Preface

The following document was developed to facilitate the use of agricolae package in R, it is understood that the user knows the statistical methodology for the design and analysis of experiments and through the use of the functions programmed in agricolae facilitate the generation of the field book experimental design and their analysis. The first part document describes the use of graph.freq role is complementary to the hist function of R functions to facilitate the collection of statistics and frequency table, statistics or grouped data histogram based training grouped data and graphics as frequency polygon or ogive; second part is the development of experimental plans and numbering of the units as used in an agricultural experiment; a third part corresponding to the comparative tests and finally provides agricolae miscellaneous additional functions applied in agricultural research and stability functions, soil consistency, late blight simulation and others.

1 Introduction

The package agricolae offers a broad functionality in the design of experiments, especially for experiments in agriculture and improvements of plants, which can also be used for other purposes. It contains the following designs: lattice, alpha, cyclic, balanced incomplete block designs, complete randomized blocks, Latin, Graeco-Latin, augmented block designs, split plot and strip plot. It also has several procedures of experimental data analysis, such as the comparisons of treatments of Waller-Duncan, Bonferroni, Duncan, Student-Newman-Keuls, Scheffe, Ryan, Einot and Gabriel and Welsch multiple range test or the classic LSD and Tukey; and non-parametric comparisons, such as Kruskal-Wallis, Friedman, Durbin, Median and Waerden, stability analysis, and other procedures applied in genetics, as well as procedures in biodiversity and descriptive statistics, De Mendiburu (2009).

1.1 Installation

The main program of R should be already installed in the platform of your computer (Windows, Linux or MAC). If it is not installed yet, you can download it from the R project (www.r-project.org) of a repository CRAN, R Core Team (2017).

> install.packages("agricolae") Once the agricolae package is installed, it needs to be made accessible to the current R session by the command:
> library(agricolae)

For online help facilities or the details of a particular command (such as the function `waller.test`) you can type:

> help(package="agricolae")
> help(waller.test)

For a complete functionality, `agricolae` requires other packages

**MASS:** for the generalized inverse used in the function `PBIB.test`
**nlme:** for the methods REML and LM in `PBIB.test`
**klaR:** for the function `triplot` used in the function `AMMI`
**Cluster:** for the use of the function `consensus`
**spdep:** for the between genotypes spatial relation in biplot of the function `AMMI`
**algDesign:** for the balanced incomplete block design `design.bib`

### 1.2 Use in R

Since `agricolae` is a package of functions, these are operational when they are called directly from the console of R and are integrated to all the base functions of R. The following orders are frequent:

> detach(package:agricolae) # detach package agricole
> library(agricolae) # Load the package to the memory
> designs<-apropos("design")
> print(designs[substr(designs,1,6)="design"], row.names=FALSE)

```
[1] "design.ab"    "design.alpha"  "design.bib"
[4] "design.crd"   "design.cyclic" "design.dau"
[7] "design.graeco" "design.lattice" "design.lsd"
[10] "design.rcbd"  "design.split"  "design.strip"
[13] "design.youden"
```

For the use of symbols that do not appear in the keyboard in Spanish, such as:

~, [, ], &, ^, |, <, >, {, }, \%, or others, use the table ASCII code.

> library(agricolae) # Load the package to the memory:

In order to continue with the command line, do not forget to close the open windows with any R order. For help:

```
help(graph.freq)
? (graph.freq)
str(normal.freq)
example(join.freq)
```

### 1.3 Data set in agricolae

> A<-as.data.frame(data(package="agricolae")$results[,3:4])
> head(A)
2 Descriptive statistics

The package \texttt{agricolae} provides some complementary functions to the \texttt{R} program, specifically for the management of the histogram and function \texttt{hist}.

2.1 Histogram

The histogram is constructed with the function \texttt{graph.freq} and is associated to other functions: \texttt{polygon.freq}, \texttt{table.freq}, \texttt{stat.freq}. See Figures: 1, 2 and 3 for more details.

Example. Data generated in \texttt{R}. (students' weight).

```r
> weight<-c( 68, 53, 69.5, 55, 71, 63, 76.5, 65.5, 69, 75, 76, 57, 70.5, 71.5, 56, 81.5, + 69, 59, 67.5, 61, 68, 59.5, 56.5, 73, 61, 72.5, 71.5, 59.5, 74.5, 63)
> print(summary(weight))
   Min. 1st Qu.  Median    Mean 3rd Qu.  Max.
   53.00  59.88   68.00   66.45  71.50   81.50
```

2.2 Statistics and Frequency tables

Statistics: mean, median, mode and standard deviation of the grouped data.

```r
> stat.freq(h1)

$variance
[1] 51.37655

$mean
[1] 66.6

$median
[1] 68.36

$mode
   [- -] mode
[1,] 67.4 72.2 70.45455
```

Frequency tables: Use \texttt{table.freq}, \texttt{stat.freq} and \texttt{summary}

The \texttt{table.freq} is equal to \texttt{summary}()
> par(mfrow=c(1,2),mar=c(4,4,0,1),cex=0.6)
> h1<- graph.freq(weight,col=colors()[84],frequency=1,las=2,density=20,ylim=c(0,12),ylab="Frequency")
> x<-h1$breaks
> h2<- plot(h1, frequency =2, axes= FALSE,ylim=c(0,0.4),xlab="weight",ylab="Relative (%)")
> polygon.freq(h2, col=colors()[84], lwd=2, frequency =2)
> axis(1,x,cex=0.6,las=2)
> y<-seq(0,0.4,0.1)
> axis(2, y,y*100,cex=0.6,las=1)

Figure 1: Absolute and relative frequency with polygon.

Limits class: **Lower and Upper**

Class point: **Main**

Frequency: **Frequency**

Percentage frequency: **Percentage**

Cumulative frequency: **CF**

Cumulative percentage frequency: **CPF**

> print(summary(h1),row.names=FALSE)

<table>
<thead>
<tr>
<th>Lower</th>
<th>Upper</th>
<th>Main</th>
<th>Frequency</th>
<th>Percentage</th>
<th>CF</th>
<th>CPF</th>
</tr>
</thead>
<tbody>
<tr>
<td>53.0</td>
<td>57.8</td>
<td>55.4</td>
<td>5</td>
<td>16.7</td>
<td>5</td>
<td>16.7</td>
</tr>
<tr>
<td>57.8</td>
<td>62.6</td>
<td>60.2</td>
<td>5</td>
<td>16.7</td>
<td>10</td>
<td>33.3</td>
</tr>
<tr>
<td>62.6</td>
<td>67.4</td>
<td>65.0</td>
<td>3</td>
<td>10.0</td>
<td>13</td>
<td>43.3</td>
</tr>
<tr>
<td>67.4</td>
<td>72.2</td>
<td>69.8</td>
<td>10</td>
<td>33.3</td>
<td>23</td>
<td>76.7</td>
</tr>
<tr>
<td>72.2</td>
<td>77.0</td>
<td>74.6</td>
<td>6</td>
<td>20.0</td>
<td>29</td>
<td>96.7</td>
</tr>
<tr>
<td>77.0</td>
<td>81.8</td>
<td>79.4</td>
<td>1</td>
<td>3.3</td>
<td>30</td>
<td>100.0</td>
</tr>
</tbody>
</table>

### 2.3 Histogram manipulation functions

You can extract information from a histogram such as class intervals *intervals.freq*, attract new intervals with the *sturges.freq* function or to join classes with *join.freq* function. It is also possible to reproduce the graph with the same creator *graph.freq* or function *plot* and overlay normal function with *normal.freq* be it a histogram in absolute scale, relative or density. The following examples illustrates these properties.

> sturges.freq(weight)
$\textbf{maximum} \\
[1] 81.5

$\textbf{minimum} \\
[1] 53

$\textbf{amplitude} \\
[1] 29

$\textbf{classes} \\
[1] 6

$\textbf{interval} \\
[1] 4.8

$\textbf{breaks} \\
[1] 53.0 57.8 62.6 67.4 72.2 77.0 81.8

> intervals.freq(h1)

<table>
<thead>
<tr>
<th>lower</th>
<th>upper</th>
<th>freq</th>
</tr>
</thead>
<tbody>
<tr>
<td>53.0</td>
<td>57.8</td>
<td>60.2</td>
</tr>
<tr>
<td>57.8</td>
<td>62.6</td>
<td>69.8</td>
</tr>
<tr>
<td>62.6</td>
<td>67.4</td>
<td>74.6</td>
</tr>
<tr>
<td>67.4</td>
<td>72.2</td>
<td>79.4</td>
</tr>
<tr>
<td>72.2</td>
<td>77.0</td>
<td>81.8</td>
</tr>
<tr>
<td>77.0</td>
<td>81.8</td>
<td>84.6</td>
</tr>
</tbody>
</table>

> join.freq(h1,1:3) -> h3
> print(summary(h3))

<table>
<thead>
<tr>
<th>Lower</th>
<th>Upper</th>
<th>Main Frequency</th>
<th>Percentage</th>
<th>CF</th>
<th>CPF</th>
</tr>
</thead>
<tbody>
<tr>
<td>53.0</td>
<td>67.4</td>
<td>60.2</td>
<td>13</td>
<td>43.3</td>
<td>13</td>
</tr>
<tr>
<td>67.4</td>
<td>72.2</td>
<td>69.8</td>
<td>10</td>
<td>33.3</td>
<td>23</td>
</tr>
<tr>
<td>72.2</td>
<td>77.0</td>
<td>74.6</td>
<td>6</td>
<td>20.0</td>
<td>29</td>
</tr>
<tr>
<td>77.0</td>
<td>81.8</td>
<td>79.4</td>
<td>1</td>
<td>3.3</td>
<td>30</td>
</tr>
</tbody>
</table>

2.4 hist() and graph.freq() based on grouped data

The \texttt{hist} and \texttt{graph.freq} have the same characteristics, only \texttt{f2} allows build histogram from grouped data.

0–10 (3)  
10–20 (8)  
20–30 (15)  
30–40 (18)  
40–50 (6)

> print(summary(h5),row.names=FALSE)
Figure 2: Join frequency and relative frequency with normal and Ogive.

Figure 3: hist() function and histogram defined class
<table>
<thead>
<tr>
<th>Lower</th>
<th>Upper</th>
<th>Main Frequency</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>10</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>10</td>
<td>20</td>
<td>15</td>
<td>8</td>
</tr>
<tr>
<td>20</td>
<td>30</td>
<td>25</td>
<td>15</td>
</tr>
<tr>
<td>30</td>
<td>40</td>
<td>35</td>
<td>18</td>
</tr>
<tr>
<td>40</td>
<td>50</td>
<td>45</td>
<td>6</td>
</tr>
</tbody>
</table>

3 Experiment designs

The package **agricolae** presents special functions for the creation of the field book for experimental designs. Due to the random generation, this package is quite used in agricultural research.

For this generation, certain parameters are required, as for example the name of each treatment, the number of repetitions, and others, according to the design, Cochran and Cox (1957); kueh (2000); Le Clerg and Leonard and Erwin and Warren and Andrew (1992); Montgomery (2002). There are other parameters of random generation, as the seed to reproduce the same random generation or the generation method (See the reference manual of **agricolae**).

http://cran.at.r-project.org/web/packages/agricolae/agricolae.pdf

**Important parameters in the generation of design:**

- **series:** A constant that is used to set numerical tag blocks, eg number = 2, the labels will be: 101, 102, for the first row or block, 201, 202, for the following, in the case of completely randomized design, the numbering is sequential.

- **design:** Some features of the design requested agricolae be applied specifically to design.ab(factorial) or design.split (split plot) and their possible values are: "rcbd", "crd" and "lsd".

- **seed:** The seed for the random generation and its value is any real value, if the value is zero, it has no reproducible generation, in this case copy of value of the outdesign$parameters.

- **kinds:** the random generation method, by default "Super-Duper".

- **first:** For some designs is not required random the first repetition, especially in the block design, if you want to switch to random, change to TRUE.

- **randomization:** TRUE or FALSE. If false, randomization is not performed

**Output design:**

- **parameters:** the input to generation design, include the seed to generation random, if seed=0, the program generate one value and it is possible reproduce the design.

- **book:** field book

- **statistics:** the information statistics the design for example efficiency index, number of treatments.

- **sketch:** distribution of treatments in the field.

**The enumeration of the plots**

zigzag is a function that allows you to place the numbering of the plots in the direction of serpentine: The zigzag is output generated by one design: blocks, Latin square, graeco, split plot, strip plot, into blocks factorial, balanced incomplete block, cyclic lattice, alpha and augmented blocks.

- **fieldbook:** output zigzag, contain field book.
3.1 Completely randomized design

It generates completely a randomized design with equal or different repetition. "Random" uses the methods of number generation in R. The seed is by set.seed(seed, kinds). They only require the names of the treatments and the number of their repetitions and its parameters are:

```r
> str(design.crd)
function (trt, r, serie = 2, seed = 0, kinds = "Super-Duper",
    randomization = TRUE)
```

```r
> trt <- c("A", "B", "C")
> repeticion <- c(4, 3, 4)
> outdesign <- design.crd(trt, r = repeticion, seed = 777, serie = 0)
> book1 <- outdesign$book
> head(book1)

   plots r trt
   1  1  1  B
   2  2  1  A
   3  3  2  A
   4  4  1  C
   5  5  2  C
   6  6  3  A
```

Excel: write.csv(book1, "book1.csv", row.names = FALSE)

3.2 Randomized complete block design

It generates field book and sketch to Randomized Complete Block Design. "Random" uses the methods of number generation in R. The seed is by set.seed(seed, kinds). They require the names of the treatments and the number of blocks and its parameters are:

```r
> str(design.rcbd)
function (trt, r, serie = 2, seed = 0, kinds = "Super-Duper",
    first = TRUE, continue = FALSE, randomization = TRUE)
```

```r
> trt <- c("A", "B", "C", "D", "E")
> repeticion <- 4
> outdesign <- design.rcbd(trt, r = repeticion, seed = -513, serie = 2)
> # book2 <- outdesign$book
> book2 <- zigzag(outdesign) # zigzag numeration
> print(outdesign$sketch)

[1,] "D" "E" "B" "C" "E" "A" "B"
[2,] "E" "A" "D" "B" "C" "D" "C"
[3,] "E" "D" "B" "A" "C" "E" "D"
[4,] "A" "E" "C" "B" "D" "E" "C"
```

8
3.3 Latin square design

It generates Latin Square Design. "Random" uses the methods of number generation in R. The seed is by set.seed(seed, kinds). They require the names of the treatments and its parameters are:

> str(design.lsd)

function (trt, serie = 2, seed = 0, kinds = "Super-Duper",
    first = TRUE, randomization = TRUE)

> trt <- c("A", "B", "C", "D")
> outdesign <- design.lsd(trt, seed=543, serie=2)
> print(outdesign$sketch)

[1,] "C"  "A"  "B"  "D"
[2,] "D"  "B"  "C"  "A"
[3,] "B"  "D"  "A"  "C"
[4,] "A"  "C"  "D"  "B"

Serpentine enumeration:

> book <- zigzag(outdesign)
> print(matrix(book[,1],byrow = TRUE, ncol = 4))

[1,] 101 102 103 104
[2,] 204 203 202 201
[3,] 301 302 303 304
[4,] 404 403 402 401

3.4 Graeco-Latin designs

A graeco - latin square is a KxK pattern that permits the study of k treatments simultaneously with three different blocking variables, each at k levels. The function is only for squares of the odd numbers and even numbers (4, 8, 10 and 12). They require the names of the treatments of each factor of study and its parameters are:

> str(design.graeco)

function (trt1, trt2, serie = 2, seed = 0, kinds = "Super-Duper",
    randomization = TRUE)
> trt1 <- c("A", "B", "C", "D")
> trt2 <- 1:4
> outdesign <- design.graeco(trt1, trt2, seed=543, serie=2)
> print(outdesign$sketch)

[1,] "A 1" "D 4" "B 3" "C 2"
[2,] "D 3" "A 2" "C 1" "B 4"
[3,] "B 2" "C 3" "A 4" "D 1"
[4,] "C 4" "B 1" "D 2" "A 3"

Serpentine enumeration:

> book <- zigzag(outdesign)
> print(matrix(book[,1], byrow = TRUE, ncol = 4))

[1,] 101 102 103 104
[2,] 204 203 202 201
[3,] 301 302 303 304
[4,] 404 403 402 401

3.5 Youden design

Such designs are referred to as Youden squares since they were introduced by Youden (1937) after Yates (1936) considered the special case of column equal to number treatment minus 1. "Random" uses the methods of number generation in R. The seed is by set.seed(seed, kinds). They require the names of the treatments of each factor of study and its parameters are:

> str(design.youden)

function (trt, r, serie = 2, seed = 0, kinds = "Super-Duper",
first = TRUE, randomization = TRUE)

> varieties<-c("perricholi","yungay","maria bonita","tomasa")
> r<-3
> outdesign <-design.youden(varieties,r,serie=2,seed=23)
> print(outdesign$sketch)

[1,] "maria bonita" "perricholi" "tomasa"
[2,] "yungay" "tomasa" "maria bonita"
[3,] "tomasa" "yungay" "perricholi"
[4,] "perricholi" "maria bonita" "yungay"

> book <- outdesign$book
> print(book) # field book.

plots row col varieties
1 101 1 1 maria bonita
> print(matrix(as.numeric(book[,1]),byrow = TRUE, ncol = r))

[,1] [,2] [,3]  
[1,] 101 102 103  
[2,] 201 202 203  
[3,] 301 302 303  
[4,] 401 402 403  

Serpentine enumeration:

> book <- zigzag(outdesign)
> print(matrix(as.numeric(book[,1]),byrow = TRUE, ncol = r))

[,1] [,2] [,3]  
[1,] 101 102 103  
[2,] 203 202 201  
[3,] 301 302 303  
[4,] 403 402 401  

3.6 Balanced Incomplete Block Designs

Creates Randomized Balanced Incomplete Block Design. "Random" uses the methods of number generation in R. The seed is by set.seed(seed, kinds). They require the names of the treatments and the size of the block and its parameters are:

> str(design.bib)

function (trt, k, r = NULL, serie = 2, seed = 0, kinds = "Super-Duper", maxRep = 20, randomization = TRUE)

> trt <- c("A", "B", "C", "D", "E")
> k <- 4
> outdesign <- design.bib(trt, k, seed=543, serie=2)

Parameters BIB
===============
Lambda : 3
treatmeans : 5  
Block size : 4  
Blocks   : 5  
Replication: 4

Efficiency factor 0.9375

<<< Book >>>

> book5 <- outdesign$book  
> outdesign$statistics

<table>
<thead>
<tr>
<th>lambda</th>
<th>treatmeans</th>
<th>blockSize</th>
<th>blocks</th>
<th>r</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>5</td>
<td>4</td>
<td>5 4</td>
</tr>
</tbody>
</table>

> outdesign$parameters

$design
[1] "bib"

$trt
[1] "A" "B" "C" "D" "E"

$k
[1] 4

$serie
[1] 2

$seed
[1] 543

$kinds
[1] "Super-Duper"

According to the produced information, they are five blocks of size 4, being the matrix:

> outdesign$sketch

[1,] "D" "B" "E" "C"  
[2,] "E" "A" "C" "D"  
[3,] "D" "B" "E" "A"  
[4,] "E" "A" "C" "D"  
[5,] "B" "C" "E" "A"

It can be observed that the treatments have four repetitions. The parameter lambda has three repetitions, which means that a couple of treatments are together on three occasions. For example, B and E are found in the blocks I, II and V.

Serpentine enumeration:
> book <- zigzag(outdesign)
> matrix(book[,1],byrow = TRUE, ncol = 4)

[1,] 101 102 103 104
[2,] 204 203 202 201
[3,] 301 302 303 304
[4,] 404 403 402 401
[5,] 501 502 503 504

3.7 Cyclic designs

They require the names of the treatments, the size of the block and the number of repetitions. This
design is used for 6 to 30 treatments. The repetitions are a multiple of the size of the block; if they
are six treatments and the size is 3, then the repetitions can be 6, 9, 12, etc. and its parameters are:

> str(design.cyclic)

function (trt, k, r, serie = 2, rowcol = FALSE, seed = 0,
        kinds = "Super-Duper", randomization = TRUE)

> trt <- c("A", "B", "C", "D", "E", "F")
> outdesign <- design.cyclic(trt,k=3, r=6, seed=543, serie=2)
cyclic design
Generator block basic:
 1 2 4
 1 3 2

Parameters
-------------
treatmeans : 6
Block size : 3
Replication: 6

> book6 <- outdesign$book
> outdesign$sketch[[1]]

    [,1] [,2] [,3]
[1,] "A" "E" "D"
[2,] "D" "F" "C"
[3,] "A" "D" "B"
[4,] "A" "C" "F"
[5,] "C" "B" "E"
[6,] "B" "E" "F"

> outdesign$sketch[[2]]
12 blocks of 4 treatments each have been generated. **Serpentine enumeration:**

```r
> book <- zigzag(outdesign)
> array(book$plots,c(3,6,2))->X
> t(X[,1])
[,1] [,2] [,3]
[1,] 101 102 103
[2,] 106 105 104
[3,] 107 108 109
[4,] 112 111 110
[5,] 113 114 115
[6,] 118 117 116

> t(X[,2])
[,1] [,2] [,3]
[1,] 201 202 203
[2,] 206 205 204
[3,] 207 208 209
[4,] 212 211 210
[5,] 213 214 215
[6,] 218 217 216
```

### 3.8 Lattice designs

SIMPLE and TRIPLE lattice designs. It randomizes treatments in k x k lattice. They require a number of treatments of a perfect square; for example 9, 16, 25, 36, 49, etc. and its parameters are:

```r
> str(design.lattice)
function (trt, r = 3, serie = 2, seed = 0, kinds = "Super-Duper",
 randomization = TRUE)
```

They can generate a simple lattice (2 rep.) or a triple lattice (3 rep.) generating a triple lattice design for 9 treatments 3x3

```r
> trt<-letters[1:9]
> outdesign <-design.lattice(trt, r = 3, serie = 2, seed = 33,
+ kinds = "Super-Duper")
```
Lattice design, triple 3 x 3

Efficiency factor
\( (E) \), \( 0.7272727 \)

<<< Book >>>

> book7 <- outdesign$book
> outdesign$parameters

$design
[1] "lattice"

$type
[1] "triple"

$strt
[1] "a" "b" "c" "d" "e" "f" "g" "h" "i"

$r
[1] 3

$serie
[1] 2

$seed
[1] 33

$kinds
[1] "Super-Duper"

> outdesign$sketch

$rep1
   [,1] [,2] [,3]
[1,]  "i"  "d"  "a"
[2,]  "b"  "c"  "e"
[3,]  "h"  "f"  "g"

$rep2
   [,1] [,2] [,3]
[1,]  "c"  "f"  "d"
[2,]  "b"  "h"  "i"
[3,]  "e"  "g"  "a"

$rep3
   [,1] [,2] [,3]
[1,]  "e"  "b"  "d"
[2,]  "b"  "f"  "a"
[3,]  "c"  "g"  "i"
> head(book7)

    plots r block trt
 1 101 1 1 i
 2 102 1 1 d
 3 103 1 1 a
 4 104 1 2 b
 5 105 1 2 c
 6 106 1 2 e

Serpentine enumeration:

> book <- zigzag(outdesign)
> array(book$plots,c(3,3,3)) -> X
> t(X[,1])

     [,1] [,2] [,3]
[1,] 101 102 103
[2,] 106 105 104
[3,] 107 108 109

> t(X[,2])

     [,1] [,2] [,3]
[1,] 201 202 203
[2,] 206 205 204
[3,] 207 208 209

> t(X[,3])

     [,1] [,2] [,3]
[1,] 301 302 303
[2,] 306 305 304
[3,] 307 308 309

3.9 Alpha designs

Generates an alpha designs starting from the alpha design fixing under the series formulated by Patterson and Williams. These designs are generated by the alpha arrangements. They are similar to the lattice designs, but the tables are rectangular $s$ by $k$ (with $s$ blocks and $k<s$ columns. The number of treatments should be equal to $s*k$ and all the experimental units $r*s*k$ (r replications) and its parameters are:

> str(design.alpha)

function (trt, k, r, serie = 2, seed = 0, kinds = "Super-Duper",
          randomization = TRUE)

> trt <- letters[1:15]
> outdesign <- design.alpha(trt,k=3,r=2,seed=543)
Parameters Alpha Design
=======================
Treatments: 15
Block size: 3
Blocks: 5
Replication: 2

Efficiency factor
(E) 0.6363636

<<< Book >>>

> book8 <- outdesign$book
> outdesign$statistics

treatments blocks Efficiency
values 15 5 0.6363636

> outdesign$sketch

$rep1
    [,1] [,2] [,3]
   [1,] "l" "m" "e"
   [2,] "g" "c" "i"
   [3,] "o" "k" "d"
   [4,] "h" "f" "j"
   [5,] "a" "n" "b"

$rep2
    [,1] [,2] [,3]
   [1,] "o" "a" "m"
   [2,] "1" "k" "g"
   [3,] "d" "n" "h"
   [4,] "j" "b" "c"
   [5,] "f" "i" "e"

> # codification of the plots
> A<-array(book8[,1], c(3,5,2))
> t(A[,1])

     [,1] [,2] [,3]
    [1,] 101 102 103
    [2,] 104 105 106
    [3,] 107 108 109
    [4,] 110 111 112
    [5,] 113 114 115

> t(A[,2])
Serpentine enumeration:

```r
> book <- zigzag(outdesign)
> A <- array(book[,1], c(3,5,2))
> t(A[,,1])

[,1] [,2] [,3]
[1,] 101 102 103
[2,] 106 105 104
[3,] 107 108 109
[4,] 112 111 110
[5,] 113 114 115

> t(A[,,2])

[,1] [,2] [,3]
[1,] 201 202 203
[2,] 206 205 204
[3,] 207 208 209
[4,] 212 211 210
[5,] 213 214 215
```

3.10 Augmented block designs

These are designs for two types of treatments: the control treatments (common) and the increased treatments. The common treatments are applied in complete randomized blocks, and the increased treatments, at random. Each treatment should be applied in any block once only. It is understood that the common treatments are of a greater interest; the standard error of the difference is much smaller than when between two increased ones in different blocks. The function `design.dau()` achieves this purpose and its parameters are:

```r
> str(design.dau)
function (trt1, trt2, r, serie = 2, seed = 0, kinds = "Super-Duper", 
   name = "trt", randomization = TRUE)
```

```r
> rm(list=ls())
> trt1 <- c("A", "B", "C", "D")
> trt2 <- c("t", "u", "v", "w", "x", "y", "z")
> outdesign <- design.dau(trt1, trt2, r=5, seed=543, serie=2)
> book9 <- outdesign$book
> with(book9, by(trt, block, as.character))
```
For augmented completely randomized design, use the function `design.crd()`.

### 3.11 Split plot designs

These designs have two factors, one is applied in plots and is defined as `trt1` in a randomized complete block design; and a second factor as `trt2`, which is applied in the subplots of each plot applied at
random. The function `design.split()` permits to find the experimental plan for this design and its parameters are:

```r
> str(design.split)
function (trt1, trt2, r = NULL, design = c("rcbd", "crd", "lsd"), serie = 2, seed = 0, kinds = "Super-Duper", first = TRUE, randomization = TRUE)
```

Aplication

```r
> trt1<-c("A","B","C","D")
> trt2<-c("a","b","c")
> outdesign <-design.split(trt1,trt2,r=3,serie=2,seed=543)
> book10 <- outdesign$book
> head(book10)
```

```
plots splots block trt1 trt2
1 101 1 1 A c
2 101 2 1 A a
3 101 3 1 A b
4 102 1 1 D b
5 102 2 1 D c
6 102 3 1 D a
```

```r
> p<-book10$trt1[seq(1,36,3)]
> q<-NULL
> for(i in 1:12)
+ q <- c(q,paste(book10$trt2[3*(i-1)+1],book10$trt2[3*(i-1)+2], book10$trt2[3*(i-1)+3]))
```

In plots:

```r
> print(t(matrix(p,c(4,3))))
```

```
[1,] "A" "D" "B" "C"
[2,] "A" "C" "B" "D"
[3,] "A" "C" "B" "D"
```

In sub plots (split plot)

```r
> print(t(matrix(q,c(4,3))))
```

```
[1,] "c a b" "b c a" "b c a" "a b c"
[2,] "b a c" "a b c" "a c b" "b c a"
[3,] "a b c" "a c b" "a c b" "c a b"
```
Serpentine enumeration:

```r
> book <- zigzag(outdesign)
> head(book, 5)

plots splots block trt1 trt2
1 101 1 1 A c
2 101 2 1 A a
3 101 3 1 A b
4 102 1 1 D b
5 102 2 1 D c
```

### 3.12 Strip-plot designs

These designs are used when there are two types of treatments (factors) and are applied separately in large plots, called bands, in a vertical and horizontal direction of the block, obtaining the divided blocks. Each block constitutes a repetition and its parameters are:

```r
> str(design.strip)

function (trt1, trt2, r, serie = 2, seed = 0, kinds = "Super-Duper",
         randomization = TRUE)
```

Application

```r
> trt1 <- c("A", "B", "C", "D")
> trt2 <- c("a", "b", "c")
> outdesign <- design.strip(trt1, trt2, r = 3, serie = 2, seed = 543)
> book11 <- outdesign$book
> head(book11)

plots block trt1 trt2
1 101 1 A a
2 102 1 A b
3 103 1 A c
4 104 1 D a
5 105 1 D b
6 106 1 D c
```

```r
t3 <- paste(book11$trt1, book11$trt2)
B1 <- t(matrix(t3[1:12], c(4, 3)))
B2 <- t(matrix(t3[13:24], c(3, 4)))
B3 <- t(matrix(t3[25:36], c(3, 4)))
print(B1)

[1,] "A a" "A b" "A c" "D a"
[2,] "D b" "D c" "B a" "B b"
[3,] "B c" "C a" "C b" "C c"
```
> print(B2)

    [,1] [,2] [,3]
[1,] "D a" "D b" "D c"
[2,] "A a" "A b" "A c"
[3,] "B a" "B b" "B c"
[4,] "C a" "C b" "C c"

> print(B3)

    [,1] [,2] [,3]
[1,] "B b" "B c" "B a"
[2,] "D b" "D c" "D a"
[3,] "C b" "C c" "C a"
[4,] "A b" "A c" "A a"

Serpentine enumeration:

> book <- zigzag(outdesign)
> head(book)

       plots block trt1 trt2
1      101     1   A   a
2      102     1   A   b
3      103     1   A   c
4      106     1   D   a
5      105     1   D   b
6      104     1   D   c

> array(book$plots,c(3,4,3))->X
> t(X[,1])

    [,1]  [,2]  [,3]
[1,] 101  102  103
[2,] 106  105  104
[3,] 107  108  109
[4,] 112  111  110

> t(X[,2])

    [,1]  [,2]  [,3]
[1,] 201  202  203
[2,] 206  205  204
[3,] 207  208  209
[4,] 212  211  210

> t(X[,3])

    [,1]  [,2]  [,3]
[1,] 301  302  303
[2,] 306  305  304
[3,] 307  308  309
[4,] 312  311  310

22
3.13 Factorial

The full factorial of n factors applied to an experimental design (CRD, RCBD and LSD) is common and this procedure in *agricolae* applies the factorial to one of these three designs and its parameters are:

```r
> str(design.ab)

function (trt, r = NULL, serie = 2, design = c("rcbd", "crd", "lsd"), seed = 0, kinds = "Super-Duper", first = TRUE, randomization = TRUE)
```

To generate the factorial, you need to create a vector of levels of each factor, the method automatically generates up to 25 factors and "r" repetitions.

```r
> trt <- c(4,2,3) # three factors with 4, 2 and 3 levels.
```

to crd and rcbd designs, it is necessary to value "r" as the number of repetitions, this can be a vector if unequal to equal or constant repetition (recommended).

```r
> trt<-c(3,2) # factorial 3x2
> outdesign <- design.ab(trt, r=3, serie=2)
> book12 <- outdesign$book
> head(book12) # print of the field book

plots block A B
1 101 1 3 1
2 102 1 2 2
3 103 1 1 1
4 104 1 1 2
5 105 1 3 2
6 106 1 2 1

Serpentine enumeration:

```r
> book <- zigzag(outdesign)
> head(book)

plots block A B
1 101 1 3 1
2 102 1 2 2
3 103 1 1 1
4 104 1 1 2
5 105 1 3 2
6 106 1 2 1
```

factorial 2 x 2 x 2 with 5 replications in completely randomized design.

```r
> trt<-c(2,2,2)
> crd<-design.ab(trt, r=5, serie=2,design="crd")
> names(crd)
```
[1] "parameters" "book"

> crd$parameters

$design
[1] "factorial"

$strt
[1] "1 1 1" "1 1 2" "1 2 1" "1 2 2" "2 1 1" "2 1 2" "2 2 1"
[8] "2 2 2"

$r
[1] 5 5 5 5 5 5 5 5

$serie
[1] 2

$seed
[1] 970386955

$kinds
[1] "Super-Duper"

[[7]]
[1] TRUE

$applied
[1] "crd"

> head(crd$book)

   plots  r  A  B  C
1    101 1 2 2 1
2    102 1 1 1 2
3    103 1 2 1 2
4    104 1 2 1 1
5    105 1 2 2 2
6    106 2 2 1 2

4  Multiple comparisons

For the analyses, the following functions of agricolae are used: LSD.test, HSD.test, duncan.test, scheffe.test, waller.test, SNK.test, REGW.test, Steel and Torry and Dickey (1997); Hsu (1996) and durbin.test, kruskal, friedman, waerden.test and Median.test, Conover (1999).

For every statistical analysis, the data should be organized in columns. For the demonstration, the agricolae database will be used.

The sweetpotato data correspond to a completely random experiment in field with plots of 50 sweet potato plants, subjected to the virus effect and to a control without virus (See the reference manual of the package).
> data(sweetpotato)
> model<-aov(yield~virus, data=sweetpotato)
> cv.model(model)

[1] 17.1666

> with(sweetpotato,mean(yield))

[1] 27.625

Model parameters: Degrees of freedom and variance of the error:

> df<-df.residual(model)
> MSerror<-deviance(model)/df

4.1 The Least Significant Difference (LSD)

It includes the multiple comparison through the method of the minimum significant difference (Least Significant Difference), Steel and Torry and Dickey (1997).

> # comparison <- LSD.test(yield,virus,df,MSerror)
> LSD.test(model, "virus",console=TRUE)

Study: model ~ "virus"

LSD t Test for yield

Mean Square Error: 22.48917

virus, means and individual ( 95 %) CI

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th>LCL</th>
<th>UCL</th>
<th>Min</th>
<th>Max</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>cc</td>
<td>24.40000</td>
<td>3.609709</td>
<td>3</td>
<td>18.086268</td>
<td>30.71373</td>
<td>21.7</td>
<td>28.5</td>
</tr>
<tr>
<td>fc</td>
<td>12.86667</td>
<td>2.159475</td>
<td>3</td>
<td>6.552935</td>
<td>19.18040</td>
<td>10.6</td>
<td>14.9</td>
</tr>
<tr>
<td>ff</td>
<td>36.33333</td>
<td>7.333030</td>
<td>3</td>
<td>30.019601</td>
<td>42.64707</td>
<td>28.0</td>
<td>41.8</td>
</tr>
<tr>
<td>oo</td>
<td>36.90000</td>
<td>4.300000</td>
<td>3</td>
<td>30.586268</td>
<td>43.21373</td>
<td>32.1</td>
<td>40.4</td>
</tr>
</tbody>
</table>

Alpha: 0.05 ; DF Error: 8
Critical Value of t: 2.306004

least Significant Difference: 8.928965

Treatments with the same letter are not significantly different.

yield groups
oo 36.90000    a
ff 36.33333    a
cc 24.40000    b
fc 12.86667    c
In the function `LSD.test`, the multiple comparison was carried out. In order to obtain the probabilities of the comparisons, it should be indicated that groups are not required; thus:

```r
> # comparison <- LSD.test(yield, virus, df, MSerror, group=FALSE)
> outLSD <- LSD.test(model, "virus", group=FALSE, console=TRUE)
```

Study: `model ~ "virus"

LSD t Test for `yield`

Mean Square Error: 22.48917

virus, means and individual (95%) CI

| yield std r LCL  UCL  Min  Max |
|---|---|---|---|---|---|
| cc 24.40000 3.609709 3 18.086268 30.71373 21.7 28.5 |
| fc 12.86667 2.159475 3 6.552935 19.18040 10.6 14.9 |
| ff 36.33333 7.333030 3 30.019601 42.64707 28.0 41.8 |
| oo 36.90000 4.300000 3 30.586268 43.21373 32.1 40.4 |

Alpha: 0.05 ; DF Error: 8
Critical Value of t: 2.306004

Comparison between treatments means

| difference pvalue signif. LCL  UCL |
|---|---|---|---|---|
| cc - fc 11.5333333 0.0176 * 2.604368 20.462299 |
| cc - ff -11.9333333 0.0151 * -20.862299 -3.004368 |
| cc - oo -12.5000000 0.0121 * -21.428965 -3.571035 |
| fc - ff -23.4666667 0.0003 *** -32.395632 -14.537701 |
| fc - oo -24.0333333 0.0003 *** -32.962299 -15.104368 |
| ff - oo -0.5666667 0.8873 -9.495632 8.362299 |

Signif. codes:
0 *** 0.001 ** 0.01 * 0.05 . 0.1 ’ ’ 1

```r
> options(digits=2)
> print(outLSD)
```

$statistics

| MSerror Df Mean CV t.value LSD |
|---|---|---|---|---|
| 22 8 28 17 2.3 8.9 |

$params

| test p.adjusted name.t ntr alpha |
|---|---|---|---|
| Fisher-LSD none virus 4 0.05 |

$means

| yield std r LCL  UCL  Min  Max Q25  Q50  Q75 |
|---|---|---|---|---|---|---|---|
| cc 24 3.6 3 18.1 31 22 28 22 23 26 |

26
### $\text{comparison}$

<table>
<thead>
<tr>
<th></th>
<th>difference</th>
<th>pvalue</th>
<th>signif.</th>
<th>LCL</th>
<th>UCL</th>
</tr>
</thead>
<tbody>
<tr>
<td>cc - fc</td>
<td>11.53</td>
<td>0.0176</td>
<td>*</td>
<td>2.6</td>
<td>20.5</td>
</tr>
<tr>
<td>cc - ff</td>
<td>-11.93</td>
<td>0.0151</td>
<td>*</td>
<td>-20.9</td>
<td>-3.0</td>
</tr>
<tr>
<td>cc - oo</td>
<td>-12.50</td>
<td>0.0121</td>
<td>*</td>
<td>-21.4</td>
<td>-3.6</td>
</tr>
<tr>
<td>fc - ff</td>
<td>-23.47</td>
<td>0.0003</td>
<td>***</td>
<td>-32.4</td>
<td>-14.5</td>
</tr>
<tr>
<td>fc - oo</td>
<td>-24.03</td>
<td>0.0003</td>
<td>***</td>
<td>-33.0</td>
<td>-15.1</td>
</tr>
<tr>
<td>ff - oo</td>
<td>-0.57</td>
<td>0.8873</td>
<td>-</td>
<td>-9.5</td>
<td>8.4</td>
</tr>
</tbody>
</table>

### $\text{groups}$

NULL

attr("class")
[1] "group"

#### 4.2 holm, homeml, hochberg, bonferroni, BH, BY, fdr

With the function *LSD.test* we can make adjustments to the probabilities found, as for example the adjustment by Bonferroni, holm and other options see Adjust P-values for Multiple Comparisons, function *p.adjust(stats)*, R Core Team (2017).

```r
> LSD.test(model, "virus", group=FALSE, p.adj= "bon",console=TRUE)
```

Study: model ~ "virus"

LSD t Test for yield
P value adjustment method: bonferroni

Mean Square Error: 22

virus, means and individual (95 %) CI

<table>
<thead>
<tr>
<th>yield</th>
<th>std</th>
<th>r</th>
<th>LCL</th>
<th>UCL</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>cc</td>
<td>24</td>
<td>3</td>
<td>18.1</td>
<td>31</td>
<td>22</td>
<td>28</td>
</tr>
<tr>
<td>fc</td>
<td>13</td>
<td>2.2</td>
<td>6.6</td>
<td>19</td>
<td>11</td>
<td>15</td>
</tr>
<tr>
<td>ff</td>
<td>36</td>
<td>7.3</td>
<td>30.0</td>
<td>43</td>
<td>28</td>
<td>42</td>
</tr>
<tr>
<td>oo</td>
<td>37</td>
<td>4.3</td>
<td>30.6</td>
<td>43</td>
<td>32</td>
<td>40</td>
</tr>
</tbody>
</table>

Alpha: 0.05 ; DF Error: 8
Critical Value of t: 3.5

Comparison between treatments means

<table>
<thead>
<tr>
<th>difference</th>
<th>pvalue</th>
<th>signif.</th>
<th>LCL</th>
<th>UCL</th>
</tr>
</thead>
<tbody>
<tr>
<td>cc - fc</td>
<td>11.53</td>
<td>0.1058</td>
<td>-1.9</td>
<td>25.0</td>
</tr>
<tr>
<td>cc - ff</td>
<td>-11.93</td>
<td>0.0904</td>
<td>-25.4</td>
<td>1.54</td>
</tr>
</tbody>
</table>
> out<-LSD.test(model, "virus", group=TRUE, p.adj= "holm")
> print(out$group)

yield groups
oo 37 a
ff 36 a
cc 24 b
fc 13 c

> out<-LSD.test(model, "virus", group=FALSE, p.adj= "holm")
> print(out$comparison)

difference pvalue signif.
cc - fc 11.53 0.0484 *
cf - ff -11.93 0.0484 *
cf - oo -12.50 0.0484 *
cf - oo -24.03 0.0015 **
ff - oo -0.57 1.0000 -14.0 12.90

Other comparison tests can be applied, such as duncan, Student-Newman-Keuls, tukey and waller-duncan.

For Duncan, use the function duncan.test; for Student-Newman-Keuls, the function SNK.test; for Tukey, the function HSD.test; for Scheffe, the function scheffe.test and for Waller-Duncan, the function waller.test. The arguments are the same. Waller also requires the value of F-calculated of the ANOVA treatments. If the model is used as a parameter, this is no longer necessary.

4.3 Duncan’s New Multiple-Range Test

It corresponds to the Duncan’s Test, Steel and Torry and Dickey (1997).

> duncan.test(model, "virus",console=TRUE)

Study: model ~ "virus"

Duncan’s new multiple range test
for yield

Mean Square Error: 22

virus, means

yield std r Min Max
cc 24 3.6 3 22 28
**4.4 Student-Newman-Keuls**

Student, Newman and Keuls helped to improve the Newman-Keuls test of 1939, which was known as the Keuls method, *Steel and Torry and Dickey* (1997).

```r
> # SNK.test(model, "virus", alpha=0.05,console=TRUE)
> SNK.test(model, "virus", group=FALSE,console=TRUE)
```

Study: `model ~ "virus"`

Student Newman Keuls Test
for `yield`

Mean Square Error: 22

<table>
<thead>
<tr>
<th>virus, means</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>yield std r Min Max</code></td>
</tr>
<tr>
<td>cc 24 3.6 3 22 28</td>
</tr>
<tr>
<td>fc 13 2.2 3 11 15</td>
</tr>
<tr>
<td>ff 36 7.3 3 28 42</td>
</tr>
<tr>
<td>oo 37 4.3 3 32 40</td>
</tr>
</tbody>
</table>

Comparison between treatments means

<table>
<thead>
<tr>
<th>difference</th>
<th>pvalue</th>
<th>signif.</th>
<th>LCL</th>
<th>UCL</th>
</tr>
</thead>
<tbody>
<tr>
<td>cc - fc</td>
<td>11.53</td>
<td>0.0176</td>
<td>*</td>
<td>2.6</td>
</tr>
<tr>
<td>cc - ff</td>
<td>-11.93</td>
<td>0.0151</td>
<td>*</td>
<td>-20.9</td>
</tr>
<tr>
<td>cc - oo</td>
<td>-12.50</td>
<td>0.0291</td>
<td>*</td>
<td>-23.6</td>
</tr>
<tr>
<td>fc - ff</td>
<td>-23.47</td>
<td>0.0008</td>
<td>***</td>
<td>-34.5</td>
</tr>
<tr>
<td>fc - oo</td>
<td>-24.03</td>
<td>0.0012</td>
<td>**</td>
<td>-36.4</td>
</tr>
<tr>
<td>ff - oo</td>
<td>-0.57</td>
<td>0.8873</td>
<td></td>
<td>-9.5</td>
</tr>
</tbody>
</table>
4.5 Ryan, Einot and Gabriel and Welsch

Multiple range tests for all pairwise comparisons, to obtain a confident inequalities multiple range tests, Hsu (1996).

\[
\text{\# REGW.test(model, "virus", alpha=0.05,console=TRUE)}
\]
\[
\text{\# REGW.test(model, "virus", group=FALSE,console=TRUE)}
\]

Study: model ~ "virus"

Ryan, Einot and Gabriel and Welsch multiple range test for yield

Mean Square Error: 22

virus, means

\[
\begin{array}{cccc}
\text{yield} & \text{std} & \text{r} & \text{Min} & \text{Max} \\
cc & 24 & 3.6 & 3 & 22 & 28 \\
fcc & 13 & 2.2 & 3 & 11 & 15 \\
ff & 36 & 7.3 & 3 & 28 & 42 \\
oo & 37 & 4.3 & 3 & 32 & 40 \\
\end{array}
\]

Comparison between treatments means

\[
\begin{array}{cccccc}
\text{difference} & \text{pvalue} & \text{signif.} & \text{LCL} & \text{UCL} \\
cc - fc & 11.53 & 0.0350 & * & 0.91 & 22.16 \\
cc - ff & -11.93 & 0.0360 & * & -23.00 & -0.87 \\
cc - oo & -12.50 & 0.0482 & * & -24.90 & -0.10 \\
fcc - ff & -23.47 & 0.0006 & *** & -34.09 & -12.84 \\
fcc - oo & -24.03 & 0.0007 & *** & -35.10 & -12.97 \\
ff - oo & -0.57 & 0.9873 & & -11.19 & 10.06 \\
\end{array}
\]

4.6 Tukey’s W Procedure (HSD)

This studentized range test, created by Tukey in 1953, is known as the Tukey’s HSD (Honestly Significant Differences), Steel and Torry and Dickey (1997).

\[
\text{\# outHSD<- HSD.test(model, "virus",console=TRUE)}
\]

Study: model ~ "virus"

HSD Test for yield

Mean Square Error: 22

virus, means

\[
\begin{array}{cccc}
\text{yield} & \text{std} & \text{r} & \text{Min} & \text{Max} \\
cc & 24 & 3.6 & 3 & 22 & 28 \\
\end{array}
\]
yield groups
oo  37  a
ff  36  ab
cc  24  bc
fc  13  c

> outHSD

$statistics

MSerror Df Mean CV MSD
 22   8  28  17  12

$parameters

test name.t ntr StudentizedRange alpha
Tukey  virus  4  4.5  0.05

$means

yield std r Min Max Q25 Q50 Q75
cc  24  3.6 3  22  28  22  23  26
fc  13  2.2 3  11  15  12  13  14
ff  36  7.3 3  28  42  34  39  40
oo  37  4.3 3  32  40  35  38  39

$comparison

NULL

$groups

yield groups
oo  37  a
ff  36  ab
cc  24  bc
fc  13  c

attr("class")
[1] "group"

4.7 Waller-Duncan’s Bayesian K-Ratio T-Test

Duncan continued the multiple comparison procedures, introducing the criterion of minimizing both experimental errors; for this, he used the Bayes’ theorem, obtaining one new test called Waller-Duncan,
Waller and Duncan (1969); Steel and Torry and Dickey (1997).

> # variance analysis:
> anova(model)

Analysis of Variance Table

Response: yield

<table>
<thead>
<tr>
<th></th>
<th>Df</th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>F value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>virus</td>
<td>3</td>
<td>1170</td>
<td>390</td>
<td>17.3</td>
<td>0.00073***</td>
</tr>
<tr>
<td>Residuals</td>
<td>8</td>
<td>180</td>
<td>22</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

---

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> with(sweetpotato, waller.test(yield, virus, df, MSError, Fc= 17.345, group=FALSE, console=TRUE))

Study: yield ~ virus

Waller-Duncan K-ratio t Test for yield

This test minimizes the Bayes risk under additive loss and certain other assumptions

......

K ratio 100.0
Error Degrees of Freedom 8.0
Error Mean Square 22.5
F value 17.3
Critical Value of Waller 2.2

virus, means

<table>
<thead>
<tr>
<th>yield std r Min Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>cc 24 3.6 3 22 28</td>
</tr>
<tr>
<td>fc 13 2.2 3 11 15</td>
</tr>
<tr>
<td>ff 36 7.3 3 28 42</td>
</tr>
<tr>
<td>oo 37 4.3 3 32 40</td>
</tr>
</tbody>
</table>

Comparison between treatments means

<table>
<thead>
<tr>
<th>Difference significant</th>
</tr>
</thead>
<tbody>
<tr>
<td>cc - fc 11.53 TRUE</td>
</tr>
<tr>
<td>cc - ff -11.93 TRUE</td>
</tr>
<tr>
<td>cc - oo -12.50 TRUE</td>
</tr>
<tr>
<td>fc - ff -23.47 TRUE</td>
</tr>
<tr>
<td>fc - oo -24.03 TRUE</td>
</tr>
<tr>
<td>ff - oo -0.57 FALSE</td>
</tr>
</tbody>
</table>

In another case with only invoking the model object:

> outWaller <- waller.test(model, "virus", group=FALSE, console=FALSE)

32
The found object `outWaller` has information to make other procedures.

```r
> names(outWaller)
[1] "statistics" "parameters" "means" "comparison"
[5] "groups"
```

```r
> print(outWaller$comparison)

<table>
<thead>
<tr>
<th>Difference</th>
<th>Value</th>
<th>Significant</th>
</tr>
</thead>
<tbody>
<tr>
<td>cc - fc</td>
<td>11.53</td>
<td>TRUE</td>
</tr>
<tr>
<td>cc - ff</td>
<td>-11.93</td>
<td>TRUE</td>
</tr>
<tr>
<td>cc - oo</td>
<td>-12.50</td>
<td>TRUE</td>
</tr>
<tr>
<td>fc - ff</td>
<td>-23.47</td>
<td>TRUE</td>
</tr>
<tr>
<td>fc - oo</td>
<td>-24.03</td>
<td>TRUE</td>
</tr>
<tr>
<td>ff - oo</td>
<td>-0.57</td>
<td>FALSE</td>
</tr>
</tbody>
</table>
```

It is indicated that the virus effect "ff" is not significant to the control "oo".

```r
> outWaller$statistics

<table>
<thead>
<tr>
<th>Mean</th>
<th>Df</th>
<th>CV</th>
<th>MSerror</th>
<th>F.Value</th>
<th>Waller</th>
<th>CriticalDifference</th>
</tr>
</thead>
<tbody>
<tr>
<td>28</td>
<td>8</td>
<td>17</td>
<td>22</td>
<td>17</td>
<td>2.2</td>
<td>8.7</td>
</tr>
</tbody>
</table>
```

4.8 Scheffe’s Test

This method, created by Scheffe in 1959, is very general for all the possible contrasts and their confidence intervals. The confidence intervals for the averages are very broad, resulting in a very conservative test for the comparison between treatment averages, Steel and Torry and Dickey (1997).

```r
> # analysis of variance:
> scheffe.test(model,"virus", group=TRUE,console=TRUE,
+ main="Yield of sweetpotato dealt with different virus")

Study: Yield of sweetpotato
Dealt with different virus

Scheffe Test for yield

Mean Square Error : 22

virus, means

<table>
<thead>
<tr>
<th>yield</th>
<th>std</th>
<th>r Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>cc</td>
<td>24</td>
<td>3.6</td>
<td>3</td>
</tr>
<tr>
<td>fc</td>
<td>13</td>
<td>2.2</td>
<td>3</td>
</tr>
<tr>
<td>ff</td>
<td>36</td>
<td>7.3</td>
<td>3</td>
</tr>
<tr>
<td>oo</td>
<td>37</td>
<td>4.3</td>
<td>3</td>
</tr>
</tbody>
</table>
Alpha: 0.05 ; DF Error: 8
Critical Value of F: 4.1

Minimum Significant Difference: 14

Means with the same letter are not significantly different.

| yield groups | oo 37  a | ff 36  a | cc 24  ab | fc 13  b |

The minimum significant value is very high. If you require the approximate probabilities of comparison, you can use the option `group=FALSE`.

```r
> outScheffe <- scheffe.test(model,"virus", group=FALSE, console=TRUE)
```

Study: `model ~ "virus"`

Scheffe Test for yield

Mean Square Error : 22

virus, means

<table>
<thead>
<tr>
<th>yield std r Min Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>cc      24 3.6 3 22 28</td>
</tr>
<tr>
<td>fc      13 2.2 3 11 15</td>
</tr>
<tr>
<td>ff      36 7.3 3 28 42</td>
</tr>
<tr>
<td>oo      37 4.3 3 32 40</td>
</tr>
</tbody>
</table>

Alpha: 0.05 ; DF Error: 8
Critical Value of F: 4.1

Comparison between treatments means

<table>
<thead>
<tr>
<th>Difference pvalue sig LCL UCL</th>
</tr>
</thead>
<tbody>
<tr>
<td>cc - fc 11.53 0.0978 . -1 24.067</td>
</tr>
<tr>
<td>cc - ff -11.93 0.0855 . -24 0.600</td>
</tr>
<tr>
<td>cc - oo -12.50 0.0706 . -25 0.034</td>
</tr>
<tr>
<td>fc - ff -23.47 0.0023 ** -36 -10.933</td>
</tr>
<tr>
<td>fc - oo -24.03 0.0020 ** -37 -11.500</td>
</tr>
<tr>
<td>ff - oo -0.57 0.9991 -13 11.967</td>
</tr>
</tbody>
</table>

4.9 Multiple comparison in factorial treatments

In a factorial combined effects of the treatments. Comparative tests: **LSD, HSD, Waller-Duncan, Duncan, Scheffé, SNK** can be applied.
> # modelABC <-aov (y ~ A * B * C, data)
> # compare <-LSD.test (modelABC, c ("A", "B", "C"), console=TRUE)

The comparison is the combination of A:B:C.
Data RCBD design with a factorial clone x nitrogen. The response variable yield.

> yield <-scan (text =
+ "6 7 9 13 16 20 8 8 9
+ 7 8 8 12 17 18 10 9 12
+ 9 9 9 14 18 21 11 12 11
+ 8 10 10 15 16 22 9 9 9 "
+ )
> block <-gl (4, 9)
> clone <-rep (gl (3, 3, labels = c ("c1", "c2", "c3")), 4)
> nitrogen <-rep (gl (3, 1, labels = c ("n1", "n2", "n3")), 12)
> A <-data.frame (block, clone, nitrogen, yield)
> head (A)

<table>
<thead>
<tr>
<th>block</th>
<th>clone</th>
<th>nitrogen</th>
<th>yield</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>c1</td>
<td>n1</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>c1</td>
<td>n2</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>c1</td>
<td>n3</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>c2</td>
<td>n1</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>c2</td>
<td>n2</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>c2</td>
<td>n3</td>
</tr>
</tbody>
</table>

> outAOV <-aov (yield ~ block + clone * nitrogen, data = A)
> anova (outAOV)

Analysis of Variance Table

Response: yield

<table>
<thead>
<tr>
<th></th>
<th>Df</th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>F value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>block</td>
<td>3</td>
<td>21</td>
<td>6.9</td>
<td>5.82</td>
<td>0.00387**</td>
</tr>
<tr>
<td>clone</td>
<td>2</td>
<td>498</td>
<td>248.9</td>
<td>209.57</td>
<td>6.4e-16 ***</td>
</tr>
<tr>
<td>nitrogen</td>
<td>2</td>
<td>54</td>
<td>27.0</td>
<td>22.76</td>
<td>2.9e-06 ***</td>
</tr>
<tr>
<td>clone:nitrogen</td>
<td>4</td>
<td>43</td>
<td>10.8</td>
<td>9.11</td>
<td>0.00013 ***</td>
</tr>
<tr>
<td>Residuals</td>
<td>24</td>
<td>29</td>
<td>1.2</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

---

Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> outFactorial <-LSD.test (outAOV, c("clone", "nitrogen"),
+ main = "Yield ~ block + nitrogen + clone + clone:nitrogen", console=TRUE)

Study: Yield ~ block + nitrogen + clone + clone:nitrogen

LSD t Test for yield
Mean Square Error: 1.2

clone:nitrogen, means and individual (95%) CI

<table>
<thead>
<tr>
<th>yield</th>
<th>std r</th>
<th>LCL</th>
<th>UCL</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>c1:n1</td>
<td>7.5</td>
<td>1.29</td>
<td>4.6</td>
<td>8.6</td>
<td>6</td>
</tr>
<tr>
<td>c1:n2</td>
<td>8.5</td>
<td>1.29</td>
<td>7.4</td>
<td>9.6</td>
<td>7</td>
</tr>
<tr>
<td>c1:n3</td>
<td>9.0</td>
<td>0.82</td>
<td>7.9</td>
<td>10.1</td>
<td>8</td>
</tr>
<tr>
<td>c2:n1</td>
<td>13.5</td>
<td>1.29</td>
<td>12.4</td>
<td>14.6</td>
<td>12</td>
</tr>
<tr>
<td>c2:n2</td>
<td>16.8</td>
<td>0.96</td>
<td>15.6</td>
<td>17.9</td>
<td>16</td>
</tr>
<tr>
<td>c2:n3</td>
<td>20.2</td>
<td>1.71</td>
<td>19.1</td>
<td>21.4</td>
<td>18</td>
</tr>
<tr>
<td>c3:n1</td>
<td>9.5</td>
<td>1.29</td>
<td>8.4</td>
<td>10.6</td>
<td>8</td>
</tr>
<tr>
<td>c3:n2</td>
<td>9.5</td>
<td>1.73</td>
<td>8.4</td>
<td>10.6</td>
<td>8</td>
</tr>
<tr>
<td>c3:n3</td>
<td>10.2</td>
<td>1.50</td>
<td>9.1</td>
<td>11.4</td>
<td>9</td>
</tr>
</tbody>
</table>

Alpha: 0.05; DF Error: 24
Critical Value of t: 2.1

least Significant Difference: 1.6

Treatments with the same letter are not significantly different.

yield groups

<table>
<thead>
<tr>
<th>yield</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>c2:n3</td>
<td>20.2a</td>
</tr>
<tr>
<td>c2:n2</td>
<td>16.8b</td>
</tr>
<tr>
<td>c2:n1</td>
<td>13.5c</td>
</tr>
<tr>
<td>c3:n3</td>
<td>10.2d</td>
</tr>
<tr>
<td>c3:n1</td>
<td>9.5de</td>
</tr>
<tr>
<td>c3:n2</td>
<td>9.5de</td>
</tr>
<tr>
<td>c1:n3</td>
<td>9.0def</td>
</tr>
<tr>
<td>c1:n2</td>
<td>8.5ef</td>
</tr>
<tr>
<td>c1:n1</td>
<td>7.5f</td>
</tr>
</tbody>
</table>

> par(mar=c(3,3,2,0))
> pic1<-bar.err(outFactorial$means,variation="range",ylim=c(5,25), bar=FALSE,col=0,las=1)
> points(pic1$index,pic1$means,pch=18,cex=1.5,col="blue")
> axis(1,pic1$index,labels=FALSE)
> title(main="average and range\nclon:nitrogen")

4.10 Analysis of Balanced Incomplete Blocks

This analysis can come from balanced or partially balanced designs. The function BIB.test is for balanced designs, and BIB.test, for partially balanced designs. In the following example, the agricolae data will be used, Joshi (1987).

> # Example linear estimation and design of experiments. (Joshi)
> # Institute of Social Sciences Agra, India
> # 6 varieties of wheat in 10 blocks of 3 plots each.
> block<-gl(10,3)
> variety<-c(1,2,3,1,2,4,1,3,5,1,4,6,1,5,6,2,3,6,2,4,5,2,5,6,3,4,5,3,4,6)
> Y<-c(69,54,50,77,65,38,72,45,54,63,60,39,70,65,54,65,68,67,57,60,62,
+ 59,65,63,75,62,61,59,55,56)
> head(cbind(block,variety,Y))

<table>
<thead>
<tr>
<th>block</th>
<th>variety</th>
<th>Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>[1,]</td>
<td>1</td>
<td>69</td>
</tr>
<tr>
<td>[2,]</td>
<td>1</td>
<td>54</td>
</tr>
<tr>
<td>[3,]</td>
<td>1</td>
<td>50</td>
</tr>
<tr>
<td>[4,]</td>
<td>2</td>
<td>77</td>
</tr>
<tr>
<td>[5,]</td>
<td>2</td>
<td>65</td>
</tr>
<tr>
<td>[6,]</td>
<td>2</td>
<td>38</td>
</tr>
</tbody>
</table>

> BIB.test(block, variety, Y,console=TRUE)

ANALYSIS BIB: Y
Class level information
Block: 1 2 3 4 5 6 7 8 9 10
Trt : 1 2 3 4 5 6

Number of observations: 30

Analysis of Variance Table

Response: Y

<table>
<thead>
<tr>
<th>Df</th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>F value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>block.unadj</td>
<td>9</td>
<td>467</td>
<td>51.9</td>
<td>0.90</td>
</tr>
<tr>
<td>trt.adj</td>
<td>5</td>
<td>1156</td>
<td>231.3</td>
<td>4.02</td>
</tr>
<tr>
<td>Residuals</td>
<td>15</td>
<td>863</td>
<td>57.5</td>
<td></td>
</tr>
</tbody>
</table>

---

Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

coefficient of variation: 13 %
Y Means: 60

variety, statistics

<table>
<thead>
<tr>
<th>Y mean.adj</th>
<th>SE</th>
<th>r</th>
<th>std</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>70</td>
<td>5.1</td>
<td>63</td>
<td>77</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>60</td>
<td>4.9</td>
<td>54</td>
<td>65</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>59</td>
<td>12.4</td>
<td>45</td>
<td>75</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>55</td>
<td>9.8</td>
<td>38</td>
<td>62</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>61</td>
<td>4.5</td>
<td>54</td>
<td>65</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>56</td>
<td>10.8</td>
<td>39</td>
<td>67</td>
<td></td>
</tr>
</tbody>
</table>

LSD test
Std.diff : 5.4
Alpha : 0.05
LSD : 11
Parameters BIB
Lambda : 2

```
<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
</tbody>
</table>
```

```
Lambda : 2
treatmeans : 6
Block size : 3
Blocks : 10
Replication: 5

Efficiency factor 0.8

<<< Book >>>

Comparison between treatments means

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Difference</th>
<th>pvalue</th>
<th>sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 - 2</td>
<td>16.42</td>
<td>0.0080 **</td>
</tr>
<tr>
<td>1 - 3</td>
<td>16.58</td>
<td>0.0074 **</td>
</tr>
<tr>
<td>1 - 4</td>
<td>20.17</td>
<td>0.0018 **</td>
</tr>
<tr>
<td>1 - 5</td>
<td>15.08</td>
<td>0.0132 *</td>
</tr>
<tr>
<td>1 - 6</td>
<td>20.75</td>
<td>0.0016 **</td>
</tr>
<tr>
<td>2 - 3</td>
<td>0.17</td>
<td>0.9756</td>
</tr>
<tr>
<td>2 - 4</td>
<td>3.75</td>
<td>0.4952</td>
</tr>
<tr>
<td>2 - 5</td>
<td>-1.33</td>
<td>0.8070</td>
</tr>
<tr>
<td>2 - 6</td>
<td>4.33</td>
<td>0.4318</td>
</tr>
<tr>
<td>3 - 4</td>
<td>3.58</td>
<td>0.5142</td>
</tr>
<tr>
<td>3 - 5</td>
<td>-1.50</td>
<td>0.7836</td>
</tr>
<tr>
<td>3 - 6</td>
<td>4.17</td>
<td>0.4492</td>
</tr>
<tr>
<td>4 - 5</td>
<td>-5.08</td>
<td>0.3582</td>
</tr>
<tr>
<td>4 - 6</td>
<td>0.58</td>
<td>0.9148</td>
</tr>
<tr>
<td>5 - 6</td>
<td>5.67</td>
<td>0.3074</td>
</tr>
</tbody>
</table>

Treatments with the same letter are not significantly different.

Y groups

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>75</td>
</tr>
<tr>
<td>5</td>
<td>60</td>
</tr>
<tr>
<td>2</td>
<td>59</td>
</tr>
<tr>
<td>3</td>
<td>59</td>
</tr>
<tr>
<td>4</td>
<td>55</td>
</tr>
<tr>
<td>6</td>
<td>54</td>
</tr>
</tbody>
</table>

function (block, trt, Y, test = c("lsd", "tukey", "duncan", "waller", "snk"), alpha = 0.05, group = TRUE) LSD, Tukey Duncan, Waller-Duncan and SNK, can be used. The probabilities of the comparison can also be obtained. It should only be indicated: group=FALSE, thus:

```r
> out <-BIB.test(block, trt=variety, Y, test="tukey", group=FALSE, console=TRUE)
```

ANALYSIS BIB: Y

Class level information

<p>| | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
</tbody>
</table>

Number of observations: 30
Analysis of Variance Table

Response: Y

<table>
<thead>
<tr>
<th></th>
<th>Df</th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>F value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>block.unadj</td>
<td>9</td>
<td>467</td>
<td>51.9</td>
<td>0.90</td>
<td>0.547</td>
</tr>
<tr>
<td>trt.adj</td>
<td>5</td>
<td>1156</td>
<td>231.3</td>
<td>4.02</td>
<td>0.016  *</td>
</tr>
<tr>
<td>Residuals</td>
<td>15</td>
<td>863</td>
<td>57.5</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

---

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

coefficient of variation: 13 %
Y Means: 60

variety, statistics

<table>
<thead>
<tr>
<th></th>
<th>mean.adj</th>
<th>SE</th>
<th>r</th>
<th>std</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>70</td>
<td>75</td>
<td>3.7</td>
<td>5</td>
<td>63</td>
<td>77</td>
</tr>
<tr>
<td>2</td>
<td>60</td>
<td>59</td>
<td>3.7</td>
<td>5</td>
<td>54</td>
<td>65</td>
</tr>
<tr>
<td>3</td>
<td>59</td>
<td>59</td>
<td>3.7</td>
<td>5</td>
<td>45</td>
<td>75</td>
</tr>
<tr>
<td>4</td>
<td>55</td>
<td>55</td>
<td>3.7</td>
<td>5</td>
<td>38</td>
<td>62</td>
</tr>
<tr>
<td>5</td>
<td>61</td>
<td>60</td>
<td>3.7</td>
<td>5</td>
<td>54</td>
<td>65</td>
</tr>
<tr>
<td>6</td>
<td>56</td>
<td>54</td>
<td>3.7</td>
<td>5</td>
<td>39</td>
<td>67</td>
</tr>
</tbody>
</table>

Tukey
Alpha : 0.05
Std.err : 3.8
HSD : 17
Parameters BIB
Lambda : 2
treatmeans : 6
Block size : 3
Blocks : 10
Replication: 5

Efficiency factor 0.8

<<< Book >>>

Comparison between treatments means

<table>
<thead>
<tr>
<th>Difference</th>
<th>pvalue</th>
<th>sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 - 2</td>
<td>16.42</td>
<td>0.070</td>
</tr>
<tr>
<td>1 - 3</td>
<td>16.58</td>
<td>0.067</td>
</tr>
<tr>
<td>1 - 4</td>
<td>20.17</td>
<td>0.019</td>
</tr>
<tr>
<td>1 - 5</td>
<td>15.08</td>
<td>0.110</td>
</tr>
<tr>
<td>1 - 6</td>
<td>20.75</td>
<td>0.015</td>
</tr>
<tr>
<td>2 - 3</td>
<td>0.17</td>
<td>1.000</td>
</tr>
<tr>
<td>2 - 4</td>
<td>3.75</td>
<td>0.979</td>
</tr>
<tr>
<td>2 - 5</td>
<td>1.33</td>
<td>1.000</td>
</tr>
<tr>
<td>2 - 6</td>
<td>4.33</td>
<td>0.962</td>
</tr>
</tbody>
</table>
3 - 4  3.58  0.983
3 - 5  -1.50  1.000
3 - 6  4.17  0.967
4 - 5  -5.08  0.927
4 - 6  0.58  1.000
5 - 6  5.67  0.891

> names(out)

[1]  "parameters"  "statistics"  "comparison"  "means"
[5]  "groups"

> rm(block,variety)

bar.group: out$groups
bar.err: out$means

4.11 Partially Balanced Incomplete Blocks

The function \texttt{PBIB.test Joshi (1987)}, can be used for the lattice and alpha designs.

Consider the following case: Construct the alpha design with 30 treatments, 2 repetitions, and a block size equal to 3.

> # alpha design
> Genotype<-paste("geno",1:30,sep="")
> r<-2
> k<-3
> plan<-design.alpha(Genotype,k,r,seed=5)

Alpha Design (0,1) - Serie I

Parameters Alpha Design
================================
Treatmeans : 30
Block size : 3
Blocks : 10
Replication: 2

Efficiency factor
(E ) 0.62

<<< Book >>>

The generated plan is plan$book. Suppose that the corresponding observation to each experimental unit is:

> yield <-c(5,2,7,6,4,9,7,6,7,9,6,2,1,1,3,2,4,6,7,9,8,7,6,4,3,2,2,1,1,
    + 2,1,1,2,4,5,6,7,8,6,5,4,3,1,1,2,5,4,2,7,6,6,5,6,4,5,7,6,5,5,4)
The data table is constructed for the analysis. In theory, it is presumed that a design is applied and the experiment is carried out; subsequently, the study variables are observed from each experimental unit.

```r
> data<-data.frame(plan$book,yield)
> # The analysis:
> modelPBIB <- with(data,PBIB.test(block, Genotype, replication, yield, k=3, group=TRUE, console=TRUE))
```

**ANALYSIS PBIB: yield**

Class level information
- block : 20
- Genotype : 30

Number of observations: 60

Estimation Method: Residual (restricted) maximum likelihood

Parameter Estimates

<table>
<thead>
<tr>
<th></th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>block:replication</td>
<td>2.8e+00</td>
</tr>
<tr>
<td>replication</td>
<td>8.0e-09</td>
</tr>
<tr>
<td>Residual</td>
<td>2.0e+00</td>
</tr>
</tbody>
</table>

Fit Statistics

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>AIC</td>
<td>214</td>
</tr>
<tr>
<td>BIC</td>
<td>260</td>
</tr>
<tr>
<td>-2 Res Log Likelihood</td>
<td>-74</td>
</tr>
</tbody>
</table>

Analysis of Variance Table

Response: yield

<table>
<thead>
<tr>
<th>Df</th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>F value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Genotype</td>
<td>29</td>
<td>71.9</td>
<td>2.48</td>
<td>1.24</td>
</tr>
<tr>
<td>Residuals</td>
<td>11</td>
<td>22.0</td>
<td>2.00</td>
<td></td>
</tr>
</tbody>
</table>

Coefficient of variation: 31 %

yield Means: 4.5

Parameters PBIB

- Genotype 30
- block size 3
- block/replication 10
- replication 2

Efficiency factor 0.62

Comparison test lsd

Treatments with the same letter are not significantly different.
The adjusted averages can be extracted from the modelPBIB.

head(modelPBIB$means)

The comparisons:

head(modelPBIB$comparison)

The data on the adjusted averages and their variation can be illustrated with the functions plot.group and bar.err. Since the created object is very similar to the objects generated by the multiple comparisons.

Analysis of balanced lattice 3x3, 9 treatments, 4 repetitions.

Create the data in a text file: lattice3x3.txt and read with R:
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |
| 1 | 1 | 1 | 48.76 | 1 | 1 | 4 | 14.46 | 1 | 1 | 3 | 19.68 |
| 1 | 2 | 8 | 10.83 | 1 | 2 | 6 | 30.69 | 1 | 2 | 7 | 31.00 |
| 1 | 3 | 5 | 12.54 | 1 | 3 | 9 | 42.01 | 1 | 3 | 2 | 23.00 |
| 2 | 4 | 5 | 11.07 | 2 | 4 | 8 | 22.00 | 2 | 4 | 1 | 41.00 |
| 2 | 5 | 2 | 22.00 | 2 | 5 | 7 | 42.80 | 2 | 5 | 3 | 12.90 |
| 2 | 6 | 9 | 47.43 | 2 | 6 | 6 | 28.28 | 2 | 6 | 4 | 49.95 |
| 3 | 7 | 2 | 27.67 | 3 | 7 | 1 | 50.00 | 3 | 7 | 6 | 25.00 |
| 3 | 8 | 7 | 30.00 | 3 | 8 | 5 | 24.00 | 3 | 8 | 4 | 45.57 |
| 3 | 9 | 3 | 13.78 | 3 | 9 | 8 | 24.00 | 3 | 9 | 9 | 30.00 |
| 4 | 10 | 6 | 37.00 | 4 | 10 | 3 | 15.42 | 4 | 10 | 5 | 20.00 |
| 4 | 11 | 4 | 42.37 | 4 | 11 | 2 | 30.00 | 4 | 11 | 8 | 18.00 |
| 4 | 12 | 9 | 39.00 | 4 | 12 | 7 | 23.80 | 4 | 12 | 1 | 43.81 |

> trt<-c(1,8,5,5,2,9,2,7,3,6,4,9,4,6,9,8,7,6,1,5,8,3,2,7,3,7,2,1,3,4,6,4,9,5,8,1)
> yield<-c(48.76,10.83,12.54,11.07,22,47.43,27.67,30,13.78,37,42.37,39,14.46,30.69,42.01,
  + 22,42.8,28.28,50,24,24,15.42,30,23.8,19.68,31,23,41,12.9,49.95,25,45.57,30,20,18,43.81)
> sqr<-rep(gl(4,3),3)
> block<-rep(1:12,3)
> modelLattice<-PBIB.test(block,trt,sqr,yield,k=3,console=TRUE, method="VC")

ANALYSIS PBIB: yield

Class level information
block : 12
trt : 9

Number of observations: 36

Estimation Method: Variances component model

Fit Statistics
AIC        265
BIC        298

Analysis of Variance Table

Response: yield

<table>
<thead>
<tr>
<th>Df</th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>F value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>sqr</td>
<td>3</td>
<td>133</td>
<td>44</td>
<td>0.69</td>
</tr>
<tr>
<td>trt.unadj</td>
<td>8</td>
<td>3749</td>
<td>469</td>
<td>7.24</td>
</tr>
<tr>
<td>block/sqr</td>
<td>8</td>
<td>368</td>
<td>46</td>
<td>0.71</td>
</tr>
<tr>
<td>Residual</td>
<td>16</td>
<td>1036</td>
<td>65</td>
<td></td>
</tr>
</tbody>
</table>

---
Signif. codes:  
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Coefficient of variation: 28 %
yield Means: 29

Parameters PBIB
trt 9
block size 3
block/sqr 3
sqr 4

Efficiency factor 0.75

Comparison test lsd

Treatments with the same letter are not significantly different.

<table>
<thead>
<tr>
<th>yield.adj</th>
<th>groups</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>44</td>
</tr>
<tr>
<td>9</td>
<td>39</td>
</tr>
<tr>
<td>4</td>
<td>39</td>
</tr>
<tr>
<td>7</td>
<td>32</td>
</tr>
<tr>
<td>6</td>
<td>31</td>
</tr>
<tr>
<td>2</td>
<td>26</td>
</tr>
<tr>
<td>8</td>
<td>18</td>
</tr>
<tr>
<td>5</td>
<td>17</td>
</tr>
<tr>
<td>3</td>
<td>15</td>
</tr>
</tbody>
</table>

<<< to see the objects: means, comparison and groups. >>>

The adjusted averages can be extracted from the modelLattice.

print(modelLattice$means)

The comparisons:

head(modelLattice$comparison)

4.12 Augmented Blocks

The function DAU.test can be used for the analysis of the augmented block design. The data should be organized in a table, containing the blocks, treatments, and the response.

> block<-c(rep("I",7),rep("II",6),rep("III",7))
> trt<-c("A","B","C","D","g","k","l","A","B","C","D","e","i","A","B","C","D","g","k","l","A","B","C","D","e","i","A","B","C",
+ "D","f","h","j")
> yield<-c(83,77,78,70,75,74,79,81,91,79,78,92,79,87,81,89,96,82)
> head(data.frame(block, trt, yield))

<table>
<thead>
<tr>
<th>block</th>
<th>trt</th>
<th>yield</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>A</td>
<td>83</td>
</tr>
<tr>
<td>I</td>
<td>B</td>
<td>77</td>
</tr>
<tr>
<td>I</td>
<td>C</td>
<td>78</td>
</tr>
<tr>
<td>I</td>
<td>D</td>
<td>78</td>
</tr>
<tr>
<td>I</td>
<td>g</td>
<td>70</td>
</tr>
<tr>
<td>I</td>
<td>k</td>
<td>75</td>
</tr>
</tbody>
</table>

The treatments are in each block:
> by(trt,block,as.character)

block: I
[1] "A" "B" "C" "D" "g" "k" "l"
--------------------------------------------------------
block: II
[1] "A" "B" "C" "D" "e" "i"
--------------------------------------------------------
block: III
[1] "A" "B" "C" "D" "f" "h" "j"

With their respective responses:

> by(yield,block,as.character)

block: I
[1] "83" "77" "78" "78" "70" "75" "74"
--------------------------------------------------------
block: II
[1] "79" "81" "81" "91" "79" "78"
--------------------------------------------------------
block: III
[1] "92" "79" "87" "81" "89" "96" "82"

Analysis:

> modelDAU<- DAU.test(block,trt,yield,method="lsd",console=TRUE)

ANALYSIS DAU: yield
Class level information
Block: I II III
Trt : A B C D e f g h i j k l
Number of observations: 20

ANOVA, Treatment Adjusted
Analysis of Variance Table
Response: yield

<table>
<thead>
<tr>
<th></th>
<th>Df</th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>F value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>block.unadj</td>
<td>2</td>
<td>360</td>
<td>180.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>trt.adj</td>
<td>11</td>
<td>285</td>
<td>25.9</td>
<td>0.96</td>
<td>0.55</td>
</tr>
<tr>
<td>Control</td>
<td>3</td>
<td>53</td>
<td>17.6</td>
<td>0.65</td>
<td>0.61</td>
</tr>
<tr>
<td>Control + control.VS.aug.</td>
<td>8</td>
<td>232</td>
<td>29.0</td>
<td>1.08</td>
<td>0.48</td>
</tr>
<tr>
<td>Residuals</td>
<td>6</td>
<td>162</td>
<td>27.0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

ANOVA, Block Adjusted
Analysis of Variance Table

45
Response: yield

<table>
<thead>
<tr>
<th></th>
<th>Df</th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>F value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>trt.unadj</td>
<td>11</td>
<td>576</td>
<td>52.3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>block.adj</td>
<td>2</td>
<td>70</td>
<td>34.8</td>
<td>1.29</td>
<td>0.34</td>
</tr>
<tr>
<td>Control</td>
<td>3</td>
<td>53</td>
<td>17.6</td>
<td>0.65</td>
<td>0.61</td>
</tr>
<tr>
<td>Augmented</td>
<td>7</td>
<td>506</td>
<td>72.3</td>
<td>2.68</td>
<td>0.13</td>
</tr>
<tr>
<td>Control vs augmented</td>
<td>1</td>
<td>17</td>
<td>16.9</td>
<td>0.63</td>
<td>0.46</td>
</tr>
<tr>
<td>Residuals</td>
<td>6</td>
<td>162</td>
<td>27.0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

coefficient of variation: 6.4 %
yield Means: 82

Critical Differences (Between)

<table>
<thead>
<tr>
<th></th>
<th>Std Error Diff.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Two Control Treatments</td>
<td>4.2</td>
</tr>
<tr>
<td>Two Augmented Treatments (Same Block)</td>
<td>7.3</td>
</tr>
<tr>
<td>Two Augmented Treatments (Different Blocks)</td>
<td>8.2</td>
</tr>
<tr>
<td>A Augmented Treatment and A Control Treatment</td>
<td>6.4</td>
</tr>
</tbody>
</table>

Treatments with the same letter are not significantly different.

yield groups

- h 94 a
- f 86 ab
- A 85 ab
- D 83 ab
- C 82 ab
- j 80 ab
- B 79 ab
- e 78 ab
- k 78 ab
- i 77 ab
- l 77 ab
- g 73 b

Comparison between treatments means

<<< to see the objects: comparison and means >>>

> options(digits = 2)
> modelDAU$means

| yield std r Min Max Q25 Q50 Q75 mean.adj SE block |
|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| A      | 85     | 6.7    | 3      | 79     | 92     | 81     | 83     | 88     | 85     | 3.0    |
| B      | 79     | 2.0    | 3      | 77     | 81     | 78     | 79     | 80     | 79     | 3.0    |
| C      | 82     | 4.6    | 3      | 78     | 87     | 80     | 81     | 84     | 82     | 3.0    |
| D      | 83     | 6.8    | 3      | 78     | 91     | 80     | 81     | 86     | 83     | 3.0    |
| e      | 79     | NA     | 1      | 79     | 79     | 79     | 79     | 79     | 78     | 5.2    | II     |
| f      | 89     | NA     | 1      | 89     | 89     | 89     | 89     | 89     | 86     | 5.2    | III    |
| g      | 70     | NA     | 1      | 70     | 70     | 70     | 70     | 70     | 73     | 5.2    | I      |
> modelDAU<- DAU.test(block,trt,yield,method="lsd",group=FALSE,console=FALSE)
> head(modelDAU$comparison,8)

<table>
<thead>
<tr>
<th>Difference</th>
<th>pvalue</th>
<th>sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>A - B</td>
<td>5.7</td>
<td>0.23</td>
</tr>
<tr>
<td>A - C</td>
<td>2.7</td>
<td>0.55</td>
</tr>
<tr>
<td>A - D</td>
<td>1.3</td>
<td>0.76</td>
</tr>
<tr>
<td>A - e</td>
<td>6.4</td>
<td>0.35</td>
</tr>
<tr>
<td>A - f</td>
<td>-1.8</td>
<td>0.78</td>
</tr>
<tr>
<td>A - g</td>
<td>11.4</td>
<td>0.12</td>
</tr>
<tr>
<td>A - h</td>
<td>-8.8</td>
<td>0.21</td>
</tr>
<tr>
<td>A - i</td>
<td>7.4</td>
<td>0.29</td>
</tr>
</tbody>
</table>

5 Non-parametric comparisons

The functions for non-parametric multiple comparisons included in agricolae are: kruskal, waerden.test, friedman and durbin.test, Conover (1999).

The post hoc nonparametrics tests (kruskal, friedman, durbin and waerden) are using the criterium Fisher’s least significant difference (LSD).

The function kruskal is used for N samples (N>2), populations or data coming from a completely random experiment (populations = treatments).

The function waerden.test, similar to kruskal-wallis, uses a normal score instead of ranges as kruskal does.

The function friedman is used for organoleptic evaluations of different products, made by judges (every judge evaluates all the products). It can also be used for the analysis of treatments of the randomized complete block design, where the response cannot be treated through the analysis of variance.

The function durbin.test for the analysis of balanced incomplete block designs is very used for sampling tests, where the judges only evaluate a part of the treatments.

The function Median.test for the analysis the distribution is approximate with chi-squared ditribution with degree free number of groups minus one. In each comparison a table of 2x2 (pair of groups) and the criterion of greater or lesser value than the median of both are formed, the chi-square test is applied for the calculation of the probability of error that both are independent. This value is compared to the alpha level for group formation.

Montgomery book data, Montgomery (2002). Included in the agricolae package

> data(corn)
> str(corn)

'data.frame': 34 obs. of 3 variables:
$ method : int 1 1 1 1 1 1 1 1 1 1 2 ...
$ observation: int 83 91 94 89 89 96 91 92 90 91 ...
$ rx : num 11 23 28.5 17 17 31.5 23 26 19.5 23 ...
For the examples, the agricolae package data will be used.

5.1 Kruskal-Wallis

It makes the multiple comparison with Kruskal-Wallis. The parameters by default are alpha = 0.05.

```r
> str(kruskal)

function (y, trt, alpha = 0.05, p.adj = c("none", "holm",
 "hommel", "hochberg", "bonferroni", "BH", "BY",
 "fdr"), group = TRUE, main = NULL, console = FALSE)
```

Analysis

```r
> outKruskal<-with(corn,kruskal(\text{observation,method,group=TRUE, main=\"corn\", console=TRUE}))
```

\text{Study: corn}
\text{Kruskal-Wallis test's}
\text{Ties or no Ties}

\begin{itemize}
  \item \text{Critical Value: 26}
  \item \text{Degrees of freedom: 3}
  \item \text{Pvalue Chisq : 1.1e-05}
\end{itemize}

\text{method, means of the ranks}

\begin{verbatim}
observation  r
1  21.8  9
2  15.3 10
3  29.6  7
4  4.8  8
\end{verbatim}

\text{Post Hoc Analysis}

\text{t-Student: 2}
\text{Alpha : 0.05}
\text{Groups according to probability of treatment differences and alpha level.}

\text{Treatments with the same letter are not significantly different.}

\begin{verbatim}
observation groups
3  29.6  a
1  21.8  b
2  15.3  c
4  4.8  d
\end{verbatim}

The object output has the same structure of the comparisons see the functions plot.group(agricolae), bar.err(agricolae) and bar.group(agricolae).
5.2 Kruskal-Wallis: adjust P-values

To see p.adjust.methods()

\[
\text{out} \leftarrow \text{with(corn,kruskal(\text{observation,method,group=TRUE, main="corn", p.adj="holm"}))}
\]

\[
\text{print(out$group)}
\]

<table>
<thead>
<tr>
<th>observation groups</th>
<th>3</th>
<th>29.6</th>
<th>a</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>21.8</td>
<td>b</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>15.3</td>
<td>c</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>4.8</td>
<td>d</td>
</tr>
</tbody>
</table>

\[
\text{out} \leftarrow \text{with(corn,kruskal(\text{observation,method,group=FALSE, main="corn", p.adj="holm"}))}
\]

\[
\text{print(out$comparison)}
\]

<table>
<thead>
<tr>
<th>Difference</th>
<th>pvalue</th>
<th>Signif.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 - 2</td>
<td>6.5</td>
<td>0.0079</td>
</tr>
<tr>
<td>1 - 3</td>
<td>-7.7</td>
<td>0.0079</td>
</tr>
<tr>
<td>1 - 4</td>
<td>17.0</td>
<td>0.0000</td>
</tr>
<tr>
<td>2 - 3</td>
<td>-14.3</td>
<td>0.0000</td>
</tr>
<tr>
<td>2 - 4</td>
<td>10.5</td>
<td>0.0003</td>
</tr>
<tr>
<td>3 - 4</td>
<td>24.8</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

5.3 Friedman

The data consist of b mutually independent k-variate random variables called b blocks. The random variable is in a block and is associated with treatment. It makes the multiple comparison of the Friedman test with or without ties. A first result is obtained by friedman.test of R.

\[
\text{str(friedman)}
\]

function (judge, trt, evaluation, alpha = 0.05, group = TRUE, main = NULL, console = FALSE)

Analysis

\[
\text{data(grass)}
\]

\[
\text{out} \leftarrow \text{with(grass,friedman(judge, trt, evaluation, alpha=0.05, group=FALSE, + main="Data of the book of Conover", console=TRUE))}
\]

Study: Data of the book of Conover

<table>
<thead>
<tr>
<th>trt, Sum of the ranks</th>
<th>evaluation r</th>
</tr>
</thead>
<tbody>
<tr>
<td>t1</td>
<td>38 12</td>
</tr>
<tr>
<td>t2</td>
<td>24 12</td>
</tr>
<tr>
<td>t3</td>
<td>24 12</td>
</tr>
<tr>
<td>t4</td>
<td>34 12</td>
</tr>
</tbody>
</table>
Friedman's Test
===============
Adjusted for ties
Critical Value: 8.1
P.Value Chisq: 0.044
F Value: 3.2
P.Value F: 0.036

Post Hoc Analysis

Comparison between treatments
Sum of the ranks

<table>
<thead>
<tr>
<th>difference</th>
<th>pvalue signif.</th>
<th>LCL</th>
<th>UCL</th>
</tr>
</thead>
<tbody>
<tr>
<td>t1 - t2</td>
<td>14.5 0.015 *</td>
<td>3.0</td>
<td>25.98</td>
</tr>
<tr>
<td>t1 - t3</td>
<td>13.5 0.023 *</td>
<td>2.0</td>
<td>24.98</td>
</tr>
<tr>
<td>t1 - t4</td>
<td>4.0 0.483 -</td>
<td>7.5</td>
<td>15.48</td>
</tr>
<tr>
<td>t2 - t3</td>
<td>-1.0 0.860 -</td>
<td>12.5</td>
<td>10.48</td>
</tr>
<tr>
<td>t2 - t4</td>
<td>-10.5 0.072 .</td>
<td>-22.0</td>
<td>0.98</td>
</tr>
<tr>
<td>t3 - t4</td>
<td>-9.5 0.102 -</td>
<td>21.0</td>
<td>1.98</td>
</tr>
</tbody>
</table>

5.4 Waerden

A nonparametric test for several independent samples. Example applied with the sweet potato data in the agricolae basis.

```r
> str(waerden.test)
function (y, trt, alpha = 0.05, group = TRUE, main = NULL,
  console = FALSE)
```

Analysis

```r
> data(sweetpotato)
> outWaerden<-with(sweetpotato,waerden.test(yield,virus,alpha=0.01,group=TRUE,console=TRUE))
```

Study: yield ~ virus
Van der Waerden (Normal Scores) test's

Value : 8.4
Pvalue: 0.038
Degrees of Freedom: 3

virus, means of the normal score

```
yield  std r
cc -0.23 0.30 3
fc -1.06 0.35 3
ff  0.69 0.76 3
```
Post Hoc Analysis

Alpha: 0.01 ; DF Error: 8

Minimum Significant Difference: 1.3

Treatments with the same letter are not significantly different.

Means of the normal score

<table>
<thead>
<tr>
<th>score groups</th>
<th>yield</th>
<th>std</th>
<th>r</th>
</tr>
</thead>
<tbody>
<tr>
<td>ff 0.69</td>
<td>a</td>
<td></td>
<td></td>
</tr>
<tr>
<td>oo 0.60</td>
<td>a</td>
<td></td>
<td></td>
</tr>
<tr>
<td>cc -0.23</td>
<td>ab</td>
<td></td>
<td></td>
</tr>
<tr>
<td>fc -1.06</td>
<td>b</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The comparison probabilities are obtained with the parameter group = FALSE

> names(outWaerden)

[1] "statistics" "parameters" "means" "comparison"
[5] "groups"

To see outWaerden$comparison

> out<-with(sweetpotato,waerden.test(yield,virus,group=FALSE,console=TRUE))

Study: yield ~ virus
Van der Waerden (Normal Scores) test's

Value : 8.4
Pvalue: 0.038
Degrees of Freedom: 3

virus, means of the normal score

<table>
<thead>
<tr>
<th>yield</th>
<th>std</th>
<th>r</th>
</tr>
</thead>
<tbody>
<tr>
<td>cc -0.23</td>
<td>0.30</td>
<td>3</td>
</tr>
<tr>
<td>fc -1.06</td>
<td>0.35</td>
<td>3</td>
</tr>
<tr>
<td>ff 0.69</td>
<td>0.76</td>
<td>3</td>
</tr>
<tr>
<td>oo 0.60</td>
<td>0.37</td>
<td>3</td>
</tr>
</tbody>
</table>

Post Hoc Analysis

Comparison between treatments
mean of the normal score

difference pvalue signif. LCL UCL
| cc - fc | 0.827 0.0690 | -0.082 1.736 |

51
5.5 Median test

A nonparametric test for several independent samples. The median test is designed to examine whether several samples came from populations having the same median, Conover (1999). See also Figure 4.

In each comparison a table of 2x2 (pair of groups) and the criterion of greater or lesser value than the median of both are formed, the chi-square test is applied for the calculation of the probability of error that both are independent. This value is compared to the alpha level for group formation.

```
> str(Median.test)
function (y, trt, alpha = 0.05, correct = TRUE, simulate.p.value = FALSE, 
group = TRUE, main = NULL, console = TRUE)
> str(Median.test)
function (y, trt, alpha = 0.05, correct = TRUE, simulate.p.value = FALSE, 
group = TRUE, main = NULL, console = TRUE)
```

Analysis

```
> data(sweetpotato)
> outMedian<-with(sweetpotato,Median.test(yield,virus,console=TRUE))
```

The Median Test for yield ~ virus

Chi Square = 6.7  DF = 3  P.Value 0.083
Median = 28

<table>
<thead>
<tr>
<th></th>
<th>Median r</th>
<th>Min</th>
<th>Max</th>
<th>Q25</th>
<th>Q75</th>
</tr>
</thead>
<tbody>
<tr>
<td>cc</td>
<td>23</td>
<td>22</td>
<td>28</td>
<td>22</td>
<td>26</td>
</tr>
<tr>
<td>fc</td>
<td>13</td>
<td>11</td>
<td>15</td>
<td>12</td>
<td>14</td>
</tr>
<tr>
<td>ff</td>
<td>39</td>
<td>28</td>
<td>42</td>
<td>34</td>
<td>40</td>
</tr>
<tr>
<td>oo</td>
<td>38</td>
<td>32</td>
<td>40</td>
<td>35</td>
<td>39</td>
</tr>
</tbody>
</table>

Post Hoc Analysis

Groups according to probability of treatment differences and alpha level.

Treatments with the same letter are not significantly different.

```
yield groups
ff  39 a
oo  38 a
cc  23 a
fc  13 b
```
Figure 4: Grouping of treatments and its variation, Median method

> names(outMedian)

[1] "statistics" "parameters" "medians" "comparison"
[5] "groups"

> outMedian$statistics

<table>
<thead>
<tr>
<th></th>
<th>Chisq</th>
<th>Df</th>
<th>p.chisq</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>6.7</td>
<td>3</td>
<td>0.083</td>
<td>28</td>
</tr>
</tbody>
</table>

> outMedian$medians

<table>
<thead>
<tr>
<th>Group</th>
<th>Median r Min Max Q25 Q75</th>
</tr>
</thead>
<tbody>
<tr>
<td>cc</td>
<td>23 3 22 28 22 26</td>
</tr>
<tr>
<td>fc</td>
<td>13 3 11 15 12 14</td>
</tr>
<tr>
<td>ff</td>
<td>39 3 28 42 34 40</td>
</tr>
<tr>
<td>oo</td>
<td>38 3 32 40 35 39</td>
</tr>
</tbody>
</table>
5.6 Durbin

*durbin.test*: example: Myles Hollander (p. 311) Source: W. Moore and C.I. Bliss. (1942) A multiple comparison of the Durbin test for the balanced incomplete blocks for sensorial or categorical evaluation. It forms groups according to the demanded ones for level of significance (alpha); by default, 0.05.

```r
> str(durbin.test)
function (judge, trt, evaluation, alpha = 0.05, group = TRUE,
    main = NULL, console = FALSE)
```

**Analysis**

```r
days <- gl(7,3)
    + "B", "E", "G", "D", "E", "F")
toxic <- c(0.465, 0.343, 0.396, 0.602, 0.873, 0.325, 0.330, 0.423, 0.987, 0.426,
    + 0.652, 1.142, 0.989, 0.536, 0.409, 0.309, 0.609, 0.417, 0.931)
> head(data.frame(days, chemical, toxic))
days chemical toxic
1 1 A 0.46
2 1 B 0.34
3 1 D 0.40
4 2 A 0.60
5 2 C 0.87
6 2 E 0.63
```
t-Student : 2.3

Least Significant Difference
between the sum of ranks: 5

Parameters BIB
Lambda : 1
Treatments : 7
Block size : 3
Blocks : 7
Replication: 3

Comparison between treatments
Sum of the ranks

difference pvalue signif.
A - B 0 1.00
A - C -4 0.10
A - D 0 1.00
A - E 0 1.00
A - F -3 0.20
A - G 0 1.00
B - C -4 0.10
B - D 0 1.00
B - E 0 1.00
B - F -3 0.20
B - G 0 1.00
C - D 4 0.10
C - E 4 0.10
C - F 1 0.66
C - G 4 0.10
D - E 0 1.00
D - F -3 0.20
D - G 0 1.00
E - F -3 0.20
E - G 0 1.00
F - G 3 0.20

> names(out)
[1] "statistics" "parameters" "means" "rank"
[5] "comparison" "groups"

> out$statistics

        chisq.value  p.value   t.value  LSD
A - B      7.7       0.26     2.3   5
6 Graphics of the multiple comparison

The results of a comparison can be graphically seen with the functions bar.group, bar.err and diffograph.

6.1 bar.group

A function to plot horizontal or vertical bar, where the letters of groups of treatments is expressed. The function applies to all functions comparison treatments. Each object must use the group object previously generated by comparative function in indicating that group = TRUE.

element:

```r
> # model <-aov (yield ~ fertilizer, data = field)
> # out <-LSD.test (model, "fertilizer", group = TRUE)
> # bar.group (out $ group)
> str(bar.group)
function (x, horiz = FALSE, ...)
```

See Figure 4. The Median test with option group=TRUE (default) is used in the exercise.

6.2 bar.err

A function to plot horizontal or vertical bar, where the variation of the error is expressed in every treatments. The function applies to all functions comparison treatments. Each object must use the means object previously generated by the comparison function, see Figure 5

```r
> # model <-aov (yield ~ fertilizer, data = field)
> # out <-LSD.test (model, "fertilizer", group = TRUE)
> # bar.err(out$means)
> str(bar.err)
function (x, variation = c("SE", "SD", "range", "IQR"),
    horiz = FALSE, bar = TRUE, ...)
```

variation

SE: Standard error
SD: standard deviation
range: max-min

```r
> par(mfrow=c(2,2),cex=0.7,mar=c(3.5,1.5,3,1))
> C1<bar.err(modelPBIB$means[1:7, ], ylim=c(0,9), col=0, main="C1",
    + variation="range",border=3,las=2)
> C2<bar.err(modelPBIB$means[8:15,], ylim=c(0,9), col=0, main="C2",
    + variation="range", border =4,las=2)
> # Others graphic
> C3<bar.err(modelPBIB$means[16:22,], ylim=c(0,9), col=0, main="C3",
    + variation="range",border =2,las=2)
> C4<bar.err(modelPBIB$means[23:30,], ylim=c(0,9), col=0, main="C4",
```
> par(mfrow=c(2,2), mar=c(3,3,2,1), cex=0.7)
> c1<-colors()[480]; c2=colors()[65]
> bar.err(outHSD$means, variation="range", ylim=c(0,50), col=c1, las=1)
> bar.err(outHSD$means, variation="IQR", horiz=TRUE, xlim=c(0,50), col=c2, las=1)
> plot(outHSD, variation="range", las=1)
> plot(outHSD, horiz=TRUE, variation="SD", las=1)

Figure 5: Comparison between treatments
> # model : yield ~ virus
> # Important group=TRUE
> par(mfrow=c(1,2),mar=c(3,3,1,1),cex=0.8)
> x<-duncan.test(model, "virus", group=TRUE)
> plot(x,las=1)
> plot(x,variation="IQR",horiz=TRUE,las=1)

Figure 6: Grouping of treatments and its variation, Duncan method

> + variation="range", border =6,las=2)
> # Lattice graphics
> par(mar=c(2.5,2.5,1,0),cex=0.6)
> bar.group(modelLattice$group,ylim=c(0,55),density=10,las=1)

6.3 plot.group

It plots bars of the averages of treatments to compare. It uses the objects generated by a procedure of comparison like LSD (Fisher), duncan, Tukey (HSD), Student Newman Keul (SNK), Scheffe, Waller-Duncan, Ryan, Einot and Gabriel and Welsch (REGW), Kruskal Wallis, Friedman, Median, Waerden and other tests like Durbin, DAU, BIB, PBIB. The variation types are range (maximum and minimum), IQR (interquartile range), SD (standard deviation) and SE (standard error), see Figure 6.

The function: plot.group() and their arguments are x (output of test), variation = c("range", "IQR", "SE", "SD"), horiz (TRUE or FALSE), xlim, ylim and main are optional plot() parameters and others plot parameters.

6.4 diffograph

It plots bars of the averages of treatments to compare. It uses the objects generated by a procedure of comparison like LSD (Fisher), duncan, Tukey (HSD), Student Newman Keul (SNK), Scheffe, Ryan, Einot and Gabriel and Welsch (REGW), Kruskal Wallis, Friedman and Waerden, Hsu (1996), see Figure 7.
> # function (x, main = NULL, color1 = "red", color2 = "blue",
>             color3 = "black", cex.axis = 0.8, las = 1, pch = 20,
>             bty = "l", cex = 0.8, lwd = 1, xlab = "", ylab = "",
>             ...)  
> # model : yield ~ virus
> # Important group=FALSE
> x<-HSD.test(model, "virus", group=FALSE)
> diffograph(x,cex.axis=0.9,xlab="Yield",ylab="Yield",cex=0.9)

Figure 7: Mean-Mean scatter plot representation of the Tukey method
7 Stability Analysis

In agricolae there are two methods for the study of stability and the AMMI model. These are: a parametric model for a simultaneous selection in yield and stability "SHUKLA’S STABILITY VARIANCE AND KANG’S", Kang (1993) and a non-parametric method of Haynes, based on the data range.

7.1 Parametric Stability

Use the parametric model, function stability.par.

Prepare a data table where the rows and the columns are the genotypes and the environments, respectively. The data should correspond to yield averages or to another measured variable. Determine the variance of the common error for all the environments and the number of repetitions that was evaluated for every genotype. If the repetitions are different, find a harmonious average that will represent the set. Finally, assign a name to each row that will represent the genotype, Kang (1993). We will consider five environments in the following example:

```r
> options(digit=2)
> f <- system.file("external/dataStb.csv", package="agricolae")
> dataStb<-read.csv(f)
> stability.par(dataStb, rep=4, MSerror=1.8, alpha=0.1, main="Genotype",console=TRUE)
```

INTERACTIVE PROGRAM FOR CALCULATING SHUKLA’S STABILITY VARIANCE AND KANG’S YIELD - STABILITY (YSi) STATISTICS

<table>
<thead>
<tr>
<th>Genotype</th>
<th>Environmental index - covariate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Analysis of Variance</td>
<td></td>
</tr>
<tr>
<td>Df</td>
<td>Sum Sq</td>
</tr>
<tr>
<td>Total</td>
<td>203</td>
</tr>
<tr>
<td>Genotypes</td>
<td>16</td>
</tr>
<tr>
<td>Environments</td>
<td>11</td>
</tr>
<tr>
<td>Interaction</td>
<td>176</td>
</tr>
<tr>
<td>Heterogeneity</td>
<td>16</td>
</tr>
<tr>
<td>Residual</td>
<td>160</td>
</tr>
<tr>
<td>Pooled Error</td>
<td>576</td>
</tr>
</tbody>
</table>

Genotype. Stability statistics

<table>
<thead>
<tr>
<th>Mean</th>
<th>Sigma-square</th>
<th>s-square</th>
<th>Ecovalence</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>7.4</td>
<td>2.47 ns</td>
<td>2.45 ns</td>
</tr>
<tr>
<td>B</td>
<td>6.8</td>
<td>1.60 ns</td>
<td>1.43 ns</td>
</tr>
<tr>
<td>C</td>
<td>7.2</td>
<td>0.57 ns</td>
<td>0.63 ns</td>
</tr>
<tr>
<td>D</td>
<td>6.8</td>
<td>2.61 ns</td>
<td>2.13 ns</td>
</tr>
<tr>
<td>E</td>
<td>7.1</td>
<td>1.86 ns</td>
<td>2.05 ns</td>
</tr>
<tr>
<td>F</td>
<td>6.9</td>
<td>3.58 *</td>
<td>3.95 *</td>
</tr>
<tr>
<td>G</td>
<td>7.8</td>
<td>3.58 *</td>
<td>3.96 *</td>
</tr>
<tr>
<td>H</td>
<td>7.9</td>
<td>2.72 ns</td>
<td>2.12 ns</td>
</tr>
<tr>
<td>I</td>
<td>7.3</td>
<td>4.25 **</td>
<td>3.94 *</td>
</tr>
<tr>
<td>J</td>
<td>7.1</td>
<td>2.27 ns</td>
<td>2.51 ns</td>
</tr>
</tbody>
</table>

60
<table>
<thead>
<tr>
<th></th>
<th>Yield</th>
<th>Rank</th>
<th>Adj.rank</th>
<th>Adjusted</th>
<th>Stab.var</th>
<th>Stab.rating</th>
<th>YSi</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>7.4</td>
<td>13</td>
<td>1</td>
<td>14</td>
<td>2.47</td>
<td>0</td>
<td>14</td>
</tr>
<tr>
<td>B</td>
<td>6.8</td>
<td>4</td>
<td>-1</td>
<td>3</td>
<td>1.60</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>C</td>
<td>7.2</td>
<td>11</td>
<td>1</td>
<td>12</td>
<td>0.57</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>D</td>
<td>6.8</td>
<td>4</td>
<td>-1</td>
<td>3</td>
<td>2.61</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>E</td>
<td>7.1</td>
<td>9</td>
<td>1</td>
<td>10</td>
<td>1.86</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>F</td>
<td>6.9</td>
<td>8</td>
<td>-1</td>
<td>7</td>
<td>3.58</td>
<td>-4</td>
<td>3</td>
</tr>
<tr>
<td>G</td>
<td>7.8</td>
<td>16</td>
<td>2</td>
<td>18</td>
<td>3.58</td>
<td>-4</td>
<td>14</td>
</tr>
<tr>
<td>H</td>
<td>7.9</td>
<td>17</td>
<td>2</td>
<td>19</td>
<td>2.72</td>
<td>0</td>
<td>19</td>
</tr>
<tr>
<td>I</td>
<td>7.3</td>
<td>12</td>
<td>1</td>
<td>13</td>
<td>4.25</td>
<td>-8</td>
<td>5</td>
</tr>
<tr>
<td>J</td>
<td>7.1</td>
<td>10</td>
<td>1</td>
<td>11</td>
<td>2.27</td>
<td>0</td>
<td>11</td>
</tr>
<tr>
<td>K</td>
<td>6.4</td>
<td>3</td>
<td>-2</td>
<td>1</td>
<td>2.56</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>L</td>
<td>6.9</td>
<td>7</td>
<td>-1</td>
<td>6</td>
<td>1.56</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>M</td>
<td>6.8</td>
<td>6</td>
<td>-1</td>
<td>5</td>
<td>3.48</td>
<td>-4</td>
<td>1</td>
</tr>
<tr>
<td>N</td>
<td>7.5</td>
<td>14</td>
<td>1</td>
<td>15</td>
<td>5.16</td>
<td>-8</td>
<td>7</td>
</tr>
<tr>
<td>O</td>
<td>7.7</td>
<td>15</td>
<td>2</td>
<td>17</td>
<td>2.38</td>
<td>0</td>
<td>17</td>
</tr>
<tr>
<td>P</td>
<td>6.4</td>
<td>2</td>
<td>-2</td>
<td>0</td>
<td>3.45</td>
<td>-4</td>
<td>-4</td>
</tr>
<tr>
<td>Q</td>
<td>6.2</td>
<td>1</td>
<td>-3</td>
<td>-2</td>
<td>3.53</td>
<td>-4</td>
<td>-6</td>
</tr>
</tbody>
</table>

Yield Mean: 7.1
YS Mean: 6.8
LSD (0.05): 0.45


For 17 genotypes, the identification is made by letters. An error variance of 2 and 4 repetitions is assumed.

Analysis

```r
> output <- stability.par(dataStb, rep=4, MSerror=2)
> names(output)

[1] "analysis" "statistics" "stability"
```

```r
> print(output$stability)

61
```
The selected genotypes are: A, C, E, G, H, I, J and O. These genotypes have a higher yield and a lower variation. To see output analysis, the interaction is significant.

If for example there is an environmental index, it can be added as a covariate in the first five locations. For this case, the altitude of the localities is included.

```r
> data5<-dataStb[,1:5]
> altitude<-c(1200, 1300, 800, 1600, 2400)
> stability <- stability.par(data5, rep=4, MSerror=2, cova=TRUE, name.cov= "altitude", + file.cov=altitude)
```

### 7.2 Non-parametric Stability

For non-parametric stability, the function in 'agricolae' is `stability.nonpar()`. The names of the genotypes should be included in the first column, and in the other columns, the response by environments, Haynes and Lambert and Christ and Weingartner and Douches and Backlund and Secor and Fry and Stevenson (1998).

Analysis

```r
> data <- data.frame(name=row.names(dataStb), dataStb)
> output<-stability.nonpar(data, "YIELD", ranking=TRUE)
> names(output)

[1] "ranking" "statistics"

> output$statistics

MEAN es1 es2 vs1 vs2 chi.ind chi.sum
1 7.1 5.6 24 0.72 47 8.8 28
```
7.3 AMMI

The model AMMI uses the biplot constructed through the principal components generated by the interaction environment-genotype. If there is such interaction, the percentage of the two principal components would explain more than the 50% of the total variation; in such case, the biplot would be a good alternative to study the interaction environment-genotype, Crossa (1990).

The data for AMMI should come from similar experiments conducted in different environments. Homogeneity of variance of the experimental error, produced in the different environments, is required. The analysis is done by combining the experiments.

The data can be organized in columns, thus: environment, genotype, repetition, and variable. The data can also be the averages of the genotypes in each environment, but it is necessary to consider a harmonious average for the repetitions and a common variance of the error. The data should be organized in columns: environment, genotype, and variable.

When performing AMMI, this generates the Biplot, Triplot and Influence graphics, see Figure 8.

For the application, we consider the data used in the example of parametric stability (study):

**AMMI structure**

```r
> str(AMMI)

function (ENV, GEN, REP, Y, MSE = 0, console = FALSE,
   PC = FALSE)

plot.AMMI structure, plot()

> str(plot.AMMI)

function (x, first = 1, second = 2, third = 3, type = 1,
   number = FALSE, gcol = NULL, ecol = NULL, icol = NULL,
   angle = 25, lwd = 1.8, length = 0.1, xlab = NULL,
   ylab = NULL, xlim = NULL, ylim = NULL, ...)

type: 1=biplot, 2= triplot 3=influence genotype

> data(plrv)
> model<-with(plrv,AMMI(Locality, Genotype, Rep, Yield, console=FALSE))
> names(model)
[1] "ANOVA" "genXenv" "analysis" "means" "biplot"
[6] "PC"

> model$ANOVA

Analysis of Variance Table

Response: Y

<table>
<thead>
<tr>
<th></th>
<th>Df</th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>F value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ENV</td>
<td>5</td>
<td>122284</td>
<td>24457</td>
<td>257.04</td>
<td>9.1e-12 ***</td>
</tr>
<tr>
<td>REP(ENV)</td>
<td>12</td>
<td>1142</td>
<td>95</td>
<td>2.57</td>
<td>0.0029  **</td>
</tr>
</tbody>
</table>
In this case, the interaction is significant. The first two components explain 83.4%; then the biplot can provide information about the interaction genotype-environment. With the triplot, 92.8% would be explained.
To triplot require klaR package. in R execute:

```r
define the model with the AMMI function
index<-index.AMMI(model)
print(index[order(index[,3]),])
```

To Influence graphics genotype require spdep package, in R execute:

```r
plot(model,type=3). See Figure 9.
```

7.4 AMMI index and yield stability

Calculate AMMI stability value (ASV) and Yield stability index (YSI), Sabaghnia and Sabaghpour and Dehghani (2008); Purchase (1997).

```r
data(plrv)
model<- with(plrv,AMMI(Locality, Genotype, Rep, Yield, console=FALSE))
index<-index.AMMI(model)
print(index[order(index[,3]),])
```
> # Crops with better response and improved stability according AMMI.
> print(index[order(index[,4]),])

<table>
<thead>
<tr>
<th>ASV</th>
<th>YSI</th>
<th>rASV</th>
<th>rYSI</th>
<th>means</th>
</tr>
</thead>
<tbody>
<tr>
<td>141.28</td>
<td>3.15</td>
<td>24</td>
<td>23</td>
<td>1</td>
</tr>
<tr>
<td>319.20</td>
<td>4.87</td>
<td>30</td>
<td>27</td>
<td>3</td>
</tr>
<tr>
<td>235.6</td>
<td>3.31</td>
<td>28</td>
<td>24</td>
<td>4</td>
</tr>
<tr>
<td>157.26</td>
<td>2.89</td>
<td>26</td>
<td>21</td>
<td>5</td>
</tr>
<tr>
<td>450.3</td>
<td>2.37</td>
<td>23</td>
<td>17</td>
<td>6</td>
</tr>
<tr>
<td>427.7</td>
<td>0.95</td>
<td>11</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td>351.26</td>
<td>2.34</td>
<td>23</td>
<td>15</td>
<td>8</td>
</tr>
<tr>
<td>317.6</td>
<td>1.52</td>
<td>18</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>364.21</td>
<td>0.60</td>
<td>13</td>
<td>3</td>
<td>10</td>
</tr>
<tr>
<td>506.2</td>
<td>0.56</td>
<td>13</td>
<td>2</td>
<td>11</td>
</tr>
<tr>
<td>406.12</td>
<td>2.17</td>
<td>26</td>
<td>14</td>
<td>12</td>
</tr>
<tr>
<td>104.22</td>
<td>1.38</td>
<td>21</td>
<td>8</td>
<td>13</td>
</tr>
<tr>
<td>314.12</td>
<td>2.04</td>
<td>29</td>
<td>11</td>
<td>18</td>
</tr>
<tr>
<td>402.7</td>
<td>0.20</td>
<td>20</td>
<td>1</td>
<td>19</td>
</tr>
<tr>
<td>233.11</td>
<td>1.05</td>
<td>22</td>
<td>5</td>
<td>17</td>
</tr>
<tr>
<td>241.2</td>
<td>1.17</td>
<td>28</td>
<td>6</td>
<td>22</td>
</tr>
<tr>
<td>102.18</td>
<td>2.51</td>
<td>42</td>
<td>19</td>
<td>23</td>
</tr>
</tbody>
</table>

66
> par(cex=0.6,mar=c(3,3,2,1))
> data(pamCIP)
> rownames(pamCIP)<-substr(rownames(pamCIP),1,6)
> output<-consensus(pamCIP,distance="binary", method="complete", nboot=5)

Duplicates: 18
New data : 25 Records

Consensus hclust

Method distance: binary
Method cluster : complete
rows and cols : 25 107
n-bootstrap : 5
Run time : 2.3 secs

Cluster Dendrogram

Figure 10: Dendrogram, production by consensus

342.15  2.10  36  12  24  26
346.2   3.61  51  26  25  24
221.19  1.27  33  7   26  23
163.9   3.08  49  22  27  21
Desiree 5.54  56  28  28  16

8  Special functions

8.1  Consensus of dendrogram

Consensus is the degree or similarity of the vertexes of a tree regarding its branches of the constructed dendrogram. The function to apply is consensus().

The data correspond to a table, with the name of the individuals and the variables in the rows and columns respectively. For the demonstration, we will use the "pamCIP" data of 'agricolae', which correspond to molecular markers of 43 entries of a germplasm bank (rows) and 107 markers (columns).

The program identifies duplicates in the rows and can operate in both cases. The result is a dendrogram, in which the consensus percentage is included, see Figure 10.
> par(cex=0.6,mar=c(3,3,1.5,1))
> out1<-hcut(output,h=0.4,group=8,type="t",edgePar = list(lty=1:2, col=colors()[c(42,84)]),
+    main="group 8", col.text="blue", cex.text=1, las=1)

Figure 11: Dendrogram, production by hcut()

When the dendrogram is complex, it is convenient to extract part of it with the function hcut(), see Figure 11.

The obtained object “output” contains information about the process:

> names(output)
[1] "table.dend" "dendrogram" "duplicates"

Construct a classic dendrogram, execute procedure in R

use the previous result 'output'

> dend <- as.dendrogram(output$dendrogram)
> data <- output$table.dend
> head(output$table.dend)

<table>
<thead>
<tr>
<th></th>
<th>X1</th>
<th>X2</th>
<th>xaxis</th>
<th>height</th>
<th>percentage</th>
<th>groups</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-6</td>
<td>-24</td>
<td>7.5</td>
<td>0.029</td>
<td>60</td>
<td>6-24</td>
</tr>
<tr>
<td>2</td>
<td>-3</td>
<td>-4</td>
<td>19.5</td>
<td>0.036</td>
<td>40</td>
<td>3-4</td>
</tr>
<tr>
<td>3</td>
<td>-2</td>
<td>-8</td>
<td>22.5</td>
<td>0.038</td>
<td>60</td>
<td>2-8</td>
</tr>
<tr>
<td>4</td>
<td>-7</td>
<td>-10</td>
<td>10.5</td>
<td>0.038</td>
<td>60</td>
<td>7-10</td>
</tr>
<tr>
<td>5</td>
<td>-21</td>
<td>2</td>
<td>18.8</td>
<td>0.071</td>
<td>60</td>
<td>3-4-21</td>
</tr>
<tr>
<td>6</td>
<td>-16</td>
<td>3</td>
<td>21.8</td>
<td>0.074</td>
<td>40</td>
<td>2-8-16</td>
</tr>
</tbody>
</table>

> par(mar=c(3,3,1,1), cex=0.6)
> plot(dend,type="r", edgePar = list(lty=1:2, col=colors()[c(42,84)]), las=1)
> text(data[,3],data[,4],data[,5], col="blue", cex=1)

8.2 Montecarlo

It is a method for generating random numbers of an unknown distribution. It uses a data set and, through the cumulative behavior of its relative frequency, generates the possible random values that
follow the data distribution. These new numbers are used in some simulation process. The probability density of the original and simulated data can be compared, see Figure 12.

> data(soil)
> # set.seed(9473)
> simulated <- montecarlo(soil$pH,1000)
> h<-graph.freq(simulated,nclass=7,plot=FALSE)

1000 data was simulated, being the frequency table:

> round(table.freq(h),2)

<table>
<thead>
<tr>
<th>Lower</th>
<th>Upper</th>
<th>Main</th>
<th>Frequency</th>
<th>Percentage</th>
<th>CF</th>
<th>CPF</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.5</td>
<td>2.8</td>
<td>2.2</td>
<td>20</td>
<td>2.0</td>
<td>20</td>
</tr>
<tr>
<td>2</td>
<td>2.8</td>
<td>4.1</td>
<td>3.5</td>
<td>120</td>
<td>12.0</td>
<td>140</td>
</tr>
<tr>
<td>3</td>
<td>4.1</td>
<td>5.4</td>
<td>4.8</td>
<td>238</td>
<td>23.8</td>
<td>378</td>
</tr>
<tr>
<td>4</td>
<td>5.4</td>
<td>6.7</td>
<td>6.1</td>
<td>225</td>
<td>22.5</td>
<td>603</td>
</tr>
<tr>
<td>5</td>
<td>6.7</td>
<td>8.1</td>
<td>7.4</td>
<td>198</td>
<td>19.8</td>
<td>801</td>
</tr>
<tr>
<td>6</td>
<td>8.1</td>
<td>9.4</td>
<td>8.7</td>
<td>168</td>
<td>16.8</td>
<td>969</td>
</tr>
<tr>
<td>7</td>
<td>9.4</td>
<td>10.7</td>
<td>10.0</td>
<td>31</td>
<td>3.1</td>
<td>100</td>
</tr>
</tbody>
</table>

Some statistics, original data:

> summary(soil$pH)

<table>
<thead>
<tr>
<th>Min.</th>
<th>1st Qu.</th>
<th>Median</th>
<th>Mean</th>
<th>3rd Qu.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.8</td>
<td>4.7</td>
<td>6.1</td>
<td>6.2</td>
<td>7.6</td>
<td>8.4</td>
</tr>
</tbody>
</table>

Some statistics, montecarlo simulate data:
8.3 Re-Sampling in linear model

It uses the permutation method for the calculation of the probabilities of the sources of variation of ANOVA according to the linear regression model or the design used. The principle is that the Y response does not depend on the averages proposed in the model; hence, the Y values can be permuted and many model estimates can be constructed. On the basis of the patterns of the random variables of the elements under study, the probability is calculated in order to measure the significance.

For a variance analysis, the data should be prepared similarly. The function to use is: resampling.model()

> data(potato)
> potato[,1]<-as.factor(potato[,1])
> potato[,2]<-as.factor(potato[,2])
> model<="cutting~variety + date + variety:date"
> analysis<-resampling.model(model, potato, k=100)
> Xsol<-as.matrix(round(analysis$solution,2))
> print(Xsol,na.print = "")

<table>
<thead>
<tr>
<th>Df</th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>F value</th>
<th>Pr(&gt;F)</th>
<th>Resampling</th>
</tr>
</thead>
<tbody>
<tr>
<td>variety</td>
<td>1</td>
<td>25.1</td>
<td>25.1</td>
<td>7.3</td>
<td>0.02</td>
</tr>
<tr>
<td>date</td>
<td>2</td>
<td>13.9</td>
<td>7.0</td>
<td>2.0</td>
<td>0.18</td>
</tr>
<tr>
<td>variety:date</td>
<td>2</td>
<td>4.8</td>
<td>2.4</td>
<td>0.7</td>
<td>0.51</td>
</tr>
<tr>
<td>Residuals</td>
<td>12</td>
<td>41.5</td>
<td>3.5</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The function resampling.model() can be used when the errors have a different distribution from normal

8.4 Simulation in linear model

Under the assumption of normality, the function generates pseudo experimental errors under the proposed model, and determines the proportion of valid results according to the analysis of variance found.

The function is: simulation.model(). The data are prepared in a table, similarly to an analysis of variance.

Considering the example proposed in the previous procedure:

> simModel <- simulation.model(model, potato, k=100,console=TRUE)

Simulation of experiments
Under the normality assumption
---
---
---

Proposed model: cutting~variety + date + variety:date
Analysis of Variance Table
Response: cutting

<table>
<thead>
<tr>
<th>Df</th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>F value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>variety</td>
<td>1</td>
<td>25.1</td>
<td>25.09</td>
<td>7.26</td>
</tr>
<tr>
<td>date</td>
<td>2</td>
<td>13.9</td>
<td>6.95</td>
<td>2.01</td>
</tr>
<tr>
<td>variety:date</td>
<td>2</td>
<td>4.9</td>
<td>2.43</td>
<td>0.70</td>
</tr>
<tr>
<td>Residuals</td>
<td>12</td>
<td>41.5</td>
<td>3.46</td>
<td>-</td>
</tr>
</tbody>
</table>

---

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

---

Validation of the analysis of variance for the proposed model
Simulations: 100

<table>
<thead>
<tr>
<th>Df</th>
<th>F value</th>
<th>% Acceptance</th>
<th>% Rejection</th>
</tr>
</thead>
<tbody>
<tr>
<td>variety</td>
<td>1</td>
<td>7.3</td>
<td>49</td>
</tr>
<tr>
<td>date</td>
<td>2</td>
<td>2.0</td>
<td>60</td>
</tr>
<tr>
<td>variety:date</td>
<td>2</td>
<td>0.7</td>
<td>61</td>
</tr>
</tbody>
</table>

Criterion

variety nonacceptable
date acceptable
variety:date acceptable

---

The validation is referred to the percentage of decision results equal to the result of the ANOVA decision. Thus, 61% of the results simulated on the interaction variety*date gave the same result of acceptance or rejection obtained in the ANOVA.

8.5 Path Analysis

It corresponds to the "path analysis" method. The data correspond to correlation matrices of the independent ones with the dependent matrix (XY) and between the independent ones (XX).

It is necessary to assign names to the rows and columns in order to identify the direct and indirect effects.

```r
> corr.x<- matrix(c(1,0.5,0.5,1),c(2,2))
> corr.y<- rbind(0.6,0.7)
> names<-c("X1","X2")
> dimnames(corr.x)<-list(names,names)
> dimnames(corr.y)<-list(names,"Y")
> output<-path.analysis(corr.x,corr.y)
```

Direct(Diagonal) and indirect effect path coefficients

======================================================

<table>
<thead>
<tr>
<th>X1</th>
<th>X2</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1</td>
<td>0.33</td>
</tr>
<tr>
<td>X2</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Residual Effect^2 = 0.43

> output

71
8.6 Line X Tester

It corresponds to a crossbreeding analysis of a genetic design. The data should be organized in a table. Only four columns are required: repetition, females, males, and response. In case it corresponds to progenitors, the females or males field will only be filled with the corresponding one. See the heterosis data, Singh and Chaudhary (1979).

Example with the heterosis data, locality 2.

<table>
<thead>
<tr>
<th>Replication</th>
<th>Female</th>
<th>Male</th>
<th>v2</th>
</tr>
</thead>
<tbody>
<tr>
<td>109</td>
<td>1</td>
<td>LT-8</td>
<td>2.65</td>
</tr>
<tr>
<td>110</td>
<td>1</td>
<td>LT-8</td>
<td>2.26</td>
</tr>
<tr>
<td>...</td>
<td>1</td>
<td>Achirana</td>
<td>3.55</td>
</tr>
<tr>
<td>132</td>
<td>1</td>
<td>Achirana</td>
<td>3.05</td>
</tr>
<tr>
<td>...</td>
<td>1</td>
<td>&lt;NA&gt;</td>
<td>3.35</td>
</tr>
<tr>
<td>215</td>
<td>3</td>
<td>&lt;NA&gt;</td>
<td>2.91</td>
</tr>
</tbody>
</table>

where <NA> is empty.

If it is a progeny, it comes from a "Female" and a "Male." If it is a progenitor, it will only be "Female" or "Male."

The following example corresponds to data of the locality 2:

24 progenies 8 females 3 males 3 repetitions

They are 35 treatments (24, 8, 3) applied to three blocks.

```r
> rm(list=ls())
> options(digits = 2)
> data(heterosis)
> str(heterosis)
```

'data.frame': 324 obs. of 11 variables:
$ Place : num 1 1 1 1 1 1 1 1 1 1 ...
$ Replication: num 1 1 1 1 1 1 1 1 1 1 ...
$ Treatment : num 1 2 3 4 5 6 7 8 9 10 ...
$ Factor  : Factor w/ 3 levels "Control","progenie",...: 2 2 2 2 2 2 2 2 2 2 ...
$ Female  : Factor w/ 8 levels "Achirana","LT-8",...: 2 2 2 6 6 6 7 7 8 ...
$ Male    : Factor w/ 3 levels "TPS-13","TPS-67",...: 3 1 2 3 1 2 3 1 2 3 ...
$ v1      : num 0.948 1.052 1.05 1.058 1.123 ...
$ v2      : num 1.65 2.2 1.88 2.45 2.63 2.75 3 2.51 1.93 ...

72
$ v3 : num 17.2 17.8 15.6 16.5 ... 
$ v4 : num 9.93 12.45 9.3 12.77 14.13 ... 
$ v5 : num 102.6 107.4 120.5 83.8 90.4 ...

> site2<-subset(heterosis,heterosis[,1]==2)
> site2<-subset(site2[,c(2,5,6,8)],site2[,4]!="Control")
> output1<-with(site2,lineXtester(Replication, Female, Male, v2))

**ANALYSIS LINE x TESTER: v2**

**ANOVA with parents and crosses**

<table>
<thead>
<tr>
<th>Df</th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>F value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Replications</td>
<td>2</td>
<td>0.5192</td>
<td>0.2596</td>
<td>9.80</td>
</tr>
<tr>
<td>Treatments</td>
<td>34</td>
<td>16.1016</td>
<td>0.4736</td>
<td>17.88</td>
</tr>
<tr>
<td>Parents</td>
<td>10</td>
<td>7.7315</td>
<td>0.7731</td>
<td>29.19</td>
</tr>
<tr>
<td>Parents vs. Crosses</td>
<td>1</td>
<td>0.0051</td>
<td>0.0051</td>
<td>0.19</td>
</tr>
<tr>
<td>Crosses</td>
<td>23</td>
<td>8.3650</td>
<td>0.3637</td>
<td>13.73</td>
</tr>
<tr>
<td>Error</td>
<td>68</td>
<td>1.8011</td>
<td>0.0265</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>104</td>
<td>18.4219</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**ANOVA for line X tester analysis**

<table>
<thead>
<tr>
<th>Df</th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>F value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lines</td>
<td>7</td>
<td>4.98</td>
<td>0.711</td>
<td>3.6</td>
</tr>
<tr>
<td>Testers</td>
<td>2</td>
<td>0.65</td>
<td>0.325</td>
<td>1.7</td>
</tr>
<tr>
<td>Lines X Testers</td>
<td>14</td>
<td>2.74</td>
<td>0.196</td>
<td>7.4</td>
</tr>
<tr>
<td>Error</td>
<td>68</td>
<td>1.80</td>
<td>0.026</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>104</td>
<td>18.4219</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**ANOVA for line X tester analysis including parents**

<table>
<thead>
<tr>
<th>Df</th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>F value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Replications</td>
<td>2</td>
<td>0.5192</td>
<td>0.2596</td>
<td>9.80</td>
</tr>
<tr>
<td>Treatments</td>
<td>34</td>
<td>16.1016</td>
<td>0.4736</td>
<td>17.88</td>
</tr>
<tr>
<td>Parents</td>
<td>10</td>
<td>7.7315</td>
<td>0.7731</td>
<td>29.19</td>
</tr>
<tr>
<td>Parents vs. Crosses</td>
<td>1</td>
<td>0.0051</td>
<td>0.0051</td>
<td>0.19</td>
</tr>
<tr>
<td>Crosses</td>
<td>23</td>
<td>8.3650</td>
<td>0.3637</td>
<td>13.73</td>
</tr>
<tr>
<td>Lines</td>
<td>7</td>
<td>4.9755</td>
<td>0.7108</td>
<td>3.63</td>
</tr>
<tr>
<td>Testers</td>
<td>2</td>
<td>0.6494</td>
<td>0.3247</td>
<td>1.66</td>
</tr>
<tr>
<td>Lines X Testers</td>
<td>14</td>
<td>2.7401</td>
<td>0.1957</td>
<td>7.39</td>
</tr>
<tr>
<td>Error</td>
<td>68</td>
<td>1.8011</td>
<td>0.0265</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>104</td>
<td>18.4219</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**GCA Effects:**

**Lines Effects:**

<table>
<thead>
<tr>
<th>Lines</th>
<th>LT-8</th>
<th>MF-I</th>
<th>MF-II</th>
<th>Serrana</th>
<th>TPS-2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Achirana</td>
<td>0.022</td>
<td>-0.338</td>
<td>0.199</td>
<td>-0.449</td>
<td>0.058</td>
</tr>
<tr>
<td>TPS-25</td>
<td>0.414</td>
<td>0.141</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

73
Testers Effects:
TPS-13   TPS-67   TS-15
  0.087   0.046  -0.132

SCA Effects:

<table>
<thead>
<tr>
<th>Testers</th>
<th>Lines</th>
<th>TPS-13</th>
<th>TPS-67</th>
<th>TS-15</th>
</tr>
</thead>
<tbody>
<tr>
<td>Achirana</td>
<td>0.061</td>
<td>0.059</td>
<td>-0.120</td>
<td></td>
</tr>
<tr>
<td>LT-8</td>
<td>-0.435</td>
<td>0.519</td>
<td>-0.083</td>
<td></td>
</tr>
<tr>
<td>MF-I</td>
<td>-0.122</td>
<td>-0.065</td>
<td>0.187</td>
<td></td>
</tr>
<tr>
<td>MF-II</td>
<td>-0.194</td>
<td>0.047</td>
<td>0.148</td>
<td></td>
</tr>
<tr>
<td>Serrana</td>
<td>0.032</td>
<td>-0.113</td>
<td>0.081</td>
<td></td>
</tr>
<tr>
<td>TPS-2</td>
<td>0.197</td>
<td>-0.072</td>
<td>-0.124</td>
<td></td>
</tr>
<tr>
<td>TPS-25</td>
<td>0.126</td>
<td>-0.200</td>
<td>0.074</td>
<td></td>
</tr>
<tr>
<td>TPS-7</td>
<td>0.336</td>
<td>-0.173</td>
<td>-0.162</td>
<td></td>
</tr>
</tbody>
</table>

Standard Errors for Combining Ability Effects:

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>S.E. (gca for line)</td>
<td>0.054</td>
</tr>
<tr>
<td>S.E. (gca for tester)</td>
<td>0.033</td>
</tr>
<tr>
<td>S.E. (sca effect)</td>
<td>0.094</td>
</tr>
<tr>
<td>S.E. (gi - gj)line</td>
<td>0.077</td>
</tr>
<tr>
<td>S.E. (gi - gj)tester</td>
<td>0.047</td>
</tr>
<tr>
<td>S.E. (sij - skl)tester</td>
<td>0.13</td>
</tr>
</tbody>
</table>

Genetic Components:

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Cov H.S. (line)</td>
<td>0.057</td>
</tr>
<tr>
<td>Cov H.S. (tester)</td>
<td>0.0054</td>
</tr>
<tr>
<td>Cov H.S. (average)</td>
<td>0.0039</td>
</tr>
<tr>
<td>Cov F.S. (average)</td>
<td>0.13</td>
</tr>
<tr>
<td>F = 0, Adittive genetic variance:</td>
<td>0.015</td>
</tr>
<tr>
<td>F = 1, Adittive genetic variance:</td>
<td>0.0077</td>
</tr>
<tr>
<td>F = 0, Variance due to Dominance:</td>
<td>0.11</td>
</tr>
<tr>
<td>F = 1, Variance due to Dominance:</td>
<td>0.056</td>
</tr>
</tbody>
</table>

Proportional contribution of lines, testers and their interactions to total variance

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Contributions of lines</td>
<td>59</td>
</tr>
<tr>
<td>Contributions of testers</td>
<td>7.8</td>
</tr>
<tr>
<td>Contributions of lxt</td>
<td>33</td>
</tr>
</tbody>
</table>

> options(digits = 7)

8.7 Soil Uniformity

The Smith index is an indicator of the uniformity, used to determine the parcel size for research purposes. The data correspond to a matrix or table that contains the response per basic unit, a
number of n rows x m columns, and a total of n*m basic units.
For the test, we will use the rice file. The graphic is a result with the adjustment of a model for the plot size and the coefficient of variation, see Figure 13.

> uniformity <- data.frame(table$uniformity)
> head(uniformity)

<table>
<thead>
<tr>
<th>Size</th>
<th>Width</th>
<th>Length</th>
<th>plots</th>
<th>Vx</th>
<th>CV</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>648</td>
<td>9044.539</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>324</td>
<td>7816.068</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>324</td>
<td>7831.232</td>
</tr>
<tr>
<td>4</td>
<td>3</td>
<td>1</td>
<td>3</td>
<td>216</td>
<td>7347.975</td>
</tr>
<tr>
<td>5</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td>216</td>
<td>7355.216</td>
</tr>
<tr>
<td>6</td>
<td>4</td>
<td>1</td>
<td>4</td>
<td>162</td>
<td>7047.717</td>
</tr>
</tbody>
</table>

8.8 Confidence Limits In Biodiversity Indices

The biodiversity indices are widely used for measuring the presence of living things in an ecological area. Many programs indicate their value. The function of 'agricolae' is also to show the confidence intervals, which can be used for a statistical comparison. Use the bootstrap procedure. The data are organized in a table; the species are placed in a column; and in another one, the number of individuals. The indices that can be calculated with the function index.bio() of 'agricolae' are: "Margalef", "Simpson.Dom", "Simpson.Div", "Berger.Parker", "McIntosh", and "Shannon."

In the example below, we will use the data obtained in the locality of Paracsho, district of Huasahuasi, province of Tarma in the department of Junin.
The evaluation was carried out in the parcels on 17 November 2005, without insecticide application. The counted specimens were the following:

```r
> data(paracsho)
> species <- paracsho[79:87,4:6]
> species

<table>
<thead>
<tr>
<th>Orden</th>
<th>Family</th>
<th>Number.of.specimens</th>
</tr>
</thead>
<tbody>
<tr>
<td>79</td>
<td>DIPTERA</td>
<td>TIPULIDAE</td>
</tr>
<tr>
<td>80</td>
<td>LEPIDOPTERA</td>
<td>NOCTUIDAE</td>
</tr>
<tr>
<td>81</td>
<td>NOCTUIDAE</td>
<td>PYRALIDAE</td>
</tr>
<tr>
<td>82</td>
<td>HEMIPTERA</td>
<td>ANTHOCORIDAE</td>
</tr>
<tr>
<td>83</td>
<td>DIPTERA</td>
<td>TACHINIDAE</td>
</tr>
<tr>
<td>84</td>
<td>DIPTERA</td>
<td>ANTHOCORIDAE</td>
</tr>
<tr>
<td>85</td>
<td>DIPTERA</td>
<td>SCATOPHAGIDAE</td>
</tr>
<tr>
<td>86</td>
<td>DIPTERA</td>
<td>SYRPHIDAE</td>
</tr>
<tr>
<td>87</td>
<td>DIPTERA</td>
<td>MUSCIDAE</td>
</tr>
</tbody>
</table>
```

The Shannon index is:

```r
> output <- index.bio(species[,3],method="Shannon",level=95,nboot=200)

Method: Shannon

The index: 3.52304

95 percent confidence interval:

3.180131 ; 4.260501

8.9 Correlation

The function correlation() of 'agricolae' makes the correlations through the methods of Pearson, Spearman and Kendall for vectors and/or matrices. If they are two vectors, the test is carried out for one or two lines; if it is a matrix one, it determines the probabilities for a difference, whether it is greater or smaller.

For its application, consider the soil data: data(soil)

```r
> data(soil)
> correlation(soil[,2:4],method="pearson")

$correlation

<table>
<thead>
<tr>
<th></th>
<th>pH</th>
<th>EC</th>
<th>CaCO3</th>
</tr>
</thead>
<tbody>
<tr>
<td>pH</td>
<td>1.00</td>
<td>0.55</td>
<td>0.73</td>
</tr>
<tr>
<td>EC</td>
<td>0.55</td>
<td>1.00</td>
<td>0.32</td>
</tr>
<tr>
<td>CaCO3</td>
<td>0.73</td>
<td>0.32</td>
<td>1.00</td>
</tr>
</tbody>
</table>

$pvalue

<table>
<thead>
<tr>
<th></th>
<th>pH</th>
<th>EC</th>
<th>CaCO3</th>
</tr>
</thead>
<tbody>
<tr>
<td>pH</td>
<td>1.000000000</td>
<td>0.0525330</td>
<td>0.004797027</td>
</tr>
<tr>
<td>EC</td>
<td>0.052532997</td>
<td>1.0000000</td>
<td>0.294159813</td>
</tr>
</tbody>
</table>
```
CaCO3 0.004797027 0.2941598 1.000000000

$n.\text{obs}$

[1] 13

> with(soil,correlation(pH,soil[,3:4],method="pearson"))

$correlation$

<table>
<thead>
<tr>
<th></th>
<th>EC</th>
<th>CaCO3</th>
</tr>
</thead>
<tbody>
<tr>
<td>pH</td>
<td>0.55</td>
<td>0.73</td>
</tr>
</tbody>
</table>

$pvalue$

<table>
<thead>
<tr>
<th></th>
<th>EC</th>
<th>CaCO3</th>
</tr>
</thead>
<tbody>
<tr>
<td>pH</td>
<td>0.0525</td>
<td>0.0048</td>
</tr>
</tbody>
</table>

$n.\text{obs}$

[1] 13

8.10 \texttt{tapply.stat()}

Gets a functional calculation of variables grouped by study factors.

Application with 'agricolae' data:

max(yield)-min(yield) by farmer

> data(RioChillon)
> with(RioChillon$babies,tapply.stat(yield,farmer,function(x) max(x)-min(x)))

<table>
<thead>
<tr>
<th>farmer</th>
<th>yield</th>
</tr>
</thead>
<tbody>
<tr>
<td>Augusto Zambrano</td>
<td>7.5</td>
</tr>
<tr>
<td>Caballero</td>
<td>13.4</td>
</tr>
<tr>
<td>Chocas Alto</td>
<td>14.1</td>
</tr>
<tr>
<td>Felix Andia</td>
<td>19.4</td>
</tr>
<tr>
<td>Huarangal-1</td>
<td>9.8</td>
</tr>
<tr>
<td>Huarangal-2</td>
<td>9.1</td>
</tr>
<tr>
<td>Huarangal-3</td>
<td>9.4</td>
</tr>
<tr>
<td>Huatocay</td>
<td>19.4</td>
</tr>
<tr>
<td>Ignacio Polinario</td>
<td>13.1</td>
</tr>
</tbody>
</table>

It corresponds to the range of variation in the farmers' yield.

The function "tapply" can be used directly or with function.

If A is a table with columns 1,2 and 3 as category, and 5,6 and 7 as variables, then the following procedures are valid:

\texttt{tapply.stat(A[,5:7], A[,1:3],mean)}
\texttt{tapply.stat(A[,5:7], A[,1:3],function(x) mean(x,na.rm=TRUE))}
\texttt{tapply.stat(A[,c(7,6)], A[,1:2],function(x) sd(x)*100/mean(x))}
8.11 Coefficient of variation of an experiment

If "model" is the object resulting from an analysis of variance of the function aov() or lm() of R, then the function cv.model() calculates the coefficient of variation.

```r
> data(sweetpotato)
> model <- aov(yield ~ virus, data=sweetpotato)
> cv.model(model)

[1] 17.1666
```

8.12 Skewness and kurtosis

The skewness and kurtosis results, obtained by 'agricolae', are equal to the ones obtained by SAS, MiniTab, SPSS, InfoStat, and Excel.

If x represents a data set:

```r
> x<-c(3,4,5,2,3,4,5,6,4,NA,7)
skewness is calculated with:

> skewness(x)

[1] 0.3595431

and kurtosis with:

> kurtosis(x)

[1] -0.1517996
```

8.13 Tabular value of Waller-Duncan

The function Waller determines the tabular value of Waller-Duncan. For the calculation, value F is necessary, calculated from the analysis of variance of the study factor, with its freedom degrees and the estimate of the variance of the experimental error. Value K, parameter of the function is the ratio between the two types of errors (I and II). To use it, a value associated with the alpha level is assigned. When the alpha level is 0.10, 50 is assigned to K; for 0.05, K=100; and for 0.01, K=500. K can take any value.

```r
> q<-5
> f<-15
> K<-seq(10,1000,100)
> n<-length(K)
> y<-rep(0,3*n)
> dim(y)<-c(n,3)
> for(i in 1:n) y[i,1]<-waller(K[i],q,f,Fc=2)
> for(i in 1:n) y[i,2]<-waller(K[i],q,f,Fc=4)
> for(i in 1:n) y[i,3]<-waller(K[i],q,f,Fc=8)
```
Function of Waller to different value of parameters $K$ and $F_c$ The next procedure illustrates
the function for different values of $K$ with freedom degrees of 5 for the numerator and 15 for the
denominator, and values of calculated $F$, equal to 2, 4, and 8.

```R
> par(mar=c(3,3,4,1),cex=0.7)
> plot(K,y[,1],type="l",col="blue",ylab="waller",bty="l")
> lines(K,y[,2],type="l",col="brown",lty=2,lwd=2)
> lines(K,y[,3],type="l",col="green",lty=4,lwd=2)
> legend("topleft",c("2","4","8"),col=c("blue","brown","green"),lty=c(1,8,20),
+ lwd=2,title="Fc")
> title(main="Waller in function of K")

Generating table Waller-Duncan

```R
> K<-100
> Fc<-1.2
> q<-c(seq(6,20,1),30,40,100)
> f<-c(seq(4,20,2),24,30)
> n<-length(q)
> m<-length(f)
> W.D <-rep(0,n*m)
> dim(W.D)<-c(n,m)
> for (i in 1:n) {
+ for (j in 1:m) {
+ W.D[i,j]<-waller(K, q[i], f[j], Fc)
+ }
> W.D<-round(W.D,2)
> dimnames(W.D)<-list(q,f)
> cat("table: Waller Duncan k=100, F=1.2")

table: Waller Duncan k=100, F=1.2

```R
> print(W.D)

<table>
<thead>
<tr>
<th></th>
<th>4</th>
<th>6</th>
<th>8</th>
<th>10</th>
<th>12</th>
<th>14</th>
<th>16</th>
<th>18</th>
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<td>3.07</td>
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<td>3.37</td>
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<td>2.85</td>
<td>3.01</td>
<td>3.11</td>
<td>3.19</td>
<td>3.26</td>
<td>3.31</td>
<td>3.35</td>
<td>3.38</td>
<td>3.41</td>
<td>3.45</td>
<td>3.50</td>
</tr>
</tbody>
</table>
40 2.85 3.02 3.13 3.22 3.29 3.35 3.39 3.43 3.47 3.52 3.58
100 2.85 3.04 3.17 3.28 3.36 3.44 3.50 3.55 3.59 3.67 3.76

8.14 AUDPC

The area under the disease progress curve (AUDPC), see Figure 14, calculates the absolute and relative progress of the disease. It is required to measure the disease in percentage terms during several dates, preferably equidistantly.

```r
> days<-c(7,14,21,28,35,42)
> evaluation<-data.frame(E1=10,E2=40,E3=50,E4=70,E5=80,E6=90)
> print(evaluation)
E1 E2 E3 E4 E5 E6
1 10 40 50 70 80
> absolute1 <-audpc(evaluation,days)
> relative1 <-round(audpc(evaluation,days,"relative"),2)
```

8.15 AUDPS

The Area Under the Disease Progress Stairs (AUDPS), see Figure 14. A better estimate of disease progress is the area under the disease progress stairs (AUDPS). The AUDPS approach improves the estimation of disease progress by giving a weight closer to optimal to the first and last observations.

```r
> absolute2 <-audps(evaluation,days)
> relative2 <-round(audps(evaluation,days,"relative"),2)
```

8.16 Non-Additivity

Tukey’s test for non-additivity is used when there are doubts about the additivity veracity of a model. This test confirms such assumption and it is expected to accept the null hypothesis of the non-additive effect of the model.

For this test, all the experimental data used in the estimation of the linear additive model are required. Use the function nonadditivity() of 'agricolae'. For its demonstration, the experimental data "potato", of the package 'agricolae', will be used. In this case, the model corresponds to the randomized complete block design, where the treatments are the varieties.
Tukey's test of nonadditivity

cutting

P : 15.37166
Q : 77.44441

Analysis of Variance Table

<table>
<thead>
<tr>
<th>Df</th>
<th>Sum Sq</th>
<th>Mean Sq</th>
<th>F value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nonadditivity</td>
<td>1</td>
<td>3.051</td>
<td>3.0511</td>
<td>0.922</td>
</tr>
<tr>
<td>Residuals</td>
<td>14</td>
<td>46.330</td>
<td>3.3093</td>
<td></td>
</tr>
</tbody>
</table>

According to the results, the model is additive because the p.value 0.35 is greater than 0.05.

### 8.17 LATEBLIGHT

LATEBLIGHT is a mathematical model that simulates the effect of weather, host growth and resistance, and fungicide use on asexual development and growth of Phytophthora infestans on potato foliage, see Figure 15

LATEBLIGHT Version LB2004 was created in October 2004 (Andrade-Piedra et al., 2005a, b and c), based on the C-version written by B.E. Ticknor ("BET 21191 modification of cbm8d29.c"), reported by Doster et al. (1990) and described in detail by Fry et al. (1991) (This version is referred as LB1990 by Andrade-Piedra et al. [2005a]). The first version of LATEBLIGHT was developed by Bruhn and Fry (1981) and described in detail by Bruhn et al. (1980).

```r
> options(digits=2)
> f <- system.file("external/weather.csv", package="agricolae")
> weather <- read.csv(f,header=FALSE)
> f <- system.file("external/severity.csv", package="agricolae")
> severity <- read.csv(f)
> weather[,1]<-as.Date(weather[,1],format = "%m/%d/%Y")
> dates<-as.Date(dates)
> EmergDate <- as.Date("2000/01/19")
> EndEpidDate <- as.Date("2000-04-22")
> dates<-as.Date(dates)
> NoReadingsH<- 1
> RHthreshold <- 90
> WS<-weatherSeverity(weather,severity,dates,EmergDate,EndEpidDate,
> NoReadingsH,RHthreshold)
> # Parameters to Lateblight function
```
> par(mar=c(3,3,4,1),cex=0.7)
> #--------------------------
> model<-lateblight(WS, Cultivar, ApplSys, InocDate, LGR, IniSpor, SR, IE, 
+ LP, MatTime='LATESEASON', InMicCol, main=main, type="l", xlab="Time (days after emergence)", ylab="Severity (Percentage)"")

Cultivar: NICOLA

Figure 15: lateblight: LATESEASON

> InocDate="2000-03-18"
> LGR <- 0.00410
> IniSpor <- 0
> SR <- 292000000
> IE <- 1.0
> LP <- 2.82
> InMicCol <- 9
> Cultivar <- "NICOLA"
> ApplSys <- "NOFUNGICIDE"
> main<-"Cultivar: NICOLA"
> head(model$Gfile)

dates nday MeanSeverity StDevSeverity MinObs
Eval1 2000-03-25 66 0.1 0 0.1
Eval2 2000-04-09 81 20.8 25 -3.9
Eval3 2000-04-12 84 57.0 33 24.3
Eval4 2000-04-16 88 94.0 8 86.0
Eval5 2000-04-22 94 97.0 4 93.0
MaxObs
Eval1 0.1
Eval2 45.5
Eval3 89.7
Eval4 102.0
Eval5 101.0

> str(model$Ofile)
'
data.frame': 94 obs. of 13 variables:
$ Date : Date, format: "2000-01-20" ...
$ nday : num 1 2 3 4 5 6 7 8 9 10 ...
$ MicCol : num 0 0 0 0 0 0 0 0 0 0 ...
$ SimSeverity: num 0 0 0 0 0 0 0 0 0 0 ...
$ LAI : num 0.01 0.0276 0.0384 0.0492 0.06 0.086 0.112 0.138 0.164 0.19 ...
$ LatPer : num 0 2 2 2 2 2 2 2 2 2 ...
$ LesExInc : num 0 0 0 0 0 0 0 0 0 0 ...
$ AttchSp : num 0 0 0 0 0 0 0 0 0 0 ...
$ AUDPC : num 0 0 0 0 0 0 0 0 0 0 ...
$ rLP : num 0 0 0 0 0 0 0 0 0 0 ...
$ InvrLP : num 0 0 0 0 0 0 0 0 0 0 ...
$ BlPr : num 0 0 0 0 0 0 0 0 0 0 ...
$ Defol : num 0 0 0 0 0 0 0 0 0 0 ...

> head(model$Ofile[,1:7])

<table>
<thead>
<tr>
<th>Date</th>
<th>nday</th>
<th>MicCol</th>
<th>SimSeverity</th>
<th>LAI</th>
<th>LatPer</th>
<th>LesExInc</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000-01-20</td>
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</tr>
<tr>
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<tr>
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</tr>
<tr>
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<td>5</td>
<td>0</td>
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<td>0.060</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
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<td>0</td>
<td>0.086</td>
<td>0.086</td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

Repeating graphic

> x<- model$Ofile$nday
> y<- model$Ofile$SimSeverity
> w<- model$Gfile$nday
> z<- model$Gfile$MeanSeverity
> Min<-model$Gfile$MinObs
> Max<-model$Gfile$MaxObs
> par(mar=c(3,2.5,1,1),cex=0.7)
> plot(x,y,type="l",xlim=c(65,95),lwd=1.5,xlab="Time (days after emergence)",
+ ylab="Severity (Percentage)")
> points(w,z,col="red",cex=1,pch=19); npoints <- length(w)
> for ( i in 1:npoints)segments(w[i],Min[i],w[i],Max[i],lwd=1.5,col="red")
> legend("topleft",c("Disease progress curves","Weather-Severity"),
+ title="Description",lty=1,pch=c(3,19),col=c("black","red"))

References


Purchase, J. L. (1997). Parametric analysis to describe genotype environment interaction and yield stability in winter wheat Department of Agronomy, Faculty of Agriculture of the University of the Free State Bloemfontein, South Africa.


