Introductory Guide
to
S-Plus

Final Version

B.D. Ripley
Professor of Applied Statistics,
University of Oxford

e-mail: ripley@stats.ox.ac.uk

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Preface

This guide was originally written for graduate students in Statistics at the University of Oxford. The first versions were based closely on notes by Dr. Bill Venables of the Department of Statistics at the University of Adelaide, but have been updated to reflect later versions of S, the extensions of S-Plus and local facilities. Several sections, in particular 4, 6 and 11, remain close to Dr. Venables’ original material. This guide will no longer be updated, following the publication of Venables & Ripley (1994). [See p. 1. Where that takes a significantly better approach than earlier editions of these notes, the material formerly here has been dropped.]

The guide is to S-Plus, but much of it will be relevant to users of the underlying S. Extensions which are only in S-Plus include dynamic graphics (§6.3, brush and spin) and the classical statistics functions (§9). The terminology of this guide is intended to be precise, only referring to S-Plus rather than S for features unique to S-Plus.

These notes were written for a particular environment, S-Plus 3.2 on Sun SparcStations running the Open Windows windowing system. You will find a number of differences depending on your local environment. It will help to have the library ripley available — it should be in the same source as these notes. It can be also be obtained by anonymous ftp from

markov.stats.ox.ac.uk (163.1.20.1)
in file pub/S/ripley.sh.Z. It is available from statlib (see Section A.2) as

send ripley from S

Alternatively, library(MASS) from Venables & Ripley (1994) can be used.

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B.D. Ripley,
University of Oxford,
Contents

1 Introduction 1
  1.1 Starting and Finishing .......................... 1
  1.2 Getting Help .................................. 2
  1.3 Hardcopy Output ............................... 3

2 Datasets 3

3 A First Session 5

4 Simple Data Manipulation 6
  4.1 Vectors ........................................ 6
  4.2 Vector Arithmetic .............................. 6
  4.3 Generating Regular Sequences of Numbers. .... 7
  4.4 Logical Vectors. Missing Values .............. 8
  4.5 Character Vectors .............................. 8
  4.6 Index Vectors. Selecting and Modifying Subsets of a Data Set .... 9
  4.7 Arrays ......................................... 10
  4.8 Lists .......................................... 11
  4.9 Data Frames ................................... 12

5 Reading data into S 14
  5.1 Writing out data ................................ 15

6 Graphics 16
  6.1 Graphical Parameters ........................... 16
  6.2 Some Basic Plotting Functions ................ 17
  6.3 Interaction with Plots .......................... 17
  6.4 Brush and Spin ................................ 18
  6.5 Equally-scaled plots ........................... 18
7 Statistical Summaries 20
  7.1 Arithmetical Summaries ............................................. 20
  7.2 Histograms and Stem-and-Leaf Plots .............................. 20
  7.3 Boxplots ............................................................... 21

8 Distributions 22
  8.1 Q-Q Plots .............................................................. 23

9 Classical Statistics 24

10 Handling Categorical Data 27
  10.1 The Function tapply(…) and Ragged Arrays ...................... 28

11 Loops and Conditional Execution 29

12 Writing Your Own Functions 30

13 Statistical Models 32
  13.1 Model Formulas ....................................................... 32
  13.2 One-way Layouts ..................................................... 33
  13.3 Designed Experiments .............................................. 35
  13.4 Generalized Linear Models ........................................ 39
  13.5 Updating and Selecting Models ................................... 42

14 Multivariate Analysis 43

Appendix

A Libraries 45
  A.1 Library Ripley ......................................................... 46
  A.2 Sources of Libraries ............................................... 46
1 Introduction

S is a statistical language developed at AT&T’s Bell Laboratories. **S-Plus** is a binary distribution of S, with added functions, produced by the StatSci Division of MathSoft in Seattle. The S system was radically re-designed in the 1988 release and known as ‘New S’. In August 1991 a new release of what is once again called S consisted of a moderate revision of ‘New S’ together with far-ranging extensions. **S-Plus** 3.0 was introduced in late 1991, based on that release of S, with numerous additional features. **S-Plus** 3.1 was released at the very end of 1992, and **S-Plus** 3.2 in very early 1994.

The main references are:


It is not the intention of this guide to replace the books. Rather these notes are intended as a brief introduction to the capabilities of the S programming language and to how to perform some common statistical procedures within S. Users of **S-Plus** will need to consult both books, probably frequently. Both books contain some reference documentation, but the on-line versions (see §1.2) are later and definitive.

There also manuals for **S-Plus** itself, whose organization differs from release to release.

Other books include


which goes far beyond the coverage of this guide, including many topics (such as robust statistics, non-linear regressions, modern regression, survival analysis, tree-based models, time series and spatial statistics) not covered here, as well as in greater depth on what is covered.

1.1 Starting and Finishing

To start **S-Plus**, type the command

```
machine% Splus
```

After a short while (and, the first time, an initialization message) you get the **S-Plus** prompt¹:

```
>
```

This is waiting for input from you.

Technically S is a *function language* with a very simple syntax. Like most Unix based packages it is *case sensitive*, so A and a are different variables. Elementary commands consist of either *expressions* or *assignments*. If an expression is given as a command, it is evaluated, printed, and the value is discarded². An assignment also evaluates an expression and passes the value

---

¹ which can be changed, but the default is assumed here
² In fact it is kept in the (hidden) variable `.Last.value` and so can be retrieved from the ‘bin’.
to a variable but the result is not printed automatically. An expression can be as simple as 2 + 3 or a complex function call. Assignments are indicated by the assignment operator <- or =. (As the first needs two keystrokes, lazy typists use the second. However, the first is easier to read.) For example,

```r
> 2+3
[1] 5
> mean(hstart)
[1] 137.9944
> m <- mean(hstart); v <- var(hstart)
> m/sqrt(v)
[1] 3.174021
```

The [1] states that the answer is starting at the first element of a vector.

Commands are separated either by a semi-colon, ;, or by a newline. If a command is not complete at the end of a line, S will give a different prompt, namely

+ 

on second and subsequent lines and continue to read input until the command is syntactically complete.

S can be extended by writing new functions, which then can be used exactly as built-in functions (and can even replace them). How to write your own functions is covered in section 12.

### 1.2 Getting Help

S has an inbuilt help facility similar to the `man` facility of Unix. To get more information on any specific named function or dataset, for example `mean`, the command is

```r
> help(mean)
```

For a feature specified by special characters, and in a few other cases (one is `"swiss"`), the argument must be enclosed in double quotes, making it a ‘character string’:

```r
> help("[["]"
```

Help uses a window which overlays your main window. The pager accepts a number of options, including `space` for the next page and `q` to quit. (Other useful options are `1G` to go to the top and `control-b` to go back a page.) If you prefer, a separate help window (which can be left up) can be obtained by the argument `window=T`. Another way to get help is by

```r
> ?mean
```

Short help is given by the function `args`.

S-Plus also has a window-based help facility, started by

```r
> help.start(gui="openlook"
```

Click with the left mouse button on items to select categories and items. The help window can be left up, or removed by
1.3 Hardcopy Output

Graphics are printed by holding down the right button on the graph menu in a openlook() window (see §6) and releasing over the print item. This will print on the nearest laser printer (or that selected by your PRINTERS environment variable).

To record a session cut-and-paste to a textedit window, then remove your mistakes (if any) and save as a Unix file.

2 Datasets

Datasets are stored in a directory ~/.Data. They are permanent, so all the objects you create are retained until explicitly deleted. (As the directory name .Data begins with . it will normally be hidden in file listings from Unix by ls.) If there is a .Data directory in the current directory when S is invoked, that directory is used rather than ~/.Data. This provides one way to organize your S, using separate directories for each project.

In S, to get a list of names of the objects currently defined use the command

> objects()

Your own functions are also stored in .Data. To find out whether an object is a function or dataset, and what is in it, just type its name at the prompt, e.g.

> stack.x

> plot

This prints out the function, dataset, .... In the later versions of S it may print a short summary of the object. To get the full details, use

> print.default(object)

When S looks for an object, it searches in turn through a sequence of directories known as the search list. Usually the first entry in the search list is the .Data sub-directory of the current working directory. The names of the directories currently on the search list can be found by the function

> search()

The names of the objects held in any directory on the search list can be displayed by giving the ls function an argument. For example objects(2) lists the contents of the second directory in the search list. Normally the second, third and fourth directories are built-in functions, and the fifth, sixth and seventh contain standard datasets

Extra search directories can be added to this list with the attach(...) function and removed with the detach(...) function, details of which can be found in the manuals or the help fa-
cility. Note that attached directories are searched after the \texttt{.Data} directory in the order last attached to first attached.

To remove objects permanently the function \texttt{rm} is available:
\begin{verbatim}
> rm(x,y,z,in,junk,temp)
\end{verbatim}
The function \texttt{remove(...)} can be used to remove objects with non-standard names.

\textbf{Warning}

\textit{Objects in your \texttt{.Data} directory will take precedence over system objects of the same name.} This is a frequent cause of rather obscure errors, and can cause apparently correct behaviour but erroneous results. Avoid using names such as \texttt{c, s, t, glm, range, tree} for your own objects. If you get peculiar errors, clean up your \texttt{.Data} directory and try again!

\texttt{S} keeps a record of commands in the \texttt{.Audit} file in the \texttt{.Data} directory. This is a hidden file and can grow rather large. Use (from the \texttt{Unix} command line)
\begin{verbatim}
Splus TRUNC_AUDIT 0
\end{verbatim}
occasionally to clean out the audit file entirely (or omit the 0 to keep the last 0.5Mb).
3 A First Session

The sample session given below is intended to show by example some of the capabilities of the system. Work through the session given by the commands on the left of the page. Some clues as to what is going on are given at the right hand side of the page.

```r
machine% Splus
> openlook()
> library(ripley)
> help(trees)
> trees
> attach(trees)
> hist(diam)
> hist(diam, nclass=10, probability=T)
> help(hist)
> stem(diam)
> plot(diam, volume)
> trees.lm <- lm(volume ~ diam)
> summary(trees.lm)
> anova(trees.lm)
> abline(trees.lm)
> identify(diam, volume, height)
>
> par(mfrow=c(1,2))
> plot(trees.lm)
> par(mfrow=c(1,1))
> qnorm(residuals(trees.lm))
> qqnorm(studres(trees.lm))
> qline(studres(trees.lm))
> pairs(trees)
> brush(cbind(diam, height, volume))
> trees.lm2 <- lm(volume ~ diam + height)
> trees.lm3 <- lm(log(volume) ~ log(diam) + log(height))
> detach("trees")
> help(road)
> attach(road)
> plot(drivers, deaths)
> plot(drivers, deaths, log="xy")
> state <- row.names(road)
> identify(drivers, deaths, state)
> plot(fuel, deaths, log="xy")
> identify(fuel, deaths, state)
> road.mat <- cbind(drivers, fuel, deaths)
> pairs(road.mat)
> brush(road.mat, rowlab=state, spin=F)
> q()
```

Start the session.
Open the graphics window.
Add a library of functions and datasets.
use q to quit
Print out a data frame of the trees data
so that we can use names diam etc
Histogram as counts.
as probability density
Stem-and-leaf plot.
Scatter plot.
linear regression
summary of fit
analysis of variance table
plot line on scatter plot
Move mouse to plot and click with left button
to see what height is. Click middle button to quit.
set up 1 row, 2 cols for plots
plots of fitted values and [residuals] vs fitted value.
one plot again.
normal probability plot of residuals
and of Studentized residuals
line through quartiles
all pair-wise scatter plots
rotate points in 3D, select and de-select points.
Click on quit to end
multiple regression. Try functions as before
to avoid any confusion
Find the ‘odd’ states.
Set up a matrix
Look at pattern of all three
Use mouse to highlight points and check their identity. Then click on quit
Finish session
4 Simple Data Manipulation

The basic data objects in S are vectors, arrays, lists and data frames.

4.1 Vectors

S operates on named data structures. The simplest such structure is the vector, which is a single entity consisting of an ordered collection of numbers. To set up a vector named x, say, consisting of five numbers, namely 10.4, 5.6, 3.1, 6.4 and 21.7, use the S command

\[ x <- c(10.4, 5.6, 3.1, 6.4, 21.7) \]

This is an assignment statement using the function \( c(\ldots) \) taking an arbitrary number of vector arguments and whose value is the vector of its arguments.

A number occurring by itself in an expression is taken as a vector of length one.

Assignments can also be made in the other direction, using the obvious change in the assignment operator. So the same assignment could be made using

\[ c(10.4, 5.6, 3.1, 6.4, 21.7) -> x \]

If an expression is used as a complete command, the value is printed and lost. So now if we were to use the command

\[ 1/x \]

the reciprocals of the five values would be printed (and, of course, the value of x would be unchanged).

4.2 Vector Arithmetic

Vectors can be used in arithmetic expressions, in which case the operations are performed element-by-element. Vectors occurring in the same expression need not all be of the same length. If they are not, the value of the expression is a vector with the same length as the longest vector which occurs in the expression. Shorter vectors in the expression are recycled as often as need be (perhaps fractionally) until they match the length of the longest vector. In particular a constant is simply repeated. So with the above assignments the command

\[ v <- 2*x + y + 1 \]

generates a new vector v of length 11 constructed by adding together, element-by-element, \( 2 \times x \) repeated 2.2 times, \( y \) repeated just once, and \( 1 \) repeated 11 times.

The elementary arithmetic operators are the usual +, -, *, / and \( ^{\wedge} \) for raising to a power. In addition all of the common arithmetic functions are available. \( \log, \log10, \exp, \sin, \cos, \tan, \sqrt{\cdot} \), and so on, all have their usual meaning. \( \text{max} \) and \( \text{min} \) select the largest and smallest elements of an vector respectively. \( \text{range} \) is a function whose value is a vector of length two, namely \( c(\text{min}(x), \text{max}(x)) \). The element-by-element maximum and minimum of two or more vectors are given by \( \text{pmax} \) and \( \text{pmin} \). \( \text{length}(x) \) is the number of elements in \( x \), \( \text{sum}(x) \) gives the total of the elements in \( x \) and \( \text{prod}(x) \) their product.
Two statistical functions are \texttt{mean}(x), which evaluates to \(\texttt{sum}(x)/\texttt{length}(x)\) and \texttt{var}(x),
which gives the value \(\texttt{sum}((x-\texttt{mean}(x))^2)/\texttt{length}(x)-1\), the sample variance. If the argument to \texttt{var}(\ldots) is an \(n \times p\) matrix the value is a \(p \times p\) sample covariance matrix obtained from regarding the rows as independent \(p\)-variate sample vectors.

\texttt{sort}(x) returns a vector of the same size as \(x\) with the elements arranged in increasing order. Other, more flexible, sorting facilities are available (see \texttt{order}(\ldots) which produces a permutation to do the sorting, and \texttt{sort.list}).

\subsection{4.3 Generating Regular Sequences of Numbers.}

\(S\) has a number of facilities for generating commonly used sequences of numbers. For example \(1:30\) is the vector \(c(1,2,\ldots,29,30)\). The colon operator has highest priority within an expression, so, for example \(2*1:15\) is the vector \(c(2,4,6,\ldots,28,30)\). Put \(n \leftarrow 10\) and compare the sequences \(1:n-1\) and \(1:(n-1)\).

The construction \(30:1\) may be used to generate a backwards sequence.

The function \texttt{seq}(\ldots) is a more general facility for generating sequences. It has five arguments, only some of which may be specified in any one call. The first two arguments, if given, specify the beginning and end of the sequence, and if these are the only two arguments given the result is the same as the colon operator. That is, \texttt{seq}(2,10) is the same vector as \texttt{1:10}.

Parameters to \texttt{seq}(\ldots), and to many other \(S\) functions, can also be given in named form, in which case the order in which they appear is irrelevant. The first two parameters may be named \texttt{from=value} and \texttt{to=value}; thus \texttt{seq}(1,30), \texttt{seq(from=1,to=30)} and \texttt{seq(to=30,from=1)} are all the same as \texttt{1:30}. The next two parameters to \texttt{seq}(\ldots) may be named \texttt{by=value} and \texttt{length=value}, which specify a step size and a length for the sequence respectively. If neither of these is given, the default \texttt{by}=1 is assumed.

For example
\begin{verbatim}
> seq(-5,5,by=.2) -> s3
\end{verbatim}
generates in \(s3\) the vector \(c(-5.0,-4.8,-4.6,\ldots,4.6,4.8,5.0)\). Similarly
\begin{verbatim}
> s4 <- seq(length=51,from=-5,by=.2)
\end{verbatim}
generates the same vector in \(s4\).

The fifth parameter may be named \texttt{along=vector}, which if used must be the only parameter, and creates a sequence \(1,2,\ldots,\texttt{length(vector)}\), or the empty sequence if the vector is empty (as it can be).

A related function is \texttt{rep}(\ldots) which can be used for replicating a structure in various complicated ways. The simplest form is
\begin{verbatim}
> s5 <- rep(x, times=5)
\end{verbatim}
which will put five copies of \(x\) end-to-end in \(s5\).
4.4 Logical Vectors. Missing Values

As well as numerical vectors, S allows manipulation of logical quantities. The elements of a logical vector have just two possible values, represented formally as \( F \) (for ‘false’) and \( T \) (for ‘true’). (TRUE and FALSE are also valid representations.)

Logical vectors are generated by conditions. For example

\[ \text{temp} \leftarrow x > 13 \]

sets \( \text{temp} \) as a vector of the same length as \( x \) with values \( F \) corresponding to elements of \( x \) where the condition is not met and \( T \) where it is.

The logical operators are \(<, <=, >, >=, ==\) for exact equality and \(!=\) for inequality. In addition if \( c_1 \) and \( c_2 \) are logical expressions, then \( c_1 \land c_1 \) is their intersection (and), \( c_1 \lor c_2 \) is their union (or) and \( \neg c_1 \) is the negation of \( c_1 \).

Logical vectors may be used in ordinary arithmetic, in which case they are coerced into numeric vectors, \( F \) becoming 0 and \( T \) becoming 1. However there are situations where logical vectors and their coerced numeric counterparts are not equivalent.

In some cases the components of a vector may not be completely known. When an element or value is “not available” or a “missing value” in the statistical sense, a place within a vector may be reserved for it by assigning it the special value \( \text{NA} \). In general any operation on an \( \text{NA} \) becomes an \( \text{NA} \). The motivation for this rule is simply that if the specification of an operation is incomplete, the result cannot be known and hence is not available.

The function \( \text{is.na}(x) \) gives a logical vector of the same size as \( x \) with value \( T \) if and only if the corresponding element in \( x \) is \( \text{NA} \).

\[ \text{ind} \leftarrow \text{is.na}(z) \]

4.5 Character Vectors

Character quantities and character strings are used frequently in S, for example as plot labels. They are denoted by a sequence of characters delimited by the double quote character. E.g. "x-values", "New iteration results". Single quotes can also be used, in matching pairs.

Character strings may be collected into a vector by the \( c(\ldots) \) function; examples of their use will emerge frequently.

The \( \text{paste}(\ldots) \) function takes an arbitrary number of character string arguments and concatenates them into a single character string. Any numbers given among the arguments are coerced into character strings in the same way they would be if they were printed. The arguments are by default separated in the result by a single blank character, but this can be changed by the named parameter, \( \text{sep=string} \), which changes it to \( \text{string} \), possibly empty.

For example

\[ \text{labs} \leftarrow \text{paste}(c("X","Y"), 1:10, \text{sep=""}) \]

makes \( \text{labs} \) the character vector ("X1", "Y2", "X3", \ldots, "X9", "Y10"). Note in particular that recycling of short vectors takes place here too; thus \( c("X", "Y") \) is repeated 5
times to match the sequence.

The elements of a vector can be named (as well as numbered) by assigning a character vector to its names attribute, e.g.

```r
> costs <- c(26, 45, 67, 33, 51)
> names(costs) <- c("banana", "apple", "orange", "fig", "kiwi")
> costs
  banana apple orange fig kiwi
       26       45       67       33       51
```

4.6 Index Vectors. Selecting and Modifying Subsets of a Data Set

Elements of a vector may be extracted by specifying the element in square brackets, e.g. `x[5]`. More generally, subsets of a vector (or any expression that evaluates to a vector) may be selected by appending to the name of the vector an index vector in square brackets. Such index vectors can be any of four distinct types:

1. A **logical vector**. In this case the index vector must be of the same length as the vector from which elements are to be selected. Values corresponding to `T` in the index vector are selected and those corresponding to `F` omitted. For example

   ```r
   > y <- x[!is.na(x)]
   ```

   creates (or re-creates) an object `y` which will contain the non-missing values of `x`, in the same order. Note that if `x` has missing values, `y` will be shorter than `x`. Also

   ```r
   > (x+1)[(!is.na(x)) & x>0] -> z
   ```

   creates an object `z` and places in it the values of the vector `x+1` for which the corresponding value in `x` was both non-missing and positive.

2. A **vector of positive integral quantities**. In this case the values in the index vector must lie in the set `{1, 2, ..., length(x)}`. The corresponding elements of the vector are selected and concatenated, *in that order*, in the result. The index vector can be of any length and the result is of the same length as the index vector. For example `x[6]` is the sixth component of `x` and

   ```r
   > x[1:10]
   ```

   selects the first 10 elements of `x` (assuming `length(x) ≥ 10`). Also

   ```r
   > c("x","y")[rep(c(1,2,2,1),times=4)]
   ```

   (an admittedly unlikely thing to do) produces a character vector of length 16 consisting of "x", "y", "y", "x" repeated four times.

3. A **vector of negative integral quantities**. In this case the index vector specifies the values to be *excluded* rather than included. Thus

   ```r
   > y <- x[-(1:5)]
   ```

   gives `y` all but the first five elements of `x`. 
4. A vector of character strings. This possibility only applies where an object has a names attribute to identify its components. In this case a subvector of the names vector may be used in the same way as the positive integral labels in 2.

   > lunch <- fruit[c("apple","orange")]

   This option is particularly useful in connection with data frames (see §4.9).

An indexed expression can also appear on the receiving end of an assignment, in which case the assignment operation is performed only on those elements of the vector. The expression must be of the form `vector[index_vector]` as having an arbitrary expression in place of the vector name would not make sense.

The vector assigned must match the length of the index vector, and in the case of a logical index vector it must again be the same length as the vector it is indexing.

For example

   > x[is.na(x)] <- 0

replaces any missing values in `x` by zeros and

   > y[y<0] <- -y[y<0]

has the same effect as

   > y <- abs(y)

4.7 Arrays

An array can be considered as a multiply subscripted collection of data entries of the same type, for example numeric, logical or character string.

An array is defined by having a dimension vector, a vector of positive integers. If its length is `k` then the array is `k`-dimensional. The values in the dimension vector give the upper limits for each of the `k` subscripts. The lower limits are always 1. Suppose, for example, `z` is a vector of 1500 elements. The assignment

   > dim(z) <- c(3,5,100)

allows `z` to be treated as a `3 × 5 × 100` array.

Other functions such as `matrix(...)` and `array(...)` are available for simpler and more natural looking assignments in special cases, e.g.

   > z <- array(z, c(3,5,100))
   > z <- matrix(z, 3, 5)

The values in the data vector give the values in the array in the same order as they would occur in Fortran, that is, with the first subscript moving fastest and the last subscript slowest. For example if the dimension vector for an array, say `a`, is `c(3,4,2)` then there are `3 × 4 × 2 = 24` entries in `a` and the data vector holds them in the order `a[1,1,1]`, `a[2,1,1]`, ..., `a[2,4,2]`, `a[3,4,2]`. To make life easier, `matrix` has a `byrow=TRUE` parameter for data presented by row rather than by column.
Individual elements of an array may be referenced by giving the name of the array followed by the subscripts in square brackets, separated by commas. More generally, subsections of an array may be specified by giving a sequence of index vectors in place of subscripts; however if any index position is given an empty index vector, then the full range of that subscript is taken. Thus \( a[2,\ldots] \) is a \( 4 \times 2 \) array with dimension vector \( c(4,2) \) and data vector
\[
a[2,1,1], a[2,2,1], a[2,3,1], a[2,4,1], a[2,1,2], a[2,2,2], a[2,3,2], a[2,4,2],
\]
in that order. \( a[\ldots] \) stands for the entire array, which is the same as omitting the subscripts entirely and using \( a \) alone.

Arrays may be used in arithmetic expressions and the result is an array formed by element-by-element operations on the data vector. The dimension vectors of operands generally need to be the same, and this becomes the dimension vector of the result. So if \( A, B \) and \( C \) are all similar arrays, then
\[
> D <- 2*A*B + C + 1
\]
makes \( D \) a similar array with data vector the result of the evident element-by-element operations. The matrix multiplication operator is \(%*%\).

There are extensive matrix manipulation facilities, including transposes and eigenvalue, Cholesky, QR and singular-value decompositions. See help on \( t, eigen, chol, qr \) and \( svd \).

Any dimension of an array can be given a set of names using \( \text{dimnames} \), but is usually easier to use the facilities of data frames.

Matrices can be built up from given vectors and matrices by the functions \( \text{cbind}(\ldots) \) and \( \text{rbind}(\ldots) \). Informally, \( \text{cbind}(\ldots) \) forms matrices by binding together vectors or matrices horizontally, or column-wise, and \( \text{rbind}(\ldots) \) vertically, or row-wise.

### 4.8 Lists

An \( S \) list is an object consisting of an ordered collection of objects known as its components. There is no particular need for the components to be of the same mode or type, and, for example, a list could consist of a numeric vector, a logical value, a matrix, a character array, a function, and so on.

Components are always numbered and may always be referred to as such. If \( \text{trees} \) is a list, then the function \( \text{length(trees)} \) gives the number of (top level) components it has, specified as \( \text{trees[[1]]}, \text{trees[[2]]} \) and so on.

Components of lists may also be named, and in this case the component may be referred to either by giving the component name as a character string in place of the number in double square brackets, or, more conveniently, by giving an expression of the form
\[
> \text{name$component.name}
\]
for the same thing. This is a very useful convention as it makes it easier to get the right component if you forget the number, and is strongly advised. You can find out the names of the components by
\[
> \text{names(names)}
\]
and this generates much less output that printing the object, which will achieve the same purpose.

The names of components may be abbreviated down to the minimum number of letters needed to identify them uniquely. Most of the datasets are in fact lists (or can be treated as lists), so we could refer to the component `diam` of the `trees` data as `trees$d`. Similarly, many R functions return lists of results.

It is important to distinguish `trees[[1]]` from `trees[1]`. `[[...]]` is the operator used to select a single element of a list, whereas `[…]` is a general subscripting operator for vectors. Fortunately, numbered components are needed very rarely.

New lists may be formed from existing objects by the function `list(...)`. An assignment of the form

```r
> trees <- list(diam=tree.d, height=tree.h, volume=tree.v)
```

sets up a list `tree` of 3 components using the existing objects `tree.d`, `tree.h` and `tree.v` for the components and giving them names as specified by the argument names (which can be chosen freely). If these names are omitted, the components are numbered only.

Lists can be `attach`ed as well as directories, and this allows their components to be accessed as if they were stand-alone entities. Thus in the `trees` example we could have

```r
> attach(trees)
> mean(height)
```

It is wise to `detach("trees")` after use to avoid any nasty surprises.

### 4.9 Data Frames

Data frames were introduced in the August 1991 release of R, and can be thought of as closely-coupled lists of data vectors of the same length. Unlike matrices, the data vectors can be of different types, including character data. Both the rows and columns can be labelled. Consider the data frame `roads` from `library(ripley)`:  

```r
> road
   deaths drivers popden rural temp fuel
Alabama 968  158  64.0  66.0  62 119.0
Alaska  43  11.0  0.4   5.9  30  6.2
          .......... Mo 1289 234  63.0 100.0 40 180.0
Mont 259  38  4.6  72.0  29  31.0
```

which has both row and column labels. The columns can be treated as components of a list:

```r
> road$rural
   [1]  66.0  5.9  33.0  73.0 118.0  73.0  5.1  3.4  0.0  57.0  83.0  40.0
   [13] 102.0  89.0 100.0 124.0  65.0  40.0  19.0  29.0  17.0  95.0 110.0  59.0
   [25] 100.0  72.0
```

and the structure can be treated as a two-dimensional array:
Data frames can be attached just as lists can, and this allows their columns to be accessed as if they were named vectors.

A data frame can be created from vectors and matrices by the `data.frame` function. For example:

```r
> road[2,4]
        Alaska
        5.9
> road["Mo", "temp"]
   Mo
   40
> road["Mo",]
  deaths drivers popden rural temp fuel
Mo 1289   234    63   100   40   180
```

Note how the row label is carried along.

Character vectors given to `data.frame` are automatically treated as factors (see §10), unless specified within a `I()` function.
5 Reading data into S

Data objects will usually be read as values from external files. This is done most conveniently with the `scan(…)` function. To read a vector from the keyboard we can use

```r
> counts <- c(2,3,4,3,2,1,3,8,11,6,6,7,12,11,11,
+ 117,121,47,22,85,98,43,20,119,209,68,43,67,99,46,33)
```

or

```r
counts <- scan()
2 3 3 4 3 2 1 3 8 11 6 6 7 12 11 11
117 121 47 22 85 98 43 20 119 209 68 43 67 99 46 33
```

Input is terminated by a blank input line (from the terminal only, despite the documentation) or by EOF (ctrl-D in Unix). To read in a character vector we specify the vector type by the second argument:

```r
> diet <- scan("")
D E A C B F C D F B A E
F A C E D B B C E A F D
E F B D C A A B D F E C
```

To read from a `file` specify its name as the first argument, for example

```r
> counts <- scan("chd.dat")
```

Now suppose that multiple data vectors of equal length are to be read in in parallel. For example suppose that there are three vectors, the first of mode character and the remaining two of mode numeric, and the file is `input.dat`. Use `scan(…)` to read in the three vectors as a list, as follows

```r
> in <- scan("input.dat",list(id="", x=0, y=0))
```

The second argument is a dummy list structure that establishes the mode of the three vectors to be read. The result, held in `in`, is a list whose (named) components are the three vectors read in.

Matrices are usually read by row, as follows

```r
> X <- matrix(scan("light.dat"), ncol=5, byrow=T)
```

The argument `skip=` to `scan` can be used to skip header rows of files.

Data frames can be read from a file by the `read.table` function. The data file should be a table in one of a number of formats:

1. A file such as `rotifer.dat` (page 39) which has a first row naming the columns, followed by the table of numeric data can be read by

```r
> rotifer <- read.table("rotifer.dat", header=T)
```
5.1 Writing out data

2. A file laid out like the listing of a data frame. This has a first header line, and rows which contain the row label followed by the data for the columns, such as

<table>
<thead>
<tr>
<th>deaths</th>
<th>drivers</th>
<th>popden</th>
<th>rural</th>
<th>temp</th>
<th>fuel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alabama</td>
<td>968</td>
<td>158</td>
<td>64</td>
<td>66</td>
<td>62</td>
</tr>
<tr>
<td>Alaska</td>
<td>43</td>
<td>11</td>
<td>0.4</td>
<td>5.9</td>
<td>30</td>
</tr>
</tbody>
</table>

............

Note that the header has one less entry than subsequent rows. This format is read by

> road <- read.table("road.dat")

3. A table without any header. The row and column labels are then 1, \ldots, m and \ci{1} \ldots \ci{n}. However, if there exists a character column without duplicates, the first such is taken as the row labels and removed as a column.

Sometimes it is necessary to read in character strings which contain spaces. This can be done by separating the fields in the file by, for example, tabs or commas:

> usroad <- scan("road.dat", sep="\t", list(state="", deaths=0, + drivers=0, popden=0, rural=0, jantemp=0, fuel=0))

where \texttt{\t} is the usual Unix abbreviation for a tab character. This device also applies to \texttt{read.table}.

5.1 Writing out data

There are many ways to write out data from S, for example the \texttt{print.cat} and \texttt{format} commands. To write directly to a file, there are \texttt{cat}, \texttt{write} and, from S-Plus 3.2, \texttt{write.table} which is usually the simplest method. This can write a dataframe, matrix or vector, with syntax

> write.table(data, file="", sep="",")

and further arguments can be found in the help page. By default it writes out comma-separated items on rows, but the separator can be changed to space or tab ("\texttt{\t}" in Unix).

The function \texttt{write} writes a vector, with syntax

> write(data, file="data", ncolumns=5)

for numeric data, and in one column for character data. To write out a matrix \texttt{m}, use

> write(t(m), file="data", ncolumns=ncol(m))

The function \texttt{format} converts data to a line of characters, and can be used with \texttt{write} or \texttt{cat} to construct custom reports.
6 Graphics

The graphical facilities are central to S. The steps involved are as follows:

1. The type of terminal, or *device*, is declared to S at the beginning of the session:

   ```
   > openlook()
   ```

2. A command is issued to construct a plot from data. For example

   ```
   > plot(x,y)
   ```

   specifies a simple point plot where *x* and *y* are vectors giving the *x*- and *y*-coordinates of the points respectively. (The command includes a default automatic choice of axes, scales, titles and plotting characters, all of which can be overridden with additional *graphical parameters* that could be included as named arguments in the command.)

6.1 Graphical Parameters

Functions producing graphical output usually have optional additional named arguments that can be specified to override some default parameter settings and hence modify the characteristics of a plot. A short list of the main ones is as follows:

- **axes**
  - If *FALSE* all axes are suppressed. Default *TRUE*, axes are automatically constructed.

- **type**
  - Type of plot desired. Values for *c* are:
    - *p* for points only, (the default for function *plot*),
    - *l* for lines only,
    - *b* for both points and lines, (the lines miss the points),
    - *s*, *S* for step functions (*s* specifies to change now, *S* to change just before the next point),
    - *o* for overlaid points and lines,
    - *h* for high density vertical line plotting, and
    - *n* for no plotting (but axes are still found and set).

- **xlab**
  - Give labels for the *x*– and/or *y*–axes (default: the names, including suffixes, of the *x* and *y* coordinate vectors).

- **ylab**
  - A title to appear under the *x*–axis label and in smaller letters.

- **sub**
  - A title for the top of the plot in larger letters. (default: both empty).

- **main**
  - Approximate minimum and maximum values for *x*– and/or *y*–axes settings. These values are automatically rounded to make them “pretty” for axis labelling.

Other graphical parameters control the background characteristics of all subsequent plots and are usually specified by a call to the function *par*(...) . There are a great number of these parameters and the command

```
> help(par)
```

gives a complete list of them and their meanings. Some of the more commonly adjusted ones are as follows:
6.2 Some Basic Plotting Functions

The elementary plotting functions are as follows:

- **plot(x,y,...)**: Scatter plot of points with x- and y-coordinates given by the two main parameters. The pair x,y may be replaced by a single list with components labeled x and y, called a 'plot list'. Graphical parameters are particularly useful.

- **points(x,y,...)**: Add points to an existing plot (possibly using a different plotting character. Follows on from a `plot(...)` command.

- **lines(x,y,...)**: Add lines to an existing plot. Similar to points.

  Example: 
  ```r
  > plot(x,y); lines(spline(x,y))
  ```

  Will join the points of a plot by a cubic spline interpolation function. (See `help(spline)` for further information.)

- **text(x,y,labels,...)**: Add text to a plot at points given by x,y. Normally `labels` is an integer or character vector in which case `labels[i]` is plotted at point `(x[i],y[i])`. The default is `1:length(x)`.

  Example: 
  ```r
  > plot(x,y,type="n"); text(x,y)
  ```

  The graphics parameter `type="n"` suppresses the plotting of points but set up the axes, and the `text(...)` function supplies special characters (in this case just the integers by default) for the points.

- **abline(a,b,...)**: Draw a line in intercept and slope form, `(a,b)`, across an existing plot.

  Examples: 
  ```r
  > abline(h=c,...)
  > abline(v=c,...)
  ```

- **abline(lmobject,...)**: Draw a line in intercept and slope form, `(a,b)`, across an existing plot.

6.3 Interaction with Plots

**S-Plus** allows users to interact with plots, by identifying points and by adding information at places selected by mouse clicks.
6.4 Brush and Spin

These are S-Plus enhancements to allow dynamic manipulation of graphs. Spin allows three columns chosen from a matrix of data vectors to be rotated in space.

```r
> help("state")
> spin(state.x77)
```

Use the left mouse button to select three of the variables, then use the cross-shaped pad to rotate the point cloud. Finally click on quit.

```r
> brush(state.x77, hist=T)
```

includes spin and a pairs plot. Additionally one can ‘brush’ by selecting points with the left mouse button, and de-selecting them with the middle button. One can mark points in different ways, with the four symbols, and even label points if label is selected.

```r
> brush(rbind(iris[,1],iris[,2],iris[,3]))
```

Now select the first 50 points with one symbol and the last fifty with another. The intermediate nature of the middle 50 then stands out.

6.5 Equally-scaled plots

It is sometime necessary to make geometrically-square plots, for example so that distances can be assessed accurately. This is somewhat tricky, but done by the functions `eqscplot` in `library(ripley)`, which adjusts the axis scales to be equal within the current window shape.
Figure 1: Screen dump of an `openlook()` window displaying `brush` on the `iris` data, with different highlights for the three groups.
7 Statistical Summaries

7.1 Arithmetical Summaries

Standard summaries such as `mean`, `median` and `var` are available. The `var` function will take a data matrix and give the variance-covariance matrix, and `cor` computes the correlation matrix, either from two vectors or a data matrix.

There are also standard functions `max`, `min`, `range` and `quantile`. The functions `mean` and `cor` will compute trimmed summaries. More sophisticated robust summaries are available, such as `location.m` and `scale.tau` as well as via the `robust` library.

7.2 Histograms and Stem-and-Leaf Plots

The standard histogram function is `hist(x, ...)` which plots a conventional histogram. More control is available via the extra parameters. The parameter `probability=T` gives a plot of unit area rather than cell counts, and `nclass` sets the number of bins.

Densities can be estimated via the function `density`:

```r
hist(hstart, nclass=20, probability=T, ylim=c(0,0.02))
lines(density(hstart))
lines(density(hstart, width=20), lty = 3)
```

See figure 2.

![Figure 2: A histogram of hstart with two density estimates overlaid.](image)
A *stem-and-leaf* plot is an enhanced histogram:

```r
> stem(hstart)

N = 108 Median = 133.85
Quartiles = 105.2, 158.8

Decimal point is 1 place to the right of the colon

  5 : 5
  6 : 2239
  7 : 55799
  8 : 233567
  9 : 1235779
 10 : 00456
 11 : 04568
 12 : 02346667777899
 13 : 0112344456799
 14 : 1222333447999
 15 : 0013458
 16 : 0159
 17 : 66
 18 : 27
 19 : 77
 20 : 01333445667
 21 : 38
 22 : 68
 23 : 14
```

Apart from giving a visual picture of the data, this gives more detail. The actual data, in sorted order, is roughly 55, 62, 62, 63, 69, ... and this can be read off the plot. Sometimes the pattern of numbers (all odd?) gives clues. Quantiles can be computed (roughly) from the plot.

### 7.3 Boxplots

A *boxplot* is a way to look at the overall shape of a set of data. The central box shows the data between the quartiles, with the median represented by a line. ‘Whiskers’ go out to the extremes of the data, and very extreme points are shown by themselves. It is also possible to plot boxplot for groups side-by-side:

```r
> library(ripley)
> boxplot(split/nottem, cycle/nottem), names=month.abb
```

divides a time-series into months, and plots the boxplots for each month on one plot. See figure 3. Other styles of boxplot are available—see the help page.
8 Distributions

S has functions built in to (approximate) the density, cumulative distribution function and quantile function (the inverse of the CDF) for many standard distributions. There are also functions to simulate samples from these distributions. The first letter of the name indicates the function, e.g. dnorm, pnorm, qnorm, rnorm respectively.

Distributions available are:

<table>
<thead>
<tr>
<th>Distribution</th>
<th>S name</th>
<th>parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>beta</td>
<td>beta</td>
<td>shape1, shape2</td>
</tr>
<tr>
<td>binomial</td>
<td>binom</td>
<td>size, prob</td>
</tr>
<tr>
<td>Cauchy</td>
<td>cauchy</td>
<td>location, scale</td>
</tr>
<tr>
<td>chisquare</td>
<td>chisq</td>
<td>df</td>
</tr>
<tr>
<td>exponential</td>
<td>exp</td>
<td>rate</td>
</tr>
<tr>
<td>F</td>
<td>f</td>
<td>df1,df2</td>
</tr>
<tr>
<td>gamma</td>
<td>gamma</td>
<td>shape</td>
</tr>
<tr>
<td>geometric</td>
<td>geom</td>
<td>prob</td>
</tr>
<tr>
<td>hypergeometric</td>
<td>hyper</td>
<td>m, n, k</td>
</tr>
<tr>
<td>log-normal</td>
<td>lnorm</td>
<td>meanlog, sdlog</td>
</tr>
<tr>
<td>logistic</td>
<td>logis</td>
<td>loc, scale</td>
</tr>
<tr>
<td>negative binomial</td>
<td>nbinom</td>
<td>size, prob</td>
</tr>
<tr>
<td>normal</td>
<td>norm</td>
<td>mean, sd</td>
</tr>
<tr>
<td>normal range</td>
<td>nrange</td>
<td>size, sd</td>
</tr>
<tr>
<td>Poisson</td>
<td>pois</td>
<td>lambda</td>
</tr>
<tr>
<td>stable</td>
<td>stab</td>
<td>index, skewness</td>
</tr>
<tr>
<td>T</td>
<td>t</td>
<td>df</td>
</tr>
<tr>
<td>uniform</td>
<td>unif</td>
<td>min, max</td>
</tr>
<tr>
<td>Weibull</td>
<td>weibull</td>
<td>shape, scale</td>
</tr>
<tr>
<td>Wilcoxon</td>
<td>wilcox</td>
<td>m, n</td>
</tr>
</tbody>
</table>
The function sample re-samples from a data vector, with or without replacement.

8.1 Q-Q Plots

One of the best ways to compare the distribution of a sample \( x \) with a distribution is to use a Q-Q plot, of which the normal probability plot is the best-known example. Q-Q plots can also be used to compare two samples. For a sample \( x \) the quantile function is the inverse of the empirical CDF, that is

\[
\text{quantile}(p) = \min(z \mid \text{proportion } p \text{ of the data } \leq z)
\]

The function \( \text{qqplot}(x, y, \ldots) \) plots the quantile functions of two samples \( x \) and \( y \) against each other, and so compares two samples. The function \( \text{qqnorm}(x) \) replaces one of the samples by a sample at the quantiles of a standard normal distribution. This idea can be applied quite generally. For example, to test a sample against a \( t\alpha \) distribution, we use

\[
\text{plot}( \text{qt(ppoints}(x),9), \text{sort}(x) )
\]

where \( \text{ppoints} \) computes the appropriate set of probabilities for the plot.

The function \( \text{qqline} \) helps assess how straight a \( \text{qqnorm} \) plot is by plotting a straight line through the upper and lower quartiles. (See the example in §3.)
9 Classical Statistics

S-Plus 3.1 has a section on classical statistics. The same functions are used to perform tests and to calculate confidence intervals.

The table shows the amount of wear in a shoe experiment with 10 boys, an experiment reported in Box, Hunter & Hunter (1977), *Statistics for Experimenters*. There were two materials (A and B) that were randomly assigned to the left or right shoe.

<table>
<thead>
<tr>
<th>boy</th>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>13.2 (L)</td>
<td>14.0 (R)</td>
</tr>
<tr>
<td>2</td>
<td>8.2 (L)</td>
<td>8.8 (R)</td>
</tr>
<tr>
<td>3</td>
<td>10.9 (R)</td>
<td>11.2 (L)</td>
</tr>
<tr>
<td>4</td>
<td>14.3 (L)</td>
<td>14.2 (R)</td>
</tr>
<tr>
<td>5</td>
<td>10.7 (R)</td>
<td>11.8 (L)</td>
</tr>
<tr>
<td>6</td>
<td>6.6 (L)</td>
<td>6.4 (R)</td>
</tr>
<tr>
<td>7</td>
<td>9.5 (L)</td>
<td>9.8 (R)</td>
</tr>
<tr>
<td>8</td>
<td>10.8 (L)</td>
<td>11.3 (R)</td>
</tr>
<tr>
<td>9</td>
<td>8.8 (R)</td>
<td>9.3 (L)</td>
</tr>
<tr>
<td>10</td>
<td>13.3 (L)</td>
<td>13.6 (R)</td>
</tr>
</tbody>
</table>

We can use these data to illustrate one-sample and paired and unpaired two-sample tests. The rather voluminous output has been edited:

```r
> shoes <- scan(list(A=0, B=0))
1: 13.2 14.0
3: 8.2 8.8
5: 11.2 10.9
7: 14.3 14.2
9: 10.7 11.8
11: 6.6 6.4
13: 9.5 9.8
15: 10.8 11.3
17: 9.3 8.8
19: 13.3 13.6
21:
> attach(shoes)
> t.test(A, mu=10)

One-sample t-Test

data:  A
   t = 0.8127, df = 9, p-value = 0.4373
alternative hypothesis: true mean is not equal to 10
95 percent confidence interval:
  8.876427 12.383573
sample estimates:
   mean of x
```
10.63

> t.test(A)$conf.int
[1] 8.876427 12.383573
classical confidence interval; for one-sided or two-sided tests:
attr(, "conf.level"): [1] 0.95

> wilcox.test(A, mu=10)

 Exact Wilcoxon signed-rank test
data: A
signed-rank statistic V = 34, n = 10, p-value = 0.5566
alternative hypothesis: true mu is not equal to 10

> t.test(A, B)

 Standard Two-Sample t-Test
data: A and B
t = -0.3689, df = 18, p-value = 0.7165
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -2.744924  1.924924
sample estimates:
 mean of x  mean of y
   10.63    11.04

> t.test(A, B, var.equal=F)

 Welch Modified Two-Sample t-Test
data: A and B
t = -0.3689, df = 17.987, p-value = 0.7165
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -2.745046  1.925046
sample estimates:
 mean of x  mean of y
   10.63    11.04

> t.test(A, B, paired=T)

 Paired t-Test
data: A and B
t = -3.3489, df = 9, p-value = 0.0085
alternative hypothesis: true mean of differences is not equal to 0
95 percent confidence interval:
 -0.6869539 -0.1330461
...
> wilcox.test(A, B, paired=T)

Wilcoxon signed-rank test

data:  A and B
signed-rank normal statistic with correction Z = 2.4495, p-value = 0.0143

The sample size is rather small, and one might wonder about the validity of the \( t \)-distribution. An alternative for a randomized experiment such as this is to base inference on the permutation distribution of \( d \). Figure 4 shows that the agreement is very good. (As the computation of this figure uses some subtle ideas in \( S \), it is omitted: see Venables & Ripley (1994, Chapter 5.).

Figure 4: Histogram and empirical CDF of the permutation distribution of the \( t \)-test in the shoes example. The density and CDF of \( t_{0.01} \) are shown overlaid.

The list of classical tests is:

binom.test   chisq.test   cor.test   fisher.test
friedman.test kruskal.test mantelhaen.test mcnemar.test
prop.test    t.test       var.test   wilcoxon.test

Many of these have alternative methods – for cor.test there are methods "pearson", "kendall" and "spearman".
10 Handling Categorical Data

Consider a (fictitious) survey of shoppers in Britain. Amongst the variables collected for each person surveyed are sex, age, TV area\(^3\), social class\(^4\), transport used for this trip to the shops, and total spend at supermarkets. The possible values of these variables are

- **sex**: M, F
- **age**: 24, 25–44, 45–59, 60+
- **TV area**: 1, . . . , 12
- **social**: A, B, C1, C2
- **transport**: car, bus, cycle, foot
- **spend**: positive continuous

This provides examples of each of S’s types of categorical data structure. There are two main structures, *categories* and *factors*. The latter were introduced in the August 1991 release, and have almost entirely superseded the use of categories. A factor is regarded as a vector over the set of levels which have no implied order. Thus sex, TV area and transport are all factors. However, TV area is coded by number rather than by the names of the companies. These variables can be declared as

```r
sex <- factor(sex.data)
TV.area <- factor(TV.data)
transport <- factor(transport.data)
```

Internally in S levels are numbered in alphabetical order, and when factors are used as treatments in designed experiments, the order of levels may matter. For example, if we want to contrast females with males (rather than *vice versa*) we need to specify the *levels* of the factor explicitly:

```r
> sex <- factor(sex.data, levels=c("M","F"))
```

Social class is an *ordered factor* in that the classes are perceived as ordered, with “A” (professionals) regarded as highest. We can declare an order by

```r
social <- ordered(factor(social.data))
levels(social) <- levels(social)[4:1]
age <- ordered(factor(age.data),
              levels=c("-24", "25-44", "45-59", "60+"))
```

The first line orders the levels by the default (alphabetical) order. The second shows how the set of levels may be changed, in this case by reversing the existing ordering. Age is an ordered category for which it is necessary to specify the levels explicitly. Had `age.data` been specified as a continuous variable, it could have been categorized using `cut` (whose help page gives other ways to produce the categories):

```r
age.cdata <- cut(age.data, c(0, 25, 45, 60, 99))
age <- ordered(factor(age.cdata),
              levels=c("-24", "25-44", "45-59", "60+"))
```

\(^3\)Britain is covered by 12 commercial TV companies, so this provides a simple geographical variable.

\(^4\)Derived from occupation.
Some of the functions for statistical models treat ordered factors in appropriate special ways.

10.1 The Function `tapply(...)` and Ragged Arrays

To continue the previous example, suppose we have want to summarize spend by some of the factors. To calculate the sample mean income for each age-group we can now use the special function `tapply(...):

```r
giving a means vector with the components labeled by the levels

```r
> spend.means <- tapply(spend, age, mean)
```

Suppose further we needed to calculate the standard errors of the mean spends. To do this we need to write an S function to calculate the standard error for any given vector. We discuss functions more fully in §12, but since there is an inbuilt function `var(...)` to calculate the sample variance, such a function is a very simple one-liner, specified by the assignment:

```r
> spend.stderr <- function(x) sqrt(var(x)/length(x))
```

After this assignment, the standard errors are calculated by

```r
> spend.stderr <- tapply(spend, age, stderr)
```

and the values calculated are then

```r
> spend.stderr
```

The function `tapply(...)` can be used to handle more complicated indexing of a vector by multiple factors. For example, we might wish to split the spend by both age and sex:

```r
> tapply(spend, list(age, sex), mean)
```

The combination of a vector and a labelling factor is an example of what is called a ragged array, since the subclass sizes are possibly irregular. When the subclass sizes are all the same the indexing may be done implicitly and much more efficiently by using arrays. The function `apply` is the analogue of `tapply` for arrays.

The pattern of our survey can be seen by the `table` function, which takes a listing of factors and returns the contingency table as an array, e.g.

```r
> table(sex, age, TV.area, social, transport)
```
11 Loops and Conditional Execution

Commands may be grouped together in braces, \{expr_1; expr_2; \ldots; expr_m\}. The value of the group is the result of the last expression in the group evaluated. Since such a group is also an expression it may, for example, be itself included in parentheses and used as part of an even larger expression, and so on. This facility is most often used with the control statements of this section.

The control statements are very close in spirit to those of the C programming language, and only a few are mentioned here. There is a conditional construction of the form

\[
\text{if } (expr_1) \text{ expr}_2 \text{ else expr}_3
\]

where \(expr_1\) must evaluate to a logical value and the result of the entire expression is then evident.

There is also a `for`-loop construction which has the form

\[
\text{for } (name \text{ in } expr_1) \text{ expr}_2
\]

where \(name\) is a dummy, \(expr_1\) is a vector expression (often a sequence like 1:20), and \(expr_2\) is often a grouped expression with its sub-expressions written in terms of the dummy \(name\). \(expr_2\) is repeatedly evaluated as \(name\) ranges through the values in the vector result of \(expr_1\).

As an example, suppose \(\text{ind}\) is a vector of class indicators and we wish to produce separate plots of \(y\) versus \(x\) within classes. Use the `help` facility to understand the following:

\[
\begin{align*}
&> \text{yc <- split(y, ind)}; \quad \text{xc <- split(x, ind)} \\
&> \text{for } (i \text{ in } 1: \text{length(yc)}) \{ \text{plot(xc}[i], yc}[i]); \\
&\quad \quad \text{abline(lsfit(xc}[i], yc}[i])\}
\end{align*}
\]

(Note the function `split(...)` which produces a list of vectors got by splitting a larger vector according to the classes specified by a factor.)

Other looping facilities include the

\[
> \text{repeat } expr
\]

statement and the

\[
> \text{while } (\text{condition}) expr
\]

statement. The `break` statement can be used to terminate any loop abnormally, and `next` can be used to discontinue one particular cycle.

Loops in `S` are often memory-hungry, and care may be needed not to use up all of your computer’s memory. Expert advice is necessary on work-arounds.
12 Writing Your Own Functions

As we have seen informally in §10.1, the S language allows the user to create his or her own functions. These are true S functions that are stored in a special internal form and may be used in further expressions and so on. In the process the language gains enormously in power, convenience and elegance. Most of the functions supplied as part of the S system, such as `mean(...)` and `var(...)` and so on, are themselves written in S and thus do not differ materially from user written functions. (However, increasingly such functions are being re-written as internal functions to gain efficiency.) Listing these functions (by printing their name without parentheses) is a very fruitful way to gain hints for writing your own functions.

A function is defined by an assignment of the form

```r
> name <- function(arg1, arg2, ...) expression
```

The `expression` is an S expression, (usually a grouped expression), that uses the arguments, `argi`, to calculate a value. The value of the expression is the value returned for the function. A call to the function then takes the form `name(expr1, expr2, ...)` and may occur anywhere a function call is legitimate.

For example, the `IQR` function in `library(robust)` is defined as:

```r
IQR <- function(y)
{
    r <- quantile(y, c(.25, .75))
}
```

This first computes the quartiles, then returns the last value computed, their difference.

Note that any ordinary assignments done within the function are temporary and lost after exit from the function. Thus `r` is not left behind, and does not affect any other object `r`.

If global and permanent assignments are intended within a function, then the ‘superassignment’ operator, ‘`<-`’ can be used. See the `help` documentation for details, and see also the `synchronize()` function.

As a second example of a useful function, consider a function to evaluate the ‘Huber proposal 2’ robust estimator(s) of location and/or scale:

```r
hubers <- function(y, k = 1.5, mu, s, initmu = median(y), tol = 1.0e-6)
{
    y <- y[!is.na(y)]
    n <- length(y)
    if(missing(mu)) {
        mu0 <- initmu
        n1 <- n-1
    } else {
        mu0 <- mu
        mu1 <- mu
        n1 <- n
    }
    if(missing(s)) {
```


\begin{verbatim}
s0 <- mad(y)
} else {
  s0 <- s
  s1 <- s
}
th <- 2 * pnorm(k) - 1
beta <- th + k^-2 * (1 - th) - 2 * k * dnorm(k)
repeat {
  yy <- pmin(pmax(mu0 - k * s0, y), mu0 + k * s0)
  if(missing(mu)) mu1 <- sum(yy)/n
  if(missing(s)) {
    ss <- sum((yy - mu1)^2)/n1
    s1 <- sqrt(ss/beta)
  }
  if((abs(mu0 - mu1) < tol * s0) && abs(s0 - s1) < tol * s0)
    break
  mu0 <- mu1
  s0 <- s1
} list(mu = mu0, s = s0)
\end{verbatim}

This allows either of the location \( \mu \) and scale \( s \) to be specified. Optional arguments are the parameter \( k \), the initial value for \( \mu \) and a convergence tolerance. The first line removes all missing values. The \texttt{missing()} function checks if a parameter is supplied. Two constants are then calculated as functions of \( k \). The rest of the function is a loop. In general loops are inefficient in \texttt{S} and should be avoided if at all possible, but here we have no choice as the calculation is iterative. Finally the function returns two components, the location and scale.

It is sometimes useful to be able to time commands:

\begin{verbatim}
cputime <- function(x) sum(unix.time(x)[-3])
elapsed <- function(x) unix.time(x)[3]
\end{verbatim}

which return the total cpu time and the elapsed time taken by a command or sequence of commands enclosed in \{...\}. Note: as these are functions, assignments inside them are in the frame of the function rather than permanent. Alternatively, use \texttt{proc.time()} before and after a group of commands.
13 Statistical Models

These facilities form the heart of the 1991 version of S. They are based on object-oriented extensions, so that generic functions such as print know what to do with the results of various models. The two most basic notions are a data frame (§4.9) and a model formula.

13.1 Model Formulas

A model formula couples a y-vector with a model expressed in a terminology very similar to that of GLIM and GENSTAT. The form is

```r
> loss ~ hardness + tens
```

for the linear regression of loss on hardness and tens. Factors are replaced by a set of indicator variables for the regression, and can interact via the : operator (not . as this is a valid character in a variable name). Thus we can have all the following constructs:

```r
> time ~ poison + treatment + poison:treatment    # equivalent to
> time ~ poison * treatment
> strength ~ yarns/bobbins                        # nested layout
> gain ~ group + initial                          # parallel lines
> conc ~ -1 + reading                             # line thorough the origin
> conc ~ poly(reading, 2)                         # quadratic polynomial
> conc ~ ns(reading, 4, intercept=T)              # natural spline
> conc ~ s(reading)                               # smooth function, for gam
```

The syntax of a linear-model fit is

```r
lm(model formula, data frame)
```

where the names in the model formula refer to columns of the data frame, which can be omitted if it has already been attached. For example

```r
> library(ripley)
> attach(rubber)
> tyres.lm <- lm(loss ~ hard + tens)
> summary(tyres.lm)
> anova(tyres.lm)
> coefficients(tyres.lm)
> plot(fitted(tyres.lm), resid(tyres.lm))
```

This show how to extract information from a fit by the use of ancillary functions. There are no standard ancillary functions for standardized and Studentized residuals, but I have added them as stdres() and studyes() in library(ripley).
13.2 One-way Layouts

The analysis of one-way layout is best illustrated by an example. The table gives data on observed concentrations (ng/ml) of a chemical in groups of 10 patients after oral administration of almitrine bismesylate:

<table>
<thead>
<tr>
<th>subject</th>
<th>25</th>
<th>50</th>
<th>100</th>
<th>200</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>34</td>
<td>92</td>
<td>256</td>
<td>229</td>
</tr>
<tr>
<td>2</td>
<td>46</td>
<td>150</td>
<td>271</td>
<td>232</td>
</tr>
<tr>
<td>3</td>
<td>50</td>
<td>81</td>
<td>270</td>
<td>288</td>
</tr>
<tr>
<td>4</td>
<td>49</td>
<td>155</td>
<td>120</td>
<td>195</td>
</tr>
<tr>
<td>5</td>
<td>21</td>
<td>85</td>
<td>333</td>
<td>354</td>
</tr>
<tr>
<td>6</td>
<td>52</td>
<td>95</td>
<td>198</td>
<td>288</td>
</tr>
<tr>
<td>7</td>
<td>30</td>
<td>95</td>
<td>109</td>
<td>288</td>
</tr>
<tr>
<td>8</td>
<td>29</td>
<td>82</td>
<td>140</td>
<td>170</td>
</tr>
<tr>
<td>9</td>
<td>27</td>
<td>110</td>
<td>147</td>
<td>522</td>
</tr>
<tr>
<td>10</td>
<td>51</td>
<td>99</td>
<td>196</td>
<td>296</td>
</tr>
</tbody>
</table>

> stdev <- function(x) sqrt(var(x))  
> chemical <- scan("chemical.dat")  
> dose <- rep(c(25, 50, 100, 200), 10)  
> group <- factor(dose)  
> boxplot(split(chemical, dose))  
> tapply(chemical, dose, mean)  
> tapply(chemical, dose, stdev)  
> chms <- data.frame(group, chemical)  
> chms.aov <- aov(chemical ~ group, chms)  
> summary(chms.aov)  
> coefficients(chms.aov)  
> chms.aov <- aov(log(chemical) ~ group, chms)  
> summary(chms.aov)  
> summary(aov(log(chemical) ~ log(dose)+group, chms))

which gives

> summary(chms.aov)

<table>
<thead>
<tr>
<th>Df</th>
<th>Sum of Sq</th>
<th>Mean Sq</th>
<th>F Value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>group</td>
<td>3</td>
<td>356084.5</td>
<td>118694.8</td>
<td>28.91804</td>
</tr>
<tr>
<td>Residuals</td>
<td>36</td>
<td>147762.9</td>
<td>4104.5</td>
<td></td>
</tr>
</tbody>
</table>

> coefficients(chms.aov)

(Intercept)  group1  group2  group3
158.375  32.75  44.11667  42.60833

> summary(chms.aov)

<table>
<thead>
<tr>
<th>Df</th>
<th>Sum of Sq</th>
<th>Mean Sq</th>
<th>F Value</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>group</td>
<td>3</td>
<td>356084.5</td>
<td>118694.8</td>
<td>28.91804</td>
</tr>
</tbody>
</table>
The parameterization of linear models for designed experiments is a little tricky. The usual parameterization is to impose a ‘sum to zero’ constraint on the parameters for a factor. GLIM sets the parameter for the first level to zero, so that parameters for the the other levels are differences between that level and the first. By default S uses the Helmert parameterization, which compares the second and subsequent levels to the average of lower levels. The usual parameterization can be gotten as default by setting

```r
options(contrasts=c("contr.sum", "contr.poly"))
```

and the GLIM parameterization by

```r
options(contrasts=c("contr.treatment", "contr.poly"))
```

Of course, the parameterization only affects the coefficients, not the fitted values, residuals, .... The contrasts for a particular term in a fit can be changed by the `C()` function, e.g. `C(group, sum)` or using `contrasts`.

There is a ‘clever’ way to test for linearity using a re-parameterization of the factor `group` as an `ordered` factor, for which the default parameterization is polynomial in `{1, ..., #(levels)}`. (This relies on `log(dose)` having levels in an arithmetic progression. One could always use `poly(log(dose),3)` in place of `ldose`.)

```r
ldose <- ordered(factor(log(dose)))
summary.lm(aov(log(chemical) ~ ldose, chems))
```

(As far as I can see the use of `summary.lm` is necessary to get results for the individual coefficients.) This shows that the response can be regarded as quadratic in `log(dose)`:
13.3 Designed Experiments

The central concept for designed experiments is a factor. Consider the famous Box-Cox poisons data (survival times (in hours) of animals with 3 poisons and 4 antidotes, from Box & Cox (1964), *J. Roy. Statist. Soc.* B26, 211–252 and Box, Hunter & Hunter (1977), *Statistics for Experimenters*). The function `fac.design` generates the rows, columns and so on – consult its help page for full details.

```r
stimes <- scan("poison.dat")
fnames <- list(treat=LETTERS[1:4], repl=1:4, poison=c("I","II","III"))
poisons <- data.frame(fac.design(c(4,4,3), fnames), stimes)
par(mfrow=c(3,2))
plot.design(poisons) # plot main effects
plot.design(poisons, fun=median) # and using medians
attach(poisons)
plot.factor(stimes ~ treat + poison, data=poisons) # box plots
interaction.plot(treat, poison, stimes)
interaction.plot(treat, poison, stimes, fun=median)
poisons.aov <- aov(stimes ~ treat * poison) # full fit
fits <- fitted(aov(stimes ~ treat + poison))
summary(poisons.aov)
par(mfrow=c(2,2))
hist(resid(poisons.aov))
qqnorm(resid(poisons.aov))
plot(fitted(poisons.aov), resid(poisons.aov))
summary(aov(stimes ~ treat + poison + fits^2 + treat:poison))

which gives

> summary(poisons.aov)
   Df Sum of Sq  Mean Sq  F Value  Pr(F)
  treat     3  92.1206  30.70688 13.80558 0.0000038
  poison   2  103.3012  51.65062 23.22174 0.0000003
treat:poison 6  25.0138   4.16896  1.87433 0.1122506
Residuals 36  80.0725   2.22424
```

F-statistic: 74.72 on 3 and 36 degrees of freedom,
the p-value is 1.554e-15
Figure 5: Plots for Poison data
indicating the need for transformation. The \( I(\ldots) \) function protects the argument from expansion; \((\text{treat} + \text{poison})^2\) is equivalent to \(\text{treat} + \text{poison} + \text{treat:poison}\) and generally \((\text{factors})^n\) gives up to \(n\)-th order interactions.

There is no direct Box-Cox function, but we can do the operations by hand. They are quite slow (25 secs on a SparcStation IPC), due to the overhead of calling the `aov` function:

```r
xl <- seq(-2,1,by=0.1)
loglik <- as.vector(xl)
n <- length(stimes)
nlglm <- log(prod(stimes))
for(i in 1:length(xl)){
  if(abs(xl[i]) > 0.01)
    { ss <- sum((aov(stimes~xl[i] ~ treat + poison)$resid)^2)
      loglik[i] <- n*log(abs(xl[i])) - n/2*log(ss) + (xl[i]-1)*nlglm
    }
  else
    { ss <- sum((aov(log(stimes) ~ treat + poison)$resid)^2)
      loglik[i] <- - n/2*log(ss) - nlglm
    }
}
plot(xl, loglik, xlab = "Lambda", ylab = "Log Likelihood", type = "l")
lambdaht <- loglik[loglik == max(loglik)]
limit <- lambdaht - 0.5 * qchisq(0.95, 1)
abline(limit, 0)
scal <- (par("usr")[4] - par("usr")[3])/par("pin")[2]
text(c(xl[1]), limit + 0.1 * scal, " 95\%")
```

A more efficient way (4 secs) is to use the function `BoxCox` in the library `ripley`:

```r
> library(ripley)
> BoxCox(stimes ~ treat + poison)
```

Now consider a Latin square. Six litters of six piglets were ranked in order of birthweight, providing a \(6 \times 6\) table, and each piglet given one of 6 dietary supplements in a Latin square. The weight gain (in kg) over 12 weeks is given in the table.
> diet <- scan(""")
D E A C B F
C D F B A E
F A C E D B
B C E A F D
E F B D C A
A B D F E C

> wtgain <- scan()
5.74 7.21 5.92 6.58 7.24 4.83
5.92 5.74 7.88 6.53 6.73 6.05
8.18 5.87 5.41 7.49 7.44 6.43
3.58 5.21 5.61 4.39 7.63 5.44
6.05 8.16 6.27 5.84 6.71 5.77
4.95 6.35 5.56 7.50 7.04 6.22

> diet <- factor(diet)
> latin <- data.frame(fac.design(c(6,6), list(brank=1:6,litter=1:6)),
+    diet, wtgain)
> plot.design(latin)
> Diet <- C(diet, treatment)
> latin.aov <- aov(wtgain ~ brank + litter + Diet, latin)
> summary(latin.aov)
> summary.lm(latin.aov)

The last command gives t-values for the contrasts (diet ? — diet A).

> summary(latin.aov)

              Df Sum of Sq Mean Sq  F Value Pr(>F)
brank          5  7.924055 1.584809 2.788687 0.04545633
litter         5  7.720418 1.544083 2.717023 0.04962477
Diet           5 11.617512 2.323503 4.088518 0.01015490
Residuals      20 11.365990 0.568299

> summary.lm(latin.aov)

Call: aov(formula = wtgain ~ brank + litter + Diet, data = latin)
Residuals:
   Min   1Q Median   3Q  Max
-2.051 -0.2906  0.1211  0.3715  0.9061

Coefficients:
            Value Std. Error   t value Pr(>|t|)
(Intercept) 5.6052    0.3078 18.2122   0.0000

...............
DietB 0.4617    0.4352  1.0607   0.3015
DietC 0.4033    0.4352  0.9267   0.3651
DietD 0.3550    0.4352  0.8156   0.4243
DietE 0.9700    0.4352  2.2287   0.0375
DietF 1.7583    0.4352  4.0399   0.0006
13.4 Generalized Linear Models

The functions `lm` and `aov` have extensions `glm` which fits generalized linear models, and `gam` which further extends this to allow semi-parametric smooth functions in the explanatory variables. We can, for example, fit the poisons data by a gamma GLM:

```r
attach(poisons)
poisons.glm <- glm(stimes ~ treat + poison, family=Gamma)
summary(poisons.glm)
```

Once again there is a whole range of ancillary functions such as `deviance`, `predict` and `residuals`. The latter will produce a four types of residuals, but uses deviance residuals by default.

The `family` argument is also used to specify other aspects of the fit such as the link function. For example, one can have `family=binomial(link=probit)`. With the binomial the response can either be a factor (taken as first level vs the rest) or a matrix with two columns giving the number of successes and failures. There is a `quasi` family allowing user-defined models, and a robust family generator allowing robust fitting. The scope for ingenuity is unlimited!

**Binary Data**

The following example is taken from D. Collett (1991) *Modelling Binary Data*, page 217. Numbers of rotifers falling out of suspension for two species (*Polyarthra major* and *Keratella cochlearis*) are given for different fluid densities in the table, as file `rotifer.dat`:

```r
density pm.y pm.tot kc.y kc.tot
1.019 11 58 13 161
1.020 7 86 14 248
1.021 10 76 30 234
1.030 19 83 10 283
1.030 9 56 14 129
1.030 21 73 35 161
1.031 13 29 26 167
1.040 34 44 32 286
1.040 10 31 22 117
1.041 36 56 23 162
1.048 20 27 7 42
1.049 54 59 22 48
1.050 20 22 9 49
1.050 9 14 34 160
1.060 14 17 71 74
1.061 10 22 25 45
1.063 64 66 94 101
1.070 68 86 63 68
1.070 488 492 178 190
1.070 88 89 154 154
```

An annotated session follows. Several points need further explanation.
The parametrizations need careful consideration. By default S uses a linear-model parameterization, contrasting each level with the average of the previous levels. This is less useful for GLMs. The first way out below is to remove the overall mean (the \(-1\) term) which forces separate means for each species. We can also change to the GLIM parameterization by the options line.

There is a catch here. By default \texttt{factor()} numbers the factor levels in alphabetical order, so we have to force the order we want (see §10).

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure6}
\caption{Plots for Rotifer data. The square symbols and dashed line indicate species \textit{Polyartha major}.}
\end{figure}

\begin{verbatim}
rotifers <- read.table("rotifer.dat", header=T)
rotifers
attach(rotifers)
kc.prop <- kc.y/kc.tot
pm.prop <- pm.y/pm.tot
plot(density, pm.prop, type="n", ylim = c(0,1))
points(density, pm.prop, pch=0)
points(density, kc.prop)

fit separate models for each species

glm.pm <- glm(cbind(pm.y, pm.tot-pm.y) ~ density, binomial(logit))
glm.kc <- glm(cbind(kc.y, kc.tot-kc.y) ~ density, binomial(logit))
glm.pm; glm.kc

bare summaries

Now combine the two species

species <- factor(c(rep("pm",20), rep("kc",20)),
                 levels= c("pm", "kc"))
rotifier2 <- data.frame(dens = c(density, density),
                       yes = c(pm.y, kc.y), tot = c(pm.tot, kc.tot), species)
attach(rotifier2)

glm.rot <- glm(cbind(yes, tot-yes) ~ dens * species, binomial(logit))
\end{verbatim}
glm.rot <- glm(cbind(yes, tot=yes) ~ 1 + dens * species, binomial(logit))  
glm.rot <- glm(cbind(yes, tot=yes) ~ dens + species, binomial(logit))  
summary(glm.rot)  
anova(glm.rot)

Poisson Data

We consider the log-linear analysis of a contingency table. As this has two ‘history’ factors and two levels of the response, it could also be treated as binomial data. The response is the occurrence of coronary heart disease. The table is of the form:

<table>
<thead>
<tr>
<th></th>
<th>blood pressure</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>serum cholesterol</td>
</tr>
<tr>
<td></td>
<td>1  2  3   4</td>
</tr>
<tr>
<td>yes</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>2  3  3   4</td>
</tr>
<tr>
<td>2</td>
<td>3  2  1   3</td>
</tr>
<tr>
<td>3</td>
<td>8  11 6   6</td>
</tr>
<tr>
<td>4</td>
<td>7  12 11 11</td>
</tr>
<tr>
<td>no</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>117 121 47   22</td>
</tr>
<tr>
<td>2</td>
<td>85 98 43   20</td>
</tr>
<tr>
<td>3</td>
<td>119 209 68  43</td>
</tr>
<tr>
<td>4</td>
<td>67 99 46   33</td>
</tr>
</tbody>
</table>

Poisson Data

We consider the log-linear analysis of a contingency table. As this has two ‘history’ factors and two levels of the response, it could also be treated as binomial data. The response is the occurrence of coronary heart disease. The table is of the form:

\[ \begin{array}{|c|c|c|c|c|}
\hline
\text{serum cholesterol} & \text{blood pressure} \\
\hline
\text{yes} & 1 & 2 & 3 & 4 \\
\hline
1 & 2 & 3 & 3 & 4 \\
2 & 3 & 2 & 1 & 3 \\
3 & 8 & 11 & 6 & 6 \\
4 & 7 & 12 & 11 & 11 \\
\hline
\text{no} & & & & \\
\hline
1 & 117 & 121 & 47 & 22 \\
2 & 85 & 98 & 43 & 20 \\
3 & 119 & 209 & 68 & 43 \\
4 & 67 & 99 & 46 & 33 \\
\hline
\end{array} \]

with log-linear analysis:

num <- scan()
2 3 3 4 3 2 1 3 8 11 6 6 7 12 11 11 117 121 47 22 85 98 43 20 119 209 68 43 67 99 46 33

fnames <- list(press=1:4, serum=1:4, chd=c("y","n"))
kk <- data.frame(fac.design(c(4,4,2);fnames), num)
13.5 Updating and Selecting Models

There are number of facilities to update models. The `update` function takes a result of a previous fit and changes the model in some way.

`add1` and `drop1` show the (approximate) effects of adding and dropping single terms, and `step` runs a fairly general stepwise fitting procedure. (Note that S-Plus 3.x has a separate `stepwise` function for multiple regression.)
14 Multivariate Analysis

S-Plus is particularly rich in functions for exploratory multivariate analysis, such as \texttt{pairs}, \texttt{brush} and \texttt{spin}. There are also functions for classical multivariate analysis.

Clustering

The workhorses here are \texttt{dist} which computes distance matrices (also used in \texttt{cmdscale}) and \texttt{hclust} which computes a cluster tree by single-, average- or complete linkage.

\begin{verbatim}
dist hclust cutree plclust labclust clorder subtree mclust mclass mreloc
\end{verbatim}

Distance matrix calculations
Hierarchical clustering
Create groups from a cluster tree
Plot a cluster tree
Label a cluster tree plot
Re-order leaves of a cluster tree
Extract part of a cluster tree
"model-based” clustering
auxiliary functions

Graphical Methods

This is a varied collection of functions for displaying multivariate data.

\begin{verbatim}
cmdscale faces mstree stars biplot
\end{verbatim}

Classical multi-dimensional scaling
Chernoff’s faces
Minimal spanning tree
Star plots
Biplot (v 3.2)

Two analyses of socio-economic data on Swiss cantons:

\begin{verbatim}
library(ripley)
d <- dist(swiss.x)
x <- cmdscale(d)
c1 <- x[,1]; c2 <- x[,2]
eqsclplot(c1, c2, type="n") # from library(ripley)
text(c1, c2, seq(c1))

h <- hclust(d)
plclust(h)
cutree(h, 3)
plclust(clorder(h, cutree(h, 3))) # re-order tree into three groups
\end{verbatim}
Matrix Methods

The classical methods based on variance-covariance matrices.

mahalanobis  Mahalanobis distances
ccancor       Canonical correlation analysis
discr         Discriminant analysis
pcrcomp       Principal components analysis
princomp      Principal components analysis (v 3.2)
factanal      Principal components analysis (v 3.2)

An example of discriminant analysis with Fisher's iris data:

iris.var <- rbind(iris[,1], iris[,2], iris[,3])
species <- rep(1:3,rep(50,3))
iris.dis <- descr(iris.var, 3)
iris.dv <- iris.var %*% iris.dis$vars # find discriminant variables
brush(cbind(iris.dv, species))
iris.x <- iris.dv[,1]; iris.y <- iris.dv[,2]
iris.lab <- c(rep("s", 50), rep("c", 50), rep("v", 50))
plot(iris.x, iris.y, type="n", xlab="first discriminant variable",
     ylab="second discriminant variable")
text(iris.x, iris.y, iris.lab, cex=0.7)

Figure 7: Discriminant analysis
A Libraries

Libraries are a mechanism to add ‘packages’ of extra objects (functions and datasets) to S. To find out which libraries are available type

```r
> library()
```

which on one of my systems gave:

The following sections are available in the library:

<table>
<thead>
<tr>
<th>SECTION</th>
<th>BRIEF DESCRIPTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>chron</td>
<td>Functions to handle dates and times.</td>
</tr>
<tr>
<td>examples</td>
<td>Functions and objects from The New S Language.</td>
</tr>
<tr>
<td>external</td>
<td>Handle external (large) objects.</td>
</tr>
<tr>
<td>image</td>
<td>Display images.</td>
</tr>
<tr>
<td>maps</td>
<td>Display of maps with projections.</td>
</tr>
<tr>
<td>prodraw</td>
<td>Sdraw example from Programmer’s Manual.</td>
</tr>
<tr>
<td>progexam</td>
<td>Examples from Programmer’s Manual.</td>
</tr>
<tr>
<td>semantics</td>
<td>Functions from chapter 11 of The New S Language.</td>
</tr>
</tbody>
</table>

ripley     | B.D. Ripley’s teaching functions

For more information on each library section see the README file in each library section directory or in S-PLUS run:

```r
library( help = <section_name> )
```

Library sections from Venables & Ripley (1994)

‘Modern Applied Statistics with S-Plus’

<table>
<thead>
<tr>
<th>MASS</th>
<th>main library</th>
</tr>
</thead>
<tbody>
<tr>
<td>nnet</td>
<td>neural networks</td>
</tr>
<tr>
<td>spatial</td>
<td>spatial statistics</td>
</tr>
</tbody>
</table>

To find out more about a section, use

```r
> library(help=name)
```

e.g.

```r
> library(help=robust)
```

functions for robust statistics

<table>
<thead>
<tr>
<th>IQR(y)</th>
<th>inter-quartile range</th>
</tr>
</thead>
<tbody>
<tr>
<td>huber(y, k = 1.5)</td>
<td>Huber location with MAD scale</td>
</tr>
<tr>
<td>hubers(y, k = 1.5, mu, s)</td>
<td>Huber proposal 2 [with mu known, s known]</td>
</tr>
<tr>
<td>hreg(x, y, k = 1.5)</td>
<td>Huber robust regression</td>
</tr>
</tbody>
</table>

datasets

<table>
<thead>
<tr>
<th>chem</th>
<th>copper in wholemeal flour</th>
</tr>
</thead>
<tbody>
<tr>
<td>abbey</td>
<td>nickel in syenite rock</td>
</tr>
</tbody>
</table>
To use the library, invoke it by

```r
> library(name)
```

which attaches it as a data directory at the end of the search list. Thus libraries cannot over-ride standard functions nor your own functions. To make a library over-ride the system functions, use

```r
> library(name, first=T)
```

which attaches it at position 2 (after the .Data directory).

### A.1 Library ripley

This is a collection of useful functions and datasets for teaching at Oxford.

- `BoxCox(x,y)` : Box-Cox plot for transformations.
- `gl(from,to,size,x)` : replacement for GLIM `%gl`.
- `eqsplot` : equally-scaled plot function.
- `stdres(object)` : calculate standardized residuals from a fit.
- `studres(object)` : calculate Studentized residuals from a fit.

Datasets in the library are:

- `accdeaths` : US accidental deaths 1973-8
- `cement` : dataset on heat evolved in setting cements
- `cpus` : dataset on performance of cpus
- `deaths` : time series on UK lung deaths 1974-9 from Diggle
- `mdeaths, fdeaths` : as above, for males and females
- `gehan` : remission times on leukaemia patients (censored)
- `forbes` : Forbes’ dataset on boiling points, from Atkinson
- `hills` : dataset on times of Scottish hill races
- `leuk` : (uncensored) survival times on leukaemia patients
- `lh` : time series on luteinizing hormone from Diggle
- `mammals` : body weight(kg) and brain weight (g) of mammals, from Weisberg
- `mcycle` : motorcycle impact data – Silverman JRSS B 1985
- `motorette` : accelerated life testing on motorettes
- `nottem` : time-series of temperatures in Nottingham, 1920-1939
- `road` : dataset on road deaths in the US
- `rock` : dataset on relating permeability to physical measurements
- `rubber` : dataset on rubber wear
- `ships` : ship damage incidents, from McCullagh & Nelder
- `trees` : Black Cherry trees heights, diameters and volumes

### A.2 Sources of Libraries

Many S users have generously collected together their functions and datasets together into libraries and made them publically available. An archive of libraries is maintained at Carnegie-
Mellon as a service to the statistical profession by Mike Meyer. To obtain details of its contents by e-mail send a message to

statlib@lib.stat.cmu.edu

with body

send index
send index from S

Ftp to lib.stat.cmu.edu with user statlib is also available.