Statistics with R: a hands-on approach

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Contents

Chapter 1

Data review

1.1 Possibly interesting extra tidbits

In the making of this tutorial, I used several tools that you might like to access as well. Being the tedium-averse programmer I am, I use a reference manager program, in my case Zotero. You can find the full bibliography for this project, including a few entries that did not make it into the references section here because I did not cite them, at the Zotero project page.

I also want to point out awesome-public-datasets, where I foraged for the examples in this tutorial. It has several interesting datasets in the public health domain.

Finally, this tutorial is not necessarily intended to be done in order. In particular, section 2.6 should be read as needed, rather than all the beginning. Not only the section on tidying up data might be boring as a first subject on R, but it's also unlikely to make much sense without some hands-on experience using the software. However, it seemed to make sense to keep all things R together, to make it easier to find again later, when the reader encounters the unavoidable data QA issue.

1.2 Variables

When "doing science", you will be taking measurements, usually in the hopes of understanding a phenomena often in the shape of a relationship between things you are measuring. When working with this data, the nature of the things you measure (*variables*) will influence the presentation and analysis that are appropriate.

A **qualitative variable** refers to categories, or a variable recorded with words, as opposed to a **quantitative variable**, which is measured with numbers. Examples of qualitative variables would include US state, restaurant chains and college major. Quantitative variables could be time to execute a task, waist circumference, disease rate or spending amounts.

R refers to **qualitative variables** as *factors*. **Qualitative variables** can further be divided into non ordinal and **ordinal variables**, depending on whether there is a natural order among the categories. For example, dog breed (chihuahua, husky, labrador) is a non ordinal variable, whereas level of satisfaction (dissatisfied, neutral, satisfied) is ordinal.

Quantitative variables are either **discrete variables**, where measurements are done in integers, or **continuous variables**, where they come in real numbers (you could get an infinity of decimals with a theoretical instrument of infinite precision). **Discrete variables** could be number of children, cancer deaths, or wedding age. **Continuous variables** include temperature, blood sugar level, and weight.

Furthermore, when studying variables in relationship with one another, changes in a **dependent variable** are driven or explained by an **independent variable**. Typically, this means the "x" axis of a graph will be the **independent variable**, while the "y" axis will be the **dependent variable**.

1.3 Gotchas

1.3.1 Tidy data

When working with data in R, analysis will be easier if your data is *tidy*, that is, each column in your data set contains one and only one variable. Or, more completely:

1. Each variable is in its own column
2. Each observation is in its own row
3. Each value is in its own cell

(Garrett Grolemund gives an excellent introduction to the subject [2].)

For example, in a cancer dataset that we will use later, the original data is presented as in table 1.1. Here, we have four variables: cancer type, sex, number of cases, and number of deaths. While the first column is one and only one variable, the other columns mix sex with number of cases or sex with number of deaths. If you would like to analyze deaths by sex or cases per cancer type, some data manipulation will be necessary to combine the relevant columns.

Cancer Type	Cases		Deaths	
	Male	Female	Male	Female
...	...	...	...	...

Table 1.1: Cancer data set format.

If you keep your data tidy, R can usually do the combining for you, if you know how to ask nicely. As such, it is recommended that the first thing you do after successfully importing data into R is to verify it is tidy. Tools to divide or merge columns will be discussed in section 2.6.

1.3.2 Correlation is not causation, or of the importance of DoE

DoE refers to design of experiments. The common trope that “correlation is not causation” refers to the fact that because two variables vary together does not necessarily mean that one causes the other to change; for instance, they might both be responding to a common cause, when it’s not just plain old coincidence. My personal favorite exemplification of “correlation is not causation” is that the divorce rate in Maine correlates with the per capita consumption of margarine [13].

To distinguish between correlation and causation with certainty, a controlled experiment must be run. Depending on the phenomena studied, this might mean using a control group, a placebo, or directly controlling environmental conditions. For example, to determine the effect of low oxygen concentration in water on cod growth, several tanks can be set up where individual cods are randomly distributed and where oxygen levels are controlled. If you were to simply measure oxygen levels in water and cod growth at different locations and subsequently find a correlation between the two, you couldn’t tell for certain whether the difference is due to oxygen levels, or another factor like water temperature, or even the fact that cod compete with one another and that the runts, who would grow slower anyway, end up pushed into less desirable low-oxygen environments. Of course, sometimes running a controlled experiment is not feasible for practical reasons (one can’t control amount of natural sunlight, for example) or ethical reasons (having an untreated control group of people with a serious condition, when a potentially life-saving treatment might exist, is questionable).

When dealing with humans, to determine whether medication has a positive effect on an health issue, the health issue can be measured for a group who took the medication (treatment group), a group who took a placebo, and a group who took no medication at all (control group). In humans, particular effort must be placed on controlling or measuring the placebo effect, for the test subjects as well as the professionals. A recent spectacular example is the recommendation to abandon arthroscopic surgeries for knee pain because it did not show better results than physical therapy in randomized trials, despite it being the most common orthopaedic procedure in several countries [11].

Where experimental design is concerned, key factors are randomization, blocking, and replication. If terms like Completely Randomized Design, Latin Squares or Factorial Design are not familiar, I would recommend investing some time into learning the basics of experimental design before embarking in an experiment, in the interest of avoiding some common and easily remedied mistakes ([4] appears to be a well-rounded textbook).

Chapter 2

Unavoidable R before we begin

2.1 Packages

R [9] should be relatively straightforward to install: download and execute, follow the wizard instructions.

Where things get a bit more complicated is when it comes to packages. While the basic R program has a lot of functions built-in, there will come a time when you will need something that is not offered out of the box. Thankfully, R has a very dynamic community with a ton of packages. For instance, a very popular package to produce figures is `ggplot2`. Let's install it to see how packages are managed in R.

First off, to install packages in R, you will need to launch it as an administrator. If you don't, you will get the rather unhelpful message shown in figure 2.1. To launch with administrator rights, right-click on your R launcher and find the option "Run as administrator". How to do so from the Windows 10 start menu is shown in figure 2.2. (As a note, you should launch as administrator *only* when installing packages, as opposed to modifying your shortcut to always launch as administrator.)

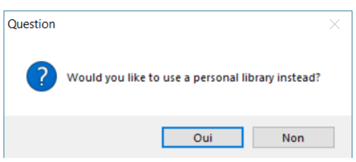


Figure 2.1: Error message displayed by R if trying to install packages without administrator rights.

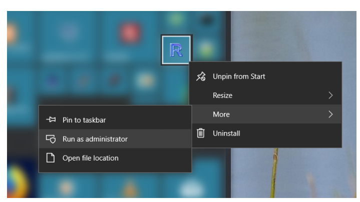
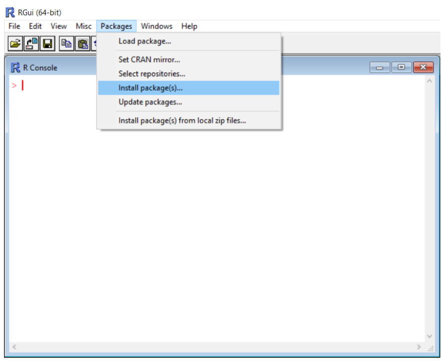
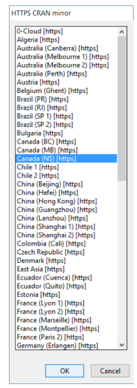


Figure 2.2: How to launch R with administrative rights.

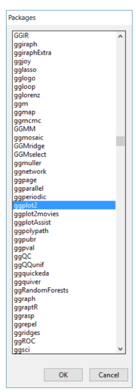
Now that R is launched as administrator, you can install `ggplot2` using either the convenient Packages menu or the command line if you're that hardcore. Personally I use the menu; after choosing a mirror (different mirrors offer different packages; Canada NS has a wide selection and is vaguely geographically close), you can select your desired package and hit "install", as shown in figure 2.3. Then you only need to wait until R is done doing its thing. If all the lines say "successfully unpacked", all good; otherwise, an error has occurred and you will have to decipher the message to figure out how to remedy the situation. (If you run into any trouble, I would first recommend updating to the latest release of R.)



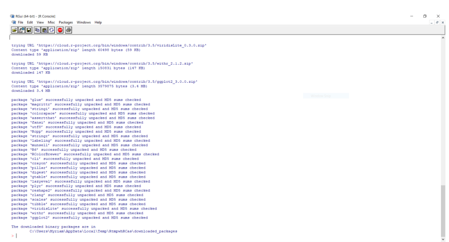
(a) Packages menu in R Gui.



(b) List of mirrors.



(c) List of packages.

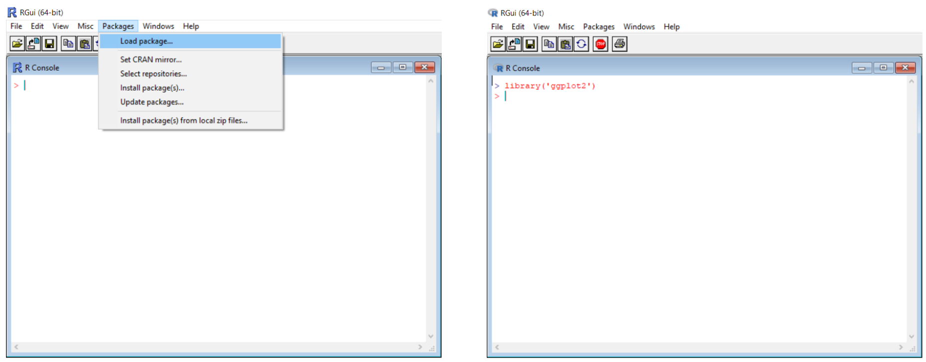


(d) All successfully unpacked: successful installation.

Figure 2.3: Package installation process.

Note that installing a package is not enough to use it; you must also load it. Again this can be done either from the menu or with the command line, as shown in figure 2.4. This operation must be repeated *every time* you restart R.

Now let's say that `ggplot2` becomes your favoritest package in the whole



(a) Packages menu in R Gui.

(b) Command to load a package in R Gui.

Figure 2.4: Loading packages in R.

world and you end up using it every day. After a week or so you will probably be very annoyed having to reload the package every time you open R. You can add packages to be loaded automatically in either of two files: `Rprofile.site` or `.Rprofile`. `Rprofile.site` is located in your R installation folder in the etc folder and is always executed. `.Rprofile` is located in the user home folder and is applied after the changes made by `Rprofile.site`. As the appropriate location to put `.Rprofile` seems to change from R version to version, I will showcase the `Rprofile.site` here. At the bottom of the file, add the following:

```
.First <- function(){
        library('ggplot2')
        # other libraries go here
}
```

2.2 Types

While relatively accessible as far as programming languages go, R is still a programming language. As such, it has a few concerns that, while painful for the non-programmers among us, are useful tools to diagnose problems, typically when importing data that has not been properly QA'd or when a function refuses to compute because the input is in a form it refuses.

Let's talk about *types*. Types refer to the nature of a variable in a computer program; is it text, a number, etc.? If it's a number, can it be any number, or integers only? This is important because computing the means of grades in a class makes sense, while computing the means of the name of the students doesn't. Further, since R is a statistical program, it also includes types not typically seen in programming languages, like factors and ordinal variables. The following table gives an overview of variable types in R.

Logical: TRUE or FALSE

Numeric: real, by the math definition (ex. 12.3). Double is a numeric with better precision.

Integer: integer, by the math definition (ex. 12).

Character: text of any length

Factor: a type that represents a **discrete variable**

Ordered: a type that represents an **ordinal variable**

List: a 1D collection of "things" (may be strings, numbers, or a mix of them)

Vector: a 1D collection of things of *one type*

Matrix: a 2D collection of things of *one type*

Array: a nD collection of things of *one type*

Data Frame: a (mostly) 2D collection of things, where each column can be of a different type

For future reference, Quick R gives an excellent introduction on the subject [8]. You can convert a variable to anything reasonable (R will turn "2" into an integer, but not "abc") using the host of `as.xyz` functions.

The data frame is of particular interest, since it allows the use of a specific syntax we will use later. A data frame is closest to a "table" you would have in your spreadsheet software: it holds values for several variables, where each column is a variable, and the headers hold sensible names.

To see which type a variable has, `class` and `str` (structure) are most informative. `class` will return the type of the variable (for example, "data frame"), while `str` will make a summary of the variable and its components, if any (for example, the various columns of a data frame).

2.3 Accessing collection elements

Some of the types presented in the previous section group several values. At some point, you'll want to access one or many of the elements, but not all. Let's say you have a data frame, for example ebola deaths by country [5]:

```
> ebola
Country Deaths
1                  Guinea   2543
2                 Liberia   4809
3            Sierra Leone   3956
4                    Mali      6
5                 Nigeria      8
6 United States of America     1
```

Notice how the line with "Country" and "Deaths" is not numbered in the output? It means R is aware it's a header and not data. *Data frame columns* (not matrices) can be accessed by their name using the `$` operator, like so:

```
> ebola$Country
[1] Guinea                   Liberia                  Sierra
↪  Leone
[4] Mali                     Nigeria                  United
↪  States of America
6 Levels: Guinea Liberia Mali Nigeria ... United States of
↪  America
```

If you want to access lines, elements or columns, you can use the `[row, column]` operator, like so:

```
> ebola[1,]
Country Deaths
1  Guinea   2543
> ebola[1,2]
[1] 2543
> ebola[,2]
Deaths
[1] 2543
[2] 4809
[3] 3956
[4] 6
[5] 8
[6] 1
```

While the `$` operator is exclusive to data frames, the `[]` is used for all collections. Vectors, lists, matrices and arrays can be accessed with the `[index]` operator for 1D structure, `[row, column]` operator for 2D structures, and `[i, j, k...]` for nD structures.

In the case you want to access several items at once, you can use a colon inside the brackets, i.e. `[begin:end]` like so:

```
> ebola[1:3,]
Country Deaths
1       Guinea   2543
2      Liberia   4809
3 Sierra Leone   3956
```

2.4 Misc

2.4.1 `c` is for concatenate

Sometimes, a function in R will use an argument that is actually a list of things; for example, the limits of the x axis are two values: the minimum and maximum values to display on the graph. Referring back to the types we just saw, R requires a `vector` of values. Since it's such a common usage, R offers a quick way to create a vector with the function `c()`.

```
> ... xlim = c(0, 100), color = c(255, 0, 0) ...
```

2.4.2 # is for comments

If you use `#` in R, it will consider anything to its right to be a *comment*, that is, not code, and it will be ignored. You can start a line with it or use it in the middle of a line. It can be useful to leave notes to yourself in long-ish scripts.

2.4.3 Use argument names

When you use a function, for example `barplot`, there are a certain number of unavoidable parameters, followed by several optional parameters. The optional parameters typically have a default value, so if you don't specify them, the function works as expected, using the default values. For example, let's consult the help page for `barplot` by typing `?barplot` at the R prompt.

```
...
barplot(height, ...)

## Default S3 method:
barplot(height, width = 1, space = NULL,
        names.arg = NULL, legend.text = NULL, beside = FALSE,
        horiz = FALSE, density = NULL, angle = 45,
        col = NULL, border = par("fg"),
        main = NULL, sub = NULL, xlab = NULL, ylab = NULL,
        xlim = NULL, ylim = NULL, xpd = TRUE, log = "",
        axes = TRUE, axisnames = TRUE,
        cex.axis = par("cex.axis"), cex.names = par("cex.axis"),
        inside = TRUE, plot = TRUE, axis.lty = 0, offset = 0,
        add = FALSE, args.legend = NULL, ...)
...
```

In this example, the parameter `height`, which is not followed by an "=" is a necessary parameter; you can't compute a bar plot without giving it some values to put in the graph! All the other parameters are optional, and the help page lists their default value.

If you decide you want your bars to be beside one another rather than stacked, you will have to set the parameter `beside`, which is the fifth optional parameter. To avoid really strange and unfortunate guesswork on R's part when it tries to figure out which parameter you set among the gazillion optional parameters, *always use the optional parameter names*, for example:

```
> heights = c(15, 5, 1, 12, 28)
> # barplot(heights, TRUE)
> # BAD!
```

```
> # Don't make R guess!
> # It's bad at it!
> barplot(heights, beside = TRUE)        # Good
```

2.5 Saving, a.k.a scripts

As long as you're doing simple things fitting on two or three lines, you probably won't feel the need to "save your file". However, as you start doing more elaborate data treatment or need to document a process used, you will want to save your progress.

One way to save is to use R's built-in `workspace`. A `workspace` is a `.RData` file that contains all the variables (used here in the computer science sense: a value that you attached a name to) you have defined since you started R. For example, if you typed the following:

```
> 1+2
[1] 3
> a = "I am text"
> x = 5+3
> y = x-8
> x
[1] 8
```

In this case, `a`, `x` and `y` would be saved in your workspace. Next time you started R, you could load the `workspace` and R would know that x is worth 8.

Another useful feature of R is the history, that is, the 250 (by default) last commands you typed in the window. You can access them by pressing the up arrow, which can be pretty handy when you want to tweak a command to fix a typo. You can save it in a `.Rhistory` file that you can also load the next time you start R.

Finally, if there is a small routine that you need to save, you can save it in a simple text file that you can load and execute. In the `File` menu, choose `New script` and type some text in the window, for instance:

```
x = c(1, 2, 3, 4, 5, 6, 7, 8, 9, 10)
y = 2*x
x
y
plot(x, y)
```

As you type the commands and press enter, nothing happens, as opposed to using the main window. To run these commands, you need to select what you want to run (for example, everything: select with ctrl+a), then press F5. If you do, you should see the outputs appearing in the main window. Once you're reassured that your basic algorithm is running, you might want to tweak the plot function to add axes and labels before re-rerunning the script. Once you're done, you can save this simple text file and have an easily viewable record of what you did.

2.6 Data: import, export, tidy

2.6.1 Import

Delimited data: `read.csv` is your friend

A typical workflow to get data from wherever into R would be as follows:

1. Copy-paste the data into your favorite spreadsheet software (Microsoft Excel, LibreOffice Calc, Google Sheets, etc.).
2. If necessary, transpose your data so that variables are in columns (rather than rows).
3. Tweak column names so they have no spaces and no special characters (é, $, etc).
4. Assign a reasonable format (text, number, thousand separators, etc.) to all columns.
5. With your operating systems using an English locale, save as csv.
6. Use `read.csv` in R with the *full path* using *forward slashes*, and the appropriate options.

As a case study, let's import the data for infant mortality [3]. Data is already in columns and country names contain no special characters. So let's just change the first column header to "Country". Next, let's set the columns B and up (excluding the header for practical reasons seen later) to format "number". You might note that the decimal separator used in this file is a comma rather than a dot. However, setting the number format should be enough for your Spreadsheet software to convert them properly. Where to set number format will vary depending on your spreadsheet program; how to apply number formatting in LibreOffice is shown in figure 2.5. In LibreOffice in particular, make sure your number format locale is English. Save the modified file in csv format.

Once in R, import the data using `read.csv`. Once that is done, however, you should always doubt that everything went well. Just to prove my point, let's examine the imported data a little more closely (see section 2.2 about data frames and section 2.3 about the `$` operator):

```
> infant = read.csv('C:/.../r-tutorial/infant.csv', header=TRUE)
> class(infant)
[1] "data.frame"
> str(infant)
'data.frame':   260 obs. of  217 variables:
$ Country: Factor w/ 260 levels "Abkhazia","Afghanistan",..: 1
 ↪  ...
$ X1800  : int  NA NA NA NA NA NA NA NA NA NA ...
$ X1801  : int  NA NA NA NA NA NA NA NA NA NA ...
# ...
```

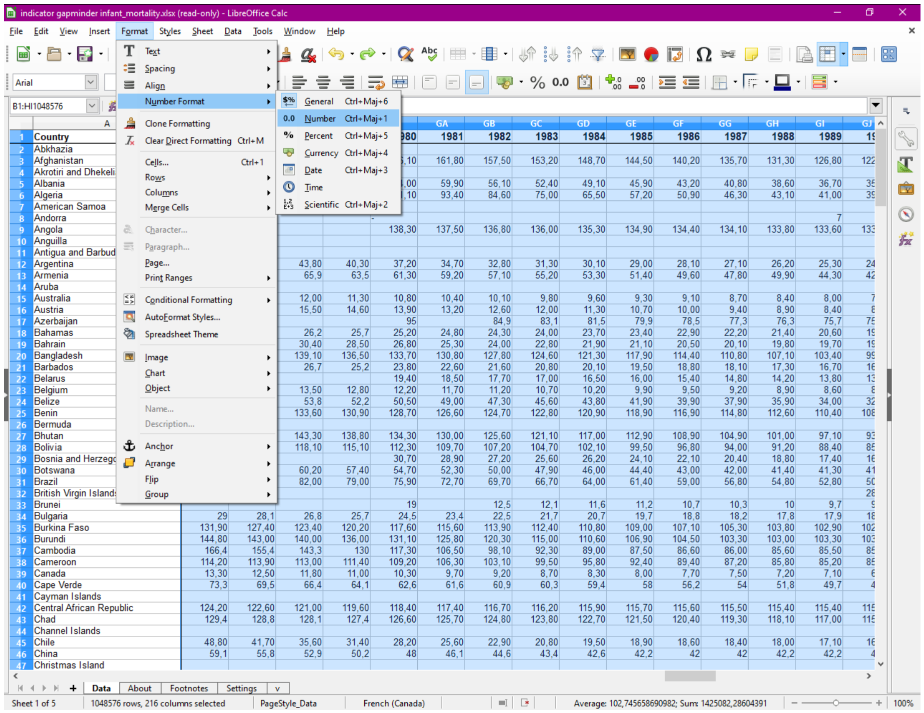


Figure 2.5: Applying number format to selected columns in LibreOffice.

```
$ X1861   : int  NA NA NA NA NA NA NA NA NA NA ...
$ X1862   : Factor w/ 11 levels "",".","110","131",..: 1 1 1 1 ...
$ X1863   : Factor w/ 13 levels "",".","106","113",..: 1 1 1 1 ...
# ...
```

Wait, what? The country is of type factor, we all agree on that, but infant mortality rate for 1862 is a factor? Let's pick 1862 and see if we can't just eyeball the problem:

```
> infant$X1862
[1]       250.00
[16]                        150.00
[31]
[46]             131.00
[61]
[76] 163.00
[91]
[106]
[121]
[136]
[151]         193.00                81.00
```

```
[166]                                                 110.00
[181]
[196]
[211]              175.00                        139.00
[226]                                    .
[241]
[256]
Levels:  . 110.00 131.00 139.00 150.00 163.00 175.00 193.00
↪  250.00 81.00
```

I don't know if you can see it, or if you think it's a speck of dust on your screen, but there's a lonely dot there somewhere between lines 226 and 241. I am going to assume it means it's a missing data point, since nothing else makes sense.

(In other languages, like French for instance, the decimal "point" is a comma, and therefore the "comma-separated" part of comma-separated value leads to some issues, not to mention the English thousand separator. This is why you set your data format in your spreadsheet: once the cell are properly formatted, your spreadsheet will export them sensibly into the csv.)

Let's try again, this time telling `read.csv` that dots are missing data:

```
> infant = read.csv("C:/.../r-tutorial/infant.csv", header=TRUE,
↪  na.strings=".")
> str(infant)
'data.frame':   260 obs. of  217 variables:
$ Country: Factor w/ 260 levels "Abkhazia","Afghanistan",..: 1 2
↪  3 5 6 7 8 9 10 11 ...
$ X1800  : num  NA NA NA NA NA NA NA NA NA NA ...
# ...
$ X1897  : num  NA NA NA NA NA NA NA NA NA NA ...
[list output truncated]
```

This looks better, however the last line displayed is for 1897. If you're a trusting person (and you should never trust a computer), you might think everything is okay now. However, I cheated and skipped ahead and tried to use this data before and encountered another QA gem. So let's make sure to display *all* the variables with a trick we will see in detail later (section 7.1.1; for now let's just say it applies `class` to every part of `infant`.

```
> sapply(infant, class)
Country     X1800     X1801     X1802     X1803     X1804
↪  X1805     X1806     X1807     X1808     X1809
"factor" "numeric" "numeric" "numeric" "numeric" "numeric"
↪  "numeric" "numeric" "numeric" "numeric" "numeric"
# ...
X1953     X1954     X1955     X1956     X1957     X1958     X1959
↪  X1960     X1961     X1962     X1963
```

```
"numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
↪  "numeric"  "factor" "numeric" "numeric" "numeric"
# ...
# See that pesky 1960?
> infant$X1960
[1]        245.00        115.40 148.20        -      208.00
↪  59.87                20.30  37.30
# ...
[256] 88.00  123.20 92.60
146 Levels:  - 100.60 101.60 102.00 102.10 102.20 105.00 106.70
↪  107.40 107.50 110.60 112.00 115.40 115.50 ... 94.00
```

So, apparently "-" also means missing data? Gods forbid the authors hit a snag while importing data and their software didn't warn them something foul was afoot (like R just did to us, thank you R) and they just pasted it in the global csv without noticing. (This is why science should be in databases. Real databases. They don't let you put a dash in a number field, they just don't.)

Now, *finally*, we get:

```
> infant = read.csv('C:/.../r-tutorial/infant.csv', header=TRUE,
↪  na.strings=c('-', '.'))
> sapply(infant, class)
Country     X1800     X1801     X1802     X1803     X1804
↪  X1805     X1806     X1807     X1808     X1809
"factor" "numeric" "numeric" "numeric" "numeric" "numeric"
↪  "numeric" "numeric" "numeric" "numeric" "numeric"
# ...
X2008     X2009     X2010     X2011     X2012     X2013     X2014
↪  X2015
"numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
↪  "numeric" "numeric"
```

Fixed-width data: `read.fwf`

In some few cases, most often when importing data from government websites who offer them up publicly in .txt format, you will encounter fixed-width data. Delimited data uses a character (most often a comma) to signify the boundary between cells of data. Fixed-width, however, always has the same number of characters for a given field. To demonstrate, figure 2.6 shows what csv (delimited) and fixed-width data look like side by side.

As a case study, let's use historic water levels for a river in Canada [7]. Data looks like this:

```
Ministère du Développement durable, de l'Environnement
     et de la Lutte contre les changements climatiques
Données validées jusqu'au 1994-09-30
Station:        070401          Portneuf - à l'amont
    des chutes Philias
```

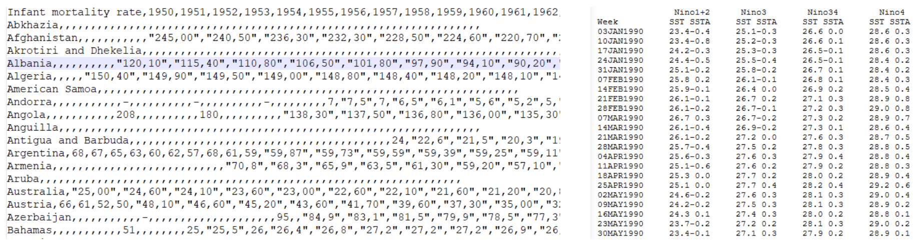


Figure 2.6: Delimited data (left) and fixed-width data (right).

```
Bassin versant: 3085 km2        Régime: Naturel
Coordonnées:     (NAD83) 48 38' 54" // -69 10' 55"

Date de création du fichier: 2012-06-30 02:40
Particularité(s):
-
-
-
Lexique:          E:  La donnée est estimée.
(Remarque)        J:  Un jaugeage a été exécuté %*à
    cette date.
MC: La donnée représente un débit moyen converti.
MJ: La donnée est une moyenne journalière.
P:  La donnée est provisoire.
PL: La donnée correspond %*à la premi\ère lecture de
    niveau d'eau de la journée.
R:  Le débit est corrigé pour tenir compte de l'effet
    de refoulement.
S:  La donnée est saisie manuellement.
Z:  La donnée provient d'une redistribution temporelle
     des données enregistrées en raison d'une dé
    fectuosité de l'appareil de mesure.

Station          Date                    Débit (m3/s)
    Remarque
070401           1973/08/17              86.60             J
070401           1973/08/18              79.90             MC
070401           1973/08/19              73.30             MC
070401           1973/08/20              68.80             MC
070401           1973/08/21              65.10             MC
070401           1973/08/22              63.70             MC
070401           1973/08/23              63.70             MC
070401           1973/08/24              62.00             MC
...
070401           1994/09/25              47.55             MC
```

```
33  070401          1994/09/26          46.74          MC
34  070401          1994/09/27          45.95          MC
35  070401          1994/09/28          46.26          MC
36  070401          1994/09/29          54.98          MC
37  070401          1994/09/30          80.23          MC
```

Save it as a text file on your computer as is. To read fixed-width data, you need to explicitly tell R the widths of each column. The popular Windows text editor Notepad++ shows column index, which allows to calculate them quickly: 6, 20, 15 and 12 (column starts with whitespace and ends with data). Furthermore, the "table" part of the file starts on line 23.

(Since there are accents in the file, if you were interested in the comments, you might want to take an extracurricular dive into encodings. Since this is an English document, I will not add another painful tangent, but as a quick note, if you ever encounter trouble importing European documents, try CP-1252 (Windows default) or ISO-8859-1 (Latin extended, covers French, German and Spanish, for instance).)

(Another note, there is a function to read Fortran files, which I never needed to use but might be useful to you. My condolences on dealing with Fortran.)

`read.fwf` is used this way:

```
> debit = read.fwf("D:/megha/Documents/r-tutorial/debit.txt",
↪  widths=c(6, 20, 15, 12), header=FALSE, skip=22,
↪  strip.white=TRUE, col.names=c('Station', 'Date', 'Debit',
↪  'Remarque'))
> str(debit)
'data.frame':   7715 obs. of  4 variables:
$ Station : int  70401 70401 70401 70401 70401 70401 70401 ...
$ Date    : Factor w/ 7715 levels "1973/08/17","1973/08/18",..: 1
↪  2 3 4 5 6 7 8 9 10 ...
$ Debit   : num  86.6 79.9 73.3 68.8 65.1 63.7 63.7 62 59.2 ...
$ Remarque: Factor w/ 5 levels "E","J","MC","R",..: 2 3 3 3 3 ...
> debit[1:5,]
Station       Date Debit Remarque
1   70401 1973/08/17  86.6        J
2   70401 1973/08/18  79.9       MC
3   70401 1973/08/19  73.3       MC
4   70401 1973/08/20  68.8       MC
5   70401 1973/08/21  65.1       MC
```

As opposed to `read.csv`, I used the argument `header=FALSE` with `read.fwf`. This is due to `read.fwf` being pickier about the header format: it wants the header to be *delimited* with a character that is not present in the rest of the file (to practice, type in `?read.fwf` in R and *attentively* read the help about the `header` argument). Since this was not the case, I manually set the column names with `col.names`. `strip.white = TRUE` automatically strips the whitespace within the columns, so your date is '1973/08/17' and not ' 1973/08/17'.

The structure of the data frame informs us that the date as been read as a factor. Since dates are their own Pandora boxes in computer science, we will not deal with them here, but you can look at section 7.3.1 if you're a masochist.

2.6.2 Export

Exporting data is useful to save it for later use or send to a spreadsheet software. Despite some internationalization issues, I would recommend using csv for the output file, since it is easy to import into spreadsheet software. In that simple case, the `write.csv` function works quite well:

```
> demo
[,1]   [,2]   [,3]   [,4]   [,5]
[1,]  82.94 115.94  89.48 101.06  91.23
[2,] 111.22 117.65  94.64 115.79 103.91
[3,]  82.10  95.96 101.11  82.44  98.84
> write.csv(demo, file='path.../demo.csv', row.names=FALSE)
```

With data frames, the column headers will make sense and, should your object have row names, you can remove the `row.names` argument.

2.6.3 Tidy

This section is quite heavy on R programmy-like stuff, so you may want to skip it until you are more familiar with R or actually need to disentangle a data set, whichever comes first.

Since their help pages are, in my opinion, easier to understand, I use the functions in the `tidyr` package, so you might want to install and load it to follow along.

n ->1 rows: `spread`

When the data is placed in a table where the name of a variable is used as a value in cells, you need to make them into columns. In other words, your table has a column of *keys* followed by a column of *values*. You can do so with the `spread` function, the result of which is represented in figure 2.7.

1 ->n rows: `gather`

When the data is placed in a table where the column headers are values of a variable, you need to put them into one column, as shown in figure 2.8. You can do so with the `gather` function.

1 ->n columns: `separate`

If one of the columns contain more than one variable, for example it is a rate written as cases/population, since number of cases and population are two sep-

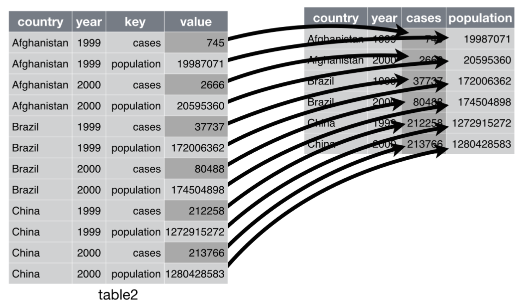


Figure 2.7: Putting variables in their own columns with `spread` (taken from [2]).

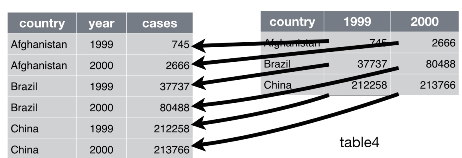


Figure 2.8: Putting a variable into only one column with `gather` (taken from [2]).

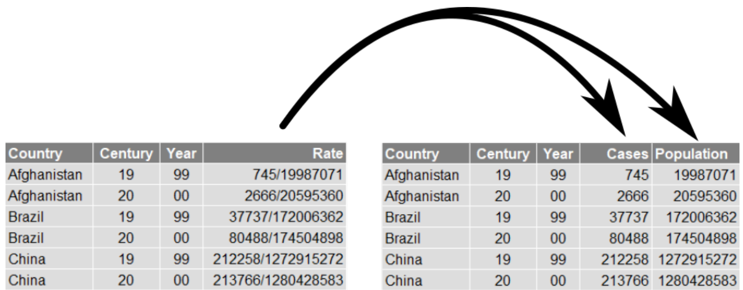
arate variables, you will need to split this column into several others. You can use the `separate` function for this, as shown in figure 2.9.

n ->1 columns: `unite`

If one variable is spread across multiple columns, for example a date split in year, month and day, while the date is a single variable, you will need to combine them into a single column. This can be done with the `unite` function, as pictured in figure 2.10.

Example

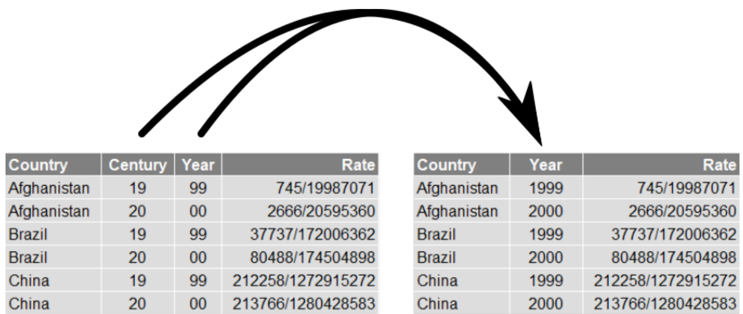
The cancer data mentioned as an example in section 1.3.1 will be used as a case study for these functions. First step is to identify the variables: cancer type, sex of patient, number of cases, and number of deaths. Here, we need to make sex its own column; and since there are two columns with female data, we will proceed in several steps: first, make all four columns one “variable” with `gather`. Arguments `key` and `value` are simply the name to give to the new columns that `gather` will create. The last argument is the columns to “gather”, while the columns not listed will be duplicated as necessary.



Country	Century	Year	Rate
Afghanistan	19	99	745/19987071
Afghanistan	20	00	2666/20595360
Brazil	19	99	37737/172006362
Brazil	20	00	80488/174504898
China	19	99	212258/1272915272
China	20	00	213766/1280428583

Country	Century	Year	Cases	Population
Afghanistan	19	99	745	19987071
Afghanistan	20	00	2666	20595360
Brazil	19	99	37737	172006362
Brazil	20	00	80488	174504898
China	19	99	212258	1272915272
China	20	00	213766	1280428583

Figure 2.9: Separate one column into two with `separate` (inspired by [2]).



Country	Century	Year	Rate
Afghanistan	19	99	745/19987071
Afghanistan	20	00	2666/20595360
Brazil	19	99	37737/172006362
Brazil	20	00	80488/174504898
China	19	99	212258/1272915272
China	20	00	213766/1280428583

Country	Year	Rate
Afghanistan	1999	745/19987071
Afghanistan	2000	2666/20595360
Brazil	1999	37737/172006362
Brazil	2000	80488/174504898
China	1999	212258/1272915272
China	2000	213766/1280428583

Figure 2.10: Merge two columns into one with `unite` (inspired by from [2]).

```
> cancer = read.csv('D:/megha/Documents/r-tutorial/cancer.csv')
> str(cancer)
'data.frame':   47 obs. of  5 variables:
$ cancer       : Factor w/ 47 levels "Acute lymphocytic
↪  leukemia",...
$ cases_male   : int  12490 7980 14250 2440 13480 16520 ...
$ cases_female : int  4620 5600 3340 820 3810 9720 5040 ...
$ deaths_male  : int  1750 1770 2480 1280 12850 6510 810 ...
$ deaths_female: int  760 880 750 360 3000 4290 640 23240 ...
> cancer = gather(cancer, key="tmpvar", value="n", 2:5)
> str(cancer)
'data.frame':   188 obs. of  3 variables:
$ cancer: Factor w/ 47 levels "Acute lymphocytic leukemia",...
$ tmpvar: chr  "cases_male" "cases_male" "cases_male" ...
$ n     : int  12490 7980 14250 2440 13480 16520 5430 49690 ...
> cancer
    cancer        tmpvar      n
1   Tongue    cases_male  12490
2    Mouth    cases_male   7980
#...
48  Tongue  cases_female   4620
```

```
49   Mouth  cases_female   5600
#...
95  Tongue   deaths_male   1750
96   Mouth   deaths_male   1770
#...
142 Tongue deaths_female    760
143  Mouth deaths_female    880
#...
```

Now, we need to separate the two words in the “tmpvar” column into two columns with `separate`. Arguments should be self-explanatory.

```
> cancer = separate(cancer, col="tmpvar", into=c("category",
↪  "sex"), sep="_")
> cancer
cancer category    sex      n
1     Tongue    cases   male  12490
2      Mouth    cases   male   7980
#...
48    Tongue    cases female   4620
49     Mouth    cases female   5600
#...
95    Tongue   deaths   male   1750
96     Mouth   deaths   male   1770
#...
142   Tongue   deaths female    760
143    Mouth   deaths female    880
#...
```

Finally, we need to bring “cases” and “deaths” back as their own column with `spread`. The argument `key` is the name of the column containing the variable names that you want to make into their own column. The argument `value` is the name of the column whose values you want to show under the new columns to be created. Other columns will be arranged accordingly.

```
> cancer = spread(cancer, key="category", value="n")
> str(cancer)
'data.frame':   94 obs. of  4 variables:
$ cancer: Factor w/ 47 levels "Acute lymphocytic leukemia",...
$ sex   : chr  "female" "male" "female" "male" ...
$ cases : int  2670 3290 9140 10380 5620 2960 1510 1940 ...
$ deaths: int  640 830 4490 6180 680 480 660 930 7340 9490 ...
> cancer
    cancer    sex  cases deaths
#...
37   Mouth female   5600    880
38   Mouth   male   7980   1770
```

```
#...
81  Tongue female   4620    760
82  Tongue   male  12490   1750
#...
```

There we go! Tidy data set!

Chapter 3

Descriptive statistics

3.1 Frequency table (1D) or contingency table (2D)

For qualitative, discrete and continuous variables

If you feel the need to make a table with your data, use a spreadsheet software. ;) R is superior in statistics and (arguably) in figures, but spreadsheets definitely have their uses when it comes to tables.

3.2 Pie chart

For qualitative and discrete variables, max 2 values

A pie chart is a graph that can be used to visually represent proportions of a **qualitative variable** or **discrete variable**. Note that they have their critics, who recommend never using them, as our brain is bad at comparing the size of slices [6].

As an example data set, let's use ebola deaths by country [5]. An excerpt giving the source data is shown in figure 3.1. Enter the data in your favorite spreadsheet software and save it as a csv. You should get the following:

```
Country,Deaths
Guinea,2543
Liberia,4809
Sierra Leone,3956
Mali,6
Nigeria,8
United States of America,1
```

Go ahead and load your small csv into R with `read.csv`. You can then use the function `pie` to produce a pie chart. However, as shown below, a naive approach might disappoint.

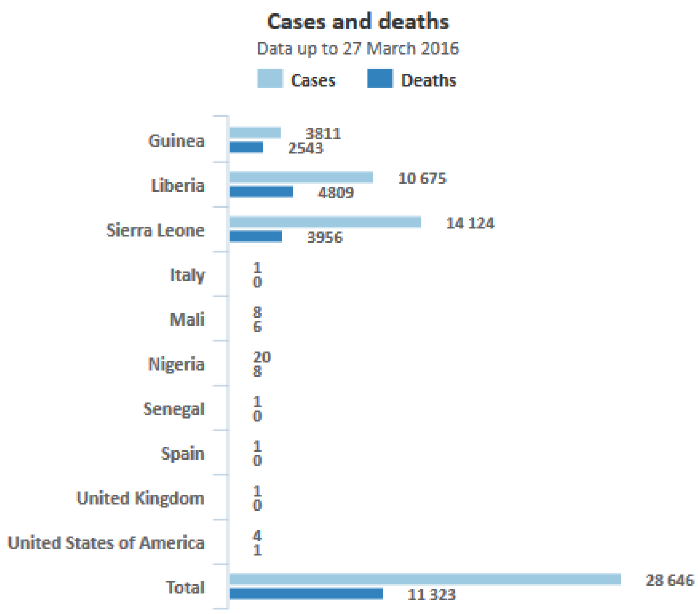


Figure 3.1: Excerpt from [5].

```
> ebola = read.csv('D:/megha/Documents/r-tutorial/ebola.csv',
↪  header=TRUE)
> ebola
                   Country Deaths
1                   Guinea   2543
2                  Liberia   4809
3             Sierra Leone   3956
4                     Mali      6
5                  Nigeria      8
6 United States of America      1
> pie(ebola)
Error in pie(ebola) : 'x' values must be positive.
```

You might be scratching your head and wondering which part of 2543 or 6 is not positive, and you'd be justified to do so. Here, one must dive into computer programming concerns to understand what is going on. The "not positive" message hints at a problem with the format or the type of the input data (see section 2.2). Let's demonstrate:

```
> values = c(2543, 4809, 3956, 6, 8, 1)
> labels = c('Guinea', 'Liberia', 'Sierra Leone', 'Mali',
↪  'Nigeria', 'United States of America')
```

```
> pie(values, labels=labels)          # works! produces figure
↪  below
> class(values)
[1] "numeric"
> class(labels)
[1] "character"
> class(ebola)
[1] "data.frame"
> class(ebola$Country)
[1] "factor"
> class(ebola$Deaths)
[1] "integer"
> pie(ebola$Deaths, labels=ebola$Country)          # works too now!
```

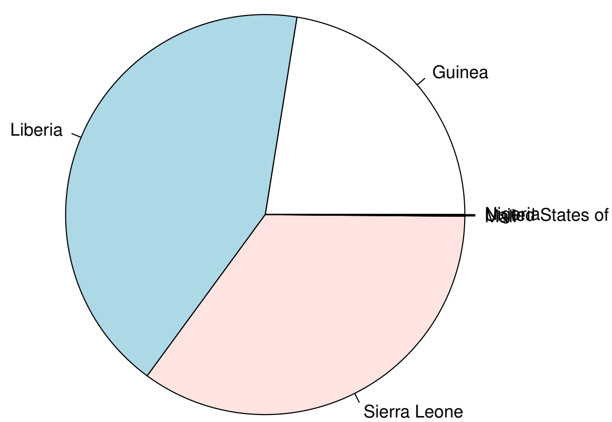


Figure 3.2: Ebola deaths in 2015-2016 by country.

Technically, `read.csv` returns a `data.frame`, while `pie` only accepts numbers. Accessing the columns of the data frame (see section 2.3) to feed `pie` the right types of arguments allows it to produce the expected figure.

Now that we have our basic pie chart, you might be thinking, “That squiggle on the right with the tiny pie slices is quite unseemly”. In addition, you might want to tweak other aspects of the graph, like adding a title or choosing colors.

We will discuss common graph properties in a following section, to keep it all in the same place. As a note, all options are always listed in the function's help page.

Let's just deal with the pie-chart specific problem of small slices here (I reiterate, you should run away, run away into the arms of a bar chart.), and add a percent annotation, as that is a common occurrence. R does not offer an option to deal with small slices out of the box (probably because it tells you in its own manual to use bar charts instead), so let's just manually tweak the labels:

```
> labels = as.character(ebola$Country)
> labels[4]='Others'
> labels[5:6]=''
> labels
[1] "Guinea"       "Liberia"      "Sierra Leone" "Others"
↪  ""
[6] ""
> percents = ebola$Deaths/sum(ebola$Deaths)*100
> percents
[1] 22.458712355 42.471076570 34.937737349  0.052989490
↪  0.070652654
[6]  0.008831582
> percents[4] = sum(percents[4:6])
> percents
[1] 22.458712355 42.471076570 34.937737349  0.132473726
↪  0.070652654
[6]  0.008831582
> percents = round(percents, 2)
> percents
[1] 22.46 42.47 34.94  0.13  0.07  0.01
> labels[1:4] = paste(labels[1:4], percents[1:4], '%')
> labels
[1] "Guinea 22.46 %"       "Liberia 42.47 %"      "Sierra Leone
↪  34.94 %"
[4] "Others 0.13 %"
> pie(ebola$Deaths, labels)
```

Hacky, but it works, and no more time should be dedicated to pie charts, so let's move on.

3.3 Bar chart

For qualitative and discrete variables

A bar chart, sometimes called a line graph, is used to represent a **qualitative variable** or a **discrete variable**, and the bars *do not touch*. As an example, data on infant mortality by country can be found at Gapminder [3]. The import process is detailed in section 2.6.1.

A barplot is relatively straightforward to produce with R, but we will see all "common" (imho) plot options here, so tie your winter hat down with wire, you'll be sitting here a while. Let's start by simply plotting infant mortality rate by country. To keep the plot readable, let's choose a subset of G8 countries: Canada, France, Germany, Italy, Japan, Russia, United Kingdom and United States of America. Let's also start by studying the mortality rate in 2000. First, we will select each of the countries by its row number, then we will stitch the G8 back together with a function called `rbind`, which binds data frames together by row, as long as all data frames have the same columns.

```
> canada = infant[38,]
> france = infant[77,]
> germany = infant[83,]
> italy = infant[109,]
> japan = infant[111,]
> russia = infant[186,]
> uk = infant[240,]
> usa = infant[241,]
> g8 = rbind(canada, france, germany, italy, japan, russia, uk,
↪  usa)
```

Producing a barplot now is easy:

```
> barplot(g8$X2000, names.arg=g8$Country)
```

Several things are wrong with this graph. Glaringly, a bar should not extend beyond its axis. Axes are set as plot options with `xlim` and `ylim`. Also, should you want a box around the graph, `bty` takes care of that. Usually. Bar plots are special and you need to all an extra function after your plot appears. See all graph options with `?par`, which we will use a lot more as we customize our graphs.

```
> barplot(g8$X2000, names.arg=g8$Country, ylim=c(0,20),
↪  bty='o')
> # why oh why won't bty work like everywhere else!
> box()
```

You probably also want all country names to show up. Easiest way to do that is to tilt the axis label text. Here we will learn about `par`, used *before* your graph function to specify general plotting settings. For this next iteration, let's do a few things at once. First, let's make all labels perpendicular to their axis with `par` and `las`. Let's also demonstrate color manipulation by making each country's bar the dominant color on their flag (I may have made some arbitrary choices) with `col`.

```
> colors = c('red', 'blue', 'black', 'green', 'white', 'snow',
↪  'purple', 'purple4')
> par(las=2)                # axis labels: perpendicular
```

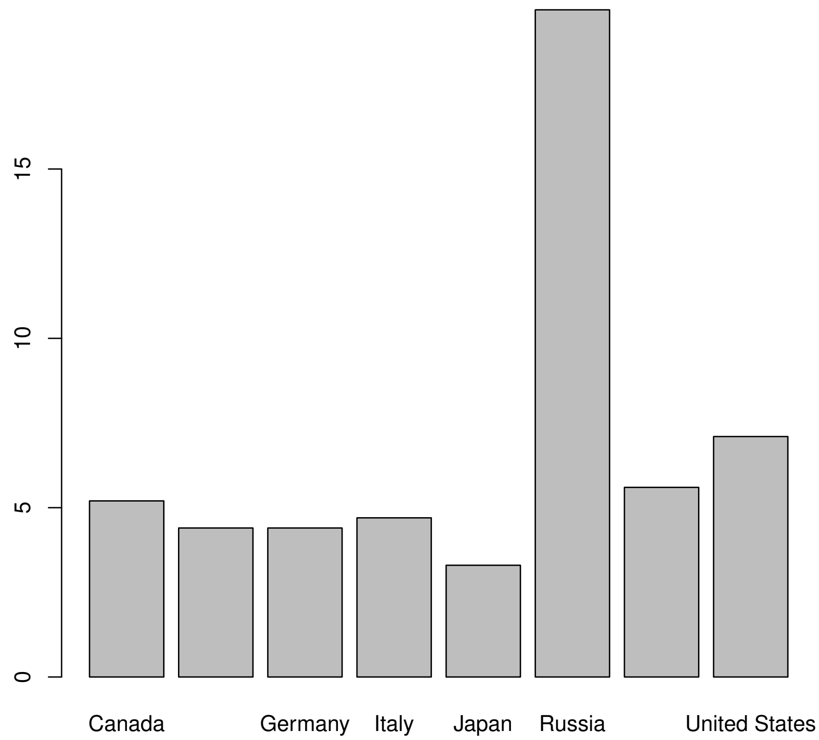


Figure 3.3: Simplest bar plot: infant mortality rate per country.

```
> barplot(g8$X2000, names.arg=g8$Country, ylim=c(0,20),
↪  col=colors)
> box()
```

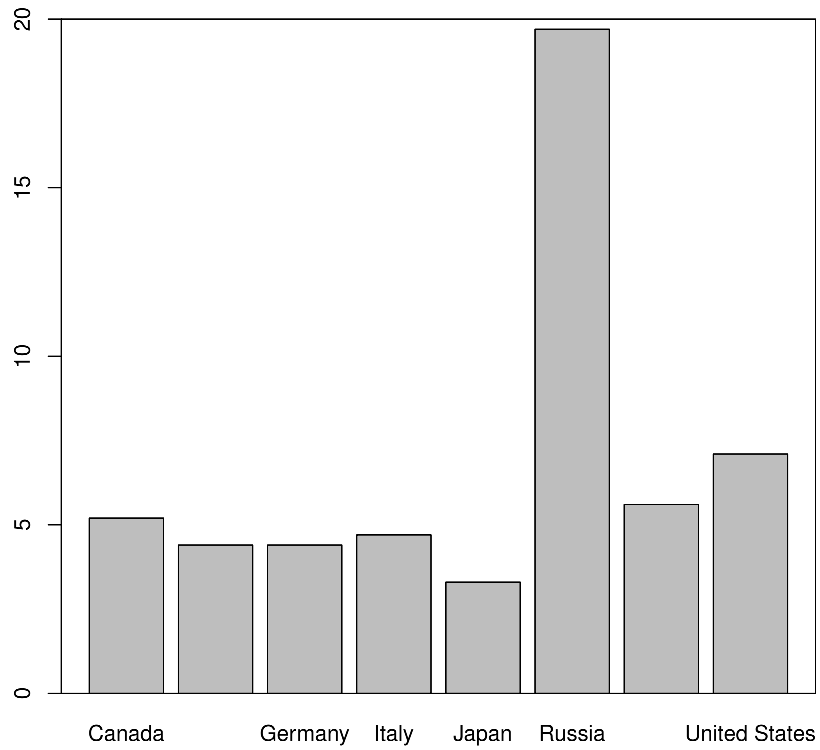


Figure 3.4: Simple bar plot: infant mortality rate per country, axis set.

Colors in R

Colors in R can be specified by their names, if they are among R's list of predefined colors, which you can see by calling `colors()`.

A more visually helpful version can be found at Color Chart [1] which, incidentally, has other fascinating references about the use of color in science (good vs. bad color ramps, color blindness, etc).

Additionally, colors can be specified in other formats like `#RRGGBB`. These values can be found with graphics software or off a color generator on the internet.

Finally, if color space is a concern, additional functions exist: `rgb`, `hsv`, `hcl`, `gray` and `rainbow`.

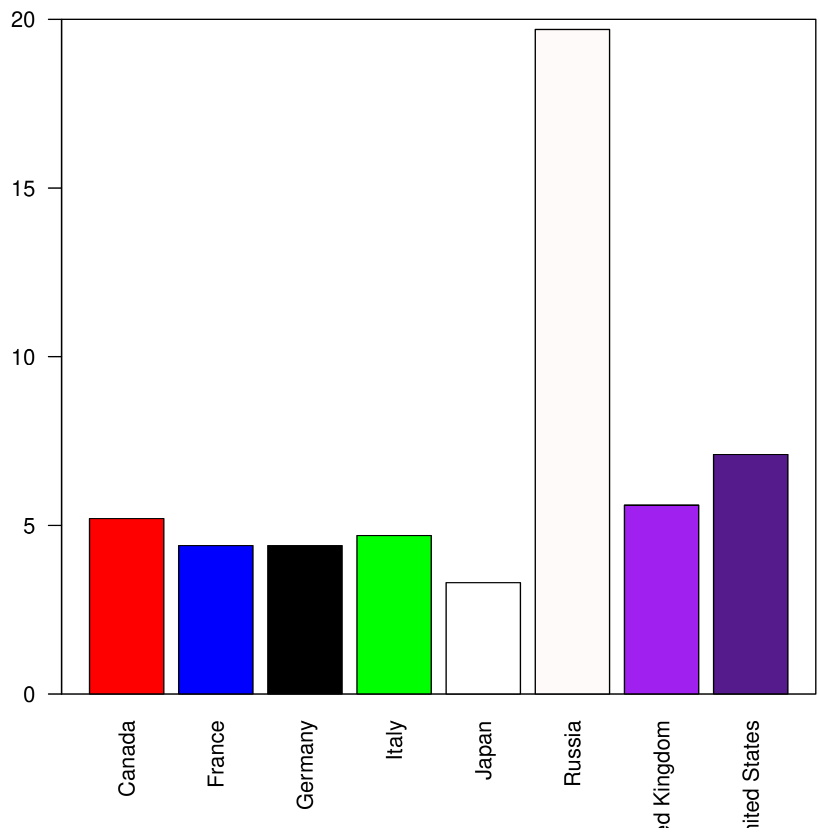


Figure 3.5: Psychedelic bar plot: infant mortality rate per country, axis set, labels perpendicular, colors.

With the country names printed at the vertical, they are running out of space at the bottom of the graph. More margin is needed there. Figures have two types of margins in R: outer and inner. The inner margin is used to draw the figure title and the axis ticks and labels and can be set in inches with `mai=c(bottom, left, top, right)` or in lines with `mar=c(bottom, left, top, right)`. The outer margin is outside the figure; it makes more sense when several plots are displayed together, as we will do a few exercises down the line. The outer margin as well can be set in inches with `omi=c(bottom, left, top, right)` or in lines with `oma=c(bottom, left, top, right)`. As for the appropriate margin necessary to display the full country name, that's a matter of trial and error. Starting with the current parameters' value of inner margin, I found that a value of 8 worked well.

```
par()$mar
[1] 5.1 4.1 4.1 2.1
> # mar = c(bottom, left, top, right)
> par(mar=c(8, 4.1, 4.1, 2.1))
> barplot(g8$X2000, names.arg=g8$Country, ylim=c(0,20),
↪  col=colors)
> box()
```

Now, bar charts often use stacked bars. For example, let's use cancer rates [12]. This data includes number of cases and number of deaths by sex and cancer type. If the thing you would most like to compare is the number of cancer by type, you would stack the sexes into one bar, and make one bar for new cases and one bar for deaths. Data can most easily be copy-pasted into a Spreadsheet software from Table 1 of the peer-reviewed article version of the report [10]. After removing sum lines and columns, removing the thousand separator, tweaking header names, saving as csv and importing into R, you can produce your bar chart:

```
> cancer =
↪  read.csv('C:/Users/Myriam/Documents/r-tutorial/cancer.csv')
> cancer
                              cancer cases_male cases_female
                              ↪  deaths_male deaths_female
1                             Tongue      12490         4620
↪  1750           760
2                              Mouth       7980         5600
↪  1770           880
...
47 Other & unspecified primary sites      16520        15290
↪  23950          20610
> str(cancer)
'data.frame':   47 obs. of  5 variables:
 $ cancer       : Factor w/ 47 levels "Acute lymphocytic
 ↪  leukemia",..: 41 19 32 27 10 38 36 9 34 3 ...
 $ cases_male   : int  12490 7980 14250 2440 13480 16520 ...
 $ cases_female : int  4620 5600 3340 820 3810 9720 ...
 $ deaths_male  : int  1750 1770 2480 1280 12850 6510 ...
 $ deaths_female: int  760 880 750 360 3000 4290  ...
```

3.4 Histogram

For continuous variables

3.5 Line graph

3.6 Scatter graph

3.7 Box and whiskers graph

3.8 Center tendency measurements

3.8.1 Mean

3.8.2 Median

3.8.3 Mode

3.9 Dispersion measurements

3.9.1 Range

3.9.2 Variance

3.9.3 Standard deviation

3.9.4 Coefficient of variation

3.9.5 Quartiles and percentiles

3.10 Shape measurements

3.10.1 Skewness

3.10.2 Kurtosis

3.10.3 L-moments

Chapter 4

Probabilities

4.1 Factorial

4.2 Combinations

4.3 Permutations

4.4 Probability Mass/Density Function

Chapter 5

Statistics

5.1 Binomial distribution

5.2 Multinomial distribution

5.3 Poisson distribution

5.4 Inverse binomial distribution

5.5 Hypergeometric distribution

5.6 Normal distribution

5.7 Exponential distribution

5.8 Gamma distribution

5.9 c2 distribution

5.10 Fisher-Snedecor distribution

5.11 Student's law

Chapter 6

Inferential statistics

6.1 Student's test

6.2 Student's paired test

6.3 Bartlett's test

6.4 Single-factor ANOVA

6.5 c2 test

6.6 Wilcoxon-Mann-Whitney test

6.7 Kolmogorov-Smirnov test

6.8 Kruskal-Wallis test

6.9 Pearson's test

6.10 Spearman's test

6.11 Kendall's test

6.12 Simple linear regression

6.13 Multiple linear regression

Chapter 7

Programming

7.1 Sequence, iteration, branching

7.1.1 Iteration

7.1.2 Branching

7.2 Functions

7.3 Misc

7.3.1 Dates

Chapter 8

Cheat sheet

8.1 Plumbing

?	?exact_function_name
??	??keyword
class	class(R_variable)
str	str(R_variable)
colnames	colnames(R_variable)
as.integer	as.integer(R_variable)
rbind	rbind(var, var...)
cbind	cbind(var, var...)

8.2 Data import and export

read.csv	read.csv(’delimited_data.csv’, header=TRUE, sep=”,”, dec=”.”)
read.fwf	read.fwf(’fixed_width_data.txt’, widths=c(10, 5, 4), header=FALSE, skip=2, strip.white=TRUE,
write.csv	write.csv(R_variable, file=’desired_file_name.csv’, row.names=FALSE, append=FALSE)

Bibliography

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Glossary

continuous variable A variable that refers to continuous data, i.e. that can take on an infinite number of values (ex. height in mm), as opposed to categorical data (ex. color of eyes). 5

dependent variable The "explained" variable in a relationship, the one we try to understand as a consequence of another factor. For example, when studying the effect of smoking on lung cancer, lung cancer is the dependent variable.. 5

discrete variable A variable that refers to categorical data (ex. color of eyes), as opposed to continuous data (ex. height in mm). 5, 10, 25, 28

independent variable The "explaining" variable in a relationship, the one that drives a phenomena. For example, when trying to understand the causes of diabetes, body mass index would be an independent variable.. 5

ordinal variable A qualitative variable where the values can be ordered (ex. small, medium, large). 5, 10

qualitative variable A variable that is recorded with words rather than numbers (ex. color of eyes, state of mind). 4, 5, 25, 28

quantitative variable A variable that is measured with numbers (ex. number of cases, height in mm). 4, 5