LA MOLINA NATIONAL AGRARIAN UNIVERSITY

FACULTY OF ECONOMICS AND PLANNING
DEPARTMENT OF STATISTICS AND INFORMATICS

Agricolae

version 1.1-3

PRACTICAL MANUAL

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PREFACE

R is a functional programming system exclusive to manage data in statistics and related sciences, such as mathematics, in environments like Windows, Linux and MAC. ‘Agricolae’ is a package of functions for R applied to agricultural research.

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, divided parcels, divided blocks. It also has several procedures of experimental data analysis, such as the comparisons of treatments of Waller-Duncan, Bonferroni, Duncan, Student-Newman-Keuls, Scheffe, or the classic LSD and Tukey; and non-parametric comparisons, such as Kruskal-Wallis, Friedman, Durbin and Waerden, stability analysis, and other procedures applied in genetics, as well as procedures in biodiversity and descriptive statistics.

For more details on the use of ‘agricolae’, see the reference manual and the aid system in HTML, which can be found in the menu of R.

1 INSTALLATION OF AGRICOLAE AND USE IN R

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 Development Core Team, 2012). As it is a free program, no identification is required. The packages can be incorporated through an installation process, directly from the platform of R.

‘Agricolae’ is a package for R, and as such its installation is just like any other package of R.

For Windows, the R program (version 2.15.2 or higher) is required.

If the R program is already installed in Windows or in another platform, the installation of ‘agricolae’ can be done directly from the console of R through Internet, that is

```
install.packages("agricolae)
```

A repository should be selected and the system is installed automatically.

If there is no Internet connection, it is necessary to copy the file agricolae_1.1-3. zip for Windows from the page of the R project.

The file agricolae_1.1-3.zip (De Mendiburu, 2012) can be downloaded from the R repository in the following addresses: www.r-project.org or http://cran.at.r-project.org/web/packages/agricolae/index.html

The file can be directly incorporated into R installing from the console with the following instruction set if the file is located in the address E:
install.packages("E:/agricolae_1.1-3.zip)

It can also be installed from the R menu:

Packages, Install package(s) from local zip files…. Selecting the file zip does not require any unpacking.

For a complete functionality, 'agricolae' requires other packages.

MASS: for the generalized inverse used in the function PBIB.test()
klaR: for the function triplot() used in the function AMMI()
akima: for the use of the function interpp() used in grid3p() for interpolation
Cluster: for the use of the function consensus()

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:
Load the package to the memory: library(agricolae)
Download: detach(package:agricolae)

Once the package is loaded, you can:
List the database: data(package="agricolae")
Load the sweet potato data: data(sweetpotato)
See its structure: str(sweetpotato)
Publish its content: fix(sweetpotato)

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

For help: help(sweetpotato); ? sweetpotato
To search any functions: apropos("design")

```
[1] "design.ab"       "design.alpha"    "design.bib"      "design.crd"
[5] "design.cyclic"   "design.dau"      "design.graeco"   "design.lattice"
[9] "design.lsd"      "design.rcbd"     "design.split"    "design.strip"
```

For the use of symbols that do not appear in the keyboard in Spanish, such as: ~, [,], &, ^, |. <, >, {, }, % or others, use the table 6.10.

2 DESCRIPTIVE STATISTICS

The package ‘agricolae’ provides some complementary functions to the R program, specifically for the management of the histogram.

2.1 HISTOGRAM

The histogram is constructed with the function graph.freq() and is associated to other functions: polygon.freq, table.freq, stat.freq, intervals.freq, sturges.freq, join.freq, ojiva.freq, and normal.freq.

Example 1.1 Data generated in R. (students’ weight). Figure 2.1

```
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)-> weight
```

Load the package ‘agricolae’:

```
library(agricolae)
par(mfrow=c(2,2),cex=0.7)
h1<- graph.freq(weight, col="yellow", frequency =1, main="Absolute
frequency", axes=FALSE)
axis(1,h1$breaks)
axis(2,0:10)
h2<- graph.freq(weight, frequency =2, main=" polygon of frequency",
axes=FALSE)
axis(1,h2$breaks)
axis(2,seq(0,0.3,0.1))
polygon.freq(h2, col="blue", lwd=2, frequency =2)
h3<- graph.freq(weight, col="brown", frequency =3, main="density",
axes=FALSE)
axis(1,h2$breaks)
h4<- graph.freq(weight, col="blue", frequency =3, main=" normal
density", density=4, axes=FALSE)
axis(1,h2$breaks)
normal.freq(h4, col="red", lty=4,lwd=2, frequency=3)
```

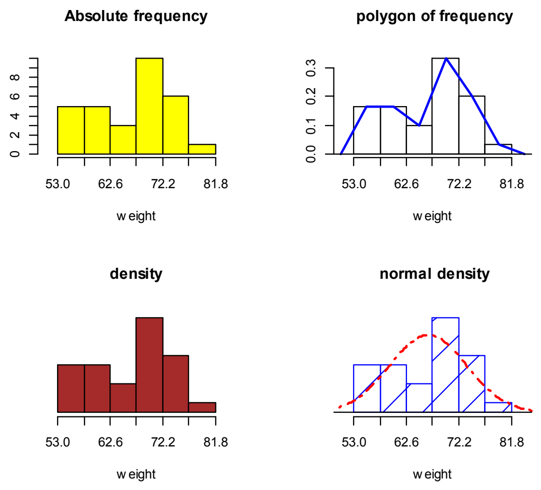

Figure 2.1 Histograms, polygon and density

2.2 HANDLING SCALES

It refers to the scale changes in the axes. Figure 2.2

```
par(mfrow=c(2,2),cex=0.7)
h5<- graph.freq(weight, axes=FALSE, frequency =1, main="Absolute
frequency")
axis(1,h5$breaks,las=2)
axis(2,h5$count)
h6<- graph.freq(weight, axes=FALSE, nclass=5, main="frecuency with 5
classes")
axis(1,h6$breaks,las=2)
axis(2,seq(0,10))
normal.freq(h6,col="red")
h7<- graph.freq(weight, density=6, col="blue", frequency =3,
main="density", axes=FALSE)
lines(density(weight),col="brown",lwd=2)
axis(1,h7$breaks,las=2)
h8<- graph.freq(weight, border=0, frequency =3, main="polygon and
density", axes=FALSE)
polygon.freq(h8,col="blue", frequency =3)
lines(density(weight),col="brown",lwd=2)
axis(1,h7$breaks,las=2)
```

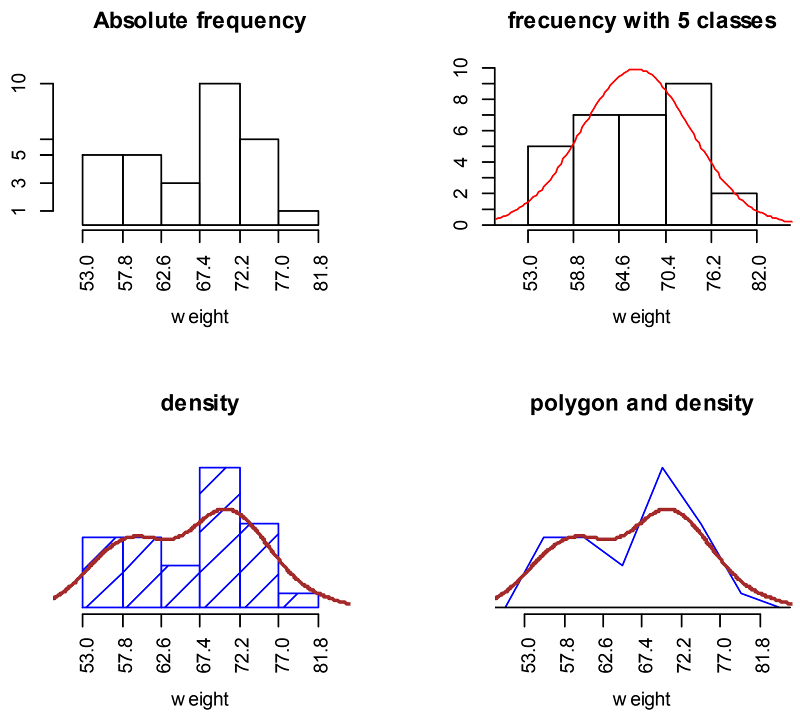

Figure 2.2. Scale change of the axes of coordinates

```
h9<-ojiva.freq(h5,axes=FALSE,type="b", main="ojiva of h5",
col="red")
axis(2,round(h9[,2],1),las=2)
axis(1,round(h9[,1],1),las=2)
```

2.3 FREQUENCY TABLES AND STATISTICS

Rounded off to two decimals:

```
round(table.freq(h6), 2)

  Lower Upper Main freq relative CF  RCF
   53.0  58.8 55.9    5     0.17  5 0.17
   58.8  64.6 61.7    7     0.23 12 0.40
   64.6  70.4 67.5    7     0.23 19 0.63
   70.4  76.2 73.3    9     0.30 28 0.93
   76.2  82.0 79.1    2     0.07 30 1.00
```

```
stat.freq(h6)
$variance
[1] 50.42133
$mean
[1] 66.72667
$median
[1] 67.08571
$mode
[ -     - ]      mode
 70.4  76.2   71.68889
```

2.4 REPRODUCING HISTOGRAMS AND USE OF hist()

The class of graph.freq() is graph.freq. Figure 2.3

Reproducing the histogram h6 (5 classes)

```
h10<-plot(h6, axes=FALSE, main="frequency with 5 classes")
axis(1,h6$breaks,las=2)
axis(2,seq(0,10))
normal.freq(h6,col="red")
round(summary(h6),2)

  Lower Upper Main freq relative CF  RCF
   53.0  58.8 55.9    5     0.17  5 0.17
   58.8  64.6 61.7    7     0.23 12 0.40
   64.6  70.4 67.5    7     0.23 19 0.63
   70.4  76.2 73.3    9     0.30 28 0.93
   76.2  82.0 79.1    2     0.07 30 1.00
```

The class types of the functions hist() and graph.freq() are 'histogram' and 'graph.freq', respectively. However, it is possible to establish compatibility between both functions.

```
hh <- hist(weight,nclass=5, plot=FALSE) # Reports 7 classes
# hist(weight,nclass=4) # Reports 4 classes
```

In order to show the relative frequencies, you can use graph.freq() with the object hh created by hist(), without modifying the classes.

```
h11<-graph.freq(hh, frequency=2,
col=colors()[367],main="relative",axes=F)
axis(1,h11$breaks,las=2)
axis(2,round(h11$relative,2),las=2)
```

See the summaries: > summary(hh), summary(h11)

The functions of 'agricolae' for the management of histograms function correctly on the objects created by the function hist() of R.

2.5 HISTOGRAM BASED ON GROUPED DATA

If there are grouped data, you can graphic and obtain the histogram summaries with the function graph.freq(), as, for example, in the following table:

0-10	10-20	20-30	30-40	40-50
3	8	15	18	6

```
In R we have:
classes <- c(0, 10, 20, 30, 40, 50)
frec <- c(3, 8, 15, 18, 6)
h12 <- graph.freq(classes,counts=frec, xlab="Classes",
main="Classes")
summary(h12)

  Lower Upper Main freq relative CF  RCF
      0    10    5    3     0.06  3 0.06
     10    20   15    8     0.16 11 0.22
     20    30   25   15     0.30 26 0.52
     30    40   35   18     0.36 44 0.88
     40    50   45    6     0.12 50 1.00
```

All the functions of ‘agricolae’ can be applied, including plot().

```
plot(h11, frequency=2, col=colors()[367],main="relative",axes=F)
axis(1,h11$breaks,las=2)
axis(2,round(h11$relative,2),las=2)
plot(h12, xlab="Classes", main="Classes")
```

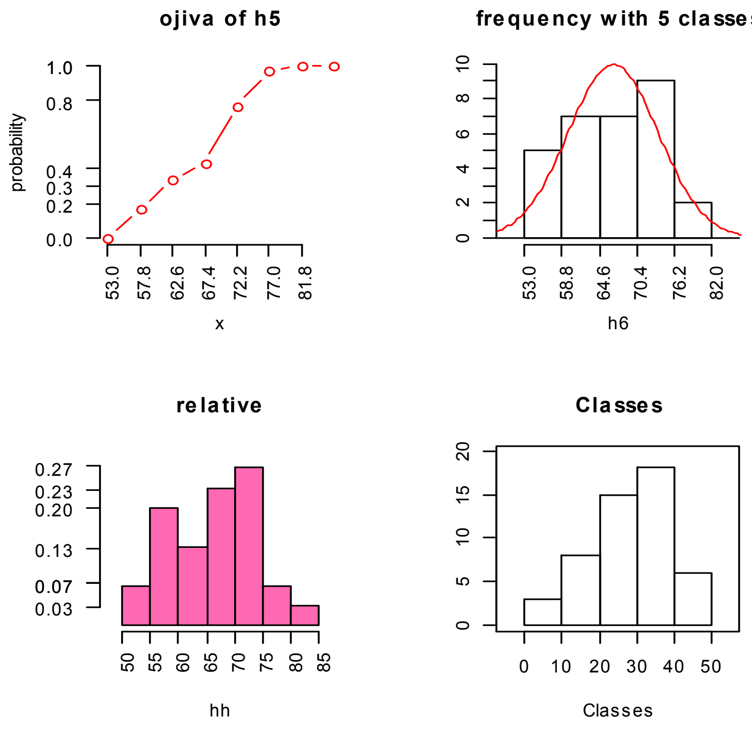

Figure 2.3 New scales for the histograms

2.6 JOINING CLASSES

Knowing the students' weight, the original intervals can be changed, joining, for example:

```
intervals.freq(h5$breaks)
     lower upper
[1,]  53.2  58.0
[2,]  58.0  62.8
[3,]  62.8  67.6
[4,]  67.6  72.4
[5,]  72.4  77.2
[6,]  77.2  82.0
```

```
nuevas<- join.freq(h5$breaks,1:2)
intervals.freq(nuevas)
     lower upper
[1,]  53.2  62.8
[2,]  62.8  67.6
[3,]  67.6  72.4
[4,]  72.4  77.2
[5,]  77.2  82.0
h13 <- graph.freq(peso, breaks=nuevas)
```

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, 1992; Kuehl, 2000; Montgomery, 2002; LeClerg, 1962). 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 agriculture http://cran.at.r-project.org/web/packages/agricolae/agricolae.pdf)

3.1 COMPLETELY RANDOMIZED DESIGNS

They only require the names of the treatments and the number of their repetitions.

```
trt <- c("A", "B", "C")
repetition <- c(4, 3, 4)
plan1 <- design.crd(trt,r=repetition)
```

```
   plots trt r
1      1   A 1
2      2   C 1
3      3   A 2
4      4   A 3
5      5   B 1
6      6   C 2
7      7   C 3
8      8   B 2
9      9   A 4
10    10   B 3
11    11   C 4
```

Excel:
```
write.csv(plan1,"plan1.csv",row.names=FALSE)
```

3.2 RANDOMIZED COMPLETE BLOCK DESIGN

They require the names of the treatments and the number of blocks.

```
trt <- c("A", "B", "C")
repetition <- 4
plan2 <- design.rcbd(trt,r=repetition, seed=5, number=101,
first=FALSE)
t(matrix(plan2[ ,3],c(3,4)))
     [,1] [,2] [,3]
[1,] "A"  "B"  "C"
[2,] "C"  "A"  "B"
[3,] "C"  "A"  "B"
[4,] "A"  "C"  "B"
```

The plan can be sent to excel as a field book.

3.3 LATIN SQUARE DESIGNS

They require the names of the treatments.

```
trt <- c("A", "B", "C", "D")
plan3 <- design.lsd(trt, seed=55, number=101, first=FALSE)
t(matrix(plan3[,4],c(4,4)))
      [,1] [,2] [,3] [,4]
[1,] "A"  "B"  "D"  "C"
[2,] "B"  "C"  "A"  "D"
[3,] "D"  "A"  "C"  "B"
[4,] "C"  "D"  "B"  "A"
```

3.4 GRAECO-LATIN DESIGNS

They require the names of the treatments of each factor of study.

```
T1 <- c("A", "B", "C", "D")
T2 <- 1:4
plan4 <- design.graeco(T1,T2, seed=55, number=101)
t(matrix(paste(plan4[ ,4],plan4[ ,5] ),c(4,4)))

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

3.5 BALANCED INCOMPLETE BLOCK DESIGNS

They require the names of the treatments and the size of the block.

```
trt <- c("A", "B", "C", "D", "Control")
k <- 4
plan5 <- design.bib(trt,k, seed=55, number=101)
```

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

Efficiency factor 0.9375

<<< Book >>>
```

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

```
t(matrix(plan5[ ,3],c(4,5)))
     [,1]      [,2]      [,3]      [,4]
[1,] "B"       "Control" "C"       "A"
[2,] "D"       "A"       "C"       "B"
[3,] "B"       "C"       "Control" "D"
[4,] "C"       "D"       "A"       "Control"
[5,] "Control" "B"       "D"       "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, III and V.

3.6 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.

```
trt <- c("A", "B", "C", "D", "E", "F")
plan5 <- design.cyclic(trt,k=3, r=6, seed=55, number=101)

cyclic design
Generator block basic:
1 2 4
1 3 2

Parameters
===================
treatments:  6
Block size:  3
Replication: 6

> plan5$design[[1]]
     [,1] [,2] [,3]
[1,] "F"  "A"  "C"
[2,] "A"  "D"  "B"
[3,] "B"  "C"  "E"
[4,] "D"  "F"  "C"
[5,] "A"  "D"  "E"
[6,] "B"  "E"  "F"
```

```
> plan5$design[[2]]
     [,1] [,2] [,3]
[1,] "D"  "E"  "C"
[2,] "E"  "F"  "D"
[3,] "B"  "C"  "D"
[4,] "A"  "F"  "E"
[5,] "C"  "B"  "A"
[6,] "B"  "F"  "A"
```

12 blocks of 4 treatments each have been generated.

3.7 LATTICE DESIGNS

They require a number of treatments of a perfect square; for example 9, 16, 25, 36, 49, etc.

They can generate a simple lattice (2 rep.) or a triple lattice (3 rep.)

generating a triple lattice design for 9 treatments 3x3

```
plan6 <- design.lattice(k=3, seed=55, number=101)

print(plan6)

$square1
      [,1] [,2] [,3]
[1,]     1    4    8
[2,]     2    9    3
[3,]     5    7    6
$square2
       [,1] [,2] [,3]
[1,]      2    1    5
[2,]      9    4    7
[3,]      3    8    6
$square3
       [,1] [,2] [,3]
[1,]      2    4    6
[2,]      3    1    7
[3,]      9    8    5

$plan
   plots sqr block trt
1    101   1     1   1
2    102   1     1   4
...
27   127   3     9   5
```

3.8 ALPHA DESIGNS

These designs are generated by the alpha arrangements (Patterson & Williams, 1976). They are similar to the lattice designs, but the tables are rectangular, with *s* blocks x *k* treatments. The number of treatments should be equal to s*k and all the experimental units, r*s*k.

```
Genotype<-paste("geno", 1:15, sep = "")
plan7 <- design.alpha(Genotype,k=3,r=2,seed=55)
```

```
alpha design (0,1) - Serie  I

Parameters Alpha design
=======================
treatmeans : 15
Block size : 3
Blocks     : 5
Replication: 2

Efficiency factor
(E ) 0.6363636

<<< Book >>>

plan7$design$rep1
     [,1]     [,2]     [,3]
[1,] "geno8"  "geno4"  "geno10"
[2,] "geno1"  "geno12" "geno14"
[3,] "geno6"  "geno2"  "geno15"
[4,] "geno7"  "geno3"  "geno11"
[5,] "geno13" "geno9"  "geno5"

plan7$design$rep2
     [,1]     [,2]     [,3]
[1,] "geno13" "geno7"  "geno1"
[2,] "geno8"  "geno5"  "geno14"
[3,] "geno4"  "geno11" "geno15"
[4,] "geno6"  "geno3"  "geno12"
[5,] "geno10" "geno2"  "geno9"
```

3.9 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.

```
common <- c("A", "B", "C", "D")
others <- c("t","u","v","w","x","y","z")
plan8 <- design.dau(common,others, r=5, seed=55, number=101)
by(plan8$trt, plan8$block,function(x) as.character(x))
block: 1
[1] "D" "A" "v" "C" "B" "u"
------------------------------------------------------------
block: 2
[1] "t" "D" "A" "x" "B" "C"
------------------------------------------------------------
block: 3
[1] "D" "C" "B" "A" "w"
------------------------------------------------------------
block: 4
[1] "A" "C" "D" "B" "y"
------------------------------------------------------------
```

```
block: 5
[1] "z" "A" "B" "D" "C"

print(plan8)

   plots block trt
1    101     1   A
2    102     1   t
3    103     1   B
4    104     1   D
...
32   132     5   D
```

For augmented randomized complete block designs, use the function design.crd().

3.10 SPLIT-PLOT DESIGNS

These designs have two factors, one is applied in plots and is defined as A in a randomized complete block design; and a second factor, 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.

```
t1<-c("A","B","C","D")
t2<-c("a","b","c")
plan9 <-design.split(t1,t2,r=3,number=101,seed=45, first=FALSE)
print(plan9)
   plots block t1 t2
1    101     1  A  b
2    101     1  A  a
3    101     1  A  c
4    102     1  B  c
. . .
36   112     3  D  c
p<-plan9$t1[seq(1,36,3)]
q<-NULL
for(i in 1:12) q<-c(q,paste(plan9$t2[3*(i-1)+1],plan9$t2[3*(i-
1)+2],plan9$t2[3*(i-1)+3]))

In the plots

> print(t(matrix(p,c(4,3)) ))
     [,1] [,2] [,3] [,4]
[1,] "A"  "B"  "C"  "D"
[2,] "B"  "D"  "C"  "A"
[3,] "A"  "B"  "C"  "D"
> print(t(matrix(q,c(4,3)) ))
     [,1]    [,2]    [,3]    [,4]
[1,] "b a c" "c b a" "a b c" "b a c"
[2,] "a c b" "a c b" "b a c" "b a c"
[3,] "c b a" "c a b" "a c b" "a b c"
```

3.11 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.

```
t1<-c("A","B","C")
t2<-c("a","b","c","d")
```

```
plan10 <-design.strip(t1,t2,r=3,number=101,seed=45)
print(plan10)

   plots block t1 t2
1    101     1  B  b
2    102     1  B  a
3    103     1  B  d
4    104     1  B  c
...
36   136     3  A  c

t3<-paste(plan10$t1,plan10$t2)
B1<-t(matrix(t3[1:12],c(4,3)))
B2<-t(matrix(t3[13:24],c(4,3)))
B3<-t(matrix(t3[25:36],c(4,3)))

> print(B1)
     [,1]  [,2]  [,3]  [,4]
[1,] "B b" "B a" "B d" "B c"
[2,] "C b" "C a" "C d" "C c"
[3,] "A b" "A a" "A d" "A c"
> print(B2)
     [,1]  [,2]  [,3]  [,4]
[1,] "A c" "A a" "A d" "A b"
[2,] "C c" "C a" "C d" "C b"
[3,] "B c" "B a" "B d" "B b"
> print(B3)
     [,1]  [,2]  [,3]  [,4]
[1,] "B d" "B a" "B b" "B c"
[2,] "C d" "C a" "C b" "C c"
[3,] "A d" "A a" "A b" "A c"
```

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() (Steel, 1996) and durbin.test(), kruskal(), friedman() and waerden.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] 17.16660
attach(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, 1997).

```
# comparison <- LSD.test(yield,virus,df,MSerror)
LSD.test(model, "virus")
Study:

LSD t Test for yield

Mean Square Error:  22.48917

virus,  means and individual ( 95 %) CI

      yield  std.err r       LCL      UCL Min. Max.
cc 24.40000 2.084067 3 19.594134 29.20587 21.7 28.5
fc 12.86667 1.246774 3  9.991602 15.74173 10.6 14.9
ff 36.33333 4.233727 3 26.570341 46.09633 28.0 41.8
oo 36.90000 2.482606 3 31.175100 42.62490 32.1 40.4

alpha: 0.05 ; Df Error: 8
Critical Value of t: 2.306004

Least Significant Difference 8.928965
Means with the same letter are not significantly different.

Groups, Treatments and means
a        oo      36.9
a        ff      36.33
b        cc      24.4
c        fc      12.87
```

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:

```
# comparison <- LSD.test(yield, virus,df, MSerror, group=F)
comparison <-LSD.test(model, "virus", group=F)

LSD t Test for yield

Mean Square Error:  22.48917

virus,  means and individual ( 95 %) CI

      yield  std.err r       LCL      UCL Min. Max.
cc 24.40000 2.084067 3 19.594134 29.20587 21.7 28.5
fc 12.86667 1.246774 3  9.991602 15.74173 10.6 14.9
ff 36.33333 4.233727 3 26.570341 46.09633 28.0 41.8
oo 36.90000 2.482606 3 31.175100 42.62490 32.1 40.4
```

```
alpha: 0.05 ; Df Error: 8
Critical Value of t: 2.306004

Comparison between treatments means

         Difference       pvalue sig        LCL        UCL
cc - fc  11.5333333 0.0176377595   *   2.604368  20.462299
cc - ff -11.9333333 0.0150730851   * -20.862299  -3.004368
cc - oo -12.5000000 0.0120884239   * -21.428965  -3.571035
fc - ff -23.4666667 0.0003023690 *** -32.395632 -14.537701
fc - oo -24.0333333 0.0002574929 *** -32.962299 -15.104368
ff - oo  -0.5666667 0.8872673216      -9.495632   8.362299
```

The significance code “sig” is interpreted as:

```
"***": p.valor < 0.001
"** ": 0.001 <p.valor < 0.01
"*  ": 0.01 < p.valor < 0.05
".  ": 0.05 < p.valor < 0.10
```

```
> comparison

$statistics
    Mean      CV  MSerror
  27.625 17.1666 22.48917

$parameters
  Df ntr  t.value
   8   4 2.306004

$means
      yield  std.err r       LCL      UCL Min. Max.
cc 24.40000 2.084067 3 19.594134 29.20587 21.7 28.5
fc 12.86667 1.246774 3  9.991602 15.74173 10.6 14.9
ff 36.33333 4.233727 3 26.570341 46.09633 28.0 41.8
oo 36.90000 2.482606 3 31.175100 42.62490 32.1 40.4

$comparison
         Difference       pvalue sig        LCL        UCL
cc - fc  11.5333333 0.0176377595   *   2.604368  20.462299
cc - ff -11.9333333 0.0150730851   * -20.862299  -3.004368
cc - oo -12.5000000 0.0120884239   * -21.428965  -3.571035
fc - ff -23.4666667 0.0003023690 *** -32.395632 -14.537701
fc - oo -24.0333333 0.0002574929 *** -32.962299 -15.104368
ff - oo  -0.5666667 0.8872673216      -9.495632   8.362299

$groups
NULL
```

4.2 BONFERRONI

With the function LSD.test() we can make adjustments to the probabilities found, as for example the adjustment by Bonferroni.

```
LSD.test(model, "virus", group=F, p.adj= "bon")

LSD t Test for yield
P value adjustment method: bonferroni

alpha: 0.05 ; Df Error: 8
Critical Value of t: 3.478879

Comparison between treatments means

          Difference   pvalue sig        LCL         UCL
cc - fc   11.5333333 0.105827      -1.937064  25.0037305
cc - ff  -11.9333333 0.090439    . -25.403730   1.5370638
cc - oo  -12.5000000 0.072531    . -25.970397   0.9703971
fc - ff  -23.4666667 0.001814   ** -36.937064  -9.9962695
fc - oo  -24.0333333 0.001545   ** -37.503730 -10.5629362
ff - oo   -0.5666667 1.000000     -14.037064  12.9037305
```

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 parameters 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, 1997).

```
duncan.test(model, "virus")

Duncan's new multiple range test
for yield

Mean Square Error:  22.48917

virus,  means

      yield  std.err r Min. Max.
cc 24.40000 2.084067 3 21.7 28.5
fc 12.86667 1.246774 3 10.6 14.9
ff 36.33333 4.233727 3 28.0 41.8
oo 36.90000 2.482606 3 32.1 40.4

alpha: 0.05 ; Df Error: 8

Critical Range
       2        3        4
8.928965 9.304825 9.514910
```

```
Means with the same letter are not significantly different.

Groups, Treatments and means
a        oo      36.9
a        ff      36.33
b        cc      24.4
c        fc      12.87
```

```
duncan.test(model, "virus", group=FALSE)
```

```
Duncan's new multiple range test
for yield

Mean Square Error:  22.48917

alpha: 0.05 ; Df Error: 8

Critical Range
       2        3        4
8.928965 9.304825 9.514910

Comparison between treatments means

         Difference   pvalue sig        LCL        UCL
cc - fc  11.5333333 0.017638   *   2.604368  20.462299
cc - ff -11.9333333 0.015073   * -20.862299  -3.004368
cc - oo -12.5000000 0.014544   * -21.804825  -3.195175
fc - ff -23.4666667 0.000388 *** -32.771492 -14.161842
fc - oo -24.0333333 0.000387 *** -33.548244 -14.518423
ff - oo  -0.5666667 0.887267      -9.495632   8.362299
```

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, 1997).

```
SNK.test(model, "virus", alpha=0.05)
```

```
Student Newman Keuls Test
for yield

Mean Square Error:  22.48917

virus,  means

      yield  std.err r Min. Max.
cc 24.40000 2.084067 3 21.7 28.5
fc 12.86667 1.246774 3 10.6 14.9
ff 36.33333 4.233727 3 28.0 41.8
oo 36.90000 2.482606 3 32.1 40.4

alpha: 0.05 ; Df Error: 8

Critical Range
        2         3         4
 8.928965 11.064170 12.399670
```

```
Means with the same letter are not significantly different.

Groups, Treatments and means
a        oo      36.9
a        ff      36.33
b        cc      24.4
c        fc      12.87
```

```
SNK.test(model, "virus", group=FALSE)
```

```
Student Newman Keuls Test
for yield

Mean Square Error:  22.48917

alpha: 0.05 ; Df Error: 8

Critical Range
        2         3         4
 8.928965 11.064170 12.399670

Comparison between treatments means

       Difference   pvalue sig        LCL        UCL
cc-fc  11.5333333 0.017638   *   2.604368  20.462299
cc-ff -11.9333333 0.015073   * -20.862299  -3.004368
cc-oo -12.5000000 0.029089   * -23.564170  -1.435830
fc-ff -23.4666667 0.000777 *** -34.530836 -12.402497
fc-oo -24.0333333 0.001162  ** -36.433003 -11.633664
ff-oo  -0.5666667 0.887267      -9.495632   8.362299
```

4.5 TUKEY'S W PROCEDURE (HSD)

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

```
comparison1 <- HSD.test(model, "virus")
```

```
HSD Test for yield

Mean Square Error:  22.48917

virus,  means

      yield  std.err r Min. Max.
cc 24.40000 2.084067 3 21.7 28.5
fc 12.86667 1.246774 3 10.6 14.9
ff 36.33333 4.233727 3 28.0 41.8
oo 36.90000 2.482606 3 32.1 40.4

alpha: 0.05 ; Df Error: 8
Critical Value of Studentized Range: 4.52881

Honestly Significant Difference: 12.39967

Means with the same letter are not significantly different.
```

```
Groups, Treatments and means
a        oo      36.9
ab       ff      36.33
bc       cc      24.4
c        fc      12.87
```

```
> comparison1
```

```
$statistics
    Mean      CV  MSerror      HSD
  27.625 17.1666 22.48917 12.39967

$parameters
  Df ntr StudentizedRange
   8   4          4.52881

$means
      yield  std.err r Min. Max.
cc 24.40000 2.084067 3 21.7 28.5
fc 12.86667 1.246774 3 10.6 14.9
ff 36.33333 4.233727 3 28.0 41.8
oo 36.90000 2.482606 3 32.1 40.4

$comparison
NULL

$groups
  trt    means  M
1  oo 36.90000  a
2  ff 36.33333 ab
3  cc 24.40000 bc
4  fc 12.86667  c
```

4.6 WALLER-DUNCAN'S BAYESIAN K-RATIO t-TEST

In 1975, 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 (Steel, 1997).

```
# variance analysis:

anova(model)
```

```
Analysis of Variance Table

Response: yield
          Df  Sum Sq Mean Sq F value    Pr(>F)
virus      3 1170.21  390.07  17.345 0.0007334 ***
Residuals  8  179.91   22.49
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The value of calculated F is 17,345. For the comparetive treatment analysis, it is required that 'sweetpotato' be active, thus:

```
attach(sweetpotato)
```

then:

```
waller.test(yield,virus,df,MSerror,Fc= 17.345, group=F)

In another case with only invoking the model object:

comparison2 <- waller.test(model, "virus", group=FALSE)

Waller-Duncan K-ratio t Test for yield

This test minimizes the Bayes risk under additive
loss and certain other assumptions.
                                ......
K ratio                    100.00000
Error Degrees of Freedom     8.00000
Error Mean Square           22.48917
F value                     17.34478
Critical Value of Waller     2.23600

virus,  means

      yield  std.err r Min. Max.
cc 24.40000 2.084067 3 21.7 28.5
fc 12.86667 1.246774 3 10.6 14.9
ff 36.33333 4.233727 3 28.0 41.8
oo 36.90000 2.482606 3 32.1 40.4

Minimum Significant Difference 8.657906
Comparison between treatments means

        Difference significant
cc - fc 11.5333333        TRUE
ff - cc 11.9333333        TRUE
oo - cc 12.5000000        TRUE
ff - fc 23.4666667        TRUE
oo - fc 24.0333333        TRUE
oo - ff  0.5666667       FALSE
```

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

The found object “compare” has information to make other procedures.

```
> names(comparison2)
[1] "statistics" "parameters" "means"      "comparison" "groups"

> comparison2$statistics

    Mean      CV  MSerror  F.Value CriticalDifference
  27.625 17.1666 22.48917 17.34478           8.657906
```

4.7 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, 1997).

```
# analysis of variance:
```

```
model<-aov(yield~virus, data=sweetpotato)
scheffe.test(model,"virus", group=TRUE,
main="Yield of sweetpotato\nDealt with different virus")

Study: Yield of sweetpotato
Dealt with different virus

Scheffe Test for yield

Mean Square Error  : 22.48917

virus,  means

      yield  std.err r Min. Max.
cc 24.40000 2.084067 3 21.7 28.5
fc 12.86667 1.246774 3 10.6 14.9
ff 36.33333 4.233727 3 28.0 41.8
oo 36.90000 2.482606 3 32.1 40.4

alpha: 0.05 ; Df Error: 8
Critical Value of F: 4.066181

Minimum Significant Difference: 13.52368

Means with the same letter are not significantly different.

Groups, Treatments and means
a        oo      36.9
a        ff      36.33
ab       cc      24.4
b        fc      12.87
```

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

```
comparison3 <- scheffe.test(model,"virus", group=FALSE)

Study:

Scheffe Test for yield

Mean Square Error  : 22.48917

virus,  means

      yield  std.err r Min. Max.
cc 24.40000 2.084067 3 21.7 28.5
fc 12.86667 1.246774 3 10.6 14.9
ff 36.33333 4.233727 3 28.0 41.8
oo 36.90000 2.482606 3 32.1 40.4

alpha: 0.05 ; Df Error: 8
Critical Value of F: 4.066181
```

```
Comparison between treatments means

          Difference   pvalue sig        LCL         UCL
cc - fc   11.5333333 0.097816   .  -1.000348  24.0670149
cc - ff  -11.9333333 0.085487   . -24.467015   0.6003483
cc - oo  -12.5000000 0.070607   . -25.033682   0.0336816
fc - ff  -23.4666667 0.002331  ** -36.000348 -10.9329851
fc - oo  -24.0333333 0.001998  ** -36.567015 -11.4996517
ff - oo   -0.5666667 0.999099     -13.100348  11.9670149
```

4.8 MULTIPLE COMPARISON IN FACTORIAL TREATMENTS

In a factorial combined effects of the treatments. Comparetive tests: LSD, HSD, Waller-Duncan, Duncan, Scheffé, SNK can be applied.

```
model <-aov (y ~ A * B * C, data)
compare <-LSD.test (model, c ("A", "B", "C"))
```

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)
```

```
  block clone nitrogen yield
1     1    c1       n1     6
2     1    c1       n2     7
3     1    c1       n3     9
4     1    c2       n1    13
5     1    c2       n2    16
6     1    c2       n3    20
```

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

```
Analysis of Variance Table

Response: yield
               Df Sum Sq Mean Sq  F value    Pr(>F)
block           3  20.75   6.917   5.8246 0.0038746 **
clone           2 497.72 248.861 209.5673 6.370e-16 ***
nitrogen        2  54.06  27.028  22.7602 2.865e-06 ***
clone:nitrogen  4  43.28  10.819   9.1111 0.0001265 ***
Residuals      24  28.50   1.187
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
out <-LSD.test (model, c("clone", "nitrogen"), main = "Yield ~ block
+ nitrogen + clone + clone:nitrogen")

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

LSD t Test for yield

Mean Square Error:  1.1875

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

      yield   std.err r       LCL       UCL Min. Max.
c1:n1  7.50 0.6454972 4  6.167759  8.832241    6    9
c1:n2  8.50 0.6454972 4  7.167759  9.832241    7   10
c1:n3  9.00 0.4082483 4  8.157417  9.842583    8   10
c2:n1 13.50 0.6454972 4 12.167759 14.832241   12   15
c2:n2 16.75 0.4787136 4 15.761984 17.738016   16   18
c2:n3 20.25 0.8539126 4 18.487611 22.012389   18   22
c3:n1  9.50 0.6454972 4  8.167759 10.832241    8   11
c3:n2  9.50 0.8660254 4  7.712611 11.287389    8   12
c3:n3 10.25 0.7500000 4  8.702076 11.797924    9   12

alpha: 0.05 ; Df Error: 24
Critical Value of t: 2.063899

Least Significant Difference 1.590341
Means with the same letter are not significantly different.

Groups, Treatments and means
a        c2:n3   20.25
b        c2:n2   16.75
c        c2:n1   13.5
d        c3:n3   10.25
de       c3:n1   9.5
de       c3:n2   9.5
def      c1:n3   9
ef       c1:n2   8.5
f        c1:n1   7.5

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

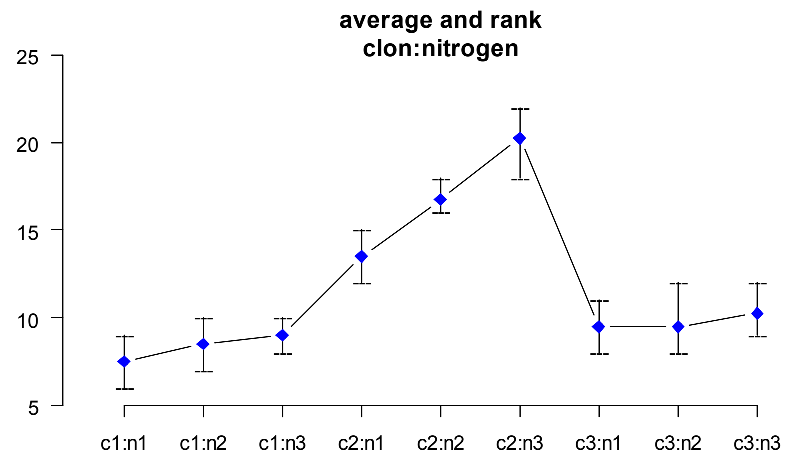

Figure 4.1 Combined clone:nitrogen

4.9 GRAPHICS OF THE MULTIPLE COMPARISON

The results of a comparison can be graphically seen with the functions bar.group() and bar.err().
The found object of one comparison is the entry for these functions, Figure 4.2.
The objects compare1 and compare2 are used in the following exercise:

comparison1, for the functions bar.group() and bar.err()
comparison2, for the function bar.err()

```
par(mfrow=c(2,2))
c1<-colors()[480]; c2=colors()[65]; c3=colors()[15];
c4=colors()[140]
G1<-bar.group(comparison1$groups, ylim=c(0,45),
main="Tukey\nG1",col=c1)
G2<-bar.group(comparison1$groups, horiz=T, xlim=c(0,45),
main="Tukey\nG2",col=c2)
G3<-bar.err(comparison2$means, variation="std",ylim=c(0,45), col=c3,
main="Standard deviation\nG3")
G4<-bar.err(comparison2$means, horiz=T, xlim=c(0,45), col=c4,
variation="SE",,main="Standard error \nG4")
```

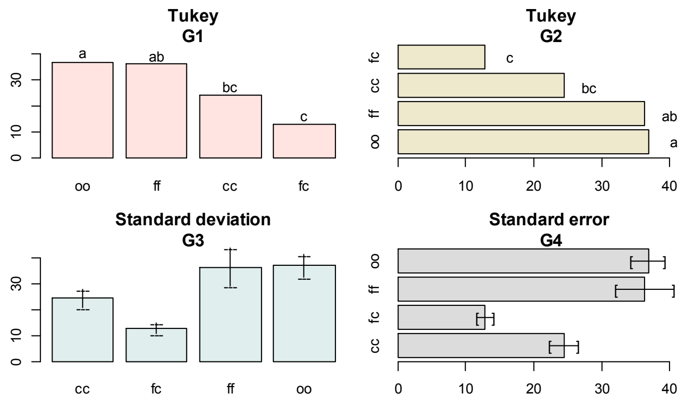

Figure 4.2 Comparison between treatments

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 PBIB.test(), for partially balanced designs. In the following example, the ‘agricolae’ data will be used.

```
#Example linear estimation and design of experiments. (Joshi, 1987)
# Profesor de Estadistica, Institute of Social Sciences Agra, India
# 6 variedades de trigo en 10 bloques de 3 parcelas cada una.
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)

BIB.test(block, variety, y)
```

```
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
            Df  Sum Sq Mean Sq F value  Pr(>F)
block.unadj  9  466.97  51.885  0.9019 0.54712
trt.adj      5 1156.44 231.289  4.0206 0.01629 *
Residuals   15  862.89  57.526
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

coefficient of variation: 12.6 %
y Means: 60.3

variety,  statistics

     y mean.adj       SE r  std.err Min. Max.
1 70.2 75.13333 3.728552 5 2.267157   63   77
2 60.0 58.71667 3.728552 5 2.190890   54   65
3 59.4 58.55000 3.728552 5 5.537147   45   75
4 55.0 54.96667 3.728552 5 4.404543   38   62
5 61.4 60.05000 3.728552 5 2.014944   54   65
6 55.8 54.38333 3.728552 5 4.810405   39   67

LSD test
Std.diff   : 5.363111
Alpha      : 0.05
LSD        : 11.4312
Parameters BIB
Lambda     : 2
treatmeans : 6
Block size : 3
Blocks     : 10
```

```
Replication: 5

Efficiency factor 0.8

<<< Book >>>

Means with the same letter are not significantly different.

Comparison of treatments

Groups, Treatments and means
a        1       75.13
b        5       60.05
b        2       58.72
b        3       58.55
b        4       54.97
b        6       54.38
```

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:

```
out <-BIB.test(block, trt=variety, y, test="tukey",group=FALSE)
```

```
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
            Df  Sum Sq Mean Sq F value  Pr(>F)
block.unadj  9  466.97  51.885  0.9019 0.54712
trt.adj      5 1156.44 231.289  4.0206 0.01629 *
Residuals   15  862.89  57.526
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

coefficient of variation: 12.6 %
y Means: 60.3

variety,  statistics

     y mean.adj       SE r  std.err Min. Max.
1 70.2 75.13333 3.728552 5 2.267157   63   77
2 60.0 58.71667 3.728552 5 2.190890   54   65
3 59.4 58.55000 3.728552 5 5.537147   45   75
4 55.0 54.96667 3.728552 5 4.404543   38   62
5 61.4 60.05000 3.728552 5 2.014944   54   65
6 55.8 54.38333 3.728552 5 4.810405   39   67

Tukey
Alpha      : 0.05
```

```
Std.err    : 3.792292
HSD        : 17.42458
Parameters BIB
Lambda     : 2
treatmeans : 6
Block size : 3
Blocks     : 10
Replication: 5

Efficiency factor 0.8

<<< Book >>>

Comparison between treatments means
      Difference   pvalue sig
1 - 2 16.4166667 0.070509   .
1 - 3 16.5833333 0.066649   .
1 - 4 20.1666667 0.019092   *
1 - 5 15.0833333 0.109602
1 - 6 20.7500000 0.015510   *
2 - 3  0.1666667 1.000000
2 - 4  3.7500000 0.979184
2 - 5 -1.3333333 0.999840
2 - 6  4.3333333 0.961588
3 - 4  3.5833333 0.982927
3 - 5 -1.5000000 0.999715
3 - 6  4.1666667 0.967375
4 - 5 -5.0833333 0.927273
4 - 6  0.5833333 0.999997
5 - 6  5.6666667 0.890815
```

The found "outl" object can be used for the functions bar.group() and bar.err() for the bar graphics, in the same way as previously.

```
names(out)
[1] "parameters" "statistics" "comparison" "means" "groups"

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

4.10 PARTIALLY BALANCED INCOMPLETE BLOCKS

The function 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.

```
library(agricolae)
library(MASS)
library(lme4)
# 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 ) 0.6170213

<<< 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.

```
data<-data.frame(plan$book,yield)
rm(yield,Genotype)
```

The analysis:

```
attach(data)
model <- PBIB.test(block, Genotype, replication, yield, k=3,
group=TRUE)
detach(data)

ANALYSIS PBIB:  yield

Class level information
block : 20
Genotype : 30

Number of observations:  60

Estimation Method:  REML

Parameter Estimates
                  Variance
block:replication 2.834033
replication       0.000000
Residual          2.003098

                      Fit Statistics
-2 Res Log Likelihood       147.6594
AIC                         215.6594
BIC                         286.8671

Analysis of Variance Table
```

```
Response: yield
          Df Sum Sq Mean Sq F value Pr(>F)
Genotype  29 72.006  2.4830  1.2396 0.3668
Residuals 11 22.034  2.0031

coefficient of variation: 31.2 %
yield Means: 4.533333

Parameters PBIB
                   .
Genotype          30
block size         3
block/replication 10
replication        2

Efficiency factor 0.6170213

Means with the same letter are not significantly different.

Groups, Treatments and means
a        20      7.729
ab       13      6.715
ab       1       6.505
abc      8       6.192
abcd     24      6.032
abcd     23      5.735
abcd     10      5.473
abcd     16      5.455
abcd     21      5.14
abcd     22      5.069
abcd     4       4.874
abcd     3       4.794
abcd     14      4.742
abcd     15      4.587
abcd     27      4.563
abcd     7       4.424
abcd     5       4.286
abcd     19      4.198
abcd     6       4.165
abcd     25      3.978
abcd     17      3.943
bcd      2       3.628
bcd      28      3.495
bcd      11      3.379
bcd      26      3.341
bcd      9       3.052
bcd      30      3
bcd      12      2.879
cd       29      2.44
d        18      2.186

Comparison between treatments means and its name

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

The adjusted averages can be extracted from the model.

```
model$means
```

```
        yield trt mean.adj        SE r std.err Min. Max.
geno1     7.5   1 6.504752 1.313644 2     1.5    6    9
geno10    4.5   2 3.628197 1.313644 2     0.5    4    5
geno11    5.5   3 4.793619 1.310726 2     0.5    5    6
geno12    4.0   4 4.873879 1.313644 2     3.0    1    7
...
geno8     3.0  29 2.439878 1.310726 2     1.0    2    4
geno9     3.5  30 2.999638 1.310726 2     1.5    2    5
```

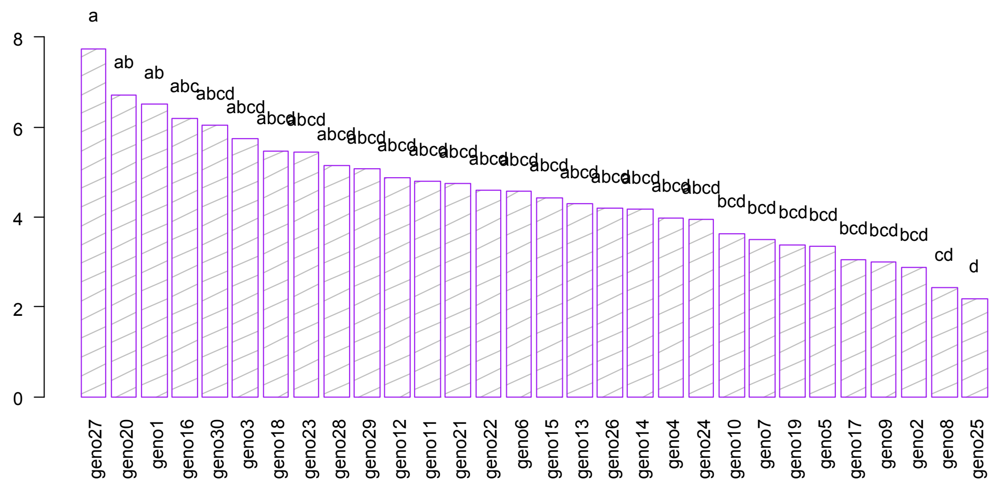

Figure 4.3. Treatment Groups.

The comparisons:

```
model$comparison

          Difference   stderr   pvalue
1 - 2     2.87655507 1.844369 0.147134
1 - 3     1.71113250 1.576446 0.300944
1 - 4     1.63087260 1.727016 0.365282
1 - 5     2.21879565 1.853044 0.256324
.....
27 - 30   1.56381175 1.812351 0.406632
28 - 29   1.05522604 1.850095 0.579894
28 - 30   0.49546622 1.847786 0.793552
29 - 30  -0.55975982 1.587129 0.730988
```

The data on the adjusted averages and their standard error can be illustrated (figure 4.2), since the created object is very similar to the objects generated by the multiple comparisons.

```
par(mfrow=c(2,2),cex=0.6)
C1<-bar.err(model$means[1:7, ], ylim=c(0,9), col=0, main="C1",
variation="rank",border=3)
C2<-bar.err(model$means[8:15,], ylim=c(0,9), col=0, main="C2",
variation="rank", border =4)
```

```
C3<-bar.err(model$means[16:22,], ylim=c(0,9), col=0, main="C3",
variation="rank",border =2)
C4<-bar.err(model$means[23:30,], ylim=c(0,9), col=0, main="C4",
variation="rank", border =6)
```

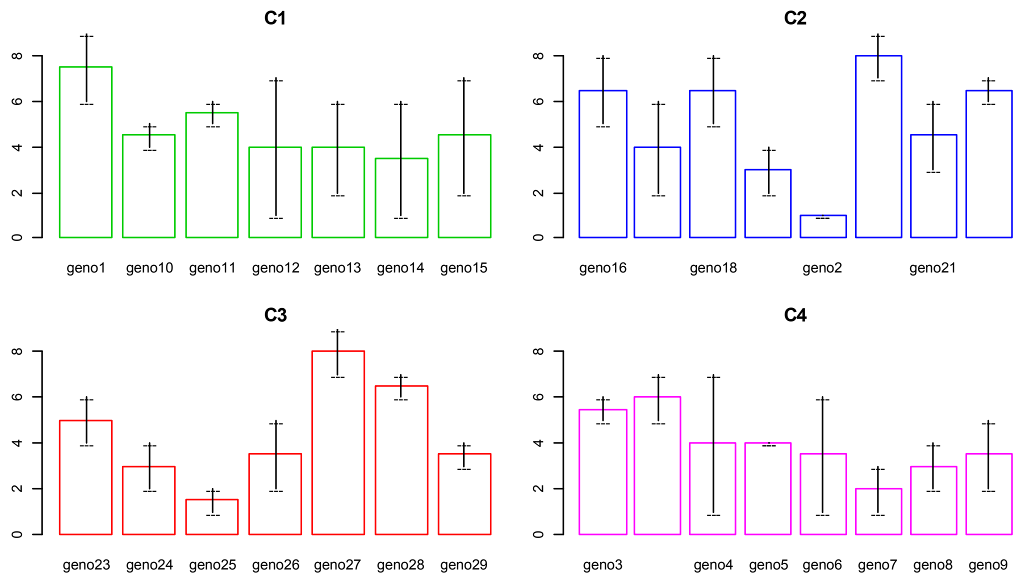

Figure 4.4. Rank in each treatment.

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

Create the data in a text file: latice3x3.txt and read with R:

sqr	block	trt	yield
1	1	1	48.76
1	2	8	10.83
1	3	5	12.54
2	4	5	11.07
2	5	2	22.00
2	6	9	47.43
3	7	2	27.67
3	8	7	30.00
3	9	3	13.78
4	10	6	37.00
4	11	4	42.37
4	12	9	39.00
1	1	4	14.46
1	2	6	30.69
1	3	9	42.01
2	4	8	22.00
2	5	7	42.80
2	6	6	28.28
3	7	1	50.00
3	8	5	24.00
3	9	8	24.00
4	10	3	15.42
4	11	2	30.00
4	12	7	23.80
1	1	3	19.68
1	2	7	31.00
1	3	2	23.00
2	4	1	41.00
2	5	3	12.90
2	6	4	49.95
3	7	6	25.00
3	8	4	45.57
3	9	9	30.00
4	10	5	20.00
4	11	8	18.00
4	12	1	43.81

```
library(agricolae)
library(MASS)
library(lme4)
A<-read.table("latice3x3.txt", header=T)
attach(A)
model2<-PBIB.test(block,trt,sqr,yield,k=3)
detach(A)
```

```
ANALYSIS PBIB:  yield

Class level information
```

```
block : 12
trt : 9

Number of observations:  36

Estimation Method:  REML

Parameter Estimates
          Variance
block:sqr  0.00000
sqr        0.00000
Residual  56.93724

                      Fit Statistics
-2 Res Log Likelihood       198.2320
AIC                         224.2320
BIC                         244.8177

Analysis of Variance Table

Response: yield
          Df  Sum Sq Mean Sq F value    Pr(>F)
trt        8 3749.4  468.68  8.2315 0.0001987 ***
Residuals 16  911.0   56.94
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

coefficient of variation: 25.9 %
yield Means: 29.16167

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

Efficiency factor 0.75

Means with the same letter are not significantly different.

Groups, Treatments and means
a        1       45.89
ab       9       39.61
ab       4       38.09
bc       7       31.9
bc       6       30.24
cd       2       25.67
d        8       18.71
d        5       16.9
d        3       15.44

Comparison between treatments means and its name

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

par(mar=c(3,3,0,0))
bar.group(model2$group,ylim=c(0,52),density=10)
```

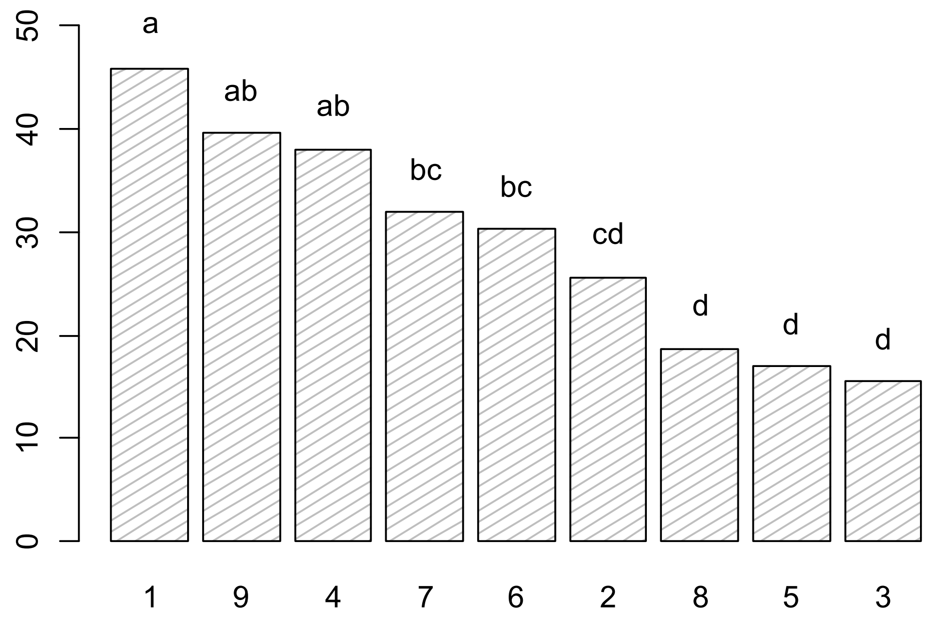

Figure 4.5. Treatment Groups.

```
model2$means
```

```
    yield trt mean.adj       SE r  std.err  Min.  Max.
1 45.8925   1  45.8925 3.772839 4 2.108860 41.00 50.00
2 25.6675   2  25.6675 3.772839 4 1.900585 22.00 30.00
3 15.4450   3  15.4450 3.772839 4 1.505133 12.90 19.68
4 38.0875   4  38.0875 3.772839 4 8.027584 14.46 49.95
5 16.9025   5  16.9025 3.772839 4 3.068910 11.07 24.00
6 30.2425   6  30.2425 3.772839 4 2.536390 25.00 37.00
7 31.9000   7  31.9000 3.772839 4 3.966947 23.80 42.80
8 18.7075   8  18.7075 3.772839 4 2.906984 10.83 24.00
9 39.6100   9  39.6100 3.772839 4 3.647335 30.00 47.43
```

```
model2$comparison
```

```
      Difference   stderr   pvalue
1 - 2    20.2250 5.335599 0.001604
1 - 3    30.4475 5.335599 0.000032
1 - 4     7.8050 5.335599 0.162884
1 - 5    28.9900 5.335599 0.000056
1 - 6    15.6500 5.335599 0.009746
.....
8 - 9   -20.9025 5.335599 0.001228
```

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","f","h","j")
yield<-c(83,77,78,78,70,75,74,79,81,81,91,79,78,92,79,87,81,89,96,
82)
data.frame(block, trt, yield)
   block trt yield
1      I   A    83
2      I   B    77
3      I   C    78
4      I   D    78
5      I   g    70
6      I   k    75
7      I   l    74
8     II   A    79
9     II   B    81
10    II   C    81
11    II   D    91
12    II   e    79
13    II   i    78
14   III   A    92
15   III   B    79
16   III   C    87
17   III   D    81
18   III   f    89
19   III   h    96
20   III   j    82
```

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

model<- DAU.test(block,trt,yield,method="lsd")

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
                         Df Sum Sq Mean Sq F value Pr(>F)
block.unadj               2 360.07 180.036
trt.adj                  11 285.10  25.918  0.9609 0.5499
Control                   3  52.92  17.639  0.6540 0.6092
Control + control.VS.aug.  8 232.18  29.022  1.0760 0.4779
Residuals                 6 161.83  26.972

ANOVA, Block Adjusted
Analysis of Variance Table

Response: yield
                    Df Sum Sq Mean Sq F value Pr(>F)
trt.unadj           11 575.67  52.333
block.adj            2  69.50  34.750  1.2884 0.3424
Control              3  52.92  17.639  0.6540 0.6092
Augmented            7 505.88  72.268  2.6793 0.1253
Control vs augmented  1  16.88  16.875  0.6256 0.4591
Residuals            6 161.83  26.972

coefficient of variation: 6.4 %
yield Means: 81.5

Critical Differences (Between)         Std Error Diff.

Two Control Treatments                        4.240458
Two Augmented Treatments (Same Block)         7.344688
Two Augmented Treatments(Different Blocks)    8.211611
A Augmented Treatment and A Control Treatment 6.360687

Means with the same letter are not significantly different.

Groups, Treatments and means
a        h       93.5
ab       f       86.5
ab       A       84.67
ab       D       83.33
ab       C       82
ab       j       79.5
ab       B       79
ab       e       78.25
ab       k       78.25
ab       i       77.25
ab       l       77.25
b        g       73.25

Comparison between treatments means

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

model$means
```

```
     yield   std.err r Min. Max. mean.adj       SE block
A 84.66667 11.532563 3   79   92 84.66667 2.998456
B 79.00000  3.464102 3   77   81 79.00000 2.998456
C 82.00000  7.937254 3   78   87 82.00000 2.998456
D 83.33333 11.789826 3   78   91 83.33333 2.998456
e 79.00000        NA 1   79   79 78.25000 5.193479    II
f 89.00000        NA 1   89   89 86.50000 5.193479   III
g 70.00000        NA 1   70   70 73.25000 5.193479     I
h 96.00000        NA 1   96   96 93.50000 5.193479   III
i 78.00000        NA 1   78   78 77.25000 5.193479    II
j 82.00000        NA 1   82   82 79.50000 5.193479   III
k 75.00000        NA 1   75   75 78.25000 5.193479     I
l 74.00000        NA 1   74   74 77.25000 5.193479     I
```

```
model<- DAU.test(block,trt,yield,method="lsd",group=F)
> head(model$comparison,10)
      Difference   pvalue sig
A - B   5.666667 0.229886
A - C   2.666667 0.552612
A - D   1.333333 0.763840
A - e   6.416667 0.352008
A - f  -1.833333 0.782870
A - g  11.416667 0.122820
A - h  -8.833333 0.214268
A - i   7.416667 0.287856
A - j   5.166667 0.447652
A - k   6.416667 0.352008
```

4.13 NON-PARAMETRIC COMPARISONS

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

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.

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

```
library(agricolae)
data(corn)
attach(corn)
str(corn)
```

```
'data.frame':   34 obs. of 3 variables:
 $ method     : int  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.

4.14 KRUSKAL-WALLIS

```
out<-kruskal(observation,method,group=TRUE, main="corn")
Study: corn
Kruskal-Wallis test's
Ties or no Ties

Value: 25.62884
degrees of freedom: 3
Pvalue chisq  : 1.140573e-05

method,  means of the ranks

  observation  r
1    21.83333  9
2    15.30000 10
3    29.57143  7
4     4.81250  8

t-Student: 2.042272
Alpha     : 0.05
LSD       : 4.9175

Harmonic Mean of Cell Sizes  8.351284
Means with the same letter are not significantly different

Groups, Treatments and mean of the ranks
a        3       29.57
b        1       21.83
c        2       15.3
d        4       4.812
```

The object "compares" has the same structure of the comparisons (figure 4.3).

```
par(cex=0.8,mar=c(3,3,1,0))
bar.group(out$groups,ylim=c(0,35),col=colors()[45])
```

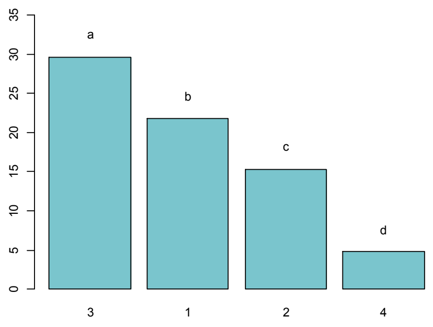

Figure 4.6. Comparison according to Kruskal-Wallis.

4.15 FRIEDMAN

```
friedman()

rm(list=ls())
library(agricolae)
data(grass)
attach(grass)
out<-friedman(judge,trt, evaluation,alpha=0.05, group=FALSE,
main="Data of the book of Conover")

Study: Data of the book of Conover

trt,  Sum of the ranks

   evaluation  r
t1       38.0 12
t2       23.5 12
t3       24.5 12
t4       34.0 12

Friedman's Test
===============
Adjusted for ties
Value: 8.097345
Pvalue chisq : 0.04404214
F value : 3.192198
Pvalue F: 0.03621547

Alpha     : 0.05
t-Student : 2.034515

Comparison between treatments
Sum of the ranks

        Difference   pvalue sig    LCL   UCL
t1 - t2       14.5 0.014896   *   3.02 25.98
t1 - t3       13.5 0.022602   *   2.02 24.98
t1 - t4        4.0 0.483434      -7.48 15.48
t2 - t3       -1.0 0.860438     -12.48 10.48
t2 - t4      -10.5 0.071736   . -21.98  0.98
t3 - t4       -9.5 0.101742     -20.98  1.98
```

4.16 WAERDEN

waerden.test(), with the sweet potato data in the ‘agricolae’ basis.

```
data(sweetpotato)
attach(sweetpotato)
out<-waerden.test(yield,virus,alpha=0.01,group=TRUE)

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

Value : 8.409979
Pvalue: 0.03825667
Degrees of freedom:  3
```

```
virus,  means of the normal score

        yield   std.err r
cc -0.2328353 0.1748697 3
fc -1.0601764 0.2002213 3
ff  0.6885684 0.4396858 3
oo  0.6044433 0.2160981 3

t-Student: 3.355387
Alpha    : 0.01
LSD      : 1.322487

Means with the same letter are not significantly different

Groups, Treatments and means of the normal score
a        ff      0.6886
a        oo      0.6044
ab       cc      -0.2328
b        fc      -1.06
```

The comparison probabilities are obtained with the parameter group=FALSE.

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

To see out$comparison

```
out<-waerden.test(yield,virus,group=F)
detach(sweetpotato)

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

Value : 8.409979
Pvalue: 0.03825667
Degrees of freedom:  3

virus,  means of the normal score

        yield   std.err r
cc -0.2328353 0.1748697 3
fc -1.0601764 0.2002213 3
ff  0.6885684 0.4396858 3
oo  0.6044433 0.2160981 3

Comparison between treatments means
mean of the normal score

        Difference   pvalue sig.         LCL         UCL
cc - fc  0.8273411 0.069032    . -0.08154345  1.73622564
cc - ff -0.9214037 0.047582    * -1.83028827 -0.01251917
cc - oo -0.8372786 0.066376    . -1.74616316  0.07160593
fc - ff -1.7487448 0.002176   ** -2.65762936 -0.83986026
fc - oo -1.6646197 0.002902   ** -2.57350426 -0.75573516
ff - oo  0.0841251 0.836322      -0.82475944  0.99300965
```

4.17 DURBIN

durbin(); example: Myles Hollander (p. 311) Source: W. Moore and C.I. Bliss. (1942)

```
days <-gl(7,3)
chemical<-c("A","B","D","A","C","E","C","D","G","A","F","G",
"B","C","F", "B","E","G","D","E","F")
toxic<-c(0.465,0.343,0.396,0.602,0.873,0.634,0.875,0.325,0.330,
0.423,0.987,0.426,0.652,1.142,0.989,0.536,0.409,0.309,
0.609,0.417,0.931)

out<-durbin.test(days,chemical,toxic,group=F,
main="Logarithm of the toxic dose")

Study: Logarithm of the toxic dose
chemical,  Sum of ranks

  sum
A   5
B   5
C   9
D   5
E   5
F   8
G   5

Durbin Test
===========
Value      : 7.714286
Df 1       : 6
P-value    : 0.2597916
Alpha      : 0.05
Df 2       : 8
t-Student  : 2.306004

Least Significant Difference
between the sum of ranks:  5.00689

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

Comparison between treatments sum of the ranks

      Difference   pvalue sig
A - B          0 1.000000
A - C         -4 0.102688
A - D          0 1.000000
A - E          0 1.000000
A - F         -3 0.204420
A - G          0 1.000000
....
E - F         -3 0.204420
E - G          0 1.000000
F - G          3 0.204420
```

5 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”, and a non-parametric method of Haynes, based on the data range.

5.1 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. We will consider five environments in the following example:

```
v1 <- c(10.2, 8.8, 8.8, 9.3, 9.6, 7.2, 8.4, 9.6, 7.9, 10, 9.3, 8.0, 10.1, 9.4, 10.8, 6.3, 7.4)
v2 <- c(7, 7.8, 7.0, 6.9, 7, 8.3, 7.4, 6.5, 6.8, 7.9, 7.3, 6.8, 8.1, 7.1, 7.1, 6.4, 4.1)
v3 <- c(5.3, 4.4, 5.3, 4.4, 5.5, 4.6, 6.2, 6.0, 6.5, 5.3, 5.7, 4.4, 4.2, 5.6, 5.8, 3.9, 3.8)
v4 <- c(7.8, 5.9, 7.3, 5.9, 7.8, 6.3, 7.9, 7.5, 7.6, 5.4, 5.6, 7.8, 6.5, 8.1, 7.5, 5.0, 5.4)
v5 <- c(9, 9.2, 8.8, 10.6, 8.3, 9.3, 9.6, 8.8, 7.9, 9.1, 7.7, 9.5, 9.4, 9.4, 10.3, 8.8, 8.7)
```

For 17 genotypes, the identification is made by letters.

```
study <- data.frame(v1, v2, v3, v4, v5)
rownames(study) <- LETTERS[1:17]
```

An error variance of 2 and 4 repetitions is assumed.

```
stability <- stability.par(study, rep=4, MSerror=2)
```

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

 Environmental index  - covariate

 Analysis of Variance

              d.f. Sum of Squares Mean Squares     F p.value
TOTAL           84      1035.6075
GENOTYPES       16       120.0875       7.5055  2.65   0.003
ENVIRONMENTS     4       734.2475     183.5619 91.78  <0.001
INTERACTION     64       181.2725       2.8324  1.42   0.033
HETEROGENEITY   16        52.7128       3.2945  1.23   0.281
RESIDUAL        48       128.5597       2.6783  1.34  0.0815
POOLED ERROR   240                           2

 Genotype. Stability statistics

  Mean Sigma-square  . s-square  . Ecovalence
A 7.86     1.671833 ns 2.209084 ns   6.567031
```

```
B 7.22     1.822233 ns 1.977299 ns   7.097855
C 7.44     0.233967 ns 0.134103 ns   1.492208
D 7.42     4.079567 ns 1.443859 ns  15.064913
E 7.64     2.037967 ns 2.369090 ns   7.859266
F 7.14     5.161967  * 6.763106  *  18.885149
G 7.90     1.759300 ns 1.058092 ns   6.875737
H 7.68     1.757167 ns 2.028880 ns   6.868208
I 7.34     5.495300  * 0.423680 ns  20.061619
J 7.54     4.129967 ns 5.125514 ns  15.242796
K 7.12     3.848900 ns 4.360772 ns  14.250796
L 7.30     2.675300 ns 3.610982 ns  10.108678
M 7.66     3.473167 ns 2.198229 ns  12.924678
N 7.92     0.806233 ns 1.097156 ns   3.511972
O 8.30     1.951300 ns 1.459578 ns   7.553384
P 6.08     3.647833 ns 4.919102 ns  13.541149
Q 5.88     3.598500 ns 4.353030 ns  13.367031


Signif. codes:  0 '**' 0.01 '*' 0.05 'ns' 1

Simultaneous selection for yield and stability  (++)

  Yield Rank Adj.rank Adjusted Stab.var Stab.rating YSi ...
A  7.86   14        1       15 1.671833           0  15   +
B  7.22    5       -1        4 1.822233           0   4
C  7.44    9        1       10 0.233967           0  10   +
D  7.42    8        1        9 4.079567          -2   7
E  7.64   11        1       12 2.037967           0  12   +
F  7.14    4       -1        3 5.161967          -4  -1
G  7.90   15        1       16 1.759300           0  16   +
H  7.68   13        1       14 1.757167           0  14   +
I  7.34    7       -1        6 5.495300          -4   2
J  7.54   10        1       11 4.129967          -2   9   +
K  7.12    3       -1        2 3.848900           0   2
L  7.30    6       -1        5 2.675300           0   5
M  7.66   12        1       13 3.473167           0  13   +
N  7.92   16        1       17 0.806233           0  17   +
O  8.30   17        2       19 1.951300           0  19   +
P  6.08    2       -2        0 3.647833           0   0
Q  5.88    1       -3       -2 3.598500           0  -2

 Yield Mean: 7.378824
 YS    Mean: 8.352941
 LSD (0.05): 0.7384513
 - - - - - - - - - - -
 +   selected genotype
 ++  Reference: Kang, M. S. 1993. Simultaneous selection for yield
 and stability: Consequences for growers. Agron. J. 85:754-757.
```

The selected genotypes are: A, C, E, G, H, J, M, N and O. These genotypes have a higher yield and a lower variation. According to the ANOVA, the interaction is significant.

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

```
altitude<-c(1200, 1300, 800, 1600, 2400)
```

```
stability <- stability.par(study,rep=4,MSerror=2, cova=TRUE,
name.cov= "altitude", file.cov= altitude)
```

5.2 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.

```
data <- data.frame(name=row.names(study), study)
out<-stability.nonpar(data, "YIELD", ranking=TRUE)

Nonparametric Method for Stability Analysis
-------------------------------------------

Estimation and test of nonparametric measures
Variable: YIELD

Ranking...
    v1   v2 v3   v4   v5
A 16.0  8.0  9 14.0  8.0
B  7.5 14.0  5  5.5 10.0
C  7.5  8.0  9  9.0  6.0
D  9.5  6.0  5  5.5 17.0
E 12.5  8.0 11 14.0  3.0
F  2.0 17.0  7  7.0 11.0
G  6.0 13.0 16 16.0 15.0
H 12.5  3.0 15 10.5  6.0
I  4.0  4.5 17 12.0  2.0
J 14.0 15.0  9  2.5  9.0
K  9.5 12.0 13  4.0  1.0
L  5.0  4.5  5 14.0 14.0
M 15.0 16.0  3  8.0 12.5
N 11.0 10.5 12 17.0 12.5
O 17.0 10.5 14 10.5 16.0
P  1.0  2.0  2  1.0  6.0
Q  3.0  1.0  1  2.5  4.0

Statistics...
  Mean Rank  s1   Z1   s2   Z2
A 7.86   14 5.4 0.02 21.5 0.04
B 7.22    5 6.2 0.12 25.7 0.02
C 7.44    9 3.0 2.73  7.5 1.83
D 7.42    8 7.4 1.20 36.5 1.05
E 7.64   11 5.6 0.00 21.8 0.03
F 7.14    4 7.8 1.81 39.2 1.55
G 7.90   15 5.2 0.08 18.7 0.19
H 7.68   13 6.2 0.12 25.3 0.01
I 7.34    7 8.8 3.87 51.5 5.08
J 7.54   10 7.2 0.94 34.3 0.71
K 7.12    3 7.8 1.81 43.0 2.43
L 7.30    6 7.4 1.20 34.7 0.77
M 7.66   12 7.6 1.49 38.2 1.36
N 7.92   16 4.2 0.82 14.8 0.57
O 8.30   17 7.0 0.71 31.7 0.40
P 6.08    2 6.6 0.35 27.7 0.09
Q 5.88    1 7.0 0.71 32.3 0.46
```

```
------------------------
Sum of Z1:  17.97158
Sum of Z2:  16.59462
------------------------

Test...
The  Z-statistics  are  measures  of  stability.  The  test  for  the
significance
of  the  sum  of  Z1  or  Z2  are  compared  to  a  Chi-Square  value  of
chi.sum.
individual Z1 or Z2 are compared to a Chi-square value of chi.ind.

      MEAN      es1 es2      vs1   vs2  chi.ind  chi.sum
1 7.378824 5.647059  24 2.566667 148.8 8.843605 27.58711
---
expectation and variance: es1, es2, vs1, vs2
```

5.3 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.

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 graphics; see figure 5.1.

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

```
par(mar=c(4,4,0,0))
rdto <- c(study[,1], study[,2], study[,3], study[,4], study[,5])
environment <- gl(5,17)
genotype <- rep(rownames(study),5)
model<-AMMI(ENV=environment,  GEN=genotype,  REP=4,  Y=rdto,  MSE=2,
ylim=c(-2,2), xlim=c(-2,2), number=FALSE)


ANALYSIS AMMI:  rdto
Class level information

ENV:  1 2 3 4 5
```

```
GEN:  A B C D E F G H I J K L M N O P Q
REP:  4

Number of means:  85

Dependent Variable: rdto

Analysis of variance
           Df   Sum Sq    Mean Sq  F value       Pr(>F)
ENV         4 734.2475 183.561882
REP(ENV)   15
GEN        16 120.0875   7.505471 3.752735 3.406054e-06
ENV:GEN    64 181.2725   2.832382 1.416191 3.279630e-02
Residuals 240 480.0000   2.000000

Coeff var       Mean rdto
19.16584         7.378824

Analysis
    percent acum Df   Sum.Sq  Mean.Sq F.value    Pr.F
PC1    38.0 38.0 19 68.96258 3.629609    1.81 0.0225
PC2    29.8 67.8 17 54.02864 3.178155    1.59 0.0675
PC3    22.5 90.3 15 40.84756 2.723170    1.36 0.1680
PC4     9.6 99.9 13 17.43370 1.341054    0.67 0.7915
PC5     0.0 99.9 11  0.00000 0.000000    0.00 1.0000
```

```
require(klaR)
par(mar=c(4,4,0,0))
model<-AMMI(ENV=environment,  GEN=genotype,  REP=4,  Y=rdto,  MSE=2,
graph="triplot",number=F)
```

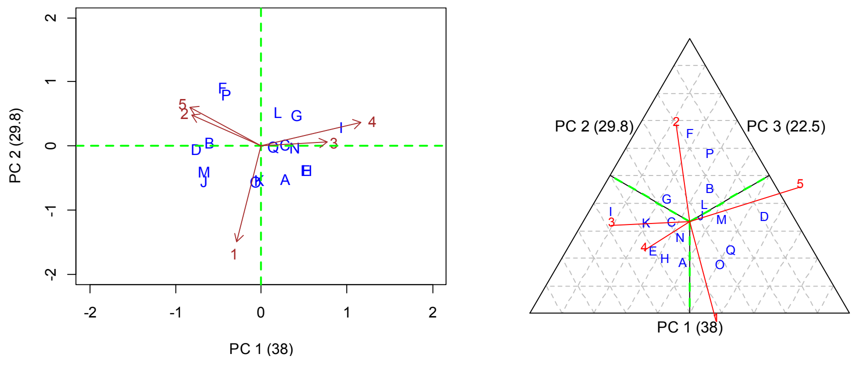

Figure 5.1. Biplot and Triplot

In this case, the interaction is significant. The first two components explain 67.8%; then the biplot can provide information about the interaction genotype-environment. With the triplot, 90.3% would be explained.

6 SPECIAL FUNCTIONS

6.1 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, figure 6.1.

```
data(pamCIP)
rownames(pamCIP)<-substr(rownames(pamCIP),1,6)
par(cex=0.8)
output<-consensus(pamCIP,distance="binary", method="complete",
nboot=500)
```

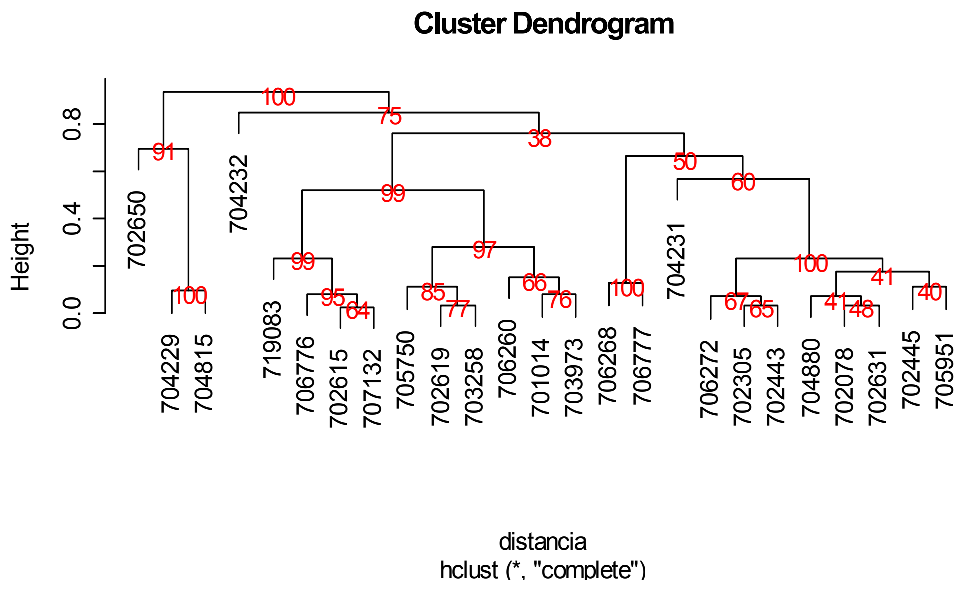

Figure 6.1. Dendrogram, production by consensus()

```
Duplicates: 18
New data   : 25 Records

Consensus hclust

Method distance: binary
Method cluster : complete
rows and cols  : 25 107
n-bootstrap    : 500
Run time       : 20.469 secs
```

When the dendrogram is complex, it is convenient to extract part of it with the function hcut(), figure 6.2.

```
hcut(output,h=0.4,group=8,type="t",edgePar = list(lty=1:2,
col=2:1),main="group 8" ,col.text="blue",cex.text=1)
```

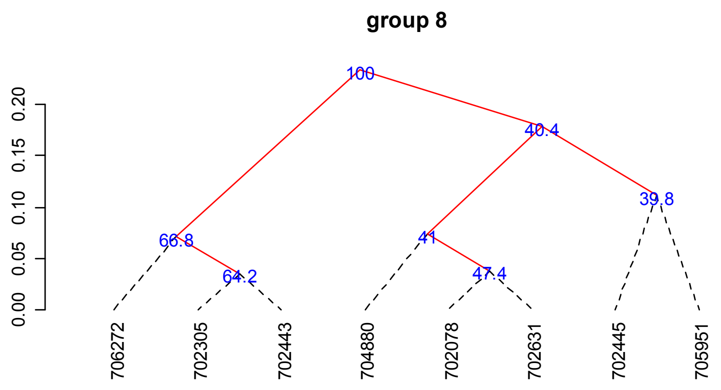

Figure 6.2. Dendrogram, production by hcut()

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

```
names(output)

[1] "table.dend" "dendrogram" "duplicates"
```

This means that we can know the duplicates, reconstruct the tree diagram and maintain the interactions.

```
output$table.dend

    X1  X2      xaxis     height percentage groups
1   -6 -24   7.500000 0.02857143  64.0       6-24
2   -3  -4  19.500000 0.03571429  64.2       3-4
. . .
24  21  23   5.099609 0.93617021 100.0       1-2-3-4-5-6-7-8-9-10-11-
12-13-14-15-16-17-18-19-20-21-22-23-24-25
```

Reproduce the dendrogram:

```
dend<-output$dendrogram
data<-output$table.dend
plot(dend)
text(data[,3],data[,4],data[,5])
```

Construct a classic dendrogram, figure 6.3

```
dend<-as.dendrogram(output$dendrogram)
plot(dend,type="r",edgePar = list(lty=1:2, col=2:1))
text(data[,3],data[,4],data[,5],col="blue",cex=1)
```

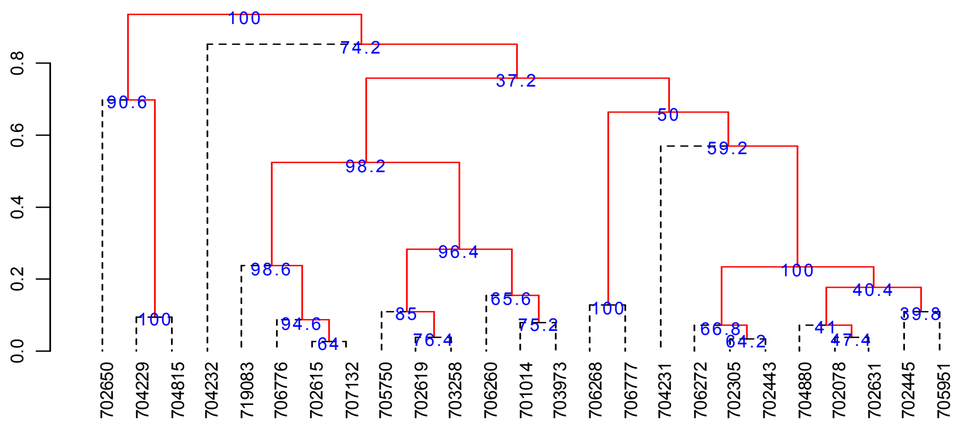

Figure 6.3. Classic dendrogram

6.2 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, figure 6.4.

```
data(soil)
set.seed(9473)
simulated <- montecarlo(soil$pH,1000)
par(mar=c(3,0,2,1))
plot(density(soil$pH),axes=F,main="pH density of the soil\ncon
Ralstonia",xlab="",lwd=4)
lines(density(simulated), col="blue", lty=4,lwd=4)
h<-graph.freq(simulated,plot=F)
axis(1,0:12)
legend("topright",c("Original","Simulated"),lty=c(1,4),col=c("black"
, "blue"), lwd=4)
```

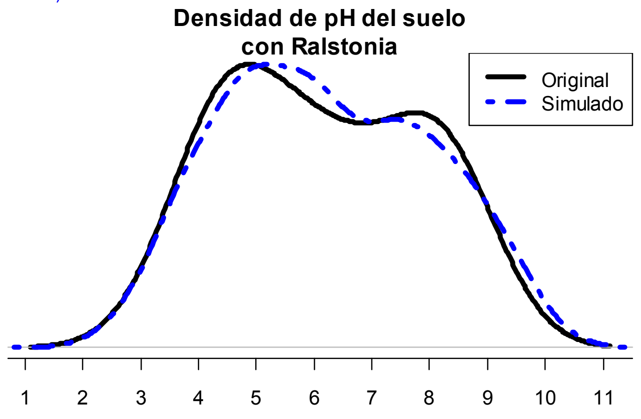

Figure 6.4. Distribution of the simulated and the original data

1000 data have been generated, being the frequency table:

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

  Lower Upper  Main freq relative   CF  RCF
   2.00  2.79  2.40   12     0.01   12 0.01
   2.79  3.58  3.19   50     0.05   62 0.06
. . . .
   9.11  9.90  9.51   49     0.05  989 0.99
   9.90 10.69 10.30   11     0.01 1000 1.00
```

Some statistics:

```
summary(soil$pH)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  3.800   4.700   6.100   6.154   7.600   8.400 

summary(simulated)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.443   4.698   6.022   6.209   7.762  10.950 
```

6.3 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 permutated 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=1000)

Resampling of the experiments
- - - - - - - - - - - - - - 
Proposed model: cutting~variety + date + variety:date 
---
Resampling of the analysis of variance for the proposed model
Determination of the P-Value by Resampling
Samples: 1000 

             Df    Sum Sq   Mean Sq   F value     Pr(>F) Resampling
variety       1 25.086806 25.086806 7.2580377 0.01952218      0.025
date          2 13.891758  6.945879 2.0095604 0.17670768      0.200
variety:date  2  4.853025  2.426513 0.7020312 0.51483592      0.530
Residuals    12 41.477005  3.456417                                
---
```

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

6.4 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:

```
model <- simulation.model(model, potato, k=1000)
```

```
Simulation of experiments
Under the normality assumption
- - - - - - - - - - - - - - - -
Proposed model: cutting~variety + date + variety:date
Analysis of Variance Table

Response: cutting
             Df Sum Sq Mean Sq F value  Pr(>F)
variety       1 25.087  25.087  7.2580 0.01952 *
date          2 13.892   6.946  2.0096 0.17671
variety:date  2  4.853   2.427  0.7020 0.51484
Residuals    12 41.477   3.456
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
---
Validation of the analysis of variance for the proposed model
Simulations: 1000

             Df   F value % Acceptance % Rejection  Criterion
variety       1 7.2580377         51.5        48.5 acceptable
date          2 2.0095604         61.1        38.9 acceptable
variety:date  2 0.7020312         67.5        32.5 acceptable
---
```

The validation is referred to the percentage of decision results equal to the result of the ANOVA decision. Thus, 67.5% of the results simulated on the interaction variety*date gave the same result of acceptance or rejection obtained in the ANOVA.

6.5 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.

```
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
======================================================
          X1        X2
X1 0.3333333 0.2666667
X2 0.1666667 0.5333333

Residual Effect^2 =  0.4266667

> output
$Coeff
          X1        X2
X1 0.3333333 0.2666667
X2 0.1666667 0.5333333

$Residual
[1] 0.4266667
```

6.6 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.

```
Example with the heterosis data, locality 2.

    Replication   Female   Male   v2
109           1     LT-8  TS-15 2.65
110           1     LT-8 TPS-13 2.26
...
131           1 Achirana TPS-13 3.55
132           1 Achirana TPS-67 3.05
133           1     LT-8   <NA> 2.93
134           1    TPS-2   <NA> 2.91
...
140           1 Achirana   <NA> 3.35
...
215           3     <NA> TPS-67 2.91

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.

data(heterosis)
site2<-subset(heterosis,heterosis[,1]==2)
site2<-subset(site2[,c(2,5,6,8)],site2[,4]!="Control")
attach(site2)
```

```
output1<-lineXtester(Replication, Female, Male, v2)
detach(site2)

ANALYSIS LINE x TESTER:  v2

ANOVA with parents and crosses
==============================
                     Df        Sum Sq     Mean Sq F value Pr(>F)
Replications          2  0.519190476 0.259595238   9.801 0.0002
Treatments           34 16.101605714 0.473576639  17.879 0.0000
Parents              10  7.731490909 0.773149091  29.189 0.0000
Parents vs. Crosses   1  0.005082861 0.005082861   0.192 0.6626
Crosses              23  8.365031944 0.363697041  13.731 0.0000
Error                68  1.801142857 0.026487395
Total               104 18.421939048

ANOVA for line X tester analysis
================================
                Df    Sum Sq    Mean Sq F value Pr(>F)
Lines            7 4.9755431 0.71079187   3.632 0.0191
Testers          2 0.6493861 0.32469306   1.659 0.2256
Lines X Testers 14 2.7401028 0.19572163   7.389 0.0000
Error           68 1.8011429 0.02648739

ANOVA for line X tester analysis including parents
==================================================
                     Df        Sum Sq     Mean Sq F value Pr(>F)
Replications          2  0.519190476 0.259595238   9.801 0.0002
Treatments           34 16.101605714 0.473576639  17.879 0.0000
Parents              10  7.731490909 0.773149091  29.189 0.0000
Parents vs. Crosses   1  0.005082861 0.005082861   0.192 0.6626
Crosses              23  8.365031944 0.363697041  13.731 0.0000
Lines                 7  4.975543056 0.710791865   3.632 0.0191
Testers               2  0.649386111 0.324693056   1.659 0.2256
Lines X Testers      14  2.740102778 0.195721627   7.389 0.0000
Error                68  1.801142857 0.026487395
Total               104 18.421939048

GCA Effects:
===========
Lines Effects:
Achirana   LT-8   MF-I    MF-II  Serrana    TPS-2   TPS-25    TPS-7
 0.022   -0.338  0.199   -0.449    0.058   -0.047    0.414    0.141

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

SCA Effects:
===========
          Testers
Lines      TPS-13 TPS-67  TS-15
  Achirana  0.061  0.059 -0.120
  LT-8     -0.435  0.519 -0.083
  MF-I     -0.122 -0.065  0.187
  MF-II    -0.194  0.047  0.148
  Serrana   0.032 -0.113  0.081
  TPS-2     0.197 -0.072 -0.124
  TPS-25    0.126 -0.200  0.074
  TPS-7     0.336 -0.173 -0.162

Standard Errors for Combining Ability Effects:
==============================================
S.E. (gca for line)    : 0.05424983
S.E. (gca for tester) : 0.0332211
S.E. (sca effect)      : 0.09396346
S.E. (gi - gj)line     : 0.07672084
S.E. (gi - gj)tester  : 0.04698173
S.E. (sij - skl)tester: 0.1328844

Genetic Components:
==================
Cov H.S. (line)    : 0.05723003
Cov H.S. (tester) : 0.00537381
Cov H.S. (average): 0.003867302
Cov F.S. (average): 0.1279716

F = 0, Adittive genetic variance: 0.01546921
F = 1, Adittive genetic variance: 0.007734604
F = 0, Variance due to Dominance: 0.1128228
F = 1, Variance due to Dominance: 0.05641141

Proportional contribution of lines, testers
 and their interactions to total variance
===========================================
Contributions of lines   : 59.48026
Contributions of testers: 7.763104
Contributions of lxt     : 32.75663
```

6.7 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 parcel size and the coefficient of variation, figure 6.5.

```
data(rice)
table<-index.smith(rice,
 main="Interaction between the CV and the parcel size" ,col="red",
type="l",xlab="Size")
uniformity <- data.frame(table$uniformity)
uniformity
      Size Width Length plots       Vx   CV
1      1     1       1     648  9044.539 13.0
2      2     1       2     324  7816.068 12.1
3      2     2       1     324  7831.232 12.1
...
40   162      9      18        4 4009.765  8.6
```

The size is the product of the width x the length of the parcel, and the rectangle size is the product of the width x the length.

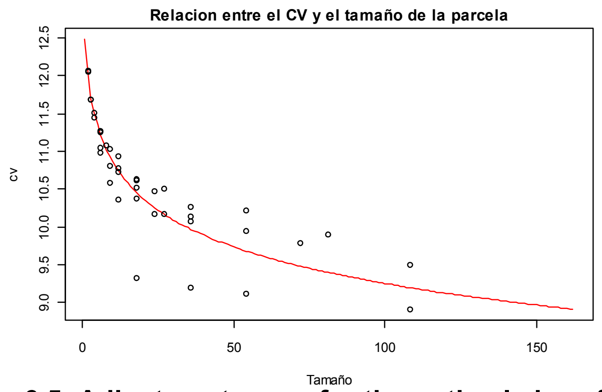

Figure 6.5. Adjustment curve for the optimal size of parcel

6.8 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 Junín.

The evaluation was carried out in the parcels on 17 November 2005, without insecticide application. The counted specimens were the following:

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

```
         Order        Family Number.of.specimens
79      DIPTERA      TIPULIDAE                   3
80 LEPIDOPTERA      NOCTUIDAE                   1
81   NOCTUIDAE      PYRALIDAE                   3
82   HEMIPTERA  ANTHOCORIDAE                   1
83     DIPTERA     TACHINIDAE                  16
84     DIPTERA  ANTHOCORIDAE                   3
85     DIPTERA SCATOPHAGIDAE                   5
86     DIPTERA      SYRPHIDAE                   1
87     DIPTERA       MUSCIDAE                   3
```

The Shannon index is:

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

Method: Shannon
Index: 3.52304

95 percent confidence interval:
 3.088775 ; 4.286088
```

6.9 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)

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

Correlation Analysis

Method     : pearson
Alternative: two.sided

$correlation
        pH   EC CaCO3
pH    1.00 0.55  0.73
EC    0.55 1.00  0.32
CaCO3 0.73 0.32  1.00

$pvalue
               pH        EC       CaCO3
pH    1.000000000 0.0525330 0.004797027
EC    0.052532997 1.0000000 0.294159813
CaCO3 0.004797027 0.2941598 1.000000000

$n.obs
[1] 13

attach(soil)
correlation(pH,soil[,3:4],method="pearson")
Correlation Analysis

Method     : pearson
Alternative: two.sided

$correlation
     EC CaCO3
pH 0.55  0.73
$pvalue
       EC  CaCO3
pH 0.0525 0.0048
$n.obs
[1] 13
```

```
correlation(pH,CaCO3,method="pearson")

Pearson's product-moment correlation

data: pH and CaCO3
t = 3.520169 , df = 11 , p-value = 0.004797027
alternative hypothesis: true rho is not equal to 0
sample estimates:
cor
 0.7278362
```

6.10 OTHER FUNCTIONS

Desirability functions that facilitate the data management:

tapply.stat()   Calculation of statesmen and mathematical operations in columns of a table in relation to grouped factors.

Factor and variable table

Application with 'agricolae' data:

```
data(RioChillon)
attach(RioChillon$babies)
tapply.stat(yield,farmer,function(x) max(x)-min(x))
detach(RioChillon$babies)

             farmer yield
1  AugustoZambrano   7.5
2        Caballero  13.4
3       ChocasAlto  14.1
4       FelixAndia  19.4
5      Huarangal-1   9.8
6      Huarangal-2   9.1
7      Huarangal-3   9.4
8         Huatocay  19.4
9 IgnacioPolinario  13.1
```

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 factors, and 5,6 and 7 as variables, then the following procedures are valid:

```
tapply.stat(A[,5:7], A[,1:3],mean)
tapply.stat(A[,5:7], A[,1:3],function(x) mean(x,na.rm=TRUE))
tapply.stat(A[,c(7,6)], A[,1:2],function(x) sd(x)*100/mean(x))
```

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.

```
data(sweetpotato)
```

```
model <- model<-aov(yield ~ virus, data=sweetpotato)
cv.model(model)
[1] 17.16660
```

Skewness and curtosis

The skewness and curtosis results, obtained by ‘agricolae’, are equal to the ones obtained by SAS, MiniTab, SPSS, InfoStat, and Excel.

If x represents a data set:

```
> x<-c(3,4,5,2,3,4,5,6,4,NA,7)
```

skewness is calculated with:

```
> skewness(x)
[1] 0.3595431
```

and curtosis with:

```
> kurtosis(x)
[1]-0.1517996
```

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.

Figure 6.6 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.

```
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)
plot(K,y[,1],type="l",col="blue",ylab="waller")
lines(K,y[,2],type="l",col="red",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","red","green"),lty=c(1,
8,20),lwd=2,title="Fc")
title(main="Waller in function of K")
```

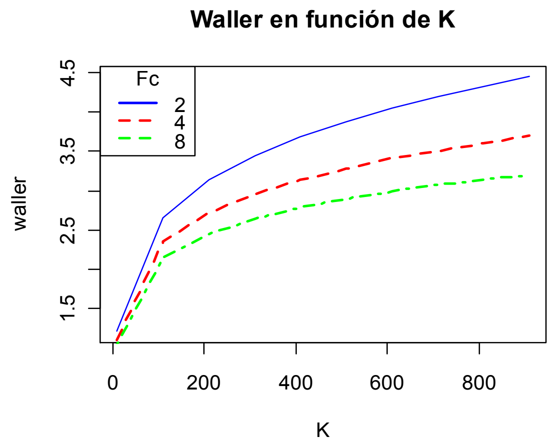

Figure 6.6. Function of Waller to different value of parameters K and Fc

AUDPC

The area under the disease progress curve (AUDPC), (see figure 6.7), calculates the absolute and relative progress of the disease. It is required to measure the disease in percentage terms during several dates, preferably equidistantly.

```
days<-c(7,14,21,28,35,42)
evaluation<-data.frame(E1=10,E2=40,E3=50,E4=70,E5=80,E6=90)
plot(days,
evaluation,type="h",ylim=c(0,100),axes=F,col="red",xlab="Days",
ylab="Evaluation")
lines(days,evaluation,col="red")
axis(1,days)
axis(2,seq(0,100,20),las=2)
abline(v=7,h=100,lty=4,lwd=2,col="blue")
abline(v=42,h=0,lty=4,lwd=2,col="blue")
audpc(evaluation,days)
audpc(evaluation,days,"relative")
text(15,80,"Audpc Absolute = 2030")
text(15,70,"Audpc Relative = 0.58")
```

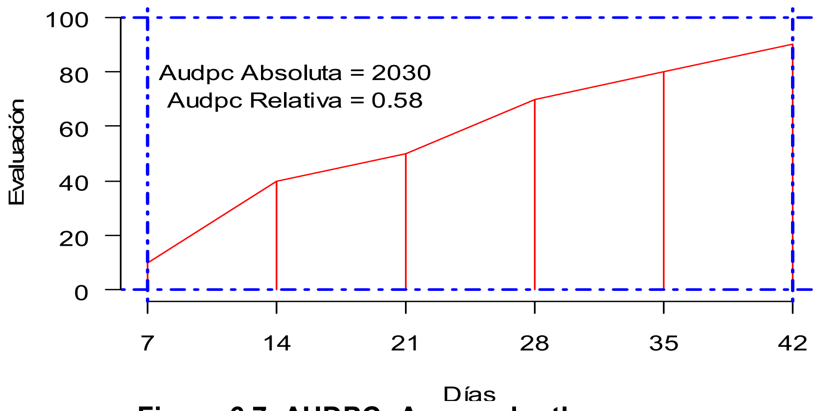

Figure 6.7. AUDPC: Area under the curve

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.

```
data(potato)
potato[,1]<-as.factor(potato[,1])
model<-lm(cutting ~ date + variety,potato)
df<-df.residual(model)
MSerror<-deviance(model)/df
attach(potato)
analysis<-nonadditivity(cutting, date, variety, df, MSerror)
detach(potato)
```

```
Tukey's test of non-additivity
cutting

P : 15.37166
Q : 77.4444

Analysis of Variance Table

Response: residual
              Df Sum Sq Mean Sq F value Pr(>F)
Non-additivity 1  3.051   3.051   0.922 0.3532
Residuals     14 46.330   3.309
```

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

Table 6.10. ASCII Character Code Reference for the use of symbols

ASCII Codes Table used in R					
Code	**Symbol**	**Code**	**Symbol**	**Code**	**Symbol**
92	**}**	**124**	**|**	**64**	**@**
47	**/**	**60**	**<**	**94**	**^**
91	**[**	**62**	**>**	**35**	**#**
93	**]**	**61**	**=**	**36**	**$**
40	**(**	**34**	**“**	**37**	**%**
41	**)**	**126**	**~**	**38**	**&**
123	**{**	**58**	**:**	**39**	**‘**
125	**}**	**59**	**;**		

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