Using R at Grattan Institute

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Contents

Welcome

This guide is designed for everyone who uses – or would like to use – R at Grattan Institute.

It does two main things:

1. Shows you how to use R to complete common analytical tasks you'll face at Grattan.
2. Sets out some guidelines and good practices when using R at Grattan.

As a guide to using R, this website is helpful but incomplete. We can't possibly cover - or anticipate - all the skills you might need to know. If you make it to the end of this guide and want to learn more, start by reading R for Data Science by Hadley Wickham and Garrett Grolemund. It's free.

Any complaints or comments about this guide can be sent to Matt or Will, respectively.

Chapter 1

Introduction to R

Most people reading this guide will know what R is. But if you don't - that's OK!

If you have used R before and are comfortable enough with it, you might want to skip to the next page. This page is intended for people who are unfamiliar with R.

1.1 What is R?

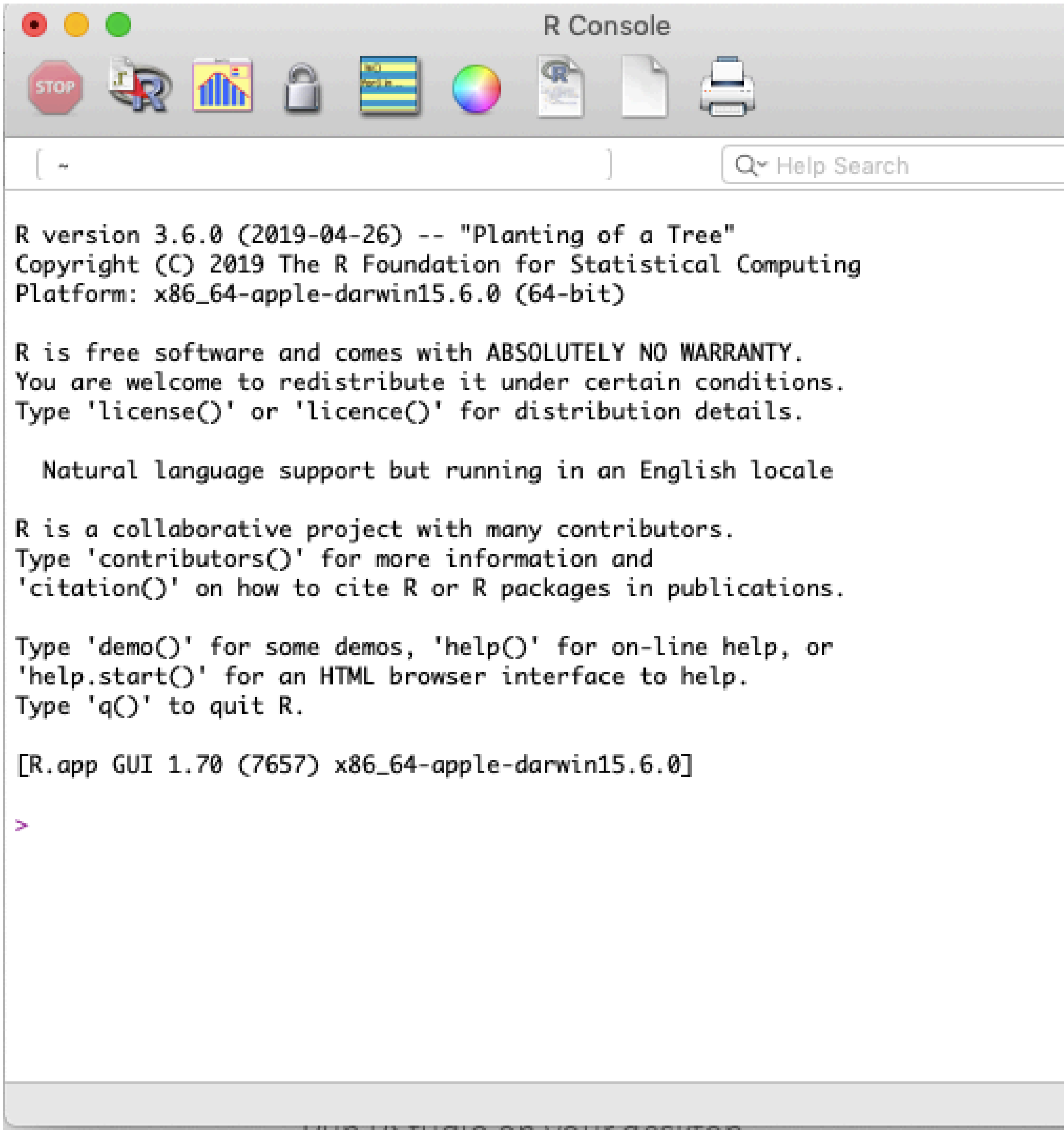
R is a programming language that is designed by and for statisticians, data scientists, and other people who work with data. It's free - you can download R at no charge. It's also open source - you can view and (if you're game) modify the code that underlies the R language. R is available for all major computing platforms including Windows, macOS, and Linux.

R has a lot in common with other statistical software like SAS, Stata, SPSS or Eviews. You can use those software packages to read data, manipulate it, generate summary statistics, estimate models, and so on. You can use R for all those things and more. You interact with R by writing code. This is a little different to Stata or SPSS, which allow you to do at least part of your analyses by clicking on menus and buttons. This means the initial learning curve for R can be a little steeper than for something like SPSS, but there are great benefits to a code-based approach to data analysis (see the next page for more on this).

R also has some overlap with general purpose programming languages like Python. But R is more focused on the sort of tasks that statisticians, data scientists, and academic researchers do.

R is quite old, having been first released publicly in 1995, but it's also growing and changing rapidly. A lot of developments in R come in the form of new add-on pieces of software - known as 'packages' - that extend R's functionality in some way. We cover packages more later in this page.

When you open R itself, you're confronted with a few disclaimers and a command prompt, similar in appearance to the Terminal on macOS or command prompt in Windows.


R Console
STOP
Help Search
~
R version 3.6.0 (2019-04-26) -- "Planting of a Tree"
Copyright (C) 2019 The R Foundation for Statistical Computing
Platform: x86_64-apple-darwin15.6.0 (64-bit)
R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.
Natural language support but running in an English locale
R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.
Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.
[R.app GUI 1.70 (7657) x86_64-apple-darwin15.6.0]
>

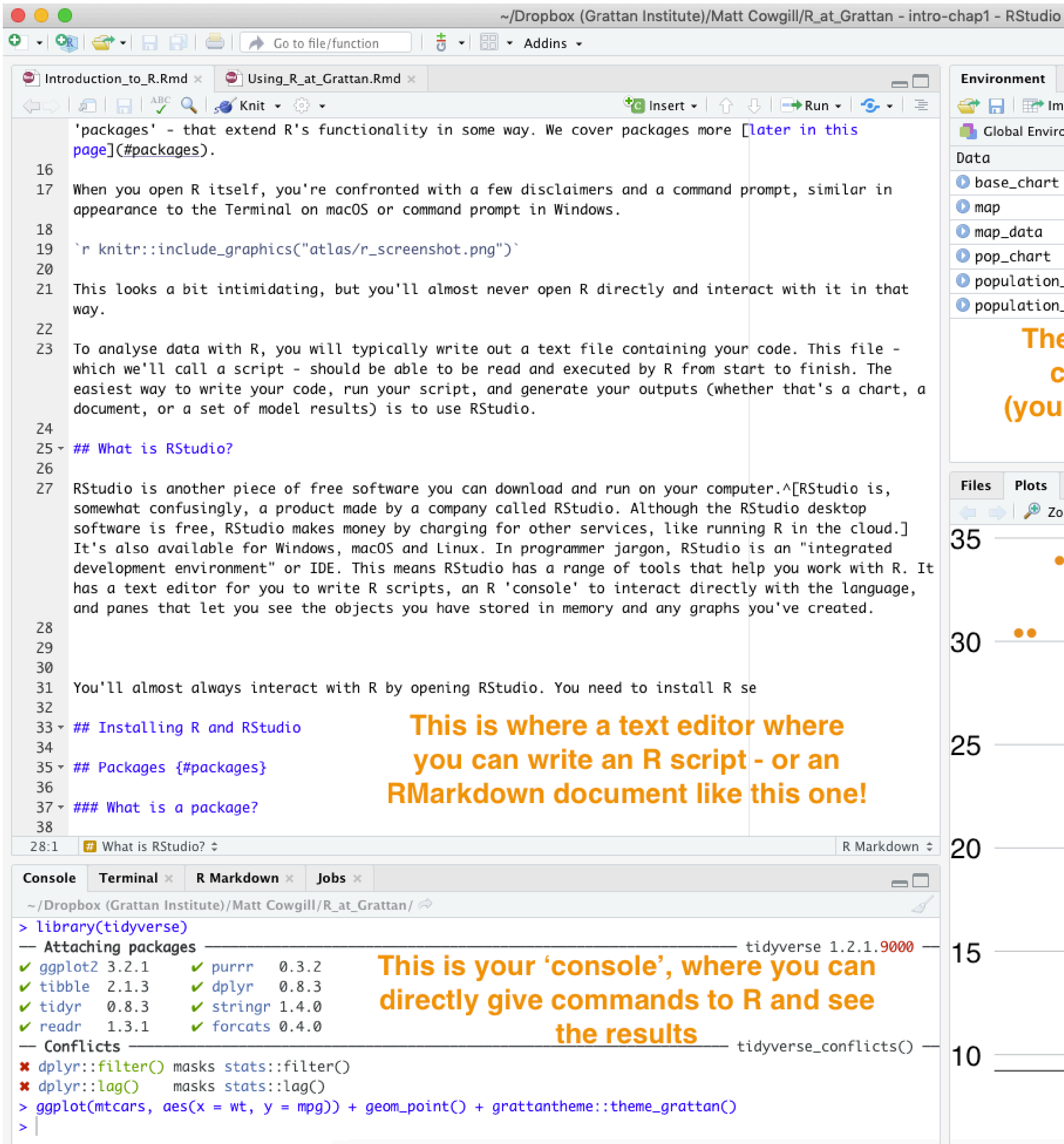
This looks a bit intimidating, but you'll almost never open R directly and interact with it in that way.

To analyse data with R, you will typically write out a text file containing your code. This file - which we'll call a script - should be able to be read and executed by R from start to finish. The easiest way to write your code, run your script, and generate your outputs (whether that's a chart, a document, or a set of model results) is to use RStudio.

1.2 What is RStudio?

RStudio is another piece of free software you can download and run on your computer.[1] It's also available for Windows, macOS and Linux. In programmer jargon, RStudio is an "integrated development environment" or IDE. This means RStudio has a range of tools that help you work with R. It has a text editor for you to write R scripts, an R 'console' to interact directly with the language, and panes that let you see the objects you have stored in memory and any graphs you've created.

[1] RStudio is, somewhat confusingly, a product made by a company called RStudio. Although the RStudio desktop software is free, RStudio makes money by charging for other services, like running R in the cloud. When we refer to RStudio, we're referring to the desktop software unless we make it clear that we mean the company.


~/Dropbox (Grattan Institute)/Matt Cowgill/R_at_Grattan - intro-chap1 - RStudio
Go to file/function
Addins
Introduction_to_R.Rmd
Using_R_at_Grattan.Rmd
Knit
Insert
Run
'packages' - that extend R's functionality in some way. We cover packages more [later in this page](#packages).
When you open R itself, you're confronted with a few disclaimers and a command prompt, similar in appearance to the Terminal on macOS or command prompt in Windows.
`r knitr::include_graphics("atlas/r_screenshot.png")`
This looks a bit intimidating, but you'll almost never open R directly and interact with it in that way.
To analyse data with R, you will typically write out a text file containing your code. This file - which we'll call a script - should be able to be read and executed by R from start to finish. The easiest way to write your code, run your script, and generate your outputs (whether that's a chart, a document, or a set of model results) is to use RStudio.
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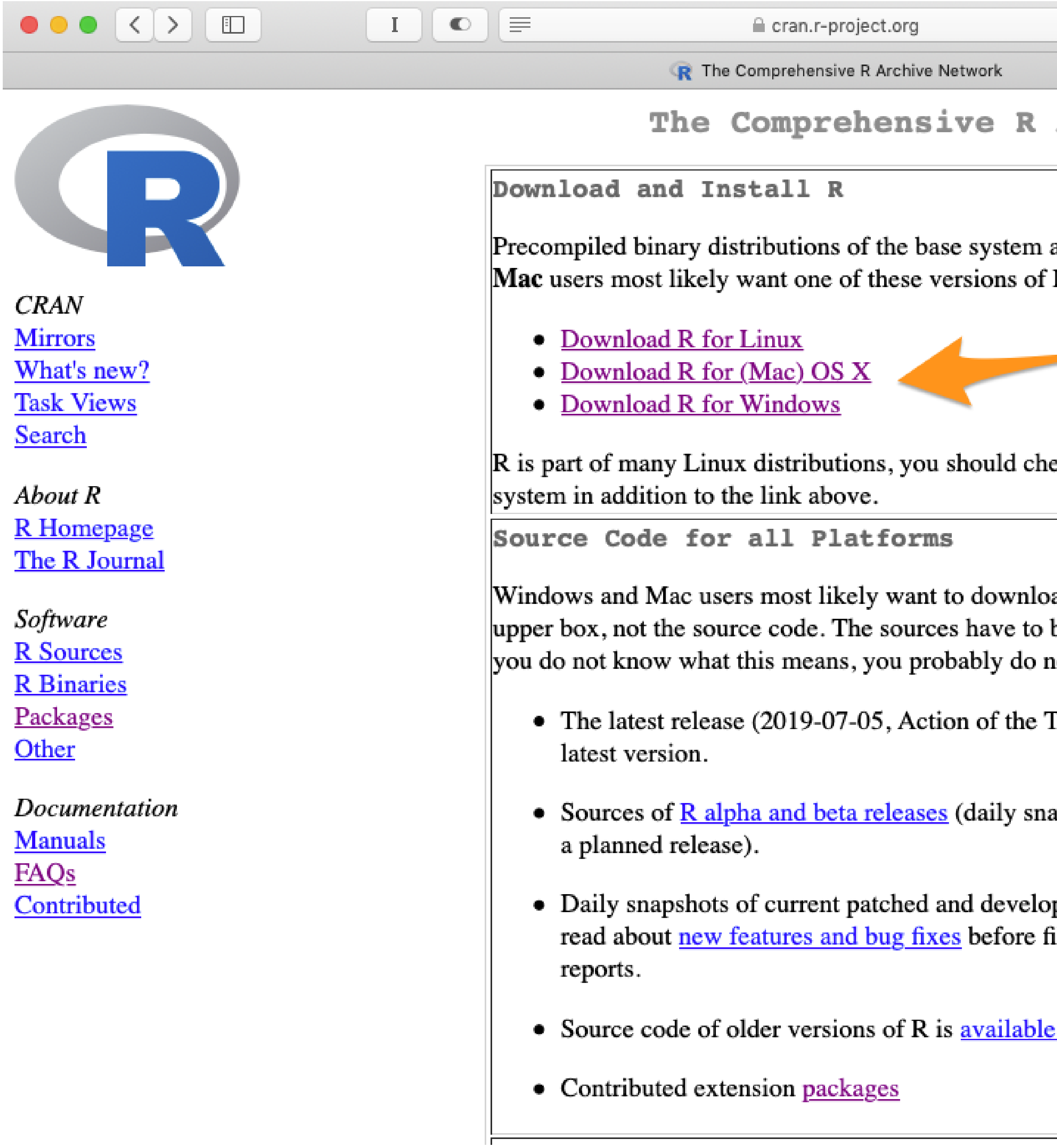
You'll almost always interact with R by opening RStudio. You need to install R se
Installing R and RStudio
Packages {#packages}
What is a package?
This is where a text editor where you can write an R script - or an RMarkdown document like this one!
28:1
What is RStudio?
R Markdown
Console
Terminal
R Markdown
Jobs
~/Dropbox (Grattan Institute)/Matt Cowgill/R_at_Grattan/
> library(tidyverse)
── Attaching packages ── tidyverse 1.2.1.9000 ──
✔ ggplot2 3.2.1 ✔ purrr 0.3.2
✔ tibble 2.1.3 ✔ dplyr 0.8.3
✔ tidyr 0.8.3 ✔ stringr 1.4.0
✔ readr 1.3.1 ✔ forcats 0.4.0
── Conflicts ── tidyverse_conflicts() ──
✖ dplyr::filter() masks stats::filter()
✖ dplyr::lag() masks stats::lag()
> ggplot(mtcars, aes(x = wt, y = mpg)) + geom_point() + grattantheme::theme_grattan()
This is your 'console', where you can directly give commands to R and see the results
Environment
Global Enviro
Data
base_chart
map
map_data
pop_chart
Files
Plots
35
30
25
20
15
10

You'll almost always interact with R by opening RStudio.

1.3 Installing R and RStudio

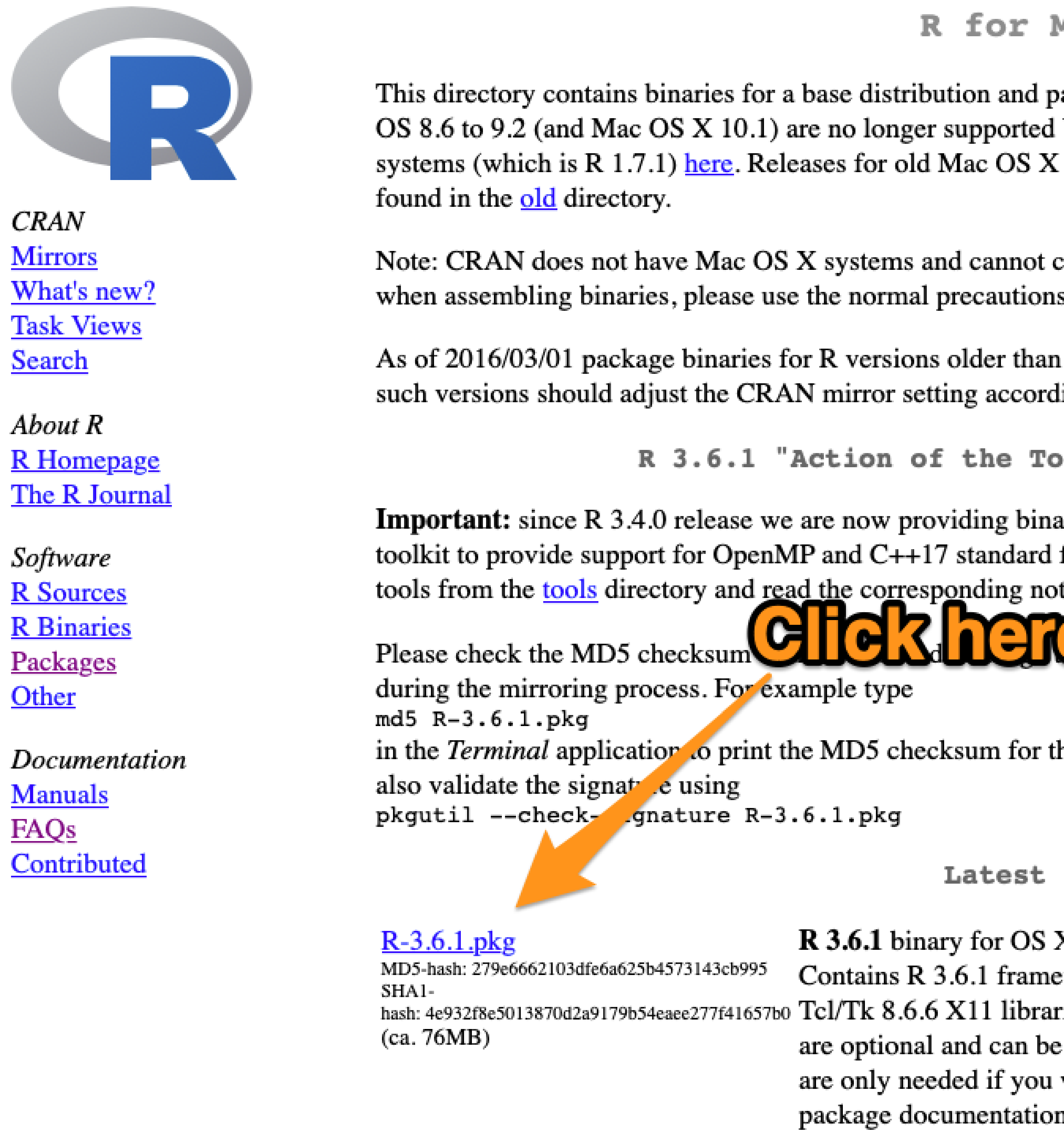
Although you'll usually work with R by opening RStudio, you need to install both R and RStudio separately.

Install R by going to CRAN, the Comprehensive R Archive Network. CRAN is a community-run website that houses R itself as well as a broad range of R packages.

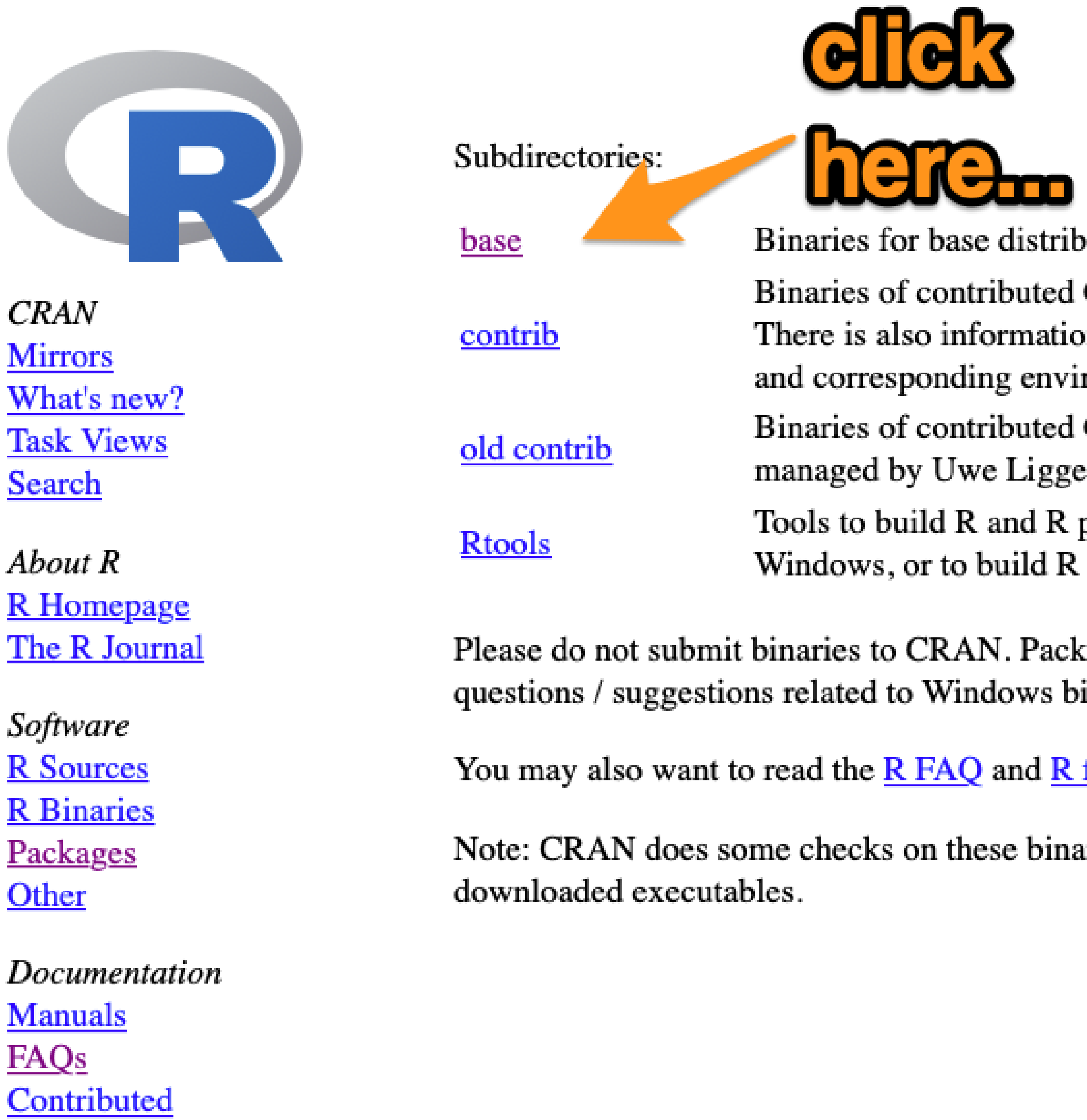

cran.r-project.org
The Comprehensive R Archive Network
The Comprehensive R
CRAN
Mirrors
What's new?
Task Views
Search
About R
R Homepage
The R Journal
Software
R Sources
R Binaries
Packages
Other
Documentation
Manuals
FAQs
Contributed
Download and Install R
Precompiled binary distributions of the base system a
Mac users most likely want one of these versions of
Download R for Linux
Download R for (Mac) OS X
Download R for Windows
R is part of many Linux distributions, you should che
system in addition to the link above.
Source Code for all Platforms
Windows and Mac users most likely want to downloa
upper box, not the source code. The sources have to b
you do not know what this means, you probably do n
The latest release (2019-07-05, Action of the T
latest version.
Sources of R alpha and beta releases (daily sna
a planned release).
Daily snapshots of current patched and develop
read about new features and bug fixes before fi
reports.
Source code of older versions of R is available
Contributed extension packages

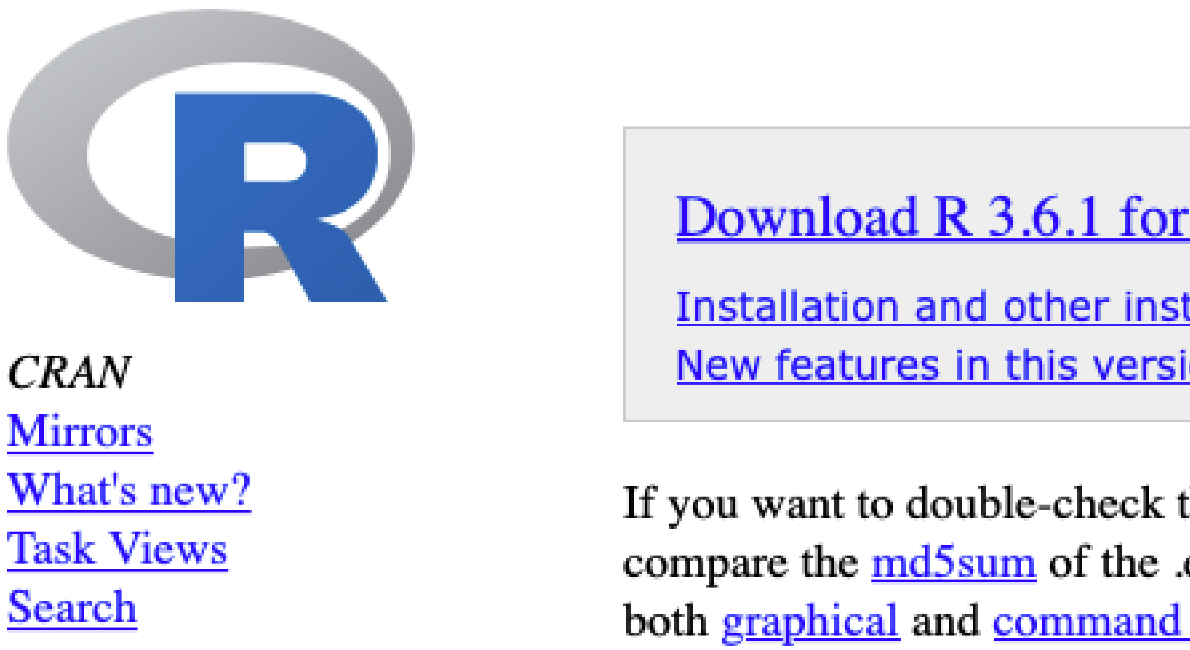
You want to download the latest base R release, as a ‘binary’. Don’t worry, you don’t need to know what a binary is.

For macOS, the page will look like this:


CRAN
Mirrors
What's new?
Task Views
Search
About R
R Homepage
The R Journal
Software
R Sources
R Binaries
Packages
Other
Documentation
Manuals
FAQs
Contributed
R for M
This directory contains binaries for a base distribution and pa
OS 8.6 to 9.2 (and Mac OS X 10.1) are no longer supported
systems (which is R 1.7.1) here. Releases for old Mac OS X
found in the old directory.
Note: CRAN does not have Mac OS X systems and cannot c
when assembling binaries, please use the normal precautions
As of 2016/03/01 package binaries for R versions older than
such versions should adjust the CRAN mirror setting accordi
R 3.6.1 "Action of the To
Important: since R 3.4.0 release we are now providing bina
toolkit to provide support for OpenMP and C++17 standard
tools from the tools directory and read the corresponding not
Click here
Please check the MD5 checksum
during the mirroring process. For example type
md5 R-3.6.1.pkg
in the Terminal application to print the MD5 checksum for th
also validate the signature using
pkgutil --check-signature R-3.6.1.pkg
Latest
R-3.6.1.pkg
MD5-hash: 279e6662103dfe6a625b4573143cb995
SHA1-
hash: 4e932f8e5013870d2a9179b54eaee277f41657b0
(ca. 76MB)
R 3.6.1 binary for OS X
Contains R 3.6.1 frame
Tcl/Tk 8.6.6 X11 librar
are optional and can be
are only needed if you
package documentation

For Windows, you'll need to click on the 'base' version, and then click again to start the download.


click here...
CRAN
Mirrors
What's new?
Task Views
Search
About R
R Homepage
The R Journal
Software
R Sources
R Binaries
Packages
Other
Documentation
Manuals
FAQs
Contributed
Subdirectories:
base
Binaries for base distrib
contrib
Binaries of contributed
There is also informatio
and corresponding envi
old contrib
Binaries of contributed
managed by Uwe Ligge
Rtools
Tools to build R and R p
Windows, or to build R
Please do not submit binaries to CRAN. Pack
questions / suggestions related to Windows bi
You may also want to read the R FAQ and R
Note: CRAN does some checks on these bina
downloaded executables.



Once you've installed R, you'll need to install RStudio. Go to the RStudio website and install the latest version of RStudio Desktop (open source license).

Once they're both installed, get started by opening RStudio.

1.4 Packages

R comes with a lot of functions - commands - built in to do a broad range of data tasks. You could, if you really wanted, import a dataset, clean it up, estimate a model, and make a plot all using the functions that come with R - known as 'base R'[2].

But a lot of our work at Grattan uses add-on software to base R, known as 'packages'. Some packages, like the popular 'dplyr', make it quicker and/or easier to do tasks that you could otherwise do in base R. Other packages expand the possibilities of what R can do - like fitting a machine learning model, for example.

Like R itself, packages are free and open source. You can install them from within RStudio.

[2]Technically some of the 'built-in' functions are part of packages, like the `tools`, `utils` and `stats` packages that come with R. We'll refer to all these as base R.

At Grattan, we make heavy use of a set of related packages known collectively as the `tidyverse`. We'll cover these more in a later chapter.

1.4.1 Installing packages

You'll typically install packages using the console in RStudio. That's the part of the window that, by default, sits in the bottom-left corner of the screen.

In our work at Grattan, we use packages from two different source: CRAN and Github. The main difference you need to know about is that we use different commands to install packages from these two sources.

To install a package from CRAN, we use the command `install.packages()`.

For example, this code will install the `ggplot2` package from CRAN:

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

To install a package from Github, we use the function `install_github()`. Unfortunately, this package doesn't come with R - it's part of the `devtools` package. First, we install devtools from CRAN:

```
install.packages("devtools")
```

Now we can install packages from Github using the `install_github()` function from the `devtools` package. For example, here's how we would install the Grattan ggplot2 theme, which we'll discuss later in this website:

```
devtools::install_github("mattcowgill/grattantheme", dependencies = TRUE)
```

1.4.2 Using packages

Before using a function that comes from a package, as opposed to base R, you need to tell R where to look for the function. There are two main ways to do that.

We can either load (aka 'attach') the package by using the `library()` function:

```
library(devtools)

# Now that the `devtools` package is loaded, we can use its `install_github()` function:

install_github("mattcowgill/grattantheme")
```

Or, we can use two colons - `::` - to tell R to use an individual function from a package without loading it:

```
devtools::install_github("mattcowgill/grattantheme")
```

It usually makes sense to load a package with `library()`, unless you only need to use one of its function once or twice. There's no harm to using the `::` operator even if you have already loaded a package with `library()`. This can remove ambiguity both for R and for humans reading your code, particularly if you're using an obscure function - it makes it clearer where the function comes from.

Chapter 2

Why use R?

We can break this question into two parts: 1. Why use script-based software to analyse data? 2. Why use R, specifically?

2.1 Why use script-based software?

1. Make your analysis reproducible by setting out the complete series of steps taken from raw data to final output.
2. Work with large data sets.

2.2 Why use R specifically?

```
library(tidyverse)
```

Chapter 3

Using R at Grattan

3.1 Using R projects for a fully reproducible workflow.

Finally adhering to the 'hit by a bus' rule.

Having a clear, consistent structure for our analyses means that our work is more easily checked and revised, including by ourselves in the future. A small investment of time up front to set up your analysis will save time (your own and others') down the track.

Cover: 1. setwd() and machine-speficic filepaths are bad 2. relative file paths are good 3. RStudio projects are an easy, reproducible way to set your wd

3.1.1 Filepaths

Filepaths should be relative to the working directory, and the working directory should be set by the project.

Good

```
hes <- read_csv("data/HES/hes1516.csv")
grattan_save("images/expenditure_by_income.pdf")
```

Bad

```
hes <- read_csv("/Users/mcowgill/Desktop/hes1516.csv")
hes <- read_csb("C:\Users\mcowgill\Desktop\hes1516.csv")
grattan_save("/Users/mcowgill/Desktop/images/expenditure_by_income.pdf")
```

3.1.2 Keep your scripts manageable

As a general rule of thumb, use one script per output. It should be clear what your script is trying to do (use comments!).

Consider breaking your analysis into pieces. For example:

- 01_import.R
- 02_tidy.R
- 03_model.R
- 04_visualise.R

Don't include interactive work (like `View(mydf)`, `str(mydf)`, `mean(mydf$variable)`, etc.) in your saved script.

3.1.3 Use subfolders of your project folder

Remember the hit-by-a-bus rule. It should be easy for any Grattan colleague to open your project folder and get up to speed with what it does. Putting all your files - raw data, scripts, output - in the one folder makes it harder to understand how your work fits together.

Use subfolders to clearly separate your code, raw data, and output.

3.2 Grattan coding style guide

Short summary of why

Link to style guide

3.3 What is the tidyverse and why do we use it?

Introduce following chapters

3.4 An introduction to RMarkdown

3.5 Resources in this package

- Starting a piece of analysis 'cheat sheet'.
- Updated style guide.
- Written guide/slides.

Chapter 4

Data Visualisation

This chapter explores data visualisation broadly, and how to 'do' data visualisation in R specifically.

The next chapter – the Visualisation Cookbook – gives more practical advice for the charts you might want to create.

4.1 Introduction to data visualisation

You can use data visualisation to **examine and explore** your data, and to **present** a finding to your audience. Both of these elements are important.

When you start using a dataset, you should look at it.[1] Plot histograms of variables-of-interest to spot outliers. Explore correlations between variables with scatter plots and lines-of-best-fit. Check how many observations are in particular groups with bar charts. Identify variables that have missing or coded-missing values. Use faceting to explore differences in the above between groups, and do it interactively with non-static plots.

These **exploratory plots** are just for you and your team. They don't need to be perfectly labelled, the right size, in the Grattan palette, or be particularly interesting. They're built and used only to help you and your team explore the data. Through this process, you can become confident your data is *what you think it is.*

When you choose to **present a visualisation to a reader**, you have to make decisions about what they can and cannot see. You need to highlight or omit

[1] From Kieran Healy's *Data Vizualization: A Practical Introduction*: 'You should look at your data. Graphs and charts let you explore and learn about the structure of the information you collect. Good data visualizations also make it easier to communicate your ideas and findings to other people.'

particular things to help them better understand the message you are presenting.

This requires important *technical* decisions: what data to use, what 'stat' to present it with — *show every data point, show a distribution function, show the average or the median?* — and on what scale — *raw numbers, on a log scale, as a proportion of a total?*.

It also requires *aesthetic* decisions. What colours in the Grattan palette would work best? Where should the labels be placed and how could they be phrased to succinctly convey meaning? Should data points be represented by lines, or bars, or dots, or balloons, or shades of colour?

All of these decisions need to made with two things in mind:

1. Rigour, accuracy, legitimacy: the chart needs to be honest.
2. The reader: the chart needs to help the reader understand something, and it must convince them to pay attention.

At the margins, sometimes these two ideas can be in conflict. Maybe a 70-word definition in the middle of your chart would improve its technical accuracy, but it could confuse the average reader and reduce the chart's impact.

Similarly, a bar chart is often the safest way to display data. Like our prose, our charts need to be designed for an interested teenager. But we need to *earn* their interest. If your reader has seen four similar bar charts in a row and has stopped paying attention by the fifth, your point loses its punch.[2]

The way we design charts – much like our writing – should always be honest, clear and engaging to the reader.

This chapter shows how you can do this with R. It starts with the 'grammar of graphics' concepts of a package called `ggplot`, and explains how to make those charts 'Grattan-y'. The next chapter gives you the when-to-use and how-to-make particular charts.

4.2 Set-up and packages

This section uses the package `ggplot2` to visualise data, and `dplyr` functions to manipulate data. Both of these packages are loaded with `tidyverse`. The `scales` package helps with labelling your axes.

The `grattantheme` package is used to make charts look Grattan-y. The `absmapsdata` package is used to help make maps.

```
library(tidyverse)
library(grattantheme)
```

[2]'Bar charts are evidence that you are dead inside' – Amanda Cox, data editor for the New York Times.

```
library(ggrepel)
library(scales)
```

For most charts in this chapter, we'll use the `sa3_income` data summarised below.[3] It is a long dataset containing the median income and number of workers by SA3, occupation and sex between 2010 and 2015. We will also create a `professionals` subset that only includes people in professional occupations in 2015:

```
sa3_income <- read_csv("data/sa3_income.csv")

professionals <- sa3_income %>%
  select(-sa4_name, -gcc_name) %>%
  filter(year == 2015,
         occupation == "Professionals",
         !is.na(median_income),
         !sex == "Persons")

# Show the first six rows of the new dataset
head(professionals)
```

```
## # A tibble: 6 x 9
##     sa3 sa3_name sa3_sqkm occupation sex    year median_income
##   <dbl> <chr>       <dbl> <chr>      <chr> <dbl>         <dbl>
## 1 10102 Queanbe~    6511. Professio~ Fema~  2015         76203
## 2 10102 Queanbe~    6511. Professio~ Males  2015         99528
## 3 10103 Snowy M~   14283. Professio~ Fema~  2015         62424
## 4 10103 Snowy M~   14283. Professio~ Males  2015         81856
## 5 10104 South C~    9865. Professio~ Fema~  2015         56986
## 6 10104 South C~    9865. Professio~ Males  2015         72664
## # ... with 2 more variables: average_income <dbl>, workers <dbl>
```

4.3 Concepts

The `ggplot2` package is based on the **g**rammar of **g**raphics. …

The main ingredients to a `ggplot` chart are:

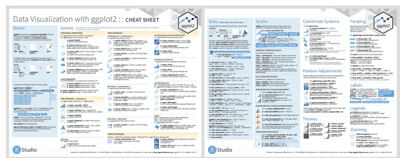
- **Data**: what data should be plotted.
  - e.g. `data`
- **Aesthetics**: what variables should be linked to what chart elements.
  - e.g. `aes(x = population, y = age)` to connect the `population` variable to the `x` axis, and the `age` variable to the `y` axis.
- **Geoms**: how the data should be plotted.

[3] From ABS Employee income by occupation and sex, 2010-11 to 2015-16

  - e.g. `geom_point()` will produce a scatter plot, `geom_col` will produce a column chart, `geom_line()` will produce a line chart.

Each plot you make will be made up of these three elements. The full list of standard geoms is listed in the `tidyverse` documentation.

`ggplot` also has a 'cheat sheet' that contains many of the often-used elements of a plot, which you can download here.



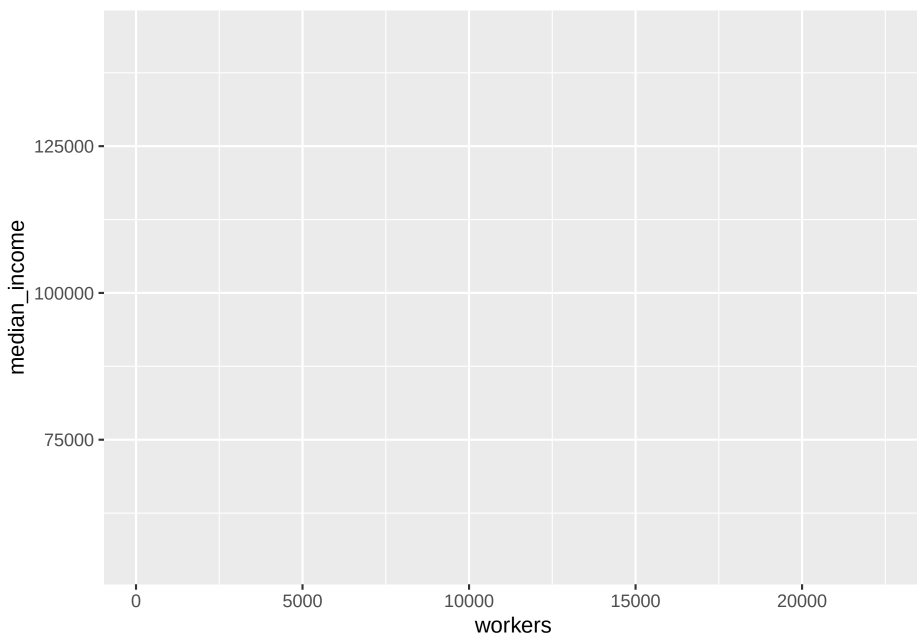
For example, you can plot a column chart by passing the `sa3_income` dataset into `ggplot()` ("make a chart with this data"). This completes the first step – data – and produces an empty plot:

```
professionals %>%
        ggplot()
```


Next, set the `aes` (aesthetics) to `x = state` ("make the x-axis represent state"), `y = pop` ("the y-axis should represent population"), and `fill = year` ("the fill colour represents year"). Now `ggplot` knows where things should *go*.

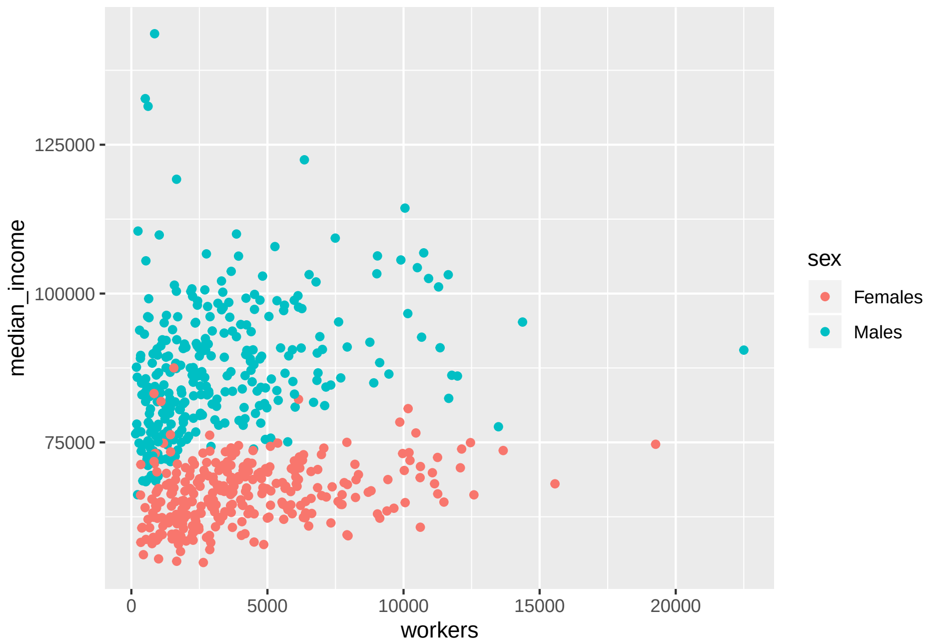
If we just plot that, you'll see that `ggplot` knows a little bit more about what we're trying to do. It has the states on the x-axis and range of populations on the y-axis:

```
professionals %>%
        ggplot(aes(x = workers,
                   y = median_income,
                   colour = sex))
```



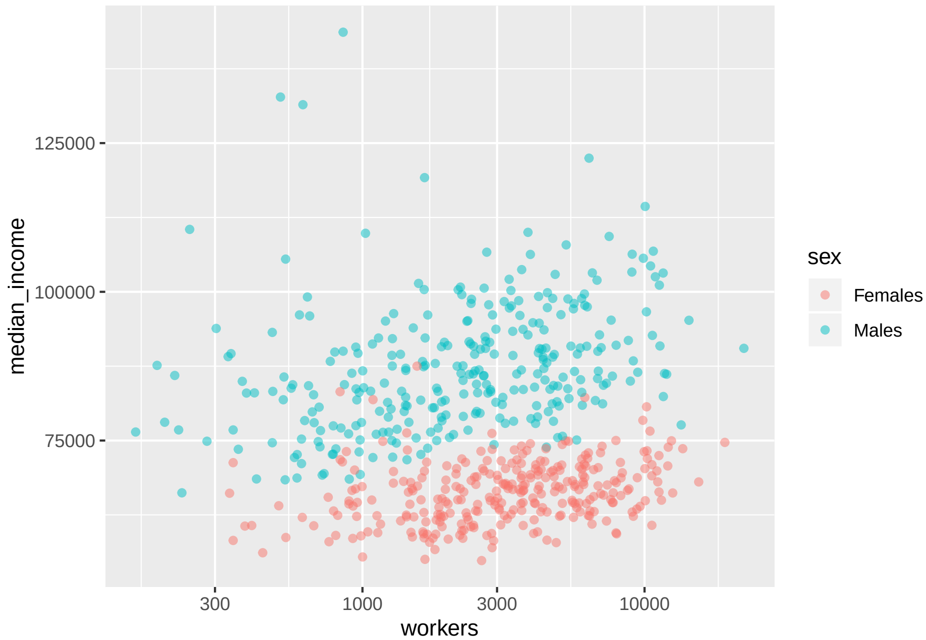
Now that `ggplot` knows where things should go, it needs to how to *plot* them on the chart. For this we use `geoms`. Tell `ggplot` to take the things it knows and plot them as a column chart by using `geom_col`:

```
professionals %>%
        ggplot(aes(x = workers,
                   y = median_income,
                   colour = sex)) +
        geom_point()
```



Great! There are a couple of quick things we can do to make the chart a bit clearer. There are points for each group in each year, which we probably don't need. So filter the data before you pass it to `ggplot` to just include 2015: `filter(year == 2015)`. There will still be lots of overlapping points, so set the opacity to below one with `alpha = 0.5`. The `workers` x-axis can be changed to a log scale with `scale_x_log10`.

```
professionals %>%
        ggplot(aes(x = workers,
                   y = median_income,
                   colour = sex)) +
        geom_point(alpha = .5) +
        scale_x_log10()
```



That looks a bit better. The following sections in this chapter will cover a broad range of charts and designs, but they will all use the same building-blocks of `data`, `aes`, and `geom`.

The rest of the chapter will explore:

- Exploratory data visualisation
- Grattanising your charts and choosing colours
- Saving charts according to Grattan templates
- Making bar, line, scatter and distribution plots
- Making maps and interactive charts
- Adding chart labels

4.4 Exploratory data visualisation

Plotting your data early in the analysis stage can help you quickly identify outliers, oddities, things that don't look quite right.

4.5 Making Grattan-y charts

The `grattantheme` package contains functions that help *Grattanise* your charts. It is hosted here: https://github.com/mattcowgill/grattantheme

You can install it with `remotes::install_github` from the package:

```
install.packages("remotes")
remotes::install_github("mattcowgill/grattantheme")
```

The key functions of `grattantheme` are:

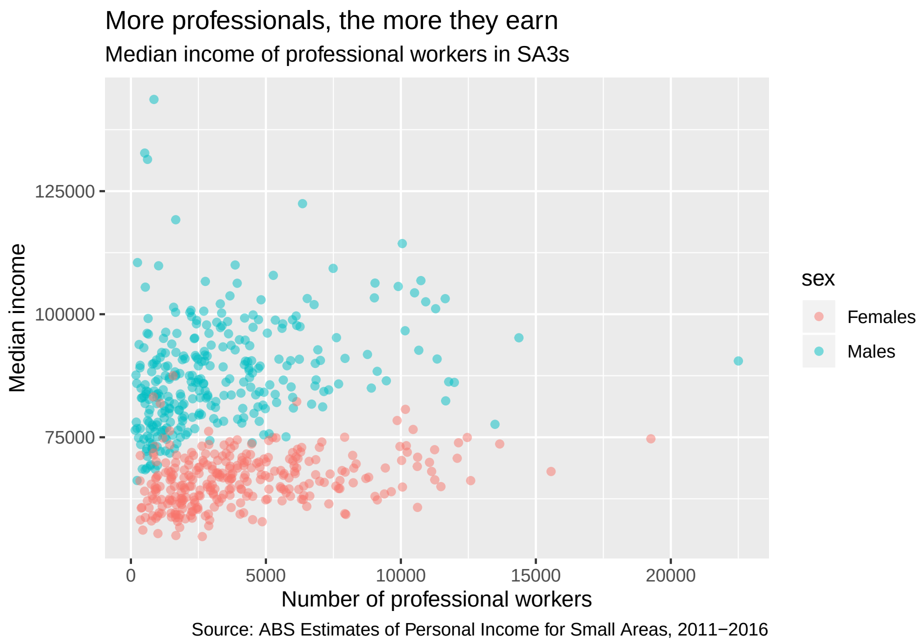
- `theme_grattan`: set size, font and colour defaults that adhere to the Grattan style guide.
- `grattan_y_continuous`: sets the right defaults for a continuous y-axis.
- `grattan_colour_continuous`: pulls colours from the Grattan colour palette for `colour` aesthetics.
- `grattan_fill_continuous`: pulls colours from the Grattan colour palette for `fill` aesthetics.
- `grattan_save`: a save function that exports charts in correct report or presentation dimensions.

This section will run through some examples of *Grattanising* charts. The `ggplot` functions are explored in more detail in the next section.

4.5.1 Making Grattan charts

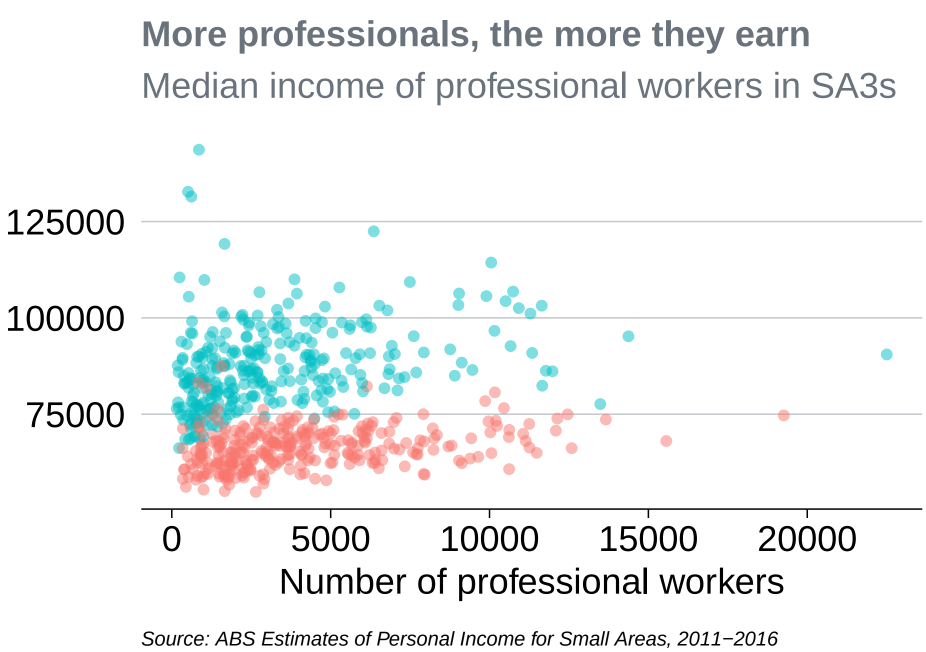
Start with a scatterplot, similar to the one made above:

```
base_chart <- professionals %>%
        ggplot(aes(x = workers,
                   y = median_income,
                   colour = sex)) +
        geom_point(alpha = .5) +
        labs(title = "More professionals, the more they earn",
             subtitle = "Median income of professional workers in SA3s",
             x = "Number of professional workers",
             y = "Median income",
             caption = "Source: ABS Estimates of Personal Income for Small Areas, 2011

base_chart
```



Let's make it Grattany. First, add `theme_grattan` to your plot:

```
base_chart +
        theme_grattan()
```



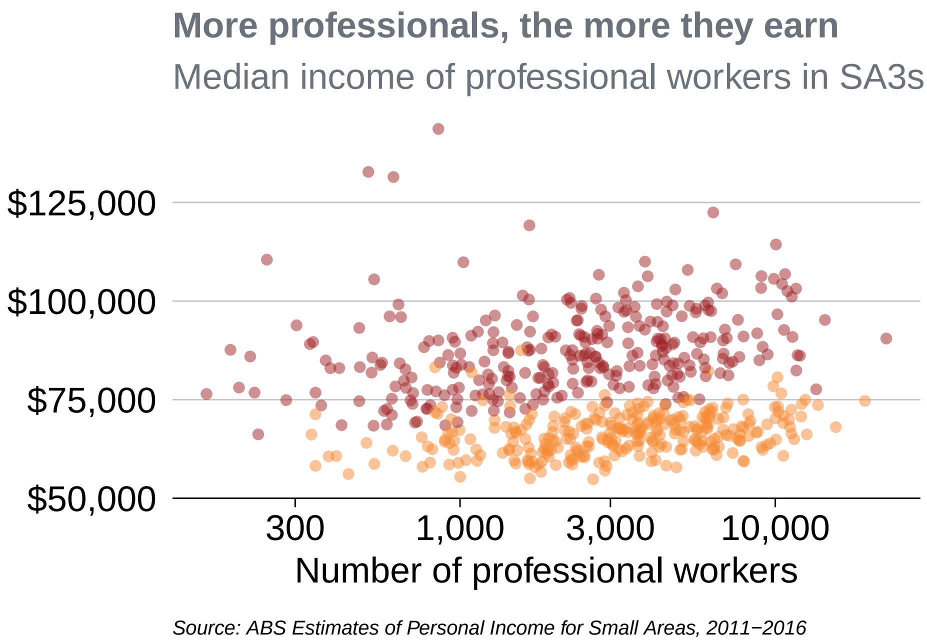
Then use `grattan_y_continuous` to adjust the y-axis. This takes the same arguments as the standard `scale_y_continuous` function, but has Grattan defaults built in. Use it to set the labels as dollars (with `scales::dollar()`) and to give the y-axis some breathing room (starting at $50,000 rather than the minimum point). Also add `scale_x_log10` to make the x-axis a log10 scale, telling it to format the labels as numbers with commas (using `scales::comma()`).[4]

```
base_chart +
        theme_grattan() +
        grattan_y_continuous(labels = dollar, limits = c(50e3, NA)) +
        scale_x_log10(labels = comma)
```

To define `colour` colours, use `grattan_colour_manual` with the number of colours you need (two, in this case):

```
prof_chart <- base_chart +
        theme_grattan() +
        grattan_y_continuous(labels = dollar, limits = c(50e3, NA)) +
        scale_x_log10(labels = comma) +
        grattan_colour_manual(2)

prof_chart
```

[4] The `dollar` and `comma` commands are functions, but can be used without `()`. Using `dollar()` or `comma()` works too, and you can provide arguments that adjust their output: eg `dollar(suffix = "million")`



Nice chart! Now you can save it and share it with the world.

4.5.2 Saving Grattan charts

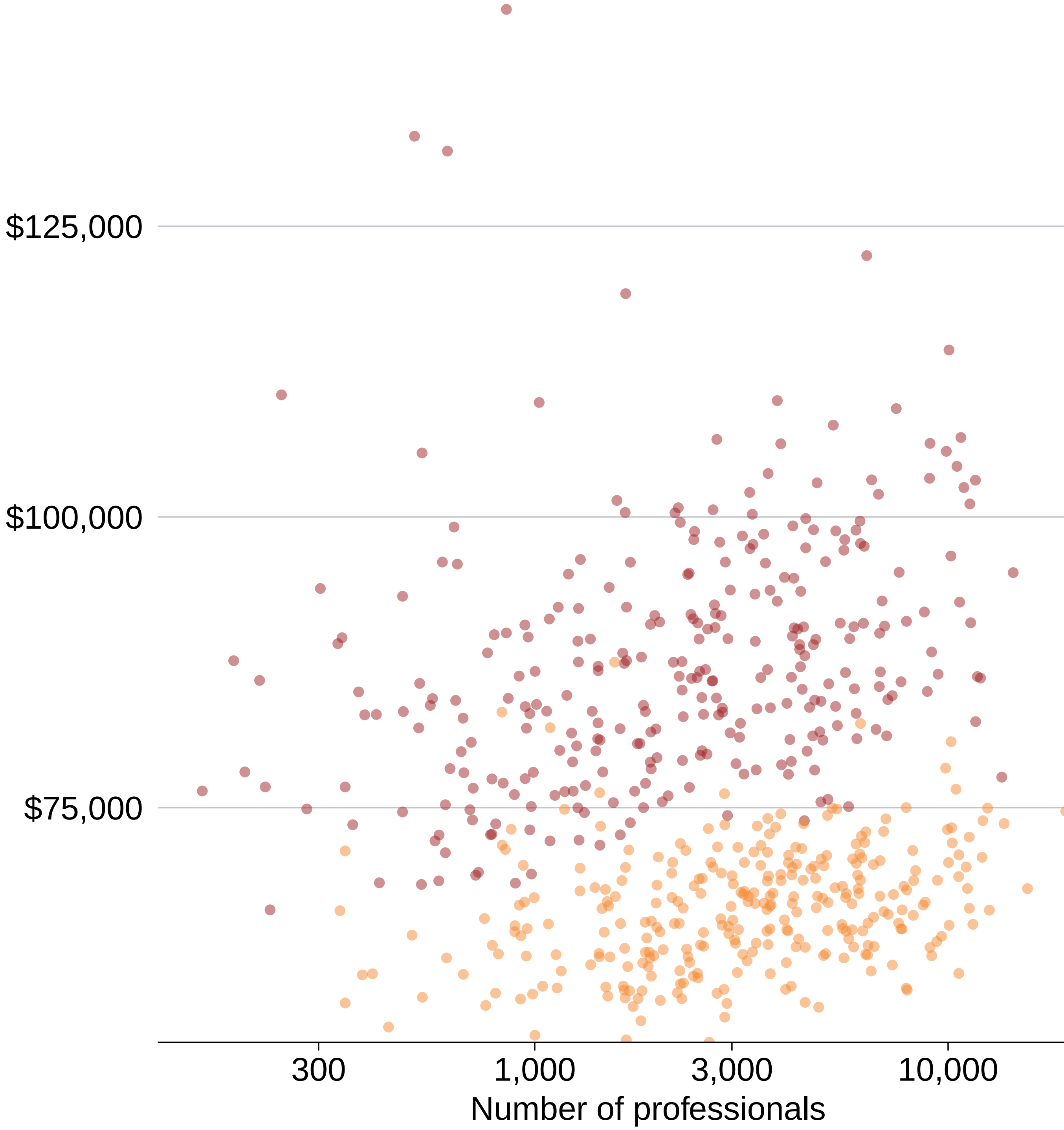
The `grattan_save` function saves your charts according to Grattan templates. It takes these arguments:

- `filename`: the path, name and file-type of your saved chart. eg: `"atlas/professionals_chart.pdf"`.
- `object`: the R object that you want to save. eg: `prof_chart`. If left blank, it grabs the last chart that was displayed.
- `type`: the Grattan template to be used. This is one of:
  - `"normal"` The default. Use for normal Grattan report charts, or to paste into a 4:3 PowerPoint slide. Width: 22.2cm, height: 14.5cm.
  - `"normal_169"` Only useful for pasting into a 16:9 format Grattan PowerPoint slide. Width: 30cm, height: 14.5cm.
  - `"tiny"` Fills the width of a column in a Grattan report, but is shorter than usual. Width: 22.2cm, height: 11.1cm.
  - `"wholecolumn"` Takes up a whole column in a Grattan report. Width: 22.2cm, height: 22.2cm.
  - `"fullpage"` Fills a whole page of a Grattan report. Width: 44.3cm, height: 22.2cm.
  - `"fullslide"` Creates an image that looks like a 4:3 Grattan PowerPoint slide, complete with logo. Width: 25.4cm, height: 19.0cm.

  - `"fullslide_169"` Creates‘ an image that looks like a 16:9 Grattan PowerPoint slide, complete with logo. Use this to drop into standard presentations. Width: 33.9cm, height: 19.0cm
  - `"blog"` Creates a 4:3 image that looks like a Grattan PowerPoint slide, but with less border whitespace than ‘fullslide’.”
  - `"fullslide_44" Creates` an image that looks like a 4:4 Grattan PowerPoint slide. This may be useful for taller charts for the Grattan blog; not useful for any other purpose. Width: 25.4cm, height: 25.4cm.
  - Set `type = "all"` to save your chart in all available sizes.
- `height`: override the height set by `type`. This can be useful for really long charts in blogposts.
- `save_data`: exports a `csv` file containing the data used in the chart.
- `force_labs`: override the removal of labels for a particular `type`. eg `force_labs = TRUE` will keep the y-axis label.

To save the `prof_chart` plot created above as a whole-column chart for a **report**:

```
grattan_save("atlas/professionals_chart_report.pdf", prof_chart, type = "wholecolumn")
```

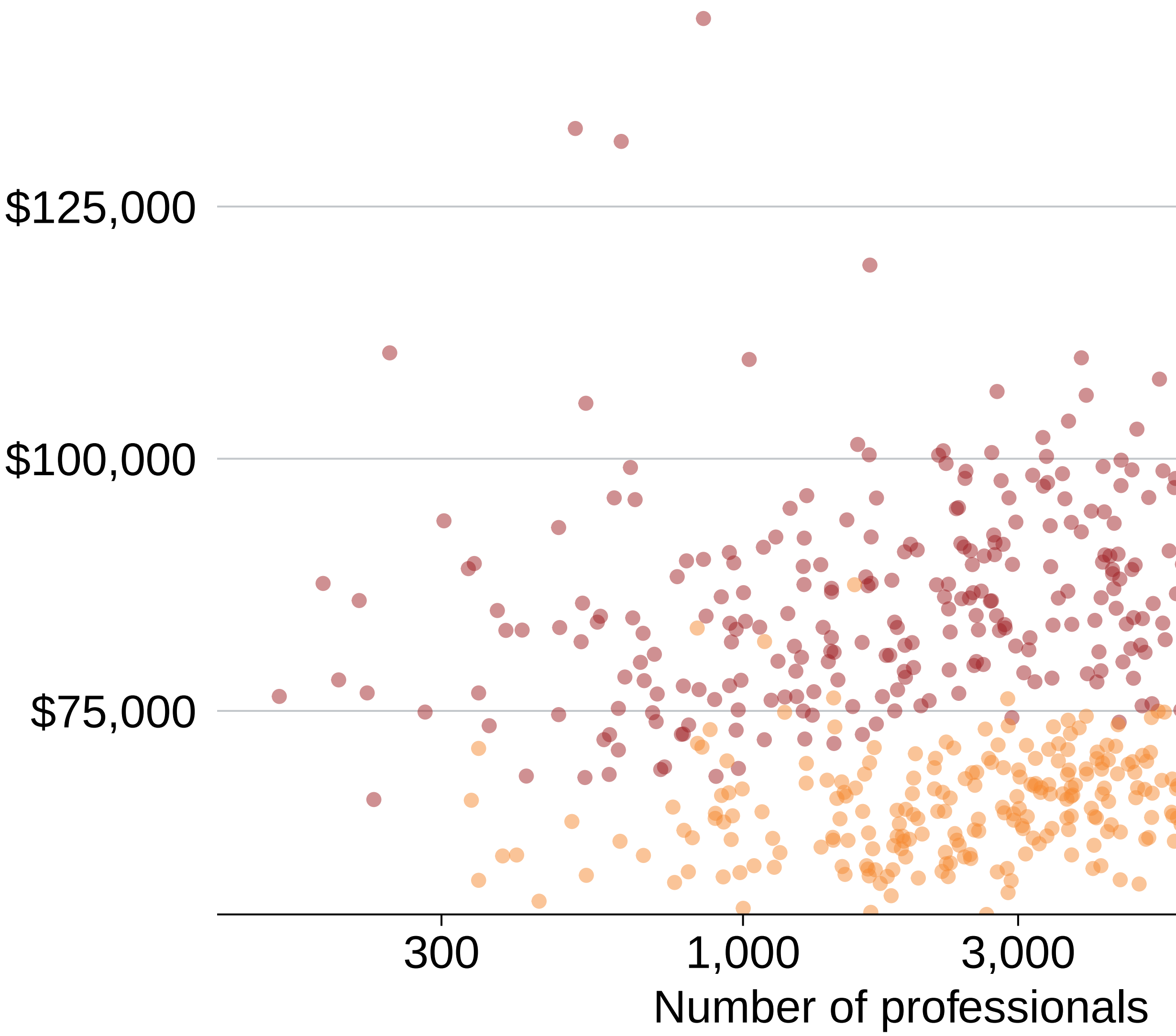

$125,000
$100,000
$75,000
300
1,000
3,000
10,000
Number of professionals

To save it as a **presentation** slide instead, use `type = "fullslide"`:

```
grattan_save("atlas/professionals_chart_presentation.pdf", prof_chart, type = "fullsli
```

More professionals, the more they earn

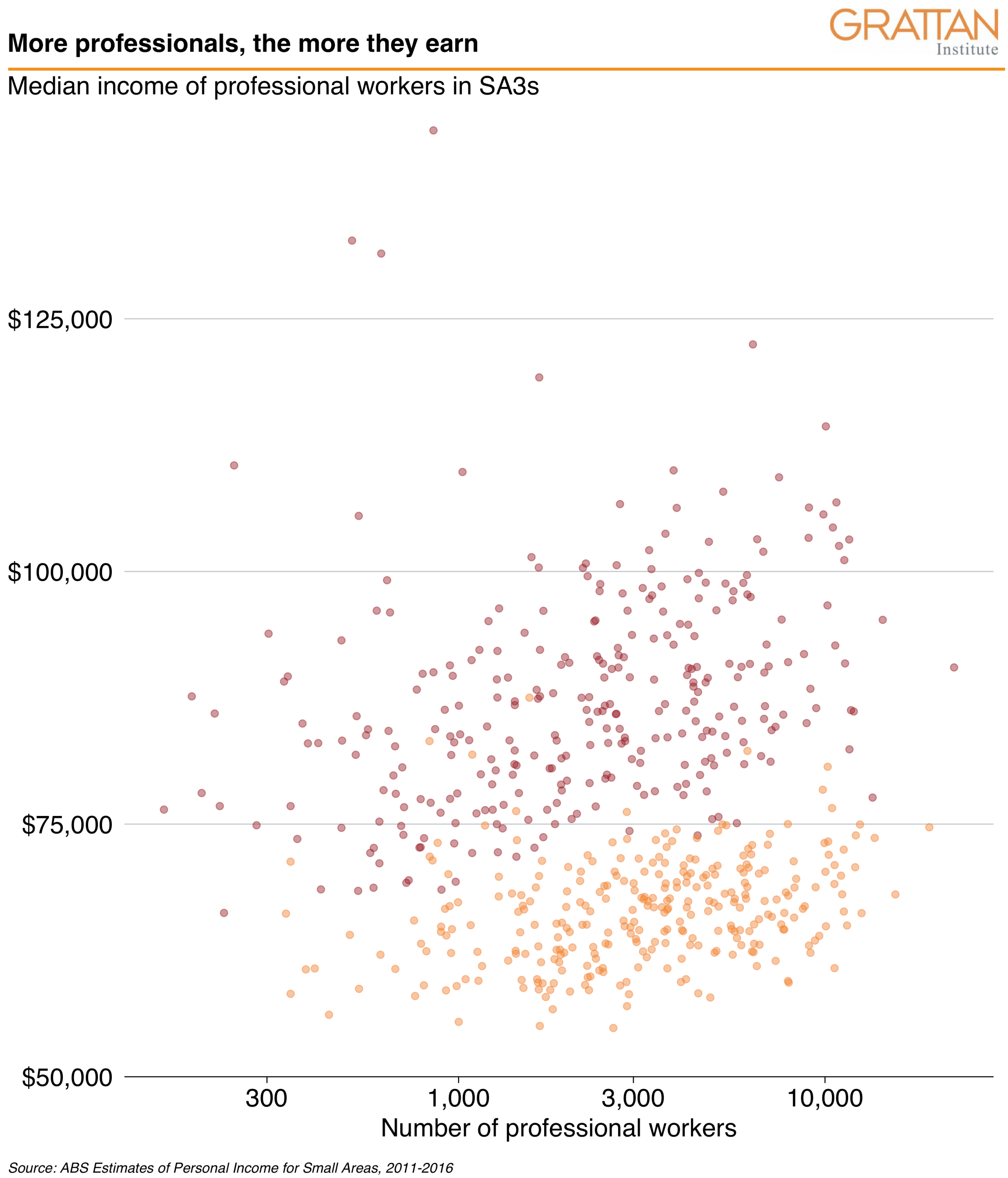
SA3 areas by number of professionals and thier median in



Source: ABS Estimates of Personal Income for Small Areas, 2011−2016

Or, if you want to emphasise the point in a *really tall* chart for a **blogpost**, you can use `type = "blog"` and adjust the `height` to be 50cm. Also note that because this is for the blog, you should save it as a `png` file:

```
grattan_save("atlas/professionals_chart_blog.png", prof_chart,
             type = "blog", height = 30)
```


More professionals, the more they earn
GRATTAN Institute
Median income of professional workers in SA3s
$125,000
$100,000
$75,000
$50,000
300
1,000
3,000
10,000
Number of professional workers
Source: ABS Estimates of Personal Income for Small Areas, 2011-2016

And that's it! The following sections will go into more detail about different chart types in R, but you'll mostly use the same basic `grattantheme` formatting you've used here.

4.6 Adding labels

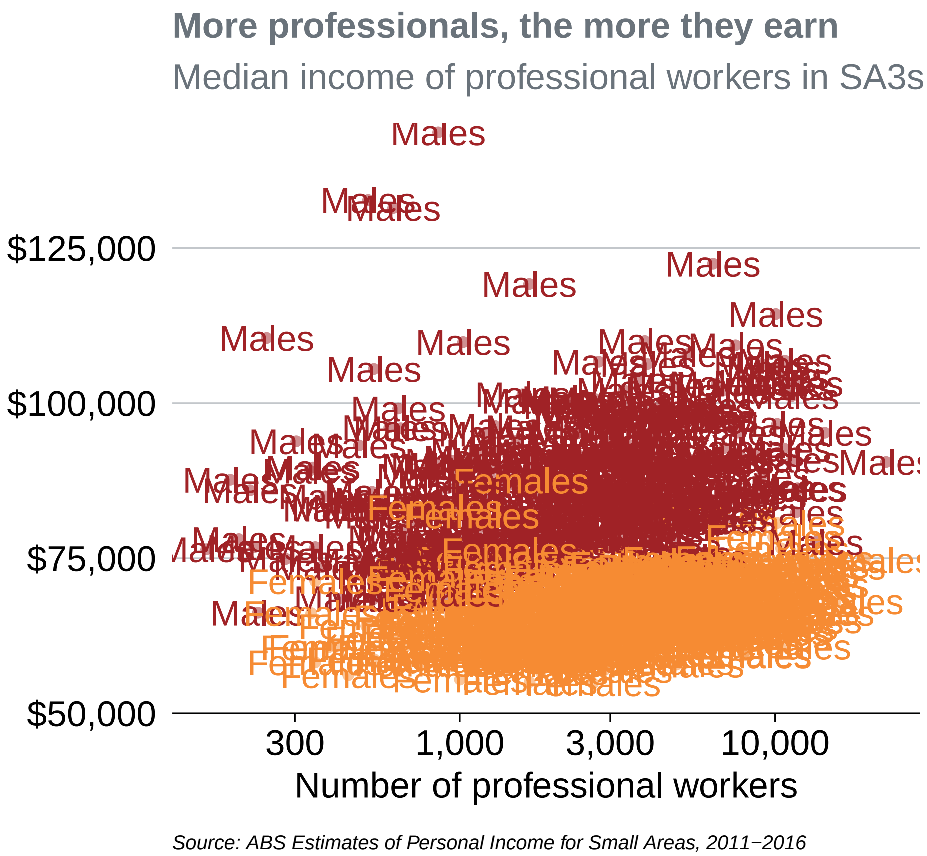
Labels can be a bit finicky – especially compared to labelling charts visually in PowerPoint. ...

Labels can be done in two broad ways:

1. Labelling every single data point on your chart. Grattan charts rarely do this.
2. Labelling some of the data points on your chart. This is how you label Grattan charts: label on item in a group and let the reader join the dots.

We'll look at the first approach so you can get a feel for how the labelling geoms – `geom_label` and `geom_text` (and some useful extensions) – work. It won't be pretty.

```
prof_chart +
  geom_text(aes(label = sex))
```



Great! That looks *terrible*. `geom_text` is labelling each individual point because it has been told to do so. Just like `geom_point`, it takes the `x` and `y` aesthetics of each observation, then plots the `label` at that location. But we just want to label one of the points for `female` and one for `male`.

To do this, we can create a new dataset that just contains one observation each. Here, you're filtering the dataset to include *only* the female/male observations that have the most people:

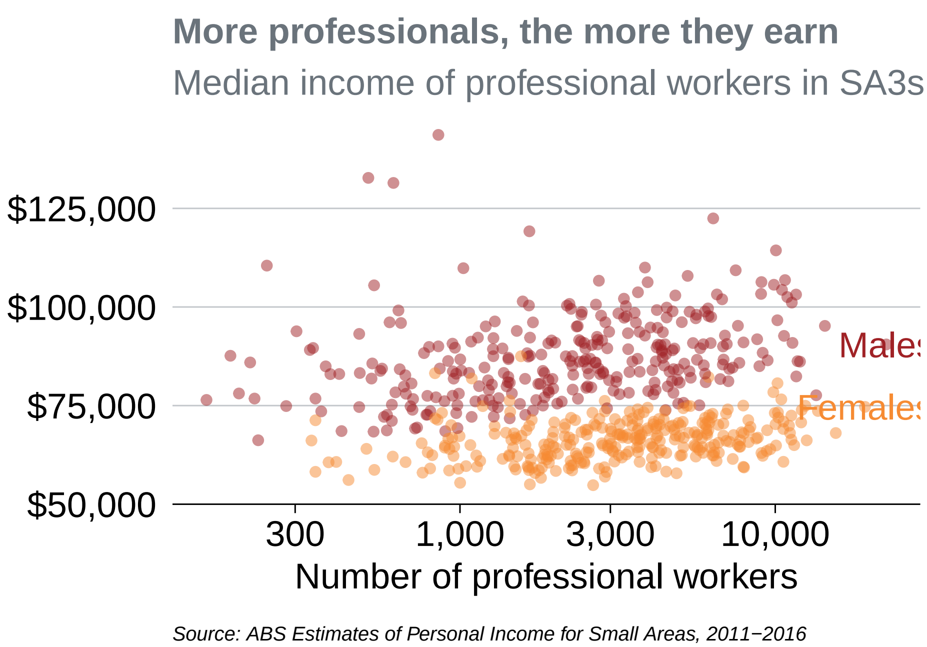
```
label_data <- professionals %>%
  group_by(sex) %>%
  filter(workers == max(workers)) %>%
  ungroup()

label_data
```

```
## # A tibble: 2 x 9
##      sa3 sa3_name sa3_sqkm occupation sex    year median_income
##    <dbl> <chr>       <dbl> <chr>      <chr> <dbl>         <dbl>
## 1 11703 Sydney ~     25.1 Professio~ Fema~  2015         74684
```

```
## 2 11703 Sydney ~     25.1 Professio~ Males  2015         90502
## # ... with 2 more variables: average_income <dbl>, workers <dbl>
```

And then tell `geom_text` to look at *that* dataset:

```
prof_chart +
  geom_text(data = label_data,
            aes(label = sex))
```

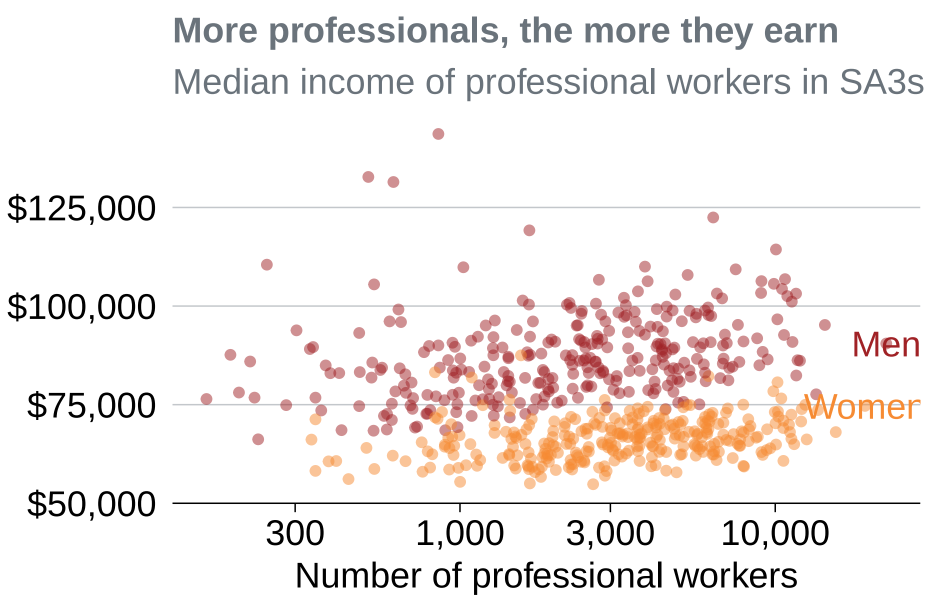


Okay, not bad. The labels go off the chart. You could fix this by shortening the labels either inside the `label_data`:

```
label_data_short <- label_data %>%
  mutate(sex_label = if_else(sex == "Females",
                             "Women",
                             "Men"))

prof_chart +
  geom_text(data = label_data_short,
            aes(label = sex_label))
```

Or you could adjust the label values directly inside the aesthetics call. Note that this means you have to provide a vector that is the same length as the number of observations in the data (a length of two, in this case).

```
prof_chart +
  geom_text(data = label_data,
            aes(label = c("Women", "Men")))
```



To have more freedom over *where* your labels are placed, you can create a dataset yourself. Add the `x` and `y` values for your labels, and the label names.[5]

```
self_label <- tribble(
~sex,       ~sex_label, ~workers,    ~median_income,
"Females",     "Women",     23000,             55000,
"Males",         "Men",     23000,            110000)


self_label
```

```
## # A tibble: 2 x 4
##   sex     sex_label workers median_income
##   <chr>   <chr>       <dbl>         <dbl>
## 1 Females Women       23000         55000
## 2 Males   Men         23000        110000
```

```
prof_chart +
  geom_text(data = self_label,
            aes(label = sex_label),
            hjust = 1)
```

[5] We are using the `tribble` function here to make it a little bit clearer what values apply to which sex. The ‘normal’ way to create a tibble is with the `tibble` function: `tibble(x = c(10, 100), y = c(100, 10))`, etc.


More professionals, the more they earn
Median income of professional workers in SA3s
$125,000
$100,000
$75,000
$50,000
Men
Women
300
1,000
3,000
10,000
Number of professional workers
Source: ABS Estimates of Personal Income for Small Areas, 2011−2016

Chapter 5

Chart cookbook

This section takes you through a few often-used chart types.

Chapter 6

Set up

```r
library(tidyverse)
library(grattantheme)
library(ggrepel)
library(absmapsdata)
library(sf)
library(scales)
```

The `sa3_income` dataset will be used for all key examples in this chapter.[1] It is a long dataset from the ABS that contains the median income and number of workers by Statistical Area 3, occupation and sex between 2010 and 2015.

```r
sa3_income <- read_csv("data/sa3_income.csv") %>%
  filter(!is.na(median_income),
         !is.na(average_income))
```

```
## Parsed with column specification:
## cols(
##   sa3 = col_double(),
##   sa3_name = col_character(),
##   sa3_sqkm = col_double(),
##   sa4_name = col_character(),
##   gcc_name = col_character(),
##   occupation = col_character(),
##   sex = col_character(),
##   year = col_double(),
##   median_income = col_double(),
##   average_income = col_double(),
##   workers = col_double()
```

[1] From ABS Employee income by occupation and sex, 2010-11 to 2015-16

```
## )
```

```r
head(sa3_income)
```

```
## # A tibble: 6 x 11
##     sa3 sa3_name sa3_sqkm sa4_name gcc_name occupation sex    year
##   <dbl> <chr>       <dbl> <chr>    <chr>    <chr>      <chr> <dbl>
## 1 10102 Queanbe~    6511. Capital~ Rest of~ Clerical ~ Fema~  2010
## 2 10102 Queanbe~    6511. Capital~ Rest of~ Clerical ~ Fema~  2011
## 3 10102 Queanbe~    6511. Capital~ Rest of~ Clerical ~ Fema~  2012
## 4 10102 Queanbe~    6511. Capital~ Rest of~ Clerical ~ Fema~  2013
## 5 10102 Queanbe~    6511. Capital~ Rest of~ Clerical ~ Fema~  2014
## 6 10102 Queanbe~    6511. Capital~ Rest of~ Clerical ~ Fema~  2015
## # ... with 3 more variables: median_income <dbl>, average_income <dbl>,
## #   workers <dbl>
```

6.1 Bar charts

Bar charts are made with `geom_bar` or `geom_col`. Creating a bar chart will look something like this:

```r
ggplot(data = <data>) +
  geom_bar(aes(x = <xvar>, y = <yvar>),
     stat = <STAT>,
     position = <POSITION>
  )
```

It has two key arguments: `stat` and `position`.

First, `stat` defines what kind of *operation* the function will do on the dataset before plotting. Some options are:

- `"count"`, the **default**: count the number of observations in a particular group, and plot that number. This is useful when you're using microdata. When this is the case, there is no need for a `y` aesthetic.
- `"sum"`: sum the values of the `y` aesthetic.
- `"identity"`: directly report the values of the `y` aesthetic. This is how PowerPoint and Excel charts work.

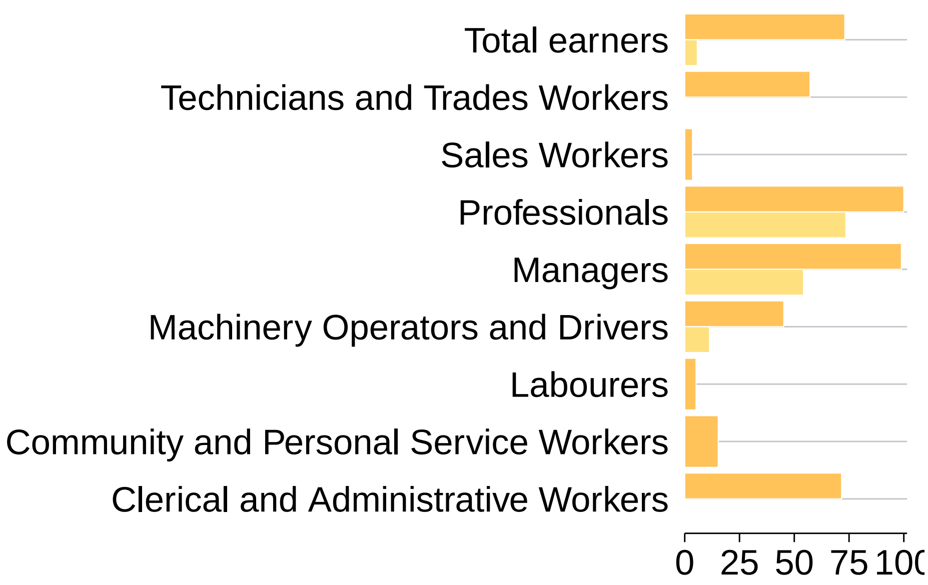
You can use `geom_col` instead, as a shortcut for `geom_bar(stat = "identity)`.

Second, `position`, dictates how multiple bars occupying the same x-axis position will positioned. The options are:

- `"stack"`, the default: bars in the same group are stacked atop one another.
- `"dodge"`: bars in the same group are positioned next to one another.
- `"fill"`: bars in the same group are stacked and all fill to 100 per cent.

Let's look at a bar chart that shows the proportion of areas where people earn less than $50,000 in each occupation type:

```
data <- sa3_income %>%
  filter(!sex == "Persons") %>%
  mutate(under = average_income < 60e3) %>%
  group_by(occupation, sex, under) %>%
  summarise(n = sum(workers)) %>%
  mutate(pc = n / sum(n)) %>%
  filter(under == FALSE)


data %>%
  ggplot(aes(x = occupation,
             y = pc * 100,
             fill = sex)) +
  geom_bar(stat = "identity",
           position = "dodge") +
  theme_grattan() +
  grattan_y_continuous(labels = comma) +
  grattan_fill_manual(6) +
  labs(x = "",
       y = "") +
  coord_flip()
```



You can also **order** the groups in your chart by a variable. If you want to order states by population, use `reorder` inside `aes`:

To flip the chart – a useful move when you have long labels – add `coord_flipped` (ie 'flip coordinates') and tell `theme_grattan` that the plot is flipped using `flipped = TRUE`.

Our long numeric labels means the chart clips them off a bit at the end. We can deal with this in two ways:

1. Adjust the limits of the axis to accommodate the long labels, meaning we will have to define our own axis-label breaks using the `seq` function[2]:
2. Add empty space at the top of the chart to accommodate the long labels:

6.2 Line charts

A line chart has one key aesthetic: `group`. This tells `ggplot` how to connect individual lines.

You can also add dots for each year by layering `geom_point` on top of `geom_line`:

If you wanted to show each state individually, you could **facet** your chart so that a separate plot was produced for each state:

To tidy this up, we can:

1. shorten the years to be "13", "14", etc instead of "2013", "2014", etc (via the `x` aesthetic)
2. shorten the y-axis labels to "millions" (via the `y` aesthetic)
3. add a black horizontal line at the bottom of each facet
4. give the facets a bit of room by adjusting `panel.spacing`
5. define our own x-axis label breaks to just show `13`, `15` and `17`

6.3 Scatter plots

Scatter plots require `x` and `y` aesthetics. These can then be coloured and faceted.

First, create a dataset that we'll use for scatter plots. Take the `population_table` dataset and transform it to have one variable for population in 2013, and another for population in 2018:

Then plot it

It looks like the areas with the largest population grew the most between 2013 and 2018. To explore the relationship further, you can add a line-of-best-fit with `geom_smooth`:

[2] `seq(x1, x2, y)` will return a vector of numbers between `x1` and `x2`, spaced by `y`. For example: `seq(0, 10, 2)` will produce `0 2 4 6 8 10`

You could colour-code positive and negative changes from within the `geom_point` aesthetic. Making a change there won't pass through to the `geom_smooth` aesthetic, so your line-of-best-fit will apply to all data points.

Like the charts above, you could facet this by state to see if there were any interesting patterns. We'll filter out ACT and NT because they only have one and two data points (SA4s) in them, respectively.

6.4 Distributions

`geom_histogram` `geom_density`

`ggridges::`

6.5 Maps

6.5.1 `sf` objects

[what is]

6.5.2 Using `absmapsdata`

The `absmapsdata` contains compressed, and tidied `sf` objects containing geometric information about ABS data structures. The included objects are:

- Statistical Area 1 2011 and 2016: `sa12011` or `sa12016`
- Statistical Area 2 2011 and 2016: `sa22011` or `sa22016`
- Statistical Area 3 2011 and 2016: `sa32011` or `sa32016`
- Statistical Area 4 2011 and 2016: `sa42011` or `sa42016`
- Greater Capital Cities 2011 and 2016: `gcc2011` or `gcc2016`
- Remoteness Areas 2011 and 2016: `ra2011` or `ra2016`
- State 2011 and 2016: `state2011` or `state2016`
- Commonwealth Electoral Divisions 2018: `ced2018`
- State Electoral Divisions 2018:`sed2018`
- Local Government Areas 2016 and 2018: `lga2016` or `lga2018`
- Postcodes 2016: `postcodes2016`

You can install the package from Github:

```
remotes::install_github("wfmackey/absmapsdata")
library(absmapsdata)
```

You will also need the `sf` package installed to handle the `sf` objects:

```r
install.packages("sf")
library(sf)
```

6.5.3 Making choropleth maps

Choropleth maps break an area into 'bits', and colours each 'bit' according to a variable.

SA4 is the largest non-state statistical area in the ABS ASGS standard.

You can join the `sf` objects from `absmapsdata` to your dataset using `left_join`. The variable names might be different – eg `sa4_name` compared to `sa4_name_2016` – so use the `by` function to match them.

You then plot a map like you would any other `ggplot`: provide your data, then choose your `aes` and your `geom`. For maps with `sf` objects, the **key aesthetic** is `geometry = geometry`, and the **key geom** is `geom_sf`.

The argument `lwd` controls the line width of area borders.

Note that RStudio takes a long time to render a map in the

Showing all of Australia on a single map is difficult: there are enormous areas that are home to few people which dominate the space. Showing individual states or capital city areas can sometimes be useful.

To do this, filter the `map_data` object:

6.5.3.1 Adding labels to maps

You can add labels to choropleth maps with the standard `geom_text` or `geom_label`. Because it is likely that some labels will overlap, `ggrepel::geom_text_repel` or `ggrepel::geom_label_repel` is usually the better option.

To use `geom_(text|label)_repel`, you need to tell `ggrepel` where in

```r
map <- map_data %>%
        filter(state == "Vic") %>%
        ggplot(aes(geometry = geometry)) +
        geom_sf(aes(fill = pop_change),
                lwd = .1,
                colour = "black") +
        theme_void() +
        grattan_fill_manual(discrete = FALSE,
                            palette = "diverging",
                            limits = c(-20, 20),
                            breaks = seq(-20, 20, 10)) +
```

```
  geom_label_repel(aes(label = sa4_name),
                   stat = "sf_coordinates", nudge_x = 1000, segment.alpha = .5,
                   size = 4,
                   direction = "y",
                   label.size = 0,
                   label.padding = unit(0.1, "lines"),
                   colour = "grey50",
                   segment.color = "grey50") +
  scale_y_continuous(expand = expand_scale(mult = c(0, .2))) +
  theme(legend.position = "top") +
  labs(fill = "Population \nchange")

map
```

6.6 Creating simple interactive graphs with `plotly`

`plotly::ggplotly()`

Chapter 7

Reading data

7.1 Importing data

7.1.1 Reading CSV files

7.1.1.1 `read_csv()`

The `read_csv()` function from the `tidyverse` is quicker and smarter than `read.csv` in base R.

Pitfalls: 1. read_csv is quicker because it surveys a sample of the data

We can also compress `.csv` files into `.zip` files and read them *directly* using `read_csv()`:

```r
read_csv("data/my_data.zip")
```

This is useful for two reasons:

1. The data takes up less room on your computer; and
2. The original data, which shouldn't ever be directly edited, is protected and cannot be directly edited.

7.1.1.2 `data.table::fread()`

The `fread` function from `data.table` is quicker than both `read.csv` and `read_csv`.

7.1.2 `readxl::read_excel()`

7.1.3 `rio`

7.1.4 `readabs`

7.2 Reading common files:

- TableBuilder CSVSTRINGs
- HES household file
- SIH
- LSAY and derivatives

See data directory for a list of microdata available to Grattan.

7.3 Appropriately renaming variables

As shown in the style guide

Add `rename_abs` function to a common Grattan package?

7.4 Getting to tidy data

`pivot_long()` and `pivot_wide()` *Make sure these are stable btw*

Chapter 8

Different data types

8.1 Tidy data

Other data structures

8.2 Dates with `lubridate::`

The `lubridate::` package

8.3 Strings with `stringr::`

- Replacing values
- Matching values
- Separating columns

8.4 Factors with `forcats::`

- Dangers with factors

Chapter 9

Data transformation

9.1 The pipe

9.2 Key `dplyr` functions:

All have the same syntax structure, which enable pipe-chains.

9.3 Filter with `filter()`

9.4 Arrange with `arrange()`

9.5 Select variables with `select()`

9.6 Group data with `group_by()`

9.7 Edit and add new variables with `mutate()`

9.7.1 Cases when you should use `case_when()`

9.8 Summarise data with `summarise()`

9.9 Joining datasets with `*_join()`

Chapter 10

Analysis

Chapter 11

Creating functions

11.1 It can be useful to make your own function

Why on earth would you create your own function?

11.2 Defining simple functions

11.3 More complex functions

11.4 Sets of functions

11.5 Using `purrr::map`

11.6 Sharing your useful functions with Grattan

Chapter 12

Version control

12.1 Version control is important and intimidating

Version control is great!

12.2 Github

We use Github to version-control and share reports in LaTeX, so you're already a bit set-up.

12.3 Git

Using Git within R Studio...