$V^{(s)} = \text{tr}((\mathbf{S}_E + \mathbf{S}_H)^{-1} \mathbf{S}_H) = \sum_{i=1}^s \frac{\lambda_i}{(1 + \lambda_i)} = \sum_{i=1}^s \theta_i;$$

is the Pillai's statistic, see Muirhead (1982, p. 466), Rencher (1995, 168), Kres (1983, p. 6) and Seber (1984, p. 414), among many others.

Then

$$sW^{(s)} = \text{tr}(\mathbf{S}_E(\mathbf{S}_E + \mathbf{S}_H)^{-1}) = \sum_{i=1}^s (1 - \theta_i).$$

Now, as in Section 2, a similar result for the exact distribution of the $W^{(s)}$ -statistic can be derived:

Exactly as before, if $\Theta^* = ((1 - \theta_1), \dots, (1 - \theta_s))' = (\theta_1^*, \dots, \theta_s^*)'$, the distribution of Θ^* and Θ are the same, so, by interchanging m and h

$$sV^{(s)*} = \sum_{i=1}^s \theta_i^* \sim \text{Pillai's } V^{(s)}, \quad \text{with } m \text{ and } h \text{ interchanged}$$

and by noting that $sV^{(s)*} = sW^{(s)}$, we have

$$sW^{(s)} \sim \text{Pillai's } V^{(s)}, \quad \text{with } m \text{ and } h \text{ interchanged}$$

In summary,

Theorem 2. *The distribution of the $W^{(s)}$ -statistic can be obtained from the distribution of $V^{(s)}$ -statistic, by interchanging ν_H and ν_E . This is*

$$W_{\nu_H, \nu_E}^{(s)} \stackrel{d}{=} \frac{1}{s} V_{\nu_E, \nu_H}^{(s)}$$

where the statistics $V^{(s)}$ and $W^{(s)}$ were denoted with subindexes to indicate the interchange between the parameters ν_E and ν_H .

Note that this behavior of the parameters can be seen in the approximated distributions of both statistics given in Pillai (1955, eqs. (5) and (6), respectively).

5. EXACT DISTRIBUTION OF THE DEMPSTER CRITERION

For the case of one or two samples, Dempster (1958) and Dempster (1960) propose a non exact proof for testing the hypothesis (1.2). For the general case ($p > 2$), Fujikoshi *et al.* (2004) propose the following statistic

$$T_D = (\text{tr}\mathbf{S}_H)/(\text{tr}\mathbf{S}_E);$$

which is termed the Dempster trace criterion.

Dempster's criterion is rarely used. This is because its exact and asymptotic distribution are given in terms of the matrix of parameters Σ .

Fujikoshi *et al.* (2004) derive asymptotic null and nonnull distributions of Dempster trace criterion when $n \rightarrow \infty$ and $p \rightarrow \infty$. They prove that

$$\frac{\tilde{T}_D}{\sigma_D} \xrightarrow{d} \mathcal{N}(0, 1), \quad (5.1)$$

where \xrightarrow{d} denotes convergence in distribution, and

$$\tilde{T}_D = \sqrt{p} \left\{ n \frac{\text{tr}\mathbf{S}_H}{\text{tr}\mathbf{S}_E} - \nu_H \right\},$$

and

$$\sigma_D = \frac{\sqrt{2\nu_H (\text{tr}\Sigma^2)/p}}{(\text{tr}\Sigma)/p}.$$

For a practical situation, a (n, p) -consistent estimator is given by

$$\widehat{\sigma}_D = \frac{\sqrt{2\nu_H \{(\text{tr}\mathbf{S}_E^2)/n^2 - (\text{tr}\mathbf{S}_E)^2/n^3\}/p}}{(\text{tr}\mathbf{S}_E)/(np)}.$$

Next we derive the exact null distribution and the moments of the Dempster trace criterion.

Theorem 3. *When $\nu_H > p - 1$ and $\nu_E > p - 1$, the exact null distribution of T_D is*

$$\begin{aligned} f_{T_D}(t) &= |\delta^{-1}\Sigma|^{-(\nu_H+\nu_E)/2} \sum_{k=0}^{\infty} \sum_{l=0}^{\infty} \frac{\beta^{II}(t; (p\nu_H + 2k)/2, (p\nu_E + 2l)/2)}{k! l!} \\ &\quad \times \sum_{\kappa} \sum_{\mu} \left(\frac{1}{2} \nu_H \right)_{\kappa} \left(\frac{1}{2} \nu_E \right)_{\mu} C_{\kappa}(\mathbf{I}_p - \delta\Sigma^{-1}) C_{\mu}(\mathbf{I}_p - \delta\Sigma^{-1}), \quad t > 0 \end{aligned}$$

where $\beta^{II}(t; b, c)$ denotes the density function of a univariate Type II Beta distribution of parameters b and c , see Gupta and Nagar (2000, p. 165); \sum_{κ} denotes summation over all the partitions $\kappa = (k_1, \dots, k_p)$, $k_1 \geq \dots \geq k_p \geq 0$, of k , $C_{\kappa}(X)$ is the zonal polynomial of X corresponding to κ and the generalised hypergeometric coefficient $(a)_{\kappa}$ is given by

$$(a)_{\kappa} = \prod_{i=1}^p (a - (i-1)/2)_{k_i}$$

$(r)_k = r(r+1)\cdots(r+k-1)$, $(a)_0 = 1$ (see Muirhead (1982, p. 258)) and $\delta \in (0, \infty)$ is an arbitrary parameter. Muirhead (1982, p. 341) proposes $\delta = 2\delta_1\delta_p/(\delta_1 + \delta_p)$ as near value to the optimal one, where δ_1, δ_p are the largest and smallest eigenvalue of Σ respectively.

Proof. Remember that $S_H \sim \mathcal{W}_p(v_H, \Sigma)$ and $S_E \sim \mathcal{W}_p(v_E, \Sigma)$ are independent. Let $X = \text{tr}S_H$ and $Y = \text{tr}S_E$, then X and Y are independent too. Using Theorem 8.3.4 in Muirhead (1982, p. 339), the joint density function of X and Y is

$$\begin{aligned} f_{X,Y}(x, y) &= |\delta^{-1}\Sigma|^{-(v_H+v_E)/2} \sum_{k=0}^{\infty} \sum_{l=0}^{\infty} \frac{1}{k! l!} g(x; p v_H/2+k, 2\delta) g(y; p v_E/2+k, 2\delta) \\ &\quad \times \sum_{\kappa} \sum_{\mu} \left(\frac{1}{2} v_H \right)_{\kappa} \left(\frac{1}{2} v_E \right)_{\mu} C_{\kappa} (\mathbf{I} - \delta \Sigma^{-1}) C_{\mu} (\mathbf{I}_p - \delta \Sigma^{-1}), \end{aligned}$$

where

$$g(x; r, 2\delta) = \frac{\exp(-x/(2\delta)) x^{r-1}}{(2\delta)^r \Gamma[r]}.$$

Making the change of variables

$$T_D = X/Y, \quad Z = Y \quad (T_D > 0, Z > 0),$$

with $dxdy = zdzdt$, the joint density function of T_D and Z is

$$\begin{aligned} |\delta^{-1}\Sigma|^{-(v_H+v_E)/2} \sum_{k=0}^{\infty} \sum_{l=0}^{\infty} \frac{z}{k! l!} g(tz; p v_H/2+k, 2\delta) g(z; p v_E/2+k, 2\delta) \\ \times \sum_{\kappa} \sum_{\mu} \left(\frac{1}{2} v_H \right)_{\kappa} \left(\frac{1}{2} v_E \right)_{\mu} C_{\kappa} (\mathbf{I}_p - \delta \Sigma^{-1}) C_{\mu} (\mathbf{I}_p - \delta \Sigma^{-1}). \end{aligned}$$

Now integrating with respect to z over $z \in (0, \infty)$ it gives the desired marginal density function of T_D . \square

Corollary 1. Observe that if in Theorem 3, $\Sigma = \delta \mathbf{I}_p$, then

$$f_{T_D}(t) = \beta^H(t; p v_H/2, p v_E/2),$$

or alternatively

$$\frac{v_E}{v_H} T_D \sim \mathcal{F}(p v_H, p v_E),$$

where $\mathcal{F}(b, c)$ is a central F-distribution with b and c degrees of freedom.

Corollary 2. Under the condition of Theorem 3 the moments of T_D are given by

$$\begin{aligned} E(T_D^h) &= |\delta^{-1}\Sigma|^{-(v_H+v_E)/2} \sum_{k=0}^{\infty} \sum_{l=0}^{\infty} \frac{\Gamma[(p v_H + 2k)/2 + h] \Gamma[(p v_E + 2l)/2 - h]}{k! l! \Gamma[(p v_H + 2k)/2] \Gamma[(p v_E + 2l)/2]} \\ &\quad \times \sum_{\kappa} \sum_{\mu} \left(\frac{1}{2} v_H \right)_{\kappa} \left(\frac{1}{2} v_E \right)_{\mu} C_{\kappa} (\mathbf{I}_p - \delta \Sigma^{-1}) C_{\mu} (\mathbf{I}_p - \delta \Sigma^{-1}). \end{aligned}$$

Similarly, if $\Sigma = \delta \mathbf{I}_p$

$$E(T_D^h) = \frac{\Gamma[p v_H/2 + h] \Gamma[p v_E/2 - h]}{\Gamma[p v_H/2] \Gamma[p v_E/2]}.$$

Proof. The proof follows easily from the moments of univariate Type II Beta distribution. \square

Remark 1. Alternative expressions of the density function and the moments of T_D given in Theorem 3 and Corollary 2 can be derived in terms of the invariant polynomials, Davis (1980); specifically, by the eq. (5.1) and (5.10) in Davis (1980), the following results are obtained (or see also Chikuse (1980)):

$$\begin{aligned} f_{T_D}(t) = & |\delta^{-1}\Sigma|^{-(\nu_H+\nu_E)/2} \sum_{k=0}^{\infty} \sum_{l=0}^{\infty} \frac{\beta^{ll}(t; (p\nu_H+2k)/2, (p\nu_E+2l)/2)}{k! l!} \\ & \times \sum_{\kappa} \sum_{\mu} \sum_{\phi \in \kappa \cdot \mu} \left(\frac{1}{2}\nu_H\right)_\kappa \left(\frac{1}{2}\nu_E\right)_\mu \left(\theta_\phi^{\kappa,\mu}\right)^2 C_\phi (\mathbf{I}_p - \delta\Sigma^{-1}), \quad t > 0, \end{aligned}$$

and

$$\begin{aligned} E(T_D^h) = & |\delta^{-1}\Sigma|^{-(\nu_H+\nu_E)/2} \sum_{k=0}^{\infty} \sum_{l=0}^{\infty} \frac{\Gamma[(p\nu_H+2k)/2+h]\Gamma[(p\nu_E+2l)/2-h]}{k! l! \Gamma[(p\nu_H+2k)/2]\Gamma[(p\nu_E+2l)/2]} \\ & \times \sum_{\kappa} \sum_{\mu} \sum_{\phi \in \kappa \cdot \mu} \left(\frac{1}{2}\nu_H\right)_\kappa \left(\frac{1}{2}\nu_E\right)_\mu \left(\theta_\phi^{\kappa,\mu}\right)^2 C_\phi (\mathbf{I}_p - \delta\Sigma^{-1}), \end{aligned}$$

where

$$\theta_\phi^{\kappa,\mu} = \frac{C_\phi^{\kappa,\mu}(\mathbf{I}_p, \mathbf{I}_p)}{C_\phi(\mathbf{I}_p)}.$$

and $C_\phi^{\kappa,\mu}(\mathbf{I}_p, \mathbf{I}_p)$ is an invariant polynomial evaluated in the identity matrix, \mathbf{I}_p .

6. EXAMPLE

The present example describes and spreads the computation of the different statistics for testing the multivariate linear hypothesis and proposes practical ways for finding the corresponding critical values by using: the published tables, the integration of the exact distribution or approximations. Also, we emphasize some directions about the use of approximations for computing the critical values; unfortunately, such considerations are not described in the texts where those approximations are established, see Kres (1983), Rencher (1995), among many others; however, in most of the original sources we can find some important directions for approximations, see for example Pillai (1955).

The following application is a modification of the example 9.4.3 of Srivastava (2002, p. 294).

Example. The original observation matrix consists of a 32 vector corresponding to the 12 responses of each rat; for our exposition, the first two dependent variables Y_1 and Y_2 are considered (i.e. the first two days). In this case we propose the following multivariate linear model:

$$\mathbf{Y} = \mathbf{X} \underset{(32 \times 2)}{\overset{\beta}{\sim}} \underset{(32 \times 5)}{+} \underset{(5 \times 2)}{\mathbf{E}} \underset{(32 \times 2)}{,}$$

where the design matrix is also provided in Srivastava (2002, p. 294) and

$$\beta = \begin{pmatrix} \beta_{01} & \beta_{02} \\ \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \\ \beta_{31} & \beta_{32} \\ \beta_{41} & \beta_{42} \end{pmatrix}.$$

We want to test the hypothesis

$$H : \mathbf{C}\beta\mathbf{M} = \mathbf{0} \quad \text{versus} \quad A : \mathbf{C}\beta\mathbf{M} \neq \mathbf{0},$$

where $\mathbf{M} = \mathbf{I}_2$ and

$$\mathbf{C} = \begin{pmatrix} 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 1 & -1 \end{pmatrix}$$

The matrices of sums of squares and sums of products due to the error and the hypothesis are, respectively,

$$\mathbf{S}_E = \begin{pmatrix} 255.80 & 112.62 \\ 112.62 & 415.25 \end{pmatrix} \quad \text{and} \quad \mathbf{S}_H = \begin{pmatrix} 10.05 & 27.55 \\ 27.55 & 81.30 \end{pmatrix}.$$

The test statistics for all the known criteria are tabulated in Table 1.

TABLE 1. Criteria to test the null hypothesis

Criteria	Statistics	$\alpha(= 0.05)$ Critical value
Wilks' Λ	0.832	0.626
Wilks' U	5.190E-4	0.025
Wilks' V	6.235E-4	0.038
Lawley-Hotelling's $U^{(s)}$	0.200	0.548
Pillai's $V^{(s)}$	0.168	0.415
Pillai's $W^{(s)}$	0.915	0.792
Pillai's $H^{(s)}$	0.908	0.969
Pillai's $R^{(s)}$	0.006	0.969
Pillai's $T^{(s)}$	0.167	3.168
Roy's λ_{\max}	0.197	0.489
Roy's θ_{\max}	0.164	0.328
Anderson's λ_{\min}	0.041	0.117
Roy's θ_{\min}	0.003	0.105
Dempster's T_D	0.136	0.182

Some definitions and comments about the results in Table 1:

(1) General remarks:

- (a) The decision rule for all the criteria is:

reject H_0 if the statistic \geq critical value

However, for Wilks' Λ and Pillai's $W^{(s)}$ criteria, the decision rule is (this class of test is known in statistical literature as **inverse test**, see Rencher (1995, p. 162)):

reject H_0 if the statistic \leq critical value.

- (b) The tables for critical values of all the criteria are tabulated in terms of the parameters (p, ν_H, ν_E) or in terms of the parameters (s, m, h) , where remember that

$$s = \min(p, \nu_H), \quad m = (|\nu_H - p| - 1)/2 \quad \text{and} \quad h = (\nu_E - p - 1)/2.$$

Besides, the tables (in general) have been computed by assuming that $p \leq \nu_H$ and $p \leq \nu_E$. If $p > \nu_H$ then use the combination of parameters $(\nu_H, p, \nu_E + \nu_H - p)$ in place of (p, ν_H, ν_E) , see Muirhead (1982, eq. (7), p. 455), Srivastava and Khatri (1979, p. 96) or Rencher (1995, p. 167).

- (c) Observe that the null hypothesis is not rejected under any criteria. This is remarkable, because usually, when several statistics are applied, in the same test, some contradictory conclusions can appear, i.e. a hypothesis can be rejected by some statistics and accepted by the remaining ones. This is due to the multidimensional nature of the space in which the vectors involved in the hypothesis lie, see Rencher (1995, p. 169). Some directions for choosing one of these tests are given by the comparison of power functions, see for example Morrison (1978, pp. 223-224), Anderson (1982, Section 8.6.5), Olson (1974) and Rencher (1995, Section 6.2), among many others.

- (2) Wilks' Λ statistic:

$$\Lambda = \frac{|\mathbf{S}_E|}{|\mathbf{S}_E + \mathbf{S}_H|} = \prod_{i=1}^s \frac{1}{1 + \lambda_i} = \prod_{i=1}^s (1 - \theta_i);$$

see Wilks (1932), Rencher (1995, p. 161) and Kres (1983, p. 5) among many others. The critical value was taken from Table 1 in Kres (1983, pp. 14-51), besides, it was computed with the correct expression by using Mathematica.

- (3) Wilks' U statistic:

$$U = \frac{|\mathbf{S}_H|}{|\mathbf{S}_E + \mathbf{S}_H|} = \prod_{i=1}^s \frac{\lambda_i}{1 + \lambda_i} = \prod_{i=1}^s \theta_i;$$

see Wilks (1932), Roy *et al.* (1971, p. 72), Seber (1984, p. 413) and Kres (1983, p. 6) among many others. This criterion is also known as Gnanadesikan's U statistic. The critical value was computed with the expression (31) in Wilks (1932) by the use of Mathematica. Observe, also, that this statistic is wrongly defined as a function of the eigenvalues λ 's and θ 's in Kres (1983, p. 6).

- (4) Wilks' V statistic:

$$V = \frac{|\mathbf{S}_H|}{|\mathbf{S}_E|} = \prod_{i=1}^s \lambda_i = \prod_{i=1}^s \frac{\theta_i}{(1 - \theta_i)};$$

see Wilks (1932), Olson (1974) and Kres (1983, p. 8). This statistic is also known as Olson's V statistic. The critical value given in the Table 1 was taken from the tables in the Appendix A.

- (5) Lawley-Hotelling's $U^{(s)}$ statistic:

$$U^{(s)} = \text{tr}(\mathbf{S}_E^{-1} \mathbf{S}_H) = \sum_{i=1}^s \lambda_i = \sum_{i=1}^s \frac{\theta_i}{(1 - \theta_i)};$$

see Muirhead (1982, p. 466), Rencher (1995, 167) and Kres (1983, p. 6) among many others. Unfortunately, the tables for the critical values do not include the minimum required possible combinations between the parameters s , m and h ; see Table 6 in Kres (1983, pp.118-135). In the example of the Table 1 we have used an F-approximation, see equation (6.30) in Rencher (1995, p. 167), see also Pillai (1955, eq. (7)). Observe that this approximation is useful for $h + s \geq 30$ when $s = 2$; when s increases by 1, $h + s$ must increase by 10 to give satisfactory results, see Pillai (1955).

- (6) Pillai's $V^{(s)}$ statistic:

$$V^{(s)} = \text{tr}((\mathbf{S}_E + \mathbf{S}_H)^{-1} \mathbf{S}_H) = \sum_{i=1}^s \frac{\lambda_i}{(1 + \lambda_i)} = \sum_{i=1}^s \theta_i;$$

see Muirhead (1982, p. 466), Rencher (1995, 168) and Kres (1983, p. 6) among many others. The corresponding critical value in the Table 1 was taken from Table 7 in Kres (1983, pp. 136-153). However, note that for the critical value, a Type I Beta approximation can be used (see Gupta and Nagar (2000, p.165)), see equation (5) in Pillai (1955), see also Rencher (1995, Section 6.1.5). This approximation is useful for $m + h \geq 30$ when $s = 2$; but, if s increases by 1, then, $m + h$ must be increased by 10, for getting satisfactory results, see Pillai (1955).

- (7) Pillai's $W^{(s)}$ statistic:

$$W^{(s)} = \text{tr}((\mathbf{S}_E + \mathbf{S}_H)^{-1} \mathbf{S}_E) = \sum_{i=1}^s \frac{1}{(1 + \lambda_i)} = \sum_{i=1}^s (1 - \theta_i) = (1 - V^{(s)}/s);$$

see Pillai (1955). For the critical values we can use a Type I Beta approximation, see equation (6) in Pillai (1955). For practical use, this approach is satisfactory for $m + h \geq 30$ when $s = 2$; but, if s increases by 1, then, $m + h$ must be increased by 10, for getting satisfactory results, see Pillai (1955). However, note the exact critical value can be obtained from $V^{(s)}$ -statistic and the expression $W^{(s)} = (1 - V^{(s)}/s)$. In fact, Table 1 contains the exact value.

- (8) Pillai's $H^{(s)}$ statistic:

$$H^{(s)} = \frac{s}{\sum_{i=1}^s (1 + \lambda_i)} = s \left\{ \sum_{i=1}^s (1 - \theta_i)^{-1} \right\}^{-1} = (1 + U^{(s)}/s)^{-1};$$

see Pillai (1955) and Kres (1983, p. 8). The corresponding critical value in the Table 1 was obtained by using a Type I Beta approximation, see equation (9) in

Pillai (1955). Here we have to apply the above mentioned practical conditions for the correct use of the approximation of the $U^{(s)}$ statistic.

- (9) Pillai's $R^{(s)}$ statistic:

$$R^{(s)} = \frac{s}{\sum_{i=1}^s \frac{1+\lambda_i}{\lambda_i}} = s \left\{ \sum_{i=1}^s \theta_i^{-1} \right\}^{-1} = (1 + U'^{(s)}/s)^{-1};$$

see Pillai (1955) and Kres (1983, p. 8). Here $U'^{(s)}$ is the same $U^{(s)}$ but with m and h interchanged. For this criterion, the corresponding critical value in the Table 1 was computed by using a Type I beta approximation, see equation (11) in Pillai (1955). Again, the same conditions explained before for the $U^{(s)}$ statistic have to be applied for a satisfactory result in the approximations. Besides, we need the conditions $m \geq 0$, or $|v_H - p| \geq 1$ for getting satisfactory approximations. The last condition was not considered by Pillai (1955), but it is required, because for a Beta distribution $\beta(a, b)$ it is known that $a > 0$, which is guaranteed when $m \geq 0$ in the approximation.

- (10) Pillai's $T^{(s)}$ statistic:

$$T^{(s)} = s \left\{ \sum_{i=1}^s \lambda_i^{-1} \right\}^{-1} = \frac{s}{\sum_{i=1}^s \frac{1-\theta_i}{\theta_i}} = \frac{R^{(s)}}{1-R^{(s)}};$$

see Pillai (1955) and Kres (1983, p. 8). In the Table 1, the critical value was obtained by using a Type II Beta (see Gupta and Nagar (2000, 165)) approximation, see equation (13) in Pillai (1955). Again, for a satisfactory approximation, including the restriction over m , we use the same rules applied to the $R^{(s)}$ statistic.

- (11) Roy's λ_{\max} :

$$\lambda_{\max} = \frac{\theta_{\max}}{1 - \theta_{\max}};$$

see Roy (1957) and Kres (1983, p. 7). The corresponding critical value in the Table 1 was obtained from table 3 in Kres (1983, pp. 62-86). Besides, we got the critical value by integrating the joint distribution of the λ 's via Mathematica.

- (12) Roy's θ_{\max} :

$$\theta_{\max} = \frac{\lambda_{\max}}{1 + \lambda_{\max}};$$

see Roy (1957), Muirhead (1982, p. 481), Rencher (1995, p. 164) and Kres (1983, p. 7) among many others. For this criterion the corresponding critical value in the Table 1 can be obtained from table 2, 4 or 5 in Kres (1983, pp. 52-61, 87-104 and 105-117, respectively). Again, Mathematica was used for finding the critical value of that criterion by integrating the joint distribution of the eigenvalues θ 's.

- (13) Anderson's λ_{\min} :

$$\lambda_{\min} = \frac{\theta_{\min}}{1 - \theta_{\min}};$$

see Roy (1957), Anderson (1982) and Kres (1983, p. 7) among many others. As above, the critical value in the Table 1 was computed via Mathematica by

integrating the joint distribution of the eigenvalues λ 's. However, note that the critical value can be determined as a function of the critical value for θ_{\min} .

- (14) Roy's θ_{\min} :

$$\theta_{\min} = \frac{\lambda_{\min}}{1 + \lambda_{\min}};$$

see Pillai (1955) and Roy (1957). Similarly to Anderson's criterion, the corresponding critical value in the Table 1 was obtained by integration of the joint distribution of the eigenvalues λ 's via Mathematica. However those values can be obtained from the distribution of θ_{\max} by using

$$\theta_{\min}(\alpha, s, v_H, v_E) = 1 - \theta_{\max}(\alpha, s, v_E, v_H),$$

see Nanda (1948); but, again, the published tables do not allow us to read the values because, they do not incorporate such combinations of the parameters; in fact there are many similar particular cases for which the critical value can not be found from those tables.

- (15) Dempster's T_D :

$$T_D = (\text{tr}\mathbf{S}_H)/(\text{tr}\mathbf{S}_E);$$

see Dempster (1958), Dempster (1960) and Fujikoshi *et al.* (2004). In this criterion, the critical value in the Table 1 was obtained by using the normal approximation (5.1).

7. CONCLUSIONS

A sort of important problems appears when we try to test a multivariate hypothesis:
 1. from a practical point of view, we know that a test of multivariate hypothesis can be performed by several criteria (for example, here we present 14 statistics for the same multivariate linear model), then the choice of the "best" statistics is an important question to solve; 2. finding the corresponding critical values is also problematic, because a few combinations of the parameters are provided in the published tables; 3. an additional problem is related with the approximations of the critical values given in the books and softwares, because most of them do not indicate the conditions for the use of those approximations; 4. only six of the 14 statistics have been studied considerably (around 70's), but even for the analyzed cases, the theoretical recommendations for their use are not clear today. In this work, we tried to answer those questions, first, by correcting some wrong published results about the probability functions associated to these criteria, to explain the historical discrepancies. Also, the exact distributions of many statistics were found, these provide the initial step in future works for obtaining theoretical comparison among the criteria. In fact, we proposed three alternative ways for determining the density of Wilks' V statistic and provided tables for a number of parameter combinations, improving the existing tables and giving the exact formula for generating any combination if necessary. With the exact densities we avoid the classical problems of using approximations without clarifying their right use. Even with the above theoretical results, which add bases for an advanced discussion or comparison among the statistics and their critical values, an important question remains about the best choice of the statistic. In particular, there are

some works about the power function, as it was explained in the general remark point (c) of the example, which recommend some statistics under certain conditions. However, mainly they study the following criteria: Wilks' Λ , Lawley-Hotelling's $U^{(s)}$, Pillai's $V^{(s)}$ and Roy's λ_{\max} , and relationships with the remaining ten statistics are not clear yet.

8. APPENDIX A. TABLES OF THE THIRD CRITERION \mathbf{V} OF S. S. WILKS (OLSON'S CRITERION)

- (1) Contents of the tables and definition of the test statistic: The tables contain the upper percentage points of the test statistic

$$V = \frac{|\mathbf{S}_H|}{|\mathbf{S}_E|} = \prod_{i=1}^s \lambda_i = \prod_{i=1}^s \frac{\theta_i}{(1 - \theta_i)} \quad \text{Wilks (1932, p. 486).}$$

Here, \mathbf{S}_H is the matrix of sums of squares and sums of products due to the hypothesis and \mathbf{S}_E is the matrix of sums of squares and sums of products due to the error. Also, $\lambda_1, \dots, \lambda_s$ are the $s = \min(\nu_H, g)$ non null eigenvalues of the matrix $\mathbf{S}_H \mathbf{S}_E^{-1}$ such that $0 < \lambda_s < \dots < \lambda_1 < \infty$ and $\theta_1, \dots, \theta_s$ are the s non null eigenvalues of the matrix $\mathbf{S}_H (\mathbf{S}_H + \mathbf{S}_E)^{-1}$ with $0 < \theta_s < \dots < \theta_1 < 1$; recall that $\lambda_i = \theta_i/(1 - \theta_i)$ and $\theta_i = \lambda_i/(1 + \lambda_i)$, $i = 1, \dots, s$.

- (2) Dimensions of the tables and definition of the parameters:

- (a) The parameter α :

α = error probability

$\alpha = 5\%$ and 1% .

- (b) The parameter p :

p = dimension of the variates

for $p = 2, 3$

- (c) The parameter ν_H :

ν_H = degree of freedom of the hypothesis

$$\text{for } \nu_H = \begin{cases} 1(1)30, 35(5)100, 120, & p = 2; \\ 3, 5, 10, 15, 20, 30, 50, 80, 100, 120, & p = 3. \end{cases}$$

- (d) The parameter ν_E :

ν_E = degree of freedom of the hypothesis

$$\text{for } \nu_E = \begin{cases} 2(1)30, 40(20)140, 170, 200, 240, 320, 440, 600, 800, 1000 \\ (p = 2); \\ 10(10)50, 80, 100, 200, 400, 600 \\ (p = 3). \end{cases}$$

These tables are valid for $p \leq \nu_H$; if $p > \nu_H$, the respective critical values can be obtained by making the following transformations in the parameters,

$$(p, \nu_H, \nu_E) \rightarrow (\nu_H, p, \nu_E + \nu_H - p).$$

TABLE 8. Upper percentage points of the test statistic V_{p,v_H,v_E} . $p = 3$ $\alpha = 0.05$

v_E	v_H										v_E
	3	5	10	15	20	30	50	80	100	120	
10	0.073322	0.700454	7.520021	27.12518	66.10158	228.4902	1075.229	4439.711	8692.978	15045.67	10
20	0.005379	0.047264	0.465367	1.611283	3.830858	12.86758	58.95089	239.3027	465.7294	802.7410	20
30	0.001358	0.011617	0.110825	0.377156	0.886524	2.935041	13.24701	53.21887	103.1730	177.3476	30
40	0.000530	0.004477	0.042014	0.141614	0.330660	1.085038	4.849324	19.34044	37.38835	64.13839	40
50	0.000259	0.002173	0.020188	0.067632	0.157224	0.512805	2.275836	9.027131	17.41264	29.82274	50
80	0.000059	0.000490	0.004485	0.014879	0.034340	0.110847	0.485705	1.906212	3.660518	6.248559	80
100	0.000030	0.000245	0.002226	0.007359	0.016939	0.054466	0.237457	0.927768	1.778092	3.030608	100
200	0.000004	0.000029	0.000262	0.000858	0.001965	0.006263	0.026990	0.104288	0.198837	0.337505	200
400	0.000000	0.000004	0.000032	0.000104	0.000237	0.000750	0.003212	0.012322	0.023410	0.039631	400
600	0.000000	0.000001	0.000009	0.000030	0.000069	0.000219	0.000936	0.003580	0.006795	0.011484	600

 $p = 3$ $\alpha = 0.01$

v_E	v_H										v_E
	3	5	10	15	20	30	50	80	100	120	
10	0.264631	1.931939	17.81384	61.22305	145.6237	491.2244	2266.356	9253.390	18049.99	31162.11	10
20	0.017034	0.110726	0.903894	2.932160	6.735621	21.81983	96.93550	386.3916	747.3104	1282.661	20
30	0.004143	0.025957	0.202688	0.641679	1.450483	4.603821	20.02558	78.66108	151.3051	258.6989	30
40	0.001590	0.009780	0.074625	0.233072	0.521909	1.635863	7.017457	27.28280	52.26909	89.11286	40
50	0.000770	0.004685	0.035243	0.109124	0.242851	0.754698	3.205514	12.36654	23.61863	40.17610	50
80	0.000173	0.001037	0.007632	0.023306	0.051338	0.157219	0.655844	2.492506	4.730317	8.008860	80
100	0.000086	0.000514	0.003755	0.011413	0.025048	0.076287	0.315991	1.193271	2.258323	3.815224	100
200	0.000010	0.000060	0.000434	0.001305	0.002842	0.008551	0.034839	0.129519	0.243347	0.408692	200
400	0.000001	0.000007	0.000052	0.000156	0.000338	0.001011	0.004080	0.015018	0.028073	0.046955	400
600	0.000000	0.000002	0.000015	0.000046	0.000099	0.000294	0.001183	0.004336	0.008089	0.013507	600

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DEPARTMENT OF STATISTICS AND COMPUTATION, UNIVERSIDAD AUTÓNOMA AGRARIA ANTONIO NARRO, 25350 BUE-
NAVISTA, SALTILLO, COAHUILA, MÉXICO

E-mail address, J. A. Díaz-García: jadiaz@uaaan.mx

DEPARTMENT OF PROBABILITY AND STATISTICS, CENTRO DE INVESTIGACIÓN EN MATEMÁTICA, A. C., JALISCO S/N,
MINERAL DE VALENCIANA, 36240 GUANAJUATO, GUANAJUATO, MÉXICO

E-mail address, F. J. Caro-Lopera: fjcaro@cimat.mx