Using R at Grattan Institute

Will Mackey and Matt Cowgill

2019-09-15

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.

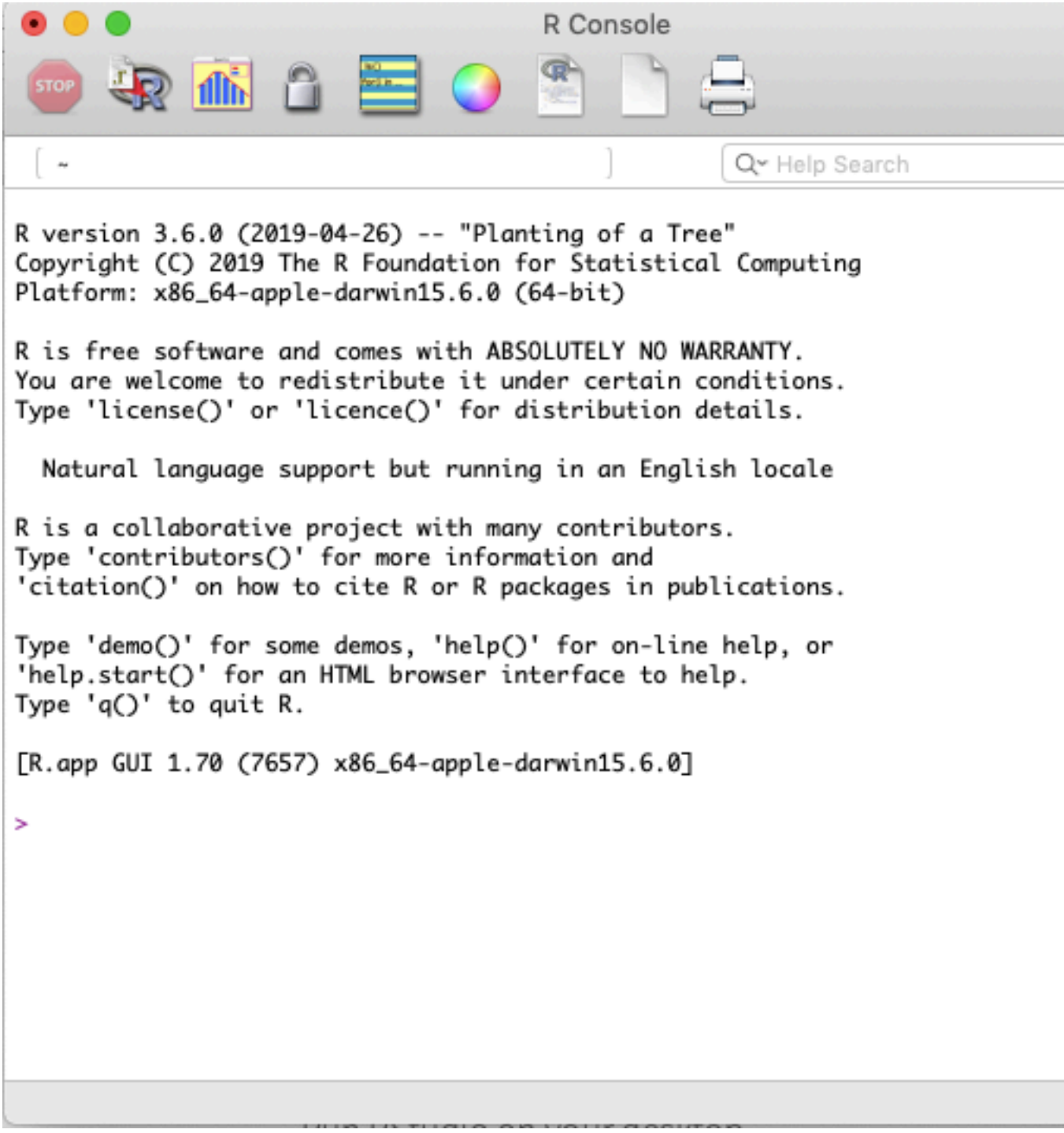
R has a lot in common with other statistical software like SAS, Stata, SPSS or Eviews. You can use those software packages to read data, manipulate it, generate summary statistics, estimate models, and so on. You can use R for all those things and more. You interact with R by writing code. This is a 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]
>

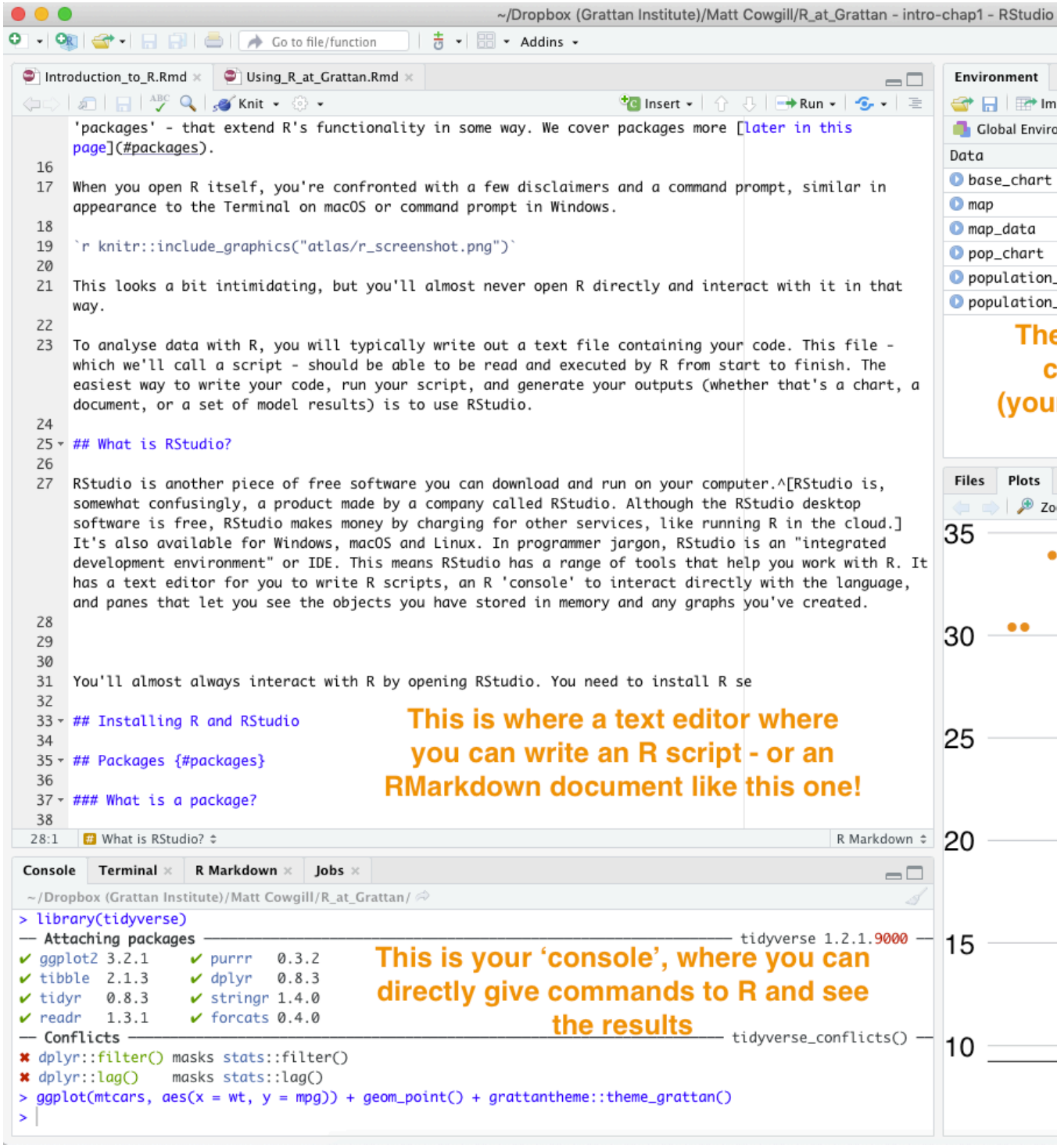
This looks a bit intimidating, but you'll almost never open R directly and interact with it in that way.

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.

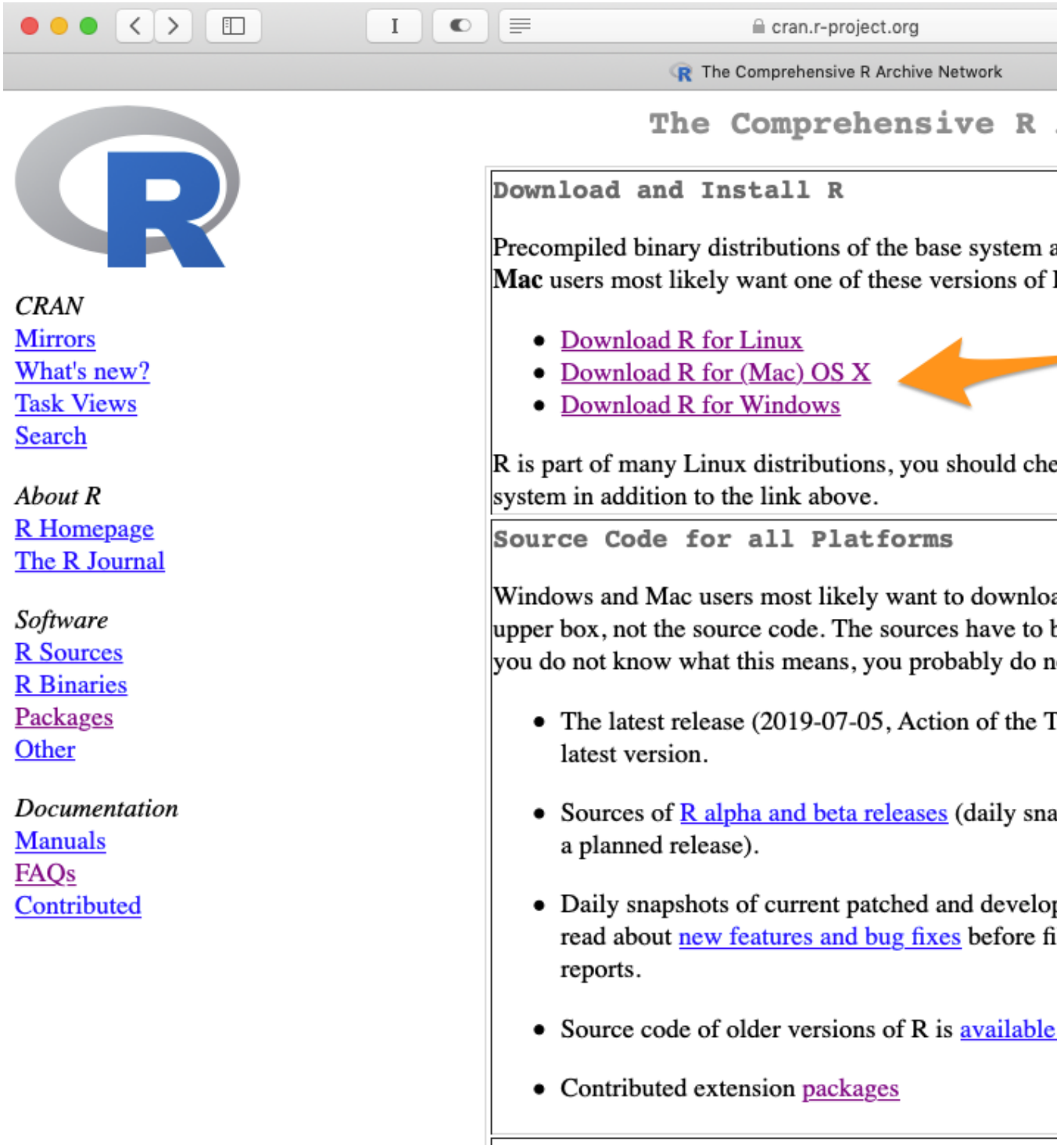

~/Dropbox (Grattan Institute)/Matt Cowgill/R_at_Grattan - intro-chap1 - RStudio
Go to file/function
Addins
Introduction_to_R.Rmd
Using_R_at_Grattan.Rmd
Knit
Insert
Run
'packages' - that extend R's functionality in some way. We cover packages more [later in this page](#packages).
When you open R itself, 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.
What is RStudio?
RStudio is another piece of free software you can download and run on your computer.^[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.] 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.
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
This is your 'console', where you can directly give commands to R and see the results
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()
Environment
Global Enviro
Data
base_chart
map
map_data
pop_chart
population_
population_
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 f
tools from the tools directory and read the corresponding not

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`

Click here

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.

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

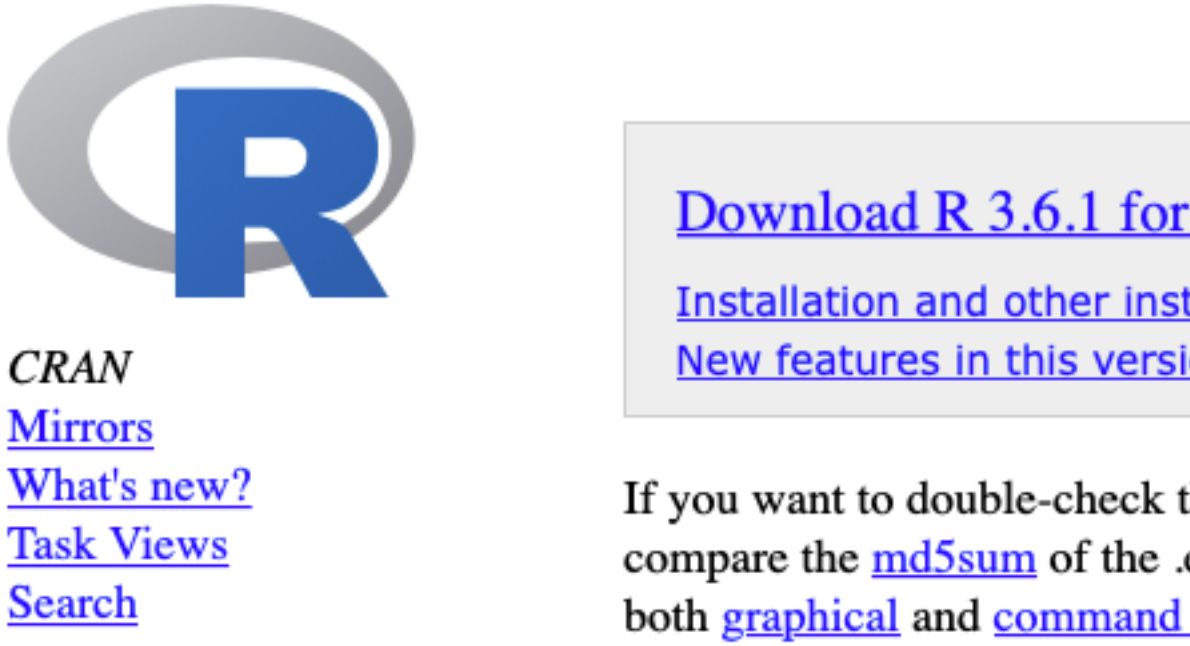
Subdirectories:

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 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)
```

```
# note: to be added to grattantheme; remove this when done
grattan_label <- function(..., size = 18) {

  .size = size / ggplot2::.pt

geom_label(...,
           fill = "white",
           label.padding = unit(0.01, "lines"),
           label.size = 0,
           size = .size)
}
```

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 gender 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),
         !gender == "Persons")

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

```
## # A tibble: 6 x 14
##     sa3 sa3_name sa3_sqkm sa3_income_perc~ state occupation occ_short prof
##   <dbl> <chr>       <dbl>            <dbl> <chr> <chr>      <chr>     <chr>
## 1 10102 Queanbe~    6511.               74 NSW   Professio~ Professi~ Prof~
## 2 10102 Queanbe~    6511.               74 NSW   Professio~ Professi~ Prof~
## 3 10102 Queanbe~    6511.               74 NSW   Professio~ Professi~ Prof~
## 4 10103 Snowy M~   14283.                7 NSW   Professio~ Professi~ Prof~
## 5 10103 Snowy M~   14283.                7 NSW   Professio~ Professi~ Prof~
## 6 10103 Snowy M~   14283.                7 NSW   Professio~ Professi~ Prof~
## # ... with 6 more variables: gender <chr>, year <dbl>,
## #   median_income <dbl>, average_income <dbl>, total_income <dbl>,
## #   workers <dbl>
```

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

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.
  - 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.

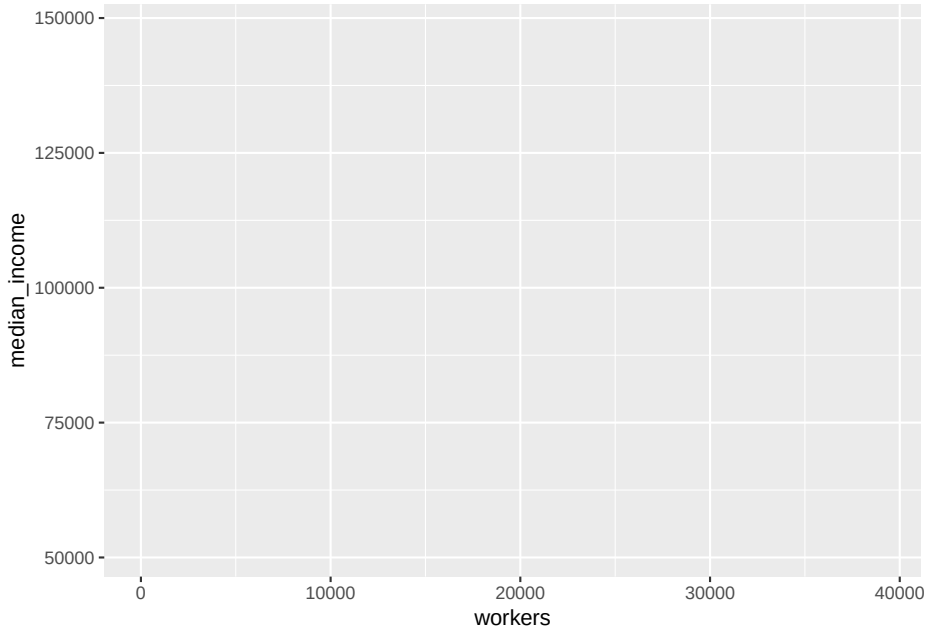
For example, you can plot a column chart by passing the `sa3_income` dataset into `ggplot()` ("make a chart with this data"). This completes the first step – data – and produces an empty plot:

```
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*.

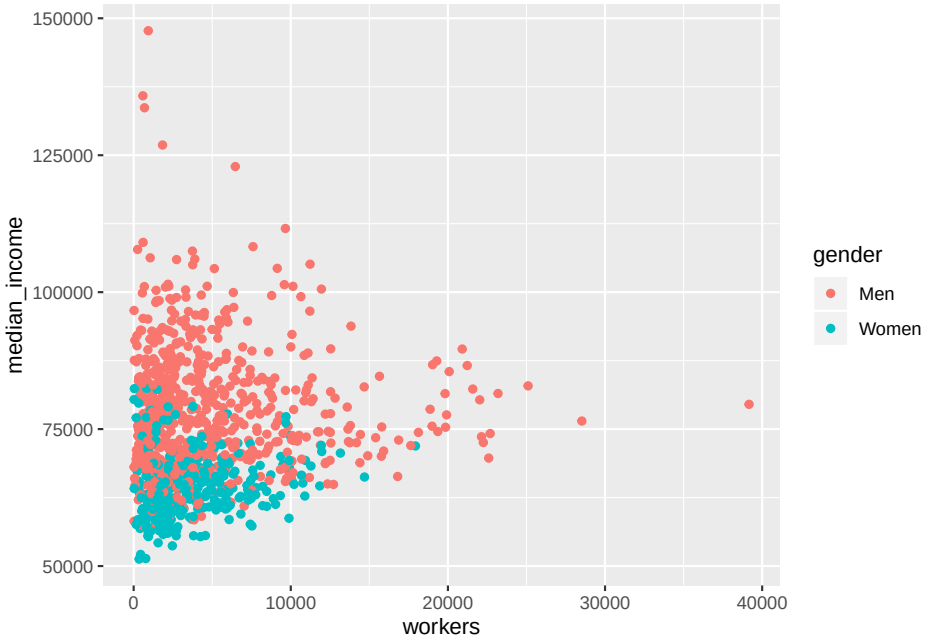
If we just plot that, you'll see that `ggplot` knows a little bit more about what we're trying to do. It has the states on the x-axis and range of populations on the y-axis:

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



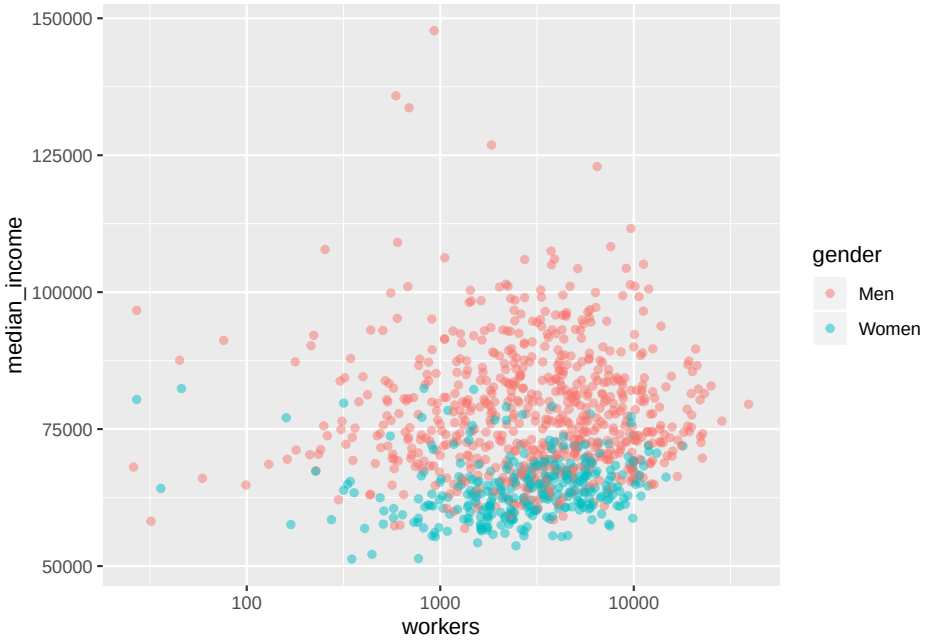
Now that `ggplot` knows where things should go, it needs to how to *plot* them on the chart. For this we use `geoms`. Tell `ggplot` to take the things it knows and plot them as a column chart by using `geom_col`:

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

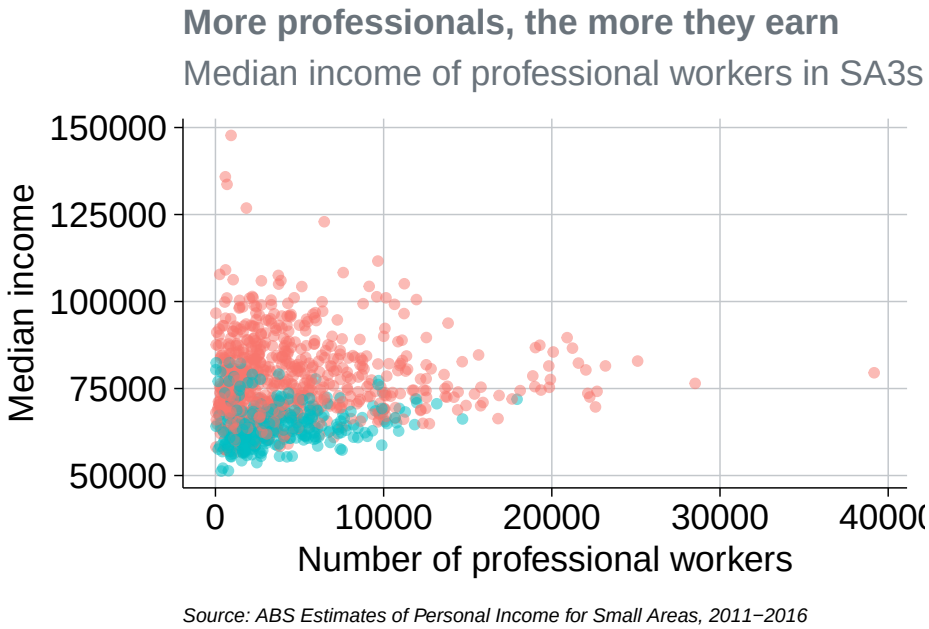
4.5.1 Making Grattan charts

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

```
base_chart <- professionals %>%
        ggplot(aes(x = workers,
                   y = median_income,
                   colour = gender)) +
        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, 2011-2016")

base_chart
```

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

```
base_chart +
        theme_grattan(chart_type = "scatter")
```



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]

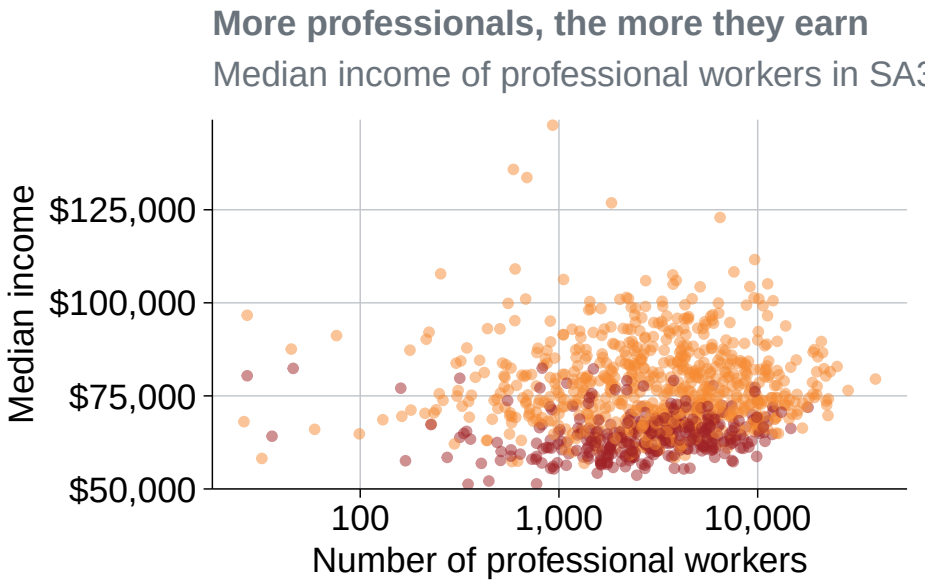
```
base_chart +
        theme_grattan(chart_type = "scatter") +
        grattan_y_continuous(labels = dollar, limits = c(50e3, NA)) +
        scale_x_log10(labels = comma)
```

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

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(chart_type = "scatter") +
        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

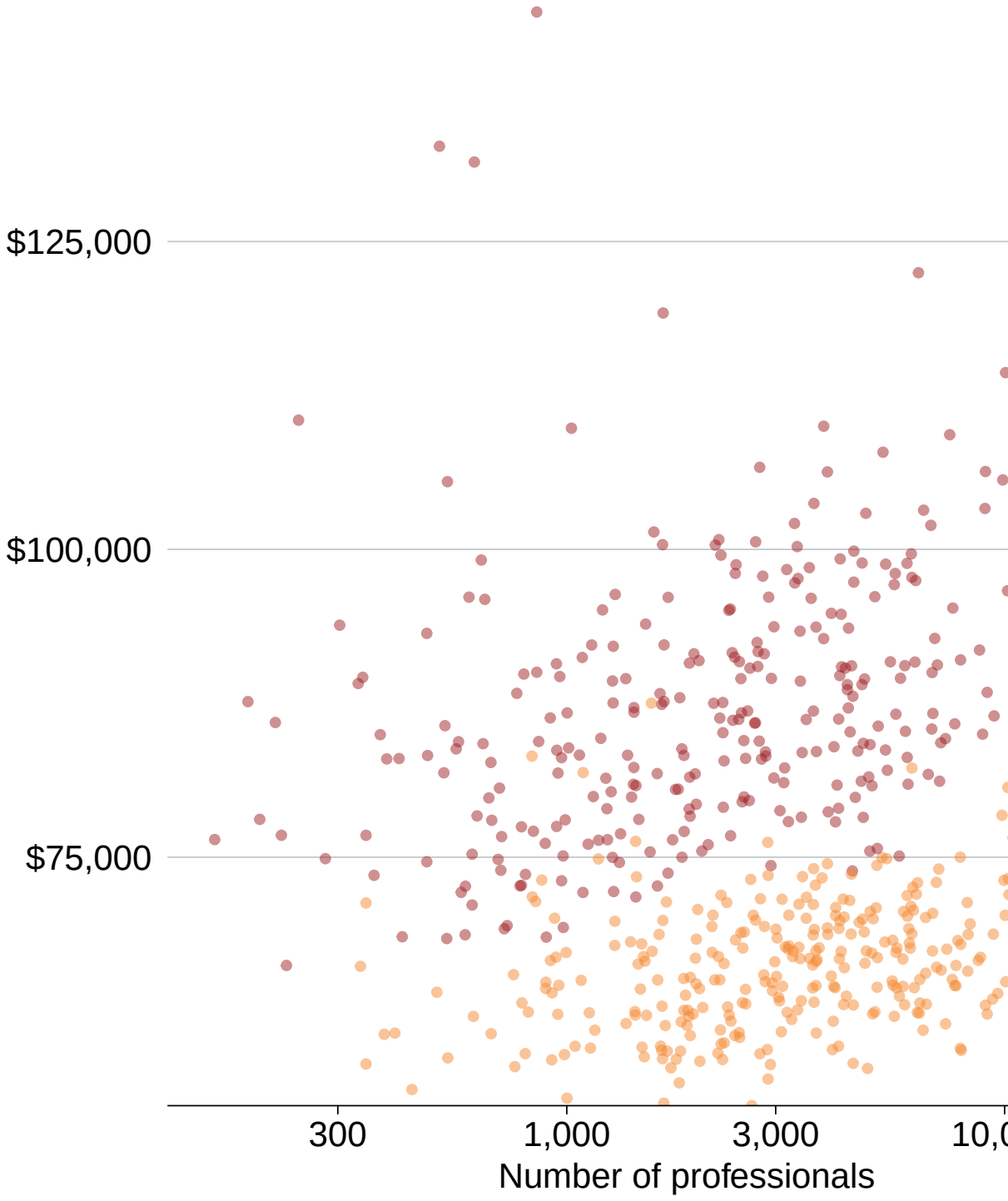
The `grattan_save` function saves your charts according to Grattan templates. It takes these arguments:

- `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")
```

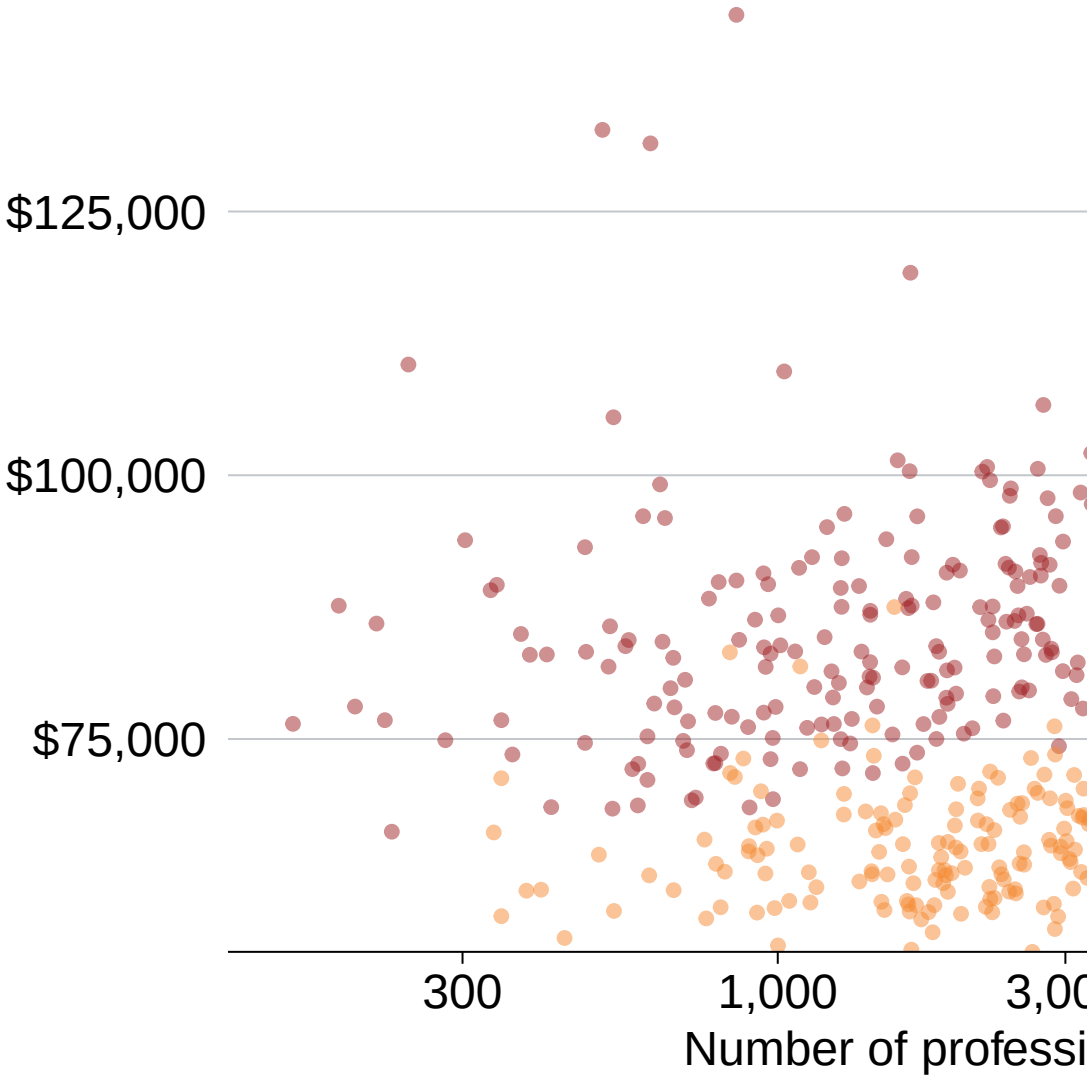

$125,000
$100,000
$75,000
300
1,000
3,000
Number of professionals

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

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

More professionals, the more they earn

SA3 areas by number of professionals and thier me



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

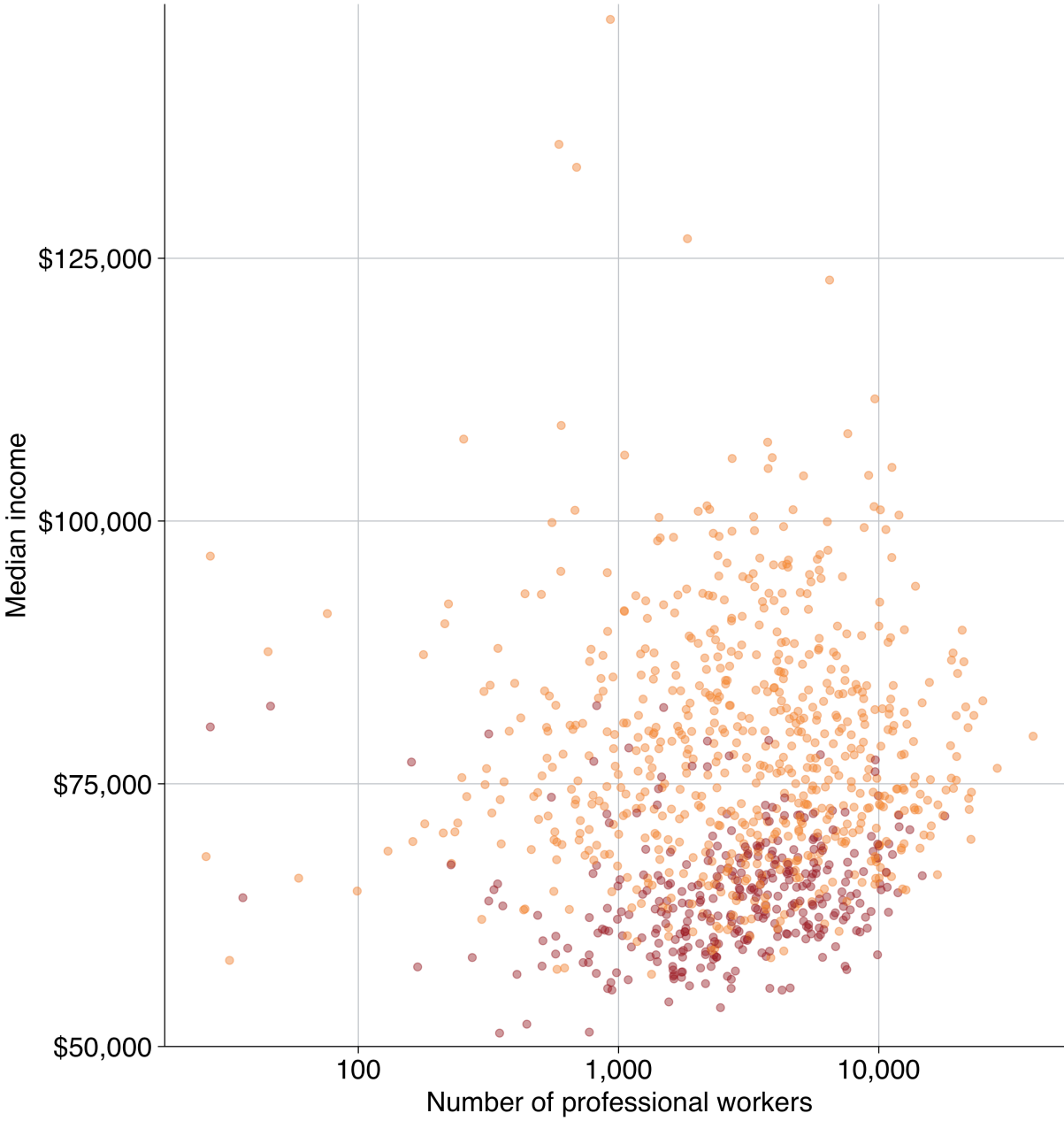
Or, if you want to emphasise the point in a *really tall* chart for a **blogpost**, you can use `type = "blog"` and adjust the `height` to be 50cm. Also note that because this is for the blog, you should save it as a `png` file:

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

More professionals, the more they earn

GRATTAN Institu

Median income of professional workers in SA3s



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

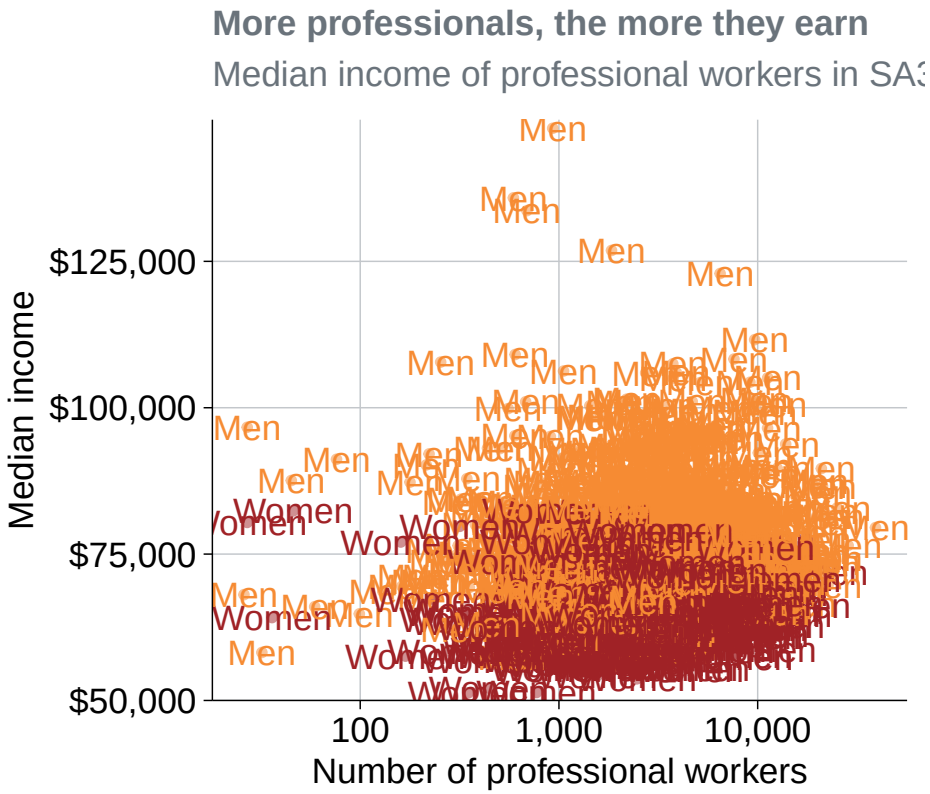
Labels can be a bit finicky – especially compared to labelling charts visually in PowerPoint. …

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 = gender))
```



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:

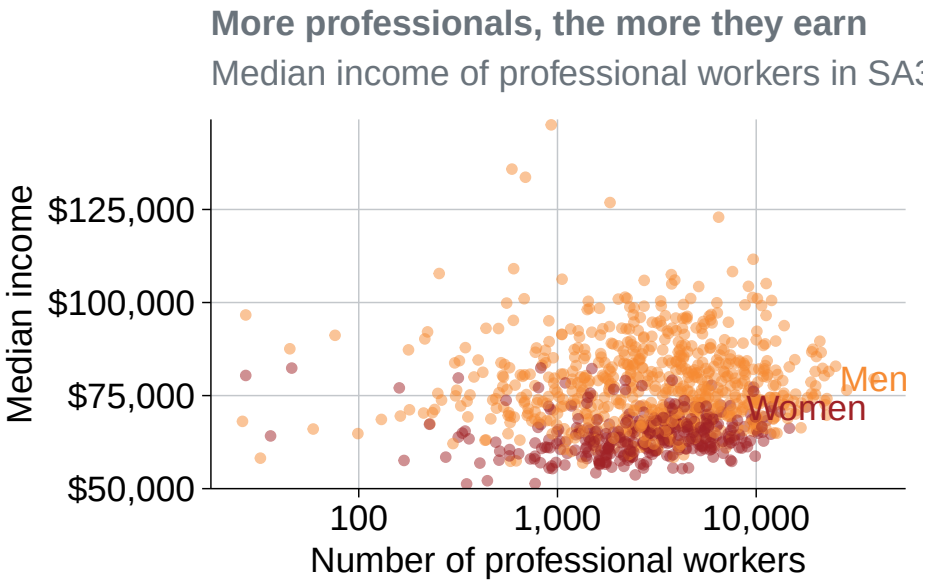
```
label_data <- professionals %>%
  group_by(gender) %>%
  filter(workers == max(workers)) %>%
  ungroup()

label_data
```

```
## # A tibble: 2 x 14
##     sa3 sa3_name sa3_sqkm sa3_income_perc~ state occupation occ_short prof
##   <dbl> <chr>       <dbl>            <dbl> <chr> <chr>      <chr>     <chr>
## 1 11703 Sydney ~     25.1               84 NSW   Professio~ Professi~ Prof~
```

```
## 2 11703 Sydney ~     25.1              84 NSW   Professio~ Professi~ Prof~
## # ... with 6 more variables: gender <chr>, year <dbl>,
## #   median_income <dbl>, average_income <dbl>, total_income <dbl>,
## #   workers <dbl>
```

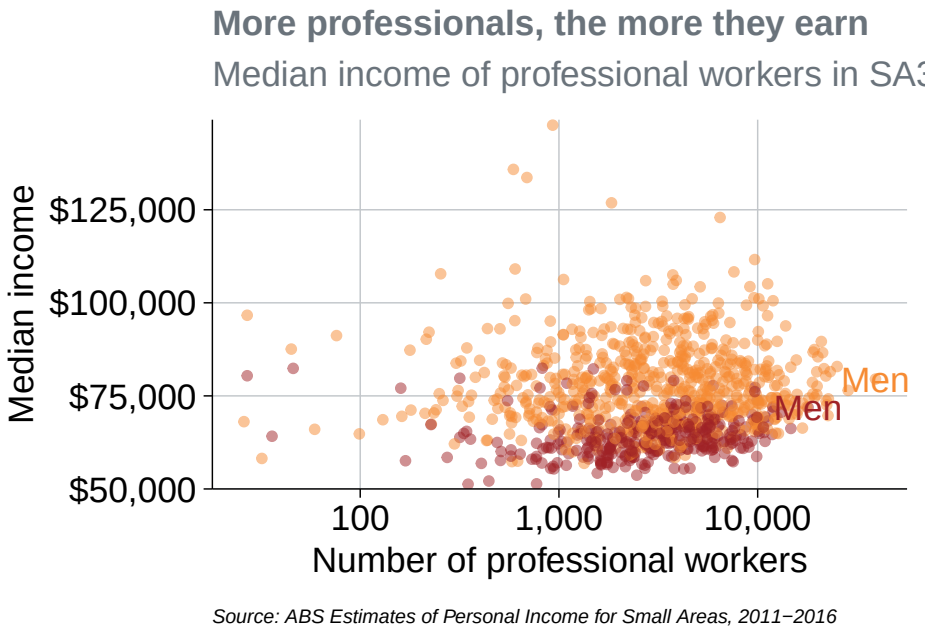
And then tell `geom_text` to look at *that* dataset:

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



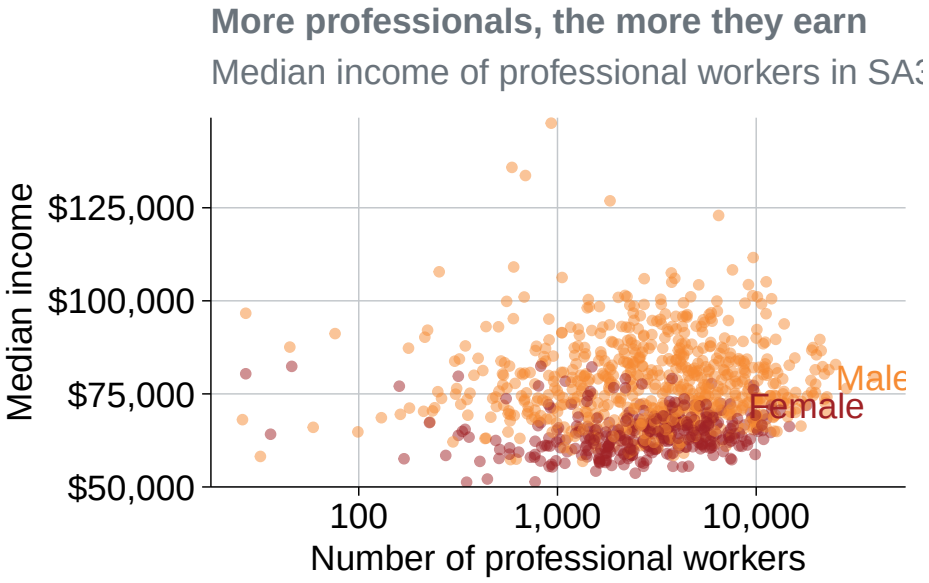
Okay, not bad. The labels go off the chart. You could fix this by shortening the labels either inside the `label_data`:

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

prof_chart +
  geom_text(data = label_data_short,
            aes(label = gender_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("Female", "Male")))
```



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

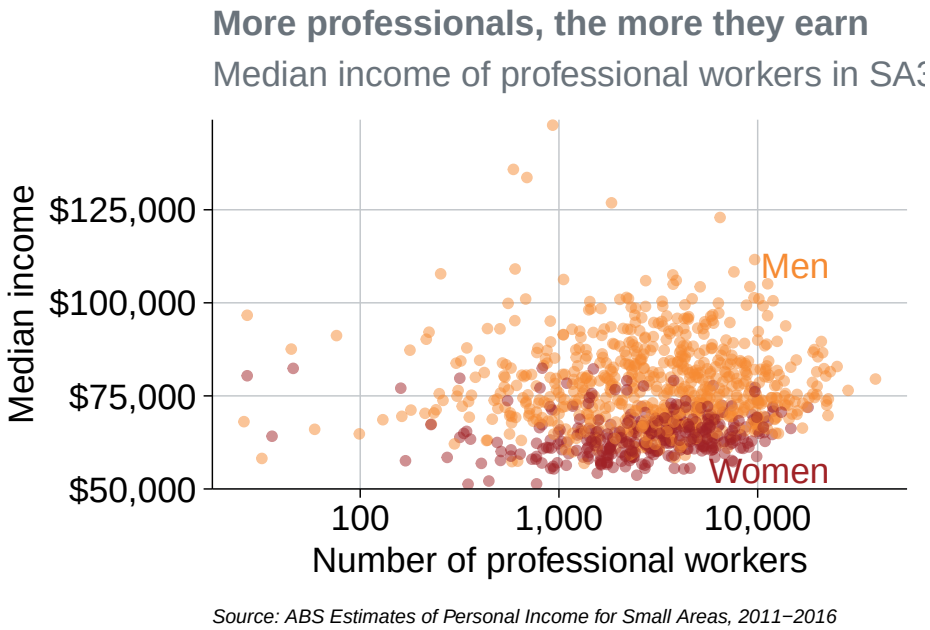
To have more freedom over *where* your labels are placed, you can create a dataset yourself. Add the `x` and `y` values for your labels, and the label names.[5]

```
self_label <- tribble(
  ~gender, ~workers,   ~median_income,
  "Women",    23000,           55000,
  "Men",      23000,          110000)


self_label
```

```
## # A tibble: 2 x 3
##   gender workers median_income
##   <chr>    <dbl>         <dbl>
## 1 Women    23000         55000
## 2 Men      23000        110000
```

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

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



[cover `annotate`]

Chapter 5

Chart cookbook

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

5.1 Set up

```
library(tidyverse)
library(grattantheme)
library(ggrepel)
library(absmapsdata)
library(sf)
library(scales)
# this might be hairy; should get `grattools` happening:
library(grattan)
```

```
# note: to be added to grattantheme; remove this when done
grattan_label_repel <- function(..., size = 18) {

  .size = size / ggplot2::.pt

  geom_label_repel(...,
                   fill = "white",
                   label.padding = unit(0.1, "lines"),
                   label.size = 0,
                   size = .size)
}


grattan_label <- function(..., size = 18) {
```

```
  .size = size / ggplot2::.pt

  geom_label(...,
                   fill = "white",
                   label.padding = unit(0.1, "lines"),
                   label.size = 0,
                   size = .size)
}
```

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 2016.

```
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(),
##   sa3_income_percentile = col_double(),
##   sa4_name = col_character(),
##   gcc_name = col_character(),
##   state = col_character(),
##   occupation = col_character(),
##   occ_short = col_character(),
##   prof = col_character(),
##   gender = col_character(),
##   year = col_double(),
##   median_income = col_double(),
##   average_income = col_double(),
##   total_income = col_double(),
##   workers = col_double()
## )
```

```
head(sa3_income)
```

```
## # A tibble: 6 x 16
##     sa3 sa3_name sa3_sqkm sa3_income_perc~ sa4_name gcc_name state
##   <dbl> <chr>       <dbl>            <dbl> <chr>    <chr>    <chr>
## 1 10102 Queanbe~    6511.               80 Capital~ Rest of~ NSW
## 2 10102 Queanbe~    6511.               76 Capital~ Rest of~ NSW
## 3 10102 Queanbe~    6511.               78 Capital~ Rest of~ NSW
```

[1] From ABS Employee income by occupation and sex, 2010-11 to 2016-16

```
## 4 10102 Queanbe~    6511.               76 Capital~ Rest of~ NSW
## 5 10102 Queanbe~    6511.               74 Capital~ Rest of~ NSW
## 6 10102 Queanbe~    6511.               79 Capital~ Rest of~ NSW
## # ... with 9 more variables: occupation <chr>, occ_short <chr>,
## #   prof <chr>, gender <chr>, year <dbl>, median_income <dbl>,
## #   average_income <dbl>, total_income <dbl>, workers <dbl>
```

5.2 Bar charts

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

```
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.

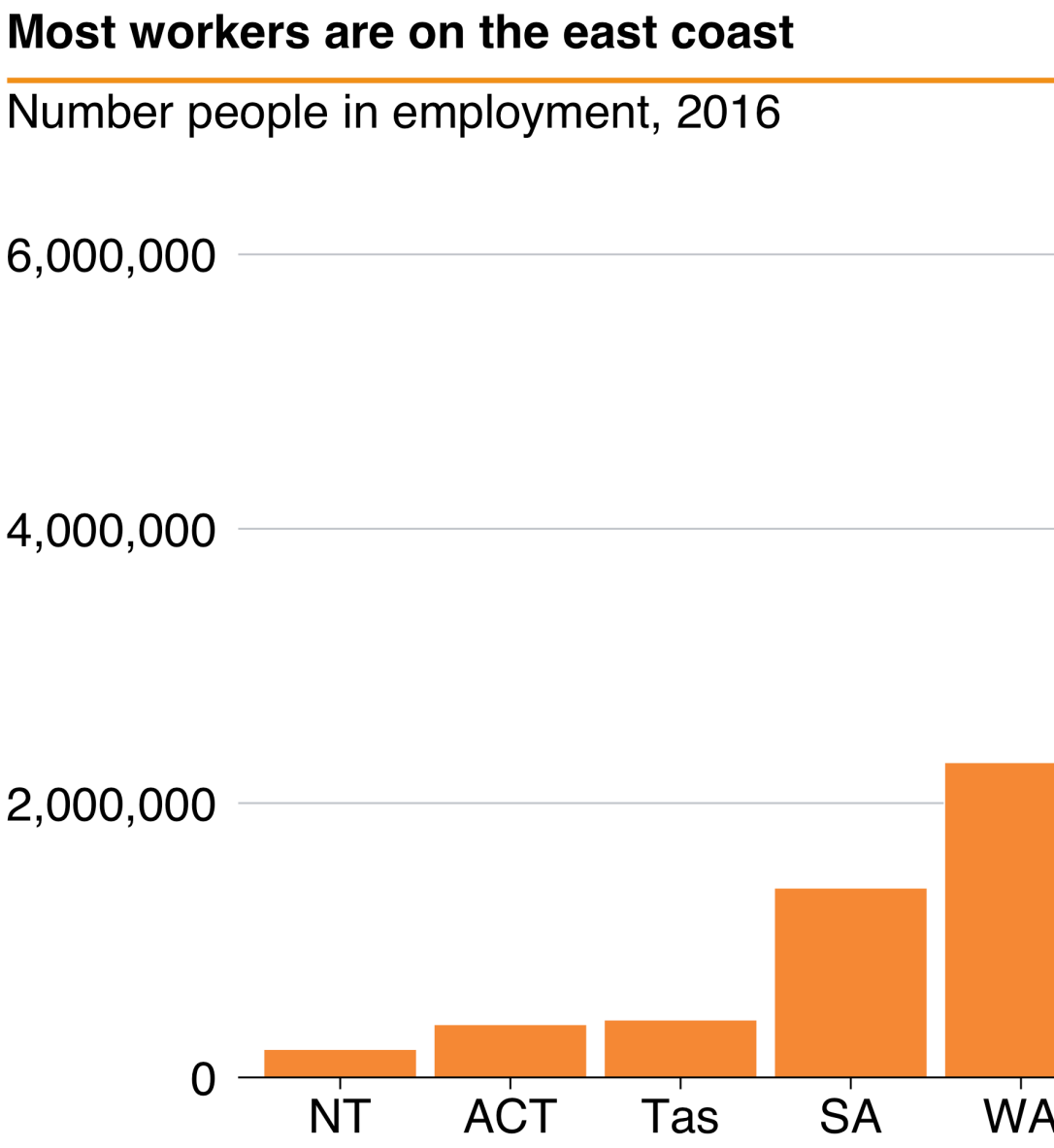
You can use `geom_col` instead, as a shortcut for `geom_bar(stat = "identity)`.

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.

5.2.1 Simple bar plot

This section will create the following vertical bar plot showing number of workers by state in 2016:



Notes: Only includes people who submitted a tax return in 2016-16.
Source: ABS (2018)

First, create the data you want to plot.

```
data <- sa3_income %>%
  filter(year == 2016) %>%
  group_by(state) %>%
  summarise(workers = sum(workers))

data
```

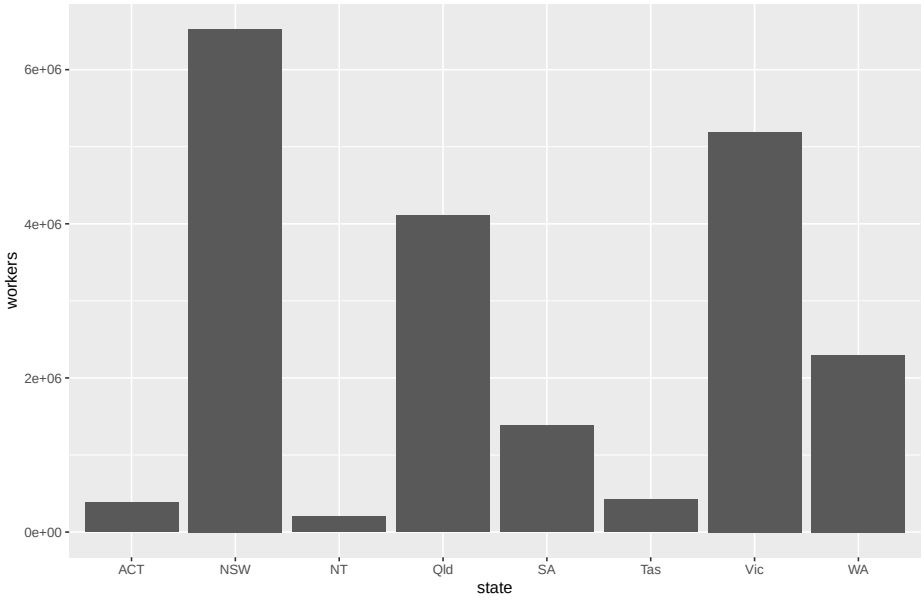
```
## # A tibble: 8 x 2
##   state workers
##   <chr>   <dbl>
## 1 ACT    386989
## 2 NSW   6527661
## 3 NT     206061
## 4 Qld   4104503
## 5 SA    1382446
## 6 Tas    420767
## 7 Vic   5190976
## 8 WA    2297081
```

Looks super: you have one observation (row) for each state you want to plot, and a value for their number of workers.

Now pass the nice, simple table to `ggplot` and add aesthetics so that `x` represents `state`, and `y` represents `workers`. Then, because the dataset contains the *actual* numbers you want on the chart, you can plot the data with `geom_col`:[2]

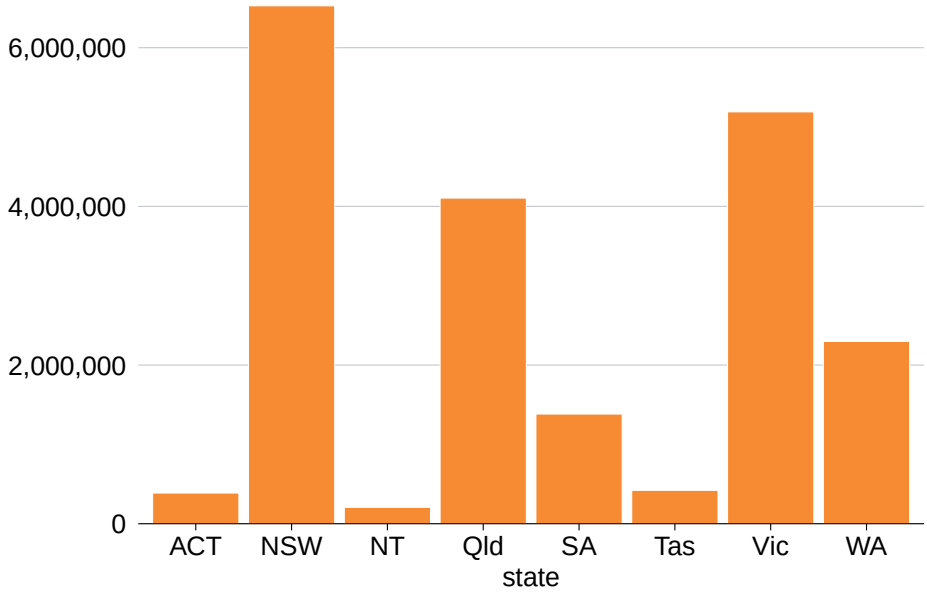
```
data %>%
  ggplot(aes(x = state,
             y = workers)) +
  geom_col()
```

[2]Remember that `geom_col` is just shorthand for `geom_bar(stat = "identity")`



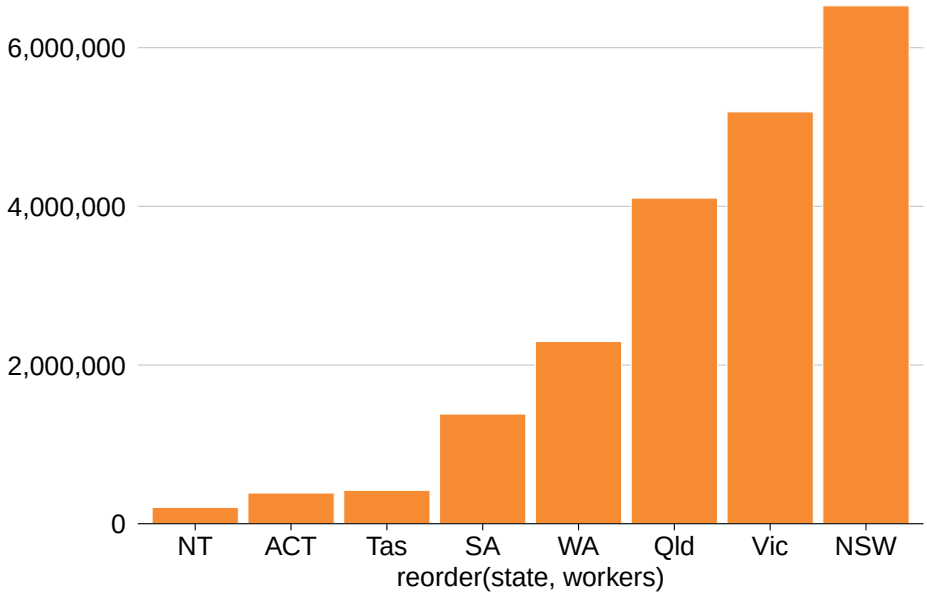
Make it Grattany by adjusting general theme defaults with `theme_grattan`, and use `grattan_y_continuous` to change the y-axis. Use labels formatted with commas (rather than scientific notation) by adding `labels = comma`.

```
data %>%
  ggplot(aes(x = state,
             y = workers)) +
  geom_col() +
  theme_grattan() +
  grattan_y_continuous(labels = comma)
```



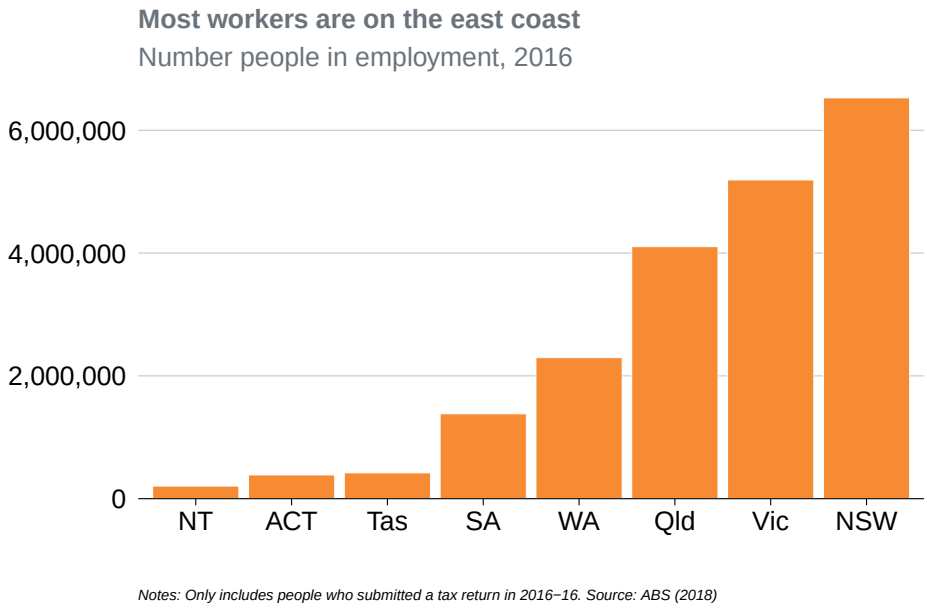
To order the states by number of workers, you can tell the `x` aesthetic that you want to `reorder` the `state` variable by `workers`:

```
data %>%
  ggplot(aes(x = reorder(state, workers), # reorder states by workers
             y = workers)) +
  geom_col() +
  theme_grattan() +
  grattan_y_continuous(labels = comma)
```



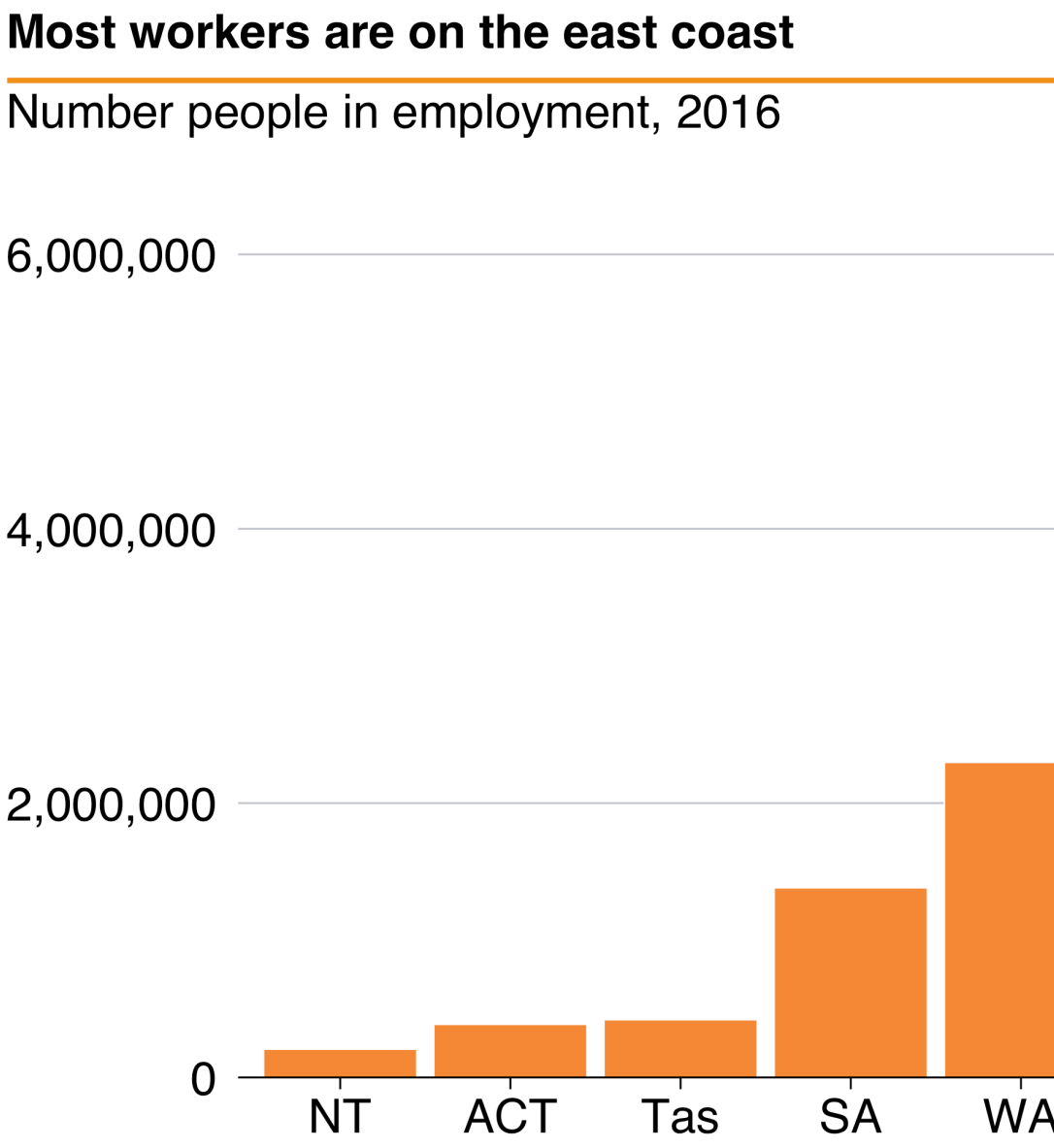
You can probably drop the x-axis label – people will understand that they're states without you explicitly saying it – and add a title and subtitle with `labs`:

```
simple_bar <- data %>%
  ggplot(aes(x = reorder(state, workers),
             y = workers)) +
  geom_col() +
  theme_grattan() +
  grattan_y_continuous(labels = comma) +
  labs(title = "Most workers are on the east coast",
       subtitle = "Number people in employment, 2016",
       x = "",
       caption = "Notes: Only includes people who submitted a tax return in 2016-16. So

simple_bar
```



Looks supreme! Now you can export as a full-slide Grattan chart using `grattan_save`:

```
grattan_save("atlas/simple_bar.pdf", simple_bar, type = "fullslide")
```



Notes: Only includes people who submitted a tax return in 2016-16.
Source: ABS (2018)

5.2.2 Bar plot with multiple series

This section will create a horizontal bar plot showing average income by state and gender in 2016:

First create the dataset you want to plot, getting the average income by state and gender in the year 2016:

```
data <- sa3_income %>%
  filter(year == 2016) %>%
  group_by(state, gender) %>%
  summarise(average_income = sum(total_income) / sum(workers))

data
```

```
## # A tibble: 16 x 3
## # Groups:   state [8]
##    state gender average_income
##    <chr> <chr>           <dbl>
##  1 ACT   Men            78141.
##  2 ACT   Women          65548.
##  3 NSW   Men            69750.
##  4 NSW   Women          53191.
##  5 NT    Men            75246.
##  6 NT    Women          58527.
##  7 Qld   Men            65108.
##  8 Qld   Women          48458.
##  9 SA    Men            60244.
## 10 SA    Women          47533.
## 11 Tas   Men            56345.
## 12 Tas   Women          45158.
## 13 Vic   Men            64908.
## 14 Vic   Women          49264.
## 15 WA    Men            76677.
## 16 WA    Women          51578.
```

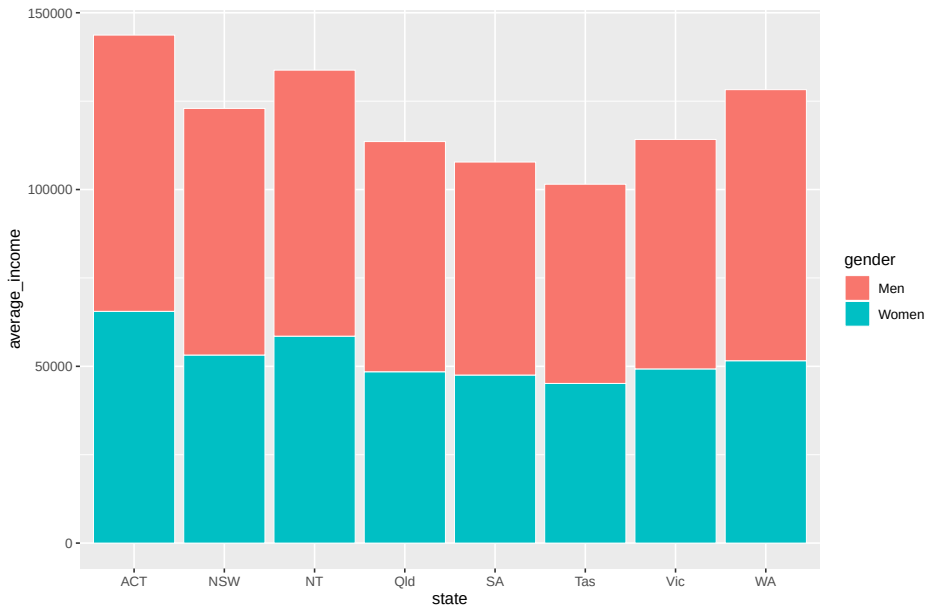
Looks terrific: you have one observation (row) for each state × gender group you want to plot, and a value for their average income. Put `state` on the x-axis, `average_income` on the y-axis, and split gender by fill-colour (`fill`).

Pass the data to `ggplot`, give it the appropriate `x` and `y` aesthetics, along with `fill` (the fill colour[3]) representing `gender`. And because you have the *actual* values for `average_income` you want to plot, use `geom_col`:[4]

[3]The aesthetic `fill` represents the 'fill' colour – the colour that fills the bars in your chart. The `colour` aesthetic controls the colours of the *lines*.

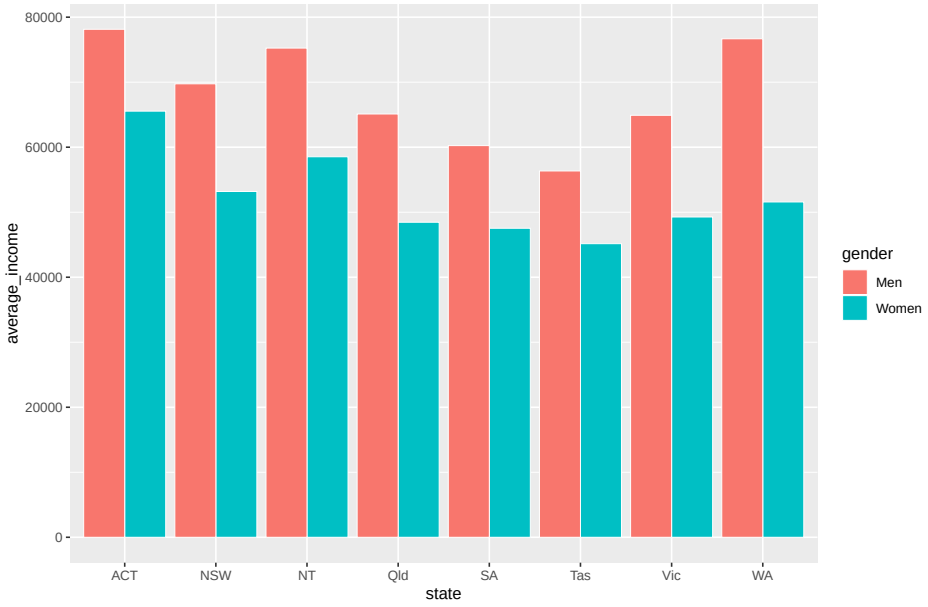
[4]`geom_col` is shorthand for `geom_bar(stat = "identity"`

```
data %>%
  ggplot(aes(x = state,
             y = average_income,
             fill = gender)) +
  geom_col()
```



The two series – women and men – created by `fill` are stacked on-top of each other by `geom_col`. You can tell it to plot them next to each other – to 'dodge' – instead with the `position` argument *within* `geom_col`:

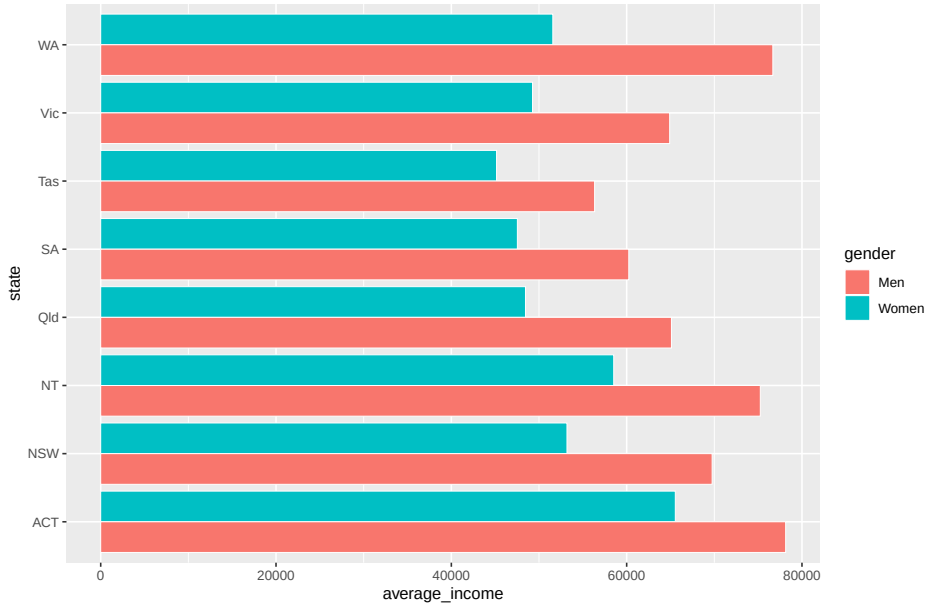
```
data %>%
  ggplot(aes(x = state,
             y = average_income,
             fill = gender)) +
  geom_col(position = "dodge") # 'dodge' the series
```



To flip the chart – a useful move when you have long labels – add `coord_flip` (ie 'flip the x and y coordinates of the chart').

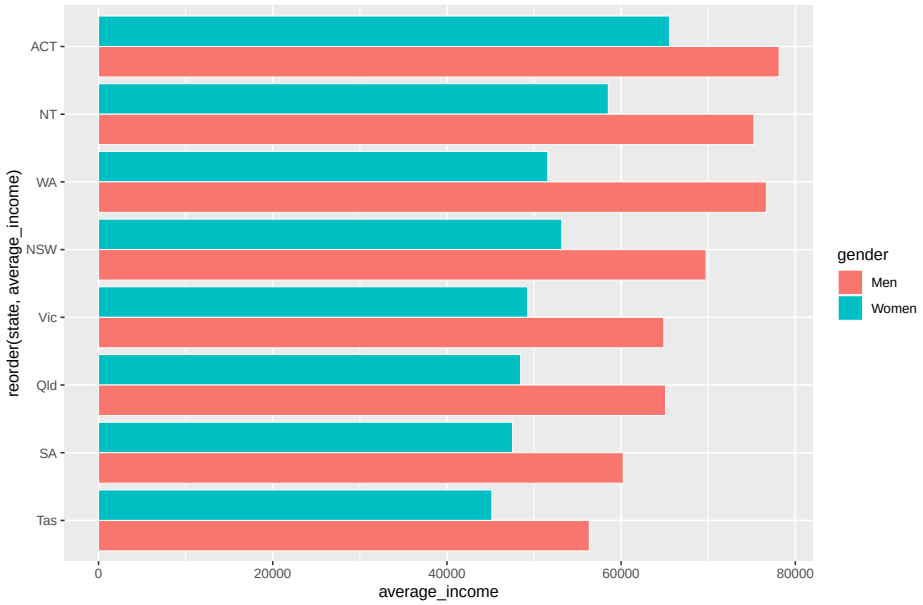
However, while the *coordinates* have been flipped, the underlying data hasn't. If you want to refer to the `average_income` axis, which now lies horizontally, you would still refer to the `y` axis (eg `grattan_y_continuous` still refers to your `y` aesthetic, `average_income`).

```
data %>%
  ggplot(aes(x = state,
             y = average_income,
             fill = gender)) +
  geom_col(position = "dodge") +
  coord_flip() # rotate the chart
```



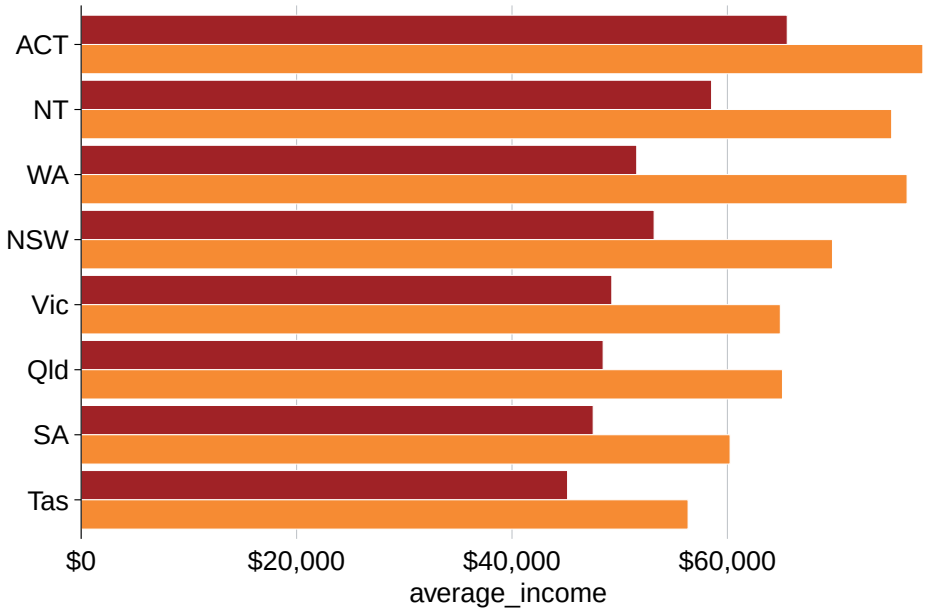
And reorder the states by average income, so that the state with the highest (combined) average income is at the top. This is done with the `reorder(var_to_reorder, var_to_reorder_by)` function when you define the `state` aesthetic:

```
data %>%
  ggplot(aes(x = reorder(state, average_income), # reorder
             y = average_income,
             fill = gender)) +
  geom_col(position = "dodge") +
  coord_flip()
```



Wonderful – that's how you want our *data* to look. Now you can Grattanise it. Note that `theme_grattan` needs to know that the coordinates were flipped so it can apply the right settings. Also tell `grattan_fill_manual` that there are two fill series.

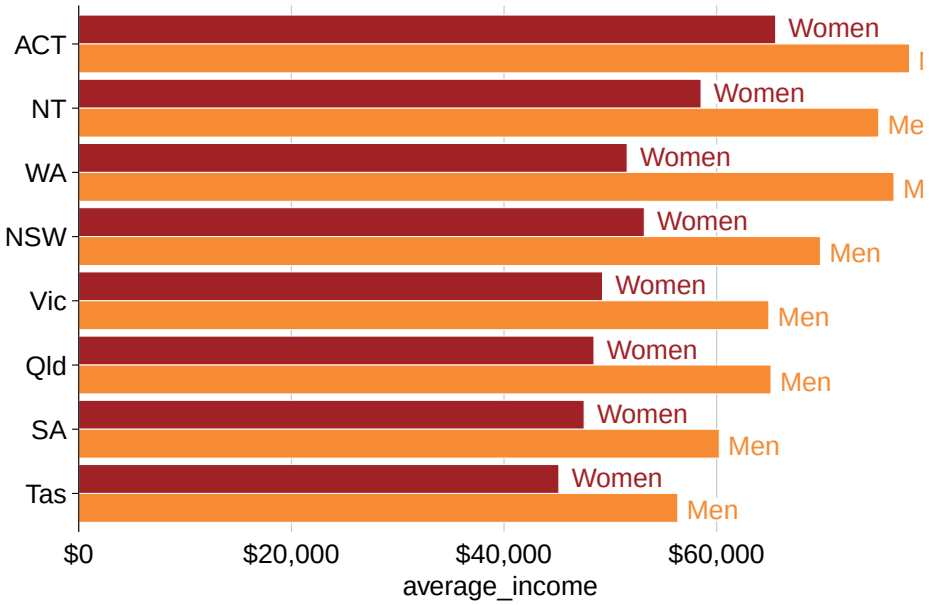
```
data %>%
  ggplot(aes(x = reorder(state, average_income),
             y = average_income,
             fill = gender)) +
  geom_col(position = "dodge") +
  coord_flip() +
  theme_grattan(flipped = TRUE) + # grattan theme
  grattan_y_continuous(labels = dollar) + # y axis
  grattan_fill_manual(2) # grattan fill colours
```



You can use `grattan_label` to **label your charts** in the Grattan style. This function is a 'wrapper' around `geom_label` that has settings that we tend to like: white background with a thin margin, 18-point font, and no border. It takes the standard arguments of `geom_label`.

Section 4.6 shows how labels are treated like data points: they need to know where to go (`x` and `y`) and what to show (`label`). But if you provide *every point* to your labelling `geom`, it will plot every label:

```
data %>%
  ggplot(aes(x = reorder(state, average_income),
             y = average_income,
             fill = gender)) +
  geom_col(position = "dodge") +
  coord_flip() +
  theme_grattan(flipped = TRUE) +
  grattan_y_continuous(labels = dollar) +
  grattan_fill_manual(2) +
  grattan_label(aes(colour = gender,  # colour the text according to gender
                    label = gender),  # label the text according to gender
            position = position_dodge(width = 1),  # position dodge with width 1
            hjust = -0.1) +  # horizontally align the label so its outside the bar
  grattan_colour_manual(2)   # define colour as two grattan colours
```



To just label *one* of the plots – ie the first one, ACT in this case – we need to tell `grattan_label`. The easiest way to do this is by **creating a label dataset beforehand**, like `label_gender` below. This just includes the observations you want to label:

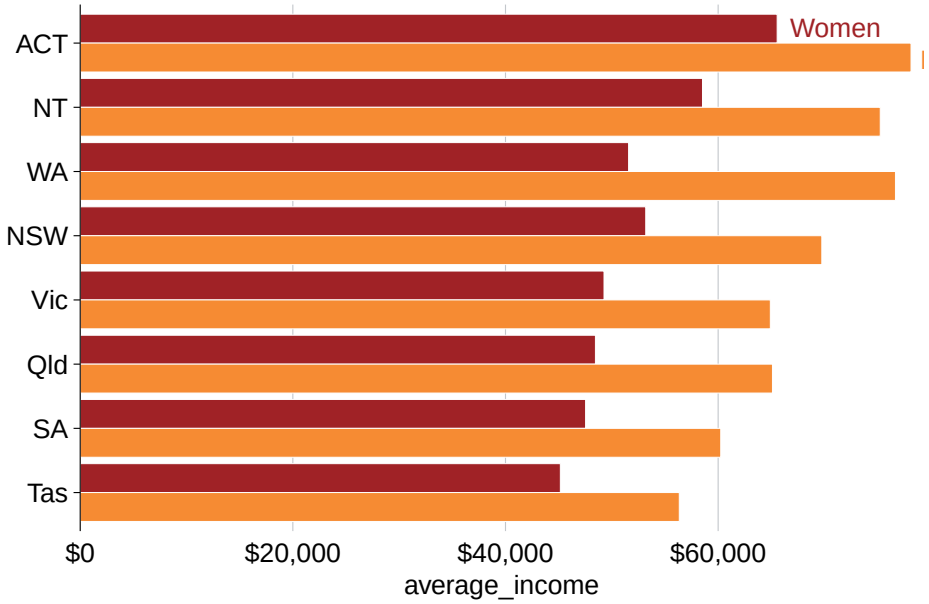
```
label_gender <- data %>%
  filter(state == "ACT")  # just want Tasmania observations

label_gender
```

```
## # A tibble: 2 x 3
## # Groups:   state [1]
##   state gender average_income
##   <chr> <chr>           <dbl>
## 1 ACT   Men            78141.
## 2 ACT   Women          65548.
```

So you can pass that `label_gender` dataset to `grattan_label`:

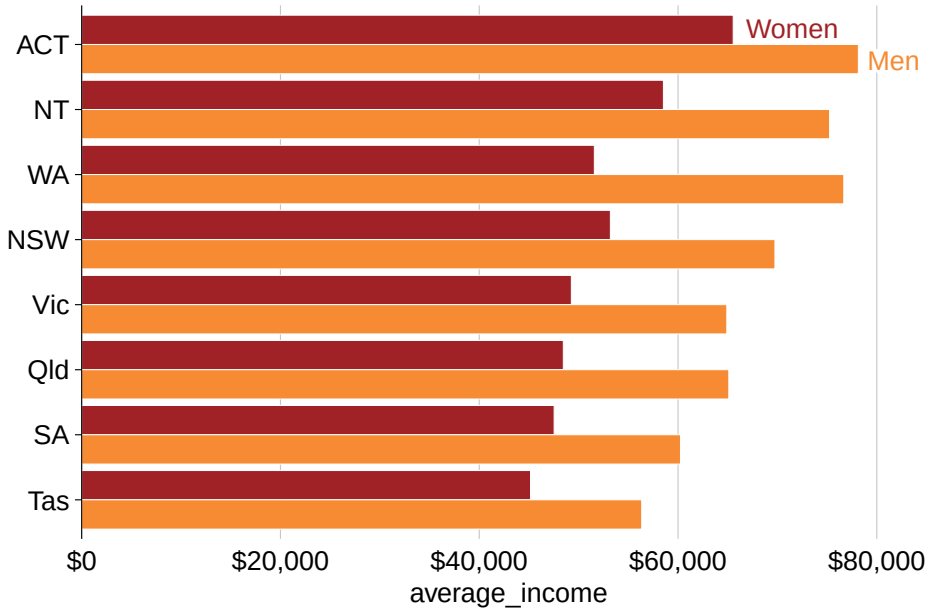
```
data %>%
  ggplot(aes(x = reorder(state, average_income),
             y = average_income,
             fill = gender)) +
  geom_col(position = "dodge") +
  coord_flip() +
  theme_grattan(flipped = TRUE) +
  grattan_y_continuous(labels = dollar) +
  grattan_fill_manual(2) +
```

```
  grattan_label(data = label_gender,  # supply the new dataset
                aes(colour = gender,
                    label = gender),
                position = position_dodge(width = 1),
                hjust = -0.1) +
  grattan_colour_manual(2)
```



Almost there! The labels go out of range a little bit, and we can fix this by expanding the plot:

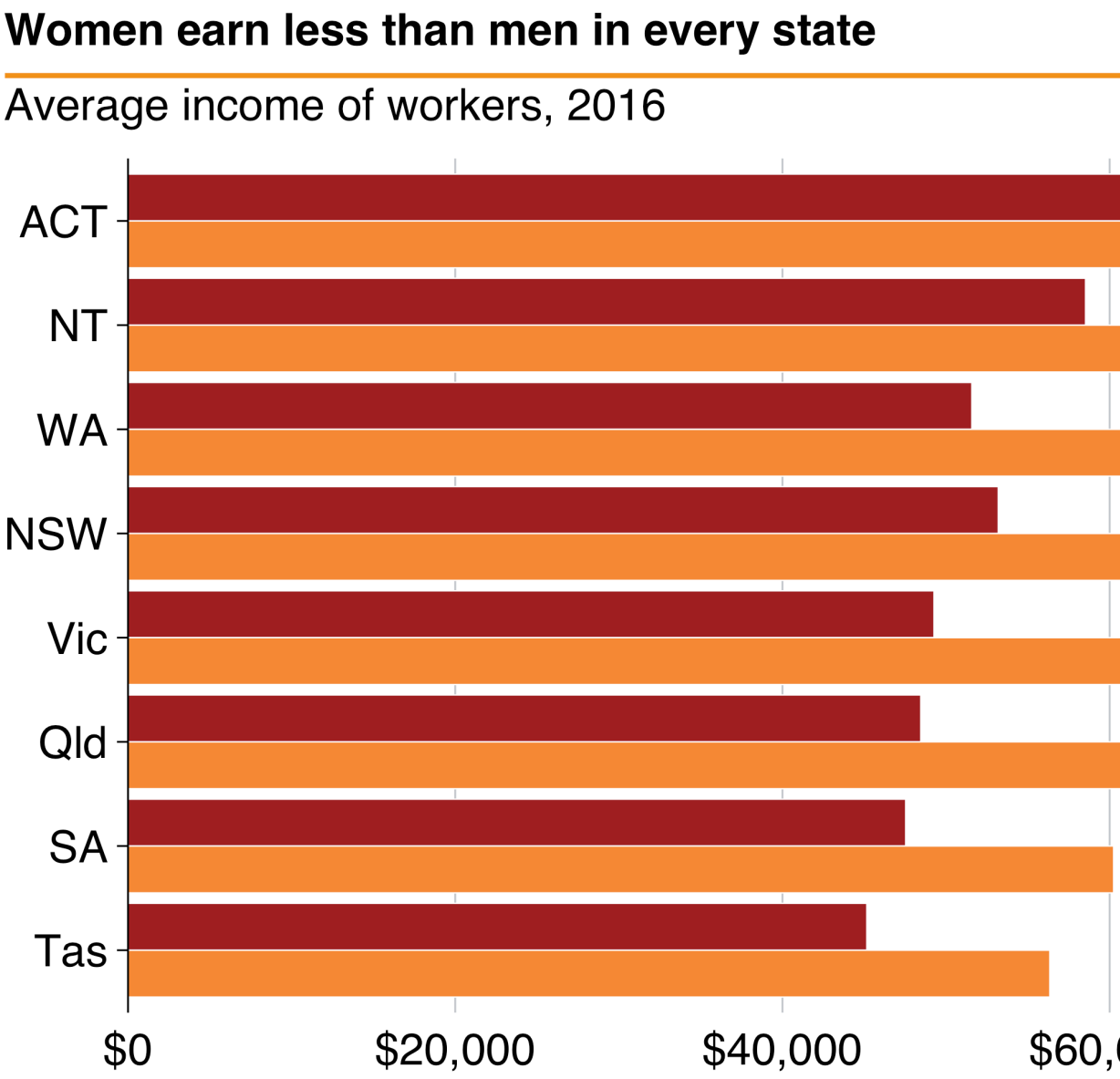
```
data %>%
  ggplot(aes(x = reorder(state, average_income),
             y = average_income,
             fill = gender)) +
  geom_col(position = "dodge") +
  coord_flip() +
  theme_grattan(flipped = TRUE) +
  grattan_y_continuous(labels = dollar,
                       expand_top = .1) + # expand the plot
  grattan_fill_manual(2) +
  grattan_label(data = label_gender,
                aes(colour = gender,
                    label = gender),
                position = position_dodge(width = 1),
                hjust = -0.1) +
  grattan_colour_manual(2)
```



Looks of the highest standard! Now you can add titles and a caption, and save using `grattan_save`:

```
multiple_bar <- data %>%
  ggplot(aes(x = reorder(state, average_income),
             y = average_income,
             fill = gender)) +
  geom_col(position = "dodge") +
  coord_flip() +
  theme_grattan(flipped = TRUE) +
  grattan_y_continuous(labels = dollar,
                       expand_top = .1) +
  grattan_fill_manual(2) +
  grattan_label(data = label_gender,
                aes(colour = gender,
                    label = gender),
                position = position_dodge(width = 1),
                hjust = -0.1) +
  grattan_colour_manual(2) +
  labs(title = "Women earn less than men in every state",
       subtitle = "Average income of workers, 2016",
       x = "",
       y = "",
       caption = "Notes: Only includes people who submitted a tax return in 2016-16. Source: ABS
```

```
grattan_save("atlas/multiple_bar.pdf", multiple_bar, type = "fullslide")
```



Notes: Only includes people who submitted a tax return in 2016-16.
Source: ABS (2018)

5.2.3 Facetted bar charts

'Facetting' a chart means you create a separate plot for each group. It's particularly useful in showing differences between more than one group. The chart you'll make in this section will show annual income by gender and state, *and* by professional and non-professional workers:

Start by creating the dataset you want to plot:

```
data <- sa3_income %>%
  group_by(state, gender, prof) %>%
  summarise(average_income = sum(total_income) / sum(workers))

data
```

```
## # A tibble: 32 x 4
## # Groups:   state, gender [16]
##    state gender prof             average_income
##    <chr> <chr>  <chr>                     <dbl>
##  1 ACT   Men    Non-professional         52545.
##  2 ACT   Men    Professional             96488.
##  3 ACT   Women  Non-professional         46151.
##  4 ACT   Women  Professional             79828.
##  5 NSW   Men    Non-professional         49182.
##  6 NSW   Men    Professional             91624.
##  7 NSW   Women  Non-professional         36772.
##  8 NSW   Women  Professional             68445.
##  9 NT    Men    Non-professional         58844.
## 10 NT    Men    Professional             87666.
## # ... with 22 more rows
```

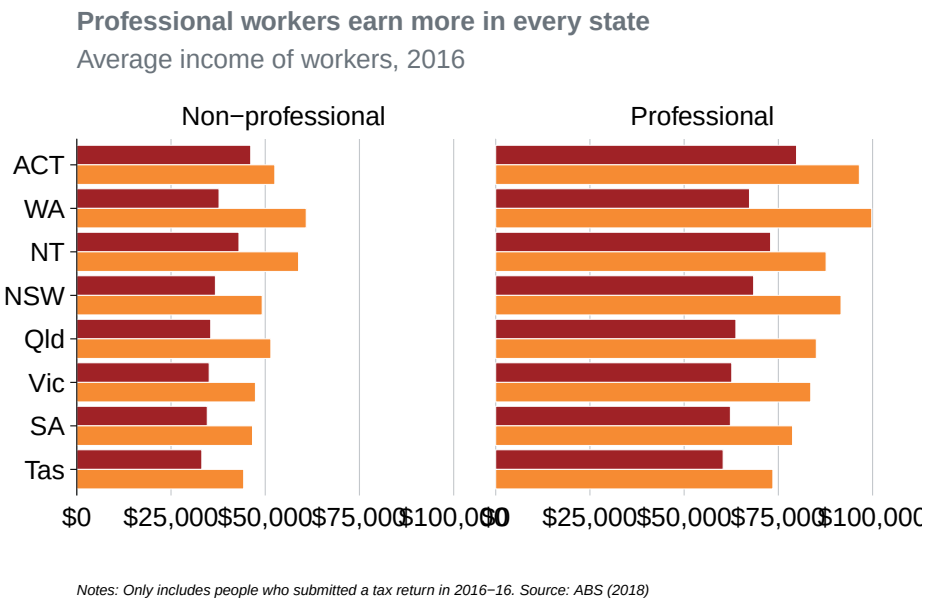
Then plot a bar chart with `geom_col` and `theme_grattan` elements, using a similar chain to the final plot of 5.2.2 (without the labelling). We'll build on this chart:

```
facet_bar <- data %>%
  ggplot(aes(x = reorder(state, average_income),
             y = average_income,
             fill = gender)) +
  geom_col(position = "dodge") +
  coord_flip() +
  theme_grattan(flipped = TRUE) +
  grattan_y_continuous(labels = dollar,
                       expand_top = .1) +
  grattan_fill_manual(2) +
  grattan_colour_manual(2) +
  labs(title = "Professional workers earn more in every state",
       subtitle = "Average income of workers, 2016",
```

```
       x = "",
       y = "",
       caption = "Notes: Only includes people who submitted a tax return in 2016-16. Source: ABS
```

You can 'facet' bar charts – and any other chart type – with the `facet_grid` or `facet_wrap` commands. The latter tends to give you more control over label placement, so let's start with that. `fadcet_wrap` asks the questions: "what variables should I create separete charts for", and "how should I place them on the page"? Tell it to use the `prof` variable with the `vars()` function.[5]

```
facet_bar +
  facet_wrap(vars(prof))
```



That's good! It does what it should. Now you just need to tidy it up a little bit by adding labels and avoiding clashes along the bottom axis.

Create labels in the same way you have done before: you only want to label one 'women' and 'men' series, so create a dataset that contains only that information:

```
label_data <- data %>%
  filter(state == "ACT",
         prof == "Non-professional")

label_data
```

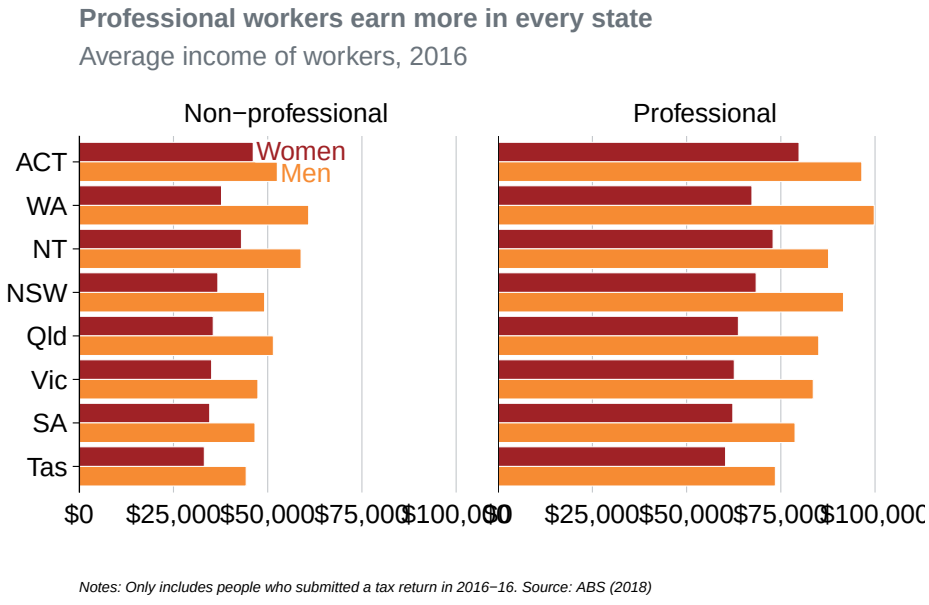
[5]The `vars()` function is sometimes used in the `tidyverse` to specifically say "I am using a variable name here". You can't use variable names directly because of legacy issues. You can learn more about it in the official documentation.

```
## # A tibble: 2 x 4
## # Groups:   state, gender [2]
##   state gender prof             average_income
##   <chr> <chr>  <chr>                     <dbl>
## 1 ACT   Men    Non-professional         52545.
## 2 ACT   Women  Non-professional         46151.
```

Good – now add that to the plot with `grattan_label`, supplying the required aesthetics and position. And use `hjust = 0` to tell the labels to be left-aligned.

To give each plot a black base axis, you can add `geom_hline()` with `yintercept = 0`.

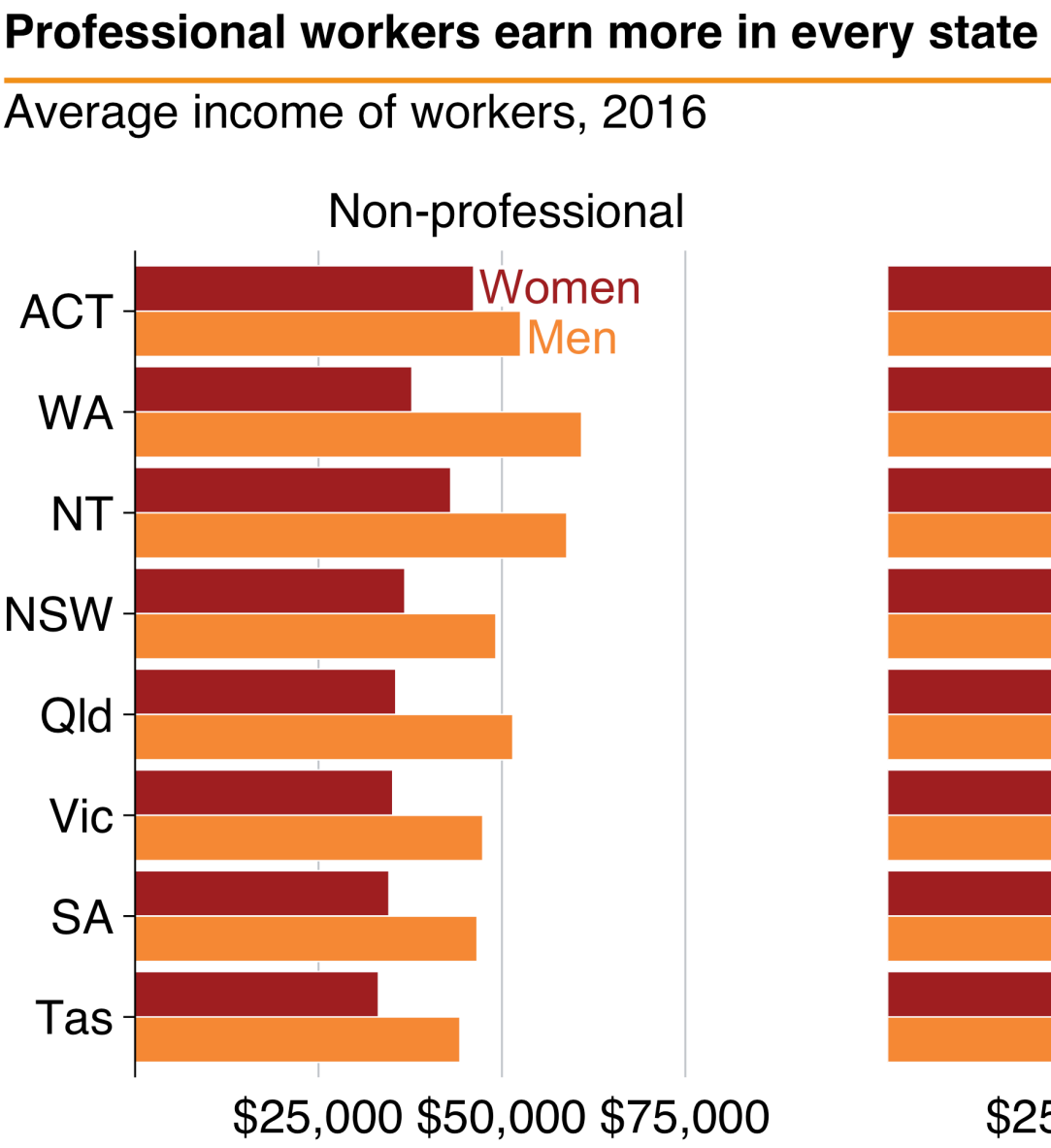
```
facet_bar +
  facet_wrap(vars(prof)) +
  geom_hline(yintercept = 0) +  # add black line
  grattan_label(data = label_data, # supply label data
                aes(label = gender,
                    colour = gender),
                position = position_dodge(width = 1),
                hjust = 0)
```



Brill! But the "$0" and "$100,000" labels are clashing along the horizontal axis. To tidy these up, we redefine the `breaks` – the points that will be labelled – to 25,000, 50,000 and 75,000 inside `grattan_y_continuous`. Putting everything together and saving the plot as a fullslide chart with `grattan_save`:

```
# Create label data
label_data <- data %>%
  filter(state == "ACT",
         prof == "Non-professional")

# Create plot
facet_bar <- data %>%
  ggplot(aes(x = reorder(state, average_income),
             y = average_income,
             fill = gender)) +
  geom_col(position = "dodge") +
  coord_flip() +
  theme_grattan(flipped = TRUE) +
  grattan_y_continuous(labels = dollar,
                       breaks = c(25e3, 50e3, 75e3)) +  # change breaks
  grattan_fill_manual(2) +
  grattan_colour_manual(2) +
  labs(title = "Professional workers earn more in every state",
       subtitle = "Average income of workers, 2016",
       x = "",
       y = "",
       caption = "Notes: Only includes people who submitted a tax return in 2016-16. Source: ABS
  facet_wrap(vars(prof)) +
  grattan_label(data = label_data,
                aes(label = gender,
                    colour = gender),
                position = position_dodge(width = 1),
                hjust = 0)
```

```
grattan_save("atlas/facet_bar.pdf", facet_bar, type = "fullslide")
```



Notes: Only includes people who submitted a tax return in 2016-16.
Source: ABS (2018)

5.3 Line charts

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

5.3.1 Simple line chart

The first line chart shows the number of workers in Australia between 2011 and 2016:

5.3.2 Line chart with multiple series

This line chart will show how **real** average income has changed for each state over the past five years:

First, take the `sa3_income` dataset and create a summary table average income by year and state. Ignore the territories for this chart.

```
data <- sa3_income %>%
  filter(!state %in% c("ACT", "NT")) %>%
  group_by(year, state) %>%
  summarise(average_income = sum(total_income) / sum(workers))

head(data)
```

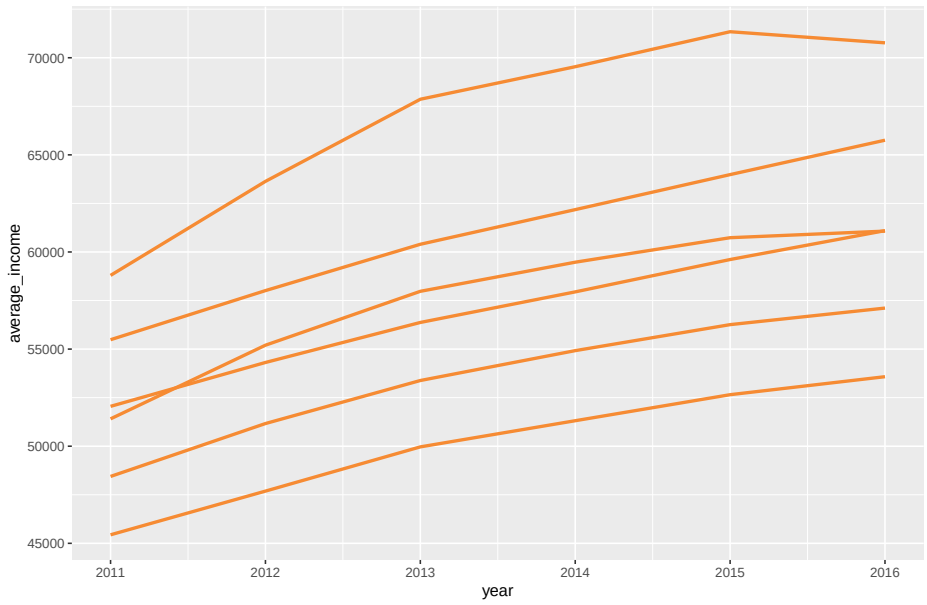
```
## # A tibble: 6 x 3
## # Groups:   year [1]
##    year state average_income
##   <dbl> <chr>          <dbl>
## 1  2011 NSW           55483.
## 2  2011 Qld           51408.
## 3  2011 SA            48443.
## 4  2011 Tas           45439.
## 5  2011 Vic           52053.
## 6  2011 WA            58795.
```

The income data presented is nominal, so you'll need to inflate to 'real' dollars using the 'cpi_inflate

Plot a line chart by taking the `data`, passing it to `ggplot` with *aes*thetics, then using `geom_line`:

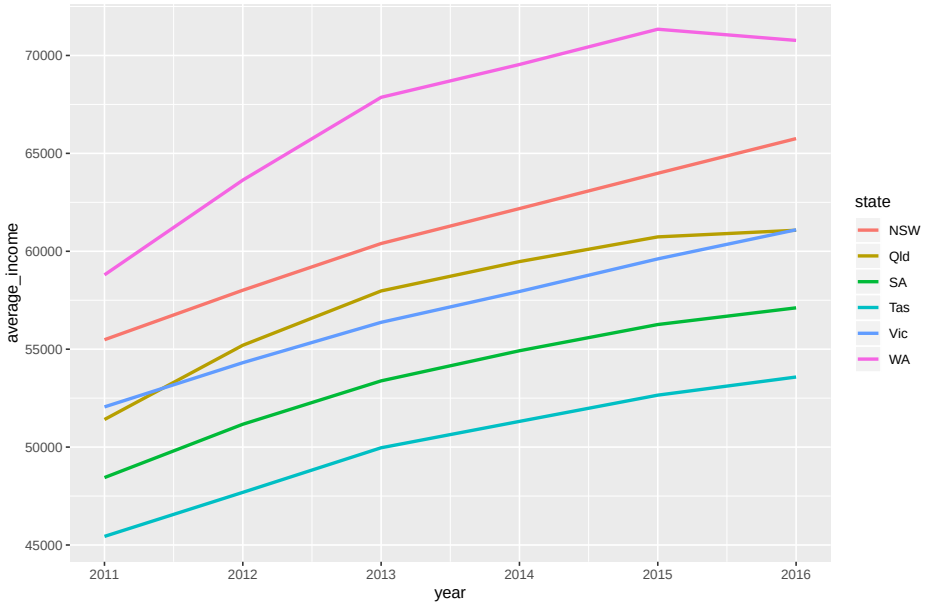
```
data %>%
  ggplot(aes(x = year,
             y = average_income,
```

```
            group = state)) +
  geom_line()
```



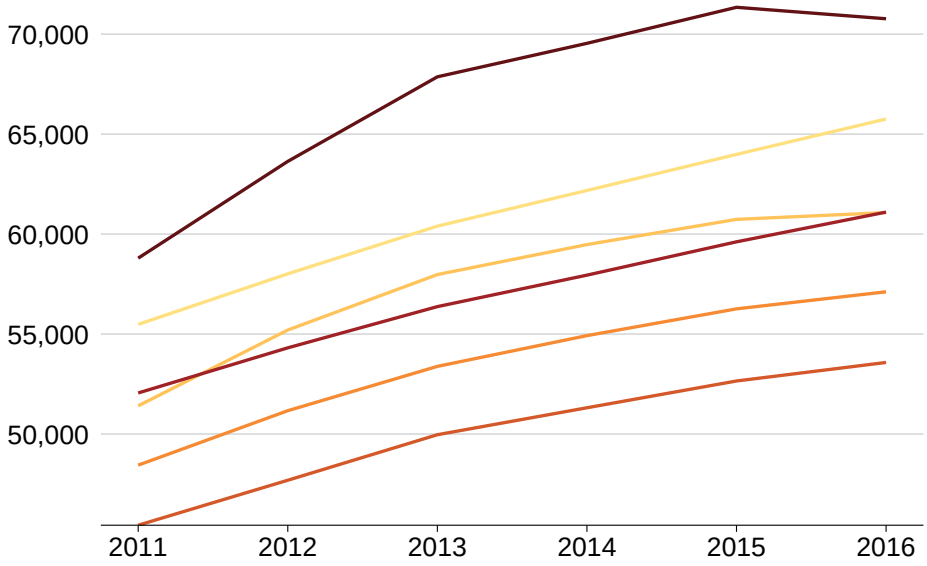
Now you can represent each `state` by colour:

```
data %>%
  ggplot(aes(x = year,
             y = average_income,
             group = state,
             colour = state)) +
  geom_line()
```



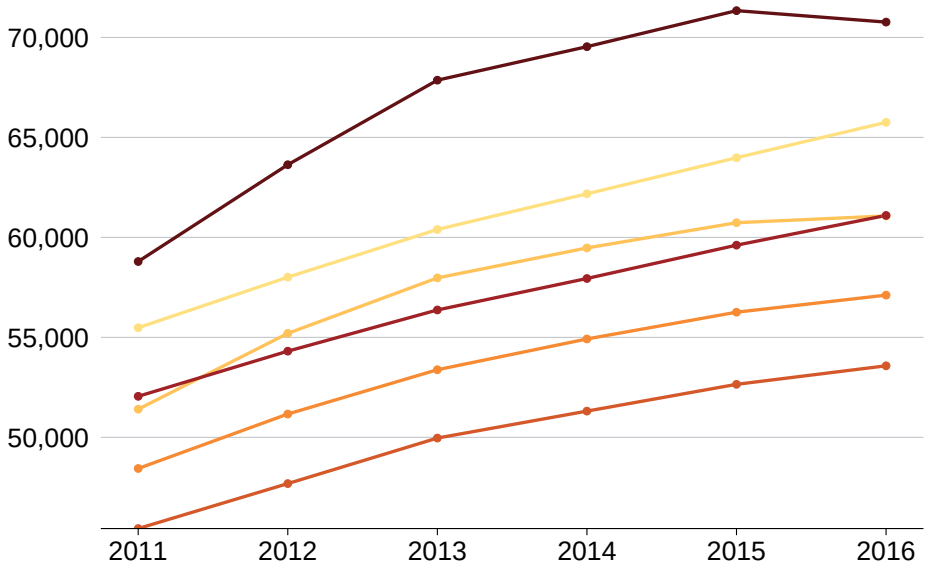
Cooler! Adding some Grattan formatting to it and define it as our 'base chart':

```
base_chart <-data %>%
  ggplot(aes(x = year,
             y = average_income,
             group = state,
             colour = state)) +
  geom_line() +
  theme_grattan() +
  grattan_y_continuous(labels = comma) +
  grattan_colour_manual(6) +
  labs(x = "",
       y = "")

base_chart
```



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

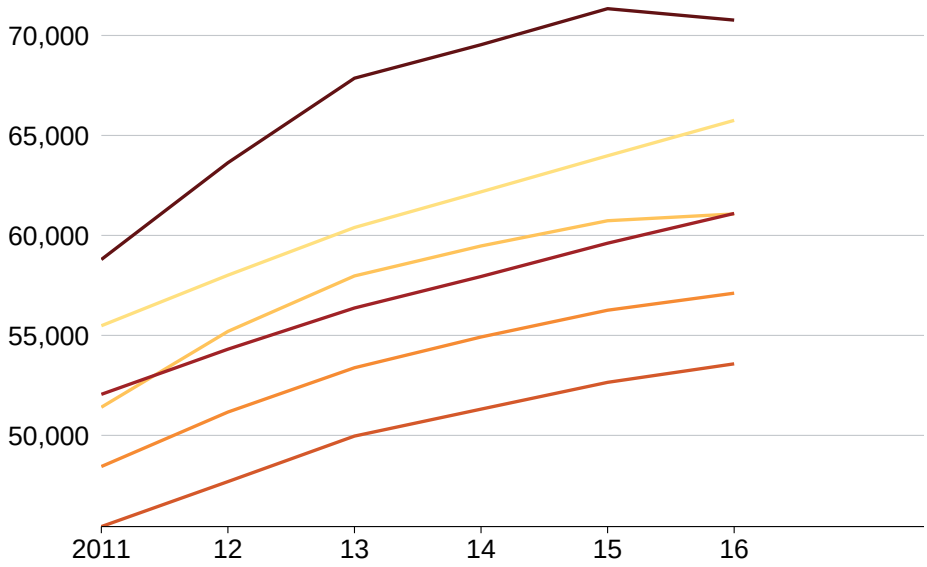
```
base_chart +
  geom_point()
```



To add labels to the end of each line, you would expand the x-axis to make room for labels and add reasonable breaks:

```
base_chart +
  grattan_x_continuous(expand_right = .3,
                       breaks = seq(2011, 2016, 1),
```

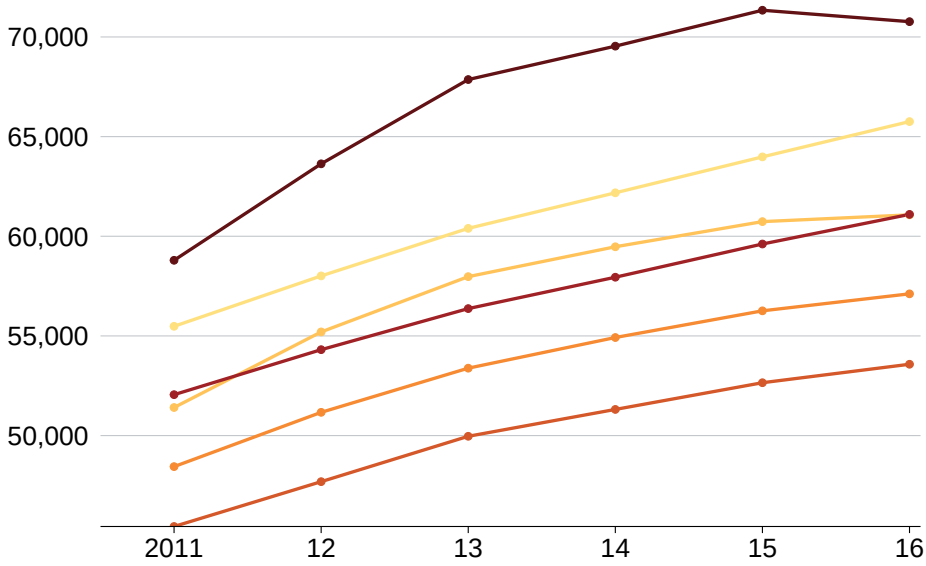
```
                        labels = c("2011", "12", "13", "14", "15", "16"))
```



Then add labels, using

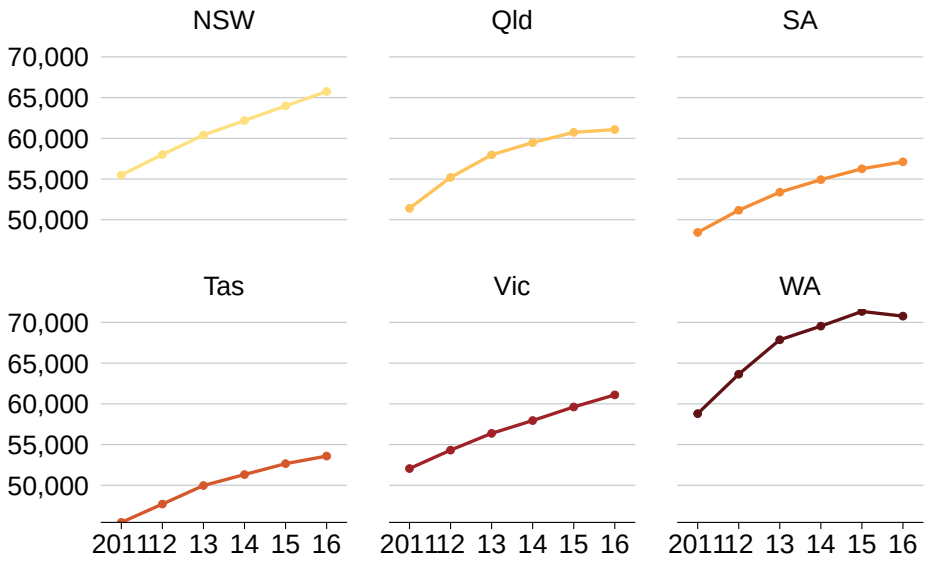
```
label_line <- data %>%
  filter(year == 2010)

base_chart +
  geom_point() +
  grattan_x_continuous(expand_left = .1,
                       breaks = seq(2011, 2016, 1),
                       labels = c("2011", "12", "13", "14", "15", "16")) +
  grattan_label(data = label_line,
                aes(label = state),
                nudge_x = -Inf,
                segment.colour = NA)
```

```
## Warning: Ignoring unknown parameters: segment.colour
```



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

```
base_chart +
  geom_point() +
    grattan_x_continuous(expand_left = .1,
                         expand_right = .1,
                         breaks = seq(2011, 2016, 1),
                         labels = c("2011", "12", "13", "14", "15", "16")) +
  theme(panel.spacing.x = unit(10, "mm")) +
  facet_wrap(state ~ .)
```



5.4 Scatter plots

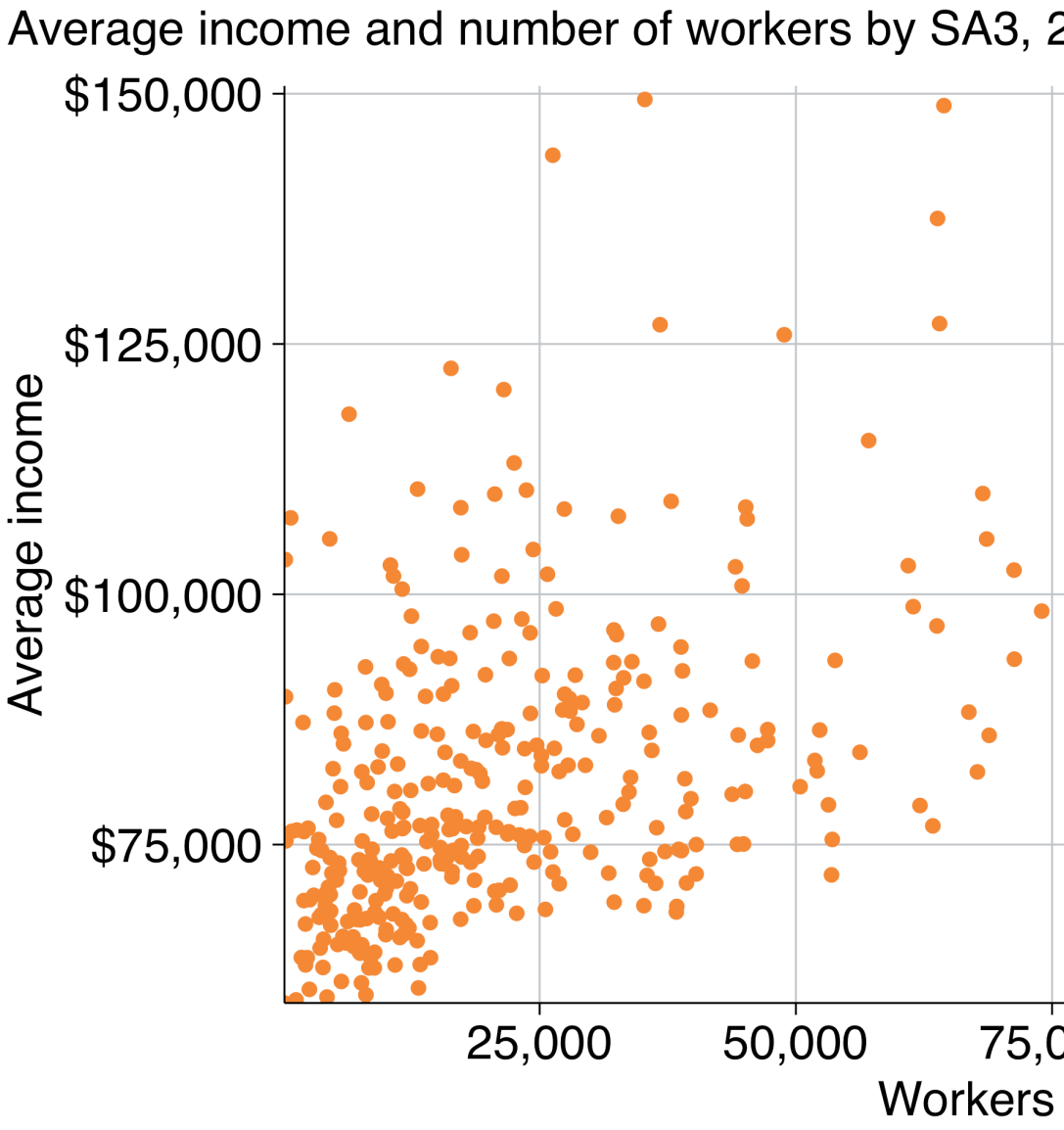
Scatter plots require `x` and `y` aesthetics. These can then be coloured and faceted.

5.4.1 Simple scatter plot

The first simple scatter plot will show the relationship between average incomes of professionals and the number of professional workers by area in 2016:

```
include_graphics("atlas/simple_scatter.png")
```

More workers, more income



Notes: Only includes people who submitted a tax return in 2016-16.
Source: ABS (2018)

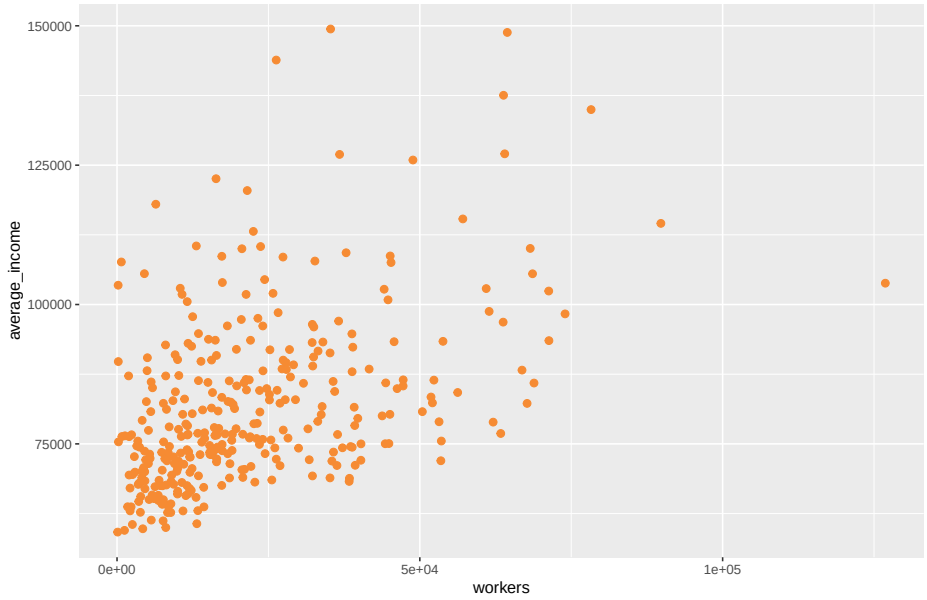
Create the dataset you want to plot:

```
data <- sa3_income %>%
  filter(year == 2016,
         prof == "Professional") %>%
  group_by(sa3_name) %>%
  summarise(workers = sum(workers),
            average_income = sum(total_income) / workers)

head(data)
```

```
## # A tibble: 6 x 3
##   sa3_name       workers average_income
##   <chr>            <dbl>          <dbl>
## 1 Adelaide City    10005         90115.
## 2 Adelaide Hills   24715         84921.
## 3 Albany           12390         70581.
## 4 Albury           16465         72305.
## 5 Alice Springs     9640         84340.
## 6 Armadale         19771         85407.
```

The dataset has one observation per SA3, and the two variables you want to plot: workers and average income. Pass the data to `ggplot`, set the aesthetics and plot with `geom_point`:

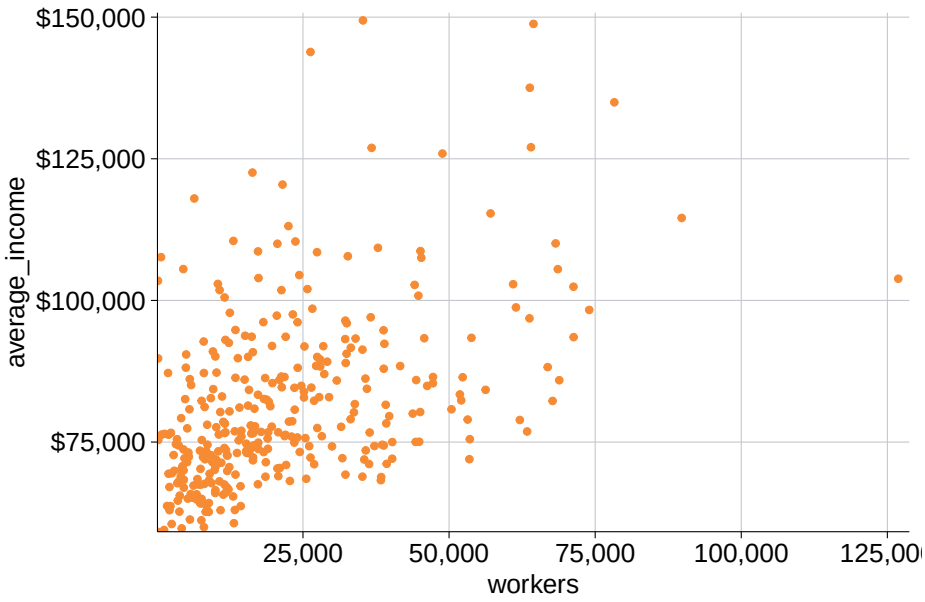
```
data %>%
  ggplot(aes(x = workers,
             y = average_income)) +
  geom_point()
```



Then add Grattan theme elements:

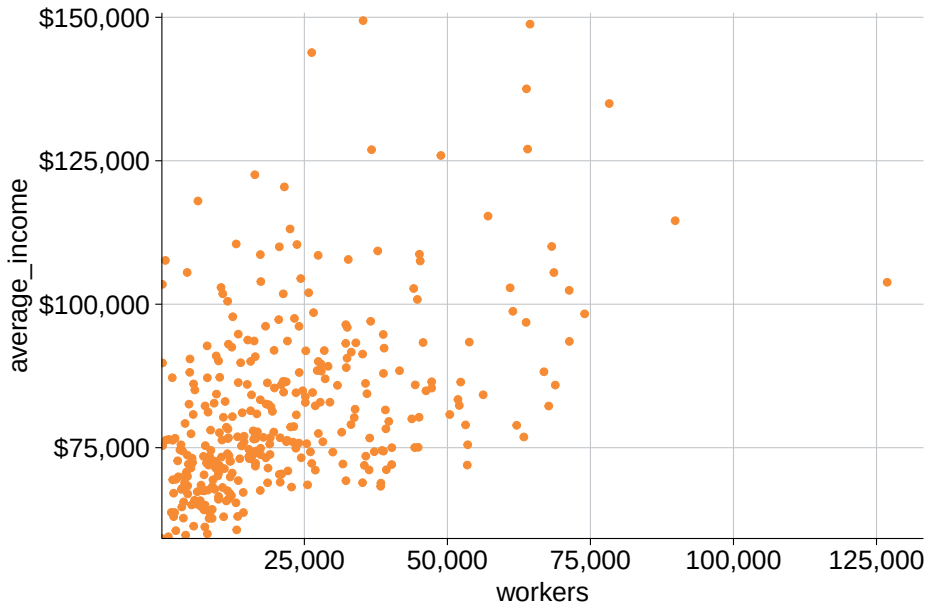
- `theme_grattan()`, telling it that the `chart_type` is a scatter plot.
- `grattan_y_continuous()`, setting the label style to `dollar`.
- `grattan_x_continuous()`, setting the label style to `comma`.

```
data %>%
  ggplot(aes(x = workers,
             y = average_income)) +
  geom_point()  +
  theme_grattan(chart_type = "scatter") +
  grattan_y_continuous(labels = dollar) +
  grattan_x_continuous(labels = comma)
```



Looks too good to be true. The last label on the x-axis goes off the page a bit so you can expand the plot to the right in the `grattan_x_continuous` element:

```
data %>%
  ggplot(aes(x = workers,
             y = average_income)) +
  geom_point()  +
  theme_grattan(chart_type = "scatter") +
  grattan_y_continuous(labels = dollar) +
  grattan_x_continuous(labels = comma,
                       expand_right = .05) # expand the right by 5%
```

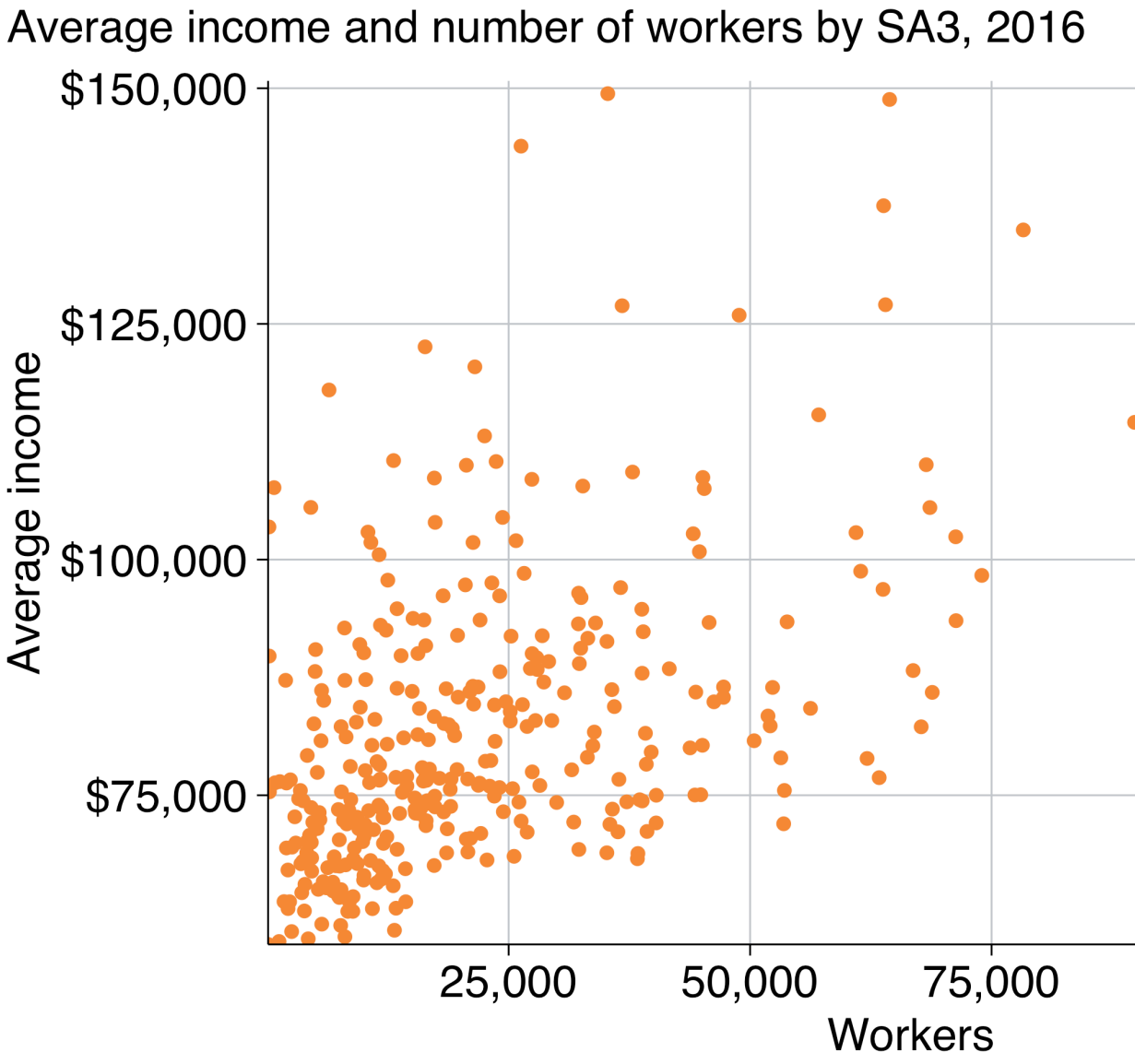


Finally, add titles and save the plot:

```
simple_scatter <- data %>%
  ggplot(aes(x = workers,
             y = average_income)) +
  geom_point()  +
  theme_grattan(chart_type = "scatter") +
  grattan_y_continuous(labels = dollar) +
  grattan_x_continuous(labels = comma,
                       expand_right = .05) +
  labs(title = "More workers, more income",
       subtitle = "Average income and number of workers by SA3, 2016",
       y = "Average income",
       x = "Workers",
       caption = "Notes: Only includes people who submitted a tax return in 2016-16. So
```

```
grattan_save("atlas/simple_scatter.pdf", simple_scatter, type = "fullslide")
```

More workers, more income



Notes: Only includes people who submitted a tax return in 2016-16.
Source: ABS (2018)

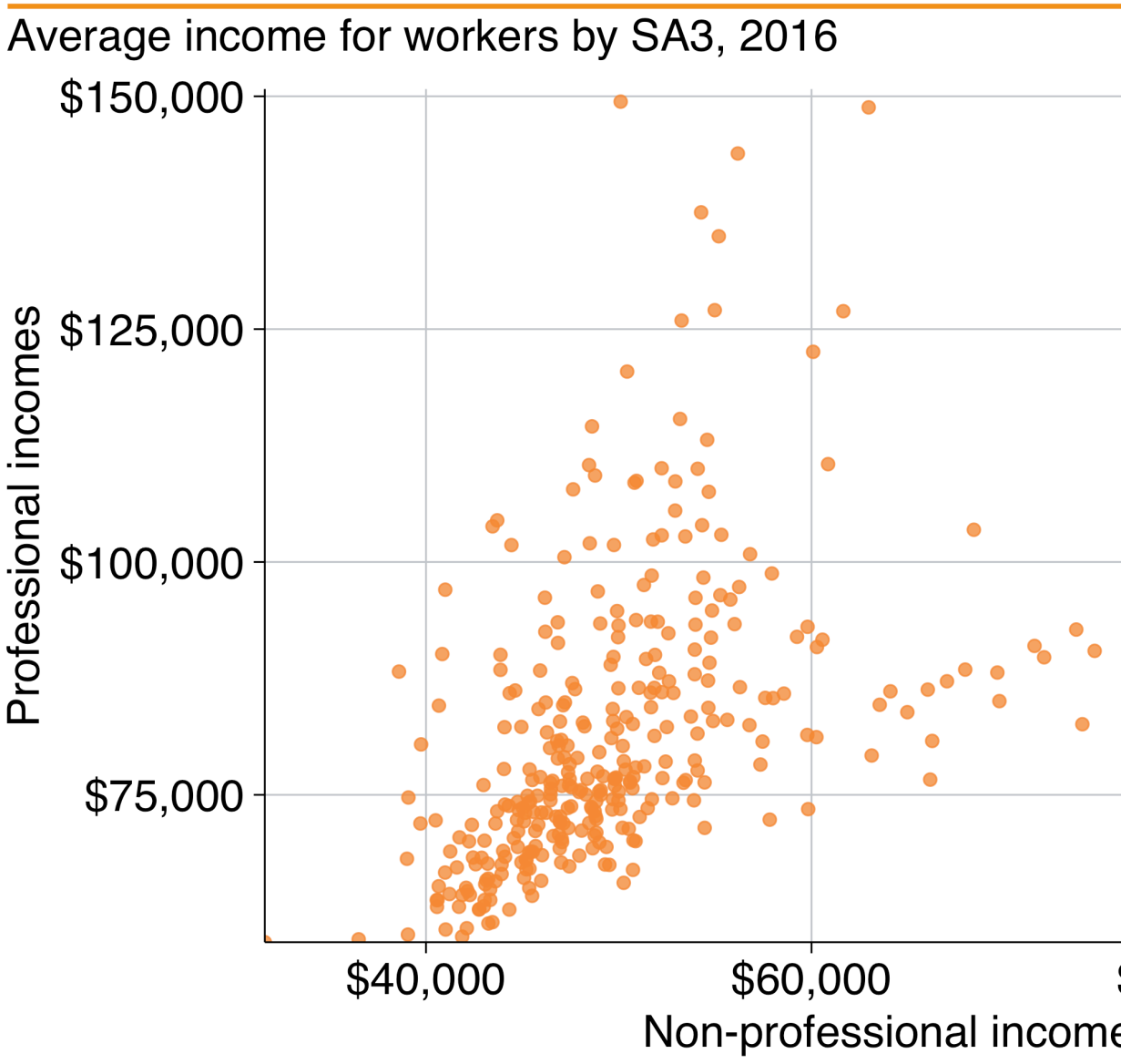
5.4.2 Scatter plot with reshaped data

The next scatter plot involves the same basic plotting principles of the chart above, but requires a bit more data manipulation before plotting.

The chart will show the wages of professional workers and non-professional workers in 2016:

```
include_graphics("atlas/scatter_reshape.png")
```

Non-professionals tend to earn more when professio do



Notes: Only includes people who submitted a tax return in 2016-16.
Source: ABS (2018)

First prepare your data. You want to find the average incomes of all professional and non-professional workers in 2016:

```
data_prep <- sa3_income %>%
  filter(year == 2016) %>%
  group_by(sa3_name, prof) %>%
  summarise(average_income = sum(total_income) / sum(workers))

head(data_prep)
```

```
## # A tibble: 6 x 3
## # Groups:   sa3_name [3]
##   sa3_name       prof             average_income
##   <chr>          <chr>                     <dbl>
## 1 Adelaide City  Non-professional         40843.
## 2 Adelaide City  Professional             90115.
## 3 Adelaide Hills Non-professional         47208.
## 4 Adelaide Hills Professional             84921.
## 5 Albany         Non-professional         46609.
## 6 Albany         Professional             70581.
```

That's good – you have the numbers you need. But think about how you're going to *plot* them using `x` and `y` aesthetics. You'll need one variable for `x = professional_income` and one variable for `y = non_professional_income`. At the moment, these are represented by different *rows*.

You can fix this by reshaping the data with the `pivot_wider` function. The three arguments you provide here are:

- `id_cols = sa3_name`: the variable `sa3_name` uniquely identifies each row in your data.
- `names_from = prof`: the variable `prof` contains the variables names for the *new* variables you are creating.
- `values_from = average_income`: the variable `average_income` contains the *values* that will fill the new variables.

After the `pivot_wider` step is complete, use `janitor::clean_names()` to convert the new `Professional` and `Non-Professional` names to `snake_case` to make them easier to use down the track:

```
data <- data_prep %>%
  pivot_wider(id_cols = sa3_name,  # variables that will stay the same
              names_from = prof,   # variables that will dictate the new names
              values_from = average_income) %>%  # these will be the values
  janitor::clean_names() # tidy up the new variable names

head(data)
```

```
## # A tibble: 6 x 3
```

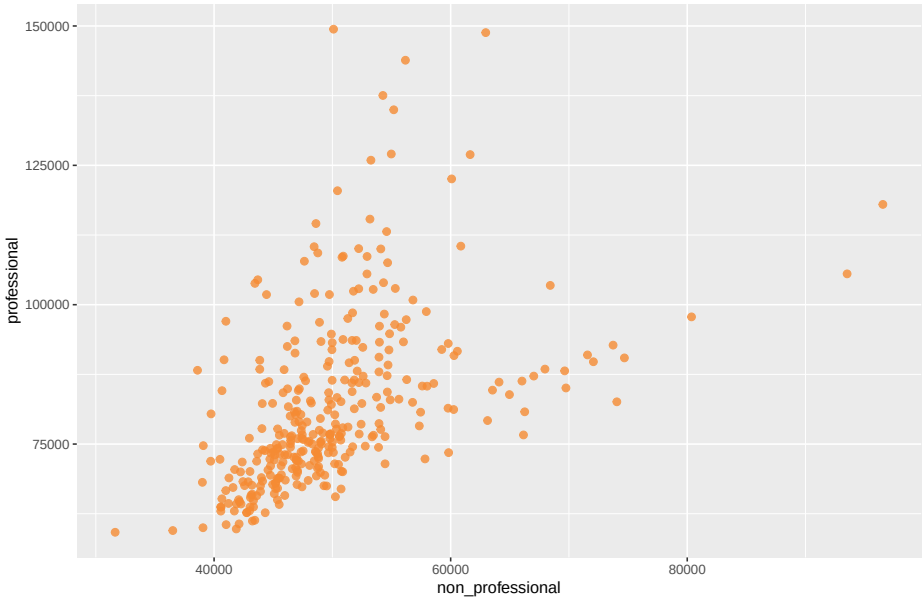
```
## # Groups:   sa3_name [6]
##   sa3_name       non_professional professional
##   <chr>                     <dbl>        <dbl>
## 1 Adelaide City            40843.       90115.
## 2 Adelaide Hills           47208.       84921.
## 3 Albany                   46609.       70581.
## 4 Albury                   44718.       72305.
## 5 Alice Springs            54647.       84340.
## 6 Armadale                 57599.       85407.
```

Getting the data in the right format for your plot – rather than 'hacking' your plot to fit your data – will save you time and effort down the line.

Now you have a dataset in the format you want to plot, you can pass it to `ggplot` and add aesthetics like you normally would.

```
data %>%
  ggplot(aes(x = non_professional,
             y = professional)) +
  geom_point(alpha = 0.8) # make the points a little transparent
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```



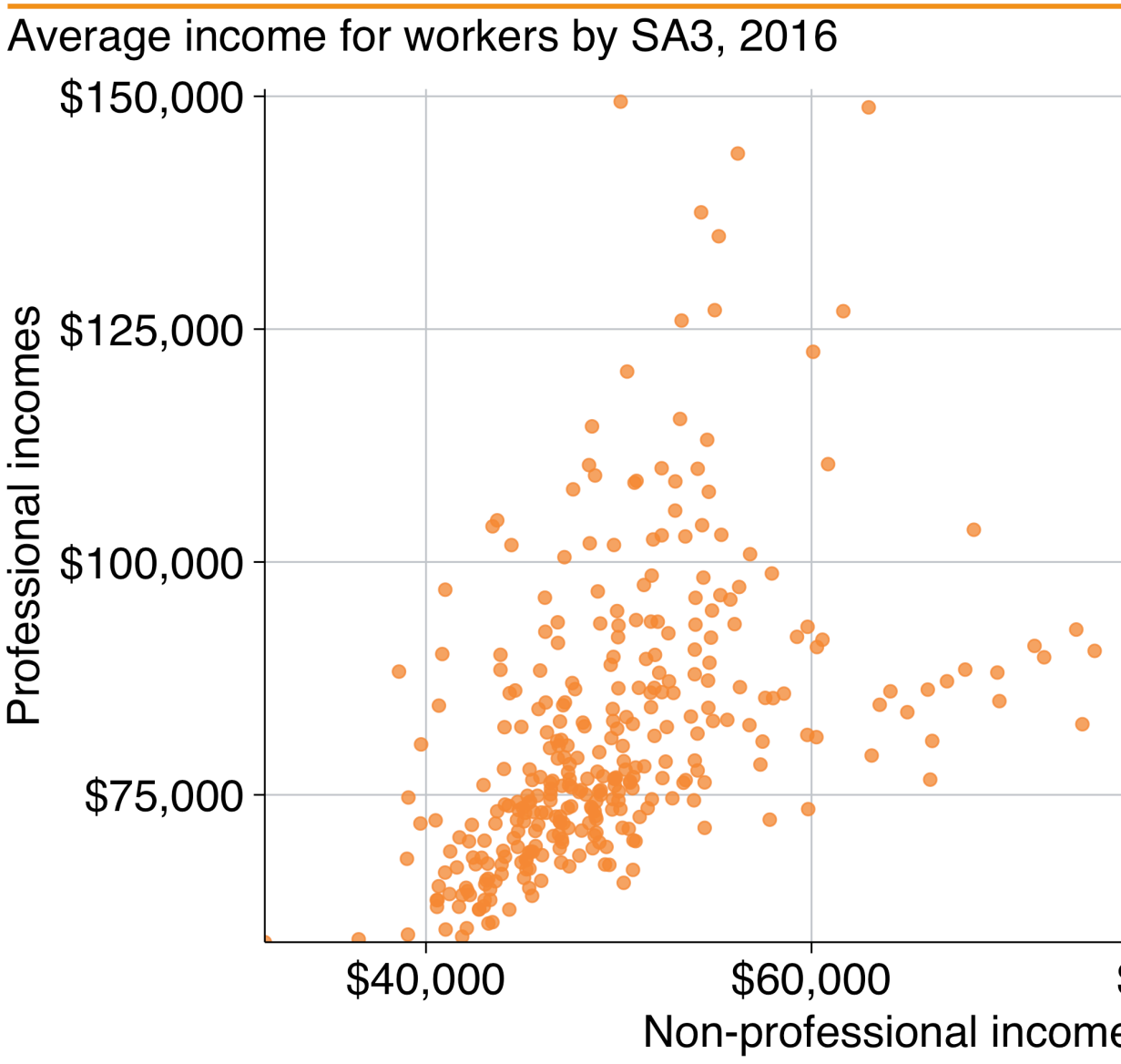
Then, like you've done before, add Grattan theme elements and titles, and save with `grattan_save`:

```
scatter_reshape <- data %>%
  ggplot(aes(x = non_professional,
             y = professional)) +
```

```
  geom_point(alpha = 0.8) +
  theme_grattan(chart_type = "scatter") +
  grattan_y_continuous(labels = dollar) +
  grattan_x_continuous(labels = dollar) +
  labs(title = "Non-professionals tend to earn more when professionals do",
       subtitle = "Average income for workers by SA3, 2016",
       y = "Professional incomes",
       x = "Non-professional incomes",
       caption = "Notes: Only includes people who submitted a tax return in 2016-16. So
```

```
grattan_save("atlas/scatter_reshape.pdf", scatter_reshape, type = "fullslide")
```

Non-professionals tend to earn more when professio do

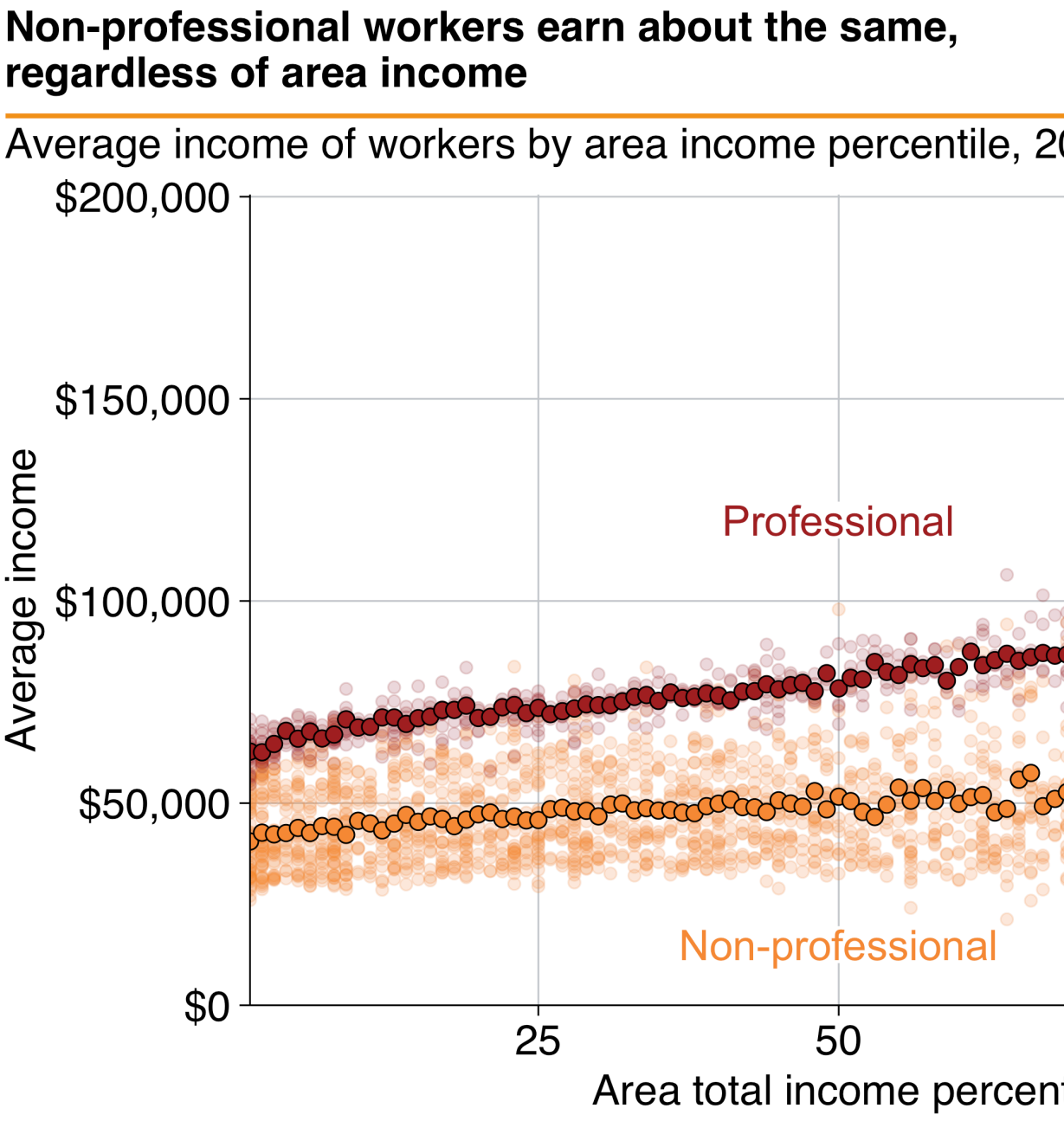


Notes: Only includes people who submitted a tax return in 2016-16.
Source: ABS (2018)

5.4.3 Layered scatter plot

For the third plot, look at the incomes of non-professional workers by their area's total income percentile:

```
include_graphics("atlas/scatter_layer.png")
```



Notes: Only includes people who submitted a tax return in 2016-16.
Source: ABS (2018)

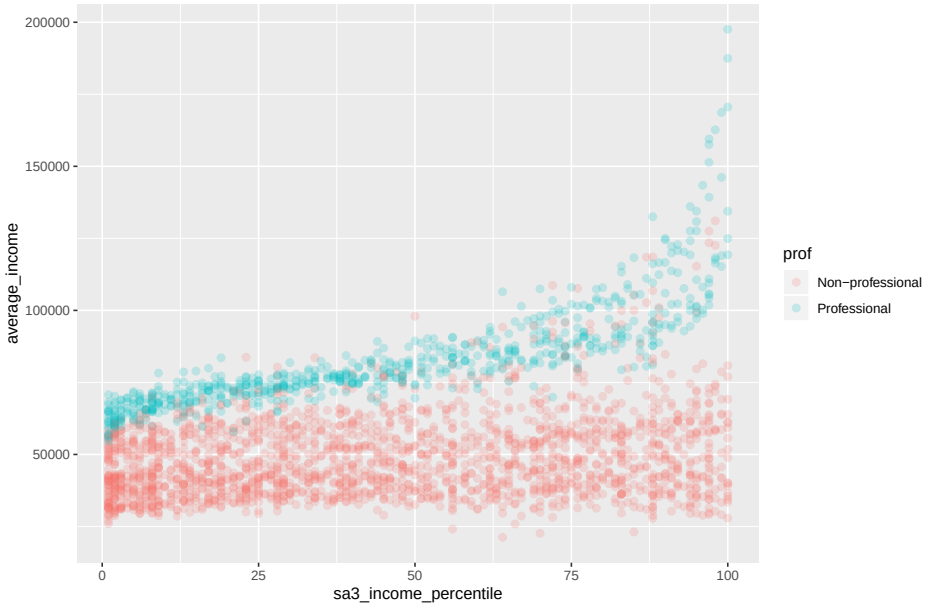
Get the data you want to plot:

```
data <- sa3_income %>%
  filter(year == 2016) %>%
  mutate(total_income = average_income * workers) %>%
  group_by(sa3_name, sa3_income_percentile, prof, occ_short) %>%
  summarise(income = sum(total_income),
            workers = sum(workers),
            average_income = income / workers)

head(data)
```

```
## # A tibble: 6 x 7
## # Groups:   sa3_name, sa3_income_percentile, prof [1]
##   sa3_name  sa3_income_perce~ prof  occ_short income workers average_income
##   <chr>                <dbl> <chr> <chr>      <dbl>   <dbl>          <dbl>
## 1 Adelaide~               66 Non-~ Admin     1.44e8    2674         53979.
## 2 Adelaide~               66 Non-~ Driver    1.85e7     396         46762.
## 3 Adelaide~               66 Non-~ Labourer  3.92e7    1516         25868.
## 4 Adelaide~               66 Non-~ Sales     5.05e7    1546         32680.
## 5 Adelaide~               66 Non-~ Service   7.75e7    2346         33034.
## 6 Adelaide~               66 Non-~ Trades    7.85e7    1525         51448.
```

To make a scatter plot with `average_income` against `sa3_income_percentile`, pass the `income` dataset to `ggplot`, add `x = sa3_income_percentile`, `y = average_income` and `colour = gender` aesthetics, then plot it with `geom_point`. Tell `geom_point` to reduce the opacity with `alpha = 0.2`, as these individual points are more of the 'background' to the plot:

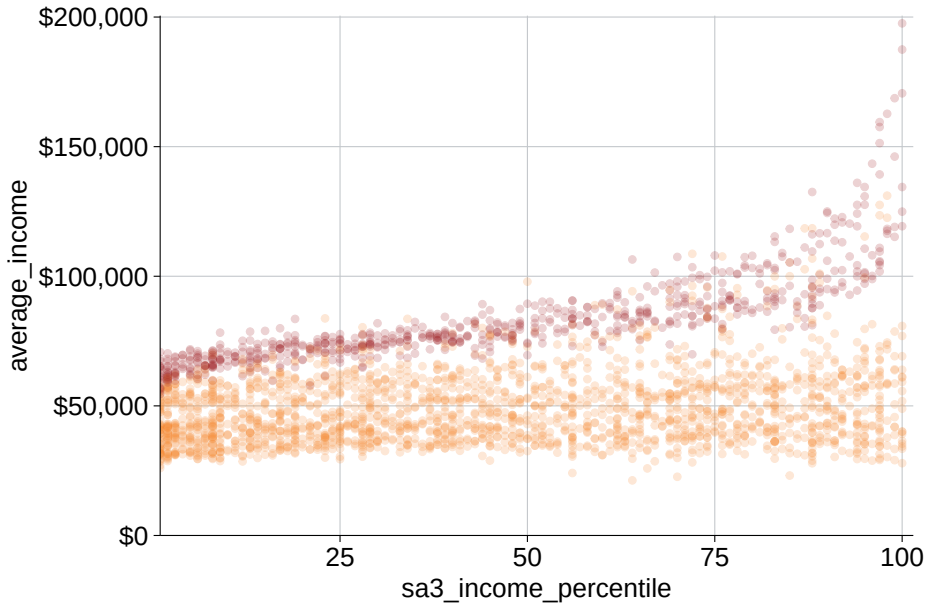
```
data %>%
  ggplot(aes(x = sa3_income_percentile,
             y = average_income,
             colour = prof)) +
  geom_point(alpha = 0.2)
```



Now add your Grattan theme elements:

- `theme_grattan()`, telling it that the `chart_type` is a scatter plot.
- `grattan_colour_manual()` with 2 colours.
- `grattan_y_continuous()`, setting the label style to `dollar`. Also tell the plot to start at zero by setting `limits = c(0, NA)` (lower, upper limits, with `NA` representing 'choose automatically'). Note that starting at zero isn't a requirement for scatter plots, but here it will give you some breathing space for your labels.
- `grattan_x_continuous()`.

```
base_chart <- data %>%
  ggplot(aes(x = sa3_income_percentile,
             y = average_income,
             colour = prof)) +
  geom_point(alpha = 0.2) +
  theme_grattan(chart_type = "scatter") +
  grattan_colour_manual(2) +
  grattan_y_continuous(labels = dollar,
                       limits = c(0, NA)) +
  grattan_x_continuous()

base_chart
```



Looks smashing! To make the point a little clearer, we can overlay a point for average income each percentile. Create a dataset that has the average income for each area and professional work category:

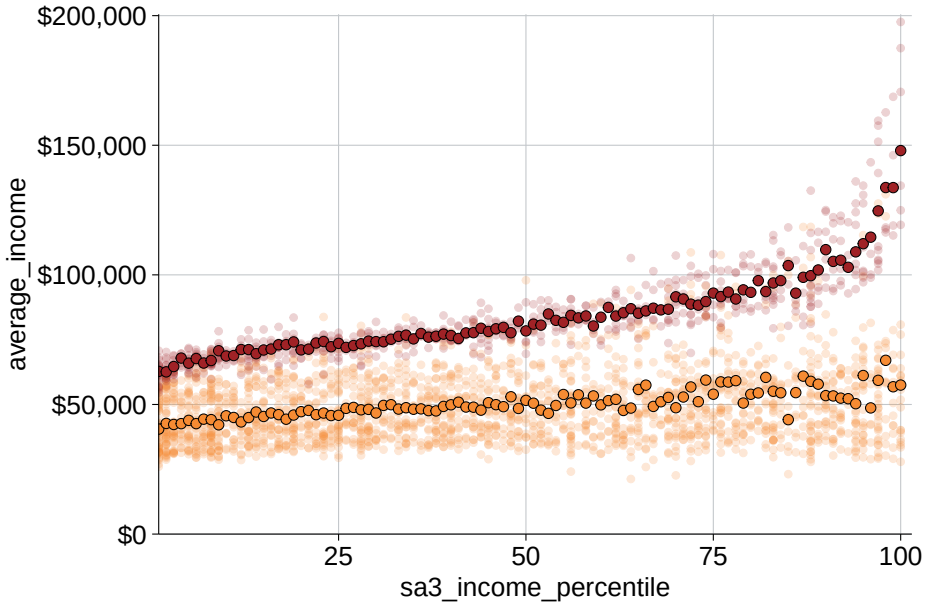
```
perc_average <- data %>%
  group_by(prof, sa3_income_percentile) %>%
  summarise(average_income = sum(income) / sum(workers))

head(perc_average)
```

```
## # A tibble: 6 x 3
## # Groups:   prof [1]
##   prof             sa3_income_percentile average_income
##   <chr>                            <dbl>          <dbl>
## 1 Non-professional                     1         40515.
## 2 Non-professional                     2         42689.
## 3 Non-professional                     3         42280.
## 4 Non-professional                     4         42600.
## 5 Non-professional                     5         43868.
## 6 Non-professional                     6         42615.
```

Then layer this on your plot by adding another `geom_point` and providing the `perc_average` data. Add a `fill` aesthetic and change the shape to `21`: a circle with a border (controlled by `colour`) and fill colour (controlled by `fill`).[6] Make the outline of the circle black with `colour` and make the `size` a little bigger:

[6] See the full list of shapes here.

```
base_chart +
  geom_point(data = perc_average,
             aes(fill = prof),
             shape = 21,
             size = 3,
             colour = "black") +
  grattan_fill_manual(2)
```



To add labels, first decide where they should go. Try positioning the "Professional" above its averages, and "Non-professional" at the bottom.

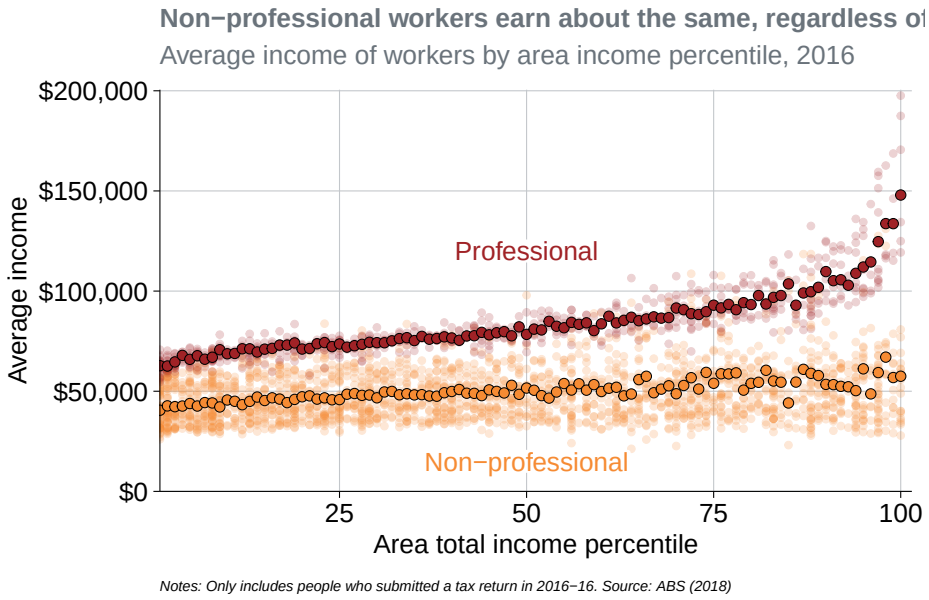
Like labelling before, you should create a new dataset with your label information, and pass that label dataset to the `grattan_label` function:

```
label_data <- tibble(
  sa3_income_percentile = c(50, 50),
  average_income = c(15e3, 120e3),
  prof =  c("Non-professional", "Professional"))
```

Finally, add the labels to the plot and give some titles:

```
base_chart +
  geom_point(data = perc_average,
             aes(fill = prof),
             shape = 21,
             size = 3,
             colour = "black") +
  grattan_fill_manual(2) +
```

```
  grattan_label(data = label_data,
                aes(label = prof)) +
  labs(title = "Non-professional workers earn about the same, regardless of area income
       subtitle = "Average income of workers by area income percentile, 2016",
       x = "Area total income percentile",
       y = "Average income",
       caption = "Notes: Only includes people who submitted a tax return in 2016-16. So
```



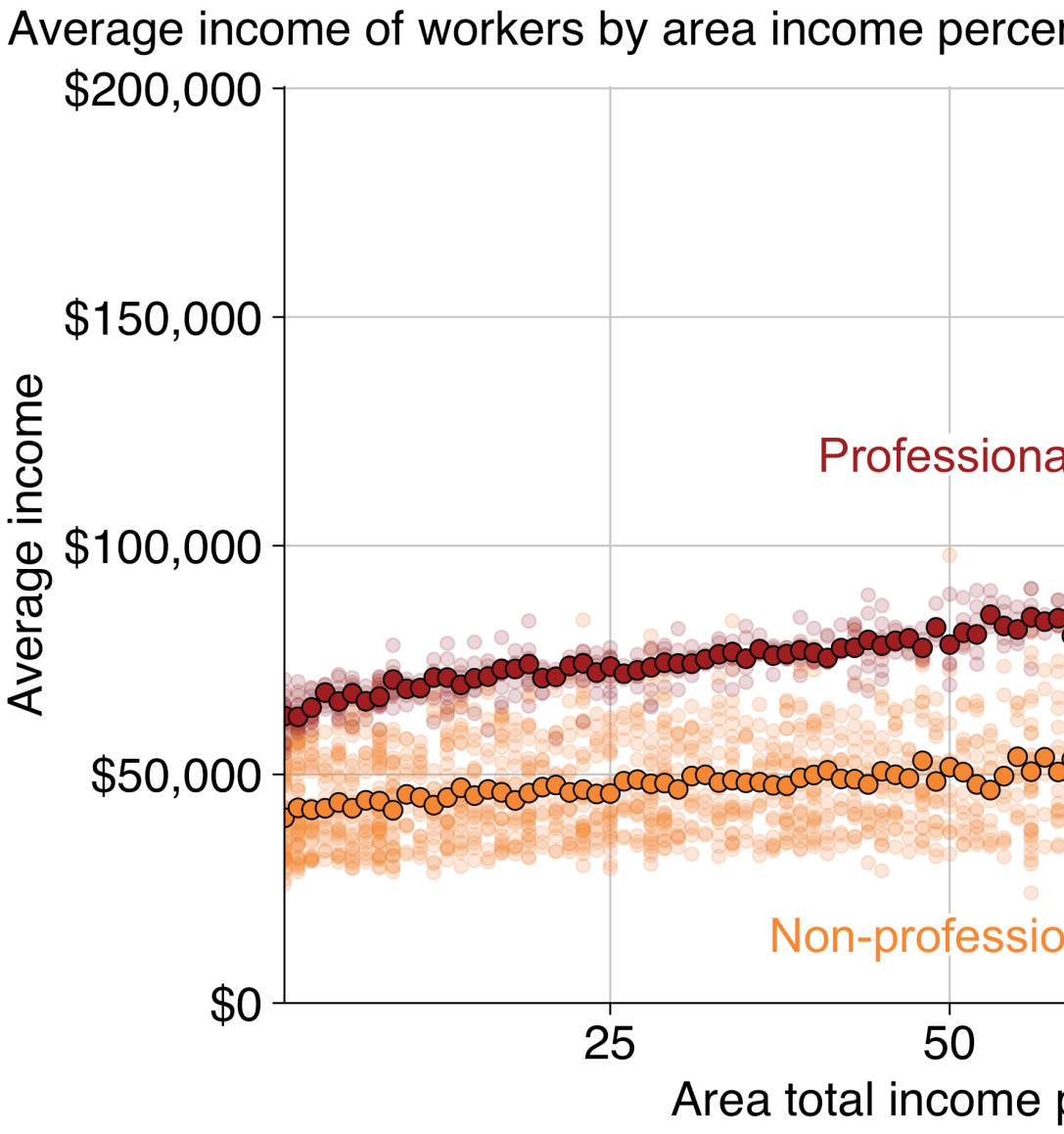
Putting that all together, your code will look something like this:

```
# Create percentage data
perc_average <- data %>%
  group_by(prof, sa3_income_percentile) %>%
  summarise(average_income = sum(income) / sum(workers))

# Create label data
label_data <- tibble(
  sa3_income_percentile = c(50, 50),
  average_income = c(15e3, 120e3),
  prof =  c("Non-professional", "Professional"))


# Plot
scatter_layer <- data %>%
  ggplot(aes(x = sa3_income_percentile,
             y = average_income,
             colour = prof)) +
```

```
  geom_point(alpha = 0.2) +
  theme_grattan(chart_type = "scatter") +
  grattan_colour_manual(2) +
  grattan_y_continuous(labels = dollar,
                       limits = c(0, NA)) +
  grattan_x_continuous() +
  geom_point(data = perc_average,
             aes(fill = prof),
             shape = 21,
             size = 3,
             colour = "black") +
  grattan_fill_manual(2) +
  grattan_label(data = label_data,
                aes(label = prof)) +
  labs(title = "Non-professional workers earn about the same, regardless of area income",
       subtitle = "Average income of workers by area income percentile, 2016",
       x = "Area total income percentile",
       y = "Average income",
       caption = "Notes: Only includes people who submitted a tax return in 2016-16. Source: ABS
```

```
grattan_save("atlas/scatter_layer.pdf", scatter_layer, type = "fullslide")
```

Non-professional workers earn about the same regardless of area income



Notes: Only includes people who submitted a tax return in 2016-16.
Source: ABS (2018)

5.4.4 Scatter plots with trendlines

5.4.5 Facetted scatter plots

5.5 Distributions

`geom_histogram` `geom_density`

`ggridges::`

5.6 Maps

5.6.1 `sf` objects

[what is]

5.6.2 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`

The package is hosted on Github and can be installed with `remotes::install_github()`

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

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

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

Now you can view `sf` objects stored in `absmapsdata`:

```
glimpse(sa32016)
```

```
## Observations: 358
## Variables: 12
## $ sa3_code_2016   <chr> "10102", "10103", "10104", "10105", "10106", "...
## $ sa3_name_2016   <chr> "Queanbeyan", "Snowy Mountains", "South Coast"...
## $ sa4_code_2016   <chr> "101", "101", "101", "101", "101", "102", "102...
## $ sa4_name_2016   <chr> "Capital Region", "Capital Region", "Capital R...
## $ gcc_code_2016   <chr> "1RNSW", "1RNSW", "1RNSW", "1RNSW", "1RNSW", "...
## $ gcc_name_2016   <chr> "Rest of NSW", "Rest of NSW", "Rest of NSW", "...
## $ state_code_2016 <chr> "1", "1", "1", "1", "1", "1", "1", "1", "1", "...
## $ state_name_2016 <chr> "New South Wales", "New South Wales", "New Sou...
## $ areasqkm_2016   <dbl> 6511.1906, 14283.4221, 9864.8680, 9099.9086, 1...
## $ cent_long       <dbl> 149.6013, 148.9415, 149.8063, 149.6054, 148.67...
## $ cent_lat        <dbl> -35.44939, -36.43952, -36.49933, -34.51814, -3...
## $ geometry        <MULTIPOLYGON [°]> MULTIPOLYGON (((149.979 -35..., M...
```

5.6.3 Making choropleth maps

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

You can join the `sf` objects from `absmapsdata` to your dataset using `left_join`. The variable names might be different – eg `sa3_name` compared to `sa3_name_2016` – so use the `by` argument to match them.

First, take the `sa3_income` dataset and join the `sf` object `sa32016` from `absmapsdata`:

```
map_data <- sa3_income %>%
  left_join(sa32016, by = c("sa3_name" = "sa3_name_2016"))
```

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:

5.6.3.1 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

```
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 = sa3_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
```

5.7 Creating simple interactive graphs with `plotly`

```
plotly::ggplotly()
```

Chapter 6

Reading data

6.1 Importing data

6.1.1 Reading CSV files

6.1.1.1 `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()`:

```
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.

6.1.1.2 `data.table::fread()`

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

6.1.2 `readxl::read_excel()`

6.1.3 `rio`

6.1.4 `readabs`

6.2 Reading common files:

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

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

6.3 Appropriately renaming variables

As shown in the style guide

Add `rename_abs` function to a common Grattan package?

6.4 Getting to tidy data

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

Chapter 7

Different data types

7.1 Tidy data

Other data structures

7.2 Dates with `lubridate::`

The `lubridate::` package

7.3 Strings with `stringr::`

- Replacing values
- Matching values
- Separating columns

7.4 Factors with `forcats::`

- Dangers with factors

Chapter 8

Data transformation

8.1 The pipe

8.2 Key `dplyr` functions:

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

8.3 Filter with `filter()`

8.4 Arrange with `arrange()`

8.5 Select variables with `select()`

8.6 Group data with `group_by()`

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

8.7.1 Cases when you should use `case_when()`

8.8 Summarise data with `summarise()`

8.9 Joining datasets with `*_join()`

Chapter 9

Analysis

Chapter 10

Creating functions

10.1 It can be useful to make your own function

Why on earth would you create your own function?

10.2 Defining simple functions

10.3 More complex functions

10.4 Sets of functions

10.5 Using `purrr::map`

10.6 Sharing your useful functions with Grattan

Chapter 11

Version control

11.1 Version control is important and intimidating

Version control is great!

11.2 Github

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

11.3 Git

Using Git within R Studio...