

David J. Stanley

PSYC6060 Course Notes

To my students,
from whom I've learn so much about teaching.

Contents

List of Tables	vii
List of Figures	ix
Preface	xi
About the Author	xiii
1 Introduction	1
1.1 A focus on workflow	1
1.2 R works with plug-ins	1
1.3 Create an account at R Studio Cloud	2
1.4 Join the class workspace	2
1.5 Exploring the R Studio Interface	4
1.5.1 Console panel	4
1.5.2 Script Panel	5
1.6 Writing your first script	6
1.6.1 Create the script file	6
1.6.2 Add a comment to your script	6
1.6.3 Background about the tidyverse	7
1.6.4 Add library(tidyverse) to your script	8
1.6.5 Activate tidyverse auto-complete for your script	8
1.7 Loading your data	9
1.7.1 Use read_csv (not read.csv) to open files.	9
1.8 Checking out your data	10
1.8.1 view(): See a spreadsheet view of your data	10
1.8.2 print(): See you data in the Console	11
1.8.3 head(): Check out the first few rows of data	11
1.8.4 tail(): Check out the last few rows of data	12
1.8.5 summary(): Quick summaries	13
1.9 Run <i>vs.</i> Source with Echo <i>vs.</i> Source	13
1.9.1 Run select text	14
1.9.2 Source (without Echo)	14
1.9.3 Source with Echo	15
1.10 Trying Source with Echo	15
1.11 A few key points about	17
1.11.1 Lists	19

1.12 That's it!	20
2 Handling Data with the Tidyverse	21
2.1 Required	21
2.2 Objective	21
2.3 Using the Console	22
2.4 Basic tidyverse commands	22
2.4.1 select()	23
2.4.2 summarise()	25
2.4.3 filter()	25
2.4.4 group_by()	27
2.4.5 mutate()	28
2.5 Advanced tidyverse commands	29
2.5.1 select()	30
2.5.2 summarise()	33
2.5.3 mutate()	35
2.6 Using help	40
2.7 Base R vs tidyverse	41
2.7.1 Tibbles vs. data frames	41
2.7.2 read.csv and data frames	41
2.7.3 read_csv and tibbles	42
3 Making your data ready for analysis	45
3.1 Required Packages	45
3.2 Objective	45
3.3 Context	46
3.4 Begin with the end in mind	48
3.4.1 Structuring data: Obtaining tidy data	49
3.5 Data collection considerations	51
3.5.1 Naming conventions	53
3.5.2 Likert-type items	53
3.5.3 ANOVA between	55
3.5.4 ANOVA within	55
3.5.5 Other information	56
3.6 Following the examples	56
3.7 Entering data into spreadsheets	57
3.8 Experiment: Between	58
3.8.1 Creating factors	59
3.8.2 Factor screening	60
3.8.3 Numeric screening	61
3.9 Experiment: Within one-way	62
3.9.1 Creating factors	63
3.9.2 Factor screening	64
3.9.3 Numeric screening	66
3.9.4 Pivot to tidy data	66

3.10 Experiment: Within N-way	68
3.10.1 Creating factors	69
3.10.2 Factor screening	71
3.10.3 Numeric screening	72
3.10.4 Pivot to tidy data	73
3.11 Surveys: Single Occassion	75
3.11.1 Creating factors	77
3.11.2 Factor screening	78
3.11.3 Numeric screening	80
3.11.4 Scale scores	81
3.12 Surveys: Multiple Occasions	86
3.12.1 Creating factors	87
3.12.2 Screening factors	89
3.12.3 Numeric screening	90
3.12.4 Scale scores	92
3.12.5 Pivot to tidy data	94
3.13 Basic descriptive statistics	95
3.13.1 skim()	95
3.13.2 apa.cor.table()	96
3.13.3 tidyverse	97
3.13.4 Cronbach's alpha	98
Appendix	101
A More to Say	101
Bibliography	103
Index	105



List of Tables

1.1	R packages are similar to smart phone apps (Kim, 2018) . . .	2
3.2	Between participant data entered one row per participant . .	50
3.3	Within participant data entered one row per participant . . .	50
3.4	A tidy data version of the within participant data	52



List of Figures

1.1	Screen shot of workspace join message.	3
1.2	Screen shot of welcome messag	3
1.3	Screen shot of starting first assignment	3
1.4	R Studio interface	4
1.5	Source button options	14
3.1	Open science in an article header	47
3.2	Data science pipeline by Roger Peng.	48
3.3	Spreadsheet entry of running data	57
3.4	Text view of CSV data	58
3.5	Raw data for item scoring	75
3.6	Word document created by apa.cor.table	96



Preface

R's emerging role in psychology will be described here..

Structure of the book

I'll put more about the structure of the book here in the future.

Software information and conventions

I used the **knitr** package (Xie, 2015) and the **bookdown** package (Xie, 2020) to compile my book. My R session information is shown below:

```
xfun::session_info()
```

```
## R version 4.0.2 (2020-06-22)
## Platform: x86_64-apple-darwin17.0 (64-bit)
## Running under: macOS Catalina 10.15.5, RStudio 1.3.959
##
## Locale: en_CA.UTF-8 / en_CA.UTF-8 / en_CA.UTF-8 / C / en_CA.UTF-8 / en_CA.UTF-8
##
## Package version:
##   askpass_1.1      base64enc_0.1.3  bookdown_0.19.1
##   compiler_4.0.2  curl_4.3         digest_0.6.25
##   evaluate_0.14    glue_1.4.1       graphics_4.0.2
##   grDevices_4.0.2 grid_4.0.2        highr_0.8
##   htmltools_0.4.0 jsonlite_1.6.1    knitr_1.28
##   lattice_0.20-41 magrittr_1.5       markdown_1.1
##   methods_4.0.2   mime_0.9          mnormt_1.5-7
##   nlme_3.1-148     openssl_1.4.1    packrat_0.5.0
```

```
## parallel_4.0.2 psych_1.9.12.31 Rcpp_1.0.4.6
## rlang_0.4.6    rmarkdown_2.2    rsconnect_0.8.16
## rstudioapi_0.11 stats_4.0.2    stringi_1.4.6
## stringr_1.4.0 sys_3.3      tinytex_0.23
## tools_4.0.2   utils_4.0.2    xfun_0.14
## yaml_2.2.1
```

Package names are in bold text (e.g., **rmarkdown**), and inline code and filenames are formatted in a typewriter font (e.g., `knitr::knit('foo.Rmd')`). Function names are followed by parentheses (e.g., `bookdown::render_book()`).

About the Author

David J. Stanley is an Associate Professor of Industrial and Organizational Psychology at the University of Guelph in Canada. He obtained his PhD from Western University in London, Ontario. David has published articles in *Advances in Methods and Practices in Psychological Science*, *Organizational Research Methods*, *Journal of Applied Psychology*, *Perspectives in Psychological Science*, *Journal of Business and Psychology*, *Journal of Vocational Behaviour*, *Journal of Personality and Social Psychology*, *Behavior Research Methods*, *Industrial and Organizational Psychology*, and *Emotion* among other journals. David also created the `apaTables` R package.



1

Introduction

Welcome! In this guide, we will teach you about statistics using the statistical software R with the interface provided by R Studio. The purpose of this chapter is to provide you with a set of activities that get you up-and-running in R quickly so get a sense of how it works. In later chapters we will revisit these same topics in more detail.

1.1 A focus on workflow

An important part of this guide is training you in a workflow that will avoid many problems than can occur when using R.

1.2 R works with plug-ins

R is a statistical language with many plug-ins called **packages** that you will use for analyses. You can think of R as being like your smartphone. To do things with your phone you need **an App** (R equivalent: a *package*) from the App Store (R equivalent: *CRAN*). Apps need to be **downloaded** (R equivalent: *install.packages*) before you can use them. To use the app you need **Open** it (R equivalent: *library command*). These similarities are illustrated in Table 1.1 below.

TABLE 1.1: R packages are similar to smart phone apps (Kim, 2018)

Smart Phone Terminology	R Terminology
App	package
App Store	CRAN
Download App from App Store	<code>install.packages("apaTables", dependencies = TRUE)</code>
Open App	<code>library("apaTables")</code>

1.3 Create an account at R Studio Cloud

R Studio Cloud¹ accounts are free and required for this guide. Please go to the website and set up a new account.

1.4 Join the class workspace

To do the assignment required for this class you need to join the class workspace on R Studio Cloud. To do so:

1. Log into R Studio Cloud (if you haven't already done so).
2. Go to your university email account and find the message with the subject "R Studio Workspace Invitation". In this message there is a link to the class R Studio Cloud workspace.
3. Click on the workspace link in the email or paste it into your web browser. You should see a screen like the one below in Figure 1.1. Click on the Join button.
4. Then you should see the welcome message illustrated in Figure 1.2. Above this message is the Projects menu option. Click on the word Project.
5. You should now see the First Project displayed as in 1.3. Click the Start button. You will then move to a view of R Studio.

¹<http://www.rstudio.cloud>

1.4 Join the class workspace

3

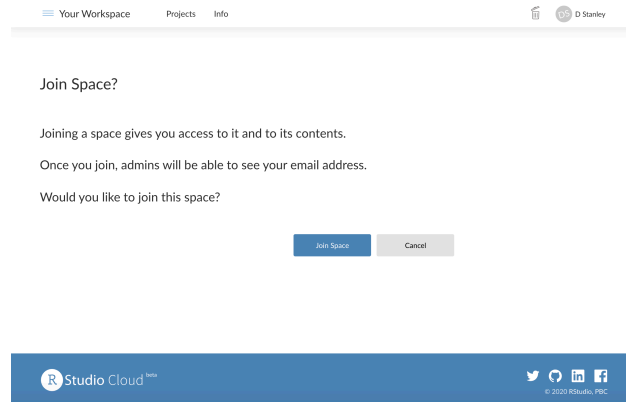


FIGURE 1.1: Screen shot of workspace join message.

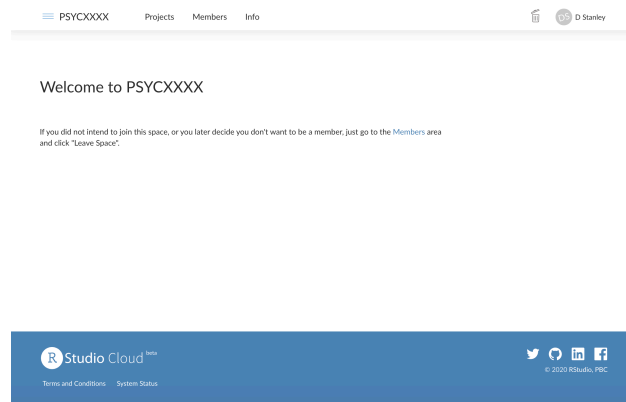


FIGURE 1.2: Screen shot of welcome messag

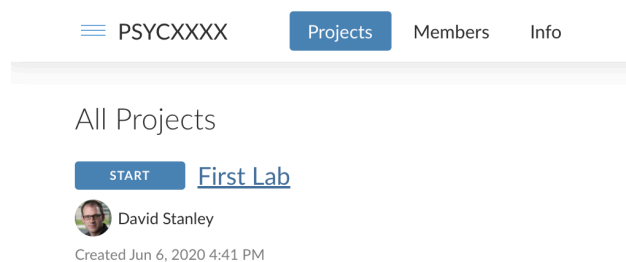


FIGURE 1.3: Screen shot of starting first assignment

5. In R Studio it is essential you use projects to keep your files organized and in the same spot. For this course, when you start an assignment on R Studio Cloud and the project will already have been made for you. Later you will learn to make your own R Studio Projects.

1.5 Exploring the R Studio Interface

Once you have opened (or created) a Project folder, you are presented with the R Studio interface. There are a few key elements to the user interface that are illustrated in Figure 1.4 In the lower right of the screen you can see the a panel with several tabs (i.e., Files, Plots, Packages, etc) that I will refer to as the Files pane. You look in this pane to see all the files associated with your project. On the left side of the screen is the Console which is an interactive pane where you type and obtain results in real time. I've placed two large grey blocks on the screen with text to more clearly identify the Console and Files panes. Not shown in this figure is the Script panel where we can store our commands for later reuse.

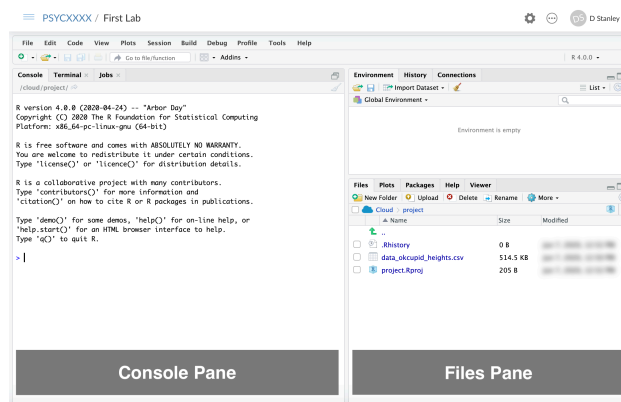


FIGURE 1.4: R Studio interface

1.5.1 Console panel

When you first start R, the Console panel is on the left side of the screen. Sometimes there are two panels on the left side (one above the other); if so, the Console panel is the lower one (and labeled accordingly). We can use R

a bit like a calculator. Try typing the following into the Console window: $8 + 6 + 7 + 5$. You can see that R immediately produced the result on a line preceded by two hashtags (`##`).

```
8 + 6 + 7 + 5
```

```
## [1] 26
```

We can also put the result into a variable to store it. Later we can use the `print` command to see that result. In the example below we add the numbers 3, 0, and 9 and store the result in the variable `my_sum`. The text “`<-`” indicate you are putting what is on the right side of the arrow into the variable on the left side of the arrow. You can think of a variable as cup into which you can put different things. In this case, imagine a real-world cup with `my_sum` written on the outside and inside the cup we have stored the sum of 3, 0, and 9 (i.e., 12).

```
my_sum <- 3 + 0 + 9
```

We can inspect the contents of the `my_sum` variable (i.e., `my_sum` cup) with the `print` command:

```
print(my_sum)
```

```
## [1] 12
```

Variables are very useful in R. We will use them to store a single number, an entire data set, the results of an analysis, or anything else.

1.5.2 Script Panel

Although you can use R with just with the Console panel, it's a better idea to use scripts via the Script panel - not visible yet. Scripts are just text files with the commands you use stored in them. You can run a script (as you will see below) using the Run or Source buttons located in the top right of the Script panel.

Scripts are valuable because if you need to run an analysis a second time you don't have to type the command in a second time. You can run the script again and again without retyping your commands. More importantly though, the script provides a record of your analyses.

A common problem in science is that after an article is published, the authors can't reproduce the numbers in the paper. You can read more about the

important problem in a surprising article in the journal *Molecular Brain*². In this article an editor reports how a request for the data underlying articles resulted in the wrong data for 40 out of 41 papers. Long story short – keep track of the data and scripts you use for your paper. In a later chapter, it’s generally poor practice to manipulate or modify or analyze your data using any menu driven software because this approach does not provide a record of what you have done.

1.6 Writing your first script

1.6.1 Create the script file

Create a script in your R Studio project by using the menu File > New File > R Script.

Save the file with an appropriate name using the File menu. The file will be saved in your Project folder. A common, and good, convention for naming is to start all script names with the word “script” and separate words with an underscore. You might save this first script file with the name “script_my_first_one.R”. The advantage of beginning all script files with the word script is that when you look at your list of files alphabetically, all the script files will cluster together. Likewise, it’s a good idea to save all data files such that they begin with “data_”. This way all the data files will cluster together in your directory view as well. You can see there is already a data file with this convention called “data_okcupid.csv”.

You can see as discussed previously, we are trying to instill an effective workflow as you learn R. Using a good naming convention (that is consistent with what others use) is part of the workflow. When you write your scripts it’s a good idea to follow the tidyverse style guide³ for script names, variable name, file names, and more.

1.6.2 Add a comment to your script

In the previous section you created your first script. We begin by adding a comment to the script. A comment is something that will be read by humans rather than the computer/R. You make comments for other people that will read your code and need to understand what you have done. However, realize

²<https://molecularbrain.biomedcentral.com/articles/10.1186/s13041-020-0552-2>

³<https://style.tidyverse.org>

that you are also making comments for your future self as illustrated in an XKCD cartoon⁴.

A good way to start every script is with a comment that includes the date of your script (or even better when you installed your packages, more on this later). Like smartphone apps, packages are updated regularly. Sometimes after a package is updated it will no longer work with an older script. Fortunately, the checkpoint package⁵ lets users role back the clock and use older versions of packages. Adding a comment with the date of your script will help future users (including you) to use your script with the same version of the package used when you wrote the script. Dating your script is an important part of an effective and reproducible workflow.

```
# Code written on: YYYY/MM/DD
# By: John Smith
```

Note that in the above comment I used the internationally accepted date format order Year/Month/Day. Some people use the mnemonic *Your My Dream* to remember this order. Wikipedia provides more information about the Internationally Date Format ISO 8601⁶.

Moving forward, I suggest you use comments to make your own personal notes in your own code as your write it.

1.6.3 Background about the tidyverse

There are generally two broad ways of using R, the older way and the newer way. Using R the older way is referred to as using base R. A more modern approach to using R is the tidyverse. The tidyverse represents a collection of packages the work together to give R a modern workflow. These packages do many things to help the data analyst (loading data, rearranging data, graphing, etc.). We will use the tidyverse approach to R in this guide.

As noted the tidyverse is a collection of packages. Each package adds new commands to R. The number of packages and correspondingly the number of new commands added to R by the tidyverse is large. Below is a list of the tidyverse packages:

```
## [1] "broom"      "cli"        "crayon"     "dbplyr"
## [5] "dplyr"      "forcats"    "ggplot2"    "haven"
## [9] "hms"        "httr"       "jsonlite"   "lubridate"
## [13] "magrittr"   "modelr"     "pillar"     "purrr"
```

⁴<https://xkcd.com/1421/>

⁵<https://cran.r-project.org/web/packages/checkpoint/index.html>

⁶https://en.wikipedia.org/wiki/ISO_8601

```
## [17] "readr"      "readxl"      "reprex"      "rlang"  
## [21] "rstudioapi" "rvest"       "stringr"     "tibble"  
## [25] "tidyr"      "xml2"        "tidyverse"
```

Before you can use a package it needs to be installed – this is the same as downloading an app from the App Store. Normally, you can install a **single** packages with the `install.packages` command. Previously, you needed run an `install.package` command for every package in the tidyverse as illustrated below (though we no longer use this approach).

```
# The old way of installing the tidyverse packages  
# Like downloading apps from the app store  
  
install.packages("broom", dep = TRUE)  
install.packages("cli", dep = TRUE)  
install.packages("ggplot", dep = TRUE)  
# etc
```

Fortunately, the tidyverse packages can now be installed with a single `install.packages` command. Specifically, the `install.packages` command below will install all of the packages listed above.

Class note: For the “First Lab”, I’ve done the `install.packages` for you. So there is no need to use the `install.packages` command below in this first lab.

```
install.packages("tidyverse", dep = TRUE)
```

1.6.4 Add `library(tidyverse)` to your script

The tidyverse is now installed, so we need to activate it. We do that with the `library` command. Put the library line below at the top of your script file (below your comment):

```
# Code written on: YYYY/MM/DD  
# By: John Smith  
library(tidyverse)
```

1.6.5 Activate tidyverse auto-complete for your script

Select the `library(tidyverse)` text with your mouse/track-pad so that it is highlighted. Then click the Run button in the upper right of the Script panel.

Doing this “runs” the selected text. After you click the Run button you should see text like the following the Console panel:

```
## -- Attaching packages ----- tidyverse 1.3.0 --
## v ggplot2 3.3.1      v purrr   0.3.4
## v tibble  3.0.1      v dplyr   1.0.0
## v tidyr   1.1.0      v stringr 1.4.0
## v readr   1.3.1      v forcats 0.5.0

## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

When you use `library(tidyverse)` to activate the tidyverse you activate the most commonly used subset of the tidyverse packages. In the output you see checkmarks beside names of the tidyverse packages you have activated.

By activating these packages you have added new commands to R that you will use. Sometimes these packages replace older versions of commands in R. The “Conflicts” section in the output shows you where the packages you activated replaced older R commands with newer R commands. You can activate the other tidyverse package by running a library command for each package – if needed. No need to do so now.

Most importantly, running the `library(tidyverse)` prior to entering the rest of your script allows R Studio to present auto-complete options when typing your text. Remember to start each script with the `library(tidyverse)` command and then Run it so you get the autocomplete options for the rest of the commands you enter.

1.7 Loading your data

1.7.1 Use `read_csv` (not `read.csv`) to open files.

If you inspect the Files pane on the right of the screen you see the **data_okcupid.csv** data file in our project directory. We will load this data with the commands below. If you followed the steps above, you should have auto-complete for the tidyverse commands you type for now in – in the current R session. Enter the command below into your script. As you start to type `read_csv` you will likely be presented with an auto-complete option. You can use the arrow keys to move up and down the list of options to select the one you want - then press tab to select it.

Once your command looks like the one below select the text and click on the “Run” button.

```
okcupid_profiles <- read_csv(file = "data_okcupid.csv")

## Parsed with column specification:
## cols(
##   age = col_double(),
##   diet = col_character(),
##   height = col_double(),
##   pets = col_character(),
##   sex = col_character(),
##   status = col_character()
## )
```

The output indicates that you have loaded a data file and the type of data in each column. The sex column is of type `col_character` which indicates it contains text/letters. Most of the columns are of the type character. The age and height columns contain numbers are correspondingly indicated to be the type `col_double`. The label `col_double` indicates that a column of numbers represented in R with high precision⁷. There are other ways of representing numbers in R but this is the type we will see/use most often.

1.8 Checking out your data

There many ways of viewing the actual data you loaded. A few of these are illustrated now.

1.8.1 `view()`: See a spreadsheet view of your data

You can inspect your data in a spreadsheet view by using the `view` command. Do NOT add this command to your script file – EVER. Adding it to the script can cause substantial problems. Type this command in the Console.

```
view(okcupid_profiles)
```

⁷https://en.wikipedia.org/wiki/Double-precision_floating-point_format

1.8.2 print(): See you data in the Console

You can inspect the first few rows of your data with the `print()` command. It is OK to add a print command to your script. Try the `print()` command below in the Console:

```
print(okcupid_profiles)
```

```
## # A tibble: 59,946 x 6
##   age diet      height pets      sex status
##   <dbl> <chr>    <dbl> <chr>    <chr> <chr>
## 1  22 strictly an~  75 likes dogs and l~ m   single
## 2  35 mostly other  70 likes dogs and l~ m   single
## 3  38 anything      68 has cats      m   availa~
## 4  23 vegetarian    71 likes cats      m   single
## 5  29 <NA>          66 likes dogs and l~ m   single
## 6  29 mostly anyt~  67 likes cats      m   single
## 7  32 strictly an~  65 likes dogs and l~ f   single
## 8  31 mostly anyt~  65 likes dogs and l~ f   single
## 9  24 strictly an~  67 likes dogs and l~ f   single
## 10 37 mostly anyt~  65 likes dogs and l~ m   single
## # ... with 59,936 more rows
```

1.8.3 head(): Check out the first few rows of data

You can inspect the first few rows of your data with the `head()` command. Try the command below in the Console:

```
head(okcupid_profiles)
```

```
## # A tibble: 6 x 6
##   age diet      height pets      sex status
##   <dbl> <chr>    <dbl> <chr>    <chr> <chr>
## 1  22 strictly any~  75 likes dogs and l~ m   single
## 2  35 mostly other  70 likes dogs and l~ m   single
## 3  38 anything      68 has cats      m   availa~
## 4  23 vegetarian    71 likes cats      m   single
## 5  29 <NA>          66 likes dogs and l~ m   single
## 6  29 mostly anyt~  67 likes cats      m   single
```

You can be even more specific and indicate you only want the first three row of your data with the `head()` command. Try the command below in the Console:

```
head(okcupid_profiles, 3)
```

```
## # A tibble: 3 x 6
##   age diet          height pets          sex status
##   <dbl> <chr>        <dbl> <chr>        <chr> <chr>
## 1  22 strictly any~    75 likes dogs and l~ m   single
## 2  35 mostly other    70 likes dogs and l~ m   single
## 3  38 anything        68 has cats          m   availa~
```

1.8.4 tail(): Check out the last few rows of data

You can inspect the last few rows of your data with the `tail()` command. Try the command below in the Console:

```
tail(okcupid_profiles)
```

```
## # A tibble: 6 x 6
##   age diet          height pets          sex status
##   <dbl> <chr>        <dbl> <chr>        <chr> <chr>
## 1  31 <NA>         62 likes dogs          f   single
## 2  59 <NA>         62 has dogs           f   single
## 3  24 mostly anyt~    72 likes dogs and lik~ m   single
## 4  42 mostly anyt~    71 <NA>                m   single
## 5  27 mostly anyt~    73 likes dogs and lik~ m   single
## 6  39 <NA>         68 likes dogs and lik~ m   single
```

You can be even more specific and indicate you only want the last three row of your data with the `tail()` command. Try the command below in the Console:

```
tail(okcupid_profiles, 3)
```

```
## # A tibble: 3 x 6
##   age diet          height pets          sex status
##   <dbl> <chr>        <dbl> <chr>        <chr> <chr>
## 1  42 mostly anyt~    71 <NA>                m   single
## 2  27 mostly anyt~    73 likes dogs and lik~ m   single
## 3  39 <NA>         68 likes dogs and lik~ m   single
```

1.8.5 summary(): Quick summaries

You can a short summary of your data with the `summary()` command. Note that we will use the `summary()` command in many places in the guide. The output of the `summary()` command changes depending on what you give it - that is put inside the brackets. You can give the `summary()` command many things such as data, the results of a regression analysis, etc.

Try the command below in the Console. You will see that `summary()` give the mean and median for each of the numeric variables (age and height).

```
summary(okcupid_profiles)
```

```
##      age      diet      height
##  Min.   : 18.0   Length:59946   Min.    : 1.0
##  1st Qu.: 26.0   Class  :character   1st Qu.:66.0
##  Median : 30.0   Mode   :character   Median :68.0
##  Mean   : 32.3                      Mean   :68.3
##  3rd Qu.: 37.0                      3rd Qu.:71.0
##  Max.   :110.0                      Max.   :95.0
##                                     NA's   :3
##      pets      sex      status
## Length:59946   Length:59946   Length:59946
## Class :character Class :character   Class :character
## Mode  :character Mode  :character   Mode  :character
##
##
##
```

1.9 Run vs. Source with Echo vs. Source

There are different ways of running commands in R. So far you have used two of these. You can enter them into the Console as we have done already. Or you can put them in your script select the text and clickk the Run button. There are four ways of running commands in your script.

You can:

1. Console: Enter commands directly
2. Script: Select the command(s) and press the Run button.

3. Script: Source (Without Echo)
4. Script: Source With Echo

Two of these approaches involve using the Source button, see Figure 1.5. You bring up the options for the Source button, illustrated in this figure, by clicking on the small arrow to the right of the word Source.

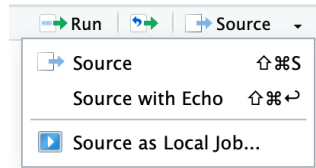


FIGURE 1.5: Source button options

1.9.1 Run select text

The Run button will run the text you highlight and present the relevant output. You have used this command a fair amount already.

I strongly suggest you **ONLY** use the Run button when testing a command to make sure it works or to debug a script. Or to run `library(tidyverse)` as you start working on your script so that you get the autocomplete options.

In general, you should always try to execute your R Scripts using the Source with Echo command (preceded by a Restart, see below). This ensures your script will work beginning to end for you in the future and for others that attempt to use it. Using the Run button in an ad lib basis can create output that is not reproducible.

1.9.2 Source (without Echo)

Source (without Echo) is not designed for the typical analysis workflow. It is mostly helpful when you run simulations. When you run Source (without Echo) much of the output you would wish to read is suppressed. In general, avoid this option. If you use it, you often won't see what you want to see in the output.

1.9.3 Source with Echo

The Source with Echo command runs all of the contents of a script and presents the output in the R console. This is the approach you should use to running your scripts in most cases.

Prior to running Source with Echo (or just Source), it's always a good idea to restart R. This makes sure you clear the computer memory of any errors from any previous runs.

So you should do the following EVERY time you run your script.

1. Use the menu item: **Session > Restart R**
2. Click the down arrow beside the Source button, and click on Source With Echo

This will clear potentially problematic previous stats, run the script commands, and display the output in the Console. Moving forward we will use this approach for running scripts. Once you have used Source with Echo once, you can just click the Source button and it will use Source with Echo automatically (without the need to use the pull down option for selecting Source with Echo).



- Using Restart R before you run a script, or R code in general, is a critical workflow tip.

1.10 Trying Source with Echo

Put the head(), tail(), and summary() command we used previously into your script. Then save your script using using the File > Save menu. Your script should appear as below.

```
# Code written on: YYYY/MM/DD
# By: John Smith
library(tidyverse)

okcupid_profiles <- read_csv(file = "data_okcupid.csv")
```

```
head(okcupid_profiles)

tail(okcupid_profiles)

summary(okcupid_profiles)
```

Now do the following:

1. Use the menu item: **Session > Restart R**
2. Click the down arrow beside the Source button, and click on Source With Echo

You should see the output below:

```
# Code written on: YYYY/MM/DD
# By: John Smith
library(tidyverse)

okcupid_profiles <- read_csv(file = "data_okcupid.csv")

## Parsed with column specification:
## cols(
##   age = col_double(),
##   diet = col_character(),
##   height = col_double(),
##   pets = col_character(),
##   sex = col_character(),
##   status = col_character()
## )

head(okcupid_profiles)

## # A tibble: 6 x 6
##   age diet          height pets          sex status
##   <dbl> <chr>         <dbl> <chr>         <chr> <chr>
## 1    22 strictly any~    75 likes dogs and l~ m   single
## 2    35 mostly other    70 likes dogs and l~ m   single
## 3    38 anything        68 has cats          m   availa~
## 4    23 vegetarian      71 likes cats          m   single
## 5    29 <NA>            66 likes dogs and l~ m   single
## 6    29 mostly anyth~    67 likes cats          m   single
```

```
tail(okcupid_profiles)
```

```
## # A tibble: 6 x 6
##   age diet      height pets      sex status
##   <dbl> <chr>    <dbl> <chr>    <chr> <chr>
## 1   31 <NA>      62 likes dogs    f    single
## 2   59 <NA>      62 has dogs      f    single
## 3   24 mostly anyt~ 72 likes dogs and lik~ m    single
## 4   42 mostly anyt~ 71 <NA>          m    single
## 5   27 mostly anyt~ 73 likes dogs and lik~ m    single
## 6   39 <NA>      68 likes dogs and lik~ m    single
```

```
summary(okcupid_profiles)
```

```
##      age      diet      height
## Min.   : 18.0  Length:59946  Min.   : 1.0
## 1st Qu.: 26.0  Class :character  1st Qu.:66.0
## Median : 30.0  Mode  :character  Median :68.0
## Mean   : 32.3                      Mean   :68.3
## 3rd Qu.: 37.0                      3rd Qu.:71.0
## Max.   :110.0                      Max.   :95.0
##                                     NA's   :3
##      pets      sex      status
## Length:59946  Length:59946  Length:59946
## Class :character  Class :character  Class :character
## Mode  :character  Mode  :character  Mode  :character
##
##
##
##
```

Congratulations you just ran your first script!

1.11 A few key points about

Sometimes you will need to send a command additional information. Moreover, that information often needs to be grouped together into a vector or a list before you can send it to the command. We'll learn more about doing so in the future but here is a quick over view of vectors and lists to provide a foundation for future chapters.

1.11.0.1 Vector of numbers

We can create a vector of only numbers using the “c” function - which you can think of as being short for “combine” (or concatenate). In the commands below we create a vector of a few even numbers called “even_numbers”.

```
even_numbers <- c(2, 4, 6, 8, 10)
```

```
print(even_numbers)
```

```
## [1]  2  4  6  8 10
```

We can obtain the second number in the vector using the following notation:

```
print(even_numbers[2])
```

```
## [1] 4
```

1.11.0.2 Vector of characters

We can also create vectors using only characters. Note that I use **SHIFT RETURN** after each comma to move to the next line.

```
favourite_things <- c("copper kettles",  
                      "woolen mittens",  
                      "brown paper packages")
```

```
print(favourite_things)
```

```
## [1] "copper kettles"      "woolen mittens"  
## [3] "brown paper packages"
```

As before, can obtain the second item in the vector using the following notation:

```
print(favourite_things[2])
```

```
## [1] "woolen mittens"
```


1.11.1 Lists

Lists are similar to vectors in that you can create them and access items by their numeric position. Vectors must be all characters or all numbers. Lists can be a mix of characters or numbers. Most importantly items in lists can be accessed by their label. Note that I use **SHIFT RETURN** after each comma to move to the next line in the code below.

```
my_list <- list(last_name = "Smith",
               first_name = "John",
               office_number = 1913)

print(my_list)
```

```
## $last_name
## [1] "Smith"
##
## $first_name
## [1] "John"
##
## $office_number
## [1] 1913
```

You can access an item in a list using double brackets:

```
print(my_list[2])
```

```
## $first_name
## [1] "John"
```

You can access an item in a list by its label/name using the dollar sign:

```
print(my_list$last_name)
```

```
## [1] "Smith"
```

```
print(my_list$office_number)
```

```
## [1] 1913
```

1.12 That's it!

Congratulations! You've reached the end of the introduction to R. Take a break, have a cookie, and read some more about R tomorrow!

2

Handling Data with the Tidyverse

2.1 Required

The following packages must be installed before starting this chapter.

Required Packages
tidyverse

The following data files are used in this chapter:

Required Data
data_okcupid.csv
data_experiment.csv

2.2 Objective

The objective of this chapter is to familiarize you with some key commands in the tidyverse. These commands are used in isolation of each other for the most part. In the next chapter we will use these commands in a more coordinated way as we load a data set and move it from raw data to data that is ready for analysis (i.e., analytic data). You can start this project by Starting the class assignment on R Studio Cloud that corresponds to the chapter name.

2.3 Using the Console

All of the commands in this chapter should be typed into the Console within R. If you see a command split over multiple lines, use SHIFT-RETURN (macOS) or SHIFT-ENTER (Windows) to move the next line that is part of the same command.

2.4 Basic tidyverse commands

If you inspect the Files tab on the lower-right panel in R Studio you will see the file `data_okcupid.csv`. The code below loads that file.

```
library(tidyverse)
okcupid_profiles <- read_csv("data_okcupid.csv")
```

You can see the first few rows of the data using the `print()` command. Each row presents a person whereas each column represents a variable. If you have a large number of columns you will only see the first several columns with this approach to viewing your data.

```
print(okcupid_profiles)
```

```
## # A tibble: 59,946 x 6
##   age diet      height pets      sex status
##   <dbl> <chr>    <dbl> <chr>    <chr> <chr>
## 1  22 strictly an~  75 likes dogs and l~ m single
## 2  35 mostly other  70 likes dogs and l~ m single
## 3  38 anything      68 has cats      m availa~
## 4  23 vegetarian    71 likes cats      m single
## 5  29 <NA>          66 likes dogs and l~ m single
## 6  29 mostly anyt~  67 likes cats      m single
## 7  32 strictly an~  65 likes dogs and l~ f single
## 8  31 mostly anyt~  65 likes dogs and l~ f single
## 9  24 strictly an~  67 likes dogs and l~ f single
## 10 37 mostly anyt~  65 likes dogs and l~ m single
## # ... with 59,936 more rows
```

But it's also helpful just to see a list of the columns in the data with the `glimpse()` command:

```
glimpse(okcupid_profiles)
```

```
## Rows: 59,946
## Columns: 6
## $ age      <dbl> 22, 35, 38, 23, 29, 29, 32, 31, 24, 37, ...
## $ diet     <chr> "strictly anything", "mostly other", "an...
## $ height   <dbl> 75, 70, 68, 71, 66, 67, 65, 65, 67, 65, ...
## $ pets     <chr> "likes dogs and likes cats", "likes dogs...
## $ sex      <chr> "m", "m", "m", "m", "m", "m", "f", "f", ...
## $ status   <chr> "single", "single", "available", "single..."
```

The `glimpse()` command is useful but is quickly allows you to see all of the columns. Moreover, it allows you to see the type for each column. Types were briefly discussed in the last chapter. Notice in the output beside each column name some columns are labeled which is short for double – a type of numeric column. Other columns are labeled which is short for character – meaning the columns contain characters. These designations will become important in the next chapter as we prepare data for analysis.

2.4.1 `select()`

The `select()` command allows you to obtain a subset of the columns in your data. The commands below can be used to obtain the age and height columns. You can read the command as: take the `okcupid_profiles` data and then select the age and height columns. The “%>%” symbol can be read as “and then”. You can see that this code prints out the data with just the age and height columns. Remember, use SHIFT-ENTER or SHIFT-RETURN to move the next line in the block of code.

```
okcupid_profiles %>%
  select(age, height)
```

```
## # A tibble: 59,946 x 2
##   age height
##   <dbl> <dbl>
## 1    22     75
## 2    35     70
## 3    38     68
## 4    23     71
## 5    29     66
```

```
## 6      29      67
## 7      32      65
## 8      31      65
## 9      24      67
## 10     37      65
## # ... with 59,936 more rows
```

Of course, it's usually of little help to just print the subset of the data. It's better to store it in a new data. In the command below we store the resulting data in a new data set called `new_data`.

```
new_data <- okcupid_profiles %>%
  select(age, height)
```

The `glimpse()` command shows us that only the age and height columns are in `new_data`.

```
glimpse(new_data)
```

```
## Rows: 59,946
## Columns: 2
## $ age      <dbl> 22, 35, 38, 23, 29, 29, 32, 31, 24, 37, ...
## $ height   <dbl> 75, 70, 68, 71, 66, 67, 65, 65, 67, 65, ...
```

In the above example we indicated the columns we wanted to retain from the `okcupid_profiles` data using the `select()` command. However, we can also indicate the columns we want to drop from `okcupid_profiles` using a minus sign (-) in front of the columns we specify in the `select()` command.

```
new_data <- okcupid_profiles %>% select(-age, -height)
```

The `glimpse()` command shows us that we kept all the columns except the age and height columns when we created `new_data`.

```
glimpse(new_data)
```

```
## Rows: 59,946
## Columns: 4
## $ diet      <chr> "strictly anything", "mostly other", "an...
## $ pets      <chr> "likes dogs and likes cats", "likes dogs...
## $ sex       <chr> "m", "m", "m", "m", "m", "m", "f", "f", ...
## $ status    <chr> "single", "single", "available", "single..."
```

2.4.2 summarise()

The `summarise()` command can be used to generate descriptive statistics for a specified column. You can easily calculate column descriptive statistics using the corresponding commands for `mean()`, `sd()`, `min()`, `max()`, among others. In the example below we calculate the mean for the age column.

In code below `mean(age, na.rm = TRUE)` indicates to R that it should calculate the mean of the age column. The `na.rm` indicates how missing values should be handled. The `na` stands for not available; in R missing values are classified as Not Available or NA. The `rm` stands for remove. Consequently, `na.rm` is asking: “Should we remove missing values when calculating the mean?” The `TRUE` indicates that yes, missing values should be removed when calculating the mean. The result of this calculation is placed into a variable labelled `age_mean`, though we could have used any label we wanted instead of `age_mean`. We see that the mean of the age column is, with rounding, 32.3.

```
okcupid_profiles %>%  
  summarise(age_mean = mean(age, na.rm = TRUE))
```

```
## # A tibble: 1 x 1  
##   age_mean  
##   <dbl>  
## 1      32.3
```

More than one calculation can occur in the same `summarise()` command. You can easily add the calculation for the standard deviation with the `sd()` command.

```
okcupid_profiles %>%  
  summarise(age_mean = mean(age, na.rm = TRUE),  
            age_sd = sd(age, na.rm = TRUE))
```

```
## # A tibble: 1 x 2  
##   age_mean age_sd  
##   <dbl> <dbl>  
## 1      32.3   9.45
```

2.4.3 filter()

The `filter()` command allows you to obtain a subset of the rows in your data. In the example below we create a new data set with just the males from the original data.

Notice the structure of the original data below in the `glimpse()` output. There is a column called `sex` that uses `m` and `f` to indicate male and female, respectively. Also notice that there are 59946 rows in the `okcupid_profiles` data.

```
glimpse(okcupid_profiles)
```

```
## Rows: 59,946
## Columns: 6
## $ age      <dbl> 22, 35, 38, 23, 29, 29, 32, 31, 24, 37, ...
## $ diet     <chr> "strictly anything", "mostly other", "an...
## $ height   <dbl> 75, 70, 68, 71, 66, 67, 65, 65, 67, 65, ...
## $ pets     <chr> "likes dogs and likes cats", "likes dogs...
## $ sex      <chr> "m", "m", "m", "m", "m", "m", "f", "f", ...
## $ status   <chr> "single", "single", "available", "single..."
```

We use the `filter` command to select a subset of the rows based on the contents of any column. In this case the `sex` column. Notice the double equals sign is used to indicate “equal to”. The reason a double equals sign is used here (instead of a single equals sign) is to distinguish it from the use of the single equals sign in the `summarise` command above. In the `summarise` command above, the single equal sign was used to indicate “assign to”. That is assign to `age_mean` the mean of the column `age` after it is calculated. A single equals sign indicates “assign to” whereas a double equals sign indicates “is equal to”.

```
okcupid_males <- okcupid_profiles %>%
  filter(sex == "m")
```

We use `glimpse()` to inspect these all male data. Notice that only the letter `m` is in the `sex` column - indicating only males are in the data set. Also notice that there are 35829 rows in the `okcupid_males` data; fewer people because males are a subset of the total number of rows.

```
glimpse(okcupid_males)
```

```
## Rows: 35,829
## Columns: 6
## $ age      <dbl> 22, 35, 38, 23, 29, 29, 37, 35, 28, 24, ...
## $ diet     <chr> "strictly anything", "mostly other", "an...
## $ height   <dbl> 75, 70, 68, 71, 66, 67, 65, 70, 72, 72, ...
## $ pets     <chr> "likes dogs and likes cats", "likes dogs...
## $ sex      <chr> "m", "m", "m", "m", "m", "m", "m", "m", ...
## $ status   <chr> "single", "single", "available", "single..."
```

The `filter` command can be combined with the `summarise` command to get

the descriptive statistics for males without the hassle of creating a new data. This is again done using the `%>%` “and then” operator.

```
okcupid_profiles %>%  
  filter(sex == "m") %>%  
  summarise(age_mean = mean(age, na.rm = TRUE),  
            age_sd = sd(age, na.rm = TRUE))
```

```
## # A tibble: 1 x 2  
##   age_mean age_sd  
##   <dbl> <dbl>  
## 1     32.0   9.03
```

We see that for the 35829 females the mean age is 32.0 and the standard deviation is 9.0.

Likewise, we can obtain the descriptive statistics for females with only a slight modification, changing `m` to `f` in the filter command:

```
okcupid_profiles %>%  
  filter(sex == "f") %>%  
  summarise(age_mean = mean(age, na.rm = TRUE),  
            age_sd = sd(age, na.rm = TRUE))
```

```
## # A tibble: 1 x 2  
##   age_mean age_sd  
##   <dbl> <dbl>  
## 1     32.8  10.0
```

We see that for the 24117 females the mean age is 32.8 and the standard deviation is 10.0.

2.4.4 group_by()

The process we used with the filter command would quickly become onerous if we had many subgroups for a column. Consequently, it's often better to use the `group()` command to calculate descriptive statistics for the levels (e.g., male/female) of a variable. By telling the computer to `group_by()` `sex` the `summarise` command is run separately for every level of `sex` (i.e., `m` and `f`).

```
okcupid_profiles %>%  
  group_by(sex) %>%  
  summarise(age_mean = mean(age, na.rm = TRUE),  
            age_sd = sd(age, na.rm = TRUE))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
## # A tibble: 2 x 3
##   sex    age_mean age_sd
##   <chr>    <dbl>  <dbl>
## 1 f         32.8   10.0
## 2 m         32.0    9.03
```

Fortunately, it's possible to use more than one grouping variable with the `group_by()` command. In the code below we group by sex and status (i.e., dating status).

```
okcupid_profiles %>%
  group_by(sex, status) %>%
  summarise(age_mean = mean(age, na.rm = TRUE),
            age_sd = sd(age, na.rm = TRUE))

## `summarise()` regrouping output by 'sex' (override with `.groups` argument)
## # A tibble: 10 x 4
## # Groups:   sex [2]
##   sex    status    age_mean age_sd
##   <chr> <chr>        <dbl>  <dbl>
## 1 f    available    32.2    8.54
## 2 f    married      33.7    8.13
## 3 f    seeing someone 28.1    6.44
## 4 f    single         33.0   10.2
## 5 f    unknown       27.8    5.91
## 6 m    available    34.8    9.40
## 7 m    married      38.7   10.1
## 8 m    seeing someone 30.8    7.06
## 9 m    single        31.9    9.04
## 10 m   unknown       40.7    8.87
```

The resulting output provide for age the mean and standard deviation for every combination of sex and dating status. The first five rows provide output for females at every level of dating status whereas the subsequent five rows provide output for males at every level of dating status.

2.4.5 `mutate()`

The `mutate()` command can be used to calculate a new column in a data. In the example below we calculate a new column called `age_centered` which is

the new version of the `age_centered` column where the mean of the column has been removed from every value. This is merely an example of the many different types of calculations that can be performed to create a new column using `mutate()`.

```
okcupid_profiles <- okcupid_profiles %>%
  mutate(age_centered = age - mean(age, na.rm = TRUE))
```

Notice that the `glimpse()` command reveals that after we use the `mutate()` command there is a new column called `age_centered`.

```
glimpse(okcupid_profiles)

## Rows: 59,946
## Columns: 7
## $ age      <dbl> 22, 35, 38, 23, 29, 29, 32, 31, 24...
## $ diet     <chr> "strictly anything", "mostly other...
## $ height   <dbl> 75, 70, 68, 71, 66, 67, 65, 65, 67...
## $ pets     <chr> "likes dogs and likes cats", "like...
## $ sex      <chr> "m", "m", "m", "m", "m", "m", "f",...
## $ status   <chr> "single", "single", "available", "...
## $ age_centered <dbl> -10.3403, 2.6597, 5.6597, -9.3403,...
```

2.5 Advanced tidyverse commands

In this advanced selection we revisit the commands from the basic tidyverse section but use more complicated code to either select or apply an action to more than one column at a time. We will indicate the columns that we want to select or apply an action to using: `starts_with()`, `ends_with()`, `contains()`, `matches()`, or `where()`. The first four of these are used to indicate columns based on column names. In contrast, the last command, `where()`, is used to indicate the columns based on the column type (numeric, character, factor, etc.).

We will review all five commands for indicating the columns we want in the `select()` selection below. Following that we will, for brevity, typically use only one of the five commands when illustrating how they work with `summarise()` and `mutate()`.

We begin by loading a new data.

```
library(tidyverse)
data_exp <- read_csv("data_experiment.csv")
```

```
## Parsed with column specification:
## cols(
##   id = col_double(),
##   sex = col_character(),
##   t1_vomit = col_double(),
##   t1_aggression = col_double(),
##   t2_vomit = col_double(),
##   t2_aggression = col_double()
## )
```

The `glimpse()` command reveals that this is a small data where every row represents one rat. The sex of the rat is recorded as well as, for each of two time points, a rating of vomiting and aggression.

```
glimpse(data_exp)

## Rows: 6
## Columns: 6
## $ id          <dbl> 1, 2, 3, 4, 5, 6
## $ sex         <chr> "male", "female", "male", "female..."
## $ t1_vomit    <dbl> 3, 2, 0, 3, 2, 1
## $ t1_aggression <dbl> 5, 6, 4, 7, 3, 8
## $ t2_vomit    <dbl> 2, 1, 1, 2, 1, 2
## $ t2_aggression <dbl> 6, 7, 6, 7, 5, 8
```

2.5.1 select()

2.5.1.1 select() using column name

2.5.1.1.1 starts_with()

`starts_with()` allows us to select columns based on how the column name begins. Here we put the columns that begin with “t1” into a new data called `data_time1`.

```
data_time1 <- data_exp %>%
  select(starts_with("t1"))
```

The `glimpse` command shows us the new data only contains the columns that begin with “t1”

```
glimpse(data_time1)
```

```
## Rows: 6
## Columns: 2
## $ t1_vomit      <dbl> 3, 2, 0, 3, 2, 1
## $ t1_aggression <dbl> 5, 6, 4, 7, 3, 8
```

2.5.1.1.2 `ends_with()`

`ends_with()` allows us to select columns based on how the column name ends. Here we put the columns that end with “aggression” into a new data set called `data_aggression`.

```
data_aggression <- data_exp %>%
  select(ends_with("aggression"))
```

```
glimpse(data_aggression)
```

```
## Rows: 6
## Columns: 2
## $ t1_aggression <dbl> 5, 6, 4, 7, 3, 8
## $ t2_aggression <dbl> 6, 7, 6, 7, 5, 8
```

2.5.1.1.3 `contains()`

`contains()` allows us to select columns based on the contents of the column name. Here we put the columns that have “_” in the name into a new data set called `new_data`.

```
new_data <- data_exp %>%
  select(contains("_"))
```

```
glimpse(new_data)
```

```
## Rows: 6
## Columns: 4
## $ t1_vomit      <dbl> 3, 2, 0, 3, 2, 1
```

```
## $ t1_aggression <dbl> 5, 6, 4, 7, 3, 8
## $ t2_vomit      <dbl> 2, 1, 1, 2, 1, 2
## $ t2_aggression <dbl> 6, 7, 6, 7, 5, 8
```

2.5.1.1.4 `matches()`

It's also possible to use *regex* (regular expression) to select columns. Regex is a powerful way to specify search/matching requirements for text - in this case the text of column names. An explanation of regex is beyond the scope of this chapter. But the example below selects any column with an underscore in the column name followed by any character. The result is the same as the above for the `contains()` command. However, the `matches()` command is more flexible than the `contains()` command and can take into account substantially more complicated situations.

```
data_matched<- data_exp %>%
  select(matches("_."))
```

You can see the columns selected using regex:

```
glimpse(data_matched)
```

```
## Rows: 6
## Columns: 4
## $ t1_vomit      <dbl> 3, 2, 0, 3, 2, 1
## $ t1_aggression <dbl> 5, 6, 4, 7, 3, 8
## $ t2_vomit      <dbl> 2, 1, 1, 2, 1, 2
## $ t2_aggression <dbl> 6, 7, 6, 7, 5, 8
```

You can learn about regex at [RegexOne](https://regexone.com)¹ and test your regex specification at [Regex101](https://regex101.com)². Ideally though, as we discuss in the next chapter, you can use naming conventions that are sufficiently considered that you don't need regex, or only rarely. The reason for this is that regex can be challenging to use. As Twitter user @ThatJenPerson noted "Regex is like tequila: use it to try to solve a problem and now you have two problems." Nonetheless, at one or two points in the future we will use regex to solve a problem (but not tequila).

2.5.1.2 `select()` using column type

If many cases we will want to select or perform an action on a column based on whether the column is a numeric, character, or factor column (indicated in

¹<https://regexone.com>

²<https://regex101.com>

glimpse output as dbl, chr, and fct, respectively). We will learn more about factors later in this chapter. Each of these column types can be selected by using `is.numeric`, `is.character`, or `is.factor`, respectively, in combination with the `where()` command.

We can select numeric columns using `where()` and `is.numeric`:

```
data_numeric_columns <- data_exp %>%  
  select(where(is.numeric))
```

You can see the new data contains only the numeric columns:

```
glimpse(data_numeric_columns)  
  
## Rows: 6  
## Columns: 5  
## $ id          <dbl> 1, 2, 3, 4, 5, 6  
## $ t1_vomit     <dbl> 3, 2, 0, 3, 2, 1  
## $ t1_aggression <dbl> 5, 6, 4, 7, 3, 8  
## $ t2_vomit     <dbl> 2, 1, 1, 2, 1, 2  
## $ t2_aggression <dbl> 6, 7, 6, 7, 5, 8
```

We can select numeric columns using `where()` and `is.character`:

```
data_character_columns <- data_exp %>%  
  select(where(is.character))
```

You can see the new data contains only the character columns:

```
glimpse(data_character_columns)  
  
## Rows: 6  
## Columns: 1  
## $ sex <chr> "male", "female", "male", "female", "male", ...
```

If a future chapter you will see how we can select factors using `where(is.factor)`.

2.5.2 summarise()

The `summarise()` command can summarise multiple columns when combined with `starts_with()`, `ends_with()`, `contains()`, `matches()`, and `where()`. However, to use these powerful tools for indicating columns with the `summarise` command we need to help of the `across` command (i.e., across multiple columns).

If we want to obtain the mean of all the columns that start with “t1” we use the commands below. The `across` command requires that we indicate the columns we want via the `.cols` argument and the command/function we want to run on those columns via the `.fns` argument. In the example below, we also add `na.rm = TRUE` at the end; this is something we send to the `mean` command to let it know how we want to handle missing data.

```
data_exp %>%
  summarise(across(.cols = starts_with("t1"),
                    .fns = mean,
                    na.rm = TRUE))
```

```
## # A tibble: 1 x 2
##   t1_vomit t1_aggression
##   <dbl>      <dbl>
## 1      1.83         5.5
```

If you want to get fancy, you can also add this `.names` argument below which tells R to call label each output mean by the column name followed by “_mean”.

```
data_exp %>%
  summarise(across(.cols = starts_with("t1"),
                    .fns = mean,
                    na.rm = TRUE,
                    .names = "{col}_mean"))
```

```
## # A tibble: 1 x 2
##   t1_vomit_mean t1_aggression_mean
##   <dbl>          <dbl>
## 1      1.83         5.5
```

Often you want to calculate more than one statistic for each column. For example, you might want the mean, standard deviation, min, and max. These statistics can be calculated via the `mean`, `sd`, `min`, and `max` commands, respectively. However, you need to create a list with the statistics you desire.

Below we create a list of the descriptive statistics we desire called `desired_statistics`, but you can use any name you want. This list only needs to be specified once, but we will repeat it in the examples below for clarity.

```
desired_descriptives <- list(
  mean = ~mean(.x, na.rm = TRUE),
  sd = ~sd(.x, na.rm = TRUE)
)
```


Once you have created the list of descriptive statistics you want you can run the command below to obtain those statistics. However, as you will see the output is too wide to be helpful.

```
data_exp %>%
  summarise(across(.cols = starts_with("t1"),
                    .fns = desired_descriptives))

## # A tibble: 1 x 4
##   t1_vomit_mean t1_vomit_sd t1_aggression_m~
##           <dbl>       <dbl>       <dbl>
## 1           1.83         1.17         5.5
## # ... with 1 more variable: t1_aggression_sd <dbl>
```

Consequently, we add the `t()` command (i.e., transpose command) to the end of the summarise request to get a more readable list of statistics:

```
desired_descriptives <- list(
  mean = ~mean(.x, na.rm = TRUE),
  sd = ~sd(.x, na.rm = TRUE)
)

data_exp %>%
  summarise(across(.cols = starts_with("t1"),
                    .fns = desired_descriptives)) %>%
  t()

##           [,1]
## t1_vomit_mean 1.833
## t1_vomit_sd   1.169
## t1_aggression_mean 5.500
## t1_aggression_sd 1.871
```

Note that in the across command above we could also have used: `ends_with()`, `contains()`, `matches()`, or `where()`.

2.5.3 mutate()

The `mutate` command can also be applied to multiple columns using the `across()` command. However, sometimes we need to embed our calculation in a custom function. Below is a custom function called `make_centered`. This custom function takes the values in a column and subtracts the column mean from each value in the column. This is the same task we did the `mutate()` command in the basic tidyverse section above.

```
make_centered <- function(values) {
  values_out <- values - mean(values, na.rm = TRUE)
  return(values_out)
}
```

The `glimpse()` command shows us all the column names. Also notice the values in the aggression columns are integers.

```
glimpse(data_exp)

## Rows: 6
## Columns: 6
## $ id      <dbl> 1, 2, 3, 4, 5, 6
## $ sex     <chr> "male", "female", "male", "female..."
## $ t1_vomit <dbl> 3, 2, 0, 3, 2, 1
## $ t1_aggression <dbl> 5, 6, 4, 7, 3, 8
## $ t2_vomit <dbl> 2, 1, 1, 2, 1, 2
## $ t2_aggression <dbl> 6, 7, 6, 7, 5, 8
```

We combine the `mutate()` command with the `across()` command and our custom `make_centered()` command below. The command “centers” or subtracts the mean from any column that ends with “aggression”.

```
data_exp <- data_exp %>%
  mutate(across(.cols = ends_with("aggression"),
    .fns = make_centered))
```

You can see via the `glimpse()` output that the contents of all the columns that end with “aggression” have changed. Every value in one these columns has had the column mean subtracted from it.

```
glimpse(data_exp)

## Rows: 6
## Columns: 6
## $ id      <dbl> 1, 2, 3, 4, 5, 6
## $ sex     <chr> "male", "female", "male", "female..."
## $ t1_vomit <dbl> 3, 2, 0, 3, 2, 1
## $ t1_aggression <dbl> -0.5, 0.5, -1.5, 1.5, -2.5, 2.5
## $ t2_vomit <dbl> 2, 1, 1, 2, 1, 2
## $ t2_aggression <dbl> -0.5, 0.5, -0.5, 0.5, -1.5, 1.5
```

Note that in the `across` command above we could also have used: `starts_with()`, `contains()`, `matches()`, or `where()`.

2.5.3.1 mutate() across rows

Researchers often want to average within rows and across columns to create a new column. That is for each participant (i.e., rat in the current data) we might want to calculate a vomit score that is the average of the two time points (that we will call vomit_avg).

To average within rows (and across columns) we use the `rowwise()` command to inform R of our intent. After we do the necessary calculations though we have to shut off the `rowwise()` calculation state by using the `ungroup()` command. As well, when we are averaging within rows we have to use `c_across()` instead of `across()`. The commands below creates a new column called vomit_avg which the average of the vomit ratings across both times. As before, we also include `na.rm = TRUE` so the computer drops missing values (if present) when calculating the mean.

```
data_exp <- data_exp %>%
  rowwise() %>%
  mutate(vomit_avg = mean( c_across(cols = ends_with("vomit")),
                           na.rm = TRUE)) %>%
  ungroup()
```

You can see the new column we created with the `glimpse()` command:

```
glimpse(data_exp)

## Rows: 6
## Columns: 7
## $ id      <dbl> 1, 2, 3, 4, 5, 6
## $ sex     <chr> "male", "female", "male", "female..."
## $ t1_vomit <dbl> 3, 2, 0, 3, 2, 1
## $ t1_aggression <dbl> -0.5, 0.5, -1.5, 1.5, -2.5, 2.5
## $ t2_vomit <dbl> 2, 1, 1, 2, 1, 2
## $ t2_aggression <dbl> -0.5, 0.5, -0.5, 0.5, -1.5, 1.5
## $ vomit_avg <dbl> 2.5, 1.5, 0.5, 2.5, 1.5, 1.5
```

The `print()` command could make it easier to see the new column is the average of the other two, but if we used the command below it wouldn't work. Why? There are too many columns in the data set so only the first few columns are show.

```
print(data_exp)
```

To see how the new column, vomit_avg, is the average of the other vomit

columns we use the `select` command before `print()`. This prints only the relevant columns. When this is done, it's easy to see how the values in the `vomit_avg` column are the mean of the other two columns.

```
data_exp %>%
  select(contains("vomit")) %>%
  print()

## # A tibble: 6 x 3
##   t1_vomit t2_vomit vomit_avg
##   <dbl>    <dbl>    <dbl>
## 1         3         2         2.5
## 2         2         1         1.5
## 3         0         1         0.5
## 4         3         2         2.5
## 5         2         1         1.5
## 6         1         2         1.5
```

2.5.3.2 `mutate()` for factors

In R it is critical that you identify categorical variable as categorical variables. In R categorical variables are referred to as factors. For humans, a factor like sex has three possible levels: female, male, intersex.

An inspection of the `glimpse()` command output reveals that the sex column has the type character - as indicated by `<chr>`. Also notice as you inspect this output that we use words (e.g., female) to indicate the sex in the column rather than a number represent a female participant (e.g., 2). This is the preferred but less common approach to entering data.

```
glimpse(data_exp)

## Rows: 6
## Columns: 7
## $ id          <dbl> 1, 2, 3, 4, 5, 6
## $ sex         <chr> "male", "female", "male", "female..."
## $ t1_vomit     <dbl> 3, 2, 0, 3, 2, 1
## $ t1_aggression <dbl> -0.5, 0.5, -1.5, 1.5, -2.5, 2.5
## $ t2_vomit     <dbl> 2, 1, 1, 2, 1, 2
## $ t2_aggression <dbl> -0.5, 0.5, -0.5, 0.5, -1.5, 1.5
## $ vomit_avg    <dbl> 2.5, 1.5, 0.5, 2.5, 1.5, 1.5
```

We need to convert the sex column to a factor in order for R to handle it appropriately in analyses. Failure to indicate column is a factor could result in R

conducting all the analyses and presenting the incorrect results. Consequently, it is critical that we convert the column to a factor. Fortunately, that is easily done using the `as_factor()` command (there is also an `as.factor` command if `as_factor` won't work for some reason).

We convert the sex column to a factor with this code:

```
data_exp <- data_exp %>%  
  mutate(sex = as_factor(sex))
```

You can confirm this worked with the `glimpse()` command:

```
glimpse(data_exp)  
  
## Rows: 6  
## Columns: 7  
## $ id          <dbl> 1, 2, 3, 4, 5, 6  
## $ sex         <fct> male, female, male, female, male,...  
## $ t1_vomit     <dbl> 3, 2, 0, 3, 2, 1  
## $ t1_aggression <dbl> -0.5, 0.5, -1.5, 1.5, -2.5, 2.5  
## $ t2_vomit     <dbl> 2, 1, 1, 2, 1, 2  
## $ t2_aggression <dbl> -0.5, 0.5, -0.5, 0.5, -1.5, 1.5  
## $ vomit_avg    <dbl> 2.5, 1.5, 0.5, 2.5, 1.5, 1.5
```

If you entered your data using words for each level of sex (e.g., male, female) you're done at this point. However, if you used numbers to represent each level of sex in your data there is one more step. Imagine your data was entered in a poorly advised manner, such that 1 was used to indicate male, 2 was used to indicate female, and 3 was used to indicate intersex. If this was the case, you need to indicate to R what each of those value represents. We do that with the code below.

```
data_exp <- data_exp %>%  
  mutate(sex = fct_recode(sex,  
                           male = "1",  
                           female = "2",  
                           intersex = "3"))
```

2.6 Using help

In order to become an efficient at analyzing data using R, you will need to become adapt at reading and understanding the help files associated with each command. After you have activated a package using the library command (e.g., `library(tidyverse)`) you can access the help page for every command in that package. To access the help page simply type a question mark followed by the command you want to know how to use (no space between them). The code below bring up the help page for the `select()` command. Notice I put the `library()` command first - just an reminder that this needs to be done prior to using help for that package. Try the commands below in the Console:

```
library(tidyverse)
?select
```

Examine the page that appears on the Help tab in the panel in the lower right of your screen. Read through the help file comparing what you read there to what we have learned about the `select` command. Notice how the help file tells you about the argument you send into the `select()` command and also what the `select` command returns when it receives those commands. Pay particular attention to the examples near the bottom of the help page. At the very bottom of the help page you will see [Package dplyr version 1.0.0 Index]. This tell you the `select()` command is from the dplyr package (part of the tidyverse). Notice that the word Index is underlined. Click on the word Index. You will be presented with list of other commands in the dplyr package.

As you become more experienced with R help pages how you will learn to use new commands. Examine the help pages for the commands below by typing a question mark into the Console followed by the command name. Note that for `filter` and `starts_with` you will be presented with a menu instead of help page. This typically occurs because the command is in more than one package. If this does occur, read through the options you are presented with to try and figure out which one you wanted Typically, you want the first option. If you're not sure, try one. It's it's not what you want use the back arrow in the Help panel to go back and pick another one.

- `mutate`
- `filter`
- `starts_with`

2.7 Base R vs tidyverse

All of the commands used to this point in the chapter have been the tidyverse approach to using R. That is the approach we will normally use. However, it's important to note that there is another way of using R, called base R.

Sometimes students have problems with their code when they mix and match these approaches using a bit of both. We will be using the tidyverse approach to using R but on the internet you will often see sample code that uses the older base R approach. A bit of background knowledge is helpful for understanding why we do things one way (e.g., `read_csv` with the tidyverse) instead of another (e.g., `read.csv` with base R).

2.7.1 Tibbles vs. data frames

When you load data into R it is typically represented in one of two formats inside the computer - depending on the command you used. The original format for representing a data set in R is the data frame. You will see this term used frequently when you read about R. When you load data using `read.csv` your data is loaded into a data frame in the computer. That is your data is represented in the memory of the computer in particular format and structure called a data frame. This contrasts with the newer tidyverse approach to representing data in the computer called a tibble - which is just a newer more advanced version of the data frame.

2.7.2 `read.csv` and data frames

When you read data into R using the command `read.csv` (with a period) you load the data into a data frame (base R).

```
my_dataframe <- read.csv(file = "data_okcupid.csv")
```

Notice that when you print a data frame it does not show you the number of rows or columns above the data like our example did with the `okcupid_profiles` data. Likewise, it does not show you the type of data in each column (e.g, `dbl`, `fct`, `chr`). But, it also list all of your data rather than just the first few rows (as the tibble does). As a result in the output below I show only the first 10 rows of the output - because all the rows are printed in your Console with a data frame (too much to show here).

```
print(my_dataframe)
```

```
##   age      diet height      pets
## 1  22 strictly anything    75 likes dogs and likes cats
## 2  35      mostly other    70 likes dogs and likes cats
## 3  38      anything      68      has cats
## 4  23      vegetarian    71      likes cats
## 5  29      <NA>      66 likes dogs and likes cats
## 6  29 mostly anything    67      likes cats
## 7  32 strictly anything    65 likes dogs and likes cats
## 8  31 mostly anything    65 likes dogs and likes cats
## 9  24 strictly anything    67 likes dogs and likes cats
## 10 37 mostly anything    65 likes dogs and likes cats
##   sex      status
## 1   m      single
## 2   m      single
## 3   m available
## 4   m      single
## 5   m      single
## 6   m      single
## 7   f      single
## 8   f      single
## 9   f      single
## 10  m      single
```

2.7.3 read_csv and tibbles

When you read data into R using the command `read_csv` (with an underscore) you load the data into a tibble (tidyverse).

```
my_tibble <- read_csv(file = "data_okcupid.csv")
```

```
## Parsed with column specification:
## cols(
##   age = col_double(),
##   diet = col_character(),
##   height = col_double(),
##   pets = col_character(),
##   sex = col_character(),
##   status = col_character()
## )
```

The tibble is modern version of the data frame. Notice that when you print a

tibble it DOES show you the number of rows and columns. As well, it shows you the type of data in each column. Importantly, the tibble only provides the first few rows of output so it doesn't fill your screen.

```
print(my_tibble)
```

```
## # A tibble: 59,946 x 6
##   age diet      height pets      sex status
##   <dbl> <chr>    <dbl> <chr>    <chr> <chr>
## 1  22 strictly an~  75 likes dogs and 1~ m   single
## 2  35 mostly other  70 likes dogs and 1~ m   single
## 3  38 anything     68 has cats      m   availa~
## 4  23 vegetarian   71 likes cats     m   single
## 5  29 <NA>         66 likes dogs and 1~ m   single
## 6  29 mostly anyt~  67 likes cats     m   single
## 7  32 strictly an~  65 likes dogs and 1~ f   single
## 8  31 mostly anyt~  65 likes dogs and 1~ f   single
## 9  24 strictly an~  67 likes dogs and 1~ f   single
## 10 37 mostly anyt~  65 likes dogs and 1~ m   single
## # ... with 59,936 more rows
```

In short you should always use tibbles (i.e., use `read_csv` not `read.csv`). The differences between data frames and tibbles run deeper than the superficial output provided here. On some rare occasions an old package or command may not work with a tibble so you need to make it a data frame. You can do so with the commands below. We will flag these rare occurrences to you in the next.

```
# Create a data frame from a tibble
new_dataframe <- as.data.frame(my_tibble)
```



3

Making your data ready for analysis

Use skim instead of summary?

3.1 Required Packages

This chapter requires the following packages are installed:

Required Packages
apaTables
HMisc
janitor
psych
tidyverse

Important Note: that you should NOT use `library(psych)` at any point. There are major conflicts between the `psych` package and the `tidyverse`. We will access the `psych` package command by preceding each command with `psych::` instead of using `library(psych)`.

3.2 Objective

Advice is not right or the best - but it is a system. Encourage you to evolve your own system. But perhaps not in the first few months/years of using R until you see the benefits of this system - and correspondingly it's shortcomings.

Warning you need mastery of the Handling data in the tidyverse chapter before doing this chapter.

3.3 Context

Due to a number of high profile failure to replicate study results (Nosek, 2015) it's become increasingly clear that there is a general crisis of confidence in many areas of science (Baker, 2016). Statistical (and other) explanations have been offered (Simmons et al., 2011) for why it's hard to replicate results across different sets of data. However, scientists are also finding it challenging to recreate the numbers in their papers using their own data. Indeed, the editor of *Molecular Brain* asked authors to submit the data used to create the numbers in published papers and found that the wrong data was submitted for 40 out of 41 papers (Miyakawa, 2020).

Consequently, some researchers have suggested that it is critical to distinguish between replication and reproducibility (Patil P., 2019). Replication refers to trying to obtain the same result from a different data sets. Reproducibility refers to trying to obtain the same results from the same data set. Unfortunately, some authors use these two terms interchangeably and fail to make any distinction between them. I encourage you to make the distinction and the use the terms consist with use suggested by (Patil P., 2019).

It may seem that reproducibility should be given - but it's not. Correspondingly, there a trend is for journals and authors to adopt Transparency and Openness Promotion (TOP) guidelines¹. These guidelines involve such things as making your materials, data, code, and analysis scripts available on public repositories so anyone can check your data. A new open science journal rating system has even emerged called the TOP Factor².

The idea is not that open science articles are more trustworthy than other types of articles – the idea is that trust doesn't play a role. Anyone can inspect the data using the scripts and data provided by authors. It's really just the same as making your science available for auditing the way financial records can be audited. But just like in the world of business some people don't like the idea of make it possible for other to audit their work. The problems reported at *Molecular Brain* (doubtless is common to many journals) are likely avoided with open science - because the data and scripts needed to reproduce the numbers in the articles are uploaded prior to publication.

The TOP open science guidelines have made an impact and some newer journals, such as *Meta Psychology*, have fully embraced open science. Figure 3.1 shows the header from an article³ in *Meta Psychology* that clearly delineates the open science attributes of the article that used computer simulations

¹<https://www.cos.io/our-services/top-guidelines>

²<https://topfactor.org>

³<https://open.lnu.se/index.php/metapsychology/article/view/1630/2266>

(instead of participant data). Take note that the header even specifies who checked that the analyses in the article were reproducible.

Meta-Psychology, 2020, vol 4, MP.2019.1630
<https://doi.org/10.15626/MP.2019.1630>
 Article type: Original Article
 Published under the CC-BY4.0 license



Open data: N/A
 Open materials: Yes
 Open and reproducible analysis: Yes
 Open reviews and editorial process: Yes
 Preregistration: N/A

Edited by: Rickard Carlsson
 Reviewed by: Thom Baguley, Julia Haaf,
 Paul-Christian Bürkner
 Analysis reproduced by: Erin Buchanan
 All supplementary files can be accessed at OSF:
<https://doi.org/10.17605/OSF.IO/3UZAM>

FIGURE 3.1: Open science in an article header

In Canada, the majority of university research is funded by the Federal Government's Tri-Agency (i.e., NSERC, SSHRC, CIHR). The agency has a new draft Data Management Policy⁴ in which they state that “*The agencies believe that research data collected with the use of public funds belong, to the fullest extent possible, in the public domain and available for reuse by others.*” This perspective of the funding agency differs from that of some researchers who incorrectly believe “they own their data”. In Canada at least, the government makes it clear that tax payers fund the research so the data is public property. Additionally the Tri-Agency Data Management policy clearly indicates the responsibilities of funded researchers:

”Responsibilities of researchers include:

- incorporating data management best practices into their research;
- developing data management plans to guide the responsible collection, formatting, preservation and sharing of their data throughout the entire life cycle of a research project and beyond;
- following the requirements of applicable institutional and/or funding agency policies and professional or disciplinary standards;
- acknowledging and citing data sets that contribute to their research; and
- staying abreast of standards and expectations of their disciplinary community.”

As a result of this perspective on data, it's important that you think about structuring your data for reuse by yourself and others before you collect it. Toward this end, you will see documentation of your data file via data code books is critical.

⁴https://www.ic.gc.ca/eic/site/063.nsf/eng/h_83F7624E.html

3.4 Begin with the end in mind

In this chapter we will walk you through the steps from data collection, data entry, loading raw data, and the creation of data you will analyze, analytic data, via preprocessing scripts. These steps are outlined in Figure 3.2. This figure makes a clear distinction between raw data and analytic data. Raw data refers to the data as you entered it into a spreadsheet or received it from survey software. Analytic data is the data that has been structured and processed so that it is ready for analysis. This pre-processing could include such things as identifying categorical variables to the computer, combining multiple items measuring the same thing into scale scores, among other tasks.

It's critical that you don't think of analysis of your results as being completely removed from the data collection and data entry choices you make. Poor choices at the data collection and data entry stage can make your life substantially more complicated when it comes time to write the preprocessing script that will convert your raw data to analytic data. The mantra of this chapter is *begin with the end in mind*.

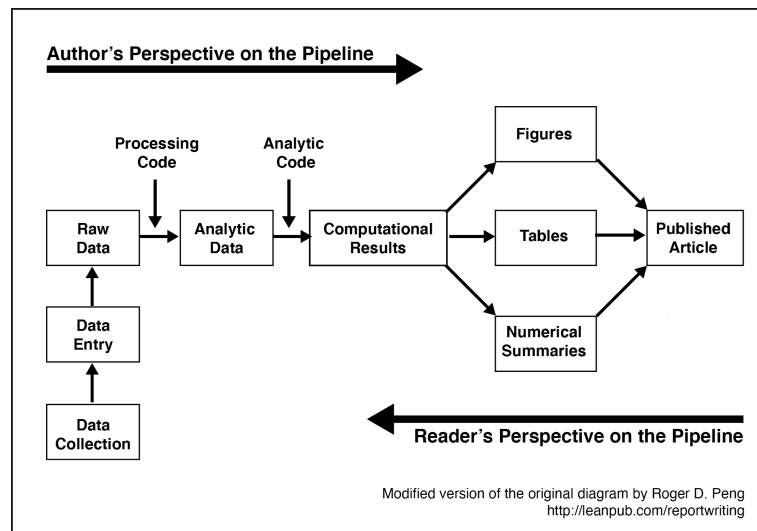


FIGURE 3.2: Data science pipeline by Roger Peng.

It's difficult to begin with the end in mind when you haven't read later chapters. So here we will provide you with some general thoughts around different approaches to structuring data files and the naming conventions you use when creating those data files.

3.4.1 Structuring data: Obtaining tidy data

When conducting analyses in R it is typically necessary to have data in a format called tidy data (Wickham, 2014). tidy data⁵ as defined by Hadley involves (among other requirements) that:

1. Each variable forms a column.
2. Each observation forms a row.

The tidy data format can be initially challenging for some researchers to understand because it is based on thinking about, and structuring data, in terms of observations/measurements instead of participants. In this section we will describe common approaches to entering animal and human participant data and how they can be done keeping the tidy data requirement in mind. It's not essential that data be entered in a tidy data format but it is essential that you enter data in manner that makes it easy to later convert data to a tidy data format. When dealing with animal or human participant data it's common to enter data into a spreadsheet. Each row of the spreadsheet is typically used to represent a single participant and each column of the spreadsheet is used to represent a variable.

Between participant data. Consider Table 3.2 which illustrates between participant data for six human participants running 5 kilometers. The first column is id, which indicates there are six unique participants and provides an identification number for each of them. The id is the variable and there is one observation per row - so the id column conforms to tidy data specification. The second column is sex, which is a variable, and there is one observation per row, so sex also conforms to the tidy data specification. Finally, there is a last column five_km_time which is a variable with one observation per row - also conforming to tidy data specification. Thus, single occasion between subject data like this conforms to the tidy data specification. There is usually nothing you need to do to convert between participant data (or cross-sectional data) to be in a tidy data format.

Within participant data. Consider Table 3.3 which illustrates within participant data for six human participants running 5 kilometers - but on three different occasions. The first column is id, which indicates there are six unique participants and provides an identification number for each of them. The id is the variable and there is one observation per row - so the id column conforms to tidy data specification. The second column is sex, which is a variable, and there is one observation per row, so sex also conforms to the tidy data specification. Next, there are three different columns (march, may, july) representing the levels of a single variable. That is the within subject variable is occasion and the levels of that variable are march, june, and july. The march

⁵<https://cran.r-project.org/web/packages/tidyr/vignettes/tidy-data.html>

TABLE 3.2: Between participant data entered one row per participant

id	sex	elapsed_time
1	male	40
2	female	35
3	male	38
4	female	33
5	male	42
6	female	36

TABLE 3.3: Within participant data entered one row per participant

id	sex	march	may	july
1	male	40	37	35
2	female	35	32	30
3	male	38	35	33
4	female	33	30	28
5	male	42	39	37
6	female	36	33	31

column contains the times for participants in March. The may column contains the times for participants in May. The july column contains the times for participants in July, These three columns are not in a tidy data format.

The problem with the format of the data in Table 3.3 is that march, may, and july are levels of single variable, occasion, that is not represented in the data. Nowhere in the Table 3.3 can you see the label occasion. This single variable is presented over three columns - a very confusing situation. Moreover, due to the way the columns are labeled it's not clear what is being measured. Nowhere in Table 3.3 can you see the variable elapsed_time. Thus with the format used in 3.3 you don't know what the predictor (occasion) is nor do you know the dependent variable (elapsed_time.). Thus, a major problem with entering data in this format is that there are hidden variables in the data and you need insider knowledge to know the columns represent. That said, this is not necessarily a terrible way to enter your data as long as you have all of this missing information documented in a data code book.

Disadvantages one row per participant	Advantages one row per participant
1) Predictor variable (<i>occasion</i>) is hidden and spread over multiple columns	1) Easy to enter this way

Disadvantages one row per participant	Advantages one row per participant
<hr/>	
2) Unclear that each month is a level of the predictor variable <i>occasion</i>	
3) Dependent variable (<i>elapsed_time</i>) is not indicated	
4) Unclear that <i>elapsed_time</i> is the measurement in each month column	
<hr/>	

Fortunately, the problems with Table 3.3 can be largely resolved by converting the data to the a tidy data format. This can be done with the `pivot_long()` command that we will learn about later in the chapter. Thus, we can enter the data in the easy to enter format of Table 3.3 but then later convert it to a tidy data format. After this conversion the data will be appear as in Table 3.4. For `elapsed_time` variable this data is now in the tidy data format. Each row corresponds to a single `elapsed_time` observed. Each column corresponds to a single variable. Somewhat problematically, however, `sex` is repeated three times for each person (i.e., over the three rows) - and this can be confusing. However, if the focus in on analyzing elapsed time this tidy data format makes sense. Importantly, there is an `id` column for each participant so R knows that this information is repeated for each participant and is not confused by the repeating the `sex` designation over three rows. In directly, this illustrates the importance of having an `id` column to indicate each unique participant.

Why did we walk you through this technical treatment of structuring data within the computer at this point in time? So that you pay attention to the advice the follows. You can see at this point that you may well need to re-structure your data for certain analyses. The ability to do so quickly and easily depends upon you following the advice in the rest of this chapter around the naming conventions for variables and other aspects of your analyses. You can imagine the challenges for converting the data in Figure 3.3 to the data in Figure 3.4 by hand. You want to be able to automate that process and others - which is made substantially easier if you following the forthcoming advice about naming conventions in the tidyverse.

3.5 Data collection considerations

Data can be collected in a wide variety of way. Regardless of the methods of location researchers typically come to data in one of two way: 1) a research assistant enters the data into a spreadsheet type interface, or 2) the data is ob-

TABLE 3.4: A tidy data version of the within participant data

id	sex	occasion	elapsed_time
1	male	march	40
1	male	may	37
1	male	july	35
2	female	march	35
2	female	may	32
2	female	july	30
3	male	march	38
3	male	may	35
3	male	july	33
4	female	march	33
4	female	may	30
4	female	july	28
5	male	march	42
5	male	may	39
5	male	july	37
6	female	march	36
6	female	may	33
6	female	july	31

tained as the output from computer software (e.g., Qualtrics, SurveyMonkey, Noldus, etc.).

Regardless of the approach it is critical to name your variables appropriately. For those using software, such as Qualtrics, this means setting up the survey to using appropriate variable names PRIOR to data collection - so the exported file has desirable variable names. For spreadsheet users, this means setting up the spreadsheet the data will be recorded in with column names that are amenable to the future analyses you want to conduct.

Although failure to take this thoughtful approach at the data collection stage can be overcome - it is only overcome with substantial manual effort. Therefore, as noted previously, we strongly encourage you to following the naming conventions we espouse here where you set up your data recording regime. Additionally, we encourage you to give careful thought in advance to the codes you will use to record missing data.

3.5.1 Naming conventions

To make your life easier down the road, it is critical you set up your spreadsheet or online survey such that it uses a naming convention prior to data collection. The naming conventions suggested here are adapted from the tidyverse style guide⁶.

- Lowercase letters only
- If two word column names are necessary, only use the underscore (" _ ") character to separate words in the name.
- Avoid short uncontextualized variable names like q1, q2, q3, etc.
- Do use moderate length column names. Aim to achieve a unique prefix for related columns so that those columns can be selected using the `starts_with()` command. Be sure to avoid short two or three letter prefixes for item names. Use moderate length unique item prefixes so that it will easy to select with those columns using `start_with()` in that you don't accidentally get additionally columns you don't want - that have a similar prefix. See Likert-type item section below for details.
- If you have a column name that represents levels of two repeated measures variables only use the underscore character to separate the levels of the different variables. See within-participant ANOVA section below for details.

3.5.2 Likert-type items

A Likert-type item is typically composed of a statement that participants are asked to agree or disagree with. For example, participants could be asked to indicate the extent to which they agree a number of statements such as "I like my job". They would then be presented with response scale such as: 1 - Strongly Disagree, 2 - Moderately Disagree, 3 - Neutral, 4, Moderately Agree, 5 - Strongly Agree. A common question is how should I enter the data?

- **Enter numeric responses not the labels.** You should enter the numeric value for each item response (e.g., 5) into your data - not the label (e.g., Strongly Agree). The labels associated with each value can be applied later in a script, if needed.
- **High numbers should be associated with more of the construct being measured.** When designing your survey or data collection tools, it is important that you set of the response options appropriately. If you scale measures job satisfaction, it is important that you collect data in a manner that ensures high numbers on the job satisfaction scale indicate high levels of job satisfaction. Therefore, assigning numbers make sense using the 5-point

⁶<https://style.tidyverse.org>

scale: 1 - Strongly Disagree, 2 - Moderately Disagree, 3 - Neutral, 4, Moderately Agree, 5 - Strongly Agree. With this approach high response numbers indicate more job satisfaction. However, using the opposite scale would not make sense: 1 - Strongly Agree, 2 - Moderately Agree, 3 - Neutral, 4, Moderately Disagree, 5 - Strongly Disagree. With this opposite scale high numbers on a job satisfaction scale would indicate lower levels of job satisfaction - a very confusing situation. Avoid this situation, assign numbers so that higher numbers are associated with more of the construct being measured.

- **Use appropriate item names.** As described in the naming convention section, use moderate length names with different labels for each subscale.
- **Use moderate length column names unique to each subscale.** Imagine you have a survey with an 18-item commitment scale (Meyer et al., 1993) composed of three 6-item subscales: affective, normative, and continuance commitment. It would be a poor choice to prefix the labels of all 18 columns in your data with “commit” such that the names would be commit1, commit2, commit3, etc. The problem with this approach is that it fails to distinguishing between the three subscales in naming convention; making it impossible to select the items for a single subscale using `starts_with()`. A better, but still poor choice for a naming convention would be use a two letter prefix for the three scale such ac, nc, and cc. This would result in names for the columns like ac1, ac2, ac3, etc. This is an improvement because you could apparently (but likely not) select the columns using `starts_with(“ac”)`. The problem with these short names is that there could be many columns in data set that start with “ac” beside the affective commitment items. You might want to select the affective commitment items using `starts_with(“ac”)`; but you would get all the affective commitment item columns but also all the columns measuring other variables that also start with “ac”. Therefore, it’s a good idea to use a moderate length unique prefix for column names. For example, you might use prefixes like affectcom, normcom, and contincom for the three subscales. This would create column names like affectcom1, affectcom2, affectcom3, etc. These column prefixes are unlikely to be duplicated in other places in your column name conventions making it easy to select those columns using a command like `starts_with(“affectcom”)`.
- **Indicate in the item name if the item is reversed keyed** Sometimes with Likert-type items, an item is reverse keyed. For example, on a job satisfaction scale participants will typically respond to items that reflect job satisfaction using the scale: 1 - Strongly Disagree, 2 - Moderately Disagree, 3 - Neutral, 4, Moderately Agree, 5 - Strongly Agree. Higher numbers indicate more job satisfaction. Sometimes however, some items will use the same 1 to 5 response scale but be worded “I hate my job”. Responding with a 5 to this item would indicate high job dissatisfaction not high job satisfaction - to the response will need to be flipped in your analysis script after data

collection (i.e., 1 need to become a 5 and vice versa). To make it easier to do so, you should indicate if an item is reverse keyed in the item name. The procedure for doing so is outlined in the next point.

- **Indicate in the item name the range for reverse key items.** If an item is reverse-keyed, the process for the flipping the scores depends upon the range of a scale. Although 5-point scale are common, any number of points are possible. The process for correcting a reverse key item depends upon: 1) the number of points on the scale, and 2) the range of the points on the scale. The reverse-key item correction process is different for an item that uses a 5-point scale ranging from 1 to 5 and from 0 to 4. Both are 5-point scale but your correction process will be different. Therefore, for reverse key items add as suffix at the end of each item name that indicates an item is reverse keyed and the range of the item. For example, if the third job satisfaction item was reversed keyed on scale using a 1 to 5 response format you might name the item: `jobsat3_rev15`. The suffix `”_rev15”` indicates the item is reverse keyed and the range of responses used on the item is 1 to 5. Be sure to set up your survey with this naming convention when you collect your data.
- If you collect items over multiple time points use a prefix with a short code to indicate the time followed by and underscore. For example, if you had a multi-item self-esteem scale you might call the column for the first time `”t1_esteem1_rev15”`. This indicate that you have for time 1 (t1), the first self-esteem item (esteem1) and that item is reverse keyed on a 1 to 5 scale.

3.5.3 ANOVA between

Avoid numerical representation of categorical variables. Don’t use 1 or 2 to represent sex. Use male and female in your spreadsheet - likewise in your survey program. Likewise, for between participant variables `drug_condition` don’t use 1 or 2 use “drug” and “placebo” but the actually drug name would be better.s

3.5.4 ANOVA within

If you have a study that involves a within-participant ANOVA.

One-way repeated measure predictor. == See example above with run times.

Multi-way repeated measures predictors. If you have a column name that represents levels of two repeated measures variables only use the underscore character to separate the levels of the different variables. For example, if imagine you are a food researcher interested in taste ratings as a dependent various foods and contexts. You have food type (i.e., `food_type`) as a predictor with

three levels (pizza, steak, burger). You have a second predictor temperature with two levels (hot, cold). All participants taste all foods at all temperatures. Thus, six columns are required for each participant: `pizza_hot`, `pizza_cold`, `steak_hot`, `steak_cold`, `burger_hot`, and `burger_cold`. Notice how each name contains one level of each predictor variable. The levels by the two predictor variables are separated by a single underscore. This should be the only underscore in the variable name because that underscore will be used by the computer when changing the data to the tidy format. If you had two underscores an name like “italian_pizza_hot” you would confuse the `pivot_longer()` command when it attempts to create a tidy version of the data. The computer would think there were three repeated levels variables instead of two. Thus, when dealing with repeated measures predictors, only use underscores to separate levels of predictor variables.

3.5.5 Other information

education, income, etc

3.6 Following the examples

Below we present example scripts transforming raw data to analytic data for various study designs (experimental and survey). These scripts illustrate the value of using the naming conventions outlined previously. Follow along with the projects by placing the data in your R Studio project folder and typing your own script. Resist the urge to cut and paste from this document. After learning and teaching scripting for years, there we’ve found there is substantial benefit to the process of simply typing the script yourself.

Setup an R Studio project using one of these approaches:

R Studio in the Cloud Assignment 1. The data should be in the assignment project automatically. Just start the assignment.

R Studio in the Cloud, custom project 1. Create a new Project using the web interface

2. Upload your data files in using the upload button in the Files pane

R Studio Local Computer, custom project 1. Create a folder on your computer for the analysis

2. Place your data files in that folder
3. Use the menu item File > New Project... to start the project
4. On the window that appears select “Existing Directory”
5. On the next screen, press the “Browse” button and find/select the folder with your data
6. Press the Create Project Button

Regardless of whether you are working from the cloud or locally you should now have an R Studio project with your data files in it. Using Projects.

As you read each of these example scripts pay attention to the redundancy. Regardless of the type of data you analyze there is a great deal of consistency in terms of how all of the scripts start.

Also as you follow along on your computer, be sure to use `read_csv` when you load data not `read.csv` (the base R approach). Also note how in the N-way repeated measures design we were forced to deal with a situation where the research assistant indicated male and female using numbers instead of words when entering the data.

3.7 Entering data into spreadsheets

The first example uses a data file `data_ex_between.csv` that corresponds to an example where we recorded the run times for a number of male and female participants. How did we create this data file. We used a spreadsheet to enter the data, as illustrated in Figure 3.3. Programs like Microsoft Excel and Google Sheets are good options for entering data.

id	sex	elapsed_time
1	male	40
2	female	35
3	male	38
4	female	33
5	male	42
6	female	36

FIGURE 3.3: Spreadsheet entry of running data

The key to using these types of programs is to save the data as a .csv file when you are done. CSV is short for Comma Separated Values. After entering the data in Figure 3.3 we saved it as `data_ex_between.csv`. There is no need

to do so, but if you were to open this file in a text editor (such as TextEdit on a Mac or Notepad on Windows) you would see the information displayed in Figure 3.4. You can see there is one row per person and the columns are created by separating each values by a comma; hence, comma separated values.

```
id,sex,elapsed_time
1,male,40
2,female,35
3,male,38
4,female,33
5,male,42
6,female,36
```

FIGURE 3.4: Text view of CSV data

There are many ways to save data, but the CSV data is one of the better ones because it is a non-proprietary format. Some software, such as SPSS, using a proprietary format (e.g., .sav for SPSS) the make it challenging to access that data if you don't have that (often expensive software). One of our goals as scientists is to make it easy for others to audit our work - so that science can be self-correcting. Therefore, choose an open format for your data like .csv.

3.8 Experiment: Between

Ensure your data is in the folder. Start a new script with the name. In that script enter the commands below.

We can load the `data_ex_between.csv` data by creating a script with commands below. As noted previously, these data corresponds to a design where the researcher is interested in comparing run times (`elapsed_time`) based on sex (male/female). This section outlines a workflow appropriate for when you plan to conduct independent groups t-tests or a between-participants ANOVA.

```
# Date: YYYY-MM-DD
# Name: your name here
# Example: Between-participant experiment

# Load data
library(tidyverse)

my_missing_value_codes <- c("-999", "", "NA")
```



```
raw_data_beween <- read_csv(file = "data_ex_between.csv",  
                             na = my_missing_value_codes)  
  
analytic_data_between <- raw_data_beween
```

After loading the data we do initial cleaning to remove empty row/columns and ensure proper naming for columns:

```
library(janitor)  
  
# Initial cleaning  
analytic_data_between <- analytic_data_between %>%  
  remove_empty("rows") %>%  
  remove_empty("cols") %>%  
  clean_names()
```

You can confirm the column names following our naming convention with the `glimpse` command - and see the data type for each column.

```
glimpse(analytic_data_between)  
  
## Rows: 6  
## Columns: 3  
## $ id          <dbl> 1, 2, 3, 4, 5, 6  
## $ sex         <chr> "male", "female", "male", "female"...  
## $ elapsed_time <dbl> 40, 35, 38, 33, 42, 36
```

3.8.1 Creating factors

Following initial cleaning, identify categorical variables as factors. If you plan to conduct an ANOVA - it's critical that all predictor variables are converted to factors. Inspect `glimpse()` output - if you followed our data entry naming conventions categorical variables should be of the type character. We have one variable `sex` that is categorical that is of type character (i.e., `chr`). The participant id column is categorical as well, but of type double (i.e., `dbl`) which is a numeric column.

```
glimpse(analytic_data_between)
```

```
## Rows: 6  
## Columns: 3
```

```
## $ id          <dbl> 1, 2, 3, 4, 5, 6
## $ sex         <chr> "male", "female", "male", "female"...
## $ elapsed_time <dbl> 40, 35, 38, 33, 42, 36
```

You can quickly convert all character columns to factors using the code below:

```
# Turn all columns that are of type character into factors
analytic_data_between <- analytic_data_between %>%
  mutate(across(.cols = where(is.character),
    .fns = as_factor))
```

The participant identification number in the id column is a numeric column, so we have handle that column on it's own.

```
analytic_data_between <- analytic_data_between %>%
  mutate(id = as_factor(id))
```

You can ensure all of these columns are now factors using the `glimpse()` command.

```
glimpse(analytic_data_between)

## Rows: 6
## Columns: 3
## $ id          <fct> 1, 2, 3, 4, 5, 6
## $ sex         <fct> male, female, male, female, male, ...
## $ elapsed_time <dbl> 40, 35, 38, 33, 42, 36
```

Inspect the output of the `glimpse()` command and make sure you have coverted all categorical variables to factors - especially those you will use as predictors.

3.8.2 Factor screening

Inspect the levels of each factor carefully. Make sure that there not any levels present that are incorrect. For example, you wouldn't want to the following levels for sex: male, mmale, female. Obviously, mmale is an incorrectly typed version of male. Scan all the factor in your data for eronious factor levels. The code below displays the factor levels:

```
analytic_data_between %>%
  select(where(is.factor)) %>%
  summary()
```

```
## id      sex
## 1:1  male :3
## 2:1 female:3
## 3:1
## 4:1
## 5:1
## 6:1
```

Also inspect the output of the above `summary()` command paying attention to the order of the levels in the factors. The order influences how text output and graphs are generated. In these data, the sex column has two levels: male and female in that order. Below we adjust the order of the sex variable because we want the x-axis of a future graph to display columns in the left to right order: female, male.

```
# Custom reordering of factor levels
analytic_data_between <- analytic_data_between %>%
  mutate(sex = fct_relevel(sex,
                           "female",
                           "male"))
```

You can see the new order of the factor levels with `summary()`:

```
analytic_data_between %>%
  select(where(is.factor)) %>%
  summary()

## id      sex
## 1:1  female:3
## 2:1  male :3
## 3:1
## 4:1
## 5:1
## 6:1
```

3.8.3 Numeric screening

For numeric variables, you should search for impossible values. For example, in the context of this example you want to ensure none of the `elapsed_times` are impossible or so large they appear to be data entry errors.

One options for doing so is the `summary` command again. This time, however, we use “`is.numeric`” in the `where()` command.

```
analytic_data_between %>%
  select(where(is.numeric)) %>%
  summary()
```

```
## elapsed_time
## Min.      :33.0
## 1st Qu.   :35.2
## Median    :37.0
## Mean      :37.3
## 3rd Qu.   :39.5
## Max.      :42.0
```

Scan the min and max values for each variable to ensure there are not any impossible values. If necessary, got back to the original data source and fix these impossible value. Alternatively, you might need to change them to missing values (i.e., NA values). Once this is complete, you are done preparing your between participant analytic data.

3.9 Experiment: Within one-way

The one-way within-participant ANOVA example uses the data file `data_ex_within.csv`. Initial loading of the file, including the specification of missing data codes, is provided by the code below. The data corresponds to a designs where the researcher is interested in comparing run times (`elapsed_time`) across three different occasions (march/may/june).

```
# Date: YYYY-MM-DD
# Name: your name here
# Example: Within-participant experiment

# Load data
library(tidyverse)

my_missing_value_codes <- c("-999", "", "NA")

raw_data_within <- read_csv(file = "data_ex_within.csv",
                             na = my_missing_value_codes)

## Parsed with column specification:
## cols(
```

```
## id = col_double(),  
## sex = col_character(),  
## march = col_double(),  
## may = col_double(),  
## july = col_double()  
## )
```

```
analytic_data_within <- raw_data_within
```

After loading the data we do initial cleaning to remove empty row/columns and ensure proper naming for columns:

```
library(janitor)  
  
# Initial cleaning  
analytic_data_within <- analytic_data_within %>%  
  remove_empty("rows") %>%  
  remove_empty("cols") %>%  
  clean_names()
```

You can confirm the column names following our naming convention with the `glimpse` command - and see the data type for each column.

```
glimpse(analytic_data_within)  
  
## Rows: 6  
## Columns: 5  
## $ id    <dbl> 1, 2, 3, 4, 5, 6  
## $ sex   <chr> "male", "female", "male", "female", "male..."  
## $ march <dbl> 40, 35, 38, 33, 42, 36  
## $ may   <dbl> 37, 32, 35, 30, 39, 33  
## $ july  <dbl> 35, 30, 33, 28, 37, 31
```

3.9.1 Creating factors

Following initial cleaning, identify categorical variables as factors. If you plan to conduct an ANOVA - it's critical that all predictor variables are converted to factors. Inspect `glimpse()` output - if you followed our data entry naming conventions categorical variables should be of the type character. We have one variable `sex` that is categorical that is of type character (i.e., `chr`). The participant `id` column is categorical as well, but of type double (i.e., `dbl`) which is a numeric column.

```
glimpse(analytic_data_within)
```

```
## Rows: 6
## Columns: 5
## $ id    <dbl> 1, 2, 3, 4, 5, 6
## $ sex   <chr> "male", "female", "male", "female", "male..."
## $ march <dbl> 40, 35, 38, 33, 42, 36
## $ may   <dbl> 37, 32, 35, 30, 39, 33
## $ july  <dbl> 35, 30, 33, 28, 37, 31
```

You can quickly convert all character columns to factors using the code below:

```
# Turn all columns that are of type character into factors
analytic_data_within <- analytic_data_within %>%
  mutate(across(.cols = where(is.character),
    .fns = as_factor))
```

The participant identification number in the id column is a numeric column, so we have handle that column on it's own.

```
analytic_data_within <- analytic_data_within %>%
  mutate(id = as_factor(id))
```

You can ensure all of these columns are now factors using the `glimpse()` command.

```
glimpse(analytic_data_within)
```

```
## Rows: 6
## Columns: 5
## $ id    <fct> 1, 2, 3, 4, 5, 6
## $ sex   <fct> male, female, male, female, male, female
## $ march <dbl> 40, 35, 38, 33, 42, 36
## $ may   <dbl> 37, 32, 35, 30, 39, 33
## $ july  <dbl> 35, 30, 33, 28, 37, 31
```

Inspect the output of the `glimpse()` command and make sure you have converted all categorical variables to factors - especially those you will use as predictors.

3.9.2 Factor screening

Inspect the levels of each factor carefully. Make sure that there not any levels present that are incorrect. For example, you wouldn't want to the following

levels for sex: male, mmale, female. Obviously, mmale is an incorrectly typed version of male. Scan all the factor in your data for erroneous factor levels. The code below displays the factor levels:

```
analytic_data_within %>%
  select(where(is.factor)) %>%
  summary()
```

```
## id      sex
## 1:1  male  :3
## 2:1  female:3
## 3:1
## 4:1
## 5:1
## 6:1
```

Also inspect the output of the above `summary()` command paying attention to the order of the levels in the factors. The order influences how text output and graphs are generated. In these data, the sex column has two levels: male and female in that order. Below we adjust the order of the sex variable because we want the x-axis of a future graph to display columns in the left to right order: female, male.

```
# Custom reordering of factor levels
analytic_data_within <- analytic_data_within %>%
  mutate(sex = fct_relevel(sex,
                           "female",
                           "male"))
```

You can see the new order of the factor levels with `summary()`:

```
analytic_data_within %>%
  select(where(is.factor)) %>%
  summary()
```

```
## id      sex
## 1:1  female:3
## 2:1  male  :3
## 3:1
## 4:1
## 5:1
## 6:1
```

3.9.3 Numeric screening

For numeric variables, you should search for impossible values. For example, in the context of this example you want to ensure none of the `elapsed_times` are impossible or so large they appear to be data entry errors.

One options for doing so is the `summary` command again. This time, however, we use “`is.numeric`” in the `where()` command.

```
analytic_data_within %>%
  select(where(is.numeric)) %>%
  summary()
```

```
##      march      may      july
##  Min.   :33.0   Min.   :30.0   Min.   :28.0
##  1st Qu.:35.2   1st Qu.:32.2   1st Qu.:30.2
##  Median :37.0   Median :34.0   Median :32.0
##  Mean   :37.3   Mean   :34.3   Mean   :32.3
##  3rd Qu.:39.5   3rd Qu.:36.5   3rd Qu.:34.5
##  Max.   :42.0   Max.   :39.0   Max.   :37.0
```

Scan the min and max values for each variable to ensure there are not any impossible values. If necessary, got back to the original data source and fix these impossible value. Alternatively, you might need to change them to missing values (i.e., NA values). Once this is complete, you are done preparing your between participant analytic data.

3.9.4 Pivot to tidy data

The analytic data in it's current for does not conform to the the tidy data specification. Inspect the data with the `print()` command. Notice the there is not column for occasion. The levels of occasion are spread across three columns. Correspondingly, elapsed time is spread across multiple columns in the same row and is not labeled as elapsed time. We need to restructure the data into the tidy data format so that we have a single elapsed time observation per row and a single column per variable.

```
print(analytic_data_within)
```

```
## # A tibble: 6 x 5
##   id  sex  march  may  july
##   <fct> <fct> <dbl> <dbl> <dbl>
## 1 1    male    40    37    35
## 2 2    female  35    32    30
```



```
## 3 3    male    38    35    33
## 4 4    female  33    30    28
## 5 5    male    42    39    37
## 6 6    female  36    33    31
```

The `pivot_longer()` command below converts our data to the tidy data format. In this command we specify the the columns march, may, and june are all levels of a single variable called occasion. We specify the columns involved with the `cols` argument. The code `march:july` after the `cols` argument indicates to the computer to use the march column and the july column and all the columns in between. Each column name represents a level of the variable occasion. The `names_to` argument is used to indicate that a new column called occasion should be created to hold the different months. The `value_to` argument is used to indicate that a new column called elapsed_time should be created to hold all the values from the march, may, and july column.

```
analytic_data_within_tidy <- analytic_data_within %>%
  pivot_longer(cols = march:july,
               names_to = "occasion",
               values_to = "elapsed_time"
  )
```

You can see the data in the new format below.

```
print(analytic_data_within_tidy)

## # A tibble: 18 x 4
##   id    sex    occasion elapsed_time
##   <fct> <fct> <chr>         <dbl>
## 1 1    male    march         40
## 2 1    male    may           37
## 3 1    male    july          35
## 4 2    female  march         35
## 5 2    female  may           32
## 6 2    female  july          30
## 7 3    male    march         38
## 8 3    male    may           35
## 9 3    male    july          33
## 10 4    female  march         33
## 11 4    female  may           30
## 12 4    female  july          28
## 13 5    male    march         42
## 14 5    male    may           39
## 15 5    male    july          37
## 16 6    female  march         36
```

```
## 17 6      female may          33
## 18 6      female july         31
```

But notice that the new column occasion is of the type character. We need it to be a factor. So use the code below to do so:

```
analytic_data_within_tidy <- analytic_data_within_tidy %>%
  mutate(occasion = as_factor(occasion))
```

You can confirm that occasion is now a factor with the `glimpse()` command. Once this is complete, you are done preparing your one-way within participant analytic data.

```
glimpse(analytic_data_within_tidy)

## Rows: 18
## Columns: 4
## $ id      <fct> 1, 1, 1, 2, 2, 2, 3, 3, 3, 4, 4, 4...
## $ sex     <fct> male, male, male, female, female, ...
## $ occasion <fct> march, may, july, march, may, july...
## $ elapsed_time <dbl> 40, 37, 35, 35, 32, 30, 38, 35, 33...
```

3.10 Experiment: Within N-way

The N-way within-participant ANOVA example uses the data file `data_food.csv`. Initial loading of the file, including the specification of missing data codes, is provided by the code below. The data corresponds to a designs where the researcher is interested in assessing the taste of food as a function of food type (pizza/steak/burger) and temperature (hot/cold).

```
# Date: YYYY-MM-DD
# Name: your name here
# Example: Within-participant experiment

# Load data
library(tidyverse)

my_missing_value_codes <- c("-999", "", "NA")

raw_data_within_nway <- read_csv(file = "data_food.csv",
```

```
na = my_missing_value_codes)

analytic_data_within_nway <- raw_data_within_nway
```

After loading the data we do initial cleaning to remove empty row/columns and ensure proper naming for columns:

```
library(janitor)

# Initial cleaning
analytic_data_within_nway <- analytic_data_within_nway %>%
  remove_empty("rows") %>%
  remove_empty("cols") %>%
  clean_names()
```

You can confirm the column names following our naming convention with the `glimpse` command - and see the data type for each column.

```
glimpse(analytic_data_within_nway)

## Rows: 6
## Columns: 8
## $ id      <dbl> 1, 2, 3, 4, 5, 6
## $ sex     <dbl> 1, 2, 1, 2, 1, 2
## $ pizza_hot <dbl> 7, 8, 7, 8, 7, 9
## $ pizza_cold <dbl> 6, 7, 5, 7, 6, 7
## $ steak_hot <dbl> 6, 6, 7, 7, 8, 7
## $ steak_cold <dbl> 3, 3, 4, 5, 7, 8
## $ burger_hot <dbl> 7, 8, 7, 8, 7, 8
## $ burger_cold <dbl> 4, 3, 3, 3, 2, 5
```

3.10.1 Creating factors

Following initial cleaning, identify categorical variables as factors. If you plan to conduct an ANOVA - it's critical that all predictor variables are converted to factors. Inspect `glimpse()` output - if you followed our data entry naming conventions categorical variables should be of the type character. We have one variable `sex` that is categorical that is of type character (i.e., `chr`). The participant `id` column is categorical as well, but of type double (i.e., `dbl`) which is a numeric column.

```
glimpse(analytic_data_within_nway)
```

```
## Rows: 6
## Columns: 8
## $ id      <dbl> 1, 2, 3, 4, 5, 6
## $ sex     <dbl> 1, 2, 1, 2, 1, 2
## $ pizza_hot <dbl> 7, 8, 7, 8, 7, 9
## $ pizza_cold <dbl> 6, 7, 5, 7, 6, 7
## $ steak_hot <dbl> 6, 6, 7, 7, 8, 7
## $ steak_cold <dbl> 3, 3, 4, 5, 7, 8
## $ burger_hot <dbl> 7, 8, 7, 8, 7, 8
## $ burger_cold <dbl> 4, 3, 3, 3, 2, 5
```

The sex column is a numeric column, so we have handle that column on it's own.

```
analytic_data_within_nway <-analytic_data_within_nway %>%
  mutate(sex = as_factor(sex))
```

Now the sex column is a factor but we have to tell the computer that 1 indicates male and 2 indicates female.

```
analytic_data_within_nway <-analytic_data_within_nway %>%
  mutate(sex = fct_recode(sex,
                           male = "1",
                           female = "2"))
```

The participant identification number in the id column is a numeric column, so we have handle that column on it's own.

```
analytic_data_within_nway <-analytic_data_within_nway %>%
  mutate(id = as_factor(id))
```

You can ensure all of these columns are now factors using the glimpse() command.

```
glimpse(analytic_data_within_nway)
```

```
## Rows: 6
## Columns: 8
## $ id      <fct> 1, 2, 3, 4, 5, 6
## $ sex     <fct> male, female, male, female, male, f...
```

```
## $ pizza_hot    <dbl> 7, 8, 7, 8, 7, 9
## $ pizza_cold   <dbl> 6, 7, 5, 7, 6, 7
## $ steak_hot    <dbl> 6, 6, 7, 7, 8, 7
## $ steak_cold   <dbl> 3, 3, 4, 5, 7, 8
## $ burger_hot   <dbl> 7, 8, 7, 8, 7, 8
## $ burger_cold  <dbl> 4, 3, 3, 3, 2, 5
```

Inspect the output of the `glimpse()` command and make sure you have converted all categorical variables to factors - especially those you will use as predictors.

3.10.2 Factor screening

Inspect the levels of each factor carefully. Make sure that there not any levels present that are incorrect. For example, you wouldn't want to the following levels for sex: male, mmale, female. Obviously, mmale is an incorrectly typed version of male. Scan all the factor in your data for eronious factor levels. The code below displays the factor levels:

```
analytic_data_within_nway %>%
  select(where(is.factor)) %>%
  summary()
```

```
## id      sex
## 1:1    male :3
## 2:1    female:3
## 3:1
## 4:1
## 5:1
## 6:1
```

Also inspect the output of the above `summary()` command paying attention to the order of the levels in the factors. The order influences how text output and graphs are generated. In these data, the sex column has two levels: male and female in that order. Below we adjust the order of the sex variable because we want the x-axis of a future graph to display columns in the left to right order: female, male.

```
# Custom reordering of factor levels
analytic_data_within_nway <- analytic_data_within_nway %>%
  mutate(sex = fct_relevel(sex,
                           "female",
                           "male"))
```

You can see the new order of the factor levels with `summary()`:

```
analytic_data_within_nway %>%
  select(where(is.factor)) %>%
  summary()
```

```
## id      sex
## 1:1    female:3
## 2:1    male  :3
## 3:1
## 4:1
## 5:1
## 6:1
```

3.10.3 Numeric screening

For numeric variables, you should search for impossible values. For example, in the context of this example you want to ensure none of the `elapsed_times` are impossible or so large they appear to be data entry errors.

One options for doing so is the `summary` command again. This time, however, we use “`is.numeric`” in the `where()` command.

```
analytic_data_within_nway %>%
  select(where(is.numeric)) %>%
  summary()
```

```
## pizza_hot    pizza_cold    steak_hot
## Min.      :7.00    Min.      :5.00    Min.      :6.00
## 1st Qu.:7.00    1st Qu.:6.00    1st Qu.:6.25
## Median :7.50    Median :6.50    Median :7.00
## Mean    :7.67    Mean    :6.33    Mean    :6.83
## 3rd Qu.:8.00    3rd Qu.:7.00    3rd Qu.:7.00
## Max.     :9.00    Max.     :7.00    Max.     :8.00
## steak_cold    burger_hot    burger_cold
## Min.      :3.00    Min.      :7.0    Min.      :2.00
## 1st Qu.:3.25    1st Qu.:7.0    1st Qu.:3.00
## Median :4.50    Median :7.5    Median :3.00
## Mean    :5.00    Mean    :7.5    Mean    :3.33
## 3rd Qu.:6.50    3rd Qu.:8.0    3rd Qu.:3.75
## Max.     :8.00    Max.     :8.0    Max.     :5.00
```

Scan the min and max values for each variable to ensure there are not any impossible values. If necessary, go back to the original data source and fix these impossible value. Alternatively, you might need to change them to missing

values (i.e., NA values). Once this is complete, you are done preparing your between participant analytic data.

3.10.4 Pivot to tidy data

The analytic data in it's current for does not conform to the the tidy data specification. Inspect the data with the `print()` command. Notice the there is not column for occasion. The levels of occasion are spread across three columns. Correspondingly, elapsed time is spread across multiple columns in the same row and is not labeled as elapsed time. We need to restructure the data into the tidy data format so that we have a single elapsed time observation per row and a single column per variable.

```
print(analytic_data_within_nway)

## # A tibble: 6 x 8
##   id    sex  pizza_hot pizza_cold steak_hot steak_cold
##   <fct> <fct>    <dbl>     <dbl>    <dbl>    <dbl>
## 1 1    male      7         6        6         3
## 2 2    fema~     8         7        6         3
## 3 3    male      7         5        7         4
## 4 4    fema~     8         7        7         5
## 5 5    male      7         6        8         7
## 6 6    fema~     9         7        7         8
## # ... with 2 more variables: burger_hot <dbl>,
## #   burger_cold <dbl>
```

The `pivot_long()` command below coverts our data to the tidy data format. In this command we specify the the columns march, may, and june are all levels of a single variable called occasion. We specify the columns involved with the `cols` argument. The code `march:july` after the `cols` argument indicates to the computer to use the march column and the july column and all the columns in between. Each column name represents a level of the variable occasion. The `names_to` argument is used to indicate that a new column called occasion should be created to hold the different months. The `value_to` argument is used to indicate that a new column called elapsed_time should be created to hold all the values from the march, may, and july column.

```
analytic_data_nway_tidy <- analytic_data_within_nway %>%
  pivot_longer(pizza_hot:burger_cold,
               names_to = c("food", "temperature"),
               names_sep = "_",
```

```

        values_to = "taste"
    )

```

You can see the data in the new format below.

```

print(analytic_data_nway_tidy)

## # A tibble: 36 x 5
##   id    sex    food    temperature taste
##   <fct> <fct> <chr>    <chr>         <dbl>
## 1 1    male    pizza    hot           7
## 2 1    male    pizza    cold          6
## 3 1    male    steak    hot           6
## 4 1    male    steak    cold          3
## 5 1    male    burger    hot           7
## 6 1    male    burger    cold          4
## 7 2    female  pizza    hot           8
## 8 2    female  pizza    cold          7
## 9 2    female  steak    hot           6
## 10 2    female  steak    cold          3
## # ... with 26 more rows

```

But notice that the new column occasion is of the type character. We need it to be a factor. So use the code below to do so:

```

analytic_data_nway_tidy <- analytic_data_nway_tidy %>%
  mutate(food = as_factor(food),
         temperature = as_factor(temperature))

```

You can confirm that occasion is now a factor with the `glimpse()` command. Once this is complete, you are done preparing your one-way within participant analytic data.

```

glimpse(analytic_data_nway_tidy)

## Rows: 36
## Columns: 5
## $ id      <fct> 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2,...
## $ sex     <fct> male, male, male, male, male, male, ...
## $ food    <fct> pizza, pizza, steak, steak, burger, ...
## $ temperature <fct> hot, cold, hot, cold, hot, cold, ho...
## $ taste   <dbl> 7, 6, 6, 3, 7, 4, 8, 7, 6, 3, 8, 3,...

```


3.11 Surveys: Single Occassion

Even assuming you did everything right there is still a fair amount of work to get things started paragraph here...

We begin by examining the data as originally entered into a spreadsheet. In Figure 3.5 you see a screen shot of the initial raw data as a researcher might receive it. Take careful note of the numerous -999 values used to indicate missing values. As part of creating the analytic data that we will analyze we need to indicate to the computer that the -999 are not data but codes to represent missing values.

id	age	sex	SE1	SE2	SE3	SE4	SE5	SE6	SE7	SE8	SE9	SE10
1	23	male	3	2	4	3	4	3	1	3	-999	5
2	22	female	4	3	4	4	4	5	1	-999	5	-999
3	18	male	4	3	4	4	4	4	1	3	5	5
4	23	female	3	2	3	3	4	3	-999	3	4	4
5	22	male	3	2	4	4	4	3	1	3	4	5
6	17	female	3	3	4	4	-999	3	1	3	4	4
7	23	male	3	2	-999	4	-999	3	2	3	4	4
8	22	female	4	3	4	4	4	5	1	3	5	5
9	17	male	4	3	4	3	4	3	2	3	-999	5
10	21	female	4	3	3	4	4	3	2	3	4	5
11	20	male	3	2	4	-999	3	3	3	3	-999	4
12	17	female	4	2	4	4	4	4	1	3	5	-999
13	24	male	-999	-999	4	3	4	4	3	3	4	4
14	17	female	-999	3	-999	3	3	3	2	2	4	5
15	19	male	3	2	4	4	3	3	1	3	4	4
16	19	female	3	2	-999	-999	-999	4	1	3	5	4
17	21	male	3	2	-999	3	3	3	2	2	4	4
18	21	female	3	2	3	3	3	3	3	2	3	4
19	19	male	3	3	4	4	-999	3	1	3	4	5

FIGURE 3.5: Raw data for item scoring

- Create a new script in your project and save it with the name "script_raw_to_analytic.R"
- Type the code below into that script

```
# Date: YYYY-MM-DD
# Name: your name here
# Example: single occasion survey

# Load data
library(tidyverse)

my_missing_value_codes <- c("-999", "", "NA")
```

```
raw_data_survey <- read_csv(file = "data_item_scoring.csv",
                             na = my_missing_value_codes)
```

```
## Parsed with column specification:
## cols(
##   id = col_double(),
##   age = col_double(),
##   sex = col_character(),
##   eye_color = col_character(),
##   esteem1 = col_double(),
##   esteem2 = col_double(),
##   esteem3 = col_double(),
##   esteem4 = col_double(),
##   esteem5_rev15 = col_double(),
##   jobsat1 = col_double(),
##   jobsat2_rev15 = col_double(),
##   jobsat3 = col_double(),
##   jobsat4 = col_double(),
##   jobsat5 = col_double()
## )
```

```
analytic_data_survey <- raw_data_survey
```

Remove empty row and columns from your data using the `remove_empty_cols()` and `remove_empty_rows()`, respectively. As well, clean the names of your columns to ensure they conform to tidyverse naming conventions.

```
library(janitor)

# Initial cleaning
analytic_data_survey <- analytic_data_survey %>%
  remove_empty("rows") %>%
  remove_empty("cols") %>%
  clean_names()
```

You can confirm the column names following our naming convention with the `glimpse` command - and see the data type for each column.

```
glimpse(analytic_data_survey)
```

```
## Rows: 300
```

```
## Columns: 14
## $ id      <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11...
## $ age     <dbl> 23, 22, 18, 23, 22, 17, 23, 22, 1...
## $ sex     <chr> "male", "female", "male", "female...
## $ eye_color <chr> "blue", "brown", "hazel", "blue",...
## $ esteem1 <dbl> 3, 4, 4, 3, 3, 3, 3, 4, 4, 4, 3, ...
## $ esteem2 <dbl> 2, 3, 3, 2, 2, 3, 2, 3, 3, 3, 2, ...
## $ esteem3 <dbl> 4, 4, 4, 3, 4, 4, NA, 4, 4, 3, 4,...
## $ esteem4 <dbl> 3, 4, 4, 3, 4, 4, 4, 4, 3, 4, NA,...
## $ esteem5_rev15 <dbl> 2, 2, 2, 2, 2, NA, NA, 2, 2, 2, 3...
## $ jobsat1 <dbl> 3, 5, 4, 3, 3, 3, 3, 5, 3, 3, 3, ...
## $ jobsat2_rev15 <dbl> 1, 1, 1, NA, 1, 1, 2, 1, 2, 2, 3,...
## $ jobsat3 <dbl> 3, NA, 3, 3, 3, 3, 3, 3, 3, 3, 3,...
## $ jobsat4 <dbl> NA, 5, 5, 4, 4, 4, 4, 5, NA, 4, N...
## $ jobsat5 <dbl> 5, NA, 5, 4, 5, 4, 4, 5, 5, 5, 4,...
```

3.11.1 Creating factors

Following initial cleaning, identify categorical variables as factors. If you plan to conduct an ANOVA - it's critical that all predictor variables are converted to factors. Inspect `glimpse()` output - if you followed our data entry naming conventions categorical variables should be of the type character

```
glimpse(analytic_data_survey)
```

```
## Rows: 300
## Columns: 14
## $ id      <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11...
## $ age     <dbl> 23, 22, 18, 23, 22, 17, 23, 22, 1...
## $ sex     <chr> "male", "female", "male", "female...
## $ eye_color <chr> "blue", "brown", "hazel", "blue",...
## $ esteem1 <dbl> 3, 4, 4, 3, 3, 3, 3, 4, 4, 4, 3, ...
## $ esteem2 <dbl> 2, 3, 3, 2, 2, 3, 2, 3, 3, 3, 2, ...
## $ esteem3 <dbl> 4, 4, 4, 3, 4, 4, NA, 4, 4, 3, 4,...
## $ esteem4 <dbl> 3, 4, 4, 3, 4, 4, 4, 4, 3, 4, NA,...
## $ esteem5_rev15 <dbl> 2, 2, 2, 2, 2, NA, NA, 2, 2, 2, 3...
## $ jobsat1 <dbl> 3, 5, 4, 3, 3, 3, 3, 5, 3, 3, 3, ...
## $ jobsat2_rev15 <dbl> 1, 1, 1, NA, 1, 1, 2, 1, 2, 2, 3,...
## $ jobsat3 <dbl> 3, NA, 3, 3, 3, 3, 3, 3, 3, 3, 3,...
## $ jobsat4 <dbl> NA, 5, 5, 4, 4, 4, 4, 5, NA, 4, N...
## $ jobsat5 <dbl> 5, NA, 5, 4, 5, 4, 4, 5, 5, 5, 4,...
```

You can quickly convert all character columns to factors using the code below:

```
# Turn all columns that are of type character into factors
analytic_data_survey <- analytic_data_survey %>%
  mutate(across(.cols = where(is.character),
    .fns = as_factor))
```

The participant identification number in the id column is a numeric column, so we have handle that column on it's own.

```
analytic_data_survey <- analytic_data_survey %>%
  mutate(id = as_factor(id))
```

You can ensure all of these columns are now factors using the `glimpse()` command.

```
glimpse(analytic_data_survey)

## Rows: 300
## Columns: 14
## $ id          <fct> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11...
## $ age         <dbl> 23, 22, 18, 23, 22, 17, 23, 22, 1...
## $ sex         <fct> male, female, male, female, male,...
## $ eye_color   <fct> blue, brown, hazel, blue, NA, haz...
## $ esteem1     <dbl> 3, 4, 4, 3, 3, 3, 3, 4, 4, 4, 3, ...
## $ esteem2     <dbl> 2, 3, 3, 2, 2, 3, 2, 3, 3, 3, 2, ...
## $ esteem3     <dbl> 4, 4, 4, 3, 4, 4, NA, 4, 4, 3, 4,...
## $ esteem4     <dbl> 3, 4, 4, 3, 4, 4, 4, 4, 3, 4, NA,...
## $ esteem5_rev15 <dbl> 2, 2, 2, 2, 2, NA, NA, 2, 2, 2, 3...
## $ jobsat1     <dbl> 3, 5, 4, 3, 3, 3, 3, 5, 3, 3, 3, ...
## $ jobsat2_rev15 <dbl> 1, 1, 1, NA, 1, 1, 2, 1, 2, 2, 3,...
## $ jobsat3     <dbl> 3, NA, 3, 3, 3, 3, 3, 3, 3, 3, 3,...
## $ jobsat4     <dbl> NA, 5, 5, 4, 4, 4, 4, 5, NA, 4, N...
## $ jobsat5     <dbl> 5, NA, 5, 4, 5, 4, 4, 5, 5, 5, 4,...
```

Inspect the output of the `glimpse()` command and make sure you have covered all categorical variables to factors - especially those you will use as predictors.

3.11.2 Factor screening

Inspect the levels of each factor carefully. Make sure that there not any levels present that are incorrect. For example, you wouldn't want to the following levels for sex: male, mmale, female. Obviously, mmale is an incorrectly typed version of male. Scan all the factor in your data for eronious factor levels. The code below displays the factor levels:

```
analytic_data_survey %>%
  select(where(is.factor)) %>%
  summary()
```

```
##           id           sex      eye_color
##  1      :  1    male    :147    blue : 99
##  2      :  1   female  :149   brown: 98
##  3      :  1  intersex:  2   hazel:100
##  4      :  1    NA's   :  2    NA's :  3
##  5      :  1
##  6      :  1
## (Other):294
```

Also inspect the output of the above `summary()` command paying attention to the order of the levels in the factors. The order influences how text output and graphs are generated. In these data, the `sex` column has two levels: `male` and `female` in that order. Below we adjust the order of the `sex` variable because we want the x-axis of a future graph to display columns in the left to right order: `female`, `male`.

```
# Custom reordering of factor levels
analytic_data_survey <- analytic_data_survey %>%
  mutate(sex = fct_relevel(sex,
                           "intersex",
                           "female",
                           "male"))
```

For eye color, we want to future graph to be have the most common eye colors on the left so we reorder the factor levels:

```
# Reordering factor levels by frequency
analytic_data_survey <- analytic_data_survey %>%
  mutate(eye_color = fct_infreq(eye_color))
```

You can see the new order of the factor levels with `summary()`:

```
analytic_data_survey %>%
  select(where(is.factor)) %>%
  summary()
```

```
##           id           sex      eye_color
##  1      :  1  intersex:  2   hazel:100
##  2      :  1   female  :149   blue : 99
```

```
## 3      : 1   male      :147   brown: 98
## 4      : 1   NA's      : 2   NA's : 3
## 5      : 1
## 6      : 1
## (Other):294
```

3.11.3 Numeric screening

For numeric variables, you should search for impossible values. For example, in the context of this example you want to ensure none of the `elapsed_times` are impossible or so large they appear to be data entry errors.

One options for doing so is the summary command again. This time, however, we use “`is.numeric`” in the `where()` command. However, when a survey has a large number of variables this type of output can become challenging to intrepret.

```
analytic_data_survey %>%
  select(where(is.numeric)) %>%
  summary()
```

With larger numers of variables, it’s a good idea to use the `skimr` package. Additionally, it makes sense to look at sets of items rather than all of the variables at once. This is because sometime items and different response formats. For example, for one measure this responses may range from 1 to 5 whereas for another measure responses could range from 1 to 7. This is undesirable from a psychometric point of view, as discussed previously, but it if happens it makes sense to look at items in sets.

Start by examining the range of non-scale items. In this case it’s only age. Examine the output to see if any of the age values are unreasonable. In the output `p0` and `p100` indicate the 0th percentile and the 100th percentile; that is the min an max values for the variable. Check to make sure none of the age values are unreasonably low or high. If they are, you may need to check the original data source or replace them with missing values.

```
library(skimr)
analytic_data_survey %>%
  select(age) %>%
  skim_without_charts()
```

```
##   skim_variable n_missing mean   sd p0 p50 p100
## 1             age         3 20.52 2.05 17  20   24
```

Look the items in the first scale, self-esteem. Possible items responses for this scale range from 1 to 5, make sure they are all in this range. In the output p0 and p100 indicate the 0th percentile and the 100th percentile; that is the minimum and maximum values for the variable in these data. Examine the output to see if any of the esteem values are unreasonable (i.e., fall outside the 1 to 5 range). If any values fall outside this range, you may need to check the original data source or replace them with missing values - as described previously.

```
analytic_data_survey %>%
  select(starts_with("esteem")) %>%
  skim()
```

```
##   skim_variable n_missing mean    sd p0 p50 p100
## 1      esteem1      24 3.39 0.54  3   3    5
## 2      esteem2      28 2.35 0.48  2   2    3
## 3      esteem3      31 3.96 0.37  3   4    5
## 4      esteem4      15 3.54 0.50  3   4    4
## 5 esteem5_rev15      35 2.22 0.47  1   2    3
```

Follow the same process for the job satisfaction items. Possible items responses for this scale range from 1 to 5, make sure they are all in this range. If any values fall outside this range, you may need to check the original data source or replace them with missing values - as described previously.

```
analytic_data_survey %>%
  select(starts_with("jobsat")) %>%
  skim_without_charts()
```

```
##   skim_variable n_missing mean    sd p0 p50 p100
## 1      jobsat1      25 3.34 0.51  3   3    5
## 2 jobsat2_rev15      27 1.51 0.61  1   1    3
## 3      jobsat3      28 2.84 0.37  2   3    3
## 4      jobsat4      35 4.29 0.70  3   4    5
## 5      jobsat5      24 4.57 0.61  3   5    5
```

3.11.4 Scale scores

Scale scores involve averaging, for each person, their score over several items to create an overall scale score. The first step in the creation of scales is correcting the values of any reverse-keyed items, as described previously.

3.11.4.1 Reverse key items

The way you deal with reverse-keyed items depends on how you scored them. Imagine you had a 5-point scale. You could have scored the scale with the values 1, 2, 3, 4, and 5. Alternatively, you could have scored the scale with the values 0, 1, 2, 3, and 4. In this example, we scored the data using the 1 to 5 system. So we'll use that. Later I'll show you how to deal with the other scoring system (0 to 4).

We need to take items that were reversed-key when the participant wrote them and recode those responses. We do that with using the *mutate* command.

In this data file all the reverse-keyed were identified with the suffix "_rev15" in the column names. This suffix indicates the item was reverse-keyed and that the original scale used the response points 1 to 5. We can see those items with the *glimpse()* command below. Notice that there are two reverse keyed items - both on difference scales.

```
analytic_data_survey %>%
  select(ends_with("_rev15")) %>%
  glimpse()
```

```
## Rows: 300
## Columns: 2
## $ esteem5_rev15 <dbl> 2, 2, 2, 2, 2, NA, NA, 2, 2, 2, 3...
## $ jobsat2_rev15 <dbl> 1, 1, 1, NA, 1, 1, 2, 1, 2, 2, 3,...
```

To correct a reverse-keyed items that ranges where the lowest possible rating value is a 1 (i.e, 1 on a 1 to 5 scale), we simply subtract all the scores from one more than the highest possible rating. For example, if a 1 to 5 response scale was used we subtract each response from 6 to obtain the recoded value.

Original value	Math	Recoded value
1	6 - 1	5
2	6 - 2	4
3	6 - 3	3
4	6 - 4	2
5	6 - 5	1

The code below: * selects each column that ends with "_rev15" (i.e., both esteem and jobsat scales) * subtracts each value in that column from 6 * renames the column by removing "_rev15" because the reverse coding is complete.


```
analytic_data_survey <- analytic_data_survey %>%
  mutate(6 - across(.cols = ends_with("_rev15")) ) %>%
  rename_with(.fn = str_remove,
              .cols = ends_with("_rev15"),
              pattern = "_rev15")
```

You can use the `glimpse()` command to see the result of your work. If you compare this to values from the previous `glimpse()` command you can see they have changed. Also notice the column names no longer indicate the items are reverse-keyed.

```
glimpse(analytic_data_survey)
```

```
## Rows: 300
## Columns: 14
## $ id      <fct> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12...
## $ age     <dbl> 23, 22, 18, 23, 22, 17, 23, 22, 17, N...
## $ sex     <fct> male, female, male, female, male, fem...
## $ eye_color <fct> blue, brown, hazel, blue, NA, hazel, ...
## $ esteem1 <dbl> 3, 4, 4, 3, 3, 3, 3, 4, 4, 4, 3, 4, N...
## $ esteem2 <dbl> 2, 3, 3, 2, 2, 3, 2, 3, 3, 3, 2, 2, N...
## $ esteem3 <dbl> 4, 4, 4, 3, 4, 4, NA, 4, 4, 3, 4, 4, ...
## $ esteem4 <dbl> 3, 4, 4, 3, 4, 4, 4, 4, 3, 4, NA, 4, ...
## $ esteem5 <dbl> 4, 4, 4, 4, 4, NA, NA, 4, 4, 4, 3, 4,...
## $ jobsat1 <dbl> 3, 5, 4, 3, 3, 3, 3, 5, 3, 3, 3, 4, 4...
## $ jobsat2 <dbl> 5, 5, 5, NA, 5, 5, 4, 5, 4, 4, 3, 5, ...
## $ jobsat3 <dbl> 3, NA, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, ...
## $ jobsat4 <dbl> NA, 5, 5, 4, 4, 4, 4, 5, NA, 4, NA, 5...
## $ jobsat5 <dbl> 5, NA, 5, 4, 5, 4, 4, 5, 5, 5, 4, NA,...
```



- If your scale had used response options numbered 0 to 4 the math is different. For each item you would use subtract values from the highest possible point (i.e, 4) instead of one larger than the highest possible point.

Original value	Math	Recoded value
0	4 - 0	4
1	4 - 1	3
2	4 - 2	2
3	4 - 3	1
4	4 - 4	0

Thus the mutate command would instead be:

```
mutate(4 - across(.cols = ends_with("__rev15"))) )
```

3.11.4.2 Creating scores

The process we use for creating scale scores deletes item level data from `analytic_data_survey`. This is a desirable aspect of the process as it removes information we are no longer interested in from our analytic data. That said, before we create scale score, we create a backup on the item level data called `analytic_data_items`. We will need to use this backup later to compute the reliability of the scales we are creating.

```
analytic_data_items <- analytic_data_survey
```

We want to make a `self_esteem` scale and plan to select items using `starts_with("esteem")`. But prior to doing this we make sure the `start_with()` command only gives us the items we want - and not additional unwanted items. The output below confirms there are not problems associated with using `starts_with("esteem")`.

```
# confirm select will select the columns you want (and not others)
analytic_data_survey %>%
  select(starts_with("esteem")) %>%
  glimpse()
```

```
## Rows: 300
```

```
## Columns: 5
## $ esteem1 <dbl> 3, 4, 4, 3, 3, 3, 3, 4, 4, 4, 3, 4, NA,...
## $ esteem2 <dbl> 2, 3, 3, 2, 2, 3, 2, 3, 3, 3, 2, 2, NA,...
## $ esteem3 <dbl> 4, 4, 4, 3, 4, 4, NA, 4, 4, 3, 4, 4, 4,...
## $ esteem4 <dbl> 3, 4, 4, 3, 4, 4, 4, 4, 3, 4, NA, 4, 3,...
## $ esteem5 <dbl> 4, 4, 4, 4, 4, NA, NA, 4, 4, 4, 3, 4, 4...
```

Likewise, we want to make a `job_sat` scale and plan to select items using `starts_with("jobsat")`. The code and output below using `starts_with("jobsat")` only returns the items we are interested in.

```
# confirm select will select the columns you want (and not others)
analytic_data_survey %>%
  select(starts_with("jobsat")) %>%
  glimpse()
```

```
## Rows: 300
## Columns: 5
## $ jobsat1 <dbl> 3, 5, 4, 3, 3, 3, 3, 5, 3, 3, 3, 4, 4, ...
## $ jobsat2 <dbl> 5, 5, 5, NA, 5, 5, 4, 5, 4, 4, 3, 5, 3,...
## $ jobsat3 <dbl> 3, NA, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,...
## $ jobsat4 <dbl> NA, 5, 5, 4, 4, 4, 4, 5, NA, 4, NA, 5, ...
## $ jobsat5 <dbl> 5, NA, 5, 4, 5, 4, 4, 5, 5, 5, 4, NA, 4...
```

We compute the scale scores using the `rowwise()` command. The `mean()` command provides the mean of columns by default - not people. We use the `rowwise()` command in the code below so that the `mean()` command will work across columns rather than within columns. The `mutate` command calculates the scale score for each person. The `c_across()` command combined with the `starts_with()` command ensure the items we want averaged together are the items that are averaged together. Notice there is a separate `mutate` line for each scale. The `ungroup()` command turns off the `rowwise()` command. We end the code block by removing the item-level data from the data set.

```
analytic_data_survey <- analytic_data_survey %>%
  rowwise() %>%
  mutate(self_esteem = mean(c_across(starts_with("esteem")),
                             na.rm = TRUE)) %>%
  mutate(job_sat = mean(c_across(starts_with("jobsat")),
                         na.rm = TRUE)) %>%
  ungroup() %>%
  select(-starts_with("esteem")) %>%
  select(-starts_with("jobsat"))
```

We can see our data now has the self esteem column, a job_sat column, and that all of the item level data has been removed.

```
glimpse(analytic_data_survey)
```

```
## Rows: 300
## Columns: 6
## $ id      <fct> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, ...
## $ age     <dbl> 23, 22, 18, 23, 22, 17, 23, 22, 17, ...
## $ sex     <fct> male, female, male, female, male, f...
## $ eye_color <fct> blue, brown, hazel, blue, NA, hazel...
## $ self_esteem <dbl> 3.200, 3.800, 3.800, 3.000, 3.400, ...
## $ job_sat  <dbl> 4.00, 5.00, 4.40, 3.50, 4.00, 3.80, ...
```

These data are ready for analysis.

3.12 Surveys: Multiple Occasions

```
library(tidyverse)
```

```
raw_data_occasions <- read_csv("data_item_time.csv")
```

```
analytic_data_occasions <- raw_data_occasions
```

```
glimpse(analytic_data_occasions)
```

```
## Rows: 300
## Columns: 24
## $ id      <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, ...
## $ age     <dbl> 23, 22, 18, 23, 22, 17, 23, 22, ...
## $ sex     <chr> "male", "female", "male", "fem...
## $ eye_color <chr> "blue", "brown", "hazel", "blu...
## $ t1_esteem1 <dbl> 3, 4, 4, 3, 3, 3, 3, 4, 4, 4, ...
## $ t1_esteem2 <dbl> 2, 3, 3, 2, 2, 3, 2, 3, 3, 3, ...
## $ t1_esteem3 <dbl> 4, 4, 4, 3, 4, 4, NA, 4, 4, 3, ...
## $ t1_esteem4 <dbl> 3, 4, 4, 3, 4, 4, 4, 4, 3, 4, ...
## $ t1_esteem5_rev15 <dbl> 2, 2, 2, 2, 2, NA, NA, 2, 2, 2...
## $ t1_jobsat1 <dbl> 3, 5, 4, 3, 3, 3, 3, 5, 3, 3, ...
```

```
## $ t1_jobsat2_rev15 <dbl> 1, 1, 1, NA, 1, 1, 2, 1, 2, 2,...
## $ t1_jobsat3       <dbl> 3, NA, 3, 3, 3, 3, 3, 3, 3, 3,...
## $ t1_jobsat4       <dbl> NA, 5, 5, 4, 4, 4, 4, 5, NA, 4...
## $ t1_jobsat5       <dbl> 5, NA, 5, 4, 5, 4, 4, 5, 5, 5,...
## $ t2_esteem1       <dbl> 4, 5, 5, 4, NA, 4, 4, 5, 5, 5,...
## $ t2_esteem2       <dbl> 3, 4, 4, 3, 3, 4, 3, 4, 4, 4, ...
## $ t2_esteem3       <dbl> 5, 5, 5, 4, 5, 5, 3, 5, 5, 4, ...
## $ t2_esteem4       <dbl> 4, 5, 5, 4, 5, 5, 5, 5, 4, 5, ...
## $ t2_esteem5_rev15 <dbl> 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, ...
## $ t2_jobsat1       <dbl> 4, 6, 5, 4, 4, 4, 4, 6, 4, NA,...
## $ t2_jobsat2_rev15 <dbl> 2, 2, 2, 3, 2, 2, 3, 2, 3, 3, ...
## $ t2_jobsat3       <dbl> 4, 3, 4, 4, 4, 4, 4, 4, 4, 4, ...
## $ t2_jobsat4       <dbl> 3, 6, 6, 5, 5, 5, 5, 6, 3, 5, ...
## $ t2_jobsat5       <dbl> 6, 3, 6, 5, NA, 5, 5, 6, 6, 6,...
```

3.12.1 Creating factors

Following initial cleaning, identify categorical variables as factors. If you plan to conduct an ANOVA - it's critical that all predictor variables are converted to factors. Inspect `glimpse()` output - if you followed our data entry naming conventions categorical variables should be of the type character

```
glimpse(analytic_data_occasions)
```

```
## Rows: 300
## Columns: 24
## $ id          <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10,...
## $ age         <dbl> 23, 22, 18, 23, 22, 17, 23, 22...
## $ sex         <chr> "male", "female", "male", "fem...
## $ eye_color   <chr> "blue", "brown", "hazel", "blu...
## $ t1_esteem1  <dbl> 3, 4, 4, 3, 3, 3, 3, 4, 4, 4, ...
## $ t1_esteem2  <dbl> 2, 3, 3, 2, 2, 3, 2, 3, 3, 3, ...
## $ t1_esteem3  <dbl> 4, 4, 4, 3, 4, 4, NA, 4, 4, 3,...
## $ t1_esteem4  <dbl> 3, 4, 4, 3, 4, 4, 4, 4, 3, 4, ...
## $ t1_esteem5_rev15 <dbl> 2, 2, 2, 2, 2, NA, NA, 2, 2, 2...
## $ t1_jobsat1  <dbl> 3, 5, 4, 3, 3, 3, 3, 5, 3, 3, ...
## $ t1_jobsat2_rev15 <dbl> 1, 1, 1, NA, 1, 1, 2, 1, 2, 2,...
## $ t1_jobsat3  <dbl> 3, NA, 3, 3, 3, 3, 3, 3, 3, 3,...
## $ t1_jobsat4  <dbl> NA, 5, 5, 4, 4, 4, 4, 5, NA, 4...
## $ t1_jobsat5  <dbl> 5, NA, 5, 4, 5, 4, 4, 5, 5, 5,...
## $ t2_esteem1  <dbl> 4, 5, 5, 4, NA, 4, 4, 5, 5, 5,...
## $ t2_esteem2  <dbl> 3, 4, 4, 3, 3, 4, 3, 4, 4, 4, ...
## $ t2_esteem3  <dbl> 5, 5, 5, 4, 5, 5, 3, 5, 5, 4, ...
```

```
## $ t2_esteem4      <dbl> 4, 5, 5, 4, 5, 5, 5, 5, 4, 5, ...
## $ t2_esteem5_rev15 <dbl> 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, ...
## $ t2_jobsat1      <dbl> 4, 6, 5, 4, 4, 4, 4, 6, 4, NA, ...
## $ t2_jobsat2_rev15 <dbl> 2, 2, 2, 3, 2, 2, 3, 2, 3, 3, ...
## $ t2_jobsat3      <dbl> 4, 3, 4, 4, 4, 4, 4, 4, 4, 4, ...
## $ t2_jobsat4      <dbl> 3, 6, 6, 5, 5, 5, 5, 6, 3, 5, ...
## $ t2_jobsat5      <dbl> 6, 3, 6, 5, NA, 5, 5, 6, 6, 6, ...
```

You can quickly convert all character columns to factors using the code below. In this case, that will convert the sex and eye_colour columns to factors.

```
analytic_data_occasions <- analytic_data_occasions %>%
  mutate(across(.cols = where(is.character),
    .fns = as_factor))
```

The participant identification number in the id column is a numeric column, so we have handle that column on it's own.

```
analytic_data_occasions <- analytic_data_occasions %>%
  mutate(id = as_factor(id))
```

You can ensure all of these columns are now factors using the glimpse() command.

```
glimpse(analytic_data_occasions)

## Rows: 300
## Columns: 24
## $ id          <fct> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, ...
## $ age         <dbl> 23, 22, 18, 23, 22, 17, 23, 22, ...
## $ sex         <fct> male, female, male, female, ma...
## $ eye_color   <fct> blue, brown, hazel, blue, NA, ...
## $ t1_esteem1  <dbl> 3, 4, 4, 3, 3, 3, 3, 4, 4, 4, ...
## $ t1_esteem2  <dbl> 2, 3, 3, 2, 2, 3, 2, 3, 3, 3, ...
## $ t1_esteem3  <dbl> 4, 4, 4, 3, 4, 4, NA, 4, 4, 3, ...
## $ t1_esteem4  <dbl> 3, 4, 4, 3, 4, 4, 4, 4, 3, 4, ...
## $ t1_esteem5_rev15 <dbl> 2, 2, 2, 2, 2, NA, NA, 2, 2, 2, ...
## $ t1_jobsat1  <dbl> 3, 5, 4, 3, 3, 3, 3, 5, 3, 3, ...
## $ t1_jobsat2_rev15 <dbl> 1, 1, 1, NA, 1, 1, 2, 1, 2, 2, ...
## $ t1_jobsat3  <dbl> 3, NA, 3, 3, 3, 3, 3, 3, 3, 3, ...
## $ t1_jobsat4  <dbl> NA, 5, 5, 4, 4, 4, 4, 5, NA, 4, ...
## $ t1_jobsat5  <dbl> 5, NA, 5, 4, 5, 4, 4, 5, 5, 5, ...
## $ t2_esteem1  <dbl> 4, 5, 5, 4, NA, 4, 4, 5, 5, 5, ...
## $ t2_esteem2  <dbl> 3, 4, 4, 3, 3, 4, 3, 4, 4, 4, ...
```

```
## $ t2_esteem3      <dbl> 5, 5, 5, 4, 5, 5, 3, 5, 5, 4, ...
## $ t2_esteem4      <dbl> 4, 5, 5, 4, 5, 5, 5, 5, 4, 5, ...
## $ t2_esteem5_rev15 <dbl> 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, ...
## $ t2_jobsat1       <dbl> 4, 6, 5, 4, 4, 4, 4, 6, 4, NA, ...
## $ t2_jobsat2_rev15 <dbl> 2, 2, 2, 3, 2, 2, 3, 2, 3, 3, ...
## $ t2_jobsat3       <dbl> 4, 3, 4, 4, 4, 4, 4, 4, 4, 4, ...
## $ t2_jobsat4       <dbl> 3, 6, 6, 5, 5, 5, 5, 6, 3, 5, ...
## $ t2_jobsat5       <dbl> 6, 3, 6, 5, NA, 5, 5, 6, 6, 6, ...
```

Inspect the output of the `glimpse()` command and make sure you have converted all categorical variables to factors - especially those you will use as predictors.

3.12.2 Screening factors

Inspect the levels of each factor carefully. Make sure that there not any levels present that are incorrect. For example, you wouldn't want to the following levels for sex: male, mmale, female. Obviously, mmale is an incorrectly typed version of male. Scan all the factor in your data for eronious factor levels. The code below displays the factor levels:

```
analytic_data_occasions %>%
  select(where(is.factor)) %>%
  summary()
```

```
##      id      sex      eye_color
## 1      : 1  male    :147  blue : 99
## 2      : 1  female :149  brown: 98
## 3      : 1  intersex: 2  hazel:100
## 4      : 1  NA's    : 2  NA's : 3
## 5      : 1
## 6      : 1
## (Other):294
```

Also inspect the output of the above `summary()` command paying attention to the order of the levels in the factors. The order influences how text output and graphs are generated. In these data, the sex column has two levels: male and female in that order. Below we adjust the order of the sex variable because we want the x-axis of a future graph to display columns in the left to right order: female, male.

```
# Custom reordering of factor levels for sex
analytic_data_occasions <- analytic_data_occasions %>%
  mutate(sex = fct_relevel(sex,
                           "intersex",
```

```
"female",
"male"))
```

For eye color, we want to future graph to be have the most common eye colors on the left so we reorder the factor levels:

```
# Reordering factor levels by frequency
analytic_data_occasions <- analytic_data_occasions %>%
  mutate(eye_color = fct_infreq(eye_color))
```

You can see the new order of the factor levels with `summary()`:

```
analytic_data_occasions %>%
  select(where(is.factor)) %>%
  summary()
```

```
##      id      sex      eye_color
## 1      : 1  intersex: 2  hazel:100
## 2      : 1  female  :149  blue : 99
## 3      : 1  male    :147  brown: 98
## 4      : 1  NA's    : 2  NA's : 3
## 5      : 1
## 6      : 1
## (Other):294
```

3.12.3 Numeric screening

For numeric variables, you should search for impossible values. For example, in the context of this example you want to ensure none of the `elapsed_times` are impossible or so large they appear to be data entry errors.

One options for doing so is the `summary` command again. This time, however, we use “`is.numeric`” in the `where()` command. However, when a survey has a large number of variables this type of output can become challenging to intrepret.

```
analytic_data_occasions %>%
  select(where(is.numeric)) %>%
  summary()
```

With larger numers of variables, it’s a good idea to use the `skimr` package.

Additionally, it makes sense to look at sets of items rather than all of the variables at once. This is because sometime items and different response formats. For example, for one measure this responses may range from 1 to 5 whereas for another measure responses could range from 1 to 7. This is undesirable from a psychometric point of view, as discussed previously, but it if happens it makes sense to look at items in sets.

Start by examining the range of non-scale items. In this case it's only age. Examine the output to see if any of the age values are unreasonable. In the output p0 and p100 indicate the 0th percentile and the 100th percentile; that is the min and max values for the variable. Check to make sure none of the age values are unreasonably low or high. If they are, you may need to check the original data source or replace them with missing values.

```
library(skimr)
analytic_data_occasions %>%
  select(age) %>%
  skim()
```

```
##   skim_variable n_missing mean   sd p0 p50 p100
## 1              age          3 20.52 2.05 17  20   24
```

Look the items in the first scale, self-esteem. Possible items responses for this scale range from 1 to 5, make sure they are all in this range. In the output p0 and p100 indicate the 0th percentile and the 100th percentile; that is the minimum and maximum values for the variable in these data. Examine the output to see if any of the esteem values are unreasonable (i.e., fall outside the 1 to 5 range). If any values fall outside this range, you may need to check the original data source or replace them with missing values - as described previously.

```
analytic_data_occasions %>%
  select(starts_with("t1_esteem")) %>%
  skim()
```

```
##       skim_variable n_missing mean   sd p0 p50 p100
## 1      t1_esteem1          24 3.39 0.54  3  3   5
## 2      t1_esteem2          28 2.35 0.48  2  2   3
## 3      t1_esteem3          31 3.96 0.37  3  4   5
## 4      t1_esteem4          15 3.54 0.50  3  4   4
## 5 t1_esteem5_rev15          35 2.22 0.47  1  2   3
```

Follow the same process t2_esteem items, t1_jobsat items, and t2_jobsat items. Possible items responses for these scale ranges from 1 to 5, make sure all responses are all in this range. If any values fall outside this range, you may

need to check the original data source or replace them with missing values - as described previously.

3.12.4 Scale scores

3.12.4.1 Reverse key items

Scale scores involve averaging, for each person, their score over several items to create an overall scale score. The first step in the creation of scales is correcting the values of any reverse-keyed items, as described previously. The logic of the math behind this correction is described previously in Surveys: Single occasion.

In these data, the items use a 1 to 5 response scale so we use the reverse item correction for response scales that begin with 1. See Surveys: Single occasion for how to handle a response format that begins with zero - the math is different.

The code below: * selects each column that ends with "_rev15" (i.e., both esteem and jobsat scales) * subtracts each value in that column from 6 * renames the column by removing "_rev15" because the reverse coding is complete.

```
# Reverse code items
analytic_data_occasions <- analytic_data_occasions %>%
  mutate(6 - across(.cols = ends_with("_rev15")) ) %>%
  rename_with(.fn = str_remove,
             .cols = ends_with("_rev15"),
             pattern = "_rev15")
```

3.12.4.2 Creating scores

The process we use for creating scale scores deletes item level data from `analytic_data_survey`. This is a desirable aspect of the process as it removes information we are no longer interested in from our analytic data. That said, before we create scale score, we create a backup on the item level data called `analytic_data_items`. We will need to use this backup later to compute the reliability of the scales we are creating.

```
analytic_occasions_items <- analytic_data_occasions
```

We want to make a self-esteem scale and plan to select items using `starts_with("esteem")`. But prior to doing this we make sure the `start_with()` command only gives us the items we want - and not additional unwanted

items. The output below confirms there are not problems associated with using `starts_with("esteem")`.

```
analytic_data_occasions %>%
  select(starts_with("t1_esteem")) %>%
  glimpse()

## Rows: 300
## Columns: 5
## $ t1_esteem1 <dbl> 3, 4, 4, 3, 3, 3, 3, 4, 4, 4, 3, 4, ...
## $ t1_esteem2 <dbl> 2, 3, 3, 2, 2, 3, 2, 3, 3, 3, 2, 2, ...
## $ t1_esteem3 <dbl> 4, 4, 4, 3, 4, 4, NA, 4, 4, 3, 4, 4, ...
## $ t1_esteem4 <dbl> 3, 4, 4, 3, 4, 4, 4, 4, 3, 4, NA, 4, ...
## $ t1_esteem5 <dbl> 4, 4, 4, 4, 4, NA, NA, 4, 4, 4, 3, 4, ...
```

Repeat this set of commands using `t2_esteem`, `t1_jobsat`, and `t2_jobsat`. Make sure that those terms select only the relevant items and not others.

```
analytic_data_occasions <- analytic_data_occasions %>%
  rowwise() %>%
  mutate(esteem_t1 = mean(c_across(starts_with("t1_esteem")),
                           na.rm = TRUE)) %>%
  mutate(esteem_t2 = mean(c_across(starts_with("t2_esteem")),
                           na.rm = TRUE)) %>%
  mutate(jobsat_t1 = mean(c_across(starts_with("t1_jobsat")),
                           na.rm = TRUE)) %>%
  mutate(jobsat_t2 = mean(c_across(starts_with("t2_jobsat")),
                           na.rm = TRUE)) %>%
  ungroup() %>%
  select(-starts_with("t1_esteem")) %>%
  select(-starts_with("t2_esteem")) %>%
  select(-starts_with("t1_jobsat")) %>%
  select(-starts_with("t2_jobsat"))
```

```
glimpse(analytic_data_occasions)
```

```
## Rows: 300
## Columns: 8
## $ id      <fct> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12...
## $ age     <dbl> 23, 22, 18, 23, 22, 17, 23, 22, 17, N...
## $ sex     <fct> male, female, male, female, male, fem...
## $ eye_color <fct> blue, brown, hazel, blue, NA, hazel, ...
## $ esteem_t1 <dbl> 3.200, 3.800, 3.800, 3.000, 3.400, 3....
```

```
## $ esteem_t2 <dbl> 3.8, 4.4, 4.4, 3.6, 4.0, 4.2, 3.6, 4....
## $ jobsat_t1 <dbl> 4.00, 5.00, 4.40, 3.50, 4.00, 3.80, 3...
## $ jobsat_t2 <dbl> 4.20, 4.40, 5.00, 4.20, 4.25, 4.40, 4...
```

3.12.5 Pivot to tidy data

But now comes the complicated point where you need to pivot the data to longer.

```
print(analytic_data_occasions)
```

```
## # A tibble: 300 x 8
##   id    age sex   eye_color esteem_t1 esteem_t2 jobsat_t1
##   <fct> <dbl> <fct> <fct>         <dbl>    <dbl>    <dbl>
## 1 1      23 male  blue          3.2      3.8      4
## 2 2      22 fema~ brown          3.8      4.4      5
## 3 3      18 male  hazel          3.8      4.4     4.4
## 4 4      23 fema~ blue           3      3.6     3.5
## 5 5      22 male  <NA>          3.4      4       4
## 6 6      17 fema~ hazel          3.5      4.2     3.8
## 7 7      23 male  blue           3      3.6     3.6
## 8 8      22 fema~ brown          3.8      4.4     4.6
## 9 9      17 male  hazel          3.6      4.2     3.75
## 10 10     NA fema~ blue           3.6      4.2     3.8
## # ... with 290 more rows, and 1 more variable:
## #   jobsat_t2 <dbl>
```

The `pivot_longer()` command below converts our data to the tidy data format. In this command we specify the columns with data by using `esteem_t1:jobsat_t2`, this selects these two columns and all of the columns between them. Each of these columns represents a dependent variable at a particular time in the format “variable_time” (e.g., `esteem_t1`). The code `names_to = c(“value”, “time”)` explains this format to R. It indicates first part of the column name contains the name of the variable (expressed in the code as “value”). It also indicates that the second part of the column name represents time. The line `names_sep = “_”` tells the R that the underscore character is used to separate the first part of the name from the second part of the name. When this code is executed it creates a tidy version of data set stored in `analytic_survey_tidy`.

```
analytic_occasion_tidy <- analytic_data_occasions %>%
  pivot_longer(esteem_t1:jobsat_t2,
```

```
names_to = c(".value", "time"),
names_sep = "_")
```

You can see the new data with the `print()` command. Notice that each participant has multiple rows associated with them.

```
print(analytic_occasion_tidy)
```

```
## # A tibble: 600 x 7
##   id    age sex   eye_color time  esteem jobsat
##   <fct> <dbl> <fct>   <fct>    <chr>   <dbl>   <dbl>
##  1 1      23 male   blue     t1       3.2     4
##  2 1      23 male   blue     t2       3.8     4.2
##  3 2      22 female brown    t1       3.8     5
##  4 2      22 female brown    t2       4.4     4.4
##  5 3      18 male   hazel    t1       3.8     4.4
##  6 3      18 male   hazel    t2       4.4     5
##  7 4      23 female blue     t1       3       3.5
##  8 4      23 female blue     t2       3.6     4.2
##  9 5      22 male   <NA>    t1       3.4     4
## 10 5      22 male   <NA>    t2       4       4.25
## # ... with 590 more rows
```

You now have three data sets. The data `analytic_occasion_tidy` is appropriate for conducting a repeated measures ANOVA. The data `analytic_data_occasions` is appropriate for calculating descriptive statistics and correlations. The data `analytic_occasions_items` is appropriate for calculating the reliability of the scales you constructed. These data are ready for analysis.

3.13 Basic descriptive statistics

3.13.1 `skim()`

One approach is the `skim()` command from the `skimr` package. This quickly provides the basic descriptive statistics. In the output for this command there are also several columns that begin with `p`: `p0`, `p25`, `p50`, `p75`, and `p100` (`p25` and `p75` omitted in output due to space). These columns correspond to the 0th, 25th, 50th, 75th, and 100th percentiles, respectively. The median is the 50th percentile. The interquartile range is the range between `p25` and `p75`. Notice that we run this command on the “wide” version of the

data (analytic_data_occasions) rather than tidy version of the data (analytic_occasion_tidy).

```
library(skimr)
skim(analytic_data_occasions)
```

```
##   skim_variable n_missing mean  sd   p0  p50  p100
## 1      age         3 20.52 2.05 17.0 20.0 24.00
## 2  esteem_t1         0  3.40 0.32  2.5  3.4  4.25
## 3  esteem_t2         0  3.93 0.34  3.2  4.0  4.80
## 4  jobsat_t1         0  3.91 0.43  2.0  4.0  5.00
## 5  jobsat_t2         0  4.37 0.42  3.0  4.4  5.25
```

3.13.2 apa.cor.table()

Another approach is the `apa.cor.table()` command from the `apaTables` package. This quickly provides the basic descriptive statistics as well as correlations among variable. As well, it will even create a Word document with this information, see Figure 3.6. Notice that we run this command on the “wide” version of the data (analytic_data_occasions) rather than tidy version of the data (analytic_occasion_tidy).

```
library(apaTables)
analytic_data_survey %>%
  select(where(is.numeric)) %>%
  apa.cor.table(filename = "apa_descriptives.doc")
```

Means, standard deviations, and correlations with confidence intervals

Variable	<i>M</i>	<i>SD</i>	1	2	3	4
1. age	20.52	2.05				
2. esteem_t1	3.40	0.32	-.04 [-.15, .08]			
3. esteem_t2	3.93	0.34	.01 [-.10, .13]	.84** [.80, .87]		
4. jobsat_t1	3.91	0.43	-.00 [-.12, .11]	.64** [.56, .70]	.56** [.48, .63]	
5. jobsat_t2	4.37	0.42	-.02 [-.13, .10]	.58** [.50, .65]	.52** [.43, .60]	.82** [.77, .85]

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). * indicates $p < .05$. ** indicates $p < .01$.

FIGURE 3.6: Word document created by `apa.cor.table`

3.13.3 tidyverse

A final approach uses tidyverse commands. This approach is oddly long - and we won't describe how it works in detail. But, based on the information in the previous chapter you should be able to work out how this code works. Even though this code is long - it provide the ultimate in flexibility. If a new statistics is development that you want to use, you can simply include the command for it in the `desired_descriptives` list and it will be included in your table. Notice that we run this command on the “wide” version of the data (`analytic_data_occasions`) rather than tidy version of the data (`analytic_occasion_tidy`).

```
library(tidyverse)
# HMisc package must be installed.
# Library command not needed for HMisc package.

desired_descriptives <- list(
  mean = ~mean(.x, na.rm = TRUE),
  CI95_LL = ~Hmisc::smean.cl.normal(.x)[2],
  CI95_UL = ~Hmisc::smean.cl.normal(.x)[3],
  sd = ~sd(.x, na.rm = TRUE),
  min = ~min(.x, na.rm = TRUE),
  max = ~max(.x, na.rm = TRUE),
  n = ~sum(!is.na(.x))
)

row_sum <- analytic_data_occasions %>%
  summarise(across(.cols = where(is.numeric),
    .fns = desired_descriptives,
    .names = "{col}__{fn}"))

long_summary <- row_sum %>%
  pivot_longer(cols = everything(),
    names_to = c("var", "stat"),
    names_sep = c("__"),
    values_to = "value")

summary_table <- long_summary %>%
  pivot_wider(names_from = stat,
    values_from = value)

summary_table_rounded <- summary_table %>%
  mutate(across(.cols = where(is.numeric),
    .fns= round,
```

```

        digits = 3)) %>%
  as.data.frame()

print(summary_table_rounded)

```

```

##           var   mean CI95_LL CI95_UL    sd min  max  n
## 1          age 20.522  20.288  20.756 2.048 17.0 24.00 297
## 2 esteem_t1   3.403   3.366   3.440 0.324  2.5  4.25 300
## 3 esteem_t2   3.927   3.889   3.966 0.337  3.2  4.80 300
## 4 jobsat_t1   3.905   3.856   3.955 0.435  2.0  5.00 300
## 5 jobsat_t2   4.368   4.320   4.416 0.425  3.0  5.25 300

```

3.13.4 Cronbach's alpha

If you want Cronbach's alpha to estimate the reliability of the scale, you can use the `alpha` command from the `psych` package with the code below. Note we have to use the item level data we created a copy of, called `analytic_data_items`. The `glimpse()` command illustrates this file has all the original items (after reverse-coding has been fixed).

```

analytic_data_items %>%
  glimpse()

```

```

## Rows: 300
## Columns: 14
## $ id      <fct> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12...
## $ age     <dbl> 23, 22, 18, 23, 22, 17, 23, 22, 17, N...
## $ sex     <fct> male, female, male, female, male, fem...
## $ eye_color <fct> blue, brown, hazel, blue, NA, hazel, ...
## $ esteem1 <dbl> 3, 4, 4, 3, 3, 3, 3, 4, 4, 4, 3, 4, N...
## $ esteem2 <dbl> 2, 3, 3, 2, 2, 3, 2, 3, 3, 3, 2, 2, N...
## $ esteem3 <dbl> 4, 4, 4, 3, 4, 4, NA, 4, 4, 3, 4, 4, ...
## $ esteem4 <dbl> 3, 4, 4, 3, 4, 4, 4, 4, 4, 3, 4, NA, 4, ...
## $ esteem5 <dbl> 4, 4, 4, 4, 4, NA, NA, 4, 4, 4, 3, 4,...
## $ jobsat1 <dbl> 3, 5, 4, 3, 3, 3, 3, 5, 3, 3, 3, 4, 4...
## $ jobsat2 <dbl> 5, 5, 5, NA, 5, 5, 4, 5, 4, 4, 3, 5, ...
## $ jobsat3 <dbl> 3, NA, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, ...
## $ jobsat4 <dbl> NA, 5, 5, 4, 4, 4, 4, 5, NA, 4, NA, 5...
## $ jobsat5 <dbl> 5, NA, 5, 4, 5, 4, 4, 5, 5, 5, 4, NA,...

```

We calculated reliability using `psych::alpha()` command. Cronbach's alpha is labeled "raw alpha" in the output. Cronbach's alpha is an estimate of the

proportion of variability in observed scores that is due to actual differences among participants (rather than measurement error).

```
rx_alpha <- analytic_occasions_items %>%
  select(starts_with("t1_esteem")) %>%
  psych::alpha()

print(rx_alpha$total)
```

```
## raw_alpha std.alpha G6(smc) average_r S/N ase mean
## 0.6622 0.6634 0.6173 0.2827 1.97 0.03035 3.403
## sd median_r
## 0.3239 0.2927
```



A

More to Say

Yeah! I have finished my book, but I have more to say about some topics. Let me explain them in this appendix.

To know more about **bookdown**, see <https://bookdown.org>.



Bibliography

- Baker, M. (2016). 1500 scientists lift the lid on reproducibility. *Nature*, 533.
- Meyer, J. P., Allen, N. J., and Smith, C. A. (1993). Commitment to organizations and occupations: Extension and test of a three-component conceptualization. *Journal of applied psychology*, 78(4):538.
- Miyakawa, T. (2020). No raw data, no science: another possible source of the reproducibility crisis. *Mol Brain*, 13(24).
- Nosek (2015). Estimating the reproducibility of psychological science. *Science*, 349.
- Patil P., Peng R.D., . L. J. (2019). A visual tool for defining reproducibility and replicability. *Nat Hum Behav*, 3:650–652.
- Simmons, J. P., Nelson, L. D., and Simonsohn, U. (2011). False-positive psychology: Undisclosed flexibility in data collection and analysis allows presenting anything as significant. *Psychological science*, 22(11):1359–1366.
- Wickham, H. (2014). Tidy data. *The Journal of Statistical Software*, 59.
- Xie, Y. (2015). *Dynamic Documents with R and knitr*. Chapman and Hall/CRC, Boca Raton, Florida, 2nd edition. ISBN 978-1498716963.
- Xie, Y. (2020). *bookdown: Authoring Books and Technical Documents with R Markdown*. R package version 0.19.1.



Index

bookdown, [ix](#)

date format, [7](#)

knitr, [ix](#)

R Studio Cloud, [2](#), [7](#)

tidyverse, [7](#)