An Introductory Workshop on Data Transformation, Statistics and Reporting with R

Evan Cortens and Stephen Childs

October 23, 2022

Introductions

Introductions

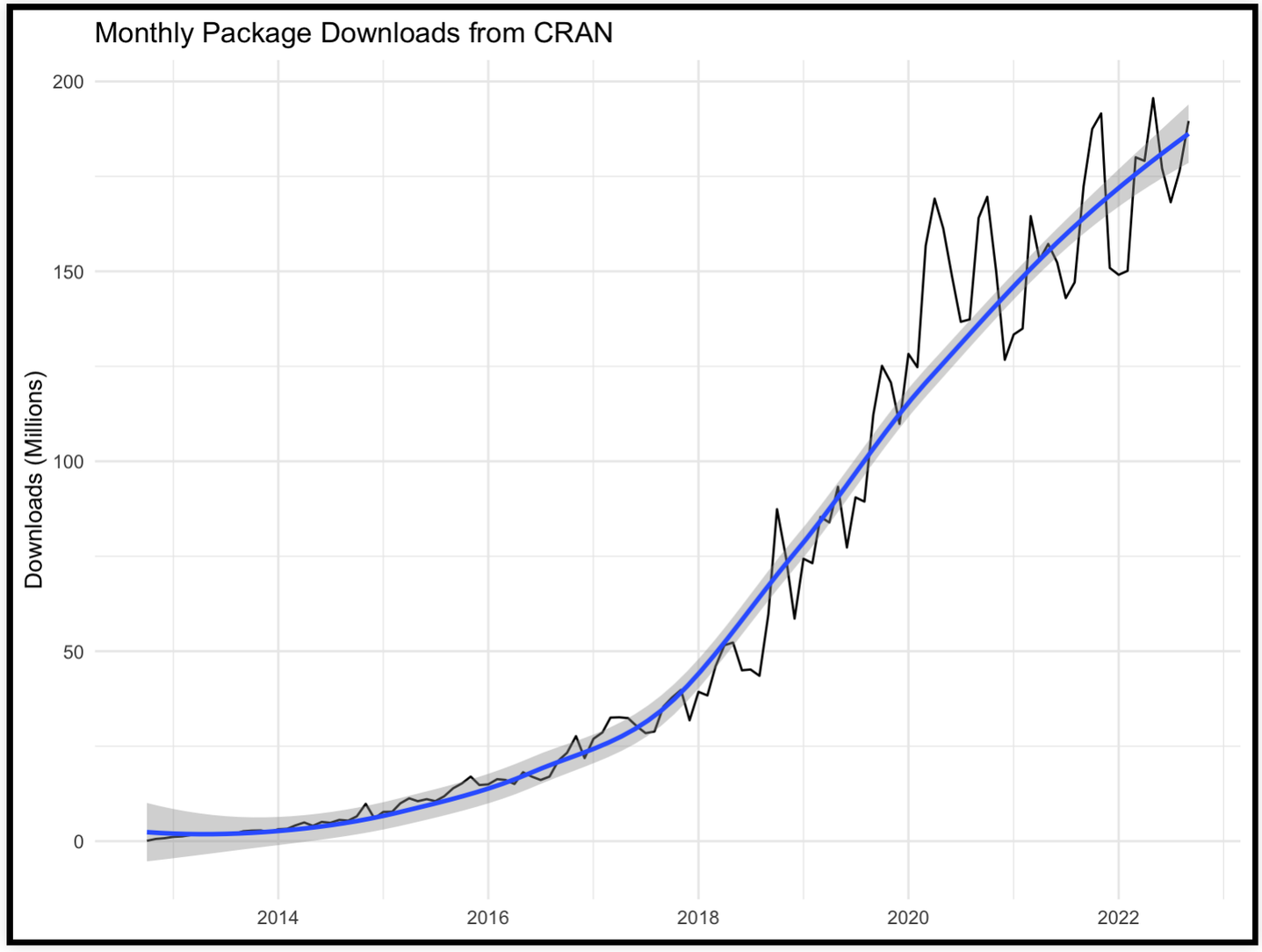
- Who are you/where do you work?
- What software/tools do you spend most time with? (Excel? SPSS? Tableau? etc)
- Do you have any programming experience? (Python? C? Javascript?)
- What do you hope to get out of this workshop? How do you see yourself using R in an IR environment?s

Why use R?

Why use R?

- Free
- Open-source
- A “statistical” programming language
  - Generally accepted by academic statisticians
  - Thoroughly grounded in statistical theory
- A great community
  - Help and support
  - Innovation and development
- R is a stable, well-supported language
  - Major corporate backing

Growing fast!



Some history

- Based on the S programming language
  - Dates from the late 1970s, substantially revised in the late 1980s
  - (there is still a commercial version, S-PLUS)
- R was first developed at the University of Auckland
  - Ross Ihaka and Robert Gentleman
  - First developed in 1993
  - Stable public release in 2000
- RStudio
  - IDE, generally recognized as high quality, even outside R
  - Development began in 2008, first public release in February 2011
    - Version 1.0 in Fall 2016
  - There have been other IDEs for R in the past, but since RStudio came on the scene, most are no longer seriously maintained

Some history

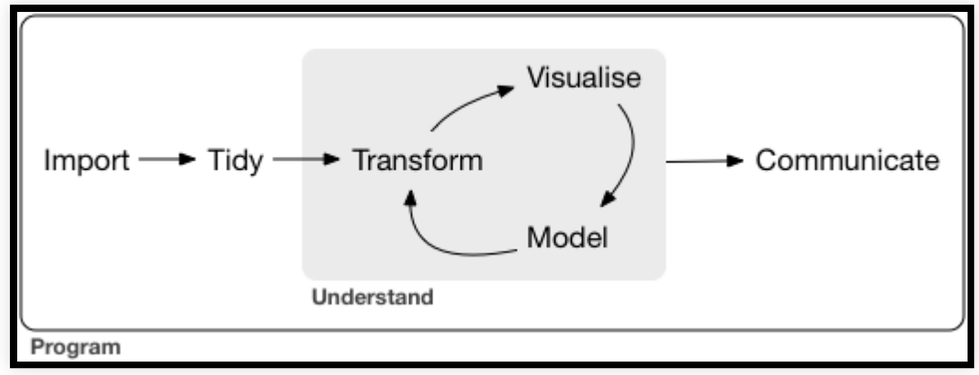
Why is this relevant?

- You'll likely notice some quirks in R that differ from other programming languages you make have worked in–the unique history often explains why.
- Explains R's position as a "statistical programming language":
  - Think stats/data first, programming second.

Today's approach / Learning outcomes

Today's approach/Learning outcomes

In learning R today, we'll take an approach, used in *R for Data Science* (Wickham & Grolemund, 2017), diagrammed like this:



One of the strengths of R: every step of this workflow can be done using it!

Import

- Loading the data!
- For IR-type tasks, this will generally be from data files or directly from databases.
- Other possibilities include web APIs, or even web scraping

Tidy

- "Tidy data" (Wickham, 2014)
  - Each column is a variable, each row is an observation.
- Doing this kind of work up front, right after loading, lets you focus on the modelling/analysis/visualization problem at hand, rather than having to rework your data at each stage of your analysis.

Transform / Visualize / Model

- Repeat these three steps as necessary:

Transform

- Together with tidying, sometimes called *data wrangling*
  - Filtering (selecting specific observations)
  - Mutating (creating new variables)
  - Summarizing (means, counts, etc)

Visualise

- For both exploratory purposes and production/communication

Model

- Complementary to visualisation
- For the “precise exploration” of “specific questions”

Communicate

- The final output, whether it's just for yourself, your colleagues, or a wider audience
- Increasingly, there's a trend toward "reproducible research" which integrates even the communication step (final paper, report, etc) into the code/analysis.

Housekeeping

Installing R and RStudio

- Instructions sent via email, links:
  - https://cran.rstudio.org/
  - https://www.rstudio.com/products/rstudio/download/#d
- `install.packages('tidyverse')`

Basic R

- An interpreted language (like Python)
- Code can be run as:
  - scripts (programatically / non-interactively)
  - from the prompt (interactively)
- R uses an REPL (Read-Evaluate-Print Loop) just like Python
  - Using R as a calculator (demonstration)

Outline

Outline

1. Visualisation
2. Transformation
3. Importing and ‘wrangling’
4. Modeling
5. Hands-on portion using what we’ve learned

Visualisation

Let's load the tidyverse package

```
library(tidyverse)
```

A package only needs to be *installed* once (per major version, e.g. 3.3.x to 3.4.x), but must be *loaded* every time.

The ‘mpg’ data set

Data on the fuel efficiency of 38 models of cars between 1999 and 2008 from the US EPA:

```
mpg
```

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

The Grammar of Graphics

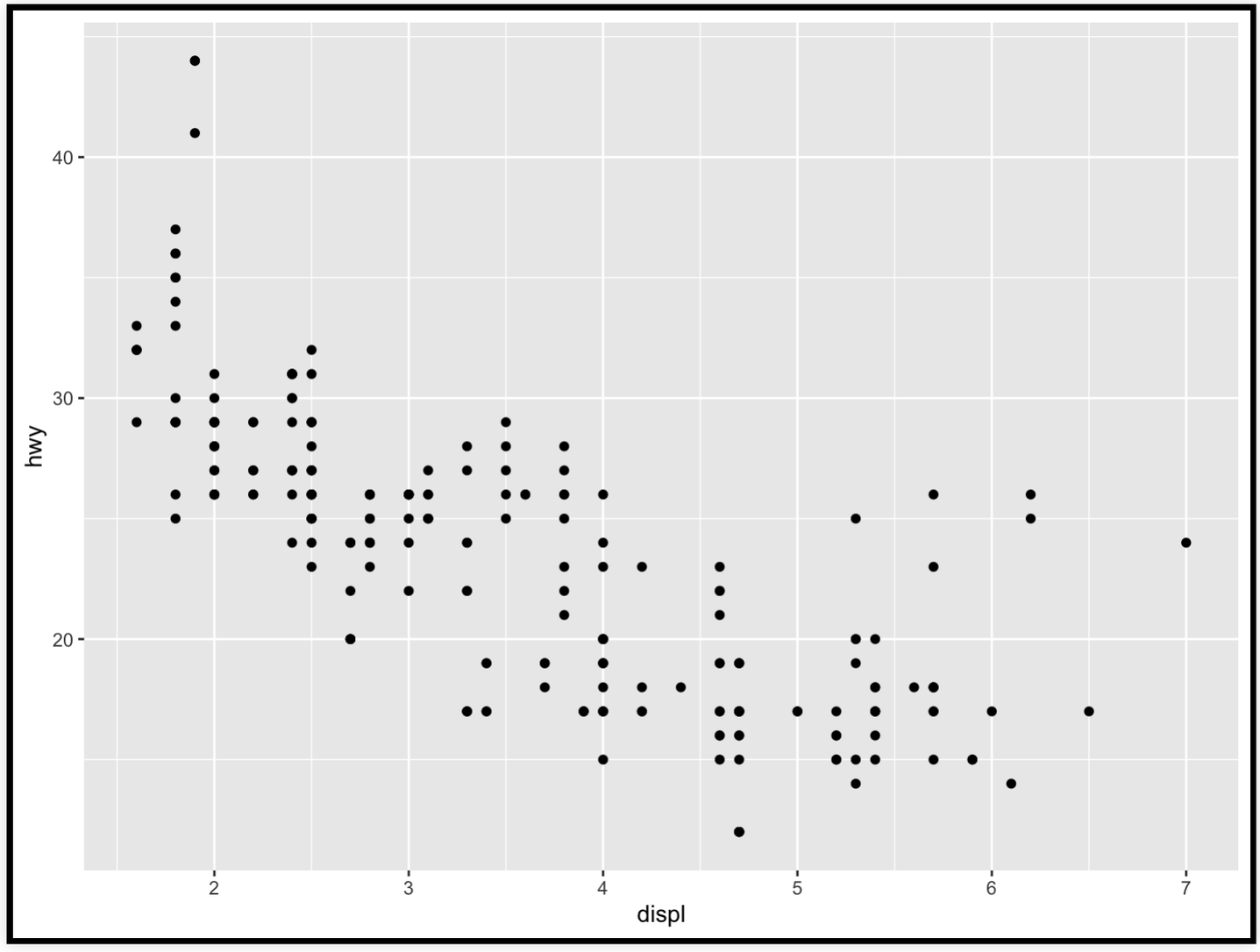
- Layers
- Inheritance
- Mapping (`aes`)

Our First Plot

- A car's highway mileage (mpg) vs its engine size (displacement in litres).
- What might the relationship be?

Our First Plot

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



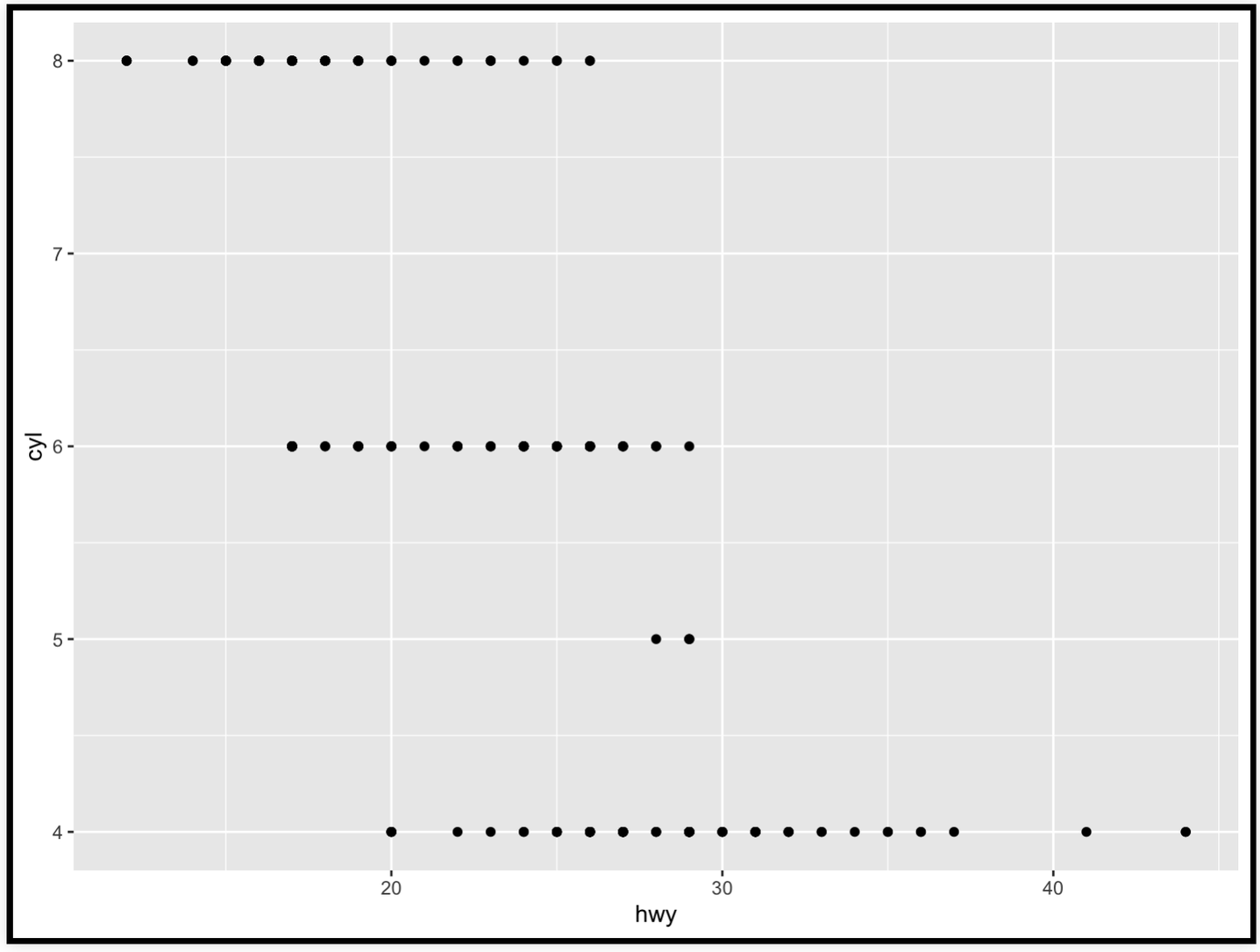
- As engine size increases, fuel efficiency decreases, roughly.

Exercises

- The first scatterplot was highway mileage vs displacement: how can we make it city mileage vs displacement?
- Make a scatterplot of `hwy` vs `cyl`.
- What about a scatterplot of `class` vs `drv`?

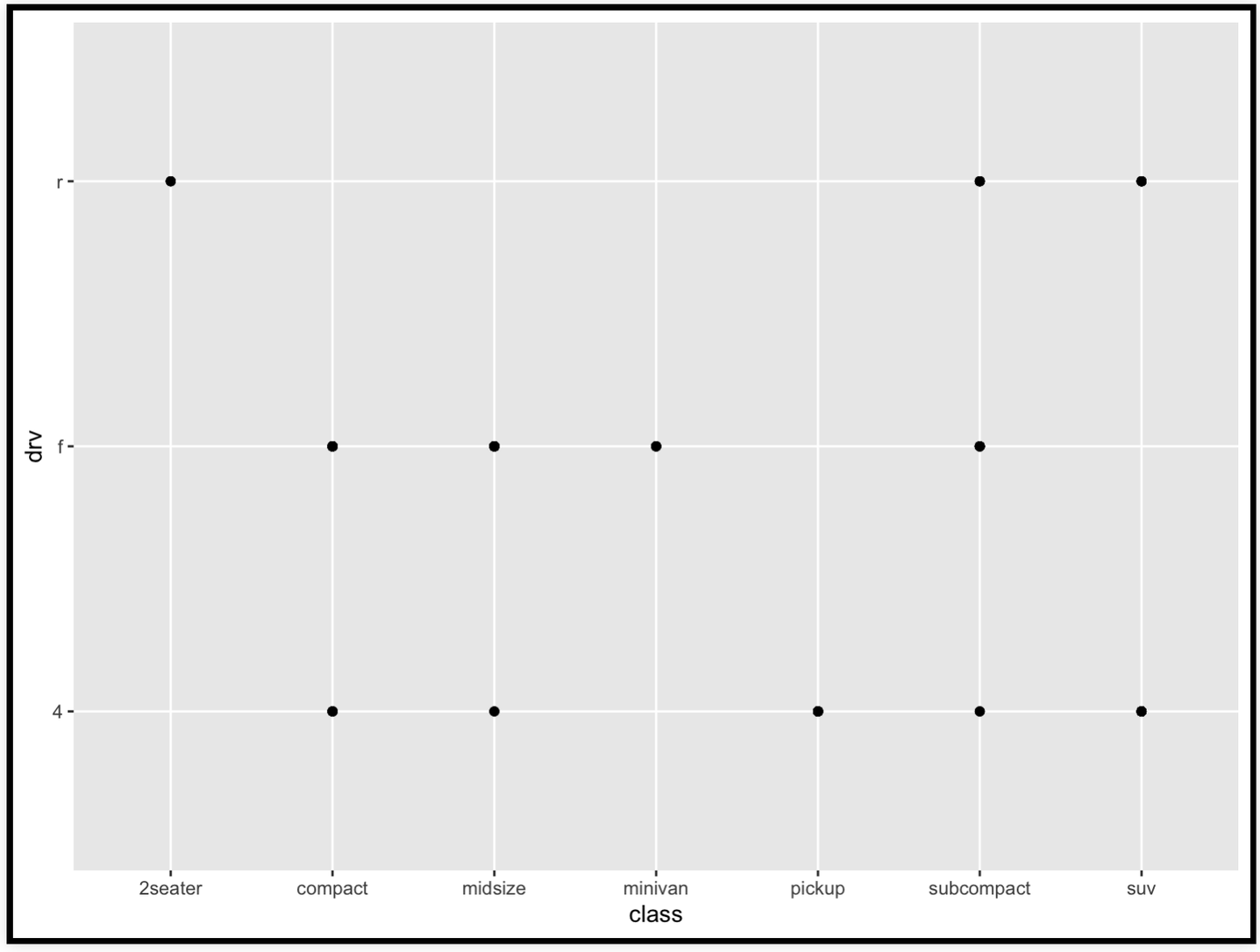
Hwy vs cyl

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



Class vs drv

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

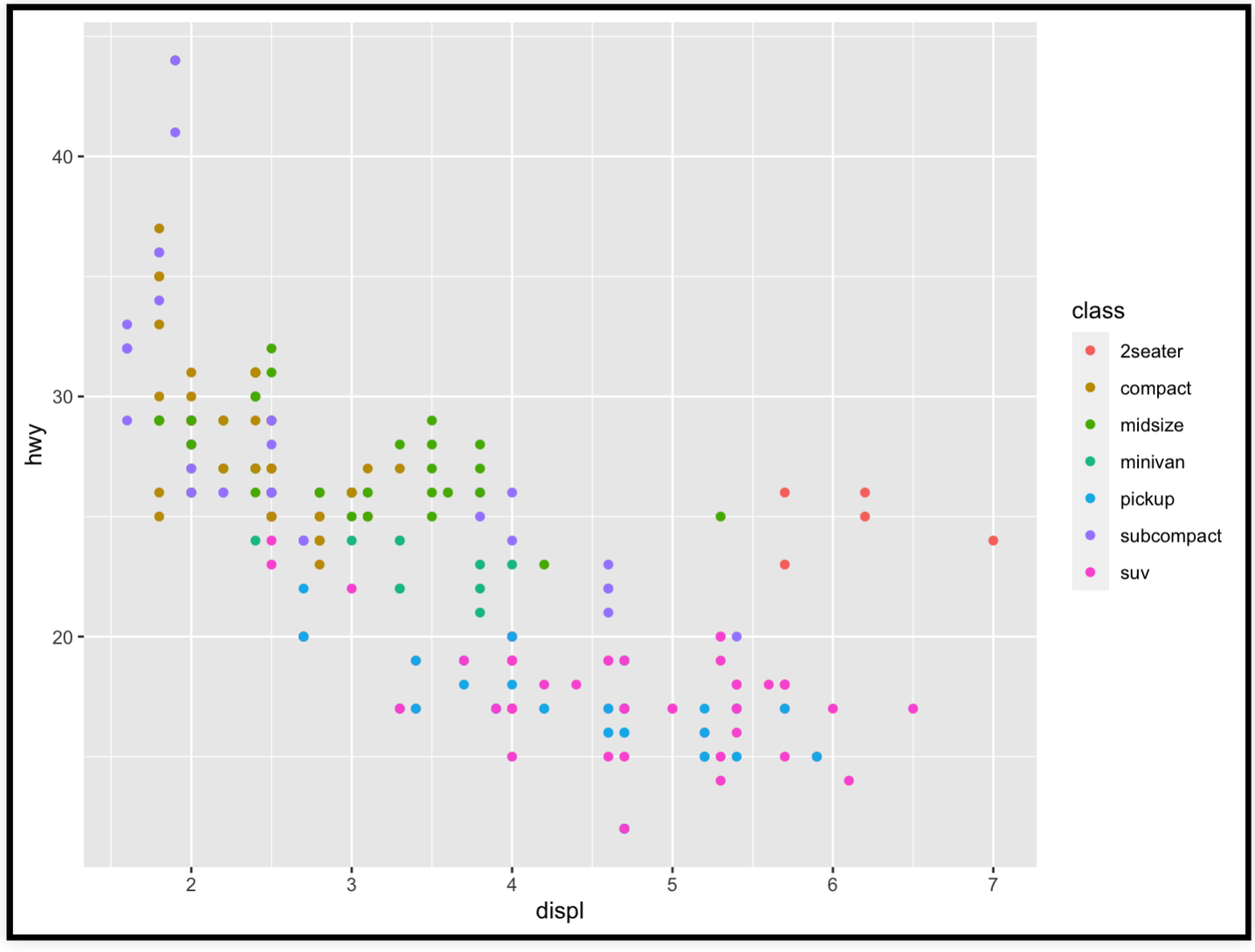


What's going on here? How might we make it more useful?

Additional aesthetics

What about those outliers? Use the `color` aesthetic.

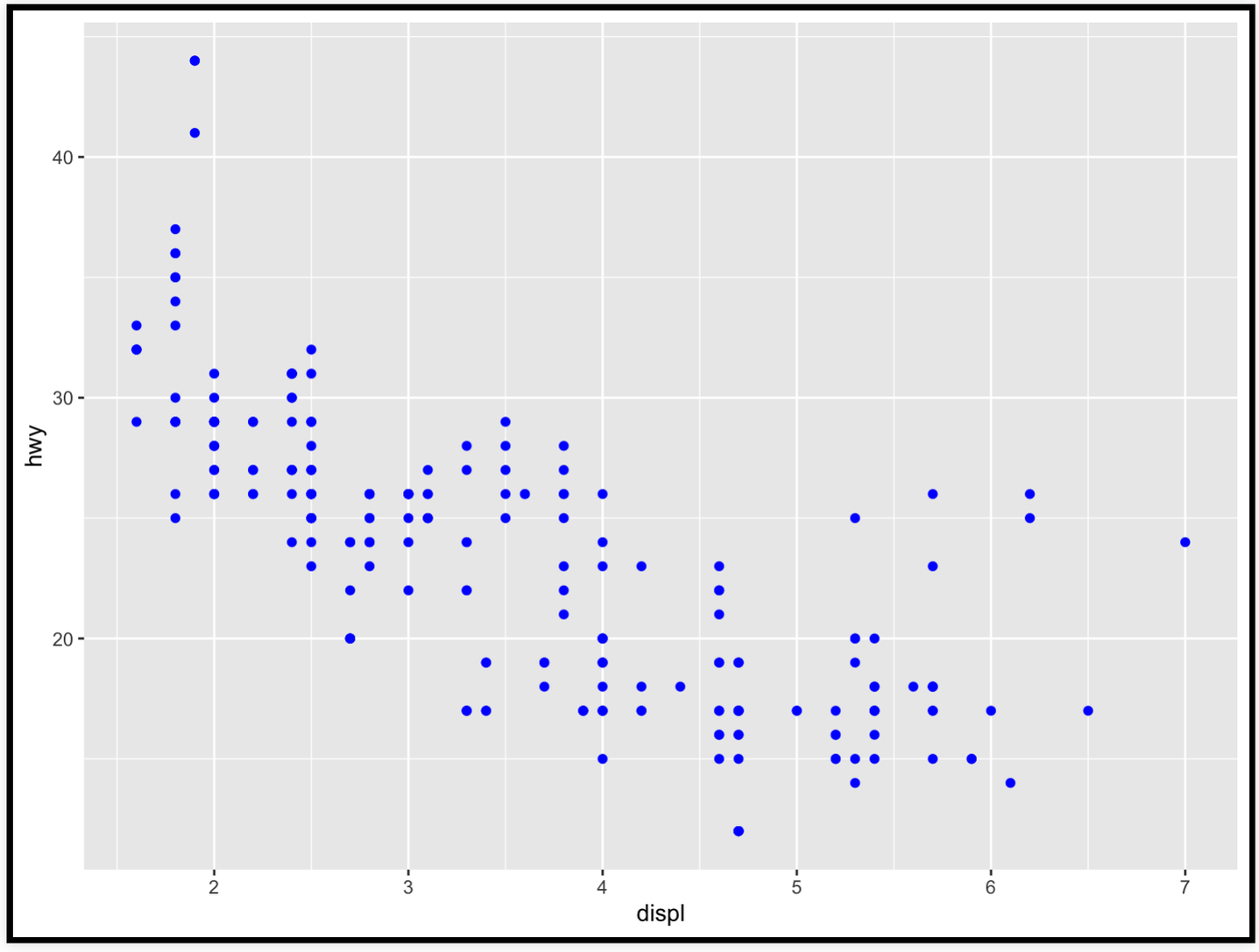
```
ggplot(data = mpg) +
  geom_point(mapping = aes(x = displ, y = hwy, color = class))
```



‘Unmapped’ aesthetics

What’s happening here?

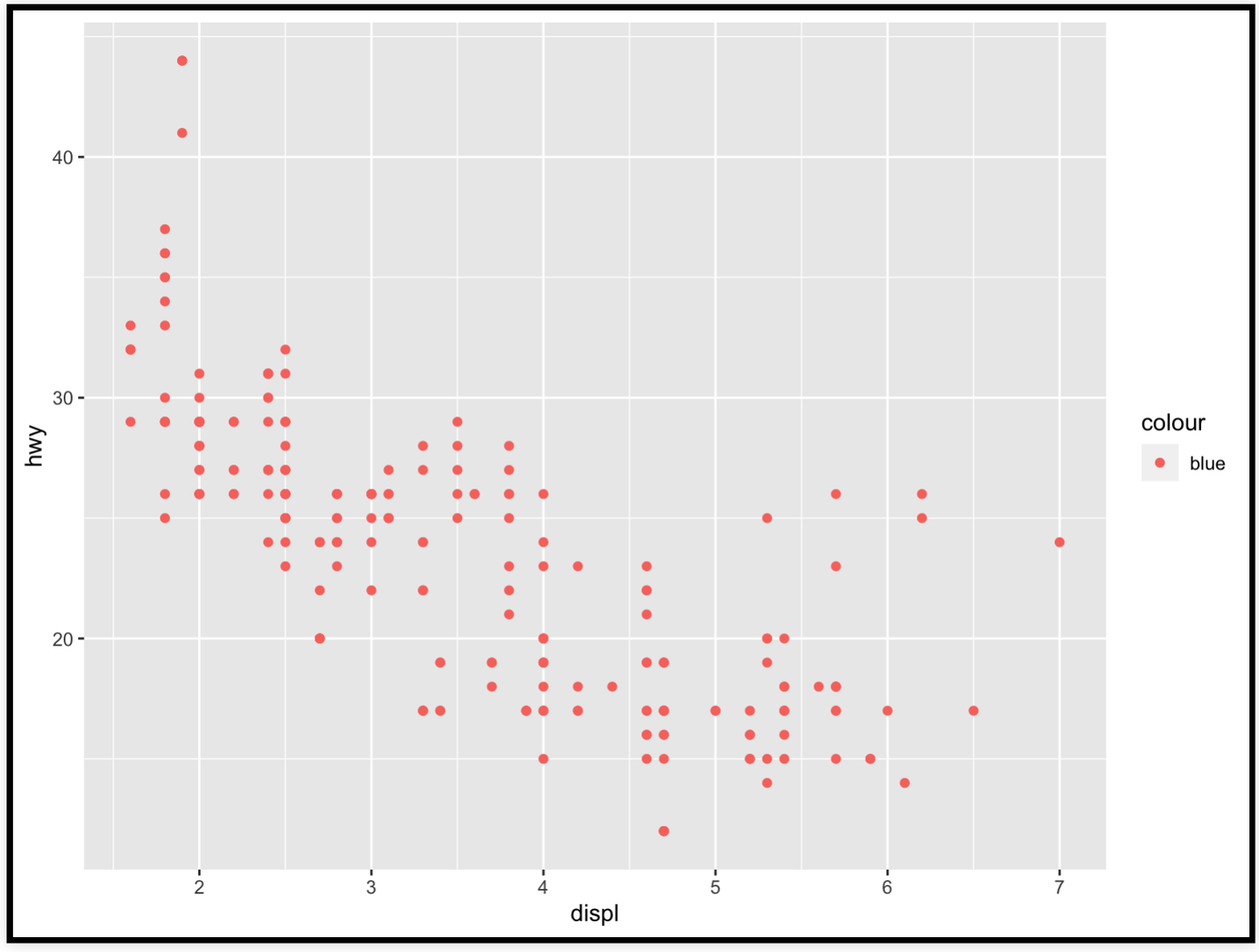
```
ggplot(data = mpg) +
  geom_point(mapping = aes(x = displ, y = hwy), color = "blue")
```



What's gone wrong?

What's happened here? What colour are the points? Why?

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

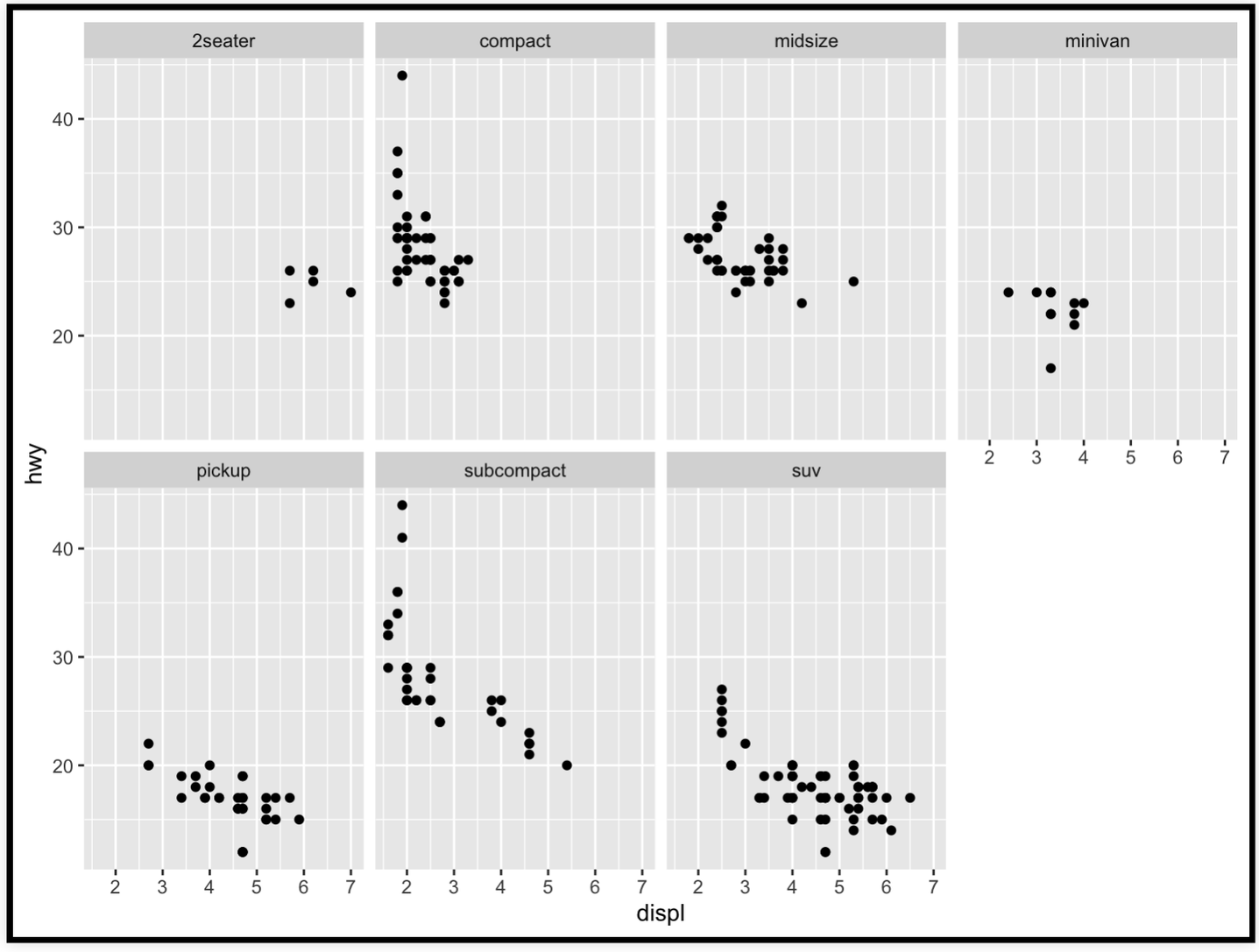


Exercises

- `mpg` variable types: which are categorical, which are continuous?
- `?mpg`
- Map a continuous variable to colour, size, and shape: how are these aesthetics different for categorical vs continuous?
- What happens if you map an aesthetic to something other than a variable name, like `aes(color = displ < 5)`?

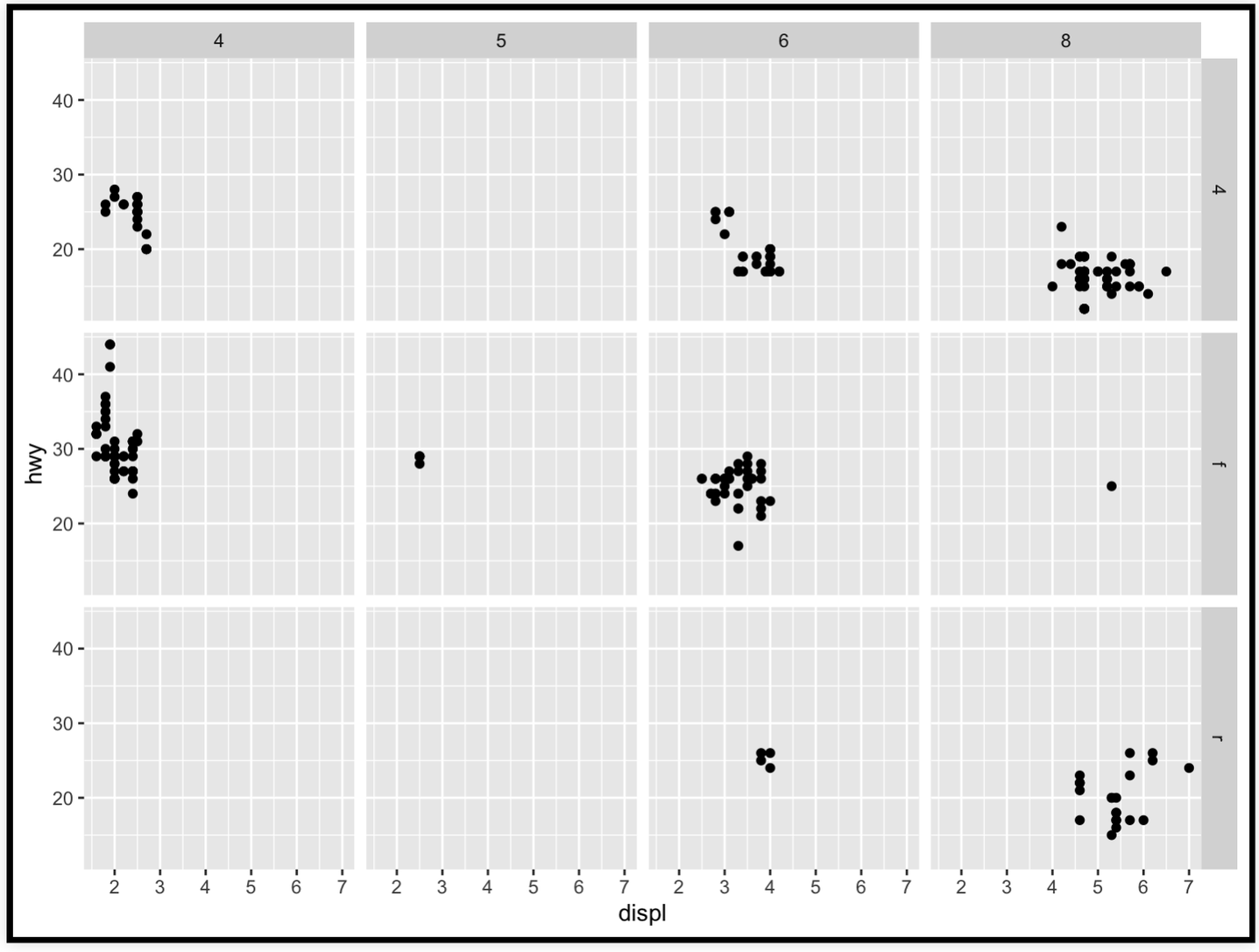
Facets: One Variable

```
ggplot(data = mpg) +
  geom_point(mapping = aes(x = displ, y = hwy)) +
  facet_wrap(~ class, nrow = 2)
```



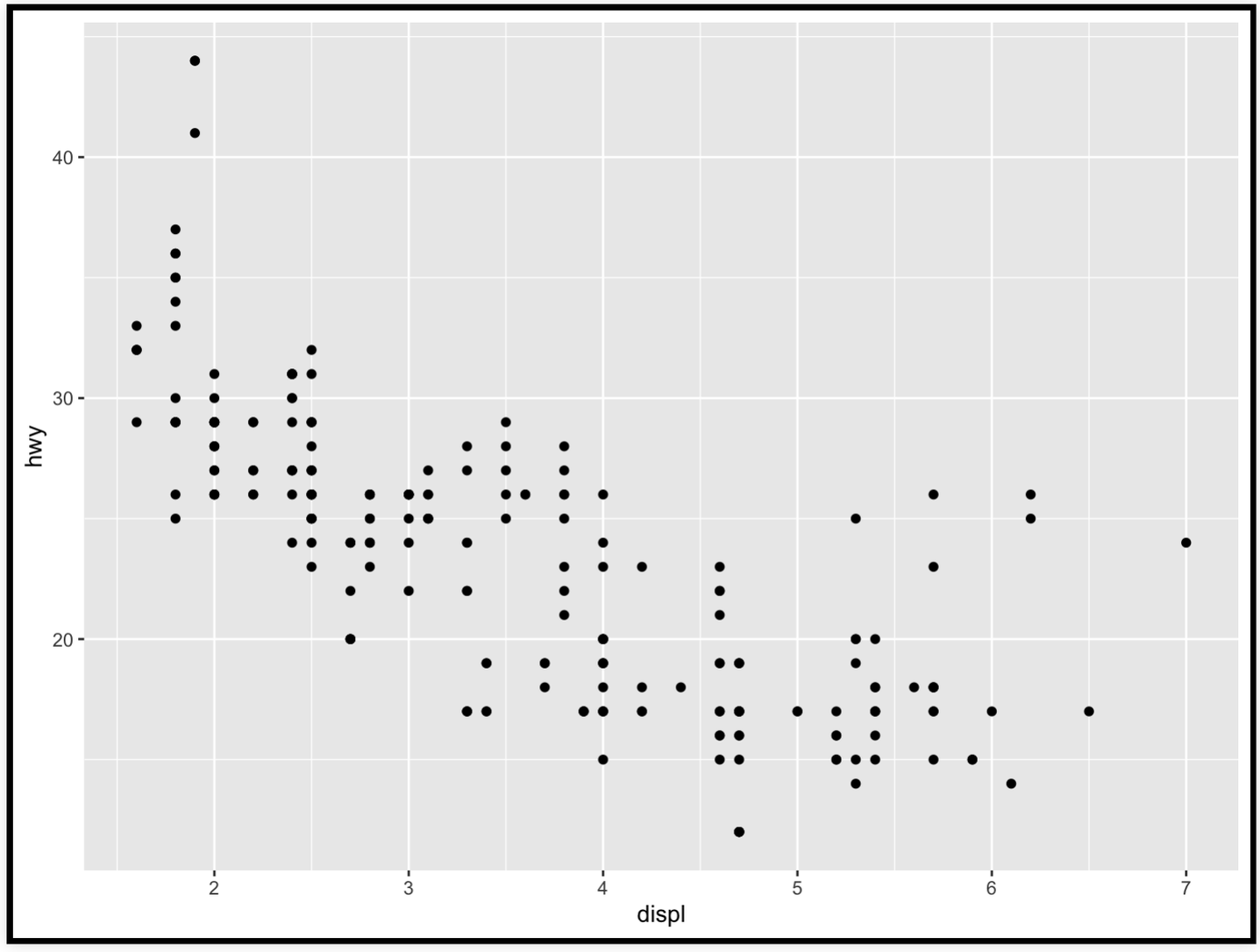
Facets: Two Variables

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



Other “geoms” (geometries)

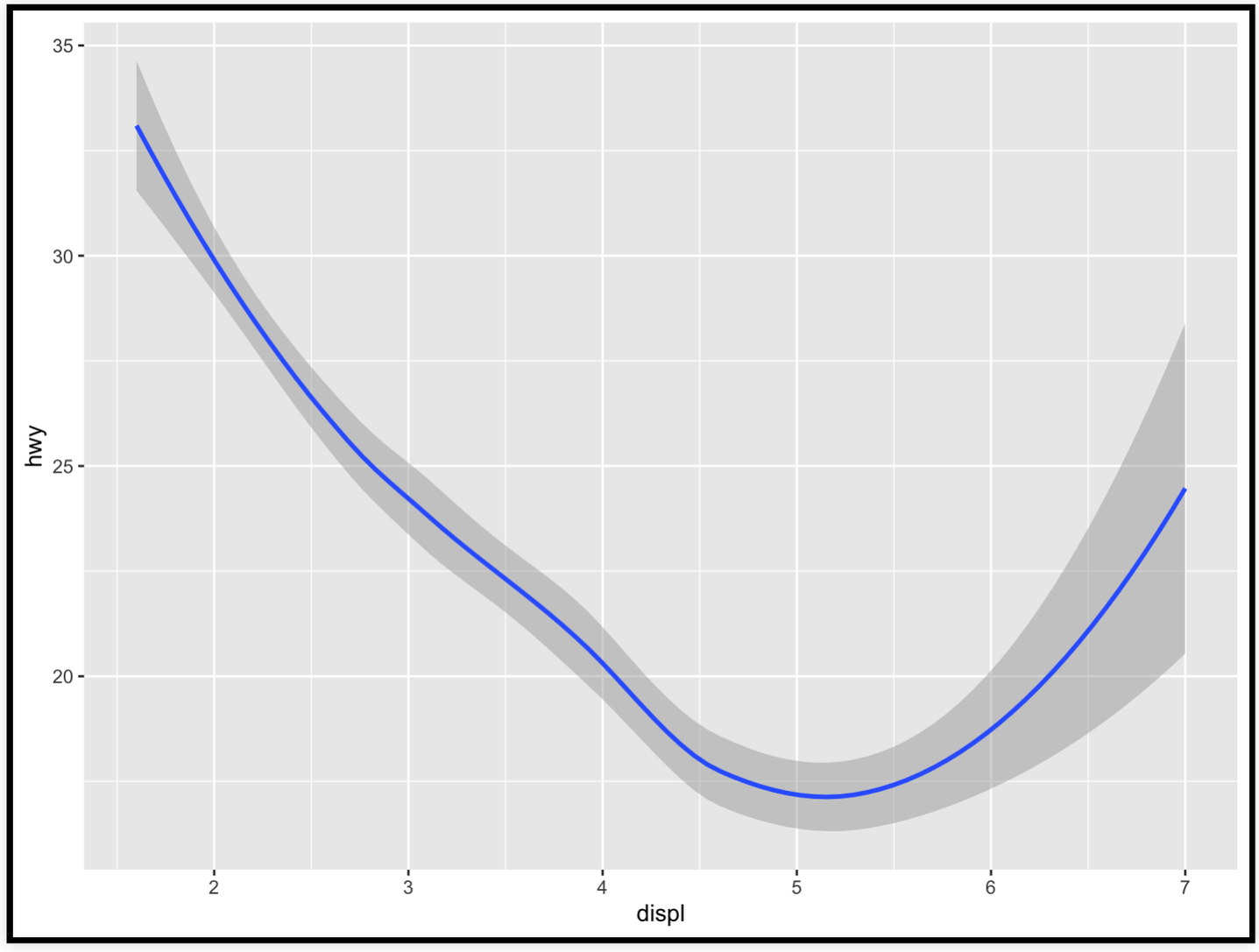
```
ggplot(data = mpg) +
  geom_point(mapping = aes(x = displ, y = hwy))
```



Smooth

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

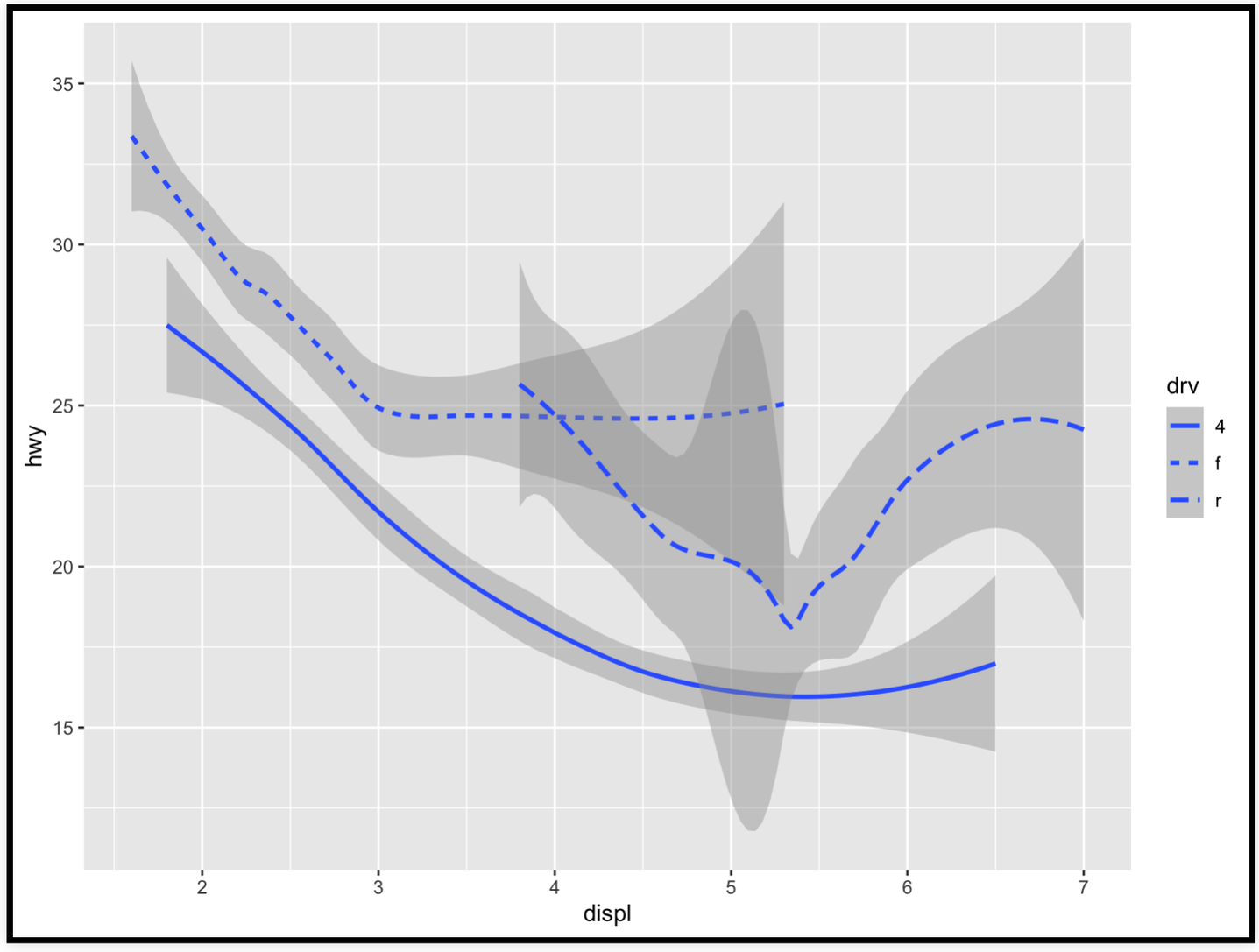
```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



Smooth aesthetics

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

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



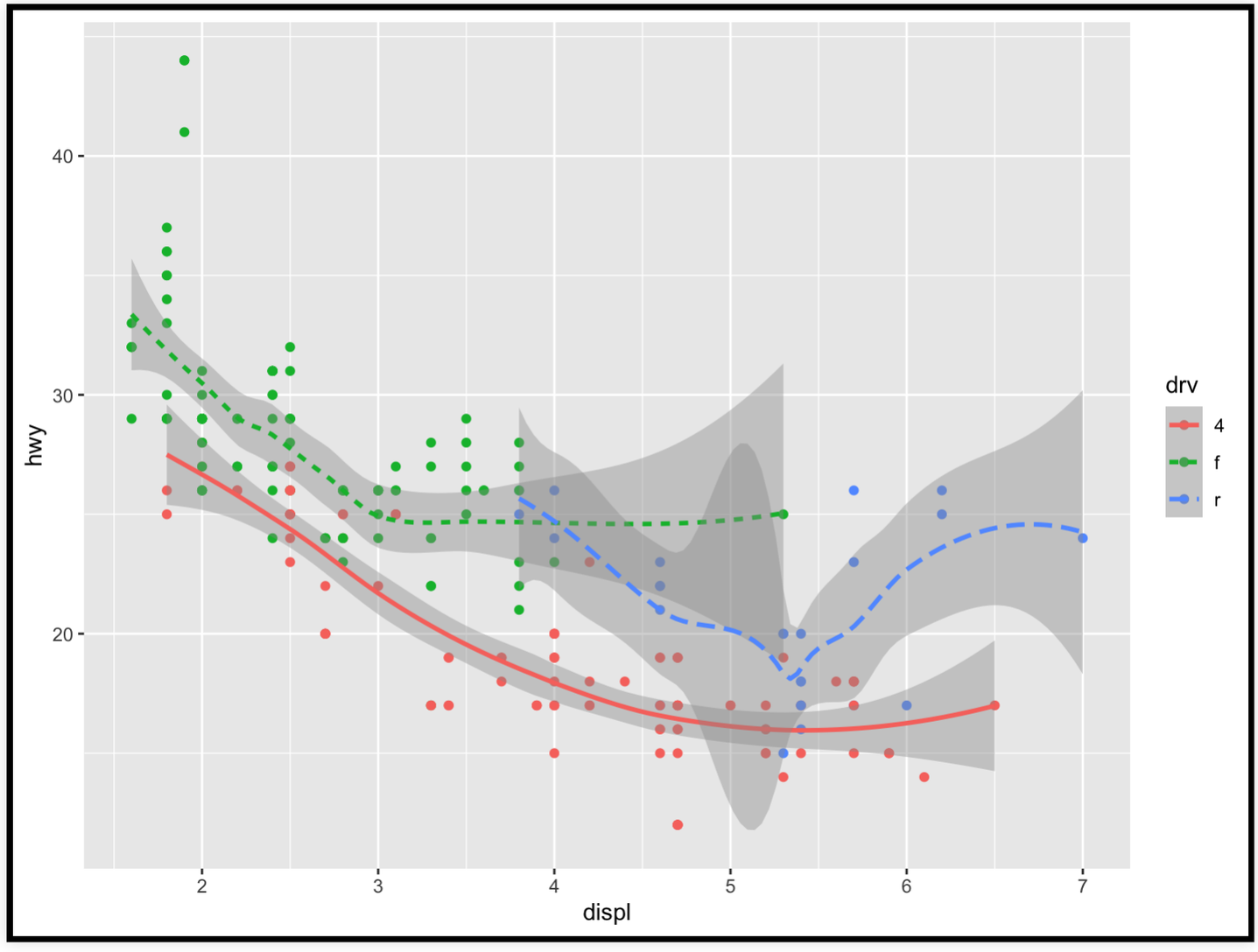
Which aesthetics do geoms have?

```
?geom_smooth
```

Clearer?

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

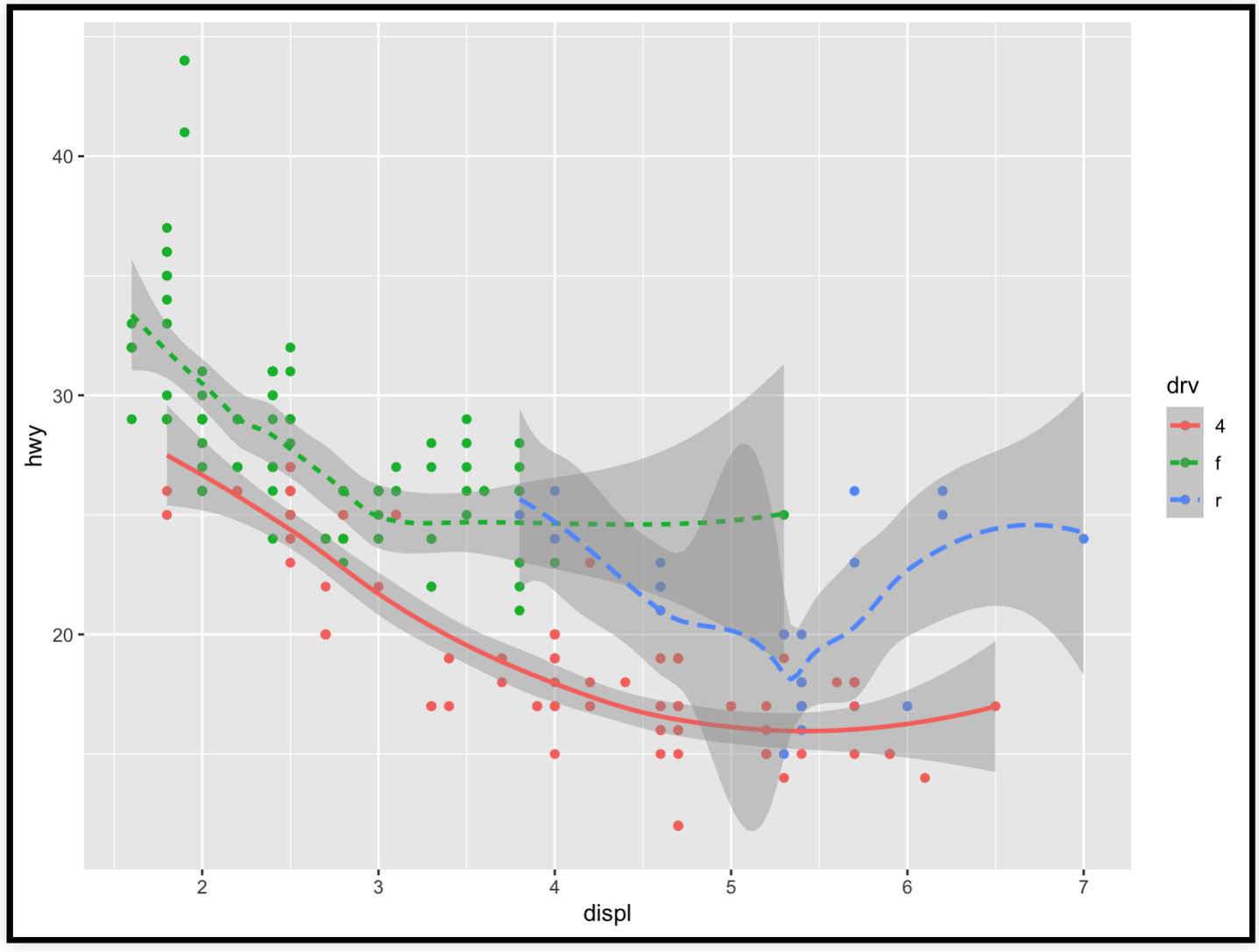
```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



Reducing Duplication

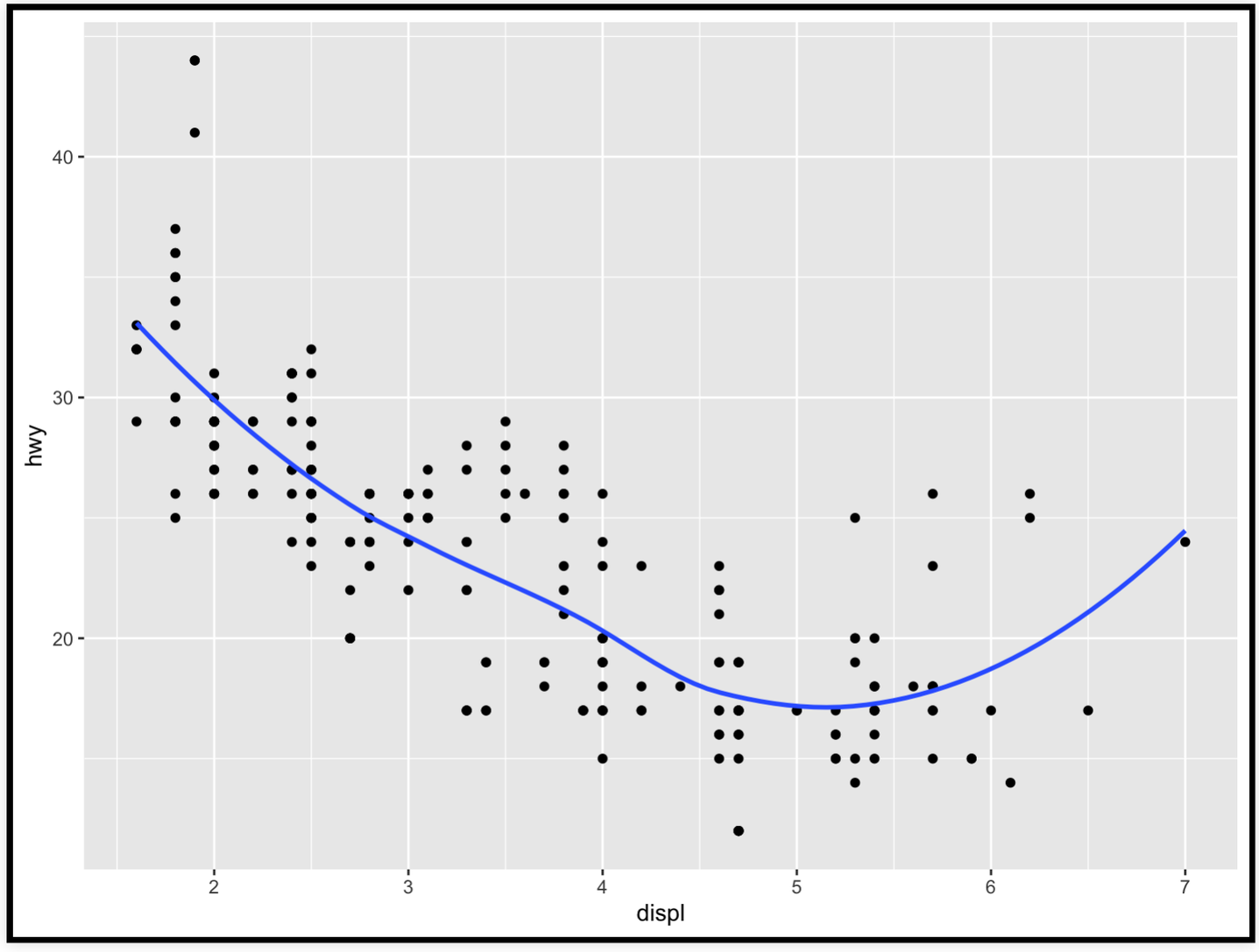
```
ggplot(data = mpg, mapping = aes(x = displ, y = hwy, color = drv)) +
  geom_point() +
  geom_smooth(mapping = aes(linetype = drv))
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



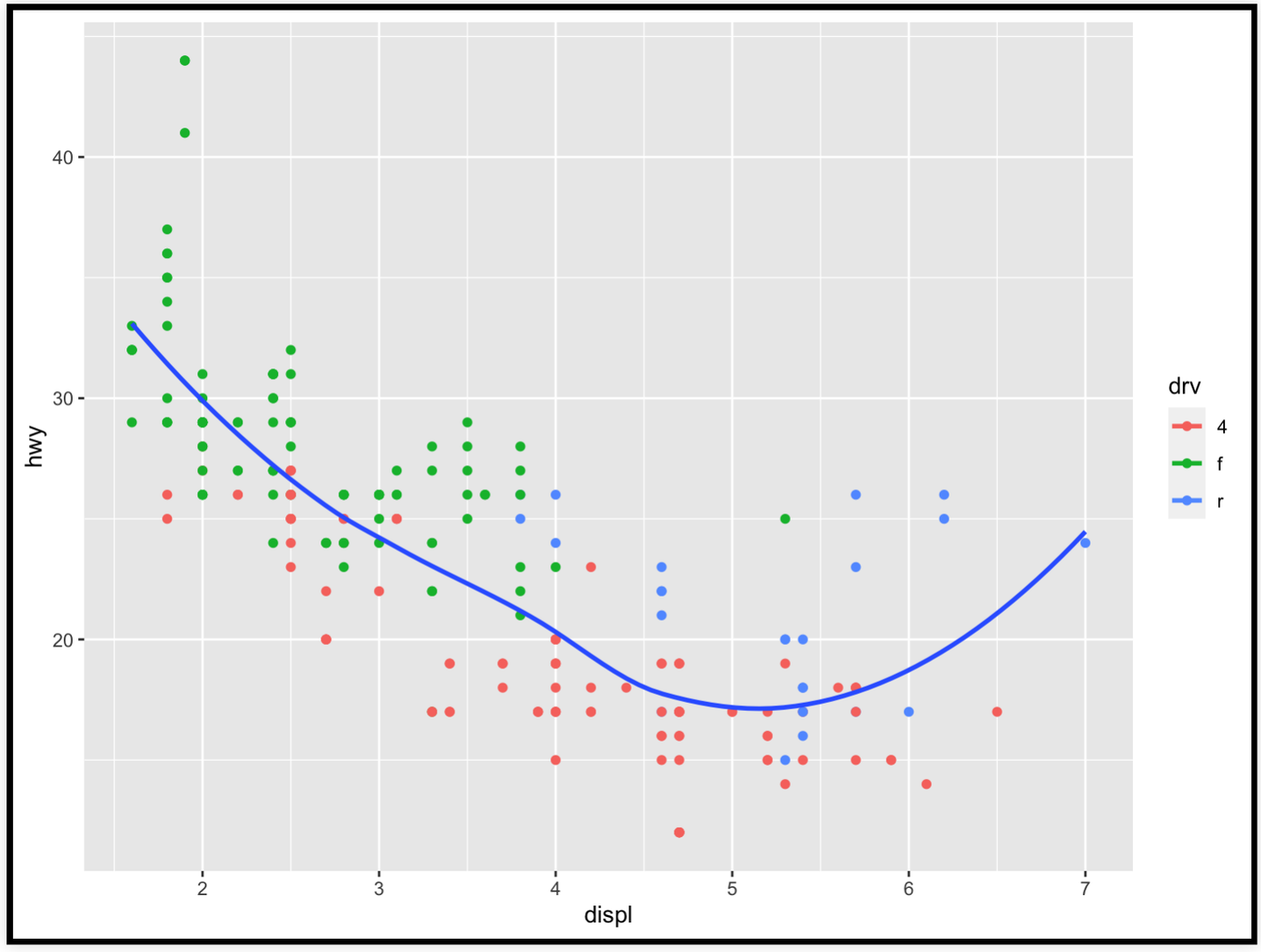
Exercise: Recreate:

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



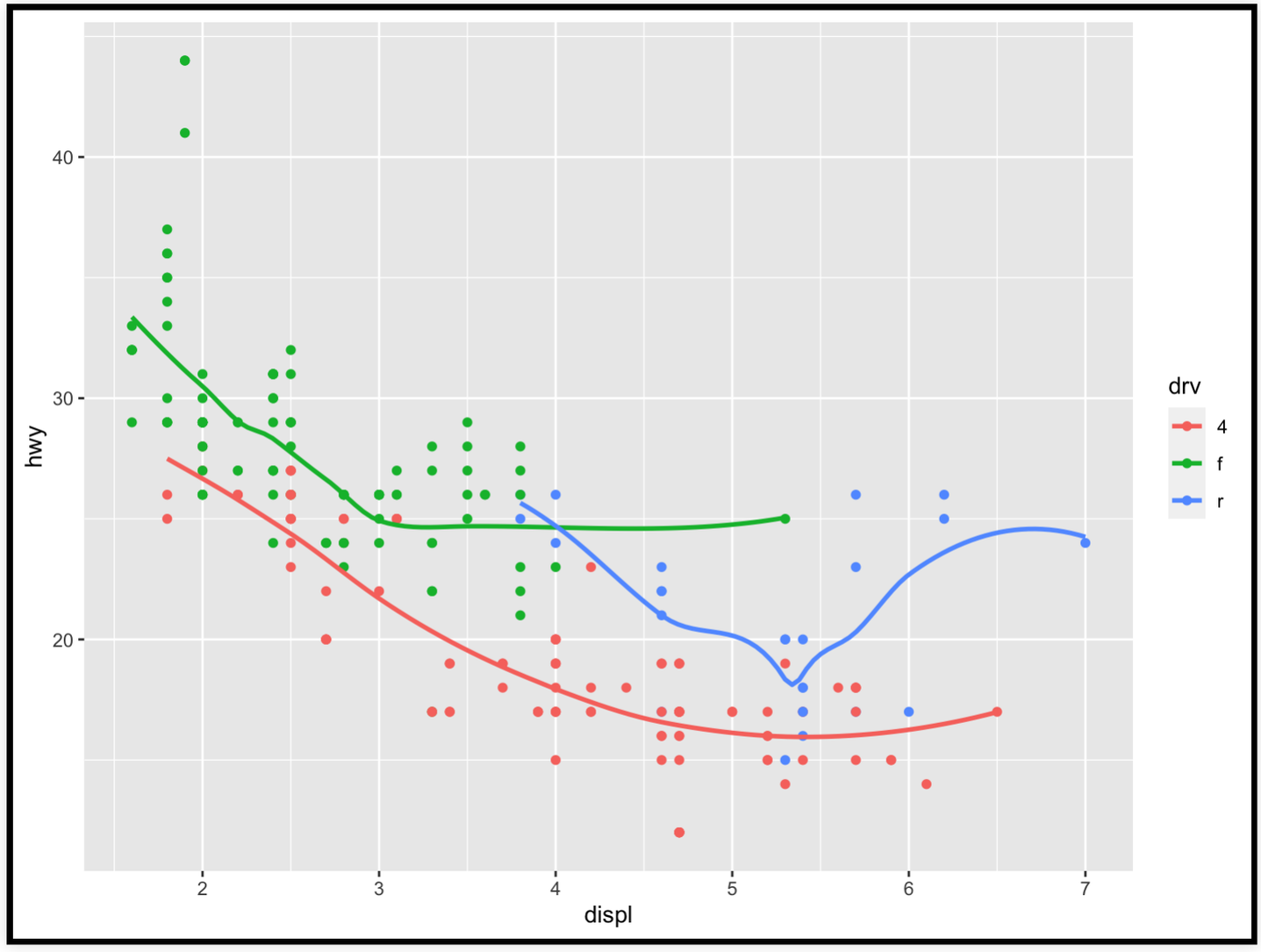
Exercise: Recreate:

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



Exercise: Recreate:

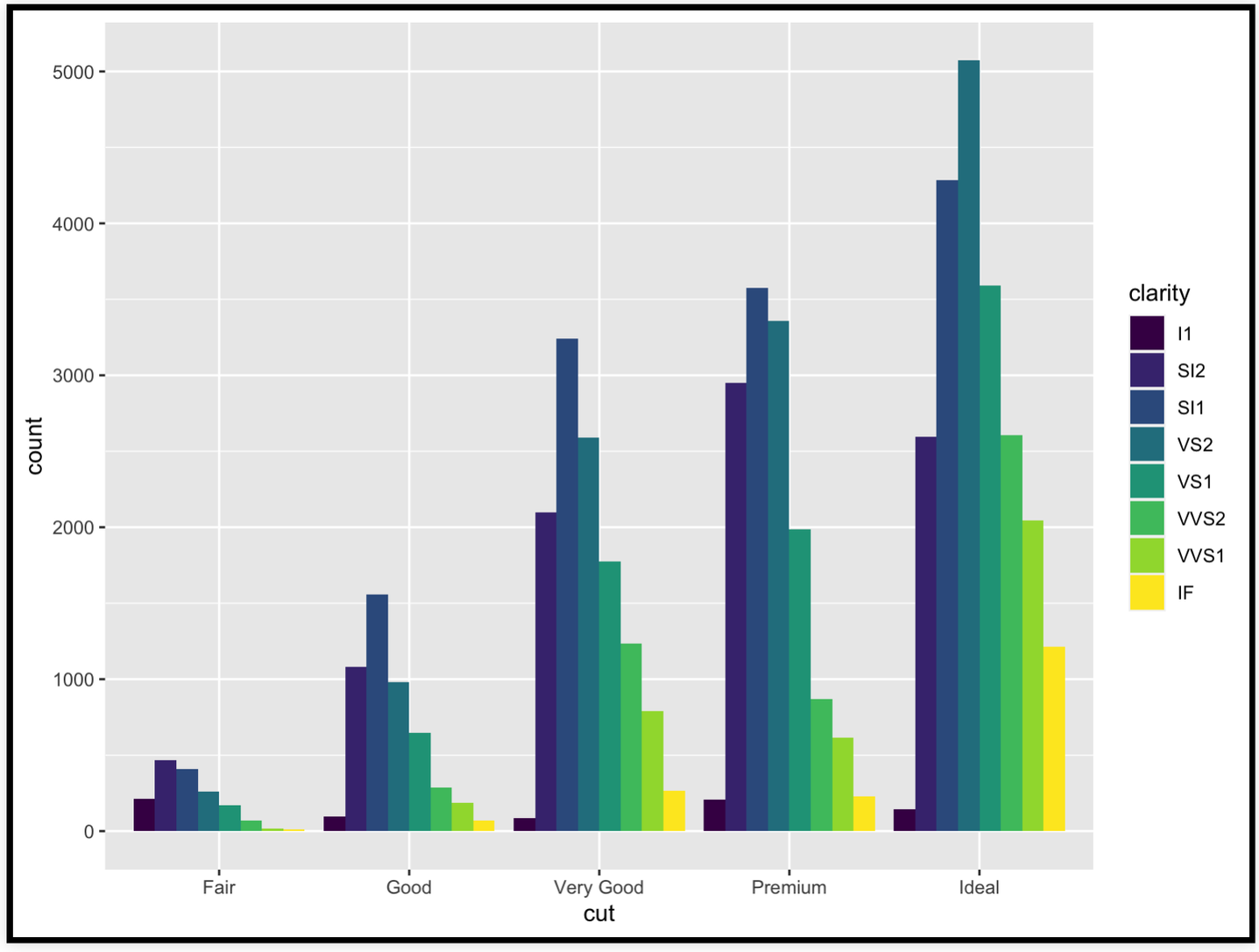
```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



One last visualization

A common scenario:

```
ggplot(data = diamonds) +
  geom_bar(mapping = aes(x = cut, fill = clarity), position = "dodge")
```



Coding basics

R as a calculator

```
1 / 200 * 30
```

```
## [1] 0.15
```

```
(59 + 73 + 2) / 3
```

```
## [1] 44.66667
```

```
sin(pi / 2)
```

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

Assignments

```
x <- 3 * 4
```

Calling functions

Calling R functions, in general:

```
function_name(arg1 = val1, arg2 = val2, ...)
```

An example function, `seq`:

```
seq(1, 10)
```

```
##  [1]  1  2  3  4  5  6  7  8  9 10
```

Data wrangling with `dplyr` and `tidyr` (`tidyverse`)

Create RStudio project

1. File | New Project…
2. New Directory
3. Empty Project
4. Under “Directory name:” put in “CIRPA 2022”, under “Create project as a subdirectory of:”, pick somewhere you’ll remember.
5. Click “Create Project”, and RStudio will refresh, with your new project loaded.

Download the data

We'll look at Statistics Canada CANSIM Table 0477-0058 which covers university revenues.

To save time, I've already downloaded the data from CANSIM. You can get it here:

https://evancortens.com/cirpa/04770058-eng.csv.gz

Load the data

We'll use `read_csv()` from `readr`, which I prefer to the base R function, as it has some more sensible defaults, and it's faster.

```
revenue_raw <- read_csv('04770058-eng.csv.gz')
```

```
## Rows: 122240 Columns: 8
## ── Column specification ────────────────────────────────────────────────────
## Delimiter: ","
## chr (7): Ref_Date, GEO, SCHOOL, REVENUE, FUND, Vector, Coordinate
## dbl (1): Value
##
## ℹ Use `spec()` to retrieve the full column specification for this data.
## ℹ Specify the column types or set `show_col_types = FALSE` to quiet this
```

The `read_csv()` function tells us that it guessed the types of the various columns. In this situation, the default guesses are fine, but of course we can force it to treat columns certain ways if we wish.

What does the data look like?

```
revenue_raw
```

```
## # A tibble: 122,240 × 8
##    Ref_Date  GEO    SCHOOL                          REVENUE FUND  Vector Coord…¹
##    <chr>     <chr>  <chr>                           <chr>   <chr> <chr>  <chr>
##  1 2000/2001 Canada Total universities and … Total … Tota… v8070… 1.1.1.1
##  2 2001/2002 Canada Total universities and … Total … Tota… v8070… 1.1.1.1
##  3 2002/2003 Canada Total universities and … Total … Tota… v8070… 1.1.1.1
##  4 2003/2004 Canada Total universities and … Total … Tota… v8070… 1.1.1.1
##  5 2004/2005 Canada Total universities and … Total … Tota… v8070… 1.1.1.1
##  6 2005/2006 Canada Total universities and … Total … Tota… v8070… 1.1.1.1
##  7 2006/2007 Canada Total universities and … Total … Tota… v8070… 1.1.1.1
##  8 2007/2008 Canada Total universities and … Total … Tota… v8070… 1.1.1.1
##  9 2008/2009 Canada Total universities and … Total … Tota… v8070… 1.1.1.1
## 10 2009/2010 Canada Total universities and … Total … Tota… v8070… 1.1.1.1
## # … with 122,230 more rows, and abbreviated variable name ¹Coordinate
```

We have 8 columns and 122,240 rows of data. `read_csv()` brings the data in as a `tibble`, which is just an R "data frame", but with some handy defaults, some of which we're seeing here. For instance, it gives us the size of the data frame in rows and columns, the types of the columns (e.g., "<chr>" for character) and only prints the first 10 rows, instead of overwhelming us with all of the data.

What does the data look like?

```
View(revenue_raw) # in RStudio
```

Or click the icon in the `Environment` tab.

What does the data look like?

```
head(revenue_raw, 1) # show just the first row
```

- *Ref_Date*: fiscal year
- *GEO*: province or whole country
- *SCHOOL*: Direct participation in CAUBO survey, or via Statistics Canada, or combined (we'll just look at this)
- *REVENUE*: Type of income (e.g., tuition, provincial government, SSHRC, etc)
- *FUND*: Classification of income "in accordance with activities or objectives as specified by donors, … regulations, restrictions, or limitations" (We're just going to look at "Total funds (x 1,000)", but the distinctions are important for full analysis)
- *Vector*: a CANSIM unique identifier
- *Coordinate*: ditto
- *Value*: the actual dollar value (x 1,000, per the FUND heading)

What makes data “tidy”?

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

(See Wickham, 2014 and *R for Data Science*, chapter 12)

Is the CANSIM data tidy?

- Nope! So let’s tidy it.

dplyr basics

- Pick observations by their values (`filter()`).
- Reorder the rows (`arrange()`).
- Pick variables by their names (`select()`).
- Create new variables with functions of existing variables (`mutate()`).
- Collapse many values down to a single summary (`summarise()`).
- All can be used in conjunction with `group_by()`

dplyr cheat sheet

https://www.rstudio.com/resources/cheatsheets/

(or Help | Cheatsheets in RStudio!)

`filter()` the rows we want

```
filter(revenue_raw,
       SCHOOL == 'Total universities and colleges',
       FUND == 'Total funds (x 1,000)')
```

```
## # A tibble: 5,632 × 8
##    Ref_Date  GEO    SCHOOL                        REVENUE FUND  Vector Coord…¹
##    <chr>     <chr>  <chr>                         <chr>   <chr> <chr>  <chr>
##  1 2000/2001 Canada Total universities and colle… Total … Tota… v8070… 1.1.1.1
##  2 2001/2002 Canada Total universities and colle… Total … Tota… v8070… 1.1.1.1
##  3 2002/2003 Canada Total universities and colle… Total … Tota… v8070… 1.1.1.1
##  4 2003/2004 Canada Total universities and colle… Total … Tota… v8070… 1.1.1.1
##  5 2004/2005 Canada Total universities and colle… Total … Tota… v8070… 1.1.1.1
##  6 2005/2006 Canada Total universities and colle… Total … Tota… v8070… 1.1.1.1
##  7 2006/2007 Canada Total universities and colle… Total … Tota… v8070… 1.1.1.1
##  8 2007/2008 Canada Total universities and colle… Total … Tota… v8070… 1.1.1.1
##  9 2008/2009 Canada Total universities and colle… Total … Tota… v8070… 1.1.1.1
## 10 2009/2010 Canada Total universities and colle… Total … Tota… v8070… 1.1.1.1
## # … with 5,622 more rows, and abbreviated variable name ¹Coordinate
```

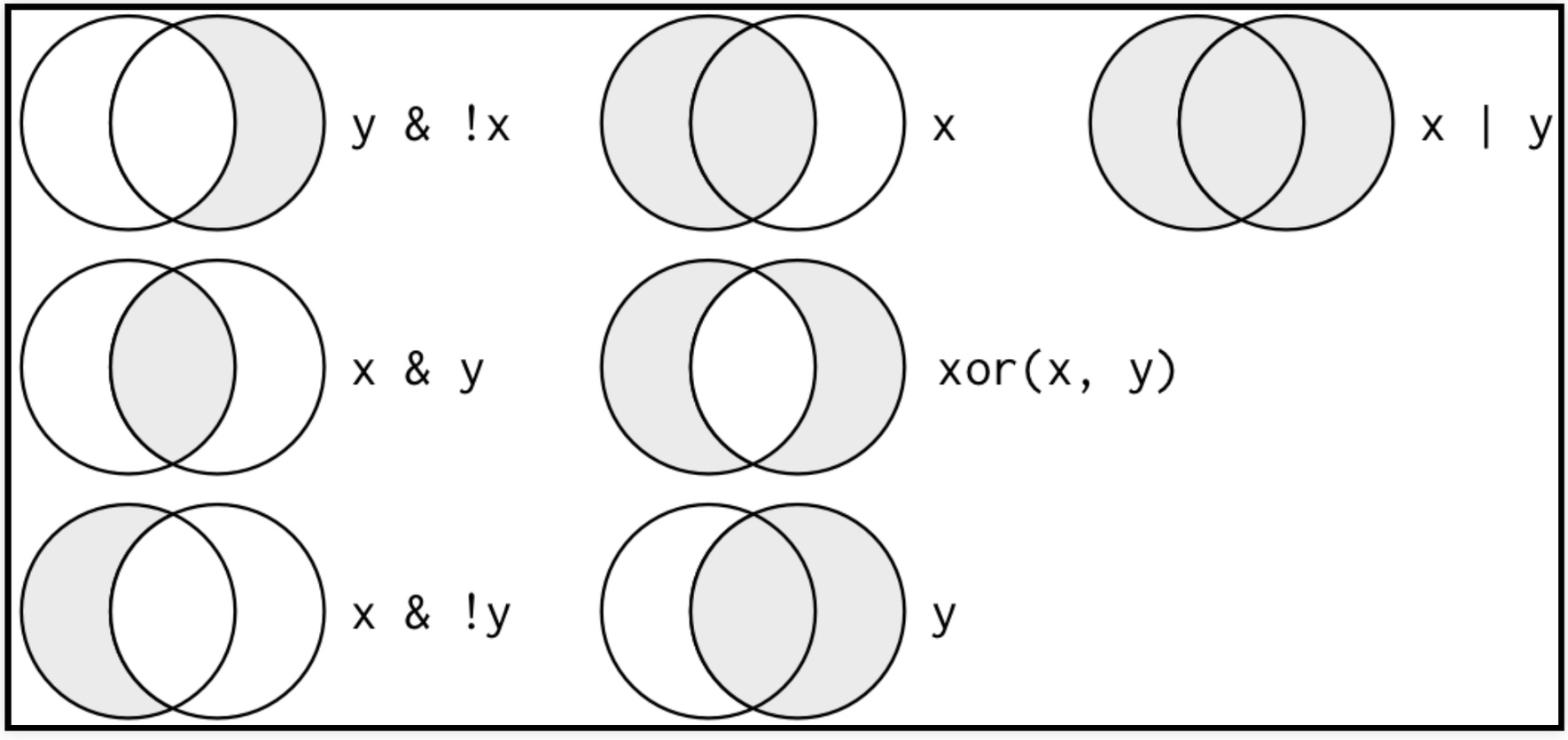
`filter()` help tells us that everything after the first argument (i.e., the "…") are: "Logical predicates defined in terms of the variables in .data. Multiple conditions are combined with &."

Comparison operators

```
>   # greater than
>=  # greater than or equal to
<   # less than
<=  # less than or equal to
!=  # not equal
==  # equal

%in% # not quite a comparison operator, but handy
     # x %in% y is true if the values of vector x are present in vector y
```

Logical operators

Other operators we can use with `filter()`:



Complete set of boolean operations. `x` is the left-hand circle, `y` is the right-hand circle, and the shaded regions show which parts each operator selects.

filter()

In other words, the previous command is equivalent to this:

```
filter(revenue_raw,
       SCHOOL == 'Total universities and colleges' &
         FUND == 'Total funds (x 1,000)')
```

```
## # A tibble: 5,632 × 8
##    Ref_Date  GEO    SCHOOL                          REVENUE FUND  Vector Coord…¹
##    <chr>     <chr>  <chr>                           <chr>   <chr> <chr>  <chr>
##  1 2000/2001 Canada Total universities and colleges Total … Tota… v8070… 1.1.1.1
##  2 2001/2002 Canada Total universities and colleges Total … Tota… v8070… 1.1.1.1
##  3 2002/2003 Canada Total universities and colleges Total … Tota… v8070… 1.1.1.1
##  4 2003/2004 Canada Total universities and colleges Total … Tota… v8070… 1.1.1.1
##  5 2004/2005 Canada Total universities and colleges Total … Tota… v8070… 1.1.1.1
##  6 2005/2006 Canada Total universities and colleges Total … Tota… v8070… 1.1.1.1
##  7 2006/2007 Canada Total universities and colleges Total … Tota… v8070… 1.1.1.1
##  8 2007/2008 Canada Total universities and colleges Total … Tota… v8070… 1.1.1.1
##  9 2008/2009 Canada Total universities and colleges Total … Tota… v8070… 1.1.1.1
## 10 2009/2010 Canada Total universities and colleges Total … Tota… v8070… 1.1.1.1
## # … with 5,622 more rows, and abbreviated variable name ¹Coordinate
```

I prefer this notation, as it's more explicit.

`filter()`

But, one more thing: we need to assign the return value of the `filter()` function back to a variable:

```
revenue <- filter(revenue_raw,
                  SCHOOL == 'Total universities and colleges' &
                    FUND == 'Total funds (x 1,000)')
```

Shortcut for assignment operator: Alt-Hyphen in RStudio

Combining operations

A new variable for each step gets cumbersome, so `dplyr` provides an operator, the pipe (`%>%`) that combines operations:

```
revenue_long <- revenue_raw %>%
  # only rows matching this
  filter(SCHOOL == 'Total universities and colleges' &
                   FUND == 'Total funds (x 1,000)') %>%
  # remove these columns
  select(-SCHOOL, -FUND, -Vector, -Coordinate) %>%
  # fix up the date column
  mutate(Ref_Date = as.integer(stringr::str_sub(Ref_Date, 1, 4)))
```

`x %>% f(y)` turns into `f(x, y)`, and
`x %>% f(y) %>% g(z)` turns into `g(f(x, y), z)` etc.

Shortcut for pipe operator: Ctrl-Shift-M or Cmd-Shift-M in RStudio

```
head(revenue_long, 1) # looks good so far!
```

```
## # A tibble: 1 × 4
##   Ref_Date GEO    REVENUE           Value
##      <int> <chr>  <chr>             <dbl>
## 1     2000 Canada Total revenues 16224715
```

Select helper functions

- There are a number of helper functions you can use within select():
  - `starts_with("abc")`: matches names that begin with "abc".
  - `ends_with("xyz")`: matches names that end with "xyz".
  - `contains("ijk")`: matches names that contain "ijk".
  - `matches("(.)\\1")`: selects variables that match a regular expression.
  - `num_range("x", 1:3)`: matches x1, x2 and x3.
  - `all_of(vector)`: all of the columns in the specified character vector
  - `any_of(vector)`: any of the columns in the specified character vector

Tidy data with `tidyr`

The two main `tidyr` functions:

- `pivot_longer(data, cols, names_to, values_to)`: "lengthens" the data by moving the column names into `names_to` column and the values going into the `values_to` column.
- `pivot_wider(data, names_from, values_from)`: "widens" the data by taking the names in `names_from` and making them into columns, with the values from `values_from`

`tidyr` Cheatsheet

https://www.rstudio.com/resources/cheatsheets/ (Data Import Cheatsheet)

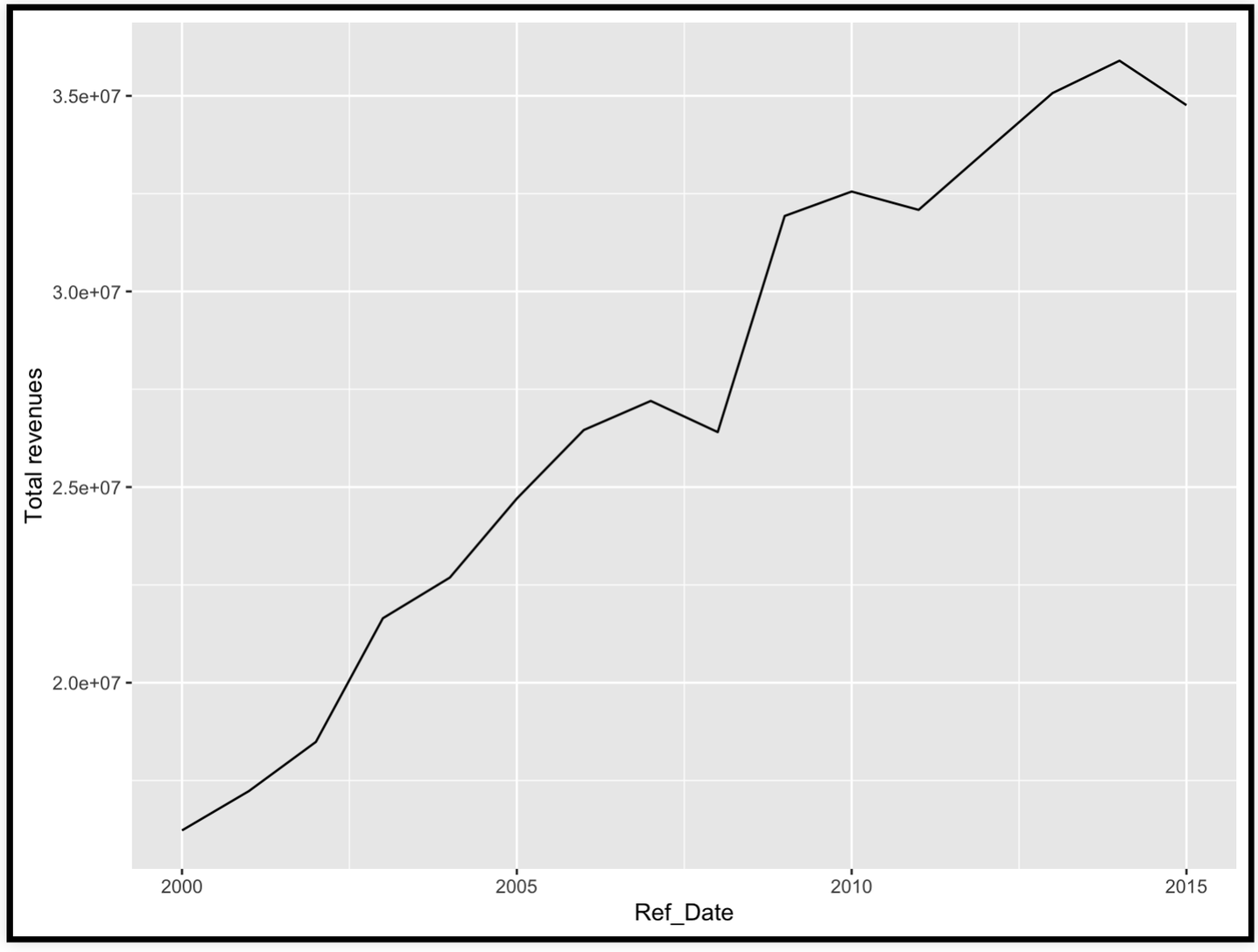
pivot_wider() CANSIM

```
revenue <- revenue_long %>%
  pivot_wider(names_from = REVENUE, values_from = Value)

revenue
```

```
## # A tibble: 176 × 34
##    Ref_D…¹ GEO   Total…² Federal Socia…³ Healt…⁴ Natur…⁵ Canad…⁶ Canad…⁷
##      <int> <chr>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>
##  1    2000 Cana…  1.62e7 1554234  104306   41527  473482  329025  212418
##  2    2001 Cana…  1.72e7 1846138  109511   34669  483512  422909  206617
##  3    2002 Cana…  1.85e7 2223239  133368   43599  510230  508327  371589
##  4    2003 Cana…  2.16e7 2534964  178803   30157  574109  560899  411999
##  5    2004 Cana…  2.27e7 2635758  203082   30426  623673  613012  323399
##  6    2005 Cana…  2.47e7 2833294  221604   37168  630643  694191  400625
##  7    2006 Cana…  2.65e7 2874651  222010   42011  687339  684999  337794
##  8    2007 Cana…  2.72e7 3060336  220779   57051  734866  725863  371047
##  9    2008 Cana…  2.64e7 3075585  236172   36454  745260  795806  288544
## 10    2009 Cana…  3.19e7 3752740  250356   52515  826710  824641  345899
## # … with 166 more rows, 24 more variables: `Other federal` <dbl>,
## #   `Non-federal` <dbl>, Provincial <dbl>, Municipal <dbl>,
## #   `Other provinces` <dbl>, Foreign <dbl>, `Tuition and other fees` <dbl
## #   `Credit courses tuiton` <dbl>, `Non-credit tution` <dbl>,
```

Visualizing

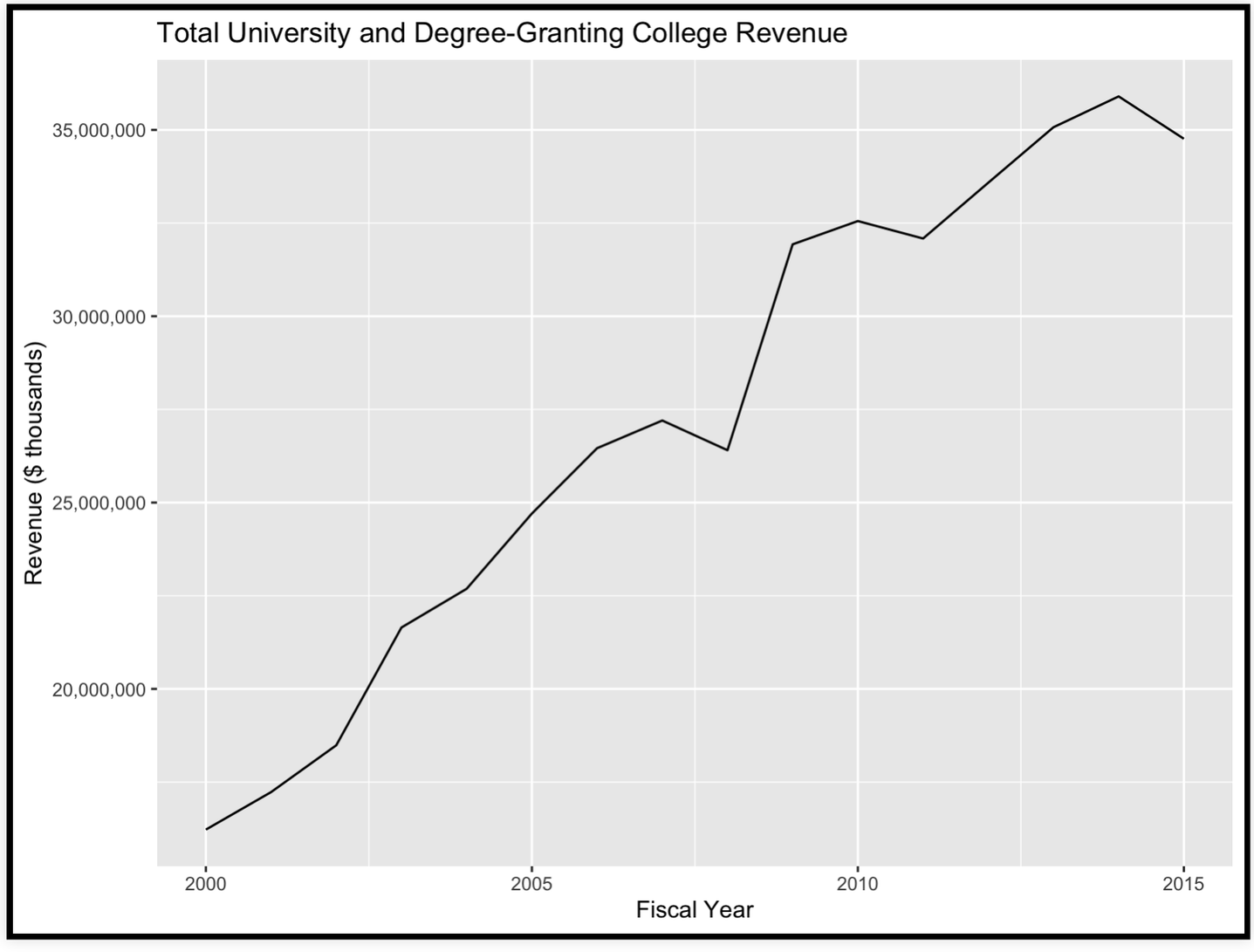
```
revenue %>%
  filter(GEO == 'Canada') %>%
  # pass the result to ggplot() as the first argument
  ggplot(aes(Ref_Date, `Total revenues`)) +
  # now it switches to + to combine, which is ggplot's way
  geom_line()
```



Not the prettiest, but it works!

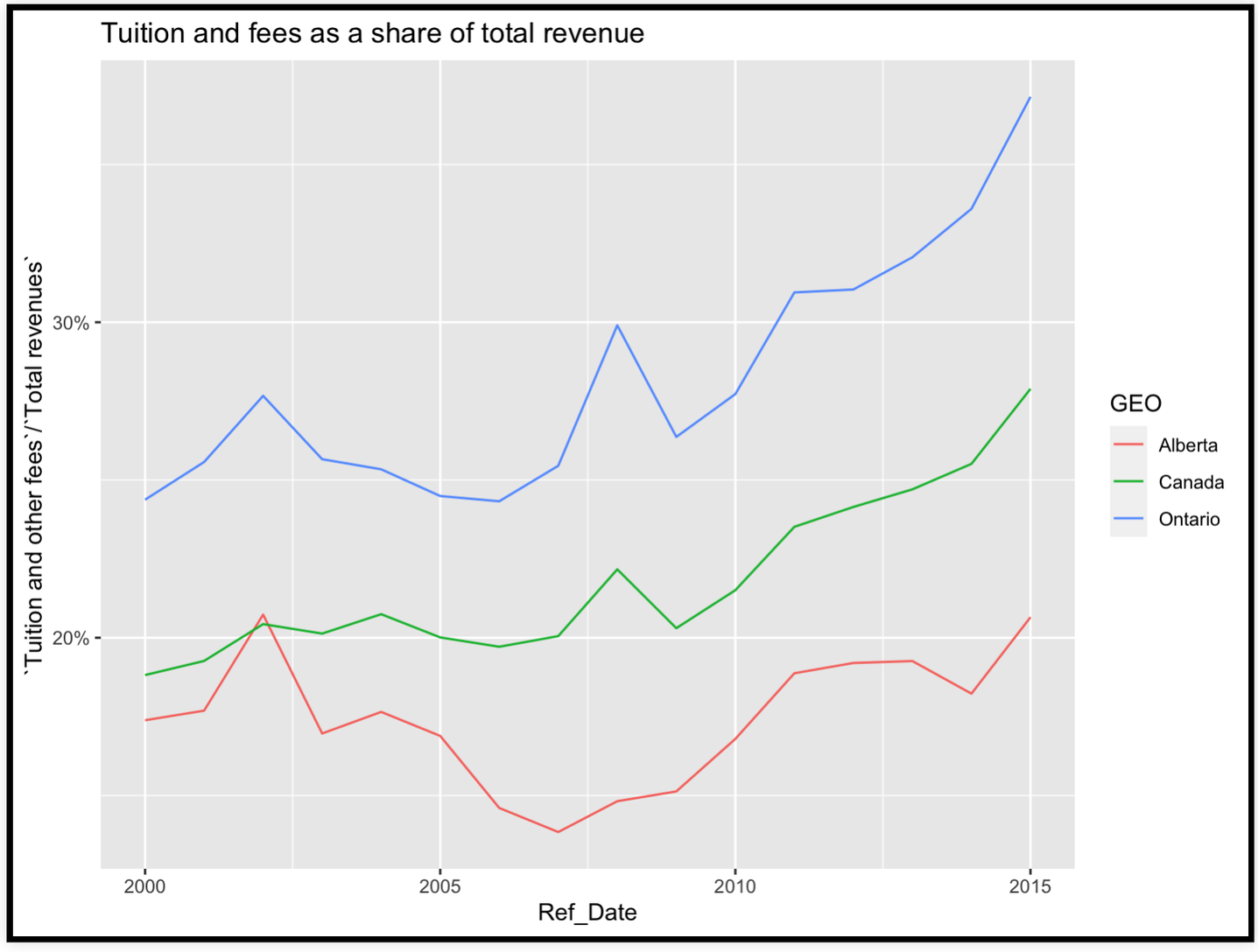
Visualizing: Labels

```
revenue %>%
  filter(GEO == 'Canada') %>%
  ggplot(aes(Ref_Date, `Total revenues`)) +
  geom_line() +
  labs(title = 'Total University and Degree-Granting College Revenue',
       x = 'Fiscal Year', y = 'Revenue ($ thousands)') +
  scale_y_continuous(labels = scales::comma)
```



Inline Calculation

```
revenue %>%
  filter(GEO %in% c('Canada', 'Alberta', 'Ontario')) %>%
  ggplot(aes(Ref_Date, `Tuition and other fees` / `Total revenues`, color
         = GEO)) +
  geom_line() +
  labs(title = 'Tuition and fees as a share of total revenue') +
  scale_y_continuous(labels = scales::percent)
```



Exercises

1. Visualize another variable
2. Set some appropriate labels and scales
3. Graph a time subset (e.g., between 2005 and 2010)

Other `dplyr` "verbs"

Which province had the most tuition revenue in 2010?

```
revenue %>%
  filter(GEO != 'Canada', Ref_Date == 2010) %>%
  select(GEO, `Tuition and other fees`) %>%
  arrange(desc(`Tuition and other fees`))
```

```
## # A tibble: 10 × 2
##    GEO                          `Tuition and other fees`
##    <chr>                                           <dbl>
##  1 Ontario                                       3563011
##  2 British Columbia                              1009476
##  3 Quebec                                         825943
##  4 Alberta                                        711973
##  5 Nova Scotia                                    305597
##  6 Manitoba                                       176165
##  7 Saskatchewan                                   173600
##  8 New Brunswick                                  146213
##  9 Newfoundland and Labrador                       61537
## 10 Prince Edward Island                            27878
```

Create a new column

```
revenue %>%
  select(Ref_Date, GEO, `Tuition and other fees`, `Total revenues`) %>%
  mutate(tuition_share = `Tuition and other fees` / `Total revenues`)
```

```
## # A tibble: 176 × 5
##    Ref_Date GEO    `Tuition and other fees` `Total revenues` tuition_shar
##       <int> <chr>                    <dbl>            <dbl>         <dbl
##  1     2000 Canada                 3052960         16224715         0.18
##  2     2001 Canada                 3319524         17231250         0.19
##  3     2002 Canada                 3777453         18488133         0.20
##  4     2003 Canada                 4358013         21647925         0.20
##  5     2004 Canada                 4706894         22687437         0.20
##  6     2005 Canada                 4943699         24705347         0.20
##  7     2006 Canada                 5216088         26458623         0.19
##  8     2007 Canada                 5454375         27201804         0.20
##  9     2008 Canada                 5853354         26405228         0.22
## 10     2009 Canada                 6482539         31929458         0.20
## # … with 166 more rows
```

Keeps the same number of rows

Useful "mutations"

- Arithmetic: `+, -, *, /, ^`
- Modular arithmetic: `%/%` (integer division), `%%` (remainder)
- Logs: `log(), log2(), log10()`
- Offsets: `lead()`, `lag()`
- Cumulative and rolling aggregates: `cumsum()`, `cumprod()`, `cummin()`, `cummax()`, `cummean()`
- Logical comparisons: `<, <=, >, >=, !=, ==`
- Ranking: `min_rank()`, `row_number()`, `dense_rank()`, `percent_rank()`, `cume_dist()`, `ntile()`
- `if_else()`
- `dplyr::recode()`
- `case_when()`

Summarize (aggregate)

```
revenue %>%
  group_by(GEO) %>%
  summarise(avg_endowment_revenue = mean(Endowment)) %>%
  arrange(-avg_endowment_revenue)
```

```
## # A tibble: 11 × 2
##    GEO                          avg_endowment_revenue
##    <chr>                                        <dbl>
##  1 Canada                                     526071.
##  2 Ontario                                    211475.
##  3 Quebec                                      87323.
##  4 Alberta                                     80069
##  5 British Columbia                            75752.
##  6 Nova Scotia                                 31148.
##  7 Saskatchewan                                21256.
##  8 New Brunswick                               13778.
##  9 Newfoundland and Labrador                    2878.
## 10 Manitoba                                     1646.
## 11 Prince Edward Island                          747.
```

Useful summarising functions:

- `mean(x)`, `median(x)`
- `sd(x)`, `IQR(x)` (interquartile range), `mad(x)` (median absolute deviation)
- `min(x)`, `max(x)`, `quantile(x, 0.25)`
- `first(x)`, `nth(x, 2)`, `last(x)`
- `n(x)`, `n_distinct(x)`
- Counts and proportions of logical values: `sum(x > 10)`, `mean(y == 0)`
  - `TRUE` is converted to 1 and `FALSE` to 0

Exercise:

Compute the total tuition revenue of the three western-most provinces in 2007.

```
revenue %>%
  filter(GEO %in% c('British Columbia', 'Alberta', 'Saskatchewan'),
         Ref_Date == 2007) %>%
  summarise(sum(`Tuition and other fees`))
```

```
## # A tibble: 1 × 1
##   `sum(\`Tuition and other fees\`)`
##                               <dbl>
## 1                           1374509
```

Group by new variable

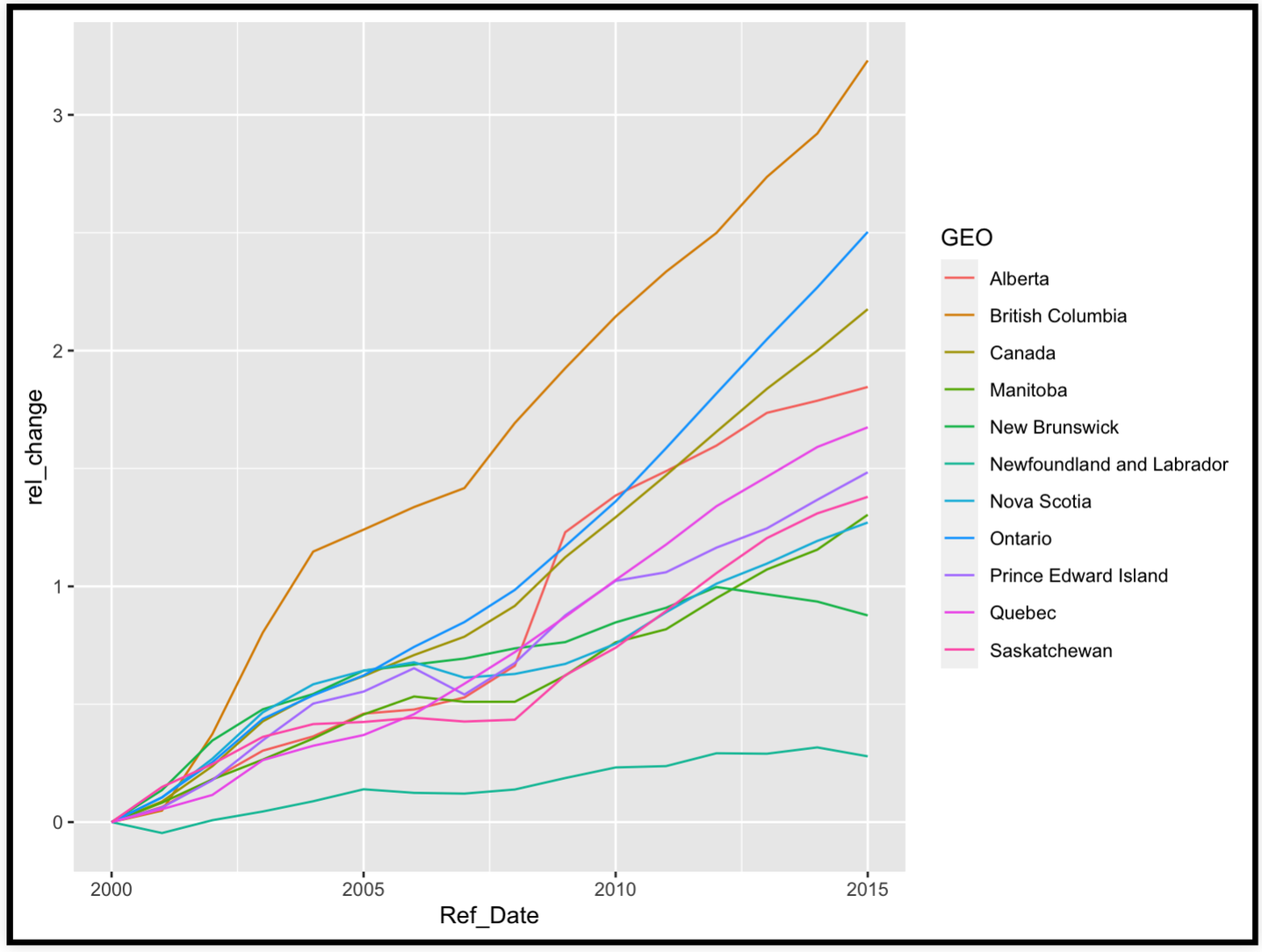
These three provinces compared to all other provinces and national average.

```
revenue %>%
  filter(Ref_Date == 2007) %>%
  mutate(category = case_when(
    GEO %in% c('British Columbia', 'Alberta', 'Saskatchewan') ~ '3 Western
        Provinces',
    GEO == 'Canada' ~ GEO,
    TRUE ~ 'All Other Provinces'
  )) %>%
  group_by(category) %>%
  summarise(sum(`Tuition and other fees`))
```

```
## # A tibble: 3 × 2
##   category            `sum(\`Tuition and other fees\`)`
##   <chr>                                          <dbl>
## 1 3 Western Provinces                          1374509
## 2 All Other Provinces                          4079866
## 3 Canada                                       5454375
```

Change relative first year

```
tuition_relative_change <- revenue %>%
  arrange(Ref_Date, GEO) %>%
  group_by(GEO) %>%
  mutate(rel_change = (`Tuition and other fees` - first(`Tuition and other
        fees`)) / first(`Tuition and other fees`)) %>%
  select(Ref_Date, GEO, `Tuition and other fees`, rel_change)

ggplot(tuition_relative_change, aes(Ref_Date, rel_change, color = GEO)) +
  geom_line()
```


rel_change
3
2
1
0
2000
2005
2010
2015
Ref_Date
GEO
Alberta
British Columbia
Canada
Manitoba
New Brunswick
Newfoundland and Labrador
Nova Scotia
Ontario
Prince Edward Island
Quebec
Saskatchewan

Logical sums

Count years with positive endowment income by province

```
revenue %>%
  group_by(GEO) %>%
  summarise(num_pos_endow = sum(Endowment > 0))
```

```
## # A tibble: 11 × 2
##    GEO                          num_pos_endow
##    <chr>                                <int>
##  1 Alberta                                 13
##  2 British Columbia                        13
##  3 Canada                                  13
##  4 Manitoba                                14
##  5 New Brunswick                           13
##  6 Newfoundland and Labrador               13
##  7 Nova Scotia                             14
##  8 Ontario                                 12
##  9 Prince Edward Island                    13
## 10 Quebec                                  16
## 11 Saskatchewan                            12
```

Exercises

- Compare the Maritimes to the rest of Canada on one or more variable
- Between 2005 and 2007, which provinces received more than $100 M in Total grants?
- Which provinces, other than Nova Scotia and Ontario, had more than $20 M in Endowmennt income in 2003?
- Which province was in “third place” in total revenue in 2012?

purrr (quickly)

```
revenue %>%
  filter(GEO != 'Canada') %>%
  group_by(Ref_Date) %>%
  summarise(revenue_quantiles = list(quantile(`Total revenues`, c(0.25,
        0.5, 0.75)))) %>%
  mutate(
    low_25 = map_dbl(revenue_quantiles, "25%"),
    mid = map_dbl(revenue_quantiles, '50%'),
    high_75 = map_dbl(revenue_quantiles, '75%')
  )
```

```
## # A tibble: 16 × 5
##    Ref_Date revenue_quantiles  low_25      mid  high_75
##       <int> <list>              <dbl>    <dbl>    <dbl>
##  1     2000 <dbl [3]>         424965   681742. 1944551.
##  2     2001 <dbl [3]>         417664.  700424  2126550.
##  3     2002 <dbl [3]>         465112.  729434  2378510.
##  4     2003 <dbl [3]>         480404.  804636. 2708008.
##  5     2004 <dbl [3]>         530995.  853132. 2818174.
##  6     2005 <dbl [3]>         560023.  911819  3257599.
##  7     2006 <dbl [3]>         616412.  964536. 3320636.
##  8     2007 <dbl [3]>         592927.  944042. 3560364.
##  9     2008 <dbl [3]>         568461.  968932. 3404852.
## 10     2009 <dbl [3]>         741016. 1161066  4363439.
## 11     2010 <dbl [3]>         787082. 1213456  4436956.
## 12     2011 <dbl [3]>         775059. 1169906. 4177081
## 13     2012 <dbl [3]>         799797. 1240542  4296184.
## 14     2013 <dbl [3]>         791843. 1298845  4437751.
```

Vectors (and other types)

Missing data

```
NA > 5
```

```
## [1] NA
```

```
10 == NA
```

```
## [1] NA
```

```
NA + 10
```

```
## [1] NA
```

What about this?

```
NA / 2
```

Filtering and NAs

```
x <- NA
is.na(x)
```

```
## [1] TRUE
```

`filter()` only includes rows where the condition is `TRUE`; it excludes both `FALSE` and `NA` values. If you want to preserve missing values, ask for them explicitly:

```
test_data <- tibble(x = c(1, NA, 3))
filter(test_data, x > 1)
```

```
## # A tibble: 1 × 1
##       x
##   <dbl>
## 1     3
```

```
filter(test_data, is.na(x) | x > 1)
```

```
## # A tibble: 2 × 1
##       x
##   <dbl>
## 1    NA
## 2     3
```

Dealing with vectors…

```r
c(1, 2, 3)
```

```
## [1] 1 2 3
```

```r
1:3
```

```
## [1] 1 2 3
```

Dealing with vectors…

```
1:3 + 1:9
```

```
## [1]  2  4  6  5  7  9  8 10 12
```

What about…

```
1:3 + 1:10
```

Dealing with vectors…

```
1:3 + 1:10
```

```
## Warning in 1:3 + 1:10: longer object length is not a multiple of shorter
## length
```

```
##  [1]  2  4  6  5  7  9  8 10 12 11
```

What happened?

Missing values

```
mean(c(1,2,3))
```

```
## [1] 2
```

What do we expect here?

```
mean(c(1,NA,3))
```

Missing values

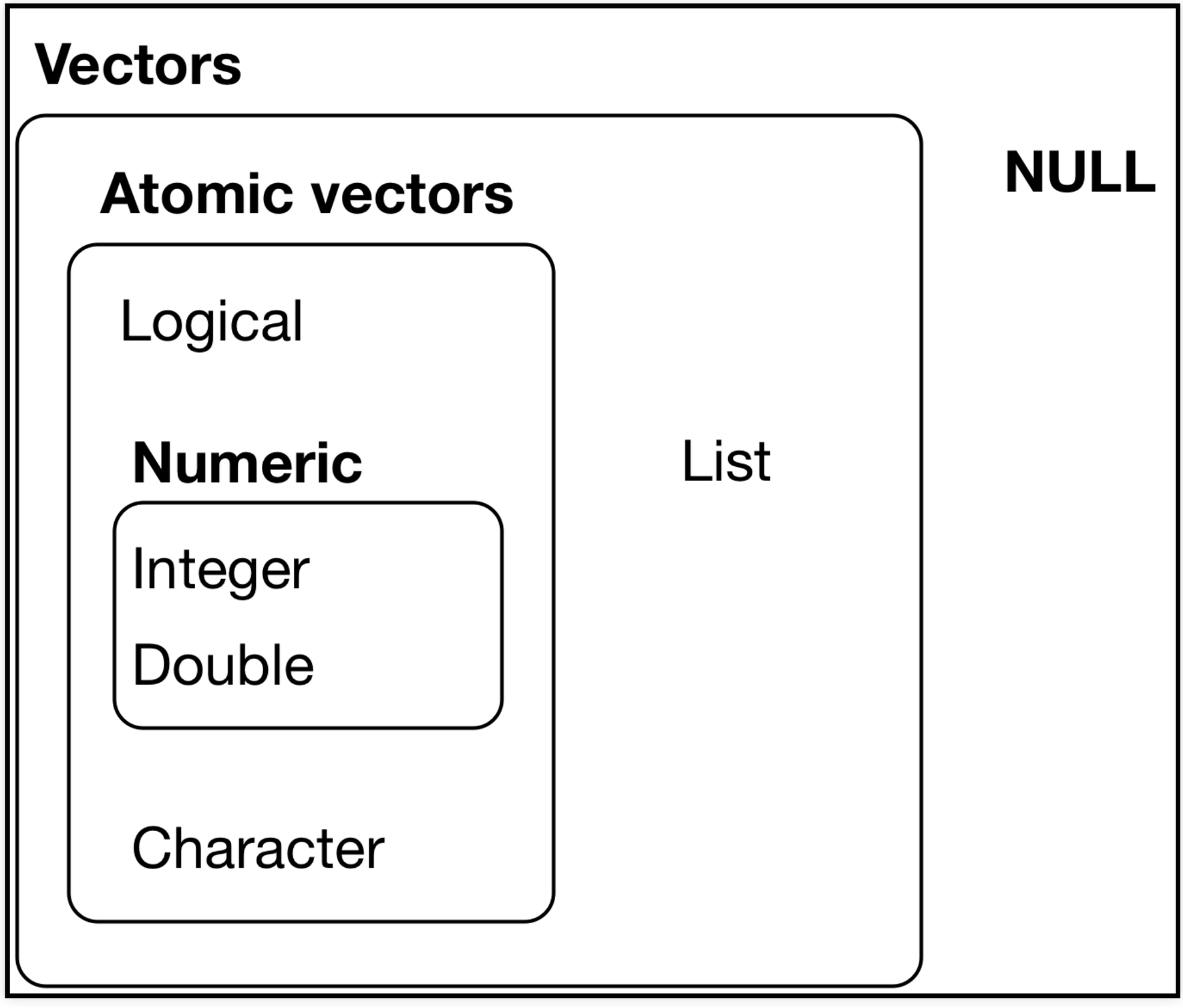
```r
mean(c(1,NA,3))
```

```
## [1] NA
```

```r
mean(c(1,NA,3), na.rm = TRUE)
```

```
## [1] 2
```

Vectors


Vectors
Atomic vectors
Logical
Numeric
Integer
Double
Character
List
NULL

Vectors

- Coercion (explicit and implicit)
  - Type hierarchy
- Atomic vectors (homogenous) vs lists (can nest/heterogeneous)
- Names
- Subsetting

Vectors: Naming

```
c(x = 1, y = 2, z = 4)
```

```
## x y z
## 1 2 4
```

```
set_names(1:3, c("a", "b", "c"))
```

```
## a b c
## 1 2 3
```

Vectors: Subsetting

```r
# positive values
x <- c("one", "two", "three", "four", "five")
x[c(3, 2, 5)]
```

```
## [1] "three" "two"   "five"
```

```r
# negative values
x[c(-1, -3, -5)]
```

```
## [1] "two"  "four"
```

```r
#> [1] "two"  "four"

# subset a named vector w/character vector
x <- c(abc = 1, def = 2, xyz = 5)
x[c("xyz", "def")]
```

```
## xyz def
##   5   2
```

Vectors: Logical subsetting

```r
x <- c(10, 3, NA, 5, 8, 1, NA)

# All non-missing values of x
x[!is.na(x)]
```

```
## [1] 10  3  5  8  1
```

```r
#> [1] 10  3  5  8  1

# All even (or missing!) values of x
x[x %% 2 == 0]
```

```
## [1] 10 NA  8 NA
```

```r
#> [1] 10 NA  8 NA
```

Lists

```
x <- list(1, 2, 3)
x
```

```
## [[1]]
## [1] 1
##
## [[2]]
## [1] 2
##
## [[3]]
## [1] 3
```

```
str(x) # str...ucture
```

```
## List of 3
##  $ : num 1
##  $ : num 2
##  $ : num 3
```

Lists: Can contain different types of objects:

```r
y <- list("a", 1L, 1.5, TRUE)
str(y)
```

```
## List of 4
##  $ : chr "a"
##  $ : int 1
##  $ : num 1.5
##  $ : logi TRUE
```

Lists: Or other lists:

```r
z <- list(list(1, 2), list(3, 4))
str(z)
```

```
## List of 2
##  $ :List of 2
##   ..$ : num 1
##   ..$ : num 2
##  $ :List of 2
##   ..$ : num 3
##   ..$ : num 4
```

Modeling

When we have the data the way we want it, we want to ask questions about it. To determine the relationship between parts of the data.

This can range from exploratory modeling (to better understand the data) to more formally trying to establish relationships between variables. The process is the same for both, but the mindset is different.

Types of Modeling

- define a family of models - expressed as an equation - you are trying to estimate the **parameters** of the question
- generate a fitted model that fills in the parameters
- You are trying to get the model from the family that best fits the data.
- That doesn't mean it's a "good" or "true" model.

Simulated Data

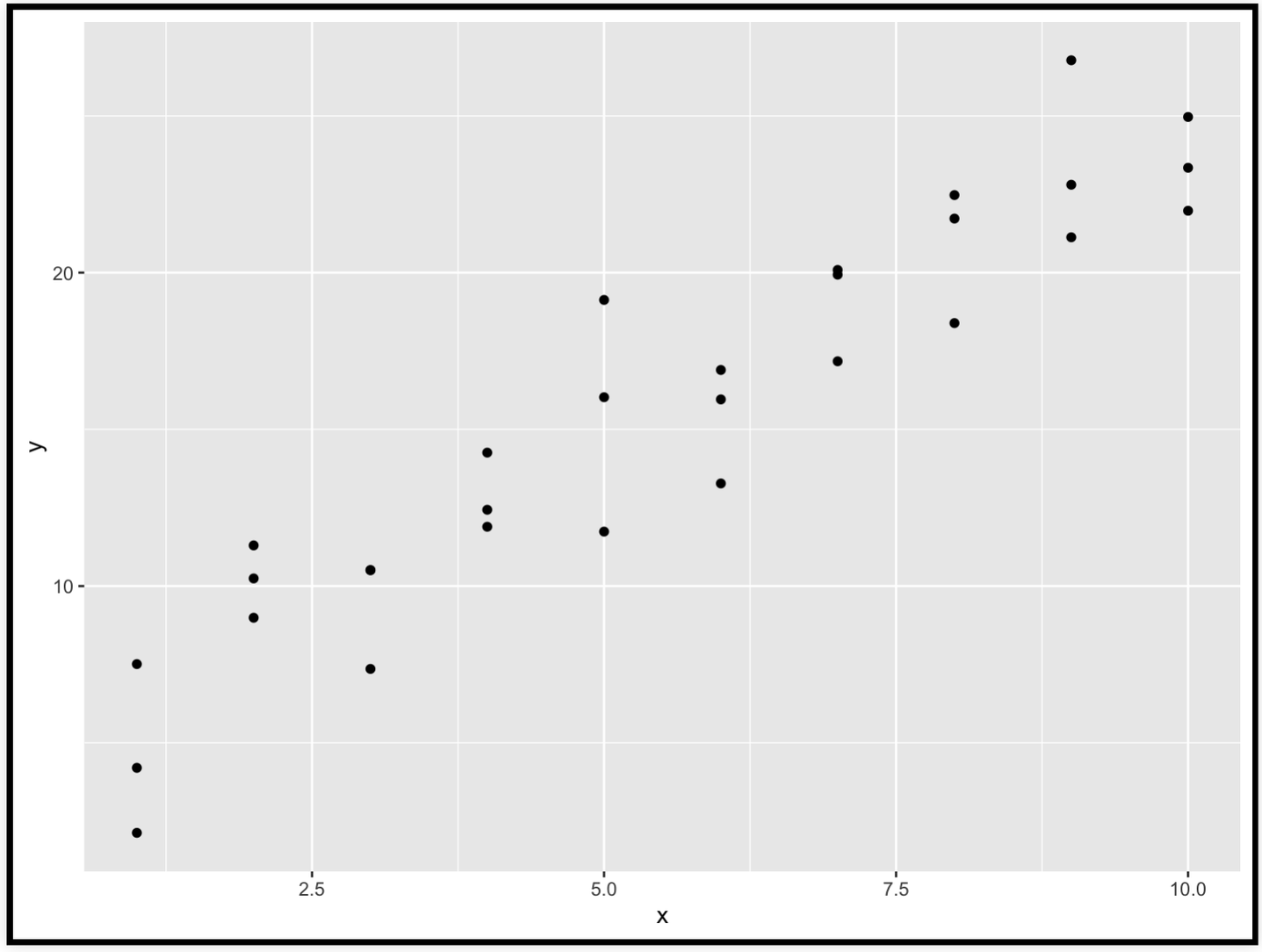
The `modelr` package has a simulated dataset called `sim1`.

```
library(modelr)
sim1
```

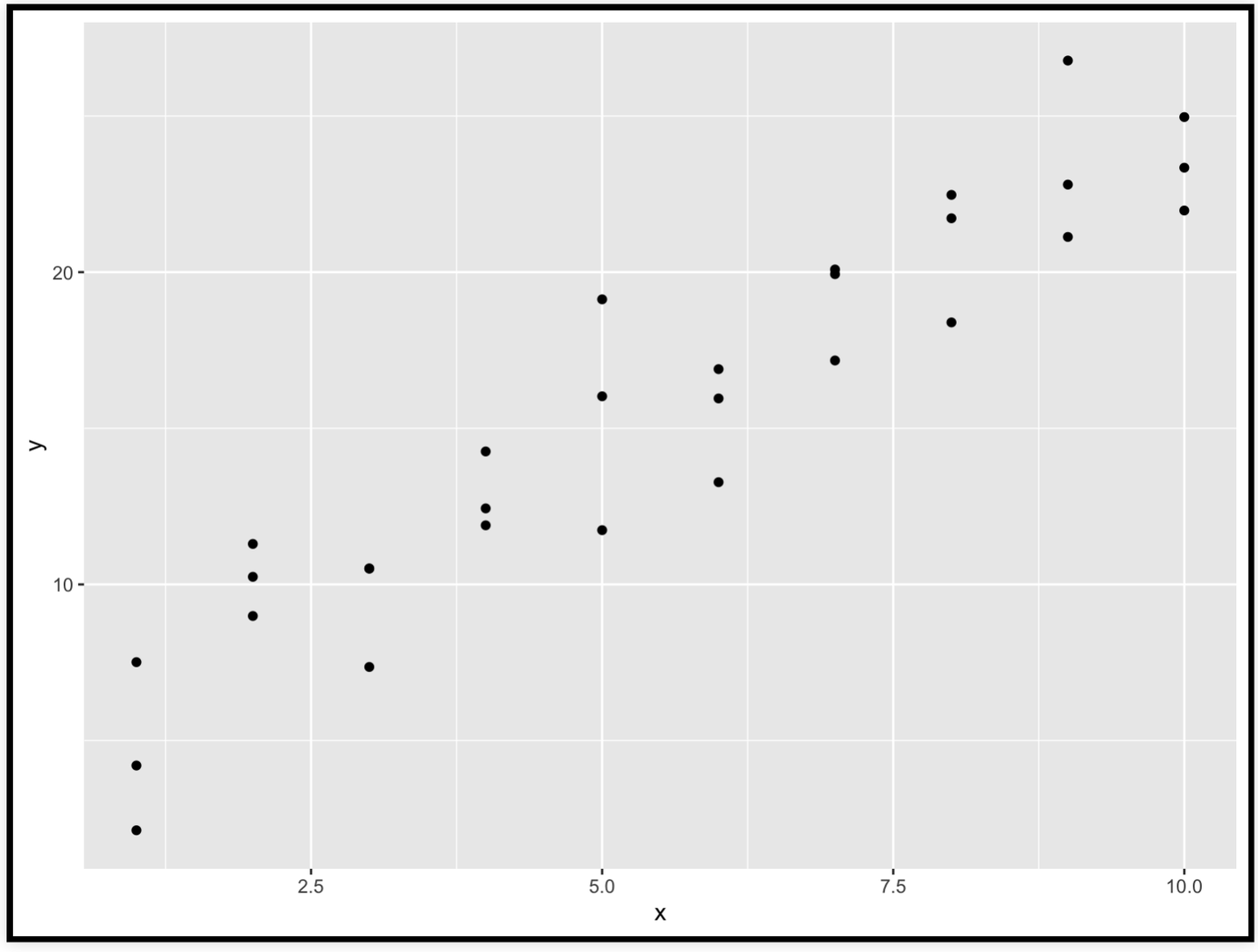
```
## # A tibble: 30 × 2
##         x     y
##     <int> <dbl>
##  1      1  4.20
##  2      1  7.51
##  3      1  2.13
##  4      2  8.99
##  5      2 10.2
##  6      2 11.3
##  7      3  7.36
##  8      3 10.5
##  9      3 10.5
## 10      4 12.4
## # … with 20 more rows
```

Plotting `sim1`

```
ggplot(sim1, aes(x, y)) +
  geom_point()
```



Plotting `sim1`

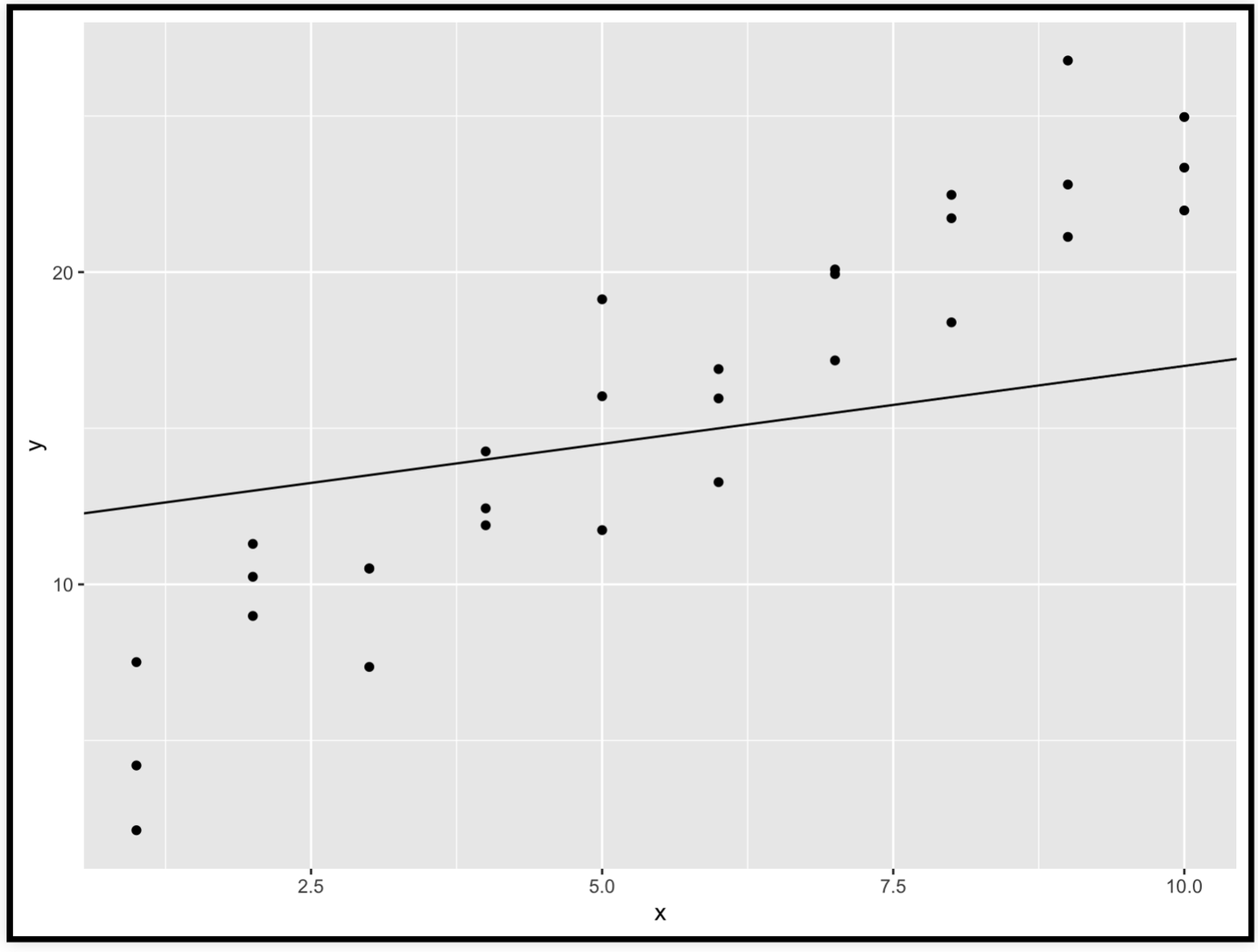


- we can see that there is a pattern from the scatter plot
- the pattern looks like a straight line

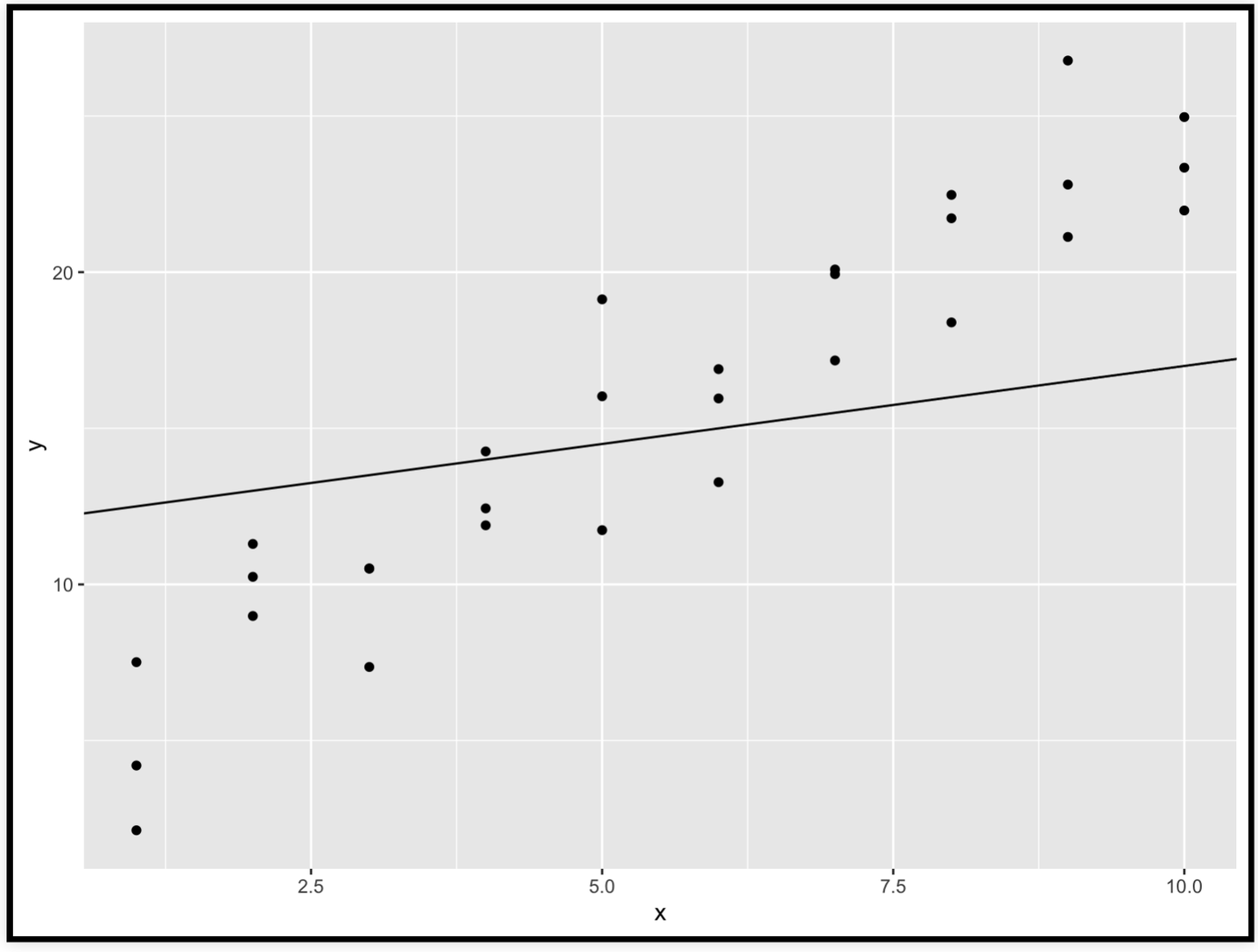
Using `geom_abline`

`geom_abline` plots a linear equation

```
ggplot(sim1, aes(x, y)) +
  geom_point() +
  geom_abline(aes(intercept = 12, slope = 0.5))
```



Using `geom_abline`



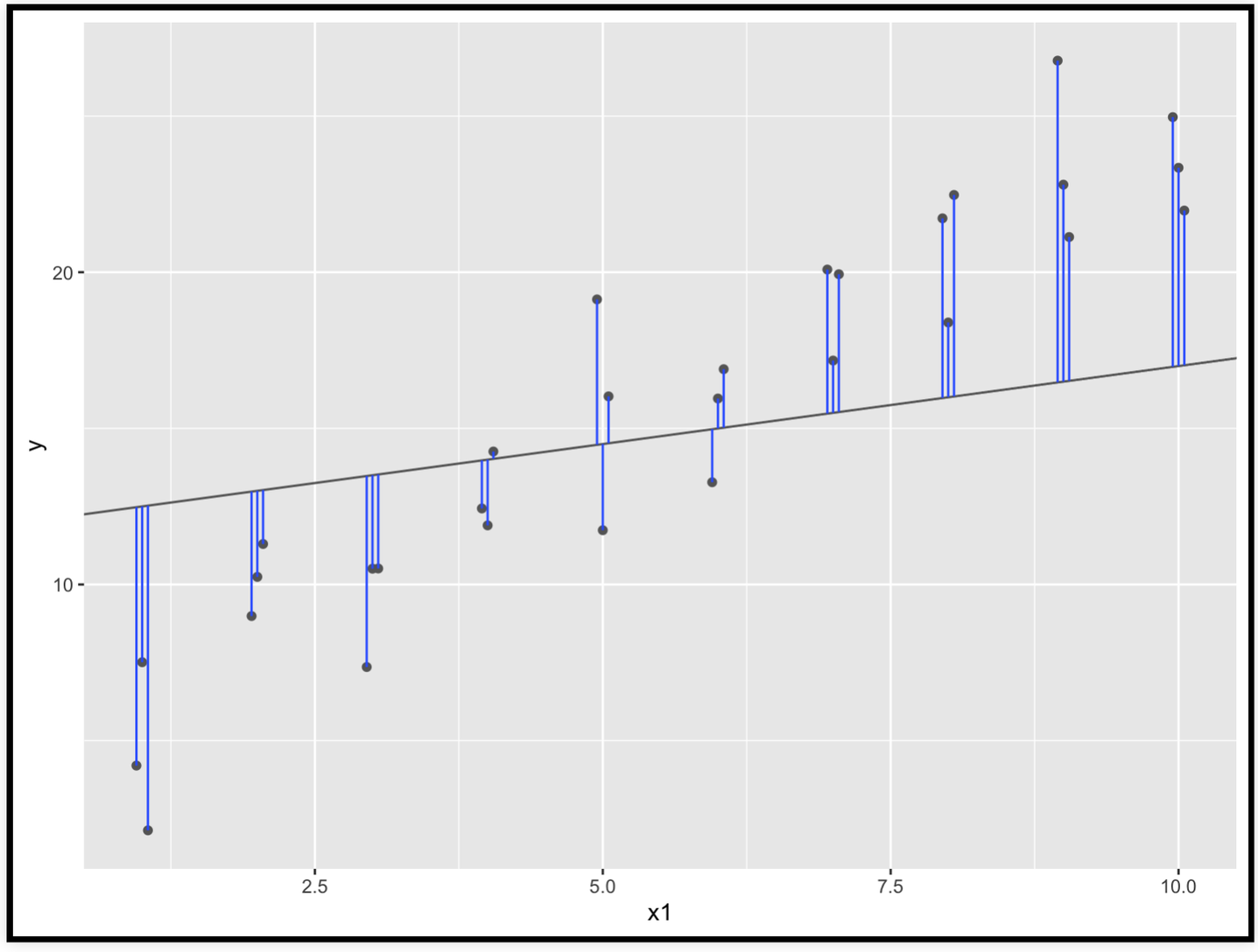
That's just one model - how can we tell if it's good or not?

Exercise

1. Try plotting different models on the plot using `geom_abline`. Can you get something that looks like a better model?

Evaluating Predictive Models

We look at the difference between the predictions and the actual data.



Defining a model as an R function

We can find this for any model by creating an R function. We take the intercept and add the slope multiplied by **x**.

```
model1 <- function(data, a) {
  a[1] + data$x * a[2]
}

model1(sim1, c(12, 0.5))
```

```
##  [1] 12.5 12.5 12.5 13.0 13.0 13.0 13.5 13.5 13.5 14.0 14.0 14.0 14.5 14.
## [16] 15.0 15.0 15.0 15.5 15.5 15.5 16.0 16.0 16.0 16.5 16.5 16.5 17.0 17.
```

Difference between predicted and actual

Once we have the model's prediction, we can look at the difference between those and what the actual data is.

```
measure_distance <- function(data, mod) {
  diff <- data$y - model1(data, mod)
  diff
}
measure_distance(sim1, c(12, 0.5))
```

```
##  [1]  -8.3000870  -4.9893659 -10.3745272  -4.0111426  -2.7568946  -1.703
##  [7]  -6.1436353  -2.9946506  -2.9883992  -1.5654109  -2.1073988   0.257
## [13]   4.6300498  -2.7619788   1.5248539  -1.7260230   0.9559750   1.894
## [19]   4.5859927   1.6718503   4.4363088   5.7259025   2.3909129   6.475
## [25]  10.2770099   6.3051098   4.6283053   7.9680994   6.3464221   4.975
```

Using squared distances

We want to both put all distances as positive numbers and more heavily penalize predictions that are far from the actual values - so we square the diffference.

```
measure_distance <- function(data, mod) {
  diff <- data$y - model1(data, mod)
  diff ^ 2
}
measure_distance(sim1, c(12, 0.5))
```

```
##  [1]  68.89144476  24.89377199 107.63081509  16.08926474   7.60046760
##  [6]   2.90081117  37.74425497   8.96793224   8.93052986   2.45051128
## [11]   4.44112956   0.06654547  21.43736106   7.62852691   2.32517942
## [16]   2.97915534   0.91388814   3.59025256  21.03132891   2.79508358
## [21]  19.68083613  32.78595957   5.71646454  41.93278203 105.61693163
## [26]  39.75440948  21.42120989  63.49060769  40.27707338  24.75262198
```

Summary Measure of Distance

We want to summarize it - so we take the mean across all the predictions and take the square root to put the differences back in terms of the original units.

```
measure_distance <- function(data, mod) {
  diff <- data$y - model1(data, mod)
  sqrt(mean(diff ^ 2))
}
measure_distance(sim1, c(12, 0.5))
```

```
## [1] 4.995789
```

Use this Method to Choose a Model

So, to choose between models – we can just put in different values.

```
measure_distance(sim1, c(7, 1.5))
```

```
## [1] 2.665212
```

Use this function to try a few different models.

Random Models

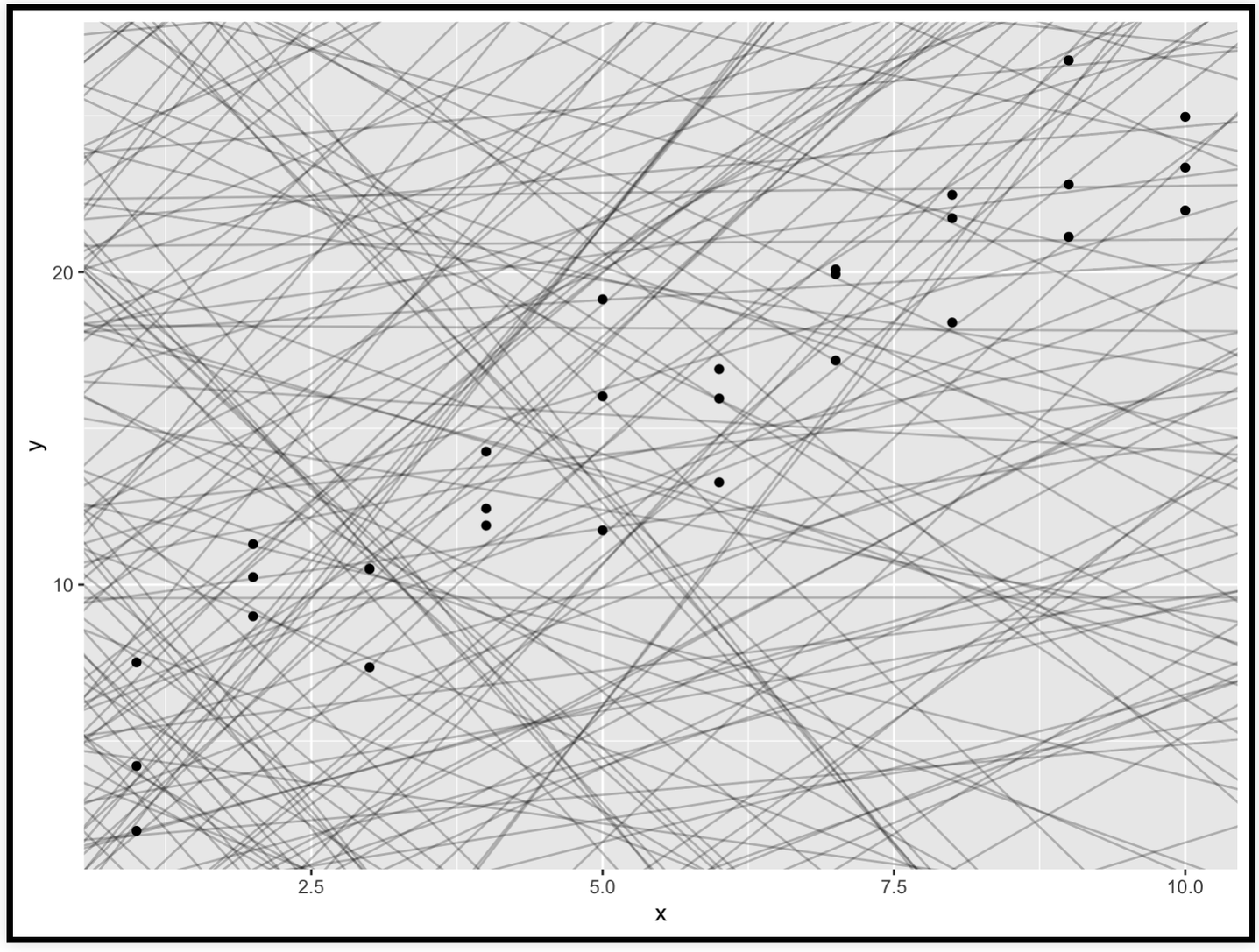
Instead of guessing ourselves, we have the computer generate a lot of models and pick the one with the lowest error.

```
models <- tibble(
  a1 = runif(250, -20, 40),
  a2 = runif(250, -5, 5)
)

sim1_dist <- function(a1, a2) {
  measure_distance(sim1, c(a1, a2))
}

models %>%
  mutate(dist = purrr::map2_dbl(a1, a2, sim1_dist)) -> models
models
```

```
## # A tibble: 250 × 3
##         a1      a2  dist
##      <dbl>   <dbl> <dbl>
##   1 -0.431  3.33    4.85
##   2 -6.97   1.33   15.5
##   3  2.68   0.657  10.3
##   4 -0.650  4.43   10.9
##   5 -0.137  4.35   10.8
##   6 33.5   -4.17   18.7
##   7  1.11  -4.41   42.9
##   8 18.3   -0.0199  6.87
##   9 -4.27   3.17    4.51
## 10  7.52  -4.26   36.4
## # … with 240 more rows
```

Plot the Random Models

```
ggplot(sim1, aes(x, y)) +
  geom_abline(aes(intercept = a1, slope = a2), data = models, alpha = 1/4)
        +
  geom_point()
```



The 10 Best Models

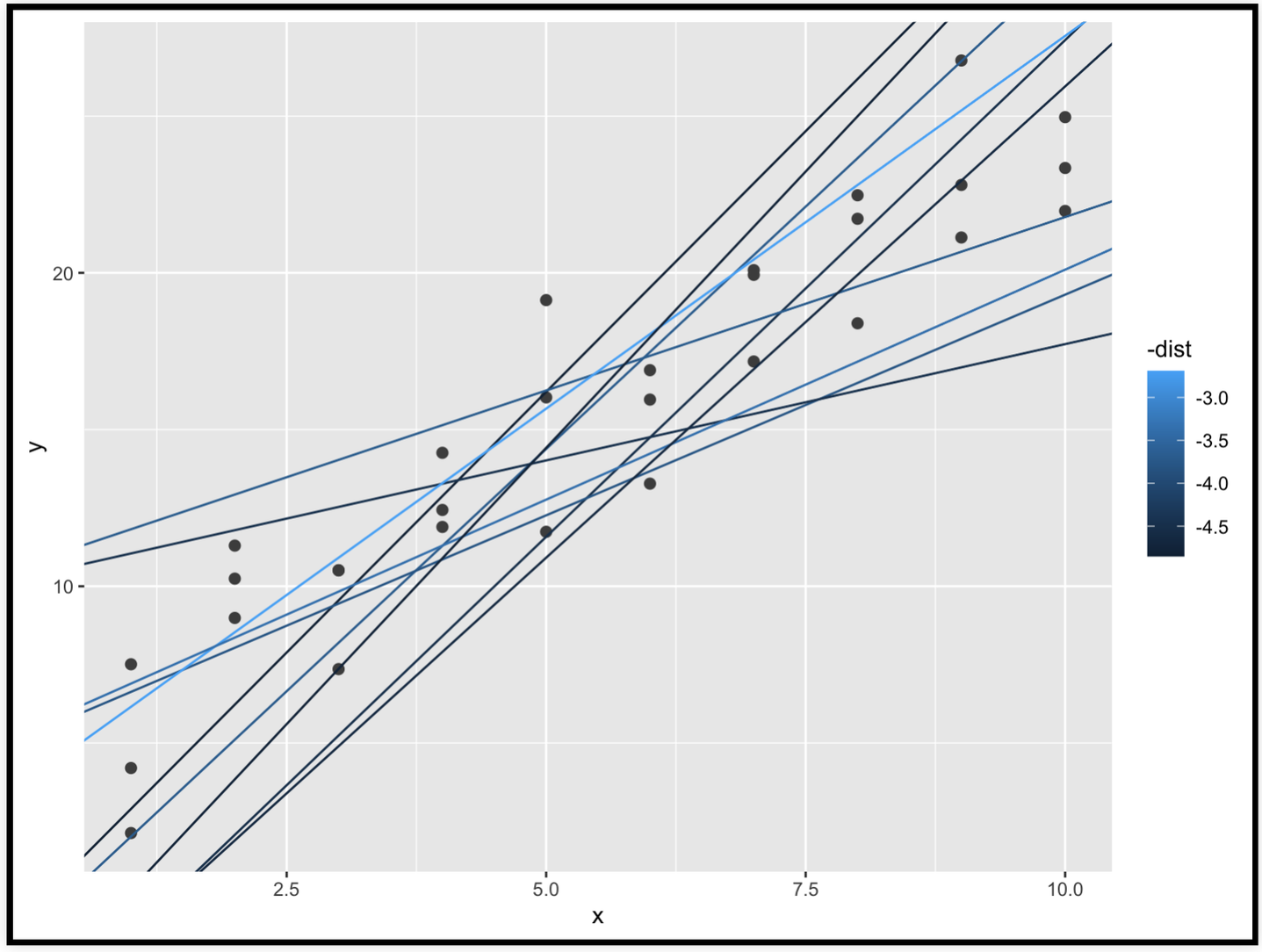
```
models %>%
  filter(rank(dist) <= 10) %>%
  arrange(dist)
```

```
## # A tibble: 10 × 3
##         a1    a2  dist
##      <dbl> <dbl> <dbl>
##  1  3.77  2.38   2.69
##  2  5.43  1.47   3.37
##  3 10.7   1.11   3.68
##  4 -1.08  3.09   3.69
##  5  5.22  1.41   3.79
##  6 10.3   0.743  4.46
##  7 -4.27  3.17   4.51
##  8 -4.13  3.01   4.65
##  9 -3.21  3.53   4.79
## 10 -0.431 3.33   4.85
```

Plot all the random models.

Plot those models on the data. Lighter colored models are closer.

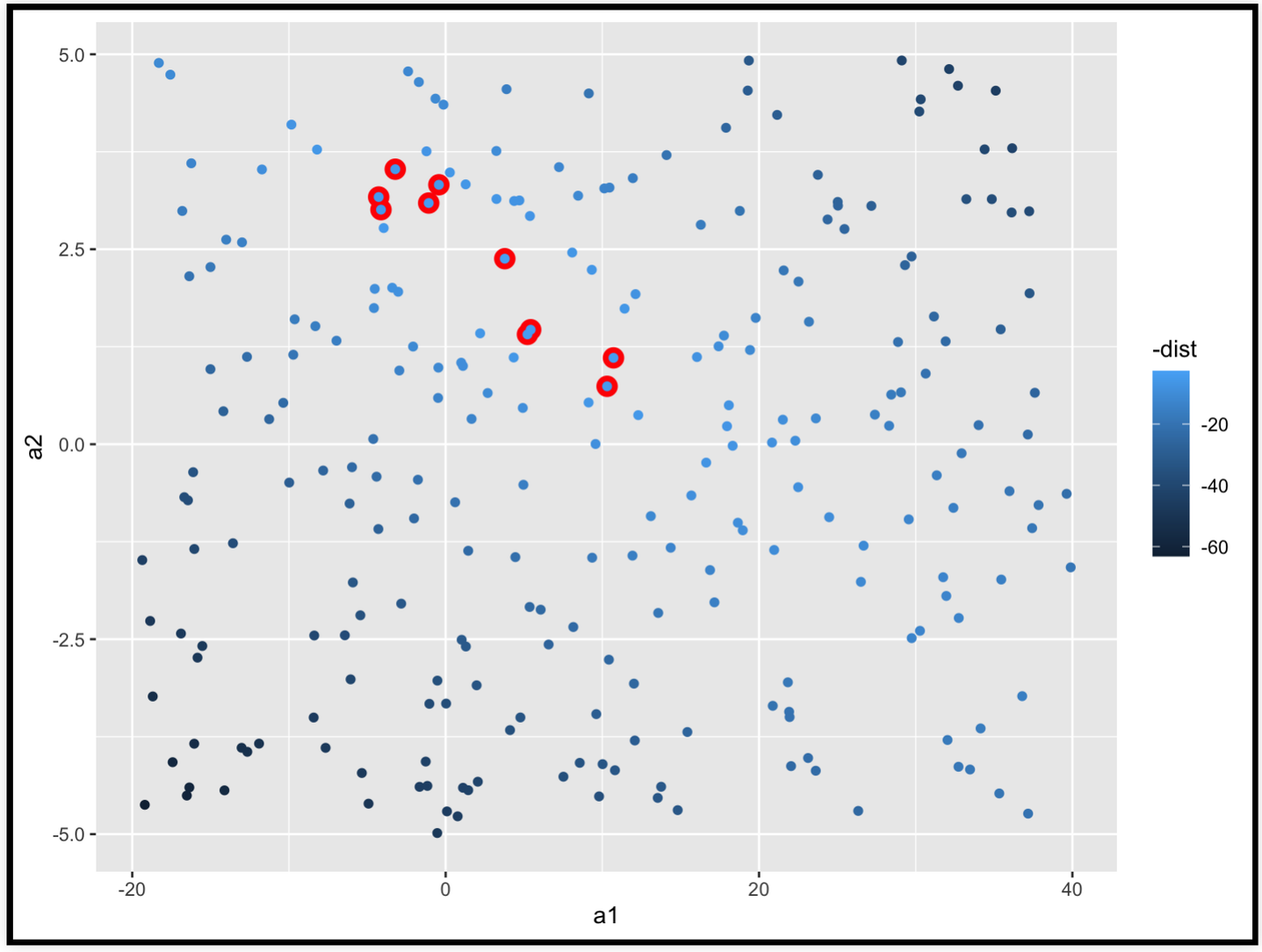
```
ggplot(sim1, aes(x, y)) +
  geom_point(size = 2, color = "grey30") +
  geom_abline(aes(intercept = a1, slope = a2, color = -dist),
    data = filter(models, rank(dist) <= 10))
```


20
10
y
2.5
5.0
7.5
10.0
x
-dist
-3.0
-3.5
-4.0
-4.5

Move to Parameter Space

We plot every model, with distance as color. We highlight our 10 best models in red.

```
ggplot(models, aes(a1, a2)) +
  geom_point(data = filter(models, rank(dist) <= 10), size = 4, colour =
        "red") +
  geom_point(aes(colour = -dist))
```


5.0
2.5
0.0
-2.5
-5.0
a2
-20
0
20
40
a1
-dist
-20
-40
-60

Zoom In

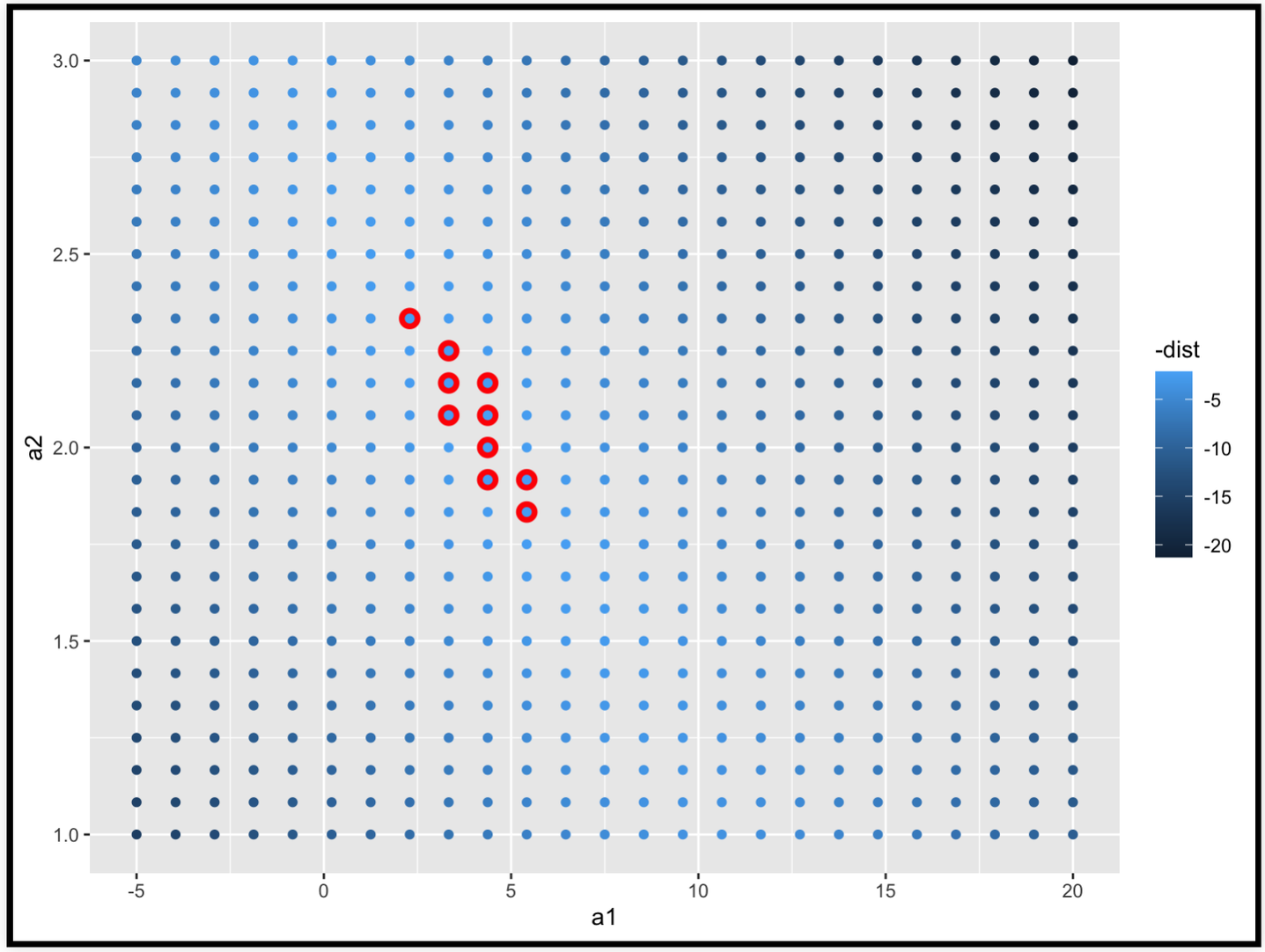
We are interested in the area where all the best random models are. It is unlikely that one of our random models is the **best** model. So, you can zoom in on the area where the best models tend to be. We create a regular grid of model parameters.

```
grid <- expand.grid(
  a1 = seq(-5, 20, length = 25),
  a2 = seq(1, 3, length = 25)
  ) %>%
  mutate(dist = purrr::map2_dbl(a1, a2, sim1_dist))
```

Plot the new best 10 models

Note the axes.

```
grid %>%
  ggplot(aes(a1, a2)) +
  geom_point(data = filter(grid, rank(dist) <= 10), size = 4, colour =
        "red") +
  geom_point(aes(colour = -dist))
```



The new best 10 models

What do we get as the new best 10 models?

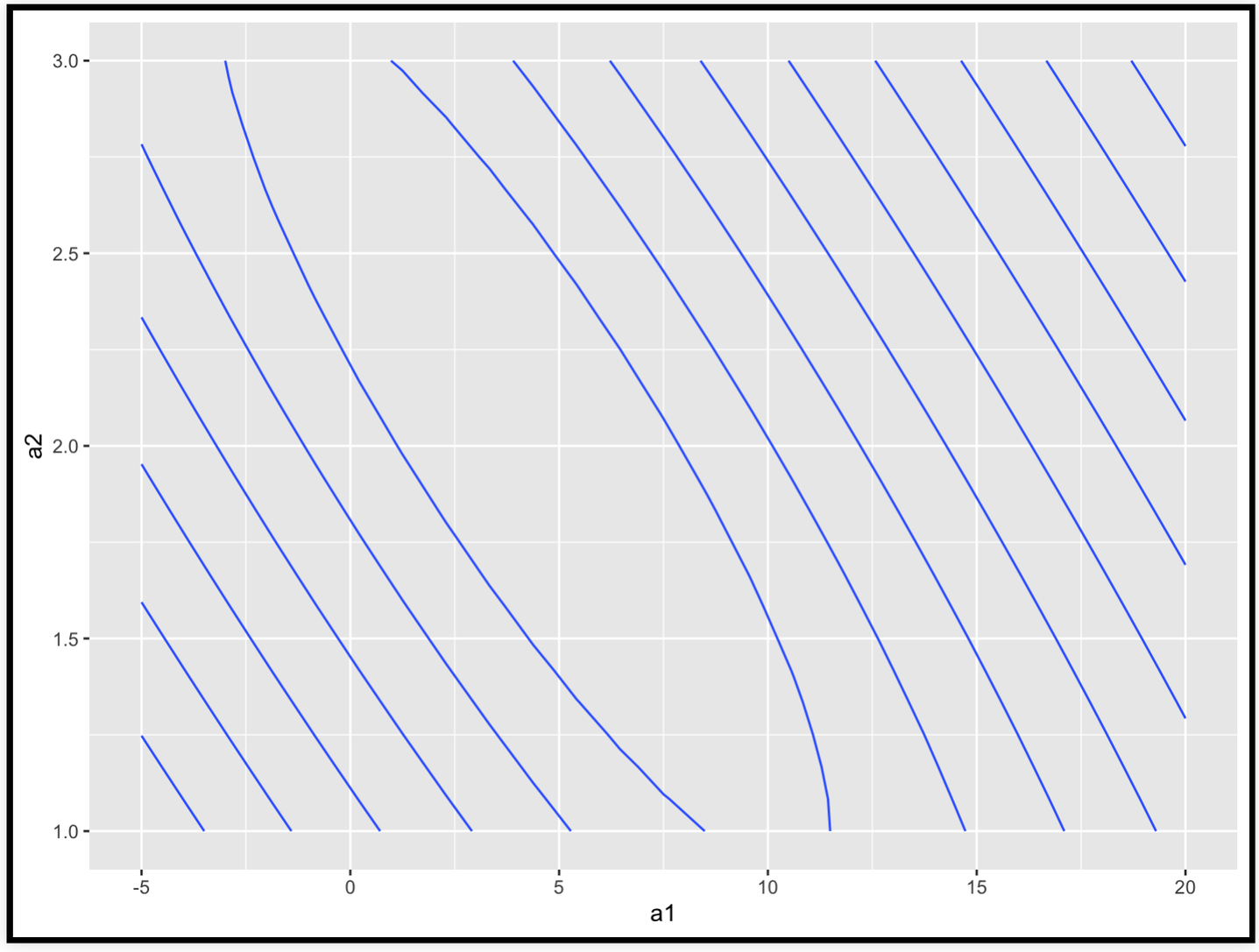
```
grid %>%
  filter(rank(dist) <= 10) %>%
  arrange(dist)
```

```
##          a1       a2     dist
## 1  4.375000 2.000000 2.137234
## 2  4.375000 2.083333 2.155409
## 3  3.333333 2.166667 2.168677
## 4  5.416667 1.916667 2.210294
## 5  3.333333 2.250000 2.212637
## 6  5.416667 1.833333 2.218550
## 7  4.375000 1.916667 2.241533
## 8  3.333333 2.083333 2.246169
## 9  4.375000 2.166667 2.293149
## 10 2.291667 2.333333 2.308274
```

Contour Map

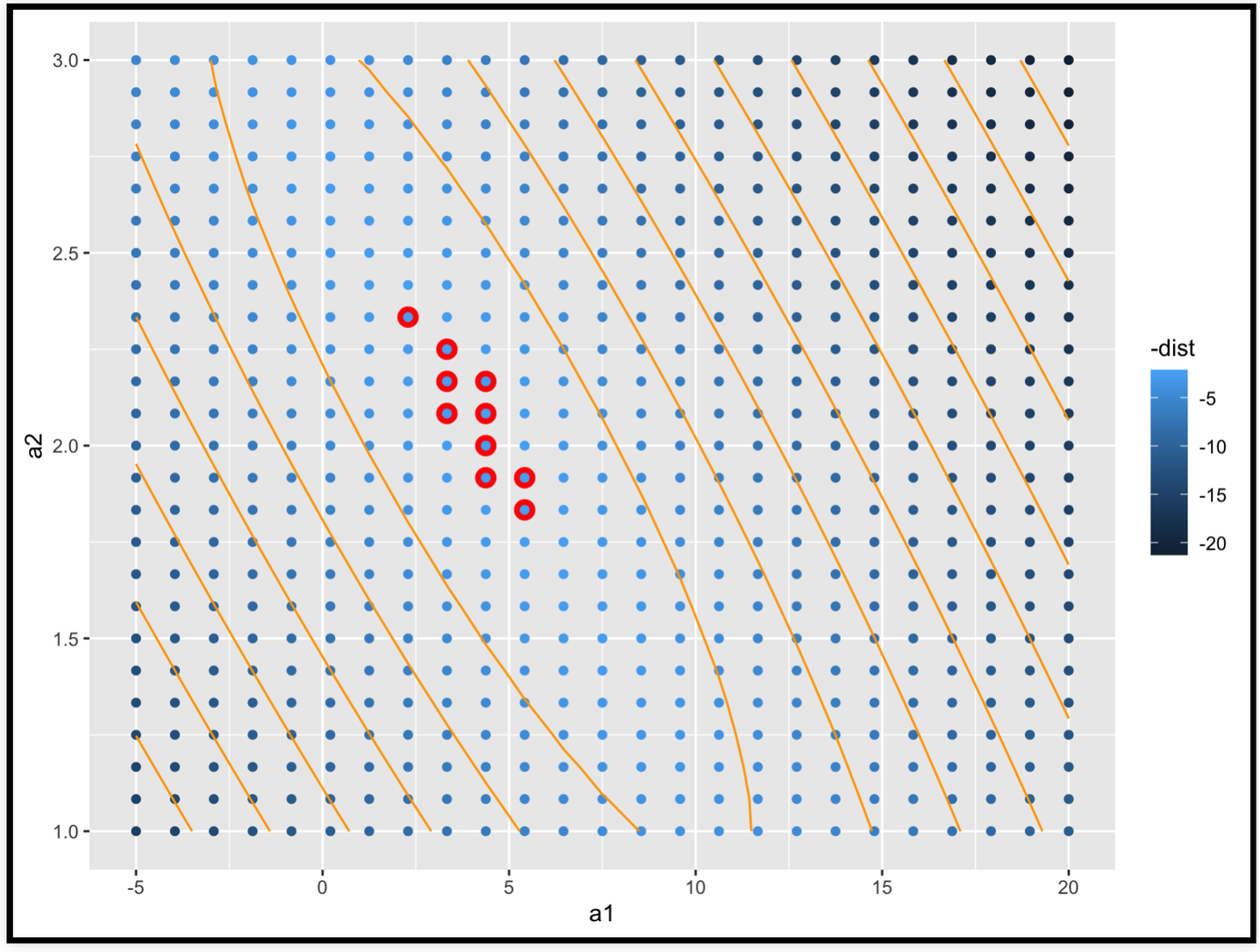
The contour lines represent equal “bins” of distance.

```
grid %>%
  ggplot(aes(a1, a2, z=-dist)) + geom_contour()
```



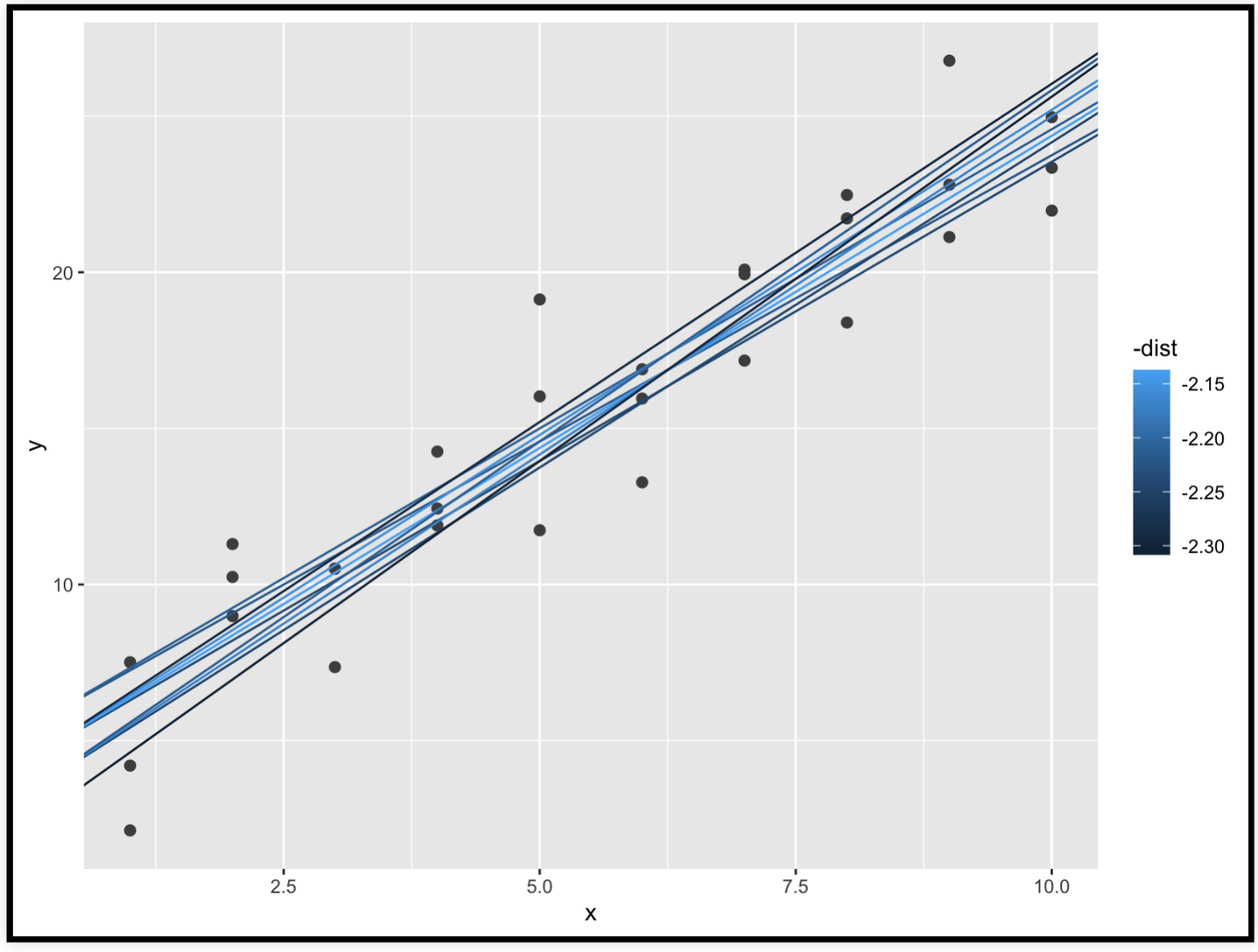
Contour Map (2)

```
grid %>%
  ggplot(aes(a1, a2)) +
  geom_point(data = filter(grid, rank(dist) <= 10), size = 4, colour =
        "red") +
  geom_point(aes(colour = -dist)) +
  geom_contour(aes(z = -dist), colour = "orange")
```



Overlay those 10 best models on the data.

```
ggplot(sim1, aes(x, y)) +
  geom_point(size = 2, colour = "grey30") +
  geom_abline(
    aes(intercept = a1, slope = a2, colour = -dist),
    data = filter(grid, rank(dist) <= 10)
  )
```



Optimize the models

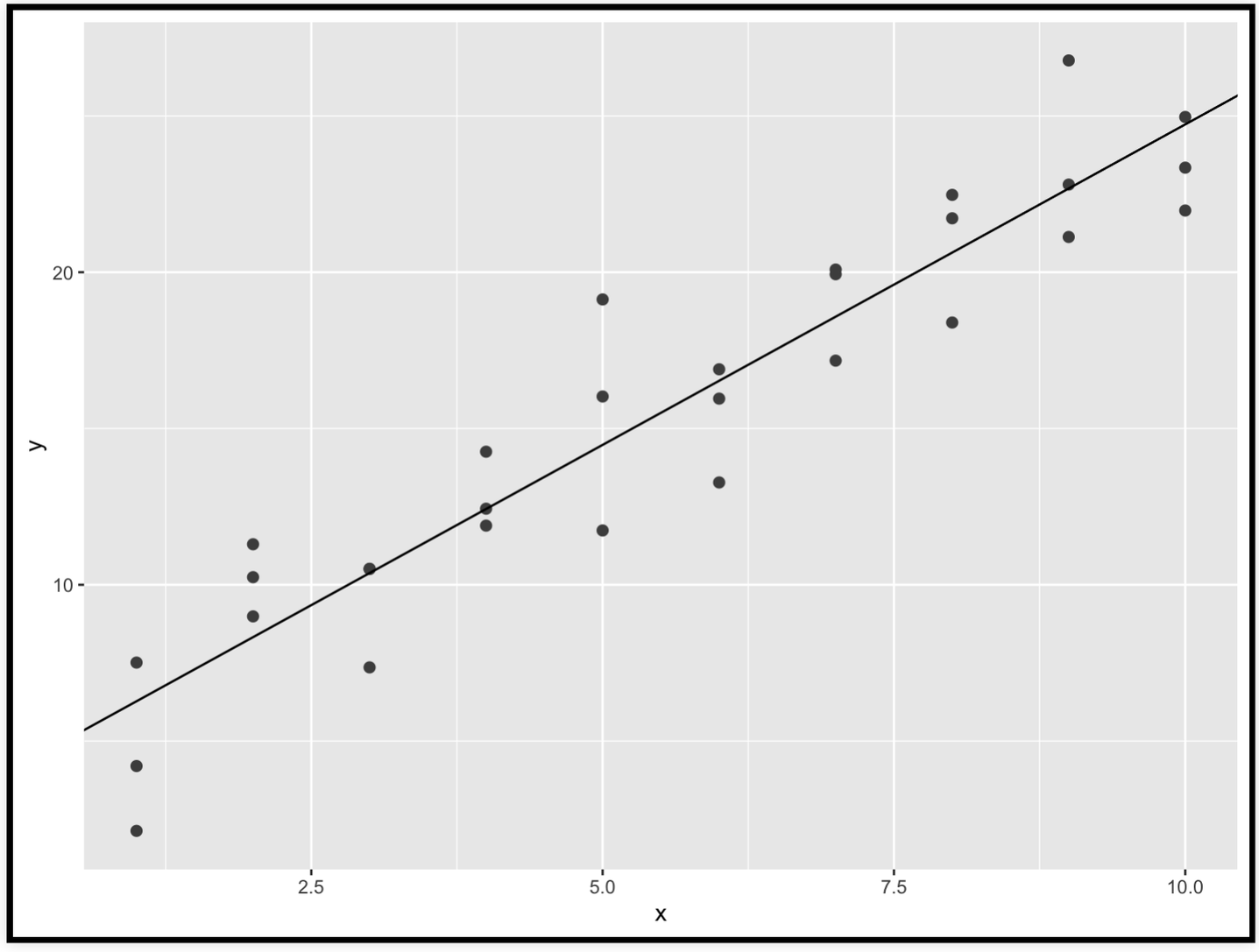
The `optim` function chooses the parameters that minimize distance. The `c(0,0)` is the starting point.

```
best <- optim(c(0, 0), measure_distance, data = sim1)
best$par
```

```
## [1] 4.222248 2.051204
```

Plot the optimal model

```
ggplot(sim1, aes(x, y)) +
  geom_point(size = 2, colour = "grey30") +
  geom_abline(intercept = best$par[1], slope = best$par[2])
```



R can do all of this in 1 command

Of course, R has a tool to do this whole process automatically. This is our standard OLS regression.

```
sim1_mod <- lm(y ~ x, data = sim1)
coef(sim1_mod)
```

```
## (Intercept)           x
##    4.220822    2.051533
```

Generate Predictions

We can use a model object like `sim1_mod` to generate predictions. We an start with an empty grid.

```
grid <- sim1 %>%
  data_grid(x)
grid
```

```
## # A tibble: 10 × 1
##        x
##    <int>
##  1     1
##  2     2
##  3     3
##  4     4
##  5     5
##  6     6
##  7     7
##  8     8
##  9     9
## 10    10
```

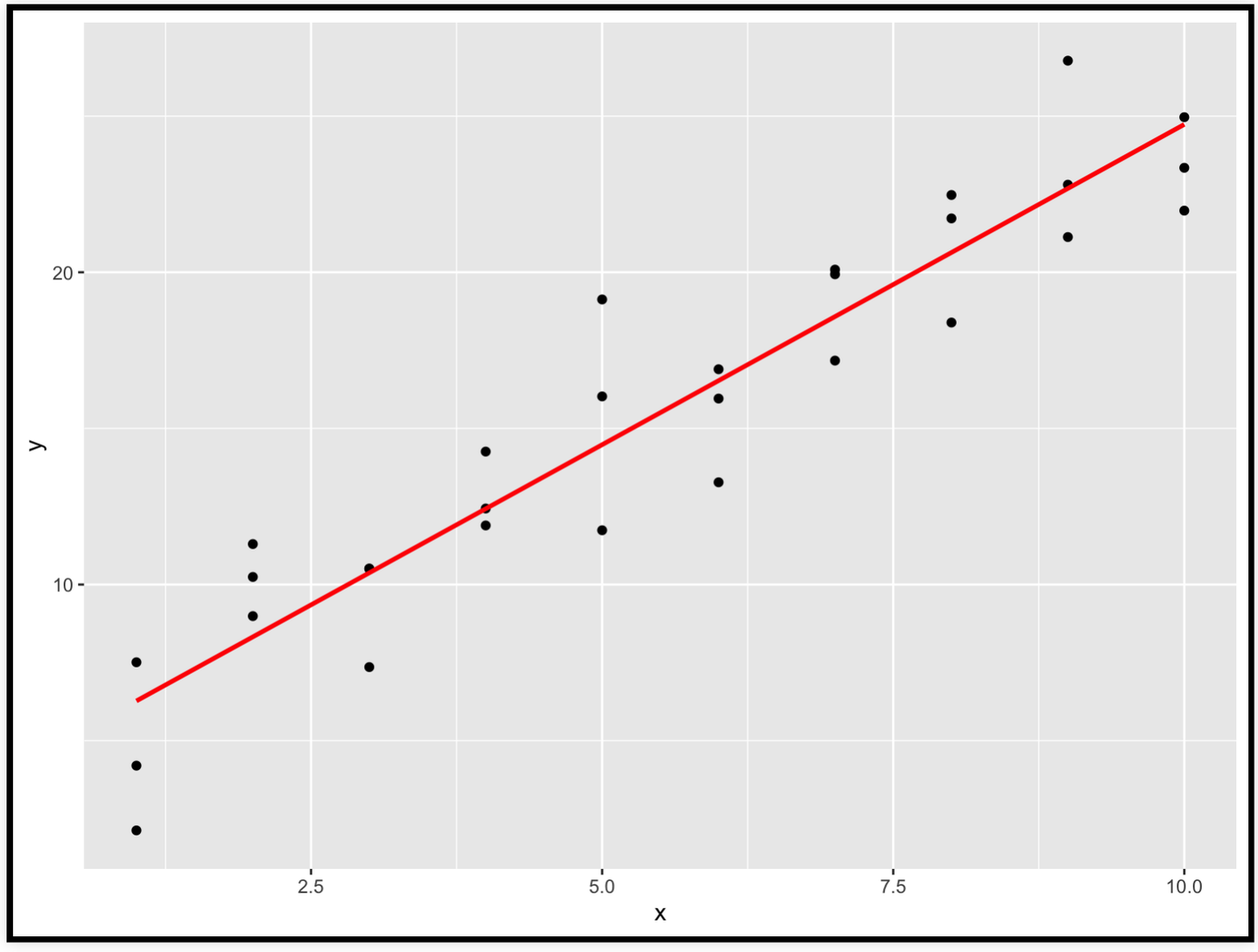
Generate Predictions (2)

```
grid <- grid %>%
  add_predictions(sim1_mod)
grid
```

```
## # A tibble: 10 × 2
##        x  pred
##    <int> <dbl>
##  1     1  6.27
##  2     2  8.32
##  3     3 10.4
##  4     4 12.4
##  5     5 14.5
##  6     6 16.5
##  7     7 18.6
##  8     8 20.6
##  9     9 22.7
## 10    10 24.7
```

Plot those predictions using `geom_line`.

```
ggplot(sim1, aes(x)) +
  geom_point(aes(y = y)) +
  geom_line(aes(y = pred), data = grid, colour = "red", size = 1)
```



Add residuals

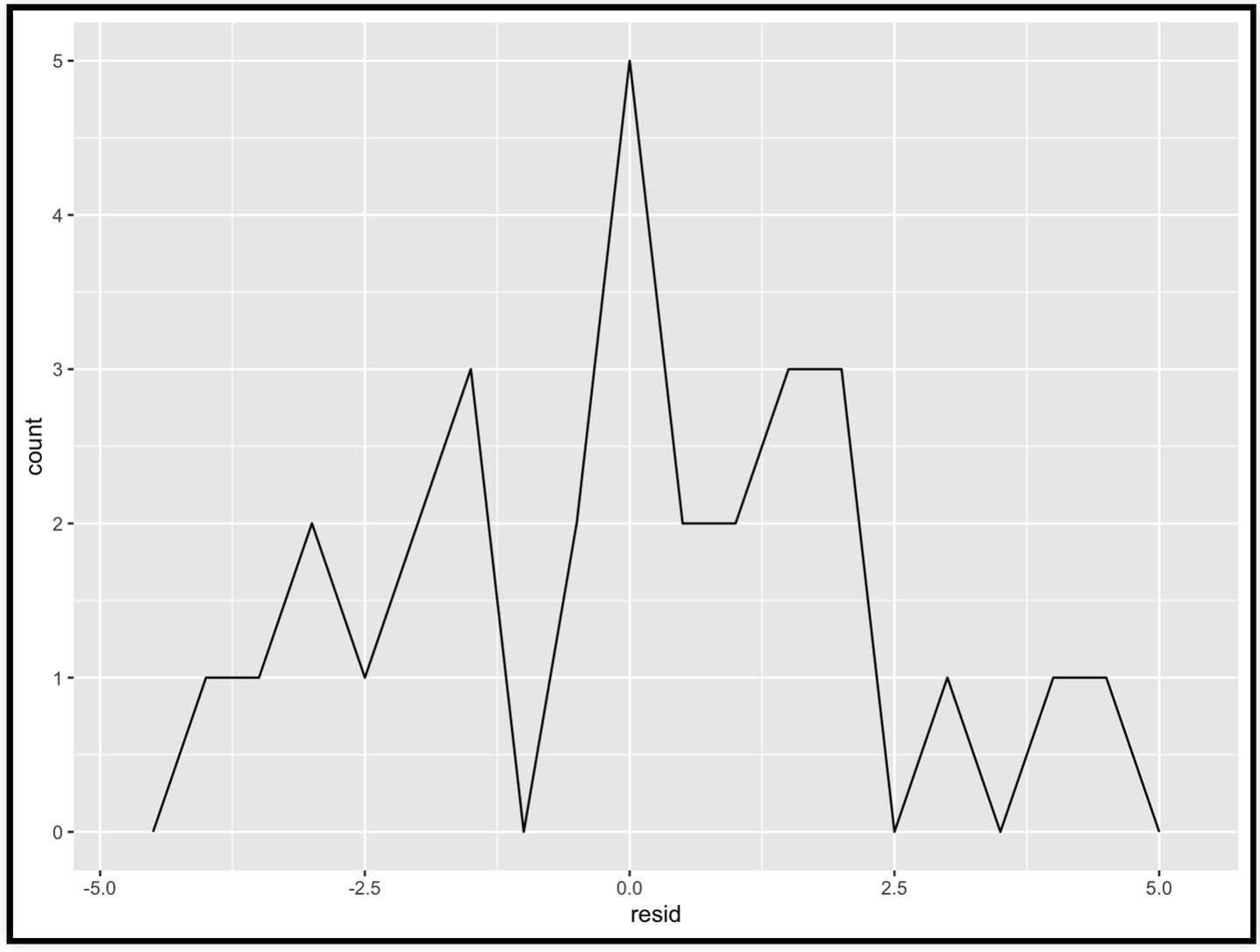
Add residuals. We need to use the original dataset.

```
sim1 <- sim1 %>%
  add_residuals(sim1_mod)
sim1
```

```
## # A tibble: 30 × 3
##         x     y    resid
##     <int> <dbl>    <dbl>
##  1      1  4.20 -2.07
##  2      1  7.51  1.24
##  3      1  2.13 -4.15
##  4      2  8.99  0.665
##  5      2 10.2   1.92
##  6      2 11.3   2.97
##  7      3  7.36 -3.02
##  8      3 10.5   0.130
##  9      3 10.5   0.136
## 10      4 12.4   0.00763
## # … with 20 more rows
```

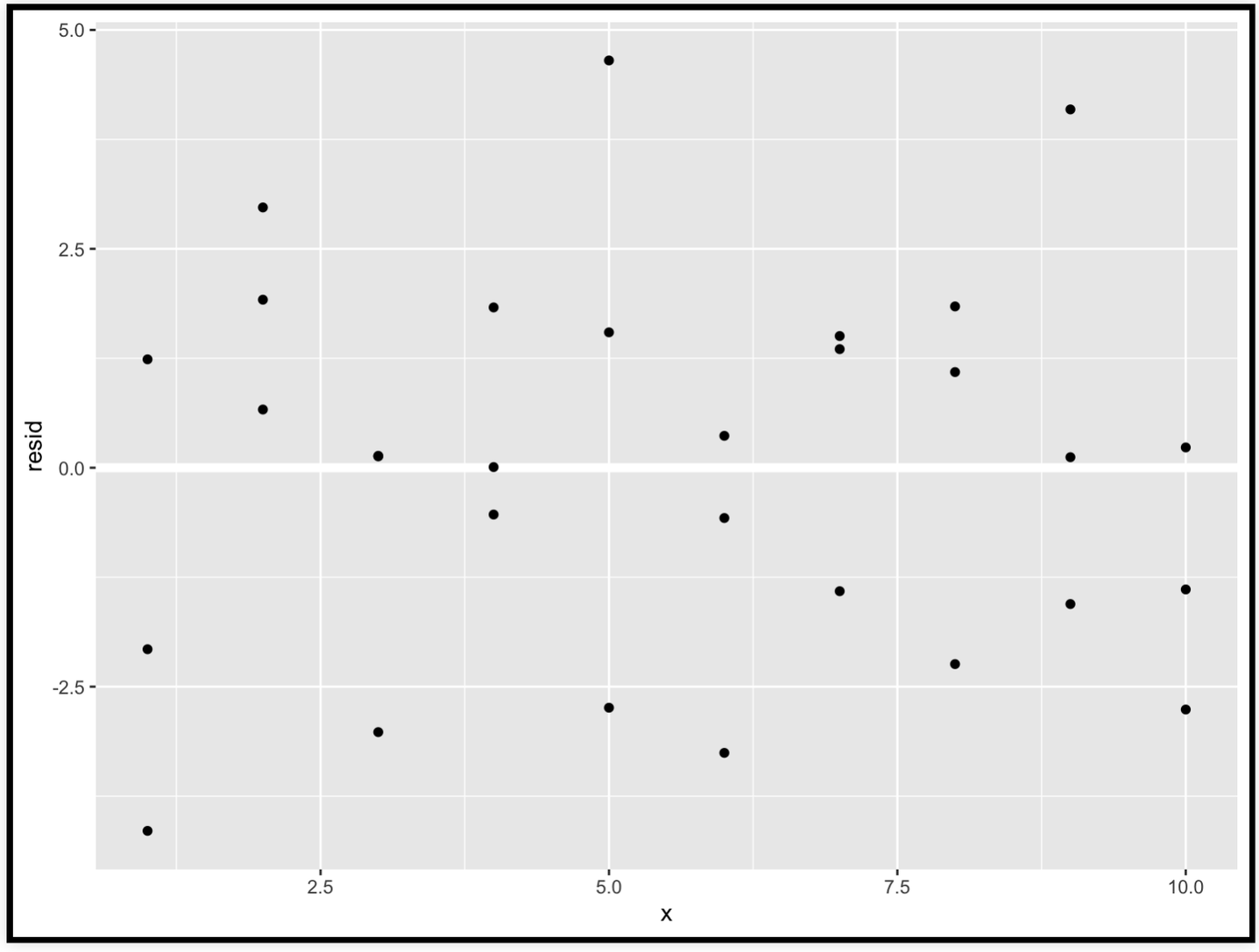
Plot Residuals

```
ggplot(sim1, aes(resid)) +
  geom_freqpoly(binwidth = 0.5)
```



Plot Residuals

```
ggplot(sim1, aes(x, resid)) +
  geom_ref_line(h = 0) +
  geom_point()
```



Statistical Methods

- Aside from modeling, R has commonly used statistical functions built in.
- You can automate the generation of these results (check out the `broom` package)

t-tests

```
t.test(disp ~ vs, data = mtcars)
```

```
##
##  Welch Two Sample t-test
##
## data:  disp by vs
## t = 5.9416, df = 26.977, p-value = 2.477e-06
## alternative hypothesis: true difference in means between group 0 and grou
## 95 percent confidence interval:
##  114.3628 235.0229
## sample estimates:
## mean in group 0 mean in group 1
##        307.1500        132.4571
```

Correlation

```
cor.test(mtcars$disp, mtcars$mpg)
```

```
##
##  Pearson's product-moment correlation
##
## data:  mtcars$disp and mtcars$mpg
## t = -8.7472, df = 30, p-value = 9.38e-10
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.9233594 -0.7081376
## sample estimates:
##       cor
## -0.8475514
```

Chi Squared (1)

Using survey data on Smoking and Exercise

```
survey <- MASS::survey
tbl <- table(survey$Smoke, survey$Exer)
tbl
```

```
##
##          Freq None Some
##    Heavy    7    1    3
##    Never   87   18   84
##    Occas   12    3    4
##    Regul    9    1    7
```

Chi Squared (2)

```
chisq.test(tbl)
```

```
##
##  Pearson's Chi-squared test
##
## data:  tbl
## X-squared = 5.4885, df = 6, p-value = 0.4828
```

Resource: Which statistical test?

https://stats.oarc.ucla.edu/other/mult-pkg/whatstat/

Additional Resources

Online Resources

Start here:

- R for Data Science http://r4ds.had.co.nz/
- UBC STAT 545 http://stat545.com/
- Hands on Programming with R https://rstudio-education.github.io/hopr/

Online Resources

Additional:

- Advanced R http://adv-r.had.co.nz/
- R Packages http://r-pkgs.had.co.nz/
- Software Carpentry R Lesson
  http://swcarpentry.github.io/r-novice-inflammation/
- Data Carpentry R for Social Scientsts
  https://datacarpentry.org/r-socialsci/

For help/community:

- http://stackoverflow.com/questions/tagged/r
- https://twitter.com/search?q=%23rstats
- https://www.r-project.org/mail.html (Though they're not terribly welcoming to newbies sometimes…)

Print Books

- https://us.sagepub.com/en-us/nam/discovering-statistics-using-r/book236067%20
- https://us.sagepub.com/en-us/nam/an-r-companion-to-applied-regression/book233899
- http://shop.oreilly.com/product/0636920028574.do

References

- Wickham, Hadley (2014). https://www.jstatsoft.org/article/view/v059i10