

Basic Course on R: Introduction and History

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28 Oct - 1 Nov 2019

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1 Course Overview

In the first part of the course we are introduced to the R software package, or *environment*, and learn about R, how to interact with it and its basic programming elements. In the second part of the course we'll learn how to use R for its intended function: doing statistics quickly and effectively.

We will cover essential topics including how to use R and why we use it; objects, classes and functions; and creating, importing, saving, manipulating, combining, sub-setting and plotting data.

By the end of the first couple of introductory days I expect that you can write your own code and have a reasonable understanding of what's going on when you cut and paste other people's code, which is typical of how people get started with R (or any other language for that matter).

Day 1

- Introduction, R history, getting familiar with R console, RStudio
- Objects, data structures, classes, using functions, arguments
- Containers, names, selection rules, accessing data.frame elements, lists

Day 2

- Entering, importing & manipulating data with `c()`, `cbind()`, `rbind()`, `dim()`; importing from a file; working directory
- Basic plotting of boxplots, bargraphs, scatterplots & line graphs
- Plotting with ggplot2

Day 3

- Hypothesis testing & confidence intervals part 1: summary statistics, *t*-test, Mann-Whitney *U* test
- Hypothesis testing & confidence intervals part 2: correlations, ANOVA, chi-squared test
- Distribution-free ANOVA

Day 4

- Basic linear regression, diagnostics and plotting
- Basics of logistic regression
- Programming structures 1: creating your own functions, if/else functions, loops

Day 5

- Programming structures 2: scope, recursion, replacement, search path
- Object-oriented programming and performance enhancement: generic functions and methods, memory optimization

2 Introduction

2.1 History

Before R there was the statistical analysis program, S, developed at Bell Laboratories in 1976 by John Chambers. S was later commercialised as S-PLUS. John Chambers is also a current member of the R core group responsible for developing R.

Ross Ihaka and Robert Gentleman of Dept of Statistics, University of Auckland, New Zealand begin coding (1991) the S clone, R, as an open source alternative for academic use. Together with the ‘R core group’ they released version 1 under the GNU Public License (GPL) v2 and v3 in 2000. The name, R, probably derives from the first letter of the creator’s names. http://cran.r-project.org/doc/FAQ/R-FAQ.html#Why-is-R-named-R_003f

I installed R in 2006 to analyse Affymetrix microarray data with various BioConductor packages: customised normalisation methods I wanted to try were best performed with BioConductor. Complex statistical methods were *only* practically possible using R. I also learned to use a plethora of other programs and apps including TM4, BRB-Arraytools, EASE/DAVID, Ingenuity Pathway Analysis, Partek, Spotfire, etc. But it quickly became obvious that bioinformaticians developed and published their work most often as an R package or script. Since 2010 most of my work was bioinformatics. I eschewed Excel and other programs on Windows in favour of R on Linux and have steadily increased my productivity since. Although many books and online resources exist to learn R/BioConductor, there remains a lack of educational support in The Netherlands and in many parts of the world.

2.2 Strengths and weaknesses

I attribute much of R’s success to its open source, GNU GPL v2 license: created by users for users to run well on Linux, Apple and Windows. These licenses give everyone the freedom to use, the freedom to distribute and the freedom to contribute their own intellectual input to the project. The result is that performance and fitness of purpose is and always will be the primary focus. I attribute R’s limited general use to its

steep learning curve for non-programmers. Base R is also yet to take advantage of the multi-threaded architecture of current computing technology.

2.3 Get it

2.3.1 Install it

To get R on your PC **first** you need to install the core R application. Of course you'll need to download the version for your operating system and architecture first.

For Linux: <https://cran.r-project.org/bin/linux/>

For Mac: <https://cran.r-project.org/bin/macosx/>

For Windows: <https://cran.r-project.org/bin/windows/>

Although R for Windows (and Mac?) ships with a basic text editor, and it's possible to execute code from the terminal under linux, a fully featured editor increases convenience and productivity. Grab an awesome text editor:

RStudio: <https://www.rstudio.com/products/rstudio/>

Emacs/ESS: <http://ess.r-project.org/index.php?Section=download>

Here's a full list available editors: [https://en.wikipedia.org/wiki/R_\(programming_language\)#Interfaces](https://en.wikipedia.org/wiki/R_(programming_language)#Interfaces)

2.4 Not convinced?

r4stats.com has a nice evaluation of R's value 'in the field'. <http://r4stats.com/articles/popularity/>

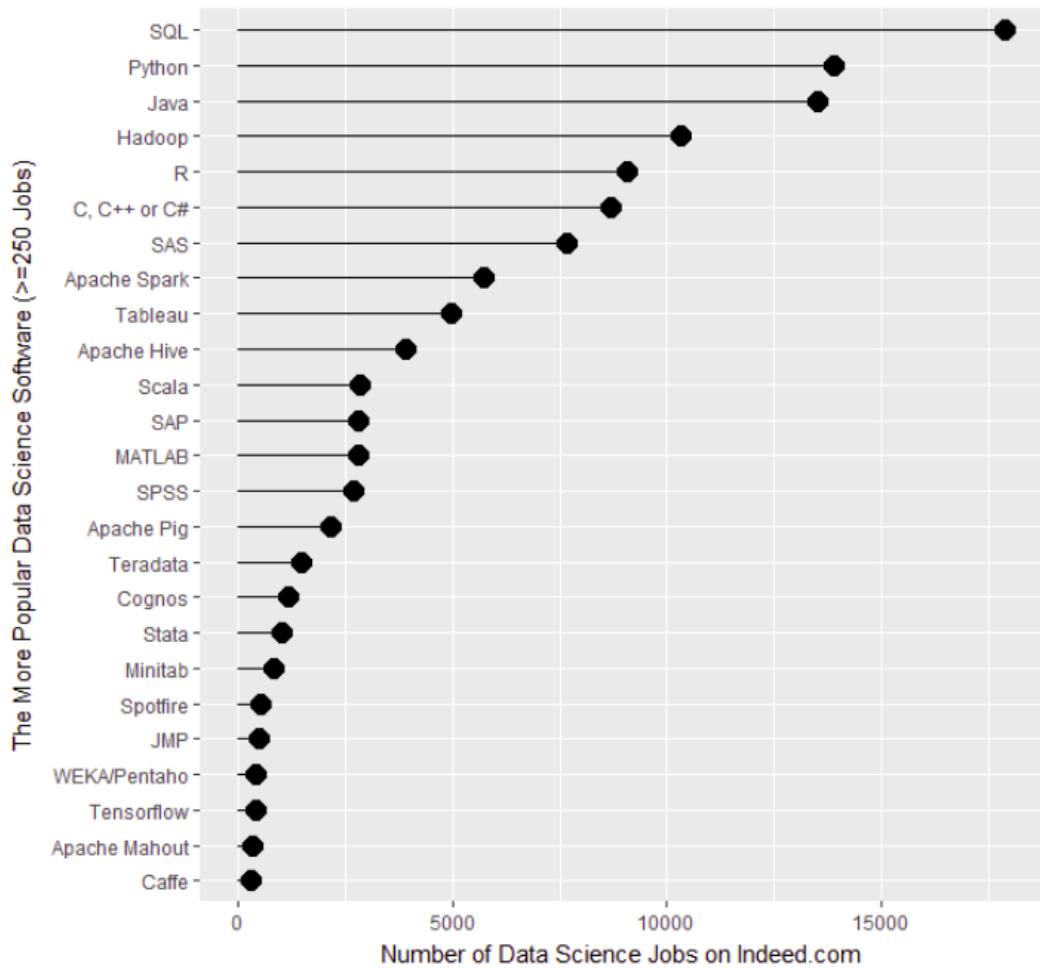
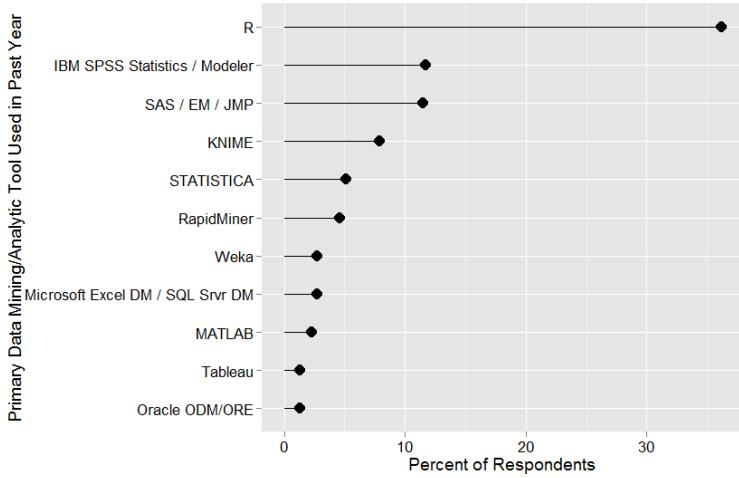
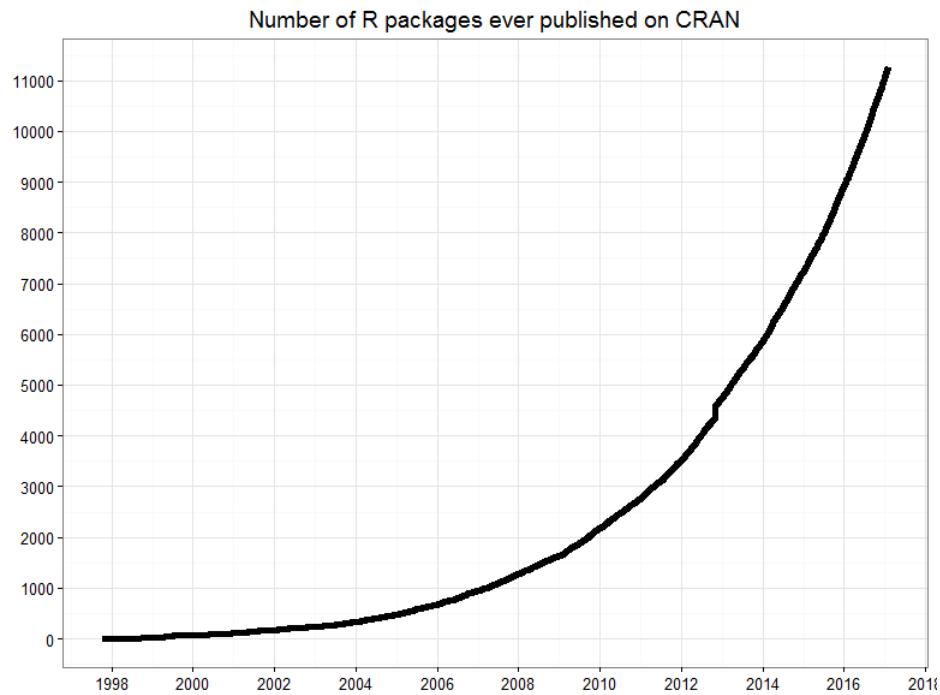


Figure 1a. The number of data science jobs for the more popular software (those with 250 jobs or more, 2/2017).

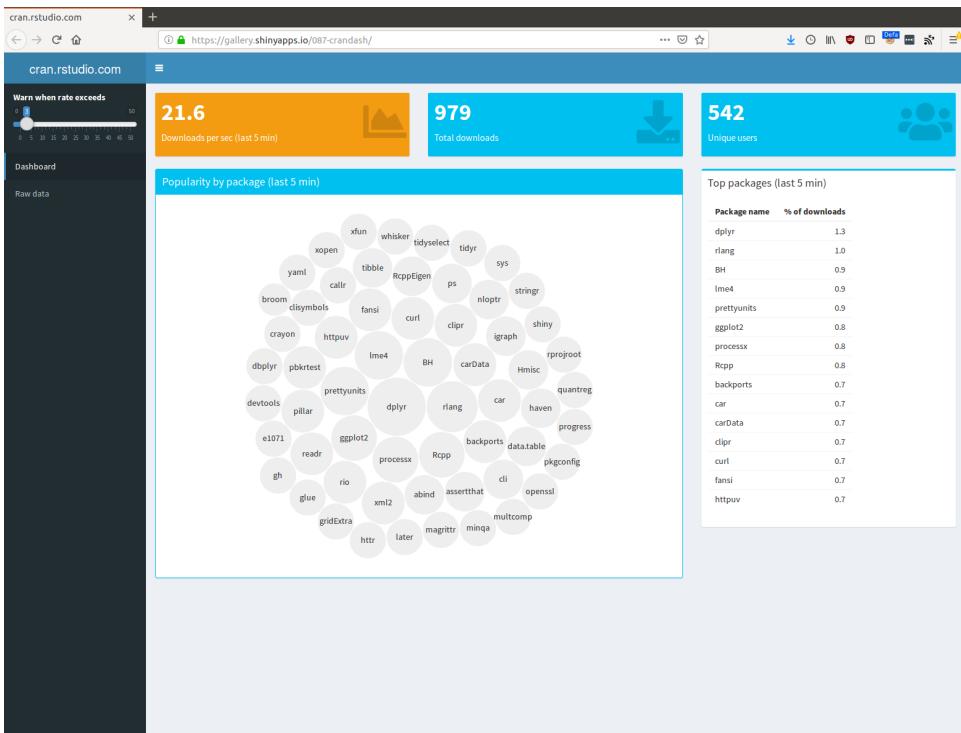
<https://i0.wp.com/r4stats.com/wp-content/uploads/2017/02/Fig-1a-IndeedJobs-2017.png>



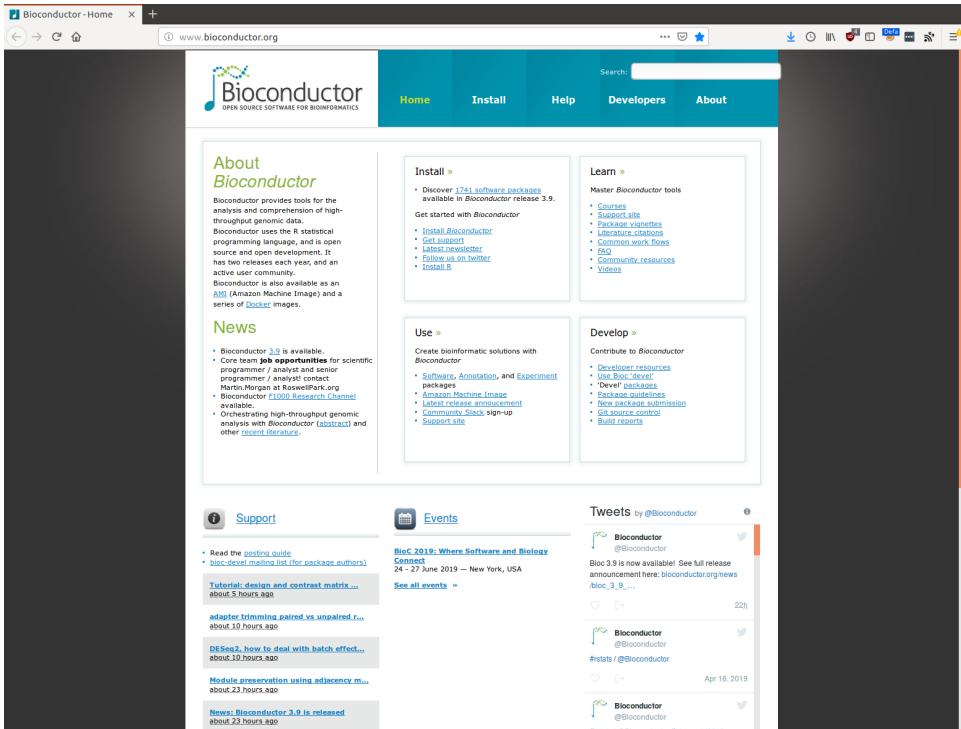
R is the most used software for getting data mining and big data “done”. https://i1.wp.com/datasciencepopularity.com/wp-content/uploads/2015/10/fig_6a_rexersurveyprimarytools.png



There's an enormous number of packages offering custom functionality. <https://revolution-computing.typepad.com/.a/6a010534b1db25970b01b8d2594d25970c-pi>



Which people are downloading rabidly! <https://gallery.shinyapps.io/087-crandash/>



Bioconductor, initiated in 2001 for the analysis of genomics data, has grown from 15 to (currently) 1741 software packages for omics and life science analyses. <http://www.bioconductor.org>

bioconductor.org/

The screenshot shows a blog post titled "List of Companies using R" posted by Deepanshu Bhalla on January 1, 2017, at 9:45am. The post discusses R's popularity in data analysis and includes logos of companies like Facebook, Google, BCG, Twitter, Ford, Uber, McKinsey & Company, and Microsoft. A sidebar on the right shows a sign-in form for Data Science Central and a promotional box for a webinar.

Used internally by lots of big, profitable companies. <https://www.datasciencecentral.com/profiles/blogs/list-of-companies-using-r> and <https://www.listendata.com/2016/12/companies-using-r.html>

The screenshot shows a New York Times article titled "Data Analysts Captivated by R's Power". The article features photos of Robert Gentleman and Ross Ihaka, and discusses R's history and popularity in data analysis. The article is dated January 6, 2009, and is written by ASHLEE VANCE.

Has gained the popular media's attention. http://www.nytimes.com/2009/01/07/technology/business-computing/07program.html?_r=0

The screenshot captures a web browser displaying an article from the Forbes website. The article is titled "Names You Need to Know in 2011: R Data Analysis Software". The page layout includes a header with the Forbes logo and various news headlines. Below the header, there's a sidebar featuring a profile picture of Steve McNally, his title as a contributor, and a "Follow" button. The main content area contains the article's text, which discusses R as a powerful statistical computing language. It also includes a 3D scatter plot illustrating data points across three dimensions: prestige, education, and income. The overall design is typical of a professional news publication's digital format.

<http://www.forbes.com/sites/smcnally/2010/11/10/names-you-need-to-know-in-2011-r-data-analysis-software/>

Many other statistical and analytical programs have implemented connectors to enable running R code within them, including ‘competitors’ like SPSS, MatLab and SAS. Despite this R’s popularity continues to grow. In contrast to the ‘workhorse’ languages like C and Python which are used to build many programs, R is first and foremost a statistics focussed language. Despite this, it’s close to being in the top 20 of the most popular computing languages.

TIOBE Index for May 2019

May Headline: Statistical language R falls out of the TIOBE index top 20

After having been in the top 20 for about 3 years, statistical language R dropped out this month. This is quite surprising because the field of statistical programming is still booming, especially thanks to the popularity of data mining and artificial intelligence. It seems that there is a consolidation going on in the statistical programming market. Python has become the big winner. A possible reason for this is that statistical programming is finding its way from university to industry nowadays and Python is more accepted by the industry.

The TIOBE Programming Community index is an indicator of the popularity of programming languages. The index is updated once a month. The ratings are based on the number of skilled engineers world-wide, courses and third party vendors. Popular search engines such as Google, Bing, Yahoo!, Wikipedia, Amazon, YouTube and Baidu are used to calculate the ratings. It is important to note that the TIOBE index is not about the *best* programming language or the language in which *most lines of code* have been written.

The index can be used to check whether your programming skills are still up to date or to make a strategic decision about what programming language should be adopted when starting to build a new software system. The definition of the TIOBE index can be found [here](#).

May 2019	May 2018	Change	Programming Language	Ratings	Change
1	1		Java	16.005%	-0.38%
2	2		C	14.243%	+0.24%
3	3		C++	8.095%	+0.43%
4	4		Python	7.830%	+2.64%
5	6	▲	Visual Basic .NET	5.193%	+1.07%
6	5	▼	C#	3.984%	-0.42%
7	8	▲	JavaScript	2.690%	-0.23%
8	9	▲	SQL	2.555%	+0.57%
9	7	▼	PHP	2.489%	-0.83%
10	13	▲	Assembly language	1.816%	+0.82%
11	15	▲	Objective-C	1.626%	+0.69%
12	12		Delphi/Object Pascal	1.406%	+0.39%
13	18	▲	Perl	1.394%	+0.48%
14	16	▲	MATLAB	1.366%	+0.44%
15	10	▼	Ruby	1.343%	+0.16%
16	17	▲	Visual Basic	1.317%	+0.40%
17	91	▲	Groovy	1.173%	+1.06%
18	19	▲	Swift	1.150%	+0.24%
19	14	▼	Go	1.114%	+0.14%
20	22	▲	PL/SQL	1.017%	+0.12%

<https://www.tiobe.com/tiobe-index/#null>

Link to current Tiobe index

3 What *is* R and how do we use it

3.1 Definition(s)

- **Wikipedia:** ‘R is a programming language and free software environment for statistical computing and graphics supported by the R Foundation for Statistical Computing. The R language is widely used among statisticians and data miners for developing statistical software[7] and data analysis.’ [http://en.wikipedia.org/wiki/R_\(programming_language\)](http://en.wikipedia.org/wiki/R_(programming_language))
- **Comprehensive R Archive Network (CRAN):** ‘R is “GNU S”, a freely available language and environment for statistical computing and graphics which provides a wide variety of statistical and graphical techniques: linear and non-linear modelling, statistical tests, time series analysis, classification, clustering, etc.’ <https://cloud.r-project.org/>.
- **The R Journal - Facets of R:** ‘This paper considers six characteristics, which we will call facets. They characterize R as:
 1. an interface to computational procedures of many kinds;
 2. interactive, hands-on in real time;
 3. functional in its model of programming;
 4. object-oriented, everything is an object;
 5. modular, built from standardized pieces; and,
 6. collaborative, a world-wide, open-source effort.’

By John M. Chambers

- **My definition:** A command based, object oriented and functional language; in contrast to excel which is a cell centric, spreadsheet managing graphical user interface (GUI).

```
newObject <- function(oldObject)

object(s):          oldObject, newObject, and function()
assignment:         <-
expression:         function(oldObject)
```

3.2 How does R work?

You type commands, also known as “expressions,” into a text editor or terminal and send them to R for evaluation. R evaluates the command, prints the command (by default), then the result of the evaluated command, if any.

In short you apply functions to objects, or “call” a function on an object, e.g.:

```
x <- c(1, 3, 5) #create an object  
mean(x)           #calculate the arithmetic mean of the values in x  
## [1] 3
```

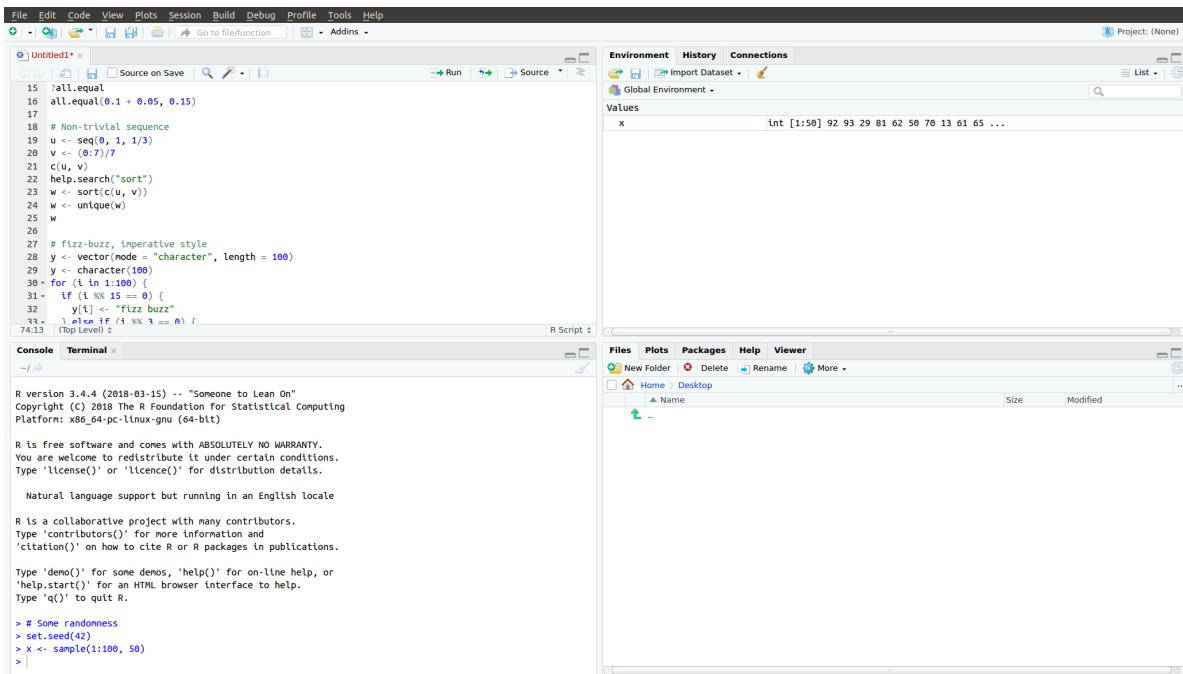
3.3 How we interact with R

Not surprisingly everything about R is built on the principle of KISS, i.e., keep it simple stupid.

- We get things done in R by typing commands and asking R to execute them with the `enter` key. Assuming you know the commands, it couldn’t be any simpler.
- The “front end” of R, the part that receives your commands, is the *terminal*. You can type your commands directly into the terminal and hit `enter` to do your work. But if you need thousands of commands for a specific task, or want to share your method, this approach gets tiring fast.
- Since the commands are just text, it’s easy to write a series of commands using any program built for working with text, i.e., text editors and word processors, to create *code* or a *script*, to get something done.
- The easiest, most efficient way to write R code is using a text editor or *integrated development environment*, like RStudio or Emacs/ESS as mentioned earlier.

3.3.1 RStudio: the easiest way to work with R

For most users, especially those new to R, RStudio is probably the best IDE to use. Like everything about R, you’re free to choose whatever editor you like. For Windows platforms, you could just use the basic editor that’s bundled with the downloadable installer. Let’s have a look at an RStudio “session”.



There are four panes.

- The top left is the source pane. **Do your typing in this pane.**
- The bottom left is your console. This is a window looking into what R is actually doing. **Even though it's fine to type your commands in this pane at the R '>' prompt, avoid this:** your commands are less conveniently stored and rerun than your source code in the editor pane.
- Top right: environment pane
- Bottom left: files pane

Type your commands in the source pane and send them to R using the keyboard shortcut **Ctrl + Enter**. This will send the line of code your cursor is on to R if no code is selected; or if there is code selected, then only the selected code is sent. Open RStudio on your PC and try it now. Since programming is all about typing commands using a keyboard, not pointing and clicking, you might appreciate lots of keyboard shortcuts. Here's an awesome cheatsheet of RStudio keyboard shortcuts.

A few other things about RStudio:

- move the focus between panes using the key board shortcuts **Ctrl + 1** and **Ctrl + 2** for the source and console panes respectively
- the little asterisk next your source code file name indicates unsaved code
- **save your source code!**

3.4 Backslashes

One more thing I want to mention is how R interprets backslashes and forwardslashes, i.e. \ and / respectively, as relates to defining the locations of files on your PC. James McDonald does a better job of clarifying this than I otherwise would http://cran.r-project.org/doc/contrib/Lemon-kickstart/kr_scrpt.html:

“Let’s pause to note a little historical bifurcation that has caused almost as much strife as the question of exactly what the <Delete> key should do. The convention that the slash (/) character is used as a separator in the notation for a filesystem path is not universal. PC-DOS, for example, used the backslash (\). Like Fords vs Chevrolets, French vs English, and whether you crack the egg at the big or small end, it doesn’t really matter a rat’s behind which one you use as long as it works. To make it work in R, however, where the *NIX convention of using the backslash as an escape character is respected, you will have to double backslashes in paths for them to be read properly. Thus if the filename above was: C:\JIM\PSYCH\ADOLDRUG\PARTYUSE1.R

I would have to refer to it as: C:\\JIM\\\\PSYCH\\\\ADOLDRUG\\\\PARTYUSE1.R in an R script.”

4 Getting Help

1. Online help. The first place to look. Also works when you’re actually *offline*:

```
?help  
help(help)
```

Broader search:

```
??help  
apropos("help")          # quotes are needed
```

It’s fun, try them out!

2. Google. And when you’re actually *online*, often the *first* place and *last* place you’ll go when you have no idea is Google.
3. Package Vignette’s. Where the online help is devoid of the context often needed to grasp the full potential and logical use of functions, vignette’s is the best place to find such information, with extended examples, and often more. For example, see the limma <http://www.bioconductor.org/packages/release/bioc/vignettes/limma/inst/doc/usersguide.pdf>
4. Mailing Lists. R-help <http://www.r-project.org/mail.html>. Do check first using Google or the R-help searchable archives <http://tolstoy.newcastle.edu>.

au/~rking/R/ first if your question has already been asked and has the answer to solve your issue.

5. Other lists: <https://stat.ethz.ch/mailman/listinfo>
6. Stack Overflow <https://stackoverflow.com>. Probably more questions and answers posted here than on the mailing list.

4.1 Trouble shooting

- Clean your environment and start again to be sure your messy environment isn't the cause of your issue. In RStudio, click the broom in the Environment tab; in any R session you can also run:

```
# not run:  
rm(list=ls())  
ls()
```

- Start R without any customisations, i.e., omit loading the `.Rprofile` and `.Renviron` customisation files. From the command line:
`R --vanilla`
- `trace.back()` function: very helpful pinpointing the source of an error, and thus its cause.

4.2 Further resources

- R focused search engine: <http://www.Rseek.org>
- Aggregator of all R blogs: <http://www.r-bloggers.com>
- Quick-R: <http://www.statmethods.net/>
- R on Youtube: <http://www.youtube.com/watch?v=mL27TAJGlWc>
- R in two minutes: <http://www.twotorials.com/>
- The list of reference texts: <http://www.r-project.org/doc/bib/R-publications.html>
- This course not enough? There's a excellent free online introduction to R here: <https://www.computerworld.com/article/2497143/business-intelligence-beginner-s-guide.html>
- And more..
<http://www.ats.ucla.edu/stat/r/>

http://zoonek2.free.fr/UNIX/48_R/02.html

- *A First Course in Statistical Programming with R.* W. John Braun and Duncan J. Murdoch. Cambridge University Press, 2007
*I love this book, beautifully explores the programming aspects of R.

5 Document License

GNU General Public License v2.0 or higher (GPL>=v2)

Basic Course on R: Objects and Functions

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1 Things you can have: object classes and modes

Any *thing* in R is of a certain type, defined as a `class` and `mode`. As an analogy, think of numbers as *fruits* and text as *vegetables*. They're not the same, although they can be analysed, or 'cooked' like one another.

1.1 Numbers

Fruits.

```
class(1)
## [1] "numeric"

mode(1)
## [1] "numeric"

class(2.3123)
## [1] "numeric"

an_integer <- as.integer(2.3123)
an_integer
## [1] 2

class(an_integer)
## [1] "integer"

mode(an_integer)
## [1] "numeric"
```

Change the class to numeric:

```
numeric_again <- as.numeric(an_integer)
class(numeric_again)
## [1] "numeric"
```

1.2 Text

The *veggies*.

```
class("a")
## [1] "character"

mode("a")
## [1] "character"

class("1")
## [1] "character"

mode("1")
## [1] "character"

a_factor <- factor("a")
a_factor
## [1] a
## Levels: a

class(a_factor)
## [1] "factor"

mode(a_factor)
## [1] "numeric"
```

1.3 Logical

It can only be a *yes* or a *no*. More specifically, a TRUE or a FALSE.

```
class(TRUE)
## [1] "logical"

class(FALSE)
## [1] "logical"

mode(TRUE)
## [1] "logical"
```

1.4 Functions

An object that does something to the fruits and veggies, a *frying pan!*

2 Containers: more object classes and modes

Besides the basic types of things, there are different *containers* available to hold these things which are also defined by `class` and `mode`. Containers are thus things, or `objects`, that you can put other things, or `objects`, into to conveniently hold them while we work with them.

2.1 Vectors are an ordered series of elements

Think of them like a *string* or a *chain*.

```
a_vector <- c(1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12)
class(a_vector)

## [1] "numeric"

mode(a_vector)

## [1] "numeric"

length(a_vector)

## [1] 12

ano_vector <- c(1)
length(x = ano_vector)

## [1] 1
```

Combine vectors to make another vector:

```
combined_vec <- c(a_vector, ano_vector)
combined_vec

## [1] 1 2 3 4 5 6 7 8 9 10 11 12 1
```

2.2 Matrices are vectors with two dimensions

Matrices are like a spread sheet in that they have rows and columns. In addition the contents have a specific, column on column order or sequence exactly equivalent to a

vector. Think of them like a *string on a tray*. Matrices consist of only one type or *class* of data.

```
a_matrix <- matrix(data = a_vector)
a_matrix

##      [,1]
## [1,]    1
## [2,]    2
## [3,]    3
## [4,]    4
## [5,]    5
## [6,]    6
## [7,]    7
## [8,]    8
## [9,]    9
## [10,]   10
## [11,]   11
## [12,]   12

a_vector

##  [1]  1  2  3  4  5  6  7  8  9 10 11 12

dim(a_matrix)

## [1] 12  1

ano_matrix <- matrix(data = a_vector, nrow = 3)
ano_matrix

##      [,1] [,2] [,3] [,4]
## [1,]    1    4    7   10
## [2,]    2    5    8   11
## [3,]    3    6    9   12

dim(ano_matrix)

## [1] 3 4

letters_mat <- matrix(data = letters[1:12], nrow = 3)

class(a_matrix)

## [1] "matrix"

mode(a_matrix)

## [1] "numeric"
```

```
class(letters_mat)
## [1] "matrix"
mode(letters_mat)
## [1] "character"
```

2.3 Arrays are matrices with multiple dimensions

```
an_array <- array(letters[1:12], c(2, 2, 3))
an_array

## , , 1
##
##      [,1] [,2]
## [1,] "a"  "c"
## [2,] "b"  "d"
##
## , , 2
##
##      [,1] [,2]
## [1,] "e"  "g"
## [2,] "f"  "h"
##
## , , 3
##
##      [,1] [,2]
## [1,] "i"  "k"
## [2,] "j"  "l"

class(an_array)
## [1] "array"
mode(an_array)
## [1] "character"
```

2.4 Lists hold just about anything and everything

Similar to vectors, lists have a specific order or sequence. Unlike vectors however, each element of a list can be of any `class` or `mode`. Think of them like a *shopping list* of: a string of fruit, a tray of veggies, another sublist of items

```

a_list <- list(a_vector, a_matrix, letters_mat)
a_list

## [[1]]
## [1] 1 2 3 4 5 6 7 8 9 10 11 12
##
## [[2]]
##      [,1]
## [1,]    1
## [2,]    2
## [3,]    3
## [4,]    4
## [5,]    5
## [6,]    6
## [7,]    7
## [8,]    8
## [9,]    9
## [10,]   10
## [11,]   11
## [12,]   12
##
## [[3]]
##      [,1] [,2] [,3] [,4]
## [1,] "a"  "d"  "g"  "j"
## [2,] "b"  "e"  "h"  "k"
## [3,] "c"  "f"  "i"  "l"

class(a_list)

## [1] "list"

mode(a_list)

## [1] "list"

named_list <- list("vec" = a_vector, "mat" = a_matrix,
                    "lets" = letters_mat,
                    "log" = matrix(rep(c(TRUE, FALSE), 5), nrow = 5),
                    "lis" = list(1:5, letters[1:9]))
named_list

## $vec
## [1] 1 2 3 4 5 6 7 8 9 10 11 12
##
## $mat

```

```

##      [,1]
## [1,]    1
## [2,]    2
## [3,]    3
## [4,]    4
## [5,]    5
## [6,]    6
## [7,]    7
## [8,]    8
## [9,]    9
## [10,]   10
## [11,]   11
## [12,]   12
##
## $lets
##      [,1] [,2] [,3] [,4]
## [1,] "a"  "d"  "g"  "j"
## [2,] "b"  "e"  "h"  "k"
## [3,] "c"  "f"  "i"  "l"
##
## $log
##      [,1] [,2]
## [1,] TRUE FALSE
## [2,] FALSE TRUE
## [3,] TRUE FALSE
## [4,] FALSE TRUE
## [5,] TRUE FALSE
##
## $lis
## $lis[[1]]
## [1] 1 2 3 4 5
##
## $lis[[2]]
## [1] "a" "b" "c" "d" "e" "f" "g" "h" "i"
class(named_list)

## [1] "list"

mode(named_list)

## [1] "list"

named_list[["log"]]

```

```
##      [,1]  [,2]
## [1,] TRUE FALSE
## [2,] FALSE TRUE
## [3,] TRUE FALSE
## [4,] FALSE TRUE
## [5,] TRUE FALSE

class(named_list[["log"]])
## [1] "matrix"

mode(named_list[["log"]])
## [1] "logical"
```

2.5 Data frames are special lists

Data frames are even more similar to the familiar excel spreadsheets: a series, or `list` of equal length columns, or `vectors`. Notably, the columns (`vectors`) can be of different classes, unlike a matrix or array.

```

aDF <- data.frame("vec" = a_vector, "lets" = letters[1:12])
aDF

##      vec lets
## 1      1    a
## 2      2    b
## 3      3    c
## 4      4    d
## 5      5    e
## 6      6    f
## 7      7    g
## 8      8    h
## 9      9    i
## 10    10   j
## 11    11   k
## 12    12   l

dim(aDF)
## [1] 12  2
class(aDF)
## [1] "data.frame"
mode(aDF)
## [1] "list"
str(aDF)
## 'data.frame': 12 obs. of  2 variables:
##   $ vec : num  1 2 3 4 5 6 7 8 9 10 ...
##   $ lets: Factor w/ 12 levels "a","b","c","d",...: 1 2 3 4 5 6 7 8 9 10 ...
aDF[, 1]
##  [1] 1 2 3 4 5 6 7 8 9 10 11 12
class(aDF[, 1])
## [1] "numeric"
mode(aDF[, 1])
## [1] "numeric"
aDF[, 2]
##  [1] a b c d e f g h i j k l

```

```

## Levels: a b c d e f g h i j k l

class(aDF[, 2])
## [1] "factor"

mode(aDF[, 2])
## [1] "numeric"

str(aDF[, 1])
## num [1:12] 1 2 3 4 5 6 7 8 9 10 ...

```

It's important to understand that the things we work with in R have a 'mode' and a 'class'. The mode is a mutually exclusive classification of an object's basic structure and the class is a property used to determine how functions operate with object. Pay attention to your modes and classes.

3 Functions are things you can do

R comes with predefined functions which do many things from basic file management to complex statistics. To get started, below are some oft used functions. This default set of functions is easily extended by defining your own functions and adding those defined by others conveniently in CRAN and BioConductor packages:

<http://stat.ethz.ch/R-manual/R-patched/library/base/html/00Index.html>
http://cran.r-project.org/web/packages/available_packages_by_name.html
<http://www.bioconductor.org/packages/release/bioc/>

Functions are expressed as:

`function.name()`, e.g., `t.test()`

or,

an operator, e.g., `+`

Note that operators can be expressed in `function.name()` format by enclosing in double quotes, e.g. `"+"`(). This is occasionally required for some expressions.

Easily obtain functions from other R users using `install.packages()`:

```

install.packages("packageName",
                 lib = "/directory/to/my custom R library",
                 repos = "http://cran.xl-mirror.nl")

```

The package name must be quoted when installing. Besides installing the package on your PC, you need to load it into your R session before you can use it:

```
library("packageName")      ## quotes are optional when loading a package
```

3.1 The Arithmetic Operators

That is, R as a *calculator*.

```
x <- 10
y <- 3
x + y
## [1] 13

x - y
## [1] 7

x * y
## [1] 30

x / y
## [1] 3.333333

x ^ y          # exponentiation
## [1] 1000

x %% y         # modular arithmetic, remainder after division
## [1] 1

x %/% y       # integer part of a fraction
## [1] 3
```

How these functions work on vectors:

```
a_vector
## [1] 1 2 3 4 5 6 7 8 9 10 11 12
```

3.1.1 By the way, R is Green

By design, R *recycles* data without telling you, at least when the recycling fits neatly.

```
a_vector + x                      # x is recycled without warning  
## [1] 11 12 13 14 15 16 17 18 19 20 21 22
```

Operators can also be used in the `function.name()` format. Note the quotes:

```
"+"
```

```
(a_vector, x)  
## [1] 11 12 13 14 15 16 17 18 19 20 21 22  
  
a_vector - y  
## [1] -2 -1  0  1  2  3  4  5  6  7  8  9  
  
a_vector + a_vector  
## [1]  2  4  6  8 10 12 14 16 18 20 22 24  
  
vec_of_thr <- c(2, 4, 6)  
a_vector  
## [1]  1  2  3  4  5  6  7  8  9 10 11 12  
  
a_vector + vec_of_thr          # recycled without warning  
## [1]  3  6  9  6  9 12  9 12 15 12 15 18  
  
vec_of_fi <- c(1, 2, 3, 4, 5)  
a_vector  
## [1]  1  2  3  4  5  6  7  8  9 10 11 12
```

When it doesn't fit neatly, you'll get a warning:

```
a_vector + vec_of_fi          # warning  
## Warning in a_vector + vec_of_fi: longer object length is not a multiple  
of shorter object length  
## [1]  2  4  6  8 10  7  9 11 13 15 12 14  
  
## NULL
```

How these functions work on matrices:

```
ano_matrix  
##      [,1] [,2] [,3] [,4]  
## [1,]    1     4     7    10
```

```

## [2,]    2    5    8   11
## [3,]    3    6    9   12
ano_matrix + x

##      [,1] [,2] [,3] [,4]
## [1,]    11   14   17   20
## [2,]    12   15   18   21
## [3,]    13   16   19   22
ano_matrix - y

##      [,1] [,2] [,3] [,4]
## [1,]   -2    1    4    7
## [2,]   -1    2    5    8
## [3,]    0    3    6    9
ano_matrix + ano_matrix

##      [,1] [,2] [,3] [,4]
## [1,]     2     8   14   20
## [2,]     4    10   16   22
## [3,]     6    12   18   24
ano_matrix * ano_matrix

##      [,1] [,2] [,3] [,4]
## [1,]     1    16   49  100
## [2,]     4    25   64  121
## [3,]     9    36   81  144

```

3.2 Functions you'll use to interact with data

Relational Operators:

```

x < y
## [1] FALSE

x > y
## [1] TRUE

x <= y
## [1] FALSE

x >= y

```

```
## [1] TRUE  
x == y  
## [1] FALSE  
x != y  
## [1] TRUE
```

3.3 Functions you need to get work done with R

R has an extensive set of built-in *functions*, a few of which are listed below:

Print structure of an object:

```
str()
```

Print structure of an object:

```
class()
```

First six elements/rows:

```
head()
```

Last six elements/rows:

```
tail()
```

List all objects and functions held in your global environment:

```
ls()
```

Generate a sequence:

```
seq(from = 1, to = 10, by = 2)
```

Or, use the : operator:

```
1:10
```

```
## [1] 1 2 3 4 5 6 7 8 9 10
```

Run the entire contents of a script:

```
source("myScript.R")
```

Each function accepts one or more values passed to it as *arguments*, performs computations or operations on those values, and returns a result.

To perform a ***function call***, type the name of the function with the values of its argument(s) in parentheses, then hit ‘Enter’. For example:

```
sqrt(2)  
## [1] 1.414214
```

Values passed as arguments can be in the form of variables, such as `x` below:

```
x <- 2  
sqrt(x)  
## [1] 1.414214
```

or they can be entire expressions, such as `x^2 + 5` below:

```
sqrt(x^2 + 5)  
## [1] 3
```

3.4 Viewing a Function’s Formal Arguments

Most functions take multiple arguments, each of which has a name, and some of which are optional.

One way to see what arguments a function takes and which ones are optional is to use the function:

```
args()
```

Another way to view a function’s arguments is to look at its help file (e.g. `?sqrt`).

For example, to see what arguments `round()` takes (using `args()`), we’d type:

```
args(round)  
## function (x, digits = 0)  
## NULL
```

We see that `round()` has two arguments, `x`, a numeric value to be rounded, and `digits`, an integer specifying the number of decimal places to round to. Thus to round 4.679 to 2 decimal places, we type:

```
round(4.679, 2)  
## [1] 4.68
```

3.5 Optional Arguments and Default Values

The specification `digits = 0` in the output from `args(round)` tells us that `digits` has a ***default value*** of 0. This means that it's an ***optional argument*** and if no value is passed for that argument, rounding is done to 0 decimal places (i.e. to the nearest integer).

3.6 Positional Matching and Named Argument Matching

When we type

```
round(4.679, 2)  
## [1] 4.68
```

R knows, by ***positional matching***, that the first value, 4.679, is the value to be rounded and the second one, 2, is the number of decimal places to round to.

We can also specify values for the arguments by name. For example:

```
round(x = 4.679, digits = 2)  
## [1] 4.68
```

When ***named argument matching*** is used, as above, the order of the arguments is irrelevant. For example, we get the same result by typing:

```
round(digits = 2, x = 4.679)  
## [1] 4.68
```

The two types of argument specification (positional and named argument matching) can be mixed in the same function call.

3.7 Formal Arguments and Actual Arguments

In the function call

```
round(x = 4.679, digits = 2)
```

the values 4.679 and 2 passed to `round()` are referred to as ***actual arguments***.

The ***formal arguments*** for the function `round()` are `x` and `digits`, to which we pass the actual values 4.679 and 2.

Look at the arguments for the function `signif()`:

```
args(signif)
## function (x, digits = 6)
## NULL
```

`signif()` prints the value passed for `x` to the number of significant digits specified by `digits`.

3.8 Variable Number of Arguments Using “...”

- Functions can be written to take a variable number of arguments. The argument name “...” in the function definition will match any number of arguments.
- For example, here’s a function that returns the mean of all the values in an arbitrary number of vectors:

```
meanOfAll <- function(...) {
  return(mean(c(...)))
}
```

The command

```
meanOfAll(usSales, europeSales, otherSales)
```

would combine the three vectors and take the mean of all the data. The effect of `c(...)` is as if `c()` were called with the same three arguments passed to `meanOfAll()`.

- Many of R’s built-in functions take a variable number of arguments. For example look at the help files for `list()` and `c()`.

4 Saving and restoring your session

Because the typical way of using R involves writing text into a file with the `.r` or `.R` extension it’s natural to save your commands written for a specific purpose in this `my-r-file.r`. Hopefully you’re doing this right now. However there are other bits and pieces of your R session described below you may want or need to save.

Save all objects to the working directory in a file called `.RData`:

```
save.image()
```

Or give the file a name:

```
save.image("mySession.RData")
```

Save all commands entered into the R console during your session to the working directory in a file called `.Rhistory`:

```
savehistory()
```

Such a file may be hidden by default in some file browsers, including linux.

Note that this typically occurs (console dependent) by default when you quit your R session. If an `.Rhistory` file already exists from a previous session, the current session is appended to the end of this file and saved. Thus, by design, a complete log of your work is saved together with your script file, if your console session contains less than 512 lines.

Save specific objects:

```
save(object_1, object_2, object_3, file = "rObjects123.RData")
```

Restore or load previous sessions or objects:

```
load("mySession.RData")      # load from the working directory
```

Load `.Rhistory` file to access the history from the console:

```
loadhistory()
```

5 Miscellaneous Tips

R is case sensitive:

```
c("Hello" == "hello", "goodbye" == "goodbye")  
## [1] FALSE TRUE
```

And is *very* sensitive in general:

```
# c("Hello" == "hello" "goodbye" == "goodbye") # not run
```

Missing data. NA 'Not Available' is how R defines a missing value i.e., an empty cell in excel

```
c(1, NA, 3, 4, NA)  
## [1] 1 NA 3 4 NA
```

R is an environment. What's in yours?

```
ls()                      # global environment  
objects()                # alias for ls()
```

Too many objects cluttering up your environment and computer memory? Remove the ones you don't need:

```
rm(object_name)
```

What is the current *working directory* where files are saved and loaded from by default?

```
getwd()
```

Need to set or change the current working directory?

```
setwd(dir = "c:\\Windows\\Users\\karl\\My Documents\\R stuff")  
setwd(dir = "c:/Windows/Users/karl/My Documents/R stuff")
```

Note the double backslashes required by R running under Windows. Single forward slashes, the Unix convention works equivalently.

Also be aware that if you started your R session by double clicking a `file.name.r` file, by design the directory where this file resides is set as the working directory. This directory is also a good place, and the default place, to store the respective `.RData` and `.Rhistory` files if you have any. When these files are present in the same directory they will be loaded automatically, unless you explicitly tell R not to load them by using the `--no-restore-data` argument when starting R.

Quit your R session:

```
q()                      # not run
```

Object names can not begin with numbers. For example:

```
## 3vector <- c(2, 4, 6)      # not run
```

But can end with numbers if necessary:

```
vector3 <- c(2, 4, 6)
```

Try to code with style, for example:

<https://google.github.io/styleguide/Rguide.xml>

<http://adv-r.had.co.nz/Style.html>

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Basic Course on R: Objects and Functions Practical

Karl Brand* and Elizabeth Ribble†

28 Oct - 1 Nov 2019

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1 Objects and Functions

1.1 Function Arguments

- (a) Look at the help file for the function `mean()`. How many arguments does function have? What types of vectors are accepted?
- (b) Use the function `mean()` to calculate the mean of the following values (note the NA and use named argument matching):

1 2 NA 6

- (c) Do (b) again but rearrange the arguments.
- (d) Do (b) again using positional matching.
- (e) Determine the class of `mean()` using `class()`.
- (f) Determine the class of `mean()` using `str()`.
- (g) Determine the class of the value output in part (d) using `class()`.
- (h) Determine the class of the value output in part (d) using `str()`.

1.2 Use R as a calculator to calculate the following values:

$$17^4, \quad 45 - 2 \cdot 3, \quad (45 - 2) \cdot 3$$

1.3 Use the operators `%%` and `%/%` to do the following:

- (a) Calculate the remainder after dividing 29,079 into 184,277,809.
- (b) How many times does 29,079 go into 184,277,809 (i.e. what's the “integer divide” value)?

1.4 Do the last calculation from Q1.4 in another way, like this:

```
a <- 45  
b <- 2  
c <- 3  
d <- (a - b) * c
```

Now check what `a`, `b`, `c`, and `d` are. You can just type the variable name (e.g. `a`) and hit ‘Control’ then ‘Return’ or use the command `print(a)`.

1.5 Do the following to practice saving and opening files in R.

- (a) Look at the variables (or other objects) that are stored in your Workspace by typing either `objects()` or `ls()`.
- (b) Check your working directory by typing `getwd()`. Now change it to a different directory - preferably your own flash drive - by using the function `setwd()`, for example:

```
setwd("C:/Users/Elizabeth/My Documents/R Course")
```

- (c) Use the function “`save.image()`” to save your R session to a file called `YourLastName_practical1.RData` (replace `YourLastName` with your last name). Note that this will save a `.RData` file that contains only those objects you see when you run `ls()`. It does not save any code you typed into the console or into the source pane.
- (d) Use the RStudio “File” drop-down menu to save your R source code to a file called `YourLastName_practical1.R` (replace `YourLastName` with your last name). Note that this will only save the text you’ve typed into the source pane. It does not save any objects or anything typed into or ran through the console.
- (e) Use the function “`save()`” to save only the objects `myFirstList` and `pets` to a file called `YourLastName_objects.RData` (replace `YourLastName` with your last name).
- (f) Now close out RStudio entirely, select “Save” or “Yes” in any dialog boxes that pop up, and then reopen RStudio. Is your source code still there?

- (g) Run `ls()`; are your objects still there?
- (h) You can change these kinds of options by going to “Tools - Global Options”. Go there and deselect “Restore .RData into workspace at startup”. Then close RStudio and choose to save the .RData file.
- (i) Reopen RStudio; your environment should be empty. Load your objects back in using `load()` (e.g. `load("Ribble_practical1.RData")`) and then run `ls()` again. Do you see your objects now?
- (j) Check what the working directory is by again running `getwd()` - has it been reset?

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Basic Course on R: Objects and Functions Practical Answers

Karl Brand* and Elizabeth Ribble†

28 Oct - 1 Nov 2019

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1 Objects and Functions

1.1 Function Arguments

- (a) Look at the help file for the function `mean()`. How many arguments does function have? What types of vectors are accepted? What is the default setting for dealing with NA values?

Three arguments (plus further arguments). Numerical and logical vectors are accepted. The default setting is to NOT remove NA (missing) values.

- (b) Use the function `mean()` to calculate the mean of the following values (note the NA and use named argument matching):

1 2 NA 6

```
mean(x = c(1, 2, NA, 6), na.rm = TRUE)
## [1] 3
```

- (c) Do (b) again but rearrange the arguments.

```
mean(na.rm = TRUE, x = c(1, 2, NA, 6))
## [1] 3
```

- (d) Do (b) again using positional matching.

```
mean(c(1, 2, NA, 6), 0, TRUE)
## [1] 3
```

- (e) Determine the class of `mean()` using `class()`.

```
class(mean)
## [1] "function"
```

The class is “function”.

- (f) Determine the class of `mean()` using `str()`.

```
str(mean)
## function (x, ...)
```

The class is “function”.

- (g) Determine the class of the value output in part (d) using `class()`.

```
class(mean(c(1, 2, NA, 6), 0, TRUE))  
## [1] "numeric"
```

The class is “numeric”.

- (h) Determine the class of the value output in part (d) using `str()`.

```
str(mean(c(1, 2, NA, 6), 0, TRUE))  
## num 3
```

The “num” means the class is “numeric”.

1.2 Use R as a calculator to calculate the following values:

$$17^4, \quad 45 - 2 \cdot 3, \quad (45 - 2) \cdot 3$$

```
17^4  
## [1] 83521  
45 - 2 * 3  
## [1] 39  
(45 - 2) * 3  
## [1] 129
```

1.3 Use the operators `%%` and `%/%` to do the following:

- (a) Calculate the remainder after dividing 29,079 into 184,277,809.

```
184277809 %% 29079  
## [1] 4186
```

- (b) How many times does 29,079 go into 184,277,809 (i.e. what’s the “integer divide” value)?

```
184277809 %/% 29079  
## [1] 6337
```

1.4 Do the last calculation from Q1.4 in another way, like this:

```
a <- 45  
b <- 2  
c <- 3  
d <- (a - b) * c
```

Now check what **a**, **b**, **c**, and **d** are. You can just type the variable name (e.g. **a**) and hit ‘Control’ then ‘Return’ or use the command **print(a)**.

```
a <- 45  
b <- 2  
c <- 3  
d <- (a - b) * c  
  
a  
## [1] 45  
  
b  
## [1] 2  
  
c  
## [1] 3  
  
d  
## [1] 129
```

1.5 Do the following to practice saving and opening files in R.

- (a) Look at the variables (or other objects) that are stored in your Workspace by typing either **objects()** or **ls()**.

Answers will vary.

- (b) Check your working directory by typing **getwd()**. Now change it to a different directory - preferably your own flash drive - by using the function **setwd()**, for example:

```
setwd("C:/Users/Elizabeth/My Documents/R Course")
```

Answers will vary.

- (c) Use the function “**save.image()**” to save your R session to a file called **YourLastName_practical1.RData** (replace YourLastName with your last name). Note that this will save a .RData file that contains only those objects you see when

you run `ls()`. It does not save any code you typed into the console or into the source pane.

```
save.image(file = "Ribble_practical1.RData")
```

- (d) Use the RStudio “File” drop-down menu to save your R source code to a file called `YourLastName_practical1.R` (replace YourLastName with your last name). Note that this will only save the text you’ve typed into the source pane. It does not save any objects or anything typed into or ran through the console.

```
savehistory(file = "Ribble_practical1.Rhistory")
```

You may get this error: ‘`Error in savehistory(file) : no history available to save`’ This means no commands have been directly entered into your *console*, but only from your text editor, which is of course its own permanent record, assuming you save it!

- (e) Use the function “`save()`” to save only the objects `myFirstList` and `pets` to a file called `YourLastName_objects.RData` (replace YourLastName with your last name).

```
save(myFirstList, pets, file = "Ribble_objects.RData")
```

- (f) Now close out RStudio entirely, select “Save” or “Yes” in any dialog boxes that pop up, and then reopen RStudio. Is your source code still there?

It should be; the default in RStudio is to keep source code open!

- (g) Run `ls()`; are your objects still there?

The objects available in your previous session are still available and RStudio reloads them for the new session.

- (h) You can change these kinds of options by going to “Tools - Global Options”. Go there and deselect “Restore .RData into workspace at startup”. Then close RStudio and choose to save the .RData file.

- (i) Reopen RStudio; your environment should be empty. Load your objects back in using `load()` (e.g. `load("Ribble_practical1.RData")`) and then run `ls()` again. Do you see your objects now?

They should appear after you’ve loaded in the file that contained your previously created objects.

- (j) Check what the working directory is by again running `getwd()` - has it been reset?

It should have been reset to the default RStudio working directory. This means everytime you open RStudio you should specify your desired working directory!

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Basic Course on R: Manipulating / Selecting Data

Karl Brand* and Elizabeth Ribble†

28 Oct - 1 Nov 2019

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1 Manipulating / Selecting Data

1.1 Indexing

Select data from vectors, arrays, lists, rows/columns in matrices and data.frames, using

- Explicit numeric selection
- Named element selection
- Logical and relational filtering

1.1.1 Explicit numeric selection

We can specify positions or *indices* i in numbers of the data we wish to select using square brackets which are the ‘extract’ function, i.e., `object[i]`.

```
x <- c(11, 10, 12, 15)
x[2]

## [1] 10

y <- c(13, 17, 21, 18)
y[c(2, 3)]

## [1] 17 21

m <- matrix(c(x, y), ncol = 2)
m

##      [,1] [,2]
## [1,]    11   13
## [2,]    10   17
## [3,]    12   21
## [4,]    15   18

m[, 1]

## [1] 11 10 12 15

m[c(2, 4), 1:2]

##      [,1] [,2]
## [1,]    10   17
## [2,]    15   18
```

We can also use negative indices to remove/exclude elements we do not want:

```
x[-2]  
  
## [1] 11 12 15  
  
m[, -c(1, 3)]  
  
## [1] 13 17 21 18
```

1.1.2 Named element selection

Here we make use of the `names` attribute:

```
names(x) <- c("a", "b", "c", "d")  
x  
  
## a b c d  
## 11 10 12 15  
  
str(x)  
  
##  Named num [1:4] 11 10 12 15  
##  - attr(*, "names")= chr [1:4] "a" "b" "c" "d"  
  
x["b"]  
  
## b  
## 10  
  
row.names(m) <- LETTERS[1:4]  
m  
  
## [,1] [,2]  
## A 11 13  
## B 10 17  
## C 12 21  
## D 15 18  
  
m["A", ]  
  
## [1] 11 13
```

Note that this is case sensitive and that LETTERS is different from letters.

We can even combine the use of numbers and names:

```
m["A", 2]  
## A  
## 13
```

Let's look at an example where row names are gene symbols and column names are sample IDs:

```
mygenes <- data.frame(samp1 = c(33, 22, 12),  
                      samp2 = c(44, 111, 13),  
                      samp3 = c(33, 53, 65))  
row.names(mygenes) <- c("CRP", "BRCA1", "HOXA")  
mygenes  
  
##      samp1 samp2 samp3  
## CRP     33    44    33  
## BRCA1   22    111   53  
## HOXA    12    13    65  
  
mygenes["CRP", ]  
  
##      samp1 samp2 samp3  
## CRP     33    44    33  
  
mygenes[, "samp1"]  
  
## [1] 33 22 12  
  
mygenes[, c("samp1", "samp3")]  
  
##      samp1 samp3  
## CRP     33    33  
## BRCA1   22    53  
## HOXA    12    65  
  
mygenes["HOXA", "samp2"]  
  
## [1] 13
```

Note that we can also change the names of a `data.frame` in the same way we would do so for a `list` using the `names` attribute:

```
names(mygenes) <- c("samp10", "samp20", "samp30")
mygenes

##      samp10 samp20 samp30
## CRP      33     44     33
## BRCA1    22     111    53
## HOXA     12     13     65

## but let's change it back...
names(mygenes) <- c("samp1", "samp2", "samp3")
```

Note that the `colnames` function also performs the same job for data frames.

1.1.3 Logical and relational filtering

Expressions like `<`, `<=`, `|`, and `!=` can also be used to select data:

```
x

##  a  b  c  d
## 11 10 12 15

y

## [1] 13 17 21 18

keep <- c(TRUE, TRUE, FALSE, FALSE, TRUE)
x[keep]

##      a      b <NA>
##      11     10    NA

x[y >= 18]

##      c      d
##      12     15
```

Why?

```

y>=18

## [1] FALSE FALSE  TRUE  TRUE

which(y >= 18)

## [1] 3 4

x[x <= 11 | x == 15]

##  a  b  d
## 11 10 15

x[x != 10]

##  a  c  d
## 11 12 15

```

This works for factors as well:

```

gender <- factor(c("M", "M", "F", "F"))
gender

## [1] M M F F
## Levels: F M

males <- gender[gender == "M"]
levels(males)

## [1] "F" "M"

```

1.2 Other useful functions

Besides square brackets ([, [[), other useful functions exist for selecting data: `duplicated`, `match()`, `%in%`, `grep`, `is.na` and `$`.

To select e.g. rows that are not duplicated:

```

mm <- matrix(c(x, x, y, y), nrow = 4, byrow = T)

```

```

mm

##      [,1] [,2] [,3] [,4]
## [1,]    11   10   12   15
## [2,]    11   10   12   15
## [3,]    13   17   21   18
## [4,]    13   17   21   18

mm[!duplicated(mm), ]

##      [,1] [,2] [,3] [,4]
## [1,]    11   10   12   15
## [2,]    13   17   21   18

```

The above can also be done with `unique`, but the use of `duplicated` might be more appropriate in more complex situations:

```

unique(mm)

##      [,1] [,2] [,3] [,4]
## [1,]    11   10   12   15
## [2,]    13   17   21   18

```

Calling `match` returns the position of the first match of its first argument in the second argument:

```

match(c("a", "b"), c("a", "c", "a", "b", "a", "b"))

## [1] 1 4

```

whereas `%in%` tells you whether the elements of the first argument appear in the second argument:

```

c("a", "b", "d") %in% c("a", "c", "a", "b", "a", "b")

## [1] TRUE TRUE FALSE

```

Recall our data frame `mygenes`:

```

mygenes

##      samp1 samp2 samp3
## CRP     33    44    33
## BRCA1   22    111   53
## HOXA    12    13    65

```

```
is.data.frame(mygenes)  
## [1] TRUE
```

Note that since `mygenes` is a data frame, it is therefore also an array, which means we can select by the name of the elements in the array:

```
mygenes[match(c("samp1", "samp3"), colnames(mygenes))]  
  
##      samp1 samp3  
## CRP     33    33  
## BRCA1   22    53  
## HOXA    12    65  
  
mygenes[colnames(mygenes) %in% c("samp1", "samp4")]  
  
##      samp1  
## CRP     33  
## BRCA1   22  
## HOXA    12
```

However, in this case we could just use the names...

```
mygenes[c("samp1", "samp3")]  
  
##      samp1 samp3  
## CRP     33    33  
## BRCA1   22    53  
## HOXA    12    65
```

But this gives an error:

```
mygenes[c("samp1", "samp30")] ## not run
```

where this does not:

```
mygenes[colnames(mygenes) %in% c("samp1", "samp30")]  
  
##      samp1  
## CRP     33  
## BRCA1   22  
## HOXA    12
```

We can also use functions like `grep` to search for the names we are interested in:

```
mygenes[grep(2, names(mygenes))]

##      samp2
## CRP     44
## BRCA1   111
## HOXA    13

mygenes[grep("A", row.names(mygenes)), ]

##      samp1 samp2 samp3
## BRCA1   22    111    53
## HOXA    12    13     65
```

If we want to find or exclude data with missing values, we can use `is.na`:

```
z <- c(1:4, NA, 5:10)
z

## [1] 1 2 3 4 NA 5 6 7 8 9 10

is.na(z)

## [1] FALSE FALSE FALSE FALSE  TRUE FALSE FALSE FALSE FALSE FALSE

which(is.na(z))

## [1] 5

z[!is.na(z)]

## [1] 1 2 3 4 5 6 7 8 9 10
```

Double brackets `[[` and `$` extract *single* elements of objects, whereas `[` can extract multiple elements. Recall that a data frame is a special list, where each column is an element of a list:

```
## retrieve element
mygenes[[3]]

## [1] 33 53 65
```

```

## retrieve element
mygenes$samp3

## [1] 33 53 65

## subset
mygenes[3]

##      samp3
## CRP      33
## BRCA1    53
## HOXA     65

```

These work for lists as well:

```

mygenelist <- list(mygenes = mygenes, mygenes2 = mygenes * 2)
mygenelist

## $mygenes
##      samp1 samp2 samp3
## CRP      33     44     33
## BRCA1    22     111    53
## HOXA     12     13     65
##
## $mygenes2
##      samp1 samp2 samp3
## CRP      66     88     66
## BRCA1    44     222    106
## HOXA     24     26     130

## retrieve list element
mygenelist[[1]]

##      samp1 samp2 samp3
## CRP      33     44     33
## BRCA1    22     111    53
## HOXA     12     13     65

mygenelist$mygenes

##      samp1 samp2 samp3
## CRP      33     44     33
## BRCA1    22     111    53
## HOXA     12     13     65

```

```

## subset list
mygenelist[1]

## $mygenes
##      samp1 samp2 samp3
## CRP     33    44    33
## BRCA1   22    111   53
## HOXA    12    13    65

```

And we can even combine \$ with [:

```

mygenelist$mygenes[2]

##      samp2
## CRP     44
## BRCA1   111
## HOXA    13

```

The \$ notation is useful for accessing elements of objects output by functions, e.g. a *t*-test:

```

tt <- t.test(x, y)
names(tt)

## [1] "statistic"    "parameter"    "p.value"      "conf.int"      "estimate"
## [6] "null.value"   "alternative"  "method"       "data.name"

tt$p.value

## [1] 0.04342819

tt$estimate

## mean of x mean of y
##      12.00      17.25

```

Basic Course on R: Manipulating Data Practical

Karl Brand* and Elizabeth Ribble†

28 Oct - 1 Nov 2019

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1 Manipulating / Selecting Data

1.1 Answer the following without typing the commands into R. Use ? if you're not sure what the object is or what the function does.

1.1.1 What is

```
length(letters)
```

1.1.2 What is

```
length(letters == LETTERS)
```

1.1.3 What is

```
which(letters %in% c("a", "d"))
```

1.1.4 What is

```
which(c("a", 7, "d") %in% letters)
```

1.1.5 What is

```
letters[LETTERS > "W"]
```

1.1.6 What is

```
letters[!LETTERS > "C"]
```

1.1.7 What is

```
seq(from = 1, to = 20, by = 3)
```

1.1.8 Why is `x` filled in the way it is? Hint: read about the arguments for `matrix!`

```
x <- matrix(8:11, nrow = 6, ncol = 4)
x

##      [,1] [,2] [,3] [,4]
## [1,]     8   10    8   10
## [2,]     9   11    9   11
## [3,]    10    8   10    8
## [4,]    11    9   11    9
## [5,]     8   10    8   10
## [6,]     9   11    9   11
```

1.1.9 What are

```
x + 4
x + x
2 * x
x / c(2, 3, 4, 5)
x[, 3] + 2 * x[, 2]
nrow(x)
x[x[, 3] > 10, ]
```

1.2 Use R to answer the following.

1.2.1 Create a vector (using `c()`) called `a` (i.e. assign it to an object called `a`) with four elements which are the integers 5 to 8 (inclusive).

1.2.2 Display element 2 of `a`.

1.2.3 Display element 4 of `a`.

1.2.4 Calculate the product of elements 2 and 4 of `a`.

1.2.5 Assign the integers 3 and 4 to object `b` and use `b` to select elements 3 and 4 of object `a`.

1.2.6 Display every element of `a` except element 2.

1.2.7 Display every element of `a` except elements 3 and 4.

1.2.8 Display only those elements of `a` that are greater than or equal to 6.

1.2.9 Display only those elements of `a` that are not equal to 7.

1.2.10 Use the `list` function to create an object `ab` which is a list of the two objects `a` and `b`.

1.2.11 Display `ab`.

1.2.12 Change the names of the elements in `ab` to “`a`” and “`b`”.

1.2.13 Display `ab` again. What has changed?

1.2.14 Create this matrix `m`:

```
m <- matrix(1:9, nrow = 3, byrow = T)
m

##      [,1] [,2] [,3]
## [1,]    1    2    3
## [2,]    4    5    6
## [3,]    7    8    9
```

Why are the numbers 1, 2, and 3 in the first row and not the first column?

1.2.15 Display the element on the second row and second column of `m`.

1.2.16 Display only the 2nd row of `m`.

1.2.17 Display only the 3rd column of `m`.

1.2.18 Display only the 2nd and 3rd columns of `m`. Do so in two different ways.

If you want to save your work: save your R session and/or source code!

Basic Course on R: Manipulating Data Practical Answers

Karl Brand* and Elizabeth Ribble†

28 Oct - 1 Nov 2019

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1 Manipulating / Selecting Data

1.1 Answer the following without typing the commands into R. Use ? if you're not sure what the object is or what the function does.

1.1.1 What is

```
length(letters)
```

26

1.1.2 What is

```
length(letters == LETTERS)
```

26

1.1.3 What is

```
which(letters %in% c("a", "d"))
```

1, 4

1.1.4 What is

```
which(c("a", 7, "d") %in% letters)
```

1, 3

1.1.5 What is

```
letters[LETTERS > "W"]
```

x, y, z

1.1.6 What is

```
letters[!LETTERS > "C"]
```

a, b, c

1.1.7 What is

```
seq(from = 1, to = 20, by = 3)
```

1, 4, 7, 10, 13, 16, 19

1.1.8 Why is `x` filled in the way it is? Hint: read about the arguments for `matrix!`

```
x <- matrix(8:11, nrow = 6, ncol = 4)
x

##      [,1] [,2] [,3] [,4]
## [1,]    8   10    8   10
## [2,]    9   11    9   11
## [3,]   10    8   10    8
## [4,]   11    9   11    9
## [5,]    8   10    8   10
## [6,]    9   11    9   11
```

`x` looks this way because we defined the number of rows to be 6 and the number of columns to be 4, the default `byrow` is FALSE so the array is filled columnwise, and the numbers 8:11 are repeated until the array is filled.

1.1.9 What are

```
x + 4
x + x
2 * x
x / c(2, 3, 4, 5)
x[, 3] + 2 * x[, 2]
nrow(x)
x[x[, 3] > 10, ]
```

- 4 added to each value of `x`
- 2 multiplied by each value of `x`
- 2 multiplied by each value of `x`
- columns of `x` are divided by the vector `c(2, 3, 4, 5)`; the vector is recycled so that the first and third columns are still the same and the second and fourth columns are still the same
- a single vector with values from the third column of `x` added to two times the second column of `x`

- 6
- the 4th row of x , since it's the only row where the third column is greater than 10

1.2 Use R to answer the following.

1.2.1 Create a vector (using `c()`) called `a` (i.e. assign it to an object called `a`) with four elements which are the integers 5 to 8 (inclusive).

```
a <- 5:8
```

1.2.2 Display element 2 of `a`.

```
a[2]
```

```
## [1] 6
```

1.2.3 Display element 4 of `a`.

```
a[4]
```

```
## [1] 8
```

1.2.4 Calculate the product of elements 2 and 4 of `a`.

```
a[2] * a[4]
```

```
## [1] 48
```

1.2.5 Assign the integers 3 and 4 to object `b` and use `b` to select elements 3 and 4 of object `a`.

```
b <- c(3, 4)
```

```
# or
```

```
b <- 3:4
```

```
a[b]
```

```
## [1] 7 8
```

1.2.6 Display every element of **a** except element 2.

```
a[-2]
```

```
## [1] 5 7 8
```

1.2.7 Display every element of **a** except elements 3 and 4.

```
a[-c(3:4)]
```

```
## [1] 5 6
```

1.2.8 Display only those elements of **a** that are greater than or equal to 6.

```
a[a >= 6]
```

```
## [1] 6 7 8
```

1.2.9 Display only those elements of **a** that are not equal to 7.

```
a[a != 7]
```

```
## [1] 5 6 8
```

1.2.10 Use the **list** function to create an object **ab** which is a list of the two objects **a** and **b**.

```
ab <- list(a, b)
```

1.2.11 Display **ab**.

```
ab
```

```
## [[1]]  
## [1] 5 6 7 8  
##  
## [[2]]  
## [1] 3 4
```

1.2.12 Change the names of the elements in **ab** to “a” and “b”.

```
names(ab) <- c("a", "b")
```

1.2.13 Display `ab` again. What has changed?

```
ab

## $a
## [1] 5 6 7 8
##
## $b
## [1] 3 4
```

Displaying `ab` now shows `$a` and `$b` in place of the original `[[1]]` and `[[2]]`. This indicates how to select and subset the list when we have names versus having no names.

1.2.14 Create this matrix `m`:

```
m <- matrix(1:9, nrow=3, byrow=T)
m

##      [,1] [,2] [,3]
## [1,]    1    2    3
## [2,]    4    5    6
## [3,]    7    8    9
```

Why are the numbers 1, 2, and 3 in the first row and not the first column?

Because we set the argument `byrow` equal to TRUE.

1.2.15 Display the element on the second row and second column of `m`.

```
m[2, 2]

## [1] 5
```

1.2.16 Display only the 2nd row of `m`.

```
m[2, ]
## [1] 4 5 6
```

1.2.17 Display only the 3rd column of `m`.

```
m[, 3]
```

```
## [1] 3 6 9
```

1.2.18 Display only the 2nd and 3rd columns of `m`. Do so in two different ways.

```
m[, 2:3]
```

```
##      [,1] [,2]
## [1,]     2     3
## [2,]     5     6
## [3,]     8     9
```

```
m[, -1]
```

```
##      [,1] [,2]
## [1,]     2     3
## [2,]     5     6
## [3,]     8     9
```

If you want to save your work: save your R session and/or source code!

Basic Course on R: Entering and Importing Data

Karl Brand* and Elizabeth Ribble†

28 Oct - 1 Nov 2019

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1 Entering and Importing Data

1.1 Entering Data

In the previous section we created a couple of short vectors, a small matrix, a data frame, and a list. There are many ways to create such objects, especially by utilizing a few convenient functions, and many combinations of these data types are also possible.

1.1.1 A few functions to get started

The most basic function presented first is one we've seen before: the combine function: `c`. This combines into a vector the entries passed to it, so long as they are of the same class:

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

## [1] 1 2 3 4

a <- c(1:10, 100)
a

## [1] 1 2 3 4 5 6 7 8 9 10 100
```

If we want to replicate numbers in the vector, we can type them out (e.g. 1, 1, 1, ...) or use the function `rep`, with the number to be replicated followed by the number of times to replicate it:

```
b <- rep(x = 1, times = 11)
b

## [1] 1 1 1 1 1 1 1 1 1 1 1
```

The function `seq` generates a sequence of numbers based on the specified start, end and increment of the sequence:

```
d <- seq(from = 1, to = 110, by = 10)
d

## [1] 1 11 21 31 41 51 61 71 81 91 101
```

To bind two or more vectors (or data frames) together, we can use `cbind` (to combine columns) or `rbind` (to combine rows):

```

abdc <- cbind(a, b, d)
abdc

##      a b   d
## [1,] 1 1   1
## [2,] 2 1  11
## [3,] 3 1  21
## [4,] 4 1  31
## [5,] 5 1  41
## [6,] 6 1  51
## [7,] 7 1  61
## [8,] 8 1  71
## [9,] 9 1  81
## [10,] 10 1  91
## [11,] 100 1 101

abdr <- rbind(a, b, d)
abdr

## [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11]
## a    1    2    3    4    5    6    7    8    9    10   100
## b    1    1    1    1    1    1    1    1    1    1    1
## d    1   11   21   31   41   51   61   71   81   91   101

```

We can use `View` to look at the data - it displays the data values along with the names of the columns:

```
View(abdr)
```

or, to just get the dimension of the resulting object, use `dim`, `nrow` or `ncol`:

```

dim(abdr)

## [1] 3 11

nrow(abdr)

## [1] 3

ncol(abdr)

## [1] 11

```

And remember `str()` will display the data structure and `class()` the class:

```
str(abdr)

##  num [1:3, 1:11] 1 1 1 2 1 11 3 1 21 4 ...
##  - attr(*, "dimnames")=List of 2
##    ..$ : chr [1:3] "a" "b" "d"
##    ..$ : NULL

class(abdr)

## [1] "matrix"
```

1.1.2 Merging data frames

Suppose we want to add some new samples to `mygenes`:

```
mygenes <- data.frame(samp1 = c(33, 22, 12),
                      samp2 = c(44, 111, 13),
                      samp3 = c(33, 53, 65))
row.names(mygenes) <- c("CRP", "BRCA1", "HOXA")
```

but we happen to have the rows (here, genes) in a different order than before, and in fact we have an extra gene as well:

```
newsamp <- data.frame(samp4 = c(56, 13, 106, 10),
                      samp5 = c(45, 15, 99, 13))
row.names(newsamp) <- c("CRP", "HOXA", "BRCA1", "GAPDH")
newsamp

##      samp4 samp5
## CRP     56    45
## HOXA    13    15
## BRCA1   106   99
## GAPDH   10    13
```

We can't use e.g. `cbind` because not only are the dimensions different, but the row order differs. The `merge` function solves this problem: it concatenates based on matching attributes. Use the argument `by` to specify what columns to merge by, i.e., the name(s) of a column(s), or the row names:

```

mygenes2 <- merge(x = mygenes, y = newsamp, by = "row.names")
mygenes2

##   Row.names samp1 samp2 samp3 samp4 samp5
## 1    BRCA1    22   111    53   106    99
## 2      CRP    33    44    33    56    45
## 3     HOXA    12    13    65    13    15

```

The default setting however is to not include anything that doesn't match, so above we lost our new gene, GAPDH. We can force the function to keep all rows of the first and/or second argument with the arguments `all`, `all.x`, or `all.y`:

```

mygenes2 <- merge(x = mygenes, y = newsamp, by = "row.names", all.y = TRUE)
mygenes2

##   Row.names samp1 samp2 samp3 samp4 samp5
## 1    BRCA1    22   111    53   106    99
## 2      CRP    33    44    33    56    45
## 3     GAPDH    NA     NA     NA    10    13
## 4     HOXA    12    13    65    13    15

```

To be conservative and keep everything, use `all = TRUE`. Note that for every column of the first argument that didn't have a value for GAPDH we now have an `NA`. Also note that the row names are no longer the row names, but instead have been put in a new column. We can leave it as it is, and perhaps change the name (as shown in the first line of code below), or use our indexing and naming skills to create another data frame with the row names back where they were:

```

names(mygenes2)[1] <- "gene"
## or
mygenes3 <- mygenes2[, -1]
row.names(mygenes3) <- mygenes2[, 1]
mygenes3

##       samp1 samp2 samp3 samp4 samp5
## BRCA1    22   111    53   106    99
## CRP     33    44    33    56    45
## GAPDH    NA     NA     NA    10    13
## HOXA    12    13    65    13    15

```

1.1.3 Concatenating strings

The function `paste` is great for (re)naming, writing, and creating data. For example, in the last section we created the data frame `mygenes` by entering the name of each data

frame element as follows:

```
mygenes <- data.frame(samp1 = c(33, 22, 12),  
                      samp2 = c(44, 111, 13),  
                      samp3 = c(33, 53, 65))
```

but with a naming convention where the same text is repeated several times (“samp”) it is handy to be able to type it in only once:

```
mygenes <- data.frame(c(33, 22, 12),  
                      c(44, 111, 13),  
                      c(33, 53, 65))  
names(mygenes) <- paste("samp", 1:3, sep = "")  
row.names(mygenes) <- c("CRP", "BRCA1", "HOXA")  
mygenes  
  
##      samp1 samp2 samp3  
## CRP     33    44    33  
## BRCA1   22    111   53  
## HOXA    12    13    65
```

Note the `sep` argument specifies how to separate the strings we are pasting together. We can use any character we want for this parameter:

```
paste("The", "Club", sep = " Mickey Mouse ")  
  
## [1] "The Mickey Mouse Club"
```

By default `sep = " "`. That is, omitting `sep` in the `paste` function will insert spaces:

```
paste("The", "Mickey", "Mouse", "Club")  
  
## [1] "The Mickey Mouse Club"
```

In the next subsection we’ll see how `paste` can be helpful for reading and writing files.

1.2 Importing from a Dataset or File

1.2.1 Importing from a built-in dataset

Many R packages come with built-in datasets. Extracting these data are straightforward using `data()`. Invoking this will output a list of all available datasets in a new window:

```
data()
```

If we introduce the name of the dataset, then the function loads that dataset into the workspace:

```
HairEyeColor

## , , Sex = Male
##
##      Eye
## Hair   Brown Blue Hazel Green
## Black    32   11    10     3
## Brown    53   50    25    15
## Red      10   10     7     7
## Blond     3   30     5     8
##
## , , Sex = Female
##
##      Eye
## Hair   Brown Blue Hazel Green
## Black    36    9     5     2
## Brown    66   34    29    14
## Red      16    7     7     7
## Blond     4   64     5     8
```

1.2.2 Importing from a file

Suppose we have collected some data that we want to analyze in R and the data are in matrix format in e.g. a .txt or .csv file. Then we can read this in with a function like `read.table` and assign the output to an object:

```
data <- read.table(file = "Rcourse_data.txt",
                   header = TRUE, row.names = 1)
data

##      cohort age
## 1001 disease 34
## 1002 control 38
## 1003 disease 22
## 1004 disease 50
## 1005 control 46
## 1006 control 27
```

```
## 1007 disease 44
## 1008 control 49
## 1009 control 33
## 1010 disease 30
```

In the arguments we can specify things like:

- the separator e.g., `sep = "\t"` for tab separated (.txt) or `sep = ","` for comma separated (.csv) files;
- the header (as above);
- which column contains the row names (as above);
- whether to skip any columns or fill in blank lines with `NA`;

and so on. The function `read.csv` is the same as `read.table` but uses the default `sep = ","` for reading in .csv files (note that `read.csv2` has default `sep = ";"` and `dec = ",,"`).

Also be aware of R's default behaviour of converting columns of text strings in a data frame into the class `factor`. You may not want your column of text strings to be factors, if so, set the argument `stringsAsFactors = FALSE` in the `read.table()` function.

Now suppose the file we want isn't in our working directory (displayed by calling `getwd()`). Then we can type in the path in the name of the file:

```
data <- read.table(file = "C:/temp/Rcourse_data.txt",
                    header = TRUE,
                    row.names = 1)
data
```

But let's say we have a lot of files to read in from places other than our working directory and don't want to keep typing in the same parts of a path every time. Then we can `paste`:

```
mydir <- "C:/temp"
newfile <- paste(mydir, "Rcourse_data.txt", sep = "/")
data <- read.table(file = newfile,
                   header = TRUE,
                   row.names = 1)
```

See also `?file.path` which is built specifically for this purpose, whereas `paste` has more general utility.

1.3 Writing to a File

Now suppose we've done some analysis and want to store our results outside of R. The functions `write.table` and `write.csv` do this:

```
write.table(x = data, file = "C:/temp/results.txt", sep = "\t")
## or
write.csv(x = data, file = "C:/temp/results.csv")
```

We specified the separator in `write.table` (default is a space), but the default in `write.csv` is a comma. If you do not want to write the row names to the file, set the argument `row.names = FALSE`.

Note we can change the location of our working directory using `setwd()` so that we don't have to worry about specifying a path over and over when reading/writing files, e.g.:

```
# not run
setwd("C:/Users/Documents/RSTUFF")
```

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Basic Course on R: Entering and Importing Data Practical

Karl Brand* and Elizabeth Ribble†

28 Oct - 1 Nov 2019

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1 Entering and Importing Data

1.1 Use R to do the following exercises.

1.1.1 Enter the following into a data structure with the name `color`:

- purple
- yellow
- red
- brown
- green
- purple
- red
- purple

1.1.2 Display the 2nd element of `color`.

1.1.3 Enter the following into a data structure with the name `weight`:

- 23
- 21
- 18
- 26
- 25
- 22
- 26
- 19

1.1.4 What are the lengths of `color` and `weight`? Use a function to answer this.

1.1.5 Join `color` and `weight` together using `cbind()` and assign it to the object `micecbind`.

1.1.6 What is the data structure of `micecbind`? What are the dimensions? Are the weights still numbers (`num`) or were they converted to characters (`chr`)?

1.1.7 Now join `color` and `weight` together using `data.frame()` with argument `stringsAsFactors = FALSE` and assign it to the object `micedf`.

1.1.8 What is the data structure of `micedf`? What are the dimensions? Are the weights still numbers (`num`) or were they converted to characters (`chr`)?

1.1.9 Display only the 3rd row of `micedf`.

1.1.10 Display only the 2nd column (“weight”) of `micedf`. Do so in two different ways.

1.1.11 Display the dimensions of `micedf`.

1.1.12 Assign the following strings to the row names of `micedf`:

- mouse1
- mouse2
- mouse3
- mouse4
- mouse5
- mouse6
- mouse7
- mouse8

Hint: try using `paste`.

1.1.13 Create a list containing three elements and assign it to `mylist`:

- `micedf`
- A data frame of `micedf` with a new column called `double` that is 2 times the second column of `micedf` (`weight`).
- The names of `micedf`.

1.1.14 Assign these names to `mylist`: `first`, `second`, `third`.

1.1.15 Display `mylist`. What does it look like?

1.1.16 Display only the second element of `mylist`. Do so in two different ways.

1.1.17 Write `micedf` to a file called “micedf1.csv”.

1.1.18 Open “micedf1.csv” in Excel and describe what you see. Repeat the step above but do not include row names and call the file “micedf2.csv”. How is the output different from “micedf1.csv”?

1.1.19 Now read in “micedf1.csv” and “micedf2.csv” into R in two new objects (`newmice1` and `newmice2`, respectively). Describe any differences between the two objects. What are the dimensions of each object?

1.1.20 Read in “micedf1.csv” into R (assign to object `newmice3`). Use the argument `row.names` to indicate that the first column should be row names and do not allow strings to be turned into factors. Display the object and the structure of the object and describe how it is different from `newmice1` and `micedf`. What are the dimensions of `newmice3`?

1.2 Use R to do the following exercises on the Puromycin data.

1.2.1 Load the Puromycin data using the `data()` function.

1.2.2 What is the data structure of `Puromycin`? What are the dimensions (use a function other than `str`)?

1.2.3 What are the names of `Puromycin`? Use a function other than `str`.

1.2.4 What are the levels of the `state` variable? Use a function other than `str`.

1.2.5 Display the rate for all concentrations less than 0.10 in the treated group.

1.2.6 What are the row indices for the concentrations of 0.22?

If you want to save your work: save your R session and/or source code!

Basic Course on R: Entering and Importing Data Practical Answers

Karl Brand* and Elizabeth Ribble†

28 Oct - 1 Nov 2019

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1 Entering and Importing Data

1.1 Use R to do the following exercises.

1.1.1 Enter the following into a data structure with the name `color`:

- purple
- yellow
- red
- brown
- green
- purple
- red
- purple

```
color <- c("purple", "yellow", "red", "brown", "green",
          "purple", "red", "purple")
```

1.1.2 Display the 2nd element of `color`.

```
color[2]  
## [1] "yellow"
```

1.1.3 Enter the following into a data structure with the name `weight`:

- 23
- 21
- 18
- 26
- 25
- 22
- 26
- 19

```
weight <- c(23, 21, 18, 26, 25, 22, 26, 19)
```

1.1.4 What are the lengths of `color` and `weight`? Use a function to answer this.

```
length(color)
```

```
## [1] 8
```

```
length(weight)
```

```
## [1] 8
```

1.1.5 Join `color` and `weight` together using `cbind()` and assign it to the object `micecbind`.

```
micecbind <- cbind(color = color, weight = weight)
```

1.1.6 What is the data structure of `micecbind`? What are the dimensions? Are the weights still numbers (`num`) or were they converted to characters (`chr`)?

```
micecbind
```

```
##      color    weight
## [1,] "purple" "23"
## [2,] "yellow" "21"
## [3,] "red"    "18"
## [4,] "brown"   "26"
## [5,] "green"   "25"
## [6,] "purple"  "22"
## [7,] "red"    "26"
## [8,] "purple"  "19"
```

```
str(micecbind)
```

```
##  chr [1:8, 1:2] "purple" "yellow" "red" "brown" "green" "purple" "red" ...
##  - attr(*, "dimnames")=List of 2
##    ..$ : NULL
##    ..$ : chr [1:2] "color" "weight"
```

```
dim(micecbind)
```

```
## [1] 8 2
```

Using `str` we see that `micebind` is a matrix with dimensions 8×2 and the weights were converted to characters, which we don't want! The function `dim` can also be used to extract only the dimensions.

- 1.1.7 Now join `color` and `weight` together using `data.frame()` with argument `stringsAsFactors = FALSE` and assign it to the object `micedf`.

```
micedf <- data.frame(color = color, weight = weight, stringsAsFactors = FALSE)
```

- 1.1.8 What is the data structure of `micedf`? What are the dimensions? Are the weights still numbers (`num`) or were they converted to characters (`chr`)?

```
micedf

##      color weight
## 1 purple     23
## 2 yellow    21
## 3 red       18
## 4 brown     26
## 5 green     25
## 6 purple    22
## 7 red       26
## 8 purple    19

str(micedf)

## 'data.frame': 8 obs. of  2 variables:
##   $ color : chr  "purple" "yellow" "red" "brown" ...
##   $ weight: num  23 21 18 26 25 22 26 19

dim(micedf)

## [1] 8 2
```

Using `str` we see that `micedf` is a data frame with dimensions 8×2 , with variable `color` a character vector and `weight` a numeric vector. The function `dim` can also be used to extract only the dimensions. Thankfully the weights were not converted to characters!

1.1.9 Display only the 3rd row of `micedf`.

```
micedf[3, ]  
  
##   color weight  
## 3   red     18
```

1.1.10 Display only the 2nd column (“weight”) of `micedf`. Do so in two different ways.

Any two of the following are satisfactory:

```
micedf[, 2]  
micedf[, -1]  
micedf[, "weight"]  
micedf[[2]]  
micedf$weight  
micedf["weight"]
```

1.1.11 Display the dimensions of `micedf`.

```
dim(micedf)  
  
## [1] 8 2
```

1.1.12 Assign the following strings to the row names of `micedf`:

- mouse1
- mouse2
- mouse3
- mouse4
- mouse5
- mouse6
- mouse7
- mouse8

Hint: try using `paste`.

```
row.names(micedf) <- paste("mouse", 1:8, sep = "")
```

1.1.13 Create a list containing three elements and assign it to `mylist`:

- `micedf`
- A data frame of `micedf` with a new column called `double` that is 2 times the second column of `micedf` (`weight`). (Did you get an error? Make sure that the second column is numeric and if it isn't, change it!)
- The names of `micedf`.

```
mylist <- list(micedf,
                data.frame(micedf, double = 2 * micedf$weight),
                names(micedf))
```

1.1.14 Assign these names to `mylist`: `first`, `second`, `third`.

```
names(mylist) <- c("first", "second", "third")
```

1.1.15 Display `mylist`. What does it look like?

```
mylist

## $first
##           color weight
## mouse1   purple    23
## mouse2  yellow    21
## mouse3    red     18
## mouse4  brown    26
## mouse5   green    25
## mouse6   purple    22
## mouse7    red     26
## mouse8   purple    19
##
## $second
##           color weight double
## mouse1   purple    23     46
## mouse2  yellow    21     42
## mouse3    red     18     36
## mouse4  brown    26     52
```

```
## mouse5 green    25    50
## mouse6 purple   22    44
## mouse7 red     26    52
## mouse8 purple   19    38
##
## $third
## [1] "color"  "weight"
```

A list with three items with the given names preceded by \$. The first two entries are data frames and have row names, but the third does not (it is a character vector).

1.1.16 Display only the second element of mylist. Do so in two different ways.

Any two of the following are satisfactory:

```
mylist[[2]] ## extract
mylist$second ## extract
mylist[2] ## subset
mylist[-c(1, 3)] ## subset
mylist["second"] ## subset
```

1.1.17 Write micedf to a file called “micedf1.csv” in the course directory.

```
write.csv(micedf, "micedf1.csv")
```

1.1.18 Open “micedf1.csv” in Excel and describe what you see. Repeat the step above but do not include row names and call the file “micedf2.csv”. How is the output different from “micedf1.csv”?

The file “micedf1.csv” looks exactly like the data frame when displayed in R.

```
write.csv(micedf, "micedf2.csv", row.names = FALSE)
```

The file “micedf2.csv” looks just like the data frame above, but it is missing the row names.

1.1.19 Now read in “micedf1.csv” and “micedf2.csv” into R in two new objects (`newmice1` and `newmice2`, respectively). Describe any differences between the two objects. What are the dimensions of each object?

```

newmice1 <- read.csv("micedf1.csv")
newmice2 <- read.csv("micedf2.csv")
str(newmice1)

## 'data.frame': 8 obs. of  3 variables:
## $ X      : Factor w/ 8 levels "mouse1","mouse2",...: 1 2 3 4 5 6 7 8
## $ color  : Factor w/ 5 levels "brown","green",...: 3 5 4 1 2 3 4 3
## $ weight: int  23 21 18 26 25 22 26 19

str(newmice2)

## 'data.frame': 8 obs. of  2 variables:
## $ color  : Factor w/ 5 levels "brown","green",...: 3 5 4 1 2 3 4 3
## $ weight: int  23 21 18 26 25 22 26 19

newmice1

##      X color weight
## 1 mouse1 purple    23
## 2 mouse2 yellow   21
## 3 mouse3 red     18
## 4 mouse4 brown    26
## 5 mouse5 green   25
## 6 mouse6 purple   22
## 7 mouse7 red     26
## 8 mouse8 purple   19

newmice2

##      color weight
## 1 purple    23
## 2 yellow   21
## 3 red     18
## 4 brown    26
## 5 green   25
## 6 purple   22
## 7 red     26
## 8 purple   19

```

The first file was written with row names, but when we read it into R, the row

names are now just a column in the data frame. Because there was an empty cell in the space where a column name should have been, R names it X. The second file had no row names, and, just like the first file, is given the default row names of 1 to the number of rows. The dimensions are 8 x 3 and 8 x 2, respectively (seen in the output of the `str` call).

- 1.1.20 Read in “micedf1.csv” into R (assign to object `newmice3`). Use the argument `row.names` to indicate that the first column should be row names and do not allow strings to be turned into factors. Display the object and the structure of the object and describe how it is different from `newmice1` and `micedf`. What are the dimensions of `newmice3`?

```
newmice3 <- read.csv(paste(mydir, "micedf1.csv", sep="/"),
                      row.names = 1, stringsAsFactors = F)
```

```
str(newmice3)

## 'data.frame': 8 obs. of  2 variables:
## $ color : chr  "purple" "yellow" "red" "brown" ...
## $ weight: int  23 21 18 26 25 22 26 19

newmice3

##      color weight
## mouse1 purple    23
## mouse2 yellow   21
## mouse3 red     18
## mouse4 brown    26
## mouse5 green   25
## mouse6 purple   22
## mouse7 red     26
## mouse8 purple   19
```

The new object `newmice3` now has row names where in `newmice1` they were treated as a variable in the data frame. The `color` variable was not converted to a factor, unlike in `newmice1`. The new object `micedf` is now (nearly) identical to the original `micedf`. It has the same row names and dimensions as `micedf`. The only difference is the class of `weight` is an integer instead of just “numeric” (more specific). The dimensions are 8 x 2.

1.2 Use R to do the following exercises on the Puromycin data.

1.2.1 Load the Puromycin data using the `data()` function.

```
data(Puromycin)
```

1.2.2 What is the data structure of `Puromycin`? What are the dimensions? Do not just display the data (this is not convenient for large datasets).

```
str(Puromycin)
```

```
## 'data.frame': 23 obs. of 3 variables:  
## $ conc : num 0.02 0.02 0.06 0.06 0.11 ...  
## $ rate : num 76 47 97 107 123 ...  
## $ state: Factor w/ 2 levels "treated","untreated": 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 ...  
## - attr(*, "reference")= chr "A1.3, p. 269"
```

Using `str` we see that `Puromycin` is a data frame with dimensions 23 x 3, with variables `conc` and `rate` numeric vectors and `state` a factor with 2 levels.

1.2.3 What are the names of `Puromycin`? Use a function other than `str`.

```
names(Puromycin)
```

```
## [1] "conc" "rate" "state"
```

1.2.4 What are the levels of the `state` variable? Use a function other than `str`.

```
levels(Puromycin$state)
```

```
## [1] "treated" "untreated"
```

1.2.5 Display the rate for all concentrations less than 0.10 in the treated group.

```
Puromycin[Puromycin$conc < .10 & Puromycin$state == "treated", "rate"]  
  
## [1] 76 47 97 107  
  
## or  
Puromycin$rate[Puromycin$conc < .10 & Puromycin$state == "treated"]
```

```
## [1] 76 47 97 107

## or
Puromycin[["rate"]][Puromycin$conc < .10 & Puromycin$state == "treated"]

## [1] 76 47 97 107
```

1.2.6 What are the row indices for the concentrations of 0.22?

```
which(Puromycin$conc == 0.22)

## [1] 7 8 19 20
```

If you want to save your work: save your R session and/or source code!

Basic Course on R: Basic Plotting

Karl Brand* and Elizabeth Ribble†

28 Oct - 1 Nov 2019

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1 Basic Plotting

R is a very powerful tool for producing custom graphics ranging from basic scatterplots to 3D plots. In this introduction to plotting we will learn how to create basic graphs like scatterplots, line graphs and bar charts, as well as histograms and boxplots, all of which are available in the base package. Different methods for saving plots will be introduced. We will use the data `ToothGrowth` throughout the following examples:

```
data(ToothGrowth)
str(ToothGrowth)

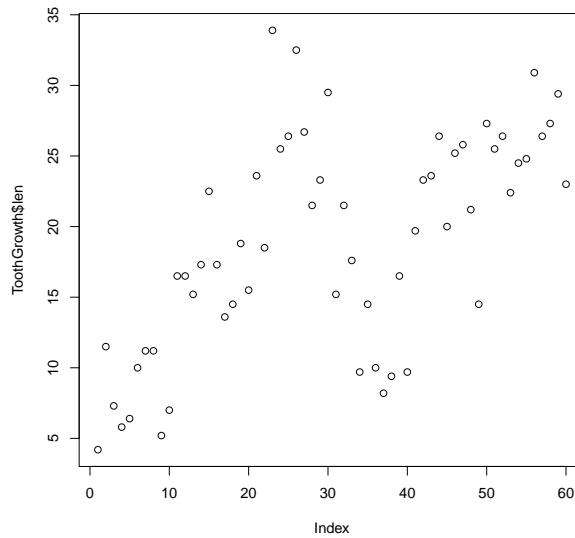
## 'data.frame': 60 obs. of 3 variables:
##   $ len : num  4.2 11.5 7.3 5.8 6.4 10 11.2 11.2 5.2 7 ...
##   $ supp: Factor w/ 2 levels "OJ","VC": 2 2 2 2 2 2 2 2 2 ...
##   $ dose: num  0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 ...
```

1.1 Scatterplots and Line Graphs

1.1.1 Scatterplots

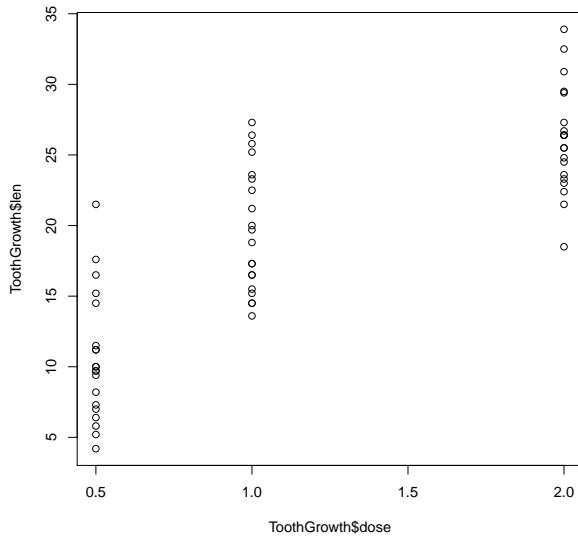
The `plot` function is the most basic function for plotting continuous data. If we use `plot` on one variable, the values of the variable will be plotted against their index, i.e., the order of the data within the object they're stored:

```
plot(ToothGrowth$len)
```



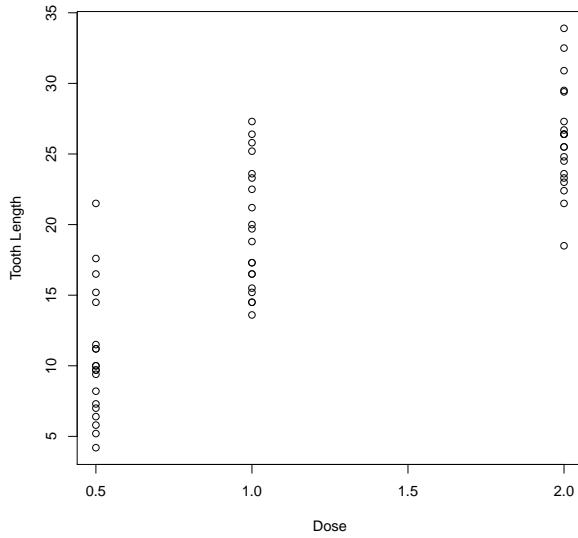
With two variables `plot` puts the first variable on the x-axis and the second variable on the y-axis (y versus x):

```
plot(ToothGrowth$dose, ToothGrowth$len)
```



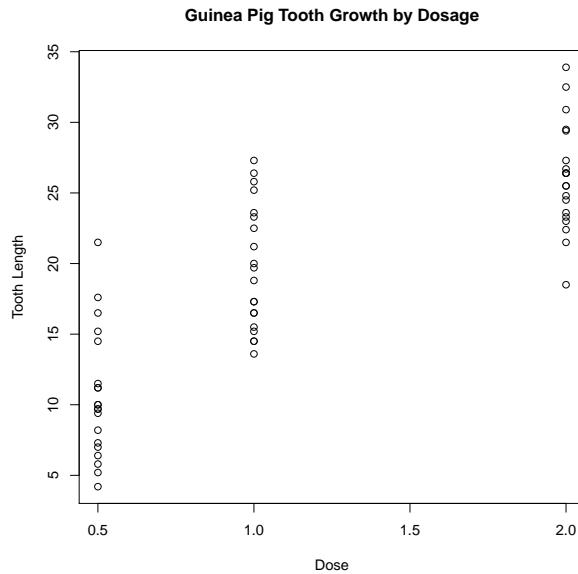
Many parameters are available for customizing your plot. See `?par` for an extensive list. We will just look at a couple here, like changing the axis labels:

```
plot(ToothGrowth$dose, ToothGrowth$len, xlab = "Dose",
      ylab = "Tooth Length")
```



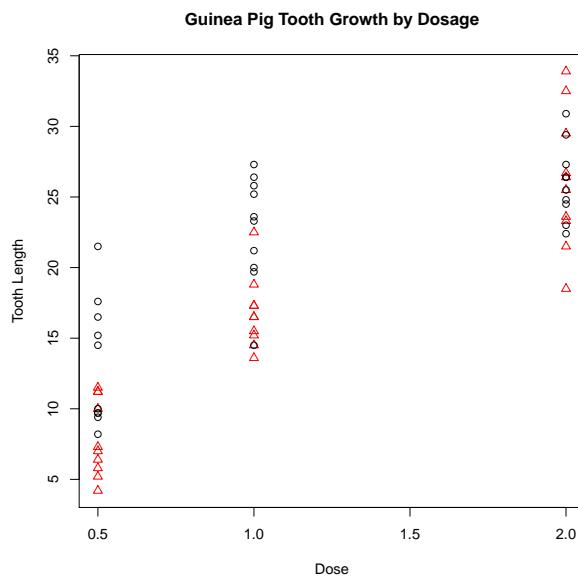
We can also add a title:

```
plot(ToothGrowth$dose, ToothGrowth$len, xlab = "Dose",
      ylab = "Tooth Length", main = "Guinea Pig Tooth Growth by Dosage")
```



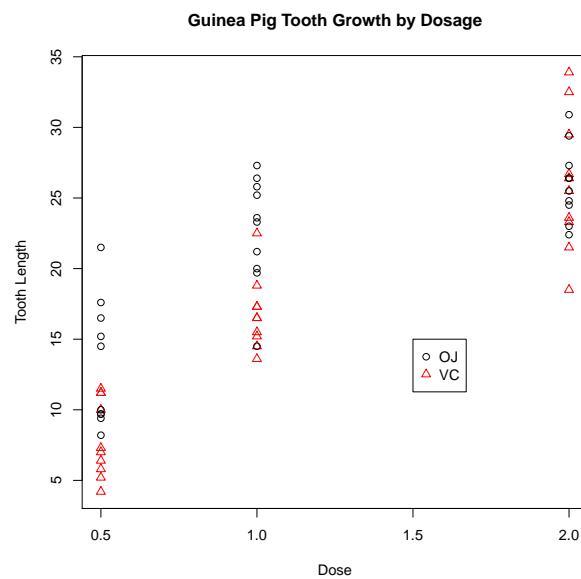
and even change the colors and characters of specific points:

```
plot(ToothGrowth$dose, ToothGrowth$len, xlab = "Dose",
      ylab = "Tooth Length", main = "Guinea Pig Tooth Growth by Dosage",
      col = ToothGrowth$supp, pch = as.numeric(ToothGrowth$supp))
```



The `legend` function adds a legend so we can easily identify which points represent which groups:

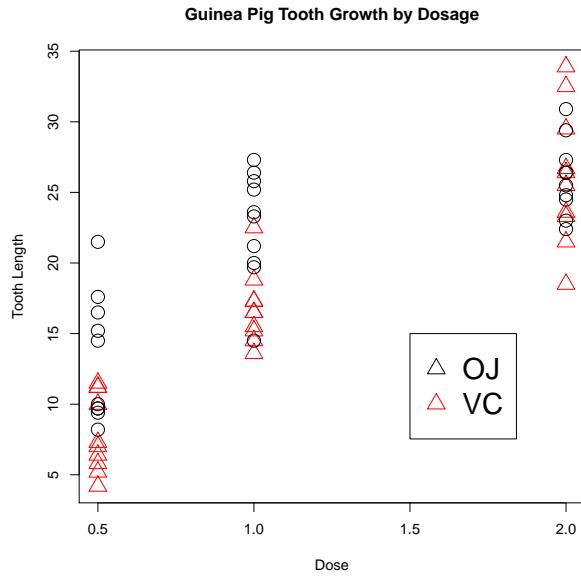
```
plot(ToothGrowth$dose, ToothGrowth$len, xlab = "Dose",
      ylab = "Tooth Length", main = "Guinea Pig Tooth Growth by Dosage",
      col = ToothGrowth$supp, pch = as.numeric(ToothGrowth$supp))
legend(1.5, 15, c("OJ", "VC"), col = 1:2,
      pch = 1:2)
```



The location of the legend can also be specified by stating a region of the plot e.g. "bottomright" to place it in the very bottom righthand corner of the plot.

The argument `cex` stands for “character expansion” and will enlarge the size of points:

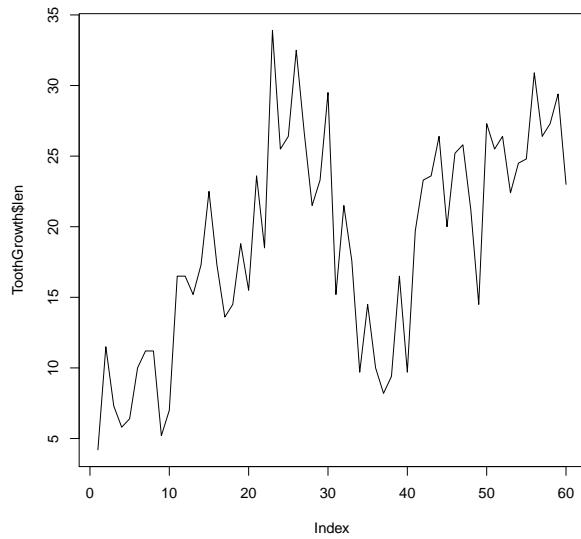
```
plot(ToothGrowth$dose, ToothGrowth$len, xlab = "Dose",
      ylab = "Tooth Length", main = "Guinea Pig Tooth Growth by Dosage",
      col = ToothGrowth$supp, pch = as.numeric(ToothGrowth$supp),
      cex = 2)
legend(1.5, 15, c("OJ", "VC"), col = 1:2,
      pch = as.numeric(ToothGrowth$supp), cex=2)
```



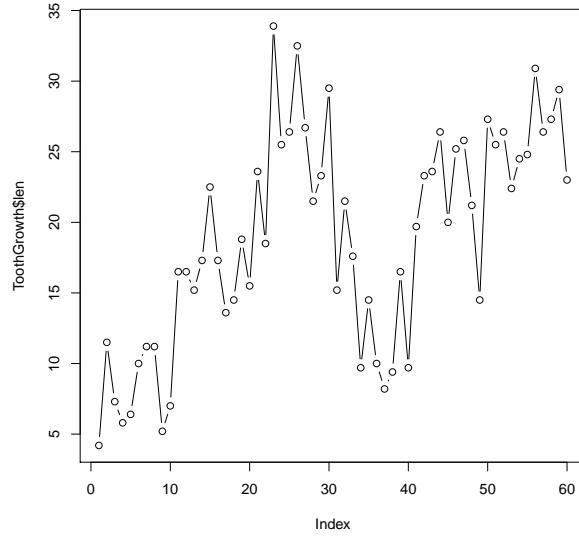
1.1.2 Line Graphs

To create a plot using lines instead of points, we can actually still use `plot`, but we need to specify the type of plot we want, e.g.:

```
plot(ToothGrowth$len, type = "l") # note type is the letter l for "line"
```

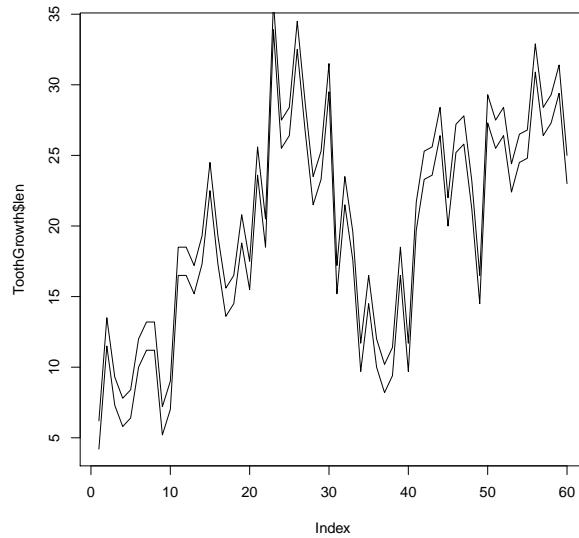


```
plot(ToothGrowth$len, type = "b") # note type is the letter b for "both"
```



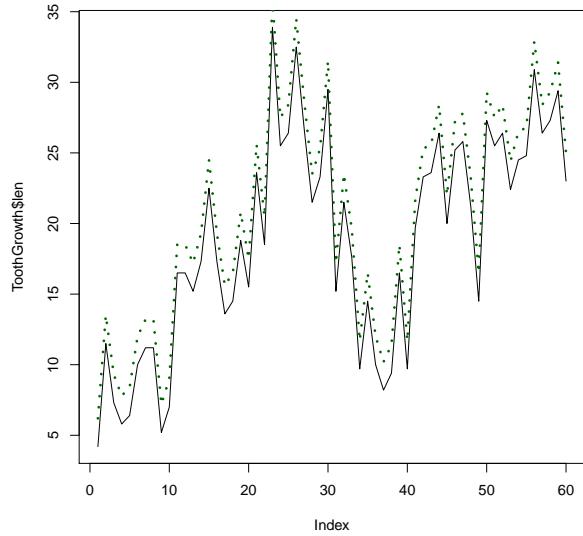
We can add additional lines by calling `lines`:

```
plot(ToothGrowth$len, type = "l")
lines(ToothGrowth$len + 2)
```



The line type, width, and color can be adjusted as follows:

```
plot(ToothGrowth$len, type = "l")
lines(ToothGrowth$len + 2, lty = 3, lwd = 3, col = "darkgreen")
```

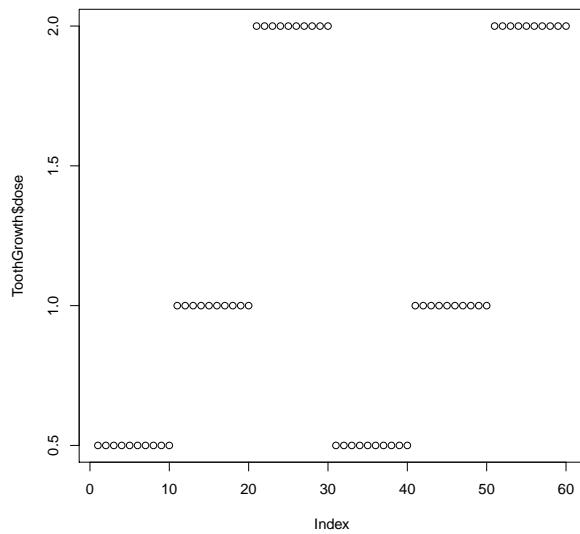


1.2 Bar Charts and Histograms

1.2.1 Bar Charts

Viewing categorical data in a scatterplot often doesn't make sense. For example, if we want to see the number of guinea pigs who received each dosage, the following doesn't provide this information in the most intuitive format:

```
plot(ToothGrowth$dose)
```

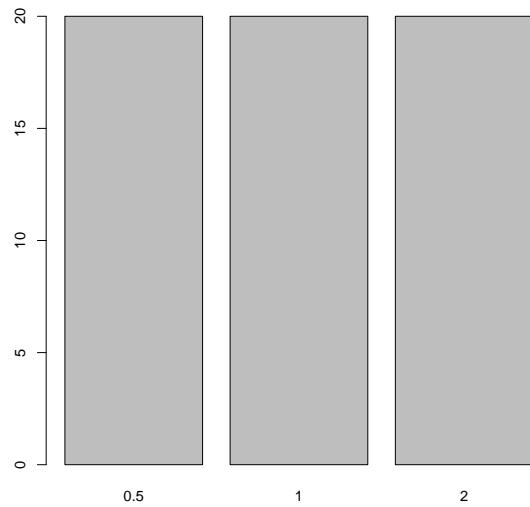


Instead we can use bar charts to visualize the frequencies or proportions within each category. Note that we have to use a frequency table of the counts (using `table`):

```
table(ToothGrowth$dose)

##
## 0.5   1    2
## 20   20   20
```

```
barplot(table(ToothGrowth$dose))
```

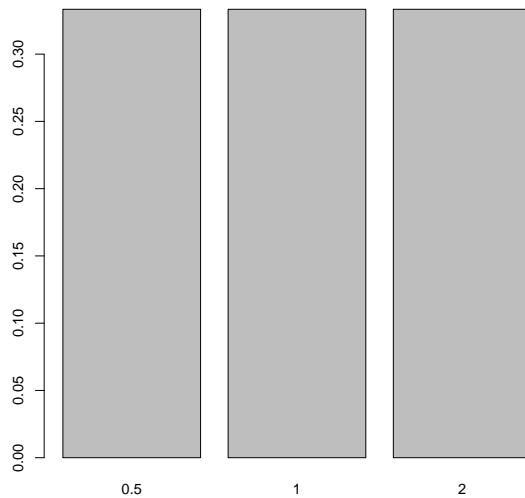


We can plot proportions instead of frequencies, as is often helpful (though not in this case):

```
props <- table(ToothGrowth$dose)/nrow(ToothGrowth)
props

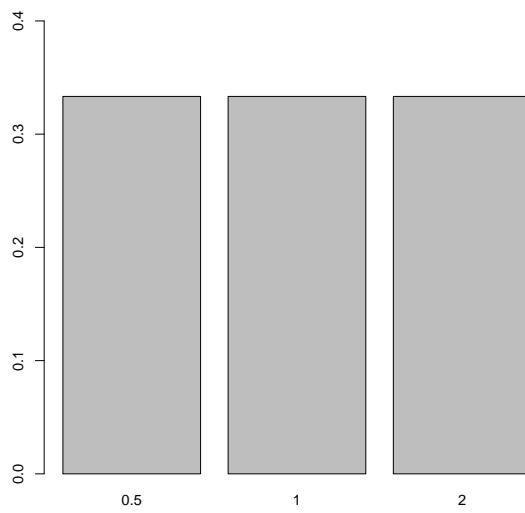
## 
##      0.5      1      2
## 0.3333333 0.3333333 0.3333333
```

```
barplot(props)
```



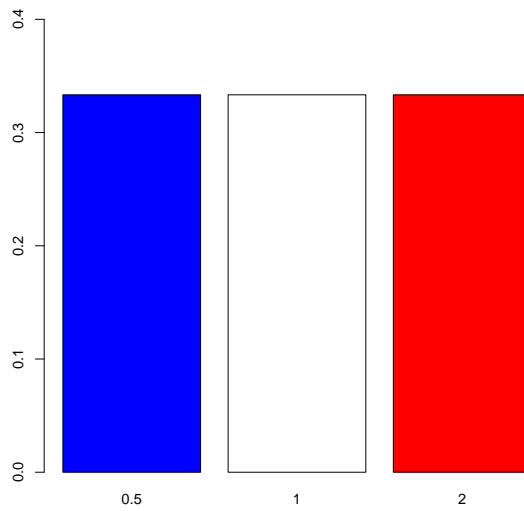
Note that the y-axis doesn't quite extend to the height of the bars. The range of the y-axis is easily change in plots by adjusting the parameter `ylim` (similarly `xlim` for the x-axis):

```
barplot(props, ylim = c(0, .4))
```



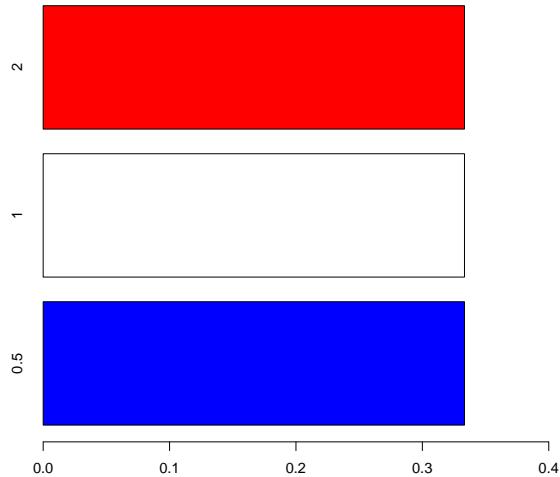
Yet again, there are many parameters available for customizing the plot. Let's try changing the width and colors of the bars:

```
barplot(props, ylim = c(0, .4),
        width = .2, col = c("blue", "white", "red"))
```



And we can plot the bars horizontally, if preferable:

```
barplot(props, xlim = c(0, .4),
        width = .2, col = c("blue", "white", "red"),
        horiz = TRUE)
```

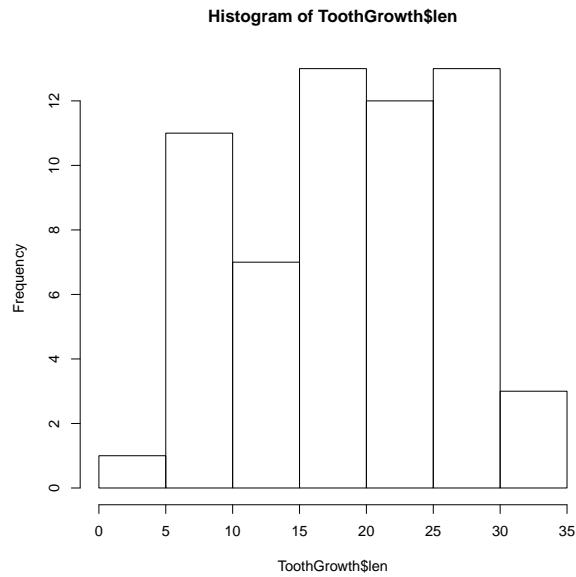


Note that we adjusted the range of the x-axis now instead of the y-axis.

1.2.2 Histograms

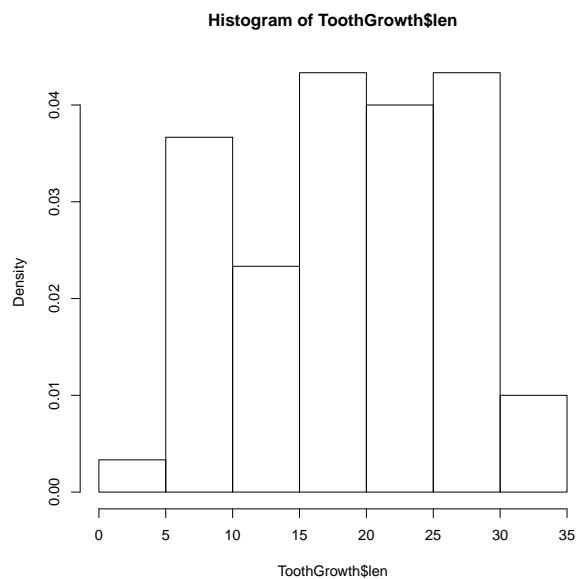
A bar chart is slightly different from a histogram. We use bar charts to plot frequencies (or proportions) of values present in categories. Continuous data don't have categories, so to make a similar plot we have to create "categories". They are often called bins or cells and are created by defining ranges in which the frequencies are calculated. Thankfully, R will do this, and plot the histogram, when we call the function `hist`:

```
hist(ToothGrowth$len)
```



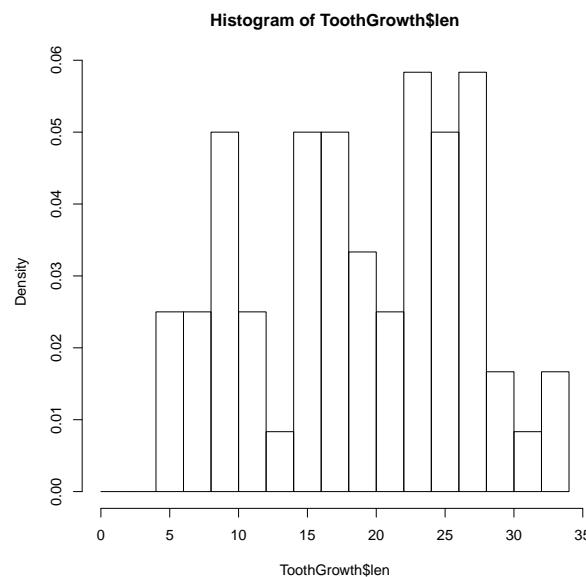
Note that in a histogram the sides of the cells touch, whereas they do not in a bar chart.
We can also plot the proportions, now called “density”, by changing a single parameter:

```
hist(ToothGrowth$len, freq = FALSE)
```



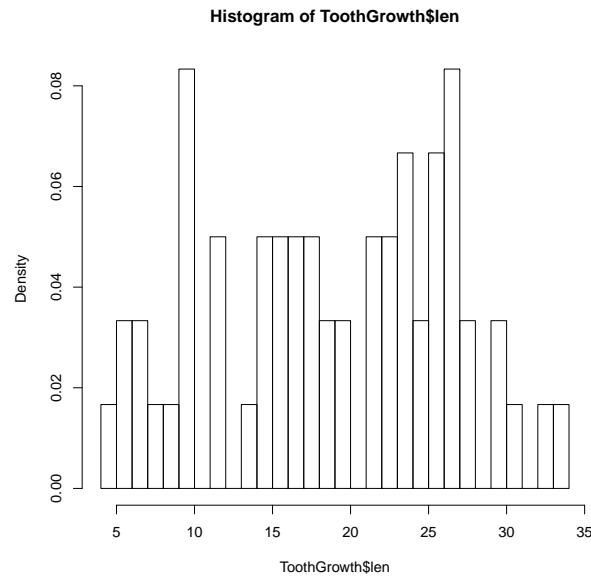
In the next graph we plot the histogram with a different bin width by specifying where to make the breakpoints between the bars:

```
hist(ToothGrowth$len, freq = FALSE, breaks = seq(0, 35, 2))
```



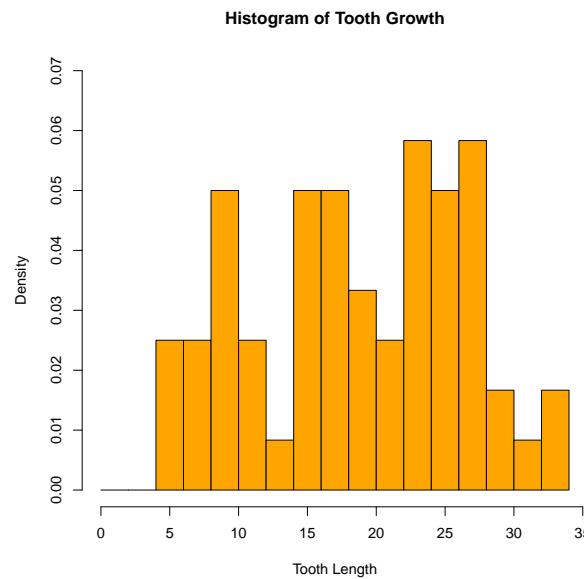
Note how the granularity of the plot changes with the width of the bin. We can also change the breaks by defining the number of cells to use:

```
hist(ToothGrowth$len, freq = FALSE, breaks = 25)
```



The same parameters that change the axes and labels are applicable here:

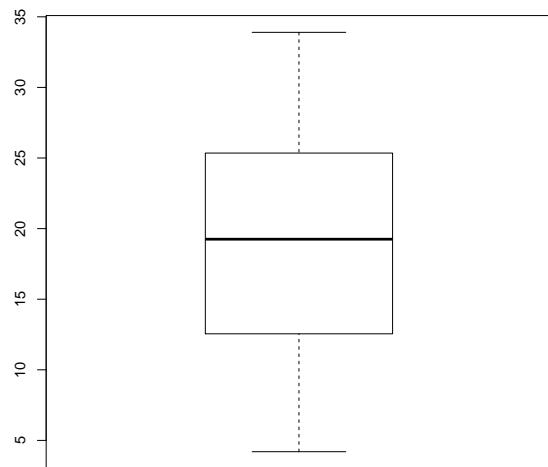
```
hist(ToothGrowth$len, freq = FALSE, breaks = seq(0, 35, 2),
     main = "Histogram of Tooth Growth", xlab = "Tooth Length",
     ylim = c(0, .07), col = "orange")
```



1.3 Boxplots

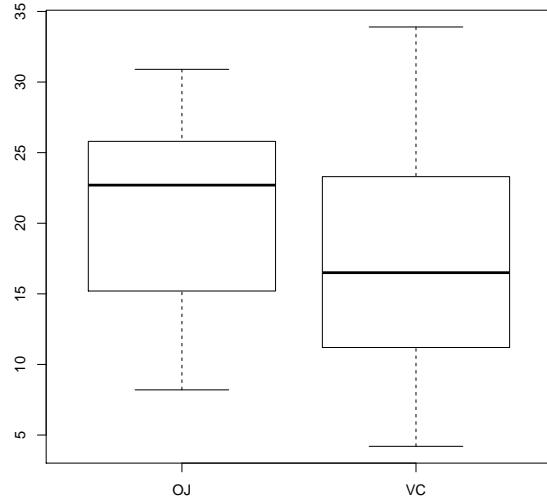
A boxplot is another graph we use to view the distribution of a continuous variable. It displays the specified quantiles of the data in the following way:

```
boxplot(ToothGrowth$len)
```



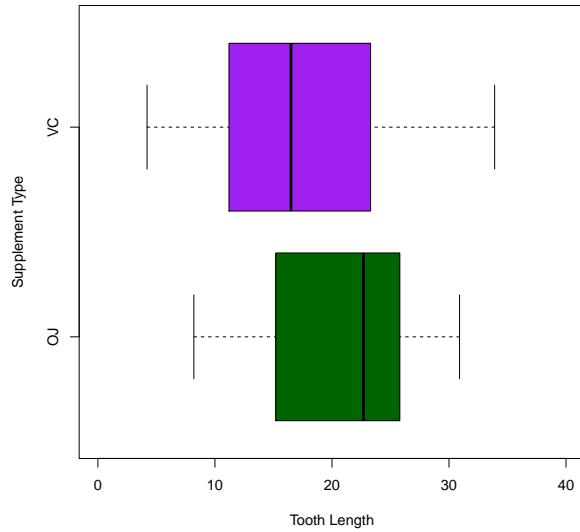
A single boxplot is nice for visualizing the distribution of one variable, but plotting several side by side allows for a simultaneous comparison of distributions. Here we will use the formula notation. The format $y \sim x$, where y is a numeric vector and x is a factor, tells the boxplot function that we want to separate the continuous y values into as many boxplots as there are levels of the factor x .

```
boxplot(ToothGrowth$len~ToothGrowth$supp)
```



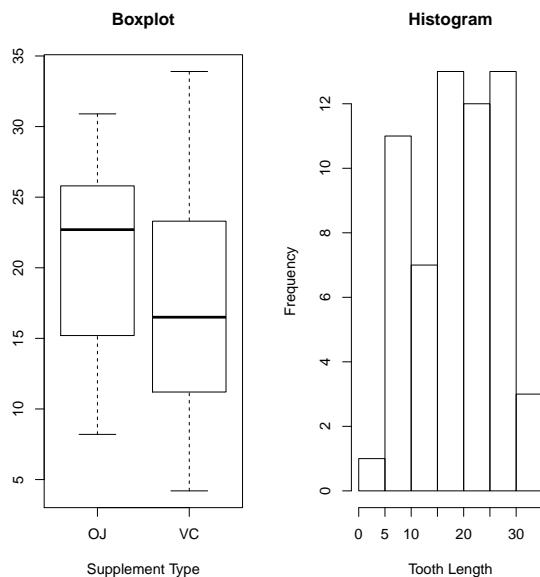
Just like in the bar chart, we can plot the boxes horizontally and change the colors, labels and axes:

```
boxplot(ToothGrowth$len~ToothGrowth$supp,  
       col = c("darkgreen", "purple"),  
       ylab = "Supplement Type", xlab = "Tooth Length",  
       ylim = c(0, 40), horizontal = TRUE)
```



The settings of the parameters of a plot, including the margins, can be specified by calling `par()` before creating a plot. One nice setting we'll introduce here is how to put multiple plots into one graphics device:

```
par(mfrow = c(1, 2))
boxplot(ToothGrowth$len ~ ToothGrowth$supp, main = "Boxplot",
        xlab = "Supplement Type")
hist(ToothGrowth$len, main = "Histogram", xlab = "Tooth Length")
```



The settings will stay fixed until we close the device (e.g. by calling `dev.off()`) or reset `par` (e.g. `par(mfrow = c(1, 1))`). It is highly recommended to get familiar with the help page for `par` to control graphing parameters to create custom graphs.

Another helpful function is `axis`, which allows the specification of custom axis labels (e.g. where to put them and at what angle). See `?axis` for more information.

1.4 Saving Plots

Up until now we have been creating graphs in a single graphics window that gets overwritten every time we create new plots. If we want to save the images created, we can use “Export” in RStudio to specify what type of file we want to write, its size, location, and name.

Alternatively we can use functions such as `png`, `pdf`, and `jpeg`. Since we can save our code and not our mouse clicks, the use of these functions avoids any confusion about how an image was written, allows for quick simple changes, and provides a convenient way to reproduce multiple, similar plots. For example:

```

# note: run getwd() to see the working directory -
# that is the directory to which files will be written
pdf("plot1.pdf", width = 6, height = 9)
boxplot(ToothGrowth$len~ToothGrowth$supp,
        col = c("darkgreen", "purple"),
        xlab = "Supplement Type", ylab = "Tooth Length",
        ylim = c(0, 40), horizontal = TRUE)
dev.off()

## pdf
## 2

pdf("plot2.pdf", width = 4, height = 8)
boxplot(ToothGrowth$len~ToothGrowth$supp,
        col = c("darkgreen", "purple"),
        xlab = "Supplement Type", ylab = "Tooth Length",
        ylim = c(0, 40), horizontal = TRUE)
dev.off()

## pdf
## 2

```

Note that you have to call `dev.off()` to finish writing the image to the file. If more than one device is open, the return of that function will display a number larger than 1.

The units for the width and height arguments of `pdf` are in inches (7 by 7), but the default for e.g. `png` is pixels (there is an argument `units` to change it to `in`, `cm`, or `mm`):

```

png("plot1.png", units = "in", res = 300,
    width = 6, height = 9)
boxplot(ToothGrowth$len~ToothGrowth$supp,
        col = c("darkgreen", "purple"),
        xlab = "Supplement Type", ylab = "Tooth Length",
        ylim = c(0, 40), horizontal = TRUE)
dev.off()

## pdf
## 2

```

Basic Course on R: Basic Plotting Practical

Karl Brand* and Elizabeth Ribble†

28 Oct - 1 Nov 2019

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1 Basic Plotting

1.1 Use R to do the following exercises on the BOD data.

1.1.1 Display the built-in dataset called `BOD` by running `BOD`.

1.1.2 What is the data structure of `BOD`? What are the dimensions?

1.1.3 What are the names of `BOD`? Use a function other than `str`.

1.1.4 Make a line graph of demand versus time, where the line is a deep pink dot-dashed line [Hint: run `?par` and look for the parameter `lty` to see the line types]. Add a blue dashed line of 1.1 times the demand and give it a thickness of 2 using the line width parameter `lwd`. Make sure both lines are entirely visible by adjusting the range of `y` using the parameter `ylim` in the original plot.

1.2 Use R to do the following exercises on the chickwts data.

1.2.1 Display the built-in `chickwts` data.

1.2.2 What is the data structure of `chickwts`? What are the dimensions?

1.2.3 What are the names of `chickwts`? Use a function other than `str`.

1.2.4 What are the levels of `feed`?

1.2.5 Make the following plots in one 2 x 2 image:

- A bar chart of the feed types, each bar a different color.
- A bar chart of the proportions of feed types, each bar a different color.
- A boxplot of the weights by feed type, each box a different color.
- A horizontal boxplot of the weights by feed type, each box a different color.

1.3 Use R to do the following exercises on the Puromycin data.

- 1.3.1 Display the built-in *Puromycin* data.
- 1.3.2 Make a scatterplot of the rate versus the concentration. Describe the relationship.

- 1.3.3 Make a scatterplot of the rate versus the log of the concentration. Describe the relationship.

- 1.3.4 Make a scatterplot of the rate versus the log of the concentration and color the points by treatment group (**state**). Describe what you see.

- 1.3.5 Make a scatterplot of the rate versus the log of the concentration, color the points by treatment group (**state**), label the x-axis “Concentration” and the y-axis “Rate”, and label the plot “Puromycin”.

- 1.3.6 Add a legend to the above plot indicating what the points represent.

- 1.3.7 Make a boxplot of the treated versus untreated rates. Using the function **pdf**, save the image to a file with a width and height of 7 inches.

- 1.3.8 Make a histogram of the frequency of concentrations. What is the width of the bins?

- 1.3.9 Make a histogram of the frequency of concentrations with a bin width of 0.10. How is this different from the histogram above?

- 1.3.10 Plot the histograms side by side in the same graphic window and make sure they have the same range on the y-axis. Does this make it easier to answer the question of how the two histograms differ?

If you want to save your work: save your R session and/or source code!

Basic Course on R: Basic Plotting Practical Answers

Karl Brand* and Elizabeth Ribble†

28 Oct - 1 Nov 2019

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1 Basic Plotting

1.1 Use R to do the following exercises on the BOD data.

1.1.1 Display the built-in dataset called BOD by running BOD.

```
BOD

##   Time demand
## 1    1    8.3
## 2    2   10.3
## 3    3   19.0
## 4    4   16.0
## 5    5   15.6
## 6    7   19.8
```

1.1.2 What is the data structure of BOD? What are the dimensions?

```
str(BOD)

## 'data.frame': 6 obs. of  2 variables:
## $ Time : num  1 2 3 4 5 7
## $ demand: num  8.3 10.3 19 16 15.6 19.8
## - attr(*, "reference")= chr "A1.4, p. 270"
```

Using `str` we see that BOD is a data frame with dimensions 6 x 2, each variable (`Time` and `demand`) a numeric vector.

1.1.3 What are the names of BOD? Use a function other than `str`.

```
names(BOD)

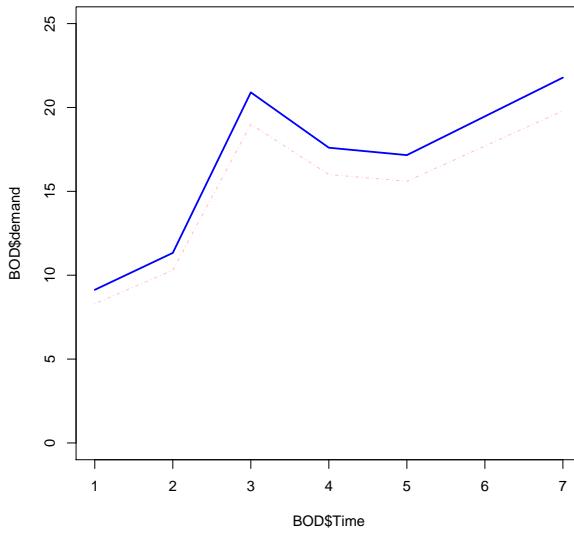
## [1] "Time"    "demand"
```

1.1.4 Make a line graph of demand versus time, where the line is a deep pink dot-dashed line [Hint: run `?par` and look for the parameter `lty` to see the line types]. Add a blue dashed line of 1.1 times the demand and give it a thickness of 2 using the line width parameter `lwd`. Make sure both lines are entirely visible by adjusting the range of y using the parameter `ylim` in the original plot.

```

plot(BOD$Time, BOD$demand, type = "l", lty = 4,
      col = "pink", ylim = c(0, 25))
lines(BOD$Time, 1.1 * BOD$demand, lwd = 2, col = "blue")

```



1.2 Use R to do the following exercises on the chickwts data.

1.2.1 Display the built-in chickwts data.

```
chickwts
```

1.2.2 What is the data structure of chickwts? What are the dimensions?

```

str(chickwts)

## 'data.frame': 71 obs. of  2 variables:
## $ weight: num  179 160 136 227 217 168 108 124 143 140 ...
## $ feed   : Factor w/ 6 levels "casein","horsebean",...: 2 2 2 2 2 2 2 2 2 2 ...

```

Using `str` we see that `chickwts` is a data frame with dimensions 71 x 2, with variable `weight` a numeric vector and `feed` a factor with 6 levels.

1.2.3 What are the names of chickwts? Use a function other than `str`.

```
names(chickwts)

## [1] "weight" "feed"
```

1.2.4 What are the levels of `feed`?

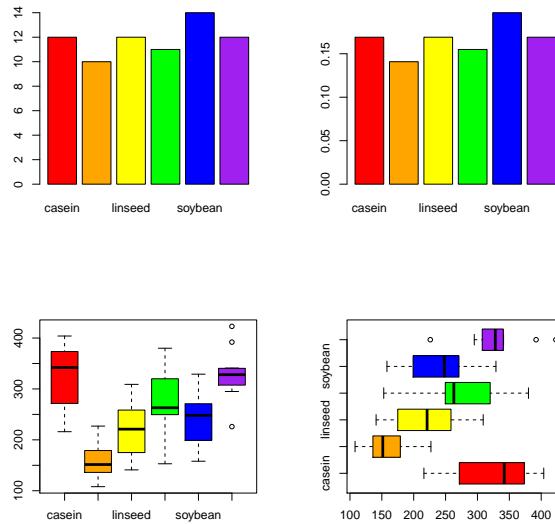
```
levels(chickwts$feed)

## [1] "casein"      "horsebean"    "linseed"     "meatmeal"    "soybean"     "sunflower"
```

1.2.5 Make the following plots in one 2 x 2 image:

- A bar chart of the feed types, each bar a different color.
- A bar chart of the proportions of feed types, each bar a different color.
- A boxplot of the weights by feed type, each box a different color.
- A horizontal boxplot of the weights by feed type, each box a different color.

```
par(mfrow = c(2, 2))
barplot(table(chickwts$feed),
        col = c("red", "orange", "yellow",
               "green", "blue", "purple"))
barplot(table(chickwts$feed)/length(chickwts$feed),
        col = c("red", "orange", "yellow",
               "green", "blue", "purple"))
boxplot(chickwts$weight~chickwts$feed,
        col = c("red", "orange", "yellow",
               "green", "blue", "purple"))
boxplot(chickwts$weight~chickwts$feed,
        col = c("red", "orange", "yellow",
               "green", "blue", "purple"),
        horizontal = TRUE)
```



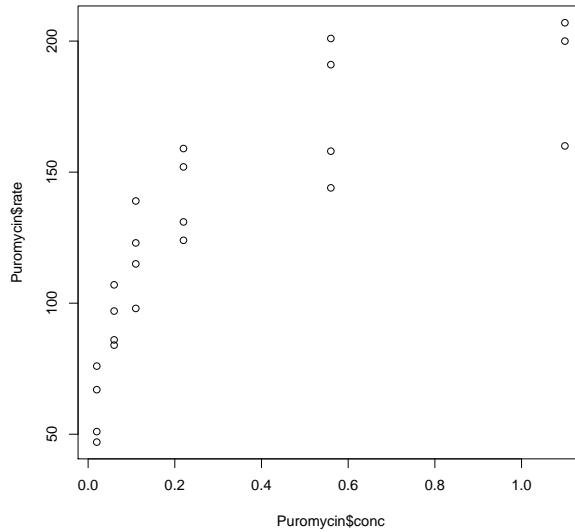
1.3 Use R to do the following exercises on the Puromycin data.

1.3.1 Display the built-in Puromycin data.

```
Puromycin
```

1.3.2 Make a scatterplot of the rate versus the concentration. Describe the relationship.

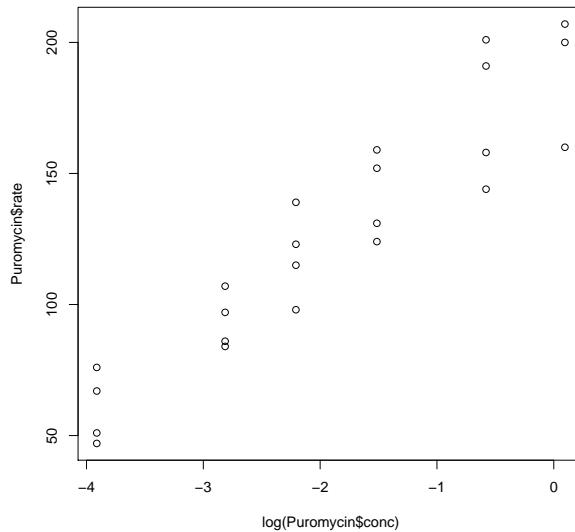
```
plot(Puromycin$conc, Puromycin$rate)
```



The rate increases faster at lower concentrations than at higher concentrations.

1.3.3 Make a scatterplot of the rate versus the log of the concentration. Describe the relationship.

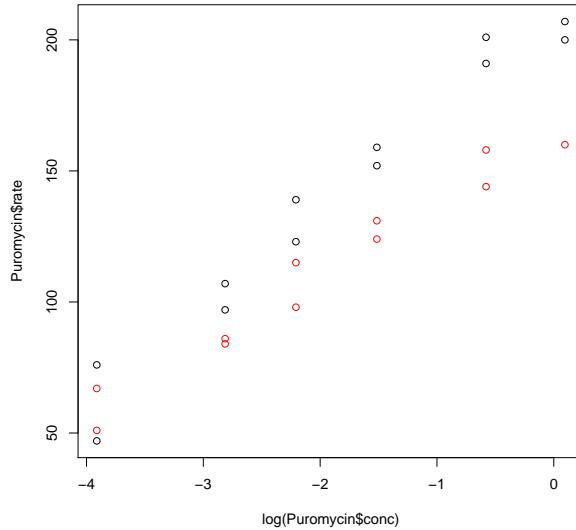
```
plot(log(Puromycin$conc), Puromycin$rate)
```



The two variables have a linear relationship.

- 1.3.4 Make a scatterplot of the rate versus the log of the concentration and color the points by treatment group (`state`). Describe what you see.

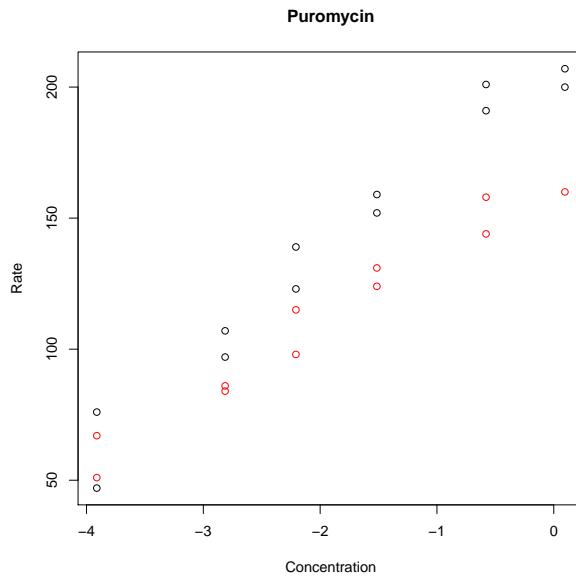
```
plot(log(Puromycin$conc), Puromycin$rate, col = Puromycin$state)
```



It appears that the the treated group has higher rates than the untreated group, on average. (Note that default colors are black for the first level and red for the second level).

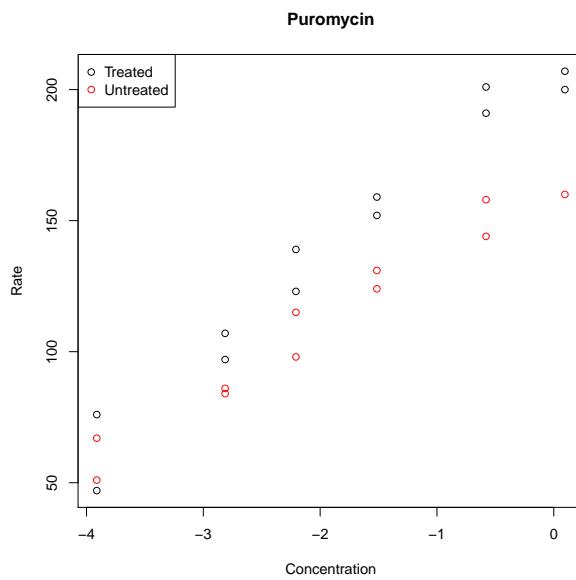
- 1.3.5 Make a scatterplot of the rate versus the log of the concentration, color the points by treatment group (`state`), label the x-axis “Concentration” and the y-axis “Rate”, and label the plot “Puromycin”.

```
plot(log(Puromycin$conc), Puromycin$rate, col = Puromycin$state,
      xlab = "Concentration", ylab = "Rate", main = "Puromycin")
```



1.3.6 Add a legend to the above plot indicating what the points represent.

```
plot(log(Puromycin$conc), Puromycin$rate, col = Puromycin$state,
      xlab = "Concentration", ylab = "Rate", main = "Puromycin")
legend("topleft", c("Treated", "Untreated"), col = 1:2, pch = 1)
```



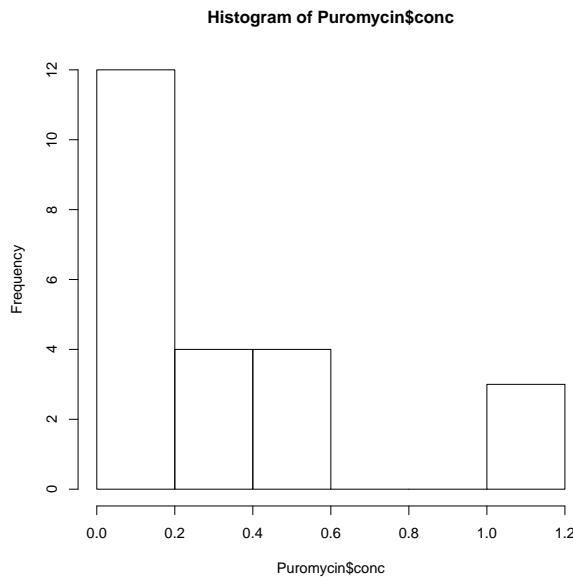
- 1.3.7 Make a boxplot of the treated versus untreated rates. Using the function `pdf`, save the image to a file with a width and height of 7 inches.

```
pdf("puromycin.pdf",width = 7, height = 7)
boxplot(Puromycin$rate~Puromycin$state)
dev.off()

## pdf
## 2
```

- 1.3.8 Make a histogram of the frequency of concentrations. What is the width of the bins?

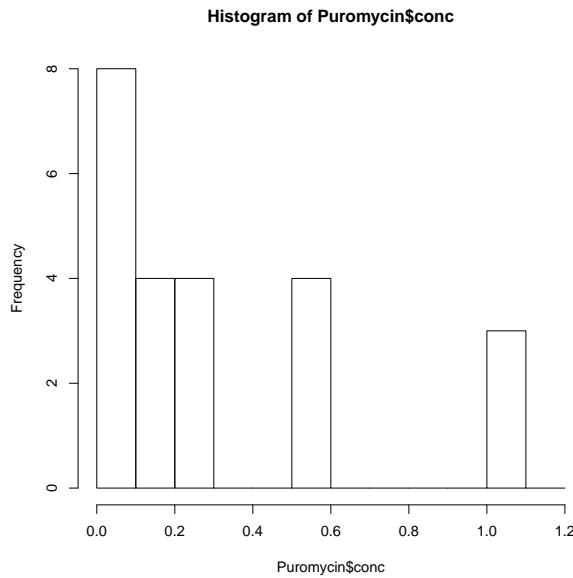
```
hist(Puromycin$conc)
```



The bin width is 0.20.

- 1.3.9 Make a histogram of the frequency of concentrations with a bin width of 0.10. How is this different from the histogram above?

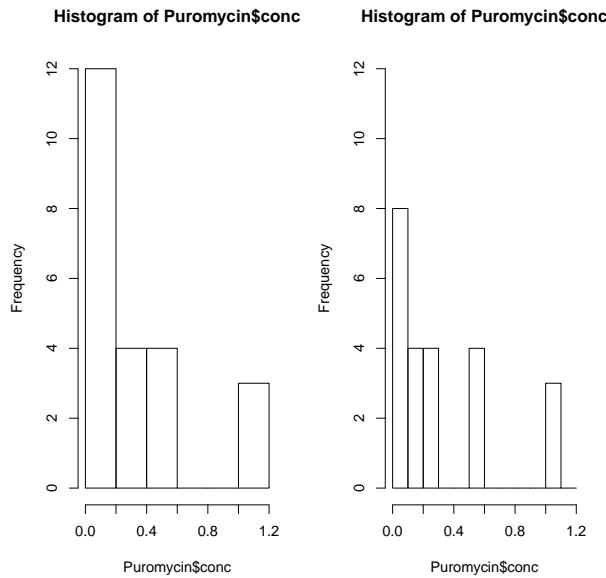
```
hist(Puromycin$conc, breaks = seq(0, 1.2, .10))
```



The bins are narrower, so we see in finer detail the distribution of the concentrations.

- 1.3.10 Plot the two histograms (bin widths 0.20 and 0.10) side by side in the same graphic window and make sure they have the same range on the y-axis. Does this make it easier to answer the question of how the two histograms differ?

```
par(mfrow = c(1, 2))
hist(Puromycin$conc, ylim = c(0, 12))
hist(Puromycin$conc, breaks = seq(0, 1.2, .10), ylim = c(0, 12))
```



In some situations it may be of use to view plots simultaneously. In this case, on the right we see clearly that more values are between 0 and 0.10 than 0.10 and 0.20 whereas the plot on the left does not display this information. In the histogram on the right we see that no concentrations fall between 0.30 and 0.50, whereas this is not apparent in the histogram on the left.

If you want to save your work: save your R session and/or source code!

Basic Course on **R**: Using ggplot2

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Oct 28th - Nov 1st, 2019

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1 Using ggplot2: Lecture

The basic plotting functions of R are nice to quickly visualize data, however, the strength of R is that it has many packages with extra functionality created by others that you can use. ggplot2 is one of those packages, created by Hadley Wickham. ggplot2 allows you to build more sophisticated plots in R using a “Grammar of Graphics” (therefore GGplot).

If ggplot2 is not yet available for you we need to install and load the ggplot2 library like so.

```
install.packages("ggplot2")
library(ggplot2)
```

ggplot2 is a very extensive package, so it is impossible to show all the possibilities during this course. If you would like to experiment further, the ggplot manual at <http://ggplot2.tidyverse.org/reference/index.html> is the place to go. A large variety of functionallities are listed there, including example plots.

1.1 Grammar of graphics

The grammar of graphics consists of a number of “layers”, which generate a ggplot, when correctly put together. These five basic layers will be discussed here:

- Data
- Aesthetics
- Geometries
- Facets
- Scales
- Themes

1.2 Data

The basis of each plot is the data. To plot data with ggplot the data needs to be of the class “data.frame”. The structure of your data.frame is important when you want to plot it with ggplot. Each variable you want to use has to be in a separate column in your data.frame. Take for example the “Indometh” dataset which comes with R.

```
?Indometh
```

The “Indometh” dataset describes the pharmacokinetics of indomethacin after intravenous injection of indomethacin in six subjects. The data.frame has three columns one containing the subject number, one containing the time of sampling in hours, and one containing the indomethacin concentration ug/ml. This dataset is easily plotted with ggplot because it is a data.frame and every column contains a separate variable.

```
##   Subject time conc
## 1       1 0.25 1.50
## 2       1 0.50 0.94
## 3       1 0.75 0.78
## 4       1 1.00 0.48
## 5       1 1.25 0.37
## 6       1 2.00 0.19
```

An example of a badly formatted dataset for visualization with ggplot is a dataset of monthly deaths from lung diseases in the UK:

```
?ldeaths
```

This dataset contains three separate datasets for female, male and both male and female deaths (ldeaths, fdeaths, and mdeaths). The columns contain values per month and the rows indicate the year.

```
##      Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
## 1974 3035 2552 2704 2554 2014 1655 1721 1524 1596 2074 2199 2512
## 1975 2933 2889 2938 2497 1870 1726 1607 1545 1396 1787 2076 2837
## 1976 2787 3891 3179 2011 1636 1580 1489 1300 1356 1653 2013 2823
## 1977 3102 2294 2385 2444 1748 1554 1498 1361 1346 1564 1640 2293
## 1978 2815 3137 2679 1969 1870 1633 1529 1366 1357 1570 1535 2491
## 1979 3084 2605 2573 2143 1693 1504 1461 1354 1333 1492 1781 1915
```

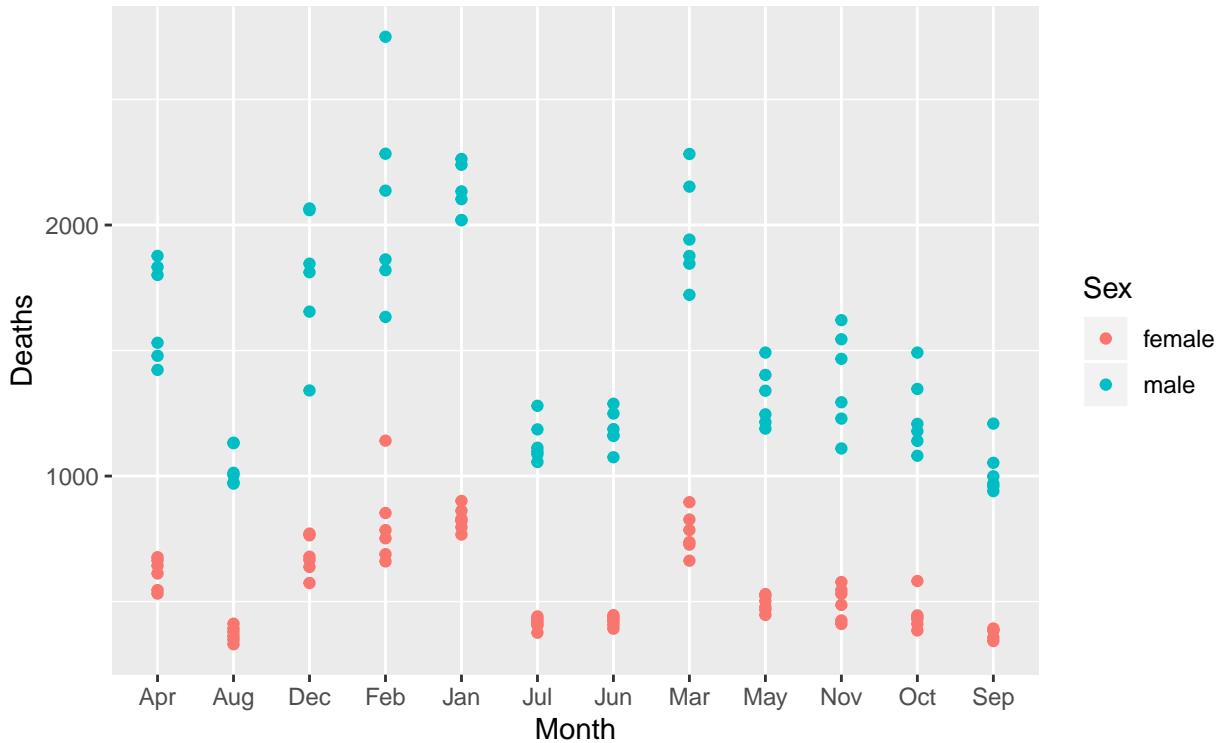
This dataset cannot be easily plotted using ggplot for three reasons:

- The dataset is not of the class data.frame
- The male and female datasets are separated in two objects
- The columns do not represent distinct variable values

We can use some more advanced R data reshaping to get these datasets in the right shape.

```
##   Deaths Year Month   Sex
## 1    901 1974    Jan female
## 2    689 1974    Feb female
## 3    827 1974    Mar female
## 4    677 1974    Apr female
## 5    522 1974    May female
## 6    406 1974    Jun female
```

```
ggplot(data, aes(x=Month, y=Deaths, color=Sex)) + geom_point()
```



However, it is much more easy to keep in mind that **any variable that you want to use as a part of your ggplot should get its own column** when you are designing your dataset (in Excel). With the data in the right class and the right format we can easily call the ggplot function, and add a scatter plot layer to it.

1.3 Aesthetics

After figuring out what data to plot, it is necessary to indicate how to plot it. Aesthetics are used to indicate how to plot what. As we saw in the plot of the ldeaths data we start with indicating what data.frame to plot and use aes() to indicate what to plot on the x axis, the y axis and what to use as color. We do not have to indicate what to plot where and which color to give to which category. We simply map a column of our data.frame to an aesthetic. Depending on the geom we use there are a number of aesthetics that can be mapped to a variable:

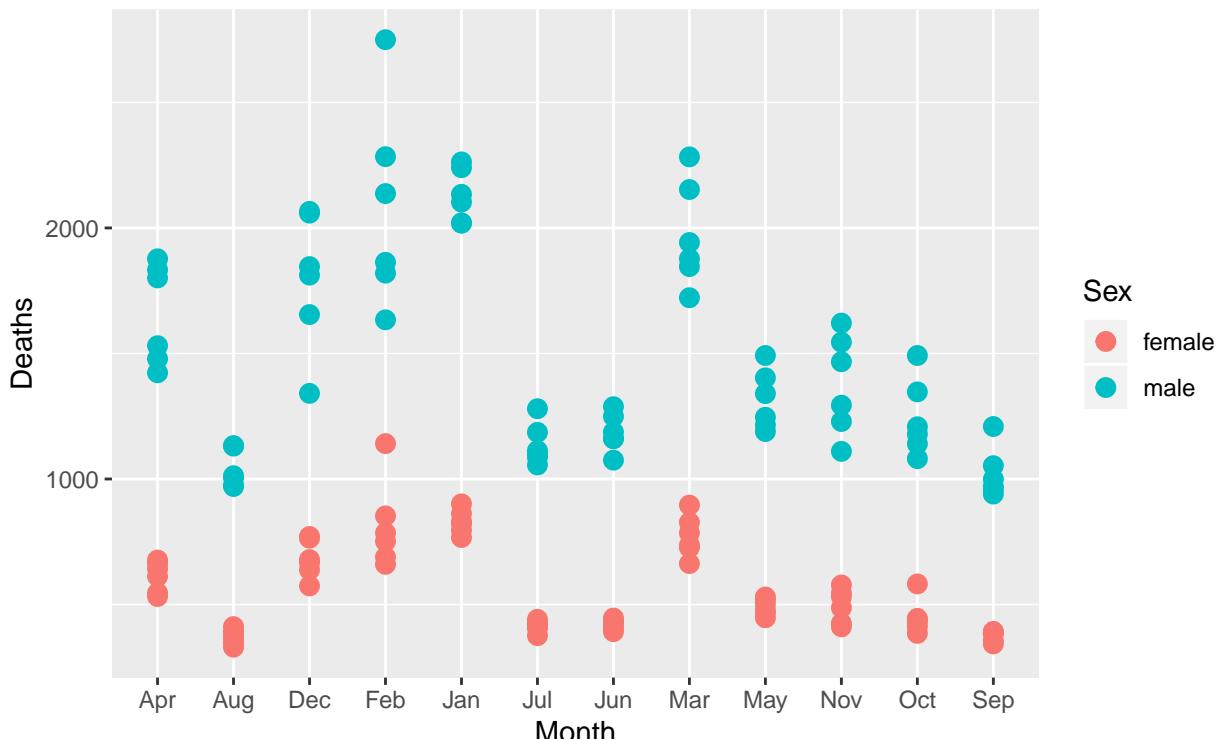
- x
- y
- color
- fill
- size
- alpha
- linetype
- labels
- shape
- group

Aesthetics can also be specified per geom layer. This allows plotting multiple geom layers with different aesthetics. However, when using one data source and one geom layer this will result in exactly the same plot.

```
ggplot(data) + geom_point(aes(x=Month, y=Deaths, color=Sex))
```

We can also use plotting parameters without mapping them to a variable to change all dots in the geom_point. This can only be done in the geom itself.

```
ggplot(data, aes(x=Month, y=Deaths, color=Sex)) + geom_point(size=3)
```



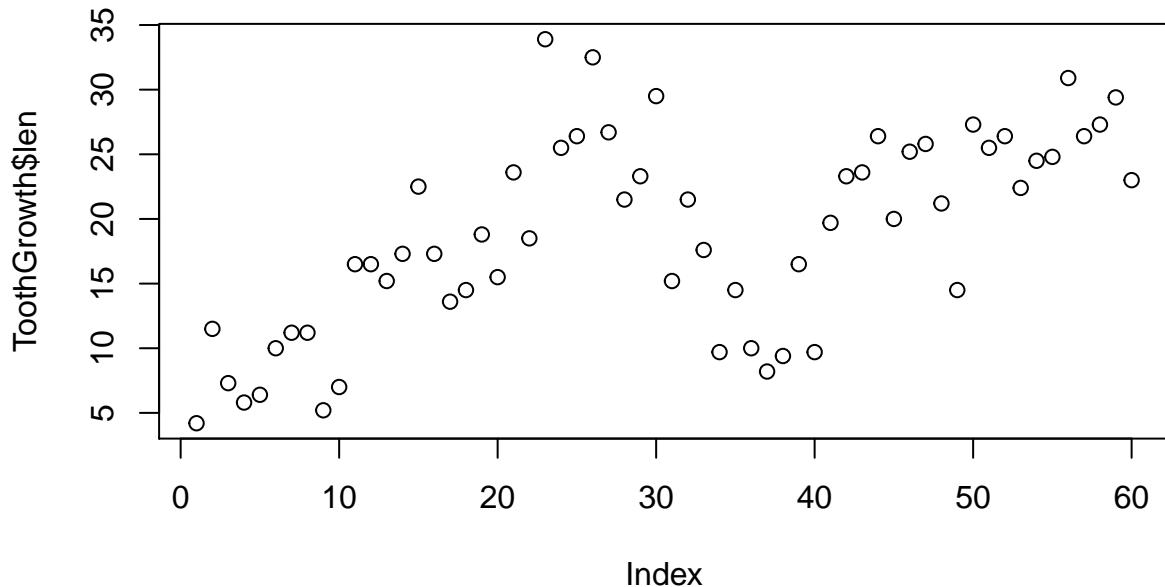
1.4 Geometries

For the previous ggplots we have used the `geom_point` function which generates a scatter plot layer that can be added to the `ggplot`. “`point`” is one of the many geometry layers available in the `ggplot` library. There are over thirty different geoms in `ggplot` which can be found at <http://ggplot2.tidyverse.org/reference/index.html>. We will have a look at the plot types that we have already encountered using the basic R plotting functions and replace them with their `ggplot` counterparts.

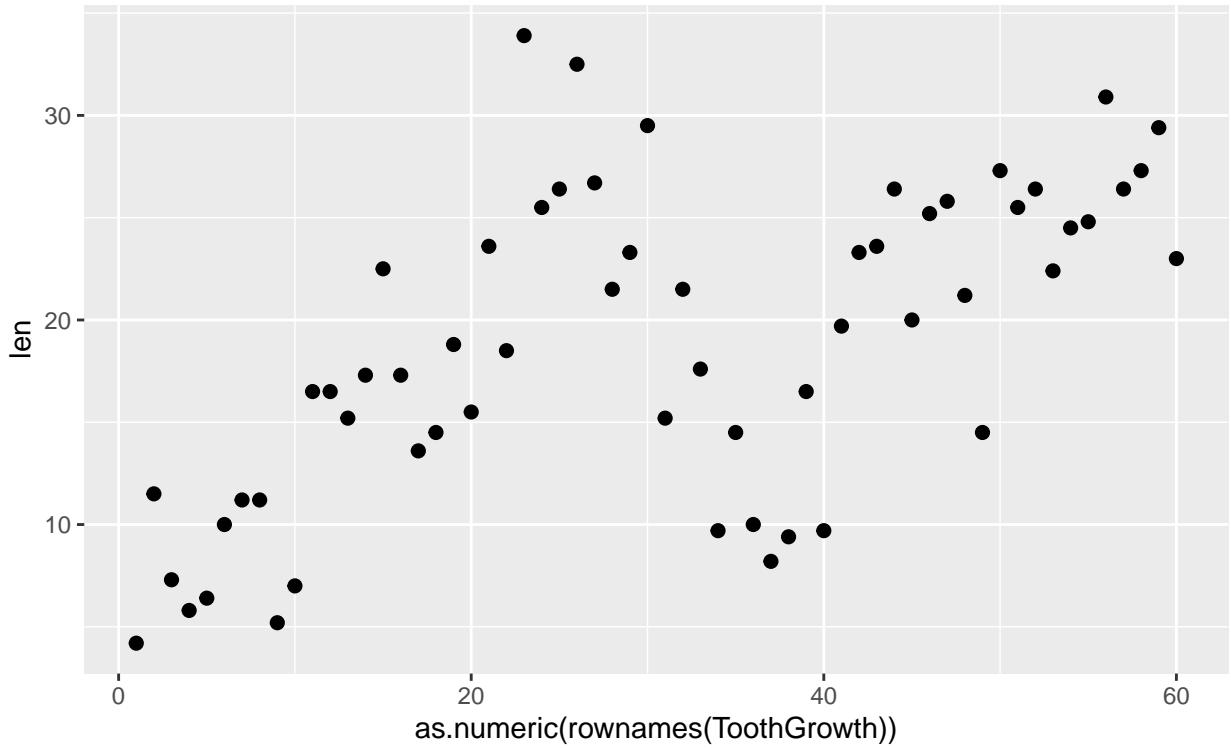
1.4.1 Scatter plots

Just like with other objects in R a `ggplot` object can be saved to a variable using “`<-`”. This makes it possible to store the basic plot in a variable and add different geoms to it. Geometries are added to a plot using “`+`”.

```
#Basic graphics:  
plot(ToothGrowth$len)
```



```
p <- ggplot(ToothGrowth)
p + geom_point(aes(x=as.numeric(rownames(ToothGrowth)), y=len), size=2)
```



We now map the numeric rownames of ToothGrowth to the x aesthetic, however, we could also create a new column called index in the data.frame.

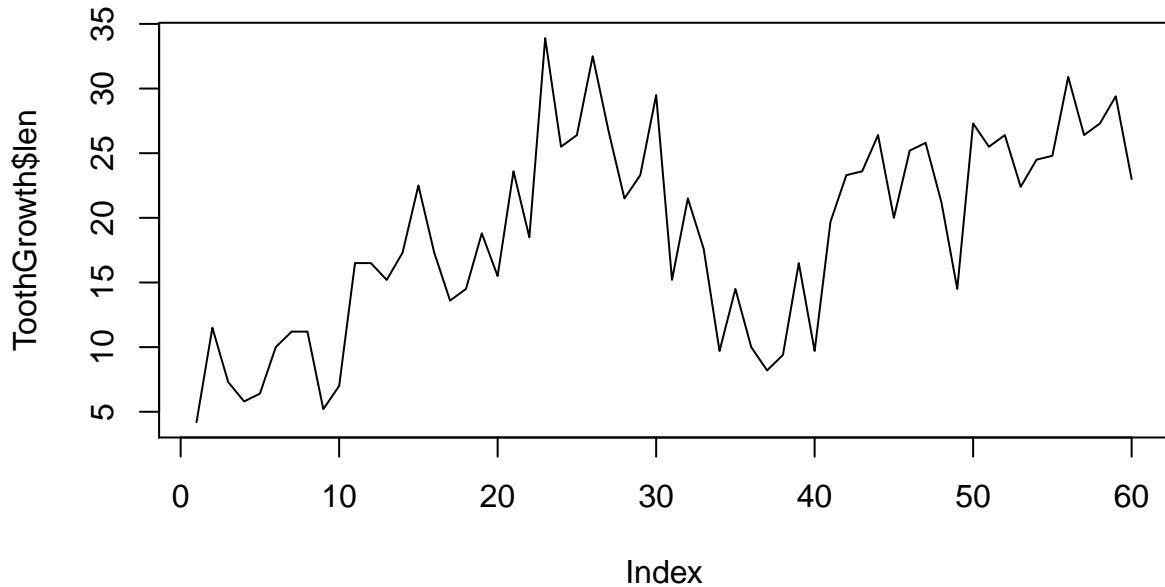
```
ToothGrowth$index <- as.numeric(rownames(ToothGrowth))
```

When we change the data of the ggplot object we saved in variable p we need to recreate the ggplot object with the new dataset.

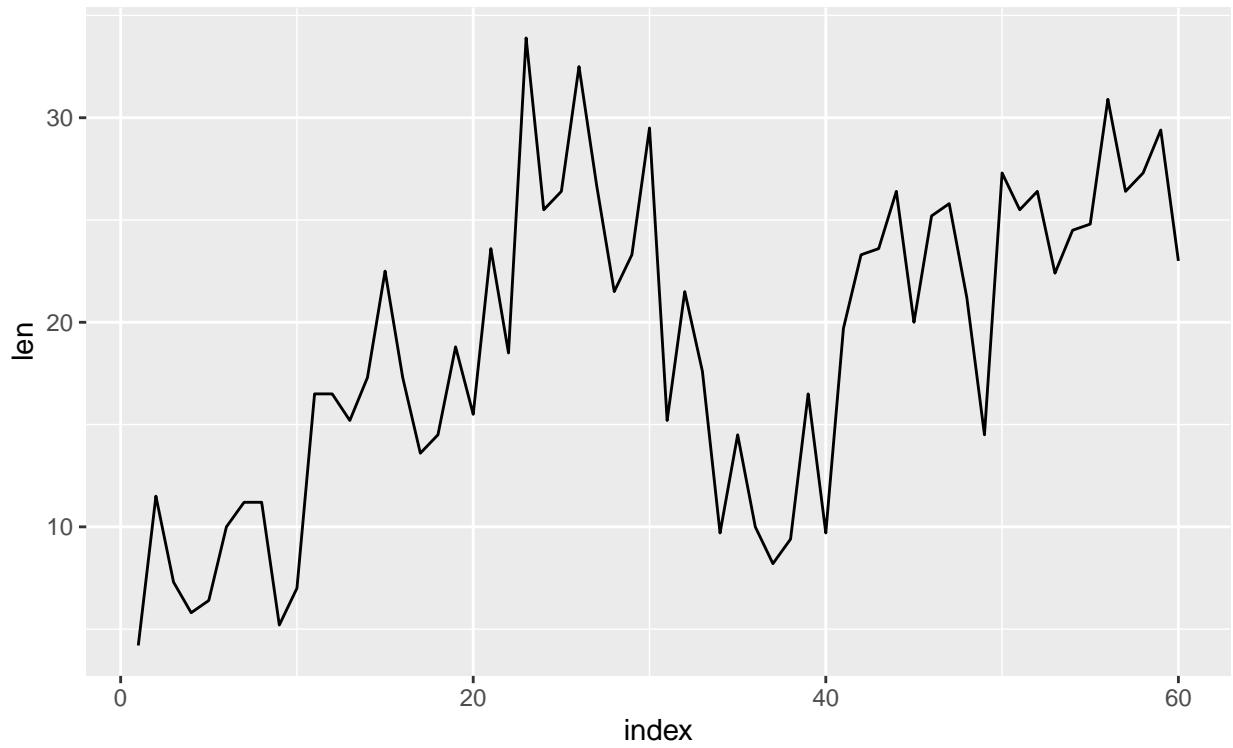
```
p <- ggplot(ToothGrowth)
```

1.4.2 Line graphs

```
#Basic graphics:  
plot(ToothGrowth$len, type = "l")
```

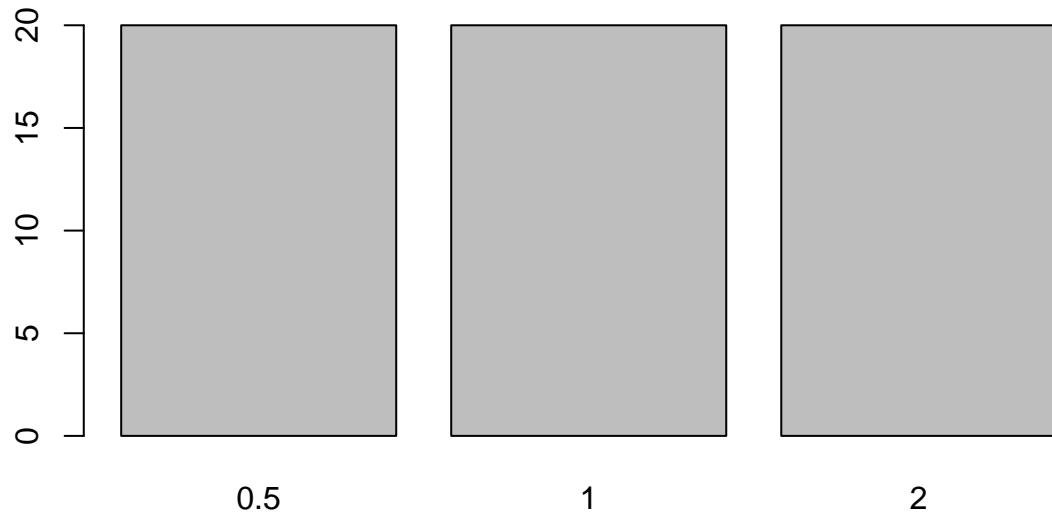


```
p + geom_line(aes(x=index, y=len))
```

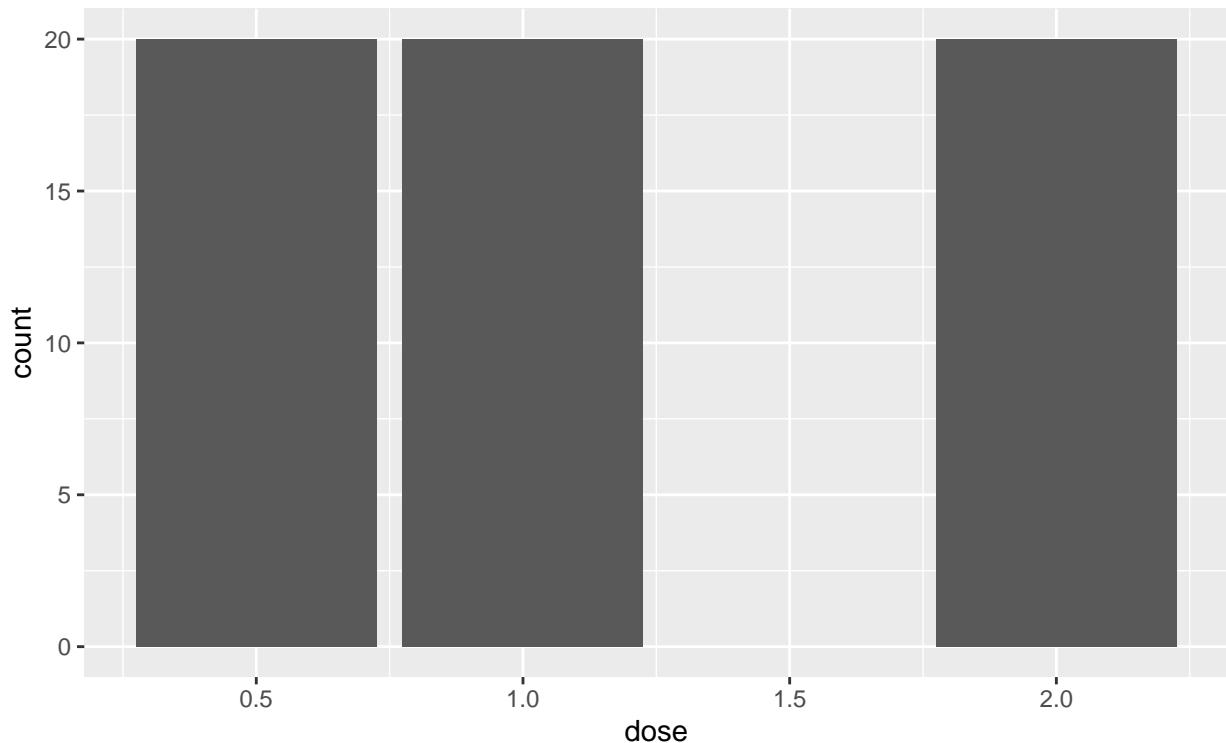


1.4.3 Bar charts

```
#Basic graphics:  
barplot(table(ToothGrowth$dose))
```

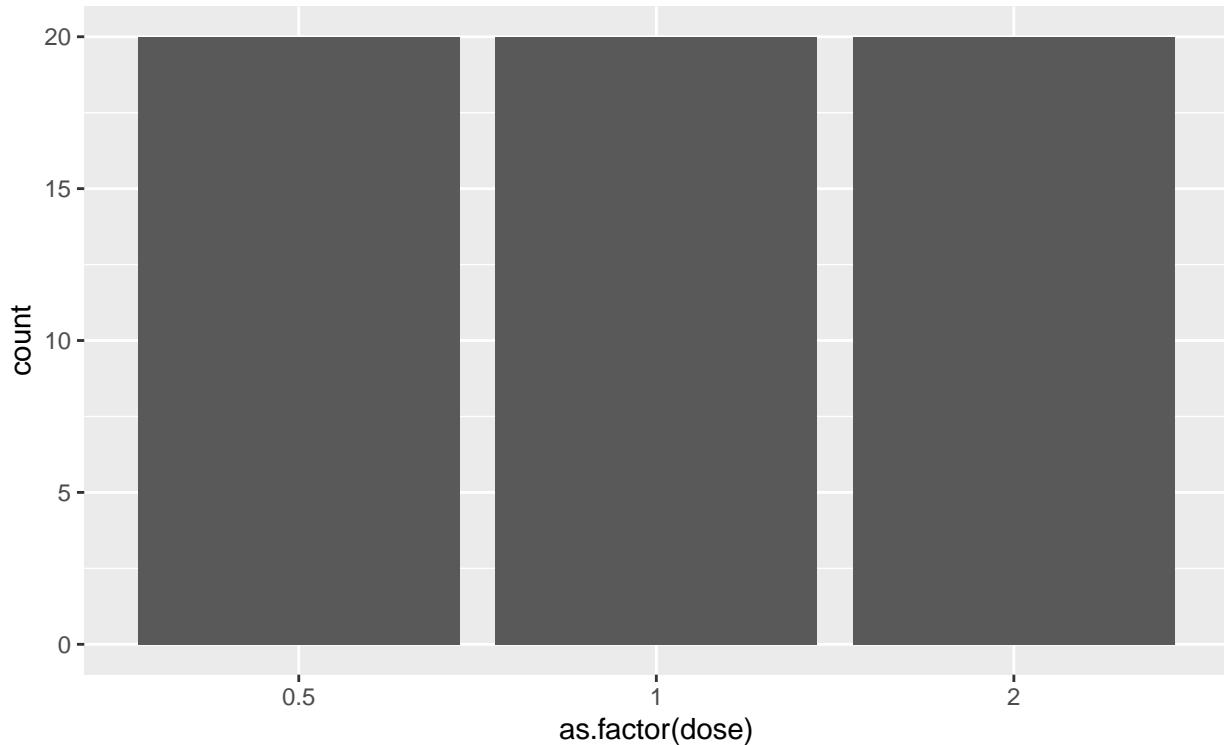


```
p + geom_bar(aes(x=dose))
```



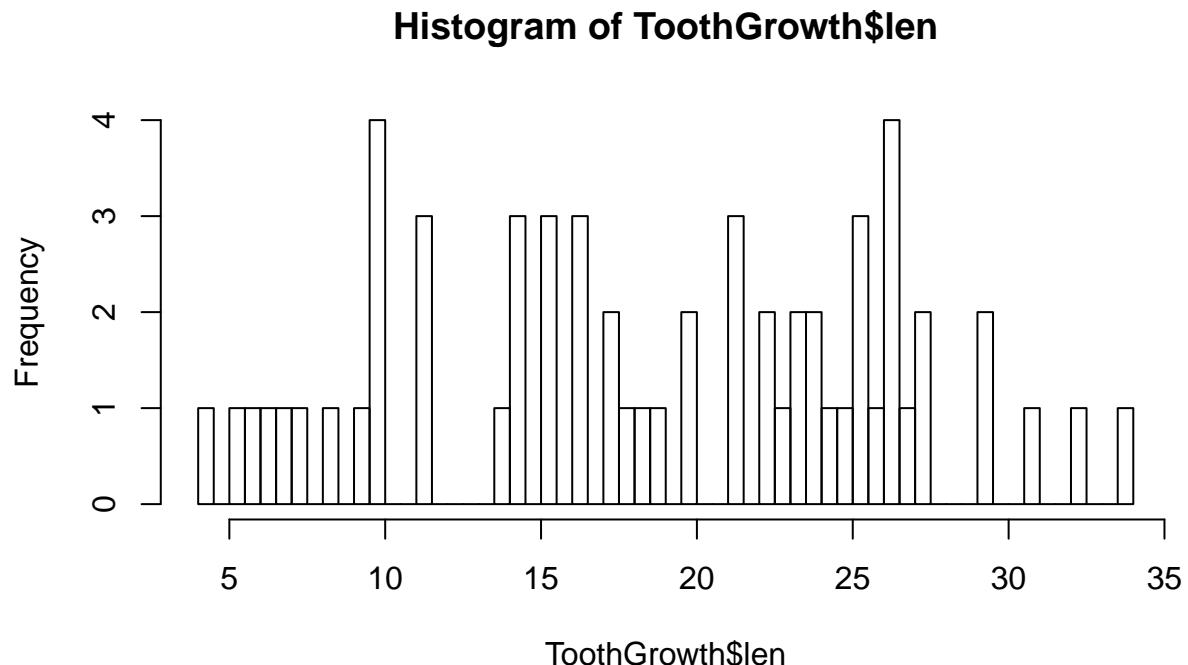
Because dose is a continuous variable, ggplot creates a x axis with a continuous scale, which is why there is an empty spot for the 1.5 dose. If we want to use a continuous value as a categorical value we can change it into a factor on the fly in the geom function:

```
p + geom_bar(aes(x=as.factor(dose)))
```

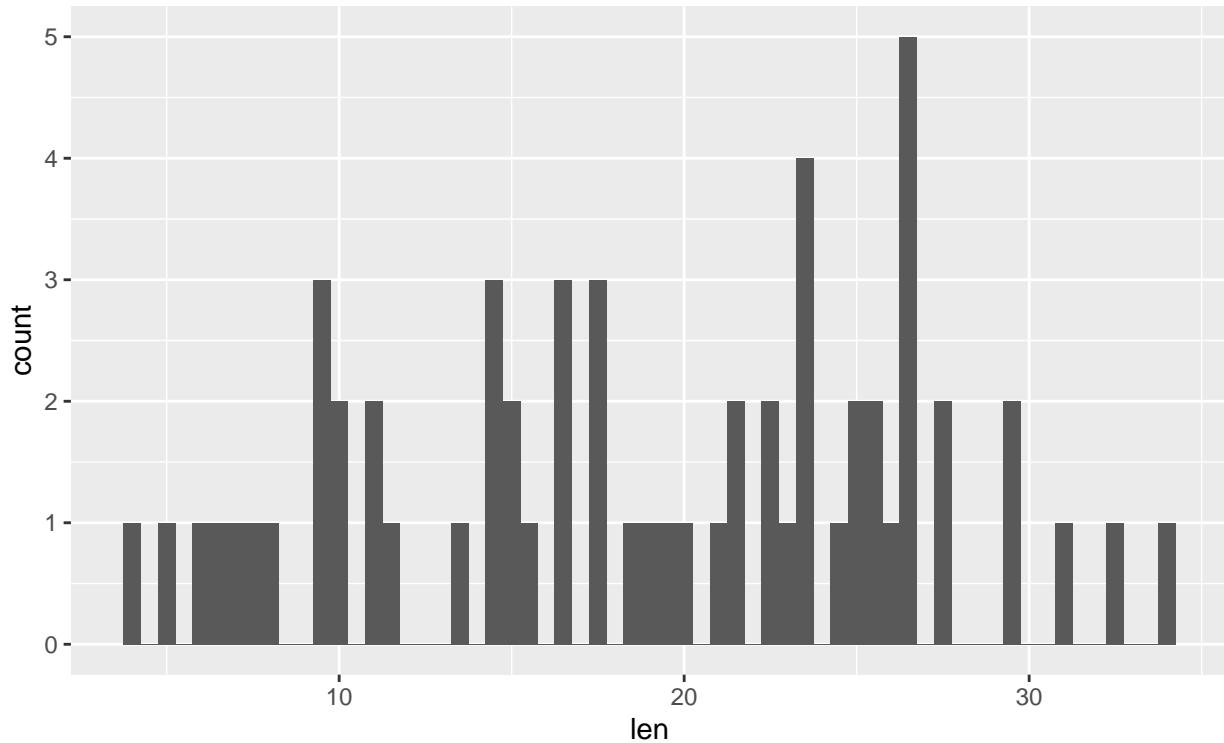


1.4.4 Histograms

```
#Basic graphics:  
hist(ToothGrowth$len, breaks = 50)
```

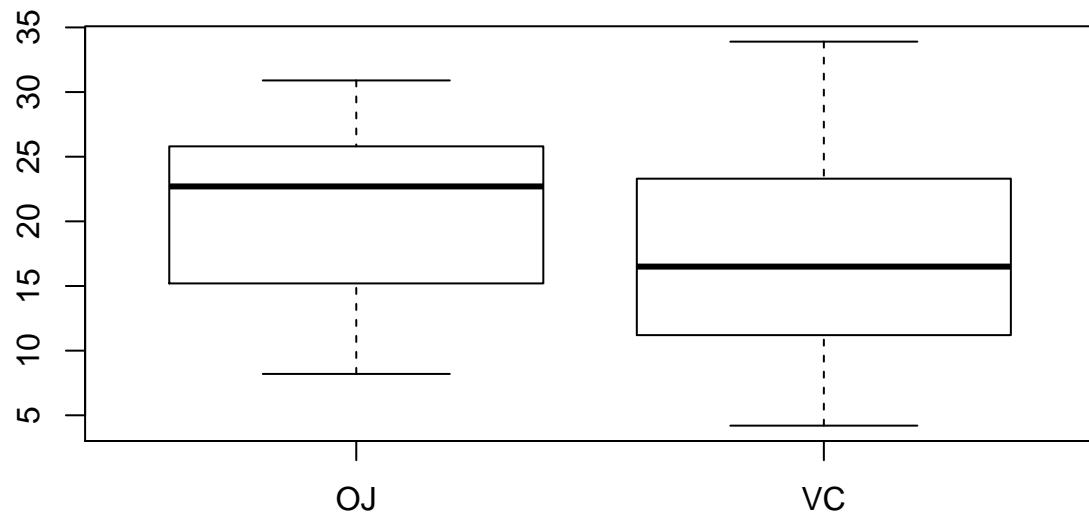


```
p + geom_histogram(aes(x=len), binwidth = 0.5)
```

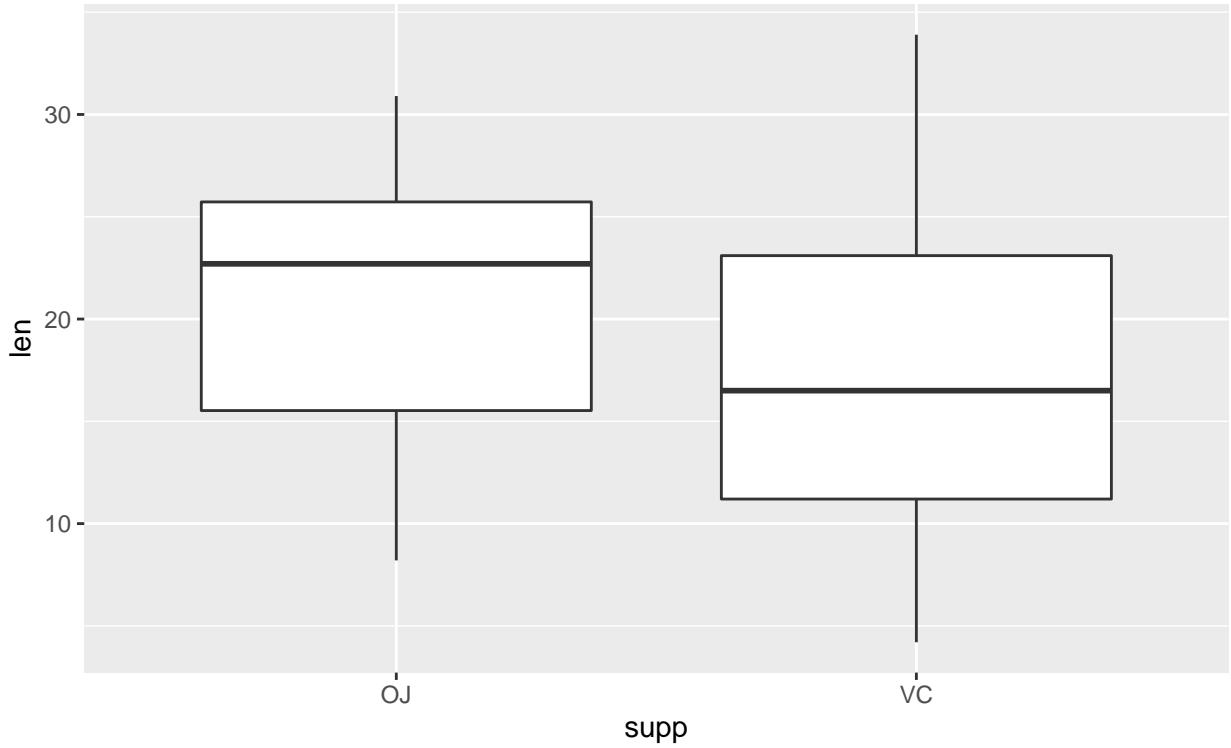


1.4.5 Box plots

```
#Basic graphics:  
boxplot(ToothGrowth$len~ToothGrowth$supp)
```

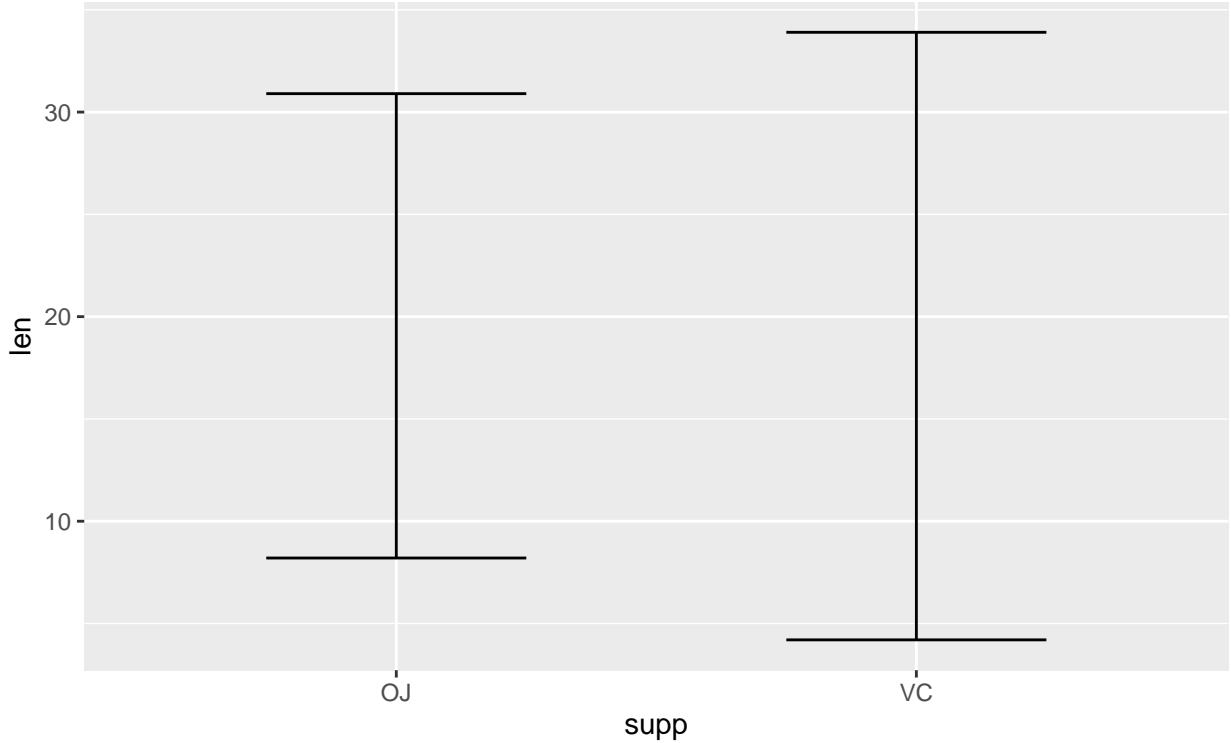


```
p + geom_boxplot(aes(x=supp,y=len))
```



If we want whiskers in our plot we can add an errorbar geom

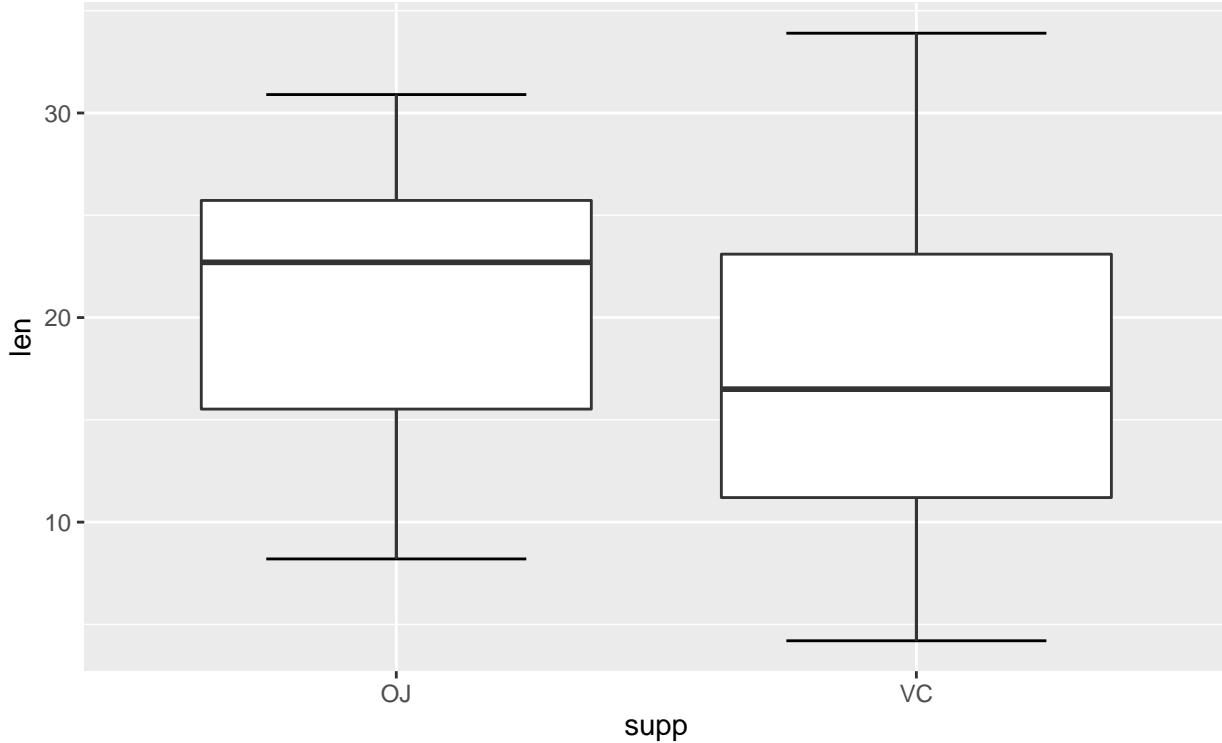
```
p + geom_errorbar(aes(x=supp, ymin=..., ymax=...), width=0.5)
```



However, as you can see, this geom requires ymin and ymax as aesthetics and does not calculate the values by itself. We could calculate the min and max values for toothlength grouped by supplement, but we will use a trick using ggplot's boxplot statistics function. (*if you want to know more, please read more about these "stat" functions online*)

First, we add the errorbars with the "stat_boxplot" function, and then add the boxplots on top of them.

```
p + stat_boxplot(aes(x=supp,y=len), geom="errorbar", width=0.5) +
  geom_boxplot(aes(x=supp,y=len))
```



As we can see the aesthetics of both geoms have to be defined separately in this plot. To reduce typing we could also write the ggplot as follows.

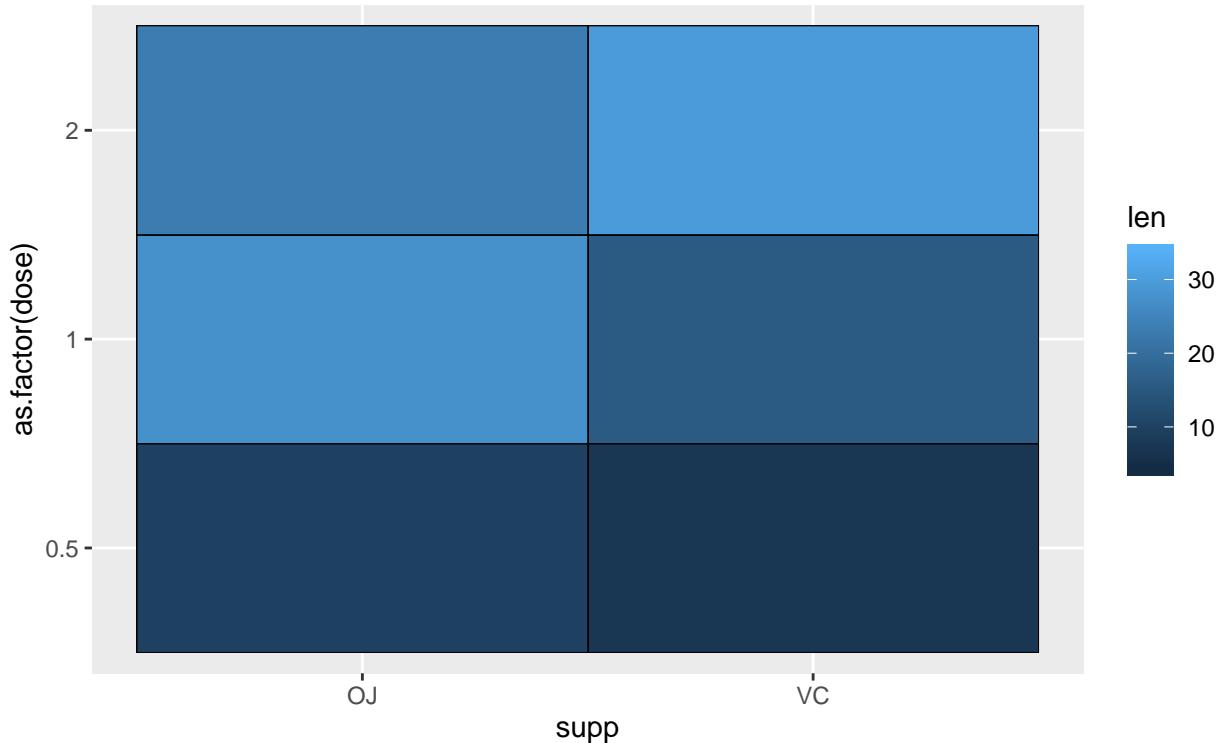
```
p <- ggplot(ToothGrowth, aes(x=supp,y=len))
p + stat_boxplot(geom="errorbar", width=0.5) + geom_boxplot()
```

When the aesthetics are specified in the base ggplot object it is not necessary to specify them in the added layers.

1.4.6 Heatmaps

One popular way of displaying large grids of data is using a heatmap. The tile geom generates a tile at each provided x and y value and uses the fill aesthetic to fill the tiles according to another variable. The border color of the tiles are can be changed by using the color aesthetic.

```
p <- ggplot(ToothGrowth)  
p + geom_tile(aes(x = supp, y = as.factor(dose), fill = len), color="black")
```



There are dedicated packages for plotting heatmaps, which also perform horizontal and vertical clustering of the tiles. These are, however, out of the scope of this course, but it should be easy to find them online.

1.5 Facets

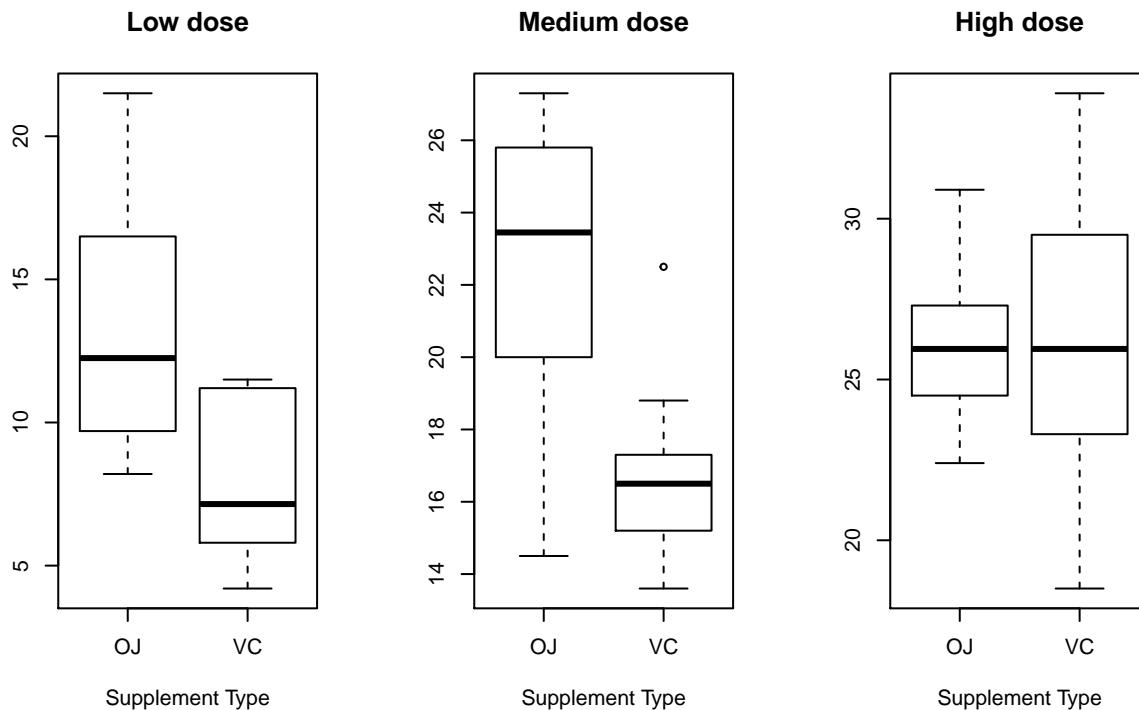
Apart from using aesthetics to map variables to, ggplot has another feature which can help visualizing data called “facets”. We have added multiple plots to the viewing window before, using “`par(mfrow=c(...,...))`”. However, after specifying how many plots should be printed in the plot viewer we have to call the plot function multiple times to populate the viewer.

If we want to compare the effect of orange juice versus vitamin C depending on the dose we can plot three boxplots next to eachother.

```
par(mfrow = c(1, 3))

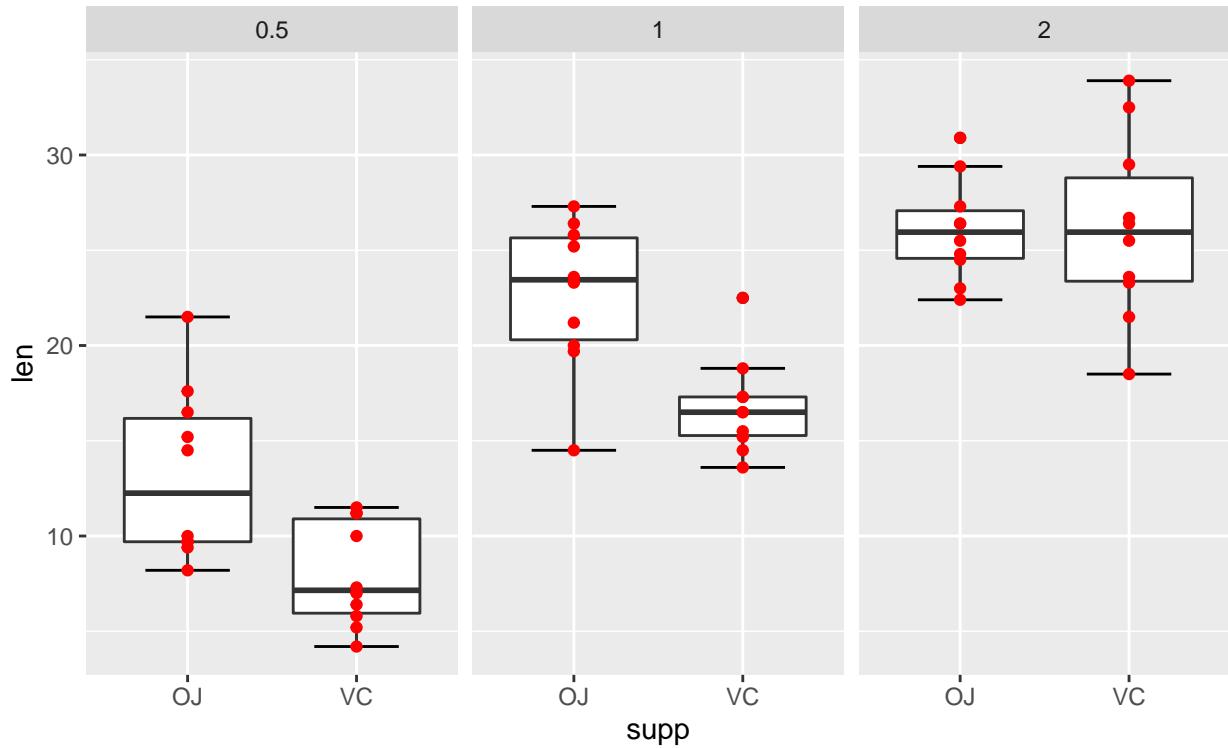
low <- ToothGrowth[which(ToothGrowth$dose==0.5),]
med <- ToothGrowth[which(ToothGrowth$dose==1),]
high <- ToothGrowth[which(ToothGrowth$dose==2),]

boxplot(low$len-low$supp, main = "Low dose", xlab = "Supplement Type")
boxplot(med$len-med$supp, main = "Medium dose", xlab = "Supplement Type")
boxplot(high$len-high$supp, main = "High dose", xlab = "Supplement Type")
```



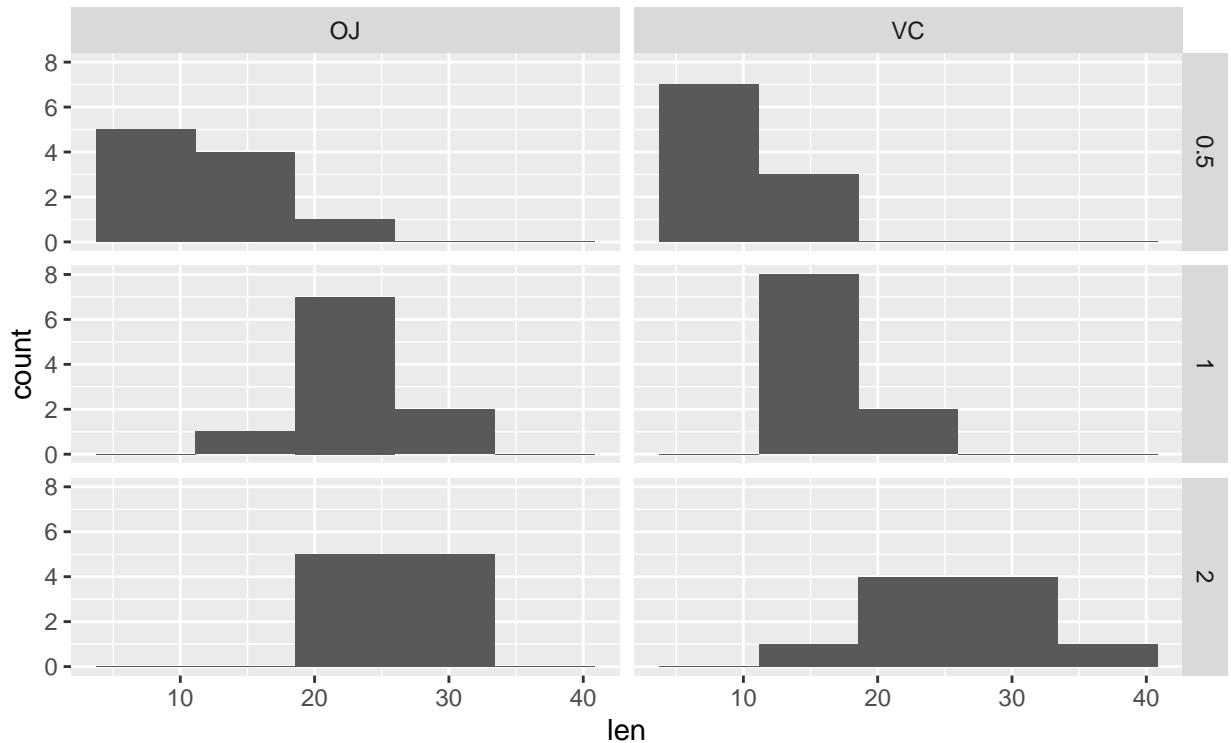
However, using ggplot we can simply map the dose column to a ggplot facet grid. The mapping of variables is not done via a `aes()`, but in formula form. Variables on the right indicate the columns in the grid and variables on the left indicate the rows of the grid. A “.” can be used if we want to use only one variable for faceting. This will also preserve the scales, making it more easy to compare the three plots. For fun, let's add the actual datapoints in an additional geom on top of the boxplot.

```
ggplot(ToothGrowth, aes(x=supp,y=len)) +
  stat_boxplot(geom="errorbar", width=0.5) +
  geom_boxplot() + geom_point(color="red") +
  facet_grid(. ~ as.factor(dose))
```



We can do the same with two variables in a grid.

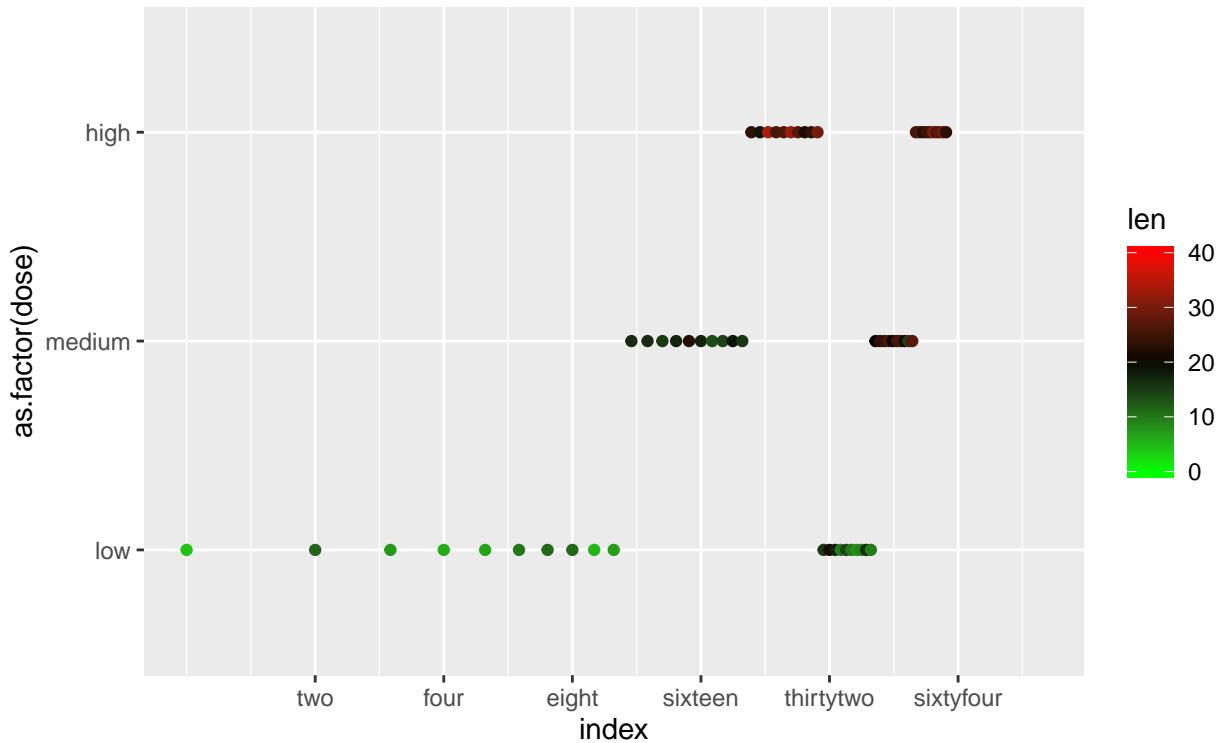
```
ggplot(ToothGrowth, aes(x=len)) +  
  geom_histogram(bins = 5) +  
  facet_grid(dose ~ as.factor(supp))
```



1.6 Scales

When mapping a variable to one of the aesthetics of a ggplot, ggplot uses the default scales. It is however possible to adjust the scales of the plot and their color using the scales functions. The scales that are generally used the most are those for the x, y, color and fill of the plot. The name of the scale depends on which scale you would like to adjust. So “scale_x_...” changes the x scale and “scale_fill_..” changes the scale of the “fill” aesthetic. The type of function to adjust the scale of one of the aesthetics depends on the aesthetic and the type of variable (continuous or discrete). Some of the possible scale adjustments, such as limits, transformation, breaks, labels, and color, are exemplified by the plot below.

```
ggplot(ToothGrowth, aes(x=index, y=as.factor(dose), color=len)) +  
  geom_point() +  
  scale_x_continuous(limits=c(1,100), trans = "log2",  
    breaks=c(2,4,8,16,32,64),  
    label=c("two", "four", "eight", "sixteen", "thirtytwo", "sixtyfour")) +  
  scale_y_discrete(label=c("low", "medium", "high")) +  
  scale_color_gradient2(limits=c(0,40), low = "green", mid = "black", high = "red",  
    midpoint = 20)
```



Have a look at the scales chapter at <http://ggplot2.tidyverse.org/reference/> to explore the other possibilities!

1.7 Themes

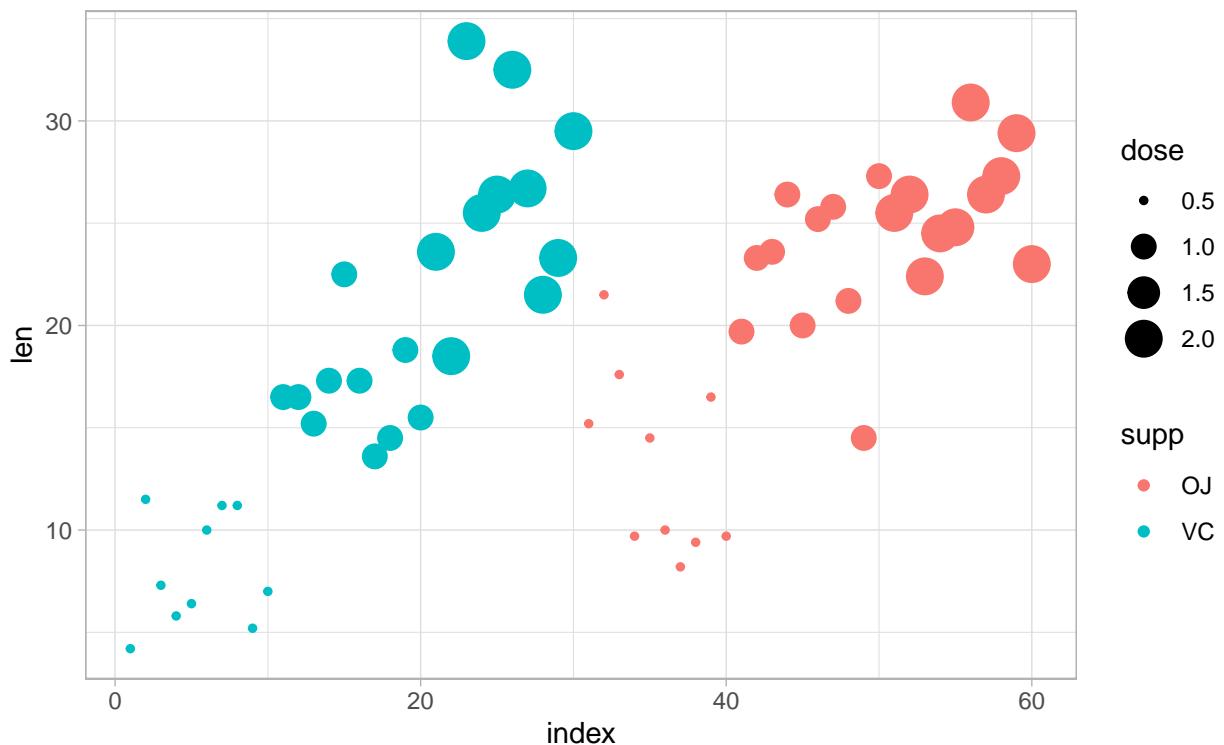
Until now we have simply mapped a variable from our dataset to an aesthetics parameter, potentially change the scales, and let ggplot handle the styling of the graph. However, ggplot has many options to customize the style of your plot using themes. There are several standard themes that we can use, however it is possible to create our own style from scratch.

The standard themes available in the ggplot package are:

- theme_gray
- theme_bw
- theme_linedraw
- theme_light
- theme_dark
- theme_minimal
- theme_classic
- theme_void

To add a standard theme we simply add the theme to the ggplot like we would with a geom.

```
p <- ggplot(ToothGrowth)
p + geom_point(aes(x = index, y = len, color = supp, size = dose)) + theme_light()
```



Custom themes can be made from scratch using the “theme()” function. To have a look at all customizable parameters visit <http://ggplot2.tidyverse.org/reference/theme.html>. Labels can be edited by adding “labs()” to the plot.

```
p <- ggplot(ToothGrowth)
p + geom_point(aes(x = index, y = len, color = supp, size = dose)) +
  theme(text = element_text(colour = "#6f898e"),
        line = element_line(color = "#163f47"),
        rect = element_rect(fill = "#163f47", color = "#163f47"),
        axis.text.x = element_text(color="black"),
        axis.text.y = element_text(color="white"),
        axis.ticks = element_line(color = "#6f898e"),
        axis.line = element_line(color = "#163f47", linetype = 1),
        legend.background = element_blank(),
        legend.key = element_blank(),
        panel.background = element_rect(fill = "#215c68", colour = "#163f47"),
        panel.border = element_blank(),
        panel.grid = element_line(color = "#163f47"),
        panel.grid.major = element_line(color = "#163f47"),
        panel.grid.minor = element_line(color = "#163f47"),
        plot.background = element_rect(fill = NULL, colour = NA, linetype = 0)
) +
  labs(title="Toothgrowth",
       subtitle = "Orange juice or Vitamin C?", x="Index", y="Toothlength",
       size="Dose", color="Supplement") +
  scale_color_manual(label=c("Orange juice","Vitamin C"),
                     values = c("VC"="green","OJ"="orange"))
```



1.8 Saving ggplots

We can save out plots by using the `ggsave()` function. `ggsave` takes two arguments, the first argument being the ggplot and the second being the location where the file should be saved. If we do not specify the complete path, it will save the plot in our current working directory (`getwd()`). The type of the file depends on the file extension we use. Possible file extensions are “`eps`”, “`ps`”, “`tex`” (pictex), “`pdf`”, “`jpeg`”, “`tiff`”, “`png`”, “`bmp`”, “`svg`” or “`wmf`” (windows only).

```
p <- ggplot(ToothGrowth)

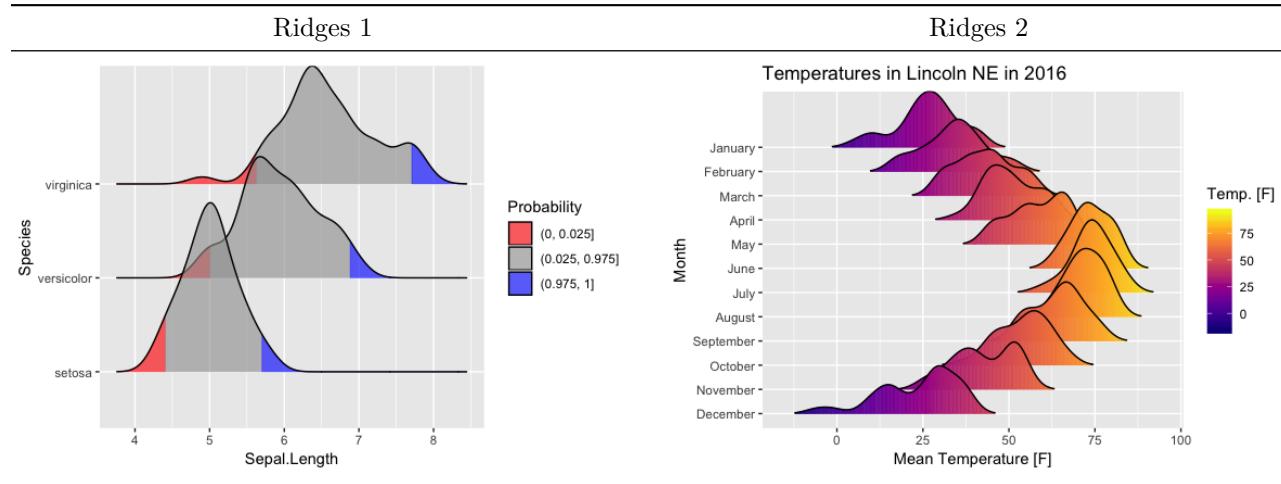
myplot <- p + geom_point(aes(x = index, y = len, color = supp, size = dose))

ggsave("my_plot.pdf", myplot)
```

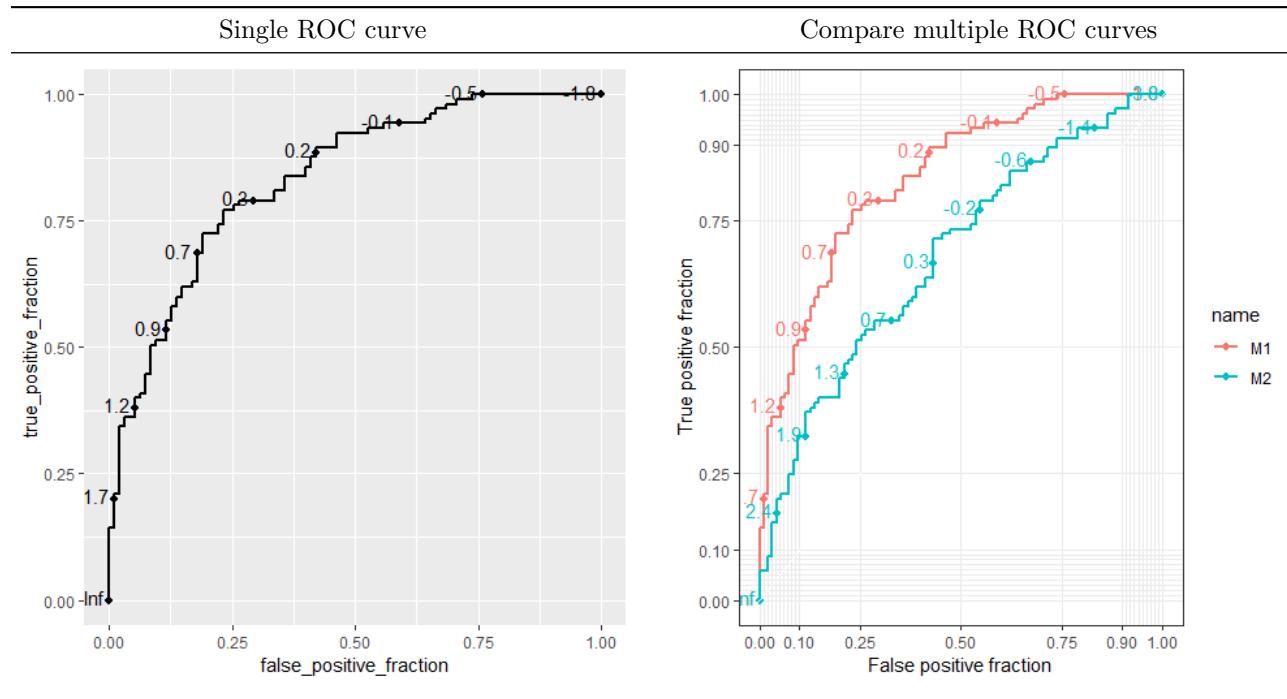
1.9 ggplot extensions

Basic ggplot functions are enough to create a rich variety of plots. However, depending on the field of research, specific plots are popular to visualize specific types of data. Sometimes these plots cannot be made directly from “basic” ggplot. Since ggplot is an open-source package, several people have extended it to fulfill the custom needs of users. Many of these ggplot extension packages can be found online with a quick google. The ggplot2 extensions gallery shows some nice examples of add-ons <http://www.ggplot2-exts.org/gallery/>. Below are a handful of examples, which we will not explain in detail, but should serve as a source of inspiration.

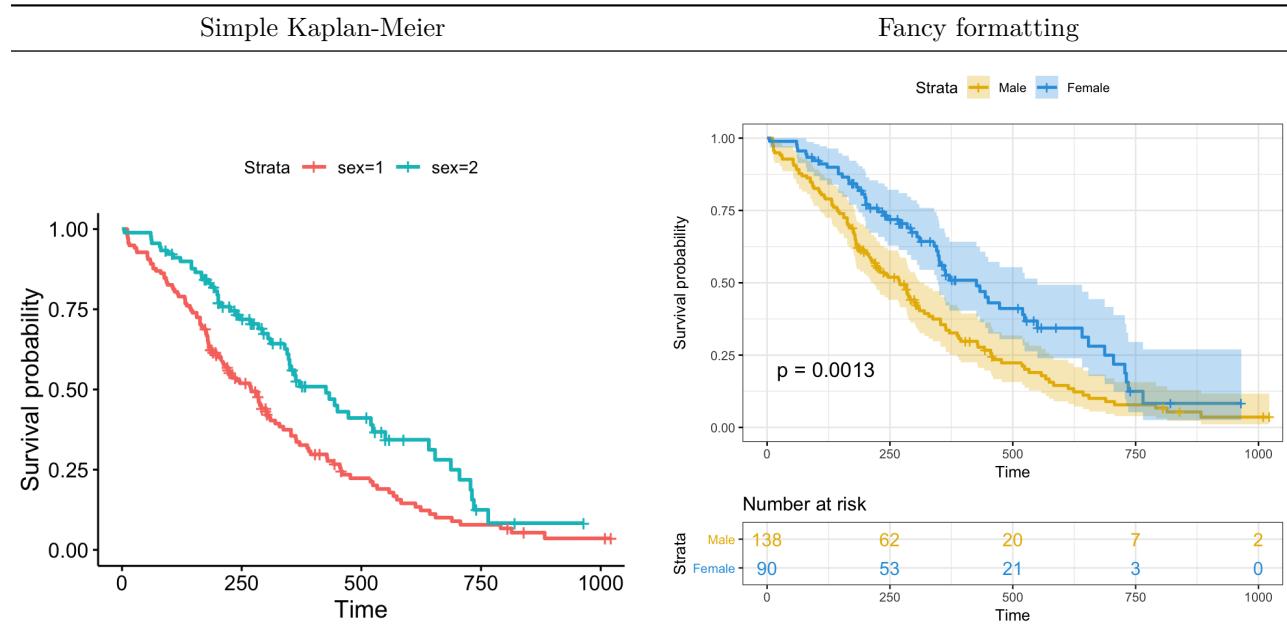
ggridges <https://cran.r-project.org/web/packages/ggridges/>



ggROC <https://cran.r-project.org/web/packages/ggroddges/>



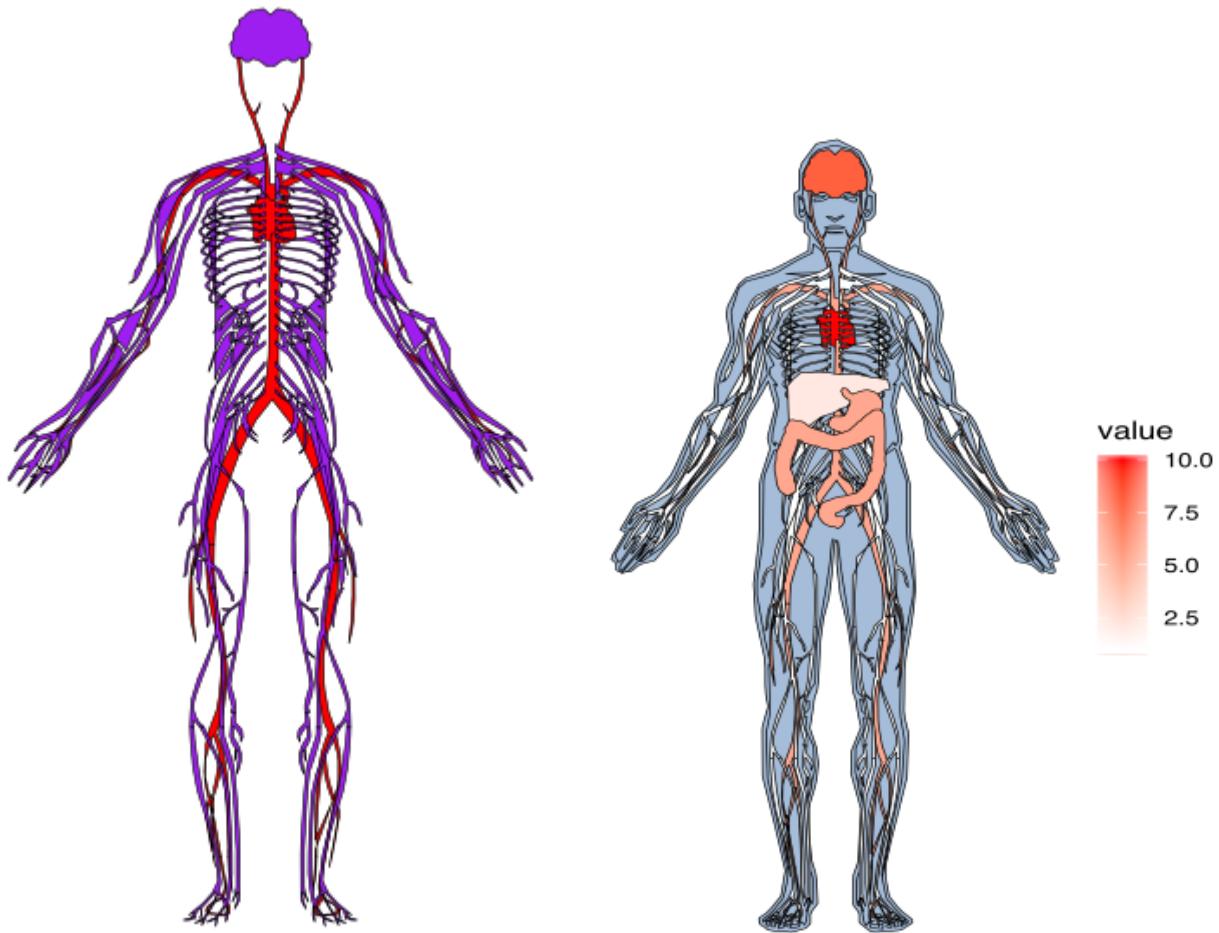
survminer <https://rpkgs.datanovia.com/survminer/index.html>



ggnatogram <https://jespermaag.github.io/blog/2018/ggnatogram/>

Nervous system

Adding data



Using ggplot: Practical

1. Load the `ggplot2` library (install it if you have to) and the `diamonds` dataset using `data()`
2. Explore the dataset using `dim()`, `str()` and `help()`, which variables are continuous, which variables are discrete? Is this dataset ready for plotting with `ggplot`?
3. Use `ggplot` to plot a scatterplot of the relationship between the diamonds" carat and their price
4. Make all dots darkblue and set the alpha value to 0.1
5. Visualize the influence of the color of a diamond on its price by mapping the diamond color to the color aesthetic
6. Use a `ggplot` barplot to visualize diamond clarity depending on color, map diamond color to x and diamond clarity to fill
7. Create a boxplot of the carat of a diamond based on its clarity and add whiskers using `stat_boxplot`
8. Add a `geom_point` layer to the previous plot mapping the diamonds price to the color
9. Create a histogram of the price of the diamonds and separate the histograms into facets using diamond color, choose a good binwidth or number of bins
10. Create a grid of facets of the same histogram by comparing both color and cut
11. Use '`aggregate(diamonds, by = list(cut = diamonds$cut, color = diamonds$color), mean)`' to calculate the mean of all variables by cut and color. Create a heatmap of the mean prices by cut and color using `geom_tile`
12. Change the title of the heatmap to "Average prices"
13. Change the gradient of the fill scale using '`scale_fill_gradient2`'. Have it go from darkblue to white to darkred, set the midpoint to 4500
14. Choose and add a theme to the heatmap, or create a theme yourself using the options listed at <http://ggplot2.tidyverse.org/reference/theme.html>

Using ggplot: Answers

1. Load the `ggplot2` library (install it if you have to) and the `diamonds` dataset using `data()`

```
# if needed install.packages("ggplot2")
library(ggplot2)
data("diamonds")
```

2. Explore the dataset using `dim()`, `str()` and `help()`, which variables are continuous, which variables are discrete? Is this dataset ready for plotting with `ggplot`?

```
dim(diamonds)
str(diamonds)
help(diamonds)
```

Cut, color, and clarity are factors, and therefore discrete. The others are numeric continuous variables.

3. Use `ggplot` to plot a scatterplot of the relationship between the diamonds' carat and their price

```
ggplot() + geom_point(data=diamonds, aes(x=carat, y=price))

#or

ggplot(diamonds) + geom_point(aes(x=carat, y=price))

#or

ggplot(diamonds, aes(x=carat, y=price)) + geom_point()
```

4. Make all dots darkblue and set the alpha value to 0.1

```
ggplot(diamonds, aes(x=carat, y=price)) + geom_point(color="darkblue", alpha=0.1)
```

5. Visualize the influence of the color of a diamond on its price by mapping the diamond color to the color aesthetic

```
#The color of the dots will be overwritten if we specify it statically
#in the geom_point function itself
ggplot(diamonds, aes(x=carat, y=price, color=color)) + geom_point(alpha=0.1)
```

6. Use a `ggplot` barplot to visualize diamond clarity depending on color, map diamond color to x and diamond clarity to fill

```
ggplot(diamonds, aes(x=color, fill=clarity)) + geom_bar()
```

7. Create a boxplot of the carat of a diamond based on its clarity and add whiskers using `stat_boxplot`

```
ggplot(diamonds, aes(x=clarity, y=carat)) +
  stat_boxplot(geom="errorbar", width=0.5) +
  geom_boxplot()
```

8. Add a geom_point layer to the previous plot mapping the diamonds price to the color

```
ggplot(diamonds, aes(x=clarity, y=carat)) +
  stat_boxplot(geom="errorbar", width=0.5) +
  geom_boxplot() +
  geom_point(aes(color=price))
```

9. Create a histogram of the price of the diamonds and separate the histograms into facets using diamond color, choose a good binwidth or number of bins

```
ggplot(diamonds, aes(x=price)) +
  geom_histogram(binwidth = 100) +
  facet_grid(color ~ .)
```

10. Create a grid of facets of the same histogram by comparing both color and cut

```
ggplot(diamonds, aes(x=price)) +
  geom_histogram(binwidth = 100) +
  facet_grid(color ~ cut)
```

11. Use ‘aggregate(diamonds, by = list(cut = diamonds\$cut, color = diamonds\$color), mean)’ to calculate the mean of all variables by cut and color. Create a heatmap of the mean prices by cut and color using geom_tile

```
#Aggregate uses a function (in this case mean) to aggregate all variables
#in a given data.frame by a list of variables given in "by".
#Note: excluding columns 2,3,4 since they are factors
#and therefore don't have means
mean.price <- aggregate(diamonds[, -c(2,3,4)],
  by = list(cutAgg = diamonds$cut, colorAgg = diamonds$color),
  mean)
ggplot(mean.price, aes(x=cutAgg, y=colorAgg, fill=price)) +
  geom_tile()
```

12. Change the title of the heatmap to “Average prices”

```
ggplot(mean.price, aes(x=cut, y=color, fill=price)) +
  geom_tile() +
  labs(title="Average prices")
```

13. Change the gradient of the fill scale using ‘scale_fill_gradient2’. Have it go from darkblue to white to darkred, set the midpoint to 4500

```
ggplot(mean.price, aes(x=cut, y=color, fill=price)) +  
  geom_tile() +  
  labs(title="Average prices") +  
  scale_fill_gradient2(low="darkblue", mid="white", high="darkred", midpoint = 4500)
```

14. Choose and add a theme to the heatmap, or create a theme yourself using the options listed at <http://ggplot2.tidyverse.org/reference/theme.html>

```
ggplot(mean.price, aes(x=cut, y=color, fill=price)) +  
  geom_tile() +  
  labs(title="Average prices") +  
  scale_fill_gradient2(low="darkblue", mid="white", high="darkred", midpoint = 4500) +  
  theme_minimal()
```

Basic Course on R: Hypothesis Testing and Confidence Intervals 1

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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1 Summary Statistics

```
Puromycin
```

```
##      conc rate     state
## 1    0.02   76 treated
## 2    0.02   47 treated
## 3    0.06   97 treated
## 4    0.06  107 treated
## 5    0.11  123 treated
## 6    0.11  139 treated
## 7    0.22  159 treated
## 8    0.22  152 treated
## 9    0.56  191 treated
## 10   0.56  201 treated
## 11   1.10  207 treated
## 12   1.10  200 treated
## 13   0.02   67 untreated
## 14   0.02   51 untreated
## 15   0.06   84 untreated
## 16   0.06   86 untreated
## 17   0.11   98 untreated
## 18   0.11  115 untreated
## 19   0.22  131 untreated
## 20   0.22  124 untreated
## 21   0.56  144 untreated
## 22   0.56  158 untreated
## 23   1.10  160 untreated
```

```
attach(Puromycin)
```

1.1 Continuous data

Measures of center:

```
mean(rate)
## [1] 126.8261
```

```

mean(rate, trim = 1/10)

## [1] 126.8947

median(rate)

## [1] 124

```

where the median is the middle of n numbers and the mean is defined as

$$\bar{x} = \sum_{i=1}^n \frac{x_i}{n}$$

Measures of spread:

```

var(rate)

## [1] 2257.514

sqrt(var(rate))

## [1] 47.5133

sd(rate)

## [1] 47.5133

```

Note that the formula for standard deviation is

$$s_x = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2}$$

(variance is s_x^2) so we could also make our own function:

```

stdev <- function(x){ sqrt(sum((x-mean(x))^2)/(length(x)-1)) }

stdev(rate)

## [1] 47.5133

IQR(rate)

## [1] 67

```

```

iqr <- function(x){
  q <- quantile(x)
  q[4]-q[2]
}
iqr(rate)

## 75%
## 67

abs(-1)

## [1] 1

mad(rate)

## [1] 51.891

MAD <- function(x){ median(abs(x-median(x)))*1.4826 }
MAD(rate)

## [1] 51.891

```

The value 1.4826 is a normalizing constant; it makes the MAD comparable to the standard deviation of a normal distribution.

Other summary statistics and useful functions:

```

summary(rate)

##      Min. 1st Qu. Median     Mean 3rd Qu.    Max.
##      47.0   91.5 124.0   126.8 158.5   207.0

quantile(rate)

##      0%    25%    50%    75%   100%
##  47.0  91.5 124.0 158.5 207.0

quantile(rate, seq(0, 1, .1))

##      0%    10%   20%   30%   40%   50%   60%   70%   80%   90%  100%
##  47.0  68.8  84.8  97.6 113.4 124.0 140.0 154.4 159.6 198.2 207.0

```

```

min(rate)

## [1] 47

max(rate)

## [1] 207

sum(rate)

## [1] 2917

log(rate[1])

## [1] 4.330733

log(rate[1], 10)

## [1] 1.880814

log10(rate[1])

## [1] 1.880814

sort(round(rate, -1))

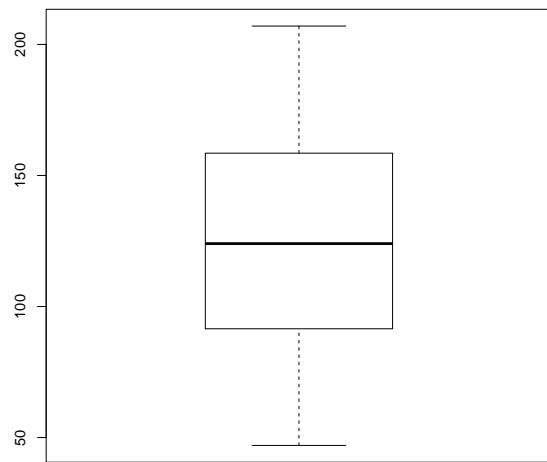
## [1] 50 50 70 80 80 90 100 100 110 120 120 120 130 140 140 150 160
## [18] 160 160 190 200 200 210

stem(rate)

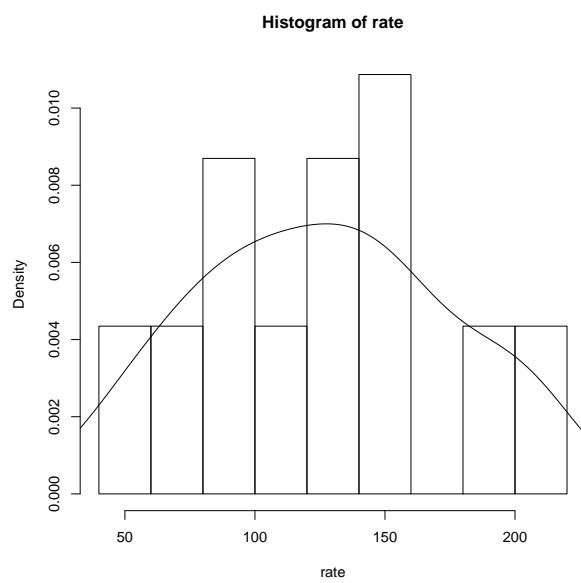
##
##      The decimal point is 2 digit(s) to the right of the |
##      0  |
##      0  | 557889
##      1  | 001222344
##      1  | 56669
##      2  | 001

```

```
boxplot(rate)
```



```
hist(rate, freq = F)  
lines(density(rate))
```



Generating random variables and selecting random samples:

```
set.seed(123)
x <- rnorm(100)
stem(x)

##
## The decimal point is at the |
##
## -2 | 30
## -1 | 75
## -1 | 3321111000
## -0 | 77777666665555
## -0 | 444433333222221100
## 0 | 01111122223334444444
## 0 | 55566677888999
## 1 | 0001122344
## 1 | 55678
## 2 | 122

y <- runif(100, 0, 1)
stem(y)

##
## The decimal point is 1 digit(s) to the left of the |
##
## 0 | 12555666777
## 1 | 0004567777
## 2 | 022234566789
## 3 | 014556
## 4 | 0000000137788
## 5 | 022345689
## 6 | 023567779
## 7 | 0023345679
## 8 | 0022377888
## 9 | 2235667778

sample(rate)

## [1] 131 76 98 84 200 191 97 158 159 124 139 67 152 86 107 51 160
## [18] 47 207 115 144 201 123
```

```

sample(rate, size = 5)

## [1] 98 97 76 124 144

sample(rate, size = 5, replace = TRUE)

## [1] 152 158 84 159 98

sample(rate, size = 5, replace = TRUE,
       prob = runif(length(rate), 0, 1))

## [1] 201 107 76 152 51

```

1.2 Categorical data

```

table(state)

## state
##   treated untreated
##       12          11

table(state)/length(state)

## state
##   treated untreated
## 0.5217391 0.4782609

```

You can also make continuous data categorical:

```

cats <- cut(rate, breaks = c(0, 53, 105, 153, 210))
table(cats)

## cats
##   (0,53] (53,105] (105,153] (153,210]
##       2         6         8         7

cats

## [1] (53,105] (0,53] (53,105] (105,153] (105,153] (105,153] (153,210]
## [8] (105,153] (153,210] (153,210] (153,210] (153,210] (53,105] (0,53]
## [15] (53,105] (53,105] (53,105] (105,153] (105,153] (105,153] (105,153]
## [22] (153,210] (153,210]
## Levels: (0,53] (53,105] (105,153] (153,210]

```

```

cats <- cut(rate, breaks = quantile(rate))
table(cats)

## cats
##  (47,91.5] (91.5,124] (124,158] (158,207]
##      5         6         5         6

```

1.3 Bivariate data

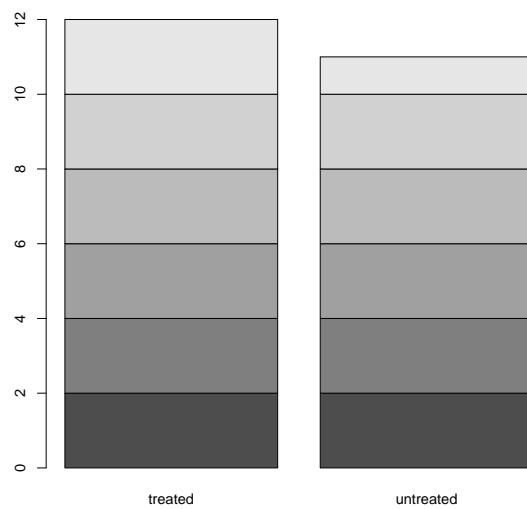
```

table(conc, state)

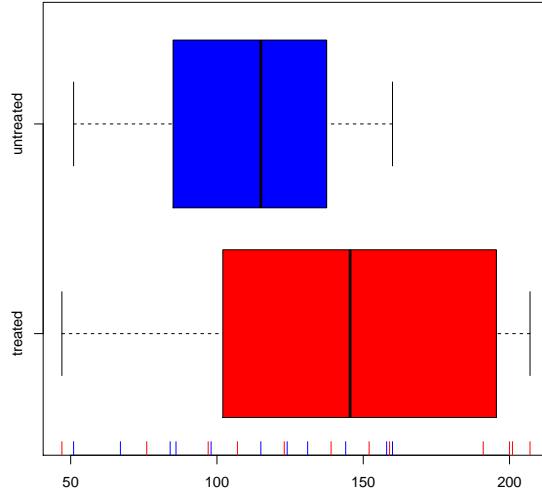
##          state
## conc   treated untreated
##  0.02      2       2
##  0.06      2       2
##  0.11      2       2
##  0.22      2       2
##  0.56      2       2
##  1.1       2       1

barplot(table(conc, state))

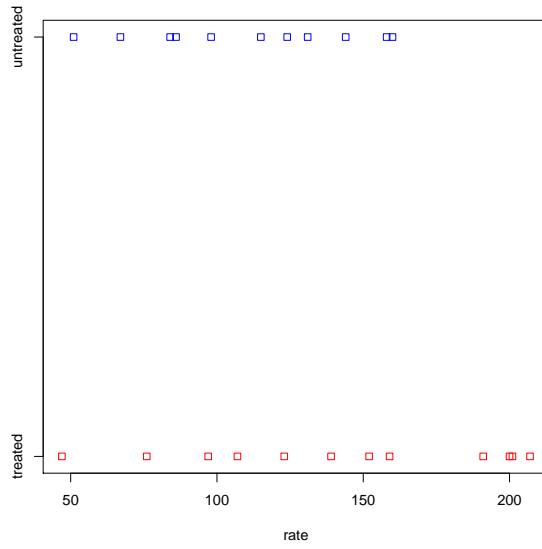
```



```
boxplot(rate~state, horizontal = TRUE, col = c("red", "blue"))
rug(rate[state=="treated"], col = "red")
rug(rate[state=="untreated"], col = "blue")
```



```
stripchart(rate~state, col = c("red", "blue"))
```



2 Hypothesis Testing and Confidence Intervals

Comparison is the most common basic principle in medical research. A statement about the truth is compared against a reference statement (the null).

- H_0 : Null hypothesis, e.g. cholesterol is comparable between men and women
- H_1 : Alternative hypothesis, e.g. men and women differ on average in cholesterol

The p -value is the probability of obtaining the observed data in the sample (or something more extreme than the observed data), given that the null hypothesis is true. The p -value is calculated based on a point estimate (e.g. mean) of the sample. The decision to reject a null hypothesis based on the p -value depends on a chosen α level.

decision	reality	
	H_0 is true	H_0 is false
do not reject H_0	yay!	type II error (β)
reject H_0	type I error (α)	yay!

For a given dataset and corresponding test statistic, we say the results of the test are “statistically significant” if the p -value is less than the pre-selected and fixed significance level, α .

Note that there is a distinction between significance and clinical relevance:

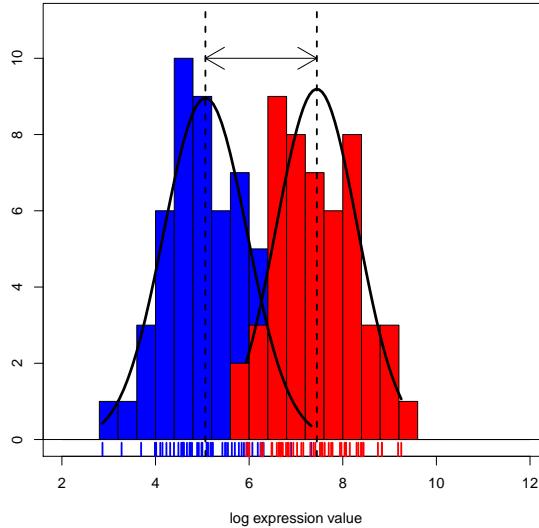
- If the sample size is large enough, even a small difference of 0.1 mmHg blood pressure can be *statistically significant* between groups, though it is not *relevant* from a clinical point of view.
- If the sample size is too small, even a sample mean of 150 mmHg can be *not statistically significantly different* from 130 mmHg, though 20 mmHg is *clinically relevant*.

A confidence interval (CI) is another way to show the reliability of a point estimate. The decision to reject or not reject the null hypothesis aligns with whether or not the CI contains the null value (e.g. H_0 : mean = 0; if CI does not contain 0 then reject, otherwise do not reject H_0). In other words, the decision made by comparing the test statistic’s p -value to α will be the same as a decision made using a $(1 - \alpha) * 100\%$ CI.

An interpretation of e.g. a 95% CI is “if the testing procedure were repeated on many (k) samples, the confidence intervals would encompass the true population parameter in 95% of the k samples” or, more abstractly, “we are 95% confident that the true [e.g. mean] lies in the confidence interval”.

2.1 *t*-Test

The *t*-test is a statistical procedure used to test for the difference in means between two independent populations. The samples should come from normal distributions (can check using e.g. `qqnorm()`) and the variances from each population are assumed to be equal.



The *t*-test in R makes a correction that does not require equal variances of the two populations. The null hypothesis is that the difference between means is 0; the alternative is that this difference is not 0.

The *t* test statistic is defined as

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

and for large values of this test statistic we reject the null hypothesis that the difference in means is 0. A large value of this *t* will produce a small *p*-value which, again, is evidence against the null hypothesis.

The Welch-Satterthwaite correction for unequal variances is

$$\text{df} = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{s_1^4}{n_1^2(n_1-1)} + \frac{s_2^4}{n_2^2(n_2-1)}}$$

The two-sample α -level confidence interval is:

$$\bar{x}_1 - \bar{x}_2 \pm t_{\alpha/2, df} \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$$

where $t_{\alpha/2, df}$ is determined by the Student's-t distribution.

Here is an example of how to do this test in R. In the plotting lecture, it appeared that the OJ recipients in the sample had a larger tooth growth than the VC recipients, on average. We can test if this is true in the larger population using a t -test. Let's set H_0 to be that the two mean tooth lengths are the same and H_a will be that the two mean tooth lengths are not equal. Let's use a 0.10 significance level, which means the probability we falsely reject the null is 0.10. Note that the function `t.test` also provides a confidence interval - the confidence level specified should be $1 - \alpha$ for the interpretations to align.

```
ttooth <- t.test(ToothGrowth$len ~ ToothGrowth$supp, conf.level = 0.90)
ttooth

##
## Welch Two Sample t-test
##
## data: ToothGrowth$len by ToothGrowth$supp
## t = 1.9153, df = 55.309, p-value = 0.06063
## alternative hypothesis: true difference in means is not equal to 0
## 90 percent confidence interval:
## 0.4682687 6.9317313
## sample estimates:
## mean in group OJ mean in group VC
##           20.66333          16.96333
```

Here the p -value is less than our chosen significance level so we reject the null. Therefore, at the 10% significance level, the data provide sufficient evidence that our alternative hypothesis, that there is a difference between using OJ and VC to grow teeth, is true.

Now consider the following example. Suppose we believe the mean reaction velocity in an enzymatic reaction will be higher in cells treated with Puromycin compared to cells not treated with Puromycin. Let's use the 0.05 significance level, allowing for a slightly smaller Type I error probability than in the previous example.

```
t.test(rate~state, alternative = "greater")

##
## Welch Two Sample t-test
##
## data: rate by state
## t = 1.6375, df = 19.578, p-value = 0.05875
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
## -1.677431      Inf
## sample estimates:
##   mean in group treated mean in group untreated
##                 141.5833                  110.7273
```

Here our p -value is greater than α so we do not reject the null hypothesis. We therefore conclude that, at the 5% significance level, the data do not provide sufficient evidence that Puromycin increases the mean reaction velocity.

We can extract statistics and calculate e.g. fold changes from the output:

```
mytest <- t.test(rate~state, alternative="greater")
mytest$p.value

## [1] 0.05874922

mytest$conf.int

## [1] -1.677431      Inf
## attr(,"conf.level")
## [1] 0.95

mytest$estimate[2]/mytest$estimate[1]

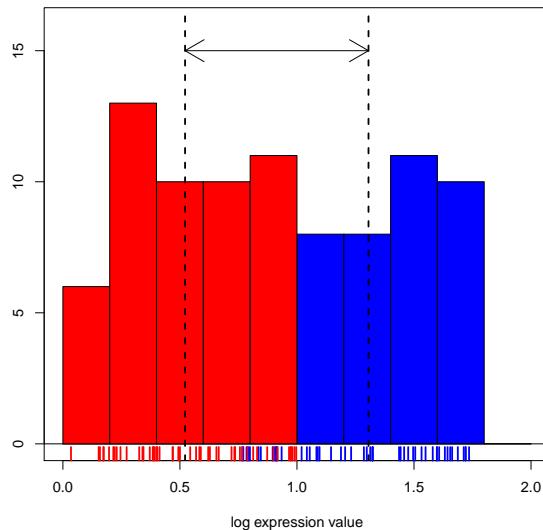
## mean in group untreated
##                 0.7820643
```

If samples are matched or paired (e.g. before/after), use argument `paired=TRUE`.

2.2 Mann-Whitney U Test

The Mann-Whitney U test (also known as the Wilcoxon Rank Sum test) is a non-parametric test for a location shift between two independent populations without assuming normality. However, the values should be sampled from two populations with

very similar distributions. The null hypothesis is that there is no shift in the centers of the distributions of the two populations; the alternative is that there is a shift.



```
wtest <- wilcox.test(rate~state,conf.int=TRUE)
wtest

## 
##  Wilcoxon rank sum test
## 
## data: rate by state
## W = 88, p-value = 0.1896
## alternative hypothesis: true location shift is not equal to 0
## 95 percent confidence interval:
## -10 75
## sample estimates:
## difference in location
##                      36

wtest$p.value

## [1] 0.1895867
```

The test statistic W in R is defined to be the sum of the ranks of one of the groups minus $n_1(n_1 + 1)/2$. The procedure to obtain a confidence interval is quite involved, but thankfully R will provide it to us upon request.

This bit of code shows how to calculate the W test statistic:

```
n1 <- length(state[state=="treated"])
n1
## [1] 12

rank(rate)

## [1] 4 1 7 9 11 14 18 16 20 22 23 21 3 2 5 6 8 10 13 12 15 17 19

rank(rate)[state=="treated"]

## [1] 4 1 7 9 11 14 18 16 20 22 23 21
sum(rank(rate)[state=="treated"])-n1*(n1+1)/2

## [1] 88
```

Basic Course on R: Hypothesis Testing and Confidence Intervals 1 Practical

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28 Oct - 1 Nov 2019

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1 Baby Data

1. Read in the data “R_data_January2015.csv” with a header and row names from the first column. Assign it to the object **babydata** and allow strings be converted to factors. Attach the data to the environment.
2. What are the dimensions of **babydata**? What is the class? Answer these questions separately with two functions and then together with one function.
3. Answer the following questions pertaining to the variable **SAH**:
 - (a) What are the 20% quantiles of **SAH**?
 - (b) What are the mean, median, variance and standard deviation of **SAH**?
 - (c) Create a stem and leaf plot of **SAH**.
 - (d) Create a histogram and a horizontal boxplot of **SAH** in one graphics window where the plot of the histogram is above the boxplot.
 - (e) Utilize all 3 graphs to describe the shape of the distribution of **SAH**.
 - (f) Log-transform **SAH** (assign it to **logSAH**).
 - (g) What are the 20% quantiles of **logSAH**?
 - (h) What are the mean, median, variance and standard deviation of **logSAH**?

- (i) Create a stem and leaf plot of `logSAH`.
- (j) Create a histogram and a horizontal boxplot of `logSAH` in one graphics window where the plot of the histogram above the boxplot.
- (k) Utilize all 3 graphs to describe the shape of the distribution of `logSAH`.
- (l) What did the log transformation do to the values of `SAH`?
- (m) Take a random sample of size 50 from `logSAH` and make a histogram. Does this distribution have a similar shape compared to that of all `logSAH` values?
- (n) Take a random sample of size 50 with replacement from `logSAH` and make a histogram. Does this distribution have a similar shape compared to that of all `logSAH` values?

4. Answer the following questions pertaining to the variable `medication`:

- (a) Use a function to create frequency table of the number of mothers taking medication and not taking medication.
- (b) Calculate the percent of the mothers who are taking medication; what is the percentage?

5. Answer the following questions pertaining to the variable `educational_level`:

- (a) Create a frequency table of the number of mothers in each education level.

- (b) Create a horizontal boxplot of the **SAH** values for the different levels of education and color each box a different color. Add a rug plot of the values where the ticks for each group have the same color as their corresponding box.
- (c) Are **triglycerides** normally distributed (make a plot to answer this question)? If not, log-transform them. Are the log-transformed values normal?
- (d) Is the average triglyceride level for highly educated mothers different from that of mothers with a low education level? Formulate a hypothesis, test it, and make a decision about whether or not you can reject the null hypothesis. Can you use a *t*-test (either on the raw or log-transformed data)? Why or why not (hint: how are the data distributed)?
- (e) Now re-do the test and make your decision to reject/not reject the null based on the confidence interval. Challenge: instead of just looking at the output, extract the confidence interval from the test output and use logical operators to answer the question of whether the interval contains the null value.

6. Answer the following questions pertaining to the variable **Status**:
 - (a) Are the average **SAH** values for the two levels of **Status** (normal brain development or intellectual disability) different? Formulate a hypothesis, test it, and make a decision about whether or not you can reject the null hypothesis. Can you use a *t*-test (either on the raw or log-transformed data)? Why or why not (hint: check distributions with plots)?
 - (b) What is the fold change of log-**SAH** between the 2 groups? Calculate it two ways: use the output from the previous test and also use the data itself (function **mean** plus logical operators).
 - (c) Make a boxplot of the **SAH** values of the 2 groups and calculate the fold change of **SAH** between the 2 groups. Does the difference seem clinically relevant? Why or why not?

Basic Course on R: Hypothesis Testing and Confidence Intervals 1 Practical Answers

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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1 Baby Data

1. Read in the data “R_data_January2015.csv” with a header and row names from the first column. Assign it to the object `babydata` and allow strings be converted to factors. Attach the data to the environment.

```
babydata <- read.csv("R_data_January2015.csv", header = T, row.names = 1)
attach(babydata)
```

2. What are the dimensions of `babydata`? What is the class? Answer these questions separately with two functions and then together with one function.

```
dim(babydata)

## [1] 190 19

class(babydata)

## [1] "data.frame"

str(babydata)

## 'data.frame': 190 obs. of 19 variables:
## $ Status           : Factor w/ 2 levels "intellectual disability",...: 1 2 1 ...
## $ iodine_deficiency: Factor w/ 2 levels "no","yes": 1 1 1 2 1 1 2 2 2 ...
## $ BMI              : int 32 23 29 22 22 24 24 28 33 32 ...
## $ educational_level: Factor w/ 3 levels "high","intermediate",...: 2 2 3 3 3 ...
## $ alcohol           : Factor w/ 2 levels "no","yes": 1 2 1 1 2 2 2 2 1 ...
## $ smoking            : Factor w/ 2 levels "no","yes": 1 2 1 1 1 1 1 1 2 1 ...
## $ medication          : Factor w/ 2 levels "no","yes": 1 1 1 1 1 1 1 1 1 1 ...
## $ birthweight         : int 2618 3541 2619 3810 4136 4030 3377 2500 4255 2952
## $ pregnancy_length_weeks: int 38 40 38 40 42 41 40 37 42 39 ...
## $ pregnancy_length_days: int 4 2 3 5 3 1 4 1 0 2 ...
## $ SAM                : num 54.5 84 61 43 83 69 79 71.5 56 42.5 ...
## $ SAH                : num 14.8 23.6 18.7 23.2 17.1 19.6 22.4 18 20 23.4 ...
## $ homocysteine        : num 18.8 15.6 15.2 16.5 19.5 17.5 14.9 22.2 19.1 16 ...
## $ cholesterol          : num 16.5 17.5 16.4 16.4 16.9 15.9 16.9 16 18.6 16.7 ...
## $ HDL                 : num 26.1 26.7 26.2 25.9 26.7 ...
## $ triglycerides        : num 8.84 7.78 7.54 8.95 7.57 7.35 7.63 7.38 8.25 8.27
## $ vitaminB12           : int 303 370 533 346 389 611 604 518 288 520 ...
## $ folicacid_serum       : num 26.4 37.8 33.7 35.1 29 28.3 33.8 31.1 27.7 33.4 ...
## $ folicacid_erys         : num 1132 1467 1528 1539 1178 ...
```

3. Answer the following questions pertaining to the variable SAH:

(a) What are the 20% quantiles of SAH?

```
quantile(SAH, seq(0, 1, .2))

##      0%     20%     40%     60%     80%    100%
## 9.40 14.80 16.46 18.00 19.82 28.50
```

(b) What are the mean, median, variance and standard deviation of SAH?

```
summary(SAH)

##      Min. 1st Qu. Median      Mean 3rd Qu.      Max.
## 9.40   15.22  17.30   17.59   19.07   28.50

## or
mean(SAH)

## [1] 17.59053

median(SAH)

## [1] 17.3

vs <- var(SAH)
vs

## [1] 11.26901

sqrt(vs)

## [1] 3.356935
```

(c) Create a stem and leaf plot of SAH.

```
stem(SAH)

##
##      The decimal point is at the |
##
##      9 | 4
##      10 | 7
##      11 | 355
##      12 | 135
##      13 | 146677999
##      14 | 0111122333455666777888899
```

```

## 15 | 0000123333455777889999
## 16 | 0000011233345557788999
## 17 | 001111223333456777788889
## 18 | 0000011122223344445555666789
## 19 | 000011222368889
## 20 | 0022245567899
## 21 | 2669
## 22 | 014
## 23 | 011124567
## 24 | 67
## 25 |
## 26 | 33
## 27 | 7
## 28 | 335

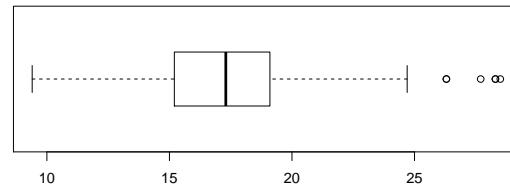
```

- (d) Create a histogram and a horizontal boxplot of **SAH** in one graphics window where the plot of the histogram is above the boxplot.

```

par(mfrow=c(2,1))
hist(SAH)
boxplot(SAH, horizontal=TRUE)

```



- (e) Utilize all 3 graphs to describe the shape of the distribution of **SAH**.

The distribution is unimodal and slightly skewed to the right.

- (f) Log-transform SAH (assign it to logSAH).

```
logSAH <- log(SAH)
```

- (g) What are the 20% quantiles of logSAH?

```
quantile(logSAH, seq(0,1,.2))  
##      0%      20%      40%      60%      80%     100%  
## 2.240710 2.694627 2.800929 2.890372 2.986689 3.349904
```

- (h) What are the mean, median, variance and standard deviation of logSAH?

```
summary(logSAH)  
##      Min.  1st Qu.   Median     Mean  3rd Qu.     Max.  
##  2.241    2.723    2.851    2.850    2.948    3.350  
  
## or  
mean(logSAH)  
## [1] 2.849985  
  
median(logSAH)  
## [1] 2.850707  
  
vls <- var(logSAH)  
vls  
  
## [1] 0.03460558  
  
sqrt(vls)  
## [1] 0.1860257
```

- (i) Create a stem and leaf plot of logSAH.

```
stem(logSAH)  
##  
##      The decimal point is 1 digit(s) to the left of the |  
##  
## 22 | 4  
## 23 | 7  
## 24 | 2449
```

```

## 25 | 137
## 26 | 0112233345555556667778889999999
## 27 | 001111123333344555667777777889999
## 28 | 000022223333344444455556677778888899999
## 29 | 0000000111112222222334444455555689999
## 30 | 001112223334457799
## 31 | 01444445667
## 32 | 0177
## 33 | 2445

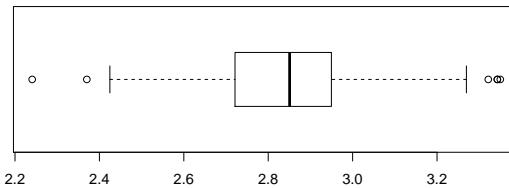
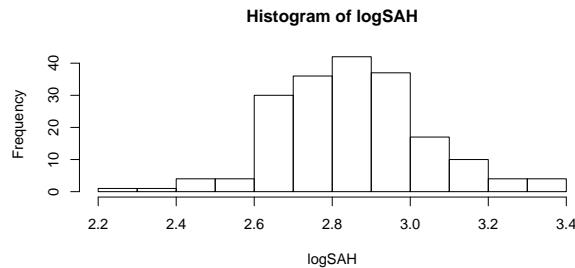
```

- (j) Create a histogram and a horizontal boxplot of `logSAH` in one graphics window where the plot of the histogram above the boxplot.

```

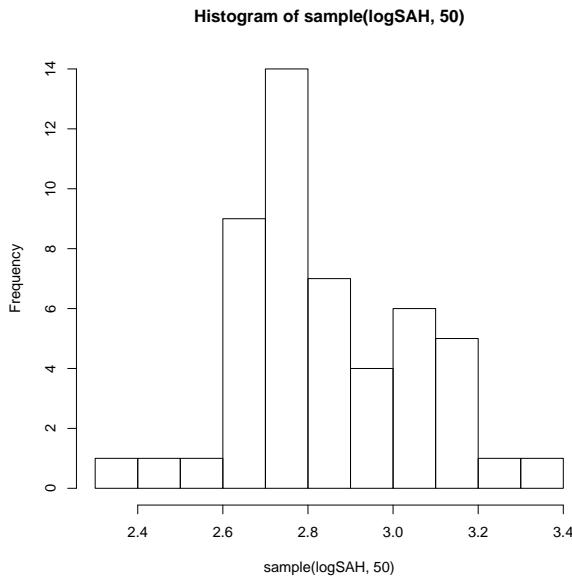
par(mfrow=c(2,1))
hist(logSAH)
boxplot(logSAH, horizontal=TRUE)

```



- (k) Utilize all 3 graphs to describe the shape of the distribution of `logSAH`.
The distribution is unimodal, symmetric and appears normal.
- (l) What did the log transformation do to the values of SAH?
Dampened the effect of skewness to make the distribution more normal and symmetric.
- (m) Take a random sample of size 50 from `logSAH` and make a histogram. Does this distribution have a similar shape compared to that of all `logSAH` values?

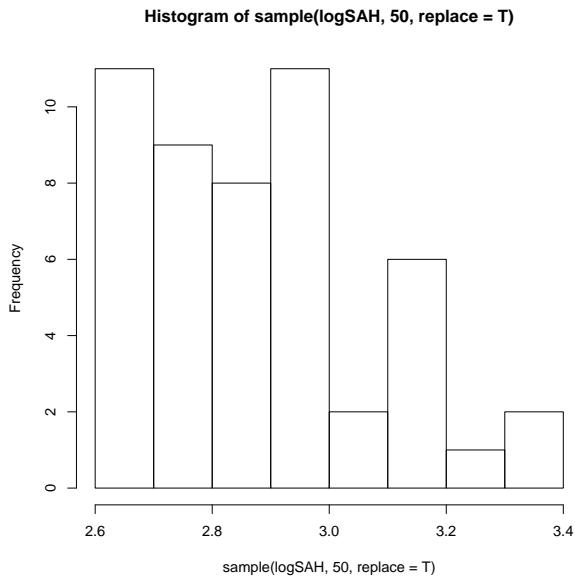
```
set.seed(1234)
hist(sample(logSAH, 50))
```



The distribution looks somewhat similar to that of the complete data.

- (n) Take a random sample of size 50 with replacement from `logSAH` and make a histogram. Does this distribution have a similar shape compared to that of all `logSAH` values?

```
set.seed(1234)
hist(sample(logSAH, 50, replace=T))
```



The distribution looks quite different from the original distribution.

4. Answer the following questions pertaining to the variable `medication`:

- (a) Use a function to create frequency table of the number of mothers taking medication and not taking medication.

```
table(medication)

## medication
##   no yes
## 159 31
```

- (b) Calculate the percent of the mothers are taking medication; what is the percentage?

```
table(medication)/length(medication)

## medication
##       no      yes
## 0.8368421 0.1631579
```

So 16.3% of mothers are taking medication.

5. Answer the following questions pertaining to the variable `educational_level`:

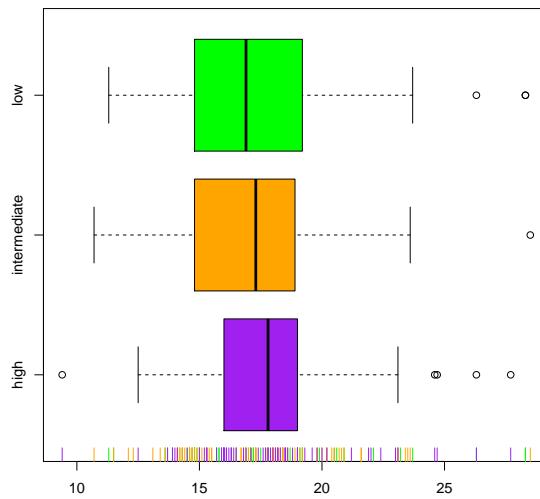
- (a) Create a frequency table of the number of mothers in each education level.

```
table(educational_level)

## educational_level
##      high intermediate      low
##      63          82          45
```

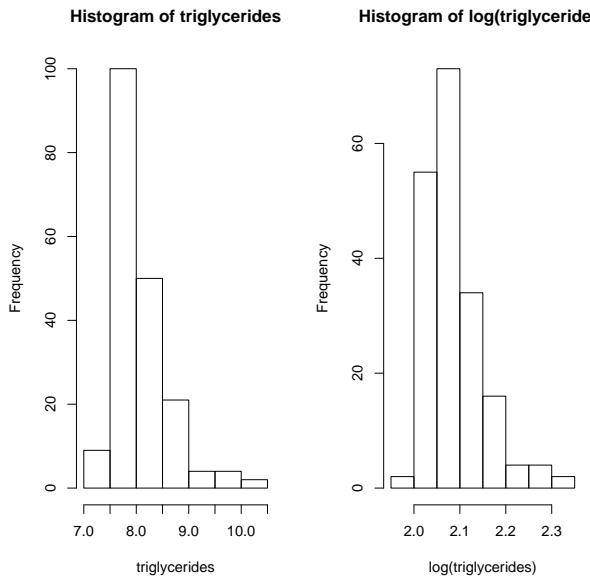
- (b) Create a horizontal boxplot of the **SAH** values for the different levels of education and color each box a different color. Add a rug plot of the values where the ticks for each group have the same color as their corresponding box.

```
boxplot(SAH ~ educational_level, horizontal=TRUE,
        col=c("purple", "orange", "green"))
rug(SAH[educational_level=="low"], col="green")
rug(SAH[educational_level=="intermediate"], col="orange")
rug(SAH[educational_level=="high"], col="purple")
```



- (c) Are **triglycerides** normally distributed (make a plot to answer this question)? If not, log-transform them. Are the log-transformed values normal?

```
par(mfrow=c(1,2))
hist(triglycerides)
hist(log(triglycerides))
```

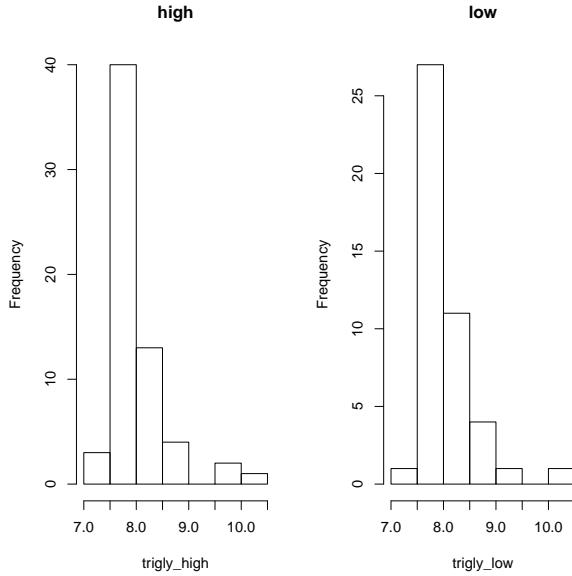


The values are skewed to the right and are still skewed after a log transformation.

- (d) Is the average triglyceride level for highly educated mothers different from that of mothers with a low education level? Formulate a hypothesis, test it, and make a decision about whether or not you can reject the null hypothesis. Can you use a *t*-test (either on the raw or log-transformed data)? Why or why not (hint: how are the data distributed)?

We cannot use the *t*-test because the data are not normally distributed, even after a log transformation! However, since the shapes of the distributions are similar, as evidenced by the below plot, we can perform a Wilcoxon Rank Sum test.

```
trigly_high <- triglycerides[educational_level=="high"]
trigly_low <- triglycerides[educational_level=="low"]
par(mfrow=c(1,2))
hist(trigly_high, main = "high")
hist(trigly_low, main = "low")
```



Our null hypothesis is that the difference in location between the low and high education levels is 0. The alternative hypothesis is that there is a difference.

```
wilcox.test(trigly_high, trigly_low)

##
##  Wilcoxon rank sum test with continuity correction
##
## data: trigly_high and trigly_low
## W = 1328, p-value = 0.5791
## alternative hypothesis: true location shift is not equal to 0
```

The *p*-value is not less than 0.05 so we fail to reject the null and conclude that we do not have enough evidence to show a statistically significant difference between the centers of the high and low mothers' triglycerides.

- (e) Now re-do the test and make your decision to reject/not reject the null based on the confidence interval. Challenge: extract the confidence interval from the test output and use logical operators to answer the question of whether the interval contains the null value.

```
wtest <- wilcox.test(trigly_high, trigly_low, conf.int=TRUE)
ciw <- wtest$conf.int
0 > ciw[1] & 0 < ciw[2]

## [1] TRUE
```

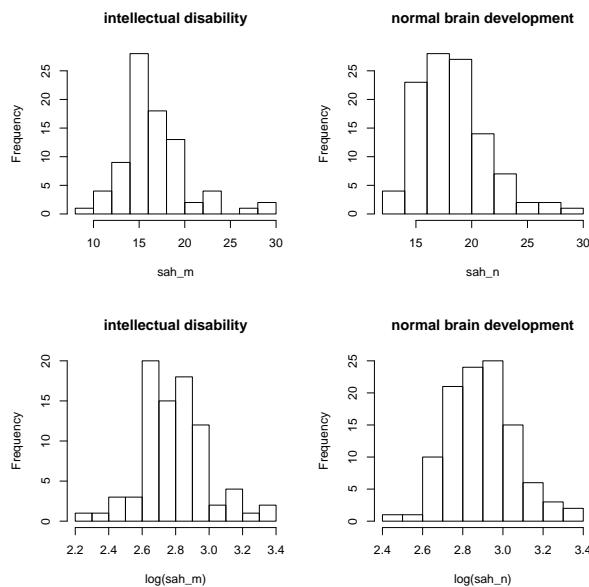
Since the confidence interval contains 0, we fail to reject the null.

6. Answer the following questions pertaining to the variable **Status**:

- (a) Are the average SAH values for the two levels of **Status** (normal brain development or intellectual disability) different? Formulate a hypothesis, test it, and make a decision about whether or not you can reject the null hypothesis. Can you use a *t*-test (either on the raw or log-transformed data)? Why or why not (hint: check distributions with plots)?

We can use the *t*-test on the log-transformed data, since they are normally distributed, as shown in the plots below.

```
sah_m <- SAH[Status=="intellectual disability"]
sah_n <- SAH[Status=="normal brain development"]
par(mfrow=c(2,2))
hist(sah_m, main = "intellectual disability")
hist(sah_n, main = "normal brain development")
hist(log(sah_m), main = "intellectual disability")
hist(log(sah_n), main = "normal brain development")
```



Our null hypothesis is that the difference in mean SAH between the two groups is 0. The alternative hypothesis is that there is a difference in means.

```
sstest <- t.test(log(SAH)~Status)
sstest
##
## Welch Two Sample t-test
##
```

```

## data: log(SAH) by Status
## t = -3.8522, df = 152.24, p-value = 0.0001721
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.15753466 -0.05072509
## sample estimates:
## mean in group intellectual disability
##                               2.790795
## mean in group normal brain development
##                               2.894925

sstest$p.value

## [1] 0.0001720599

sstest$conf.int

## [1] -0.15753466 -0.05072509
## attr(,"conf.level")
## [1] 0.95

```

The *p*-value is less than 0.05 (and 0 is not in the CI) so we can reject the null hypothesis that the difference in means between the two groups is 0. We conclude that there is a statistically significant difference between the average log-SAH of mothers with intellectually disabled children and the average log-SAH of those women whose children have normal brain development.

- (b) What is the fold change of log-SAH between the 2 groups? Calculate it two ways: use the output from the previous test and also use the data itself (function `mean` plus logical operators).

```

sstest$estimate[2]/sstest$estimate[1]

## mean in group normal brain development
##                               1.037312

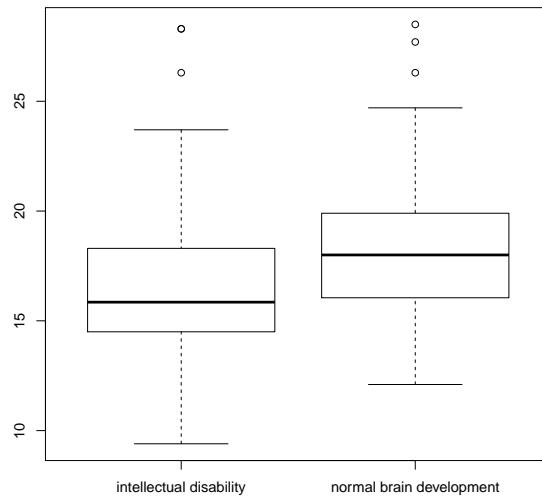
mean(log(SAH)[Status=="normal brain development"])/
  mean(log(SAH)[Status=="intellectual disability"])

## [1] 1.037312

```

- (c) Make a boxplot of the SAH values of the 2 groups and calculate the fold change of SAH between the 2 groups. Does the difference seem clinically relevant? Why or why not?

```
boxplot(SAH ~ Status)
```



```
mean(SAH[Status=="normal brain development"])/  
mean(SAH[Status=="intellectual disability"])  
## [1] 1.101694
```

The fold change is really close to one and there is actually quite a bit of overlap in the boxplots. The statistically significant difference of the log-transformed data is quite subtle and may not be relevant, though further investigation of confounding factors may elucidate the true relationship between **SAH** and brain development.

Basic Course on R: Hypothesis Testing and Confidence Intervals 2

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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Most of the following examples use the data “R_data_January2015.csv” which contains variables on mothers whose babies are either intellectually disabled or developmentally normal.

```
babies <- read.csv("R_data_January2015.csv", header=T, row.names=1)
names(babies)

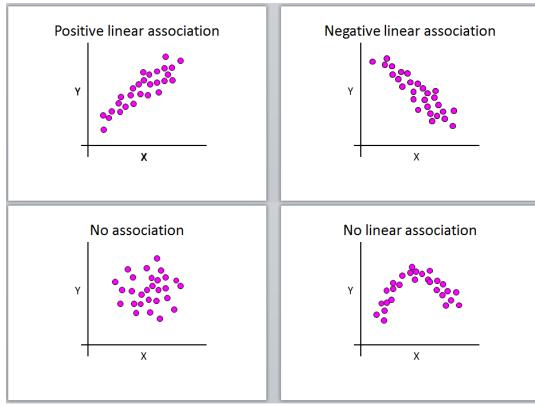
## [1] "Status"                  "iodine_deficiency"
## [3] "BMI"                     "educational_level"
## [5] "alcohol"                 "smoking"
## [7] "medication"              "birthweight"
## [9] "pregnancy_length_weeks"  "pregnancy_length_days"
## [11] "SAM"                     "SAH"
## [13] "homocysteine"            "cholesterol"
## [15] "HDL"                     "triglycerides"
## [17] "vitaminB12"              "folicacid_serum"
## [19] "folicacid_erys"

attach(babies)

## The following objects are masked from babydata:
##
##   alcohol, birthweight, BMI, cholesterol, educational_level,
##   folicacid_erys, folicacid_serum, HDL, homocysteine,
##   iodine_deficiency, medication, pregnancy_length_days,
##   pregnancy_length_weeks, SAH, SAM, smoking, Status,
##   triglycerides, vitaminB12
```

1 Correlations

If we want to know the degree of a linear association between 2 variables, we can calculate correlation. Correlation does not make any *a priori* assumptions about whether one variable is dependent on the other and is not concerned with the relationship between the variables. We have 4 general types of association to consider:



Pearson's correlation coefficient r is defined as:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}$$

and indicates to what extent two continuous variables have a linear relationship.

Pearson's r can only lie in the interval $[-1,1]$ (inclusive), where

- $r = 0$, no linear correlation
- $r > 0$, positive linear correlation
- $r < 0$, negative linear correlation
- $r = 1$, perfect positive linear correlation
- $r = -1$, perfect negative linear correlation

Note that correlation does *not* imply causation. If two variables are highly correlated you cannot infer that one is causing the other; they could both be varying along with a third, possibly unknown confounding factor (either causal or not).

We assume that the two variables x and y

- show a linear relationship
- are continuous random variables
- are normally distributed
- are independent of each other

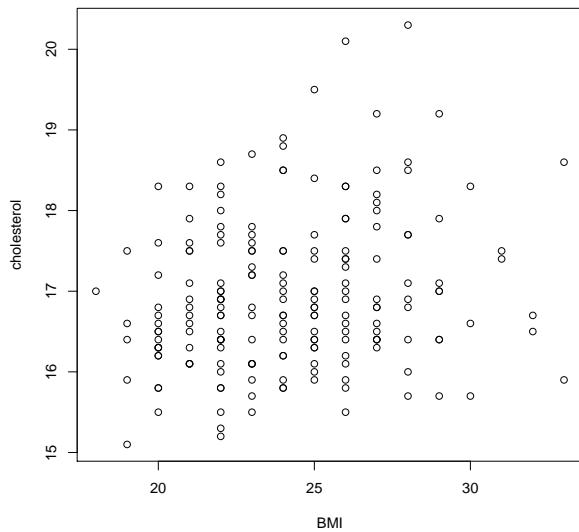
and when regressing one variable on another (e.g. linear regression, more on this later), r^2 is called the goodness of fit, which is the proportion of variance in y that can be explained by the regression on x .

If data are not normally distributed, the degree of association can be determined by the ranked correlation coefficient, Spearman's ρ , which replaces the x 's and y 's in the Pearson formula with their ranks.

R provides p -values and confidence intervals for both Pearson and Spearman correlations.

Let's look at an example of how BMI and cholesterol are associated:

```
plot(BMI, cholesterol)
```



```
cor(BMI, cholesterol)

## [1] 0.2004703

cor(BMI, cholesterol, method="spearman")

## [1] 0.1876358

cor.test(BMI, cholesterol)

##
## Pearson's product-moment correlation
##
## data: BMI and cholesterol
## t = 2.8057, df = 188, p-value = 0.00555
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## 0.05982424 0.33331173
## sample estimates:
##       cor
## 0.2004703
```

```

cor.test(BMI, cholesterol, method="spearman")

## Warning in cor.test.default(BMI, cholesterol, method = "spearman"): Cannot
compute exact p-value with ties

##
## Spearman's rank correlation rho
##
## data: BMI and cholesterol
## S = 928640, p-value = 0.009531
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##      rho
## 0.1876358

```

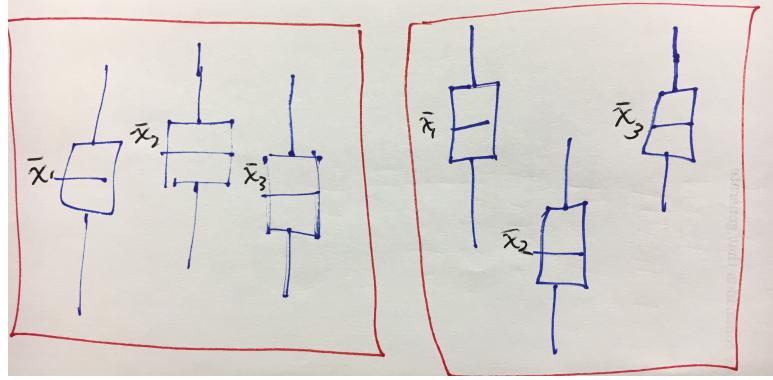
Note the *warning* message (which is not an error!) that indicates if your data have tied values (e.g. 1, 1, 3, 5) then the *p*-value is approximated and is not exact. It's nothing to worry about (especially if you're not a statistician...).

2 ANOVA

A two-sample *t*-test is used to test hypotheses about the means of two normal populations using two datasets which were sampled independently of one another from the two respective populations. An analysis of variance (ANOVA) allows for comparing the means of one variable among more than two populations (each of which is normally distributed), again under the assumption that the samples are independent.

- If the variance between groups is higher than the variance within groups, then there is evidence for a difference in means between groups.
- The null hypothesis is that the means of all groups are equal; the alternative is that at least one group has a different mean from the others.
- ANOVA does not provide which group is different nor in what direction; visualization and/or post-hoc pairwise *t*-tests can provide this information.

Here is a small illustration of the analysis of variance:



In the left image there is more variability within each of the three groups (boxplots) than between the three group means ($\bar{x}_1, \bar{x}_2, \bar{x}_3$). In the right image there is more variability between the three group means than within each of the three groups.

2.1 One-way ANOVA

Suppose we have k groups and n total samples. We first calculate between- and within-group variations (sums of squares or SS), and for this we need the mean of all data points, which is $\bar{X} = \sum x/n$. The SS (between and within) for each group i are:

$$SSB = \sum n_i(\bar{x}_i - \bar{X})^2$$

$$SSW = \sum (n - k)s_i^2$$

where s_i^2 is the variance within group i . It can be shown that $SSB + SSW = SST$, the total sum of squares $\sum(x - \bar{X})^2$ (the total variance times $n - 1$). Next we calculate the mean squared (MS) errors, which are:

- MSB for between: $SSB/(k - 1)$
- MSW for within: $SSW/(n - k)$.

The test-statistic for an ANOVA is MSB/MSW , which, to get a p -value, is compared to an F distribution on $k - 1$ and $n - k$ degrees of freedom.

The above statistics are generally presented in an ANOVA table:

	df	SS	MS	F
between	$k-1$	SSB	$SSB/(k - 1)$	MSB/MSW
within	$n-k$	SSW	$SSW/(n - k)$	
total	$n-1$	$SSW + SSB$		

As with the previous testing procedures we've seen, we compare the p -value to the pre-selected significance level. If $p \leq \alpha$ we reject the null and conclude we have evidence that at least one population (or group) mean is different from the others, while if $p > \alpha$, we fail to reject the null and conclude we do not have evidence that any of the means are different.

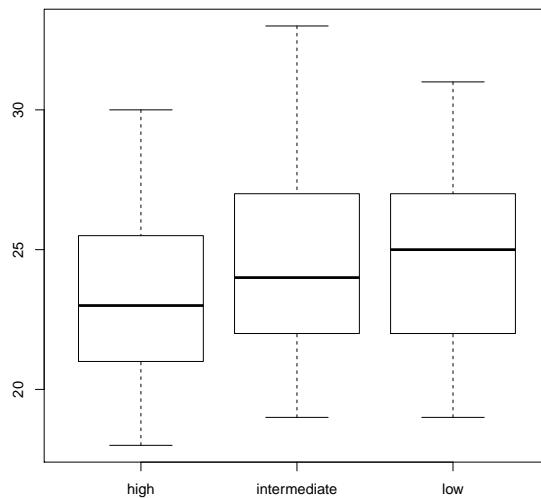
R will calculate all of the statistics for us! For example, let's test at the 5% significance level the alternative hypothesis that at least one of the mean BMIs for three different educational levels are different from the other two (versus the null of three equal means).

```
baby_aov1 <- aov(BMI ~ educational_level)
summary(baby_aov1)

##                                Df Sum Sq Mean Sq F value Pr(>F)
## educational_level          2   63.8   31.90   3.409 0.0351 *
## Residuals                  187 1749.8     9.36
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Here the F -statistic is large enough to get a p -value smaller than 0.05 so we conclude at least one population mean BMI is different from the other two. But which group is it? Let's look at a boxplot:

```
boxplot(BMI~educational_level)
```



This visual information is informative but we can actually make pairwise comparisons of all the means using Tukey's HSD. We initially used a significance level of 0.05, but will now conduct several tests and use a multiple test procedure that adjusts the family-wise error rate to 5%:

```
TukeyHSD(baby_aov1)

## Tukey multiple comparisons of means
## 95% family-wise confidence level
##
## Fit: aov(formula = BMI ~ educational_level)
##
## $educational_level
##              diff      lwr      upr   p adj
## intermediate-high 1.1397600 -0.07099027 2.350510 0.0697761
## low-high          1.3587302 -0.05180238 2.769263 0.0617385
## low-intermediate  0.2189702 -1.12174472 1.559685 0.9212512
```

Note that we use the multiple testing procedure to account for the fact that we are simultaneously performing more than one test or CI which compounds the error rates of each test. Since all of the CIs contain 0 and none of the p -values are significant at the 5% level, the initial test result is overturned! We do not actually have evidence that education level affects average BMI.

Also note you would not bother with these *posthoc* tests/CIs if your initial ANOVA results were not statistically significant.

2.2 Two-way ANOVA

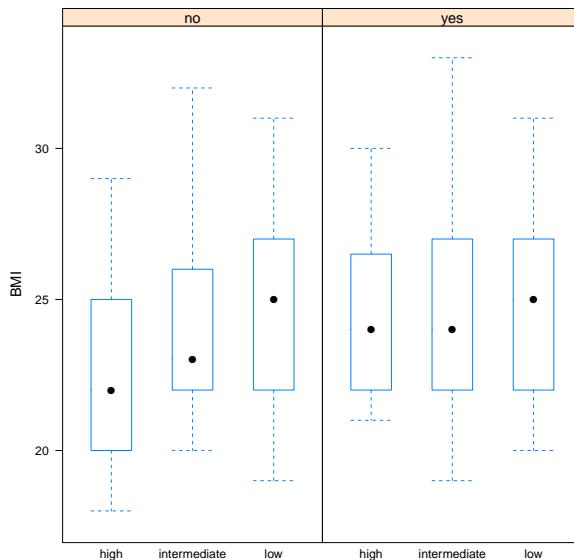
When we have two categorical explanatory variables and a continuous outcome, we can use a two-way ANOVA to determine whether the combinations of levels of the two variables have varying means in the outcome. Note that this is still a parametric test which requires normality. The ANOVA table is similar to the one-way, but an additional row is added for the second factor and an interaction between the two groups.

```
baby_aov2 <- aov(BMI ~ educational_level * iodine_deficiency)
summary(baby_aov2)

##                                     Df Sum Sq Mean Sq F value Pr(>F)
## educational_level                  2   63.8   31.90   3.441 0.0341 *
## iodine_deficiency                 1   27.4   27.40   2.955 0.0873 .
## educational_level:iodine_deficiency 2   16.6    8.32   0.898 0.4092
## Residuals                         184 1705.7    9.27
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
library(lattice)
```

```
bwplot(BMI ~ educational_level | iodine_deficiency)
```



Here the interaction is not significant so we take it out and re-run the ANOVA:

```
baby_aov2 <- aov(BMI ~ educational_level + iodine_deficiency)
summary(baby_aov2)

##                                Df Sum Sq Mean Sq F value Pr(>F)
## educational_level      2   63.8   31.90   3.445 0.0340 *
## iodine_deficiency       1   27.4   27.40   2.958 0.0871 .
## Residuals                 186 1722.4     9.26
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

It appears that educational level and iodine deficiency may have an effect on BMI.

3 χ^2 Test

A χ^2 (read: chi-squared) test of independence tests the null hypothesis that rows and columns are independent in a $c \times r$ contingency table (r is number of rows, c columns); the alternative is that they are not independent. The counts must be independent and sampled randomly. We can calculate a chi-squared statistic as follows:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

where O_i is the observed count for cell i in the table, and E_i is the expected count, calculated by multiplying the row and column totals for i divided by the overall total. The p -value for the calculated χ^2 statistic depends on the χ^2 distribution with $(r - 1)(c - 1)$ degrees of freedom. R will provide us with the statistic and p -value.

Suppose we have the following table:

	event	no event	total
treatment	20	80	100
placebo	50	50	100
total	70	130	200

and we want to know whether our treatment prevents events, that is, does the occurrence of an event depend on the type of treatment?

```
mytable <- matrix(c(20, 50, 80, 50), nrow=2)
cstest <- chisq.test(mytable)
cstest

##
## Pearson's Chi-squared test with Yates' continuity correction
##
## data: mytable
## X-squared = 18.484, df = 1, p-value = 1.714e-05

cstest$p.value

## [1] 1.713801e-05
```

Basic Course on R: Hypothesis Testing and Confidence Intervals 2 Practical

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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1 Baby Data

1. Read in the data “R_data_January2015.csv” with a header and row names from the first column. Assign it to the object `babydata` and allow strings be converted to factors. Attach the data to the environment.

2. Answer the following questions pertaining to the variables `vitaminB12` and `homocysteine`:
 - (a) What are the Pearson and Spearman correlations between `vitaminB12` and `homocysteine`? Are they similar? Formulate a hypothesis, do a test, and make a decision as to whether either the Pearson or Spearman correlation is statistically significantly. Include a scatterplot of `homocysteine` versus `vitaminB12` to support your findings.

 - (b) Plot a histogram of each variable to decide whether the Pearson correlation is appropriate to use. Is it?

 - (c) Does the correlation improve after a log transformation of both variables? Make plots and do a test on the appropriate (Spearman or Pearson - depends on distribution!) correlation to answer this question.

 - (d) Let’s see what happens when we “categorize” a continuous variable. Cut `vitaminB12` into 4 groups, where the breaks are the 5 quantile points of `vitaminB12`. Make sure you include the lowest breakpoint by specifying “`incl=TRUE`”. Assign the output to `catB12`. What are the levels of this new variable?

- (e) Using the log-transformed variable from part (c), assess how the log of `homocysteine` and `catB12` relate. Make a boxplot of `log-homocysteine` for each level of `catB12`.
 - (f) Are the means of `log-homocysteine` equal across all levels of `catB12`? Formulate a hypothesis, test it, and make a decision for statistical significance.
 - (g) Now let's see if `log-homocysteine` varies on both `smoking` and `catB12` levels. Make a boxplot of `log-homocysteine` for all combinations of the 2 categories. Then formulate a hypothesis, test it, and make a decision for statistical significance on both categorical variables.
3. We suspect that people who drink alcohol (`alcohol` is yes) might also be smokers (`smoking` is yes). Formulate a hypothesis, test it using the appropriate test, and make a decision about statistical significance. [Hint: use `table`.]

Basic Course on R: Hypothesis Testing and Confidence Intervals 2 Practical Answers

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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1 Baby Data

1. Read in the data “R_data_January2015.csv” with a header and row names from the first column. Assign it to the object `babydata` and allow strings be converted to factors. Attach the data to the environment.

```
babydata <- read.csv("R_data_January2015.csv", header=T, row.names=1)
attach(babydata)

## The following objects are masked from babies:
##
##   alcohol, birthweight, BMI, cholesterol, educational_level,
##   folicacid_erys, folicacid_serum, HDL, homocysteine,
##   iodine_deficiency, medication, pregnancy_length_days,
##   pregnancy_length_weeks, SAH, SAM, smoking, Status,
##   triglycerides, vitaminB12

## The following objects are masked from babydata (pos = 5):
##
##   alcohol, birthweight, BMI, cholesterol, educational_level,
##   folicacid_erys, folicacid_serum, HDL, homocysteine,
##   iodine_deficiency, medication, pregnancy_length_days,
##   pregnancy_length_weeks, SAH, SAM, smoking, Status,
##   triglycerides, vitaminB12
```

2. Answer the following questions pertaining to the variables `vitaminB12` and `homocysteine`:
 - (a) What are the Pearson and Spearman correlations between `vitaminB12` and `homocysteine`? Are they similar? Formulate a hypothesis, do a test, and make a decision as to whether either the Pearson or Spearman correlation is statistically significantly. Include a scatterplot of `homocysteine` versus `vitaminB12` to support your findings.

```
cor(vitaminB12, homocysteine)

## [1] -0.3024089

cor(vitaminB12, homocysteine, method="spearman")

## [1] -0.3218201

cor.test(vitaminB12, homocysteine)
```

```

## 
## Pearson's product-moment correlation
## 
## data: vitaminB12 and homocysteine
## t = -4.3501, df = 188, p-value = 2.229e-05
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## -0.4264059 -0.1672558
## sample estimates:
##       cor
## -0.3024089

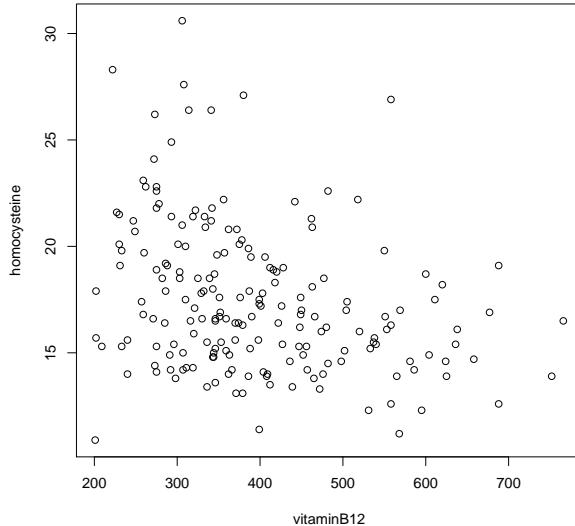
cor.test(vitaminB12, homocysteine, method="spearman")

## Warning in cor.test.default(vitaminB12, homocysteine, method =
## "spearman"): Cannot compute exact p-value with ties

## 
## Spearman's rank correlation rho
## 
## data: vitaminB12 and homocysteine
## S = 1511000, p-value = 5.962e-06
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##       rho
## -0.3218201

plot(vitaminB12,homocysteine)

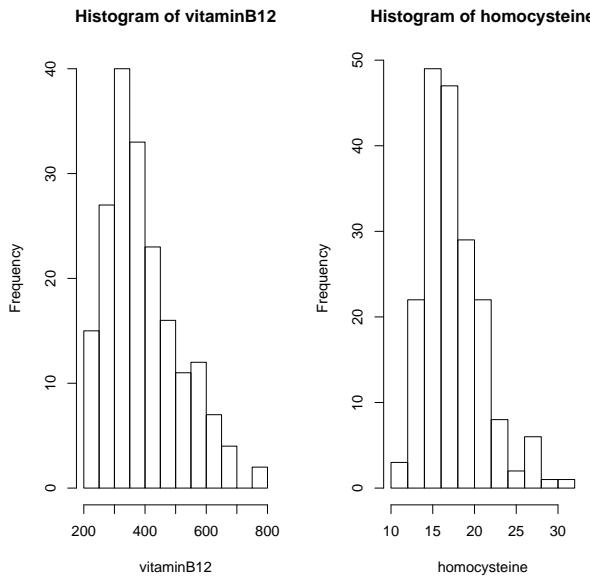
```



There does appear to be a linear association between the two variables. Our null hypothesis is that there is no association between the two measures, and our alternative hypothesis is that there is an association. The tests in both cases are statistically significant ($p\text{-value} < 0.05$ and CI doesn't contain 0) indicating there is an association between the two variables.

- (b) Plot a histogram of each variable to decide whether the Pearson correlation is appropriate to use. Is it?

```
par(mfrow=c(1, 2))
hist(vitaminB12)
hist(homocysteine)
```

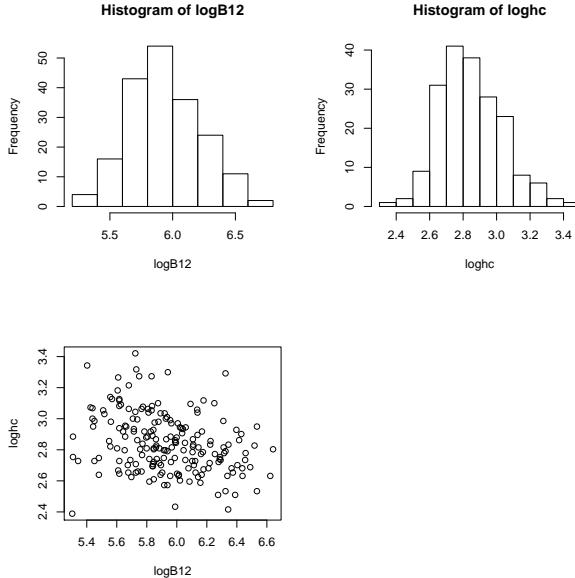


The distributions are not normal but skewed, so it is more appropriate to use the Spearman correlation.

- (c) Does the correlation improve after a log transformation of both variables? Make plots and do a test on the appropriate (Spearman or Pearson - depends on distribution!) correlation to answer this question.

```
logB12 <- log(vitaminB12)
loghc <- log(homocysteine)
par(mfrow=c(2,2))
hist(logB12)
hist(loghc)
plot(logB12, loghc)
cor(logB12, loghc)

## [1] -0.3031782
```



The log-transformed variables are normally distributed, and the relationship looks linear, so we can use the Pearson correlation. Our null hypothesis is that there is no association between the two log-transformed measures, and our alternative hypothesis is that there is an association. Note that the correlation didn't change much from the unlogged data.

```
cor.test(logB12, loghc)

##
##  Pearson's product-moment correlation
##
## data: logB12 and loghc
## t = -4.3623, df = 188, p-value = 2.119e-05
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## -0.4270986 -0.1680789
## sample estimates:
##        cor
## -0.3031782
```

The test is statistically significant ($p\text{-value} < 0.05$ and CI doesn't contain 0) indicating there is an association between the two log-transformed variables.

- (d) Let's see what happens when we “categorize” a continuous variable. Cut `vitaminB12` into 4 groups, where the breaks are the 5 quantile points of `vitaminB12`. Make sure you include the lowest breakpoint by specifying “`incl=TRUE`”. Assign the output to `catB12`. What are the levels of this new variable?

```

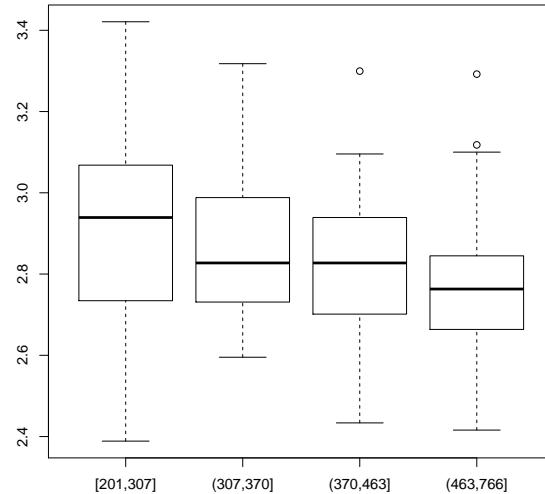
catB12 <- cut(vitaminB12, breaks=quantile(vitaminB12), incl=TRUE)
levels(catB12)

## [1] "[201,307]" "(307,370]" "(370,463]" "(463,766]"

```

- (e) Using the log-transformed variable from part (c), assess how the log of homocysteine and catB12 relate. Make a boxplot of log-homocysteine for each level of catB12.

```
boxplot(loghc~catB12)
```



There appears to be a trend: the higher levels of B12 correspond to lower levels of log-transformed homocysteine.

- (f) Are the means of log-homocysteine equal across all levels of catB12? Formulate a hypothesis, test it, and make a decision for statistical significance.
Our null hypothesis is that the mean log-homocysteine level of all categories of catB12 are equal. The alternative is that at least one of the group means differs from the other 3.

```

summary(aov(loghc~catB12))

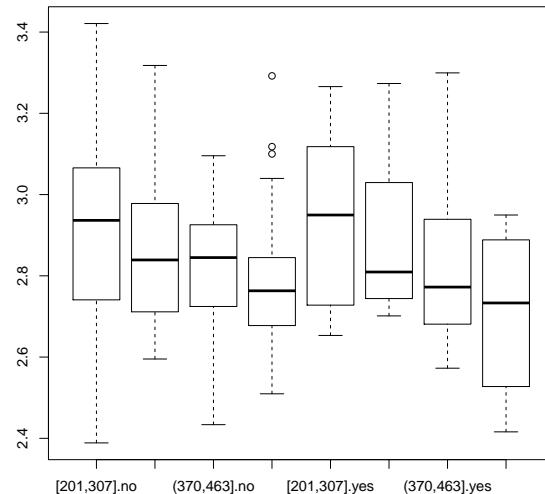
##              Df Sum Sq Mean Sq F value    Pr(>F)
## catB12          3  0.626  0.20880   6.286 0.000438 ***
## Residuals     186  6.179  0.03322
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

The p -value from an ANOVA is less than 0.05, so we conclude that there is a statistically significant difference between the mean log-homocysteine of at least one of the groups and the others. But note that this categorization of `vitaminB12` leads to a p -value that is larger than when we directly used the continuous values. This is because we are reducing the information used in the test: from 190 (nearly unique) individual data points to 190 data points that can only be 1 of 4 values/categories. It's actually recommended that you never categorize continuous variables for this exact reason!

- (g) Now let's see if log-homocysteine varies on both `smoking` and `catB12` levels. Make a boxplot of log-homocysteine for all combinations of the 2 categories. Then formulate a hypothesis, test it, and make a decision for statistical significance on both categorical variables.

```
boxplot(loghc ~ catB12 + smoking)
```



Our null hypothesis is that the mean log-homocysteine level of all combinations of categories of `catB12` and `smoking` are equal. The alternative is that at least one of the group means differs from the others.

```
summary(aov(loghc~catB12 * smoking))

##                               Df Sum Sq Mean Sq F value    Pr(>F)
## catB12                  3  0.626  0.20880   6.171 0.000512 ***
## smoking                  1  0.000  0.00006   0.002 0.965727
## catB12:smoking          3  0.020  0.00675   0.199 0.896732
## Residuals                182 6.158  0.03384
```

```

## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Since there is no statistically significant interaction between `catB12` and `smoking` we will actually proceed after removing the interaction:

```

summary(aov(loghc~catB12 + smoking))

##           Df Sum Sq Mean Sq F value    Pr(>F)
## catB12      3  0.626  0.20880   6.252 0.000458 ***
## smoking      1  0.000  0.00006   0.002 0.965502
## Residuals  185  6.178  0.03340
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

The *p*-value of homocysteine from a 2-way ANOVA test is less than 0.05, so we conclude that there is a statistically significant difference between the mean log-homocysteine of at least one of the `catB12` groups and the others (at any level of smoking). `smoking` is not significant, so there is no difference in the means of `homocysteine` in smokers and non-smokers (at any level of B12). You could now just use the model without `smoking` (see part (f)).

3. We suspect that people who drink alcohol (`alcohol` is yes) might also be smokers (`smoking` is yes). Formulate a hypothesis, test it using the appropriate test, and make a decision about statistical significance. [Hint: use `table`.]

The null hypothesis is that alcohol and smoking are independent; the alternative is that they are dependent.

```

tas <- table(alcohol, smoking)
chisq.test(tas)

##
## Pearson's Chi-squared test with Yates' continuity correction
##
## data: tas
## X-squared = 7.8407, df = 1, p-value = 0.005108

```

The *p*-value is less than 0.05 so we conclude that there is a statistically significant relationship between smoking and drinking.

Basic Course on R: Distribution-Free ANOVA

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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3 Summary of Procedures	6

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1 Kruskal-Wallis Test

The single-factor ANOVA model for comparing population or treatment means assumed that for all groups, random samples were drawn from normal populations each having the same variance. This normality assumption is required for a valid F test, but the next procedure for testing the equality of the centers of the distributions only requires that the populations have the same continuous distribution.

The null hypothesis is that all of the group centers are the same and the alternative is that at least one of the group centers is different. The Kruskal-Wallis test examines the validity of these hypotheses by working on ranks of the data without assuming the data come from a specific distribution.

The procedure starts by ranking all the data together on the assumption of the null, that if the centers of the groups are equal, the ranks from all the groups will be intermingled. If the null is false, then some samples will consist mostly of observations having small ranks in the combined sample, whereas others will consist mostly of observations having large ranks.

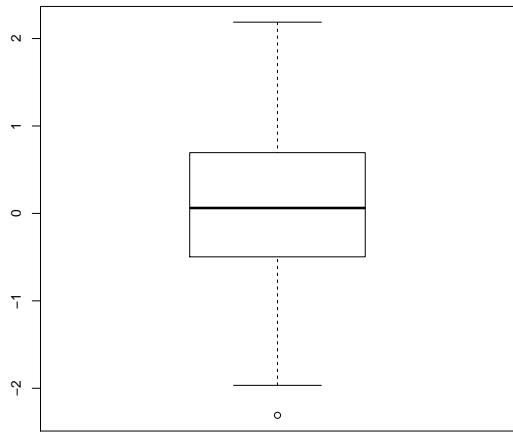
The Kruskal-Wallis test statistic is a measure of the extent to which the sums of the ranks within each group deviate from their common expected value, and the null is rejected if the computed value of the statistic indicates too great a discrepancy between observed and expected rank averages.

Example. The accompanying observations on axial stiffness index resulted from a study of metal-plate connected trusses in which five different plate lengths (4 in., 6 in., 8 in., 10 in., and 12 in.) were used.

	$i = 1 (4"):$	309.2	309.7	311.0	316.8	326.5	349.8	409.5		
	$i = 2 (6"):$	331.0	347.2	348.9	361.0	381.7	402.1	404.5		
	$i = 3 (8"):$	351.0	357.1	366.2	367.3	382.0	392.4	409.9		
	$i = 4 (10"):$	346.7	362.6	384.2	410.6	433.1	452.9	461.4		
	$i = 5 (12"):$	407.4	410.7	419.9	441.2	441.8	465.8	473.4		
							r_i	\bar{r}_i		
	$i = 1:$	1	2	3	4	5	10	49	7.00	
	$i = 2:$	6	8	9	13	17	21	22	96	13.71
<i>Ranks</i>	$i = 3:$	11	12	15	16	18	20	25	117	16.71
	$i = 4:$	7	14	19	26	29	32	33	160	22.86
	$i = 5:$	23	27	28	30	31	34	35	208	29.71

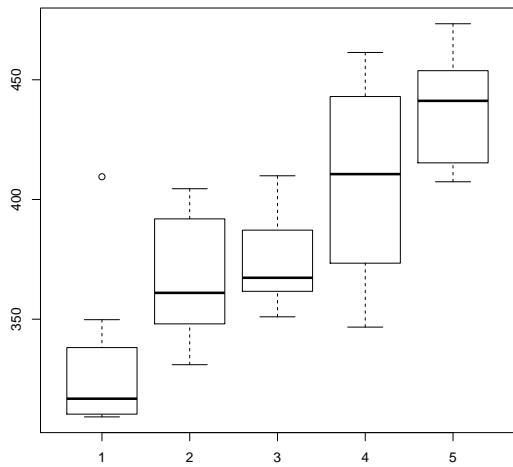
Here we read in the data and note how a boxplot of normally distributed data looks:

```
axial <- read.csv("stiffness.csv", header=T)
attach(axial)
set.seed(123)
boxplot(rnorm(100))
```



If we look at the boxplot of the stiffness values for each length, we see that the means are probably different and that the boxplots don't look very normal:

```
boxplot(stiffness~lengths)
```



The output of the Kruskal-Wallis test confirms that the means are indeed different. The *p*-value is quite small, indicating at least two of the group centers are different:

```
kruskal.test(stiffness, lengths)

##
##  Kruskal-Wallis rank sum test
##
## data: stiffness and lengths
## Kruskal-Wallis chi-squared = 20.122, df = 4, p-value = 0.0004724
```

2 Friedman's Test

In many cases we have two factors of interest instead of just one, as in the two-way ANOVA we've already looked at, but for one of the factors we know that the observations within groups will be more homogeneous (less variable) than between the groups with respect to the response values.

In this case, the levels of the factors are called **blocks** and we treat it differently from the other factor, since the presence or absence of a statistically significant result may be due to this extraneous variation rather than to the presence or absence of factor effects. Here we will not consider any interactions between the two factors, and we will not test the blocks because we already know they should have differing means.

The purpose of utilizing blocks is to filter out the variation due to the blocks. For example, a single subject can receive all treatments and the blocking is done to control for variability between subjects (and each subject acts as its own control). These are called “repeated-measures” designs: the units within a block are different instances of a treatment application. Blocks can also be taken as different time periods, locations, or observers.

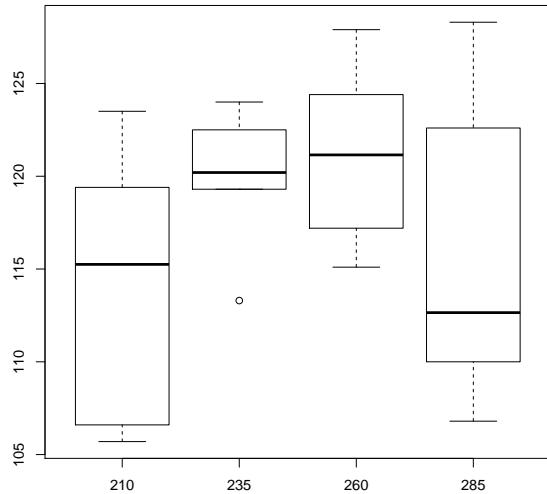
Let's take a look at an example using data on tennis rackets and the speed of the ball coming off of the racket. In one experiment four different string tensions were used, and balls projected from a machine were hit by 18 different players. The rebound speed (km/h) was determined for each tension-player combination. Consider the following data from a similar experiment with 6 players.

```
tennis <- read.csv("tennis.csv", header=T)
head(tennis)

##   tension player speed
## 1      210       1 105.7
## 2      210       2 116.6
## 3      210       3 106.6
## 4      210       4 113.9
## 5      210       5 119.4
## 6      210       6 123.5

attach(tennis)
```

```
boxplot(speed~tension)
```



So we see there are possibly varying mean speeds between the different tensions (and the speeds are not necessarily normal) and we would like to filter out the person-to-person variability.

Friedman's test ranks each observation within the blocks (here, people) and then the average rank is computed for the factor of interest (in this case, racket tension). When the null hypothesis that all of the tension median speeds are the same, the average ranks should be close to one another, but when the null is false, they will be far from one another. Friedman's test statistic measure the discrepancy between the expected value of each rank average under the null and the observed rank averages.

In R, the function is `friedman.test()` with arguments `y` (response), `groups` (factor of interest), and `blocks` (blocking factor):

```
friedman.test(speed, tension, player)

##
##  Friedman rank sum test
##
## data: speed, tension and player
## Friedman chi-squared = 7.8, df = 3, p-value = 0.05033
```

At a 10% significance level, we are able to say the data provide sufficient evidence that there is a difference in mean speed between the rackets because our p -value is less than 0.10. Note what happens if we ignore the blocks and use Kruskal-Wallis:

```
kruskal.test(speed, tension)

##
##  Kruskal-Wallis rank sum test
##
## data: speed and tension
## Kruskal-Wallis chi-squared = 3.9684, df = 3, p-value = 0.2649
```

The p -value is much larger without using blocks.

3 Summary of Procedures

Here is a table that summarizes when to use each of the procedures we've covered:

	Test one mean	Compare 2 means	Compare at least 2 means (one-way)	Compare at least 2 means (two-way)
Population(s) assumed normally distributed	one-sample t -test	two-sample t -test	ANOVA (F -test)	ANOVA (F -test)
Distribution-free	Signed rank test	Wilcoxon rank sum test	Kruskal-Wallis rank sum test	Friedman rank sum test

Basic Course on R: Distribution-Free ANOVA Practical

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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1 Dogs

1. In an experiment to study the way in which different anesthetics affect plasma epinephrine concentration, ten dogs were selected and concentration was measured while they were under the influence of the anesthetics isoflurane, halothane, and cyclopropane. Test at level 0.05 to see whether there is an anesthetic effect on concentration.

Dog	1	2	3	4	5	6	7	8	9	10
Isoflurane	0.30	0.53	1.02	0.41	0.31	0.38	0.34	0.71	0.19	0.35
Halothane	0.32	0.41	0.65	0.40	0.23	0.90	0.41	0.53	0.34	0.44
Cyclopropane	1.09	1.37	0.71	0.30	1.26	1.55	0.51	0.58	1.04	0.32

Read in the data “dogs.csv” with a header. Assign it to the object `doggies` and allow strings be converted to factors. Attach the data to the environment.

2. Answer the following questions using the dog data:
 - (a) We’re going to use Friedman’s test. Which factor represents the blocks and why?
 - (b) Make a boxplot of the concentration grouped by anesthetic. Which anesthetic do you think might be different from the others?
 - (c) Perform the appropriate Friedman’s test in R.
 - (d) What do you conclude about the effect of anesthetics on plasma epinephrine concentration (use a significance level of 0.05)?

2 Moms

3. The data in “moms.csv” on cortisol level was reported in a research paper. Experimental subjects were pregnant women whose babies were delivered between 38 and 42 weeks gestation. Group 1 individuals elected to deliver by Caesarean section before labor onset, group 2 delivered by emergency Caesarean during induced labor, and group 3 individuals experienced spontaneous labor.

Read in the data “moms.csv” with a header. Assign it to the object `mommies` and allow strings to be converted to factors. Attach the data to the environment.

4. Answer the following questions using the mom data:
 - (a) Test at significance level 0.05 for equality of the three population centers (use the Kruskal-Wallis test).
 - (b) Make a boxplot of the cortisol level grouped by C-section groups. Use it to explain why we didn’t use an F test (regular one-way ANOVA).

Basic Course on R: Distribution-Free ANOVA Practical Answers

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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1 Dogs	2
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1 Dogs

1. In an experiment to study the way in which different anesthetics affect plasma epinephrine concentration, ten dogs were selected and concentration was measured while they were under the influence of the anesthetics isoflurane, halothane, and cyclopropane. Test at level 0.05 to see whether there is an anesthetic effect on concentration.

Dog	1	2	3	4	5	6	7	8	9	10
Isoflurane	0.30	0.53	1.02	0.41	0.31	0.38	0.34	0.71	0.19	0.35
Halothane	0.32	0.41	0.65	0.40	0.23	0.90	0.41	0.53	0.34	0.44
Cyclopropane	1.09	1.37	0.71	0.30	1.26	1.55	0.51	0.58	1.04	0.32

Read in the data “dogs.csv” with a header. Assign it to the object `doggies` and allow strings be converted to factors. Attach the data to the environment.

```
doggies <- read.csv("dogs.csv", header=T)
attach(doggies)

## The following object is masked from Puromycin:
##
##     conc
```

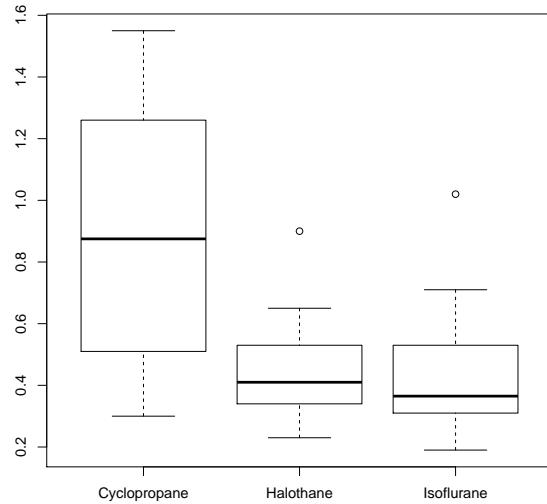
2. Answer the following questions using the dog data:

- (a) We’re going to use Friedman’s test. Which factor represents the blocks and why?

The dogs are the blocks because they should be more homogeneous within (with respect to concentration) than between dogs. This is a repeated-measures design, where the dogs are received multiple treatments and we are measuring the concentration repeatedly.

- (b) Make a boxplot of the concentration grouped by anesthetic. Which anesthetic do you think might be different from the others?

```
boxplot(conc~anesthetic)
```



Looks like the median concentration for cyclopropane is higher than the other two.

- (c) Perform the appropriate Friedman's test in R.

```
friedman.test(conc, anesthetic, dog)

##
##  Friedman rank sum test
##
## data: conc, anesthetic and dog
## Friedman chi-squared = 2.6, df = 2, p-value = 0.2725
```

- (d) What do you conclude about the effect of anesthetics on plasma epinephrine concentration (use a significance level of 0.05)?

Since the *p*-value (0.2725) is greater than 0.05, the data do not provide sufficient evidence to conclude the three anesthetics have differing effects on the plasma epinephrine concentration.

2 Moms

3. The data in “moms.csv” on cortisol level was reported in a research paper. Experimental subjects were pregnant women whose babies were delivered between 38 and 42 weeks gestation. Group 1 individuals elected to deliver by Caesarean section before labor onset, group 2 delivered by emergency Caesarean during induced labor, and

group 3 individuals experienced spontaneous labor.

Read in the data “moms.csv” with a header. Assign it to the object `mommies` and allow strings to be converted to factors. Attach the data to the environment.

```
mommies <- read.csv("moms.csv", header=T)
attach(mommies)
```

4. Answer the following questions using the mom data:

- (a) Test at significance level 0.05 for equality of the three population means (use the Kruskal-Wallis test).

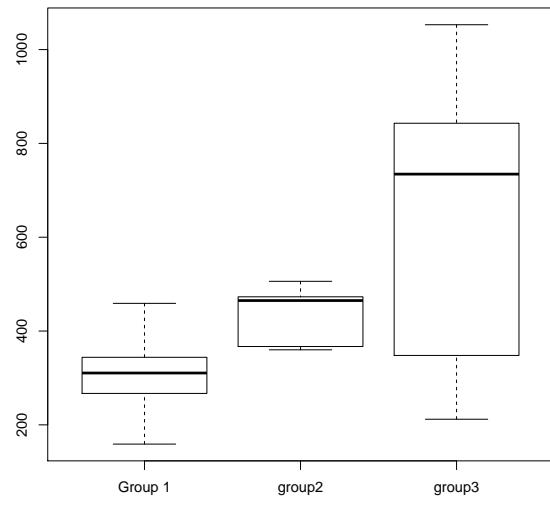
```
kruskal.test(cortisol~group)

##
##  Kruskal-Wallis rank sum test
##
## data: cortisol by group
## Kruskal-Wallis chi-squared = 9.2316, df = 2, p-value = 0.009894
```

With a *p*-value 0.009894, which is less than 0.05, we are able to reject the null that all the group medians are equal. We therefore conclude at least two of the median cortisol levels of the three groups are different.

- (b) Make a boxplot of the cortisol level grouped by C-section groups. Use it to explain why we didn’t use an *F* test (regular one-way ANOVA).

```
boxplot(cortisol~group)
```



While group 1 data appear to have been sampled from a normal distribution, we cannot say the same for groups 2 and 3. So we should not use an F test which assumes the data are normal.

Basic Course on R: Linear Regression

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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Most of the following examples use the data “R_data_January2015.csv” which contains variables on mothers whose babies are either intellectually disabled or developmentally normal.

```
babies <- read.csv("R_data_January2015.csv", header=T, row.names=1)
names(babies)

## [1] "Status"                  "iodine_deficiency"
## [3] "BMI"                     "educational_level"
## [5] "alcohol"                 "smoking"
## [7] "medication"              "birthweight"
## [9] "pregnancy_length_weeks"  "pregnancy_length_days"
## [11] "SAM"                     "SAH"
## [13] "homocysteine"            "cholesterol"
## [15] "HDL"                     "triglycerides"
## [17] "vitaminB12"              "folicacid_serum"
## [19] "folicacid_erys"

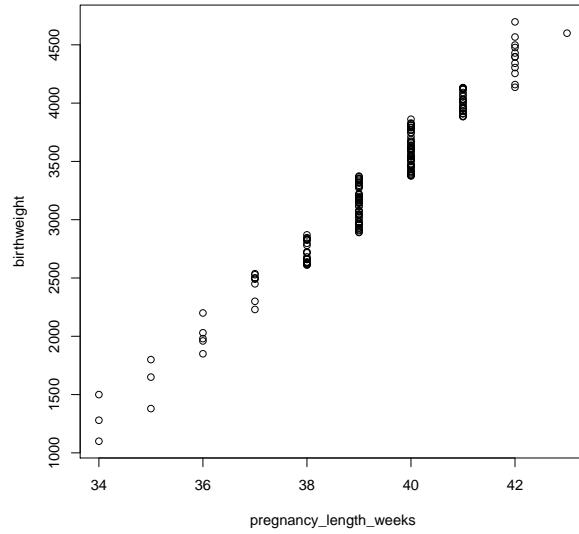
attach(babies)

## The following objects are masked from babydata (pos = 7):
## 
## alcohol, birthweight, BMI, cholesterol, educational_level,
## folicacid_erys, folicacid_serum, HDL, homocysteine,
## iodine_deficiency, medication, pregnancy_length_days,
## pregnancy_length_weeks, SAH, SAM, smoking, Status,
## triglycerides, vitaminB12
## The following objects are masked from babies (pos = 9):
## 
## alcohol, birthweight, BMI, cholesterol, educational_level,
## folicacid_erys, folicacid_serum, HDL, homocysteine,
## iodine_deficiency, medication, pregnancy_length_days,
## pregnancy_length_weeks, SAH, SAM, smoking, Status,
## triglycerides, vitaminB12
## The following objects are masked from babydata (pos = 10):
## 
## alcohol, birthweight, BMI, cholesterol, educational_level,
## folicacid_erys, folicacid_serum, HDL, homocysteine,
## iodine_deficiency, medication, pregnancy_length_days,
## pregnancy_length_weeks, SAH, SAM, smoking, Status,
## triglycerides, vitaminB12
```

1 Linear Regression Basics

There is a high positive correlation between birth weight and gestational age, but this says nothing about predictive power of the variables. We would like to explain how gestational age influences changes in birth weight.

```
plot(pregnancy_length_weeks,birthweight)
```



```
cor(pregnancy_length_weeks,birthweight)
```

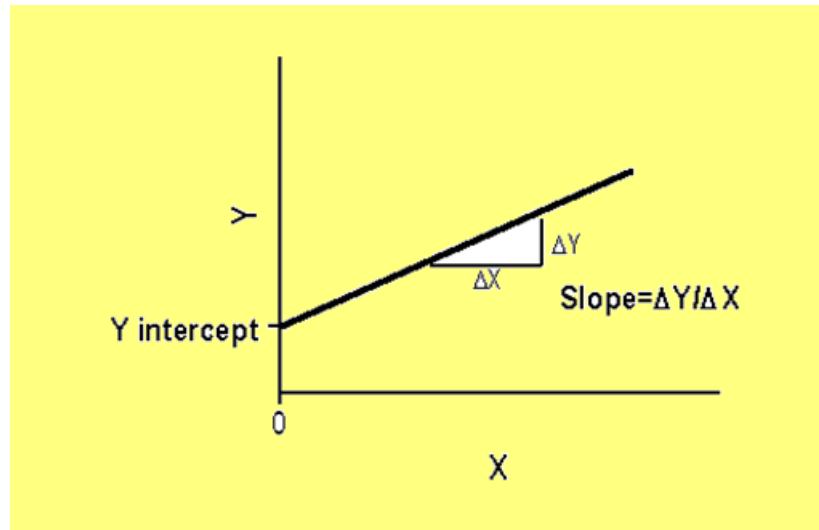
```
## [1] 0.9785784
```

We'll quantify this relationship using linear regression, distinguishing between an independent, or predictor or explanatory, variable (gestational age) and a dependent, or response or outcome, variable (birth weight). Simple linear regression uses the following model:

$$\begin{aligned} \text{response}_i &= (\text{model}_i) + \text{error}_i \\ y_i &= b_0 + b_1 X_i + \epsilon_i \end{aligned}$$

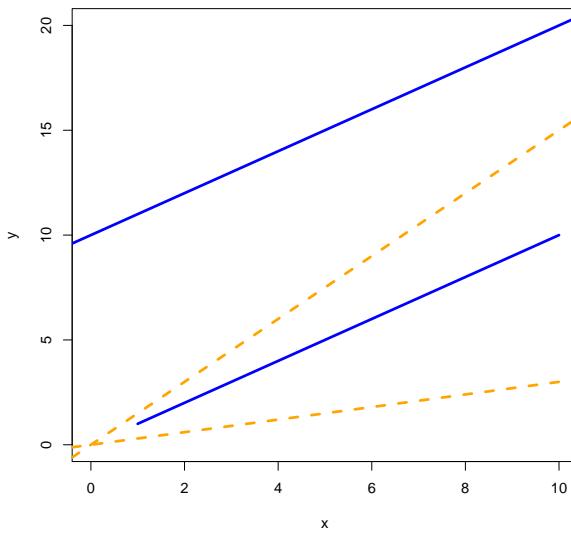
where $1 \leq i \leq n$, model is a straight line, and error is remaining variation which cannot be explained by the model.

The parameters b_0 and b_1 are the intercept and slope of a straight line, respectively:



Note that intercept and slope represent different things:

```
plot(1:10, 1:10, type="l", col="blue", lwd=3,
      ylim=c(0,20), xlim=c(0,10), xlab="x", ylab="y")
abline(0, 1.5, lty=2, col="orange", lwd=3)
abline(0, .3, lty=2, col="orange", lwd=3)
abline(10, 1, lty=1, col="blue", lwd=3)
```

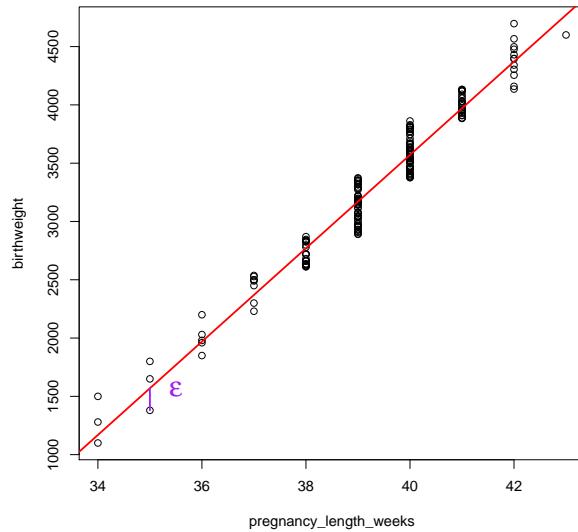


The error term ϵ_i denotes the residuals: the differences between observed values and the fitted line.

```

plot(pregnancy_length_weeks,birthweight)
abline(-12441.4, 400.3, col="red", lwd=2)
lines(c(35,35), c(1380,1568.921), lwd=2, col="purple")
text(35.5, 1560, expression(epsilon), cex=2, col="purple")

```



The b_0 and b_1 of the one straight line that best fits the data is estimated via the method of least squares. The “best” line is the one that has the lowest sum of squared residuals. The command to get these estimates in R is `lm`:

```

lm1 <- lm(birthweight ~ pregnancy_length_weeks)
lm1

##
## Call:
## lm(formula = birthweight ~ pregnancy_length_weeks)
## 
## Coefficients:
## (Intercept)  pregnancy_length_weeks
## -12441.4          400.3

```

and that's how I knew the line in the above plot should have intercept -12441.4 and slope 400.3! Also, the point on the line for 35 weeks is $-12441.4 + 400.3 * 35 = 1568.921$, which can be more accurately provided by

```
predict(lm1)[pregnancy_length_weeks==35]

##      12      73     141
## 1568.921 1568.921 1568.921
```

You can also use `predict` to predict y for x 's that are not already in your data:

```
predict(lm1, newdata=data.frame(pregnancy_length_weeks=c(seq(25,50,5)))) 

##      1      2      3      4      5      6
## -2434.0284 -432.5538 1568.9207 3570.3952 5571.8698 7573.3443
```

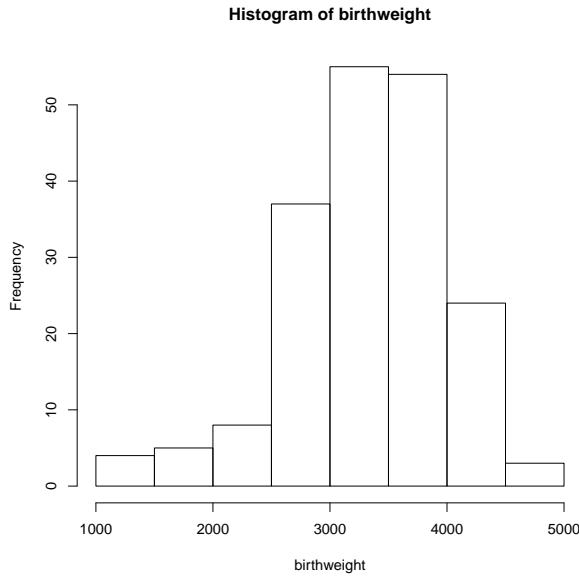
but watch out for extrapolating (predicting outside the range of your data) - clearly we can't have negative birth weights!

Now, before we make inference on or, actually, even find and use this line, we **must** check that the following assumptions hold, otherwise we will not obtain trustworthy results:

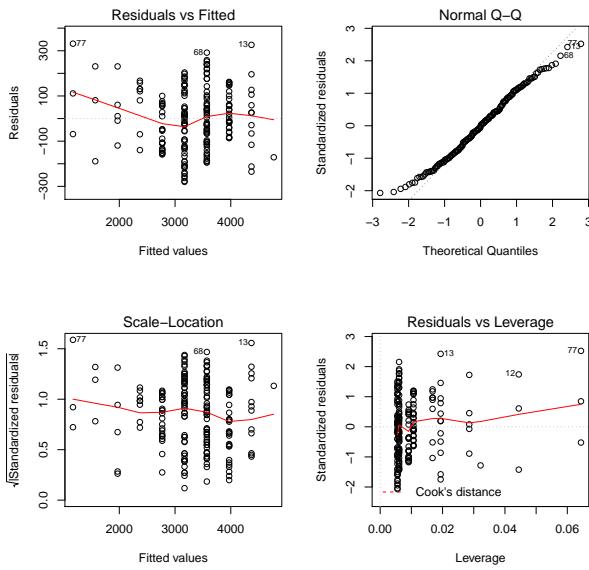
- relationship between x and y can be described by a straight line
- outcomes y are independent
- variance of residuals is constant across values of x
- residuals follow a normal distribution

To get diagnostic plots in R, we can check a histogram of the data and additionally plot our model to check that the residuals are normal and homoscedastic (have constant variance) across the weeks:

```
hist(birthweight)
```



```
par(mfrow=c(2,2))
plot(lm1)
```

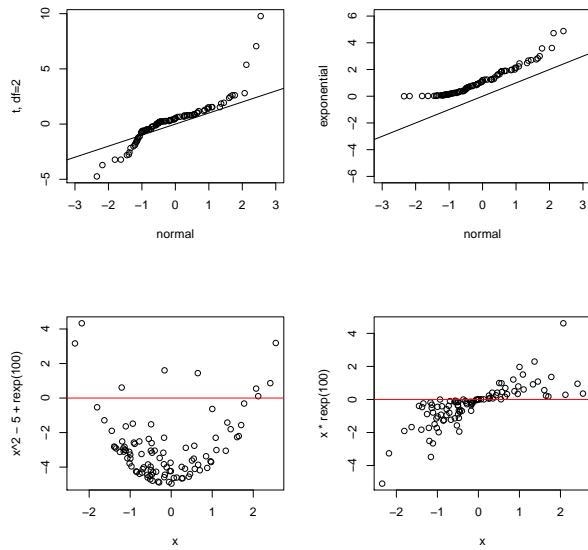


The top left plot tells us if our residuals are homoscedastic, and the top right plot displays a quantile-quantile (QQ) plot to check for normality. Here are examples of bad QQ plots and heteroscedasticity:

```

set.seed(1234)
par(mfrow=c(2,2))
x <- sort(rnorm(100))
y1 <- sort(rt(100,2))
plot(x, y1, xlim=c(-3,3), xlab="normal", ylab="t, df=2")
abline(0, 1)
y2 <- sort(rexp(100))
plot(x, y2, xlim=c(-3,3), ylim=c(-6,6), xlab="normal", ylab="exponential")
abline(0, 1)
plot(x, x^2-5+rexp(100))
abline(0, 0, col="red")
plot(x, x*rexp(100))
abline(0, 0, col="red")

```



However, the assumptions reasonably hold for our baby data, so we'll go ahead and use the model fit to make inference on the slope b_1 .

Actually, R has already done the inference...we just need to extract it from the model:

```

summary(lm1)

##
## Call:
## lm(formula = birthweight ~ pregnancy_length_weeks)

```

```

## 
## Residuals:
##   Min     1Q Median     3Q    Max
## -280.1 -106.7   -2.9  101.2  331.4
## 
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)           -12441.401    242.033 -51.40 <2e-16 ***
## pregnancy_length_weeks  400.295      6.142   65.17 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 135.7 on 188 degrees of freedom
## Multiple R-squared:  0.9576, Adjusted R-squared:  0.9574
## F-statistic:  4248 on 1 and 188 DF,  p-value: < 2.2e-16

```

R has performed a one-sample t -test on the intercept b_1 and slope b_0 to determine if they are each statistically significantly different from 0. The probabilities are quite small, so we can reject the null hypothesis that they are equal to 0 and conclude that birthweight significantly increases, on average, by 400 grams per every additional week of gestation. The intercept is (usually) unimportant and we don't really care that it is different from 0. If the p -value for the slope is not small (e.g. greater than 0.05) then we would say "we do not have enough evidence to reject the null hypothesis that the slope is 0."

Now, how good does the model actually fit our data? How well does x predict y ? In a previous lecture, I told you that the square of Pearson's correlation coefficient, r , is a measure of goodness of fit. It is the proportion of variance in y that can be explained by the model (so, x). In our example, r^2 is:

```

cor(pregnancy_length_weeks,birthweight)^2

## [1] 0.9576157

summary(lm1)$r.squared

## [1] 0.9576157

```

which means that 96% of the variability in birth weight can be explained by gestational age.

2 Multiple Linear Regression

Simple linear regression models one y on one x . If we have multiple predictor variables, we use multiple linear regression to determine if the variability in y can be explained by this set of variables. In addition to the assumptions required for a valid simple linear regression, we now include that the covariates have no perfect multicollinearity, that is there is no strong correlation between the multiple x 's. The model is

$$y = b_0 + b_1 X_1 + b_2 X_2 + \dots + b_k X_k + \epsilon_i$$

In R, the addition of an extra variable is quite straightforward:

```
cor(pregnancy_length_weeks, BMI)

## [1] 0.01068054

lm2 <- lm(birthweight ~ pregnancy_length_weeks + BMI)
lm2stats <- summary(lm2)
lm2stats

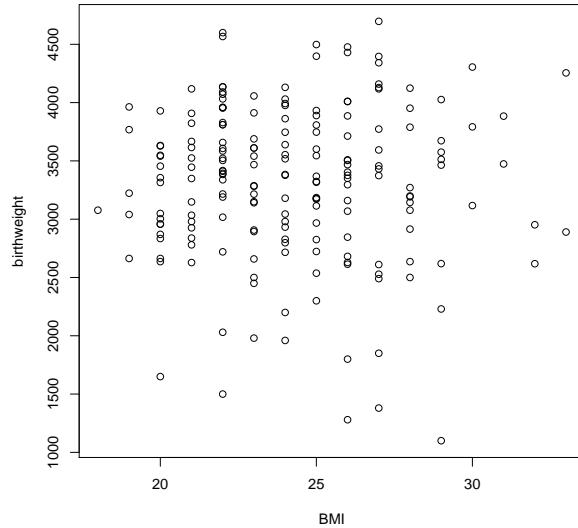
##
## Call:
## lm(formula = birthweight ~ pregnancy_length_weeks + BMI)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -279.39  -105.78    -1.85   105.25   333.50
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)             -12377.339    253.444 -48.837  <2e-16 ***
## pregnancy_length_weeks   400.351     6.147   65.133  <2e-16 ***
## BMI                     -2.738      3.190   -0.858     0.392
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 135.8 on 187 degrees of freedom
## Multiple R-squared:  0.9578, Adjusted R-squared:  0.9573
## F-statistic: 2121 on 2 and 187 DF,  p-value: < 2.2e-16
```

Since the 2 variables are uncorrelated, we can add BMI to the model. We see that it does not significantly predict birth weight, but gestational age still does. We use the adjusted r^2 to check goodness of fit:

```
lm2stats$adj.r.squared
## [1] 0.9573304
```

So adding BMI does not help explain any of the variability in birth weight (since r^2 was previously already 0.96). This is also confirmed by visualization:

```
plot(BMI,birthweight)
```



Note that the `summary` function returns a lot of information. If, for example, you wanted to extract only the p -values you could do the following:

```
names(lm2stats)
##  [1] "call"          "terms"         "residuals"      "coefficients"
##  [5] "aliased"       "sigma"        "df"            "r.squared"
##  [9] "adj.r.squared" "fstatistic"    "cov.unscaled"

lm2stats$coef[,4]
##                (Intercept) pregnancy_length_weeks           BMI
## 2.179929e-108   1.815592e-130   3.918778e-01
```

We can predict birthweights with new data:

```

predict(lm2, newdata=data.frame(pregnancy_length_weeks=32,
                                  BMI=30))

##      1
## 351.771

## same as
lm2coefs <- lm2$coef
lm2coefs[1] + lm2coefs[2]*32 + lm2coefs[3]*30

## (Intercept)
## 351.771

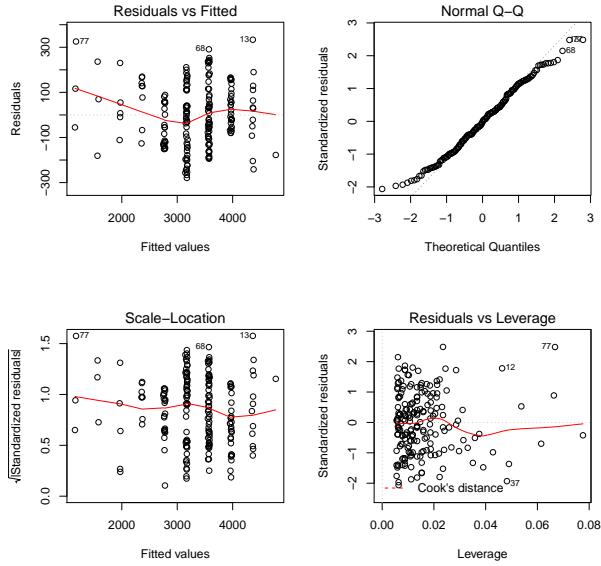
```

But we cannot forget to check assumptions!

```

par(mfrow=c(2,2))
plot(lm2)

```



Basic Course on R: Linear Regression Practical

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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1 Baby Data

1. Read in the data “R_data_January2015.csv” with a header and row names from the first column. Assign it to the object `babydata` and allow strings be converted to factors. Attach the data to the environment.
2. We previously saw that there was an association between `vitaminB12` and `homocysteine`. We will now quantify the magnitude of this relationship and see if we can explain the variabiliy of `homocysteine` with values of `vitaminB12`. Answer the following questions:
 - (a) First plot the data: a scatterplot to visualize the association (should be linear) and a histogram of the dependent variable to check for normality (normal errors are required - checking the distribution of the dependent variable is good enough for now). Do these particular assumptions appear to hold?
 - (b) You should have noticed that the dependent variable `homocysteine` is right-skewed. We need to see if a log-transformation of the data is more normally distributed. Assign the log of `homocysteine` to `loghc` and make a histogram of `loghc`. Check that it is normal by plotting it against a normal distribution (use `qqnorm()`). How does it look? More normal?
 - (c) We'll just assume everything looks good. Set up (i.e. write down) the linear regression model for modeling `loghc` against `vitaminB12` and then run it in R. Check the assumptions by plotting the residuals (should be no patterns) versus the fitted values and looking at a QQ plot of the residuals (should be straight line). Do the assumptions hold?

- (d) Assuming the assumptions hold (even if they don't), we'll make inference on the slope. Is `vitaminB12` statistically significant in the model? What percent variability does it explain in `loghc`? Write down the model with the estimates.
- (e) What is the predicted `loghc` level for a person with `vitaminB12` equal to 650? What is this value when unlogged (exponentiated)? Does it fall within the original range of values of `homocysteine` (can you guess what the name of the function is to find the range of a vector?)?
3. Now let's consider a framework where we want to use more than one predictor. We want to build a regression model for `SAM` using `vitaminB12`, `cholesterol`, `homocysteine` and `folicacid_erys` (folic acid red blood cells). Answer the following questions:
- (a) Set up (i.e. write down) the linear regression model and then run it in R. Check the assumptions by plotting the residuals versus the fitted values and looking at a QQ plot of the residuals. Do the assumptions hold?

- (b) Assuming the assumptions hold (even if they don't), we'll make inference on the slopes. Are any of the variables statistically significant in the model? What percent variability do the variables explain in **SAM**? Write down the model with the estimates.
- (c) What is the predicted **SAM** level for a person with the following:

vitaminB12 = 650
cholesterol = 17
homocysteine = 16
folicacid_erys = 1340

Basic Course on R: Linear Regression Practical Answers

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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1 Baby Data

1. Read in the data “R_data_January2015.csv” with a header and row names from the first column. Assign it to the object `babydata` and allow strings be converted to factors. Attach the data to the environment.

```
babydata <- read.csv("R_data_January2015.csv", header=T, row.names=1)
attach(babydata)

## The following objects are masked from babies (pos = 3):
##
##   alcohol, birthweight, BMI, cholesterol, educational_level,
##   folicacid_erys, folicacid_serum, HDL, homocysteine,
##   iodine_deficiency, medication, pregnancy_length_days,
##   pregnancy_length_weeks, SAH, SAM, smoking, Status,
##   triglycerides, vitaminB12

## The following objects are masked from babydata (pos = 8):
##
##   alcohol, birthweight, BMI, cholesterol, educational_level,
##   folicacid_erys, folicacid_serum, HDL, homocysteine,
##   iodine_deficiency, medication, pregnancy_length_days,
##   pregnancy_length_weeks, SAH, SAM, smoking, Status,
##   triglycerides, vitaminB12

## The following objects are masked from babies (pos = 10):
##
##   alcohol, birthweight, BMI, cholesterol, educational_level,
##   folicacid_erys, folicacid_serum, HDL, homocysteine,
##   iodine_deficiency, medication, pregnancy_length_days,
##   pregnancy_length_weeks, SAH, SAM, smoking, Status,
##   triglycerides, vitaminB12

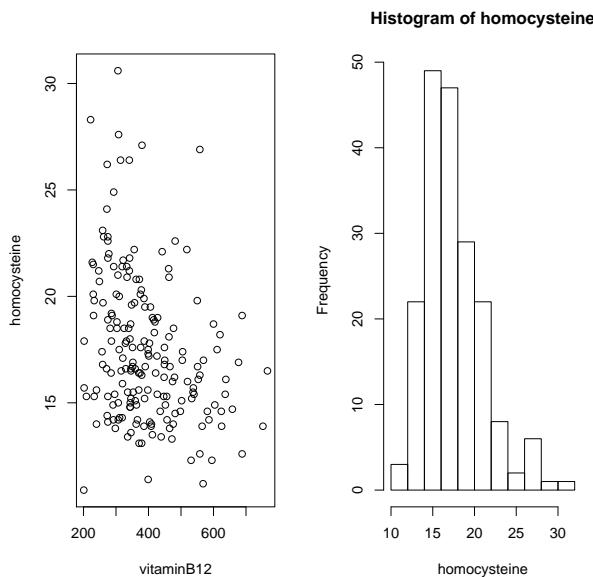
## The following objects are masked from babydata (pos = 11):
##
##   alcohol, birthweight, BMI, cholesterol, educational_level,
##   folicacid_erys, folicacid_serum, HDL, homocysteine,
##   iodine_deficiency, medication, pregnancy_length_days,
##   pregnancy_length_weeks, SAH, SAM, smoking, Status,
##   triglycerides, vitaminB12
```

2. We previously saw that there was an association between `vitaminB12` and `homocysteine`. We will now quantify the magnitude of this relationship and see if we can explain

the variability of `homocysteine` with values of `vitaminB12`. Answer the following questions:

- (a) First plot the data: a scatterplot to visualize the association (should be linear) and a histogram of the dependent variable to check for normality (normal errors are required - checking the distribution of the dependent variable is good enough for now). Do these particular assumptions appear to hold?

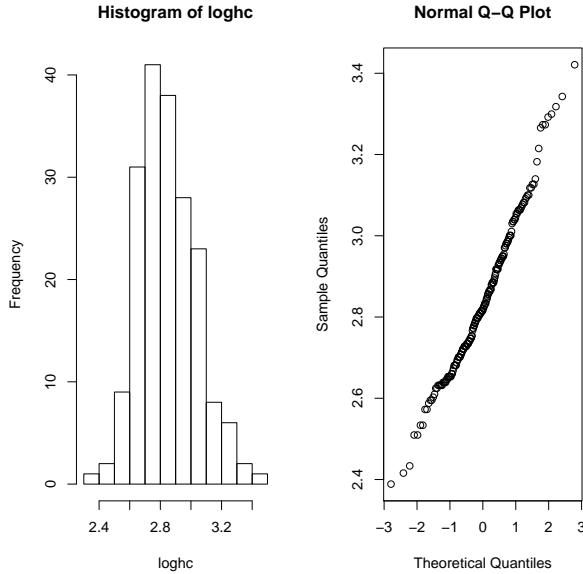
```
par(mfrow=c(1,2))
plot(vitaminB12, homocysteine)
hist(homocysteine)
```



There is a slight linear association but looks like the variable isn't normal...

- (b) You should have noticed that the dependent variable `homocysteine` is right-skewed. We need to see if a log-transformation of the data is more normally distributed. Assign the log of `homocysteine` to `loghc` and make a histogram of `loghc`. Check that it is normal by plotting it against a normal distribution (use `qqnorm()`). How does it look? More normal?

```
loghc <- log(homocysteine)
par(mfrow=c(1,2))
hist(loghc)
set.seed(1234)
qqnorm(loghc)
```



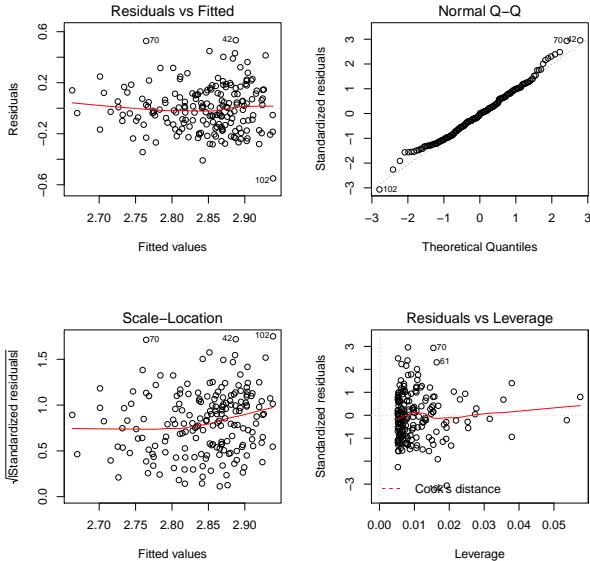
Doesn't look too bad!

- (c) We'll just assume everything looks good. Set up (i.e. write down) the linear regression model for modeling `loghc` against `vitaminB12` and then run it in R. Check the assumptions by plotting the residuals (should be no patterns) versus the fitted values and looking at a QQ plot of the residuals (should be straight line). Do the assumptions hold?

The model is

$$\text{loghc} \sim b_0 + b_1 * \text{vitaminB12} + \epsilon.$$

```
lmbh <- lm(loghc ~ vitaminB12)
par(mfrow=c(2,2))
plot(lmbh)
```



There is a slight fan pattern in the residuals, but it's not too strong. The tails of the distribution deviate from the normal quantile line, but again it's not that bad.

- (d) Assuming the assumptions hold (even if they don't), we'll make inference on the slope. Is `vitaminB12` statistically significant in the model? What percent variability does it explain in `loghc`? Write down the model with the estimates.

```
summary(lmbh)

##
## Call:
## lm(formula = loghc ~ vitaminB12)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.5501 -0.1288 -0.0041  0.1176  0.5334
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 3.0369329  0.0457556 66.373 < 2e-16 ***
## vitaminB12 -0.0004881  0.0001113 -4.386 1.92e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1812 on 188 degrees of freedom
```

```

## Multiple R-squared:  0.09281, Adjusted R-squared:  0.08799
## F-statistic: 19.23 on 1 and 188 DF,  p-value: 1.923e-05

lmbh

##
## Call:
## lm(formula = loghc ~ vitaminB12)
##
## Coefficients:
## (Intercept)  vitaminB12
##   3.0369329   -0.0004881

```

`vitaminB12` is statistically significant (*p*-value less than 0.05). It explains about 9.3 percent of the variability in `loghc`. The model with the estimates is

$$\text{loghc} \sim 3.04 - 0.0005 * \text{vitaminB12}.$$

- (e) What is the predicted `loghc` level for a person with `vitaminB12` equal to 650? What is this value when unlogged (exponentiated)? Does it fall within the original range of values of `homocysteine` (can you guess what the name of the function is to find the range of a vector?)?

```

p650 <- predict(lmbh, newdata=data.frame(vitaminB12=650))
## or
3.04 - 0.0005*650

## [1] 2.715

p650

##       1
## 2.719635

exp(p650)

##       1
## 15.17479

range(homocysteine)

## [1] 10.9 30.6

```

Yes, 15.1 is in the range of the unlogged `homocysteine` values: (10.9, 30.6).

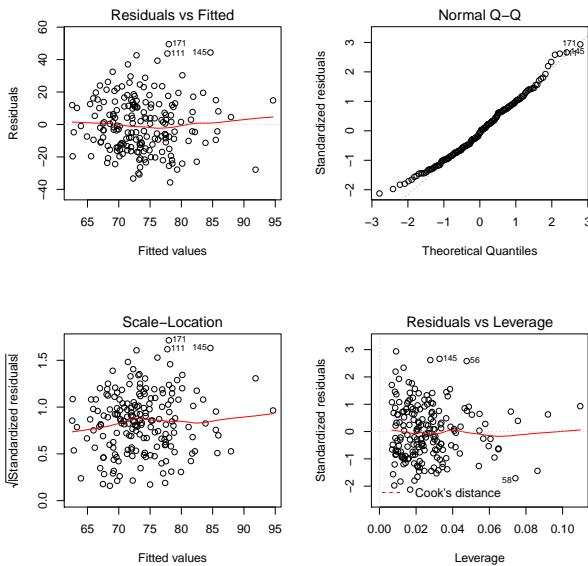
3. Now let's consider a framework where we want to use more than one predictor. We want to build a regression model for **SAM** using **vitaminB12**, **cholesterol**, **homocysteine** and **folicacid_erys** (folic acid red blood cells). Answer the following questions:

- (a) Set up (i.e. write down) the linear regression model and then run it in R. Check the assumptions by plotting the residuals versus the fitted values and looking at a QQ plot of the residuals. Do the assumptions hold?

The model is

$$\text{SAM} \sim b_0 + b_1 * \text{vitaminB12} + b_2 * \text{cholesterol} + b_3 * \text{homocysteine} + b_4 * \text{folicacid_erys} + \epsilon.$$

```
mlr <- lm(SAM ~ vitaminB12 + cholesterol + homocysteine +
            folicacid_erys)
par(mfrow=c(2,2))
plot(mlr)
```



The residuals have constant variance and are normal, so the assumptions do hold.

- (b) Assuming the assumptions hold (even if they don't), we'll make inference on the slopes. Are any of the variables statistically significant in the model? What percent variability do the variables explain in **SAM**? Write down the model with the estimates.

```

summary(mlr)

##
## Call:
## lm(formula = SAM ~ vitaminB12 + cholesterol + homocysteine +
##      folicacid_erys)
##
## Residuals:
##    Min      1Q  Median      3Q     Max 
## -35.704 -12.367 -1.047  11.972  49.505 
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 1.800739  27.877405   0.065  0.948566  
## vitaminB12 -0.002684   0.011286  -0.238  0.812288  
## cholesterol  4.583482   1.369695   3.346  0.000992 *** 
## homocysteine -0.645535   0.413510  -1.561  0.120206  
## folicacid_erys  0.005033   0.006812   0.739  0.460939  
## --- 
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 16.94 on 185 degrees of freedom
## Multiple R-squared:  0.09232, Adjusted R-squared:  0.0727 
## F-statistic: 4.704 on 4 and 185 DF,  p-value: 0.001225 

mlr

##
## Call:
## lm(formula = SAM ~ vitaminB12 + cholesterol + homocysteine +
##      folicacid_erys)
##
## Coefficients:
## (Intercept)      vitaminB12      cholesterol      homocysteine  
##           1.800739     -0.002684       4.583482     -0.645535  
## folicacid_erys          0.005033

```

Only **cholesterol** is statistically significant (*p*-value less than 0.05). The 4 variables explain 7.27 percent of the variability in **SAM**. The model with the estimates is

$$\text{SAM} \sim 1.8 - 0.003 * \text{vitaminB12} + 4.58 * \text{cholesterol} - 0.65 * \text{homocysteine} + 0.005 * \text{folicacid_erys}.$$

(c) What is the predicted SAM level for a person with the following:

```
vitaminB12 = 650  
cholesterol = 17  
homocysteine = 16  
folicacid_erys = 1340
```

```
predict(mlr, newdata=data.frame(vitaminB12=650,  
                                  cholesterol=17,  
                                  homocysteine=16,  
                                  folicacid_erys=1340))  
  
##          1  
## 74.39131
```

Basic Course on R: Logistic Regression

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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Most of the following examples use the data “R_data_January2015.csv” which contains variables on mothers whose babies are either intellectually disabled or developmentally normal.

```
babies <- read.csv("R_data_January2015.csv", header = T, row.names = 1)
names(babies)

## [1] "Status"                  "iodine_deficiency"
## [3] "BMI"                     "educational_level"
## [5] "alcohol"                 "smoking"
## [7] "medication"              "birthweight"
## [9] "pregnancy_length_weeks"  "pregnancy_length_days"
## [11] "SAM"                     "SAH"
## [13] "homocysteine"            "cholesterol"
## [15] "HDL"                     "triglycerides"
## [17] "vitaminB12"              "folicacid_serum"
## [19] "folicacid_erys"

attach(babies)

## The following objects are masked from babydata (pos = 3):
##
##   alcohol, birthweight, BMI, cholesterol, educational_level,
##   folicacid_erys, folicacid_serum, HDL, homocysteine,
##   iodine_deficiency, medication, pregnancy_length_days,
##   pregnancy_length_weeks, SAH, SAM, smoking, Status,
##   triglycerides, vitaminB12
## The following objects are masked from babies (pos = 4):
##
##   alcohol, birthweight, BMI, cholesterol, educational_level,
##   folicacid_erys, folicacid_serum, HDL, homocysteine,
##   iodine_deficiency, medication, pregnancy_length_days,
##   pregnancy_length_weeks, SAH, SAM, smoking, Status,
##   triglycerides, vitaminB12
## The following objects are masked from babydata (pos = 9):
##
##   alcohol, birthweight, BMI, cholesterol, educational_level,
##   folicacid_erys, folicacid_serum, HDL, homocysteine,
##   iodine_deficiency, medication, pregnancy_length_days,
##   pregnancy_length_weeks, SAH, SAM, smoking, Status,
##   triglycerides, vitaminB12
## The following objects are masked from babies (pos = 11):
##
```

```

##      alcohol, birthweight, BMI, cholesterol, educational_level,
##      folicacid_erys, folicacid_serum, HDL, homocysteine,
##      iodine_deficiency, medication, pregnancy_length_days,
##      pregnancy_length_weeks, SAH, SAM, smoking, Status,
##      triglycerides, vitaminB12
## The following objects are masked from babydata (pos = 12):
##
##      alcohol, birthweight, BMI, cholesterol, educational_level,
##      folicacid_erys, folicacid_serum, HDL, homocysteine,
##      iodine_deficiency, medication, pregnancy_length_days,
##      pregnancy_length_weeks, SAH, SAM, smoking, Status,
##      triglycerides, vitaminB12

```

1 When to Use Logistic Regression

There are many research topics for which the dependent variable y is binary (0/1), e.g.

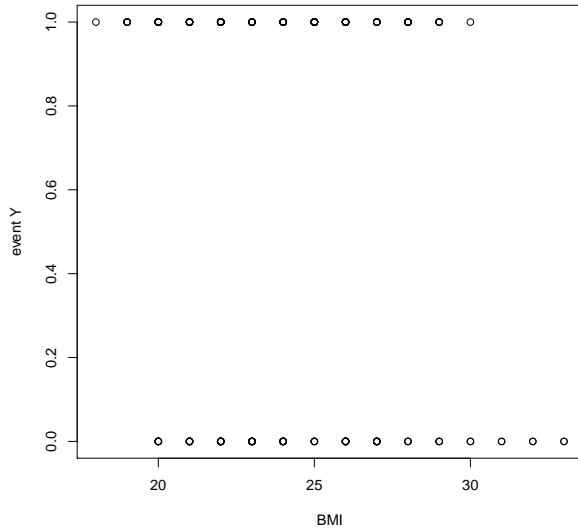
- mortality (dead/alive)
- treatment response (responder/non-responder)
- development of disease (yes/no)

and we want to predict the membership of an individual to one of the two categories based on a set of predictors.

In this situation we have to work with **probabilities**, which are numbers between 0 and 1. A value $P(y)$ that is close to **0** means that y is very **unlikely** to occur, while a value close to **1** means that y is very **likely** to occur.

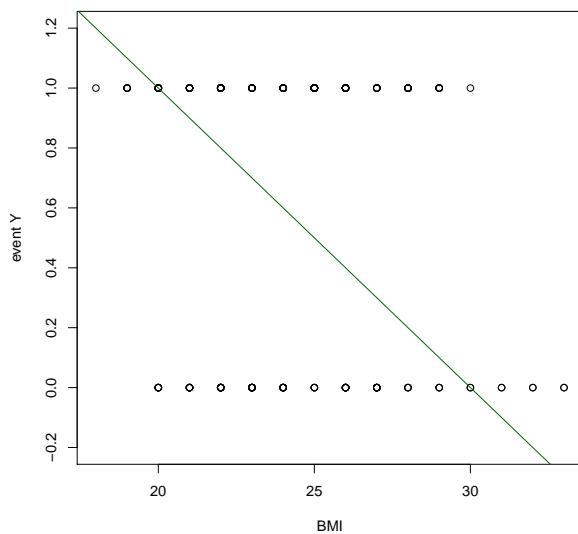
In simple/multiple linear regression a continuous variable y is predicted by continuous/categorical $x(s)$, but if y can only have 2 values (e.g. $y = 0$ or $y = 1$), how do we predict the probability that $y = 1$ given one or more predictors? Could we apply a linear regression model...?

```
plot(BMI, as.numeric(Status)-1, ylab = "event Y")
```



If we try to fit a **linear** regression model...

```
plot(BMI, as.numeric(Status)-1, ylab = "event Y", ylim = c(-.2,1.2))
abline(3, -.1, col = "darkgreen")
```



we would try to fit $P(y = 1) = b_0 + b_1x$, which doesn't work. In linear regression we assume the relationship between x and y is linear, but in the case of binary outcomes this assumption is no longer valid. Results obtained from a linear regression model wouldn't make sense! **Probabilities beyond the interval (0,1) are not interpretable.**

Instead we're going to use a logistic curve! First, note that our factor **Status** has levels that are ordered alphabetically:

```
levels(Status)

## [1] "intellectual disability"  "normal brain development"

Status[1:3]

## [1] intellectual disability  normal brain development
## [3] intellectual disability
## Levels: intellectual disability normal brain development

as.numeric(Status)[1:3]

## [1] 1 2 1
```

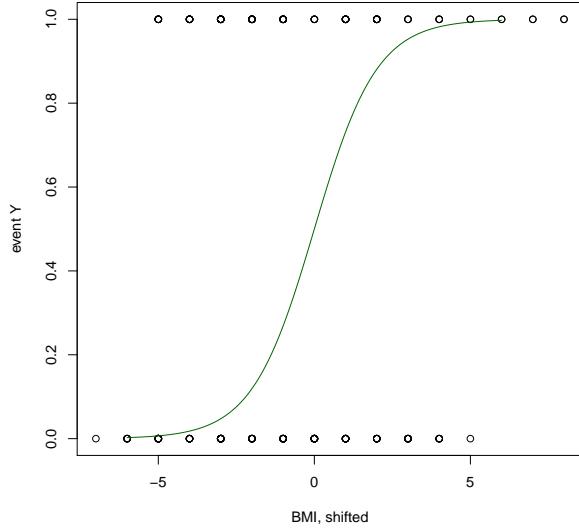
But we would prefer the non-event to be the baseline so we will change **Status** so the event $y = 1$ is intellectual disability and the non-event $y = 0$ is normal brain development. Note that this re-coding does not change the variable in **babies**.

```
newstatus <- 2-as.numeric(Status)
newstatus[1:3]

## [1] 1 0 1
```

So now our visualization should make more sense:

```
plot(BMI-25, newstatus, ylab = "event Y", xlab = "BMI, shifted")
x <- seq(-6, 6, 0.01)
lines(x, exp(x)/(1+exp(x)), type = "l", col = "darkgreen", cex = 2)
```



The formula we used for the line is $\exp(x)/(1+\exp(x))$, which is called the logistic function and it is the probability of an event, $P(y = 1)$. Let's see how to derive it...

2 Odds

We're going to start by introducing odds. The odds is the ratio of the probability that the event of interest occurs to the probability that it does not:

$$\text{odds} = \frac{P(\text{event})}{P(\text{no event})} \Leftrightarrow P(\text{event}) = \frac{\text{odds}}{1 + \text{odds}}$$

and note that $P(\text{no event})=1-P(\text{event})$. Describing the probability of event y in terms of odds has a very convenient property:

- as odds increases, $p(y = 1)$ approaches 1
- as odds decreases, $p(y = 1)$ approaches 0

The odds ratio (OR) is a way of comparing whether the probability of a certain event is the same for two groups.

Let's go back to our example from earlier:

	event	no event	total
treatment	20	80	100
placebo	50	50	100
total	70	130	200

then

Total Group				
$P(y = 1)$	$= x/n$	$= 70/200$	$= 0.35$	
odds($y = 1$)	$= p/(1 - p)$	$= 0.35/0.65$	$= 0.54$	
Treated Group				
$P_1(y = 1)$	$= x_1/n_1$	$= 20/100$	$= 0.20$	
odds ₁ ($y = 1$)	$= p_1/(1 - p_1)$	$= 0.20/0.80$	$= 0.25$	
Placebo Group				
$P_0(y = 1)$	$= x_0/n_0$	$= 50/100$	$= 0.50$	
odds ₀ ($y = 1$)	$= p_0/(1 - p_0)$	$= 0.50/0.50$	$= 1.00$	

So $\text{OR}(\text{event}) = \text{odds}_1/\text{odds}_0 = 0.25/1.00 = 0.25$. Thus the odds of an event in the treatment group is 0.25 times lower than the odds of an event in the placebo group. Conversely, $1/0.25 = 4$, so we can also say the odds of an event in the placebo group is 4 times higher than the odds of an event in the treatment group. In R:

```
treatment <- c(20, 80)
placebo <- c(50, 50)
mytable <- rbind(treatment, placebo)
mytable[1,1]*mytable[2, 2]/(mytable[1, 2]*mytable[2, 1])

## treatment
##      0.25
```

3 Simple Logistic Regression Model

We are going to use odds in the following way, where $p = P(y = 1)$ is the probability of an event:

$$\ln\left(\frac{p}{1 - p}\right) = b_0 + b_1 x$$

The function $\ln(p/(1 - p))$ is called a logit of p and it is this function of y that is linear in x instead of y itself.

This model formulation assures that the predicted probability of an event falls between 0 and 1, unlike a linear regression model. Note:

$$\ln\left(\frac{p}{1-p}\right) = b_0 + b_1x \Leftrightarrow p = \frac{e^{(b_0+b_1x)}}{1+e^{(b_0+b_1x)}}$$

so we've completed our derivation of the logistic function formula from the beginning.

Also note that we've made no assumptions about linearity, normality or homoscedasticity!

The values of the intercept and slope are estimated using the maximum likelihood method, which finds the values of the coefficients that make the observed data most likely to occur.

Statistical significance of estimate coefficients is testing with the Wald test, which is based on the χ^2 distribution (though R calls it "z"). The goodness of fit is assessed by deviance, which is based on the differences observed-expected principle. Also, the Akaike information criterion (AIC) gives a measure of the quality of the model.

The coefficients are most usefully interpreted with the following:

$$e^{b_1} = \frac{\text{odds after a unit change in the predictor}}{\text{original odds}}$$

and when x is binary, e^{b_1} is the odds ratio from the 2 by 2 contingency table!

In R:

```
lr1 <- glm(newstatus ~ BMI, family = binomial(logit))
summary(lr1)

##
## Call:
## glm(formula = newstatus ~ BMI, family = binomial(logit))
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.2759   -1.0805   -0.9168    1.2680    1.4627
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.40591    1.18095 -2.037   0.0416 *
```

```

## BMI          0.08782    0.04822   1.821   0.0685 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 259.83  on 189  degrees of freedom
## Residual deviance: 256.44  on 188  degrees of freedom
## AIC: 260.44
##
## Number of Fisher Scoring iterations: 4

```

so $\text{logit}(p) = -2.40591 + 0.08782 * \text{BMI}$. Thus the probability of having a baby with an intellectual disability when BMI is large, say 32, is:

```

logit_p1 <- -2.40591+0.08782*32
logit_p1

## [1] 0.40433

## or
predict(lr1, newdata = data.frame(BMI = 32), se.fit = TRUE)

## $fit
##       1
## 0.4043502
##
## $se.fit
## [1] 0.3995839
##
## $residual.scale
## [1] 1

p1 <- exp(logit_p1)/(1 + exp(logit_p1))
p1

## [1] 0.5997275

```

The coefficient $b_1 = 0.08782$ can be exponentiated to obtain the odds ratio:

```
summary(lr1)$coef

##           Estimate Std. Error   z value Pr(>|z|)
## (Intercept) -2.40591055 1.18095490 -2.037259 0.04162413
## BMI         0.08782065 0.04821621  1.821393 0.06854720

b1 <- summary(lr1)$coef[2, 1]
b1

## [1] 0.08782065

exp(b1)

## [1] 1.091792
```

Like multiple linear regression, we can add variables into the model here as well:

```
lr2 <- glm(newstatus ~ BMI + smoking, family = binomial(logit))
summary(lr2)$coef

##           Estimate Std. Error   z value Pr(>|z|)
## (Intercept) -2.52420359 1.22600372 -2.058887 0.039505027
## BMI         0.08128428 0.04997051  1.626645 0.103812552
## smokingyes  1.34305855 0.38824022  3.459349 0.000541482
```

Thus the probability of having a baby with an intellectual disability when BMI is large, say 32, and the mother is a smoker is:

```
mynewdata <- data.frame(BMI = 32, smoking = factor("yes"))
logit_p2 <- predict(lr2, newdata = mynewdata)
p2 <- exp(logit_p2)/(1+exp(logit_p2))
p2

##       1
## 0.8053309
```

Basic Course on R: Logistic Regression Practical

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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1 Baby Data

1. Read in the data “R_data_January2015.csv” with a header and row names from the first column. Assign it to the object `babydata` and allow strings be converted to factors. Attach the data to the environment.
2. We would like to know if `smoking` predicts `Status`. Since `Status` is a binary variable (intellectual disability or normal brain development) we need to use logistic regression. Answer the following questions:
 - (a) Write down the model with $\text{logit}(p)$, $\ln(p/(1 - p))$, on the lefthand side, but instead of writing p write $P(\text{intellectual disability})$. Then write down the formula for this probability (the probabiltiy of having a baby with an intellectual disability).
 - (b) If we run the model on the data as it is now, R will consider “normal brain development” as the event because it is second in the levels of `Status`:

```
## The following objects are masked from babydata (pos = 3):  
##  
##     alcohol, birthweight, BMI, cholesterol, educational_level,  
##     folicacid_erys, folicacid_serum, HDL, homocysteine,  
##     iodine_deficiency, medication, pregnancy_length_days,  
##     pregnancy_length_weeks, SAH, SAM, smoking, Status,  
##     triglycerides, vitaminB12  
## The following objects are masked from babies (pos = 4):  
##  
##     alcohol, birthweight, BMI, cholesterol, educational_level,  
##     folicacid_erys, folicacid_serum, HDL, homocysteine,  
##     iodine_deficiency, medication, pregnancy_length_days,  
##     pregnancy_length_weeks, SAH, SAM, smoking, Status,  
##     triglycerides, vitaminB12  
## The following objects are masked from babydata (pos = 5):  
##  
##     alcohol, birthweight, BMI, cholesterol, educational_level,
```

```

##      folicacid_erys, folicacid_serum, HDL, homocysteine,
##      iodine_deficiency, medication, pregnancy_length_days,
##      pregnancy_length_weeks, SAH, SAM, smoking, Status,
##      triglycerides, vitaminB12
## The following objects are masked from babies (pos = 6):
##
##      alcohol, birthweight, BMI, cholesterol, educational_level,
##      folicacid_erys, folicacid_serum, HDL, homocysteine,
##      iodine_deficiency, medication, pregnancy_length_days,
##      pregnancy_length_weeks, SAH, SAM, smoking, Status,
##      triglycerides, vitaminB12
## The following objects are masked from babydata (pos = 11):
##
##      alcohol, birthweight, BMI, cholesterol, educational_level,
##      folicacid_erys, folicacid_serum, HDL, homocysteine,
##      iodine_deficiency, medication, pregnancy_length_days,
##      pregnancy_length_weeks, SAH, SAM, smoking, Status,
##      triglycerides, vitaminB12
## The following objects are masked from babies (pos = 13):
##
##      alcohol, birthweight, BMI, cholesterol, educational_level,
##      folicacid_erys, folicacid_serum, HDL, homocysteine,
##      iodine_deficiency, medication, pregnancy_length_days,
##      pregnancy_length_weeks, SAH, SAM, smoking, Status,
##      triglycerides, vitaminB12
## The following objects are masked from babydata (pos = 14):
##
##      alcohol, birthweight, BMI, cholesterol, educational_level,
##      folicacid_erys, folicacid_serum, HDL, homocysteine,
##      iodine_deficiency, medication, pregnancy_length_days,
##      pregnancy_length_weeks, SAH, SAM, smoking, Status,
##      triglycerides, vitaminB12

```

```

levels(Status)
## [1] "intellectual disability" "normal brain development"

```

So we need to first change these factor levels so we treat “intellectual disability” as the event and “normal brain development” as the baseline. Run the following to change all the 1s to 2s and 2s to 1s:

```
table(Status)

## Status
##   intellectual disability normal brain development
##                   82                  108

newstatus <- factor(3-as.numeric(Status),
                     labels=c("normal brain development",
                             "intellectual disability"))
```

And to show that it worked:

```
levels(newstatus)

## [1] "normal brain development" "intellectual disability"

table(newstatus)

## newstatus
## normal brain development intellectual disability
##                               108                      82
```

- (c) Now run the regression model you set up above in R using `newstatus`. Then write down the model and probability of event with the estimates.

- (d) Can `smoking` significantly predict `newstatus`? [Hint: use `summary`.]

- (e) What is the probability of having a baby with an intellectual disability given the mother smokes?

(f) Our estimate of b_1 is the element in the 2nd row and 1st column of the coefficients from the `summary` call. What is the value of e^{b_1} ? [Hint: use `exp`.]

(g) Is the e^{b_1} that you just calculated an odds ratio? How do you interpret it?

(h) What do you think e^{b_1} would have been if we didn't change the levels of `Status`? Re-run the model using `Status` to check your answer. How does it relate to your answer from (f)?

(i) There is another way to calculate an odds ratio without using logistic regression. Suppose we have the following 2×2 contingency table:

		event	no event
predictor	yes	a	b
	no	c	d

then the odds ratio is $(a * d) / (b * c)$. Create a contingency table of `smoking` and `newstatus` [Hint: use `table`] and then calculate the odds ratio from that. Do you get the same answer as in (f)?

3. We would like to know if `smoking` and `vitaminB12` can be used to predict `newstatus`. Answer the following questions:
- (a) Set up (i.e. write down) the logit model and run it in R. Write the model with the estimates.
 - (b) Can either variable significantly predict `newstatus`?
 - (c) What is the probability of having a baby with an intellectual disability given the mother smokes and has a `vitaminB12` level of 400? What is the probability of having a baby with an intellectual disability given the mother smokes and has a `vitaminB12` level of 650?

Basic Course on R: Logistic Regression Practical Answers

Elizabeth Ribble*

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1 Baby Data

1. Read in the data “R_data_January2015.csv” with a header and row names from the first column. Assign it to the object `babydata` and allow strings be converted to factors. Attach the data to the environment.

```
babydata <- read.csv("R_data_January2015.csv", header=T, row.names=1)
attach(babydata)

## The following objects are masked from babies (pos = 3):
##
##      alcohol, birthweight, BMI, cholesterol, educational_level,
##      folicacid_erys, folicacid_serum, HDL, homocysteine,
##      iodine_deficiency, medication, pregnancy_length_days,
##      pregnancy_length_weeks, SAH, SAM, smoking, Status,
##      triglycerides, vitaminB12

## The following objects are masked from babydata (pos = 4):
##
##      alcohol, birthweight, BMI, cholesterol, educational_level,
##      folicacid_erys, folicacid_serum, HDL, homocysteine,
##      iodine_deficiency, medication, pregnancy_length_days,
##      pregnancy_length_weeks, SAH, SAM, smoking, Status,
##      triglycerides, vitaminB12

## The following objects are masked from babies (pos = 5):
##
##      alcohol, birthweight, BMI, cholesterol, educational_level,
##      folicacid_erys, folicacid_serum, HDL, homocysteine,
##      iodine_deficiency, medication, pregnancy_length_days,
##      pregnancy_length_weeks, SAH, SAM, smoking, Status,
##      triglycerides, vitaminB12

## The following objects are masked from babydata (pos = 10):
##
##      alcohol, birthweight, BMI, cholesterol, educational_level,
##      folicacid_erys, folicacid_serum, HDL, homocysteine,
##      iodine_deficiency, medication, pregnancy_length_days,
##      pregnancy_length_weeks, SAH, SAM, smoking, Status,
##      triglycerides, vitaminB12

## The following objects are masked from babies (pos = 12):
##
##      alcohol, birthweight, BMI, cholesterol, educational_level,
##      folicacid_erys, folicacid_serum, HDL, homocysteine,
```

```

##      iodine_deficiency, medication, pregnancy_length_days,
##      pregnancy_length_weeks, SAH, SAM, smoking, Status,
##      triglycerides, vitaminB12

## The following objects are masked from babydata (pos = 13):
##      alcohol, birthweight, BMI, cholesterol, educational_level,
##      folicacid_erys, folicacid_serum, HDL, homocysteine,
##      iodine_deficiency, medication, pregnancy_length_days,
##      pregnancy_length_weeks, SAH, SAM, smoking, Status,
##      triglycerides, vitaminB12

```

2. We would like to know if `smoking` predicts `Status`. Since `Status` is a binary variable (intellectual disability or normal brain development) we need to use logistic regression. Answer the following questions:

- (a) Write down the model with $\text{logit}(p)$, $\ln(p/(1 - p))$, on the lefthand side, but instead of writing p write $P(\text{intellectual disability})$. Then write down the formula for this probability (the probability of having a baby with an intellectual disability).

The model is

$$\ln \left(\frac{P(\text{intellectual disability})}{1-P(\text{intellectual disability})} \right) = b_0 + b_1 * \text{smoking}$$

and the probability of an event is

$$P(\text{intellectual disability}) = \frac{e^{b_0+b_1 * \text{smoking}}}{1+e^{b_0+b_1 * \text{smoking}}}.$$

- (b) If we run the model on the data as it is now, R will consider “normal brain development” as the event because it is second in the levels of `Status`:

```

levels(Status)
## [1] "intellectual disability" "normal brain development"

```

So we need to first change these factor levels so we treat “intellectual disability” as the event and “normal brain development” as the baseline. Run the following to change all the 1s to 2s and 2s to 1s

```

table(Status)

## Status
## intellectual disability normal brain development
##                      82                      108

```

```

newstatus <- factor(3-as.numeric(Status),
                     labels = c("normal brain development",
                               "intellectual disability"))

```

And to show that it worked:

```

levels(newstatus)

## [1] "normal brain development" "intellectual disability"

table(newstatus)

## newstatus
## normal brain development intellectual disability
##                      108                  82

```

- (c) Now run the regression model you set up above in R using `newstatus`. Then write down the model and probability of event with the estimates.

```

lrs1 <- glm(newstatus ~ smoking, family = binomial(logit))
lrs1$coef

## (Intercept)  smokingyes
##   -0.557015    1.367945

```

The model with estimates is

$$\ln \left(\frac{P(\text{intellectual disability})}{1-P(\text{intellectual disability})} \right) = -0.557 + 1.368 * \text{smoking}$$

and the probability of an event is

$$P(\text{intellectual disability}) = \frac{e^{-0.557+1.368*\text{smoking}}}{1+e^{-0.557+1.368*\text{smoking}}}.$$

- (d) Can `smoking` significantly predict `newstatus`? [Hint: use `summary`.]

```

summary(lrs1)$coef

##                   Estimate Std. Error   z value   Pr(>|z|)
## (Intercept) -0.557015  0.1691109 -3.293786 0.0009884766
## smokingyes   1.367945  0.3859647  3.544224 0.0003937712

```

The *p*-value is less than 0.05 so `smoking` can be used as a predictor for `newstatus`.

- (e) What is the probability of having a baby with an intellectual disability given the mother smokes?

```

mynew1 <- data.frame(smoking = factor("yes"))
logit_p1 <- predict(lrs1, newdata = mynew1)
p1 <- exp(logit_p1)/(1 + exp(logit_p1))
p1

##           1
## 0.6923077

```

- (f) Our estimate of b_1 is the element in the 2nd row and 1st column of the coefficients from the `summary` call. What is the value of e^{b_1} ? [Hint: use `exp`.]
- We can exponentiate b_1 to get this value:

```

exp(summary(lrs1)$coef[2, 1])

## [1] 3.927273

## or
exp(1.3679)

## [1] 3.927095

```

- (g) Is the e^{b_1} that you just calculated an odds ratio? How do you interpret it?
 Since `smoking` is binary, $e^{b_1} = e^{1.37} = 4$ is the odds ratio. Thus we can say that smoking mothers have four times higher odds of having a child with an intellectual disability compared to non-smokers.
- (h) What do you think e^{b_1} would have been if we didn't change the levels of `Status`? Re-run the model using `Status` to check your answer. How does it relate to your answer from (f)?

```

lrs2 <- glm(Status ~ smoking, family = binomial(logit))
exp(summary(lrs2)$coef[2,1])

## [1] 0.2546296

```

Switching the event to the non-event inverses the odds ratio:

```

1/exp(summary(lrs1)$coef[2,1])

## [1] 0.2546296

```

So we could have just not changed the levels of `Status` and concluded that non-smoking women have 0.25 times smaller odds of having a baby with an intellectual disability compared to smoking women. But wasn't this more fun?

- (i) There is another way to calculate an odds ratio without using logistic regression.
Suppose we have the following 2×2 contingency table:

	event	no event
predictor yes	a	b
predictor no	c	d

then the odds ratio is $(a * d) / (b * c)$. Create a contingency table of `smoking` and `newstatus` [Hint: use `table`] and then calculate the odds ratio from that. Do you get the same answer as in (f)?

```
tss <- table(smoking, newstatus)
tss[1,1]*tss[2,2]/(tss[1,2]*tss[2,1])
## [1] 3.927273
```

Same answer!

3. We would like to know if `smoking` and `vitaminB12` can be used to predict `newstatus`. Answer the following questions:

- (a) Set up (i.e. write down) the logit model and run it in R. Write the model with the estimates.

The model is

$$\ln \left(\frac{P(\text{intellectual disability})}{1-P(\text{intellectual disability})} \right) = b_0 + b_1 * \text{smoking} + b_2 * \text{vitaminB12}$$

```
lrs3 <- glm(newstatus ~ smoking + vitaminB12,
            family = binomial(logit))
lrs3$coef

## (Intercept)  smokingyes  vitaminB12
## -1.397551678  1.435938106  0.002087774
```

The model with estimates is

$$\ln \left(\frac{P(\text{intellectual disability})}{1-P(\text{intellectual disability})} \right) = -1.4 + 1.44 * \text{smoking} + 0.002 * \text{vitaminB12}$$

- (b) Can either variable significantly predict `newstatus`?

```
summary(lrs3)$coef

##                   Estimate Std. Error   z value    Pr(>|z|)
## (Intercept) -1.397551678 0.55509528 -2.517679 0.0118130962
## smokingyes   1.435938106 0.39134210  3.669266 0.0002432482
## vitaminB12    0.002087774 0.00130122  1.604474 0.1086096691
```

Yes, `smoking` is still significant ($p\text{-value} < 0.05$), but `vitaminB12` is not.

- (c) What is the probability of having a baby with an intellectual disability given the mother smokes and has a vitaminB12 level of 400? What is the probability of having a baby with an intellectual disability given the mother smokes and has a vitaminB12 level of 650?

```
mynew <- data.frame(smoking = factor(c("yes", "yes")),  
                     vitaminB12 = c(400, 650))  
logit_p <- predict(lrs3, newdata = mynew)  
p <- exp(logit_p)/(1+exp(logit_p))  
p  
##           1           2  
## 0.7054726 0.8014592
```

Basic Course on R: Programming Structures 1

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28 Oct - 1 Nov 2019

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1 if(), else, and ifelse() Statements

1.1 Conditional Execution Using if() and (Optionally) else

- Sometimes we'll want R to execute a statement only if a certain condition is met. This can be accomplished via the `if()` and (optionally) `else` statements:

```
if()      # Used to execute a statement only if the given condition  
          # is met  
else     # Used to specify an alternative statement to be executed  
          # if the condition given in if() isn't met
```

- Such *conditional execution* commands have the forms:

```
if (condition) {  
  statement1  
}
```

and

```
if (condition) {  
  statement1  
} else {  
  statement2  
}
```

- In both cases above, if `condition` is TRUE, `statement1` is executed. If `condition` is FALSE, then in the first case nothing happens. In the second case, `statement2` is executed.
- Here's a simple example:

```
x <- 5  
if (x < 10) {  
  y <- 0  
}  
y  
  
## [1] 0
```

- Here's another:

```
if (x >= 10) {
  y <- 1
} else {
  y <- 0
}
y

## [1] 0
```

- There's actually an easier way to accomplish the above task:

```
y <- if(x >= 10) 1 else 0
y

## [1] 0
```

- When using such *conditional assignment* statements, in the absence of `else`, `if()` returns `NULL` if `condition` isn't met. So

```
y <- if(condition) 1
```

is equivalent to

```
y <- if(condition) 1 else NULL
```

- In the next example, `return()` is used to terminate a function call and return a value that depends on whether or not a condition is met:

```
mySign <- function(x) {
  if(x < 0) {
    return("Negative")
  } else {
    return("Non-negative")
  }
}
```

We get:

```
mySign(13)  
## [1] "Non-negative"
```

1.2 Using if() and else with a Sequence of Statements

- `if()` and `else` can be used to conditionally execute whole *sequences* of statements, which we enclose in curly brackets `{ }`. The general form of an `if()` command is:

```
if (condition) {  
  statement1  
  statement2  
  .  
  .  
  .  
  statement1q  
}
```

which could be followed by `else` and another sequence of statements (in curly brackets) to be executed if `condition` isn't met.

1.3 Vectorized if-else: The `ifelse()` Function

- Sometimes we'll need to create a vector whose values depend on whether or not the values in another vector satisfies some condition. We use:

```
ifelse()  # Returns a vector whose values depend on whether or  
# not a given condition is met by the elements of  
# another vector
```

- `ifelse()` takes argument `test`, the condition to be met, `yes` the return value (or vector of values) when `test` is `TRUE`, and `no`, the return values (or vector of values) when `test` is `FALSE`.
- Here we convert the values in `ht` to “short” or “tall”:

```
ht <- c(69, 71, 67, 66, 72, 71, 61, 65, 73, 70, 68, 74)  
htCategory <- ifelse(ht > 69, yes = "tall", no = "short")  
htCategory
```

```
## [1] "short" "tall"  "short" "short" "tall"  "tall"  "short" "short"  
## [9] "tall"  "tall"  "short" "tall"
```

2 Looping

- *Loops* are used to *iterate* (repeat) an R statement (or set of statements). They're implemented in three ways, `for()`, `while()`, and `repeat`:

```
for()      # Repeat a set of statements a specified number of  
          # times  
while()    # Repeat a set of statements as long as a specified  
          # condition is met  
repeat     # Repeat a set of statements until a break command is  
          # encountered
```

- Two other commands, `break` and `next`, are used, respectively, to terminate a loop's iterations and to skip ahead to the next iteration:

```
break      # Terminate a loop's iterations  
next       # Skip ahead to the next iteration
```

- Here's an example in which each of the three loop types, `for()`, `while()`, and `repeat`, are used to perform a simple task, namely printing the numbers $1^2, 2^2, \dots, 5^2$ to the screen:

```
for(i in 1:5) {  
  print(i^2)  
}  
  
## [1] 1  
## [1] 4  
## [1] 9  
## [1] 16  
## [1] 25  
  
i <- 1  
while(i <= 5) {  
  print(i^2)  
  i <- i + 1  
}
```

```

## [1] 1
## [1] 4
## [1] 9
## [1] 16
## [1] 25

i <- 1
repeat {
  print(i^2)
  i <- i + 1
  if(i > 5) break
}

## [1] 1
## [1] 4
## [1] 9
## [1] 16
## [1] 25

```

2.1 for() Loops

- `for()` loops are used when we know in advance how many iterations the loop should perform.
- The general form of a `for()` loop is:

```

for(i in sequence) {
  statement1
  statement2
  .
  .
  .
  statementq
}

```

where `sequence` is a vector, `i` (whose name you're free to change) assumes the values in `sequence` one after another, each time triggering another iteration of the loop during which `statements 1 through q` are executed. The `statements` usually involve the variable `i`.

- Here's an example. Suppose we have the data frame describing someone's coin collection:

```

coins <- data.frame(Coin = c("penny", "quarter", "nickel",
                            "quarter", "dime", "penny"),
                     Year = c(1943, 1905, 1889, 1960, 1937, 1900),
                     Mint = c("Den", "SF", "Phil", "Den", "SF",
                             "Den"),
                     Condition = c("good", "fair", "excellent",
                                   "good", "poor", "good"),
                     Value = c(12.00, 55.00, 300.00, 40.00, 18.00,
                               28.00),
                     Price = c(15.00, 45.00, 375.00, 25.00, 20.00,
                               20.00))

coins

##      Coin Year Mint Condition Value Price
## 1  penny 1943  Den     good    12    15
## 2 quarter 1905   SF     fair    55    45
## 3  nickel 1889  Phil  excellent  300   375
## 4 quarter 1960  Den     good    40    25
## 5    dime 1937   SF     poor    18    20
## 6  penny 1900  Den     good    28    20

```

- If we type:

```

colMeans(coins)

## Error in colMeans(coins): 'x' must be numeric

```

we get an error message because some of the columns are non-numeric.

- We can compute the means of the numeric columns by looping over the columns, each time checking whether it's numeric before computing its mean:

```

means <- NULL
for(i in 1:ncol(coins)) {
  if (is.numeric(coins[, i])) {
    means <- c(means, mean(coins[, i]))
  }
}

```

The result is:

```
means

## [1] 1922.33333 75.50000 83.33333
```

2.2 `while()` Loops

- `while()` loops are used when we want the loop to iterate until some condition is no longer met.
- The general form of a `while()` loop is:

```
while(condition) {
  statement1
  statement2
  .
  .
  .
  statementq
}
```

where `condition` is a logical (TRUE or FALSE) expression involving a variable whose value changes over the course of the loop iterations.

- Prior to each iteration, R checks whether `condition` is TRUE or FALSE. If it's TRUE, the iteration proceeds, otherwise the iterations are terminated.

2.3 `repeat` Loops

- A `repeat` loop iterates a set of statements until a `break` statement is encountered. The general form is of a `repeat` loop is:

```
repeat {
  statement1
  statement2
  .
  .
  .
  statementq
}
```

where at least one of the **statements** should be of the form

```
if(condition) break
```

where **condition** is a logical (TRUE or FALSE) expression which may be updated during the loop's iterations.

2.3.1 Terminating an “Endless” Loop

- Once in a while we (mistakenly) write a loop that has no way of stopping, for example:

```
i <- 1
while(i <= 5) {
  print("I Cannot Stop by Myself")
}
```

- To terminate the iterations hit the **Escape** key or select **Terminate R...** in RStudio's **Session** pulldown menu.

2.4 Looping Over List Elements

- In the next example, we loop over the elements of a list, printing a list element and recording it's length during each iteration:

```
myList <- list(
  w = c(4, 4, 5, 5, 6, 6),
  x = c("a", "b", "c"),
  y = c(5, 10, 15),
  z = c("r", "s", "t", "u", "v")
)
lengths <- NULL
for(i in myList) {
  print(i)
  lengths <- c(lengths, length(i))
}

## [1] 4 4 5 5 6 6
## [1] "a" "b" "c"
## [1] 5 10 15
## [1] "r" "s" "t" "u" "v"
```

```
lengths  
## [1] 6 3 3 5
```

3 The Logical Operations “And”, “Or”, and “Not”

3.1 Logical Operations and Compound Logical Expressions

- R has *logical operators* (or *Boolean operators*) corresponding to “and” and “or”. They’re used to combine two logical expressions together to form a single *compound* logical expression. Another logical operator corresponding to “not” is used to negate a logical expression. These are written in R as:

```
&&           # "And" for logical scalars  
||            # "Or" for logical scalars  
!             # "Not" (for logical scalars or vectors)  
&            # "And" for logical vectors  
|             # "Or" for logical vectors
```

- These operate on logical (TRUE or FALSE) expressions and return TRUE or FALSE.
- The distinction between `&&` and `&`, and between `||` and `|` is this:
 - `&&` and `||` operate on logical *scalars* (single TRUE or FALSE values).
 - `&&` and `||` are the preferred operators to use in `if()` statements.
 - `&` and `|` operate elementwise on logical *vectors*.
 - `&` and `|` are the preferred operators to use in `ifelse()` statements and in square brackets `[]` when extracting subsets from vectors or data frames.

3.2 Logical Operations on Scalar Logical Expressions

- `&&` returns TRUE if both of the expressions are TRUE and it returns FALSE otherwise:

```
TRUE && TRUE  
  
## [1] TRUE  
  
TRUE && FALSE  
  
## [1] FALSE
```

- `||` returns TRUE if one or both of the expressions are TRUE and it returns FALSE otherwise:

```
FALSE || TRUE
```

```
## [1] TRUE
```

```
FALSE || FALSE
```

```
## [1] FALSE
```

- As a practical example, if we want to test whether a variable `x` lies *between* two numbers, say 60 and 70, we type:

```
x <- 75
x > 60 && x < 70
```

```
## [1] FALSE
```

and to test whether it lies *outside* the range 60 to 70, we type:

```
x < 60 || x > 70
```

```
## [1] TRUE
```

- Here's an example of using `&&` in an `if()` statement:

```
x <- 3
y <- 5
if(x < 10 && y < 10) {
  print("Both less than 10")
} else {
  print("Not both less than 10")
}

## [1] "Both less than 10"
```

- The negation operator, `!`, returns “the opposite” of a logical expression:

```
!TRUE
```

```
## [1] FALSE
```

```
!FALSE
```

```
## [1] TRUE
```

```
!(5 < 6)
```

```
## [1] FALSE
```

- Pay attention to the operator precedence for `&&`, `||`, and `!`. It can be found by typing:

```
?Syntax
```

but parentheses can be used to control the order of operations.

- If we try to apply `&&` or `||` to *vectors*, R only applies it to their first elements:

```
c(TRUE, FALSE, TRUE) && c(TRUE, TRUE, FALSE)
```

```
## [1] TRUE
```

3.3 Logical Operations on Logical Vectors

- To apply the operations “and” and “or” elementwise on two logical vectors, use `&` and `|`. For example:

```
c(TRUE, FALSE, TRUE) & c(TRUE, TRUE, FALSE)
```

```
## [1] TRUE FALSE FALSE
```

- `&` and `|` are useful in `ifelse()` statements. (Recall that `ifelse()` operates elementwise on vectors.). For example, consider the systolic and diastolic blood pressure readings:

```
systolic <- c(110, 119, 111, 113, 128)
diastolic <- c(70, 74, 88, 74, 83)
```

A blood pressure is classified as normal if the systolic level is less than 120 *and* the diastolic level is less than 80:

```
classification <- ifelse(systolic < 120 & diastolic < 80,
                           yes = "Normal",
                           no = "Abnormal")
classification

## [1] "Normal"    "Normal"    "Abnormal"   "Normal"    "Abnormal"
```

- In the next example, we use `&` in square brackets `[]` to extract rows from a data frame:

```
bpData <- data.frame(
  name = c("Joe", "Katy", "Bill", "Kim", "Mark"),
  systolic = c(110, 119, 111, 113, 128),
  diastolic = c(70, 74, 88, 74, 83))
bpData

##   name systolic diastolic
## 1 Joe     110      70
## 2 Katy    119      74
## 3 Bill    111      88
## 4 Kim     113      74
## 5 Mark    128      83
```

```
attach(bpData)
bpData[systolic < 120 & diastolic < 80, ]

##   name systolic diastolic
## 1 Joe     110      70
## 2 Katy    119      74
## 4 Kim     113      74

detach(bpData)
```

4 Writing A Function

- To write your own function, you need to use the function `function()`, specify argument(s) that will be used in the function (with or without defaults), and in curly brackets specify what the function should do (referring to the argument(s)), including whether something is returned. The general form is:

```
myFun <- function(arg1, arg2, ...) {  
  ## expressions that use the arguments  
  ## the last command is what you want the function to return  
}
```

Each line inside the function is an object assignment, a function call, a subsetting, a conditional statement, an if/else statement, a for loop, etc. - basically anything you have now learned how to do in R that you want the function to do! If you do specify arguments, you should use them.

To have the function output something, you must return the object (either the last command is just the object name or you can use `return()`). If you have multiple objects to return, I recommend returning everything as a list e.g. put this in the last line: `return(list(object1, object2))`.

- Here are a few examples of functions with no default arguments; note the different outputs:

```
do1 <- function(x, y){  
  z <- x + y  
  x  
  z  
}  
do1(x = 1, y = 3) ## note that x is not returned  
  
## [1] 4  
  
do2 <- function(x, y){  
  z <- x + y  
  return(x)  
  z  
}  
do2(x = 1, y = 3) ## note that z is returned  
  
## [1] 1
```

```

do3 <- function(x, y){
  z <- x + y
  return(list(x, z))
}
do3(x = 1, y = 3) ## x and z are returned as a single list

## [[1]]
## [1] 1
##
## [[2]]
## [1] 4

```

- Here is an example of a function with default arguments that returns a vector:

```

do4 <- function(x, y = 2){
  z1 <- x + y
  z2 <- x * y
  c(z1, z2)
}
do4(x = 1) ## uses y = 2

## [1] 3 2

do4(x = 1, y = 3) ## overwrites default value of y

## [1] 4 3

```

- Here is an example of a function that takes no arguments:

```

do5 <- function(){
  sum(2, 4, 6)
  print("Hello World!")
  return(mean(1, 3, 5))
}
do5()

## [1] "Hello World!"
## [1] 1

```

- Recall that you can create functions with variable arguments using For example, here's a function that returns the mean of all the values in an arbitrary number of vectors:

```
meanOfAll <- function(...) {
  return(mean(c(...)))
}
```

The command

```
meanOfAll(usSales, europeSales, otherSales)
```

would combine the three vectors and take the mean of all the data.

5 The source() Function

- `source()` is a nice function for reading in big chunks of R code, e.g. a set of functions that you want to use every time you start a new R session.

```
source()      # Read R commands from a text file.
```

- For example, suppose we have the following commands saved in a text file ‘C:\myRcode.txt’:

```
myFun <- function(message) {
  print(message)
}
```

```
myFun("Hello World")
```

We can execute those commands using `source()` by running:

```
source("myRcode.txt")
```

```
## [1] "Hello World"
```

6 Document License

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Basic Course on **R**: The apply family of functions

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May 18th - 24th, 2017

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1 Using apply functions to run functions on data

Once you have written a function, you would like to apply it to some piece of data. As described in the previous chapter you can simply enter some values as arguments of the function and run it. However, usually you would like to run the function on all of your data. To do that you could write a for loop that loops through your data and applies the function to the whole dataset. However, there is a special family of functions in R that make it easier to apply your function to a range of different data classes in different ways. This family of functions are called apply functions.

The apply functions make it easier to run functions over vectors, matrixes, and data.frames. We will discuss four functions of the apply family that are regularly used apply(), lapply(), sapply() and tapply().

1.1 apply()

The apply function works by “applying” a specified function to an data object. It requires 3 arguments: the data, a so-called “MARGIN”, and a function. The data can be a vector, data.frame or a matrix. The MARGIN indicates whether you want to apply the function to the rows or the columns of your data, or both. To apply the function to the rows the MARGIN should be 1, to apply it to the columns it should be 2 and to apply it to both it should be c(1,2). The function can be an existing function, such as “sum” or “mean”, or your own custom function.

As an example we will apply the function “max” to some data, in this case a matrix.

First we create a matrix of 10 by 10.

```
mat <- matrix(1:100,nrow=10)

mat

##      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10]
## [1,]    1   11   21   31   41   51   61   71   81   91
## [2,]    2   12   22   32   42   52   62   72   82   92
## [3,]    3   13   23   33   43   53   63   73   83   93
## [4,]    4   14   24   34   44   54   64   74   84   94
## [5,]    5   15   25   35   45   55   65   75   85   95
## [6,]    6   16   26   36   46   56   66   76   86   96
## [7,]    7   17   27   37   47   57   67   77   87   97
## [8,]    8   18   28   38   48   58   68   78   88   98
## [9,]    9   19   29   39   49   59   69   79   89   99
## [10,]   10   20   30   40   50   60   70   80   90   100
```

Then we apply our function “max” to the matrix rows, indicated with a 1 (notice that we do not run the function by writing max(), but we just give the name of the function that should be run: max).

```
apply(mat, 1, max)

## [1] 91 92 93 94 95 96 97 98 99 100
```

The result of applying the function max to the rows of the matrix is a vector containing the maximal values for each row.

We can also determine the maximal value in each column by using 2 as the MARGIN value.

```
apply(mat, 2, max)

## [1] 10 20 30 40 50 60 70 80 90 100
```

As mentionned before, it is also possible to apply the functions to each element in the matrix by using `c(1,2)`. In that case it doesn't make sense to determine the maximum value, so lets take the square root.

```
apply(mat, c(1,2), sqrt)
```

```
##          [,1]      [,2]      [,3]      [,4]      [,5]      [,6]      [,7]
## [1,] 1.000000 3.316625 4.582576 5.567764 6.403124 7.141428 7.810250
## [2,] 1.414214 3.464102 4.690416 5.656854 6.480741 7.211103 7.874008
## [3,] 1.732051 3.605551 4.795832 5.744563 6.557439 7.280110 7.937254
## [4,] 2.000000 3.741657 4.898979 5.830952 6.633250 7.348469 8.000000
## [5,] 2.236068 3.872983 5.000000 5.916080 6.708204 7.416198 8.062258
## [6,] 2.449490 4.000000 5.099020 6.000000 6.782330 7.483315 8.124038
## [7,] 2.645751 4.123106 5.196152 6.082763 6.855655 7.549834 8.185353
## [8,] 2.828427 4.242641 5.291503 6.164414 6.928203 7.615773 8.246211
## [9,] 3.000000 4.358899 5.385165 6.244998 7.000000 7.681146 8.306624
## [10,] 3.162278 4.472136 5.477226 6.324555 7.071068 7.745967 8.366600
##          [,8]      [,9]      [,10]
## [1,] 8.426150 9.000000 9.539392
## [2,] 8.485281 9.055385 9.591663
## [3,] 8.544004 9.110434 9.643651
## [4,] 8.602325 9.165151 9.695360
## [5,] 8.660254 9.219544 9.746794
## [6,] 8.717798 9.273618 9.797959
## [7,] 8.774964 9.327379 9.848858
## [8,] 8.831761 9.380832 9.899495
## [9,] 8.888194 9.433981 9.949874
## [10,] 8.944272 9.486833 10.000000
```

Because `sqrt` also works on matrices, it is actually unnecessary to use `apply` to run it for each element in the matrix. In cases where functions cannot directly be run on a matrix, `apply` offers a short and readable alternative to writing a nested for loop.

1.2 lapply()

The lapply function is used to run a function on list objects. Let's assume we have a list of different sized matrices and we would like to know the dimensions of these matrices. We can then run the function "dim" on the list using lapply. lapply only requires a list object and a function as arguments and always returns a list of results.

```
mylist <- list(matrix(1:16,nrow=4), matrix(1:9,nrow=3),matrix(1:4,nrow=2))

lapply(mylist, dim)

## [[1]]
## [1] 4 4
##
## [[2]]
## [1] 3 3
##
## [[3]]
## [1] 2 2
```

Because dataframes are lists of lists, it is also possible to run lapply on dataframes. In that case lapply will apply the function to the columns of the data.frame object and it returns a list of values.

```
df <- data.frame("col1"=c(1,1,1,1), "col2"=c(2,2,2,2), "col3"=c(3,3,3,3))

lapply(df, sum)

## $col1
## [1] 4
##
## $col2
## [1] 8
##
## $col3
## [1] 12
```

1.3 sapply()

sapply is a user-friendly version of lapply. The difference with lapply is that sapply tries to turn the list of results into a more user-friendly format, such as a vector or a matrix.

For the first example the results are turned into a matrix.

```
sapply(mylist, dim)

##      [,1] [,2] [,3]
## [1,]     4     3     2
## [2,]     4     3     2
```

For the second example, the results are turned into a vector.

```
sapply(df, sum)

## col1 col2 col3
##     4     8    12
```

There is no difference between lapply and sapply in how the data is used, but it gives you more flexibility in how the results are created.

1.4 tapply()

tapply lets you apply a function on groupings of your data. Imagine that you have a dataset in which a grouping factor separates your data into two groups of patients. With tapply you can apply a function to those two groups separately. The only thing tapply requires is the column you would like to apply the function to, the grouping factor and the function you would like to apply.

```
patients <- data.frame("group"=paste('grp',c(1,1,1,1,1,2,2,2,2,2),sep='-' ), "outcome"=rnorm(12))
patients

##      group     outcome
## 1  grp-1  0.22115820
## 2  grp-1  1.03751935
## 3  grp-1 -0.06887431
## 4  grp-1  0.48706043
## 5  grp-1  1.10705296
## 6  grp-1  0.09463406
## 7  grp-2  0.28877781
## 8  grp-2  0.03450461
## 9  grp-2 -0.64676566
## 10 grp-2  1.02515888
## 11 grp-2 -0.28689227
## 12 grp-2  1.11382687

tapply(patients$outcome, patients$group, mean)

##      grp-1      grp-2
## 0.4797585 0.2547684
```

It is also possible to use multiple factors in a list to create groups, which returns a matrix.

```
patients <- data.frame("group"=paste('grp',c(1,1,1,1,1,1,2,2,2,2,2),sep='-' ),
                        "serotype"=c("A","B","A","B","A","B","A","B","A","B","A","B"),
                        "outcome"=rnorm(12))

tapply(patients$outcome, list(patients$group, patients$serotype), mean)

##          A         B
## grp-1  0.5983194  0.5041594
## grp-2 -0.6070275 -0.8957907
```

These are some (trivial) examples of how you can use the apply family of functions to quickly apply a function to your data. It is possible to do the same thing by using for loops, but apply functions are generally faster to write and read. In some cases using apply to run your function can also increase the speed of your code. More on increasing the speed of your code will follow in later lectures.

Basic Course on R: Programming Structures 1 Practical

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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1 Part A: if(), else, and ifelse() and Vectorization

1. Write a function `evenOrOdd()` involving `if()` and `else` that takes an argument `x` and returns "Even" or "Odd" depending on whether or not `x` is divisible by 2. (*Do not* use the `ifelse()` function).
2. Is your function `evenOrOdd()` *vectorized*? Check by passing it the vector:

```
w <- c(3, 6, 6, 4, 7, 9, 11, 6)
```

3. Another way to determine if each element of a vector is even or odd is to use the `ifelse()` function, which serves as a vectorized version `if()` and `else`. Use `ifelse()` to obtain "Even" or "Odd" for each element of `w`.

2 Part B: Loops

1. How many times will "Frisbee Sailing" be printed to the screen in each of the following sets of commands? Try to answer without using R.

```
a) i <- 5
  while(i < 1) {
    print("Frisbee Sailing")
    i <- i + 1
  }
```

```
b) i <- 0
  while(i < 5) {
    print("Frisbee Sailing")
  }
```

```
c) i <- 0
  while(i < 5) {
    print("Frisbee Sailing")
    i <- i + 1
  }
```

2. How many times will "Masked Marvel" be printed to the screen in the following set of commands? Try to answer without using R.

```
i <- 1
repeat {
  if(i > 5) break
  print("Masked Marvel")
  i <- i + 1
}
```

3. The file **kennedys.txt** has a command to create a list containing two generations of the famous Kennedy family:

```
Kennedys <- list(
  JosephJr = character(0),
  John = c("Caroline", "JohnJr", "Patrick"),
  Rosemary = character(0),
  Kathleen = character(0),
  Eunice = c("RobertIII", "Maria", "Timothy", "Mark", "Anthony"),
  Patricia = c("Christopher", "Sydney", "Victoria", "Robin"),
  Robert = c("Kathleen", "JosephII", "RobertJr", "David",
            "MaryC", "Michael", "MaryK", "Christopher",
            "Matthew", "Douglas", "Rory"),
  Jean = c("Stephen", "William", "Amanda", "Kym"),
  Edward = c("Kara", "EdwardJr", "Patrick")
)
```

Read in the file with the use of `source()` and type `ls()` to see if the list was created (type `Kennedys` to view the object).

Loop over the list of the first generation of Kennedys, keeping track of how many children each one has in a vector.

3 Part C: Logical Operators &, |, and !

1. What will be the result of the following:

```
(10 < 20 && 15 < 16) || 9 == 10
```

2. One of the following evaluates to TRUE, the other to FALSE. Which is which?

```
4 < 3 && (5 < 6 || 8 < 9)  
(4 < 3 && 5 < 6) || 8 < 9
```

3. The data set below contains the systolic and diastolic blood pressure readings for 22 patients (and can be found in the file **BPressure.txt**).

PatientID	Systolic	Diastolic
CK	120	50
SS	96	60
FR	100	70
CP	120	75
BL	140	90
ES	120	70
CP	165	110
JI	110	40
MC	119	66
FC	125	76
RW	133	60
KD	108	54
DS	110	50
JW	130	80
BH	120	65
JW	134	80
SB	118	76
NS	122	78
GS	122	70
AB	122	78
EC	112	62
HH	122	82

- a) Read the data from **BPressure.txt** into a data frame called **bp** using **read.table()**.
- b) A person's blood pressure is classified as normal if the systolic level is below 120 and the diastolic level is below 80. Use square brackets [] to extract from **bp** the rows corresponding to patients with normal blood pressures.
- c) Now use square brackets [] to extract the rows corresponding to patients whose blood pressures aren't normal.

Basic Course on R: Programming Structures 1 Practical Answers

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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1 Part A: `if()`, `else`, and `ifelse()` and Vectorization

1. Write a function `evenOrOdd()` involving `if()` and `else` that takes an argument `x` and returns "Even" or "Odd" depending on whether or not `x` is divisible by 2. (*Do not* use the `ifelse()` function).

```
evenOrOdd <- function(x) {  
  if(x %% 2 == 0) {  
    return("Even")  
  } else {  
    return("Odd")  
  }  
}
```

2. Is your function `evenOrOdd()` *vectorized*? Check by passing it the vector:

```
w <- c(3, 6, 6, 4, 7, 9, 11, 6)
```

```
w <- c(3, 6, 6, 4, 7, 9, 11, 6)  
evenOrOdd(w)  
  
## Warning in if (x%%2 == 0) {: the condition has length > 1 and only  
## the first element will be used  
  
## [1] "Odd"
```

The function is not vectorized because it only runs on the first element!

3. Another way to determine if each element of a vector is even or odd is to use the `ifelse()` function, which serves as a vectorized version `if()` and `else`. Use `ifelse()` to obtain "Even" or "Odd" for each element of `w`.

```
w <- c(3, 6, 6, 4, 7, 9, 11, 6)  
ifelse(w %% 2 == 0, "Even", "Odd")  
  
## [1] "Odd"  "Even" "Even" "Even" "Odd"  "Odd"  "Odd"  "Even"
```

2 Part B: Loops

1. How many times will "Frisbee Sailing" be printed to the screen in each of the following sets of commands? Try to answer without using R.

```
a) i <- 5
  while(i < 1) {
    print("Frisbee Sailing")
    i <- i + 1
  }
```

It will not print because the original i is not less than 1.

```
b) ## not run
  i <- 0
  while(i < 5) {
    print("Frisbee Sailing")
  }
```

It will print indefinitely - until you hit escape on the keyboard or click stop in RStudio because i is always less than 5.

```
c) i <- 0
  while(i < 5) {
    print("Frisbee Sailing")
    i <- i + 1
  }

## [1] "Frisbee Sailing"
```

The phrase will print five times; it stops once the i+1 value reaches 5.

2. How many times will "Masked Marvel" be printed to the screen in the following set of commands? Try to answer without using R.

```
i <- 1
repeat {
  if(i > 5) break
```

```

print("Masked Marvel")
i <- i + 1
}

## [1] "Masked Marvel"

```

The phrase will print five times; it stops once the `i+1` value reaches 5.

3. The file `kennedys.txt` has a command to create a list containing two generations of the famous Kennedy family:

```

Kennedys <- list(
  JosephJr = character(0),
  John = c("Caroline", "JohnJr", "Patrick"),
  Rosemary = character(0),
  Kathleen = character(0),
  Eunice = c("RobertIII", "Maria", "Timothy", "Mark", "Anthony"),
  Patricia = c("Christopher", "Sydney", "Victoria", "Robin"),
  Robert = c("Kathleen", "JosephII", "RobertJr", "David",
             "MaryC", "Michael", "MaryK", "Christopher",
             "Matthew", "Douglas", "Rory"),
  Jean = c("Stephen", "William", "Amanda", "Kym"),
  Edward = c("Kara", "EdwardJr", "Patrick")
)

```

Read in the file with the use of `source()` and type `ls()` to see if the list was created (type `Kennedys` to view the object).

```
source("kennedys.txt")
```

Loop over the list of the first generation of Kennedys, keeping track of how many children each one has in a vector.

```

children <- NULL
for(i in Kennedys){
  children <- c(children, length(i))
}

```

```
}
```

children

```
## [1] 0 3 0 0 5 4 11 4 3
```

3 Part C: Logical Operators &, |, and !

1. What will be the result of the following:

```
(10 < 20 && 15 < 16) || 9 == 10
```

```
## [1] TRUE
```

TRUE because the first statement (in parentheses) is TRUE and the second is FALSE.

2. One of the following evaluates to TRUE, the other to FALSE. Which is which?

```
4 < 3 && (5 < 6 || 8 < 9)
```

```
## [1] FALSE
```

```
(4 < 3 && 5 < 6) || 8 < 9
```

```
## [1] TRUE
```

The first one FALSE because the first statement before `&&` is FALSE. The second one is TRUE because one of the two statements to the left and right of `||` is TRUE.

3. The data set below contains the systolic and diastolic blood pressure readings for 22 patients (and can be found in the file **BPressure.txt**).

- a) Read the data from **BPressure.txt** into a data frame called `bp` using `read.table()`.

```
bp <- read.table("BPressure.txt", header=TRUE)
```

- b) A person's blood pressure is classified as normal if the systolic level is below 120 and the diastolic level is below 80. Use square brackets [] to extract from `bp` the rows corresponding to patients with normal blood pressures.

```
bp[(bp$Systolic < 120 & bp$Diastolic < 80), ]  
##      PatientID Systolic Diastolic  
## 2          SS     96      60  
## 3          FR    100      70  
## 8          JI    110      40  
## 9          MC    119      66  
## 12         KD    108      54  
## 13         DS    110      50  
## 17         SB    118      76  
## 21         EC    112      62
```

- c) Now use square brackets [] to extract the rows corresponding to patients whose blood pressures *aren't* normal.

```
bp[!(bp$Systolic < 120 & bp$Diastolic < 80), ]  
##      PatientID Systolic Diastolic  
## 1          CK    120      50  
## 4          CP    120      75  
## 5          BL    140      90  
## 6          ES    120      70  
## 7          CP    165     110  
## 10         FC    125      76  
## 11         RW    133      60  
## 14         JW    130      80  
## 15         BH    120      65  
## 16         JW    134      80  
## 18         NS    122      78  
## 19         GS    122      70  
## 20         AB    122      78  
## 22         HH    122      82
```

Basic Course on R: The apply family of functions - Practical

David Nieuwenhuijse

May 18th - 24th, 2017

Part D: Using the apply family of functions

1. Use apply() to turn the following code into something shorter:

```
#This function determines if a number is a prime number
isPrime <- function(num){
  if (num == 2) {
    return(TRUE)
  }
  if(num > 1) {
    for(i in 2:(num-1)) {
      if ((num %% i) == 0) {
        return(FALSE)
      }
    }
  } else {
    return(FALSE)
  }

  return(TRUE)
}

#The matrix with numbers to be checked:
mat <- matrix(1:100, nrow=10)
#The matrix with answers (TRUE/FALSE)
answer <- matrix(rep(x = TRUE,100), nrow=10)

for (x in 1:10) {
  for (y in 1:10) {
    answer[x,y] <- isPrime(mat[x,y])
  }
}

#The resulting prime numbers:
mat[answer]
```

```
## [1]  2  3  5  7 11 13 17 19 23 29 31 37 41 43 47 53 59 61 67 71 73 79 83
## [24] 89 97
```

2. Answer question 2.3 again using the lapply() function.
3. Answer question 2.3 again using the sapply() function. What is the class of the output?
4. Read in the diamonds.txt dataset using read.table, make sure the headers are correctly loaded. Calculate the average price of diamonds by color and clarity using the tapply function.

Basic Course on R: The apply family of functions

David Nieuwenhuijse

May 18th - 24th, 2017

Part D: Using the apply family of functions

1. Use apply() to turn the following code into something shorter:

```
#This function determines if a number is a prime number
isPrime <- function(num){
  if (num == 2) {
    return(TRUE)
  }
  if(num > 1) {
    for(i in 2:(num-1)) {
      if ((num %% i) == 0) {
        return(FALSE)
      }
    }
  } else {
    return(FALSE)
  }

  return(TRUE)
}

#The matrix with numbers to be checked:
mat <- matrix(1:100, nrow=10)
#The matrix with answers (TRUE/FALSE)
answer <- matrix(rep(x = TRUE,100), nrow=10)

for (x in 1:10) {
  for (y in 1:10) {
    answer[x,y] <- isPrime(mat[x,y])
  }
}

#The resulting prime numbers:
mat[answer]

## [1]  2  3  5  7 11 13 17 19 23 29 31 37 41 43 47 53 59 61 67 71 73 79 83
## [24] 89 97
```

Answer:

```
#This function determines if a number is a prime number
isPrime <- function(num){
  if (num == 2) {
    return(TRUE)
  }
  if(num > 1) {
    for(i in 2:(num-1)) {
      if ((num %% i) == 0) {
```

```

        return(FALSE)
    }
}
} else {
    return(FALSE)
}

return(TRUE)
}

#The matrix with numbers to be checked:
mat <- matrix(1:100, nrow=10)

#With apply we do not need to create an answer matrix anymore
answer <- apply(mat, c(1,2), isPrime)

#The resulting prime numbers:
mat[answer]

## [1]  2  3  5  7 11 13 17 19 23 29 31 37 41 43 47 53 59 61 67 71 73 79 83
## [24] 89 97

```

2. Answer question 2.3 again using the lapply() function.

```
source("kennedys.txt")
```

```
lapply(Kennedys, length)
```

```

## $JosephJr
## [1] 0
##
## $John
## [1] 3
##
## $Rosemary
## [1] 0
##
## $Kathleen
## [1] 0
##
## $Eunice
## [1] 5
##
## $Patricia
## [1] 4
##
## $Robert
## [1] 11
##
## $Jean
## [1] 4
##
## $Edward
## [1] 3

```

3. Answer question 2.3 again using the sapply() function. What is the class of the output?

```
sapply(Kennedys, length)

## JosephJr      John Rosemary Kathleen   Eunice Patricia Robert     Jean
##          0         3         0         0         5         4        11         4
## Edward
##          3

class(sapply(Kennedys, length))

## [1] "integer"
```

4. Read in the diamonds.txt dataset using read.table, make sure the headers are correctly loaded. Calculate the average price of diamonds by color and clarity using the tapply function.

```
diamonds <- read.table("diamonds.txt", header = TRUE)

average_price <- tapply(diamonds$Price, list(diamonds$Color, diamonds$Clarity), mean)

print(average_price)

##           IF      VS1      VS2      VVS1      VVS2
## D 8035.000 3635.857 1947.500 12839.000 7319.500
## E 1813.600 4488.833 5128.571 6553.000 4273.222
## F 3079.875 4038.800 4808.000 3649.389 3553.882
## G 1499.818 3457.083 4799.778 3713.500 4196.095
## H 1993.909 4421.818 5068.714 3991.300 4315.467
## I 2025.375 4451.750 4444.000 5344.600 4884.333
```

Basic Course on R: Programming Structures 2

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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1 Environment and Scope Issues

- Each function, whether built-in or user-defined, has an associated *environment*, which can be thought of as a container that holds all of the objects present at the time the function is created.

1.1 The Top-Level (or Global) Environment

- When a function is created on the command line, its environment is the so-called *Global Environment* (or *Workspace*):

```
w <- 2
```

```
f <- function(y) {  
  d <- 3  
  return(d * (w + y))  
}
```

```
environment(f)  
  
## <environment: R_GlobalEnv>
```

- The function `objects()` (or `ls()`), when called from the command line, lists the objects in the Global Environment:

```
objects()  
  
## [1] "f"  "w"
```

1.2 Global and Local Variables

- In the function `f()` defined above, the variable `w` is said to be *global* to `f()` and the variable `d`, because it's created *within f()*, is said to be *local*.
- Global variables (like `w`) are visible from within a function, but local variables (like `d`) aren't visible from outside the function. In fact, local variables are *temporary*, and disappear when the function call is completed:

```

f(y = 1)

## [1] 9

d

## Error in eval(expr, envir, enclos): object 'd' not found

```

- When a global and local variable share the same name, the local variable is used:

```

w <- 2
d <- 4
f <- function(y) {
  d <- 3
  return(d * (w + y))
}
f(y = 1)

## [1] 9

```

- Note also that when an assignment takes place within a function, and the local variable shares its name with an existing global variable, only the local variable is affected:

```

w <- 2
d <- 4                      # This value of d will remain unchanged.
f <- function(y) {
  d <- 3                      # This doesn't affect the value of d in the
  return(d * (w + y))        # global environment (Workspace)
}
f(y = 1)

## [1] 9

d

## [1] 4

```

1.3 Nested Functions and the Scope Hierarchy

- For user-defined functions created on the command line, the global variables for that function are those in the Workspace, or *global environment*. They're listed by typing `ls()` (or `objects()`) on the command line.
- When a function is *created inside another function*, its global variables are the local variables of the outer function *plus* the outer function's global variables.
- Regardless of whether a function is created on the command line or inside another function, its local variables are the variables created inside of it *plus* its formal arguments to which values have been passed.
- For example:

```
w <- 2           # w is global to f() and therefore also to h()
f <- function(y) {
  d <- 3
  h <- function() {
    b <- 5           # b is local to h()
    return(d * (w + y))
  }
  return(h())
}
```

Above,

- `w` is global to `f()` and therefore also to `h()`.
 - `y` and `d` are local to `f()`, but global to `h()`.
 - `b` is local to `h()`.
- This *scope hierarchy* continues when multiple function definitions are *nested* inside of each other.

- We can use a `print(ls())` statement to see which objects are local to `f()`:

```
w <- 2                      # w is global to f() and therefore also to h()
f <- function(y) {
  d <- 3                      # y and d are local to f() but global to h()
  h <- function() {
    b <- 5                      # b is local to h()
    return(d * (w + y))
  }
  print(ls())
  return(h())
}
f(y = 2)

## [1] "d" "h" "y"
## [1] 12
```

- Likewise we can use a `print(environment(h))` statement to view the environment of `h()`:

```
w <- 2                      # w is global to f() and therefore also to h()
f <- function(y) {
  d <- 3                      # y and d are local to f() but global to h()
  h <- function() {
    b <- 5                      # b is local to h()
    return(d * (w + y))
  }
  print(environment(h))
  return(h())
}
f(y = 2)

## <environment: 0x48d6a00>
## [1] 12
```

In the output above, the environment of `h()` is referred to by its memory location. The *environment* of `h()` is the “container” that contains `h()` as well as the objects `d` and `y`.

1.4 Writing “Upstairs” in the Scope Hierarchy

- Sometimes we need to assign a value to a variable in the global environment from within a function. We can do so using either of the following:

```
<--      # Assign a value to a variable in the global environment
          # (Workspace).
assign() # Assign a value to a variable in the global environment
          # (Workspace).
```

- Here’s an example using the so-called *superassignment operator* <--:

```
w <- 2
d <- 4                      # This value of d will be replaced by 3.
f <- function(y) {
  d <-- 3                  # This replaces the value 4 of d in the global
  return(d * (w + y)) # environment (Workspace) by 3.
}
f(y = 2)

## [1] 12

d

## [1] 3
```

Above, the assignment of 3 to d is done in the global environment, or Workspace, overwriting the previous value (4).

- Here’s how to accomplish the same thing using `assign()`:

```
w <- 2
d <- 4                      # This value of d will be replaced by 3.
f <- function(y) {
  assign("d", 3, envir = .GlobalEnv)
  return(d * (w + y))
}
f(y = 2)

## [1] 12

d

## [1] 3
```

(Note that when `assign()` is used, `d` is written as a character string (i.e. in quotes as "`d`") and the global environment is written as `.GlobalEnv.`)

- Be aware that assignment to the variable `d` using `<->` actually results in a search up the environment hierarchy, stopping at the first level at which the name `d` is encountered. If it's not encountered, then assignment is done in the global environment. For example:

```
w <- 2
d <- 4                                # This value of d will remain unchanged.
f <- function(y) {
  d <- 5                                # This value of d will be replaced by 3.
  h <- function() {
    d <-> 3                            # This replaces the value 5 of d in the
    return(d * (w + y)) # h() and f() environments by 3.
  }
  return(h())
}
f(y = 2)

## [1] 12

d

## [1] 4
```

1.5 When Should You Use Global Variables?

- Here are suggestions about using global variables. They're especially important when your code will be shared with other R users:
 - Assignment to the global environment using `<->` or `assign()` should be used very sparingly (i.e. only when necessary) because it can accidentally overwrite existing variables.
 - The use of a global variable can be justified when that variable needs to be accessed by several different functions (that aren't nested).
 - It's generally preferable to pass variables as arguments to functions rather than accessing them from the global environment.

2 Printing a Warning Message or Terminating a Function Call Using `warning()`, `return()`, or `stop()`

- The following functions are useful for terminating a function call or just printing a warning message:

```
return()      # Terminate a function call and return a value.  
stop()       # Terminate a function call and print an error message.  
warning()    # Print a warning message (without terminating the  
             # function call).
```

2.1 Terminating a Function Call Using `if()` and `return()`

- One way to terminate a function call is with `return()` which, when encountered, immediately terminates the call and returns a value. For example:

```
mySign <- function(x) {  
  if(x < 0) return("Negative")  
  if(x > 0) return("Positive")  
  return("Zero")  
}
```

Passing `my.sign()` the value `x = 13` produces the following:

```
mySign(x = 13)  
  
## [1] "Positive"
```

(Note that the last line, `return("Zero")`, was never encountered during the call to `my.sign()`.)

2.2 Terminating a Function Call and Printing an Error Message Using `if()` and `stop()`

- Another way to terminate a function call is with `stop()`, which then prints an error message without returning a value. Here's an example:

```
myRatio <- function(x, y) {  
  if(y == 0) stop("Cannot divide by 0")  
  return(x/y)  
}
```

An attempt to pass the value 0 for y now results in the following:

```
myRatio(x = 3, y = 0)

## Error in myRatio(x = 3, y = 0): Cannot divide by 0
```

(Note that the last line, `return(x/y)`, was never encountered during the call to `myRatio()`.)

2.3 Printing a Warning Message Using `if()` and `warning()`

- `warning()` just prints a warning message to the screen without terminating the function call. Here's an example:

```
myRatio <- function(x, y) {
  if(y == 0) warning("Attempt made to divide by 0")
  return(x/y)
}
```

Now when we pass the value 0 for y the function call isn't terminated (the value `Inf` is returned), but we get the warning message:

```
myRatio(x = 3, y = 0)

## Warning in myRatio(x = 3, y = 0): Attempt made to divide by 0

## [1] Inf
```

3 Recursion

- **Recursion** is a programming technique in which a function calls itself.
- Here's an example in which the function `f()` takes a non-negative integer `x` and returns the factorial of `x`, denoted $x!$ and defined as

$$x! = \begin{cases} 1 & \text{if } x = 0 \\ x(x-1)(x-2) \cdots (2)(1) & \text{if } x > 0 \end{cases}$$

- Notice that we can write

$$x! = \begin{cases} 1 & \text{if } x = 0 \\ x(x-1)! & \text{if } x > 0 \end{cases}$$

```
f <- function(x) {
  if(x == 0) {
    return(1)
  } else {
    return(x * f(x - 1))
  }
}
f(0)

## [1] 1

f(1)

## [1] 1

f(5)

## [1] 120
```

- In general, to solve a problem of type X by writing a recursive function `f()`:
 1. Break the original problem of type X into one or more smaller problems of type X .
 2. Within `f()`, call `f()` on each of the smaller problems.
 3. Within `f()`, piece together the results of Step 2 to solve the original problem.

4 Replacement Functions

- Some of R's built-in functions can be used both to *return* a value and to *replace* a value. For example using the data frame:

```
var1 <- c(1, 2, 3)
var2 <- c(19, 20, 16)
var3 <- c("small", "medium", "large")
x <- data.frame(var1, var2, var3)
x

##   var1 var2   var3
## 1     1    19 small
## 2     2    20 medium
## 3     3    16 large
```

`names()` will both return the names of the variables in `x`:

```
names(x)

## [1] "var1" "var2" "var3"
```

and replace them:

```
names(x) <- c("IDNumber", "Weight", "Size")
names(x)

## [1] "IDNumber" "Weight"   "Size"
```

- Such functions are called *replacement functions*.
- It's possible to create user-defined replacement functions.

Basic Course on R: Programming Structures 2 Practical

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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1 Part A: Scope

- For each of the following sets of commands, give the value that will be returned by the last command. Try to answer without using R.

```
a) w <- 5
f <- function(y) {
  return(w + y)
}
f(y = 2)
```

```
b) w <- 5
f <- function(y) {
  w <- 4
  return(w + y)
}
f(y = 2)
```

- Among the variables `w`, `d`, and `y`, which are global to `f()` and which are local?

```
w <- 2
f <- function(y) {
  h <- function() {
    d <- 3
    return(w + y)
  }
  return(d * h())
}
```

- Do the following in R.

- Try:

```
myFun1 <- function() {
  a <- 2
  b <- 3
  myFun2(3)
}
myFun2 <- function(y) {
  return(y + a + b)
```

```
}
```

```
myFun1()
```

What happens?

b) Now try:

```
a <- 1
```

```
b <- 2
```

```
myFun1()
```

What happens?

4. What value for `w` will be printed in the last line below? Try to answer without using R.

```
w <- 1
```

```
f <- function(y) {
```

```
  g <- function() {
```

```
    w <<- 3
```

```
    return(2)
```

```
}
```

```
  return(g())
```

```
}
```

```
f(y = 1)
```

```
w
```

5. What value for `w` will be printed in the last line below? Try to answer without using R.

```
w <- 1
```

```
f <- function(y) {
```

```
  w <- 2
```

```
  g <- function() {
```

```
    w <<- 3
```

```
    return(2)
```

```
}
```

```
  return(g())
```

```
}
```

```
f(y = 1)
```

```
w
```

2 Part B: if() Statements, warning(), and stop()

The functions `warning()` and `stop()` are used to print a warning message and to stop the execution of the function call and print an error message. For example:

```
noNegMean <- function(x) {  
  if(all(x < 0)) {  
    stop("All values in x are negative")  
  }  
  if(any(x < 0)) {  
    x[x < 0] <- 0  
    warning("Negative values in x replaced by zero")  
  }  
  return(mean(x))  
}
```

1. The file **nonnegmean.txt** contains the above code; source it into R and then pass `noNegMean()` a vector containing some negative and some positive values. What happens?
2. What happens when you pass `noNegMean()` a vector containing all negative values?
3. Write a function `ratio()` that takes two arguments, `x` and `y`, and attempts to compute the ratio `x/y`. If both `x == 0 & y == 0`, the function should stop and print an error message about dividing 0 by 0. If `y == 0` (but not `x`), the function should print a warning message about dividing by 0, and then return `x/y` (which will be `Inf`). In all other cases, it should return `x/y`.

Test your `ratio()` function first using two nonzero values for `x` and `y`, then using a nonzero `x` but `y = 0`, and finally using `x = 0` and `y = 0`.

Basic Course on R: Programming Structures 2 Practical Answers

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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1 Part A: Scope

- For each of the following sets of commands, give the value that will be returned by the last command. Try to answer without using R.

```
a) w <- 5
f <- function(y) {
  return(w + y)
}
f(y = 2)

## [1] 7
```

This will return 7 because w is 5 and we are evaluating the function at y = 2.

```
b) w <- 5
f <- function(y) {
  w <- 4
  return(w + y)
}
f(y = 2)

## [1] 6
```

This will return 6 because w is reassigned as 4 inside the function and we are evaluating the function at y = 2.

- Among the variables w, d, and y, which are global to f() and which are local?

```
w <- 2
f <- function(y) {
  h <- function() {
    d <- 3
    return(w + y)
  }
  return(d * h())
}
```

The object w is global to f() while d and y are local to f().

3. Do the following in R.

a) Try:

```
myFun1 <- function() {  
  a <- 2  
  b <- 3  
  myFun2(3)  
}  
myFun2 <- function(y) {  
  return(y + a + b)  
}  
myFun1()  
  
## Error in myFun2(3): object 'a' not found
```

What happens?

We get an error message because `a` and `b` are local to `myFun1` so the function `myFun2` can't find them in the global environment.

b) Now try:

```
a <- 1  
b <- 2  
myFun1()  
  
## [1] 6
```

What happens?

We get the value 6 because the values `a` and `b` are global so `myFun2` can find them and use them in its commands.

4. What value for `w` will be printed in the last line below? Try to answer without using R.

```
w <- 1  
f <- function(y) {  
  g <- function() {  
    w <<- 3  
    return(2)  
  }  
  return(g())  
}  
f(y = 1)
```

```
## [1] 2

w

## [1] 3
```

We get the value 3 because the superassign operator overwrote the original assignment of w.

5. What value for w will be printed in the last line below? Try to answer without using R.

```
w <- 1
f <- function(y) {
  w <- 2
  g <- function() {
    w <<- 3
    return(2)
  }
  return(g())
}
f(y = 1)

## [1] 2

w

## [1] 1
```

We get the value 1 because the superassign operator only overwrote the assignment of w within the f() function.

2 Part B: if() Statements, warning(), and stop()

The functions `warning()` and `stop()` are used to print a warning message and to stop the execution of the function call and print an error message. For example:

```
noNegMean <- function(x) {
  if(all(x < 0)) {
    stop("All values in x are negative")
```

```

    }
  if(any(x < 0)) {
    x[x < 0] <- 0
    warning("Negative values in x replaced by zero")
  }
  return(mean(x))
}

```

1. The file **nonegmean.txt** contains the above code; source it into R and then pass `noNegMean()` a vector containing some negative and some positive values. What happens?

```

source("nonegmean.txt")
noNegMean(c(-1, 0, 1))

## Warning in noNegMean(c(-1, 0, 1)): Negative values in x replaced
## by zero

## [1] 0.3333333

```

We get the warning message and it returned 0.3333, which is the average of 0, 0, 1.

2. What happens when you pass `noNegMean()` a vector containing all negative values?

```

source("nonegmean.txt")
#noNegMean(c(-1, -1, -1)) # not run; error message

```

We get the error message and nothing is returned.

3. Write a function `ratio()` that takes two arguments, `x` and `y`, and attempts to compute the ratio `x/y`. If both `x == 0 & y == 0`, the function should stop and print an error message about dividing 0 by 0. If `y == 0` (but not `x`), the function should print a warning message about dividing by 0, and then return `x/y` (which will be `Inf`). In all other cases, it should return `x/y`.

Test your `ratio()` function first using two nonzero values for `x` and `y`, then using a nonzero `x` but `y = 0`, and finally using `x = 0` and `y = 0`.

```
ratio <- function(x,y) {
  if(x == 0 & y == 0) {
    stop("Cannot divide zero by zero.")
  }
  if(y == 0) {
    warning("Cannot divide by zero.")
  }
  ratio <- x/y
  return(ratio)
}

ratio(2,3)

## [1] 0.6666667

ratio(0,0)

## Error in ratio(0, 0): Cannot divide zero by zero.

ratio(1,0)

## Warning in ratio(1, 0): Cannot divide by zero.

## [1] Inf
```

Basic Course on R: Object-Oriented Programming

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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1 Object Oriented Programming

1.1 Objects and Classes

1.1.1 Objects

- In R, every “thing” is an *object*. The vectors `x` and `logicVec` and the matrix `X` are examples of objects:

```
x  
## [1] 2 4 2 7 9 11 9 4 2 6 7 9 9 4 3
```

```
logicVec  
## [1] TRUE FALSE TRUE
```

```
X  
##      [,1] [,2] [,3]  
## [1,]     2    11     7  
## [2,]     4     9     9  
## [3,]     2     4     9  
## [4,]     7     2     4  
## [5,]     9     6     3
```

- Objects can be passed as arguments to functions which perform operations on them and then return other objects.

1.1.2 Classes of Objects

- Each object belongs to a certain *class* of objects. We can determine what class an object belongs to using `class()` or `is.cname()`:

```
class()      # Determines the class of an object. Can also be  
             # used to assign a class to an object.  
is.cname()   # Returns TRUE if an object belongs to the class  
             # "cname" (e.g. is.numeric(), is.data.frame(), etc.)  
             # and FALSE otherwise.
```

- For example, the object `x` belongs to the *numeric vector* class, `logic.vec` belongs to the *logical vector* class, and `X` belongs to the *matrix* class:

```
class(x)

## [1] "numeric"

class(logicVec)

## [1] "logical"

class(X)

## [1] "matrix"
```

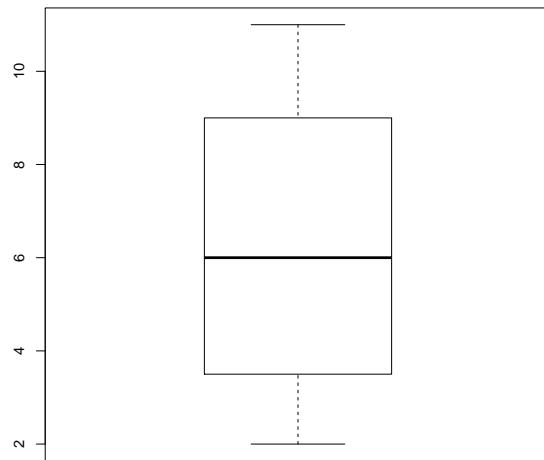
- There are two types of classes in R, **S3** classes and **S4** classes. Nearly all of R's built-in classes are the S3 type, including numeric, character, and logical vectors, matrices and arrays, lists, and data frames.

1.2 Generic Functions and Methods

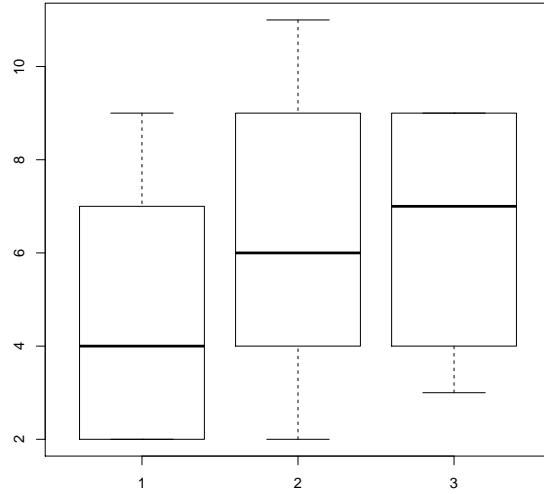
1.2.1 Generic Functions

- Some R functions only accept arguments from a single class. Others accept objects from more than one class.
- Functions that accept objects from more than one class are called *generic functions*.
- For example, `boxplot()` is a generic function because it can be passed a numeric vector *or* a matrix (among other classes of objects). Below it's first passed a vector and then a matrix:

```
boxplot(x)                      # x is a vector.
```



```
boxplot(X) # X is a matrix with 3 columns.
```



Notice that `boxplot()` does different things depending on what class of object is passed to it – when passed a vector it produces a single boxplot, but when passed a matrix, it produces side-by-side boxplots of the matrix's columns.

1.2.2 Methods

- There are actually different “versions” of the `boxplot()` function that are referred to as its *methods*.
- Each `boxplot()` *method* accepts a specific class of arguments. One method accepts vectors and another accepts matrices.
- When we pass an object to a generic function, the function determines the class of the object and then ”dispatches” it to the appropriate method.
- If we look at a generic function’s definition (by typing its name on the command line), we see that it calls another function, `UseMethod()`, which dispatches the object to the appropriate method. For example:

```
boxplot

## function (x, ...)
## UseMethod("boxplot")
## <bytecode: 0x1997d00>
## <environment: namespace:graphics>
```

- We can view the methods associated with a given generic function using:

```
methods()      # Determine the S3 methods that are associated
               # with a given generic function
showMethods() # Determine the S4 methods that are associated
               # with a given generic function
```

- For example, to see the methods for `boxplot()` type:

```
methods(boxplot)

## [1] boxplot.default  boxplot.formula* boxplot.matrix
## see '?methods' for accessing help and source code
```

- The method `boxplot.default()` is the “version” of `boxplot()` that accepts vectors. The `boxplot.matrix()` method is the one that accepts matrices. So typing

```
boxplot(x)
```

is equivalent to typing

```
boxplot.default(x)
```

and typing

```
boxplot(X)
```

is equivalent to typing

```
boxplot.matrix(X)
```

(Actually, in addition to vectors, `boxplot.default()` also accepts several other classes of objects.)

- In general, methods have names of the form `fname cname()`, where `fname()` is name of the generic function and `cname` is the class of objects that the method accepts.
- “Non-visible” methods (such as `boxplot.formula`) are ones that are “not found” when you type their name on the command line, but R can find them when it needs them. (If you need to view a “Non-visible” method’s definition you can do so using `getAnywhere()`, for example `getAnywhere(boxplot.formula)`.)
- For the other (“visible”) methods, we can view their definitions by typing their name on the command line, e.g.

```
boxplot.matrix;  
  
## function (x, use.cols = TRUE, ...)  
## {  
##     groups <- if (use.cols) {  
##         split(c(x), rep.int(1L:ncol(x), rep.int(nrow(x), ncol(x))))  
##     }  
##     else split(c(x), seq(nrow(x)))  
##     if (length(nam <- dimnames(x)[[1 + use.cols]]))  
##         names(groups) <- nam  
##     invisible(boxplot(groups, ...))  
## }  
## <bytecode: 0x7084aa0>  
## <environment: namespace:graphics>
```

2 Performance Enhancement: Speed and Memory

2.1 Writing Faster R Code

- Computationally intensive tasks, e.g. those involving very large data sets, can require excessive amounts of computing time and/or memory usage.
- Some ways of speeding up your R code are:
 - Optimizing your code by using *vectorization* (and avoiding loops), *bytecode compilation*, and other techniques.
 - Writing the computationally intensive chunks code in C or C++ and then calling them from R.
 - Using parallel R computing.
- The amount of time required to run your code will depend on:
 - The computer it's being run on.
 - The number and types of other processes (applications) that are running while your R code is being executed, such as web browsers, word processors, music players, etc.
- To test the speed of a chunk of R code, we use:

```
system.time()      # Returns the computation time required to
                   # execute a chunk of R code (in seconds)
```

- `system.time()` takes as its argument one or more R commands (enclosed by curly brackets if there are more than one), and returns time spent executing them.
- Here's an example in which we time how long it takes to add two vectors together using a loop:

```
x <- runif(100000)
y <- runif(100000)
z <- NULL
system.time(
  for(i in 1:100000) {
    z[i] <- x[i] + y[i]
  }
)

##    user  system elapsed
##  0.040  0.000  0.039
```

- The return value of `system.time()` contains three components, all reported in seconds:
 - **User time**: The CPU time spent by the *current process* (i.e. the current R session).¹
 - **System time**: The CPU time spent by the *operating system* on behalf of the current process (R session) carrying out tasks that must also be carried out on behalf of other processes (applications), e.g. input/output tasks such as accepting keyboard input, printing to the screen, opening files for reading or writing, etc.²
 - **Elapsed time**. This is the time you would get using a stopwatch, and includes time spent on processes (applications) unrelated to the R session (e.g. open web browsers, music players, word processors, etc.).

¹The **CPU** (central processing unit) is the computer’s hardware that carries out instructions of processes (applications) and the operating system, such as performing arithmetic and logical operations and input/output tasks such as receiving messages from the keyboard, printing to the screen, and writing to a file.

²The **operating system** is the computer’s software that manages processes (applications), making sure they don’t interfere with each other, and performs common services for those applications such as directing input/output, e.g. from the keyboard to the screen, to or from a file, or a to printer.

- Usually we don’t care too much whether the CPU is being used by R or by the operating system (on behalf of R). We just want to know how much total CPU time was used. **The sum of the user and system times gives the total CPU time spent executing the R code.**

2.2 Removing Unnecessary Computations from Loops

- Here are two examples, both of which add $\sqrt{2}$ to each of 100,000 numbers. The first is *inefficient*. The second improves upon the first by removing the computation of $\sqrt{2}$ from the loop because it doesn’t belong there:

1. In this code we unnecessarily compute $\sqrt{2}$ during each of 100,000 iterations of the loop:

```
x <- runif(100000)
system.time(
  for(i in 1:100000) {
    y <- sqrt(2)      # This can be moved outside the loop
    x[i] <- x[i] + y
  }
)
```

```

##      user  system elapsed
## 0.012   0.000   0.012

```

2. The code can be made more efficient by moving the command `y <- sqrt(2)` outside the loop:

```

system.time({
  y <- sqrt(2)           # This was pulled from the loop
  for(i in 1:100000) {
    x[i] <- x[i] + y
  }
})

##      user  system elapsed
## 0.012   0.000   0.009

```

- It turns out that function calls (like `sqrt(2)` above) are time consuming in R, in part because they involve setting up environments, sometimes several nested inside each other, to store local variables. The second loop above only calls `sqrt()` once (as opposed to 100,000 times), so it's faster. (The task can be performed even faster using vectorization).

2.3 Vector Preallocation

- ***Vector preallocation*** refers to creating a vector *prior* to executing a loop, and then replacing its elements during the loop's iterations. Preallocation can speed up R code.
- Here are three examples in which we use a loop to add two vectors `x` and `y` together, storing the result in another vector `z`. The first two don't use preallocation, the third does.

1. Here's an *inefficient* set of code that uses `c()` to *recreate* `z` each iteration of the loop:

```

x <- runif(100000)
y <- runif(100000)
z <- NULL                  # do not preallocate the elements of z
system.time(
  for (i in 1:100000) {
    z <- c(z, x[i] + y[i]) # R has to recreate z entirely
                            # each iteration
  }
)

```

```

)
##    user  system elapsed
##  22.340   0.000  22.343

```

2. An alternative approach is to *redimension* `z` by increasing its length one element each iteration, but this too is *inefficient* because it turns out that redimensioning a vector takes as much time as recreating it altogether:

```

z <- NULL                      # do not preallocate the elements of z
system.time(
  for (i in 1:100000) {
    z[i] <- x[i] + y[i] # R has to redimension z (change
  }                      # its length) each iteration
)

##    user  system elapsed
##  0.036   0.000   0.037

```

3. Now watch how much faster the code is when we *preallocate* space for the elements of `z` before entering the loop:

```

z <- rep(NA, 100000)      # Now preallocate 100,000 elements of z,
                           # assigning each the value NA
system.time(
  for (i in 1:100000) {
    z[i] <- x[i] + y[i] # R only has to assign to a single
  }                      # element of z, with no redimensioning
)

##    user  system elapsed
##  0.016   0.000   0.015

```

We see that preallocation speeds the code up considerably.

2.4 Using Vectorization and Avoiding Loops

- Recall that many of R's built-in functions (`sqrt()`, `abs()`, etc.) and operators ('+', '-', '*', '/', '^', etc.) are *vectorized*.
- It's usually *much* faster to use *vectorization* than to perform the same task using a loop.

- For example, below we time two sets of code that perform the same task, adding the elements of two vectors `x` and `y` together. The first uses a loop and the second the vectorized property of the ‘`+`’ operator:

```
x <- runif(100000)
y <- runif(100000)
z <- rep(NA, 100000)
```

- Here we use a loop, which is *inefficient*:

```
system.time(
  for(i in 1:length(x)) {
    z[i] <- x[i] + y[i]
  }
)
##   user   system elapsed
##  0.016   0.000   0.015
```

- Now we use vectorization to speed up the code:

```
system.time(
  z <- x + y
)
##   user   system elapsed
##  0.000   0.000   0.001
```

Note that the vectorized code was *much* faster than the loop.

- The reason why vectorization is (usually) faster than looping is that vectorized computations are carried out behind the scenes in the C language, which is much faster than R. (Recall that underlying R is a suite of C functions that R invokes when it needs them).

More precisely, vectorization usually involves fewer R function calls, which as noted can be slow. For example, although it may not look like it, in the loop above, the ‘`+`’ operation actually involves making 100,000 calls to a function “`+"`”:

```
"+"(2, 3)
## [1] 5
```

Using vectorization, the `+"`() function is only called once, at which point all further computational tasks are passed to the C language.

2.5 Bytecode Compilation

- A *bytecode compiler* translates a so-called *high-level* language like R, which is closer to human spoken language and therefore easier to understand but relatively slow, into a *low-level* language called **bytecode**, which is closer to the computer's *machine instruction language* and therefore harder to understand but much faster.
- R comes equipped with its own bytecode compiler, in the built-in package `compile`, which we can use to try to speed up our code. We'll look at one function from the `compile` package:

```
cmpfun() # Translate (compile) a function from R code to bytecode
```

- Here's an example of how `cmpfun()` is used to speed up the first example of Subsection 2.4:

```
x <- runif(100000)
y <- runif(100000)
z <- rep(NA, 100000)
library(compiler)      # The 'compiler' package comes built-in with R
f <- function() {
  for(i in 1:length(x)) {
    z[i] <<- x[i] + y[i]    # Note the use of '<<-'
  }
}
```

```
cf <- cmpfun(f)
```

```
system.time(cf())
##   user   system elapsed
##  0.024   0.000   0.025
```

We see by comparison that the compiled code runs faster than the uncompiled code in the first example of Subsection 2.4. (Note, though, that using bytecode still isn't as fast as using vectorization.)

Basic Course on R: Object-Oriented Programming Practical

Elizabeth Ribble*

28 Oct - 1 Nov 2019

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1 Part A: Object Oriented Programming

1. The *geometric mean* can be defined as the n th root of the product of n positive numbers x_1, x_2, \dots, x_n , i.e.

$$gm = (x_1 \cdot x_2 \cdots x_n)^{\frac{1}{n}}$$

Write a function `gm()` that takes a vector argument `x` containing positive numbers and returns their geometric mean. Your function should include a `stop()` statement that returns an error message if any of the values in `x` are nonpositive. **Hint:** The function `prod()` can be used to compute the product of the values in `x`.

2. Determine the class of your output by running the following:

```
class(gm(1:4))
```

3. Modify your geometric mean function, using `class()`, so that the return value has the class "geometric".

4. Verify the new class of your output is correct by running the following

```
class(gm(1:4))
```

2 Part B: Performance Enhancement: Speed

1. This problem concerns efficiency and timing code.

Using `system.time(expression)`, explore how time changes with size of the inputs (e.g. use sizes 100, 1000, 10000, 100000, 1000000, 10000000). Plot time versus input size and see if algorithm is linear, polynomial, or exponential.

- Move expressions within loops that are invariant to compute just once and assigned to a variable.
- Avoid concatenating vectors by pre-allocating and assigning to the *i*th element. i.e.

```
x <- c(); for(i in seq(along = y)) x = c(x, g(y[i]))
```

What are your conclusions?

Basic Course on R: Object-Oriented Programming Practical Answers

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1 Part A: Object Oriented Programming

1. The *geometric mean* can be defined as the n th root of the product of n positive numbers x_1, x_2, \dots, x_n , i.e.

$$gm = (x_1 \cdot x_2 \cdots x_n)^{\frac{1}{n}}$$

Write a function `gm()` that takes a vector argument `x` containing positive numbers and returns their geometric mean. Your function should include a `stop()` statement that returns an error message if any of the values in `x` are nonpositive. **Hint:** The function `prod()` can be used to compute the product of the values in `x`.

```
gm <- function(x) {  
  if(any(x <= 0)) {  
    stop("All values in the vector must be positive.")  
  }  
  else {  
    y <- prod(x)  
    geom <- y^(1/length(x))  
    return(geom)  
  }  
}
```

2. Determine the class of your output by running the following:

```
class(gm(1:4))  
  
## [1] "numeric"
```

3. Modify your geometric mean function, using `class()`, so that the return value has the class "geometric".

```
gm <- function(x) {  
  if(any(x <= 0)) {  
    stop("All values in the vector must be positive.")  
  }  
  else {  
    geom <- prod(x)^(1/length(x))  
    class(geom) <- "geometric"  
    return(geom)  
  }  
}
```

- Verify the new class of your output is correct by running the following:

```
class(gm(1:4))  
## [1] "geometric"
```

2 Part B: Performance Enhancement: Speed

- This problem concerns efficiency and timing code.

Using `system.time(expression)`, explore how time changes with size of the inputs (e.g. use sizes 100, 1000, 10000, 100000, 1000000, 10000000). Plot time versus input size and see if algorithm is linear, polynomial, or exponential.

- Move expressions within loops that are invariant to compute just once and assigned to a variable.
- Avoid concatenating vectors by pre-allocating and assigning to the *i*th element. i.e.

```
x <- c(); for(i in seq(along = y)) x = c(x, g(y[i]))
```

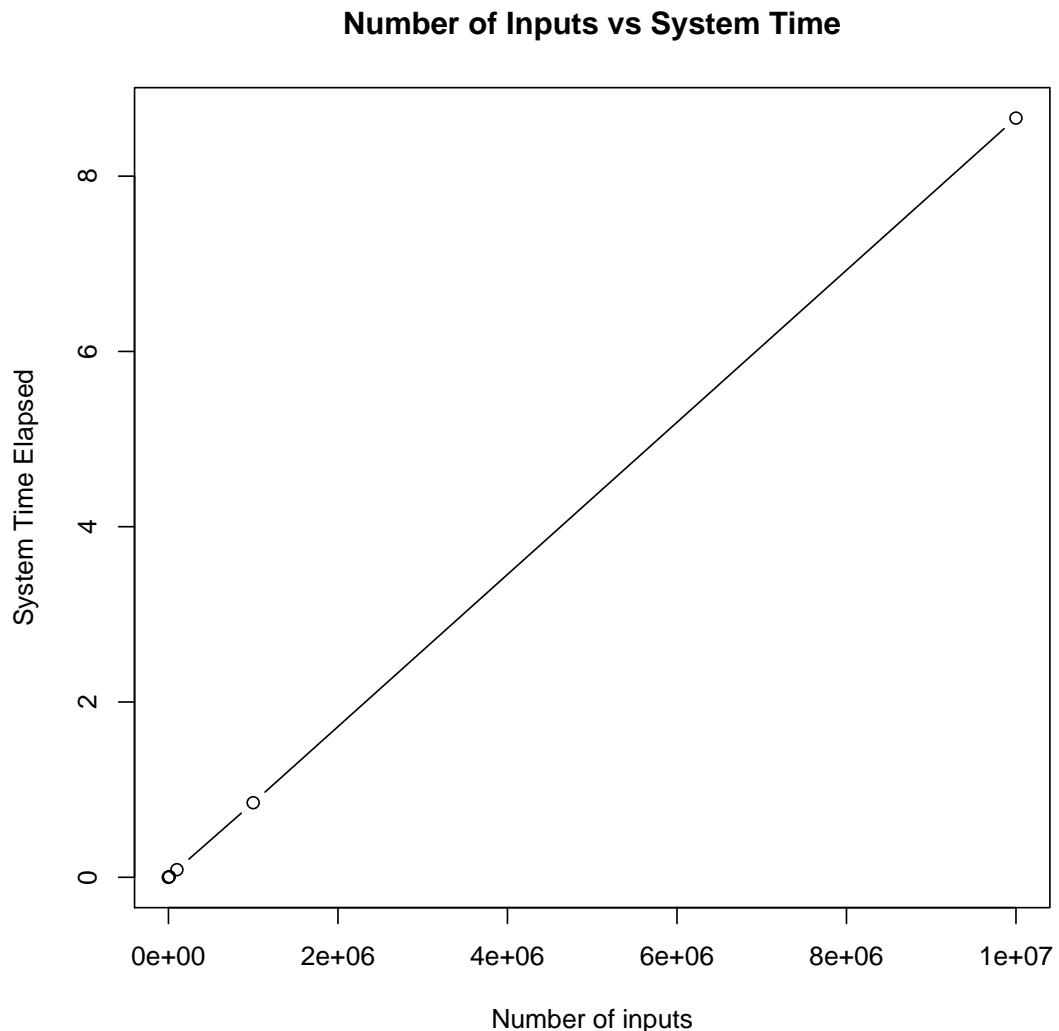
What are your conclusions?

Answers may vary.

```
time <- function(n){  
  x <- runif(n)  
  y <- sqrt(2)  
  t <- system.time( for(i in 1:n) {  
    x[i] <- x[i] + y  
  }  
 )  
  return(t[["elapsed"]])  
}  
inputs <- c(100, 10^3, 10^4, 10^5, 10^6, 10^7)  
t1 <- time(100)  
t2 <- time(10^3)  
t3 <- time(10^4)  
t4 <- time(10^5)  
t5 <- time(10^6)
```

```
t6 <- time(10^7)
timeV <- c(t1, t2, t3, t4, t5, t6)
```

```
plot(x = inputs, y = timeV, main = "Number of Inputs vs System Time",
      xlab = "Number of inputs", ylab = "System Time Elapsed",
      type = "b")
```



The scatterplot of computation time versus size of inputs is somewhat linear.

Course on R: Glossary

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18-24 May 2017

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1 Getting Help

```
? , help()      # Open the built-in html help file for a function  
# or operator (use quotes for special characters)  
??             # Search the built-in html help files for a  
# keyword or phrase (in quotes)  
RSiteSearch()  # Search the online R documentation for a keyword  
# or phrase (in quotes)  
apropos()     # Return character vector of objects containing  
# searched character string
```

2 The R Workspace

```
objects(), ls()      # List the objects in the Workspace  
rm()                # Remove objects from the Workspace  
getwd()              # Determine the current working directory  
setwd()              # Change the current working directory  
save.image()         # Save all objects in session to a .RData file  
savehistory()        # save all commands executed during current  
# session to a .Rhistory file  
save()               # save specified objects  
load()               # load a .Rdata file into session  
loadhistory()        # load a .Rhistory file into session
```

3 Reading and Writing Files

```
read.table()      # Read data from a text file into a data frame, or  
write.table()    # Write data from a data frame or matrix to a  
                 # text file  
read.csv()       # Read data from a comma separated value  
                 # (.csv) file into a data frame  
write.csv()      # Write data from a data frame or matrix to a  
                 # .csv file  
source()         # Read and execute R commands from a file
```

4 Special Values, Operators, and Functions

```
<-                  # Assigns a value to a variable  
#                   # Comment (not executed if ran)  
NULL                # Represents an "empty" variable  
args()              # View formal arguments of a function  
Inf                 # Infinity  
NaN                 # "Not a number"  
NA                  # "Not available" (a missing value)  
table()              # Create a contingency table of counts  
                     # from a factor or character vector  
class()              # Determines the class of an object  
mode()               # determines the mode of an object  
library()             # Loads a package into the current session  
trace.back()          # Trace code to source of an error  
set.seed()             # Fix random number seed (for reproducibility)  
install.packages()    # Install specified package  
data()                # Load pre-installed dataset  
paste()                # Paste characters into a single string  
letters                # character vector of lowercase letters  
LETTERS                # character vector of uppercase letters
```

5 Arithmetic Operators

```
^                      # Exponentiation
%%                     # Modulo (i.e. remainder)
%/%                    # Integer divide
* /                   # Multiplication, Division
+ -                   # Addition, Subtraction
```

6 A Few Built-in Mathematical Functions

```
sqrt()                  # Square root
abs()                   # Absolute value
sign()                  # Returns -1, 0, or +1 depending on
                        # whether its argument is negative,
                        # zero, or positive
round()                 # Round a value to a specified number
                        # of digits
signif()                # Express a value to a specified number of
                        # significant digits
floor()                 # Largest integer not greater than a value
ceiling()                # Smallest integer not less than a value
trunc()                  # Truncate a value toward 0
log(); log10()            # Natural logarithm, base 10 logarithm
exp()                   # Exponential function (e.g. exp(1) is
                        # the exponential constant e)
factorial()              # Factorial
choose()                 # Number of ways to choose x objects from
                        # n objects
sin(); cos(); tan()        # Sine, cosine, tangent
beta(); gamma()           # Beta function, gamma function
```

7 Relational and Logical Operators

```
<          # Less than
>          # Greater than
==         # Equal to
!=         # Not equal to
<=        # Less than or equal to
>=        # Greater than or equal to
&&        # "And" for logical scalars
||          # "Or" for logical scalars
!           # "Not" (for logical scalars or vectors)
&          # "And" for logical vectors
|           # "Or" for logical vectors
```

8 User-Defined Functions

```
myFunc <- function(arg1, arg2, ..., argk) {
  statement1
  statement2
  .
  .
  .
  statementq
  return(expression)
}
```

Above,

- `myFunc` is a name we choose for our function.
- `arg1, arg2, ..., argk` are names we choose for the k formal arguments.
- `statement1, statement2, ..., statementq` are a sequence of q statements (which may involve `arg1, arg2, ..., argk`).
- `expression` is evaluated and the result returned.

9 Vectors

```
c()          # Create a vector of values
length()     # Returns the number of elements in a vector
             # (sample size)
is.vector()  # Indicates whether or not an object is a vector
[ ]          # Access vector elements via their indices OR
             # extract a subset of vector elements that satisfy
             # a given condition (e.g. relational)
sort()       # Returns the data in sorted order
rev()        # Returns the data in reverse order
order()      # Returns a vector of indices such that x[order(x)]
             # returns the vector x in sorted order
seq()        # Create a sequence of values
:            # Create a sequence of integers
rep()        # Create a repeating pattern of values
any()        # Do any elements of a vector satisfy a
             # given condition?
all()        # Do all the elements of a vector satisfy a
             # given condition?
which()      # Returns the indices of the elements of a vector
             # that satisfy a given condition
which.min(), # Returns the index of the minimum (or maximum) value
which.max()  # in a vector
%in%         # Return TRUE if given value(s) contained in
             # given vector
match()      # Return position of first argument if it appears in
             # second argument (only first match returned)
duplicated() # Return TRUE if element appears in an
             # earlier position in vector
is.na()      # Returns TRUE or FALSE depending on
             # whether or not a value is NA
sample()     # Randomly permute or sample from a vector
cut()        # Convert a numeric vector into a factor based
             # on specified cut points
```

10 Factors

```
factor()           # Create a factor from a character vector
length()          # Returns the number of elements in a factor
                  # (sample size)
levels()          # Examine the levels of the factor
nlevels()         # Returns the number of levels of the factor
is.factor()        # Indicates whether or not an object is a factor
str()              # Describes the structure of a factor
as.character()    # Convert a factor to a character vector
as.numeric()       # Convert a factor to a numeric vector
```

11 Matrices (special vectors!)

```
matrix()           # Create a matrix, from a vector, with nrow
                  # rows and ncol columns
cbind(), rbind()  # Create a matrix from two or more vectors by
                  # "binding" them together in columns or rows
dim()              # Returns the dimensions (number of rows and
                  # columns) of a matrix
nrow(); ncol()     # Number of rows, number of columns of a matrix
is.matrix()        # Indicates whether an object is a matrix
[ , ]              # Access matrix elements via their row and
                  # column indices (separated by a comma)
rownames()         # View or change the row names of a matrix
colnames()         # View or change the column names of a matrix
apply()             # Apply a function separately to each row (or
                  # each column) of a matrix
```

12 Lists

```
list()                      # Create a list
length()                    # Returns the number of elements in a list
is.list()                   # Indicates whether or not an object is a list
str()                       # Describes the structure of a list
[[ ]]                       # Retrieve a list element via its index or name
$                           # Retrieve a list element via its name
[ ]                         # Access a list element via its index or name,
                           # returning a list
unlist()                    # Convert the components of a list to a vector
lapply()                     # Apply a function separately to each element of
                           # a list, returning a list
sapply()                    # Apply a function separately to each element of
                           # a list, returning a vector
names()                     # Examine or change the names of list elements
```

13 Data Frames (special lists!)

```
data.frame()      # Create a data frame from a set of vectors of  
                  # the same length  
read.table()     # Read data from a text file into a data frame  
head()           # Prints the first 6 rows of a data frame  
tail()           # Prints the last 6 rows of a data frame  
names()          # Lists the names of the variables in the data  
                  # frame  
row.names()      # View or change row names of a data frame  
nrow()           # Indicates the number of rows of a data frame  
ncol()           # Indicates the number of columns of a data frame  
dim()            # Gives the dimensions (number of rows and  
                  # columns)  
str()             # Gives the structure of a data frame  
is.data.frame()  # Indicates whether or not an object is a data  
                  # frame  
[ , ]            # Access data frame elements, rows, or columns  
                  # via their row and column indices (separated by  
                  # a comma)  
[[ ]]            # Retrieve a data frame variable (column) by  
                  # specifying its index or name  
$                # Retrieve a data frame variable (column) by  
                  # specifying its name  
rbind()          # Create a new data frame by "binding" the  
                  # rows of one data frame to those of another  
cbind()          # Create a new data frame by "binding" the  
                  # columns of one data frame to those of another  
merge()          # Merge two data frames that share one or more  
                  # variables in common  
unique()         # Return only unique rows of a data frame  
duplicated()    # Return TRUE if row appears in an  
                  # earlier row in data frame  
attach()          # Make the variables in a data frame directly  
                  # accessible by name by "attaching" the  
                  # data frame  
detach()          # "Detach" a data frame that is "attached"
```

14 Plots

```
plot()                      # Scatterplot, time-series plot
hist()                       # Histogram
boxplot()                    # Boxplot(s)
stripchart()                 # Dot plot, individual value plot
qqnorm()                     # Normal probability plot
                           # (quantile-quantile plot)
stem()                       # Stem and leaf plot
barplot()                    # Bar chart of given bar heights
pie()                        # Pie chart of given pie areas
pdf(), png(),               # Save plot to file with given extension
jpeg(), etc.                 # (follow plotting commands with dev.off())
par()                        # Function to set graphical parameters
colors()                     # View a list of names of available colors
```

15 Plotting Arguments

```
main          # Main title for the plot (in quotation marks)
sub           # Subtitle (in quotation marks)
xlab, ylab    # Labels for the x and y axes (in quotation marks)
xlim, ylim    # Limits for the x and y axes in the plot (in the
               # form c(lower, upper))
type          # Type of plot that should be drawn (e.g. points,
               # lines, etc.)
pch            # Plot character, or symbol type
cex            # Character expansion factor, i.e. size of plot
               # characters and/or text
lty, lwd       # Line type (e.g. "dashed" or "solid") and line
               # width (values greater than 1 increase the width)
col            # Color of the objects being plotted (in quotation
               # marks)
col.axis,
col.lab,      # Colors for the axes, axis labels, main title,
col.main,     # and subtitle
col.sub
bg, fg         # Background and foreground colors (in quotation
               # marks)
mfrow, mfcol   # Multiple-figure plot arrangement as an nrow by
               # ncol array (a numerical vector of the form
               # c(nrow, ncol)) - only for par()
xaxt, yaxt    # x and y axis types (specify "n" for no axis)
bty            # Type of box drawn around the plot (specify "n"
               # for none)
cex.main,
cex.axis,     # Character expansion factors, i.e. sizes of text,
cex.lab       # for main title, axis annotations, and axis labels
               # (values greater than 1 increase their sizes)
```

16 Add to Existing Plot

```
points()      # Add points to the plot at specified coordinates
symbols()    # Add various symbols to the plot (circles, squares,
# etc.)
abline()     # Add a line to the plot with given intercept a and
# slope b
lines()      # Add a line to the plot connecting specified
# coordinates
segments()   # Add line segments to the plot between pairs of
# points
curve()      # Add a curve to the plot (specify add = TRUE)
qqline()     # Add a line to a normal probability plot
arrows()     # Draw an arrow in the plot (with specified start
# and end points)
rug()        # Adds a "rug" (tick marks for observations) to plot
title()      # Add a main title to the plot (if it does not
# already have one). Can also be used to add x
# and y axis labels.
text()       # Add text to the plot at a specified set of
# coordinates
mtext()      # Add text in a margin of the plot
legend()     # Add a legend to the plot
axis()       # Add an axis to the plot on a given side
box()        # Add a box around the plot (if one does not
# already exist)
rect()       # Draw a rectangle in the plot at a given set
# of coordinates
polygon()    # Draw a polygon in the plot with a given set
# of vertices
```

17 Summary Statistics Functions

```
mean()          # The sample mean
median()        # Sample median
sd(); var()     # Sample standard deviation and variance
length()        # Number of observations (sample size)
sum()           # The sum of the values
min(); max()    # Smallest and largest values in the data set
range()         # Range (smallest and largest values)
                # of the data set
mad()           # Median absolute deviation
quantile()      # Sample quantile (percentile)
IQR()           # Interquartile range
summary()       # Five number summary (and sample mean)
lapply()         # Apply a function separately to each column of a
                # data frame, returning a list
sapply()         # Apply a function separately to each column of a
                # data frame, returning a vector
tapply()         # Compute a specified summary statistic separately
                # for each subset of a data frame via the arguments
                # X, INDEX, and FUN
aggregate()     # Compute a specified summary statistic separately
                # for each subset of a data frame via the arguments
                # x, by, and FUN
colMeans()      # Compute the mean separately for each column of a
                # data frame
colSums()        # Compute the sum separately for each column of a
                # data frame
rank()           # Assign ranks to values of a numeric vector
cor()            # Calculate Pearson's correlation coefficient or
                # Spearman's rho
```

18 Tests and Confidence Intervals

```
t.test()          # One- or two-sample (nonpooled or paired) t-test
                  # (assumes normality of each population or paired
                  # differences)
wilcox.test()    # One-sample signed rank test or two-sample
                  # Wilcoxon rank sum (a.k.a. Mann-Whitney U) test
                  # (no normality assumption)
cor.test()        # Test for the association between two variables
                  # (assumes normality of two populations)
aov()            # Perform ANOVA for differing means between two or
                  # more groups of a factor (assumes normality
                  # within groups)
summary()         # View the ANOVA table (F-test results from aov())
TukeyHSD()       # Calculate post-hoc pairwise confidence intervals
kruskal.test()   # Perform distribution-free test for differing
                  # locations between two or more groups of a factor
                  # (no normality assumption)
friedman.test()  # Perform distribution-free test for differing
                  # locations between two or more groups of a factor
                  # with a block variable (no normality assumption)
chisq.test()     # Perform chi-squared test of independence
fisher.test()    # Perform Fisher's exact test of independence
```

19 Regression

```
lm()              # Fit a linear model (simple or multiple linear
                  # regression)
glm()            # Fit generalized linear models; fits a logistic
                  # regression model when family = binomial(logit)
summary()         # View results of models fit
predict()         # Predict from results of models fit
```

20 Programming

```
if()          # Used to execute a statement only if the given
             # condition is met
else         # Used to specify an alternative statement to be
             # executed if the condition given in if() is not met
ifelse()      # Returns a vector whose values depend on whether
             # or not a given condition is met by the elements
             # of another vector
for()         # Repeat set of statements a certain number of times
while()       # Repeat a set of statements as long as a
             # specified condition is met
repeat        # Repeat a set of statements until a break
             # command is encountered
break         # Terminate iterations of a loop
next          # Skip ahead to the next iteration
<-
assign()      # Assign a value to a variable in the global
             # environment (Workspace).
return()      # Terminate a function call and return a value.
stop()        # Terminate a function call; print error message.
warning()     # Print a warning message (without terminating the
             # function call).
source()      # Read R commands from a text file.
class()        # Determines the class of an object. Can also be
             # used to assign a class to an object.
is.cname()    # Returns TRUE if an object belongs to the class
             # "cname" (e.g. is.numeric(), is.data.frame(),
             # etc.) and FALSE otherwise.
methods()     # Determine the S3 methods that are associated
             # with a given generic function
showMethods() # Determine the S4 methods that are associated
             # with a given generic function
system.time() # Returns the computation time required to
             # execute a chunk of R code (in seconds)
cmpfun()      # Translate/compile function from R code to bytecode
```