This manual is for R, version 4.1.0 Under development (2020-06-19).

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Acknowledgements

The relational databases part of this manual is based in part on an earlier manual by Douglas Bates and Saikat DebRoy. The principal author of this manual was Brian Ripley.

Many volunteers have contributed to the packages used here. The principal authors of the packages mentioned are

- **DBI** (https://CRAN.R-project.org/package=DBI): David A. James
- **dataframes2xls** (https://CRAN.R-project.org/package=dataframes2xls): Guido van Steen
- **foreign** (https://CRAN.R-project.org/package=foreign): Thomas Lumley, Saikat DebRoy, Douglas Bates, Duncan Murdoch and Roger Bivand
- **gdata** (https://CRAN.R-project.org/package=gdata): Gregory R. Warnes
- **ncdf4** (https://CRAN.R-project.org/package=ncdf4): David Pierce
- **rJava** (https://CRAN.R-project.org/package=rJava): Simon Urbanek
- **RJDBC** (https://CRAN.R-project.org/package=RJDBC): Simon Urbanek
- **RMySQL** (https://CRAN.R-project.org/package=RMySQL): David James and Saikat DebRoy
- **RNetCDF** (https://CRAN.R-project.org/package=RNetCDF): Pavel Michna
- **RODBC** (https://CRAN.R-project.org/package=RODBC): Michael Lapsley and Brian Ripley
- **ROracle** (https://CRAN.R-project.org/package=ROracle): David A. James
- **RPostgreSQL** (https://CRAN.R-project.org/package=RPostgreSQL): Sameer Kumar Prayaga and Tomoaki Nishiyama
- **RSPerl**: Duncan Temple Lang
- **RSPython**: Duncan Temple Lang
- **RSSQLite** (https://CRAN.R-project.org/package=RSSQLite): David A. James
- **SJJava**: John Chambers and Duncan Temple Lang
- **WriteXLS** (https://CRAN.R-project.org/package=WriteXLS): Marc Schwartz
- **XLConnect** (https://CRAN.R-project.org/package=XLConnect): Mirai Solutions GmbH
- **XML** (https://CRAN.R-project.org/package=XML): Duncan Temple Lang

Brian Ripley is the author of the support for connections.
1 Introduction

Reading data into a statistical system for analysis and exporting the results to some other system for report writing can be frustrating tasks that can take far more time than the statistical analysis itself, even though most readers will find the latter far more appealing.

This manual describes the import and export facilities available either in R itself or via packages which are available from CRAN or elsewhere.

Unless otherwise stated, everything described in this manual is (at least in principle) available on all platforms running R.

In general, statistical systems like R are not particularly well suited to manipulations of large-scale data. Some other systems are better than R at this, and part of the thrust of this manual is to suggest that rather than duplicating functionality in R we can make another system do the work! (For example Therneau & Grambsch (2000) commented that they preferred to do data manipulation in SAS and then use package 'survival' (https://CRAN.R-project.org/package=survival) in S for the analysis.) Database manipulation systems are often very suitable for manipulating and extracting data: several packages to interact with DBMSs are discussed here.

There are packages to allow functionality developed in languages such as 'Java', 'perl' and 'python' to be directly integrated with R code, making the use of facilities in these languages even more appropriate. (See the 'rJava' (https://CRAN.R-project.org/package=rJava) package from CRAN.)

It is also worth remembering that R like S comes from the Unix tradition of small re-usable tools, and it can be rewarding to use tools such as 'awk' and 'perl' to manipulate data before import or after export. The case study in Becker, Chambers & Wilks (1988, Chapter 9) is an example of this, where Unix tools were used to check and manipulate the data before input to S. The traditional Unix tools are now much more widely available, including for Windows.

This manual was first written in 2000, and the number of scope of R packages has increased a hundredfold since. For specialist data formats it is worth searching to see if a suitable package already exists.

1.1 Imports

The easiest form of data to import into R is a simple text file, and this will often be acceptable for problems of small or medium scale. The primary function to import from a text file is 'scan', and this underlies most of the more convenient functions discussed in Chapter 2 [Spreadsheet-like data], page 6.

However, all statistical consultants are familiar with being presented by a client with a memory stick (formerly, a floppy disc or CD-R) of data in some proprietary binary format, for example ‘an Excel spreadsheet’ or ‘an SPSS file’. Often the simplest thing to do is to use the originating application to export the data as a text file (and statistical consultants will have copies of the most common applications on their computers for that purpose). However, this is not always possible, and Chapter 3 [Importing from other statistical systems], page 12, discusses what facilities are available to access such files directly from R. For Excel spreadsheets, the available methods are summarized in Chapter 9 [Reading Excel spreadsheets], page 27.

In a few cases, data have been stored in a binary form for compactness and speed of access. One application of this that we have seen several times is imaging data, which is normally stored as a stream of bytes as represented in memory, possibly preceded by a header. Such data formats are discussed in Chapter 5 [Binary files], page 20, and Section 7.5 [Binary connections], page 24.

For much larger databases it is common to handle the data using a database management system (DBMS). There is once again the option of using the DBMS to extract a plain file, but
for many such DBMSs the extraction operation can be done directly from an R package: See Chapter 4 [Relational databases], page 14. Importing data via network connections is discussed in Chapter 8 [Network interfaces], page 26.

### 1.1.1 Encodings

Unless the file to be imported from is entirely in ASCII, it is usually necessary to know how it was encoded. For text files, a good way to find out something about its structure is the `file` command-line tool (for Windows, included in Rtools). This reports something like

- `text.Rd`: UTF-8 Unicode English text
- `text2.dat`: ISO-8859 English text
- `text3.dat`: Little-endian UTF-16 Unicode English character data, with CRLF line terminators
- `intro.dat`: UTF-8 Unicode text
- `intro.dat`: UTF-8 Unicode (with BOM) text

Modern Unix-alike systems, including macOS, are likely to produce UTF-8 files. Windows may produce what it calls ‘Unicode’ files (UCS-2LE or just possibly UTF-16LE). Otherwise most files will be in a 8-bit encoding unless from a Chinese/Japanese/Korean locale (which have a wide range of encodings in common use). It is not possible to automatically detect with certainty which 8-bit encoding (although guesses may be possible and `file` may guess as it did in the example above), so you may simply have to ask the originator for some clues (e.g. ‘Russian on Windows’).

‘BOMs’ (Byte Order Marks, [https://en.wikipedia.org/wiki/Byte_order_mark](https://en.wikipedia.org/wiki/Byte_order_mark)) cause problems for Unicode files. In the Unix world BOMs are rarely used, whereas in the Windows world they almost always are for UCS-2/UTF-16 files, and often are for UTF-8 files. The `file` utility will not even recognize UCS-2 files without a BOM, but many other utilities will refuse to read files with a BOM and the IANA standards for UTF-16LE and UTF-16BE prohibit it. We have too often been reduced to looking at the file with the command-line utility `od` or a hex editor to work out its encoding.

Note that `utf8` is not a valid encoding name (UTF-8 is), and `macintosh` is the most portable name for what is sometimes called ‘Mac Roman’ encoding.

### 1.2 Export to text files

Exporting results from R is usually a less contentious task, but there are still a number of pitfalls. There will be a target application in mind, and often a text file will be the most convenient interchange vehicle. (If a binary file is required, see Chapter 5 [Binary files], page 20.)

Function `cat` underlies the functions for exporting data. It takes a `file` argument, and the `append` argument allows a text file to be written via successive calls to `cat`. Better, especially if this is to be done many times, is to open a `file` connection for writing or appending, and `cat` to that connection, then `close` it.

The most common task is to write a matrix or data frame to file as a rectangular grid of numbers, possibly with row and column labels. This can be done by the functions `write.table` and `write`. Function `write` just writes out a matrix or vector in a specified number of columns (and transposes a matrix). Function `write.table` is more convenient, and writes out a data frame (or an object that can be coerced to a data frame) with row and column labels.

There are a number of issues that need to be considered in writing out a data frame to a text file.

---

1. The distinction is subtle, [https://en.wikipedia.org/wiki/UTF-16/UCS-2](https://en.wikipedia.org/wiki/UTF-16/UCS-2), and the use of surrogate pairs is very rare.
1. **Precision**

Most of the conversions of real/complex numbers done by these functions is to full precision, but those by `write` are governed by the current setting of `options(digits)`. For more control, use `format` on a data frame, possibly column-by-column.

2. **Header line**

R prefers the header line to have no entry for the row names, so the file looks like

```
   dist  climb  time
Greenmantle     2.5   650   16.083
...```

Some other systems require a (possibly empty) entry for the row names, which is what `write.table` will provide if argument `col.names = NA` is specified. Excel is one such system.

3. **Separator**

A common field separator to use in the file is a comma, as that is unlikely to appear in any of the fields in English-speaking countries. Such files are known as CSV (comma separated values) files, and wrapper function `write.csv` provides appropriate defaults. In some locales the comma is used as the decimal point (set this in `write.table` by `dec = ",")` and there CSV files use the semicolon as the field separator: use `write.csv2` for appropriate defaults. There is an IETF standard for CSV files (which mandates commas and CRLF line endings, for which use `eol = "\r\n"`), RFC4180 (see https://tools.ietf.org/html/rfc4180), but what is more important in practice is that the file is readable by the application it is targeted at.

Using a semicolon or tab (`sep = "\t"`) are probably the safest options.

4. **Missing values**

By default missing values are output as `NA`, but this may be changed by argument `na`. Note that NaNs are treated as `NA` by `write.table`, but not by `cat` nor `write`.

5. **Quoting strings**

By default strings are quoted (including the row and column names). Argument `quote` controls if character and factor variables are quoted: some programs, for example Mondrian (https://en.wikipedia.org/wiki/Mondrian_(software)), do not accept quoted strings.

Some care is needed if the strings contain embedded quotes. Three useful forms are

```
> df <- data.frame(a = I("a \" quote"))
> write.table(df)
"a"
"1" "a \" quote"
> write.table(df, qmethod = "double")
"a"
"1" "a "" quote"
> write.table(df, quote = FALSE, sep = ",")
a
1,a " quote```

The second is the form of escape commonly used by spreadsheets.

6. **Encodings**

Text files do not contain metadata on their encodings, so for non-ASCII data the file needs to be targeted to the application intended to read it. All of these functions can write to a `connection` which allows an encoding to be specified for the file, and `write.table` has a `fileEncoding` argument to make this easier.
The hard part is to know what file encoding to use. For use on Windows, it is best to use what Windows calls ‘Unicode’\(^2\), that is "UTF-16LE". Using UTF-8 is a good way to make portable files that will not easily be confused with any other encoding, but even macOS applications (where UTF-8 is the system encoding) may not recognize them, and Windows applications are most unlikely to. Apparently Excel:mac 2004/8 expected .csv files in "macroman" encoding (the encoding used in much earlier versions of Mac OS).

Function write.matrix in package MASS (https://CRAN.R-project.org/package=MASS) provides a specialized interface for writing matrices, with the option of writing them in blocks and thereby reducing memory usage.

It is possible to use sink to divert the standard R output to a file, and thereby capture the output of (possibly implicit) print statements. This is not usually the most efficient route, and the options(width) setting may need to be increased.

Function write.foreign in package foreign (https://CRAN.R-project.org/package=foreign) uses write.table to produce a text file and also writes a code file that will read this text file into another statistical package. There is currently support for export to SAS, SPSS and Stata.

1.3 XML

When reading data from text files, it is the responsibility of the user to know and to specify the conventions used to create that file, e.g. the comment character, whether a header line is present, the value separator, the representation for missing values (and so on) described in Section 1.2 [Export to text files], page 3. A markup language which can be used to describe not only content but also the structure of the content can make a file self-describing, so that one need not provide these details to the software reading the data.

The eXtensible Markup Language – more commonly known simply as XML – can be used to provide such structure, not only for standard datasets but also more complex data structures. XML is becoming extremely popular and is emerging as a standard for general data markup and exchange. It is being used by different communities to describe geographical data such as maps, graphical displays, mathematics and so on.

XML provides a way to specify the file’s encoding, e.g.

\[
<?xml version="1.0" encoding="UTF-8"?>
\]

although it does not require it.


yaml is another system for structuring text data, with emphasis on human-readability: it is supported by package yaml (https://CRAN.R-project.org/package=yaml).

\(^2\) Even then, Windows applications may expect a Byte Order Mark which the implementation of iconv used by R may or may not add depending on the platform.
2 Spreadsheet-like data

In Section 1.2 [Export to text files], page 3, we saw a number of variations on the format of a spreadsheet-like text file, in which the data are presented in a rectangular grid, possibly with row and column labels. In this section we consider importing such files into R.

2.1 Variations on read.table

The function read.table is the most convenient way to read in a rectangular grid of data. Because of the many possibilities, there are several other functions that call read.table but change a group of default arguments.

Beware that read.table is an inefficient way to read in very large numerical matrices: see scan below.

Some of the issues to consider are:

1. Encoding
   If the file contains non-ASCII character fields, ensure that it is read in the correct encoding. This is mainly an issue for reading Latin-1 files in a UTF-8 locale, which can be done by something like
   
   \[ \text{read.table("file.dat", fileEncoding="latin1")} \]
   
   Note that this will work in any locale which can represent Latin-1 strings, but not many Greek/Russian/Chinese/Japanese ... locales.

2. Header line
   We recommend that you specify the header argument explicitly. Conventional the header line has entries only for the columns and not for the row labels, so is one field shorter than the remaining lines. (If R sees this, it sets header = TRUE.) If presented with a file that has a (possibly empty) header field for the row labels, read it in by something like
   
   \[ \text{read.table("file.dat", header = TRUE, row.names = 1)} \]
   
   Column names can be given explicitly via the col.names; explicit names override the header line (if present).

3. Separator
   Normally looking at the file will determine the field separator to be used, but with white-space separated files there may be a choice between the default sep = "" which uses any white space (spaces, tabs or newlines) as a separator, sep = " " and sep = "\t". Note that the choice of separator affects the input of quoted strings.

   If you have a tab-delimited file containing empty fields be sure to use sep = "\t".

4. Quoting
   By default character strings can be quoted by either ‘‘” or ‘’”, and in each case all the characters up to a matching quote are taken as part of the character string. The set of valid quoting characters (which might be none) is controlled by the quote argument. For sep = "\n" the default is changed to quote = "".

   If no separator character is specified, quotes can be escaped within quoted strings by immediately preceding them by ‘\’, C-style.

   If a separator character is specified, quotes can be escaped within quoted strings by doubling them as is conventional in spreadsheets. For example

   \[ One string isn’t two,”one more" \]

   can be read by

   \[ \text{read.table("testfile", sep = ",")} \]

   This does not work with the default separator.
5. **Missing values**

By default the file is assumed to contain the character string `NA` to represent missing values, but this can be changed by the argument `na.strings`, which is a vector of one or more character representations of missing values.

Empty fields in numeric columns are also regarded as missing values. In numeric columns, the values `NaN`, `Inf` and `-Inf` are accepted.

6. **Unfilled lines**

It is quite common for a file exported from a spreadsheet to have all trailing empty fields (and their separators) omitted. To read such files set `fill = TRUE`.

7. **White space in character fields**

If a separator is specified, leading and trailing white space in character fields is regarded as part of the field. To strip the space, use argument `strip.white = TRUE`.

8. **Blank lines**

By default, `read.table` ignores empty lines. This can be changed by setting `blank.lines.skip = FALSE`, which will only be useful in conjunction with `fill = TRUE`, perhaps to use blank rows to indicate missing cases in a regular layout.

9. **Classes for the variables**

Unless you take any special action, `read.table` reads all the columns as character vectors and then tries to select a suitable class for each variable in the data frame. It tries in turn `logical`, `integer`, `numeric` and `complex`, moving on if any entry is not missing and cannot be converted.\(^1\) If all of these fail, the variable is converted to a factor.

Arguments `colClasses` and `as.is` provide greater control. Specifying `as.is = TRUE` suppresses conversion of character vectors to factors (only). Using `colClasses` allows the desired class to be set for each column in the input: it will be faster and use less memory.

Note that `colClasses` and `as.is` are specified per column, not per variable, and so include the column of row names (if any).

10. **Comments**

By default, `read.table` uses `#` as a comment character, and if this is encountered (except in quoted strings) the rest of the line is ignored. Lines containing only white space and a comment are treated as blank lines.

If it is known that there will be no comments in the data file, it is safer (and may be faster) to use `comment.char = ""`.

11. **Escapes**

Many OSes have conventions for using backslash as an escape character in text files, but Windows does not (and uses backslash in path names). It is optional in R whether such conventions are applied to data files.

Both `read.table` and `scan` have a logical argument `allowEscapes`. This is false by default, and backslashes are then only interpreted as (under circumstances described above) escaping quotes. If this set to be true, C-style escapes are interpreted, namely the control characters `\a`, `\b`, `\f`, `\n`, `\r`, `\t`, `\v` and octal and hexadecimal representations like `\040` and `\0x2A`. Any other escaped character is treated as itself, including backslash. Note that Unicode escapes such as `\uxxxx` are never interpreted.

12. **Encoding**

This can be specified by the `fileEncoding` argument, for example

```
fileEncoding = "UCS-2LE"  # Windows 'Unicode' files
```

---

1 This is normally fast as looking at the first entry rules out most of the possibilities.
fileEncoding = "UTF-8"

If you know (correctly) the file’s encoding this will almost always work. However, we know of one exception, UTF-8 files with a BOM. Some people claim that UTF-8 files should never have a BOM, but some software (apparently including Excel:mac) uses them, and many Unix-alike OSes do not accept them. So faced with a file which file reports as

intro.dat: UTF-8 Unicode (with BOM) text

it can be read on Windows by

read.table("intro.dat", fileEncoding = "UTF-8")

but on a Unix-alike might need

read.table("intro.dat", fileEncoding = "UTF-8-BOM")

(This would most likely work without specifying an encoding in a UTF-8 locale.)

Convenience functions read.csv and read.delim provide arguments to read.table appropriate for CSV and tab-delimited files exported from spreadsheets in English-speaking locales. The variations read.csv2 and read.delim2 are appropriate for use in those locales where the comma is used for the decimal point (and for read.csv2) for spreadsheets which use semicolons to separate fields.

If the options to read.table are specified incorrectly, the error message will usually be of the form

Error in scan(file = file, what = what, sep = sep, :  
line 1 did not have 5 elements

or

Error in read.table("files.dat", header = TRUE) :  
more columns than column names

This may give enough information to find the problem, but the auxiliary function count.fields can be useful to investigate further.

Efficiency can be important when reading large data grids. It will help to specify comment.char = "", colClasses as one of the atomic vector types (logical, integer, numeric, complex, character or perhaps raw) for each column, and to give nrows, the number of rows to be read (and a mild over-estimate is better than not specifying this at all). See the examples in later sections.

2.2 Fixed-width-format files

Sometimes data files have no field delimiters but have fields in pre-specified columns. This was very common in the days of punched cards, and is still sometimes used to save file space.

Function read.fwf provides a simple way to read such files, specifying a vector of field widths. The function reads the file into memory as whole lines, splits the resulting character strings, writes out a temporary tab-separated file and then calls read.table. This is adequate for small files, but for anything more complicated we recommend using the facilities of a language like perl to pre-process the file.

Function read.fortran is a similar function for fixed-format files, using Fortran-style column specifications.

2.3 Data Interchange Format (DIF)

An old format sometimes used for spreadsheet-like data is DIF, or Data Interchange format.

Function read.DIF provides a simple way to read such files. It takes arguments similar to read.table for assigning types to each of the columns.
On Windows, spreadsheet programs often store spreadsheet data copied to the clipboard in this format; \texttt{read.DIF("clipboard")} can read it from there directly. It is slightly more robust than \texttt{read.table("clipboard")} in handling spreadsheets with empty cells.

### 2.4 Using \texttt{scan} directly

Both \texttt{read.table} and \texttt{read.fwf} use \texttt{scan} to read the file, and then process the results of \texttt{scan}. They are very convenient, but sometimes it is better to use \texttt{scan} directly.

Function \texttt{scan} has many arguments, most of which we have already covered under \texttt{read.table}. The most crucial argument is \texttt{what}, which specifies a list of modes of variables to be read from the file. If the list is named, the names are used for the components of the returned list. Modes can be numeric, character or complex, and are usually specified by an example, e.g. \texttt{0}, \texttt{""} or \texttt{0i}. For example

\begin{verbatim}
cat("2 3 5 7", "11 13 17 19", file="ex.dat", sep="\n")
scan(file="ex.dat", what=list(x=0, y="", z=0), flush=TRUE)
\end{verbatim}

returns a list with three components and discards the fourth column in the file.

There is a function \texttt{readLines} which will be more convenient if all you want is to read whole lines into R for further processing.

One common use of \texttt{scan} is to read in a large matrix. Suppose file \texttt{matrix.dat} just contains the numbers for a 200 x 2000 matrix. Then we can use

\begin{verbatim}
A <- matrix(scan("matrix.dat", n = 200*2000), 200, 2000, byrow = TRUE)
\end{verbatim}

On one test this took 1 second (under Linux, 3 seconds under Windows on the same machine) whereas

\begin{verbatim}
A <- as.matrix(read.table("matrix.dat"))
\end{verbatim}
took 10 seconds (and more memory), and

\begin{verbatim}
A <- as.matrix(read.table("matrix.dat", header = FALSE, nrows = 200,
                         comment.char = "", colClasses = "numeric"))
\end{verbatim}
took 7 seconds. The difference is almost entirely due to the overhead of reading 2000 separate short columns: were they of length 2000, \texttt{scan} took 9 seconds whereas \texttt{read.table} took 18 if used efficiently (in particular, specifying \texttt{colClasses}) and 125 if used naively.

Note that timings can depend on the type read and the data. Consider reading a million distinct integers:

\begin{verbatim}
writeLines(as.character((1+1e6):2e6), "ints.dat")
xi <- scan("ints.dat", what=integer(0), n=1e6)  # 0.77s
xn <- scan("ints.dat", what=numeric(0), n=1e6)  # 0.93s
xc <- scan("ints.dat", what=character(0), n=1e6) # 0.85s
xf <- as.factor(xc) # 2.2s
DF <- read.table("ints.dat") # 4.5s
\end{verbatim}

and a million examples of a small set of codes:

\begin{verbatim}
code <- c("LMH", "SJC", "CHCH", "SPC", "SOM")
writeLines(sample(code, 1e6, replace=TRUE), "code.dat")
y <- scan("code.dat", what=character(0), n=1e6)  # 0.44s
yf <- as.factor(y) # 0.21s
DF <- read.table("code.dat") # 4.9s
DF <- read.table("code.dat", nrows=1e6) # 3.6s
\end{verbatim}

Note that these timings depend heavily on the operating system (the basic reads in Windows take at least as twice as long as these Linux times) and on the precise state of the garbage collector.
2.5 Re-shaping data

Sometimes spreadsheet data is in a compact format that gives the covariates for each subject followed by all the observations on that subject. R’s modelling functions need observations in a single column. Consider the following sample of data from repeated MRI brain measurements:

<table>
<thead>
<tr>
<th>Status</th>
<th>Age</th>
<th>V1</th>
<th>V2</th>
<th>V3</th>
<th>V4</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>23646</td>
<td>45190</td>
<td>50333</td>
<td>55166</td>
<td>66271</td>
</tr>
<tr>
<td>CC</td>
<td>26174</td>
<td>35535</td>
<td>38227</td>
<td>37911</td>
<td>41184</td>
</tr>
<tr>
<td>CC</td>
<td>27723</td>
<td>25691</td>
<td>25712</td>
<td>26144</td>
<td>26398</td>
</tr>
<tr>
<td>CC</td>
<td>27193</td>
<td>30949</td>
<td>29693</td>
<td>29754</td>
<td>30772</td>
</tr>
<tr>
<td>CC</td>
<td>24370</td>
<td>50542</td>
<td>51966</td>
<td>54341</td>
<td>54273</td>
</tr>
<tr>
<td>CC</td>
<td>28359</td>
<td>58591</td>
<td>58803</td>
<td>59435</td>
<td>61292</td>
</tr>
<tr>
<td>CC</td>
<td>25136</td>
<td>45801</td>
<td>45389</td>
<td>47197</td>
<td>47126</td>
</tr>
</tbody>
</table>

There are two covariates and up to four measurements on each subject. The data were exported from Excel as a file `mr.csv`.

We can use `stack` to help manipulate these data to give a single response:

```r
zz <- read.csv("mr.csv", strip.white = TRUE)
zzz <- cbind(zz[gl(nrow(zz), 1, 4*nrow(zz)), 1:2], stack(zz[, 3:6]))
```

with result:

<table>
<thead>
<tr>
<th>Status</th>
<th>Age</th>
<th>values</th>
<th>ind</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1</td>
<td>P</td>
<td>23646</td>
<td>V1</td>
</tr>
<tr>
<td>X2</td>
<td>CC</td>
<td>26174</td>
<td>V1</td>
</tr>
<tr>
<td>X3</td>
<td>CC</td>
<td>27723</td>
<td>V1</td>
</tr>
<tr>
<td>X4</td>
<td>CC</td>
<td>27193</td>
<td>V1</td>
</tr>
<tr>
<td>X5</td>
<td>CC</td>
<td>24370</td>
<td>V1</td>
</tr>
<tr>
<td>X6</td>
<td>CC</td>
<td>28359</td>
<td>V1</td>
</tr>
<tr>
<td>X7</td>
<td>CC</td>
<td>25136</td>
<td>V1</td>
</tr>
<tr>
<td>X11</td>
<td>P</td>
<td>23646</td>
<td>V2</td>
</tr>
</tbody>
</table>

Function `unstack` goes in the opposite direction, and may be useful for exporting data. Another way to do this is to use the function `reshape`, by

```r
> reshape(zz, idvar="id", timevar="var",
        varying=list(c("V1","V2","V3","V4")), direction="long")
```

with result:

<table>
<thead>
<tr>
<th>Status</th>
<th>Age</th>
<th>var</th>
<th>V1</th>
<th>id</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>P</td>
<td>1</td>
<td>45190</td>
<td>1</td>
</tr>
<tr>
<td>2.1</td>
<td>CC</td>
<td>1</td>
<td>35535</td>
<td>2</td>
</tr>
<tr>
<td>3.1</td>
<td>CC</td>
<td>1</td>
<td>25691</td>
<td>3</td>
</tr>
<tr>
<td>4.1</td>
<td>CC</td>
<td>1</td>
<td>30949</td>
<td>4</td>
</tr>
<tr>
<td>5.1</td>
<td>CC</td>
<td>1</td>
<td>50542</td>
<td>5</td>
</tr>
<tr>
<td>6.1</td>
<td>CC</td>
<td>1</td>
<td>58591</td>
<td>6</td>
</tr>
<tr>
<td>7.1</td>
<td>CC</td>
<td>1</td>
<td>45801</td>
<td>7</td>
</tr>
<tr>
<td>1.2</td>
<td>P</td>
<td>2</td>
<td>50333</td>
<td>1</td>
</tr>
<tr>
<td>2.2</td>
<td>CC</td>
<td>2</td>
<td>38227</td>
<td>2</td>
</tr>
</tbody>
</table>

The `reshape` function has a more complicated syntax than `stack` but can be used for data where the ‘long’ form has more than the one column in this example. With `direction="wide"`, `reshape` can also perform the opposite transformation.

Some people prefer the tools in packages `reshape` (https://CRAN.R-project.org/package=reshape), `reshape2` (https://CRAN.R-project.org/package=reshape2) and `plyr` (https://CRAN.R-project.org/package=plyr).
2.6 Flat contingency tables

Displaying higher-dimensional contingency tables in array form typically is rather inconvenient. In categorical data analysis, such information is often represented in the form of bordered two-dimensional arrays with leading rows and columns specifying the combination of factor levels corresponding to the cell counts. These rows and columns are typically “ragged” in the sense that labels are only displayed when they change, with the obvious convention that rows are read from top to bottom and columns are read from left to right. In R, such “flat” contingency tables can be created using `ftable`, which creates objects of class "ftable" with an appropriate print method.

As a simple example, consider the R standard data set `UCBAdmissions` which is a 3-dimensional contingency table resulting from classifying applicants to graduate school at UC Berkeley for the six largest departments in 1973 classified by admission and sex.

```r
> data(UCBAdmissions)
> ftable(UCBAdmissions)

<table>
<thead>
<tr>
<th>Dept</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Admit Gender</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Admitted</td>
<td>Male</td>
<td>512</td>
<td>353</td>
<td>120</td>
<td>138</td>
<td>53</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>89</td>
<td>17</td>
<td>202</td>
<td>131</td>
<td>94</td>
</tr>
<tr>
<td>Rejected</td>
<td>Male</td>
<td>313</td>
<td>207</td>
<td>205</td>
<td>279</td>
<td>138</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>19</td>
<td>8</td>
<td>391</td>
<td>244</td>
<td>299</td>
</tr>
</tbody>
</table>
```

The printed representation is clearly more useful than displaying the data as a 3-dimensional array.

There is also a function `read.ftable` for reading in flat-like contingency tables from files. This has additional arguments for dealing with variants on how exactly the information on row and column variables names and levels is represented. The help page for `read.ftable` has some useful examples. The flat tables can be converted to standard contingency tables in array form using `as.table`.

Note that flat tables are characterized by their “ragged” display of row (and maybe also column) labels. If the full grid of levels of the row variables is given, one should instead use `read.table` to read in the data, and create the contingency table from this using `xtabs`.
3 Importing from other statistical systems

In this chapter we consider the problem of reading a binary data file written by another statistical system. This is often best avoided, but may be unavoidable if the originating system is not available.

In all cases the facilities described were written for data files from specific versions of the other system (often in the early 2000s), and have not necessarily been updated for the most recent versions of the other system.

3.1 EpiInfo, Minitab, S-PLUS, SAS, SPSS, Stata, Systat

The recommended package `foreign` (https://CRAN.R-project.org/package=foreign) provides import facilities for files produced by these statistical systems, and for export to Stata. In some cases these functions may require substantially less memory than `read.table` would. `write.foreign` (See Section 1.2 [Export to text files], page 3) provides an export mechanism with support currently for SAS, SPSS and Stata.

EpiInfo versions 5 and 6 stored data in a self-describing fixed-width text format. `read.epiinfo` will read these .REC files into an R data frame. EpiData also produces data in this format.

Function `read.mtp` imports a ‘Minitab Portable Worksheet’. This returns the components of the worksheet as an R list.

Function `read.xport` reads a file in SAS Transport (XPORT) format and return a list of data frames. If SAS is available on your system, function `read.ssd` can be used to create and run a SAS script that saves a SAS permanent dataset (.ssd or .sas7bdat) in Transport format. It then calls `read.xport` to read the resulting file. (Package `Hmisc` (https://CRAN.R-project.org/package=Hmisc) has a similar function `sas.get`, also running SAS.) For those without access to SAS but running on Windows, the SAS System Viewer (a zero-cost download) can be used to open SAS datasets and export them to e.g. .csv format.

Function `read.S` which can read binary objects produced by S-PLUS 3.x, 4.x or 2000 on (32-bit) Unix or Windows (and can read them on a different OS). This is able to read many but not all S objects: in particular it can read vectors, matrices and data frames and lists containing those.

Function `data.restore` reads S-PLUS data dumps (created by `data.dump`) with the same restrictions (except that dumps from the Alpha platform can also be read). It should be possible to read data dumps from S-PLUS 5.x and later written with `data.dump(oldStyle=T)`.

If you have access to S-PLUS, it is usually more reliable to `dump` the object(s) in S-PLUS and `source` the dump file in R. For S-PLUS 5.x and later you may need to use `dump(..., oldStyle=T)`, and to read in very large objects it may be preferable to use the dump file as a batch script rather than use the `source` function.

Function `read.spss` can read files created by the ‘save’ and ‘export’ commands in SPSS. It returns a list with one component for each variable in the saved data set. SPSS variables with value labels are optionally converted to (and from) R factors.

SPSS Data Entry is an application for creating data entry forms. By default it creates data files with extra formatting information that `read.spss` cannot handle, but it is possible to export the data in an ordinary SPSS format.

Some third-party applications claim to produce data ‘in SPSS format’ but with differences in the formats: `read.spss` may or may not be able to handle these.

Stata .dta files are a binary file format. Files from versions 5 up to 12 of Stata can be read and written by functions `read.dta` and `write.dta`. Stata variables with value labels are optionally converted to (and from) R factors. For Stata versions 13 and later see CRAN packages.
readstata13 (https://CRAN.R-project.org/package=readstata13) and haven (https://CRAN.R-project.org/package=haven).

read.systat reads those Systat SAVE files that are rectangular data files (mtype = 1) written on little-endian machines (such as from Windows). These have extension .sys or (more recently) .syd.

### 3.2 Octave

Octave is a numerical linear algebra system (http://www.octave.org), and function read.octave in package foreign (https://CRAN.R-project.org/package=foreign) can read in files in Octave text data format created using the Octave command save -ascii, with support for most of the common types of variables, including the standard atomic (real and complex scalars, matrices, and N-d arrays, strings, ranges, and boolean scalars and matrices) and recursive (structs, cells, and lists) ones.
4 Relational databases

4.1 Why use a database?

There are limitations on the types of data that R handles well. Since all data being manipulated by R are resident in memory, and several copies of the data can be created during execution of a function, R is not well suited to extremely large data sets. Data objects that are more than a (few) hundred megabytes in size can cause R to run out of memory, particularly on a 32-bit operating system.

R does not easily support concurrent access to data. That is, if more than one user is accessing, and perhaps updating, the same data, the changes made by one user will not be visible to the other.

R does support persistence of data, in that you can save a data object or an entire worksheet from one session and restore it at the subsequent session, but the format of the stored data is specific to R and not easily manipulated by other systems.

Database management systems (DBMSs) and, in particular, relational DBMSs (RDBMSs) are designed to do all of these things well. Their strengths are

1. To provide fast access to selected parts of large databases.
2. Powerful ways to summarize and cross-tabulate columns in databases.
3. Store data in more organized ways than the rectangular grid model of spreadsheets and R data frames.
4. Concurrent access from multiple clients running on multiple hosts while enforcing security constraints on access to the data.
5. Ability to act as a server to a wide range of clients.

The sort of statistical applications for which DBMS might be used are to extract a 10% sample of the data, to cross-tabulate data to produce a multi-dimensional contingency table, and to extract data group by group from a database for separate analysis.

Increasingly OSes are themselves making use of DBMSs for these reasons, so it is nowadays likely that one will be already installed on your (non-Windows) OS. Akonadi (https://en.wikipedia.org/wiki/Akonadi) is used by KDE4 to store personal information. Several macOS applications, including Mail and Address Book, use SQLite.

4.2 Overview of RDBMSs

Traditionally there had been large (and expensive) commercial RDBMSs (Informix (http://www.informix.com); Oracle (https://www.oracle.com); Sybase (http://www.sybase.com); IBM’s DB2 (http://www.ibm.com/db2); Microsoft SQL Server (https://www.microsoft.com/sql-server/) on Windows) and academic and small-system databases (such as MySQL\textsuperscript{1}, PostgreSQL, Microsoft Access, …), the former marked out by much greater emphasis on data security features. The line is blurring, with MySQL and PostgreSQL having more and more high-end features, and free ‘express’ versions being made available for the commercial DBMSs.

There are other commonly used data sources, including spreadsheets, non-relational databases and even text files (possibly compressed). Open Database Connectivity (ODBC) is a standard to use all of these data sources. It originated on Windows (see https://msdn.microsoft.com/en-us/library/ms710252%28v=vs.85%29.aspx) but is also implemented on Linux/Unix/macOS.

\textsuperscript{1} and forks, notably MariaDB.
All of the packages described later in this chapter provide clients to client/server databases. The database can reside on the same machine or (more often) remotely. There is an ISO standard (in fact several: SQL92 is ISO/IEC 9075, also known as ANSI X3.135-1992, and SQL99 is coming into use) for an interface language called SQL (Structured Query Language, sometimes pronounced ‘sequel’; see Bowman et al. 1996 and Kline and Kline 2001) which these DBMSs support to varying degrees.

### 4.2.1 SQL queries

The more comprehensive R interfaces generate SQL behind the scenes for common operations, but direct use of SQL is needed for complex operations in all. Conventionally SQL is written in upper case, but many users will find it more convenient to use lower case in the R interface functions.

A relational DBMS stores data as a database of tables (or relations) which are rather similar to R data frames, in that they are made up of columns or fields of one type (numeric, character, date, currency, ...) and rows or records containing the observations for one entity.

SQL ‘queries’ are quite general operations on a relational database. The classical query is a SELECT statement of the type

```sql
SELECT State, Murder FROM USArrests WHERE Rape > 30 ORDER BY Murder
```

```sql
SELECT t.sch, c.meanses, t.sex, t.achieve
FROM student as t, school as c WHERE t.sch = c.id
```

```sql
SELECT sex, COUNT(*) FROM student GROUP BY sex
```

```sql
SELECT sch, AVG(sestat) FROM student GROUP BY sch LIMIT 10
```

The first of these selects two columns from the R data frame `USArrests` that has been copied across to a database table, subsets on a third column and asks the results be sorted. The second performs a database join on two tables `student` and `school` and returns four columns. The third and fourth queries do some cross-tabulation and return counts or averages. (The five aggregation functions are COUNT(*) and SUM, MAX, MIN and AVG, each applied to a single column.)

SELECT queries use FROM to select the table, WHERE to specify a condition for inclusion (or more than one condition separated by AND or OR), and ORDER BY to sort the result. Unlike data frames, rows in RDBMS tables are best thought of as unordered, and without an ORDER BY statement the ordering is indeterminate. You can sort (in lexicographical order) on more than one column by separating them by commas. Placing DESC after an ORDER BY puts the sort in descending order.

SELECT DISTINCT queries will only return one copy of each distinct row in the selected table.

The GROUP BY clause selects subgroups of the rows according to the criterion. If more than one column is specified (separated by commas) then multi-way cross-classifications can be summarized by one of the five aggregation functions. A HAVING clause allows the select to include or exclude groups depending on the aggregated value.

If the SELECT statement contains an ORDER BY statement that produces a unique ordering, a LIMIT clause can be added to select (by number) a contiguous block of output rows. This can be useful to retrieve rows a block at a time. (It may not be reliable unless the ordering is unique, as the LIMIT clause can be used to optimize the query.)

There are queries to create a table (CREATE TABLE, but usually one copies a data frame to the database in these interfaces), INSERT or DELETE or UPDATE data. A table is destroyed by a DROP TABLE ‘query’.
Kline and Kline (2001) discuss the details of the implementation of SQL in Microsoft SQL Server 2000, Oracle, MySQL and PostgreSQL.

4.2.2 Data types

Data can be stored in a database in various data types. The range of data types is DBMS-specific, but the SQL standard defines many types, including the following that are widely implemented (often not by the SQL name).

- **float(p)** Real number, with optional precision. Often called real or double or double precision.
- **integer** 32-bit integer. Often called int.
- **smallint** 16-bit integer
- **character(n)** fixed-length character string. Often called char.
- **character varying(n)** variable-length character string. Often called varchar. Almost always has a limit of 255 chars.
- **boolean** true or false. Sometimes called bool or bit.
- **date** calendar date
- **time** time of day
- **timestamp** date and time

There are variants on time and timestamp, with timezone. Other types widely implemented are text and blob, for large blocks of text and binary data, respectively.

The more comprehensive of the R interface packages hide the type conversion issues from the user.

4.3 R interface packages

There are several packages available on CRAN to help R communicate with DBMSs. They provide different levels of abstraction. Some provide means to copy whole data frames to and from databases. All have functions to select data within the database via SQL queries, and to retrieve the result as a whole as a data frame or in pieces (usually as groups of rows).

All except RODBC (https://CRAN.R-project.org/package=RODBC) are tied to one DBMS, but there has been a proposal for a unified ‘front-end’ package DBI (https://CRAN.R-project.org/package=DBI) in conjunction with a ‘back-end’, the most developed of which is RMySQL (https://CRAN.R-project.org/package=RMySQL). Also on CRAN are the back-ends ROracle (https://CRAN.R-project.org/package=ROracle), RPostgreSQL (https://CRAN.R-project.org/package=RPostgreSQL) and RSQLite (https://CRAN.R-project.org/package=RSQLite) (which works with the bundled DBMS SQLite, https://www.sqlite.org) and RJDBC (https://CRAN.R-project.org/package=RJDBC) (which uses Java and can connect to any DBMS that has a JDBC driver).

PL/R (http://joeconway.com/plr (http://joeconway.com/plr)) is a project to embed R into PostgreSQL.

4.3.1 Packages using DBI

Package RMySQL (https://CRAN.R-project.org/package=RMySQL) on CRAN provides an interface to the MySQL database system (see https://www.mysql.com and Dubois, 2000) or its fork MariaDB (see https://mariadb.org/). The description here applies to versions 0.5-0 and later: earlier versions had a substantially different interface. The current version requires the DBI (https://CRAN.R-project.org/package=DBI) package, and this description will apply with minor changes to all the other back-ends to DBI (https://CRAN.R-project.org/package=DBI).

MySQL exists on Unix/Linux/macOS and Windows: there is a ‘Community Edition’ released under GPL but commercial licenses are also available. MySQL was originally a ‘light and lean’ database. (It preserves the case of names where the operating file system is case-sensitive, so not on Windows.)

The call dbDriver("MySQL") returns a database connection manager object, and then a call to dbConnect opens a database connection which can subsequently be closed by a call to the generic function dbDisconnect. Use dbDriver("Oracle"), dbDriver("PostgreSQL") or dbDriver("SQLite") with those DBMSs and packages ROracle (https://CRAN.R-project.org/package=ROracle), RPostgreSQL (https://CRAN.R-project.org/package=RPostgreSQL) or RSQLite (https://CRAN.R-project.org/package=RSQLite) respectively.

SQL queries can be sent by either dbSendQuery or dbGetQuery. dbGetquery sends the query and retrieves the results as a data frame. dbSendQuery sends the query and returns an object of class inheriting from "DBIResult" which can be used to retrieve the results, and subsequently used in a call to dbClearResult to remove the result.

Function fetch is used to retrieve some or all of the rows in the query result, as a list. The function dbHasCompleted indicates if all the rows have been fetched, and dbGetRowCount returns the number of rows in the result.

These are convenient interfaces to read/write/test/delete tables in the database. dbReadTable and dbWriteTable copy to and from an R data frame, mapping the row names of the data frame to the field row_names in the MySQL table.

```r
> library(RMySQL) # will load DBI as well
> con <- dbConnect(dbDriver("MySQL"), dbname = "test")
> dbListTables(con)
[1] "arrests"
```

```r
> dbReadTable(con, "arrests")
   Murder Assault UrbanPop Rape
Alabama 13.2 236 58 21.2
Alaska 10.0 263 48 44.5
Arizona 8.1 294 80 31.0
Arkansas 8.8 190 50 19.5
...```

```r
> dbSendQuery(con, paste("select row_names, Murder from arrests",
"where Rape > 30 order by Murder"))
```

```r
   row_names Murder
1   Colorado   7.9
2    Arizona   8.1
3   California 9.0
4     Alaska 10.0
```
Chapter 4: Relational databases

5 New Mexico 11.4
6 Michigan 12.1
7 Nevada 12.2
8 Florida 15.4
> dbRemoveTable(con, "arrests")
> dbDisconnect(con)

4.3.2 Package RODBC

Package RODBC (https://CRAN.R-project.org/package=RODBC) on CRAN provides an interface to database sources supporting an ODBC interface. This is very widely available, and allows the same R code to access different database systems. RODBC (https://CRAN.R-project.org/package=RODBC) runs on Unix/Linux, Windows and macOS, and almost all database systems provide support for ODBC. We have tested Microsoft SQL Server, Access, MySQL, PostgreSQL, Oracle and IBM DB2 on Windows and MySQL, MariaDB, Oracle, PostgreSQL and SQLite on Linux.

ODBC is a client-server system, and we have happily connected to a DBMS running on a Unix server from a Windows client, and vice versa.

On Windows ODBC support is part of the OS. On Unix/Linux you will need an ODBC Driver Manager such as unixODBC (http://www.unixODBC.org) or iODBC (http://www.iODBC.org; this is pre-installed in macOS) and an installed driver for your database system.

Windows provides drivers not just for DBMSs but also for Excel (.xls) spreadsheets, DBase (.dbf) files and even text files. (The named applications do not need to be installed. Which file formats are supported depends on the versions of the drivers.) There are versions for Excel and Access 2007/2010 (go to https://www.microsoft.com/en-us/download/default.aspx, and search for ‘Office ODBC’, which will lead to AccessDatabaseEngine.exe), the ‘2007 Office System Driver’ (the latter has a version for 64-bit Windows, and that will also read earlier versions).


Many simultaneous connections are possible. A connection is opened by a call to odbcConnect or odbcDriverConnect (which on the Windows GUI allows a database to be selected via dialog boxes) which returns a handle used for subsequent access to the database. Printing a connection will provide some details of the ODBC connection, and calling odbcGetInfo will give details on the client and server.

A connection is closed by a call to close or odbcClose, and also (with a warning) when not R object refers to it and at the end of an R session.

Details of the tables on a connection can be found using sqlTables.

Function sqlSave copies an R data frame to a table in the database, and sqlFetch copies a table in the database to an R data frame.

An SQL query can be sent to the database by a call to sqlQuery. This returns the result in an R data frame. (sqlCopy sends a query to the database and saves the result as a table in the database.) A finer level of control is attained by first calling odbcQuery and then sqlGetResults to fetch the results. The latter can be used within a loop to retrieve a limited number of rows at a time, as can function sqlFetchMore.

Here is an example using PostgreSQL, for which the ODBC driver maps column and data frame names to lower case. We use a database testdb we created earlier, and had the DSN (data source name) set up in ~/.odbc.ini under unixODBC. Exactly the same code worked using MyODBC to access a MySQL database under Linux or Windows (where MySQL also
maps names to lowercase). Under Windows, DSNs are set up in the ODBC applet in the Control Panel (‘Data Sources (ODBC)’ in the ‘Administrative Tools’ section).

```r
> library(RODBC)
## tell it to map names to lower case
> channel <- odbcConnect("testdb", uid="ripley", case="tolower")
## load a data frame into the database
> data(USArrests)
> sqlSave(channel, USArrests, rownames = "state", addPK = TRUE)
> rm(USArrests)
## list the tables in the database
> sqlTables(channel)
  TABLE_QUALIFIER TABLE_OWNER TABLE_NAME TABLE_TYPE REMARKS
1 usarrests TABLE

## list it
> sqlFetch(channel, "USArrests", rownames = "state")
murder assault urbanpop rape
Alabama 13.2 236 58 21.2
Alaska 10.0 263 48 44.5
...
## an SQL query, originally on one line
> sqlQuery(channel, "select state, murder from USArrests
where rape > 30 order by murder")
state murder
1 Colorado 7.9
2 Arizona 8.1
3 California 9.0
4 Alaska 10.0
5 New Mexico 11.4
6 Michigan 12.1
7 Nevada 12.2
8 Florida 15.4

## remove the table
> sqlDrop(channel, "USArrests")
## close the connection
> odbcClose(channel)
```

As a simple example of using ODBC under Windows with a Excel spreadsheet, we can read from a spreadsheet by

```r
> library(RODBC)
> channel <- odbcConnectExcel("bdr.xls")
## list the spreadsheets
> sqlTables(channel)
  TABLE_CAT TABLE_SCHEM TABLE_NAME TABLE_TYPE REMARKS
1 C:\\bdr NA Sheet1$ SYSTEM TABLE NA
2 C:\\bdr NA Sheet2$ SYSTEM TABLE NA
3 C:\\bdr NA Sheet3$ SYSTEM TABLE NA
4 C:\\bdr NA Sheet1$Print_Area TABLE NA

## retrieve the contents of sheet 1, by either of
> sh1 <- sqlFetch(channel, "Sheet1")
> sh1 <- sqlQuery(channel, "select * from [Sheet1$]")
```

Notice that the specification of the table is different from the name returned by `sqlTables`: `sqlFetch` is able to map the differences.
5 Binary files

Binary connections (Chapter 7 [Connections], page 22) are now the preferred way to handle binary files.

5.1 Binary data formats

Packages h5 (https://CRAN.R-project.org/package=h5), Bioconductor’s rhdf5, RNetCDF (https://CRAN.R-project.org/package=RNetCDF) and ncdf4 (https://CRAN.R-project.org/package=ncdf4) on CRAN provide interfaces to NASA’s HDF5 (Hierarchical Data Format, see https://www.hdfgroup.org/HDF5/) and to UCAR’s netCDF data files (network Common Data Form, see http://www.unidata.ucar.edu/software/netcdf/).

Both of these are systems to store scientific data in array-oriented ways, including descriptions, labels, formats, units, .... HDF5 also allows groups of arrays, and the R interface maps lists to HDF5 groups, and can write numeric and character vectors and matrices.

NetCDF’s version 4 format (confusingly, implemented in netCDF 4.1.1 and later, but not in 4.0.1) includes the use of various HDF5 formats. This is handled by package ncdf4 (https://CRAN.R-project.org/package=ncdf4) whereas RNetCDF (https://CRAN.R-project.org/package=RNetCDF) handles version 3 files.

The availability of software to support these formats is somewhat limited by platform, especially on Windows.

5.2 dBase files (DBF)

dBase was a DOS program written by Ashton-Tate and later owned by Borland which has a binary flat-file format that became popular, with file extension .dbf. It has been adopted for the ‘Xbase’ family of databases, covering dBase, Clipper, FoxPro and their Windows equivalents Visual dBase, Visual Objects and Visual FoxPro (see https://www.clicketyclick.dk/databases/xbase/format). A dBase file contains a header and then a series of fields and so is most similar to an R data frame. The data itself is stored in text format, and can include character, logical and numeric fields, and other types in later versions (see for example http://www.digitalpreservation.gov/formats/fdd/fdd000325.shtml and http://www.clicketyclick.dk/databases/xbase/format/index.html).

Functions read.dbf and write.dbf provide ways to read and write basic DBF files on all R platforms. For Windows users odbcConnectDbase in package RODBC (https://CRAN.R-project.org/package=RODBC) provides more comprehensive facilities to read DBF files via Microsoft’s dBase ODBC driver (and the Visual FoxPro driver can also be used via odbcDriverConnect).
6 Image files

A particular class of binary files are those representing images, and a not uncommon request is to read such a file into R as a matrix.

There are many formats for image files (most with lots of variants), and it may be necessary to use external conversion software to first convert the image into one of the formats for which a package currently provides an R reader. A versatile example of such software is ImageMagick and its fork GraphicsMagick. These provide command-line programs `convert` and `gm convert` to convert images from one format to another: what formats they can input is determined when they are compiled, and the supported formats can be listed by e.g. `convert -list format`.

Package `pixmap` (https://CRAN.R-project.org/package=pixmap) has a function `read.pnm` to read ‘portable anymap’ images in PBM (black/white), PGM (grey) and PPM (RGB colour) formats. These are also known as ‘netpbm’ formats.

Packages `bmp` (https://CRAN.R-project.org/package=bmp), `jpeg` (https://CRAN.R-project.org/package=jpeg) and `png` (https://CRAN.R-project.org/package=png) read the formats after which they are named. See also packages `biOps` (https://CRAN.R-project.org/package=biOps) and `Momocs` (https://CRAN.R-project.org/package=Momocs), and Bioconductor package `EBImage`.

TIFF is more a meta-format, a wrapper within which a very large variety of image formats can be embedded. Packages `rtiff` (https://CRAN.R-project.org/package=rtiff) and `tiff` (https://CRAN.R-project.org/package=tiff) can read some of the sub-formats (depending on the external `libtiff` software against which they are compiled). There some facilities for specialized sub-formats, for example in Bioconductor package `beadarray`.

Raster files are common in the geographical sciences, and package `rgdal` (https://CRAN.R-project.org/package=rgdal) provides an interface to GDAL which provides some facilities of its own to read raster files and links to many others. Which formats it supports is determined when GDAL is compiled: use `gdalDrivers()` to see what these are for the build you are using. It can be useful for uncommon formats such as JPEG 2000 (which is a different format from JPEG, and not currently supported in the macOS nor Windows binary versions of `rgdal` (https://CRAN.R-project.org/package=rgdal)).
7 Connections

Connections are used in R in the sense of Chambers (1998) and Ripley (2001), a set of functions to replace the use of file names by a flexible interface to file-like objects.

7.1 Types of connections

The most familiar type of connection will be a file, and file connections are created by function file. File connections can (if the OS will allow it for the particular file) be opened for reading or writing or appending, in text or binary mode. In fact, files can be opened for both reading and writing, and R keeps a separate file position for reading and writing.

Note that by default a connection is not opened when it is created. The rule is that a function using a connection should open a connection (needed) if the connection is not already open, and close a connection after use if it opened it. In brief, leave the connection in the state you found it in. There are generic functions open and close with methods to explicitly open and close connections.

Files compressed via the algorithm used by gzip can be used as connections created by the function gzfile, whereas files compressed by bzip2 can be used via bzfile.

Unix programmers are used to dealing with special files stdin, stdout and stderr. These exist as terminal connections in R. They may be normal files, but they might also refer to input from and output to a GUI console. (Even with the standard Unix R interface, stdin refers to the lines submitted from readline rather than a file.)

The three terminal connections are always open, and cannot be opened or closed. stdout and stderr are conventionally used for normal output and error messages respectively. They may normally go to the same place, but whereas normal output can be re-directed by a call to sink, error output is sent to stderr unless re-directed by sink, type="message"). Note carefully the language used here: the connections cannot be re-directed, but output can be sent to other connections.

Text connections are another source of input. They allow R character vectors to be read as if the lines were being read from a text file. A text connection is created and opened by a call to textConnection, which copies the current contents of the character vector to an internal buffer at the time of creation.

Text connections can also be used to capture R output to a character vector. textConnection can be asked to create a new character object or append to an existing one, in both cases in the user’s workspace. The connection is opened by the call to textConnection, and at all times the complete lines output to the connection are available in the R object. Closing the connection writes any remaining output to a final element of the character vector.

Pipes are a special form of file that connects to another process, and pipe connections are created by the function pipe. Opening a pipe connection for writing (it makes no sense to append to a pipe) runs an OS command, and connects its standard input to whatever R then writes to that connection. Conversely, opening a pipe connection for input runs an OS command and makes its standard output available for R input from that connection.

URLs of types ‘http://’, ‘https://’, ‘ftp://’ and ‘file://’ can be read from using the function url. For convenience, file will also accept these as the file specification and call url.

Sockets can also be used as connections via function socketConnection on platforms which support Berkeley-like sockets (most Unix systems, Linux and Windows). Sockets can be written to or read from, and both client and server sockets can be used.
7.2 Output to connections

We have described functions `cat`, `write`, `write.table` and `sink` as writing to a file, possibly appending to a file if argument `append = TRUE`, and this is what they did prior to R version 1.2.0.

The current behaviour is equivalent, but what actually happens is that when the `file` argument is a character string, a file connection is opened (for writing or appending) and closed again at the end of the function call. If we want to repeatedly write to the same file, it is more efficient to explicitly declare and open the connection, and pass the connection object to each call to an output function. This also makes it possible to write to pipes, which was implemented earlier in a limited way via the syntax `file = "|cmd"` (which can still be used).

There is a function `writeLines` to write complete text lines to a connection.

Some simple examples are

```r
zz <- file("ex.data", "w") # open an output file connection
cat("TITLE extra line", "2 3 5 7", ",", "11 13 17",
    file = zz, sep = "\n")
cat("One more line\n", file = zz)
close(zz)
```

```r
## convert decimal point to comma in output, using a pipe (Unix)
## both R strings and (probably) the shell need \ doubled
zz <- pipe(paste("sed s/\\./,/ >", "outfile"), "w")
cat(format(round(rnorm(100), 4)), sep = "\n", file = zz)
close(zz)
```

## now look at the output file:
```r
file.show("outfile", delete.file = TRUE)
```

```r
## capture R output: use examples from help(lm)
zz <- textConnection("ex.lm.out", "w")
sink(zz)
example(lm, prompt.echo = "> ")
sink()
close(zz)
```

## now 'ex.lm.out' contains the output for further processing.
```r
## Look at it by, e.g.,
cat(ex.lm.out, sep = "\n")
```

7.3 Input from connections

The basic functions to read from connections are `scan` and `readLines`. These take a character string argument and open a file connection for the duration of the function call, but explicitly opening a file connection allows a file to be read sequentially in different formats.

Other functions that call `scan` can also make use of connections, in particular `read.table`.

Some simple examples are

```r
## read in file created in last examples
readLines("ex.data")
unlink("ex.data")
```

## read listing of current directory (Unix)
```r
readLines(pipe("ls -l"))
```
# remove trailing commas from an input file.
# Suppose we are given a file ‘data’ containing
450, 390, 467, 654, 30, 542, 334, 432, 421,
357, 497, 493, 550, 549, 467, 575, 578, 342,
446, 547, 534, 495, 979, 479
# Then read this by
scan(pipe("sed -e s/,$// data"), sep=",")

For convenience, if the file argument specifies a FTP, HTTP or HTTPS URL, the URL is
opened for reading via url. Specifying files via ‘file:///foo.bar’ is also allowed.

7.3.1 Pushback

C programmers may be familiar with the ungetc function to push back a character onto a text
input stream. R connections have the same idea in a more powerful way, in that an (essentially)
arbitrary number of lines of text can be pushed back onto a connection via a call to pushBack.

Pushbacks operate as a stack, so a read request first uses each line from the most recently
pushbacked text, then those from earlier pushbacks and finally reads from the connection itself.
Once a pushbacked line is read completely, it is cleared. The number of pending lines pushed
back can be found via a call to pushBackLength.

A simple example will show the idea.
> zz <- textConnection(LETTERS)
> readLines(zz, 2)
[1] "A" "B"
> scan(zz, "", 4)
Read 4 items
[1] "C" "D" "E" "F"
> pushBack(c("aa", "bb"), zz)
> scan(zz, "", 4)
Read 4 items
[1] "aa" "bb" "G" "H"
> close(zz)

Pushback is only available for connections opened for input in text mode.

7.4 Listing and manipulating connections

A summary of all the connections currently opened by the user can be found by
showConnections(), and a summary of all connections, including closed and terminal
connections, by showConnections(all = TRUE)

The generic function seek can be used to read and (on some connections) reset the current
position for reading or writing. Unfortunately it depends on OS facilities which may be unreliable
(e.g. with text files under Windows). Function isSeekable reports if seek can change the
position on the connection given by its argument.

The function truncate can be used to truncate a file opened for writing at its current position.
It works only for file connections, and is not implemented on all platforms.

7.5 Binary connections

Functions readBin and writeBin read to and write from binary connections. A connection is
opened in binary mode by appending "b" to the mode specification, that is using mode "rb" for
reading, and mode "wb" or "ab" (where appropriate) for writing. The functions have arguments
readBin(con, what, n = 1, size = NA, endian = .Platform$endian)
writeBin(object, con, size = NA, endian = .Platform$endian)
In each case \texttt{con} is a connection which will be opened if necessary for the duration of the call, and if a character string is given it is assumed to specify a file name.

It is slightly simpler to describe writing, so we will do that first. \texttt{object} should be an atomic vector object, that is a vector of mode \texttt{numeric}, \texttt{integer}, \texttt{logical}, \texttt{character}, \texttt{complex} or \texttt{raw}, without attributes. By default this is written to the file as a stream of bytes exactly as it is represented in memory.

\texttt{readBin} reads a stream of bytes from the file and interprets them as a vector of mode given by \texttt{what}. This can be either an object of the appropriate mode (e.g. \texttt{what=integer()} or a character string describing the mode (one of the five given in the previous paragraph or "\texttt{double}" or "\texttt{int}"). Argument \texttt{n} specifies the maximum number of vector elements to read from the connection: if fewer are available a shorter vector will be returned. Argument \texttt{signed} allows 1-byte and 2-byte integers to be read as signed (the default) or unsigned integers.

The remaining two arguments are used to write or read data for interchange with another program or another platform. By default binary data is transferred directly from memory to the connection or \textit{vice versa}. This will not suffice if the data are to be transferred to a machine with a different architecture, but between almost all R platforms the only change needed is that of byte-order. Common PCs ('ix86'-based and 'x86_64'-based machines), Compaq Alpha and Vaxen are \textit{little-endian}, whereas Sun Sparc, mc680x0 series, IBM R6000, SGI and most others are \textit{big-endian}. (Network byte-order (as used by XDR, eXternal Data Representation) is big-endian.) To transfer to or from other programs we may need to do more, for example to read 16-bit integers or write single-precision real numbers. This can be done using the \texttt{size} argument, which (usually) allows sizes 1, 2, 4, 8 for integers and logicals, and sizes 4, 8 and perhaps 12 or 16 for reals. Transferring at different sizes can lose precision, and should not be attempted for vectors containing \texttt{NA}'s.

Character strings are read and written in C format, that is as a string of bytes terminated by a zero byte. Functions \texttt{readChar} and \texttt{writeChar} provide greater flexibility.

\subsection*{7.5.1 Special values}

Functions \texttt{readBin} and \texttt{writeBin} will pass missing and special values, although this should not be attempted if a size change is involved.

The missing value for R logical and integer types is \texttt{INT_MIN}, the smallest representable \texttt{int} defined in the C header \texttt{limits.h}, normally corresponding to the bit pattern \texttt{0x80000000}.

The representation of the special values for R numeric and complex types is machine-dependent, and possibly also compiler-dependent. The simplest way to make use of them is to link an external application against the standalone \texttt{Rmath} library which exports double constants \texttt{NA_REAL}, \texttt{R_PosInf} and \texttt{R_NegInf}, and include the header \texttt{Rmath.h} which defines the macros \texttt{ISNAN} and \texttt{R_FINITE}.

If that is not possible, on all current platforms IEC 60559 (aka IEEE 754) arithmetic is used, so standard C facilities can be used to test for or set \texttt{Inf}, \texttt{-Inf} and \texttt{NaN} values. On such platforms \texttt{NA} is represented by the \texttt{NaN} value with low-word \texttt{0x7a2} (1954 in decimal).

Character missing values are written as \texttt{NA}, and there are no provision to recognize character values as missing (as this can be done by re-assigning them once read).
8 Network interfaces

Some limited facilities are available to exchange data at a lower level across network connections.

8.1 Reading from sockets

Base R comes with some facilities to communicate via BSD sockets on systems that support them (including the common Linux, Unix and Windows ports of R). One potential problem with using sockets is that these facilities are often blocked for security reasons or to force the use of Web caches, so these functions may be more useful on an intranet than externally. For new projects it is suggested that socket connections are used instead.

The earlier low-level interface is given by functions `make.socket`, `read.socket`, `write.socket` and `close.socket`.

8.2 Using `download.file`

Function `download.file` is provided to read a file from a Web resource via FTP or HTTP (including HTTPS) and write it to a file. Often this can be avoided, as functions such as `read.table` and `scan` can read directly from a URL, either by explicitly using `url` to open a connection, or implicitly using it by giving a URL as the `file` argument.
9 Reading Excel spreadsheets

The most common R data import/export question seems to be ‘how do I read an Excel spreadsheet’. This chapter collects together advice and options given earlier. Note that most of the advice is for pre-Excel 2007 spreadsheets and not the later .xlsx format.

The first piece of advice is to avoid doing so if possible! If you have access to Excel, export the data you want from Excel in tab-delimited or comma-separated form, and use read.delim or read.csv to import it into R. (You may need to use read.delim2 or read.csv2 in a locale that uses comma as the decimal point.) Exporting a DIF file and reading it using read.DIF is another possibility.

If you do not have Excel, many other programs are able to read such spreadsheets and export in a text format on both Windows and Unix, for example Gnumeric (http://www.gnome.org/projects/gnumeric/) and OpenOffice (https://www.openoffice.org). You can also cut-and-paste between the display of a spreadsheet in such a program and R: read.table will read from the R console or, under Windows, from the clipboard (via file = "clipboard" or readClipboard). The read.DIF function can also read from the clipboard.

Note that an Excel .xls file is not just a spreadsheet: such files can contain many sheets, and the sheets can contain formulae, macros and so on. Not all readers can read other than the first sheet, and may be confused by other contents of the file.

Windows users (of 32-bit R) can use odbcConnectExcel in package RODBC (https://CRAN.R-project.org/package=RODBC). This can select rows and columns from any of the sheets in an Excel spreadsheet file (at least from Excel 97–2003, depending on your ODBC drivers: by calling odbcConnect directly versions back to Excel 3.0 can be read). The version odbcConnectExcel2007 will read the Excel 2007 formats as well as earlier ones (provided the drivers are installed, including with 64-bit Windows R: see Section 4.3.2 [RODBC], page 18).

macOS users can also use RODBC (https://CRAN.R-project.org/package=RODBC) if they have a suitable driver (e.g. that from Actual Technologies).

Perl users have contributed a module OLE::SpreadSheet::ParseExcel and a program xls2csv.pl to convert Excel 95–2003 spreadsheets to CSV files. Package gdata (https://CRAN.R-project.org/package=gdata) provides a basic wrapper in its read.xls function. With suitable Perl modules installed this function can also read Excel 2007 spreadsheets.

Packages dataframes2xls (https://CRAN.R-project.org/package=dataframes2xls) and WriteXLS (https://CRAN.R-project.org/package=WriteXLS) each contain a function to write one or more data frames to an .xls file, using Python and Perl respectively.

Packages xlsx (https://CRAN.R-project.org/package=xlsx) can read and and manipulate Excel 2007 and later spreadsheets: it requires Java.

Package XLConnect (https://CRAN.R-project.org/package=XLConnect) can read, write and manipulate both Excel 97–2003 and Excel 2007/10 spreadsheets, using Java.

Package readxl (https://CRAN.R-project.org/package=readxl) can read both Excel 97–2003 and Excel 2007/10 spreadsheets, using an included C library.
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