Visualizing data

PSY9219M & PSY9251M

9/11/2021

Data frames and tibbles

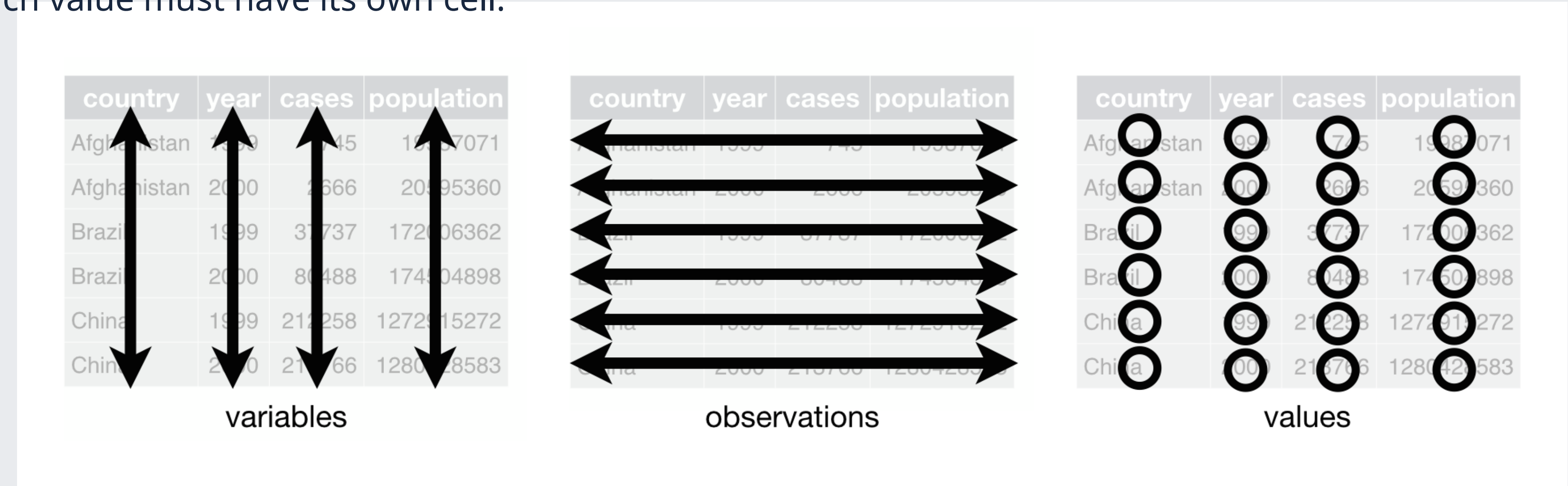
```
## # A tibble: 16 x 4
## # Groups:   Participant [8]
##    Participant Viewpoint  B1RT  B2RT
##          <int> <chr>     <dbl> <dbl>
##  1           1 Different  468.  407.
##  2           1 Same       471.  351.
##  3           2 Different  430.  393.
##  4           2 Same       514.  465.
##  5           3 Different  485.  444.
##  6           3 Same       484.  447.
##  7           4 Different  543.  360.
##  8           4 Same       535.  430.
##  9           5 Different  490.  444.
## 10           5 Same       444.  467.
## 11           6 Different  488.  392.
## 12           6 Same       517.  368.
## 13           7 Different  492.  413.
## 14           7 Same       605.  438.
## 15           8 Different  501.  414.
## 16           8 Same       435.  445.
```

Data frames/tibbles are structured tables of data.

Each column contains data of the same basic type (i.e. a column can be numeric or character, but not both).

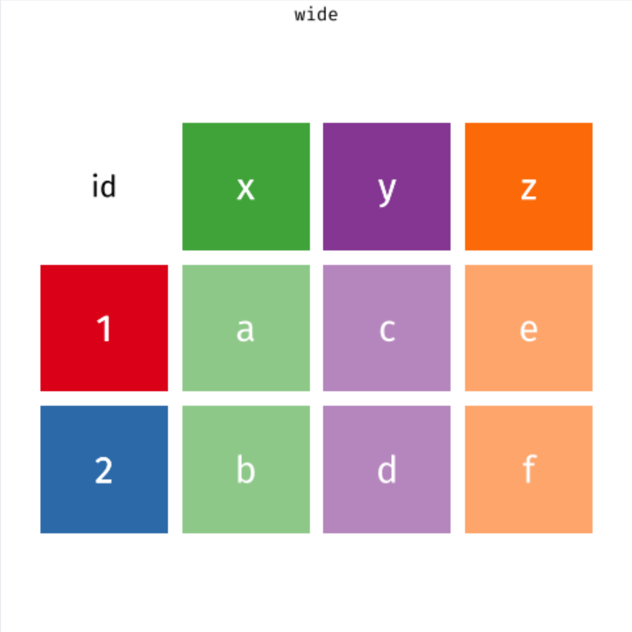
Tidy data

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



Reshaping your data

The **tidyr** package has functions for *reshaping* data in order to make it *tidy*.



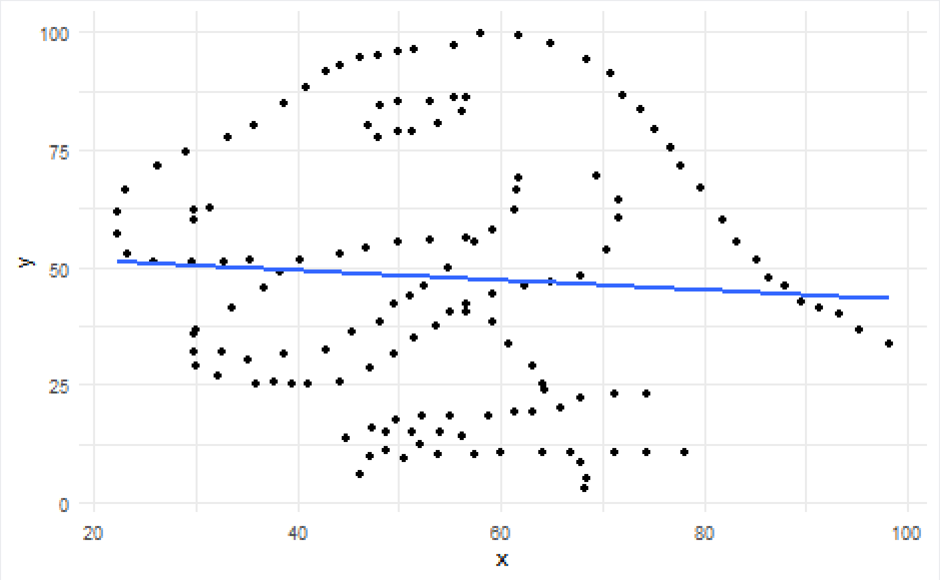
Visualizing data

Why visualize data?

1. Graphs help you rapidly examine the structure of the data.

2. Graphs help you communicate the important statistical features of data.

3. It's often easier to spot unexpected issues using graphs than staring at a bunch of numbers.



Getting a quick look at your data

Plotting helps you quickly gain an understanding of the structure of your data.

Here's some recent data about the UK's prison population.

```
## # A tibble: 22,409 x 6
##    View             Date    Establishment Sex    `Age / Custody / National~ Population
##    <chr>            <chr>   <chr>         <chr>  <chr>                           <dbl>
##  1 a Establishme~ 2015-~ Altcourse     Male   Adults (21+)                      922
##  2 a Establishme~ 2015-~ Altcourse     Male   Juveniles and Young Adult~        169
##  3 a Establishme~ 2015-~ Ashfield      Male   Adults (21+)                      389
##  4 a Establishme~ 2015-~ Askham Grange Female Adults (21+)                       NA
##  5 a Establishme~ 2015-~ Askham Grange Female Juveniles and Young Adult~         NA
##  6 a Establishme~ 2015-~ Aylesbury     Male   Adults (21+)                      113
##  7 a Establishme~ 2015-~ Aylesbury     Male   Juveniles and Young Adult~        268
##  8 a Establishme~ 2015-~ Bedford       Male   Adults (21+)                      459
##  9 a Establishme~ 2015-~ Bedford       Male   Juveniles and Young Adult~         30
## 10 a Establishme~ 2015-~ Belmarsh      Male   Adults (21+)                      794
## # ... with 22,399 more rows
```

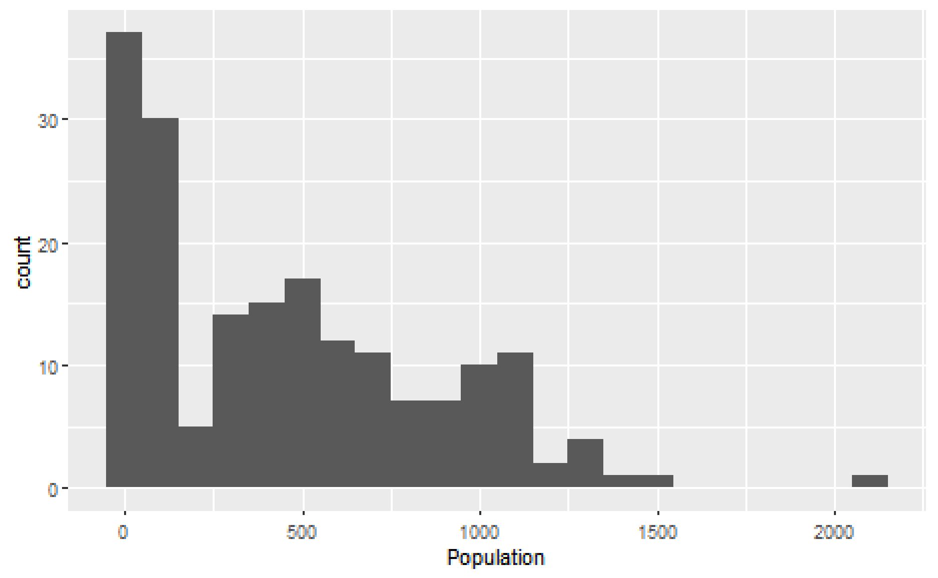
Retrieved from data.gov.uk - Contains public sector information licensed under the Open Government Licence v3.0.

Getting a quick look at your data

Let's look at the UK prison population as of December 2017, split by establishment, sex, and age group.

First we filter out all but the rows I'm interested in. Don't worry about understanding this code... (yet!)

```
pris_pop %>%
  filter(View == "a Establishment*Sex*Age G
         Date == "2017-12") %>%
  ggplot(aes(x = Population)) +
  stat_bin(binwidth = 100)
```



Getting a quick understanding of your data

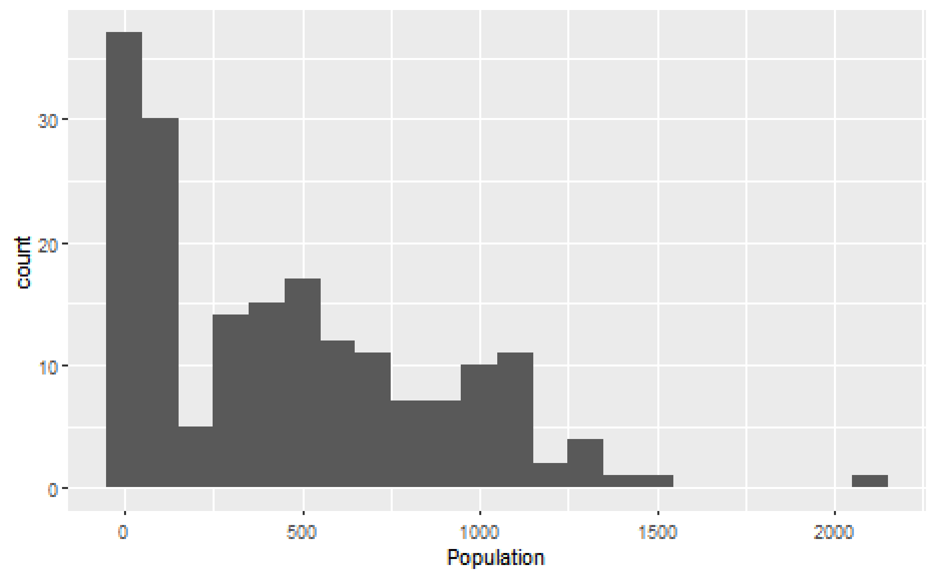
This is a histogram showing the distribution of prison populations in bins of 100 inmates.

Some obvious features:

1. The data is heavily skewed - lots of small values, few large values.

2. There may be a mixture of distributions - there's a big peak in the low numbers, then a dip, then a broader peak.

These two features suggest that there may be some structure we're missing with this plot.

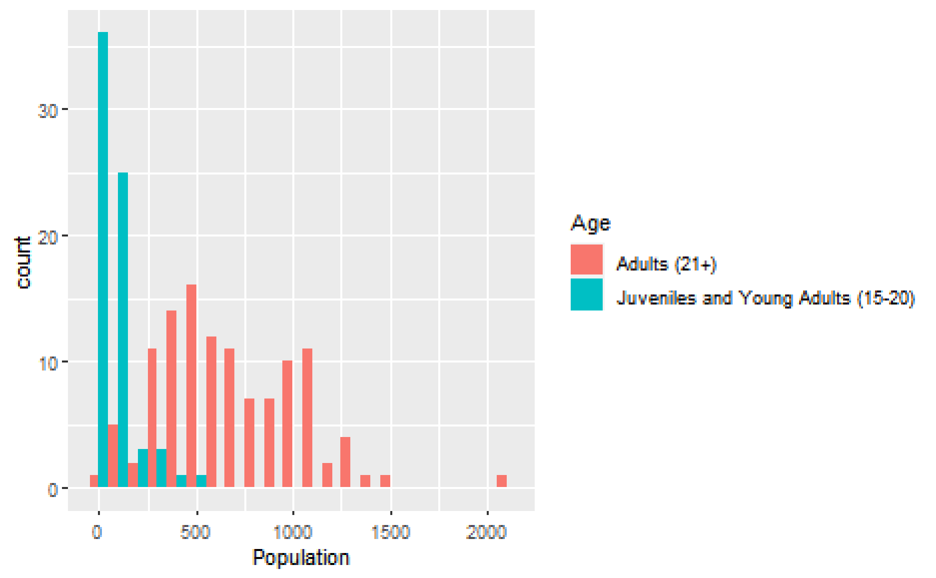


Getting a quick understanding of your data

In the data, age is coded into "Juveniles and Young Adults (15-20)" and "Adults (21+)".

Let's see if Age underlies some of the features of the first plot.

```
pris_pop %>%
  filter(View == "a Establishment*Sex*Age G
         Date == "2017-12") %>%
  ggplot(aes(x = Population,
             fill = `Age / Custody / Nation
  stat_bin(binwidth = 100,
           position = "dodge") +
  labs(fill = "Age")
```



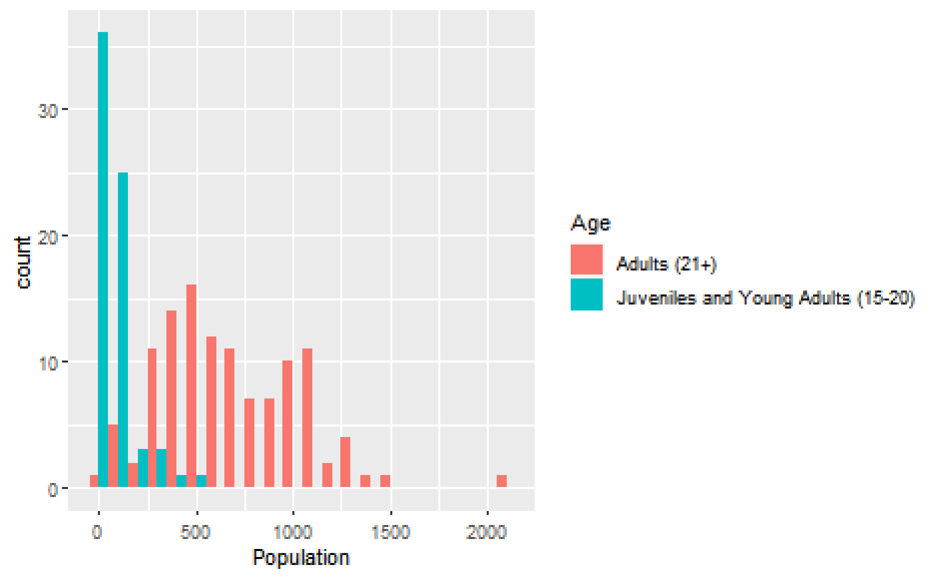
Getting a quick understanding of your data

The "Juvenile" prison population underlies the lower peak.

Typically there are fewer than 200 juveniles in a given institution.

In addition, there are far fewer juveniles in prison than adults.

Note that while many institutions hold both adults and juveniles, some hold only adults and some hold only juveniles.

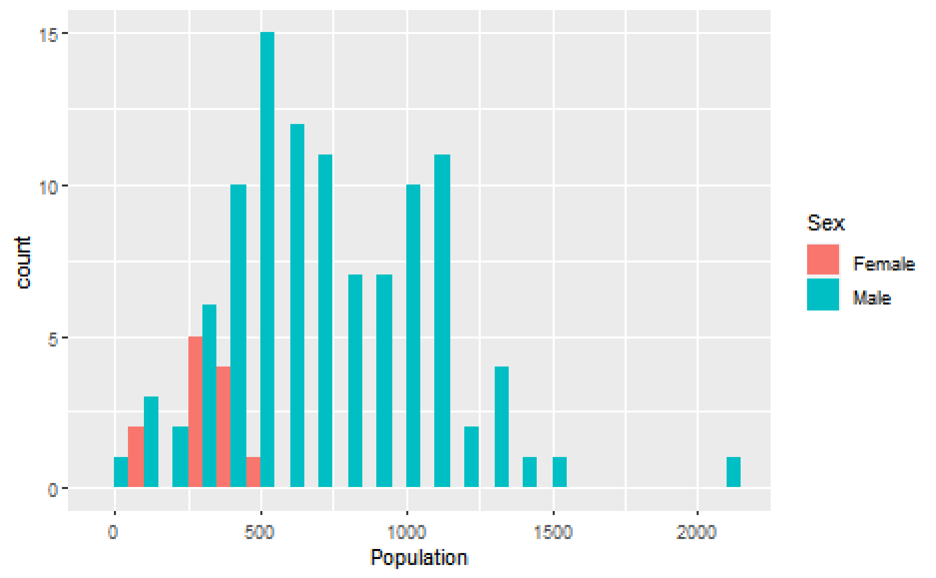


Getting a quick understanding of your data

How do prison populations vary between men and women?

Here we focus on adults, excluding juveniles from the plot.

```
pris_pop %>%
  rename(Age = `Age / Custody / Nationality
  filter(View == "a Establishment*Sex*Age G
         Date == "2017-12",
         Age == "Adults (21+)") %>%
  ggplot(aes(x = Population,
             fill = Sex)) +
  stat_bin(binwidth = 100,
           position = "dodge")
```

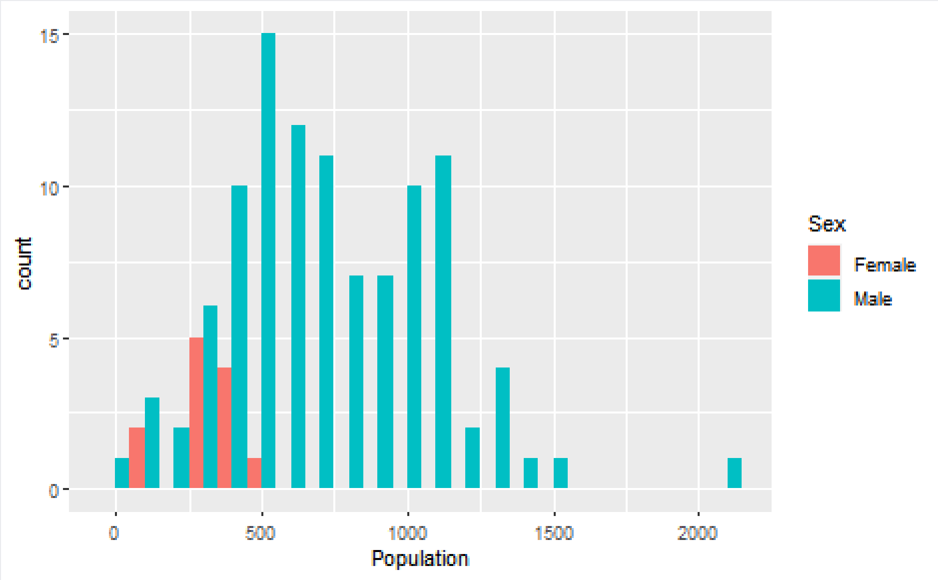


Getting a quick understanding of your data

We can clearly see that there are far more men in prison than women.

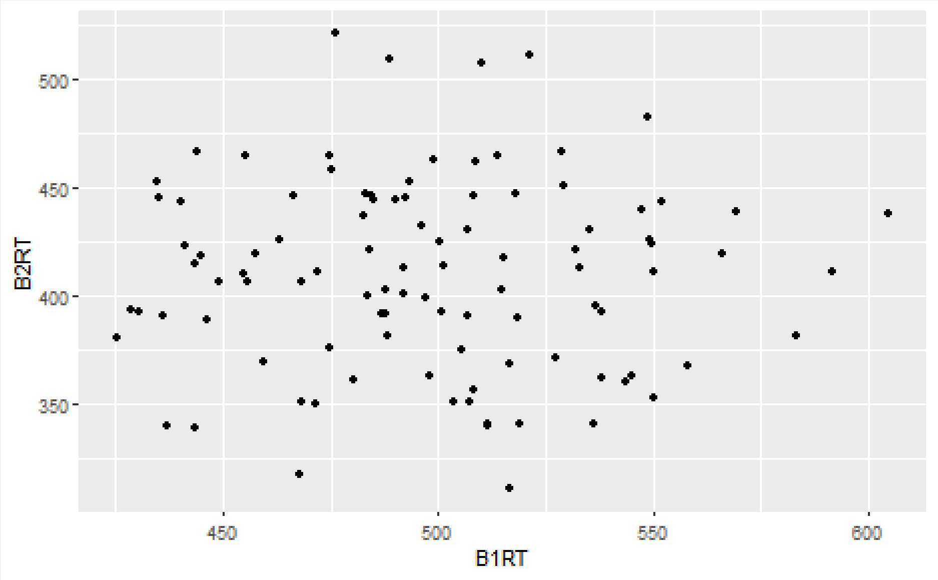
There are also far fewer institutions that hold women than institutions that hold men.

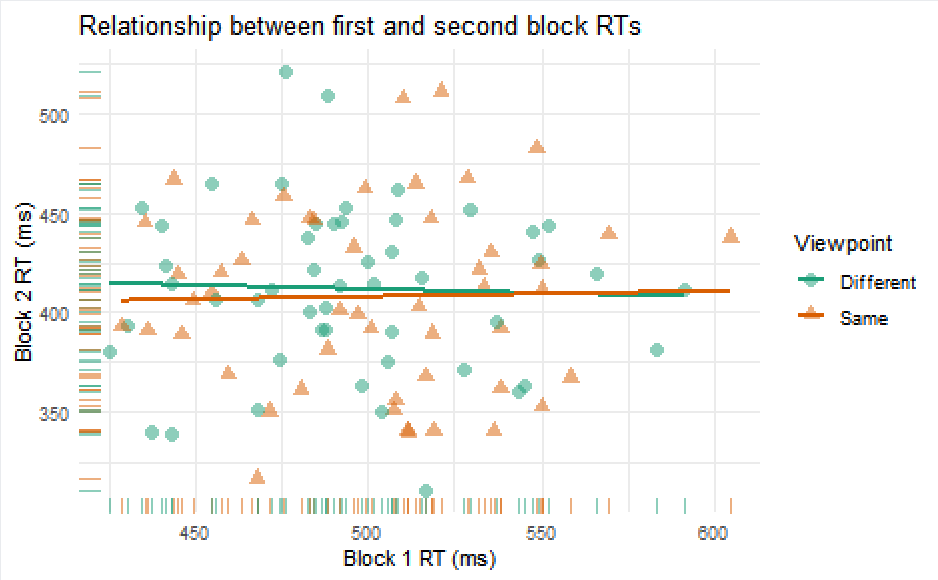
Also there are generally more men in any given institution than there are women.



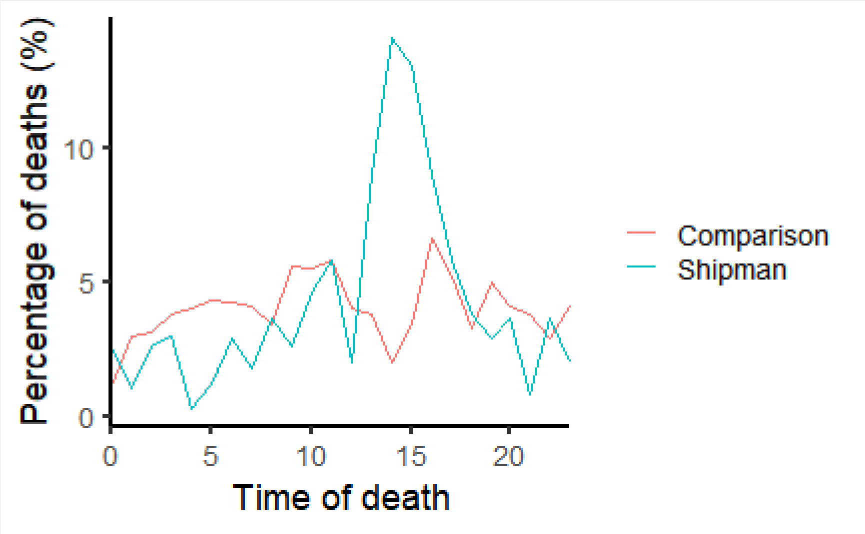
Communicating your results

Plots are also useful for showing the statistical patterns in your data to go along with statistical tests.





Communicating patterns



Strikingly different to similar GPs, many of Harold Shipman's patients died at a particular time of day.

A pattern like this passes the "inter-ocular trauma" test...

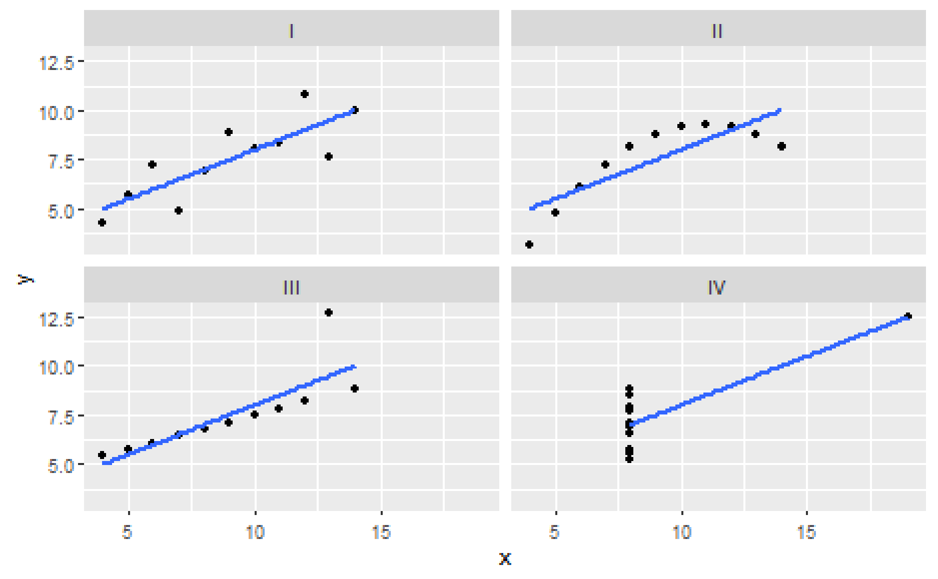
Spiegelhalter (2019), *The Art of Statistics*

Spotting problems in your data

Anscombe's Quartet

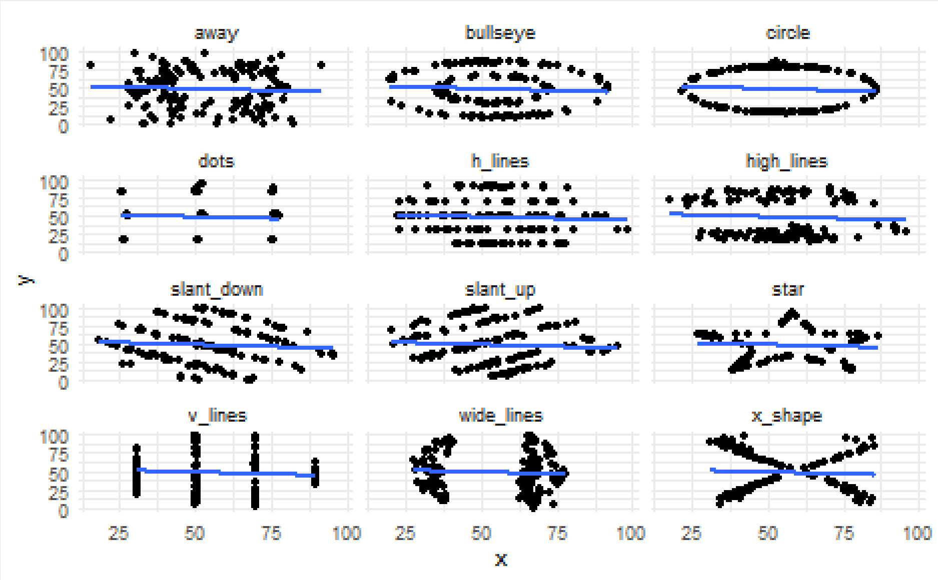
Every one of these plots shows sets of data with the same means, standard deviations, and correlation coefficients.

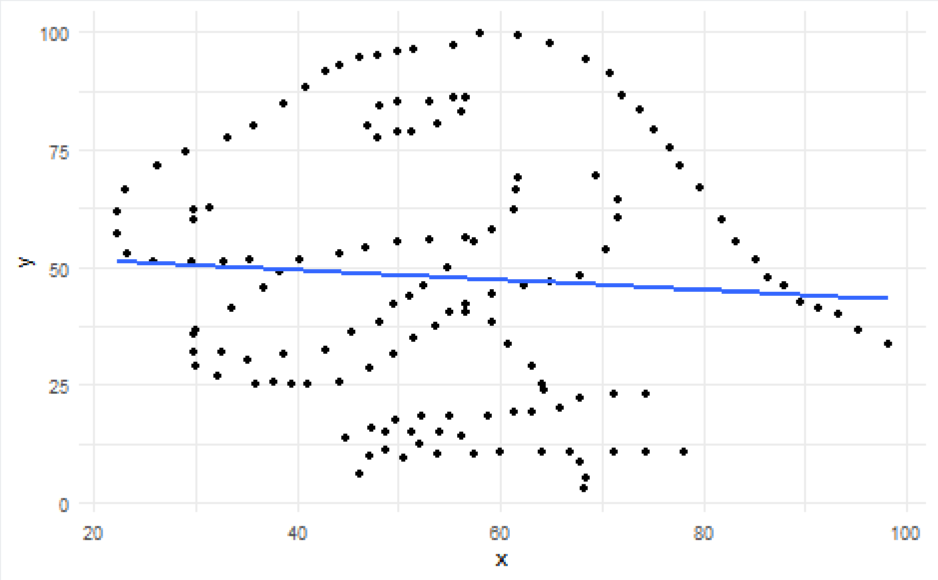
One is non-linear, one has an outlier, and one should have a categorical x-axis!



Spotting problems in your data

The Datasaurus Dozen





The Grammar of Graphics

ggplot2

ggplot2 is one of the **tidyverse** packages.

GG stands for the *Grammar* of *Graphics*.

The Grammar of Graphics is a principled approach to building plots from a few underlying structures:

1. A dataset
2. A coordinate system
3. *Geoms* (geometric shapes such as bars or points)

We begin with a blank canvas:

```
ggplot()
```

The mpg dataset

```r
mpg
```

```
## # A tibble: 234 x 11
##    manufacturer model      displ  year   cyl trans    drv     cty   hwy fl    class
##    <chr>        <chr>      <dbl> <int> <int> <chr>    <chr> <int> <int> <chr> <chr>
##  1 audi         a4           1.8  1999     4 auto(l5) f        18    29 p     comp~
##  2 audi         a4           1.8  1999     4 manual(~ f        21    29 p     comp~
##  3 audi         a4           2    2008     4 manual(~ f        20    31 p     comp~
##  4 audi         a4           2    2008     4 auto(av) f        21    30 p     comp~
##  5 audi         a4           2.8  1999     6 auto(l5) f        16    26 p     comp~
##  6 audi         a4           2.8  1999     6 manual(~ f        18    26 p     comp~
##  7 audi         a4           3.1  2008     6 auto(av) f        18    27 p     comp~
##  8 audi         a4 quattro   1.8  1999     4 manual(~ 4        18    26 p     comp~
##  9 audi         a4 quattro   1.8  1999     4 auto(l5) 4        16    25 p     comp~
## 10 audi         a4 quattro   2    2008     4 manual(~ 4        20    28 p     comp~
## # ... with 224 more rows
```

Datasets and aesthetics

The first step is to add dataset and define some *aesthetics*.

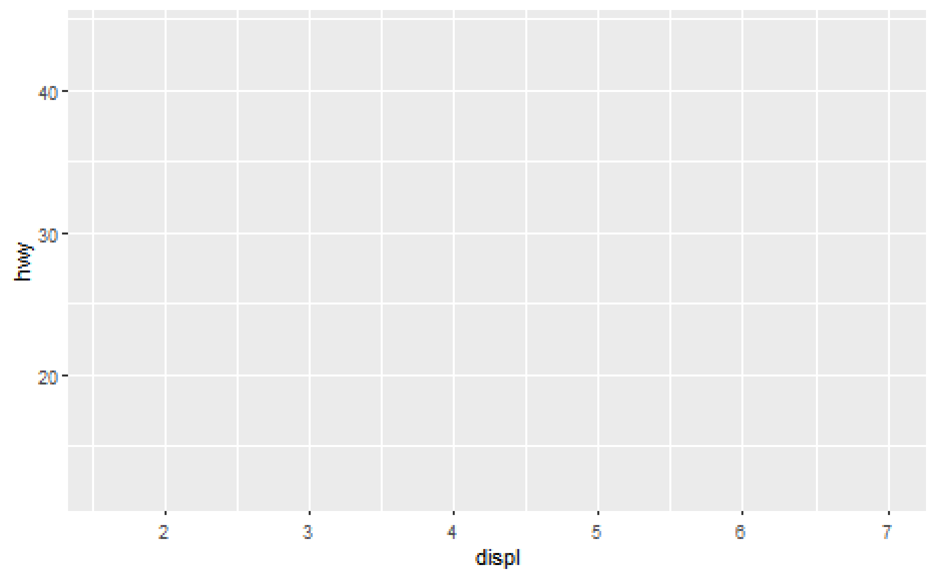
Aesthetics are how we map elements of the data to parts of the plot.

The first two arguments to `ggplot()` are `data` and `mapping`.

We use the `aes()` function within this to map columns from the data to properties of the plot.

Here we use the 'displ' and 'hwy' columns from the *mpg* dataset to set up our co-ordinate system.

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



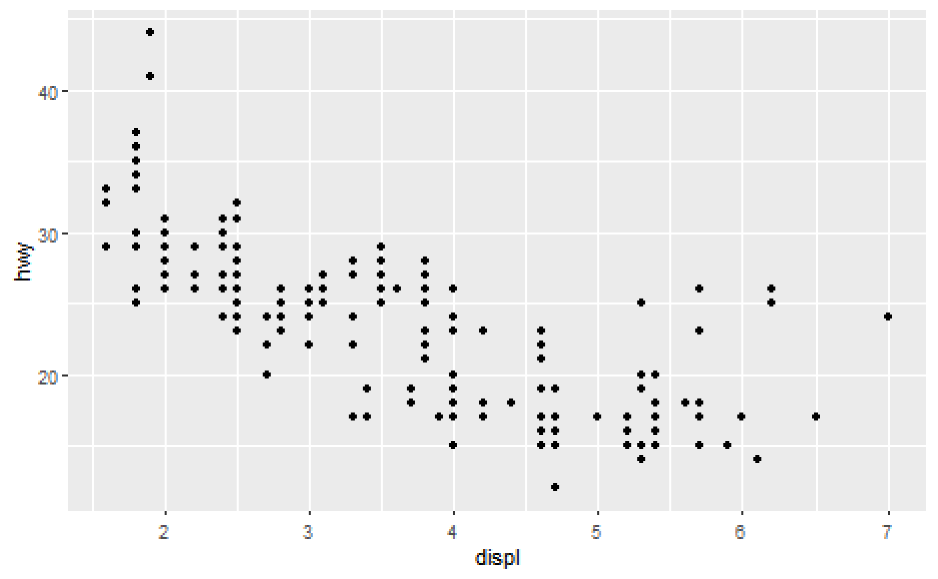
Geoms and layers

geoms are the geometric shapes we want to use to represent our data.

We add a new layer to our initial canvas using `+`, and then use one of the many `geom_*` functions to draw shapes on the new layer.

For a scatterplot, add a new layer using `geom_point()`.

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

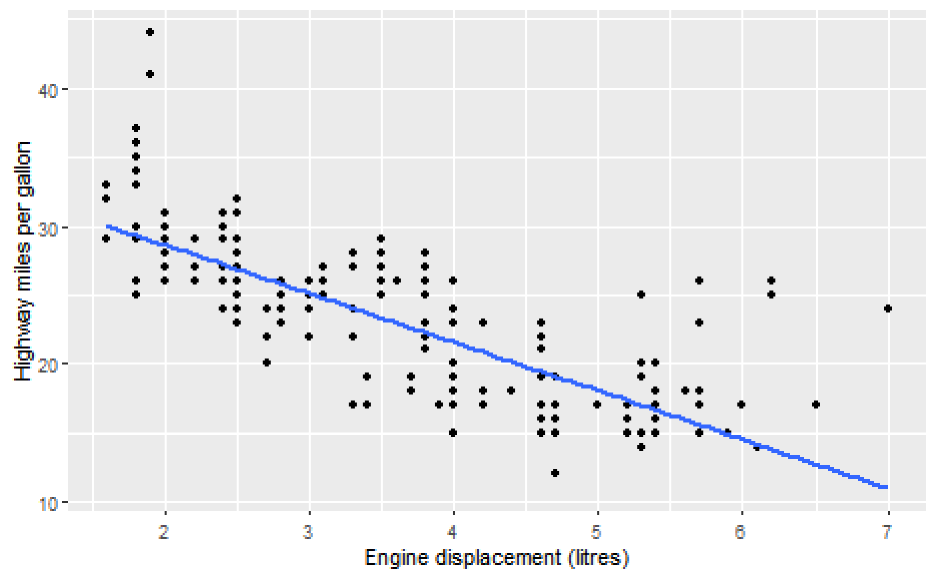


Adding a linear model

A question we're pondering is what is the relationship between the variables on x- and y-axes?

We can add a linear regression line using `geom_smooth()` and specifying "lm" (linear model) for the argument method.

```
ggplot(data = mpg,
       mapping = aes(x = displ, y = hwy)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(x = "Engine displacement (litres)",
       y = "Highway miles per gallon")
```

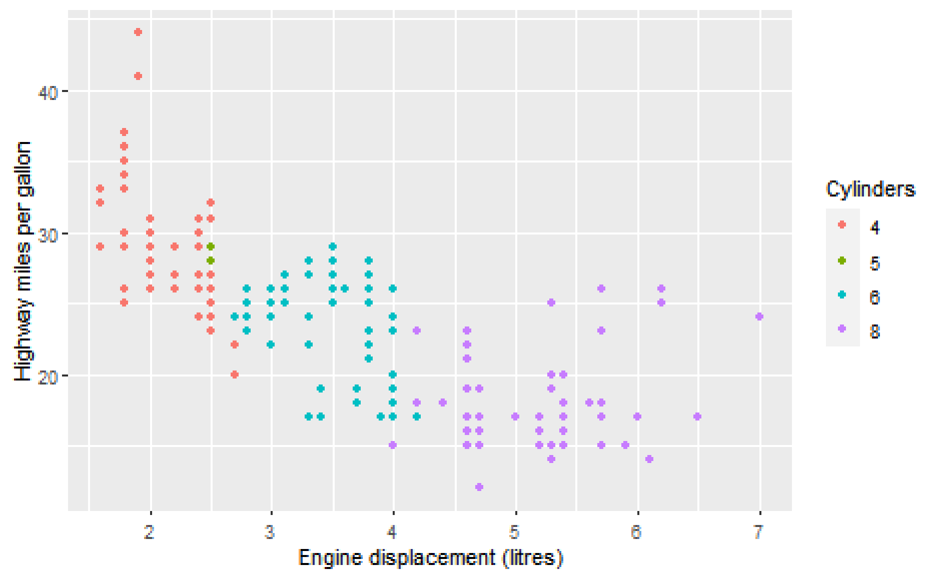


Identifying groups

Another variable we know about is the number of cylinders in the engines - the *cyl* column.

cyl only has four unique levels, so it's best treated as a categorical variable and converted to a factor using `factor()`. Here, we use colour to identify different levels of *cyl*.

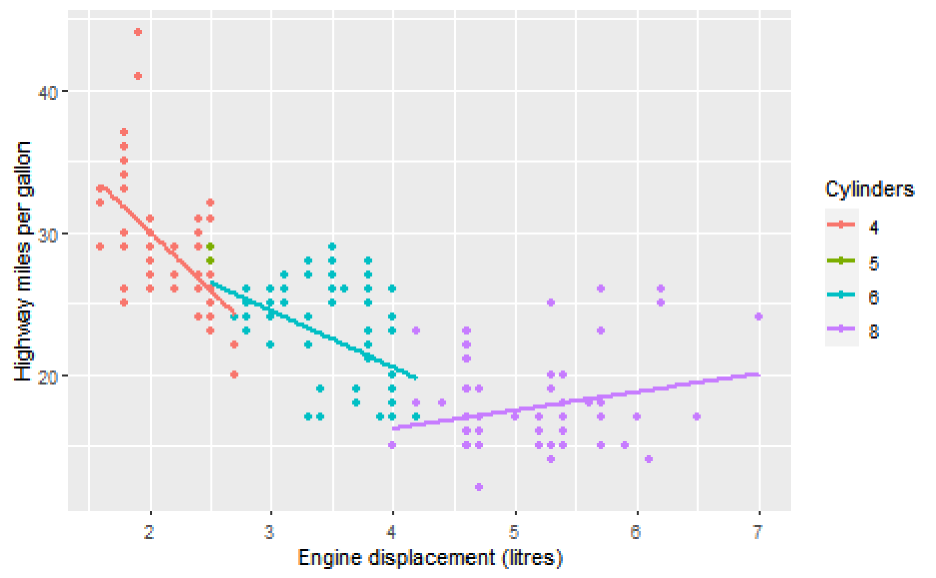
```
ggplot(data = mpg,
       mapping = aes(x = displ,
                     y = hwy,
                     colour = factor(cyl))) +
  geom_point() +
  labs(x = "Engine displacement (litres)",
       y = "Highway miles per gallon",
       colour = "Cylinders")
```



Identifying groups

And we can also add linear regression lines for each grouping of cylinders, again using `geom_smooth()`.

```
ggplot(data = mpg,
       mapping = aes(x = displ,
                     y = hwy,
                     colour = factor(cyl))) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(x = "Engine displacement (litres)",
       y = "Highway miles per gallon",
       colour = "Cylinders")
```



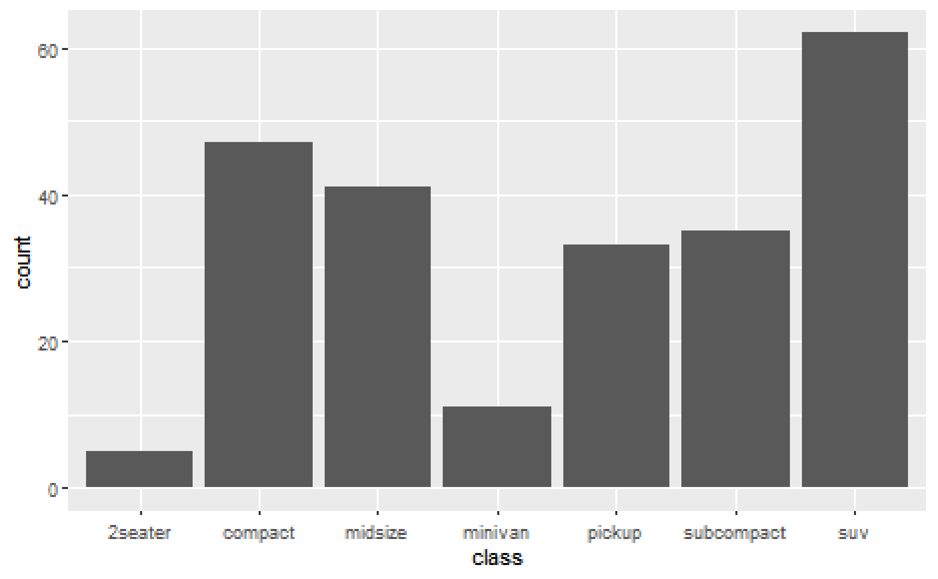
Plotting categorical and continuous data

Plotting a single categorical variable

Typically with a single categorical variable, we want a frequency count - i.e. we want to know how many times each category shows up.

A bar graph is ideal! For example, there are several different *classes* of vehicle in in the *mpg* dataset. How many times does each one show up?

```
ggplot(mpg,
       aes(x = class)) +
  geom_bar()
```



`geom_bar()` will count for us, so we don't need to supply a *y* aesthetic `aes()`.

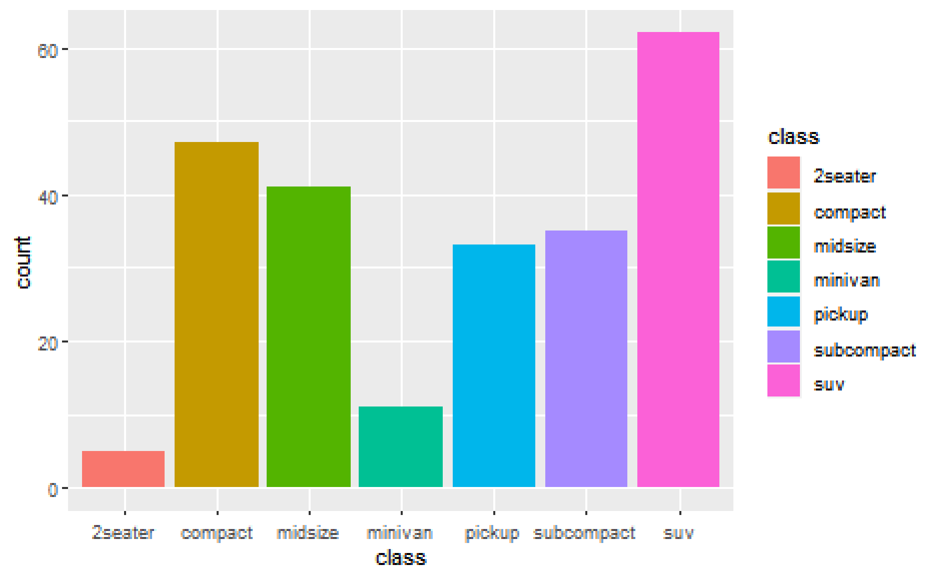
Plotting a single categorical variable

As with plots we did earlier, the bars can be coloured in.

With `geom_point()` we change the `colour` aesthetic.

For `geom_bar()` we need to change the `fill` aesthetic.

```
ggplot(mpg, aes(x = class,
                fill = class)) +
  geom_bar()
```

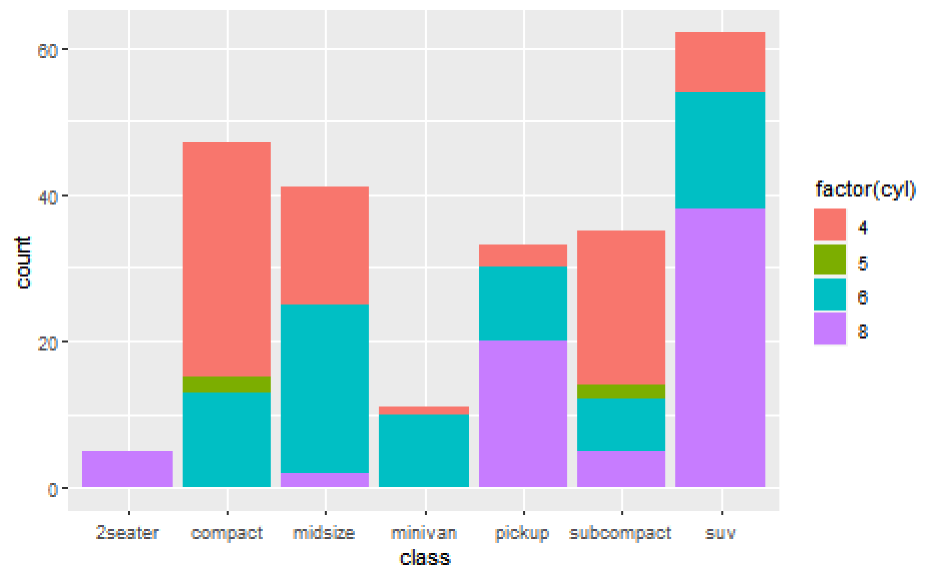


Plotting multiple categorical variables

The fill doesn't have to use the same variable as the `x` variable.

For example, you may want to see how each count breaks down into groups of another categorical variable.

```
ggplot(mpg, aes(x = class,
                fill = factor(cyl))) +
  geom_bar()
```

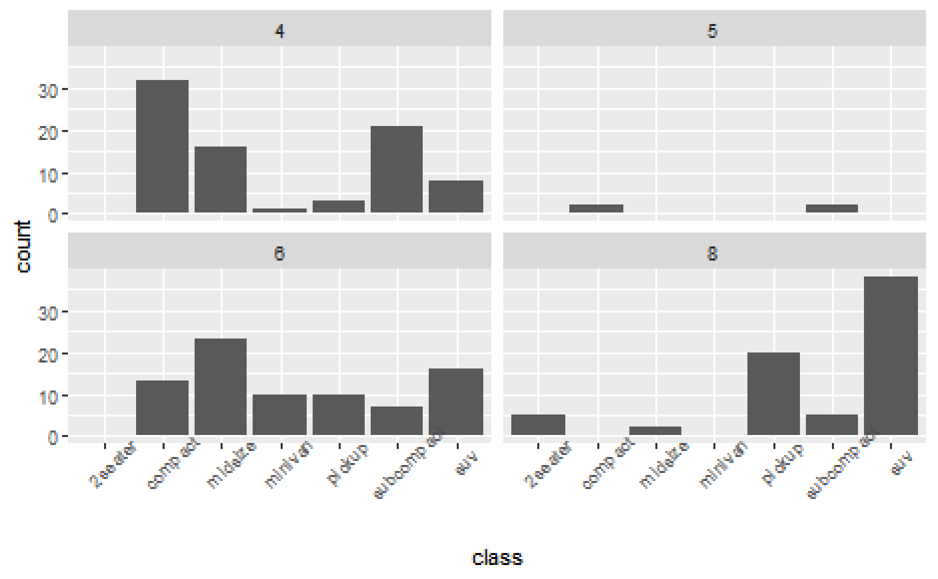


Plotting multiple categorical variables

Alternatively, you may want to produce different graphs for each level of the other categorical variable

A nice way to do that is using **facets**, adding a `facet_wrap()` or `facet_grid()` layer to the *ggplot*.

```
ggplot(mpg, aes(x = class)) +
  geom_bar() +
  facet_wrap(~factor(cyl)) +
  theme(axis.text.x = element_text(angle =
```



Plotting continuous variables

Plotting a single continuous variable

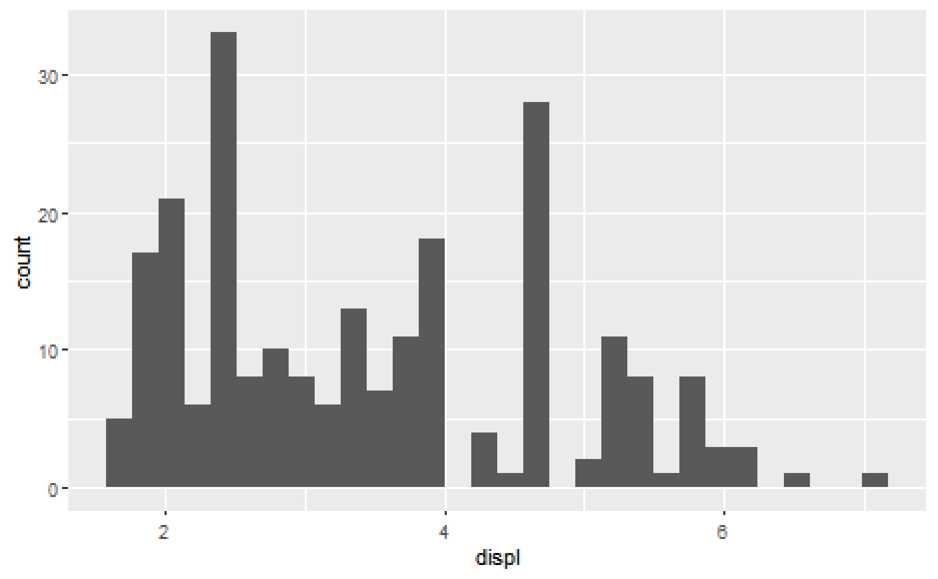
A lot of the time you'll be dealing with continuous, numerical variables.

What you often want to do is check how they are distributed (we'll go into this later in the course!).

Histograms split continuous variables up into discrete bins, and count how many of each value show up in each bin.

Here we use `geom_histogram()`. By default, it splits data into 30 bins.

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



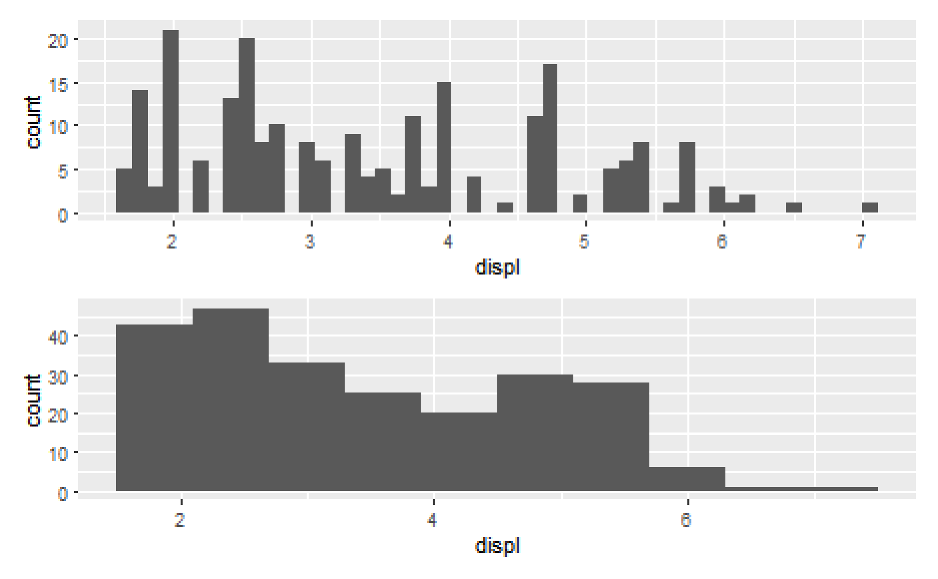
Plotting a single continuous variable

Changing the number of bins can have quite dramatic results on the plots.

There are no hard and fast rules how many bins you need.

```
ggplot(mpg, aes(x = displ)) +
  geom_histogram(bins = 50)
```

```
ggplot(mpg, aes(x = displ)) +
  geom_histogram(bins = 10)
```

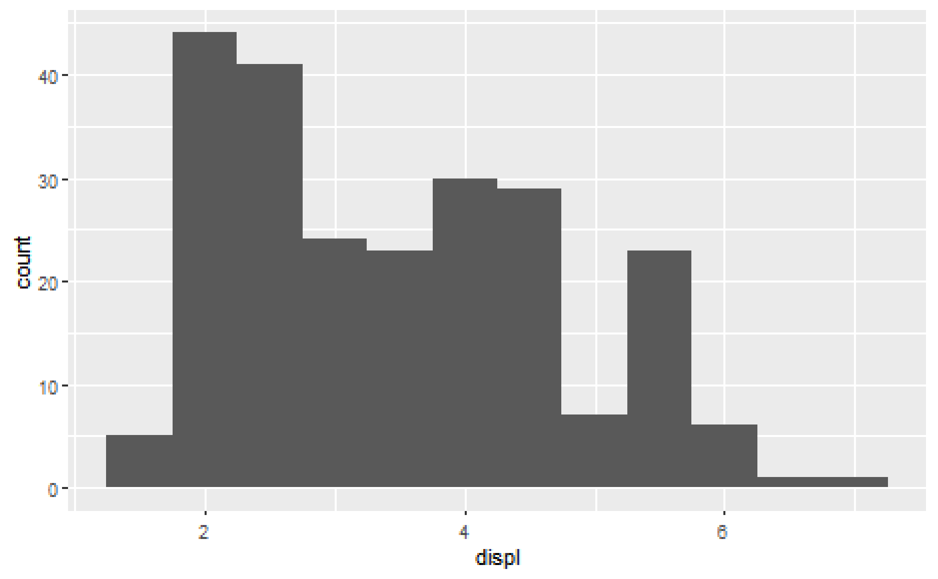


Plotting a single continuous variable

Rather than choosing a number of bins, you can also set the `binwidth`, in the same units as the variable.

For example, here it's set to make one bin every .5 units of the `displ` variable.

```
ggplot(mpg, aes(x = displ)) +
  geom_histogram(binwidth = .5)
```



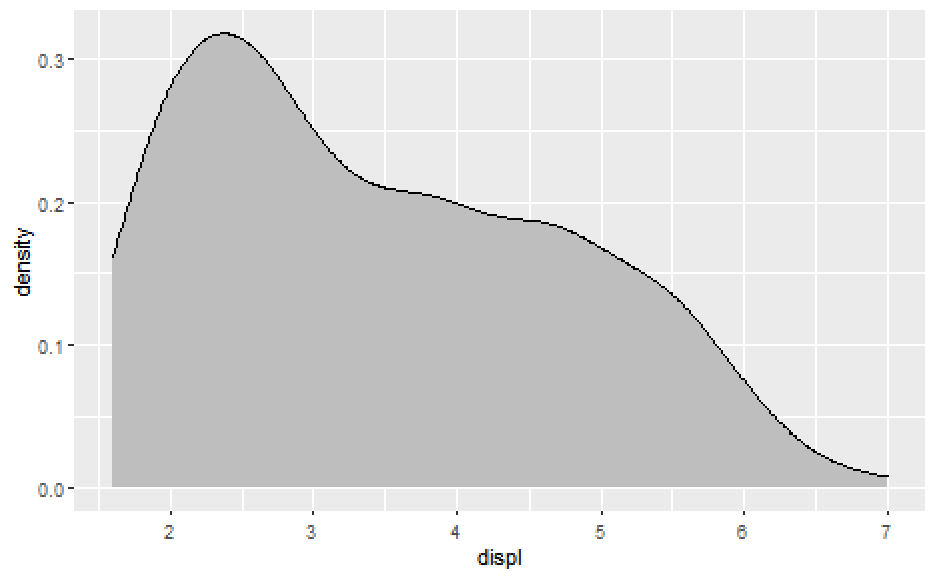
Plotting a single continuous variable

An alternative to using a histogram is to plot a **kernel density estimate (KDE)**.

An advantage of the KDE (other than the fancy-sounding name) is that it provides smooth estimate over the range of the data and is much less dependent on an arbitrary parameter like "number of bins".

We draw a KDE using `geom_density()`.

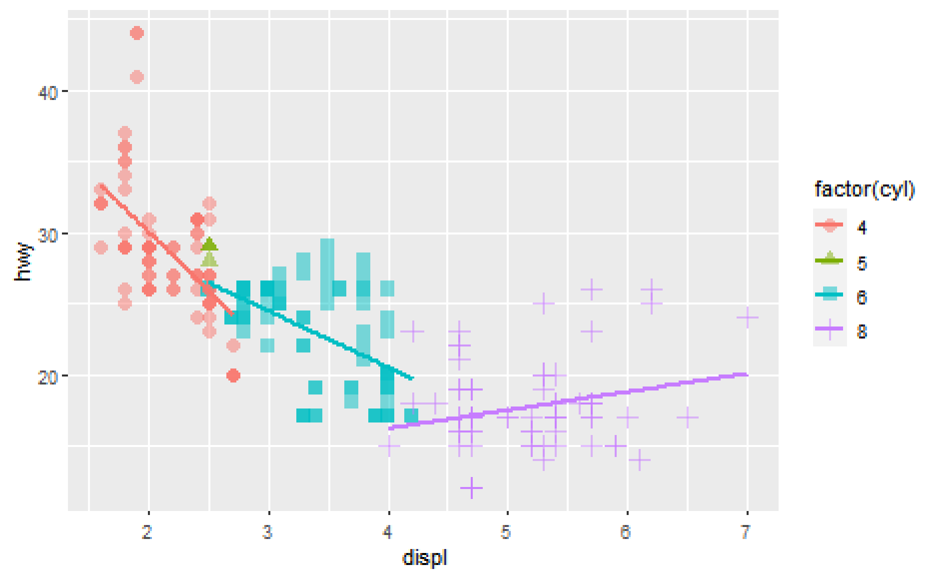
```
ggplot(mpg, aes(x = displ)) +
  geom_density(fill = "grey")
```



Plotting two continuous variables

The best type of plot for showing the relationship between two continuous variables is a **scatterplot**.

```
ggplot(data = mpg,
       mapping = aes(x = displ,
                     y = hwy,
                     colour = factor(cyl))) +
    geom_point(size = 3,
               alpha = 0.5,
               aes(shape = factor(cyl))) +
    geom_smooth(method = "lm", se = FALSE)
```



Continuous by categorical interactions

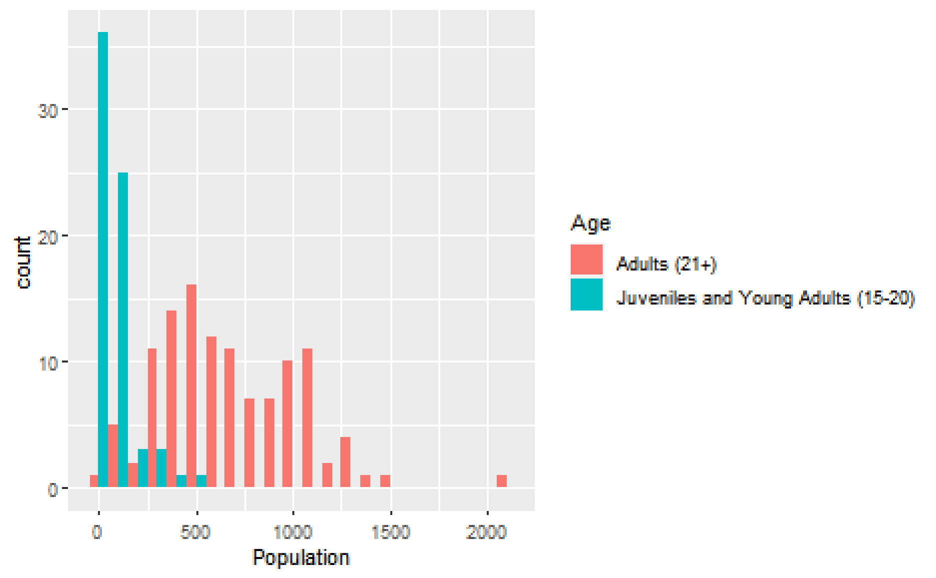
Continuous by categorical interactions

Often when working with continuous data, you have additional categorical variables.

It's often easiest to put splits based on categorical variables side-by-side on the same plot.

Here we use `geom_histogram(position = "dodge")` to put the bars side-by-side.

```
ggplot(pris_pop,
       aes(x = Population,
             fill = Age)) +
  geom_histogram(binwidth = 100,
                 position = "dodge")
```



Continuous by categorical interactions

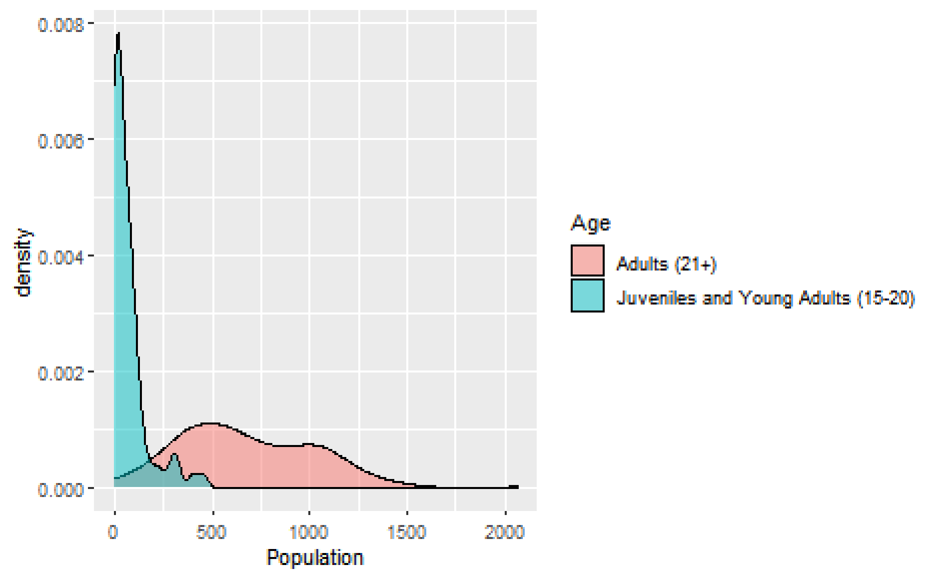
Another way to do this would be using kernel density estimates.

`geom_density()` uses the *fill* aesthetic for this.

Since the densities overlap, we can manipulate the *transparency* of the geom using the *alpha* argument.

Note that this can be applied to most *geoms* and is often useful when there is overlap.

```
ggplot(pris_pop,
       aes(x = Population,
             fill = Age)) +
  geom_density(alpha = 0.5)
```

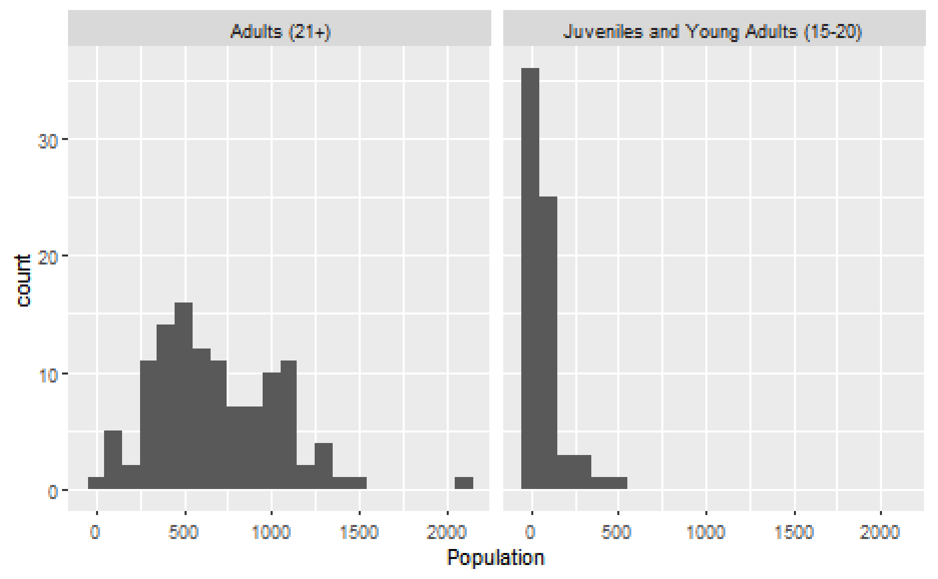


Continuous by categorical interactions

However, sometimes you'll find it helpful to produce separate "panels" for each level of a categorical variable.

We can use the `facet_wrap()` or `facet_grid()` function to produce additional panels.

```
ggplot(pris_pop,
       aes(x = Population)) +
  geom_histogram(binwidth = 100) +
    facet_wrap(~Age)
```



Continuous by categorical interactions

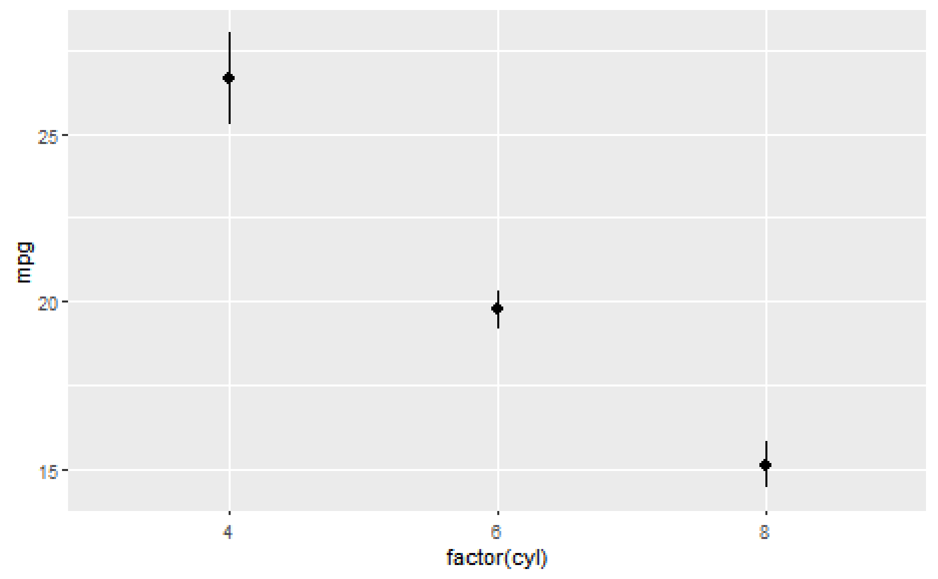
In the last few examples, we've plotted with the continuous variable on the x-axis.

We can also plot with a discrete variable on the x-axis.

In this case we want R to summarise the continuous variable, providing us with the mean and standard error for each level of *cyl* from the *mtcars* dataset.

We use `stat_summary()` to do this.

```
ggplot(mtcars,
       aes(x = factor(cyl),
           y = mpg)) +
  stat_summary()
```

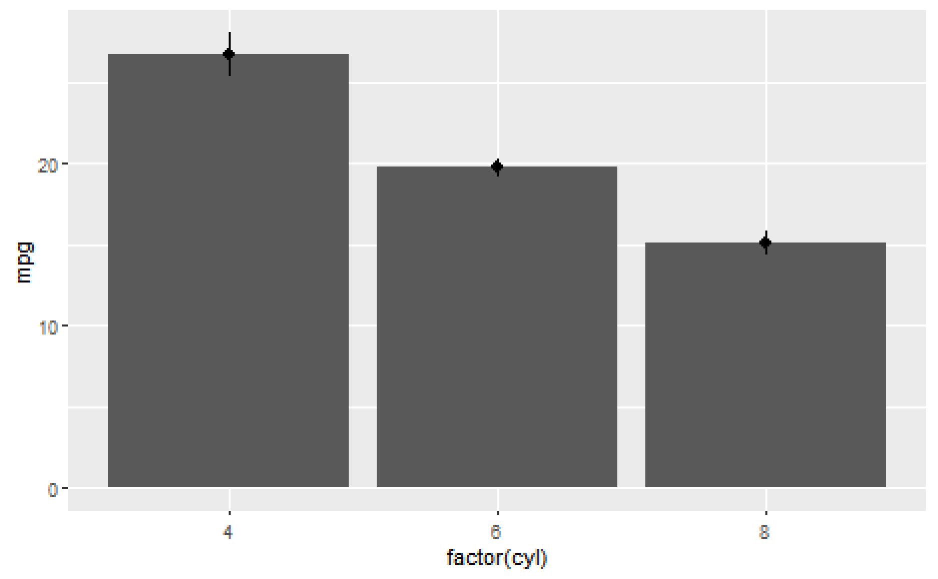


Continuous by categorical interactions

Some people like to plot bar charts, with the mean and error bars overlaid on top.

We use `stat_summary()` twice, the first time specifying that we want bars using the *geom* argument, the second time just using the defaults.

```
ggplot(mtcars,
       aes(x = factor(cyl),
           y = mpg)) +
  stat_summary(fun = mean,
               geom = "bar") +
  stat_summary(fun.data = mean_se)
```



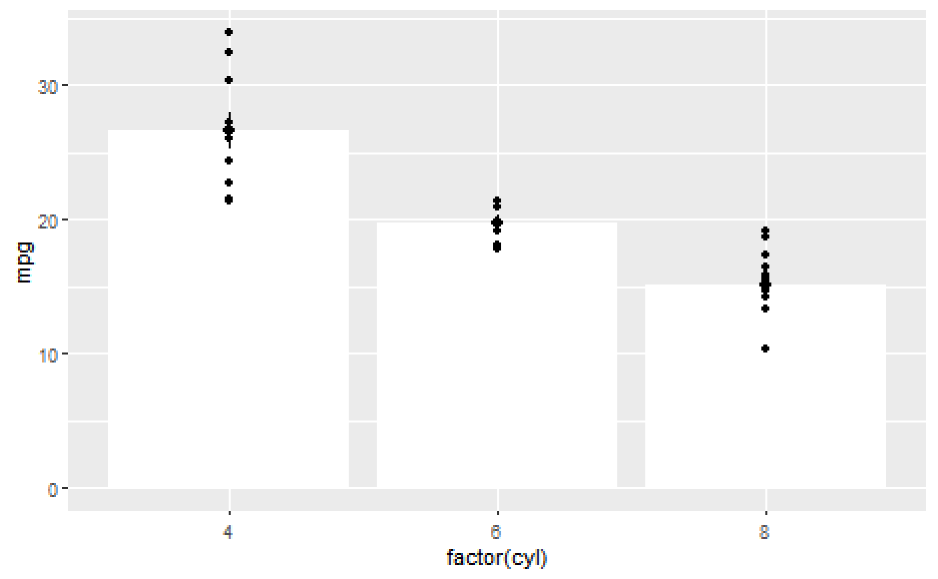
Continuous by categorical interactions

But bar charts are not a very good way to show this kind of data!

Most of the space occupied by the bars has no data in it, as we can see when we add individual points with `geom_point()`.

Stick to using bars to show counts!

```
ggplot(mtcars,
       aes(x = factor(cyl),
           y = mpg)) +
  stat_summary(fun = mean,
               geom = "bar", fill = "white"
  stat_summary(fun.data = mean_se) +
  geom_point()
```

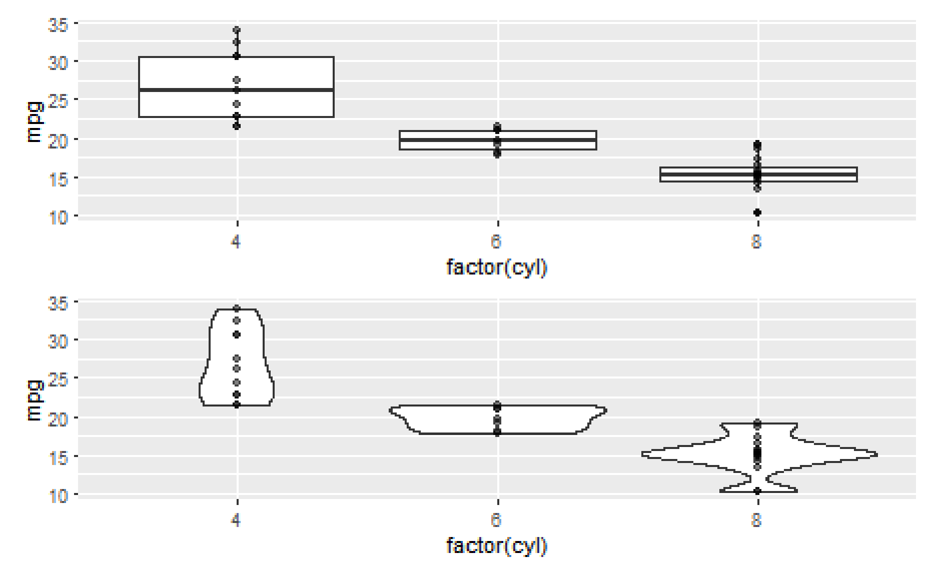


Continuous by categorical interactions

Two better alternatives are **violin plots** or **boxplots**

```
ggplot(mtcars,
       aes(x = factor(cyl),
           y = mpg)) +
  geom_boxplot() +
  geom_point(alpha = 0.5)
```

```
ggplot(mtcars,
       aes(x = factor(cyl),
           y = mpg)) +
  geom_violin() +
  geom_point(alpha = 0.5)
```



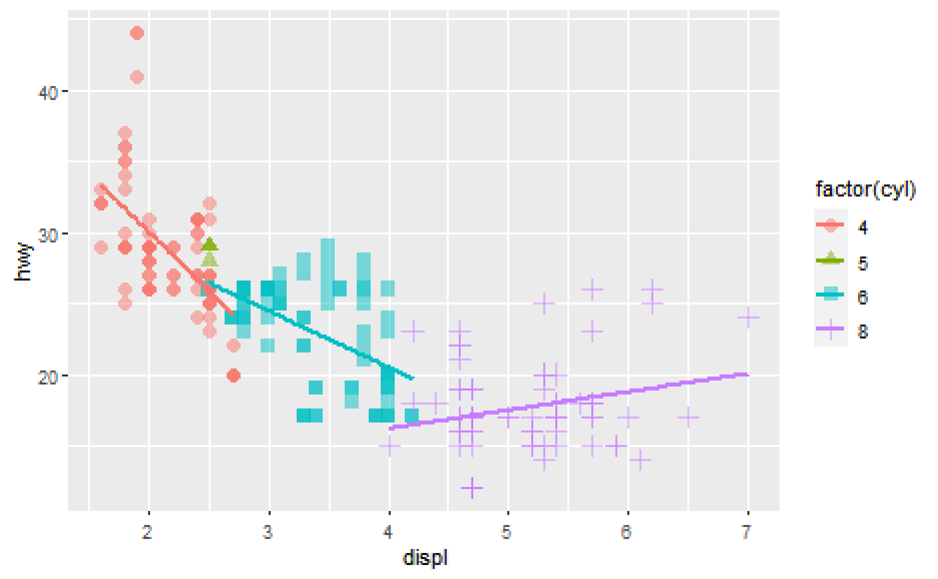
Jazzing up the plots

Better labelling

Basic plot

Better labels

Fancier Plot



Better labelling

Basic plot

Better labels

Fancier Plot

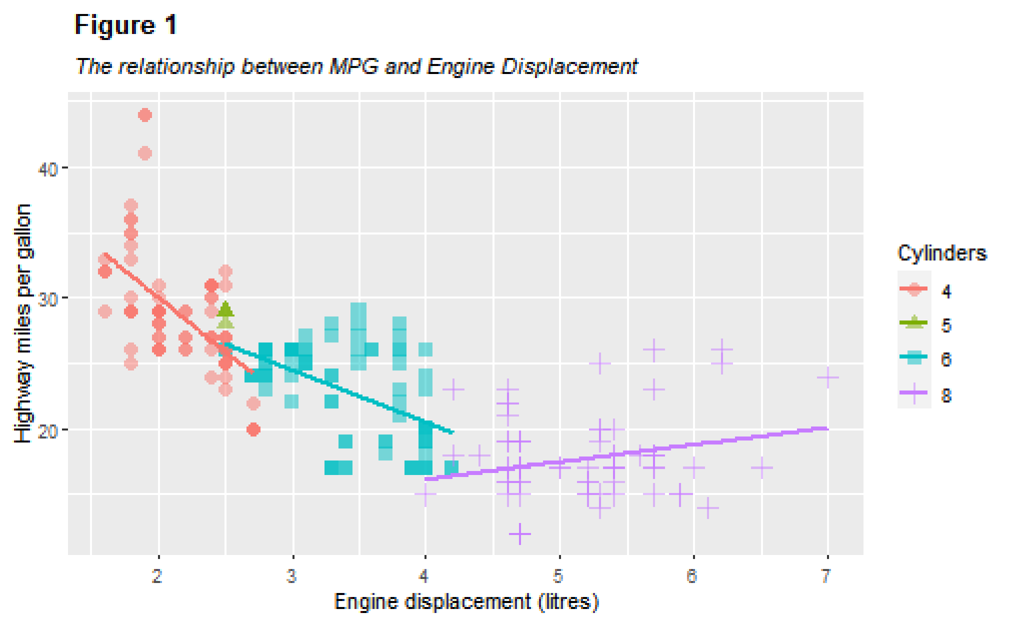
```
ggplot(data = mpg,
       mapping = aes(x = displ,
                     y = hwy,
                     colour = factor(cyl))) +
    geom_point(size = 3,
               alpha = 0.5,
               aes(shape = factor(cyl))) +
    geom_smooth(method = "lm", se = FALSE) +
    labs(x = "Engine displacement (litres)",
         y = "Highway miles per gallon",
         colour = "Cylinders",
         shape = "Cylinders",
         title = expression(~bold("Figure 1")),
         subtitle = expression(~italic("The relationship between MP
```

Better labelling

Basic plot

Better labels

Fancier Plot



Nicer overall theme

- Themes
- Basic plot
- theme_bw()
- BW plot
- theme_classic()
- Classic plot

Themes are the way `ggplot()` sets the overall look of the plots.

These can control things like:

- The colour of the background (e.g. grey or white)
- The presence of the gridlines in the background
- The choice and size of fonts for text

There are several default themes built in!

Nicer overall theme

Themes

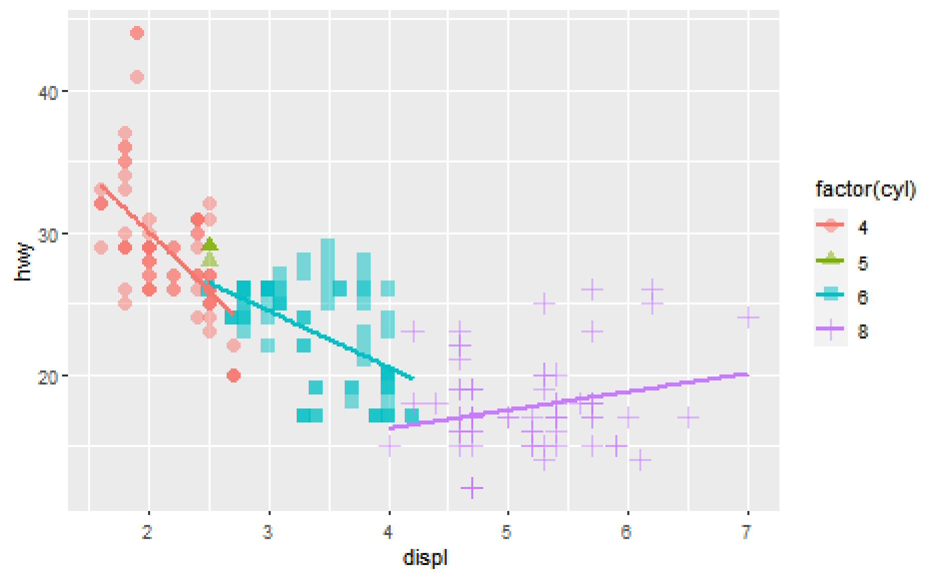
Basic plot

theme_bw()

BW plot

theme_classic()

Classic plot

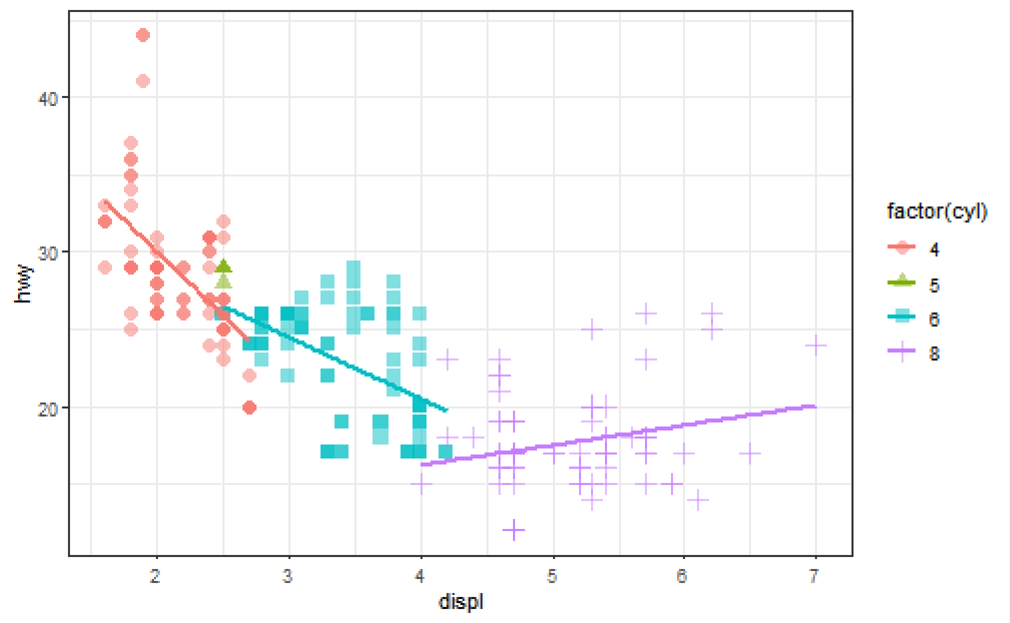


Nicer overall theme


```
ggplot(data = mpg,
       mapping = aes(x = displ,
                     y = hwy,
                     colour = factor(cyl))) +
    geom_point(size = 3,
               alpha = 0.5,
               aes(shape = factor(cyl))) +
    geom_smooth(method = "lm", se = FALSE) +
    theme_bw()
```

Nicer overall theme

- Themes
- Basic plot
- theme_bw()
- BW plot
- theme_classic()
- Classic plot



Nicer overall theme

Themes

Basic plot

theme_bw()

BW plot

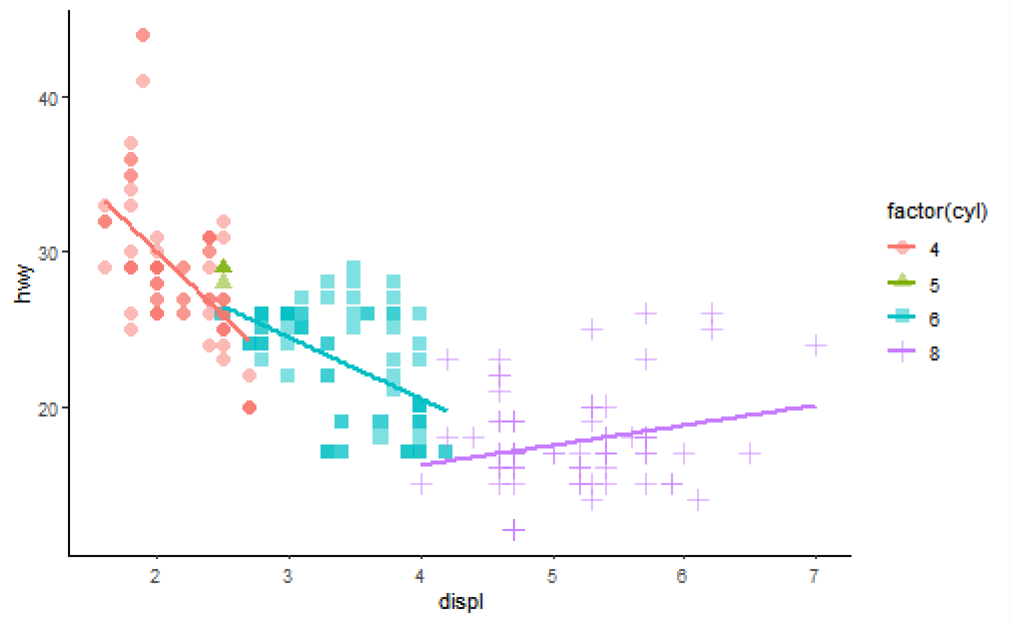
theme_classic()

Classic plot

```
ggplot(data = mpg,
       mapping = aes(x = displ,
                     y = hwy,
                     colour = factor(cyl))) +
    geom_point(size = 3,
               alpha = 0.5,
               aes(shape = factor(cyl))) +
    geom_smooth(method = "lm", se = FALSE) +
    theme_classic()
```

Nicer overall theme

- Themes
- Basic plot
- theme_bw()
- BW plot
- theme_classic()
- Classic plot

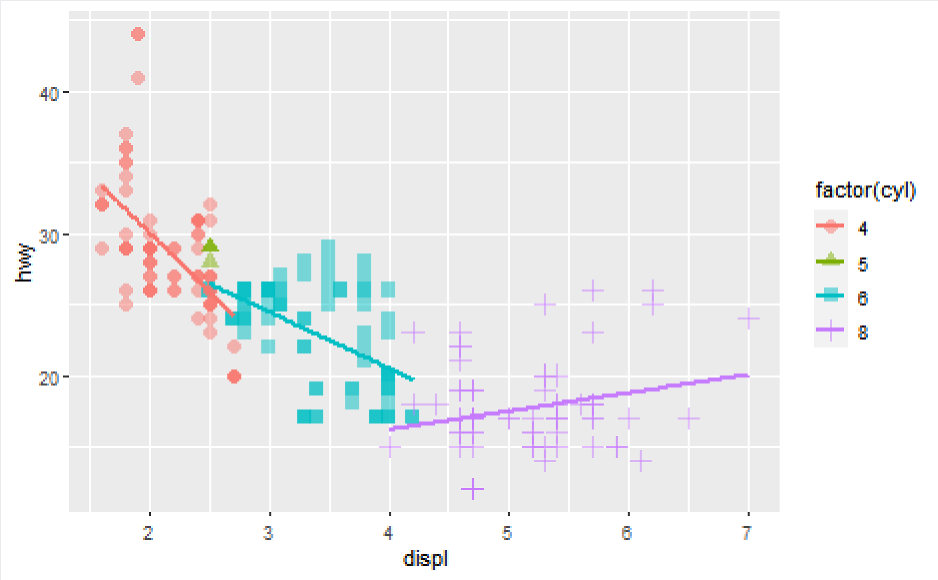


Changing the colours

Basic plot

Colour brewer

New plot



Changing the colours

Basic plot

Colour brewer

New plot

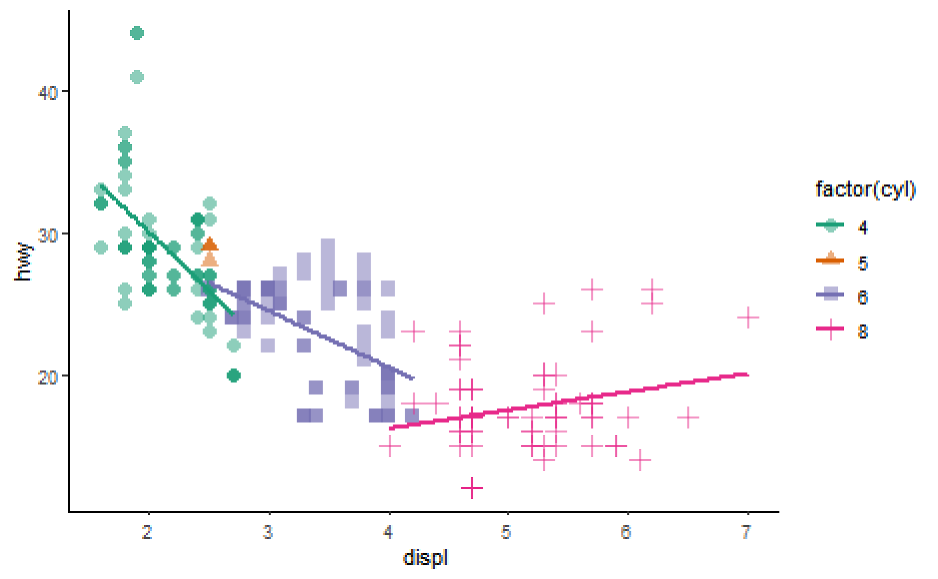
```
ggplot(data = mpg,
       mapping = aes(x = displ,
                     y = hwy,
                     colour = factor(cyl))) +
  geom_point(size = 3,
             alpha = 0.5,
             aes(shape = factor(cyl))) +
  geom_smooth(method = "lm", se = FALSE) +
  scale_colour_brewer(palette = "Dark2") +
  theme_classic()
```

Changing the colours

Basic plot

Colour brewer

New plot



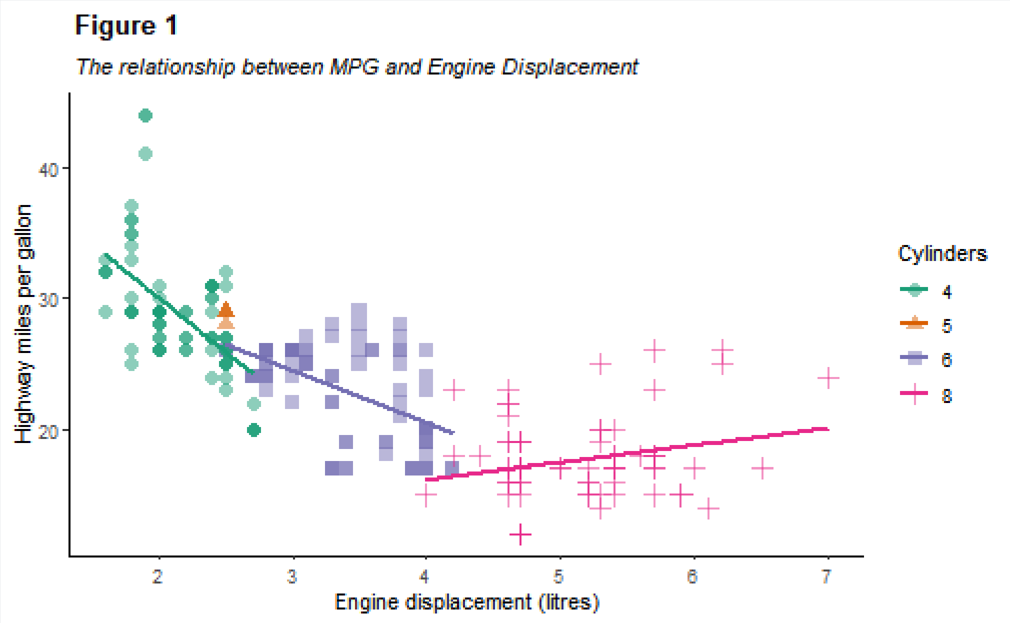
One final plot

Code The plot

```
ggplot(data = mpg,
       mapping = aes(x = displ,
                     y = hwy,
                     colour = factor(cyl))) +
  geom_point(size = 3,
             alpha = 0.5,
             aes(shape = factor(cyl))) +
  geom_smooth(method = "lm", se = FALSE) +
  labs(x = "Engine displacement (litres)",
       y = "Highway miles per gallon",
       colour = "Cylinders",
       shape = "Cylinders",
       title = expression(~bold("Figure 1")),
       subtitle = expression(~italic("The relationship between MPG and Engine Displacement
  scale_colour_brewer(palette = "Dark2") +
  theme_classic()
```

One final plot

Code | The plot



Suggested reading

For practice of this week's concepts, see the RStudio.cloud Visualize Data primer.

For more general advice on plotting, see R4DS Chapters on Graphics for Communication and Data Visualization, and Kieran Healy's Data Visualization

To prepare for next week, read R4DS Chapter on Data transformation