

Visualization, transformation and reporting with the tidyverse

Kirill Müller, Tobias Schieferdecker, Patrick Schratz

27 November 2019, 14:01 CET

Contents

Preface	5
Links	5
Package versions used	6
License	8
Speakers	8
Introduction	9
1 R and RStudio	11
1.1 R as a toolkit	11
1.2 R code examples	12
1.3 R vs. RStudio	14
1.4 R vs. R packages	14
1.5 R packages	16
1.6 .Rprofile	16
1.7 .Renviron	17
1.8 RStudio	17
1.9 RStudio Addins	21
1.10 RStudio projects	24
1.11 Alternatives to RStudio	25
I Visualization	27
2 {ggplot2} basics	29
2.1 Introduction	29
2.2 <code>geom_*</code> functions	33
2.3 Export & saving	37
2.4 Two variable plots	43
2.5 One variable plots	45
2.6 Colors and shape	47
2.7 Labels	56
3 {ggplot2} advanced	61
3.1 Facetting	61

3.2	Extensions	69
II	Tidying, transforming and importing	77
4	Transformation	79
4.1	Package: {conflicted}	79
4.2	Filtering: <code>dplyr::filter()</code>	79
4.3	Sort rows: <code>dplyr::arrange()</code>	82
4.4	The pipe	86
4.5	Pick columns: <code>dplyr::select()</code>	90
4.6	Create new columns based on old ones: <code>dplyr::mutate()</code>	92
4.7	Summarize data (by groups): <code>dplyr::summarize()</code> , <code>dplyr::group_by()</code> + <code>dplyr::ungroup()</code>	98
4.8	Summary-plots	100
5	Import	111
5.1	111
5.2	Import many files	112
6	Tidying	115
6.1	Pivoting	115
6.2	Separating and uniting	126
6.3	130
III	Reporting	131
IV	Appendix	133
7	Best practices	135
7.1	DESCRIPTION	135
7.2	R	136
7.3	roxygen2	137
7.4	testthat	137
8		139

Preface

See the controls at the top of the website for searching, font size, editing, and a link to the PDF version of the material.

```
"  
## Links to material for past workshops  
  
- [2019-04] (2019-04-zhr)  
  
- [2018-12] (2018-12-zhr)  
  
- [2018-11] (2018-11-zhr)  
  
- [2018-11] (2018-11-snb)  
  
- [2018-05] (2018-05-zhr)  
  
- [2017-10] (2017-10-zhr)  
"
```

Links

- This website: <https://krmlr.github.io/vistransrep/book>
- Scripts and installation instructions: <https://github.com/krmlr/vistransrep-proj/tree/master>
 - Prepared scripts: <https://github.com/krmlr/vistransrep-proj/tree/master/script>
- The source project for this material: <https://github.com/krmlr/vistransrep>

Package versions used

Click to expand

```
withr::with_options(list(width = 80), print(sessioninfo::session_info()))
```

```
## - Session info -----
## setting value
## version R version 3.6.1 (2017-01-27)
## os      Ubuntu 16.04.6 LTS
## system  x86_64, linux-gnu
## ui      X11
## language en_US.UTF-8
## collate en_US.UTF-8
## ctype   en_US.UTF-8
## tz      UTC
## date    2019-11-27
##
## - Packages -----
## package      * version      date      lib source
## askpass      1.1          2019-01-13 [1] CRAN (R 3.6.1)
## assertthat   0.2.1        2019-03-21 [1] CRAN (R 3.6.1)
## backports    1.1.5        2019-10-02 [1] CRAN (R 3.6.1)
## bookdown     0.16         2019-11-22 [1] CRAN (R 3.6.1)
## broom        0.5.2        2019-04-07 [1] CRAN (R 3.6.1)
## cellranger   1.1.0        2016-07-27 [1] CRAN (R 3.6.1)
## cli          1.1.0        2019-03-19 [1] CRAN (R 3.6.1)
## codetools    0.2-16       2018-12-24 [3] CRAN (R 3.6.1)
## colorspace   1.4-1        2019-03-18 [1] CRAN (R 3.6.1)
## crayon       1.3.4        2017-09-16 [1] CRAN (R 3.6.1)
## crosstalk    1.0.0        2016-12-21 [1] CRAN (R 3.6.1)
## data.table   1.12.6       2019-10-18 [1] CRAN (R 3.6.1)
## DBI          1.0.0        2018-05-02 [1] CRAN (R 3.6.1)
## dbplyr       1.4.2        2019-06-17 [1] CRAN (R 3.6.1)
## digest       0.6.23       2019-11-23 [1] CRAN (R 3.6.1)
## dplyr        * 0.8.3       2019-07-04 [1] CRAN (R 3.6.1)
## DT           0.10         2019-11-12 [1] CRAN (R 3.6.1)
## ellipsis     0.3.0        2019-09-20 [1] CRAN (R 3.6.1)
## evaluate     0.14         2019-05-28 [1] CRAN (R 3.6.1)
## fansi        0.4.0        2018-10-05 [1] CRAN (R 3.6.1)
## farver       2.0.1        2019-11-13 [1] CRAN (R 3.6.1)
## fastmap      1.0.1        2019-10-08 [1] CRAN (R 3.6.1)
## forcats      * 0.4.0       2019-02-17 [1] CRAN (R 3.6.1)
## fs           1.3.1        2019-05-06 [1] CRAN (R 3.6.1)
## generics     0.0.2        2018-11-29 [1] CRAN (R 3.6.1)
## ggplot2      * 3.2.1       2019-08-10 [1] CRAN (R 3.6.1)
```

##	ggpubr	0.2.4	2019-11-14	[1]	CRAN	(R 3.6.1)
##	ggsignif	0.6.0	2019-08-08	[1]	CRAN	(R 3.6.1)
##	git2r	0.26.1	2019-06-29	[1]	CRAN	(R 3.6.1)
##	glue	1.3.1	2019-03-12	[1]	CRAN	(R 3.6.1)
##	gtable	0.3.0	2019-03-25	[1]	CRAN	(R 3.6.1)
##	haven	2.2.0	2019-11-08	[1]	CRAN	(R 3.6.1)
##	here	* 0.1	2017-05-28	[1]	CRAN	(R 3.6.1)
##	hms	0.5.2	2019-10-30	[1]	CRAN	(R 3.6.1)
##	htmltools	0.4.0	2019-10-04	[1]	CRAN	(R 3.6.1)
##	htmlwidgets	1.5.1	2019-10-08	[1]	CRAN	(R 3.6.1)
##	httpuv	1.5.2	2019-09-11	[1]	CRAN	(R 3.6.1)
##	httr	1.4.1	2019-08-05	[1]	CRAN	(R 3.6.1)
##	jsonlite	1.6	2018-12-07	[1]	CRAN	(R 3.6.1)
##	knitr	1.26	2019-11-12	[1]	CRAN	(R 3.6.1)
##	labeling	0.3	2014-08-23	[1]	CRAN	(R 3.6.1)
##	later	1.0.0	2019-10-04	[1]	CRAN	(R 3.6.1)
##	lattice	0.20-38	2018-11-04	[3]	CRAN	(R 3.6.1)
##	lazyeval	0.2.2	2019-03-15	[1]	CRAN	(R 3.6.1)
##	leaflet	* 2.0.3	2019-11-16	[1]	CRAN	(R 3.6.1)
##	lifecycle	0.1.0	2019-08-01	[1]	CRAN	(R 3.6.1)
##	lubridate	1.7.4	2018-04-11	[1]	CRAN	(R 3.6.1)
##	magrittr	1.5	2014-11-22	[1]	CRAN	(R 3.6.1)
##	MASS	7.3-51.4	2019-03-31	[3]	CRAN	(R 3.6.1)
##	memoise	1.1.0	2017-04-21	[1]	CRAN	(R 3.6.1)
##	mime	0.7	2019-06-11	[1]	CRAN	(R 3.6.1)
##	modelr	0.1.5	2019-08-08	[1]	CRAN	(R 3.6.1)
##	munsell	0.5.0	2018-06-12	[1]	CRAN	(R 3.6.1)
##	nlme	3.1-140	2019-05-12	[3]	CRAN	(R 3.6.1)
##	nycflights13	* 1.0.1	2019-09-16	[1]	CRAN	(R 3.6.1)
##	openssl	1.4.1	2019-07-18	[1]	CRAN	(R 3.6.1)
##	pillar	1.4.2	2019-06-29	[1]	CRAN	(R 3.6.1)
##	pkgconfig	2.0.3	2019-09-22	[1]	CRAN	(R 3.6.1)
##	plotly	4.9.1	2019-11-07	[1]	CRAN	(R 3.6.1)
##	plyr	1.8.4	2016-06-08	[1]	CRAN	(R 3.6.1)
##	promises	1.1.0	2019-10-04	[1]	CRAN	(R 3.6.1)
##	purrr	* 0.3.3	2019-10-18	[1]	CRAN	(R 3.6.1)
##	R6	2.4.1	2019-11-12	[1]	CRAN	(R 3.6.1)
##	RColorBrewer	1.1-2	2014-12-07	[1]	CRAN	(R 3.6.1)
##	Rcpp	1.0.3	2019-11-08	[1]	CRAN	(R 3.6.1)
##	readr	* 1.3.1	2018-12-21	[1]	CRAN	(R 3.6.1)
##	readxl	1.3.1	2019-03-13	[1]	CRAN	(R 3.6.1)
##	reprex	0.3.0	2019-05-16	[1]	CRAN	(R 3.6.1)
##	reshape2	1.4.3	2017-12-11	[1]	CRAN	(R 3.6.1)
##	rlang	0.4.2.9000	2019-11-27	[1]	Github (r-lib/rlang@1be25e7)	
##	rmarkdown	1.18	2019-11-27	[1]	CRAN	(R 3.6.1)
##	rprojroot	1.3-2	2018-01-03	[1]	CRAN	(R 3.6.1)

```
## rstudioapi      0.10      2019-03-19 [1] CRAN (R 3.6.1)
## rvest           0.3.5      2019-11-08 [1] CRAN (R 3.6.1)
## scales          1.1.0      2019-11-18 [1] CRAN (R 3.6.1)
## sessioninfo     1.1.1      2018-11-05 [1] CRAN (R 3.6.1)
## shiny           1.4.0      2019-10-10 [1] CRAN (R 3.6.1)
## stringi         1.4.3      2019-03-12 [1] CRAN (R 3.6.1)
## stringr         * 1.4.0      2019-02-10 [1] CRAN (R 3.6.1)
## tibble          * 2.1.3      2019-06-06 [1] CRAN (R 3.6.1)
## tic             0.2.13.9021 2019-11-27 [1] Github (ropenscilabs/tic@8d76ddb)
## tidyr          * 1.0.0      2019-09-11 [1] CRAN (R 3.6.1)
## tidyselect      0.2.5      2018-10-11 [1] CRAN (R 3.6.1)
## tidyverse      * 1.3.0      2019-11-21 [1] CRAN (R 3.6.1)
## utf8            1.1.4      2018-05-24 [1] CRAN (R 3.6.1)
## vctrs           0.2.0      2019-07-05 [1] CRAN (R 3.6.1)
## viridisLite     0.3.0      2018-02-01 [1] CRAN (R 3.6.1)
## withr           2.1.2      2018-03-15 [1] CRAN (R 3.6.1)
## xaringan        0.13       2019-10-30 [1] CRAN (R 3.6.1)
## xfun            0.11       2019-11-12 [1] CRAN (R 3.6.1)
## xml2            1.2.2      2019-08-09 [1] CRAN (R 3.6.1)
## xtable          1.8-4      2019-04-21 [1] CRAN (R 3.6.1)
## yaml            2.2.0      2018-07-25 [1] CRAN (R 3.6.1)
## zeallot         0.1.0      2018-01-28 [1] CRAN (R 3.6.1)
##
## [1] /home/travis/R/Library
## [2] /usr/local/lib/R/site-library
## [3] /home/travis/R-bin/lib/R/library
```

License

Licensed under CC-BY-NC 4.0.

Speakers

Kirill Müller (@krlmlr)

Patrick Schratz (@pat-s)



- M.Sc. Geoinformatics
- Researcher/Research Engineer at University of **Jena** and **LMU Munich**
- PhD Candidate

-
- Unix & R enthusiast
 - Author/Contributor/Maintainer of several R packages:
 - (mlr3, mlr)
 - sperrorest
 - oddsratio
 - xaringan
 - circle
 - RQGIS
 - travis
 - tic
 - ...

Introduction

The **tidyverse** has quickly developed over the last years. Its first implementation as a collection of partly older packages was in the second half of 2016. All its

packages “share an underlying design philosophy, grammar, and data structures.”¹ It is for sure difficult to tell, if “learning the **tidyverse**” is a hard task, since the result of this assessment might differ from person to person. We do believe though, that there are concepts in its approach, which – when grasped – have the potential to increase one’s productivity, since code creation will seem more natural. While this might be true for all languages (once you speak it well enough, things go smoothly), in our opinion the **tidyverse** worth exploring in depth, since it is

1. consistent: an especially well designed framework that aims at making data analysis and programming intuitive,
2. evolving: constantly deepened understanding for challenges arising in modern data analysis leads to improving ergonomic user interfaces.

This course covers several topics, which everyone working more intently with the **tidyverse** almost inevitably needs to deal with at some point or another. The topics are organized in chapters that contain mostly R code with output and text. In each section, exercises are provided.

¹citation from tidyverse homepage

Chapter 1

R and RStudio

1.1 R as a toolkit

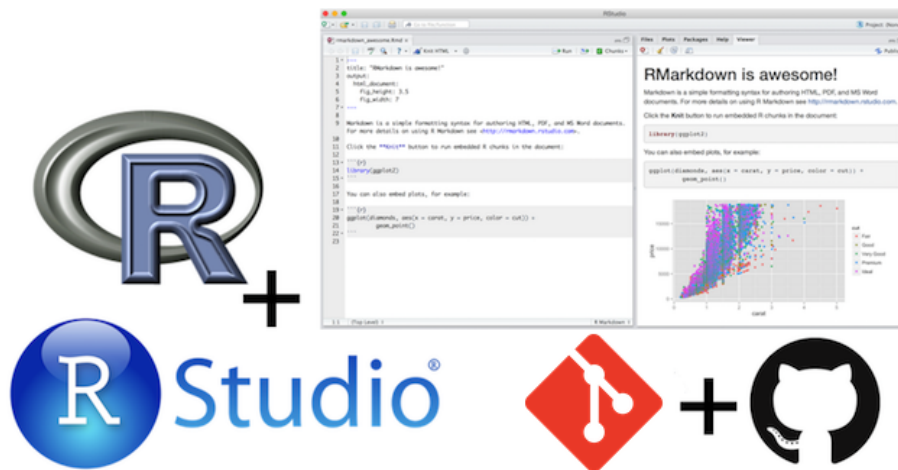
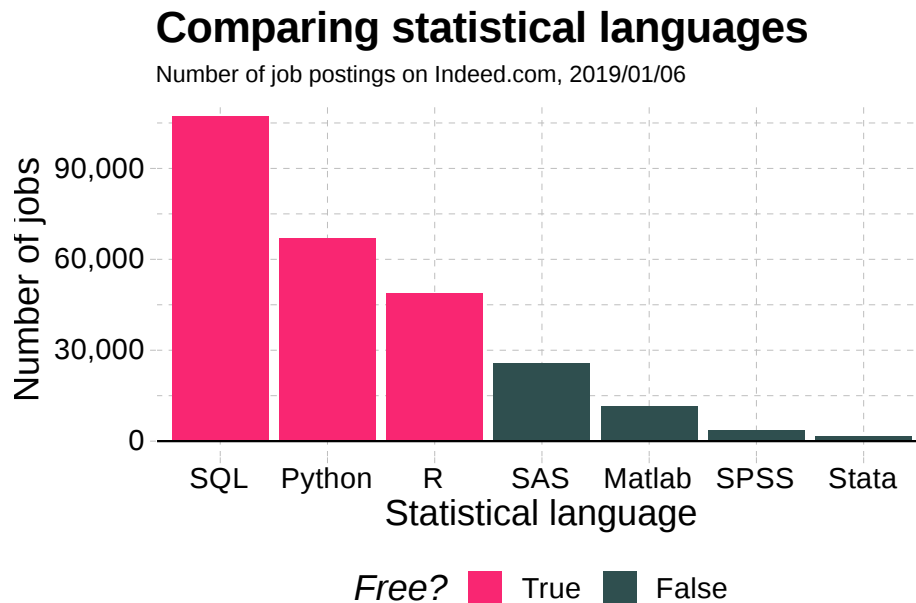


Figure 1.1: R as a toolkit

- Scriptability → R
- Literate programming (code, narrative, output in one place) → R Markdown
- Version control → Git / GitHub

1.1.1 Why R and RStudio?



1.1.2 Some R basics

- You will load packages at the **start of every new R session**.
 - “Base” R comes with tons of useful built-in functions. It also provides all the tools necessary for you to write your own functions.
 - However, many of R’s best data science functions and tools come from external packages written by other users.
- R easily and infinitely parallelizes. For free.
 - Compare the cost of a Stata/MP license, nevermind the fact that you effectively pay per core...

1.2 R code examples

1.2.1 Linear regression

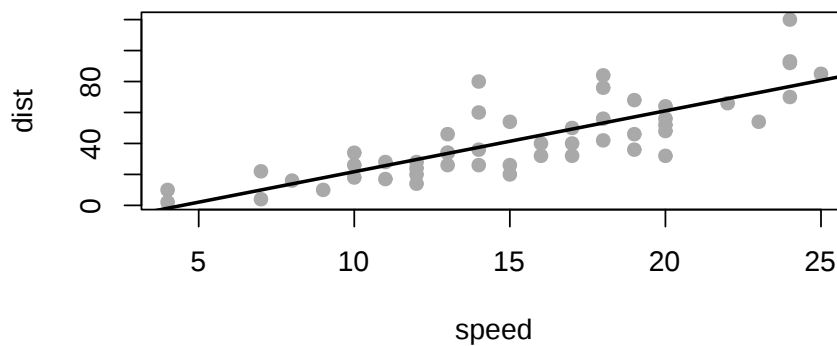
```
fit <- lm(dist ~ 1 + speed, data = cars)
summary(fit)

##
## Call:
## lm(formula = dist ~ 1 + speed, data = cars)
##
## Residuals:
```

```
##      Min      1Q  Median      3Q      Max
## -29.069  -9.525  -2.272   9.215  43.201
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -17.5791     6.7584  -2.601   0.0123 *
## speed        3.9324     0.4155   9.464 1.49e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 15.38 on 48 degrees of freedom
## Multiple R-squared:  0.6511, Adjusted R-squared:  0.6438
## F-statistic: 89.57 on 1 and 48 DF,  p-value: 1.49e-12
```

1.2.2 Base R plot

```
plot(cars, pch = 19, col = "darkgray")
abline(fit, lwd = 2)
```

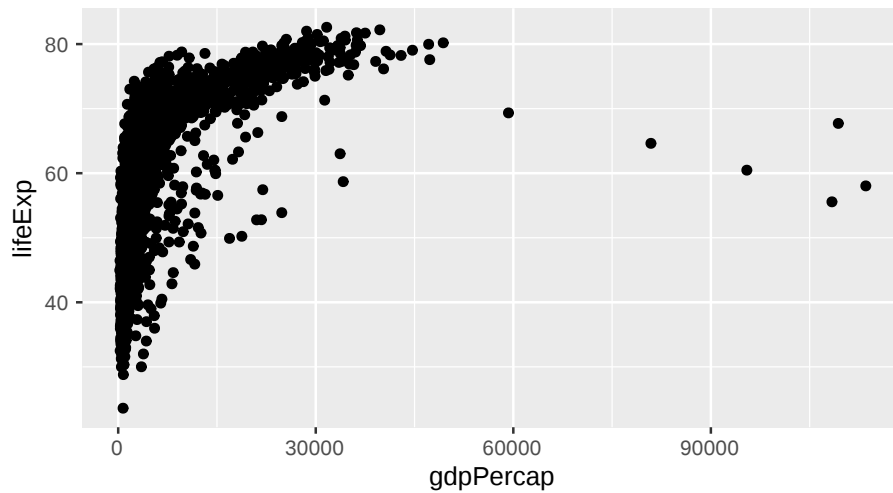


1.2.3 ggplot2

```
library(ggplot2)
library(gapminder) ## For the gapminder data

ggplot(
  data = gapminder,
```

```
mapping = aes(x = gdpPercap, y = lifeExp)
) +
geom_point()
```



1.2.4 gganimate

1.3 R vs. RStudio

- R is a statistical **programming language**
- RStudio is a convenient interface for R (an **integrated development environment**, IDE)
- At its simplest:
 - R is like a car's engine
 - RStudio is like a car's dashboard

1.4 R vs. R packages

- R packages **extend** the functionality of R by providing additional functions, data, and documentation.
- They are written by a world-wide community of R users and can be downloaded for no cost

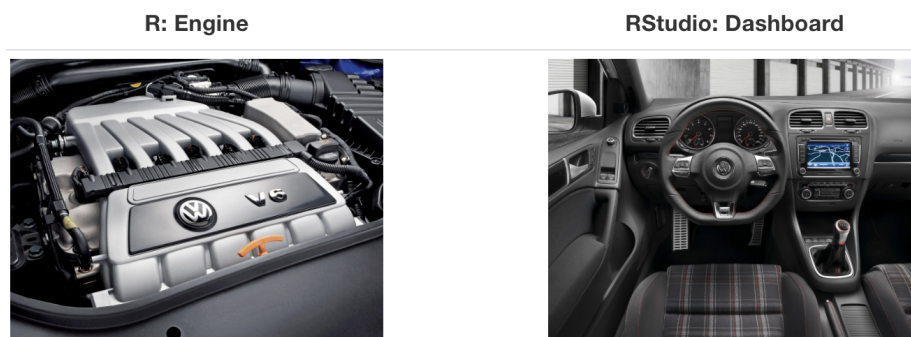


Figure 1.2: Engine vs. dashboard

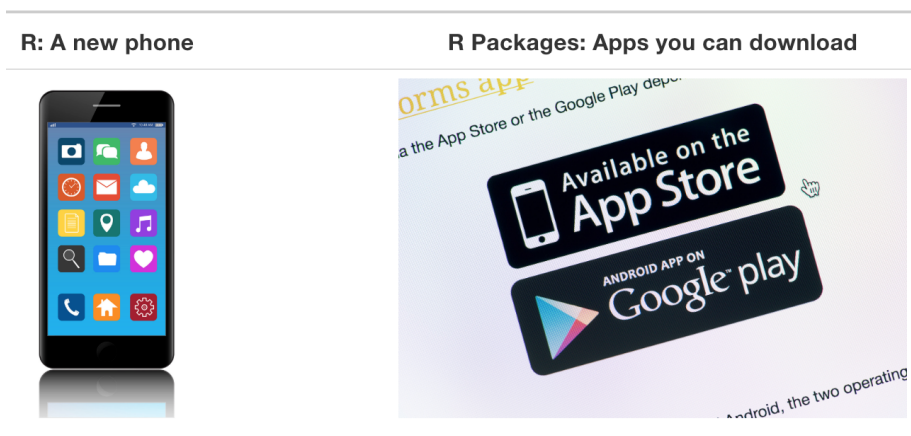


Figure 1.3: R versus R packages

1.5 R packages

- **CRAN:** A group of people who check that packages fulfill certain standards
- **Mirror:** A location on the web where to download R packages from. Because many thousand people download them daily, the load is distributed on different machines. Pick one which is geographically close to you
- **R base/recommended packages:** The base installation of R ships with a bunch of default packages. In addition, there are some more packages listed as “recommended”.

“base” packages are managed by the R core team and will only be updated for every R release.

Packages listed as “recommended” inherit the attributes of being widely used and having a long history in the R community.

```
##      Package Priority
## 1      base      base
## 2  compiler      base
## 3  datasets      base
## 4  graphics      base
## 5 grDevices      base
## 6      grid      base
## 7   methods      base
## 8 parallel      base

##      Package      Priority
## 1      boot recommended
## 2      class recommended
## 3   cluster recommended
## 4 codetools recommended
## 5   foreign recommended
## 6 KernSmooth recommended
## 7   lattice recommended
## 8      MASS recommended
## 9   Matrix recommended
## 10      mgcv recommended
## [ reached 'max' / getOption("max.print") -- omitted 2 rows ]
```

1.6 .Rprofile

- File in your home directory `~/.Rprofile`
- Will be executed before every R session starts
- Useful to set global options and for loading of often used packages

1.7 .Renviron

- File in your home directory `~/.Renviron`
- Used to set environment variables
- Used to store “Access tokens” (Github, CI provider, C++ flags)

1.8 RStudio

→ Exists to **boost** your productivity

→ Change the defaults to your liking so you *actually* can be **productive**

→ Keybindings = productivity

Since RStudio v1.3 a portable JSON settings file exists.

If you want to have sane settings without much hassle, you can execute the following R code: `source("https://bit.ly/rstudio-pat")`

This code will change/overwrite your existing RStudio settings and

- set custom keybindings
- move the console panel to the top-right (by default bottom-left)
- Enable/Disable some core settings to have a better overall experience

R scripts (source code) are written in the *Source* pane (Editor).

(Source of all following RStudio screenshots: <https://github.com/edrubin/EC525S19>)

You can use the menubar or `++N` / `+CTRL+N` to create new R scripts.

To execute commands from your R script, use `+Enter` / `CTRL+Enter`.

RStudio will execute the command in the console.

You can see the new object in the *Environment* pane.

The *History* tab records your old commands.

The *Files* pane is the file explorer.

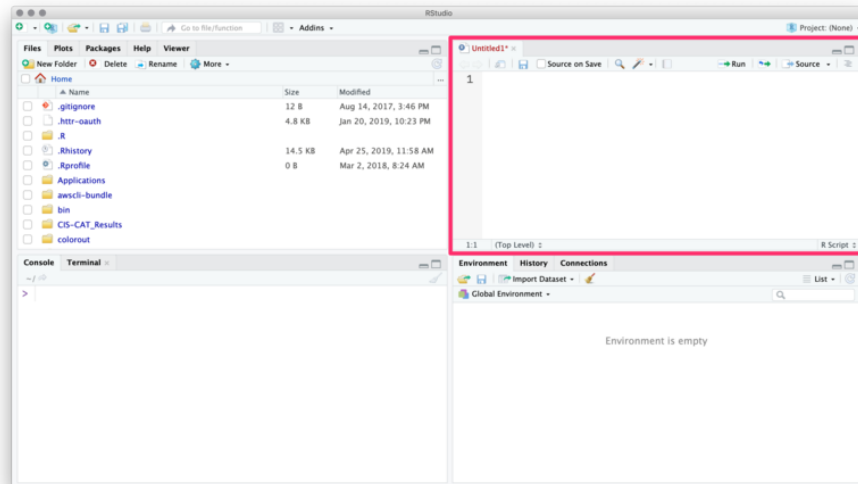


Figure 1.4: Source pane

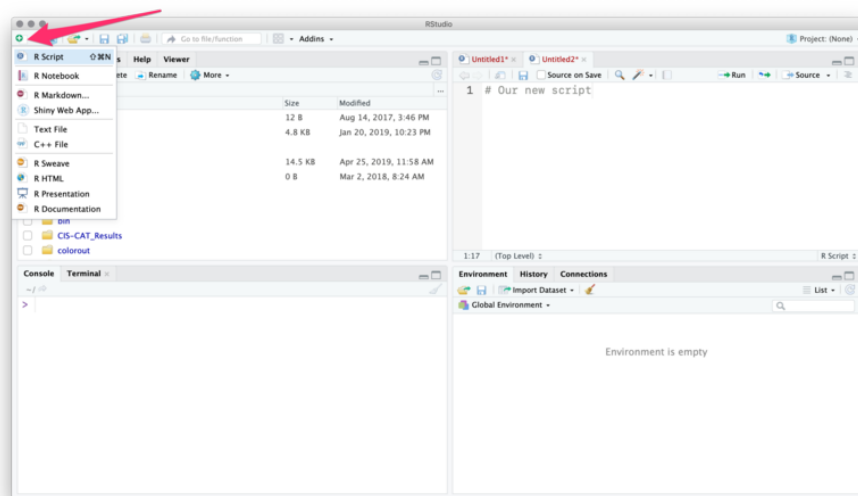


Figure 1.5: New script

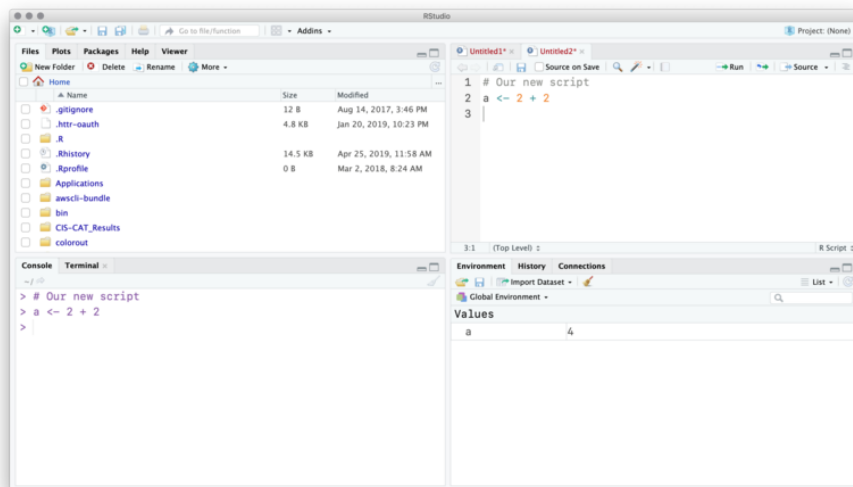


Figure 1.6: Execute commands

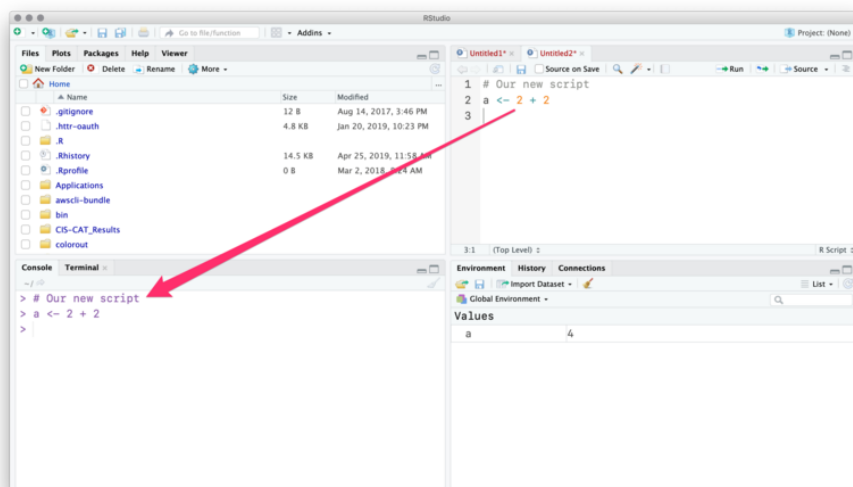


Figure 1.7: Console output

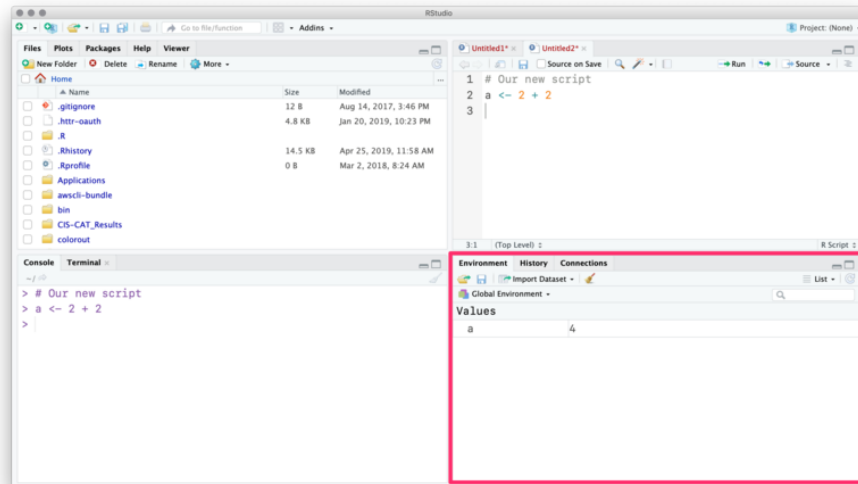


Figure 1.8: Environment pane

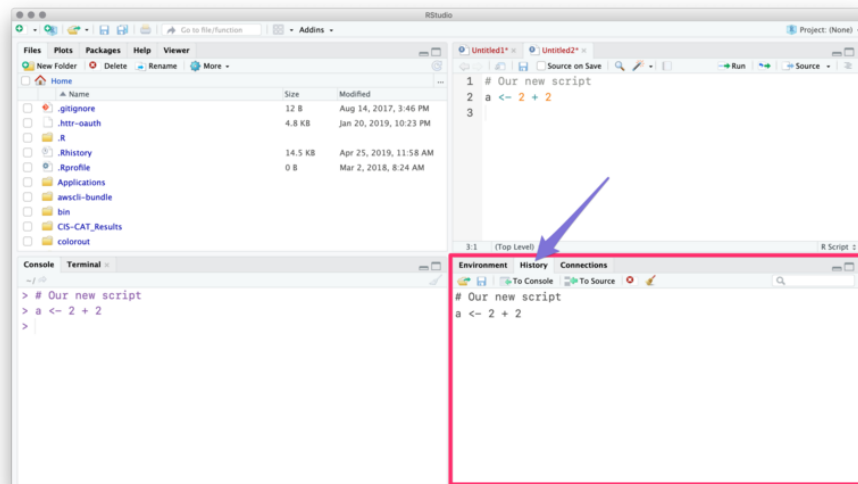


Figure 1.9: History pane

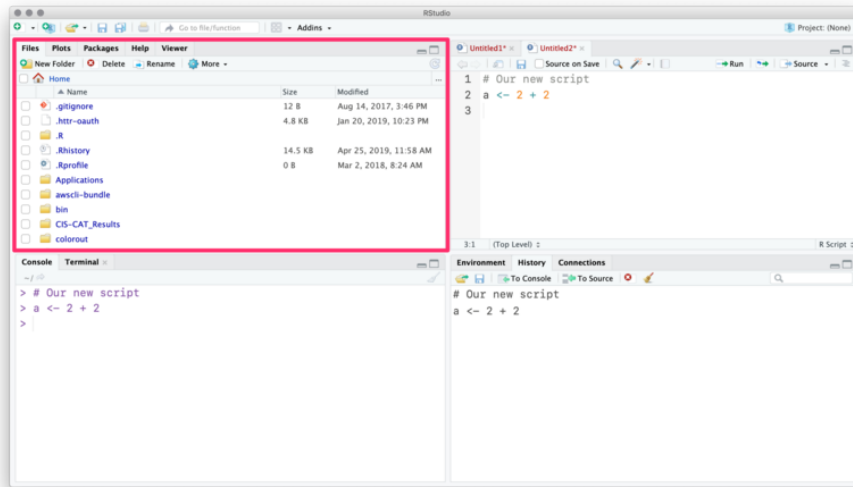


Figure 1.10: Files pane

The *Plots* pane/tab shows... plots.

Packages shows installed packages

Packages shows installed packages and whether they are *loaded*.

The *Help* tab shows help documentation (also accessible via `?`).

Finally, you can customize the actual layout

1.9 RStudio Addins

RStudio can be further enhanced by so called “addins”. These are clickable snippets that execute certain actions in RStudio.

They aim to make repetitive tasks easier and to save you time. There is an addin called `addinslist` which lists all available addins. It can be installed as a normal package from CRAN:

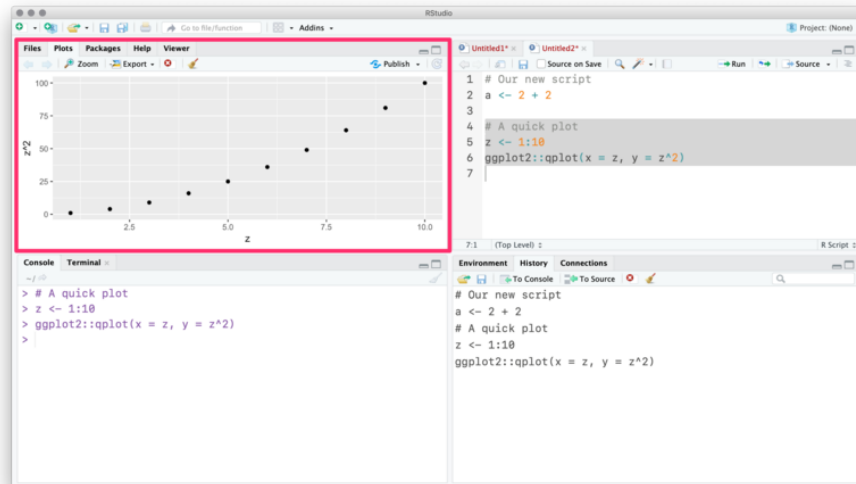


Figure 1.11: Plots pane

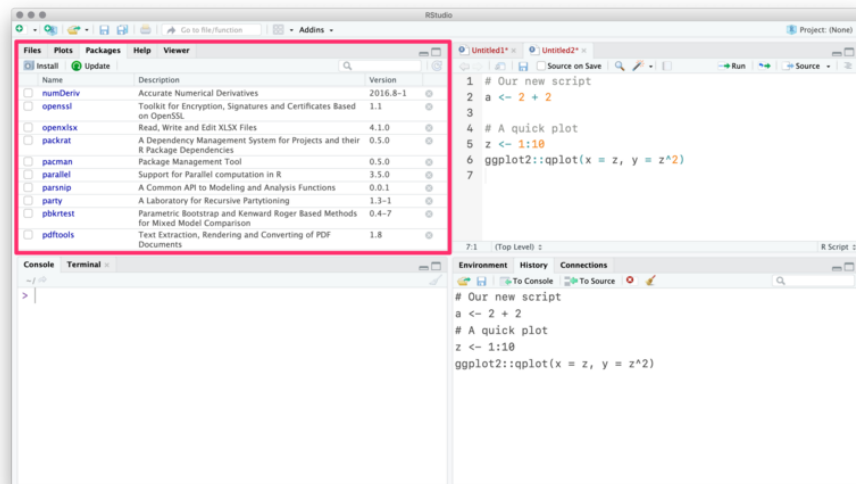


Figure 1.12: Packages pane

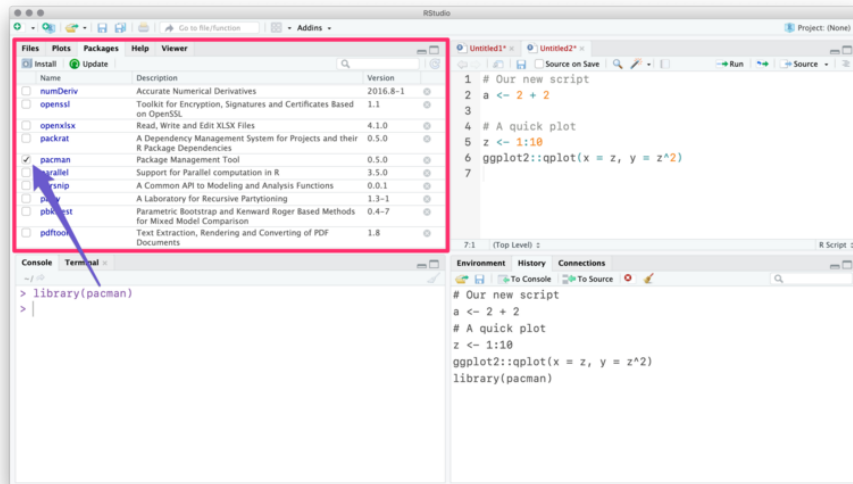


Figure 1.13: Loaded and installed packages

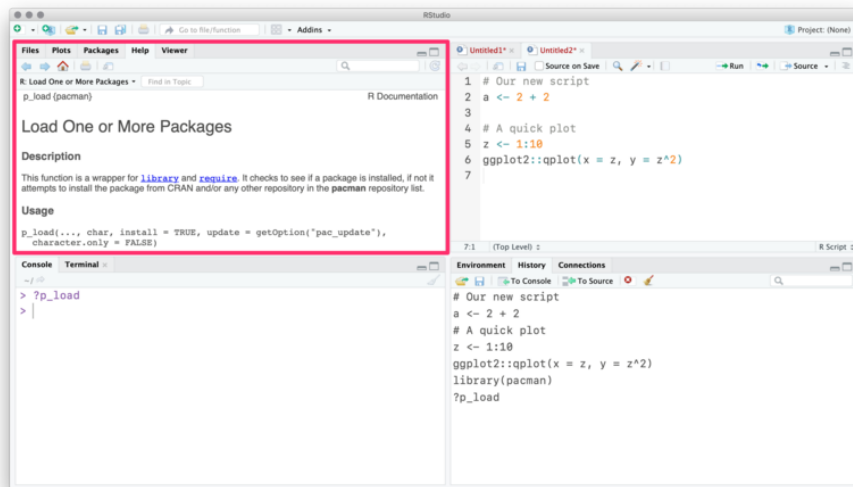


Figure 1.14: Help pane

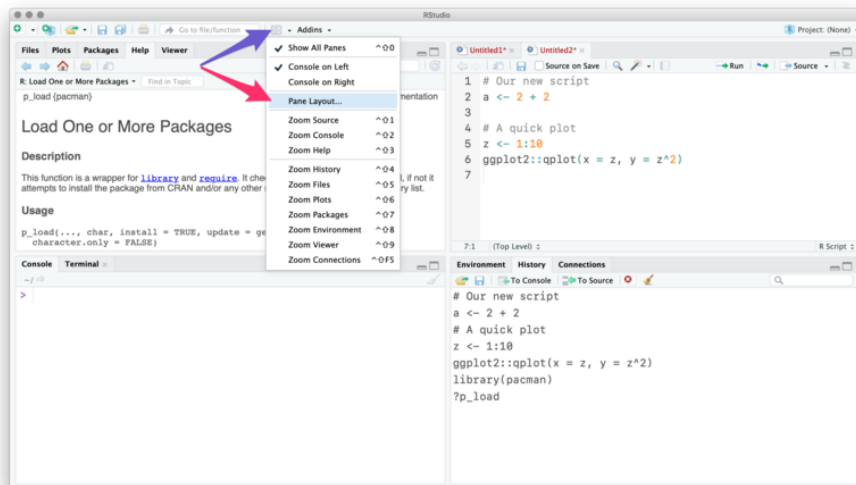


Figure 1.15: Customize layout

```
install.packages("addinslist")
```

To have an addin available in RStudio after installation, RStudio needs to be restarted.

1.10 RStudio projects

Without a project, you will need to define **long** file paths which **only exist on your machine**.

```
sample_df <- read.csv("/Users/<yourname>/somewhere/on/this/machine/sample.csv")
```

With a project, R automatically references the project's folder as the current working directory.

From there on, you can use *relative paths* to point to files.

```
sample_df <- read.csv("sample.csv")
```

Double-plus bonus: The *here* package extends *RStudio project* philosophy even more and helps in cases when not using RStudio (e.g. on the command line).

1.11 Alternatives to RStudio

- Using R directly in the terminal via radian (optimized R console interpreter)
- R is supported in other “general purpose IDE’s” (VScode, Sublime Text, Atom, Vim, etc.)

Part I

Visualization

Chapter 2

{ggplot2} basics

Embracing the grammar of graphics.

This chapter discusses plotting with the `ggplot2` package.

2.1 Introduction

Click here to show setup code.

```
library(tidyverse)
```

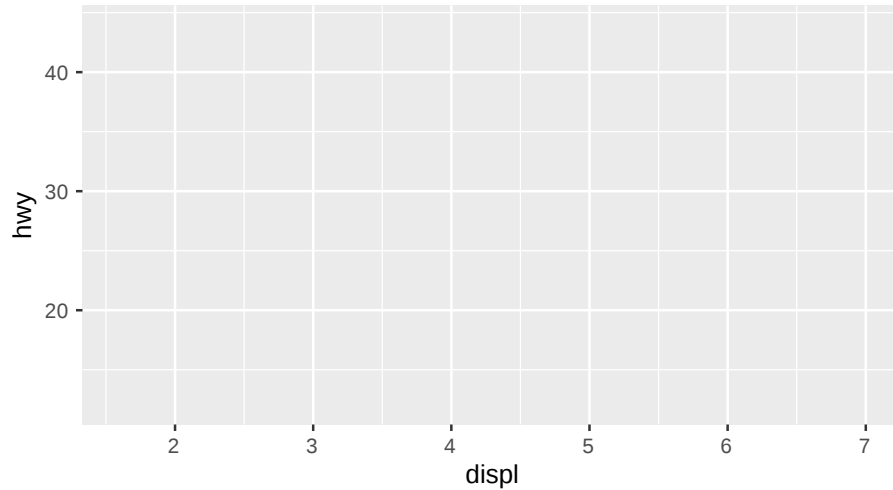
In the `{tidyverse}` the standard package for visualization is `{ggplot2}`. The functions of this package follow a quite unique logic (the “grammar of graphics”) and therefore require a special syntax. In this section we want to give a short introduction, how to get started with `{ggplot2}`.

2.1.1 Creating the plot skeleton: `ggplot()`

The main function in the package is `ggplot()`, which prepares/creates a graph. By setting the arguments of the function, you can:

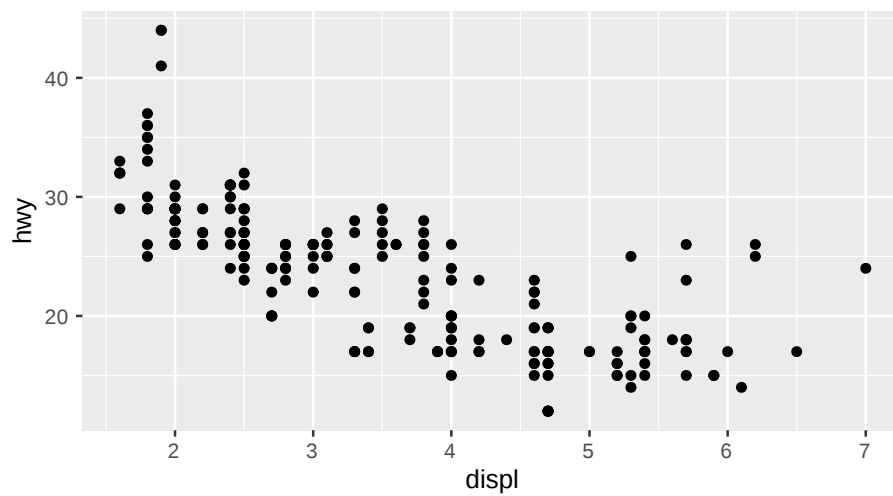
1. Choose the dataset to be plotted (argument `data`)
2. Choose the mapping of the variables to the axes (or further forms of setting apart data) in the argument `mapping`. This argument takes the result of the function `aes()`, which you will get to know in many different examples.

```
ggplot(  
  data = mpg,  
  mapping = aes(x = displ, y = hwy)  
)
```



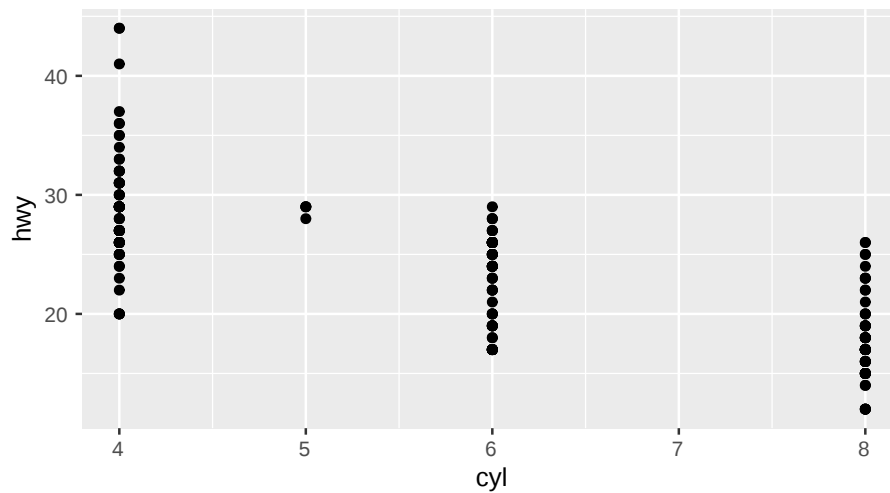
This created only an empty plot, because we did not tell {ggplot2} which geometry we want to use to display the variables we set in the `ggplot()` call. We do this by adding (with the help of the `+` operator after the `ggplot()`-call) a different function starting with `geom_` to provide this information.

```
ggplot(  
  data = mpg,  
  mapping = aes(x = displ, y = hwy)  
) +  
  geom_point()
```



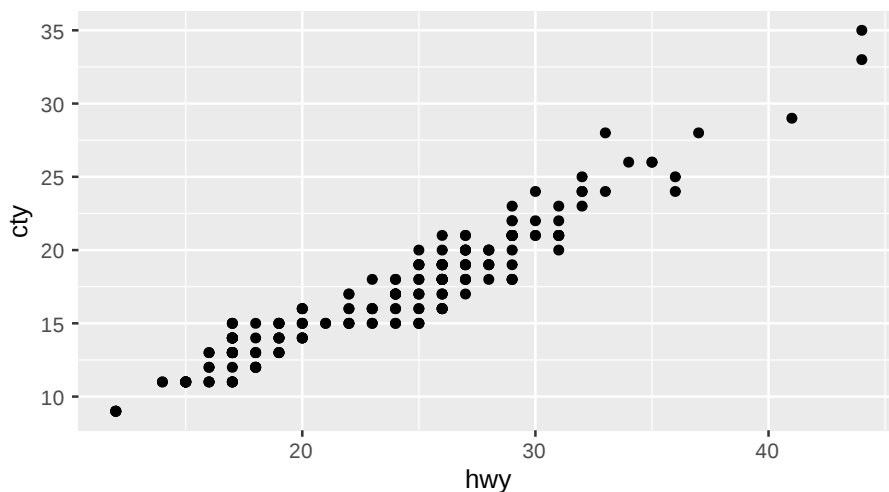
This is maybe the most basic plot you can create. To map a different variable than `disp` to the x-axis, change the respective variable name in the `aes()` argument.

```
ggplot(  
  data = mpg,  
  mapping = aes(x = cyl, y = hwy)  
) +  
  geom_point()
```



You can exchange the variables to be plotted freely, without changing anything else to the rest of the code.

```
ggplot(  
  data = mpg,  
  mapping = aes(x = hwy, y = cty)  
) +  
  geom_point()
```



Always good to have: The *ggplot2* cheatsheet (<https://github.com/rstudio/cheatsheets/blob/master/data-visualization-2.1.pdf>).

2.1.2 What is a “statistical graphic”?

Wilkinson (2005) defines a grammar to describe the basic elements of a statistical graphic:

“[...] a statistical graphic is a mapping from data to aesthetic attributes (colour, shape, size) of geometric objects (points, line, bars).”

(Wickham, 2009)

2.1.3 Terminology

- **Data:** The data to visualize – consists of variables and observations.
- **Geoms:** Geometric objects which represent the data (points, lines, polygons, etc.).
- **Mappings:** Match variables with aesthetic attributes of the (geometric) objects.
- **Scales:** Mapping of the “data units” to “physical units” of the geometric objects (e.g. length, diameter or color); defines the *legend*.
- **Coord:** System of coordinates, mapping of the data to a two dimensional plain of the graphic; defines the *axes* and *grid*.
- **Stats:** Statistical transformation of the data (5 point summary, classification, etc.).

- **Facetting:** Division and illustration of data subsets, also known as “Trellis” images.

2.1.4 The Grammar of graphics ...

is ...

a formal guideline which describes the dependencies between all elements of a statistical graphic.

isn't ...

- a manual which tells us *which graphic* should be created for a given question.
- a specification *how* a statistical graphic should look like.

2.1.5 About {ggplot2}

```
## Package: ggplot2
## Version: 3.2.1
## Title: Create Elegant Data Visualisations Using the Grammar of Graphics
## Depends: R (>= 3.2)
## Imports: digest, grDevices, grid, gtable (>= 0.1.1), lazyeval, MASS, mgcv,
##          reshape2, rlang (>= 0.3.0), scales (>= 0.5.0), stats, tibble,
##          viridisLite, withr (>= 2.0.0)
## License: GPL-2 | file LICENSE
## URL: http://ggplot2.tidyverse.org, https://github.com/tidyverse/ggplot2
## BugReports: https://github.com/tidyverse/ggplot2/issues
## Encoding: UTF-8
## Author: Hadley Wickham [aut, cre], Winston Chang [aut], Lionel Henry [aut],
##        Thomas Lin Pedersen [aut], Kohske Takahashi [aut], Claus Wilke [aut],
##        Kara Woo [aut], Hiroaki Yutani [aut], RStudio [cph]
## Maintainer: Hadley Wickham <hadley@rstudio.com>
##
## -- File:
```

2.2 *geom_** functions

```
library(tidyverse)
```

*geom_** functions are added to the main `ggplot()` call via the “+” operator and (usually) placed on a new line.

A list of all available “geoms” can be found here:

<https://ggplot2.tidyverse.org/reference/#section-layer-geoms>

The most popular ones are

- `geom_point()`
 - `geom_histogram()`
 - `geom_boxplot()`
 - `geom_bar()`
-

The `geom_*` family can be divided into three parts:

One variable plots

- `geom_hist()`
- `geom_bar()`
- etc.

Two variable plots

- `geom_point()`
- `geom_line()`
- `geom_boxplot()`
- etc.

Three variables plots

- `geom_raster()`
- `geom_sf()`
- `geom_tile()`
- etc.

2.2.1 Arguments

```
ggplot(data, mapping = aes(), ...) +  
  geom_XXX(mapping = NULL, data = NULL, stat, ...)
```

`geom_*` functions have the same basic arguments as `ggplot()`. In addition, they come with more arguments specific to the respective “geom”.

stat

The `stat` parameter defines a statistical transformation:

- if set to `"identity"`: No transformation
- if set to `boxplot`: Boxplot transformation
- etc.

position

The same applies to the `position` argument. In the example below, points are not adjusted and just visualized where they appear in the data.

In the case of boxplots, a special position arrangement function is used to arrange everything nicely: `position_dodge2()` (here denoted by `position = "dodge2"`).

```
geom_point(mapping = NULL, data = NULL, stat = "identity",
  position = "identity", ..., na.rm = FALSE, show.legend = NA,
  inherit.aes = TRUE)

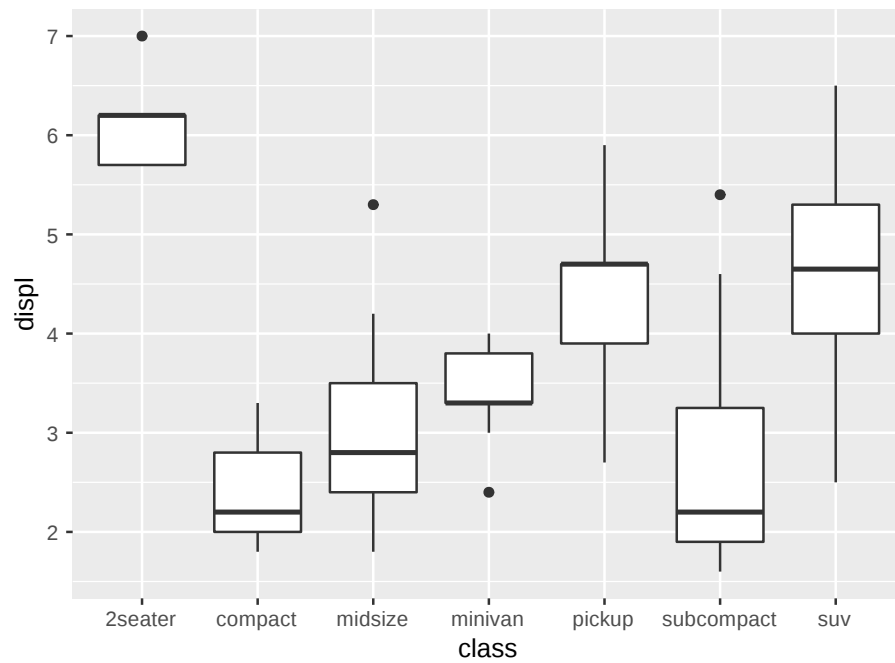
geom_boxplot(mapping = NULL, data = NULL, stat = "boxplot",
  position = "dodge2", ..., outlier.colour = NULL,
  outlier.color = NULL, outlier.fill = NULL, outlier.shape = 19,
  outlier.size = 1.5, outlier.stroke = 0.5, outlier.alpha = NULL,
  notch = FALSE, notchwidth = 0.5, varwidth = FALSE, na.rm = FALSE,
  show.legend = NA, inherit.aes = TRUE)
```

`geom_boxplot()` needs one variable to be of class `character` or `factor` (better) to initiate the grouping.

```
class(mpg$class)

## [1] "character"

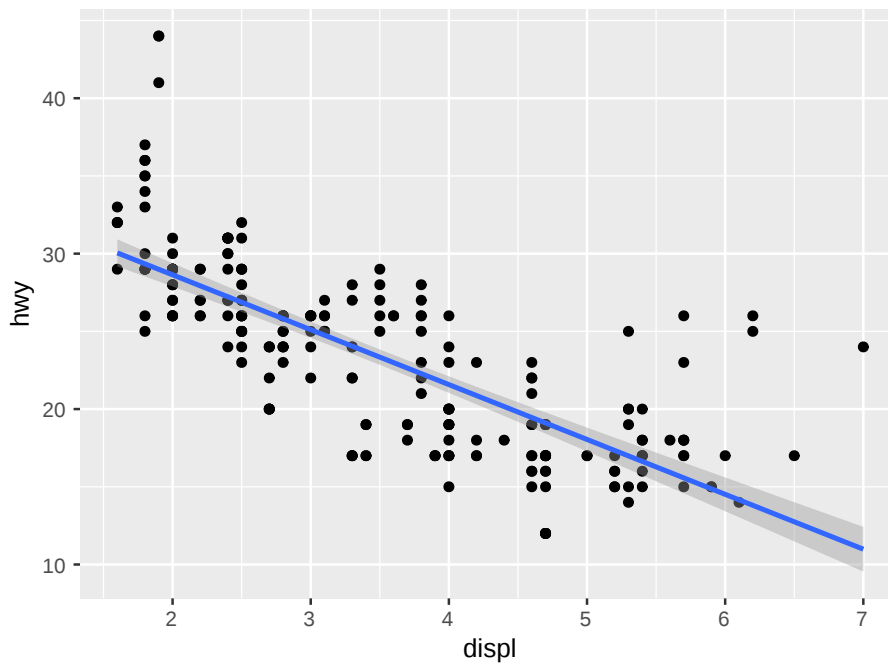
ggplot(mpg, aes(x = class, y = displ)) +
  geom_boxplot()
```



2.2.2 Combining geoms

Multiple `geom_*` functions can be used in one plot. A combination that is often used together is `geom_point()` and `geom_smooth()`

```
ggplot(mpg, aes(x = displ, y = hwy)) +  
  geom_point() +  
  geom_smooth(method = "lm")
```



Unless specified differently in the `geom_*()` call, all geoms will use the same variables.

2.2.3 Summary

The modular principle of `ggplot2` enables:

- the combination of any geometric objects (geoms).
- a high flexibility and customizability

An extensive description of all geometric objects can be found on the `ggplot2` website <https://ggplot2.tidyverse.org/reference/>.

2.3 Export & saving

```
library(tidyverse)
```

The default way to export plots in `{{ggplot2}}` is by using `ggsave()`.

It differs slightly from other “exporting” functions in R because it comes with some smart defaults:

`ggsave()` is a convenient function for saving a plot. It defaults to **saving the last plot** that you displayed, using the size of the current

graphics device. It also **guesses the type** of graphics device from the extension.

```
ggplot(mtcars, aes(mpg, wt)) +
  geom_point()

ggsave("mtcars.pdf")

## Saving 5.39 x 3 in image

ggsave("mtcars.png")

## Saving 5.39 x 3 in image
```

This might seem natural to you but is is not. Let's compare base R and *{ggplot2}*.

2.3.1 Base R vs. *{ggplot2}*

In base R

- one needs to open a specific graphic device first
- then create the plot
- and close the graphic device again.

```
png("Plot.png")
plot(mpg$displ, mpg$hwy)
dev.off()

ggplot(mpg, aes(disply, hwy)) +
  geom_point()
ggsave("Plot.png")
```

Base R plotting functions come with suboptimal defaults

- saving in pixels (differs on every monitors)
- saving as a square image
- no option to specify the DPI (dots per inch)

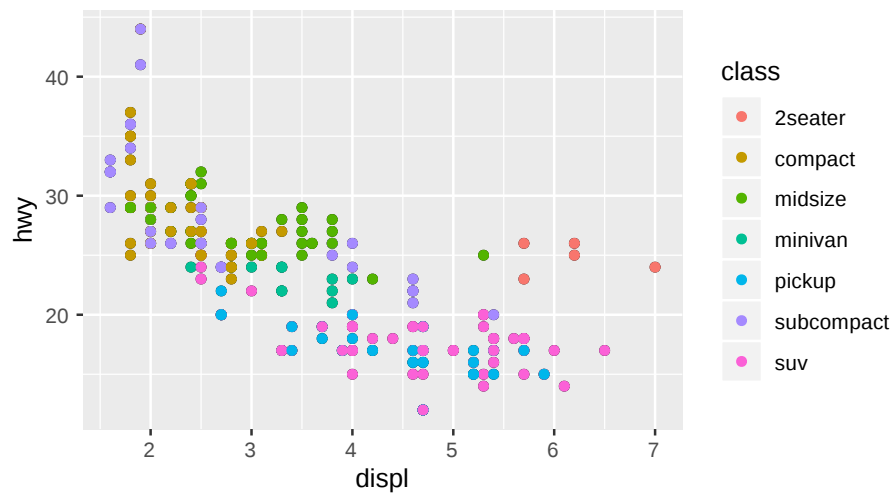
2.3.2 Storing the plot as an R object

One of the major advantages of `ggplot()` is that you can save a plot as an R object and modify it later.

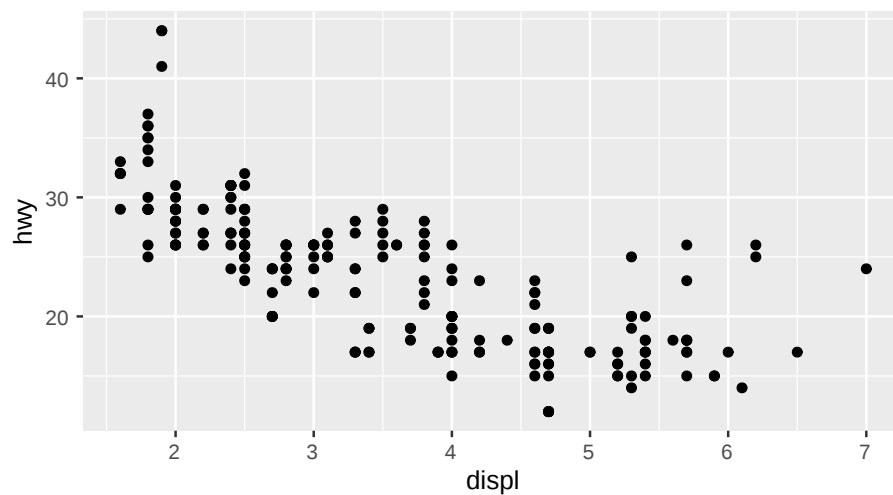
This is not possible with base R plots.

```
p <- ggplot(mpg, aes(displ, hwy)) +  
  geom_point()
```

```
p + geom_point(aes(color = class))
```



```
print(p)
```



```
str(p)
```

```
## List of 9  
## $ data      :Classes 'tbl_df', 'tbl' and 'data.frame': 234 obs. of  11 variables:  
## ..$ manufacturer: chr [1:234] "audi" "audi" "audi" "audi" ...
```

```

##   ..$ model      : chr [1:234] "a4" "a4" "a4" "a4" ...
##   ..$ displ     : num [1:234] 1.8 1.8 2 2 2.8 2.8 3.1 1.8 1.8 2 ...
##   ..$ year      : int [1:234] 1999 1999 2008 2008 1999 1999 2008 1999 2008 .
##   ..$ cyl       : int [1:234] 4 4 4 4 6 6 6 4 4 ...
##   ..$ trans     : chr [1:234] "auto(l5)" "manual(m5)" "manual(m6)" "auto(av)" ...
##   ..$ drv       : chr [1:234] "f" "f" "f" "f" ...
##   ..$ cty       : int [1:234] 18 21 20 21 16 18 18 16 20 ...
##   ..$ hwy       : int [1:234] 29 29 31 30 26 26 27 26 25 28 ...
##   ..$ fl        : chr [1:234] "p" "p" "p" "p" ...
##   ..$ class     : chr [1:234] "compact" "compact" "compact" "compact" ...
## $ layers      :List of 1
##   ..$ :Classes 'LayerInstance', 'Layer', 'ggproto', 'gg' <ggproto object: Class Layer>
##     aes_params: list
##     compute_aesthetics: function
##     compute_geom_1: function
##     compute_geom_2: function
##     compute_position: function
##     compute_statistic: function
##     data: waiver
##     draw_geom: function
##     finish_statistics: function
##     geom: <ggproto object: Class GeomPoint, Geom, gg>
##       aesthetics: function
##       default_aes: uneval
##       draw_group: function
##       draw_key: function
##       draw_layer: function
##       draw_panel: function
##       extra_params: na.rm
##       handle_na: function
##       non_missing_aes: size shape colour
##       optional_aes:
##       parameters: function
##       required_aes: x y
##       setup_data: function
##       use_defaults: function
##       super: <ggproto object: Class Geom, gg>
##     geom_params: list
##     inherit_aes: TRUE
##     layer_data: function
##     map_statistic: function
##     mapping: NULL
##     position: <ggproto object: Class PositionIdentity, Position, gg>
##       compute_layer: function
##       compute_panel: function
##       required_aes:

```



```

##      setup_data: function
##      setup_params: function
##      super: <ggproto object: Class Position, gg>
## print: function
##      setup_layer: function
##      show.legend: NA
##      stat: <ggproto object: Class StatIdentity, Stat, gg>
##      aesthetics: function
##      compute_group: function
##      compute_layer: function
##      compute_panel: function
##      default_aes: uneval
##      extra_params: na.rm
##      finish_layer: function
##      non_missing_aes:
##      parameters: function
##      required_aes:
##      retransform: TRUE
##      setup_data: function
##      setup_params: function
##      super: <ggproto object: Class Stat, gg>
##      stat_params: list
##      super: <ggproto object: Class Layer, gg>
## $ scales      :Classes 'ScalesList', 'ggproto', 'gg' <ggproto object: Class ScalesList, gg>
##      add: function
##      clone: function
##      find: function
##      get_scales: function
##      has_scale: function
##      input: function
##      n: function
##      non_position_scales: function
##      scales: list
##      super: <ggproto object: Class ScalesList, gg>
## $ mapping      :List of 2
## ..$ x: language ~displ
## .. ..- attr(*, ".Environment")=<environment: R_GlobalEnv>
## ..$ y: language ~hwy
## .. ..- attr(*, ".Environment")=<environment: R_GlobalEnv>
## ..- attr(*, "class")= chr "uneval"
## $ theme          : list()
## $ coordinates:Classes 'CoordCartesian', 'Coord', 'ggproto', 'gg' <ggproto object: Class Coord
##      aspect: function
##      backtransform_range: function
##      clip: on
##      default: TRUE

```

```
## distance: function
## expand: TRUE
## is_free: function
## is_linear: function
## labels: function
## limits: list
## modify_scales: function
## range: function
## render_axis_h: function
## render_axis_v: function
## render_bg: function
## render_fg: function
## setup_data: function
## setup_layout: function
## setup_panel_params: function
## setup_params: function
## transform: function
## super: <ggproto object: Class CoordCartesian, Coord, gg>
## $ facet      :Classes 'FacetNull', 'Facet', 'ggproto', 'gg' <ggproto object: Class
## compute_layout: function
## draw_back: function
## draw_front: function
## draw_labels: function
## draw_panels: function
## finish_data: function
## init_scales: function
## map_data: function
## params: list
## setup_data: function
## setup_params: function
## shrink: TRUE
## train_scales: function
## vars: function
## super: <ggproto object: Class FacetNull, Facet, gg>
## $ plot_env    :<environment: R_GlobalEnv>
## $ labels      :List of 2
## ..$ x: chr "displ"
## ..$ y: chr "hwy"
## - attr(*, "class")= chr [1:2] "gg" "ggplot"
```

2.3.3 Best practices for exporting

Some best practices:

- Use a reasonable high DPI. A value of “300” is ok in most cases.

- Save in “inches” and not in “pixels”. The latter always differs on screens with different resolutions (`png()` uses pixels by default.)
- Always specify a file name to ensure the right plot is chosen. Do not rely on the default behavior of `ggsave()` (even though it might seem convenient) which takes the last visualized plot.
- An alternative to `ggsave()` is `cowplot::save_plot()` which comes with sensible defaults for multi-plot arrangements.

2.4 Two variable plots

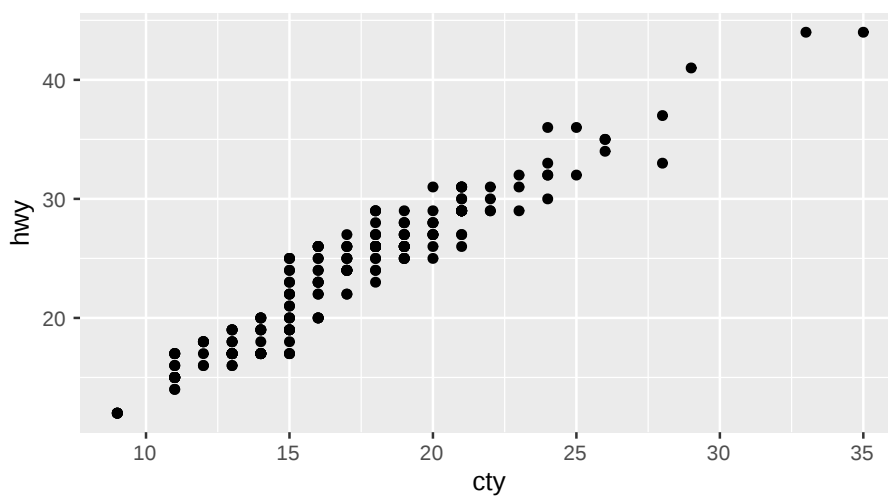
```
library(tidyverse)
```

“Two variable plots” can be split into sub-categories:

- Continuous X and Y
- Continuous X and discrete Y (and vice-versa)
- Discrete X and Y

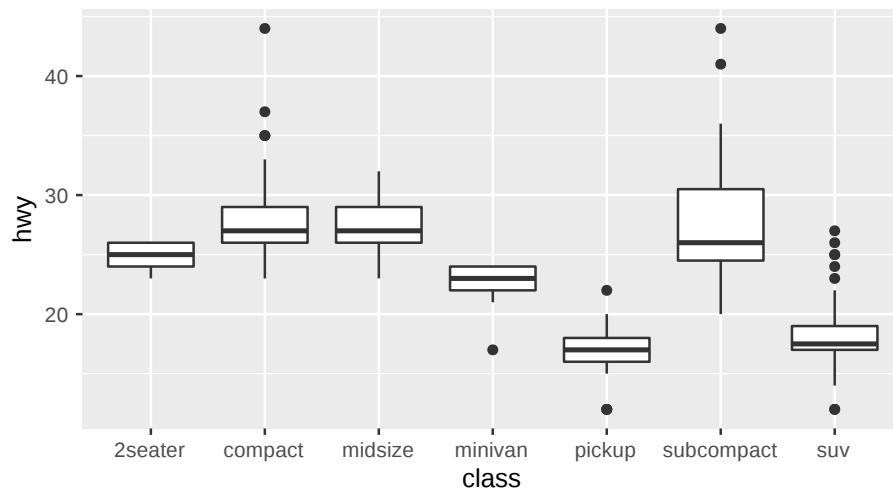
2.4.1 Continuous X and Y

```
ggplot(mpg, aes(x = cty, y = hwy)) +  
  geom_point()
```



2.4.2 Discrete X and continuous Y

```
ggplot(mpg, aes(x = class, y = hwy)) +  
  geom_boxplot()
```



2.4.3 Discrete X and Y

```
ggplot(mpg, aes(x = class, y = manufacturer)) +  
  geom_jitter()
```



2.5 One variable plots

```
library(tidyverse)
```

This type of plots visualizes ONE variable in a certain way.

To do this in a 2D space, a **statistical transformation** of the variable is required for the missing axis.

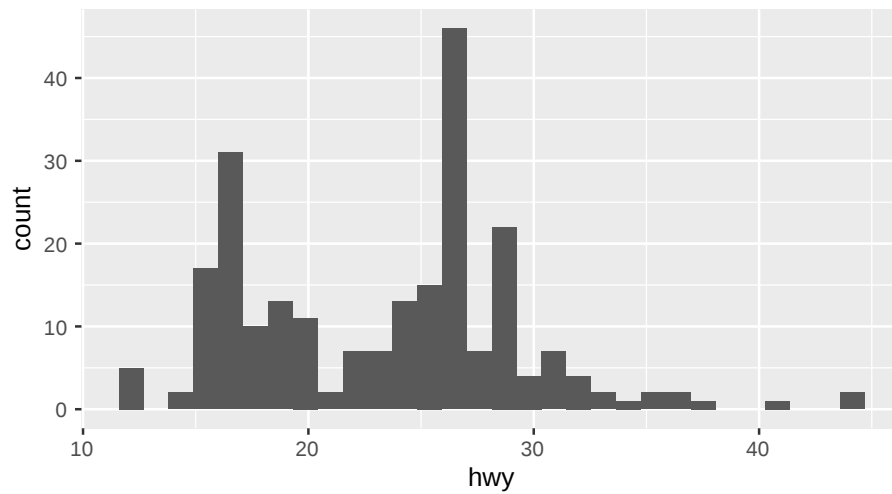
2.5.1 Continuous variables

- Histogram: Most common way - grouping the variable into equal bins
- `geom_density()`, `geom_freq()`, `geom_dotplot()` and `geom_area()` are mainly doing the same as `geom_hist()`

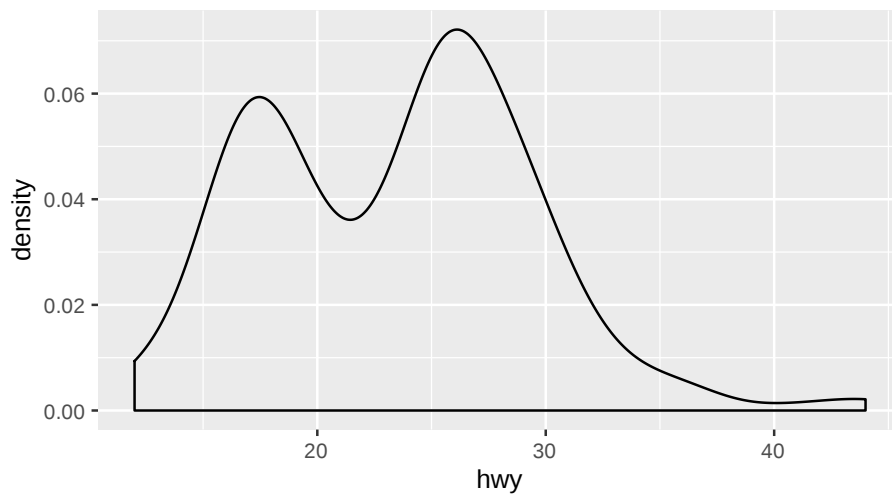
We supply only *one* variable to the `mapping` argument with the help of `aes()`. This one is automatically grouped into 30 bins.

```
ggplot(mpg, aes(x = hwy)) +  
  geom_histogram()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with  
## `binwidth`.
```



```
ggplot(mpg, aes(x = hwy)) +  
  geom_density()
```

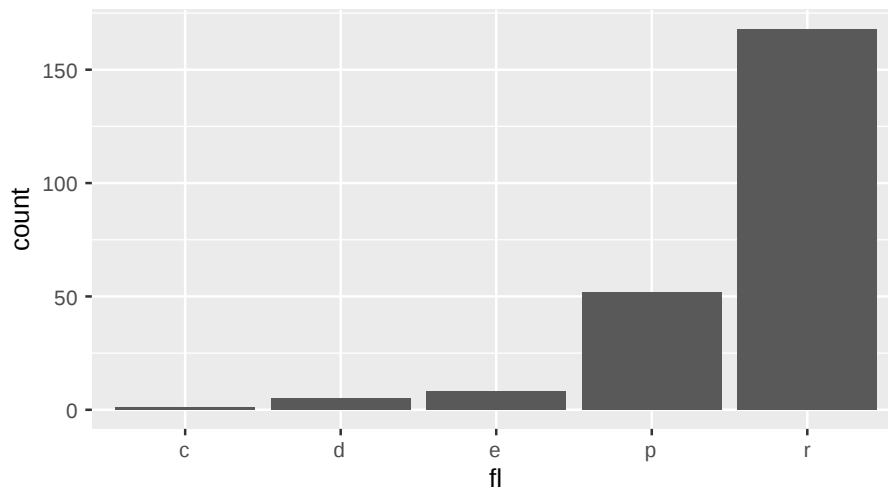


2.5.2 Discrete variables

For discrete data, there is actually only one visualization method - the bar plot.

Note the difference of `geom_bar()` compared to `geom_hist()`.

```
ggplot(mpg, aes(fl)) +  
  geom_bar()
```



2.6 Colors and shape

```
library(tidyverse)
```

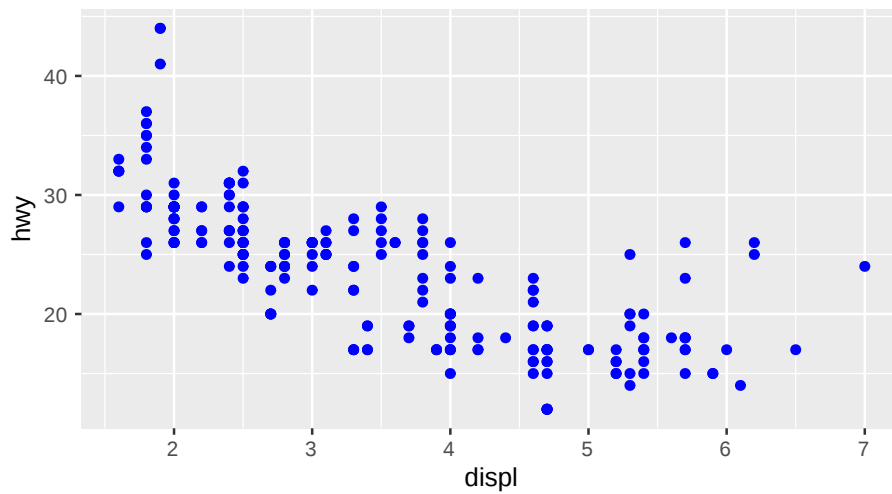
Click here to show setup code.

```
library(tidyverse)
```

2.6.1 Static colors

There are many ways to set a color for a specific geom. The simplest is to set all observations of a geom to a dedicated color, supplied as a character value.

```
ggplot(  
  data = mpg,  
  mapping = aes(x = displ, y = hwy)  
) +  
  geom_point(  
    color = "blue"  
  )
```



2.6.2 Dynamic colors

Dynamic colors, which depend on a variable of the dataset, need to be passed within an `aes()` call. A direct specification like in the example above with `color = "blue"` only works for static colors.

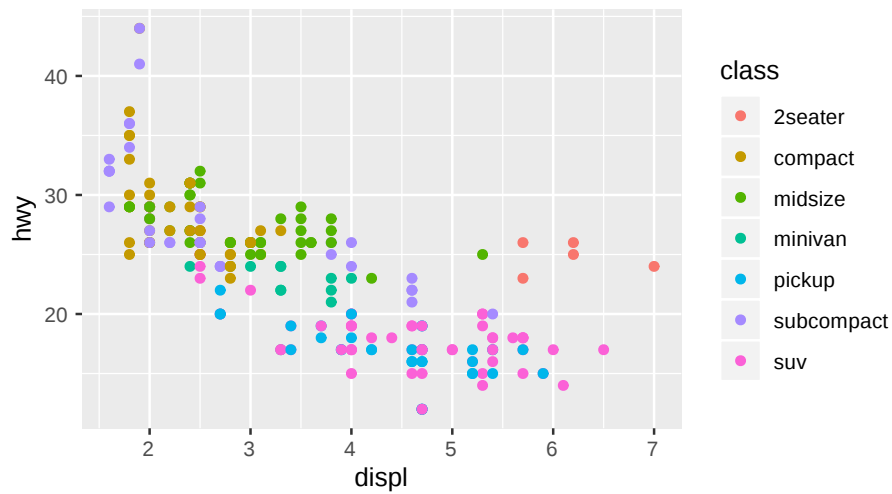
Good to know: While it is possible to include `color = class` directly in the `aes()` call of the `ggplot()` function, it is recommended to set it within the particular geom. This is for two reasons:

- When working with multiple geoms, you can use different mappings for each geom without any possibility of conflicts
- When reading the code, it becomes more clear which settings apply to which geoms

Discrete

Different colors can be mapped to the values of a variable by supplying a variable of the dataset. The `class` variable is discrete and leads to a discrete color scale.

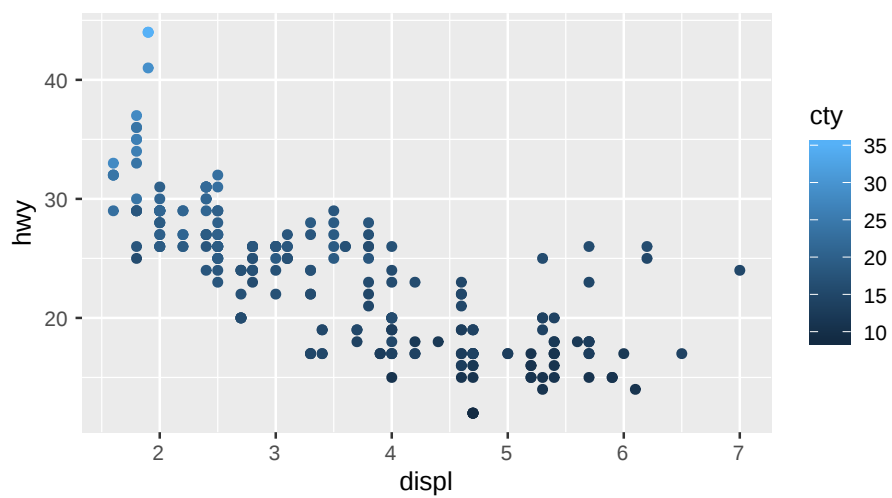
```
ggplot(  
  data = mpg,  
  mapping = aes(x = displ, y = hwy)  
) +  
  geom_point(aes(color = class))
```

Continuous

The `cty` attribute is continuous, the color scale is adapted accordingly.

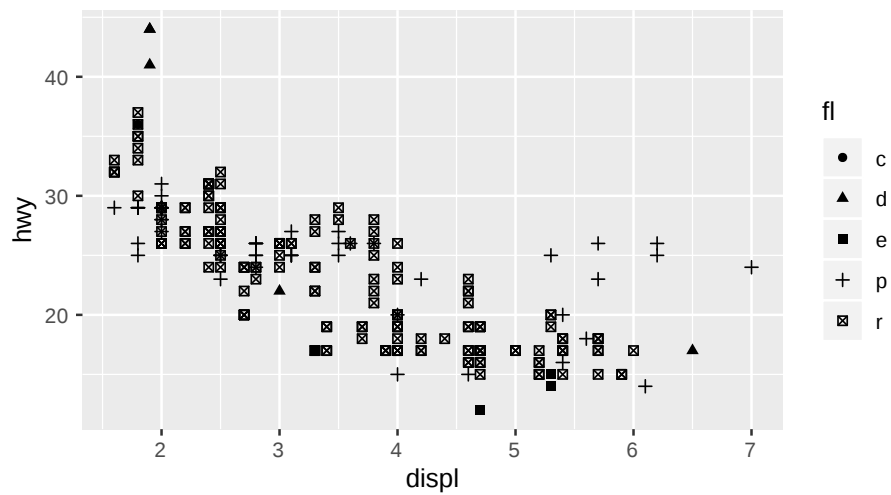
```
ggplot(
  data = mpg,
  mapping = aes(x = displ, y = hwy)
) +
  geom_point(aes(color = cty))
```



2.6.3 Shape

One more degree of freedom is the shape of the symbols to be plotted.

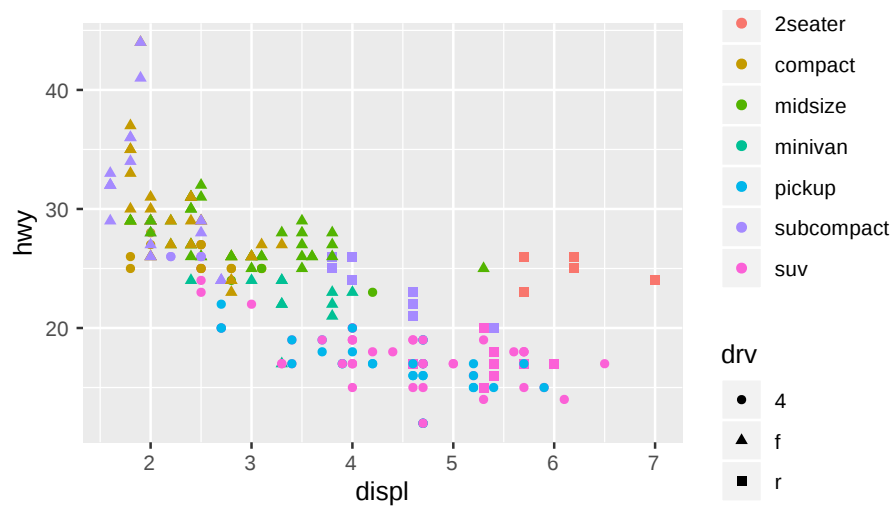
```
ggplot(
  data = mpg,
  mapping = aes(
    x = displ,
    y = hwy
  )
) +
  geom_point(aes(shape = fl))
```



2.6.4 Combining color and shape

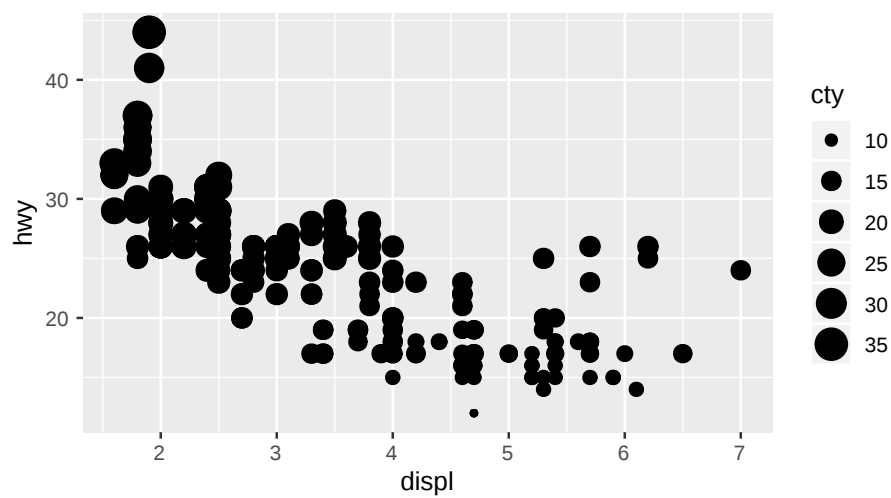
Color and shape can be combined.

```
ggplot(
  data = mpg,
  mapping = aes(
    x = displ,
    y = hwy,
  )
) +
  geom_point(aes(color = class, shape = drv))
```



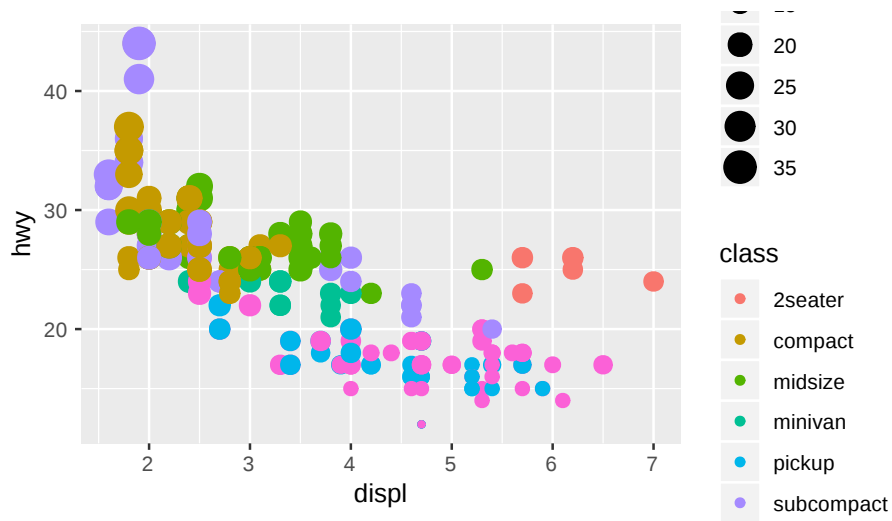
And last but not least, the size of the plotted symbols can be linked to numeric values of the mapped variable.

```
ggplot(
  data = mpg,
  mapping = aes(
    x = displ,
    y = hwy,
    size = cty
  )
) +
  geom_point()
```



You can mix different aesthetic mappings in order to produce a plot with densely packed information. However, be aware that adding too much information to a plot does not necessarily make it better.

```
ggplot(
  data = mpg,
  mapping = aes(
    x = displ,
    y = hwy,
    color = class,
    size = cty
  )
) +
  geom_point()
```

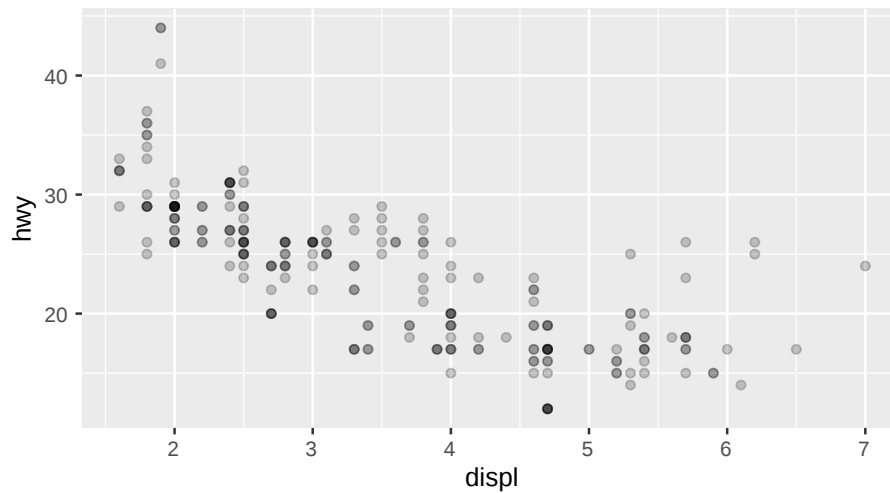


2.6.5 Transparency

Semi-transparency is another way to better display your data when observations are overlapping. This is useful to get an impression of how many data points share the same coordinates.

```
ggplot(
  data = mpg,
  mapping = aes(
    x = displ,
    y = hwy
  )
) +
```

```
geom_point(alpha = 0.2)
```



2.6.6 What can go wrong

If you try to specify a color in the `mapping`-argument of the main `ggplot()` call, you will face an error since a mapping of a variable to an aesthetic is expected.

```
ggplot(  
  data = mpg,  
  mapping = aes(  
    x = displ,  
    y = hwy,  
    color = blue  
  )  
) +  
  geom_point()
```

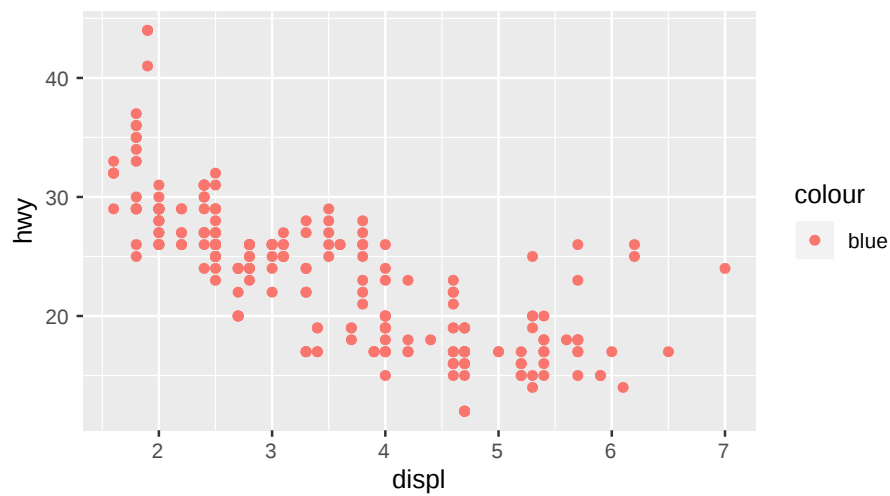
```
## Error in FUN(X[[i]], ...): object 'blue' not found
```

R treats objects without quotation marks in a special way, expecting them to be variables. Since `blue` is not a variable of `mpg`, this did not work. Use quotation marks if you mean a string, as opposed to a variable or object name.

```
mpg
## # A tibble: 234 x 11
##   manufacturer model displ  year   cyl trans drv      cty   hwy
##   <chr>          <chr> <dbl> <int> <int> <chr> <chr> <int> <int>
## 1 audi          a4      1.8  1999     4 auto~ f      18    29
## 2 audi          a4      1.8  1999     4 manu~ f      21    29
## 3 audi          a4      2    2008     4 manu~ f      20    31
## # ... with 231 more rows, and 2 more variables: fl <chr>,
## #   class <chr>
"mpg"
## [1] "mpg"
```

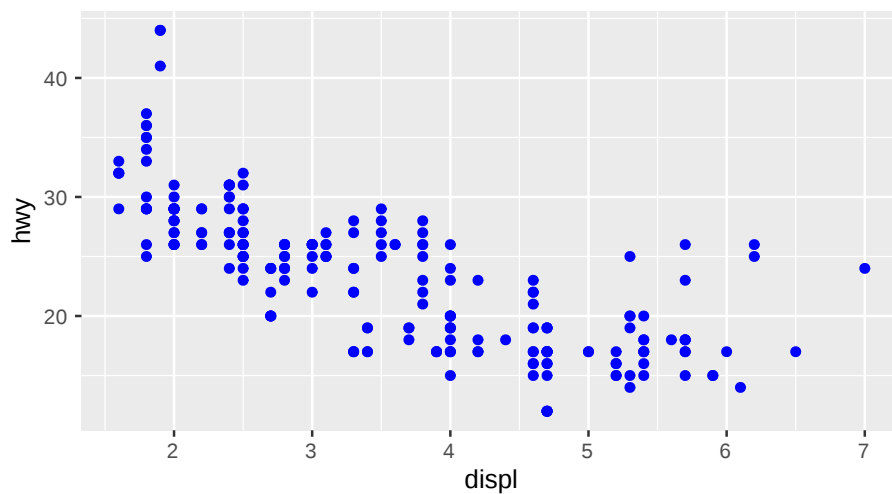
So what if we pass the color as a character variable?

```
ggplot(
  data = mpg,
  mapping = aes(
    x = displ,
    y = hwy,
    color = "blue"
  )
) +
  geom_point()
```



At least there was no error, but now the constant value `blue` is mapped to the first default color of the color mapping, which happens to be red. We could have been fooled, if it had been blue. Recall, it is best to specify geom related mappings with the respective geom function.

```
ggplot(  
  data = mpg,  
  mapping = aes(  
    x = displ,  
    y = hwy  
  )  
) +  
  geom_point(  
    color = "blue"  
  )  
)
```

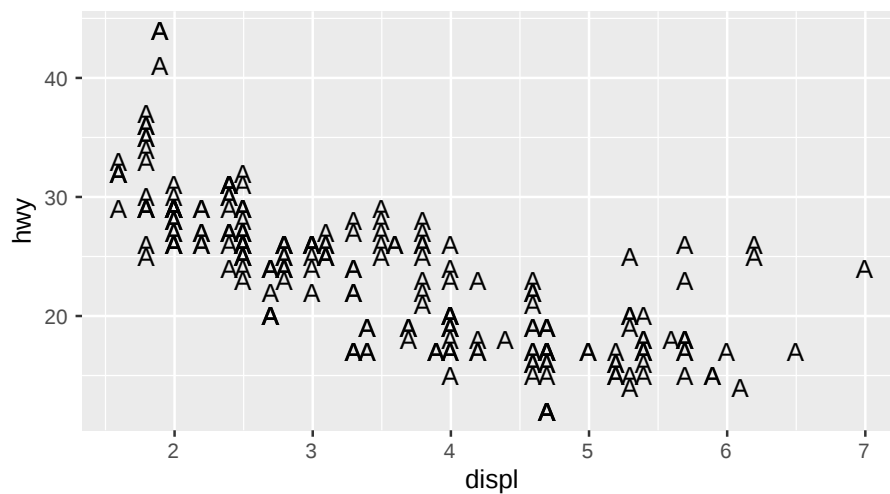


2.7 Labels

```
library(tidyverse)
```

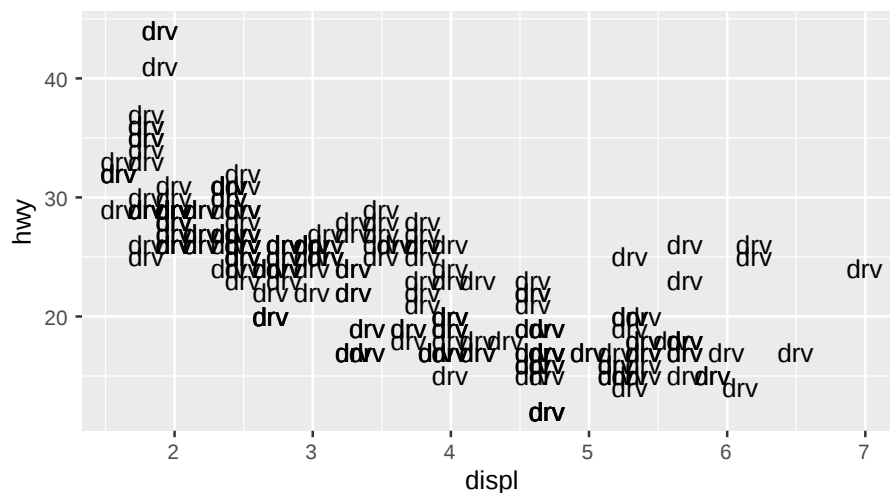
For character variables there is further way of integrating its value to a plot. `geom_text()` takes a `label` argument, which influences the plot in the following way.

```
ggplot(  
  data = mpg,  
  mapping = aes(x = displ, y = hwy)  
) +  
  geom_text(label = "A")
```

Let's try to map this argument to a variable (here: `drv`) of our dataset in the `mapping` argument of `ggplot()`.

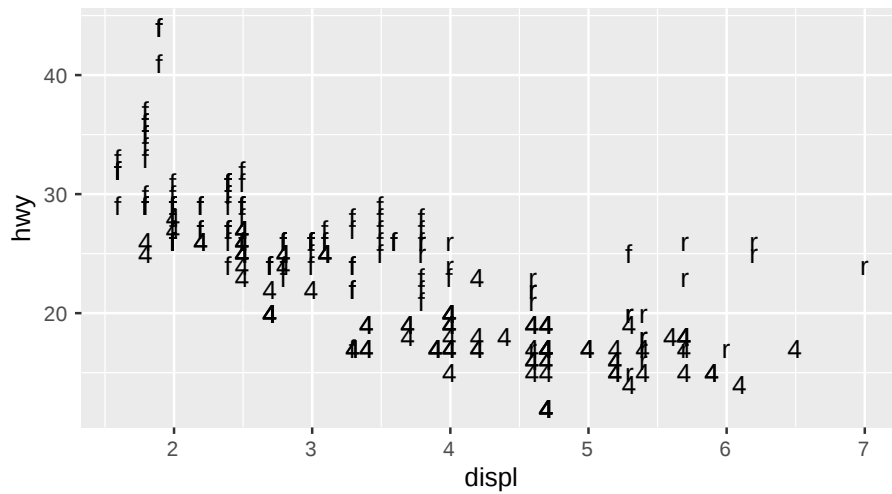
```
ggplot(
  data = mpg,
  mapping = aes(x = displ, y = hwy)
) +
  geom_text(label = "drv")
```



Right, of course we need to pass the variable without quotation marks, otherwise it is interpreted as a (constant) character variable. When changing this, a vector with the values of the variable is passed on to `geom_text()`. This is one way of

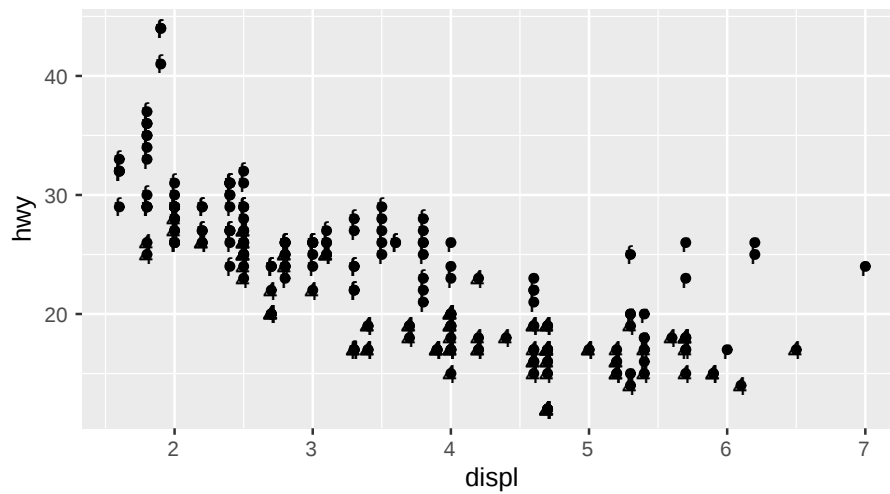
including the values of character variables in a plot.

```
ggplot(
  data = mpg,
  mapping = aes(x = displ, y = hwy)
) +
  geom_text(aes(label = drv))
```



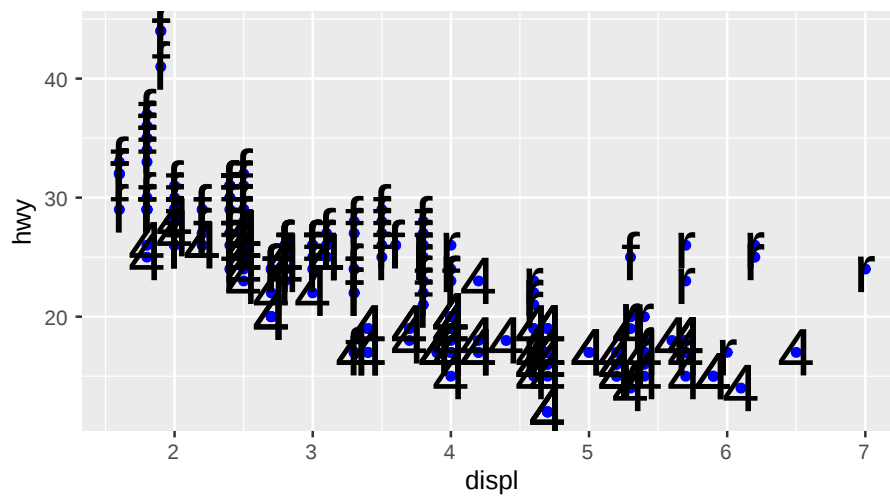
When adding more than one `geom()`-function, multiple geometries are added to the plot. However, because `geom_point()` has no support for passing a label, we can only use this mapping in `geom_text()`.

```
ggplot(
  data = mpg,
  mapping = aes(x = displ, y = hwy)
) +
  geom_point() +
  geom_text(aes(label = drv))
```



Since this looks just slightly odd, let's try to make it more apparent, what is happening.

```
ggplot(
  data = mpg,
  mapping = aes(x = displ, y = hwy)
) +
  geom_point(color = "blue") +
  geom_text(aes(label = drv), size = 10)
```



Chapter 3

{ggplot2} advanced

3.1 Facetting

Click here to show setup code.

```
library(tidyverse)
library(ggsci)
library(ggpubr)

## Loading required package: magrittr

##
## Attaching package: 'magrittr'

## The following object is masked from 'package:purrr':
##
##      set_names

## The following object is masked from 'package:tidyr':
##
##      extract

library(patchwork)
```

“Facetting” (or trellis plots, lattice plots) denotes an idea of dividing a graphic into sub-graphics based on the (categorical) values of one or more variables of a dataset.

The variables used for facetting should be passed encapsulated in `vars()`. (Before {ggplot2} v3.0.0 the default was to use a formula notation (`<variable> ~ <variable>`) to specify the facetting variables.)

```
facet_grid(facets = vars(<variable>), scales = "fixed", ...)
facet_wrap(rows = vars(<variable>), cols = vars(<variable>),
```

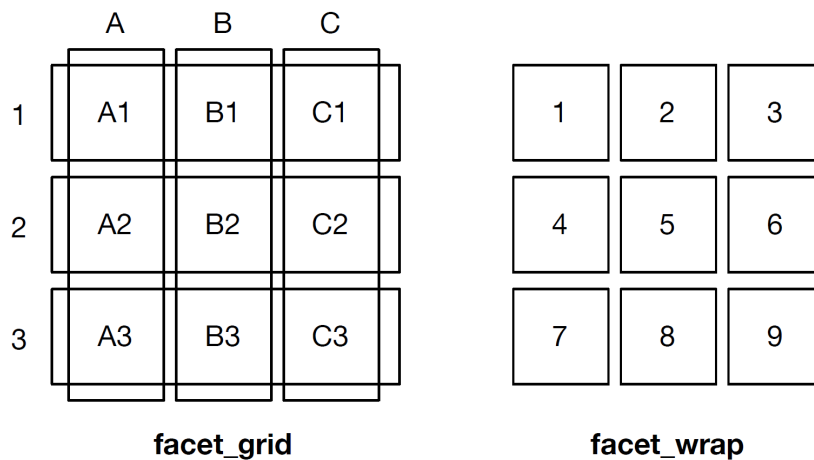
```
scales = "fixed", ...)
```

facet: Variables given via `vars()` or formula with splitting variable.

scales: Scale of the axes over the sub-graphics.

The position of `<variable>` in `facet_wrap()` denotes on which axis the facets will appear:

- `vars(<variable>)` → y-axis
- `vars(), vars(<variable>)` → x-axis

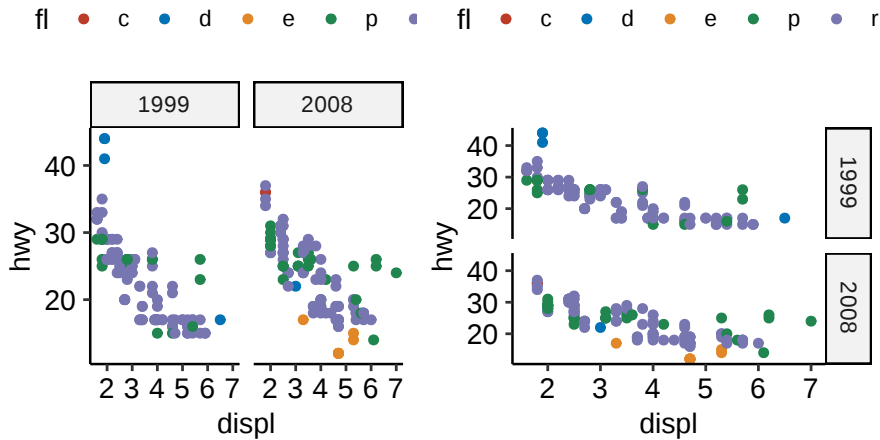


3.1.1 facet_wrap()

```
facet_x = ggplot(mpg, aes(displ, hwy)) +
  geom_point(aes(colour = fl)) +
  scale_color_nejm() +
  facet_grid(vars(), vars(year)) +
  theme_pubr()
```

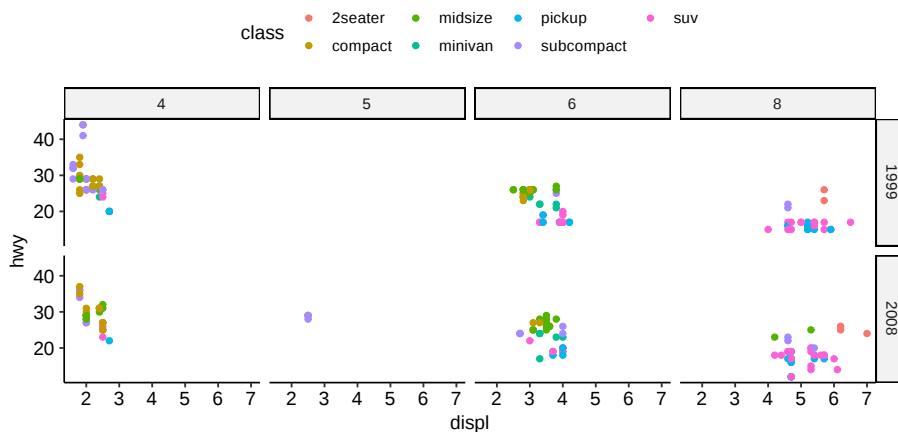
```
facet_y = ggplot(mpg, aes(displ, hwy)) +
  geom_point(aes(colour = fl)) +
  scale_color_nejm() +
  facet_grid(vars(year), vars()) +
  theme_pubr()
```

```
facet_x + facet_y
```



Facets can also be shown on both axes using different (categorical) variables. For this, `facet_grid()` is useful:

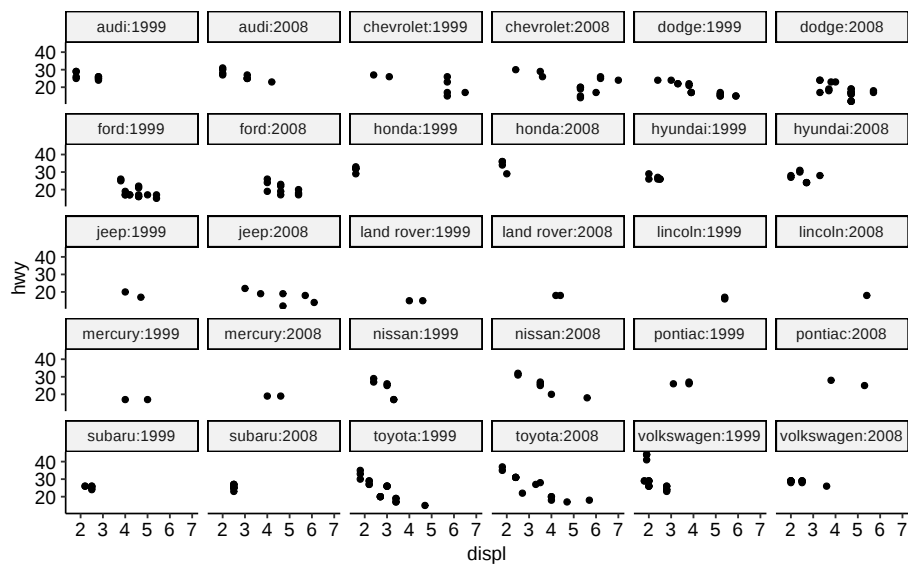
```
ggplot(mpg, aes(displ, hwy)) +
  geom_point(aes(colour = class)) +
  facet_grid(cols = vars(cyl), rows = vars(year)) +
  theme_pubr()
```



Rather than visualizing a 2D-facet plot on x and y, there is also the option to combine both in one axis. (For this to work, the variables need to be of class `factor`).

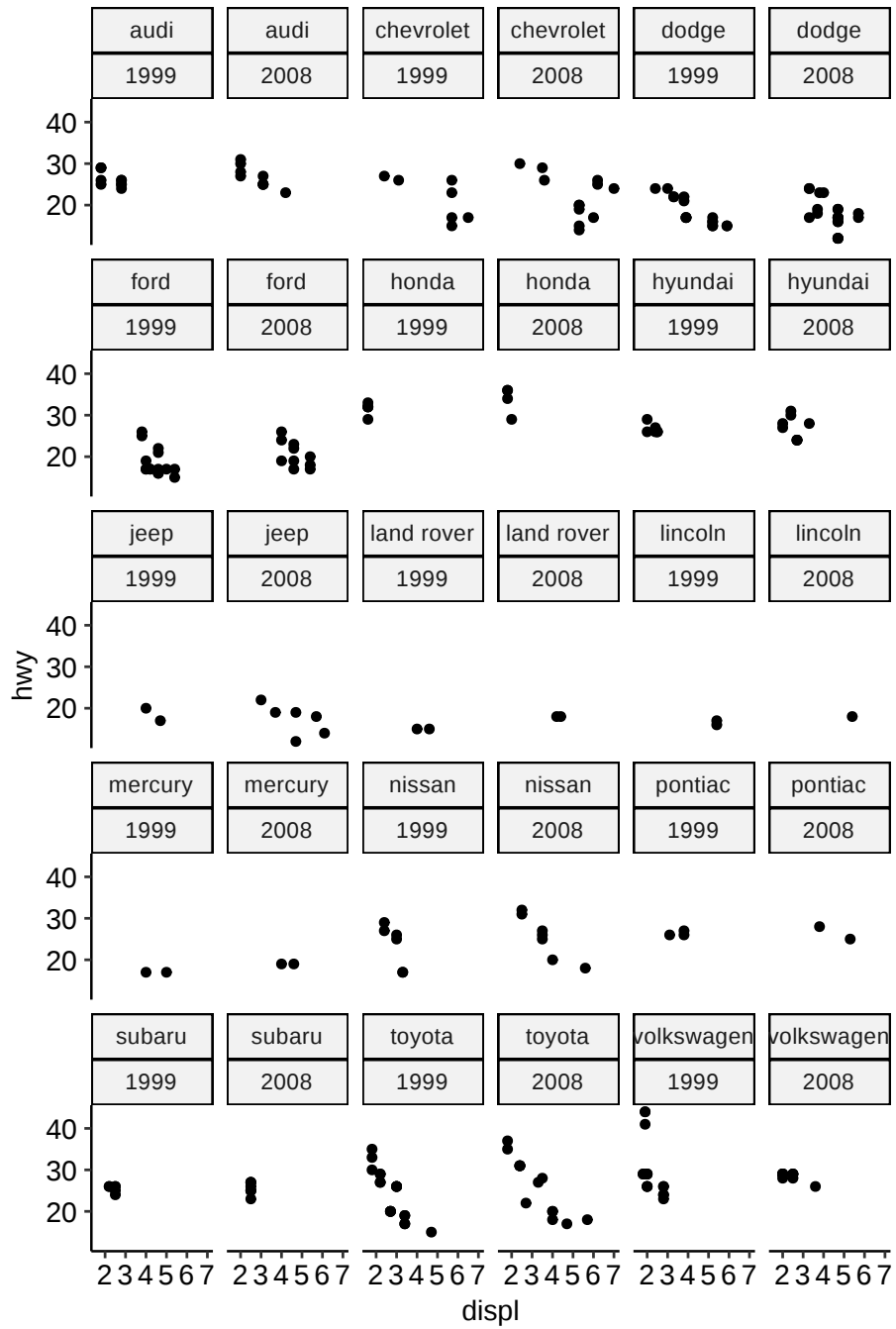
```
mpg %>%
  mutate(manufacturer = as.factor(manufacturer)) %>%
  mutate(year = as.factor(year)) %>%
```

```
ggplot(aes(displ, hwy)) +
  geom_point() +
  facet_wrap(vars(manufacturer:year)) +
  theme_pubr()
```



This is usually a better setting than doubling the facet labels - but might also be up to personal preference.

```
ggplot(mpg, aes(displ, hwy)) +
  geom_point() +
  facet_wrap(vars(manufacturer, year)) +
  theme_pubr()
```

3.1.2 facet_grid()

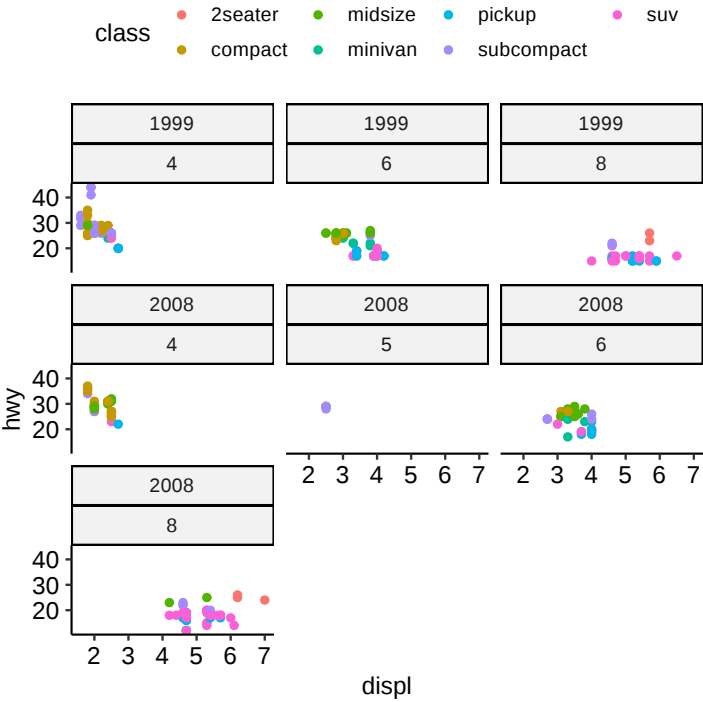
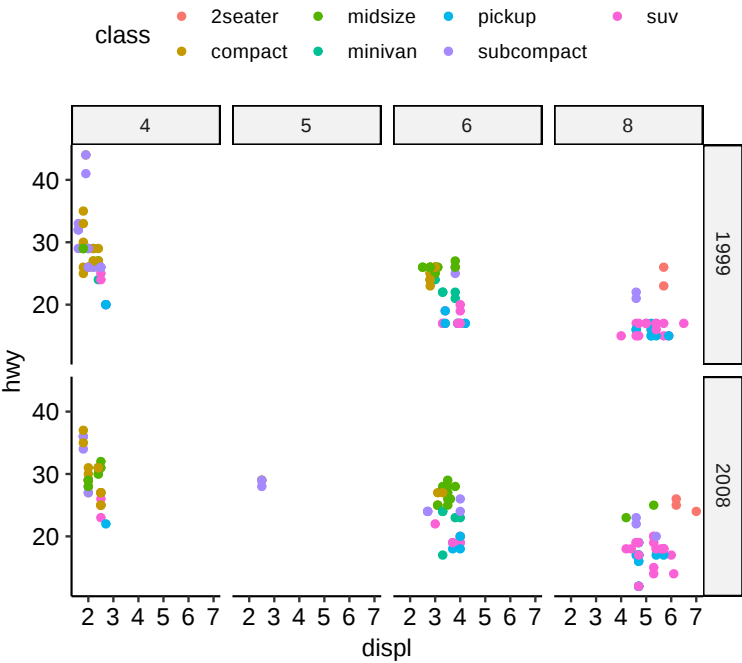
While `facet_wrap()` tries to act smart and hide non-existing combinations of sub-plots, `facet_grid()` will create a full matrix of sub-plots for all possible combinations. Most of the time when using only one categorical variable, `facet_wrap()` does a good job and is preferred over `facet_grid()`.

However, `facet_grid` might be preferred in the following cases:

- when facetting over ≥ 2 variables
- when plots of empty combinations should be shown

Let's compare how `facet_grid` and `facet_wrap` differ for 2 grouping variables where not all combinations of those contain observations:

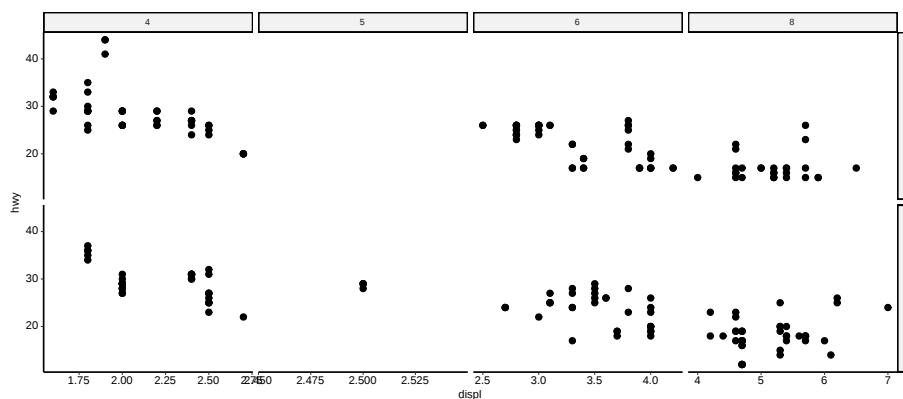
```
fc_gd = ggplot(mpg, aes(displ, hwy)) +  
  geom_point(aes(colour = class)) +  
  facet_grid(vars(year), vars(cyl)) +  
  theme_pubr()  
  
fc_wrap = ggplot(mpg, aes(displ, hwy)) +  
  geom_point(aes(colour = class)) +  
  facet_wrap(vars(year, cyl)) +  
  theme_pubr()  
  
fc_gd / fc_wrap
```



3.1.3 Scales

By default, scales are fixed across each facet (`scales = "fixed"`). This means that all sub-plots should share the same axes. By setting this argument to either `"free_x"` or `"free_y"` one can specify that each sub-plot should have its own scale.

```
ggplot(mpg, aes(displ, hwy)) +
  geom_point() +
  facet_grid(vars(year), vars(cyl), scales = "free_x") +
  theme_pubr(base_size = 7)
```



This only makes sense if the ranges for each facet differ substantially (so not in this example!). This example is good to show the confusion that this setting might introduce. People usually expect to look at **equal ranges** across facets (unless there is a good reason for it not to) and differing scales make the plot more complicated.

Keep in mind: Visualization should *simplify* data!

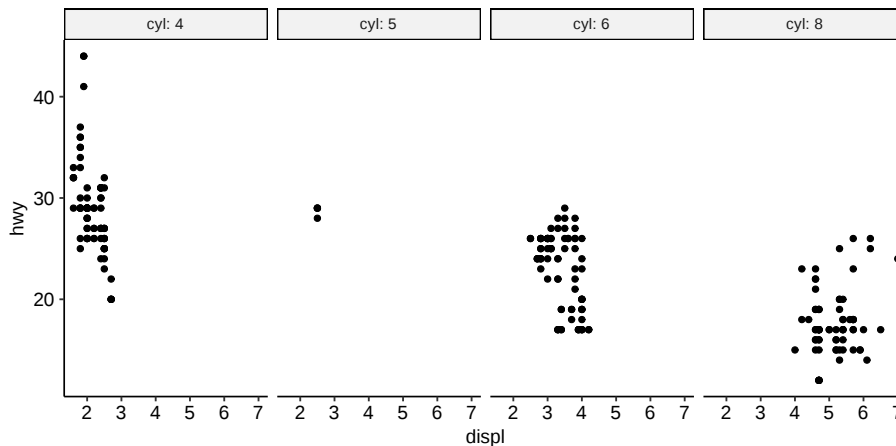
3.1.4 Renaming of facet labels

A non-trivial change that is often applied to facet plots is the (re-)naming of the facet labels. Facet labels are automatically created based on the factor levels of the respective variable. However, sometimes the raw factor levels are not descriptive enough. In these cases, it makes sense to prefix the factor level values with the column name. This can be achieved by setting the `labeller` argument of `facet_*` to `label_both`.

(An alternative would be to modify the underlying factor levels of the data so that these are descriptive right from the start.)

```
ggplot(mpg, aes(displ, hwy)) +
  geom_point() +
```

```
facet_grid(vars(), vars(cyl), labeller = label_both) +
theme_pubr()
```



3.2 Extensions

A mass of R packages extending `{ggplot2}` exists. Many are listed at <http://www.ggplot2-exts.org/gallery/>.

Here is a selected list of our favorite `{ggplot2}` extensions including some use examples.

`{ggsci}`: <https://nanx.me/ggsci/>

`{ggforce}`: <https://ggforce.data-imaginist.com/>

`{patchwork}`: <https://patchwork.data-imaginist.com/>

`{gganimate}`: <https://gganimate.com/>

`{ggtext}`: <https://github.com/clauswilke/ggtext>

`{ggiraph}`: <http://davidgohel.github.io/ggiraph>

`{ggbeeswarm}`: <https://github.com/eclarke/ggbeeswarm>

`{esquisse}`: <https://dreamrs.github.io/esquisse>

(`{ggstatsplot}`: <https://indrajeetpatil.github.io/ggstatsplot>)

(`{ggedit}`: <https://github.com/metrumresearchgroup/ggedit>)

(`{lindia}`: <https://github.com/yeukyul/lindia>)

Click here to show setup code.

```

library(tidyverse)
library(ggsci)
library(ggpubr)
library(patchwork)
library(ggpmisc)

## News about 'ggpmisc' at https://www.r4photobiology.info/

library(ggiraph)
library(ggbeeswarm)
library(gganimate)
library(ggrepel)
library(ggforce)
library(gapminder)

```

3.2.1 {ggsci}

```

p1 <- ggplot(mpg, aes(manufacturer)) +
  geom_bar(aes(fill = fl))

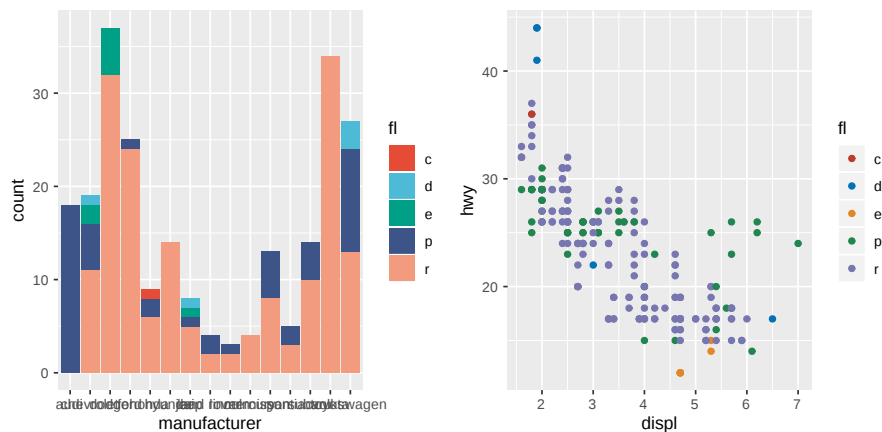
p2 <- ggplot(mpg, aes(displ, hwy)) +
  geom_point(aes(colour = fl))

library("patchwork")

p1_npg <- p1 + ggsci::scale_fill_npg()
p2_nejm <- p2 + ggsci::scale_color_nejm()

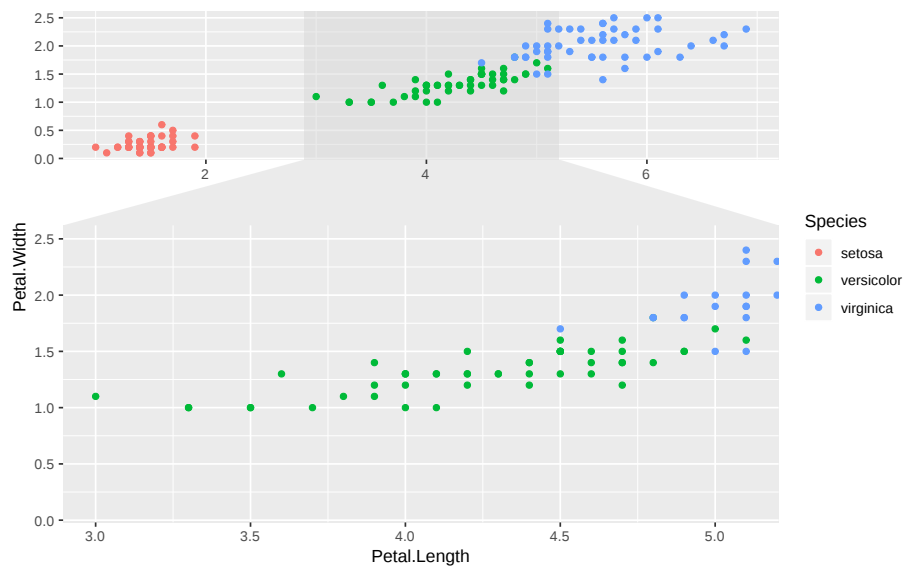
p1_npg + p2_nejm

```



3.2.2 {ggforce}

```
ggplot(iris, aes(Petal.Length, Petal.Width, colour = Species)) +
  geom_point() +
  ggforce::facet_zoom(x = Species == "versicolor")
```



3.2.3 {gganimate}

```
ggplot(gapminder, aes(gdpPerCap, lifeExp, size = pop, colour = country)) +
  geom_point(alpha = 0.7, show.legend = FALSE) +
  scale_colour_manual(values = country_colors) +
  scale_size(range = c(2, 12)) +
  scale_x_log10() +
  facet_wrap(~continent) +
  labs(title = 'Year: {frame_time}', x = 'GDP per capita', y = 'life expectancy') +
  gganimate::transition_time(year) +
  ease_aes('linear')
```

```
## Warning: No renderer available. Please install the gifski, av,
## or magick package to create animated output
```

3.2.4 {ggtext}

```
df <- data.frame(
  label = c(
    "Some text in bold.",
  )
```

```

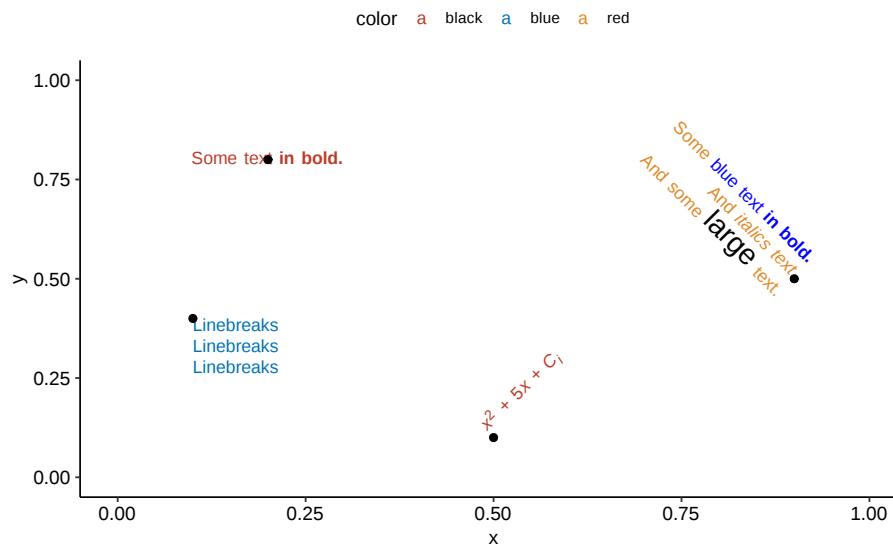
    "Linebreaks<br>Linebreaks<br>Linebreaks",
    "*x*<sup>2</sup> + 5*x* + *C*<sub>*i</sub>",
    "Some <span style='color:blue'>blue text in bold</span><br>And italics text."
    And some <span style='font-size:18pt; color:black'>large</span> text."
  ),
  x = c(.2, .1, .5, .9),
  y = c(.8, .4, .1, .5),
  hjust = c(0.5, 0, 0, 1),
  vjust = c(0.5, 1, 0, 0.5),
  angle = c(0, 0, 45, -45),
  color = c("black", "blue", "black", "red"),
  fill = c("cornsilk", "white", "lightblue1", "white")
)

```

```

ggplot(df) +
  aes(
    x, y,
    label = label, angle = angle, color = color,
    hjust = hjust, vjust = vjust
  ) +
  ggtext::geom_richtext(
    fill = NA, label.color = NA, # remove background and outline
    label.padding = grid::unit(rep(0, 4), "pt") # remove padding
  ) +
  geom_point(color = "black", size = 2) +
  scale_color_nejm() +
  xlim(0, 1) + ylim(0, 1) +
  theme_pubr()

```

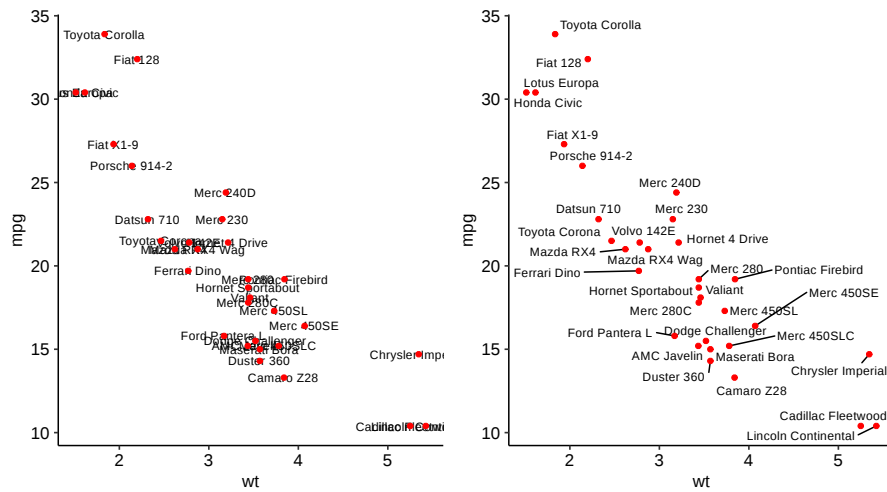



3.2.5 {ggrepel}

```
no_repel <- ggplot(mtcars, aes(wt, mpg)) +
  geom_text(label = rownames(mtcars), size = 3) +
  geom_point(color = "red") +
  theme_pubr()

with_repel <- ggplot(mtcars, aes(wt, mpg)) +
  ggrepel::geom_text_repel(label = rownames(mtcars), size = 3) +
  geom_point(color = "red") +
  theme_pubr()

no_repel + with_repel
```



3.2.6 {ggiraph}

```
gg_point <- ggplot(mtcars, aes(wt, mpg)) +
  ggiraph::geom_point_interactive(tooltip = rownames(mtcars))

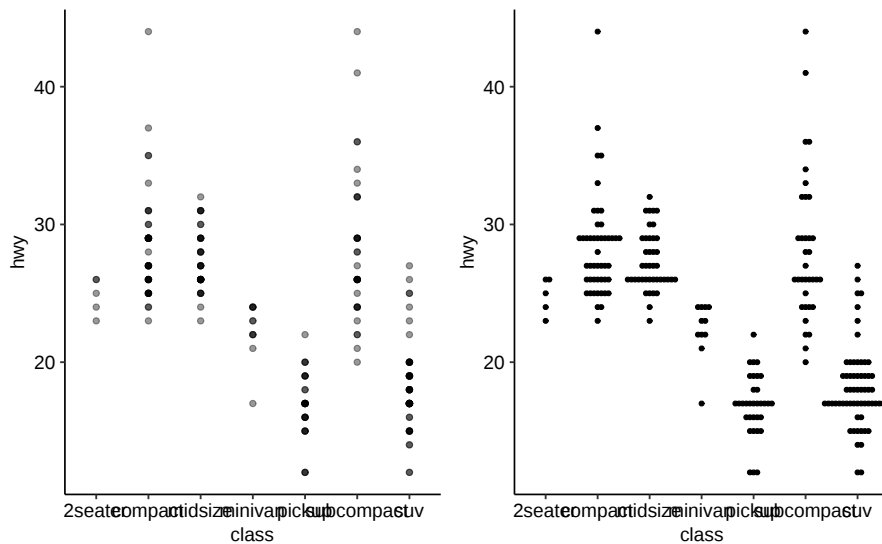
girafe(ggobj = gg_point)
```

3.2.7 {ggbeeswarm}

```
normal_overplotting <- ggplot(mpg, aes(class, hwy)) +
  geom_point(alpha = 0.4) +
  theme_pubr()

ggbeeswarm <- ggplot(mpg, aes(class, hwy)) +
  ggbeeswarm::geom_beeswarm(size = 1.1) +
  theme_pubr()

library(patchwork)
normal_overplotting + ggbeeswarm
```

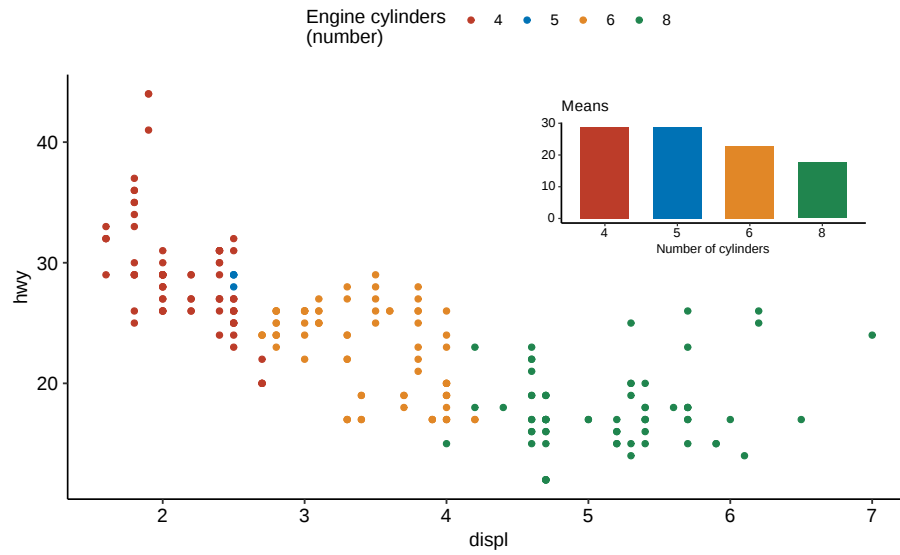


3.2.8 {ggpmisc}

```
p <- ggplot(mpg, aes(factor(cyl), hwy)) +
  stat_summary(geom = "col", fun.y = mean, width = 2 / 3, aes(fill = factor(cyl))) +
  labs(x = "Number of cylinders", y = NULL, title = "Means") +
  scale_fill_nejm(guide = FALSE)

data.tb <- tibble(
  x = 7, y = 44,
  plot = list(p +
    theme_pubr(8))
)

ggplot(mpg, aes(displ, hwy)) +
  ggpmisc::geom_plot(data = data.tb, aes(x, y, label = plot)) +
  geom_point(aes(colour = factor(cyl))) +
  scale_colour_nejm() +
  labs(
    colour = "Engine cylinders\n(number)"
  ) +
  theme_pubr()
```



3.2.9 {esquisse}

```
esquisse::esquisser(mpg)
```

Part II

Tidying, transforming and importing

Chapter 4

Transformation

Using a consistent grammar of data manipulation.

This chapter discusses data transformation with the dplyr package.

4.1 Package: {conflicted}

Click here to show setup code.

```
library(tidyverse)
library(conflicted)
conflict_prefer("filter", "dplyr")
```

```
## [conflicted] Will prefer dplyr::filter over any other package
```

This section is dedicated to show you the basic building blocks (i.e. functions) of data analysis in R within the {tidyverse}. The package providing these is {dplyr}.

Before starting, we would like to mention the package {conflicted}, which when loaded, will help detecting functions of the same name from different packages (an error is thrown in case of such situations). It furthermore helps to resolve these situations, by allowing you to choose, the function of which package you prefer (`conflicted::conflict_prefer()`). You can see an example in the setup code.

4.2 Filtering: `dplyr::filter()`

Click here to show setup code.

```
library(tidyverse)
library(nycflights13)
```

```
library(conflicted)
conflict_prefer("filter", "dplyr")
```

```
## [conflicted] Removing existing preference
```

```
## [conflicted] Will prefer dplyr::filter over any other package
```

During this lecture we will be working with data from the package {nycflights13}, which contains flights in the year 2013 with their departure in New York City (airports: JFK, LGA or EWR) to destinations in the United States, Puerto Rico, and the American Virgin Islands.

```
flights
```

```
## # A tibble: 336,776 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>       <dbl>   <int>
## 1  2013     1     1     517             515         2     830
## 2  2013     1     1     533             529         4     850
## 3  2013     1     1     542             540         2     923
## # ... with 3.368e+05 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>
```

```
?flights
```

```
?flights
```

The function `dplyr::filter()` helps you to reduce your dataset to the observations (rows) of interest. The filter condition can use any of the dataset's variables and needs to be a logical expression.

```
flights %>%
  filter(dep_time < 600)

## # A tibble: 8,730 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>       <dbl>   <int>
## 1  2013     1     1     517             515         2     830
## 2  2013     1     1     533             529         4     850
## 3  2013     1     1     542             540         2     923
## # ... with 8,727 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>
```


If you use one or more variables of the dataset in the filter condition, a vectorized evaluation of the condition is taking place. Generally you can provide any logical vector with a length equal to the number of rows (or alternatively equal to 1, if you want to keep/drop all rows).

```
flights %>%
  filter(is.na(dep_time))

## # A tibble: 8,255 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>         <dbl>   <int>
## 1  2013     1     1     NA             1630           NA       NA
## 2  2013     1     1     NA             1935           NA       NA
## 3  2013     1     1     NA             1500           NA       NA
## # ... with 8,252 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>
```

Use `&` or multiple filters to return only rows that match both criteria:

```
flights %>%
  filter(dep_time < 600 & arr_time > 2200)

## # A tibble: 0 x 19
## # ... with 19 variables: year <int>, month <int>, day <int>,
## #   dep_time <int>, sched_dep_time <int>, dep_delay <dbl>,
## #   arr_time <int>, sched_arr_time <int>, arr_delay <dbl>,
## #   carrier <chr>, flight <int>, tailnum <chr>, origin <chr>,
## #   dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
## #   minute <dbl>, time_hour <dtm>

flights %>%
  filter(dep_time >= 700 & arr_time < 800)

## # A tibble: 10,654 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>         <dbl>   <int>
## 1  2013     1     1    1929             1920           9        3
## 2  2013     1     1    1939             1840          59       29
## 3  2013     1     1    2058             2100          -2        8
## # ... with 1.065e+04 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>

flights %>%
  filter(dep_time >= 700) %>%
```

```

filter(arr_time < 800)

## # A tibble: 10,654 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>       <dbl>   <int>
## 1  2013     1     1    1929           1920         9         3
## 2  2013     1     1    1939           1840        59        29
## 3  2013     1     1    2058           2100        -2         8
## # ... with 1.065e+04 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>

```

Use `|` to return all rows that match either criterion or both:

```

flights %>%
  filter(dep_time < 600 | arr_time > 2200)

## # A tibble: 40,879 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>       <dbl>   <int>
## 1  2013     1     1     517           515         2     830
## 2  2013     1     1     533           529         4     850
## 3  2013     1     1     542           540         2     923
## # ... with 4.088e+04 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>

```

4.3 Sort rows: `dplyr::arrange()`

[Click here to show setup code.](#)

```

library(tidyverse)
library(nycflights13)

library(conflicted)
conflict_prefer("filter", "dplyr")

## [conflicted] Removing existing preference
## [conflicted] Will prefer dplyr::filter over any other package

```

The function `dplyr::arrange()` sorts the rows of the dataset according to the values of the variable(s) you are providing.

```

flights %>%
  arrange(dep_time)

## # A tibble: 336,776 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>       <dbl>   <int>
## 1  2013     1    13         1           2249         72     108
## 2  2013     1    31         1           2100        181     124
## 3  2013    11    13         1           2359          2     442
## # ... with 3.368e+05 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>

```

When providing multiple variables as arguments for ... (the ellipsis), the dataset is first sorted according to the values of the first variable. Wherever these values occur more than once, another sorting takes place within those groups, according to the second variable you provided. The same rule applies for every further variable you add to `arrange()`.

```

flights %>%
  arrange(dep_time, dep_delay)

## # A tibble: 336,776 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>       <dbl>   <int>
## 1  2013    11    13         1           2359          2     442
## 2  2013    12    16         1           2359          2     447
## 3  2013    12    20         1           2359          2     430
## # ... with 3.368e+05 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>

```

You can combine `filter()` and `arrange()`.

```

flights %>%
  filter(dep_time < 600) %>%
  filter(month >= 10) %>%
  arrange(dep_time, dep_delay) %>%
  view()

## # A tibble: 1,894 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>       <dbl>   <int>
## 1  2013    11    13         1           2359          2     442
## 2  2013    12    16         1           2359          2     447

```

```
## 3 2013    12    20         1         2359         2        430
## # ... with 1,891 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>
```

You can use `arrange()` with arbitrary expressions.

```
flights %>%
  filter(month == 4) %>%
  filter(day == 1) %>%
  arrange(is.na(dep_time)) %>%
  view()

## # A tibble: 970 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>      <dbl>   <int>
## 1  2013     4     1     454             500        -6     636
## 2  2013     4     1     509             515        -6     743
## 3  2013     4     1     526             530         -4     812
## # ... with 967 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>
```

The reason for the result you just saw in the view of the filtered dataset is, that the binary result of the expression (`TRUE`, `FALSE`) is sorted `FALSE` first (lexicographically).

Let's give it a twist:

```
flights %>%
  filter(month == 4) %>%
  filter(day == 1) %>%
  arrange(!is.na(dep_time)) %>%
  view()

## # A tibble: 970 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>      <dbl>   <int>
## 1  2013     4     1      NA             1125         NA      NA
## 2  2013     4     1      NA             1545         NA      NA
## 3  2013     4     1      NA              850         NA      NA
## # ... with 967 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
```

```
## #   time_hour <dtm>
```

Sorting the dataset according to which flights arrived earliest on April 1, 2013:

```
flights %>%
  filter(month == 4) %>%
  filter(day == 1) %>%
  arrange(arr_time) %>%
  view()

## # A tibble: 970 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>      <dbl>   <int>
## 1  2013     4     1    2243             2245        -2         6
## 2  2013     4     1    2056             1925         91         8
## 3  2013     4     1    2216             2100         76         9
## # ... with 967 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>
```

Invert the sorting by either...

```
flights %>%
  filter(month == 4) %>%
  filter(day == 1) %>%
  arrange(-arr_time) %>%
  view()

## # A tibble: 970 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>      <dbl>   <int>
## 1  2013     4     1    2027             2032         -5    2358
## 2  2013     4     1    2151             1930        141    2358
## 3  2013     4     1    2252             2245         7     2358
## # ... with 967 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>
```

... or:

```
flights %>%
  filter(month == 4) %>%
  filter(day == 1) %>%
  arrange(desc(arr_time)) %>%
  view()
```

```
## # A tibble: 970 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>      <dbl>   <int>
## 1  2013     4     1    2027             2032        -5    2358
## 2  2013     4     1    2151             1930       141    2358
## 3  2013     4     1    2252             2245         7    2358
## # ... with 967 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>
```

You can mix sorting in an ascending and a descending manner:

```
flights %>%
  filter(month == 4) %>%
  filter(day == 1) %>%
  arrange(dep_time, desc(arr_time)) %>%
  view()

## # A tibble: 970 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>      <dbl>   <int>
## 1  2013     4     1    454             500        -6    636
## 2  2013     4     1    509             515        -6    743
## 3  2013     4     1    526             530        -4    812
## # ... with 967 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>
```

4.4 The pipe

Click [here](#) to show setup code.

```
library(tidyverse)
library(nycflights13)

library(conflicted)
conflict_prefer("filter", "dplyr")

## [conflicted] Removing existing preference
## [conflicted] Will prefer dplyr::filter over any other package
```

We already heavily used it today, but what exactly are the characteristics of `%>%`, better known as “the pipe”?

```
early_flights <-
  flights %>%
  filter(dep_time < 600)
```

The above is just another way of writing:

```
early_flights <- filter(flights, dep_time < 600)
```

The manual describes this operator in detail:

```
? "%>%"
```

With the pipe, code can be read in a natural way, from left to right. The following snippet extracts

1. all early flights
2. from October till December,
3. ordered by departure time and then departure delay
4. and displays it.

Note how the reading corresponds to the code.

```
flights %>%
  filter(dep_time < 600) %>%
  filter(month >= 10) %>%
  arrange(dep_time, dep_delay) %>%
  view()

## # A tibble: 1,894 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>      <dbl>   <int>
## 1  2013    11    13         1             2359         2     442
## 2  2013    12    16         1             2359         2     447
## 3  2013    12    20         1             2359         2     430
## # ... with 1,891 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>
```

This is possible, because all transformation verbs (`filter()`, `arrange()`, `view()`) accept the main input (a tibble) as the first argument and also return a tibble.

The following three codes are equivalent, but are more difficult to write, to read and to maintain.

Naming is hard. Trying to give each intermediate result a name is exhausting. Introducing an additional step in this sequence of operations is prone to errors.

```

early_flights <- filter(flights, dep_time < 600)
early_flights_oct_dec <- filter(early_flights, month >= 10)
early_flights_oct_dec_sorted <- arrange(early_flights_oct_dec, dep_time, dep_delay)
view(early_flights_oct_dec_sorted)

## # A tibble: 1,894 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>       <dbl>   <int>
## 1  2013    11    13         1             2359         2     442
## 2  2013    12    16         1             2359         2     447
## 3  2013    12    20         1             2359         2     430
## # ... with 1,891 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>

```

We can keep using the same variable, e.g. `x`, to avoid naming. This adds noise compared to the pipe.

```

x <- flights
x <- filter(x, dep_time < 600)
x <- filter(x, month >= 10)
x <- arrange(x, dep_time, dep_delay)
view(x)

## # A tibble: 1,894 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>       <dbl>   <int>
## 1  2013    11    13         1             2359         2     442
## 2  2013    12    16         1             2359         2     447
## 3  2013    12    20         1             2359         2     430
## # ... with 1,891 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>

```

We can avoid intermediate variables. This disconnects the verbs from their arguments and is very difficult to read.

```

view(
  arrange(
    filter(
      filter(
        flights,
        dep_time < 600
      ),
      month >= 10
    )
  )
)

```



```

    ),
    dep_time, dep_delay
  )
)

## # A tibble: 1,894 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>      <dbl>   <int>
## 1  2013    11    13         1           2359         2     442
## 2  2013    12    16         1           2359         2     447
## 3  2013    12    20         1           2359         2     430
## # ... with 1,891 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>

```

4.4.1 Further advantages

When working on a code chunk consisting of subsequent transformations connected by pipes, it can be useful to end the pipeline with either `I` or `view()`.

```

flights %>%
  filter(dep_time < 600) %>%
  filter(month >= 10) %>% I

## # A tibble: 1,894 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
## * <int> <int> <int>   <int>         <int>      <dbl>   <int>
## 1  2013    10     1     447           500        -13     614
## 2  2013    10     1     522           517         5     735
## 3  2013    10     1     536           545        -9     809
## # ... with 1,891 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>

## arrange(dep_time, dep_delay) %>%
## view()

```

Once the chunk does what you expect it to do, do not forget to remove the `I` or `view()` call.

```

try(
  arrange(dep_time, dep_delay) %>%
  view()
)

```

```
## Error in arrange(dep_time, dep_delay) : object 'dep_time' not found
```

To rearrange rows, you can use the shortcut `Alt + Cursor up/down`. In a piped expression, no further editing is necessary!

4.5 Pick columns: `dplyr::select()`

Click here to show setup code.

```
library(tidyverse)
library(nycflights13)
```

```
library(conflicted)
conflict_prefer("filter", "dplyr")
```

```
## [conflicted] Removing existing preference
```

```
## [conflicted] Will prefer dplyr::filter over any other package
```

With `dplyr::select()` you can (de-)select and/or rename columns of your dataset. The basic operation is like in the following examples:

```
flights %>%
  select(year, month, day)
```

```
## # A tibble: 336,776 x 3
##   year month   day
##   <int> <int> <int>
## 1  2013     1     1
## 2  2013     1     1
## 3  2013     1     1
## # ... with 3.368e+05 more rows
```

```
flights %>%
  select(-year)
```

```
## # A tibble: 336,776 x 18
##   month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int>   <int>         <int>        <dbl>   <int>
## 1     1     1     517             515          2     830
## 2     1     1     533             529          4     850
## 3     1     1     542             540          2     923
## # ... with 3.368e+05 more rows, and 12 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>
```

Renaming works by addressing an existing column on the right hand side of an equality sign and providing the new name of the column on its left hand side.

```
flights %>%
  select(
    year, month, day,
    departure_delay = dep_delay,
    arrival_delay = arr_delay
  )

## # A tibble: 336,776 x 5
##   year month   day departure_delay arrival_delay
##   <int> <int> <int>          <dbl>          <dbl>
## 1  2013     1     1             2             11
## 2  2013     1     1             4             20
## 3  2013     1     1             2             33
## # ... with 3.368e+05 more rows
```

With backticks, it is possible, but not advised, to use arbitrary characters (including spaces) in column names:

```
flights_with_spaces <-
  flights %>%
    select(
      year, month, day,
      `Departure delay` = dep_delay,
      `Arrival delay` = arr_delay
    ) %>%
    filter(
      `Arrival delay` < 0
    )
```

Address them in the same way, if the dataset already has such variables:

```
flights_with_spaces %>%
  select(
    year, month, day,
    dep_delay = `Departure delay`,
    arr_delay = `Arrival delay`
  )

## # A tibble: 188,933 x 5
##   year month   day dep_delay arr_delay
##   <int> <int> <int>      <dbl>      <dbl>
## 1  2013     1     1        -1        -18
## 2  2013     1     1        -6        -25
## 3  2013     1     1        -3        -14
## # ... with 1.889e+05 more rows
```

The `{janitor}` package helps fixing issues with column names automatically.

Select helpers allow selecting multiple related columns conveniently.

```
flights %>%
  select(origin, dest, ends_with("_time"))

## # A tibble: 336,776 x 7
##   origin dest   dep_time sched_dep_time arr_time sched_arr_time
##   <chr>  <chr>   <int>         <int>      <int>         <int>
## 1 EWR    IAH       517           515        830          819
## 2 LGA    IAH       533           529        850          830
## 3 JFK    MIA       542           540        923          850
## # ... with 3.368e+05 more rows, and 1 more variable:
## #   air_time <dbl>
```

4.6 Create new columns based on old ones: dplyr::mutate()

Click here to show setup code.

```
library(tidyverse)
library(nycflights13)

library(conflicted)
conflict_prefer("filter", "dplyr")

## [conflicted] Removing existing preference
## [conflicted] Will prefer dplyr::filter over any other package
conflict_prefer("lag", "dplyr")

## [conflicted] Will prefer dplyr::lag over any other package
```

With `dplyr::mutate()` you can add new columns to a table, e.g. making use of the already existing variables.

How much faster than the scheduled time did the pilots manage to fly:

```
flights %>%
  mutate(recovery = dep_delay - arr_delay)

## # A tibble: 336,776 x 20
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>         <int>      <dbl>   <int>
## 1 2013     1     1     517           515         2     830
## 2 2013     1     1     533           529         4     850
## 3 2013     1     1     542           540         2     923
## # ... with 3.368e+05 more rows, and 13 more variables:
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
```

4.6. CREATE NEW COLUMNS BASED ON OLD ONES: `DPLYR::MUTATE()` 93

```
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,  
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,  
## #   time_hour <dtm>, recovery <dbl>
```

This is another building block added to the toolset:

```
flights %>%  
  mutate(recovery = dep_delay - arr_delay) %>%  
  select(dep_delay, arr_delay, recovery)  
  
## # A tibble: 336,776 x 3  
##   dep_delay arr_delay recovery  
##   <dbl>     <dbl>     <dbl>  
## 1         2         11        -9  
## 2         4         20       -16  
## 3         2         33       -31  
## # ... with 3.368e+05 more rows
```

Work with the newly created variable just like with the original ones:

```
flights %>%  
  mutate(recovery = dep_delay - arr_delay) %>%  
  select(dep_delay, arr_delay, recovery) %>%  
  arrange(recovery)  
  
## # A tibble: 336,776 x 3  
##   dep_delay arr_delay recovery  
##   <dbl>     <dbl>     <dbl>  
## 1        -2        194       -196  
## 2        -2        179       -181  
## 3        180        345       -165  
## # ... with 3.368e+05 more rows
```

Assign the results to new variables. The old ones remain unchanged.

```
recovery_data <-  
  flights %>%  
    mutate(recovery = dep_delay - arr_delay) %>%  
    select(dep_delay, arr_delay, recovery) %>%  
    arrange(recovery)  
  
recovery_data  
  
## # A tibble: 336,776 x 3  
##   dep_delay arr_delay recovery  
##   <dbl>     <dbl>     <dbl>  
## 1        -2        194       -196  
## 2        -2        179       -181  
## 3        180        345       -165  
## # ... with 3.368e+05 more rows
```

Let's look at a single airplane:

```
flights %>%
  filter(tailnum == "N14228") %>%
  select(year, month, day, dep_time, arr_time) %>%
  view()

## # A tibble: 111 x 5
##   year month   day dep_time arr_time
##   <int> <int> <int>   <int>   <int>
## 1  2013     1     1     517     830
## 2  2013     1     8    1435    1717
## 3  2013     1     9     717     812
## # ... with 108 more rows
```

Adding the departure time of the *next* flight to the current row, respectively, using `mutate()` with `lead()`:

```
flights %>%
  filter(tailnum == "N14228") %>%
  select(year, month, day, dep_time, arr_time) %>%
  mutate(lead_dep_time = lead(dep_time)) %>%
  view()

## # A tibble: 111 x 6
##   year month   day dep_time arr_time lead_dep_time
##   <int> <int> <int>   <int>   <int>         <int>
## 1  2013     1     1     517     830         1435
## 2  2013     1     8    1435    1717          717
## 3  2013     1     9     717     812         1143
## # ... with 108 more rows
```

The opposite effect to `lead()` can be realized using `lag()`:

```
flights %>%
  filter(tailnum == "N14228") %>%
  select(year, month, day, dep_time, arr_time) %>%
  mutate(lag_arr_time = lag(arr_time)) %>%
  view()

## # A tibble: 111 x 6
##   year month   day dep_time arr_time lag_arr_time
##   <int> <int> <int>   <int>   <int>         <int>
## 1  2013     1     1     517     830           NA
## 2  2013     1     8    1435    1717          830
## 3  2013     1     9     717     812         1717
## # ... with 108 more rows
```

There is even a use-case for this in our little example. How long has our airplane been absent from NYC airports between each of its flights out?

4.6. CREATE NEW COLUMNS BASED ON OLD ONES: DPLYR::MUTATE()95

```
flights %>%
  filter(tailnum == "N14228") %>%
  select(year, month, day, dep_time, arr_time) %>%
  mutate(lag_arr_time = lag(arr_time)) %>%
  mutate(ground_time = dep_time - lag_arr_time) %>%
  view()

## # A tibble: 111 x 7
##   year month   day dep_time arr_time lag_arr_time ground_time
##   <int> <int> <int>   <int>   <int>       <int>       <int>
## 1  2013     1     1     517     830          NA          NA
## 2  2013     1     8    1435    1717         830         605
## 3  2013     1     9     717     812        1717        -1000
## # ... with 108 more rows
```

The negative values occur because not everything happens on the same day, implying that our method is still in need of some refinement. Nevertheless, let's continue.

A frequently used workflow is creating a helper variable at some point in the pipeline and then dropping it later on:

```
flights %>%
  filter(tailnum == "N14228") %>%
  select(year, month, day, dep_time, arr_time) %>%
  mutate(lag_arr_time = lag(arr_time)) %>%
  mutate(ground_time = dep_time - lag_arr_time) %>%
  select(-lag_arr_time)

## # A tibble: 111 x 6
##   year month   day dep_time arr_time ground_time
##   <int> <int> <int>   <int>   <int>       <int>
## 1  2013     1     1     517     830          NA
## 2  2013     1     8    1435    1717         605
## 3  2013     1     9     717     812        -1000
## # ... with 108 more rows
```

Let's work some more with the flight data of our special plane.

```
flights %>%
  filter(tailnum == "N14228") %>%
  view()

## # A tibble: 111 x 19
##   year month   day dep_time sched_dep_time dep_delay arr_time
##   <int> <int> <int>   <int>       <int>       <dbl>   <int>
## 1  2013     1     1     517         515           2     830
## 2  2013     1     8    1435        1440          -5    1717
## 3  2013     1     9     717         700          17     812
## # ... with 108 more rows, and 12 more variables:
```

```
## #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
## #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
## #   time_hour <dtm>
```

The total air time of a plane up to and including a given flight can be calculated with `base::cumsum()`:

```
flights %>%
  filter(tailnum == "N14228") %>%
  mutate(cum_air_time = cumsum(air_time)) %>%
  select(air_time, cum_air_time) %>%
  view()

## # A tibble: 111 x 2
##   air_time cum_air_time
##   <dbl>     <dbl>
## 1     227         227
## 2     150         377
## 3      39         416
## # ... with 108 more rows
```

Creating a “flag” variable with `mutate()` which shows if a flight was on time or not:

```
flights %>%
  filter(tailnum == "N14228") %>%
  mutate(delayed = if_else(arr_delay > 0, "delayed", "on time")) %>%
  select(arr_delay, delayed)

## # A tibble: 111 x 2
##   arr_delay delayed
##   <dbl> <chr>
## 1      11 delayed
## 2     -29 on time
## 3      -3 on time
## # ... with 108 more rows
```

A more straightforward way to get the same (or at least a very similar and probably easier to work with) result:

```
flights %>%
  filter(tailnum == "N14228") %>%
  mutate(delayed = arr_delay > 0) %>%
  select(arr_delay, delayed)

## # A tibble: 111 x 2
##   arr_delay delayed
##   <dbl> <lgl>
## 1      11 TRUE
```


4.6. CREATE NEW COLUMNS BASED ON OLD ONES: `DPLYR::MUTATE()` 97

```
## 2      -29 FALSE
## 3       -3 FALSE
## # ... with 108 more rows
```

... easier to work with, because `filter()` can directly take logical arguments:

```
flights %>%
  filter(tailnum == "N14228") %>%
  mutate(delayed = arr_delay > 0) %>%
  select(arr_delay, delayed) %>%
  filter(delayed)

## # A tibble: 39 x 2
##   arr_delay delayed
##   <dbl> <lgl>
## 1      11 TRUE
## 2      39 TRUE
## 3      54 TRUE
## # ... with 36 more rows
```

Negation for inverse filtering:

```
flights %>%
  filter(tailnum == "N14228") %>%
  mutate(delayed = arr_delay > 0) %>%
  select(arr_delay, delayed) %>%
  filter(!delayed)

## # A tibble: 72 x 2
##   arr_delay delayed
##   <dbl> <lgl>
## 1      -29 FALSE
## 2       -3 FALSE
## 3      -20 FALSE
## # ... with 69 more rows
```

These are the flights that had no delay:

```
on_time_flights <-
  flights %>%
  filter(tailnum == "N14228") %>%
  mutate(delayed = arr_delay > 0) %>%
  select(arr_delay, delayed) %>%
  filter(!delayed)
```

4.7 Summarize data (by groups): `dplyr::summarize()`, `dplyr::group_by()` + `dplyr::ungroup()`

Click here to show setup code.

```
library(tidyverse)
library(nycflights13)

library(conflicted)
conflict_prefer("filter", "dplyr")

## [conflicted] Removing existing preference
## [conflicted] Will prefer dplyr::filter over any other package
conflict_prefer("lag", "dplyr")

## [conflicted] Removing existing preference
## [conflicted] Will prefer dplyr::lag over any other package
```

Often we want to draw just conclusions from larger datasets by gaining insight by using statistical (or other) methods for summarizing – and thus drastically reducing – the data: How much time did all planes spend in the air?

```
flights %>%
  select(air_time) %>%
  mutate(total_air_time = sum(air_time, na.rm = TRUE))

## # A tibble: 336,776 x 2
##   air_time total_air_time
##   <dbl>      <dbl>
## 1     227      49326610
## 2     227      49326610
## 3     160      49326610
## # ... with 3.368e+05 more rows
```

The `mutate()` call adds a new variable with the same value across all rows. To reduce the result to a single row, use `summarize()`:

```
flights %>%
  summarize(total_air_time = sum(air_time, na.rm = TRUE))

## # A tibble: 1 x 1
##   total_air_time
##   <dbl>
## 1      49326610
```

Simple counts can be computed with `n()` inside `summarize()`:

```
flights %>%
  summarize(n = n())
```

4.7. SUMMARIZE DATA (BY GROUPS): `DPLYR::SUMMARIZE()`, `DPLYR::GROUP_BY()` + `DPLYR::UNGROUP()` 99

```
## # A tibble: 1 x 1
##       n
##   <int>
## 1 336776
```

A variety of aggregate functions is supported:

```
flights %>%
  summarize(median = median(air_time, na.rm = TRUE))

## # A tibble: 1 x 1
##   median
##   <dbl>
## 1    129
```

It's possible to produce two different summarizations at once:

```
flights %>%
  summarize(
    n = n(),
    mean_air_time = mean(air_time, na.rm = TRUE),
    median_air_time = median(air_time, na.rm = TRUE)
  )

## # A tibble: 1 x 3
##       n mean_air_time median_air_time
##   <int>      <dbl>      <dbl>
## 1 336776      151.        129
```

The `summarize()` verb gains its full power in grouped operations. Surround with `group_by()` and `ungroup()` to compute summaries in groups defined by common values in one or more columns. In the next example, the same summary is computed separately for each origin airport.

```
flights %>%
  group_by(origin) %>%
  summarize(
    n = n(),
    mean_air_time = mean(air_time, na.rm = TRUE),
    median_air_time = median(air_time, na.rm = TRUE)
  ) %>%
  ungroup()

## # A tibble: 3 x 4
##   origin      n mean_air_time median_air_time
##   <chr>  <int>      <dbl>      <dbl>
## 1 EWR    120835      153.        130
## 2 JFK    111279      178.        149
## 3 LGA    104662      118.        115
```

The next example splits the data into one group for each day.

```

flights %>%
  group_by(year, month, day) %>%
  summarize(
    n = n(),
    mean_air_time = mean(air_time, na.rm = TRUE),
    median_air_time = median(air_time, na.rm = TRUE)
  ) %>%
  ungroup()

## # A tibble: 365 x 6
##   year month   day     n mean_air_time median_air_time
##   <int> <int> <int> <int>         <dbl>         <dbl>
## 1  2013     1     1   842          170.           149
## 2  2013     1     2   943          162.           148
## 3  2013     1     3   914          157.           148
## # ... with 362 more rows

```

For quick exploration, the names of the new columns can be omitted:

```

flights %>%
  group_by(year, month, day) %>%
  summarize(
    n(),
    mean(air_time, na.rm = TRUE),
    median(air_time, na.rm = TRUE)
  ) %>%
  ungroup()

## # A tibble: 365 x 6
##   year month   day `n()` `mean(air_time, n~` `median(air_time~`
##   <int> <int> <int> <int>         <dbl>         <dbl>
## 1  2013     1     1   842          170.           149
## 2  2013     1     2   943          162.           148
## 3  2013     1     3   914          157.           148
## # ... with 362 more rows

TRUE

## [1] TRUE

TRUE

## [1] TRUE

```

4.8 Summary-plots

Click here to show setup code.

```
library(tidyverse)
library(nycflights13)

library(conflicted)
conflict_prefer("filter", "dplyr")

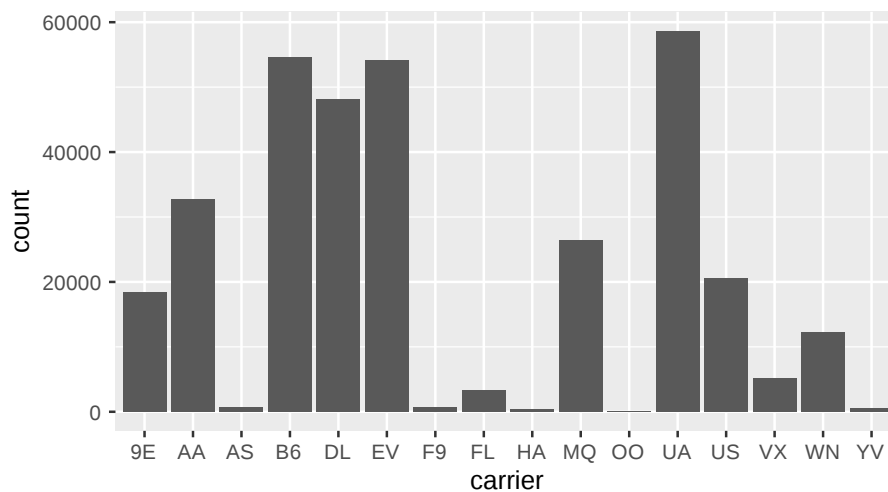
## [conflicted] Removing existing preference
## [conflicted] Will prefer dplyr::filter over any other package

conflict_prefer("lag", "dplyr")

## [conflicted] Removing existing preference
## [conflicted] Will prefer dplyr::lag over any other package
```

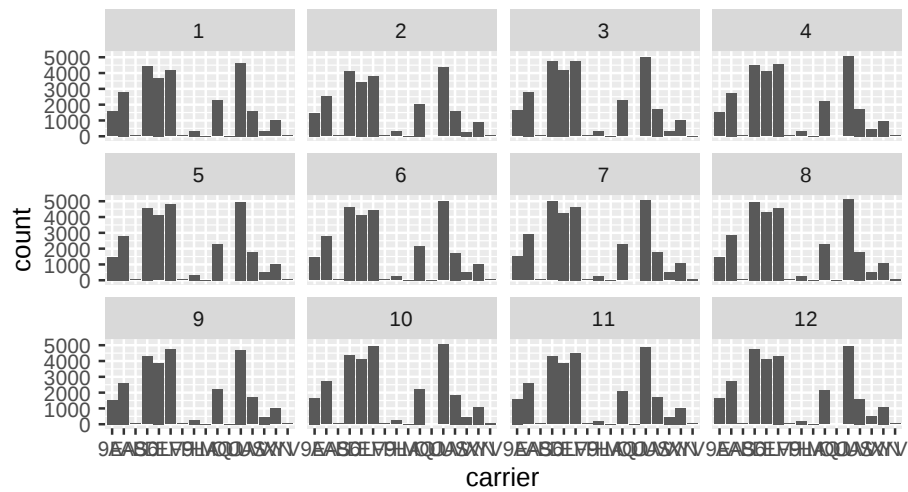
Potentially surprisingly, `mutate()` can also work with the results of a `ggplot()` call. Let's approach this step by step. Here is a basic barplot of `flights$carrier`:

```
flights %>%
  ggplot(aes(x = carrier)) +
  geom_bar()
```



Same with one facet per month:

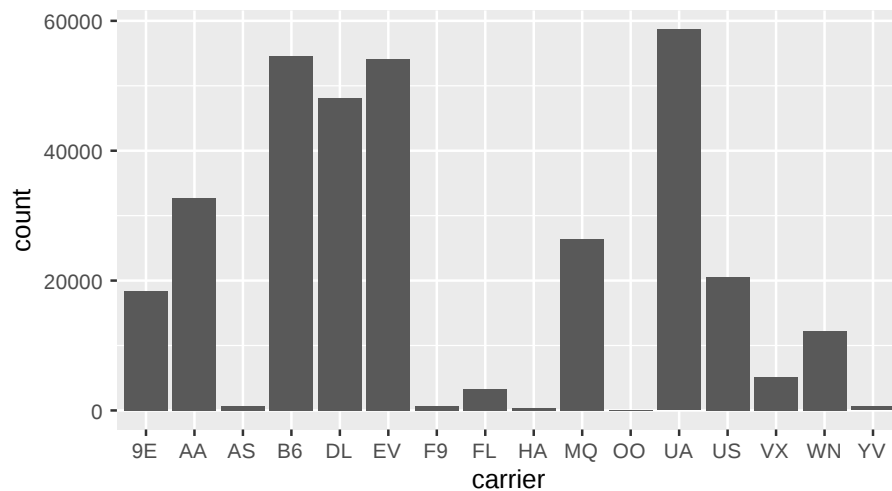
```
flights %>%
  ggplot(aes(x = carrier)) +
  geom_bar() +
  facet_wrap(~month)
```



We can extract a function that takes any data and produces a barplot of the variable `carrier`:

```
plot_fun <- function(data) {
  data %>%
    ggplot(aes(x = carrier)) +
    geom_bar()
}
```

```
plot_fun(flights)
```



The result of `ggplot()` is first and foremost an object. Only when R tries to

display it on the console a method is triggered, which causes it to show the graph in the “Viewer”. Therefore, we can use the `group_by – summarize() – ungroup()` pattern to produce one plot per group and store it in a new column:

```
plot_df <-
  flights %>%
    group_by(month) %>%
    summarize(
      plot = list(plot_fun(tibble(carrier)))
    ) %>%
    ungroup()
```

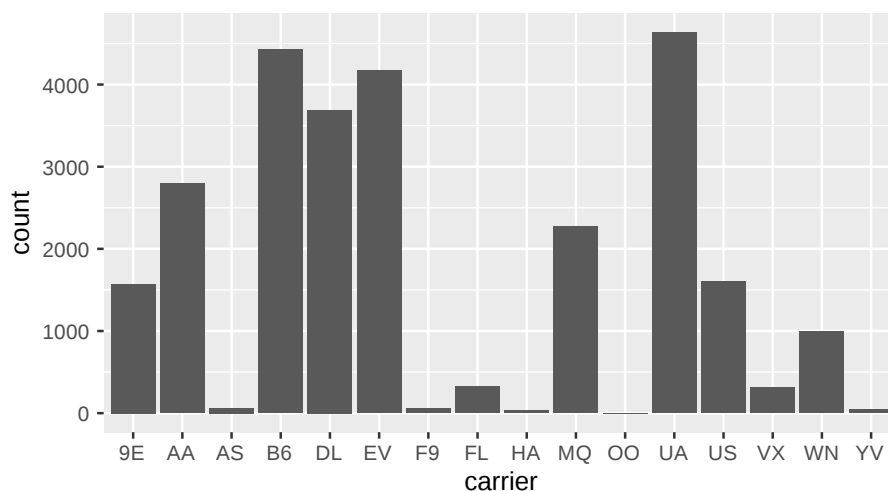
```
plot_df

## # A tibble: 12 x 2
##   month plot
##   <int> <list>
## 1     1 <gg>
## 2     2 <gg>
## 3     3 <gg>
## # ... with 9 more rows
```

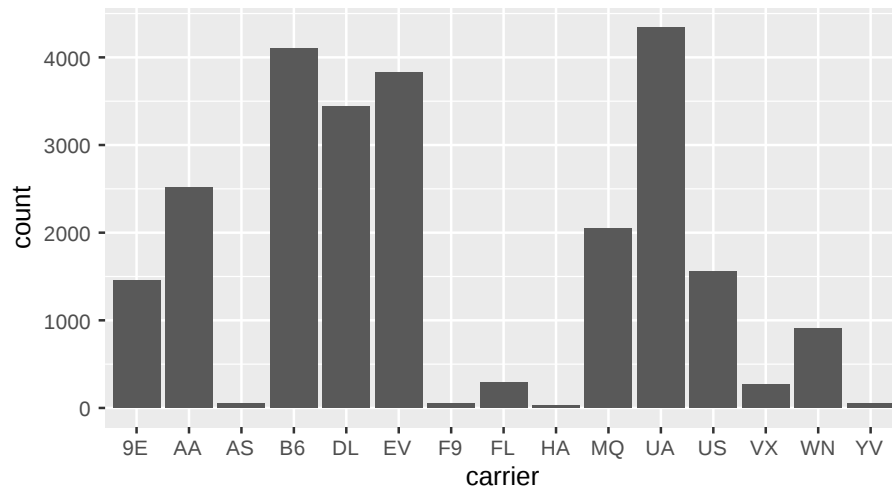
When using `dplyr::pull()` (this function “extracts” a variable from a `data.frame` and returns it as a normal vector), each of the plots will be subsequently displayed in your “Viewer”.

```
plot_df %>%
  pull()

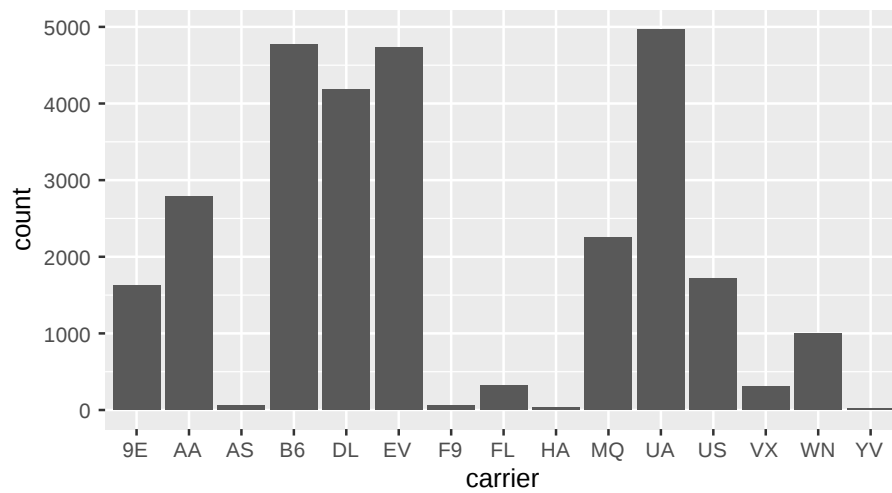
## [[1]]
```



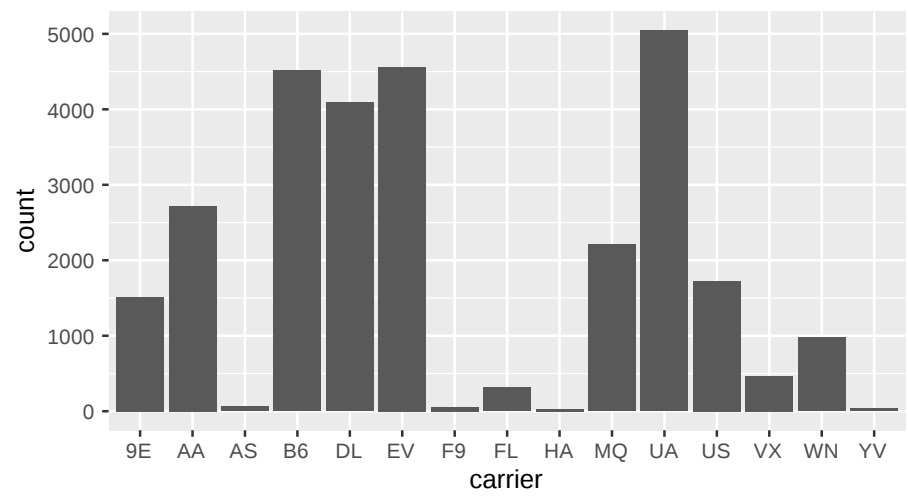
```
##  
## [[2]]
```



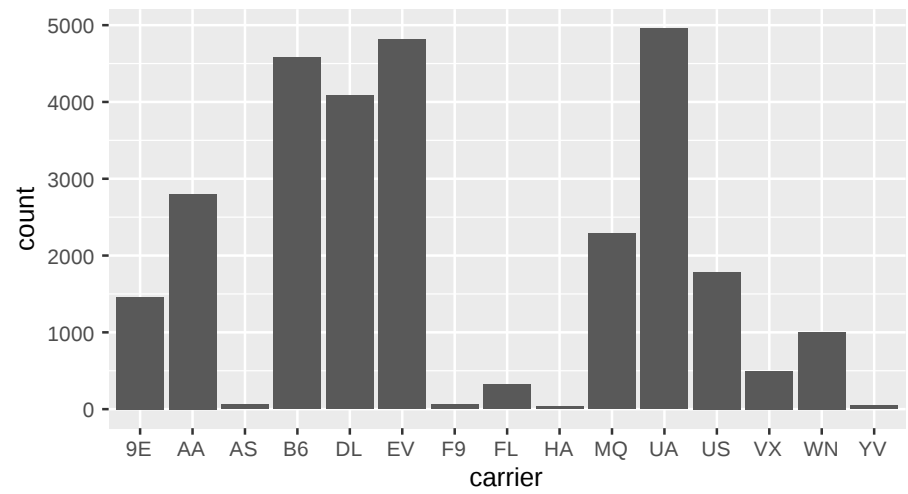
```
##  
## [[3]]
```



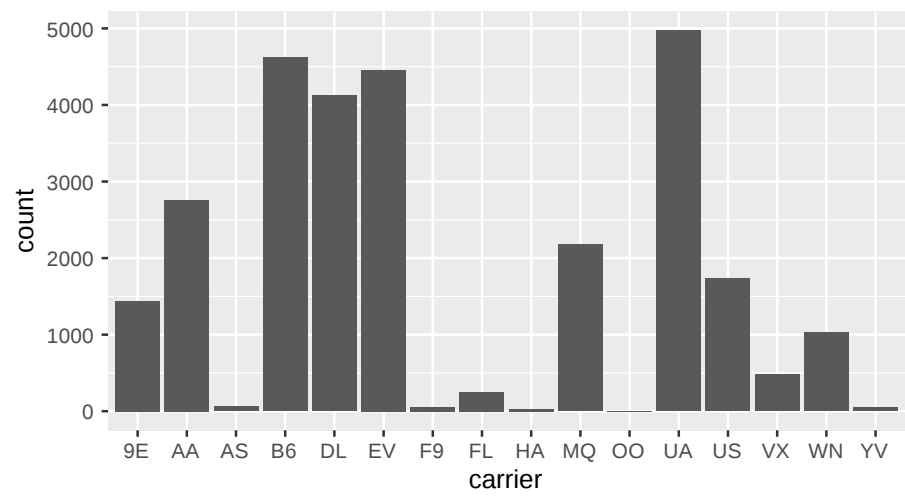
```
##  
## [[4]]
```

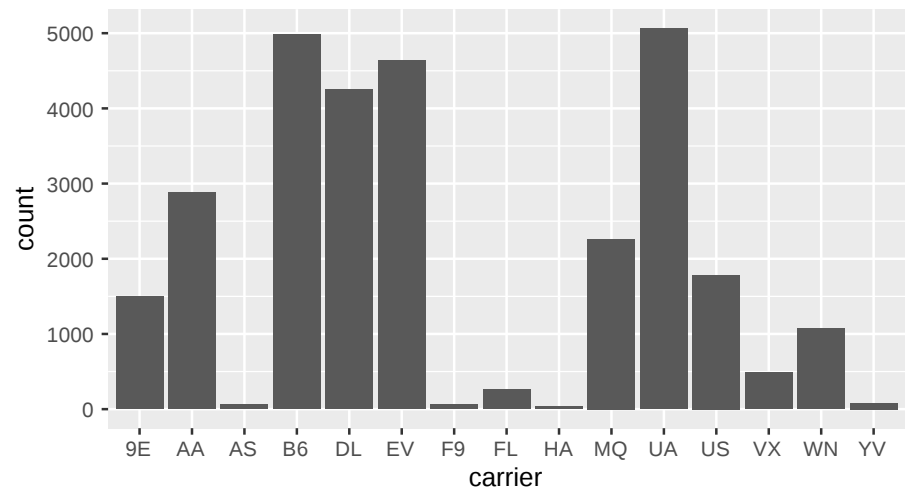
```
##  
## [[5]]
```



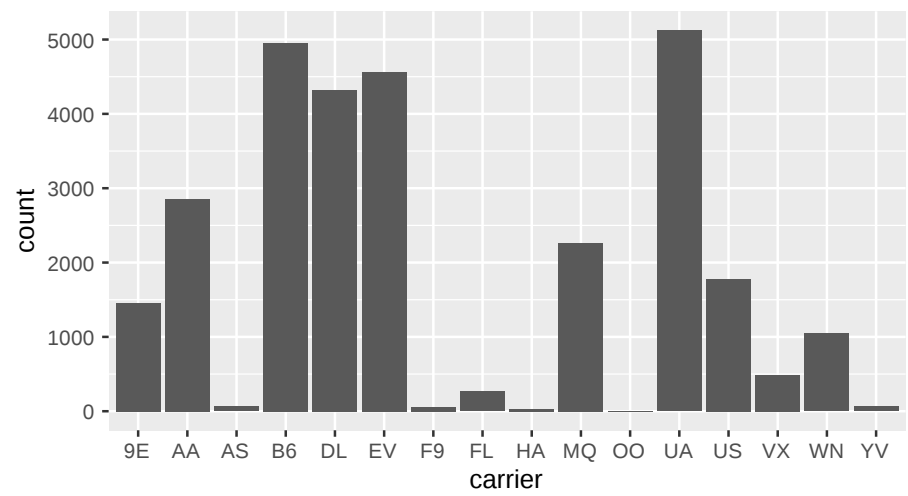
```
##  
## [[6]]
```



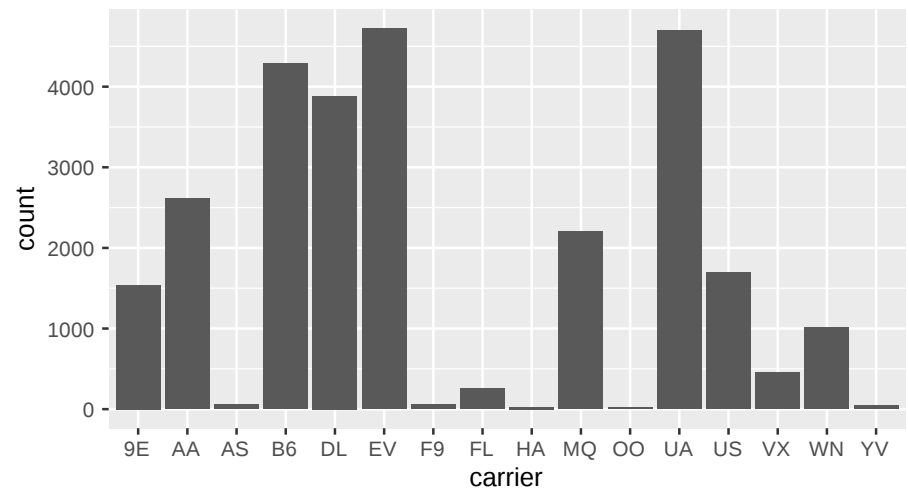
```
##  
## [[7]]
```



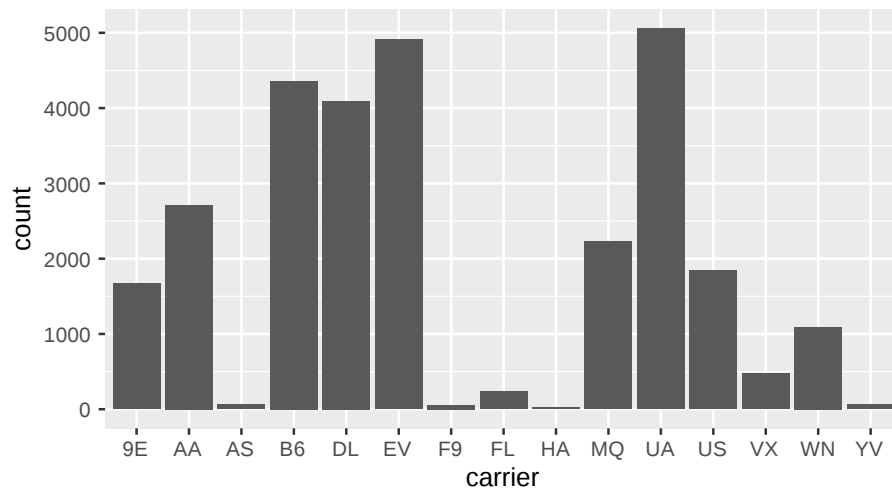
```
##  
## [[8]]
```



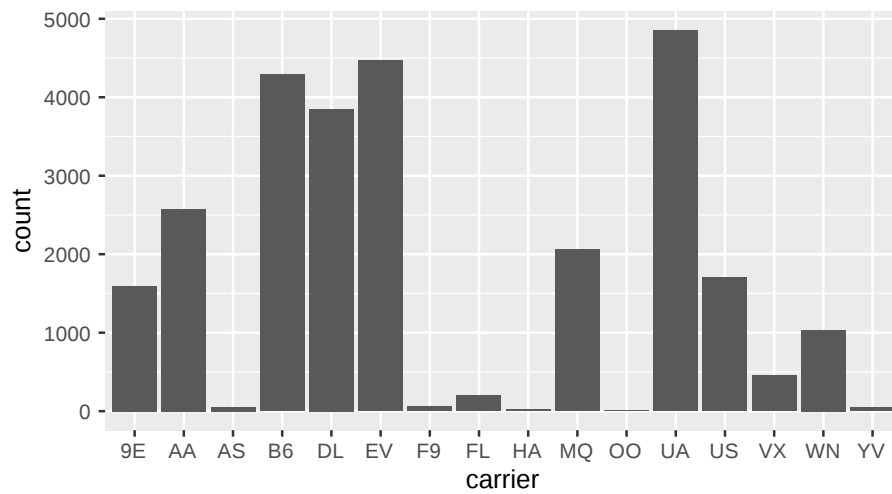
```
##  
## [[9]]
```



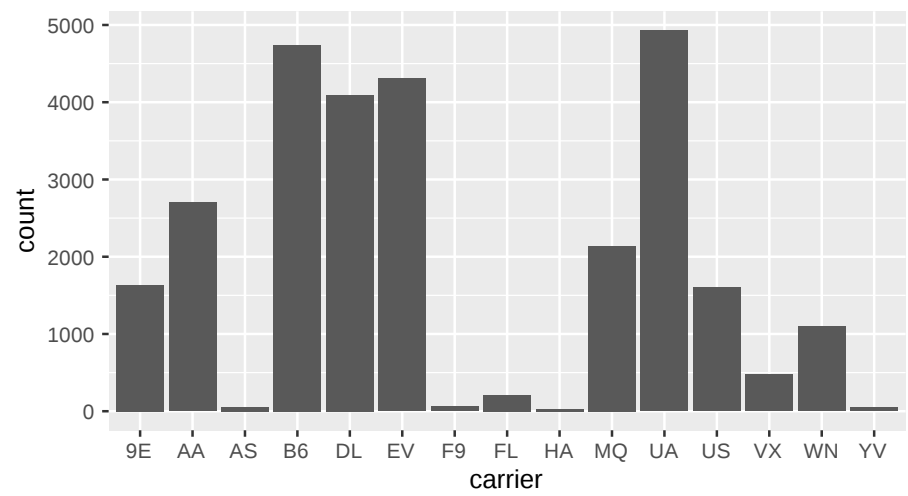
```
##  
## [[10]]
```



```
##  
## [[11]]
```



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



Use the left arrow to click through the different plots.

Chapter 5

Import

Ingesting data.

This chapter discusses data import with RStudio, with the help of the readr, readxl, and rio packages.

5.1

Click here to show setup code.

```
library(tidyverse)
library(nycflights13)

library(conflicted)
conflict_prefer("filter", "dplyr")

## [conflicted] Removing existing preference
## [conflicted] Will prefer dplyr::filter over any other package
conflict_prefer("lag", "dplyr")

## [conflicted] Removing existing preference
## [conflicted] Will prefer dplyr::lag over any other package

library(readr)
example1 <-
  read_delim(
    "data/example1.csv",
    ";",
    escape_double = FALSE, trim_ws = TRUE
  )
```

```
## Parsed with column specification:
## cols(
##   col1 = col_double(),
##   col2 = col_character(),
##   col3 = col_character()
## )

view(example1)

## # A tibble: 2 x 3
##   col1 col2 col3
##   <dbl> <chr> <chr>
## 1     1    a     X
## 2   2.5    b     Y
```

5.2 Import many files

Click here to show setup code.

```
library(tidyverse)
library(nycflights13)

library(here)

library(conflicted)
conflict_prefer("filter", "dplyr")

## [conflicted] Removing existing preference
## [conflicted] Will prefer dplyr::filter over any other package

files <- dir(path = here("data"), pattern = "[.]xlsx$", full.names = TRUE)
files

## [1] "/home/travis/build/krlmlr/vistransrep/book/data/example6a.xlsx"
## [2] "/home/travis/build/krlmlr/vistransrep/book/data/example6b.xlsx"
## [3] "/home/travis/build/krlmlr/vistransrep/book/data/example6c.xlsx"

files %>%
  rio::import_list(setclass = class(tibble()), rbind = TRUE)

## # A tibble: 6 x 5
##       id col1 col2 col3 `_file`
##   <dbl> <dbl> <chr> <chr> <chr>
## 1     1     1    a     X  /home/travis/build/krlmlr/vistransr~
## 2     1   2.5    b     Y  /home/travis/build/krlmlr/vistransr~
## 3     2   1.5    c     Z  /home/travis/build/krlmlr/vistransr~
## 4     2     2    d     W  /home/travis/build/krlmlr/vistransr~
```



```
## 5      3      4      g      J      /home/travis/build/krlmlr/vistransr~
## 6      3     3.5     f      H      /home/travis/build/krlmlr/vistransr~

list_of_tables <- rio::import_list(files, setclass = class(tibble()))
list_of_tables

## $example6a
## # A tibble: 2 x 4
##       id col1 col2 col3
##   <dbl> <dbl> <chr> <chr>
## 1     1     1     a     X
## 2     1     2.5   b     Y
##
## $example6b
## # A tibble: 2 x 4
##       id col1 col2 col3
##   <dbl> <dbl> <chr> <chr>
## 1     2     1.5 c     Z
## 2     2     2     d     W
##
## $example6c
## # A tibble: 2 x 4
##       id col1 col2 col3
##   <dbl> <dbl> <chr> <chr>
## 1     3     4     g     J
## 2     3     3.5   f     H

list_of_tables$example6b

## # A tibble: 2 x 4
##       id col1 col2 col3
##   <dbl> <dbl> <chr> <chr>
## 1     2     1.5 c     Z
## 2     2     2     d     W

try(
  list_of_tables$example6b <-
    list_of_tables$example6b %>%
      mutate(...) %>%
      select(...)
)

## Error in function_list[[i]](value) : '...' used in an incorrect context

all_tables <- bind_rows(list_of_tables, .id = "path")
all_tables

## # A tibble: 6 x 5
##   path       id col1 col2 col3
##   <chr>     <dbl> <dbl> <chr> <chr>
```

```

## 1 example6a      1  1  a    X
## 2 example6a      1  2.5 b    Y
## 3 example6b      2  1.5 c    Z
## 4 example6b      2  2    d    W
## 5 example6c      3  4    g    J
## 6 example6c      3  3.5 f    H

all_tables %>%
  filter(path == "example6b") %>%
  summarize(mean(col1), first(col2))

## # A tibble: 1 x 2
##   `mean(col1)` `first(col2)`
##   <dbl> <chr>
## 1      1.75 c

all_tables %>%
  group_by(path) %>%
  summarize(mean(col1), first(col2)) %>%
  ungroup()

## # A tibble: 3 x 3
##   path      `mean(col1)` `first(col2)`
##   <chr>          <dbl> <chr>
## 1 example6a      1.75 a
## 2 example6b      1.75 c
## 3 example6c      3.75 g

files %>%
  map_dfr(~ readxl::read_excel(.))

## # A tibble: 6 x 4
##   id  col1 col2 col3
##   <dbl> <dbl> <chr> <chr>
## 1    1    1  a    X
## 2    1    2.5 b    Y
## 3    2    1.5 c    Z
## 4    2    2    d    W
## 5    3    4    g    J
## 6    3    3.5 f    H

```

Chapter 6

Tidying

Rows, columns, cells.

This chapter discusses pivoting and data tidying with the help of the `tidyr` package.

6.1 Pivoting

Click here to show setup code.

```
library(tidyverse)
library(nycflights13)

library(conflicted)
conflict_prefer("filter", "dplyr")

## [conflicted] Removing existing preference
## [conflicted] Will prefer dplyr::filter over any other package
conflict_prefer("lag", "dplyr")

## [conflicted] Removing existing preference
## [conflicted] Will prefer dplyr::lag over any other package
```

Pivoting describes operations that help rearrange data in different ways. The following two tables contain the same data arranged differently.

```
table1

## # A tibble: 6 x 4
##   country      year cases population
##   <chr>      <int> <int>      <int>
```

```
## 1 Afghanistan 1999 745 19987071
## 2 Afghanistan 2000 2666 20595360
## 3 Brazil 1999 37737 172006362
## 4 Brazil 2000 80488 174504898
## 5 China 1999 212258 1272915272
## 6 China 2000 213766 1280428583
```

```
table2
```

```
## # A tibble: 12 x 4
##   country      year type      count
##   <chr>      <int> <chr>    <int>
## 1 Afghanistan 1999 cases      745
## 2 Afghanistan 1999 population 19987071
## 3 Afghanistan 2000 cases      2666
## # ... with 9 more rows
```

Both tables contain `country` and `year` column that describe the source of the measurements. The “wider” version, `table1`, contains two columns that hold the number of cases (of a disease) and the population for the corresponding country in the corresponding year. In the “longer” version, `table2`, the number of cases and the population are stored in the same `count` column, with the `type` column defining the measurement.

Somewhat counter-intuitively, “longer-form” data is often better suited for analyzing data. “Wider-form” data makes better use of screen space, but may be more difficult to work with.

The following example computes the maximum number of cases and population for each country. For the wider form, this requires repeating the same expression for all columns. This may work with two columns but becomes tedious once more measurements are added.

```
table1 %>%
  group_by(country) %>%
  summarize(
    max_cases = max(cases),
    max_population = max(population)
  ) %>%
  ungroup()

## # A tibble: 3 x 3
##   country      max_cases max_population
##   <chr>      <int>      <int>
## 1 Afghanistan    2666      20595360
## 2 Brazil        80488      174504898
## 3 China        213766      1280428583
```

The `_at` family of functions helps iterating over columns, but all columns still need to be enumerated. (Specifying ranges of columns is rather brittle.)

```
table1 %>%
  group_by(country) %>%
  summarize_at(
    vars(cases, population),
    max
  ) %>%
  ungroup()

## # A tibble: 3 x 3
##   country      cases population
##   <chr>      <int>      <int>
## 1 Afghanistan    2666    20595360
## 2 Brazil          80488   174504898
## 3 China          213766  1280428583
```

If the data is in the “longer” form, it is sufficient to include `type` in the grouping variables. The same code works for arbitrary number of measurements.

```
table2 %>%
  group_by(country, type) %>%
  summarize(
    max = max(count)
  ) %>%
  ungroup()

## # A tibble: 6 x 3
##   country      type      max
##   <chr>      <chr>      <int>
## 1 Afghanistan cases         2666
## 2 Afghanistan population 20595360
## 3 Brazil      cases         80488
## 4 Brazil      population 174504898
## 5 China        cases         213766
## 6 China        population 1280428583
```

The following examples give a gentle introduction into pivoting.

6.1.1 Convert to longer form

The `pivot_longer()` function takes a “wider-form” dataset and converts it to an equivalent dataset with more rows.

```
table1

## # A tibble: 6 x 4
##   country      year cases population
##   <chr>      <int> <int>      <int>
## 1 Afghanistan 1999    745   19987071
```

```
## 2 Afghanistan 2000 2666 20595360
## 3 Brazil      1999 37737 172006362
## 4 Brazil      2000 80488 174504898
## 5 China       1999 212258 1272915272
## 6 China       2000 213766 1280428583

table1 %>%
  pivot_longer(-c(country, year))

## # A tibble: 12 x 4
##   country      year name      value
##   <chr>      <int> <chr>    <int>
## 1 Afghanistan 1999 cases      745
## 2 Afghanistan 1999 population 19987071
## 3 Afghanistan 2000 cases      2666
## # ... with 9 more rows
```

The `-c(...)` notation indicates that all column except `country` and `year` are to be transformed into longer form. The column names become the contents of the new `name` column, the values are available in the `value` column.

The result of this operation isn't strictly equivalent to `table2`, we need to rename and sort differently. Alternatively, the `names_to` and `values_to` arguments allow specifying the names of the new columns.

```
table1 %>%
  pivot_longer(-c(country, year)) %>%
  rename(type = name, count = value) %>%
  arrange(country, year, type)

## # A tibble: 12 x 4
##   country      year type      count
##   <chr>      <int> <chr>    <int>
## 1 Afghanistan 1999 cases      745
## 2 Afghanistan 1999 population 19987071
## 3 Afghanistan 2000 cases      2666
## # ... with 9 more rows

table1 %>%
  pivot_longer(
    -c(country, year),
    names_to = "type",
    values_to = "count"
  ) %>%
  arrange(country, year, type)

## # A tibble: 12 x 4
##   country      year type      count
##   <chr>      <int> <chr>    <int>
## 1 Afghanistan 1999 cases      745
```

```
## 2 Afghanistan 1999 population 19987071
## 3 Afghanistan 2000 cases          2666
## # ... with 9 more rows
```

6.1.2 Convert to wider form

The `pivot_wider()` form does the inverse: it creates a dataset with fewer rows. If the `name` and `value` columns are named differently, these columns can be provided via the `names_from` and `values_from` arguments.

```
table2
```

```
## # A tibble: 12 x 4
##   country      year type      count
##   <chr>      <int> <chr>    <int>
## 1 Afghanistan 1999 cases      745
## 2 Afghanistan 1999 population 19987071
## 3 Afghanistan 2000 cases      2666
## # ... with 9 more rows
```

```
table2 %>%
```

```
  pivot_wider(names_from = type, values_from = count)
```

```
## # A tibble: 6 x 4
##   country      year cases population
##   <chr>      <int> <int>    <int>
## 1 Afghanistan 1999     745  19987071
## 2 Afghanistan 2000    2666  20595360
## 3 Brazil      1999   37737  172006362
## 4 Brazil      2000   80488  174504898
## 5 China       1999  212258  1272915272
## 6 China       2000  213766  1280428583
```

```
table2 %>%
```

```
  rename(name = type, value = count) %>%
  pivot_wider()
```

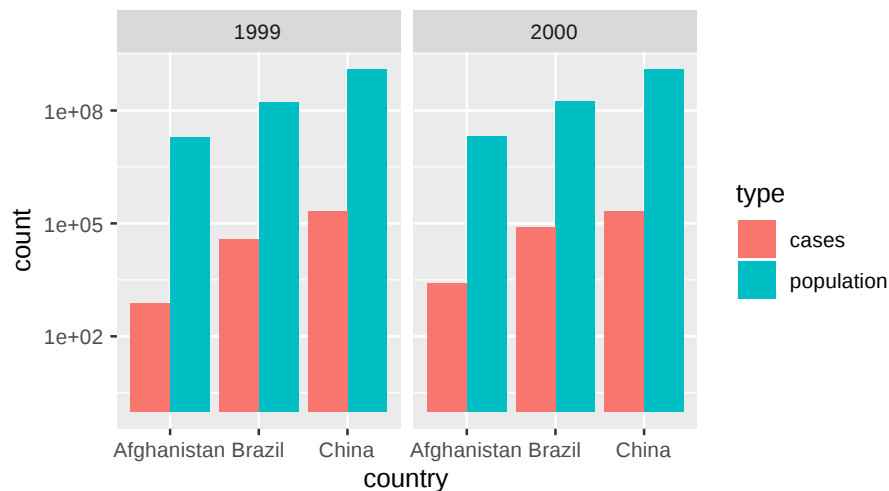
```
## # A tibble: 6 x 4
##   country      year cases population
##   <chr>      <int> <int>    <int>
## 1 Afghanistan 1999     745  19987071
## 2 Afghanistan 2000    2666  20595360
## 3 Brazil      1999   37737  172006362
## 4 Brazil      2000   80488  174504898
## 5 China       1999  212258  1272915272
## 6 China       2000  213766  1280428583
```

6.1.3 Use cases

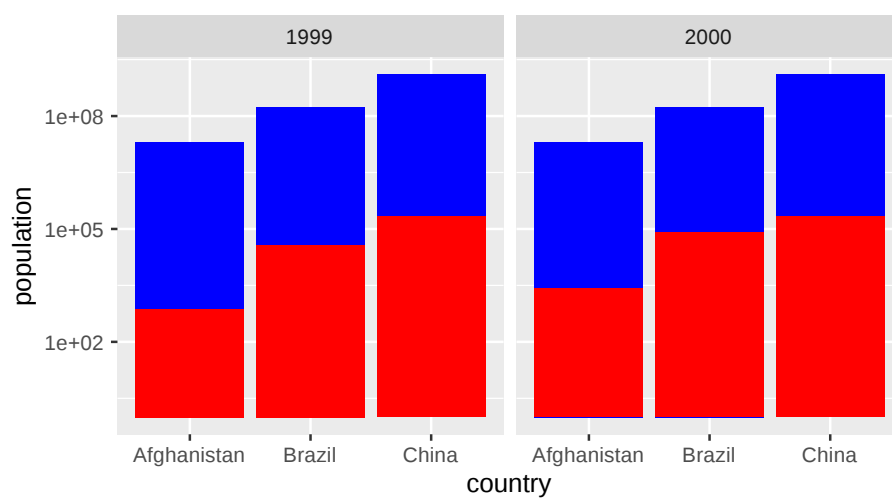
Data in “longer” form usually works better for plotting the values side by side, e.g. by assigning the type of value to an aesthetic. Recall that each row in the data produces one geometric object in the corresponding layer. For a bar chart that shows cases and population side by side, mapped to the y aesthetic, the “longer” form is more natural.

- **table2** form requires only one layer, the fill color is determined automatically, the legend is created automatically
- **table1** requires two layers, manual assignment of fill color, and manual creation of legend (not shown)

```
table2 %>%
  ggplot() +
  geom_col(aes(country, count, fill = type), position = "dodge") +
  facet_wrap(~year) +
  scale_y_log10()
```



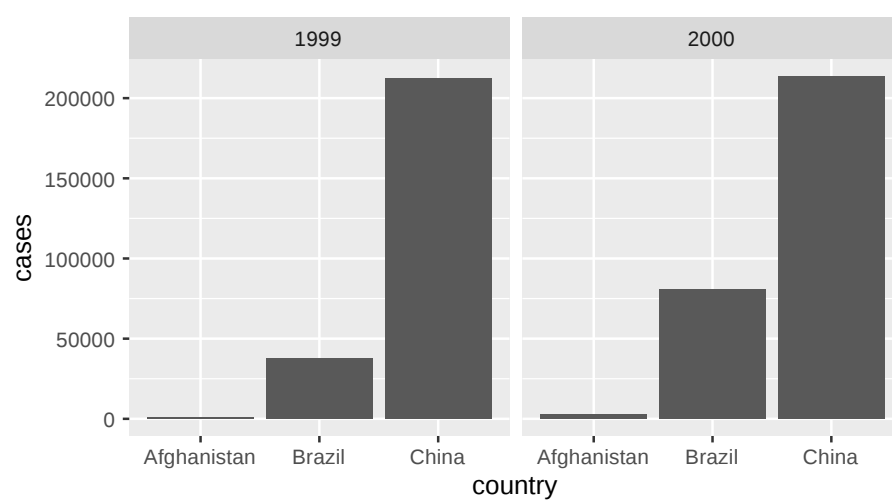
```
table1 %>%
  ggplot() +
  geom_col(aes(country, population), position = "dodge", fill = "blue") +
  geom_col(aes(country, cases), position = "dodge", fill = "red") +
  facet_wrap(~year) +
  scale_y_log10()
```

On the other hand, if only a single measurement needs to be plotted, the “wider” form is easier to work with.

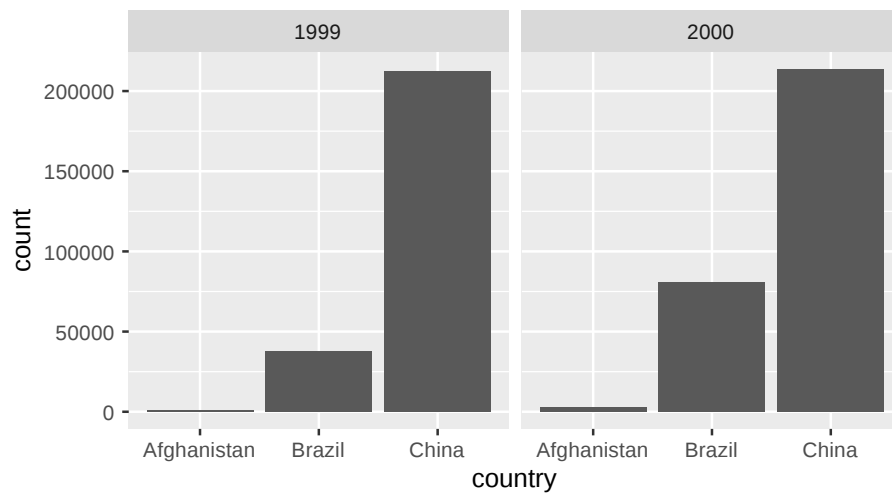
- `table1` only requires selecting the correct column
- `table2` requires a `filter()`

```
table1 %>%
  ggplot() +
  geom_col(aes(country, cases)) +
  facet_wrap(~year)
```



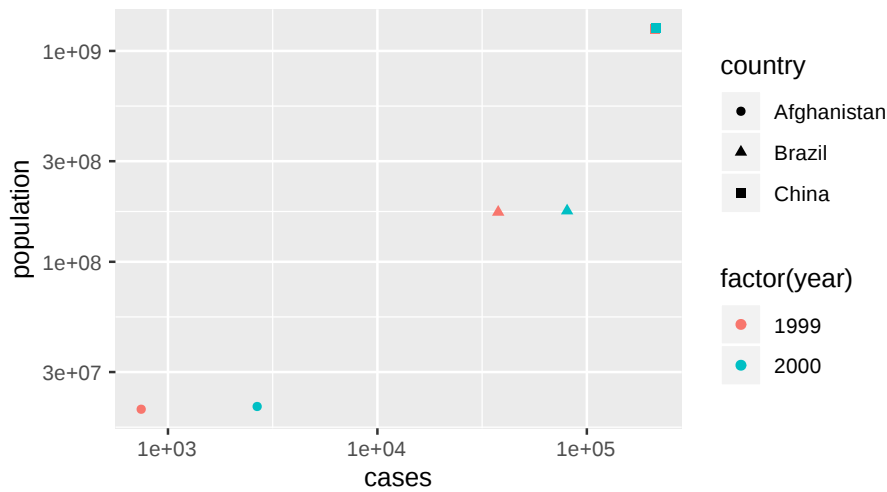
```
table2 %>%
  filter(type == "cases") %>%
```

```
ggplot() +
  geom_col(aes(country, count)) +
  facet_wrap(~year)
```



The “wider” form is also the only way to map different measures to different aesthetics, e.g. to correlate values.

```
table1 %>%
  ggplot() +
  geom_point(aes(cases, population, color = factor(year), shape = country)) +
  scale_x_log10() +
  scale_y_log10()
```



6.1.4 Combining vertically

A different view on the same data is given in the two tables `table4a` and `table4b`.

`table4a`

```
## # A tibble: 3 x 3
##   country   `1999` `2000`
## * <chr>     <int> <int>
## 1 Afghanistan    745   2666
## 2 Brazil        37737  80488
## 3 China         212258 213766
```

`table4b`

```
## # A tibble: 3 x 3
##   country   `1999` `2000`
## * <chr>     <int> <int>
## 1 Afghanistan 19987071 20595360
## 2 Brazil      172006362 174504898
## 3 China       1272915272 1280428583
```

The `bind_rows()` function combines these two parts into a single table. The `.id = "type"` setting ensures that the input datasets gain different tags in the new `type` column.

```
table4 <-
  bind_rows(
    cases = table4a,
```

```

      population = table4b,
      .id = "type"
    )
table4
## # A tibble: 6 x 4
##   type      country    `1999`    `2000`
##   <chr>    <chr>      <int>    <int>
## 1 cases   Afghanistan    745      2666
## 2 cases   Brazil        37737    80488
## 3 cases   China         212258   213766
## 4 population Afghanistan 19987071 20595360
## 5 population Brazil    172006362 174504898
## 6 population China    1272915272 1280428583

```

As before, `pivot_longer()` helps converting the results into something similar to `table2`. The result isn't quite the same yet, can you spot the difference?

```

table4 %>%
  pivot_longer(c(`1999`, `2000`))
## # A tibble: 12 x 4
##   type      country    name  value
##   <chr>    <chr>      <chr> <int>
## 1 cases   Afghanistan 1999    745
## 2 cases   Afghanistan 2000   2666
## 3 cases   Brazil      1999   37737
## # ... with 9 more rows

```

6.1.5 Tidy data

From “R for data science”:

In a tidy dataset,

1. each variable must have its own column.
2. each observation must have its own row.
3. each value must have its own cell.

The following example shows a case that violates the first two rules: WHO data arranged for optimal use of screen space. The column names define, in addition to the measurement type `new_sp`, `new_sn`, `new_ep` and `newrel`, the age and sex stratum of the corresponding measurements. One single `pivot_longer()` call transforms the data into a longer-form version with four measurement columns and one row for each age/sex stratum. The `names_pattern` is a regular expression that defines what part of the column name is stored where. (Regular expressions are a powerful tool for parsing text data, out of scope for this lecture but very much worth looking into.) The `names_to` sequence defines, for each ()

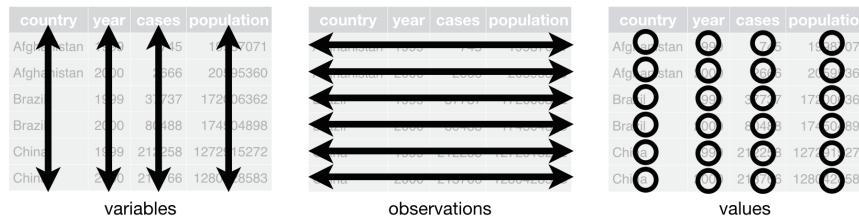


Figure 6.1: Tidy data

group in `names_pattern`, if the data encoded in the column name is stored in a new column or if it is kept as column name.

```
who %>%
  view()

## # A tibble: 7,240 x 60
##   country iso2 iso3 year new_sp_m014 new_sp_m1524
##   <chr> <chr> <chr> <int> <int> <int>
## 1 Afghan~ AF AFG 1980 NA NA
## 2 Afghan~ AF AFG 1981 NA NA
## 3 Afghan~ AF AFG 1982 NA NA
## # ... with 7,237 more rows, and 54 more variables:
## #   new_sp_m2534 <int>, new_sp_m3544 <int>,
## #   new_sp_m4554 <int>, new_sp_m5564 <int>, new_sp_m65 <int>,
## #   new_sp_f014 <int>, new_sp_f1524 <int>,
## #   new_sp_f2534 <int>, new_sp_f3544 <int>,
## #   new_sp_f4554 <int>, new_sp_f5564 <int>, new_sp_f65 <int>,
## #   new_sn_m014 <int>, new_sn_m1524 <int>,
## #   new_sn_m2534 <int>, new_sn_m3544 <int>,
## #   new_sn_m4554 <int>, new_sn_m5564 <int>, new_sn_m65 <int>,
## #   new_sn_f014 <int>, new_sn_f1524 <int>,
## #   new_sn_f2534 <int>, new_sn_f3544 <int>,
## #   new_sn_f4554 <int>, new_sn_f5564 <int>, new_sn_f65 <int>,
## #   new_ep_m014 <int>, new_ep_m1524 <int>,
## #   new_ep_m2534 <int>, new_ep_m3544 <int>,
## #   new_ep_m4554 <int>, new_ep_m5564 <int>, new_ep_m65 <int>,
## #   new_ep_f014 <int>, new_ep_f1524 <int>,
## #   new_ep_f2534 <int>, new_ep_f3544 <int>,
## #   new_ep_f4554 <int>, new_ep_f5564 <int>, new_ep_f65 <int>,
## #   newrel_m014 <int>, newrel_m1524 <int>,
## #   newrel_m2534 <int>, newrel_m3544 <int>,
## #   newrel_m4554 <int>, newrel_m5564 <int>, newrel_m65 <int>,
## #   newrel_f014 <int>, newrel_f1524 <int>,
```

```
## #   newrel_f2534 <int>, newrel_f3544 <int>,
## #   newrel_f4554 <int>, newrel_f5564 <int>, newrel_f65 <int>

who_longer <-
  who %>%
    pivot_longer(
      -(country:year),
      names_pattern = "([a-z_]+)_\\.([0-9]+)",
      names_to = c(".value", "sex", "age")
    )

who_longer

## # A tibble: 101,360 x 10
##   country iso2 iso3   year sex   age   new_sp new_sn new_ep
##   <chr>   <chr> <chr> <int> <chr> <chr>   <int>   <int>   <int>
## 1 Afghan~ AF   AFG   1980 m     014     NA     NA     NA
## 2 Afghan~ AF   AFG   1980 m    1524     NA     NA     NA
## 3 Afghan~ AF   AFG   1980 m    2534     NA     NA     NA
## # ... with 1.014e+05 more rows, and 1 more variable:
## #   newrel <int>

who_longer %>%
  count(sex, age)

## # A tibble: 14 x 3
##   sex   age     n
##   <chr> <chr> <int>
## 1 f     014   7240
## 2 f    1524  7240
## 3 f    2534  7240
## # ... with 11 more rows
```

6.2 Separating and uniting

Click here to show setup code.

```
library(tidyverse)
library(nycflights13)

library(conflicted)
conflict_prefer("filter", "dplyr")

## [conflicted] Removing existing preference
## [conflicted] Will prefer dplyr::filter over any other package
conflict_prefer("lag", "dplyr")
```

```
## [conflicted] Removing existing preference
```

```
## [conflicted] Will prefer dplyr::lag over any other package
```

The `table3` table violates the third principle of tidy data: each cell contains two values.

```
table3
```

```
## # A tibble: 6 x 3
##   country    year rate
## * <chr>      <int> <chr>
## 1 Afghanistan 1999 745/19987071
## 2 Afghanistan 2000 2666/20595360
## 3 Brazil      1999 37737/172006362
## 4 Brazil      2000 80488/174504898
## 5 China       1999 212258/1272915272
## 6 China       2000 213766/1280428583
```

The `separate()` verb offers a convenient way to deal with this situation, including automatic type conversion.

```
table3 %>%
  separate(rate, into = c("cases", "population"))

## # A tibble: 6 x 4
##   country    year cases population
##   <chr>      <int> <chr>    <chr>
## 1 Afghanistan 1999 745      19987071
## 2 Afghanistan 2000 2666     20595360
## 3 Brazil      1999 37737    172006362
## 4 Brazil      2000 80488    174504898
## 5 China       1999 212258   1272915272
## 6 China       2000 213766   1280428583

table3 %>%
  separate(rate, into = c("cases", "population"), sep = "/", convert = TRUE)

## # A tibble: 6 x 4
##   country    year cases population
##   <chr>      <int> <int>      <int>
## 1 Afghanistan 1999     745    19987071
## 2 Afghanistan 2000    2666    20595360
## 3 Brazil      1999   37737   172006362
## 4 Brazil      2000   80488   174504898
## 5 China       1999  212258  1272915272
## 6 China       2000  213766  1280428583
```

The inverse is offered by `unite()`. The data in `table5` stores year data in two columns.

```
table5
```

```
## # A tibble: 6 x 4
##   country    century year  rate
##   <chr>      <chr>  <chr> <chr>
## 1 Afghanistan 19      99    745/19987071
## 2 Afghanistan 20      00    2666/20595360
## 3 Brazil      19      99    37737/172006362
## 4 Brazil      20      00    80488/174504898
## 5 China       19      99    212258/1272915272
## 6 China       20      00    213766/1280428583
```

```
table5 %>%
  unite("year", c(century, year))
```

```
## # A tibble: 6 x 3
##   country    year  rate
##   <chr>      <chr> <chr>
## 1 Afghanistan 19_99 745/19987071
## 2 Afghanistan 20_00 2666/20595360
## 3 Brazil      19_99 37737/172006362
## 4 Brazil      20_00 80488/174504898
## 5 China       19_99 212258/1272915272
## 6 China       20_00 213766/1280428583
```

The result needs a few tweaks to finally resemble `table3`.

```
table5 %>%
  unite("year", c(century, year), sep = "")
```

```
## # A tibble: 6 x 3
##   country    year  rate
##   <chr>      <chr> <chr>
## 1 Afghanistan 1999 745/19987071
## 2 Afghanistan 2000 2666/20595360
## 3 Brazil      1999 37737/172006362
## 4 Brazil      2000 80488/174504898
## 5 China       1999 212258/1272915272
## 6 China       2000 213766/1280428583
```

```
table5 %>%
  unite("year", c(century, year), sep = "") %>%
  mutate(year = as.numeric(year))
```

```
## # A tibble: 6 x 3
##   country    year rate
##   <chr>      <dbl> <chr>
## 1 Afghanistan 1999 745/19987071
## 2 Afghanistan 2000 2666/20595360
## 3 Brazil      1999 37737/172006362
```



```
## 4 Brazil      2000 80488/174504898
## 5 China       1999 212258/1272915272
## 6 China       2000 213766/1280428583
```

See the help for further details.

```
?separate
?unite
```

6.2.1 Parsing numbers

```
thousand_separator <-
  tribble(
    ~num,
    "1'000.00",
    "2'000'000.00"
  )

thousand_separator

## # A tibble: 2 x 1
##   num
##   <chr>
## 1 1'000.00
## 2 2'000'000.00

thousand_separator %>%
  separate(num, into = c("num"))

## Warning: Expected 1 pieces. Additional pieces discarded in 2
## rows [1, 2].

## # A tibble: 2 x 1
##   num
##   <chr>
## 1 1
## 2 2

thousand_separator %>%
  mutate(num = str_replace_all(num, "[^-0-9.]", "")) %>%
  mutate(num = as.numeric(num))

## # A tibble: 2 x 1
##   num
##   <dbl>
## 1 1000
## 2 2000000
```

6.3

Click here to show setup code.

```
library(tidyverse)
library(nycflights13)

library(conflicted)
conflict_prefer("filter", "dplyr")

## [conflicted] Removing existing preference
## [conflicted] Will prefer dplyr::filter over any other package
conflict_prefer("lag", "dplyr")

## [conflicted] Removing existing preference
## [conflicted] Will prefer dplyr::lag over any other package

table2 %>%
  xtabs(count ~ ., .) %>%
  ftable()

##           type      cases population
## country   year
## Afghanistan 1999         745   19987071
##              2000        2666   20595360
## Brazil      1999       37737  172006362
##              2000       80488  174504898
## China       1999      212258 1272915272
##              2000      213766 1280428583

table2 %>%
  xtabs(count ~ ., .) %>%
  ftable(col.vars = c("year", "type"))

##           year      1999      2000
##           type  cases population cases population
## country
## Afghanistan      745   19987071      2666   20595360
## Brazil          37737  172006362      80488  174504898
## China          212258 1272915272     213766 1280428583

?`tidyr-package`

NA

## [1] NA
```

Part III

Reporting

Part IV

Appendix

Chapter 7

Best practices

R code is often organized in packages that can be installed from centralized repositories such as CRAN or GitHub. If you are new to writing R packages, this course cannot give a complete introduction into packages. It is still useful to embrace some very few concepts of R packages to gain access to a vast toolbox and also organize your code in a standardized way familiar to other users. With the first steps in place, the road to your first R package may become less steep.

- Create a `DESCRIPTION` file to declare dependencies and allow easy reloading of the functions you define
- Store your functions in `.R` files in the `R/` directory in your project
 - Scripts that you execute live in `script/` or a similar directory
- Use `roxygen2` to document your functions close to the source
- Write tests for your functions, e.g. with `testthat`

See R packages for a more comprehensive treatment.

7.1 DESCRIPTION

Create and open a new RStudio project. Then, create a `DESCRIPTION` file with `usethis::use_description()`:

```
# install.packages("usethis")
usethis::use_description()
```

Double-check success:

```
# install.packages("devtools")
devtools::load_all()
```

Declare that your project requires the tidyverse and the here package:

```
usethis::use_package("here")  
# Currently doesn't work, add manually  
# https://github.com/r-lib/usethis/issues/760  
# usethis::use_package("tidyverse")
```

7.2 R

With a DESCRIPTION file defined, create a new .R file and save it in the R/ directory. (Create this directory if it does not exist.) Create a function in this file, save the file:

```
hi <- function(text = "Hello, world!") {  
  print(text)  
  invisible(text)  
}
```

Do not source the file.

Restart R (with Ctrl + Shift + F10 in RStudio).

Run `devtools::load_all()` again, you can use the shortcut Ctrl + Shift + L or Cmd + Shift + L in RStudio.

Check that you can run `hi()` in the console:

```
hi()  
## [1] "Hello, world!"  
  
hi("Wow!")  
## [1] "Wow!"
```

Edit the function:

```
hi <- function(text = "Wow!") {  
  print(text)  
  invisible(text)  
}
```

Save the file, but do not source it.

Run `devtools::load_all()` again, you can use the shortcut Ctrl + Shift + L or Cmd + Shift + L in RStudio.

Check that the new implementation of `hi()` is active:

```
hi()  
## [1] "Wow!"
```


All functions that are required for your project are stored in this directory. Do not store executable scripts, use a `script/` directory.

7.3 roxygen2

The following intuitive annotation syntax is a standard way to create documentation for your functions:

```
#' Print a welcome message
#'
#' This function prints "Wow!", or a custom text, on the console.
#'
#' @param text The text to print, "Wow!" by default.
#'
#' @return The `text` argument, invisibly.
#'
#' @examples
#' hi()
#' hi("Hello!")
hi <- function(text = "Wow!") {
  print(text)
  invisible(text)
}
```

This annotation can be rendered to a nicely looking HTML page with the roxygen2 and pkgdown packages. All you need to do is provide (and maintain) it.

7.4 testthat

Automated tests make sure that the functions you write today continue working tomorrow. Create your first test with `usethis::use_test()`:

```
# install.packages("testthat")
usethis::use_test("hi")
```

The file `tests/testthat/test-hi.R` is created, with the following contents:

```
test_that("multiplication works", {
  expect_equal(2 * 2, 4)
})
```

Replace this predefined text with a test that makes more sense for us:

```
test_that("hi() works", {
  expect_output(hi(), "Wow")
})
```

```
    expect_output(hi("Hello"), "Hello")
  })
```

Run the new test with `devtools::test()`, you can use the shortcut Ctrl + Shift + T or Cmd + Shift + T in RStudio.

Check that the test actually detects failures by modifying the implementation of `hi()` and rerunning the test:

```
hi <- function(text = "Oops!") {
  print(text)
  invisible(text)
}
```

Run the new test with `devtools::test()`, you can use the shortcut Ctrl + Shift + T or Cmd + Shift + T in RStudio. One test should be failing now.

Chapter 8

- R for data science: <https://r4ds.had.co.nz/>
- Row oriented workflows: <https://github.com/jennybc/row-oriented-workflows#readme>
- Advanced R: <http://adv-r.had.co.nz/>
- Tidy evaluation: <https://tidyeval.tidyverse.org/>
- R packages: <http://r-pkgs.had.co.nz/>
- roxygen2: Vignettes in <https://cran.r-project.org/package=roxygen2>, especially:
 - Introduction to roxygen2
 - Generating Rd files for an overview of available tags
 - Write R documentation in Markdown
- How R searches and finds stuff: <http://blog.obeautifulcode.com/R/How-R-Searches-And-Finds-Stuff/>
- What they forgot to teach you: <https://whattheyforgot.org/>
- Parallel processing with a purrr-like interface: <https://davisvaughan.github.io/furrr/>
- Tidyverse principles: <https://principles.tidyverse.org/>
- Recursive lists to use in teaching and examples: <https://github.com/jennybc/repurrrsive>