# Getting Started With R 1

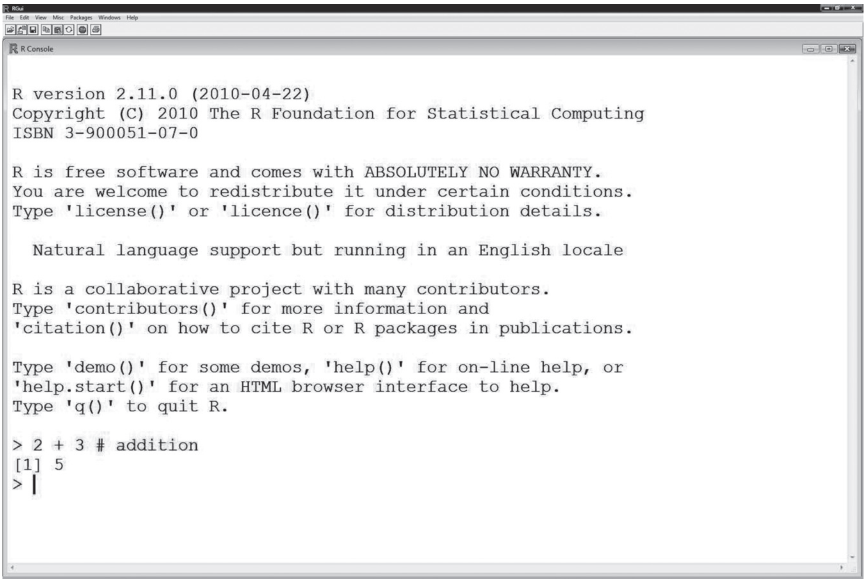
The purpose of this chapter is to introduce you to the R language and interpreter. After describing some of the basics of R, we will proceed to illustrate its use in a typical, if small, regression problem. We will then provide a brief description of R functions for familiar operations in basic statistics. The chapter concludes with an equally brief introduction to the *R Commander* graphical user interface (GUI) to R.

We know that many readers are in the habit of beginning a book at Chapter 1, skipping the Preface. The Preface to this *Companion* includes information about installing R and the **car** package on your computer. The **car** package, associated with the *R Companion to Applied Regression*, is necessary for many of the examples in the text. Moreover, the Preface includes information on the typographical and other conventions that we use in the text.

## 1.1 R Basics

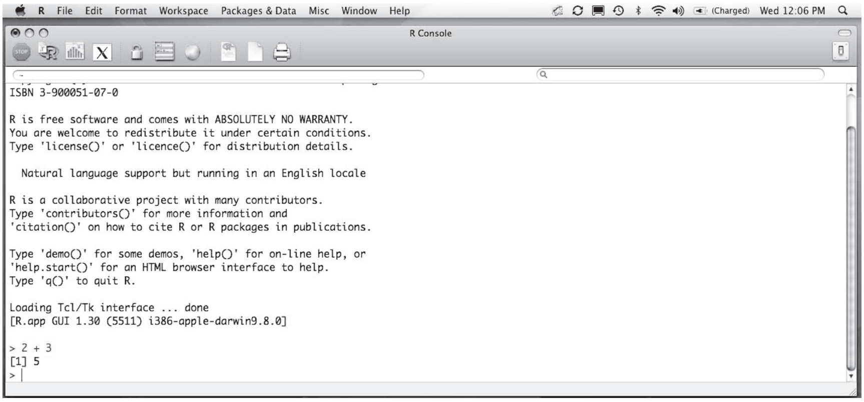
Figure 1.1 shows the *RGui* (R *G*raphical *U*ser *I*nterface) for the Windows version of R. The most important element of the *Rgui* is the *R Console* window, which initially contains an opening message followed by a line with just a *command prompt*—the greater than (>) symbol. Interaction with R takes place at the command prompt. In Figure 1.1, we typed a simple command, `2 + 3`, followed by the Enter key. R interprets and executes the command, returning the value `5`, followed by another command prompt. Figure 1.2 shows the similar *R.app* GUI for the Mac OS X version of R.

The menus in *RGui* and *R.app* provide access to many routine tasks, such as setting preferences, various editing functions, and accessing documentation. We draw your attention in particular to the *Packages* menu in the Windows *RGui* and to the *Packages & Data* menu in the Mac OS X *R.app*, both of which provide dialogs for installing and updating R packages. Unlike



```
R version 2.11.0 (2010-04-22)
Copyright (C) 2010 The R Foundation for Statistical Computing
ISBN 3-900051-07-0

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

  Natural language support but running in an English locale

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> 2 + 3 # addition
[1] 5
> |
```

**Figure 1.1** The *RGui* interface to the Windows version of R, shortly after the beginning of a session. This screen shot shows the default multiple-document interface (MDI); the single-document interface (SDI) looks similar but consists only of the *R Console* with the menu bar.



R File Edit Format Workspace Packages & Data Misc Window Help
(Charged) Wed 12:06 PM
R Console
STOP

```
ISBN 3-900051-07-0

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

  Natural language support but running in an English locale

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

Loading Tcl/Tk interface ... done
[R.app GUI 1.30 (5511) i386-apple-darwin9.8.0]

> 2 + 3
[1] 5
> |
```

**Figure 1.2** The *R.app* interface to the Mac OS X version of R.

many statistical analysis programs, the standard R menus do not provide direct access to the statistical functions in R, for which you will generally have to enter commands at the command prompt.

### 1.1.1 INTERACTING WITH THE INTERPRETER

Data analysis in R typically proceeds as an interactive dialogue with the interpreter. We type an R command at the > prompt, press the Enter key, and the interpreter responds by executing the command and, as appropriate, returning a result, producing graphical output, or sending output to a file or device.

The R language includes the usual arithmetic operators:

| | |
|---|---|
| + | addition |
| - | subtraction |
| * | multiplication |
| / | division |
| ^ or ** | exponentiation |

Here are some simple examples of arithmetic in R:

```
> 2 + 3 # addition

[1] 5

> 2 - 3 # subtraction

[1] -1

> 2*3   # multiplication

[1] 6

> 2/3   # division

[1] 0.6667

> 2^3   # exponentiation

[1] 8
```

Output lines are preceded by `[1]`. When the printed output consists of many values spread over several lines, each line begins with the index number of the first element in that line; an example will appear shortly. After the interpreter executes a command and returns a value, it waits for the next command, as signified by the > prompt. The pound sign (#) signifies a comment: Text to the right of # is ignored by the interpreter. We often take advantage of this feature to insert explanatory text to the right of commands, as in the examples above.

Several arithmetic operations may be combined to build up complex expressions:

```
> 4^2 - 3*2

[1] 10
```

In the usual notation, this command is $4^2 - 3 \times 2$. R uses standard conventions for precedence of mathematical operators. So, for example, exponentiation takes place before multiplication, which takes place before subtraction. If two operations have equal precedence, such as addition and subtraction, then they take place from left to right:

```
> 1 - 6 + 4

[1] -1
```

You can always explicitly specify the order of evaluation of an expression by using parentheses; thus, the expression `4^2 - 3*2` is equivalent to

```
> (4^2) - (3*2)

[1] 10
```

and

```
> (4 + 3)^2

[1] 49
```

is different from

```
> 4 + 3^2

[1] 13
```

Although spaces are not required to separate the elements of an arithmetic expression, judicious use of spaces can help clarify the meaning of the expression. Compare the following commands, for example:

```
> -2--3

[1] 1

> -2 - -3

[1] 1
```

Placing spaces around operators usually makes expressions more readable, as in the preceding examples. Readability of commands is generally improved by putting spaces around the binary arithmetic operators + and - but not around `*`, `/`, or `^`.

### 1.1.2 R FUNCTIONS

In addition to the common arithmetic operators, R includes many—literally hundreds—of functions for mathematical operations, for statistical data analysis, for making graphs, and for other purposes. Function *arguments* are values passed to functions, and these are specified within parentheses after the function name. For example, to calculate the natural log of 100, that is $\log_e 100$ or $\ln 100$, we type

```
> log(100)

[1] 4.605
```

To compute the log of 100 to the base 10, we specify

```
> log(100, base=10)
[1] 2
> log10(100) # equivalent
[1] 2
```

In general, arguments to R functions may be specified in the order in which they occur in the function definition or by the name of the argument followed by = (equals sign) and a value. In the command `log(100, base=10)`, the value `100` is matched to the first argument in the `log` function. The second argument, `base=10`, explicitly matches the value `10` to the argument `base`.

Different arguments are separated by commas, and for clarity, we prefer to leave a space after each comma, although these spaces are not required. Argument names may be abbreviated, as long as the abbreviation is unique; thus, the previous example may be rendered more compactly as

```
> log(100, b=10)
[1] 2
```

To obtain information about a function, use the `help` function. For example,

```
> help(log)
```

The result of executing this command is shown in abbreviated form in Figure 1.3, where the three widely separated dots (`. . .`) mean that we have elided some information. An alternative that requires less typing is to use the equivalent `?` (help) operator, `?log`.

Figure 1.3 is a typical R help page, giving first a brief description of the functions documented in the help page, followed by a listing of the available arguments, and then a discussion of the arguments. The `Details` and `Value` sections generally describe what the function does. All functions return a value, and the `log` function returns the logarithm of its first argument. Some functions, particularly those that draw graphs, don't *appear* to return a value and are used instead for the *side effect* of drawing a graph. Help pages usually include references to related functions, along with examples that you can execute to see how the documented functions work. Reading R documentation is an acquired skill, but once you become familiar with the form of the documentation, you will likely find the help pages very useful.

Help can be displayed in a help window as a plain-text file, or as an HTML page in a web browser. The HTML help format has several useful features, such as live hypertext links to other help pages, and is selected by the command `options(help_type="html")`. HTML help is the default option when R is installed.

The `help.start()` command opens a page in your web browser that gives direct access to a variety of resources, including HTML versions of the

```
log                    package:base                    R Documentation
Logarithms and Exponentials
Description:
     ’log’ computes logarithms, by default natural logarithms,
     ’log10’ computes common (i.e., base 10) logarithms, and
     ’log2’ computes binary (i.e., base 2) logarithms.  The general
     form ’log(x, base)’ computes logarithms with base ’base’.
. . .
     ’exp’ computes the exponential function.
. . .
Usage:
     log(x, base = exp(1))
     logb(x, base = exp(1))
     log10(x)
     log2(x)
. . .
     exp(x)
. . .
Arguments:
       x: a numeric or complex vector.
    base: a positive or complex number: the base with respect to which
          logarithms are computed.  Defaults to e=’exp(1)’.
Details:
     All except ’logb’ are generic functions: methods can be
     defined for them individually or via the ’Math’ group generic.
. . .
Value:
     A vector of the same length as ’x’ containing the transformed
     values.  ’log(0)’ gives ’-Inf’, and negative values give
     ’NaN’.
. . .
See Also:
     ’Trig’, ’sqrt’, ’Arithmetic’.
Examples:
     log(exp(3))
     log10(1e7)# = 7
     x <- 10^-(1+2*1:9)
     cbind(x, log(1+x), log1p(x), exp(x)-1, expm1(x))
```

**Figure 1.3** The documentation returned by the command `help(log)`. The ellipses (`. . .`) represent elided lines.

R manuals, hyperlinked help for all installed packages, a help search engine, frequently-asked-questions (FAQ) lists, and more. The `help.start()` command is so useful that you may want to put it into a startup file so that the help browser opens at the beginning of every R session (see the Preface and `?Startup`).

A novel feature of the R help system is the facility it provides to execute most examples in the help pages via the `example` command:

```
> example("log")

log> log(exp(3))
[1] 3

log> log10(1e7)  # = 7
```

```
[1] 7
. . .
```

The number `1e7` in the last example is given in scientific notation and represents $1 \times 10^7 = 10$ million.

A quick way to determine the arguments of many functions is to use the `args` function:

```
> args(log)

function (x, base = exp(1))
NULL
```

Because `base` is the second argument of the `log` function, we can also type

```
> log(100, 10)

[1] 2
```

specifying both arguments to the function (i.e., `x` and `base`) by position.

An argument to a function may have a *default* value—a value that the argument assumes if it is not explicitly specified in the function call. Defaults are shown in the function documentation and in the output of `args`. For example, the `base` argument to the `log` function defaults to `exp(1)` or $e^1 \approx 2.718$, the base of the natural logarithms.

R is largely a *functional programming language*, which means that both the standard programs that make up the language and the programs that users write are functions. Indeed, the distinction between standard and user-defined functions is somewhat artificial in R.[1] Even the arithmetic operators in R are really functions and may be used as such:

```
> '+'(2, 3)

[1] 5
```

We need to place back-ticks around `'+'` (single or double quotes also work) so that the interpreter does not get confused, but our ability to use + and the other arithmetic functions as *in-fix* operators, as in `2 + 3`, is really just syntactic "sugar," simplifying the construction of R expressions but not fundamentally altering the functional character of the language.

### 1.1.3 VECTORS AND VARIABLES

R would not be very convenient to use if we had to compute one value at a time. The arithmetic operators, and most R functions, can operate on more complex data structures than individual numbers. The simplest of these data structures is a numeric vector, or one-dimensional list of numbers.[2] In R an individual number is really a vector with a single element. A simple way to construct a vector is with the `c` function, which combines its elements:

[1] Section 1.1.6 briefly discusses user-defined functions; the topic is treated in greater depth in Chapter 8. Experienced programmers can also access programs written in Fortran and C from within R.

[2] We refer to vectors as "lists" using that term loosely, because *lists* in R are a distinct data structure (described in Section 2.3).

```
> c(1, 2, 3, 4)

[1] 1 2 3 4
```

Many other functions also return vectors as results. For example, the *sequence operator* (`:`) generates consecutive numbers, while the sequence function (`seq`) does much the same thing, but more flexibly:

```
> 1:4 # integer sequence

[1] 1 2 3 4

> 4:1

[1] 4 3 2 1

> -1:2

[1] -1  0  1  2

> seq(1, 4)

[1] 1 2 3 4

> seq(2, 8, by=2) # specify interval

[1] 2 4 6 8

> seq(0, 1, by=0.1) # non-integer sequence

 [1] 0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0

> seq(0, 1, length=11) # specify number of elements

 [1] 0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
```

The standard arithmetic operators and functions apply to vectors on an element-wise basis:

```
> c(1, 2, 3, 4)/2

[1] 0.5 1.0 1.5 2.0

> c(1, 2, 3, 4)/c(4, 3, 2, 1)

[1] 0.2500 0.6667 1.5000 4.0000

> log(c(0.1, 1, 10, 100), 10)

[1] -1  0  1  2
```

If the operands are of different lengths, then the shorter of the two is extended by repetition, as in `c(1, 2, 3, 4)/2` above; if the length of the longer operand is not a multiple of the length of the shorter one, then a warning message is printed, but the interpreter proceeds with the operation, *recycling* the elements of the shorter operand:

```
> c(1, 2, 3, 4) + c(4, 3) # no warning

[1] 5 5 7 7

> c(1, 2, 3, 4) + c(4, 3, 2) # produces warning

[1] 5 5 5 8

Warning message:
In c(1, 2, 3, 4) + c(4, 3, 2) :
  longer object length is not a multiple of shorter object length
```

R would also be of little use if we were unable to save the results returned by functions; we do so by *assigning* values to *variables*, as in the following example:

```
> x <- c(1, 2, 3, 4) # assignment
> x # print

[1] 1 2 3 4
```

The left-pointing arrow (`<-`) is the *assignment operator*; it is composed of the two characters < (less than) and - (dash or minus), with no intervening blanks, and is usually read as *gets*: “The variable `x` *gets* the value `c(1, 2, 3, 4)`.” The equals sign (=) may also be used for assignment in place of the arrow (`<-`), except inside a function call, where = is exclusively used to specify arguments by name. Because reserving the equals sign for specification of function arguments leads to clearer and less error-prone R code, we encourage you to use the arrow for assignment, even where = is allowed.[3]

As the preceding example illustrates, when the leftmost operation in a command is an assignment, nothing is printed. Typing the name of a variable, as in the second command immediately above, causes its value to be printed.

Variable names in R are composed of letters (`a`–`z`, `A`–`Z`), numerals (`0`–`9`), periods (`.`), and underscores (_), and they may be arbitrarily long. The first character must be a letter or a period, but variable names beginning with a period are reserved by convention for special purposes.[4] Names in R are case sensitive; so, for example, `x` and `X` are distinct variables. Using descriptive names, for example, `total.income` rather than `x2`, is almost always a good idea.

Three common naming styles are conventionally used in R: (1) separating the parts of a name by periods, as in `total.income`; (2) separating them by underscores, as in `total_income`; or (3) separating them by uppercase letters, termed *camel case*, as in `totalIncome`. For variable names, we prefer the first style, but this is purely a matter of taste.

R commands using defined variables simply substitute the value of the variable for its name:

[3] R also permits a right-pointing arrow for assignment, as in `2 + 3 -> x`.

[4] Nonstandard names may be used in a variety of contexts, including assignments, by enclosing the names in back-ticks, or in single or double quotes (e.g., `'first name' <- "John"`). In most circumstances, however, nonstandard names are best avoided.

```
> x/2

[1] 0.5 1.0 1.5 2.0

> (y <- sqrt(x))

[1] 1.000 1.414 1.732 2.000
```

In the last example, `sqrt` is the square-root function, and thus `sqrt(x)` is equivalent to `x^0.5`. To obtain printed output without having to type the name of the variable `y` as a separate command, we enclose the command in parentheses so that the assignment is no longer the leftmost operation. We will use this trick regularly.

Unlike in many programming languages, variables in R are dynamically defined. We need not tell the interpreter in advance how many values `x` is to hold or whether it contains integers (whole numbers), real numbers, character values, or something else. Moreover, if we wish, we may *redefine* the variable `x`:

```
(x <- rnorm(100))  # 100 standard normal random numbers

  [1]  0.58553  0.70947 -0.10930 -0.45350  0.60589 -1.81796  0.63010
  [8] -0.27618 -0.28416 -0.91932 -0.11625  1.81731  0.37063  0.52022
 [15] -0.75053  0.81690 -0.88636 -0.33158  1.12071  0.29872  0.77962
. . .
 [92] -0.85508  1.88695 -0.39182 -0.98063  0.68733 -0.50504  2.15772
 [99] -0.59980 -0.69455
```

The `rnorm` function generates standard-normal random numbers, in this case, 100 of them. Two additional arguments, not used in this example, allow us to sample values from a normal distribution with arbitrary mean and standard deviation; the defaults are `mean=0` and `sd=1`, and because we did not specify these arguments, the defaults were used. When a vector prints on more than one line, as in the last example, the index number of the leading element of each line is shown in square brackets.

The function `summary` is an example of a *generic function*: How it behaves depends on its argument. Applied as here to a numeric vector,

```
> summary(x)

   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -2.380  -0.590   0.484   0.245   0.900   2.480
```

`summary` prints the minimum and maximum values of its argument, along with the mean, median, and first and third quartiles. Applied to another kind of object—a matrix, for example—`summary` gives different information, as we will see later.

### 1.1.4 NONNUMERIC VECTORS

Vectors may also contain nonnumeric values. For example,

```
> (words <- c("To", "be", "or", "not", "to", "be"))

[1] "To"  "be"  "or"  "not" "to"  "be"
```

is a *character vector* whose elements are character strings. There are R functions to work with character data. For example, to turn this vector into a single character string:

```
> paste(words, collapse=" ")

[1] "To be or not to be"
```

The very useful `paste` function pastes strings together (and is discussed, along with other functions for manipulating character data, in Section 2.4). The `collapse` argument, as its name implies, collapses the character vector into a single string, separating the elements with whatever is between the quotation marks, in this case one blank space.

A *logical vector* has all its elements either `TRUE` or `FALSE`:

```
> (vals <- c(TRUE, TRUE, FALSE, TRUE))

[1]  TRUE  TRUE FALSE  TRUE
```

The symbols `T` and `F` may also be used as logical values, but while `TRUE` and `FALSE` are *reserved symbols* in R, `T` and `F` are not, an omission that we regard as a design flaw in the language. For example, you can perniciously assign `T <- FALSE` and `F <- TRUE` (Socrates was executed for less!). For this reason, we suggest avoiding the symbols `T` and `F`.

Functions are available for working with logical vectors. For example, the `!` operator negates a logical vector:

```
> !vals

[1] FALSE FALSE  TRUE FALSE
```

If we use logical values in arithmetic, R treats `FALSE` as if it were a zero and `TRUE` as if it were a one:

```
> sum(vals)

[1] 3
```

```
> sum(!vals)

[1] 1
```

More logical operators are described in the next section.

If we create a vector of mixed character strings, logical values, and numbers, we get back a vector of character strings:

```
> c("A", FALSE, 3.0)

[1] "A"     "FALSE" "3"
```

A vector of mixed numbers and logical values is treated as numeric, with FALSE becoming zero and TRUE becoming one. (Try it!) In the first case, we say that the logical and numeric values are *coerced* to character; in the second case, the logical values are coerced to numeric. In general, coercion in R takes place naturally and is designed to lose as little information as possible (see Section 2.6).

### 1.1.5 INDEXING VECTORS

If we wish to access—say, to print—only one of the elements of a vector, we can specify the index of the element within square brackets; for example, x[12] is the 12th element of the vector x:

```
> x[12]    # 12th element

[1] 1.817

> words[2] # second element

[1] "be"

> vals[3]     # third element

[1] FALSE
```

We may also specify a vector of indices:

```
> x[6:15] # elements 6 through 15

 [1] -1.8180  0.6301 -0.2762 -0.2842 -0.9193 -0.1162  1.8173  0.3706
 [9]  0.5202 -0.7505
```

Negative indices cause the corresponding values of the vector to be *omitted*:

```
> x[-(11:100)] # omit elements 11 through 100

 [1]  0.5855  0.7095 -0.1093 -0.4535  0.6059 -1.8180  0.6301 -0.2762
 [9] -0.2842 -0.9193
```

The parentheses around `11:100` serve to avoid generating numbers from −11 to 100, which would result in an error. (Try it!)

A vector can also be indexed by a logical vector of the same length. Logical values frequently arise through the use of *comparison operators*:

| | |
|---|---|
| == | equals |
| != | not equals |
| <= | less than or equals |
| < | less than |
| > | greater than |
| >= | greater than or equals |

The double-equals sign (==) is used for testing equality, because = is reserved for specifying function arguments and for assignment.

Logical values may also be used in conjunction with the *logical operators*:

| | |
|---|---|
| & | and |
| \| | or |

Here are some simple examples:

```
> 1 == 2

[1] FALSE

> 1 != 2

[1] TRUE

> 1 <= 2

[1] TRUE

> 1 < 1:3

[1] FALSE  TRUE  TRUE

> 3:1 > 1:3

[1]  TRUE FALSE FALSE

> 3:1 >= 1:3

[1]  TRUE  TRUE FALSE

> TRUE & c(TRUE, FALSE)

[1]  TRUE FALSE

> c(TRUE, FALSE, FALSE) | c(TRUE, TRUE, FALSE)

[1]  TRUE  TRUE FALSE
```

A somewhat more extended example illustrates the use of the comparison and logical operators:

```
> (z <- x[1:10])

 [1]  0.5855  0.7095 -0.1093 -0.4535  0.6059 -1.8180  0.6301 -0.2762
 [9] -0.2842 -0.9193
```

```
> z < -0.5
 [1] FALSE FALSE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE  TRUE
> z > 0.5
 [1]  TRUE  TRUE FALSE FALSE  TRUE FALSE  TRUE FALSE FALSE FALSE
> z < -0.5 | z > 0.5  #  < and > of higher precedence than |
 [1]  TRUE  TRUE FALSE FALSE  TRUE  TRUE  TRUE FALSE FALSE  TRUE
> abs(z) > 0.5  # absolute value
 [1]  TRUE  TRUE FALSE FALSE  TRUE  TRUE  TRUE FALSE FALSE  TRUE
> z[abs(z) > 0.5]
[1]  0.5855  0.7095  0.6059 -1.8180  0.6301 -0.9193
> z[!(abs(z) > 0.5)]
[1] -0.1093 -0.4535 -0.2762 -0.2842
```

The last of these commands uses the `!` operator, introduced in the last section, to negate the logical values returned by `abs(z) > 0.5` and thus returns the observations for which the condition is `FALSE`.

A few pointers about using these operators:

- We need to be careful in typing `z < -0.5`; although most spaces in R commands are optional, the space after < is crucial: `z <-0.5` would assign the value `0.5` to `z`. Even when spaces are not *required* around operators, they usually help to clarify R commands.
- Logical operators have lower precedence than comparison operators, and so `z < -0.5 | z > 0.5` is equivalent to `(z < -0.5) | (z > 0.5)`. When in doubt, parenthesize!
- The `abs` function returns the absolute value of its argument.
- As the last two commands illustrate, we can index a vector by a logical vector of the same length, selecting the elements with `TRUE` indices.

In addition to the vectorized *and* (`&`) and *or* (`|`) operators presented here, there are special *and* (`&&`) and *or* (`||`) operators that take individual logical values as arguments. These are often useful in writing programs (see Chapter 8).

### 1.1.6 USER-DEFINED FUNCTIONS

As you probably guessed, R includes functions for calculating many common statistical summaries, such as the mean of a vector:

```
> mean(x)
[1] 0.2452
```

Recall that x was previously defined to be a vector of 100 standard-normal random numbers. Were there no mean function, we could nevertheless have calculated the mean straightforwardly using sum and length:

```
> sum(x)/length(x)

[1] 0.2452
```

To do this repeatedly every time we need a mean would be inconvenient, and so in the absence of the standard R mean function, we could define our own mean function:

```
> myMean <- function(x) sum(x)/length(x)
```

- We define a function using the function function.[5] The arguments to function, here just x, are the *formal arguments* of the function being defined, myMean. As explained below, when the function myMean is called, an *actual argument* will appear in place of the formal argument. The remainder of the function definition is an R expression specifying the *body* of the function.
- The rule for naming functions is the same as for naming variables. We avoided using the name mean because we did not wish to *replace* the standard mean function, which is a generic function with greater utility than our simple version. For example, mean has an additional argument na.rm that tells R what to do if some of the elements of x are missing. We cannot overwrite the definitions of standard functions, but if we define a function of the same name, our version will be used in place of the standard function and is therefore said to *shadow* or *mask* the standard function. (This behavior is explained in Section 2.2.) In contrast to naming variables, in naming functions, we prefer using camel case (as in myMean) to separating words by periods (e.g., my.mean), because periods in function names play a special role in object-oriented programming in R (see Sections 1.4 and 8.7).
- The bodies of most user-defined functions are more complex than in this example, consisting of a *compound expression* comprising several simple R expressions, enclosed in braces and separated by semicolons or new-lines. We will introduce additional information about writing functions as required and take up the topic more systematically in Chapter 8.

Having defined the function myMean, we may use it in the same manner as the standard R functions. Indeed, most of the standard functions in R are themselves written in the R language.[6]

[5] We could not resist writing that sentence! Actually, however, function is a *special form*, not a true function, because its arguments (here, the formal argument x) are not evaluated. The distinction is technical, and it will do no harm to think of function as a function that returns a function as its result.

[6] Some of the standard R functions are *primitives*, in the sense that they are defined in code written in the lower-level languages C and Fortran.

```
> myMean(x)

[1] 0.2452

> y # from sqrt(c(1, 2, 3, 4))

[1] 1.000 1.414 1.732 2.000

> myMean(y)

[1] 1.537

> myMean(1:100)

[1] 50.5

> myMean(sqrt(1:100))

[1] 6.715
```

As these examples illustrate, there is no necessary correspondence between the name of the formal argument x of the function myMean and the actual argument to the function. Function arguments are evaluated by the interpreter, and it is the *value* of the argument that is passed to the function, not its name. Thus, in the last of the three examples above, the function call sqrt(1:100) must first be evaluated, and then the result is used as the argument to myMean. Function arguments, along with variables that are defined within a function, are *local* to the function: Local variables exist only while the function executes and are distinct from *global* variables of the same name. For example, the last call to myMean passed the value of sqrt(1:100) (i.e., the square roots of the integers from 1 to 100) to the argument x, but this argument did not change the contents of the global variable x (see p. 10):

```
> x

  [1]  0.58553  0.70947 -0.10930 -0.45350  0.60589 -1.81796  0.63010
. . .
 [99] -0.59980 -0.69455
```

### 1.1.7 COMMAND EDITING AND OUTPUT MANAGEMENT

In the course of typing an R command, you may find it necessary to correct or modify the command before pressing Enter. The Windows *R Console* supports command-line editing:[7]

- You can move the cursor with the left and right arrow, Home, and End keys.
- The Delete key deletes the character under the cursor.
- The Backspace key deletes the character to the left of the cursor.
- The standard Windows *Edit* menu and keyboard shortcuts may be employed, along with the mouse, to block, copy, and paste text.

[7] The menu selection *Help* → *Console* will display these hints.

- In addition, R implements a command-history mechanism that allows you to recall and edit previously entered commands without having to retype them. Use the up and down arrow keys to move backward and forward in the command history. Press Enter in the normal manner to submit a recalled, and possibly edited, command to the interpreter.

The Mac OS X *R.app* behaves similarly, and somewhat more flexibly, in conformity with the usual OS X conventions.

Writing all but the simplest functions directly at the command prompt is impractical and possibly frustrating, and so using a programming editor with R is a good idea. Both the Windows and Mac OS X implementations of R include basic programming or script editors. We recommend that new users of R use these basic editors before trying a more sophisticated programming editor. You can open a new R script in the Windows *RGui* via the *File* → *New script* menu, or an existing script file via *File* → *Open script*. Similar *New Document* and *Open Document* selections are available under the Mac OS X *R.app File* menu. By convention, R script files have names that end with the extension or file type .R—for example, mycommands.R.

We also strongly recommend the use of an editor for data analysis in R, typing commands into the editor and then submitting them for execution rather than typing them directly at the command prompt. Using an editor simplifies finding and fixing errors, especially in multiline commands, and facilitates trying variations on commands. Moreover, when you work in the editor, you build a permanent, reusable record of input to your R session as a by-product.

Using the script editor in the Windows version of R, simply type commands into the editor, select them with the mouse, and then select *Edit* → *Run line or selection* or press the key combination Control-R to send the commands to the *R Console*. The procedure is similar in Mac OS X, except that commands are sent to the R interpreter by pressing the key combination command-return.

As you work, you can save text and graphical output from R in a word-processor (e.g., Microsoft Word or OpenOffice Writer) document. Simply block and copy the text output from the *R Console* and paste it into the word-processor document, taking care to use a monospaced (i.e., typewriter) font, such as `Courier New`, so that the output lines up properly. Word processors, however, make poor programming editors, and we recommend against their use for composing scripts of R commands.

Similarly, under Windows, you can copy and paste graphs: Right-clicking on a graphics window brings up a context menu that allows you to save the graph to a file or copy it to the Windows clipboard, from which it can be pasted into a word-processor document, for example. Alternatively, you can use the graphics window's *File* menu to save a graph. Copying the graph to the clipboard as a Windows Metafile rather than as a bitmap generally produces a more satisfactory result. Using *R.app* under Mac OS X, you can save the current plot in a *Quartz* graphics device window via the *File* → *Save as* menu, which by default saves a PDF file containing the graph; you can then import the PDF file into a word-processor document.[8]

For LaTeX users, R supports a sophisticated system called Sweave for interleaving text and graphics with executable R code (for details, see Leisch, 2002, 2003). Indeed, we used Sweave to write this book!

### 1.1.8 WHEN THINGS GO WRONG

No one is perfect, and it is impossible to use a computer without making mistakes. Part of the craft of computing is learning to recognize the source of errors. We hope that the following advice and information will help you fix errors in R commands:

- Although it never hurts to be careful, do not worry too much about generating errors. An advantage of working in an interactive system is that you can proceed step by step, fixing mistakes as you go. R is also unusually forgiving in that it is designed to restore the workspace to its previous state when a command results in an error.
- If you are unsure whether a command is properly formulated or whether it will do what you intend, try it out and carefully examine the result. You can often debug commands by trying them on a scaled-down problem with an obvious answer. If the answer that you get differs from the one that you expected, focus your attention on the nature of the difference. Similarly, reworking examples from this *Companion*, from R help pages, or from textbooks or journal articles can help convince you that your programs are working properly.[9]
- When you do generate an error, don't panic! Read the error or warning message carefully. Although some R error messages are cryptic, others are informative, and it is often possible to figure out the source of the error from the message. Some of the most common errors are merely typing mistakes. For example, when the interpreter tells you that an object is not found, suspect a typing error, or that you have forgotten to load the package or read the file containing the object (e.g., a function).
- Sometimes, however, the source of an error may be subtle, particularly because an R command can generate a sequence of function calls of one function by another, and the error message may originate deep within this sequence. The `traceback` function, called with no arguments, provides information about the sequence of function calls leading up to an error. To create a simple example, we begin by writing a function to compute the variance of a variable, checking the output against the standard `var` function:

```
> myVar <- function(x) sum((x - myMean(x))^2)/(length(x) - 1)
> myVar(1:100)
```

[8] See Section 7.4 for more information on handling graphics devices in R.

[9] Sometimes, however, this testing may convince you that the published results are wrong, but that is another story.

```
[1] 841.7

> var(1:100) # check

[1] 841.7
```

We deliberately produce an error by foolishly calling `myVar` with a nonnumeric argument:

```
> letters

 [1] "a" "b" "c" "d" "e" "f" "g" "h" "i" "j" "k" "l" "m" "n" "o" "p"
[17] "q" "r" "s" "t" "u" "v" "w" "x" "y" "z"

> myVar(letters)

Error in sum(x) : invalid 'type' (character) of argument
```

The built-in variable `letters` contains the lowercase letters, and of course, calculating the variance of character data makes no sense. Although the source of the problem is obvious, the error occurs in the `sum` function, not directly in `myVar`; `traceback` shows the sequence of function calls culminating in the error:

```
> traceback()

2: myMean(x)
1: myVar(letters)
```

- Not all errors generate error messages. Indeed, the ones that do not are more pernicious, because you may fail to notice them. Always check your output for reasonableness, and follow up suspicious results.
- If you need to interrupt the execution of a command, you may do so by pressing the Esc (escape) key, by using the mouse to press the *Stop* button in the toolbar, or (under Windows) by selecting the *Misc → Stop current computation* menu item.
- There is much more information on debugging R code in Section 8.6.1.

### 1.1.9 GETTING HELP AND INFORMATION

We have already explained how to use the `help` function and `?` operator to get information about an R function. But what do you do if this information is insufficient or if you don't know the name of the function that you want to use? You may not even know whether a function to perform a specific task *exists* in the standard R distribution or in one of the contributed packages on CRAN. This is not an insignificant problem, for there are hundreds of functions in the standard R packages and literally thousands of functions in the more than 2,500 packages on CRAN.

Although there is no completely adequate solution to this problem, there are several R resources beyond `help` and `?` that can be of assistance:[10]

[10] In addition, we have already introduced the `help.start` command, and in Section 4.9, we describe the use of the `hints` function in the **hints** package to obtain information about functions that can be used with a particular R object.

- The apropos command searches for currently accessible objects whose names contain a particular character string. For example,

```
> apropos("log")

. . .
 [7] "dlogis"               "is.logical"
 [9] "log"                  "log10"
[11] "log1p"                "log2"
[13] "logb"                 "Logic"
[15] "logical"              "logLik"
. . .
```

- Casting a broader net, the help.search command searches the titles and certain other fields in the help files of all R packages installed on your system, showing the results in a pop-up window. For example, try the command help.search("loglinear") to find functions related to loglinear models (discussed in Section 5.6). The ?? operator is a synonym for help.search—for example, ??loglinear.
- If you have an active Internet connection, you can search even more broadly with the RSiteSearch function. For example, to look in all standard and CRAN packages—even those not installed on your system—for functions related to loglinear models, you can issue the command RSiteSearch("loglinear", restrict= "functions"). The results appear in a web browser. See ?RSiteSearch for details.
- The CRAN *task views* are documents that describe facilities in R for applications in specific areas such as Bayesian statistics, econometrics, psychometrics, social statistics, and spatial statistics. The approximately two-dozen task views are available via the command carWeb ("taskviews"), which uses the carWeb function from the **car** package, or directly by pointing your browser at http://cran.r-project.org/web/views/.
- The command help(package="*package-name*")—for example, help(package="car")—shows information about an installed package, such as an index of help topics documented in the package.
- Some packages contain *vignettes*, discursive documents describing the use of the package. To find out what vignettes are available in the packages installed on your system, enter the command vignette(). The command vignette(package="*package-name*") displays the vignettes available in a particular installed package, and the command vignette("*vignette-name*") or vignette("*vignette-name*", package="*package-name*") opens a specific vignette.
- The *Help* menu in the Mac OS X and Windows versions of R provides self-explanatory menu items to access help pages, online manuals, the apropos function, and links to the R websites.
- As you might expect, help on R is available on the Internet from a wide variety of sources. The website www.rseek.org provides a custom Google search engine specifically designed to look for R-related

documents (try searching for **car** using this search site). The page www.r-project.org/search.html lists other possibilities for web searching.

- Finally, *Rhelp* is a very active email list devoted to answering users' questions about R, and there are also several more specialized R mailing lists (see www.r-project.org/mail.html). Before posting a question to *Rhelp* or to one of the other email lists, however, *please carefully read the posting guide* at www.r-project.org/posting-guide.html.

### 1.1.10 CLEANING UP

User-defined variables and functions exist in R in a region of memory called the *workspace*. The R workspace can be saved at the end of a session or even during the session, in which case it is automatically loaded at the start of the next session. Different workspaces can be saved in different directories, as a means of keeping projects separate. Starting R in a directory loads the corresponding workspace.[11]

The objects function lists the names of variables and functions residing in the R workspace:

```
> objects()

[1] "myMean"   "myVar"    "vals"     "words"    "x"
[6] "y"        "z"
```

The function objects requires no arguments, but we nevertheless need to type parentheses after the function name. Were we to type only the name of the function, then objects would not be called—instead the *definition* of the objects function would be printed. (Try it!) This is an instance of the general rule that entering the name of an R object—in this case, the function objects—causes the object to be printed.

It is natural in the process of using R to define variables—and occasionally functions—that we do not want to retain. It is good general practice in R, especially if you intend to save the workspace, to clean up after yourself from time to time. To this end, we use the remove function to delete the variables x, y, z, vals and words:

```
> remove(x, y, z, vals, words)

> objects()

[1] "myMean"   "myVar"
```

We keep the functions myMean and myVar, pretending that we still intend to use them.

[11] See the R documentation for additional information on organizing separate projects.

### 1.1.11 ENDING THE R SESSION

The function `quit` or its equivalent, `q`, is used to exit from R:

```
> quit()

Save workspace image? [y/n/c]:
```

Answering `y` will save the workspace in the current directory, an operation that we generally do not recommend;[12] use `n` to avoid saving the workspace or `c` to cancel quitting. Entering `quit(save="n")` suppresses the question. You can also exit from R via the *File* menu or by clicking on the standard close-window button—the red button at the upper right in Windows and the upper left in Mac OS X.

## 1.2 An Extended Illustration: Duncan's Occupational-Prestige Regression

In this section, we illustrate how to read data from a file into an R *data frame* (data set), how to draw graphs to examine the data using both standard R functions and some of the specialized functions included in the **car** package, how to perform a linear least-squares regression analysis, and how to check the adequacy of the preliminary regression model using a variety of diagnostic methods. It is our intention both to introduce some of the capabilities of R and to convey the flavor of using R for statistical data analysis. All these topics are treated at length later in the book, so you should not be concerned if you don't understand all the details.

The data in the file Duncan.txt were originally analyzed by Duncan (1961).[13] The first few lines of the data file are as follows:

```
                   type income education  prestige
accountant         prof 62       86        82
pilot              prof 72       76        83
architect          prof 75       92        90
author             prof 55       90        76
chemist            prof 64       86        90
minister           prof 21       84        87
professor          prof 64       93        93
dentist            prof 80      100        90
```

[12] A saved workspace will be loaded automatically in a subsequent session, a situation that often results in confusion, in our experience, especially among new users of R. We therefore recommend that you start each R session with a pristine workspace and instead save the script of the commands you use during a session that you may wish to recover (see the discussion of programming editors in Section 1.1.7). Objects can then conveniently be re-created as needed by executing the commands in the saved script. Admittedly, whether to save workspaces or scripts of commands is partly a matter of preference and habit.

[13] The Duncan.txt file, along with the other files used in this text, are available on the website for this *Companion*, at the web address given in the Preface. To reproduce the example, download the data file to a convenient location on your hard disk. Alternatively, you can open a copy of the file in your web browser with the command `carWeb(data="Duncan.txt")` and then save it to your disk.

```
reporter           wc   67       87          52
engineer           prof 72       86          88
. . .
```

The first row of the file consists of variable (column) names: `type`, `income`, `education`, and `prestige`. Each subsequent row of the file contains data for one observation, with the values separated by spaces. The rows are occupations, and the first entry in each row is the name of the occupation. Because there is no variable name corresponding to the first column in the data file, the first value in each line will become a *row name* in the data frame that is constructed from the data in the file. There are 45 occupations in all, only 10 of which are shown.[14]

The variables are defined as follows:

- `type`: Type of occupation—`bc` (blue collar), `wc` (white collar), or `prof` (professional or managerial).
- `income`: Percentage of occupational incumbents in the 1950 U.S. Census who earned more than $3,500 per year (about $31,000 in 2008 U.S. dollars).
- `education`: Percentage of occupational incumbents in 1950 who were high school graduates (which, were we cynical, we would say is roughly equivalent to a PhD in 2008).
- `prestige`: Percentage of respondents in a social survey who rated the occupation as "good" or better in prestige.

Duncan used a linear least-squares regression of `prestige` on `income` and `education` to predict the prestige levels of occupations for which the income and educational levels were known but for which there were no direct prestige ratings. Duncan did not use occupational `type` in his analysis.

### 1.2.1 READING THE DATA

We will use the `read.table` function to read the data from the file Duncan.txt into a *data frame*—the standard R representation of a case-by-variable data set:

```
> Duncan <- read.table(file.choose(), header=TRUE)
```

The `file.choose` function brings up a standard open-file dialog box, allowing us to navigate to and select the Duncan.txt file; `file.choose` returns the path to this file, which becomes the first argument to `read.table`. The second argument, `header=TRUE`, alerts `read.table` to the variable names appearing in the first line of the data file. The `read.table` function returns a data frame, which we assign to `Duncan`.

[14] As we will explain in Chapter 2, we can read data into R from a very wide variety of sources and formats. The format of the data in Duncan.txt is particularly simple, however, and furnishes a convenient initial example.

The generic summary function has a *method* that is appropriate for data frames. As described in Sections 1.4 and 8.7, generic functions know how to adapt their behavior to their arguments. Thus, a function such as summary may be used appropriately with diverse kinds of objects. This ability to reuse the same generic function for many similar purposes is one of the great strengths of R. When applied to the Duncan data-frame, summary produces the following output:

```
> summary(Duncan)

   type        income        education         prestige
 bc  :21   Min.   : 7.0   Min.   :  7.0   Min.   : 3.0
 prof:18   1st Qu.:21.0   1st Qu.: 26.0   1st Qu.:16.0
 wc  : 6   Median :42.0   Median : 45.0   Median :41.0
           Mean   :41.9   Mean   : 52.6   Mean   :47.7
           3rd Qu.:64.0   3rd Qu.: 84.0   3rd Qu.:81.0
           Max.   :81.0   Max.   :100.0   Max.   :97.0
```

In the input data file, the variable type contains character data, which read.table by default converts into a *factor*—an R representation of categorical data. The summary function simply counts the number of observations in each *level* (category) of the factor. The variables income, education, and prestige are numeric, and the summary function reports the minimum, maximum, median, mean, and first and third quartiles for each numeric variable.

To access a specific variable in the data frame, we need to provide its fully qualified name—for example, Duncan$prestige for the variable prestige in the Duncan data frame. Typing the full name can get tedious, and we can avoid this repetition by using the attach function. Attaching the Duncan data frame allows us to access its columns by name, much as if we had directly defined the variables in the R workspace:

```
> attach(Duncan)
> prestige

 [1] 82 83 90 76 90 87 93 90 52 88 57 89 97 59 73 38 76 81 45 92
[21] 39 34 41 16 33 53 67 57 26 29 10 15 19 10 13 24 20  7  3 16
[41]  6 11  8 41 10
```

Reading and manipulating data is the subject of Chapter 2, where the topic is developed in much greater detail. In particular, in Section 2.2 we will show you generally better ways to work with data frames than to attach them.

### 1.2.2 EXAMINING THE DATA

A sensible place to start any data analysis, including a regression analysis, is to examine the data using a variety of graphical displays. For example, Figure 1.4 shows a histogram for the response variable prestige, produced by a call to the hist function:

```
> hist(prestige)
```

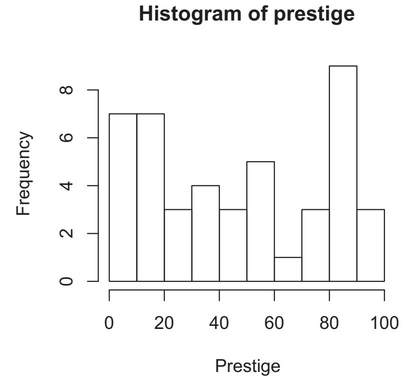


**Figure 1.4** Histogram for `prestige` in Duncan's data.

The function `hist` doesn't return a value in the *R console* but rather is used for the side effect of drawing a graph, in this case a histogram.[15] The histogram may be copied to the clipboard, saved to a file, or printed (see Section 1.1.7).

The distribution of `prestige` appears to be bimodal, with observations stacking up near the lower and upper boundaries. Because `prestige` is a percentage, this behavior is not altogether unexpected—many occupations will either be low prestige, near the lower boundary, or high prestige, near the upper boundary, with fewer occupations in the middle. Variables such as this often need to be transformed, perhaps with a logit (log-odds) or similar transformation. As it turns out, however, it will prove unnecessary to transform `prestige`.

We should also examine the distributions of the predictor variables, along with the relationship between `prestige` and each predictor, and the relationship between the two predictors. The `pairs` function in R draws a scatterplot matrix. The `pairs` function is quite flexible, and we take advantage of this flexibility by placing histograms for the variables along the diagonal of the graph. To better discern the pairwise relationships among the variables, we augment each scatterplot with a least-squares line and with a nonparametric-regression smooth:[16]

```
> pairs(cbind(prestige, income, education),
+     panel=function(x, y){
+         points(x, y)
+         abline(lm(y ~ x), lty="dashed")
+         lines(lowess(x, y))
+     },
```

[15] Like all functions, `hist` *does* return a result; in this case, however, the result is *invisible* and is a list containing the information necessary to draw the histogram. To render the result visible, put parentheses around the command: `(hist(prestige))`. Lists are discussed in Section 2.3.

[16] Nonparametric regression is discussed in the online appendix to the book. Here, the method is used simply to pass a smooth curve through the data.

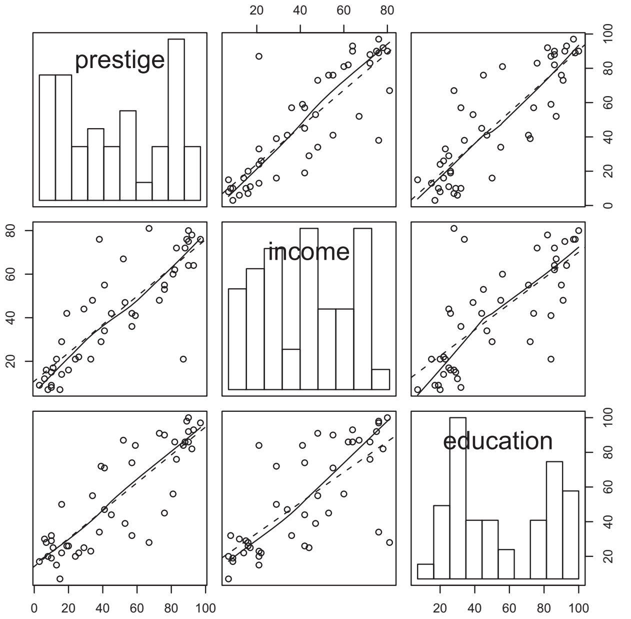


**Figure 1.5** Scatterplot matrix for `prestige`, `income`, and `education` from Duncan's data.

```
+       diag.panel=function(x){
+           par(new=TRUE)
+           hist(x, main="", axes=FALSE)
+       }
+ )
```

Don't let the apparent complexity of this command worry you. Most graphs that you will want to draw are much simpler to produce than this one. Later in this *Companion*, we will describe functions in the **car** package that simplify the drawing of interesting graphs, including scatterplot matrices. Nevertheless, this call to `pairs` allows us to illustrate the structure of commands in R:

- The `cbind` (column-`bind`) function constructs a three-column matrix from the vectors `prestige`, `income`, and `education`, as required by the `pairs` function.
- The `panel` argument to `pairs` specifies a function that draws each off-diagonal panel of the scatterplot matrix. The function must have two arguments, which we call `x` and `y`, representing the horizontal and vertical variables in each plot. The panel function can be either a predefined function or—as here—a so-called *anonymous function*, defined on the fly.[17] Our panel function consists of three commands:

[17] The function is termed *anonymous* because it literally is never given a name: The function object returned by `function` is left unassigned.

1. `points(x, y)` plots the points.

2. `abline(lm(y ~ x), lty="dashed")` draws a broken line (specified by the line type[18] `lty="dashed"`) with intercept and slope given by a linear regression of `y` on `x`, computed by the `lm` (linear-model) function. The result returned by `lm` is passed as an argument to `abline`, which uses the intercept and slope of the regression to draw a line on the plot.

3. `lines(lowess(x, y))` draws a solid line, the default line type, showing the nonparametric regression of `y` on `x`. The `lowess` function computes and returns coordinates for points on a smooth curve relating `y` to `x`; these coordinates are passed as an argument to `lines`, which connects the points with line-segments on the graph.

Because there is more than one R command in the function body, these commands are enclosed as a *block* in curly braces, `{` and `}`. We indented the lines in the command to reveal the structure of the R code; this convention is optional but advisable. If no panel function is specified, then `panel` defaults to `points`. Try the simple command:

```
> pairs(cbind(prestige, income, education))
```

or, equivalently,

```
> pairs(Duncan[ ,-1])
```

This latter form uses all the columns in the `Duncan` data set except the first.

- The `panel.diagonal` argument similarly tells `pairs` what, in addition to the variable names, to plot on the diagonal of the scatterplot matrix. The function supplied must take one argument (`x`), corresponding to the current diagonal variable:

  1. `par(new=TRUE)` prevents the `hist` function from trying to clear the graph. High-level R plotting functions, such as `plot`, `hist`, and `pairs`, by default clear the current graphics device prior to drawing a new plot. Lower-level plotting functions, such as `points`, `abline`, and `lines`, do not clear the current graphics device by default but rather add elements to an existing graph (see Section 7.1 for details).

  2. `hist(x, main="", axes=FALSE)` plots a histogram for `x`, suppressing both the main title and the axes.

[18] Chapter 7 discusses the construction of R graphics, including the selection of line types.

The resulting scatterplot matrix for prestige, income, and education appears in Figure 1.5 (p. 26). The variable names on the diagonal label the axes: For example, the scatterplot in the upper-right-hand corner has education on the horizontal axis and prestige on the vertical axis.

Like prestige, education appears to have a bimodal distribution. The distribution of income, in contrast, is best characterized as irregular. The pairwise relationships among the variables seem reasonably linear, which means that as we move from left to right across the plot, the points more or less trace out a straight line, with scatter about the line. In addition, two or three observations appear to stand out from the others.

If you frequently want to make scatterplot matrices such as this, then it would save work to write a function to do the repetitive parts of the task:

```
> scatmat <- function(...) {
+     pairs(cbind(...),
+         panel=function(x, y){
+             points(x, y)
+             abline(lm(y ~ x), lty=2)
+             lines(lowess(x, y))
+         },
+         diag.panel=function(x){
+             par(new=TRUE)
+             hist(x, main="", axes=FALSE)
+         }
+     )
+ }
```

The special formal argument ... (the *ellipses*) will match any number of actual arguments when the function is called—for example,

```
> scatmat(prestige, income, education)
```

produces a graph identical to the one in Figure 1.5. The scatterplotMatrix function in the **car** package (described in Section 3.3.2) is considerably more flexible than the scatmat function just defined.

In many graphs, we would like to identify unusual points by marking them with a descriptive label. Point identification in R is easier in a scatterplot than in a scatterplot matrix, and so we draw a separate scatterplot for education and income:

```
> plot(income, education)
> #   Use the mouse to identify points:
> identify(income, education, row.names(Duncan))

[1]  6 16 27

> row.names(Duncan)[c(6, 16, 27)]

[1] "minister"    "conductor"    "RR.engineer"
```

The plot function is the workhorse high-level plotting function in R. Called, as here, with two numeric vectors as arguments, plot draws a scatterplot of the variables given as arguments in the order first horizontal axis then vertical

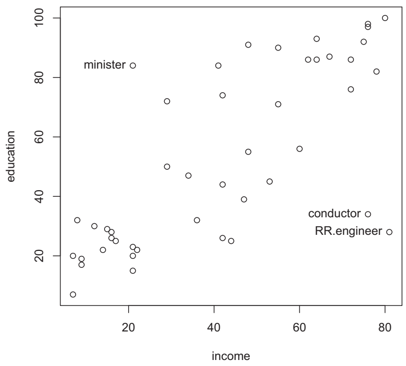


**Figure 1.6** Scatterplot of `income` by `education` for Duncan's data. Three points were labeled interactively with the mouse.

axis. The `identify` function allows us subsequently to label points interactively with a mouse. The first two arguments to `identify` give the coordinates of the points, and the third argument gives point labels; `row.names (Duncan)` extracts the observation names from the `Duncan` data frame to provide the labels. The result is shown in Figure 1.6. The `identify` command returns the indices of the identified points, as we verify by indexing into the vector of names returned by `row.names(Duncan)`. To duplicate this figure, you have to move the mouse cursor near each point to be identified, clicking the left mouse button; after identifying the points, in Windows click the right mouse button and select *Stop* to exit from `identify`, or click the *Stop* menu in the graphics device window and select *Stop locator.* In Mac OS X, press the esc key to stop identifying points.[19] In Section 3.5, we discuss both interactive and automatic point identification using the graphical functions in the **car** package.

Ministers are unusual in combining relatively low `income` with a relatively high level of `education`; railroad conductors and engineers are unusual in combining relatively high levels of `income` with relatively low `education`. None of these observations, however, are outliers in the *univariate* distributions of the three variables.

### 1.2.3 REGRESSION ANALYSIS

Duncan's interest in the data was in how `prestige` is related to `income` and `education` in combination. We have thus far addressed the distributions of the three variables and the pairwise—that is, *marginal*—relationships among them. Our plots don't directly address the *joint* dependence of

[19] Control doesn't return to the R command prompt until you exit from point-identification mode. New users of R occasionally think that R has frozen when they simply have failed to exit from `identify`.

prestige on education and income. Graphs for this purpose will be presented later. Following Duncan, we next fit a linear least-squares regression to the data to get numerical summaries for the joint dependence of prestige on the two predictors:

```
> (duncan.model <- lm(prestige ~ income + education))

Call:
lm(formula = prestige ~ income + education)

Coefficients:
(Intercept)       income    education
     -6.065        0.599        0.546
```

Because we previously attached the Duncan data frame, we can access the variables in it by name. The argument to lm is a *linear-model formula*, with the response variable, prestige, on the left of the tilde (~). The right-hand side of the model formula specifies the predictor variables in the regression, income and education. We read the formula as "prestige is regressed on income and education."

The lm function returns a linear-model object, which we assign to the variable duncan.model. As we explained in Section 1.1.3, enclosing the assignment in parentheses causes the assigned object to be printed, here producing a brief report of the results of the regression. The summary function produces a more complete report:

```
> summary(duncan.model)

Call:
lm(formula = prestige ~ income + education)

Residuals:
    Min      1Q  Median      3Q     Max
-29.538  -6.417   0.655   6.605  34.641

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -6.0647     4.2719   -1.42     0.16
income        0.5987     0.1197    5.00  1.1e-05 ***
education     0.5458     0.0983    5.56  1.7e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 13.4 on 42 degrees of freedom
Multiple R-squared: 0.828,       Adjusted R-squared: 0.82
F-statistic:  101 on 2 and 42 DF,  p-value: <2e-16
```

Both income and education have highly statistically significant, and rather large, regression coefficients: For example, holding education constant, a 1% increase in higher income earners is associated on average with an increase of about 0.6% in high prestige ratings.

R writes very small and very large numbers in scientific notation. For example, 1.1e-05 is to be read as $1.1 \times 10^{-5}$, or 0.000011, and 2e-16 $= 2 \times 10^{-16}$, which is effectively zero.

If you find the statistical significance asterisks that R prints annoying, as we do, you can suppress them, as we will in the remainder of this *Companion*, by entering the command:

```
> options(show.signif.stars=FALSE)
```

As usual, placing this command in one of R's start-up files will permanently banish the offending asterisks (see the discussion of configuring R in the Preface).[20] Linear models are described in much more detail in Chapter 4.

### 1.2.4 REGRESSION DIAGNOSTICS

Assuming that the regression in the previous section adequately summarizes the data does not make it so. It is therefore wise after fitting a regression model to check the fit using a variety of graphical and numeric procedures. The standard R distribution includes some facilities for regression diagnostics, and the **car** package associated with this book augments these capabilities. If you have not already done so, use the `library` command to load the **car** package:

```
> library(car)

Loading required package: MASS
Loading required package: nnet
Loading required package: leaps
Loading required package: survival
Loading required package: splines
```

Loading the **car** package also loads some other packages on which **car** depends.

The `lm` object `duncan.model` contains a variety of information about the regression. The `rstudent` function uses some of this information to calculate *Studentized residuals* for the model. A histogram of the Studentized residuals (Figure 1.7) is unremarkable:

```
> hist(rstudent(duncan.model))
```

Observe the sequence of operations here: `rstudent` takes the linear-model object `duncan.model`, previously returned by `lm`, as an argument and returns the Studentized residuals, which are passed to `hist`, which draws the histogram.

If the errors in the regression are normally distributed with zero means and constant variance, then the Studentized residuals are each $t$-distributed with $n - k - 2$ degrees of freedom, where $k$ is the number of coefficients in the model excluding the regression constant and $n$ is the number of observations. The generic `qqPlot` function from the **car** package, which makes *quantile-comparison plots*, has a method for linear models:

```
> qqPlot(duncan.model, labels=row.names(Duncan), id.n=3)

[1] "minister"   "reporter"   "contractor"
```

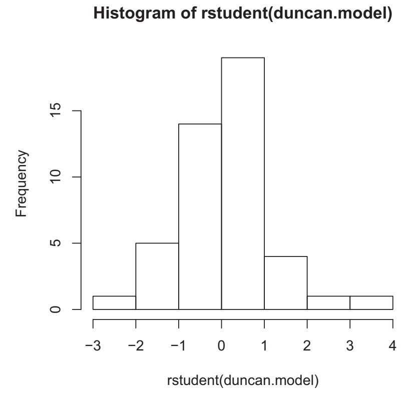


**Figure 1.7** Histogram of the Studentized residuals from the regression of `prestige` on `income` and `education`.

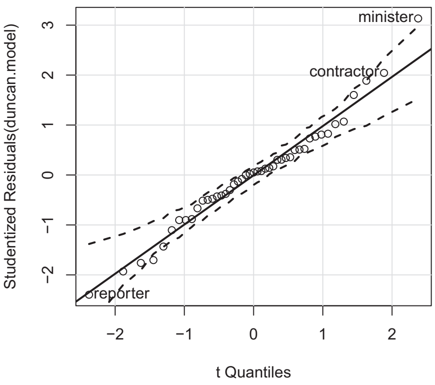


**Figure 1.8** Quantile-comparison plot for the Studentized residuals from the regression of `prestige` on `income` and `education`. The broken lines show a bootstrapped pointwise 95% confidence envelope for the points.

The resulting plot is shown in Figure 1.8. The `qqPlot` function extracts the Studentized residuals and plots them against the quantiles of the appropriate $t$-distribution. If the Studentized residuals are $t$-distributed and $n - k - 2$ is large enough so that we can ignore the correlation between the Studentized residuals, then the points should lie close to a straight line. The comparison line on the plot is drawn by default by robust regression. In this case, the residuals pull away slightly from the comparison line at both ends, suggesting that the residual distribution is a bit heavy-tailed. By default, `qqPlot` produces a bootstrapped pointwise 95% confidence envelope for the

[20] If you like the significance stars, you may need to set `options(useFancyQuotes=FALSE)` to get the legend about the stars to print correctly in some cases, for example, in a LaTeX document.

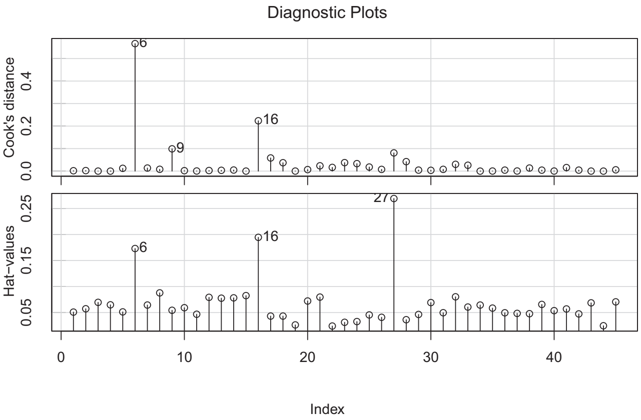


**Figure 1.9** Index plots of Cook's distance and hat-values, from the regression of `prestige` on `income` and `education`.

Studentized residuals. The residuals nearly stay within the boundaries of the envelope at both ends of the distribution.

Most of the graphical methods in the **car** package have arguments that modify the basic plot. For example, the grid lines on the graph are added by default to most **car** graphics; you can suppress the grid lines with the argument `grid=FALSE`.[21]

The **car** graphics functions also have arguments that are used to identify points by their labels. In Figure 1.8 we set the argument `labels=row.names(Duncan)` to tell the function the labels to use and the argument `id.n=3` to label three points with values on the horizontal axis farthest from the mean on the horizontal axis. The default in **car** graphical functions is `id.n=0`, to suppress point identification. Section 3.5 provides a more complete discussion of point labeling.

We proceed to check for high-leverage and influential observations by plotting *hat-values* (Section 6.3.2) and *Cook's distances* (Section 6.3.3) against the observation indices:

```
> influenceIndexPlot(duncan.model, vars=c("Cook", "hat"), id.n=3)
```

The plots are shown in Figure 1.9. We used the `id.n=3` argument to label the three most extreme points in each figure. Points are labeled by row number by default. Our attention is drawn to cases 6 and 16, which are flagged in both graphs, and which correspond to the following occupations:

```
> rownames(Duncan)[c(6, 16)]

[1] "minister"   "contractor"
```

[21] Grid lines can be added to most plots by first drawing using the `plot` function and then using the `grid` function to add the grid lines. In **car** graphics functions, we use `grid(lty=1)` to get solid-line grids rather than the dotted lines that are the default.

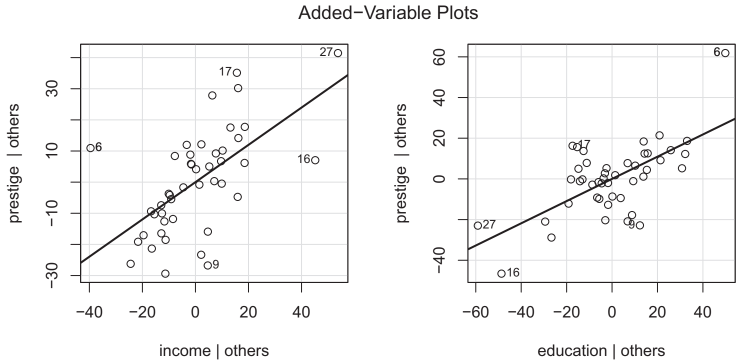


**Figure 1.10** Added-variable plots for `income` and `education` in Duncan's occupational-prestige regression.

Because the observations in a regression can be jointly as well as individually influential, we also examine *added-variable plots* for the predictors, using the `avPlots` function in the **car** package (Section 6.2.3):

```
> avPlots(duncan.model, id.n=3, id.cex=0.75)
```

Each added-variable plot displays the conditional, rather than the marginal, relationship between the response and one of the predictors. Points at the extreme left or right of the plot correspond to points that are potentially influential, and possibly jointly influential. Figure 1.10 confirms and strengthens our previous observations: We should be concerned about the occupations `minister` (6) and `conductor` (16), which work together to decrease the `income` coefficient and increase the `education` coefficient. Occupation `RR.engineer` (27) has relatively high leverage on these coefficients but is more in line with the rest of the data. The argument `id.cex=0.75` makes the labels smaller to fit well into the plot. By specifying `id.n=3`, the `avPlots` function automatically labels the three most extreme points on the horizontal axis and the three points with the largest residuals.

We next use the `crPlots` function, also in the **car** package, to generate *component-plus-residual plots* for `income` and `education` (as discussed in Section 6.4.2):

```
> crPlots(duncan.model, span=0.7)
```

The component-plus-residual plots appear in Figure 1.11. Each plot includes a least-squares line, representing the regression plane viewed edge-on in the direction of the corresponding predictor, and a nonparametric-regression smoother, with the *span* of the smoother set to 0.7 (see Section 3.2). The purpose of these plots is to detect nonlinearity, evidence of which is slight here.

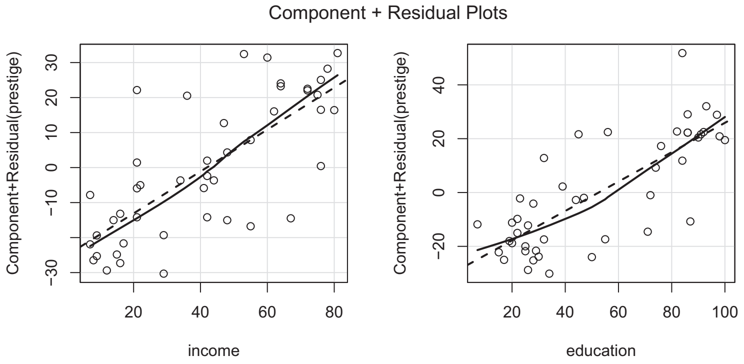


**Figure 1.11** Component-plus-residual plots for `income` and `education` in Duncan's occupational-prestige regression. The span of the nonparametric-regression smoother was set to 0.7.

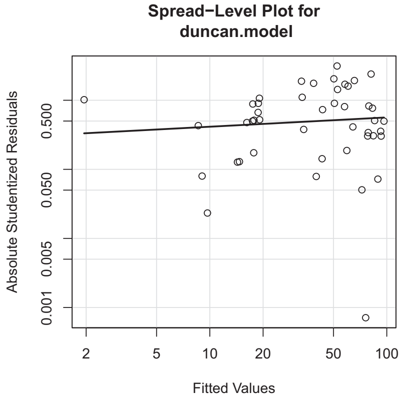


**Figure 1.12** Spread-level plot of Studentized residuals from Duncan's regression of `prestige` on `income` and `education`.

We proceed to check whether the size of the residuals changes systematically with the fitted values, using the `spreadLevelPlot` function in the **car** package, which has a method for linear models (Section 6.5.1):

```
> spreadLevelPlot(duncan.model)

Suggested power transformation:  0.8653
```

The graph produced by `spreadLevelPlot` (Figure 1.12), shows little association of residual spread with level; and the suggested power transformation of the response variable, (`prestige`)$^{0.87}$, is essentially no transformation at all because the power is quite close to one. Using the ncvTest function in the **car** package (Section 6.5.2), we follow up with score tests for nonconstant variance, checking for an association of residual spread with the fitted values and with *any* linear combination of the predictors:

```
> ncvTest(duncan.model)

Non-constant Variance Score Test
Variance formula: ~ fitted.values
Chisquare = 0.3811    Df = 1     p = 0.537

> ncvTest(duncan.model, var.formula= ~ income + education)

Non-constant Variance Score Test
Variance formula: ~ income + education
Chisquare = 0.6976    Df = 2     p = 0.7055
```

Both tests are far from statistically significant, indicating that the assumption of constant variance is tenable.

Finally, on the basis of the influential-data diagnostics, we try removing the observations minister and conductor from the regression:

```
> summary(update(duncan.model, subset=-c(6, 16)))

Call:
lm(formula = prestige ~ income + education, subset = -c(6, 16))

Residuals:
   Min     1Q Median     3Q    Max
-28.61  -5.90   1.94   5.62  21.55

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  -6.4090     3.6526   -1.75   0.0870
income        0.8674     0.1220    7.11  1.3e-08
education     0.3322     0.0987    3.36   0.0017

Residual standard error: 11.4 on 40 degrees of freedom
Multiple R-squared: 0.876,       Adjusted R-squared: 0.87
F-statistic:  141 on 2 and 40 DF,  p-value: <2e-16
```

Rather than respecifying the regression model from scratch, we refit it using the update function, removing the two potentially problematic observations via the subset argument to update. The coefficients of income and education have changed substantially with the deletion of these two observations. Further work (not shown) suggests that removing occupations 27 (RR.engineer) and 9 (reporter) does not make much of a difference.

Chapter 6 has much more extensive information on regression diagnostics in R, including the use of the various functions in the **car** package.

## 1.3 R Functions for Basic Statistics

The focus of this *Companion* is on using R for regression analysis, broadly construed. In the course of developing this subject, we will encounter, and indeed already have encountered, a variety of R functions for basic statistical methods (mean, hist, etc.), but the topic is not addressed systematically.

Table 1.1 shows the names of some standard R functions for basic data analysis. Online help, through ? or help, provides information on the usage of these functions. Where there is a substantial discussion of a function in a later chapter in the present text, the location of the discussion is indicated in the column of the table marked *Reference*. The table is not meant to be complete.

## 1.4 Generic Functions and Their Methods*

Many of the most commonly used functions in R, such as summary, print, and plot, can have very different actions depending on the arguments passed to the function.[22] For example, the summary function applied to different columns of the Duncan data frame produces different output. The summary for the variable Duncan$type is the count in each level of this factor,

```
> summary(Duncan$type)

  bc prof   wc
  21   18    6
```

while for a numeric variable, the summary includes the mean, minimum, maximum, and several quantiles:

```
> summary(Duncan$prestige)

   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    3.0    16.0    41.0    47.7    81.0    97.0
```

Similarly, the commands

```
> summary(Duncan)
> summary(lm(prestige ~ income + education, data=Duncan))
```

produce output appropriate to these objects—in the first case by summarizing each column of the Duncan data frame and in the second by returning a standard summary for a linear-regression model.

In R, allowing the same *generic function*, such as summary, to be used for many purposes is accomplished through an object-oriented programming

[22] The generic print function is invoked implicitly and automatically when an object is printed, for example, by typing the name of the object at the R command prompt, or in the event that the object returned by a function isn't assigned to a variable. The print function can also be called explicitly, however.

**Table 1.1** Some R functions for basic statistical methods. All functions are in the standard R packages; chapter references are to this *Companion.*

| *Method* | *R Function(s)* | *Reference* |
|---|---|---|
| histogram | `hist` | Ch. 3 |
| stem-and-leaf display | `stem` | Ch. 3 |
| boxplot | `boxplot` | Ch. 3 |
| scatterplot | `plot` | Ch. 3 |
| time-series plot | `ts.plot` | |
| mean | `mean` | |
| median | `median` | |
| quantiles | `quantile` | |
| extremes | `range` | |
| variance | `var` | |
| standard deviation | `sd` | |
| covariance matrix | `var`, `cov` | |
| correlations | `cor` | |
| normal density, distribution, quantiles, and random numbers | `dnorm`, `pnorm`, `qnorm`, `rnorm` | Ch. 3 |
| *t* density, distribution, quantiles, and random numbers | `dt`, `pt`, `qt`, `rt` | Ch. 3 |
| chi-square density, distribution, quantiles, and random numbers | `dchisq`, `pchisq`, `qchisq`, `rchisq` | Ch. 3 |
| *F* density, distribution, quantiles, and random numbers | `df`, `pf`, `qf`, `rf` | Ch. 3 |
| binomial probabilities, distribution, quantiles, and random numbers | `dbinom`, `pbinom`, `qbinom`, `rbinom` | Ch. 3 |
| simple regression | `lm` | Ch. 4 |
| multiple regression | `lm` | Ch. 4 |
| analysis of variance | `aov`, `lm`, `anova` | Ch. 4 |
| contingency tables | `xtabs`, `table` | Ch. 5 |
| generating random samples | `sample`, `rnorm`, etc. | |
| *t*-tests for means | `t.test` | |
| tests for proportions | `prop.test`, `binom.test` | |
| chi-square test for independence | `chisq.test` | Ch. 5 |
| various nonparametric tests | `friedman.test`, `kruskal.test`, `wilcox.test`, etc. | |

technique called *object dispatch*. The details of object dispatch are implemented differently in the S3 and S4 object systems, so named because they originated in Versions 3 and 4, respectively, of the original S language on which R is based.

Almost everything created in R is an object, such as a vector, a matrix, a linear-regression model, and so on.[23] In the S3 object system, which we describe in this section, each object is assigned a *class*, and it is the class of

[23] Indeed, everything in R that is returned by a function is an object, but some functions have *side effects* that create nonobjects, such as files and graphs.

the object that determines how generic functions process the object. We defer consideration of the S4 object system to a later chapter in the book, but it too is class based and implements a version of object dispatch.[24]

The `class` function returns the class of an object:

```
> class(Duncan$type)

[1] "factor"

> class(Duncan$prestige)

[1] "integer"

> class(Duncan)

[1] "data.frame"
```

These objects are of classes `"factor"`, `"integer"`, and `"data.frame"`, consecutively. When the function `lm` is used, an object of class `"lm"` is returned:

```
> duncan.model <- lm(prestige ~ income + education)
> class(duncan.model)

[1] "lm"
```

Generic functions operate on their arguments indirectly by calling specialized functions, referred to as *method functions* or, more compactly, as *methods*. Which method function is invoked typically depends on the class of the first argument to the generic function. For example, the generic `summary` function has the following definition:

```
> summary

function (object, ...)
UseMethod("summary")
<environment: namespace:base>
```

The generic function `summary` has one required argument, `object`, and the special argument `...` (the ellipses) for additional arguments that could be different for each `summary` method. When `UseMethod("summary")` is applied to an object of class `"lm"`, for example, R searches for a method function named `summary.lm` and, if it is found, executes the command `summary.lm(object, ...)`. It is, incidentally, perfectly possible to call `summary.lm` directly; thus, the following two commands are equivalent:

```
> summary(duncan.model)
> summary.lm(duncan.model)
```

Although the generic `summary` function has only one explicit argument, the method function `summary.lm` has additional arguments:

[24] More information on the S3 and S4 object systems is provided in Section 8.7.

```
> args(summary.lm)

function (object, correlation = FALSE, symbolic.cor = FALSE,
    ...)
NULL
```

Because the arguments `correlation` and `symbolic.cor` have default values (`FALSE`, in both cases), they need not be specified. Any additional arguments that are supplied, which are covered by `...`, could be passed to functions that might be called by `summary.lm`.

Although in this instance we can call `summary.lm` directly, many method functions are hidden in the *namespaces* of packages and cannot normally be used directly.[25] In any event, it is good R form to use method functions indirectly through their generics.

Suppose that we invoke the hypothetical generic function `fun` with argument `arg` of class `"cls"`. If there is no method function named `fun.cls`, then R looks for a method named `fun=default`. For example, objects belonging to classes without `summary` methods are printed by `summary.default`. If, under these circumstances, there is no method named `fun.default`, then R reports an error.

We can get a listing of all currently accessible method functions for the generic `summary` using the `methods` function, with hidden methods flagged by asterisks:

```
> methods(summary)

 [1] summary.aov          summary.aovlist      summary.aspell*
 [4] summary.connection   summary.data.frame   summary.Date
 [7] summary.default      summary.ecdf*        summary.factor
[10] summary.glm          summary.infl         summary.lm
. . .
[25] summary.stl*         summary.table        summary.tukeysmooth*

   Non-visible functions are asterisked
```

These methods may have different arguments beyond the first, and some method functions, for example, `summary.lm`, have their own help pages: `?summary.lm`.

Method selection is slightly more complicated for objects whose `class` is a vector of more than one element. Consider, for example, an object returned by the `glm` function (anticipating a logistic-regression example developed in Section 5.3):

```
> mod.mroz <- glm(lfp ~ ., family=binomial, data=Mroz)
> class(mod.mroz)

[1] "glm" "lm"
```

[25] For example, the `summary` method `summary.loess` is hidden in the namespace of the **stats** package; to call this function directly to summarize an object of class `"loess"`, we could reference the function with the nonintuitive name `stats:::summary=loess`.

If we invoke a generic function with `mod.mroz` as its argument, say `fun (mod.mroz)`, then the R interpreter will look first for a method named `fun.glm`; if a function by this name does not exist, then R will search next for `fun.lm`, and finally for `fun.default`. We say that the object `mod.mroz` is of *primary class* `"glm"`, and *inherits* from class `"lm"`. Inheritance permits economical programming through generalization, but it can also get us into trouble if, for example, there is no function `fun.glm` but `fun.lm` is inappropriate for `mod.mroz`. In a case such as this, the programmer of `fun.lm` should be careful to create a function `fun.glm`, which calls the default method or reports an error, as appropriate.

## 1.5 The R Commander Graphical User Interface

There are currently several statistical GUIs to R, the most extensive of which is the R Commander, implemented in the **Rcmdr** package.[26] The R Commander began as an interface to be used in an elementary statistics course but has expanded beyond that original purpose. Most of the statistical analysis described in this book can be carried out using menu items in the R Commander.

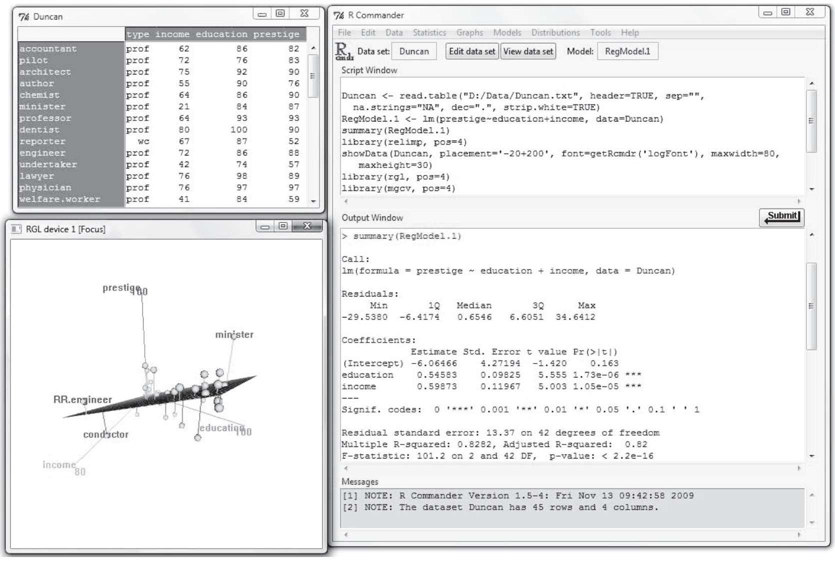
The R Commander, or any other well-designed statistical GUI, can help students learn new ideas, by separating the need for memorizing computer commands from the corresponding statistical concepts. A GUI can also assist a user who is familiar with the statistical ideas but not with R to make substantial and rapid progress. Finally, the infrequent user of R may find that a GUI provides access to the program without the burden of learning and relearning R commands.

With the good comes the bad:

- The R Commander provides access to only a small part of the capabilities of the standard R distribution and to a minuscule fraction of what's available in the more than 2,500 packages on CRAN. The user must trust that the writer of the GUI provided access to all the important functions, which is usually unlikely.
- Although the R Commander allows you to edit and reuse commands, it is generally quicker to type R commands than to generate them by drilling down through the R Commander menus.
- Learning to write R commands and to program in R will allow you to perform nonstandard tasks and to customize your work (e.g., drawing graphs—see Chapter 7) in a manner that's not possible with a GUI.

With these caveats in mind, the R Commander employs a standard menu-and-dialog-box interface that is meant to be largely self-explanatory. There are menus across the top of the main R Commander window, which is

[26] A disclaimer: We are not impartial, because one of us (Fox, 2005b) wrote the **Rcmdr** package and the other one insisted that it at least be mentioned in this chapter.



```
               type income education prestige
accountant     prof     62        86       82
pilot          prof     72        76       83
architect      prof     75        92       90
author         prof     55        90       76
chemist        prof     64        86       90
minister       prof     21        84       87
professor      prof     64        93       93
dentist        prof     80       100       90
reporter         wc     67        87       52
engineer       prof     72        86       88
undertaker     prof     42        74       57
lawyer         prof     76        98       89
physician      prof     76        97       97
welfare.worker prof     41        84       59
```

Data set: Duncan  Edit data set  View data set  Model: RegModel.1

Script Window

```
Duncan <- read.table("D:/Data/Duncan.txt", header=TRUE, sep="",
  na.strings="NA", dec=".", strip.white=TRUE)
RegModel.1 <- lm(prestige~education+income, data=Duncan)
summary(RegModel.1)
library(relimp, pos=4)
showData(Duncan, placement='-20+200', font=getRcmdr('logFont'), maxwidth=80,
   maxheight=30)
library(rgl, pos=4)
library(mgcv, pos=4)
```

Output Window

```
> summary(RegModel.1)

Call:
lm(formula = prestige ~ education + income, data = Duncan)

Residuals:
     Min       1Q   Median       3Q      Max
-29.5380  -6.4174   0.6546   6.6051  34.6412

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -6.06466    4.27194  -1.420    0.163
education    0.54583    0.09825   5.555 1.73e-06 ***
income       0.59873    0.11967   5.003 1.05e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 13.37 on 42 degrees of freedom
Multiple R-squared: 0.8282, Adjusted R-squared:  0.82
F-statistic: 101.2 on 2 and 42 DF,  p-value: < 2.2e-16
```

Messages

```
[1] NOTE: R Commander Version 1.5-4: Fri Nov 13 09:42:58 2009
[2] NOTE: The dataset Duncan has 45 rows and 4 columns.
```

**Figure 1.13** The R Commander in action.

shown, along with some other windows, at the right of the screen shot in Figure 1.13.

For example, to read the data from the file Duncan.txt into an R data frame, and to make that data frame the *active data set* in the R Commander, select *Data → Import data → from text file, clipboard, or URL*, and then complete the resulting dialog box, which allows you to navigate to the location of the data file. The R Commander generates and executes an appropriate command, which it also writes into its *Script Window*. Commands and associated printed output appear in the *Output Window*, and error and other messages in the *Messages* window. Graphs appear in a standard R graphics device window.

To continue the example, to perform a least-squares regression of `prestige` on `income` and `education`, select *Statistics → Fit models → Linear regression* (or *Linear model*), and complete the dialog. The R Commander generates an `lm` command. The linear-model object produced by the command becomes the *active model* in the R Commander, and various tests, graphs, and diagnostics can subsequently be accessed under the *Model* menu.

For more information, see the introductory manual provided by *Help → Introduction to the R Commander* and the help page produced by *Help → Commander help*. To install the **Rcmdr** package, use the command `install.packages("Rcmdr", dependencies=TRUE)`, and be prepared to wait awhile as the many direct and indirect dependencies of the **Rcmdr** are downloaded from CRAN and installed on your system.