

# R Package, Multivariate p-Value Estimation: MANOVA,Block Independence & Bartlett's M ECM Test

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*2017-12-15*

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## Introduction:

### *Name*

The name of this R package is `wmpvaer`. This stands for “Wilks MANOVA p-Value Alternative Estimation”. The first part of this package contains R programs implementing an alternative to the approximate F Statistic p calculation (used in the R MANOVA package) for the Wilk's statistic used in MANOVA with a calculation developed in 2005 by Butler and Wood. The package also supplies an S4 object so that the same statistics can be computed with other R programs other than R MANOVA.

The second part of this package computes p-values for a likelihood ratio statistic of block independence, implementing another method from Butler and Wood.

The third part of this package computes p-values for Bartlett's M test for Equality of Covariance matrices (ECM), again from Butler and Wood's 2005 paper.

## PART 1 : MANOVA,Wilks Lambda and the Wishart Distribution

The distribution of the Wilks Lambda is the ratio of two independently distributed Wishart random variables. It is so complicated (intractable) that its expression in real numbers is almost never used. Currently approximate F tests are the only widely distributed tests for estimating p values for an observed Wilks Lambda statistic.

There is another approach to approximating the Wilks Lambda distribution and p values associated with it. The moment (and cumulant) generating functions of Wilks Lambda distribution have been known since 1963. These express the Wilks Lambda distribution (on a one to one basis) in terms of complex numbers instead of real numbers. Once either the moment or cumulant generating function of a probability distribution are known saddlepoint approximation becomes feasible.

The idea of saddlepoint approximation originated with Henry Daniels in 1954 (“Saddlepoint approximations in statistics.” *Annals of Mathematical Statistics*, v. 25 ,pp. 631-650,1954). In 1980 Lugannani and Rice (“Saddlepoint Approximation for the Distribution of the Sum of Independent Random Variables” in *Advances in Probability*, Vol. 12, pp. 475-490 ,1980) extended Daniels method to the estimation of cumulative distribution functions.

In turn in 2005, in a paper written by Butler, R.W. and Wood, A.T.A. (“Approximation of Power in Multivariate Analysis” in *Statistics and Computing* Vol. 15, pp. 281-287) Butler and Wood explained how the methods developed could be applied to the otherwise intractable Wilks Lambda distribution. The system of equations, which translates the complex number representation of the Wilks Lambda distribution into a real number approximation, are lengthy and involved. However, as this package `wmpvaer` demonstrates,

they can be computed. And, with the use of the R high precision computation package Rmpfr, result in an accurate representation of the Wilks Lambda Distribution, which is in turn used to compute accurate estimates of the power of a Wilks Lambda statistic. When used retrospectively (after data is collected), “power” has a one to one relationship to p-values.

### *wmpvaer p-values created differ substantially from the R MANOVA approximations in the datasets examined*

One of the statistician W. Edwards Deming’s aphorisms was that “There is no true value of anything”. All that exists, Deming would say, are methods for deriving answers and the answers themselves. When the methods used differ so do the answers arrived at, in general.

Butler and Wood’s p approximations are derived, mathematically, directly from the Wilks distribution itself. There is no intermediate approximation requiring the F distribution. Further, there are no justifications or arguments required as to whether the F distribution matches the distribution of the ratio of two independently distributed Wishart random variables.

### *This vignette does not discuss Butler/Wood in detail*

If you want to understand the methods underlying the Butler/Wood equations, it is best read Butler and Wood’s paper. This vignette primarily concerns samples of data and R coding. The part of the Butler/Wood equations I code with this package addresses only a small portion of the applications possible (p-values).

## Samples of Data and R Coding : `wmpvaerf`

With this package, I include three datasets named respectively “plastic”, “soils”, and “wolf”. Their origins are documented in this package but all three are standard datasets used to demonstrate MANOVA analysis.

The function used to derive the Wilks power estimates and p values, using output from the R MANOVA routine, is called `wmpvaerf`. The first matrix output is a matrix composed of the Wilks values and degrees of freedom generated by R’s basic MANOVA program using the `summary(fit, test="Wilks")$stats` option and the log of this value. `wmpvaerf` also uses the R MANOVA matrix created using `summary(fit)$Eigenvalues`, but this matrix is not included in the `wmpvaerf` output.

The 2nd matrix of `wmpvaerf` output are the values of power and the p-values computed with 120 bit precision (“quadruple precision”).

The 3rd matrix of `wmpvaerf` output reformates the second for convenience and adds the values of “r-manova~p” derived from the R MANOVA program.

### Example 1: Plastic Dataset

Using the “plastic” dataset (also used as an example in R’s MANOVA function documentation), the output of `wmpvaerf` is:

```
suppressPackageStartupMessages(library(Rmpfr));
suppressPackageStartupMessages(library(doParallel));
library(wmpvaer);
# prepare data
data(plastic);
Y<-as.matrix(plastic[,1:3]);
rate<-matrix(data=(plastic$rate),nrow(plastic),1);
```

```

additive<-matrix(data=(plastic$additive),nrow(plastic),1);
# run wmpvaer function
wmpvaerf(Y~ (rate*additive));
[[1]]
      Df Wilks          ln(Wilks)
rate    1 0.381858384661142 -0.962705459891849
additive 1 0.523034895418919 -0.648107095500711
rate:additive 1 0.777105757873425 -0.252178827357477
Residuals 16

[[2]]
      Pr(x>ln(Wilks)),Power,precBits=120
rate    0.99999999999999416012239272263966343901
additive 0.99999999999999976662838952759483172
rate:additive 4.0327993146447476244262410758493742103e-28
      Pr(x<=ln(Wilks)),p Value,precBits=120
rate    5.8398776072773603365609934757202060454e-15
additive 2.3337161047240516827595468766170403915e-19
rate:additive 0.999999999999999999999999999959672006857

[[3]]
      Power,formatted  p,formatted  r-manova~p
rate    1.000000    5.839878e-15  0.003034045
additive 1.000000    2.333716e-19  0.02474528
rate:additive 4.032799e-28    1.000000  0.3017816

```

## Example 2: Wolf Dataset

This a dataset of 9 measurements of 25 wolf skulls from different locations in North America and of different sexes. This data was gathered in the 1950s through the 1970s.

Using all 9 measurements, the following R code results in the following output:

```

suppressPackageStartupMessages(library(Rmpfr));
suppressPackageStartupMessages(library(doParallel));
library(wmpvaer);
# prepare data
data(wolf) ;
location<-matrix(data=(wolf$location),nrow(wolf),1);
sex<-matrix(data=(wolf$sex),nrow(wolf),1);
wolf$sex<-NULL;
wolf$location<-NULL;
wolfm1<-as.matrix(wolf[,1:9]);
# run wmpvaer function
wmpvaerf(wolfm1 ~ (sex * location));
[[1]]
      Df Wilks          ln(Wilks)
sex    1 0.149157496173264 -1.90275250999326
location 1 0.0475427371985173 -3.0461262419613
sex:location 1 0.350558699882641 -1.04822711182898
Residuals 21

[[2]]

```

```
Pr(x>ln(Wilks)),Power,precBits=120
sex 1.4857324590782732104658260835403653041e-141
location 5.0177307230085270952680772246701146106e-111
sex:location 8.5314071452691487111207574279217208224e-182
Pr(x<=ln(Wilks)),p Value,precBits=120
sex 1
location 1
sex:location 1

[[3]]
      Power,formatted  p,formatted  r-manova~p
sex 1.485732e-141 1.000000 0.0004375614
location 5.017731e-111 1.000000 3.623591e-7
sex:location 8.531407e-182 1.000000 0.05238652
```

### Example 3: Wolf Dataset

Analysis with only the first three dependent variables in the wolf skull measurement dataset ( “palatal (roof of the mouth) length”, “post palatal length” and “zygomatic (cheek bone) width”) gives the following results:

[illegible]

## Example 4: Soils Dataset

Using the soils dataset and the following code:

```
suppressPackageStartupMessages(library(Rmpfr));
suppressPackageStartupMessages(library(doParallel));
library(wmpvaer);
# prepare data
data(soils) ;
soilsfactors<-soils[,1:3];
block<-soilsfactors[,1];
contour<-soilsfactors[,2];
depth<-soilsfactors[,3];
soilsm1<-as.matrix(soils[,4:12]);
# run wmpvaer function
wmpvaerf(soilsm1~ (block+contour*depth));
```

[[1]]

	Df	Wilks	ln(Wilks)
block	1	0.529893950626389	-0.635078385615033
contour	2	0.0900547459566442	-2.40733750517712
depth	3	0.00784550100813156	-4.8478150314671
contour:depth	6	0.249056540547014	-1.39007533782409
Residuals	35		

[[2]]

	Pr(x>ln(Wilks)),Power,precBits=120
block	1.3996043345243130514926376608683830935e-385
contour	9.6906044736244266235054149456978645867e-237
depth	1
contour:depth	2.9945935657820019207929700075265058061e-357

Pr(x<=ln(Wilks)),p Value,precBits=120

block	1
contour	1
depth	0
contour:depth	1

[[3]]

	Power,formatted	p,formatted	r-manova~p
block	1.399604e-385	1.000000	0.02365858
contour	9.690604e-237	1.000000	1.184161e-8
depth	1.000000	0.000000	6.707586e-19
contour:depth	2.994594e-357	1.000000	0.7877627

If you use all 48 observations and all 9 dependent variables, the power analysis indicates that depth distinguishes the dependent variables. This less than surprising result is that, based on this dataset, depth separates the soil types, alone. However, if you had only R MANOVA approximate p-values to consider you would come to a different conclusion.

## Samples of Data and R Coding : mlandrf

To use the estimation routines with programs other than R MANOVA, an S4 object `mlandr` was written. This object can be used with any routine that analyzes models with multiple dependent variables and that can produce E (an error sum of squares matrix) and H (a sum of squares matrix due to an hypothesis). If

E and H exist, the matrix  $E^{-1}H$  can then be created and the eigenvalues of this matrix found.

Example 1 below uses  $E^{-1}H$  eigenvalues from the plastic dataset (these are stored in workspace `eigs_plastic` with eigenvalues generated by R MANOVA). Example 2 creates the MANOVA analysis using the R function `lm()` instead. The `mlandr` S4 object is executed using the R function `mlandr`.

## Example 1: Eigs\_plastic Dataset

Using “eigs\_plastic” dataset (eigenvalues derived from  $E^{-1}H$ ), output of `mlandr` is:

```
suppressPackageStartupMessages(library(Rmpfr));
suppressPackageStartupMessages(library(doParallel));
library(methods);
library(wmpvaer);
# prepare data
data(eigs_plastic);
eigsm<-as.matrix(eigs_plastic)
colnames(eigsm)<-c(" ", " ", " ");
rownames(eigsm)<-c("rate", "additive", "rate:additive");
e_dfm<-16;
m_dfm<-c(1,1,1);
# run S4 object "mlandr" wrapper function
mlandr(e_dfm,m_dfm,eigsm);
```

[[1]]

	Df	Wilks	ln(Wilks)	p,formatted
rate	1	0.381858382	-0.962705467	5.840229e-15
additive	1	0.523034902	-0.648107084	2.333694e-19
rate:additive	1	0.777105780	-0.252178799	1.000000
Residuals	16			

[[2]]

	Pr(x>ln(Wilks)),Power,precBits=120
rate	0.999999999999999415977111235584492266749
additive	0.99999999999999997666306484403328131
rate:additive	4.0332192883861583555016042106508553074e-28

	Pr(x<=ln(Wilks)),p Value,precBits=120
rate	5.840228876441550773325067453656190984e-15
additive	2.3336935155966718690088106545727312511e-19
rate:additive	0.999999999999999999999999999959667807126

The computed Wilks statistics are slightly different from the values produced by R MANOVA. They are computed with 120 bit precision from the derived eigenvalues.

## Example 2: Plastic Dataset, MANOVA analysis using `lm()` function and `mlandr`

Use `lm()` function, create MANOVA w “plastic” dataset & derive eigenvalues from “ $E^{-1}H$ ”s :

```
suppressPackageStartupMessages(library(Rmpfr));
suppressPackageStartupMessages(library(doParallel));
library(wmpvaer);
library(methods);
# prepare data
data(plastic);
Y<-as.matrix(plastic[,1:3]);
```

```

rate<-matrix(data=(plastic$rate),nrow(plastic),1);
additive<-matrix(data=(plastic$additive),nrow(plastic),1);

# run lm( )
fit <-lm( Y ~ (rate*additive));

#compute m_df & e_df
mstats<-summary(manova(fit), test="Wilks")$stats;
fm<-as.matrix(mstats[,1]);
nrms<-nrow(fm);
m_df<-fm[1:(nrms-1),];
m_dfm<-as.matrix(fm[1:(nrms-1),]);
e_df<-fm[nrms,];

# get list of Sum of Squares matrices
ssv<-summary(manova(fit))$SS
m1<-length(ssv);

# first,derive E-Inv
em1<-ssv[[m1]]; #the last SS matrix in the ssv list is the residual matrix
e_inv<-solve(em1); # inverts the em1 matrix

# second, compute eigenvalues for an eigenvalue matrix
eigsm<-eigen((e_inv %*% ssv[[1]] ))$values
for (i in (2:(m1-1))) {
eigenvs<-eigen((e_inv %*% ssv[[i]] ))$values
eigsm<-rbind(eigsm,eigenvs);
}
colnames(eigsm)<-c(" ", " ", " ");
rownames(eigsm)<-rownames(m_dfm);

# run S4 object "mlandr" wrapper function
mlandr(e_df,m_df,eigsm);

```

```

[[1]]
      Df      Wilks      ln(Wilks)  p,formatted
rate      1  0.381858385 -0.962705460  5.839878e-15
additive   1  0.523034895 -0.648107096  2.333716e-19
rate:additive 1  0.777105758 -0.252178827      1.000000
Residuals   16

```

```

[[2]]
      Pr(x>ln(Wilks)),Power,precBits=120
rate      0.999999999999999416012239272262867868165
additive   0.999999999999999976662838952759471662
rate:additive 4.0327993146447432218058003642757760835e-28
      Pr(x<=ln(Wilks)),p Value,precBits=120
rate      5.8398776072773713213183460906789317197e-15
additive   2.3337161047240528338036152018009681945e-19
rate:additive 0.999999999999999999999999999959672006857

```

The computed Wilks statistics are slightly different from the values produced by R MANOVA. They are computed with 120 bit precision from the derived eigenvalues.

## PART 2 : p-Values for LR Test of Block Independence

### *What this problem is.*

Let  $x_i$  be a numerical vector with values assumed to be normally distributed random variables. Further, assume there are  $N$  of these vectors, that is,  $x_1, \dots, x_N$ . These could easily be placed in a matrix with  $N$  columns.

Suppose you divide the matrix into two blocks, with the number of columns in the first block  $= p_1$  and the number of columns in the second  $= p_2$ .  $p_1$  and  $p_2$  are restricted as follows:  $p_1 + p_2 = N$  and  $p_1 \leq p_2$ .

From this information compute a sample variance-covariance matrix for all the data  $A = \widehat{\Sigma}$  and a sample variance-covariance matrix  $A_{1,1} = \widehat{\Sigma}_{1,1}$  for block 1 and  $A_{2,2} = \widehat{\Sigma}_{2,2}$  for block 2. Further, compute a sample cross covariance matrix  $\widehat{\Sigma}_{1,2} = \widehat{\Sigma}_{2,1}^T$ .

A test of whether block 1 was statistically independent from block 2 (that is,  $\Sigma_{1,2} = (\Sigma_{2,1})^T = 0_{p_1, p_2}$ ) could be (Muirhead, R.J., 1982 Aspects of Multivariate Statistical Theory, John Wiley, New York, Section 11.2), a likelihood ratio test, specifically:

$$\Lambda_{BI} = \frac{|A|}{(|A_{1,1}| * |A_{2,2}|)}$$

where  $|\bullet|$  is the determinant of a matrix. The distribution of this statistic is a ratio of two independently distributed Wishart random variables, the noncentral version of which is determined by  $n = N - 1, p_1, p_2$ , and the estimated eigenvalues of the matrix  $(\Sigma_{1,1})^{-1} * \Sigma_{1,2} * (\Sigma_{2,2})^{-1} * \Sigma_{2,1}$ .

But even though the real number form of this distribution is known, it is intractable and not of much use. Butler and Wood showed how saddlepoint methods applied to the known moment generating function of the distribution of  $\Lambda_{BI}$  (along with the Lugannani and Rice approximation) converts the  $\Lambda_{BI}$  distribution into a usable real numbers form. This R package computes these methods with the functions `statsBIf` and `statsBIncdf`.

Butler and Wood did not provide some essential information for this computation in their paper. Specifically they did not provide the formula for the analytical derivative  $\widehat{K}'(s)$  (as they did for the Wilks distribution). But this derivative and the derivative for `statsECMf` (below) were found and implemented with these programs.

### *What the computed distribution provides.*

In the absence of a usable form of the  $\Lambda_{BI}$  probability distribution what this statistic  $\Lambda_{BI}$  has been used for is to, roughly, reject the null hypothesis ( $\Sigma_{1,2} = (\Sigma_{2,1})^T = 0_{p_1, p_2}$ ). If  $\Lambda_{BI}$  is “small” then reject the null hypothesis. What is small or large is not defined (other than  $\Lambda_{BI}$  is between 0 and 1).

Once you can approximate the  $\Lambda_{BI}$  probability distribution, then you can derive a p-value. A small p-value estimate means that there is a small probability of rejecting the null hypothesis in error. A well defined reason to reject a null hypothesis is found.

It turns out that, in the datasets examined, the p-value often doesn't correspond to the size of the  $\Lambda_{BI}$  value. Small values of  $\Lambda_{BI}$  can have large p-values and large values of  $\Lambda_{BI}$  can have small p-values. Conclusions based on the raw value of  $\Lambda_{BI}$  alone don't have much of a rational basis.



## Samples of Data and R Coding : statsBIf and statsBIncatf

### Example 1: Plastic Dataset, statsBIf

This is a simple example of `statsBIf` using the plastic dataset. All that is needed for `statsBIf` to run is a matrix composed of numeric values and the definition of a variable identifying what columns are in the first block.

```
suppressPackageStartupMessages(library(Rmpfr));
library(wmpvaer);
# prepare data
data(plastic);
plasticm<-as.matrix(plastic[,1:3]);
block_v<-c(2) # identify columns in block 1
statsBIf(plasticm,block_v);
c# name_blk1 c# name_blk2 lambdaBI p value
2 gloss      1 tear      0.96233358 0.9196664
3 opacity
```

### Example 2: Wolf Dataset, statsBIf

This is a more involved example using the wolf dataset. Again, all that is needed for `statsBIf` to run is a matrix composed of numeric values and the definition of a variable identifying what columns are in the first block. Since there are only 9 columns and  $p_1$  must be  $\leq p_2$ , 4 columns is the maximum size for block 1.

```
suppressPackageStartupMessages(library(Rmpfr));
library(wmpvaer);
# prepare data
data(wolf);
wolf$sex<-NULL;
wolf$location<-NULL;
wolfm1<-as.matrix(wolf[,1:9]);
block_v<-c(1,3,5,7) # identify columns in block 1
statsBIf(wolfm1,block_v);
c# name_blk1 c# name_blk2 lambdaBI p value
1 palatal_L 2 post_p_L 0.023164421 4.5817539e-05
3 zygomatic_W 4 palatal_W1
5 palatal_W2 6 postg_foramina_W
7 interorbital_W 8 braincase_W
9 crown_L
```

### Example 3: Plastic Dataset, statsBIncatf

`statsBIncatf` uses the methods in `statsBIf` to produce analysis of all columns taken  $n$  at a time. Possible values of  $n$  are from 1 to  $\text{floor}(N/2)$ , where  $N$  is the total number of columns in the data matrix. For the plastic dataset, with 3 columns, the only possible value of  $n$  is 1.

```
suppressPackageStartupMessages(library(Rmpfr));
suppressPackageStartupMessages(library(doParallel));
library(wmpvaer);
# prepare data
data(plastic);
plasticm<-as.matrix(plastic[,1:3]);
```

```

nc_at_time<-1;
statsBIncatf(plasticm,nc_at_time)
[[1]]
  c# name_blk1 c# name_blk2 lambdaBI  p value
1  tear      2  gloss      0.97154632 0.92672565
      3  opacity
[[2]]
  c# name_blk1 c# name_blk2 lambdaBI  p value
2  gloss      1  tear      0.96233358 0.9196664
      3  opacity
[[3]]
  c# name_blk1 c# name_blk2 lambdaBI  p value
3  opacity      1  tear      0.99032795 0.94404996
      2  gloss

```

This analysis is interesting, though. It presents evidence that the three dependent variables in the data, “tear”, “gloss” and “opacity” all display independence from one another.

#### Example 4: Wolf Dataset, statsBIncatf

`statsBIncatf` uses the methods in `statsBIf` to produce analysis of all columns taken  $n$  at a time. Possible values of  $n$  are from 1 to  $\text{floor}(N/2)$ , where  $N$  is the total number of columns in the data matrix. For the wolf dataset, with 9 columns,  $n$  could be from 1 to 4. However, 9 taken 4 would result in output with 126 elements, 9 taken 3, 84 elements, 9 taken 2, 36 elements. So in the interest of vignette conservation, this example shows only 9 columns taken 1 at a time in comparison with all other columns.

```

suppressPackageStartupMessages(library(Rmpfr));
suppressPackageStartupMessages(library(doParallel));
library(wmpvaer);
# prepare data
data(wolf) ;
wolf$sex<-NULL;
wolf$location<-NULL;
wolfm1<-as.matrix(wolf[,1:9]);
nc_at_time<-1;
statsBIncatf(wolfm1,nc_at_time)
[[1]]
  c# name_blk1 c# name_blk2      lambdaBI  p value
1  palatal_L  2  post_p_L      0.13862872 0.053084376
      3  zygomatic_W
      4  palatal_W1
      5  palatal_W2
      6  postg_foramina_W
      7  interorbital_W
      8  braincase_W
      9  crown_L
[[2]]
  c# name_blk1 c# name_blk2      lambdaBI  p value
2  post_p_L  1  palatal_L      0.15991961 1
      3  zygomatic_W

```

```

4 palatal_W1
5 palatal_W2
6 postg_foramina_W
7 interorbital_W
8 braincase_W
9 crown_L

```

[[3]]

```

c# name_blk1 c# name_blk2 lambdaBI p value
3 zygomatic_W 1 palatal_L 0.17606424 0
                2 post_p_L
                4 palatal_W1
                5 palatal_W2
                6 postg_foramina_W
                7 interorbital_W
                8 braincase_W
                9 crown_L

```

[[4]]

```

c# name_blk1 c# name_blk2 lambdaBI p value
4 palatal_W1 1 palatal_L 0.3088967 0.77180576
                2 post_p_L
                3 zygomatic_W
                5 palatal_W2
                6 postg_foramina_W
                7 interorbital_W
                8 braincase_W
                9 crown_L

```

[[5]]

```

c# name_blk1 c# name_blk2 lambdaBI p value
5 palatal_W2 1 palatal_L 0.23768878 0.99253059
                2 post_p_L
                3 zygomatic_W
                4 palatal_W1
                6 postg_foramina_W
                7 interorbital_W
                8 braincase_W
                9 crown_L

```

[[6]]

```

c# name_blk1 c# name_blk2 lambdaBI p value
6 postg_foramina_W 1 palatal_L 0.19112488 0.0040741843
                    2 post_p_L
                    3 zygomatic_W
                    4 palatal_W1
                    5 palatal_W2
                    7 interorbital_W
                    8 braincase_W
                    9 crown_L

```

[[7]]

```

c# name_blk1 c# name_blk2 lambdaBI p value

```

```

7  interorbital_W 1  palatal_L          0.25668665 0.97229474
                   2  post_p_L
                   3  zygomatic_W
                   4  palatal_W1
                   5  palatal_W2
                   6  postg_foramina_W
                   8  braincase_W
                   9  crown_L

[[8]]
c# name_blk1 c# name_blk2      lambdaBI  p value
8  braincase_W 1  palatal_L      0.59218481 0.85274185
                   2  post_p_L
                   3  zygomatic_W
                   4  palatal_W1
                   5  palatal_W2
                   6  postg_foramina_W
                   7  interorbital_W
                   9  crown_L

[[9]]
c# name_blk1 c# name_blk2      lambdaBI  p value
9  crown_L   1  palatal_L      0.55689771 0.85870215
                   2  post_p_L
                   3  zygomatic_W
                   4  palatal_W1
                   5  palatal_W2
                   6  postg_foramina_W
                   7  interorbital_W
                   8  braincase_W

```

## PART 3 : p-Values for Bartlett's Modified LR ECM Test

### *What this problem is.*

A description of the univariate version of Bartlett's Modified Likelihood Ratio Test can be found on the following web sites: <http://www.itl.nist.gov/div898/handbook/eda/section3/eda357.htm> "1.3.5.7.Bartlett's Test" and <http://www.itl.nist.gov/div898/handbook/eda/section3/eda3581.htm>

What is computed in this package is a multivariate version, a version with mutiple dependent variables. In terms of a data matrix it can be thought of as the transpose of block independence computed with `statsBif` above. In it, a data matrix is segregated by rows instead of columns, into two groups. A test of equality of covariances between the two groups is then performed.

The univariate version of this Barlett's test depends on a Chi-Squared distribution. The multivariate version, in turn, depends of the multivariate version of the Chi-squared distribution, the Wishart distribution, in particular a ratio of two Wishart distributed random variables.

The distribution of this multivariate Bartlett test is known, assuming random variable normality, as is its moment generating function. Bulter and Wood show how the Lugannani and Rice approximation of this known distribution can be used to derive power and p-value estimates otherwise unobtainable.

Let  $x_1, \dots, x_{N1}$  be a matrix with  $N1$  rows and  $p$  columns with data sampled from a multivariate normal

distribution,  $N_p(\mu_1, \Sigma_1)$ . And assume there is another matrix  $x_1, \dots, x_{N2}$  a matrix with  $N2$  rows and (the same)  $p$  columns sampled from a multivariate normal distribution with  $\mu_2$  and  $\Sigma_2$ .  $N1$  does not have to be equal to  $N2$ .  $\mu_1$  does not have to equal  $\mu_2$ .

The null hypothesis of equal covariance matrices (ECM) is:

$$\Sigma_1 = \Sigma_2 = \Sigma$$

A likelihood ratio test in this case is can be

$$\Lambda_{ECM} = \frac{(|A_1|)^{\frac{n1}{n}} * (|A_2|)^{\frac{n2}{n}}}{(|(A_1 + A_2)|)}$$

where  $|\bullet|$  is the determinant of a matrix.  $A_1$  and  $A_2$  are the estimated variance covariance matrices for the two data matrices. The distribution of this statistic is a ratio of two independently distributed Wishart random variables, the noncentral version of which is determined by  $n1 = N1 - 1, n2 = N2 - 1, n = n1 + n2, p$ , and the estimated eigenvalues of the matrix  $\Sigma_1 * \Sigma_2^{-1}$ .

### Example 1: Plastic Dataset, Additive Variable, statsECMf

```
suppressPackageStartupMessages(library(Rmpfr));
library(wmpvaer);
#prepare data
data(plastic)

# select obs w low additive
a1<-plastic[plastic$additive=="Low",];
# create matrix w dependent vars
low_additive<-as.matrix(a1[,1:3]);

# select obs w high additive
a2<-plastic[!(plastic$additive=="Low"),];
# create matrix w dependent vars
high_additive<-as.matrix(a2[,1:3]);

# run statsECMf with defined matrices
statsECMf(low_additive,high_additive);
lambdaECM    p value
0.049692494 7.110012e-05
```

In all wmpvaer datasets the value of  $\Lambda_{ECM}$  estimated is small as is the estimated p-value. The test rejects the null hypothesis of equality of covariance matrices for all datasets that were examined.

If  $\Sigma_1$  is equal to  $\Sigma_2$  and both are invertible matrices then  $\Sigma_1 * \Sigma_2^{-1} = I$ , an identity matrix, with all of its eigenvalues equal to 1. In the plastic additive variable example above the estimated  $\Sigma_1 * \Sigma_2^{-1}$  is:

Table 1: with Eigenvalues

	tear	gloss	opacity
tear	0.9203183	-1.526514	-0.1333428
gloss	-1.1579138	2.457798	0.2470928
opacity	-1.1065895	4.094780	0.7460240

additive_eigs	3.621349	0.4210647	0.0817264
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This matrix is far from an identity matrix and the eigenvalues are not a vector of 1s. Unless this matrix is some reasonable approximation of an identity matrix, Bartlett’s modified LR ECM test is likely to reject the null hypothesis of equal covariance matrices.

### ***Computational issue.***

For both the block independence and equivalence of covariance matrices program (`statsBIf` and `statsECMf` respectively) bisection search alone would not converge with an accurate answer. In both sets of programs, bisection search is augmented by a preliminary scan of possible solutions. For `statsBIf` this is done at fixed intervals. For `statsECMf` the solutions are selected using a random sample.

For `statsECMf`, if the program is executed repeatedly on the same dataset, slightly different p-values can result.

### **NOTE: BISECTION SEARCH FAILURE**

The programs employ bisection search at some stages. Bisection search is an elementary search method. Bisection search can fail. When the bisection search for an estimation of power fails (does not converge with enough accuracy), an error statement (with the text “No Answer”) appears.

### **NOTE: PARALLEL COMPUTATION**

This version of `wmpvaerf`, `mmandrf` was rewritten to take advantage of the R package “doParallel”. The program `statsBIncatf` employed that R package from the beginning. These versions employ only one core if only one or two cores are available. Otherwise, the number of computer cores used is the minimum of “the number of independent variables in the model in question” or “the maximum number of available cores minus one” in the case of `wmpvaerf` and `mmandrf`. In the case of `statsBIncatf`, only the last condition applies.