04 — How ggplot Thinks

Kieran Healy

January 31, 2024

Load our libraries

```r
library(here)      # manage file paths
library(socviz)    # data and some useful functions
library(tidyverse) # your friend and mine
library(gapminder) # some data
```

Nearly done with the scaffolding

✅ Thought about elements of visualization

✅ Gotten oriented to R and RStudio

✅ Knitted a document

✅ Written a bit of `ggplot` code

Nearly done with the scaffolding

- ✅ Thought about elements of visualization
- ✅ Gotten oriented to R and RStudio
- ✅ Knitted a document
- ✅ Written a bit of `ggplot` code
- ⬜ Get my data in to R
- ⬜ Make a plot with it

Reviewing the Problem Sets

Windows and Zip Files

Rendering a Project and watching it update

Strategies for debugging your code: a chunk at a time, a step at a time

In the background

Things the columns in our table can be:

Words naming *unordered* categories: e.g. Asia, Europe, America

Words naming *ordered* categories: e.g. Elementary, High School, College; *or* Strongly Agree, Agree, Neutral, Disagree, Strongly Disagree; etc.

Numbers that can take on just a quite limited range of (integer) values: e.g. number of children; years of schooling; number of people in the household. These are very close to categorical variables as well, but are more often counts.

Numbers that can take on many values in some range, depending on how precisely we measure them: e.g. distance traveled to work; height in centimeters; number of computers sold per quarter; population size

Truly “continuous” measures are comparatively rare in social science; most often encountered with aggregate quantities rather than individual ones. (Even things like “income” end up being measured with e.g. 10 categories.)

Feed ggplot tidy data

Tidy Data

What is tidy data?

gdp	lifexp	pop	continent
340	65	31	Euro
227	51	200	Amer
909	81	80	Euro
126	40	20	Asia

Tidy data

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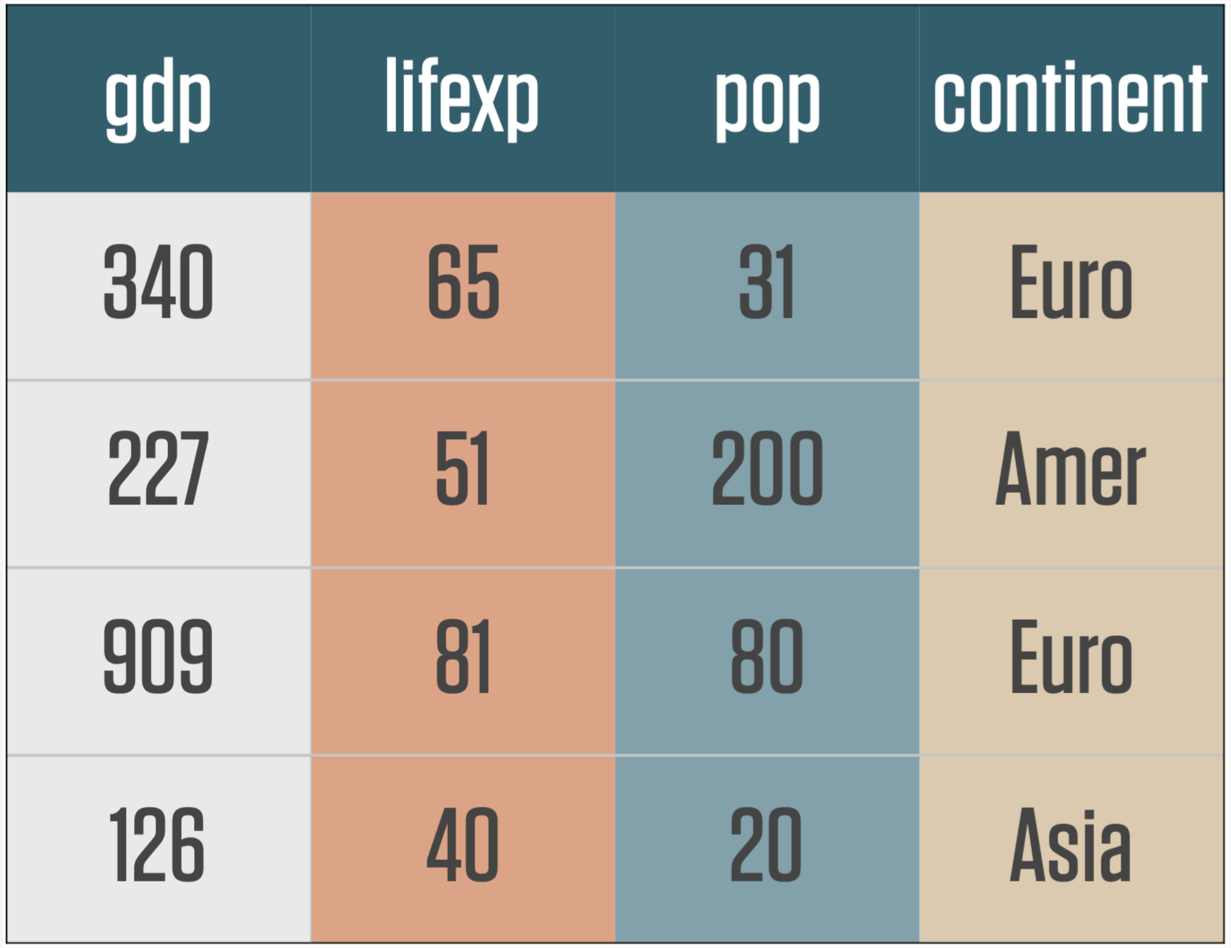

gdp	lifexp	pop	continent
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909	81	80	Euro
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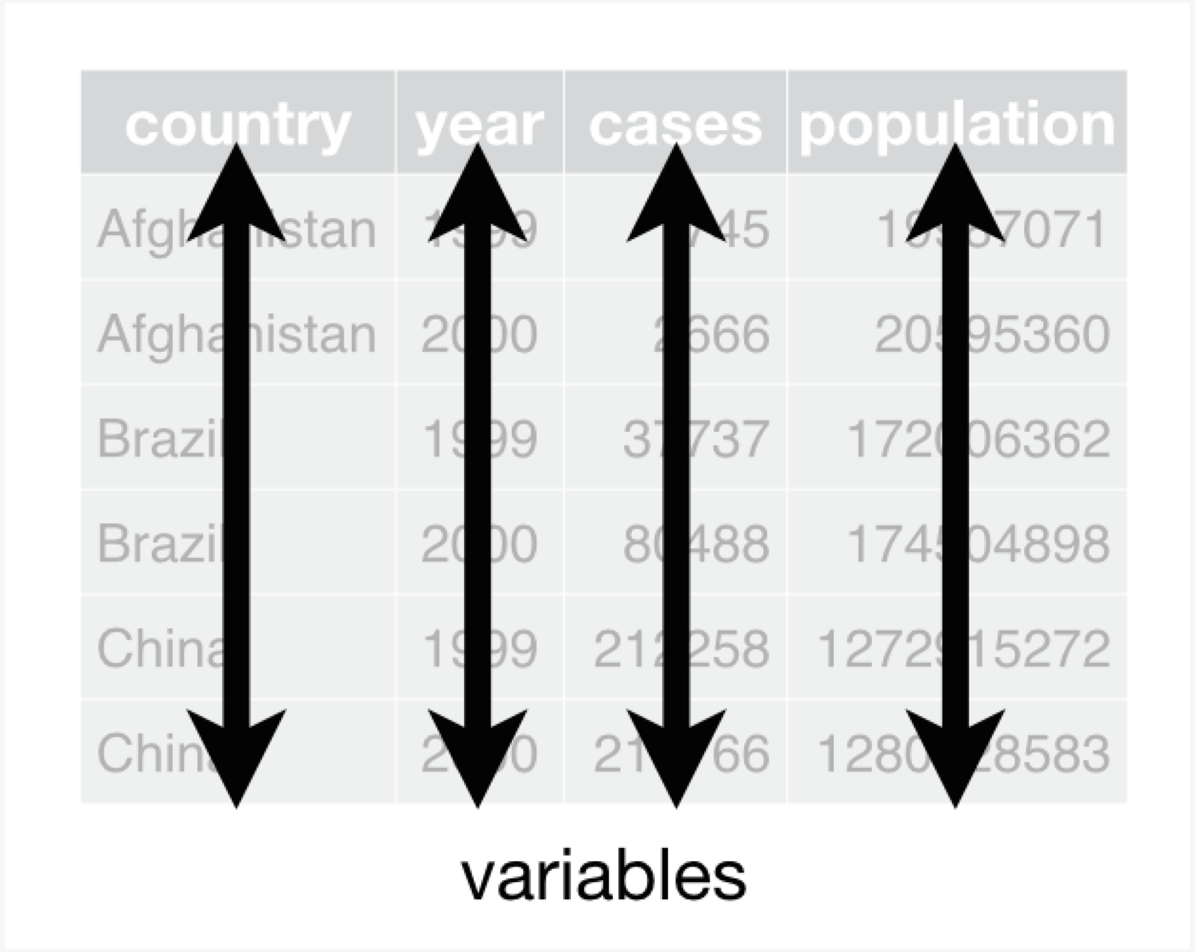
Tidy data is in *long* format

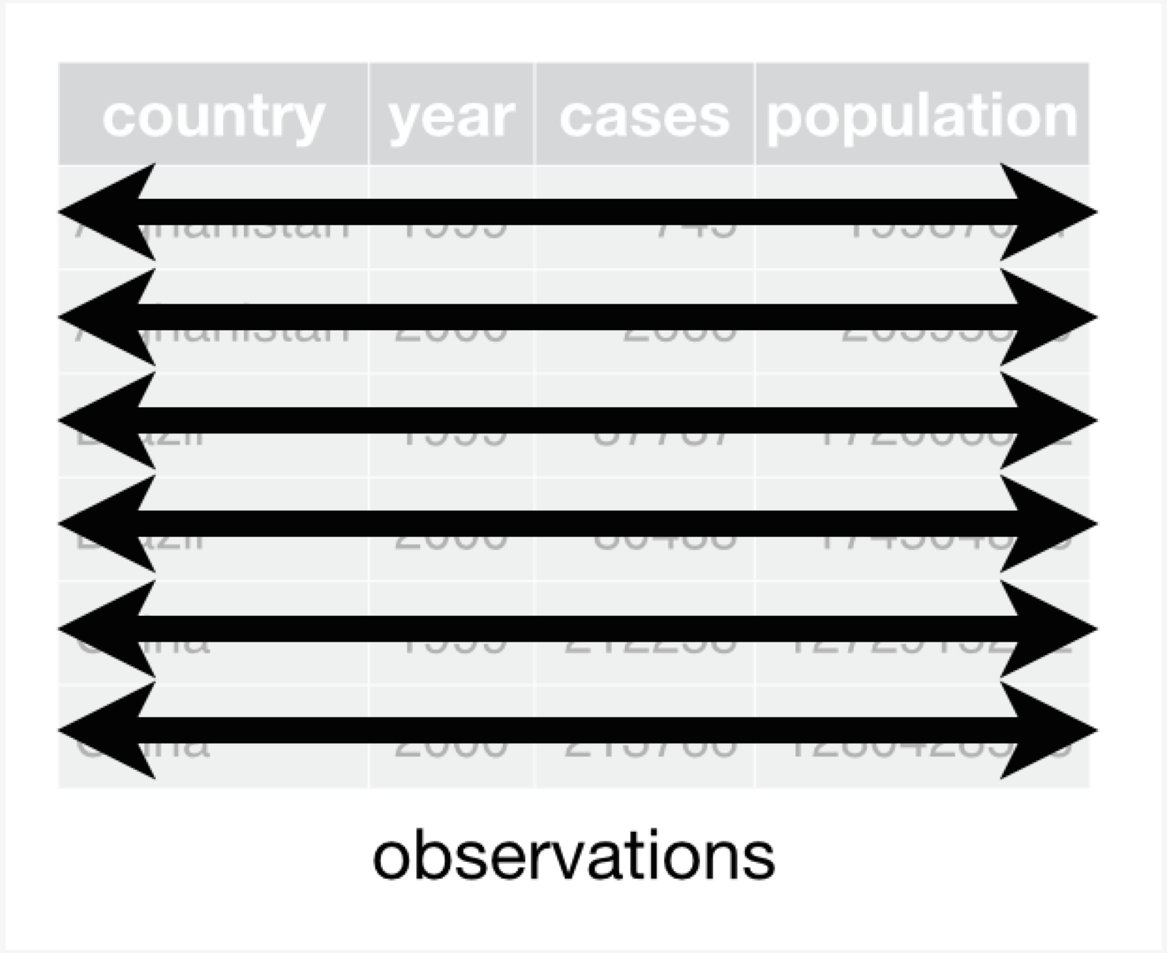
Every column is a single variable



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

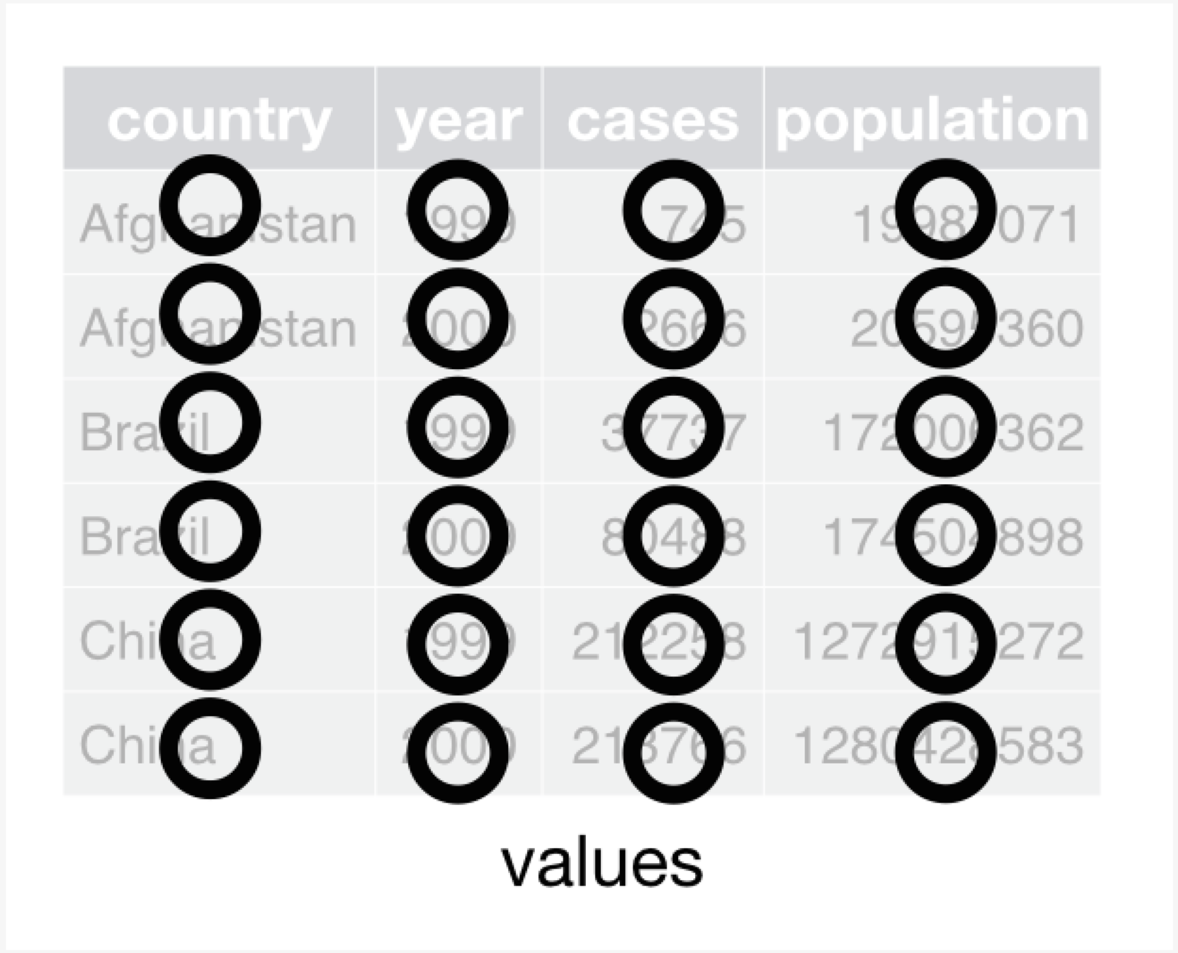
Grolemund & Wickham

Every row is a single observation



Grolemund & Wickham

Every cell is a single value



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Get your data into long format

Very, *very* often, the solution to some data-wrangling or data visualization problem in a Tidyverse-focused workflow is:

Get your data into long format

Very, *very* often, the solution to some data-wrangling or data visualization problem in a Tidyverse-focused workflow is:

First, get the data into long format

Then do the thing you want.

Untidy data exists for good reasons

Storing and printing data in long format entails a lot of *repetition*:

```r
library(palmerpenguins)
penguins |>
  group_by(species, island, year) |>
  summarize(bill = round(mean(bill_length_mm, na.rm = TRUE),2)) |>
  knitr::kable()
```

species	island	year	bill
Adelie	Biscoe	2007	38.32
Adelie	Biscoe	2008	38.70
Adelie	Biscoe	2009	39.69
Adelie	Dream	2007	39.10
Adelie	Dream	2008	38.19
Adelie	Dream	2009	38.15
Adelie	Torgersen	2007	38.80
Adelie	Torgersen	2008	38.77
Adelie	Torgersen	2009	39.31
Chinstrap	Dream	2007	48.72
Chinstrap	Dream	2008	48.70
Chinstrap	Dream	2009	49.05

Untidy data exists for good reasons

A wide format is *easier* and *more efficient* to read in print:

```r
penguins ▷
  group_by(species, island, year) ▷
  summarize(bill = round(mean(bill_length_mm, na.rm = TRUE), 2)) ▷
  pivot_wider(names_from = year, values_from = bill) ▷
  knitr::kable()
```

species	island	2007	2008	2009
Adelie	Biscoe	38.32	38.70	39.69
Adelie	Dream	39.10	38.19	38.15
Adelie	Torgersen	38.80	38.77	39.31
Chinstrap	Dream	48.72	48.70	49.05
Gentoo	Biscoe	47.01	46.94	48.50

Untidy data exists for good reasons

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penguins |>
  group_by(species, year, island) |>
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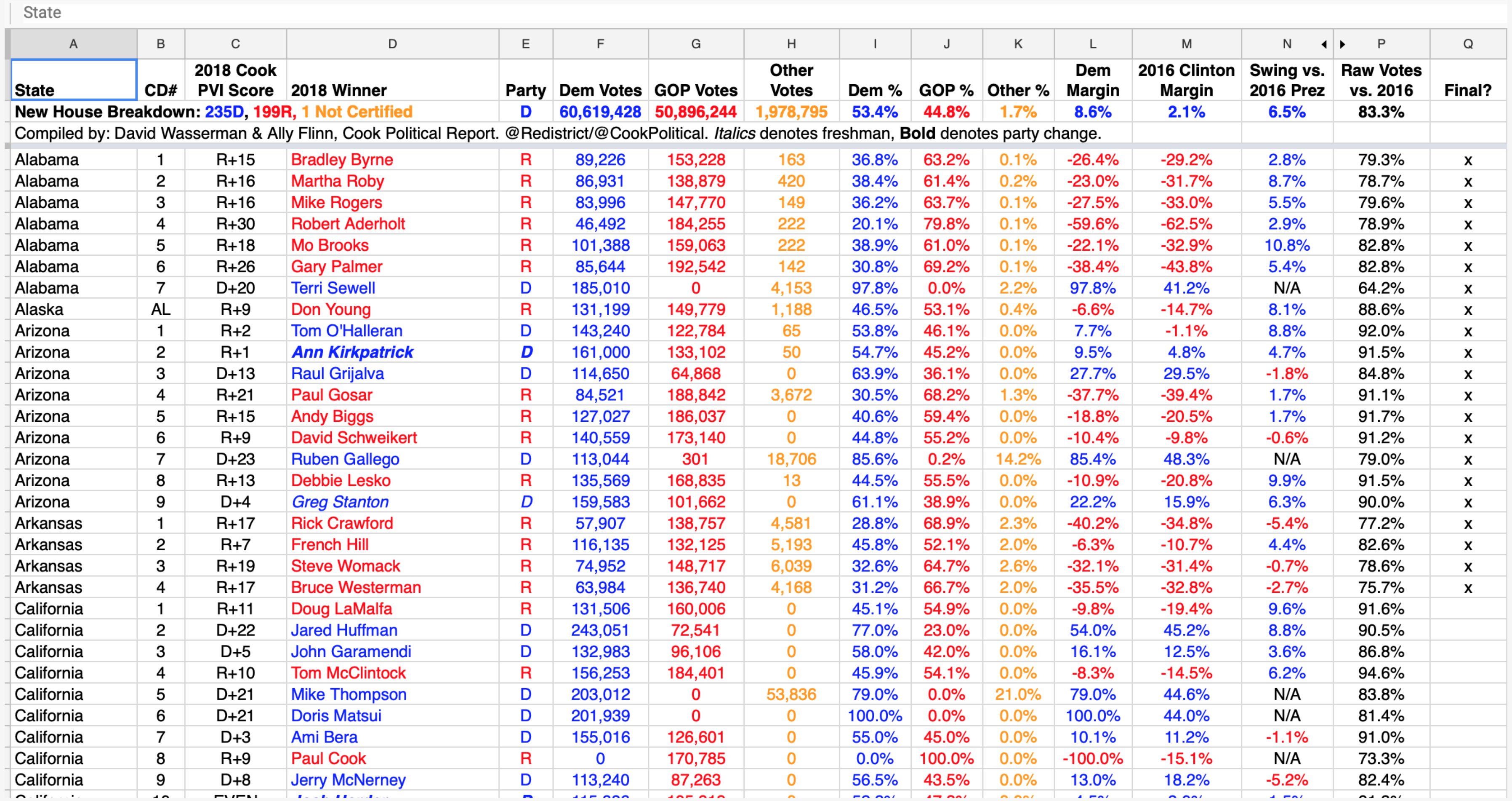
```

species	year	Biscoe	Dream	Torgersen
Adelie	2007	38.32	39.10	38.80
Adelie	2008	38.70	38.19	38.77
Adelie	2009	39.69	38.15	39.31
Chinstrap	2007	NA	48.72	NA
Chinstrap	2008	NA	48.70	NA
Chinstrap	2009	NA	49.05	NA
Gentoo	2007	47.01	NA	NA
Gentoo	2008	46.94	NA	NA
Gentoo	2009	48.50	NA	NA

But also for less good reasons



State

A	B	C	D	E	F	G	H	I	J	K	L	M	N	P	Q
State	CD#	2018 Cook PVI Score	2018 Winner	Party	Dem Votes	GOP Votes	Other Votes	Dem %	GOP %	Other %	Dem Margin	2016 Clinton Margin	Swing vs. 2016 Prez	Raw Votes vs. 2016	Final?
New House Breakdown: 235D, 199R, 1 Not Certified				**D**	**60,619,428**	**50,896,244**	**1,978,795**	**53.4%**	**44.8%**	**1.7%**	**8.6%**	**2.1%**	**6.5%**	**83.3%**	
Compiled by: David Wasserman & Ally Flinn, Cook Political Report. @Redistrict/@CookPolitical. *Italics* denotes freshman, **Bold** denotes party change.															
Alabama	1	R+15	Bradley Byrne	R	89,226	153,228	163	36.8%	63.2%	0.1%	-26.4%	-29.2%	2.8%	79.3%	x
Alabama	2	R+16	Martha Roby	R	86,931	138,879	420	38.4%	61.4%	0.2%	-23.0%	-31.7%	8.7%	78.7%	x
Alabama	3	R+16	Mike Rogers	R	83,996	147,770	149	36.2%	63.7%	0.1%	-27.5%	-33.0%	5.5%	79.6%	x
Alabama	4	R+30	Robert Aderholt	R	46,492	184,255	222	20.1%	79.8%	0.1%	-59.6%	-62.5%	2.9%	78.9%	x
Alabama	5	R+18	Mo Brooks	R	101,388	159,063	222	38.9%	61.0%	0.1%	-22.1%	-32.9%	10.8%	82.8%	x
Alabama	6	R+26	Gary Palmer	R	85,644	192,542	142	30.8%	69.2%	0.1%	-38.4%	-43.8%	5.4%	82.8%	x
Alabama	7	D+20	Terri Sewell	D	185,010	0	4,153	97.8%	0.0%	2.2%	97.8%	41.2%	N/A	64.2%	x
Alaska	AL	R+9	Don Young	R	131,199	149,779	1,188	46.5%	53.1%	0.4%	-6.6%	-14.7%	8.1%	88.6%	x
Arizona	1	R+2	Tom O'Halleran	D	143,240	122,784	65	53.8%	46.1%	0.0%	7.7%	-1.1%	8.8%	92.0%	x
Arizona	2	R+1	***Ann Kirkpatrick***	***D***	161,000	133,102	50	54.7%	45.2%	0.0%	9.5%	4.8%	4.7%	91.5%	x
Arizona	3	D+13	Raul Grijalva	D	114,650	64,868	0	63.9%	36.1%	0.0%	27.7%	29.5%	-1.8%	84.8%	x
Arizona	4	R+21	Paul Gosar	R	84,521	188,842	3,672	30.5%	68.2%	1.3%	-37.7%	-39.4%	1.7%	91.1%	x
Arizona	5	R+15	Andy Biggs	R	127,027	186,037	0	40.6%	59.4%	0.0%	-18.8%	-20.5%	1.7%	91.7%	x
Arizona	6	R+9	David Schweikert	R	140,559	173,140	0	44.8%	55.2%	0.0%	-10.4%	-9.8%	-0.6%	91.2%	x
Arizona	7	D+23	Ruben Gallego	D	113,044	301	18,706	85.6%	0.2%	14.2%	85.4%	48.3%	N/A	79.0%	x
Arizona	8	R+13	Debbie Lesko	R	135,569	168,835	13	44.5%	55.5%	0.0%	-10.9%	-20.8%	9.9%	91.5%	x
Arizona	9	D+4	*Greg Stanton*	*D*	159,583	101,662	0	61.1%	38.9%	0.0%	22.2%	15.9%	6.3%	90.0%	x
Arkansas	1	R+17	Rick Crawford	R	57,907	138,757	4,581	28.8%	68.9%	2.3%	-40.2%	-34.8%	-5.4%	77.2%	x
Arkansas	2	R+7	French Hill	R	116,135	132,125	5,193	45.8%	52.1%	2.0%	-6.3%	-10.7%	4.4%	82.6%	x
Arkansas	3	R+19	Steve Womack	R	74,952	148,717	6,039	32.6%	64.7%	2.6%	-32.1%	-31.4%	-0.7%	78.6%	x
Arkansas	4	R+17	Bruce Westerman	R	63,984	136,740	4,168	31.2%	66.7%	2.0%	-35.5%	-32.8%	-2.7%	75.7%	x
California	1	R+11	Doug LaMalfa	R	131,506	160,006	0	45.1%	54.9%	0.0%	-9.8%	-19.4%	9.6%	91.6%	
California	2	D+22	Jared Huffman	D	243,051	72,541	0	77.0%	23.0%	0.0%	54.0%	45.2%	8.8%	90.5%	
California	3	D+5	John Garamendi	D	132,983	96,106	0	58.0%	42.0%	0.0%	16.1%	12.5%	3.6%	86.8%	
California	4	R+10	Tom McClintock	R	156,253	184,401	0	45.9%	54.1%	0.0%	-8.3%	-14.5%	6.2%	94.6%	
California	5	D+21	Mike Thompson	D	203,012	0	53,836	79.0%	0.0%	21.0%	79.0%	44.6%	N/A	83.8%	
California	6	D+21	Doris Matsui	D	201,939	0	0	100.0%	0.0%	0.0%	100.0%	44.0%	N/A	81.4%	
California	7	D+3	Ami Bera	D	155,016	126,601	0	55.0%	45.0%	0.0%	10.1%	11.2%	-1.1%	91.0%	
California	8	R+9	Paul Cook	R	0	170,785	0	0.0%	100.0%	0.0%	-100.0%	-15.1%	N/A	73.3%	
California	9	D+8	Jerry McNerney	D	113,240	87,263	0	56.5%	43.5%	0.0%	13.0%	18.2%	-5.2%	82.4%	
[illegible]	10	EVEN	[illegible]	[illegible]	[illegible]	[illegible]	0	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	

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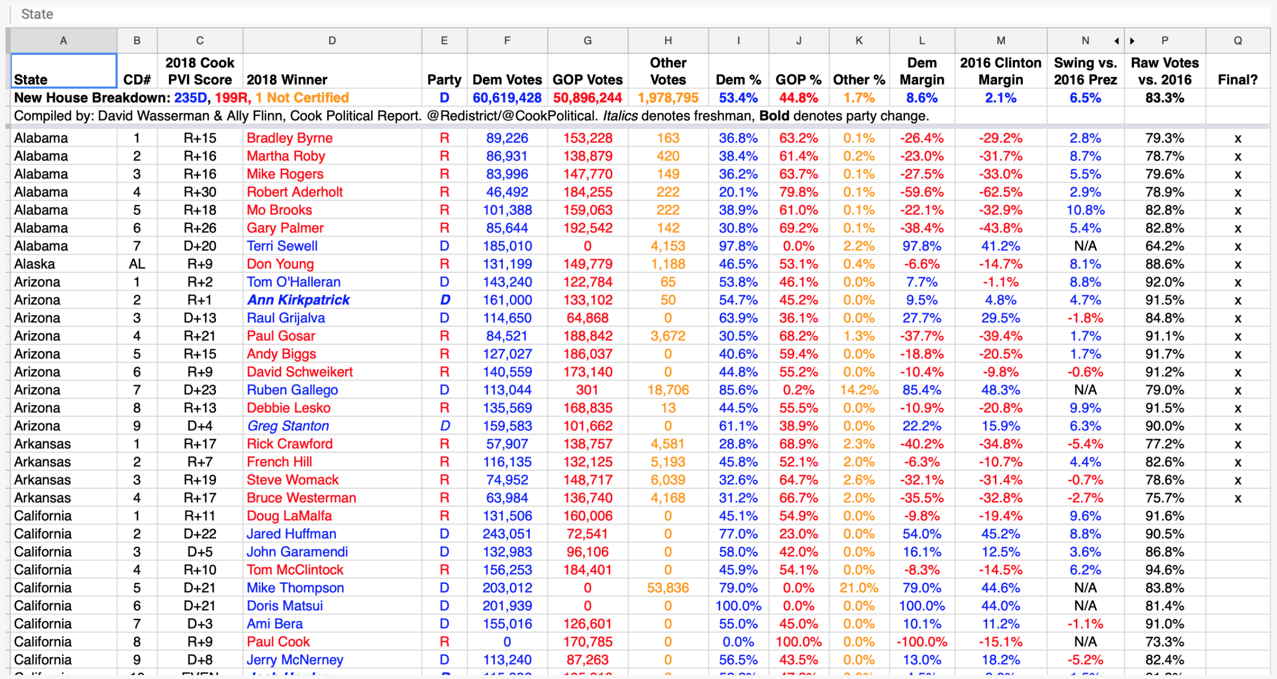

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California	9	D+8	Jerry McNerney	D	113,240	87,263	0	56.5%	43.5%	0.0%	13.0%	18.2%	-5.2%	82.4%	

- 😠 More than one header row
- 😡 Mixed data types in some columns
- 💀 Color and typography used to encode variables and their values

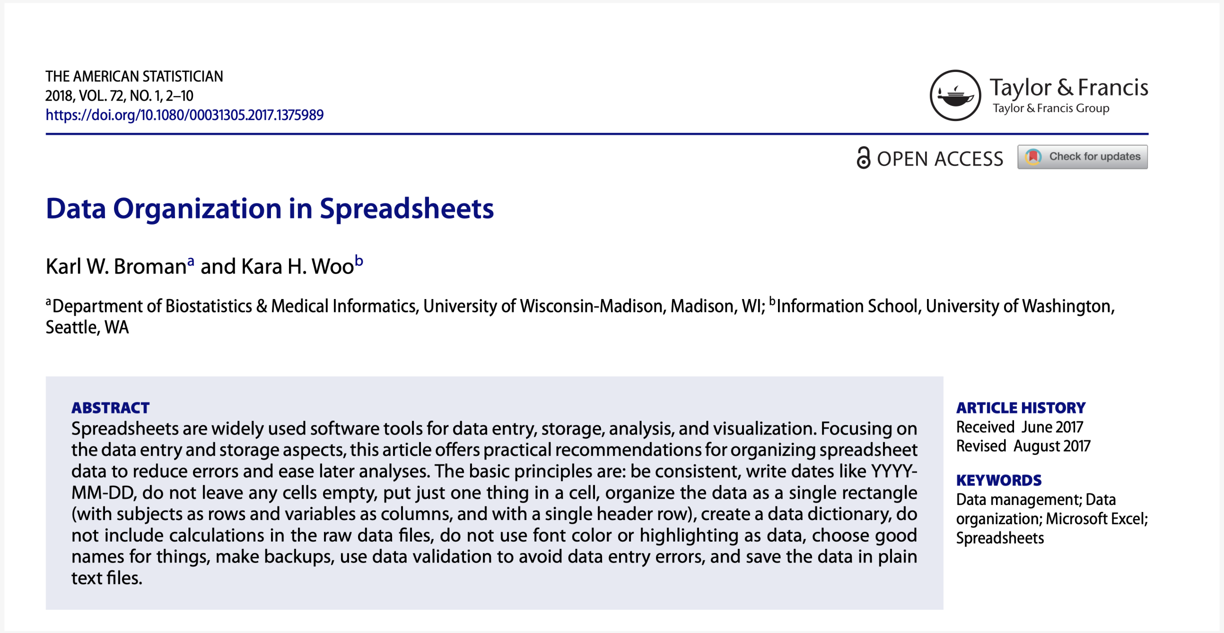
Spot the untidiness

Fix it before you import it

Prevention is better than cure!

An excellent article by Karl Broman and Kara Woo:

> Broman KW, Woo KH (2018) "Data Organization in Spreadsheets"." *The American Statistician* 78:2–10



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Data Organization in Spreadsheets

Karl W. Broman[a] and Kara H. Woo[b]

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ABSTRACT
Spreadsheets are widely used software tools for data entry, storage, analysis, and visualization. Focusing on the data entry and storage aspects, this article offers practical recommendations for organizing spreadsheet data to reduce errors and ease later analyses. The basic principles are: be consistent, write dates like YYYY-MM-DD, do not leave any cells empty, put just one thing in a cell, organize the data as a single rectangle (with subjects as rows and variables as columns, and with a single header row), create a data dictionary, do not include calculations in the raw data files, do not use font color or highlighting as data, choose good names for things, make backups, use data validation to avoid data entry errors, and save the data in plain text files.

ARTICLE HISTORY
Received June 2017
Revised August 2017

KEYWORDS
Data management; Data organization; Microsoft Excel; Spreadsheets

Data organization in spreadsheets

The most common `tidyr` operation

Pivoting from wide to long:

```
edu
```

```
# A tibble: 366 × 11
   age   sex    year total elem4 elem8   hs3   hs4 coll3 coll4 median
   <chr> <chr> <int> <int> <int> <int> <dbl> <dbl> <dbl> <dbl>  <dbl>
 1 25-34 Male   2016 21845   116   468  1427  6386  6015  7432     NA
 2 25-34 Male   2015 21427   166   488  1584  6198  5920  7071     NA
 3 25-34 Male   2014 21217   151   512  1611  6323  5910  6710     NA
 4 25-34 Male   2013 20816   161   582  1747  6058  5749  6519     NA
 5 25-34 Male   2012 20464   161   579  1707  6127  5619  6270     NA
 6 25-34 Male   2011 20985   190   657  1791  6444  5750  6151     NA
 7 25-34 Male   2010 20689   186   641  1866  6458  5587  5951     NA
 8 25-34 Male   2009 20440   184   695  1806  6495  5508  5752     NA
 9 25-34 Male   2008 20210   172   714  1874  6356  5277  5816     NA
10 25-34 Male   2007 20024   246   757  1930  6361  5137  5593     NA
# ℹ 356 more rows
```

Here, a "Level of Schooling Attained" variable is spread across the columns, from `elem4` to `coll4`. We need a *key* column called "education" with the various levels of schooling, and a corresponding *value* column containing the counts.

Wide to long with `pivot_longer()`

We're going to put the columns `elem4:coll4` into a new column, creating a new categorical measure named `education`. The numbers currently under each column will become a new `value` column corresponding to that level of education.

```r
edu |>
  pivot_longer(elem4:coll4, names_to = "education")
```

```
# A tibble: 2,196 × 7
   age   sex    year total median education value
   <chr> <chr> <int> <int>  <dbl> <chr>     <dbl>
 1 25-34 Male   2016 21845     NA elem4       116
 2 25-34 Male   2016 21845     NA elem8       468
 3 25-34 Male   2016 21845     NA hs3        1427
 4 25-34 Male   2016 21845     NA hs4        6386
 5 25-34 Male   2016 21845     NA coll3      6015
 6 25-34 Male   2016 21845     NA coll4      7432
 7 25-34 Male   2015 21427     NA elem4       166
 8 25-34 Male   2015 21427     NA elem8       488
 9 25-34 Male   2015 21427     NA hs3        1584
10 25-34 Male   2015 21427     NA hs4        6198
# ℹ 2,186 more rows
```

Wide to long with `pivot_longer()`

We can name the value column to whatever we like. Here it's a number of people.

```r
edu ▷
  pivot_longer(elem4:coll4,
               names_to = "education",
               values_to = "n")
```

```
# A tibble: 2,196 × 7
   age   sex    year total median education     n
   <chr> <chr> <int> <int>  <dbl> <chr>     <dbl>
 1 25-34 Male   2016 21845     NA elem4       116
 2 25-34 Male   2016 21845     NA elem8       468
 3 25-34 Male   2016 21845     NA hs3        1427
 4 25-34 Male   2016 21845     NA hs4        6386
 5 25-34 Male   2016 21845     NA coll3      6015
 6 25-34 Male   2016 21845     NA coll4      7432
 7 25-34 Male   2015 21427     NA elem4       166
 8 25-34 Male   2015 21427     NA elem8       488
 9 25-34 Male   2015 21427     NA hs3        1584
10 25-34 Male   2015 21427     NA hs4        6198
# ℹ 2,186 more rows
```

How to get your own data into R

Reading in CSV files

Base R has `read.csv()`

Corresponding tidyverse "underscored" version: `read_csv()`.

It is pickier and more talkative than the Base R version. Use it instead.

Where’s my data? Using `here()`

If we’re loading a file, it’s coming from *somewhere*.

If it’s a file on our hard drive somewhere, we will need to interact with the file system. We should try to do this in a way that avoids *absolute* file paths.

```
# This is not portable!
df ← read_csv("/Users/kjhealy/Documents/data/misc/project/data/mydata.csv")
```

We should also do it in a way that is *platform independent*.

This makes it easier to share your work, move it around, etc. Projects should be self-contained.

Where’s my data? Using `here()`

The `here` package, and **`here()`** function builds paths relative to the top level of your R project.

```
here() # this path will be different for you
```

```
[1] "/Users/kjhealy/Documents/courses/vsd"
```

Where's the data? Using `here()`

This seminar's files all live in an RStudio project. It looks like this:

```
/Users/kjhealy/Documents/courses/vsd
├── 00_dummy_files
├── R
├── README.md
├── README.qmd
├── _extensions
├── _freeze
├── _quarto.yml
├── _site
├── _targets
├── _targets.R
├── _variables.yml
├── about
├── assignment
├── content
├── data
├── deploy.sh
├── example
├── files
├── grades
├── html
├── images
├── index.html
├── index.qmd
├── merm.txt
├── projects
├── renv
```

I want to load files from the `data` folder, but I also want *you* to be able to load them. I'm writing this from somewhere deep in the `slides` folder, but you won't be there

Where’s the data? Using `here()`

So:

```r
## Load the file relative to the path from the top of the project, without separators, etc
organs <- read_csv(file = here("files", "data", "organdonation.csv"))
```

Where’s the data? Using `here()`

```
organs
```

```
# A tibble: 238 × 21
   country  year donors   pop pop.dens   gdp gdp.lag health health.lag pubhealth
   <chr>   <dbl>  <dbl> <dbl>    <dbl> <dbl>   <dbl>  <dbl>      <dbl>     <dbl>
 1 Austra…    NA   NA   17065    0.220 16774   16591   1300       1224       4.8
 2 Austra…  1991   12.1 17284    0.223 17171   16774   1379       1300       5.4
 3 Austra…  1992   12.4 17495    0.226 17914   17171   1455       1379       5.4
 4 Austra…  1993   12.5 17667    0.228 18883   17914   1540       1455       5.4
 5 Austra…  1994   10.2 17855    0.231 19849   18883   1626       1540       5.4
 6 Austra…  1995   10.2 18072    0.233 21079   19849   1737       1626       5.5
 7 Austra…  1996   10.6 18311    0.237 21923   21079   1846       1737       5.6
 8 Austra…  1997   10.3 18518    0.239 22961   21923   1948       1846       5.7
 9 Austra…  1998   10.5 18711    0.242 24148   22961   2077       1948       5.9
10 Austra…  1999    8.67 18926   0.244 25445   24148   2231       2077       6.1
# ℹ 228 more rows
# ℹ 11 more variables: roads <dbl>, cerebvas <dbl>, assault <dbl>,
#   external <dbl>, txp.pop <dbl>, world <chr>, opt <chr>, consent.law <chr>,
#   consent.practice <chr>, consistent <chr>, ccode <chr>
```

And there it is.

read_csv() has variants

`read_csv()` Field separator is a comma: `,`

```r
organs <- read_csv(file = here("files", "data", "organdonation.csv"))
```

`read_csv2()` Field separator is a semicolon: `;`

```r
# Example only
my_data <- read_csv2(file = here("data", "my_euro_file.csv))
```

Both are special cases of `read_delim()`

Other species are also catered to

`read_tsv()` Tab separated.

`read_fwf()` Fixed-width files.

`read_log()` Log files (i.e. computer log files).

`read_lines()` Just read in lines, without trying to parse them.

Also often useful …

`read_table()`

For data that’s separated by one (or more) columns of space.

And for foreign file formats …

The haven package provides

- `read_dta()` Stata
- `read_spss()` SPSS
- `read_sas()` SAS
- `read_xpt()` SAS Transport

Make these functions available with `library(haven)`

You can read files remotely, too

You can give these functions local files, or they can also be pointed at URLs.

Compressed files (`.zip`, `.tar.gz`) will be automatically uncompressed.

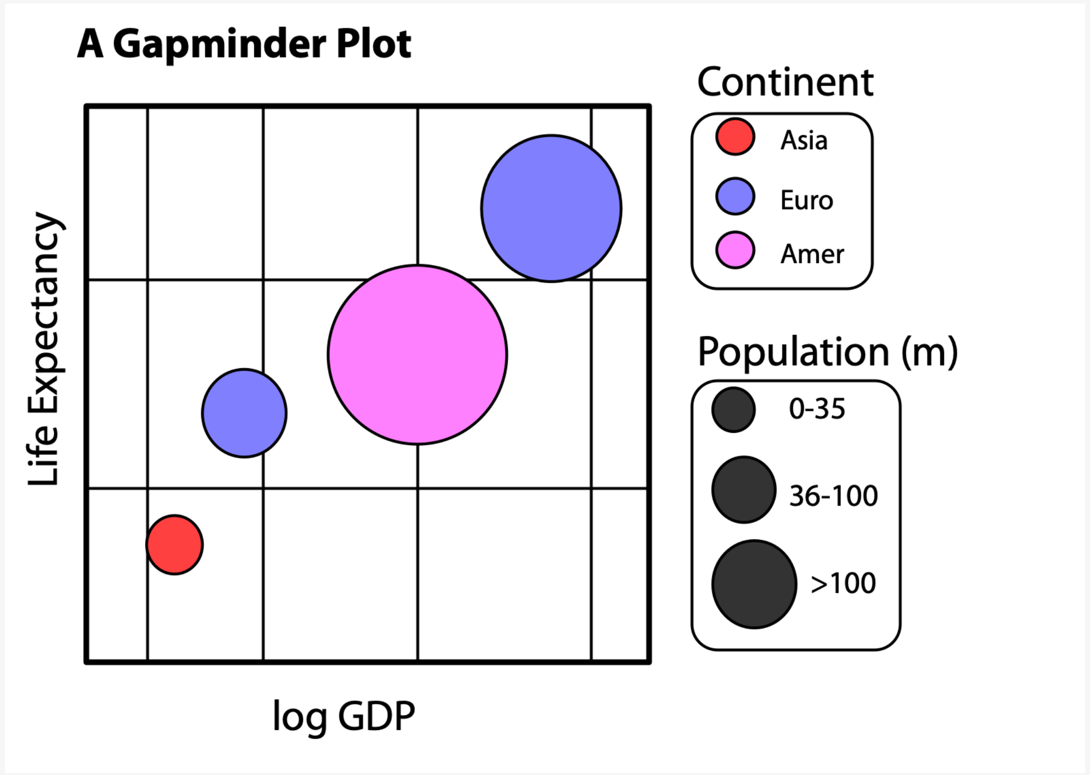
(Be careful what you download from remote locations!)

```r
organ_remote <- read_csv("http://kjhealy.co/organdonation.csv")
organ_remote
```

```
# A tibble: 238 × 21
   country  year donors   pop pop.dens   gdp gdp.lag health health.lag pubhealth
   <chr>   <dbl>  <dbl> <dbl>    <dbl> <dbl>   <dbl>  <dbl>      <dbl>     <dbl>
 1 Austra…    NA  NA    17065    0.220 16774   16591   1300       1224       4.8
 2 Austra…  1991  12.1  17284    0.223 17171   16774   1379       1300       5.4
 3 Austra…  1992  12.4  17495    0.226 17914   17171   1455       1379       5.4
 4 Austra…  1993  12.5  17667    0.228 18883   17914   1540       1455       5.4
 5 Austra…  1994  10.2  17855    0.231 19849   18883   1626       1540       5.4
 6 Austra…  1995  10.2  18072    0.233 21079   19849   1737       1626       5.5
 7 Austra…  1996  10.6  18311    0.237 21923   21079   1846       1737       5.6
 8 Austra…  1997  10.3  18518    0.239 22961   21923   1948       1846       5.7
 9 Austra…  1998  10.5  18711    0.242 24148   22961   2077       1948       5.9
10 Austra…  1999   8.67 18926    0.244 25445   24148   2231       2077       6.1
# ℹ 228 more rows
# ℹ 11 more variables: roads <dbl>, cerebvas <dbl>, assault <dbl>,
#   external <dbl>, txp.pop <dbl>, world <chr>, opt <chr>, consent.law <chr>,
#   consent.practice <chr>, consistent <chr>, ccode <chr>
```

A Plot’s Components

What we need our code to make



Data **represented** by visual elements;

like *position*, *length*, *color*, and *size*;

Each measured on some **scale**;

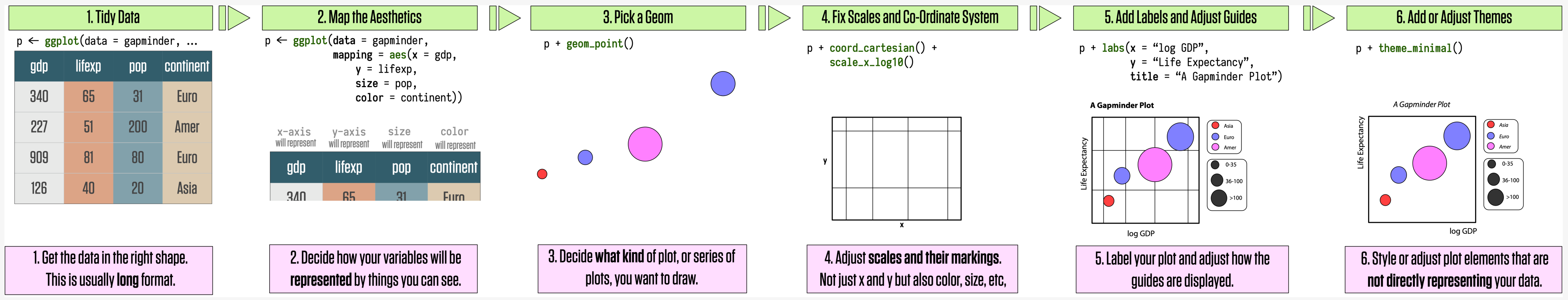
Each scale with a labeled **guide**;

With the plot itself also **titled** and labeled.

How does ggplot do this?

`ggplot`'s flow of action

Here’s the whole thing, start to finish



1. Tidy Data

```
p ← ggplot(data = gapminder, ...
```

gdp	lifexp	pop	continent
340	65	31	Euro
227	51	200	Amer
909	81	80	Euro
126	40	20	Asia

1. Get the data in the right shape. This is usually **long** format.

2. Map the Aesthetics

```
p ← ggplot(data = gapminder,
           mapping = aes(x = gdp,
               y = lifexp,
               size = pop,
               color = continent))
```

2. Decide how your variables will be **represented** by things you can see.

3. Pick a Geom

```
p + geom_point()
```

3. Decide **what kind** of plot, or series of plots, you want to draw.

4. Fix Scales and Co-Ordinate System

```
p + coord_cartesian() +
    scale_x_log10()
```

4. Adjust **scales and their markings.** Not just x and y but also color, size, etc,

5. Add Labels and Adjust Guides

```
p + labs(x = “log GDP”,
         y = “Life Expectancy”,
         title = “A Gapminder Plot”)
```

5. Label your plot and adjust how the guides are displayed.

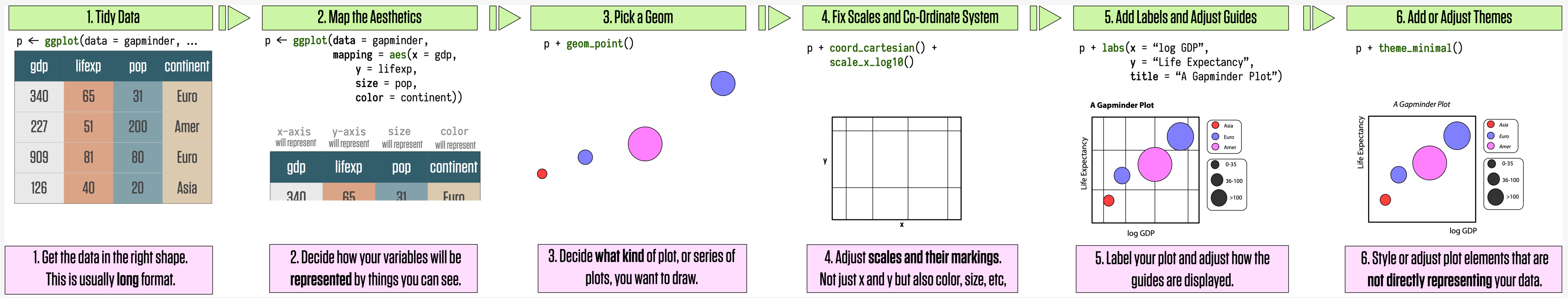
6. Add or Adjust Themes

```
p + theme_minimal()
```

6. Style or adjust plot elements that are **not directly representing** your data.

Flow of action

We'll go through it step by step



1. Tidy Data

```
p <- ggplot(data = gapminder, ...
```

gdp	lifexp	pop	continent
340	65	31	Euro
227	51	200	Amer
909	81	80	Euro
126	40	20	Asia

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p + labs(x = "log GDP",
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```

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6. Add or Adjust Themes

```
p + theme_minimal()
```

6. Style or adjust plot elements that are **not directly representing** your data.

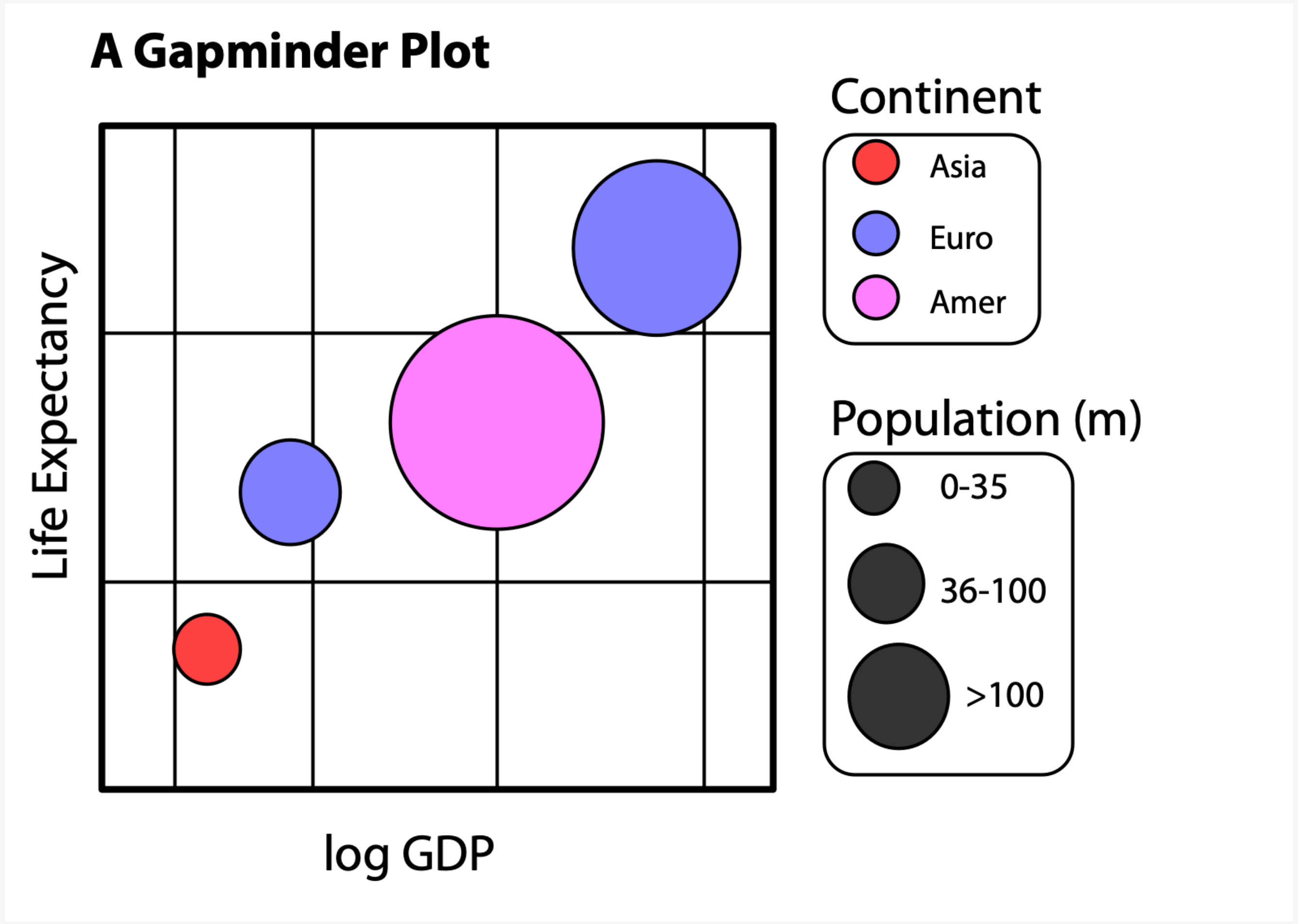
Flow of action

ggplot's flow of action

gdp	lifexp	pop	continent
340	65	31	Euro
227	51	200	Amer
909	81	80	Euro
126	40	20	Asia

What we start with

ggplot's flow of action



Where we're going

ggplot's flow of action

1. Tidy Data

```
p ← ggplot(data = gapminder, ...
```

gdp	lifexp	pop	continent
340	65	31	Euro
227	51	200	Amer
909	81	80	Euro
126	40	20	Asia

1. Get the data in the right shape. This is usually **long** format.

2. Map the Aesthetics

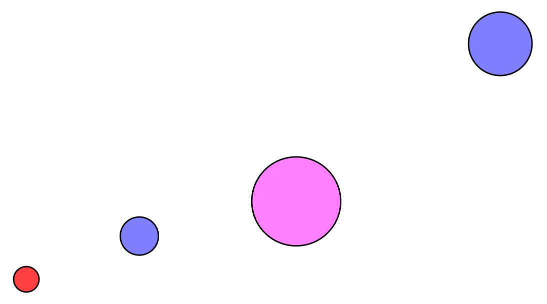
```
p ← ggplot(data = gapminder,
           mapping = aes(x = gdp,
               y = lifexp,
               size = pop,
               color = continent))
```

x-axis will represent	y-axis will represent	size will represent	color will represent
gdp	lifexp	pop	continent
340	65	31	Euro

2. Decide how your variables will be **represented** by things you can see.

3. Pick a Geom

```
p + geom_point()
```



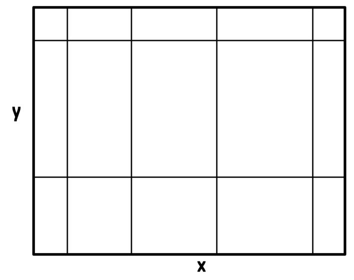
3. Decide **what kind** of plot, or series of plots, you want to draw.

Core steps

ggplot's flow of action

4. Fix Scales and Co-Ordinate System

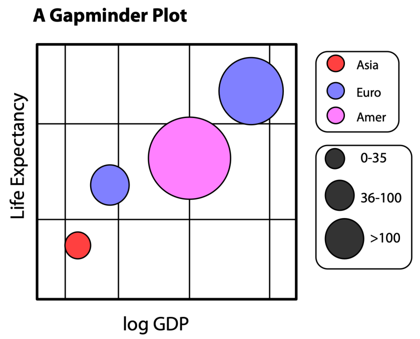
```
p + coord_cartesian() +
    scale_x_log10()
```



4. Adjust **scales and their markings.** Not just x and y but also color, size, etc,

5. Add Labels and Adjust Guides

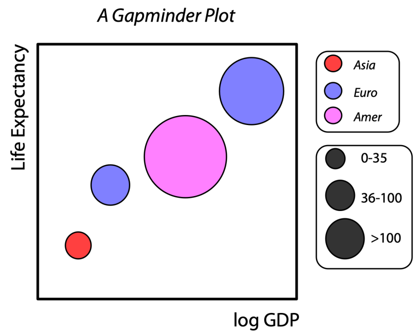
```
p + labs(x = “log GDP”,
         y = “Life Expectancy”,
         title = “A Gapminder Plot”)
```



5. Label your plot and adjust how the guides are displayed.

6. Add or Adjust Themes

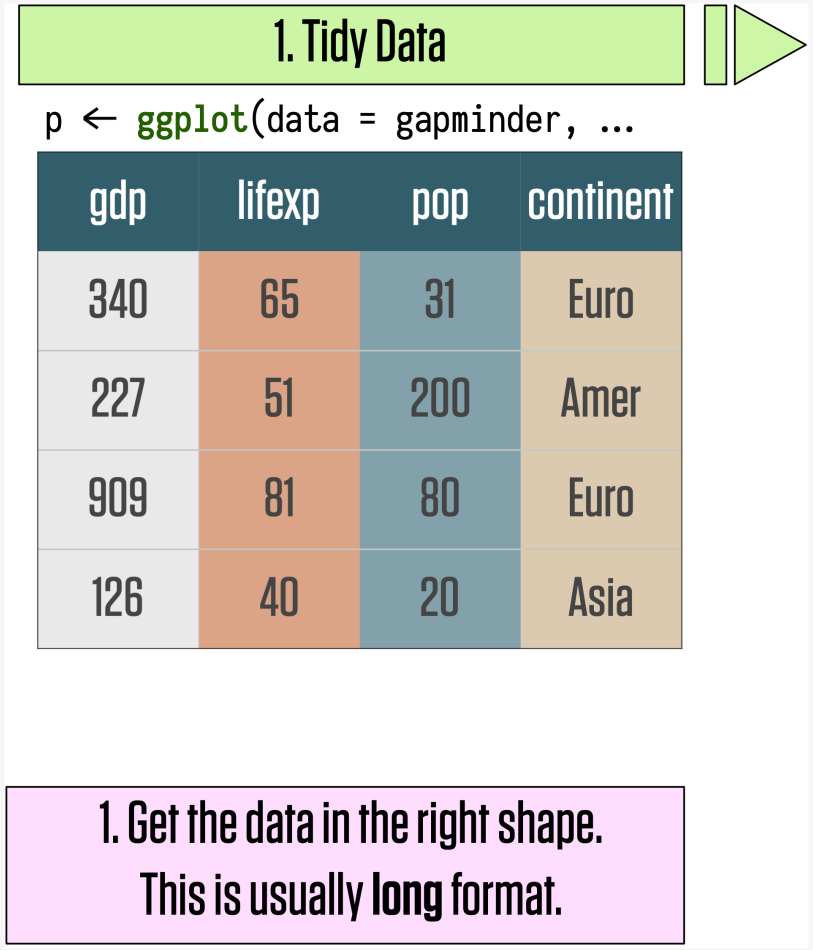
```
p + theme_minimal()
```



6. Style or adjust plot elements that are **not directly representing** your data.

Optional steps

ggplot's flow of action: required



1. Tidy Data

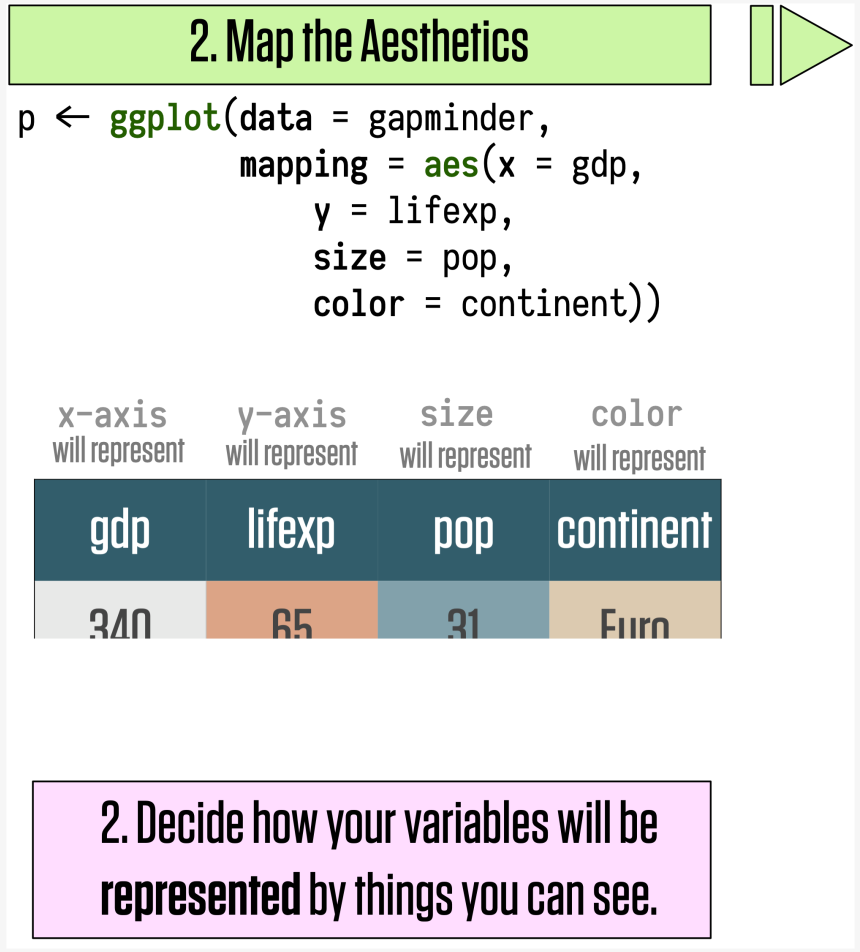
```
p <- ggplot(data = gapminder, ...
```

gdp	lifexp	pop	continent
340	65	31	Euro
227	51	200	Amer
909	81	80	Euro
126	40	20	Asia

1. Get the data in the right shape.
This is usually **long** format.

Tidy data

ggplot's flow of action: required



2. Map the Aesthetics

```
p <- ggplot(data = gapminder,
            mapping = aes(x = gdp,
                y = lifexp,
                size = pop,
                color = continent))
```

x-axis will represent	y-axis will represent	size will represent	color will represent
gdp	lifexp	pop	continent
340	65	31	Euro

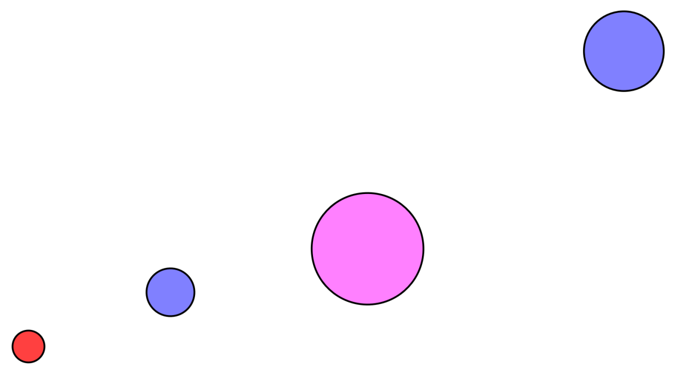
2. Decide how your variables will be **represented** by things you can see.

Aesthetic mappings

ggplot's flow of action: required

3. Pick a Geom

```
p + geom_point()
```



3. Decide **what kind** of plot, or series of plots, you want to draw.

Geom

Let’s go piece by piece

Start with the data

```r
gapminder
```

```
# A tibble: 1,704 × 6
   country     continent  year lifeExp      pop gdpPercap
   <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
 1 Afghanistan Asia       1952    28.8  8425333      779.
 2 Afghanistan Asia       1957    30.3  9240934      821.
 3 Afghanistan Asia       1962    32.0 10267083      853.
 4 Afghanistan Asia       1967    34.0 11537966      836.
 5 Afghanistan Asia       1972    36.1 13079460      740.
 6 Afghanistan Asia       1977    38.4 14880372      786.
 7 Afghanistan Asia       1982    39.9 12881816      978.
 8 Afghanistan Asia       1987    40.8 13867957      852.
 9 Afghanistan Asia       1992    41.7 16317921      649.
10 Afghanistan Asia       1997    41.8 22227415      635.
# ℹ 1,694 more rows
```

```r
dim(gapminder)
```

```
[1] 1704    6
```

Create a plot object

Data is the `gapminder` tibble.

```r
p <- ggplot(data = gapminder)
```

Map variables to aesthetics

Tell `ggplot` the variables you want represented by visual elements on the plot

```r
p <- ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y = lifeExp))
```

Map variables to aesthetics

The `mapping = aes( ... )` call links variables to things you will see on the plot.

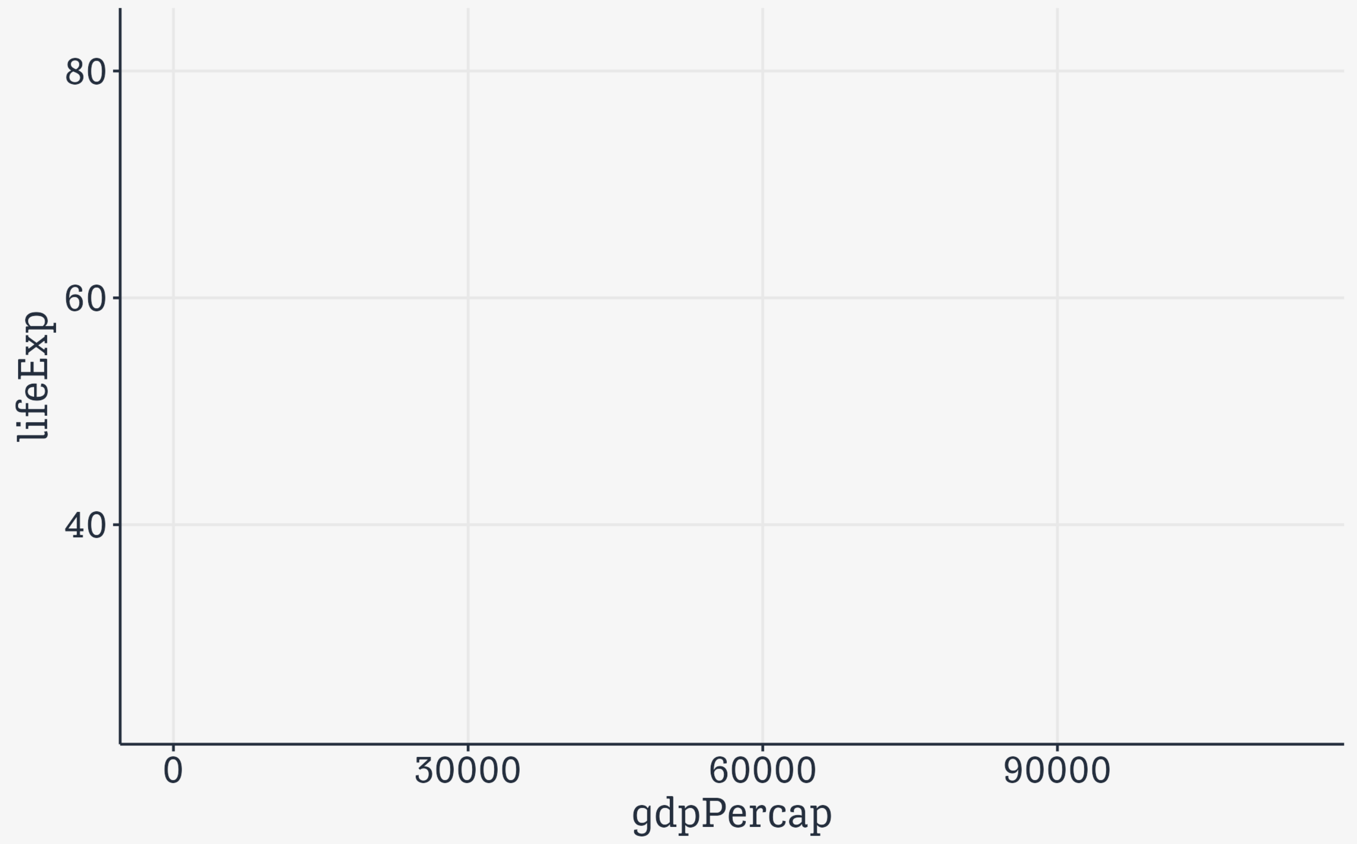
`x` and `y` represent the quantities determining position on the x and y axes.

Other aesthetic mappings can include, e.g., `color`, `shape`, `size`, and `fill`.

Mappings do not *directly* specify the particular, e.g., colors, shapes, or line styles that will appear on the plot. Rather, they establish *which variables* in the data will be represented by *which visible elements* on the plot.

p has data and mappings but no geom

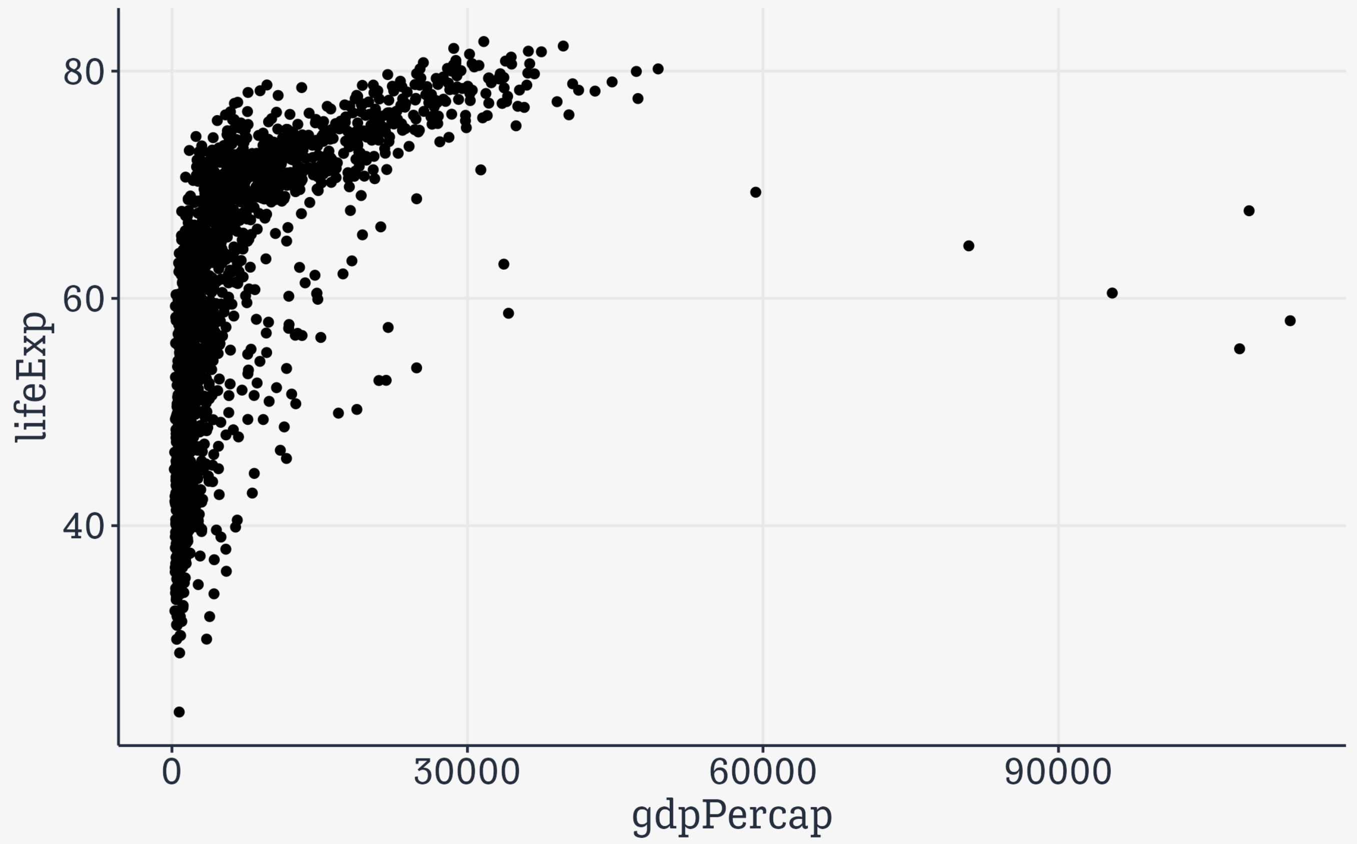
```
p
```



This empty plot has no geoms.

Add a geom

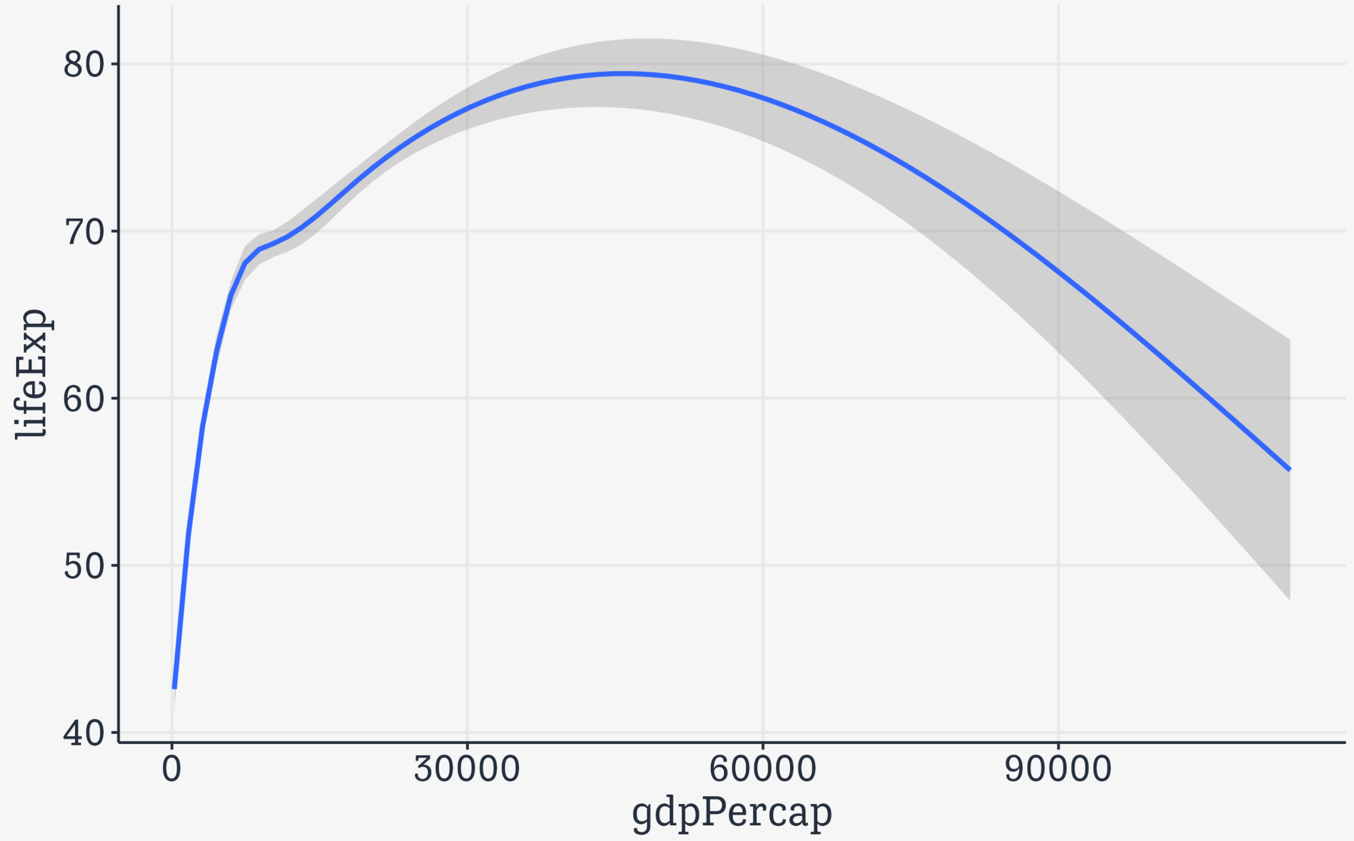
```
p + geom_point()
```



A scatterplot of Life Expectancy vs GDP

Try a different geom

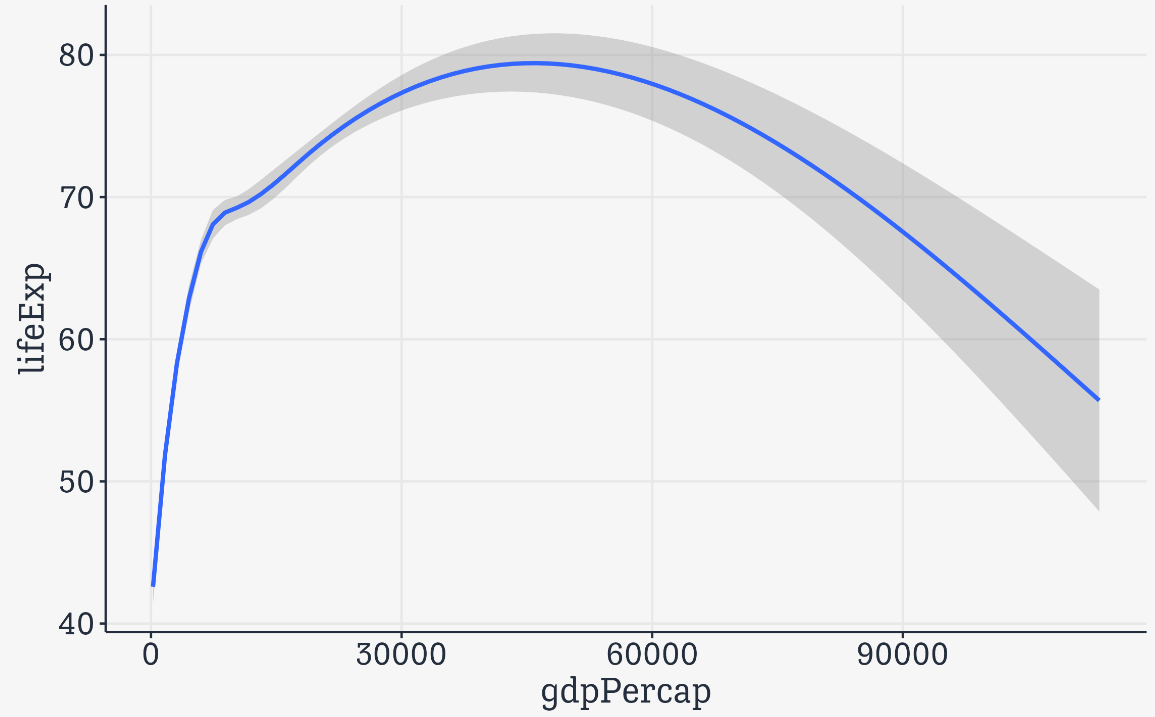
```r
p + geom_smooth()
```



A scatterplot of Life Expectancy vs GDP

Build your plots layer by layer

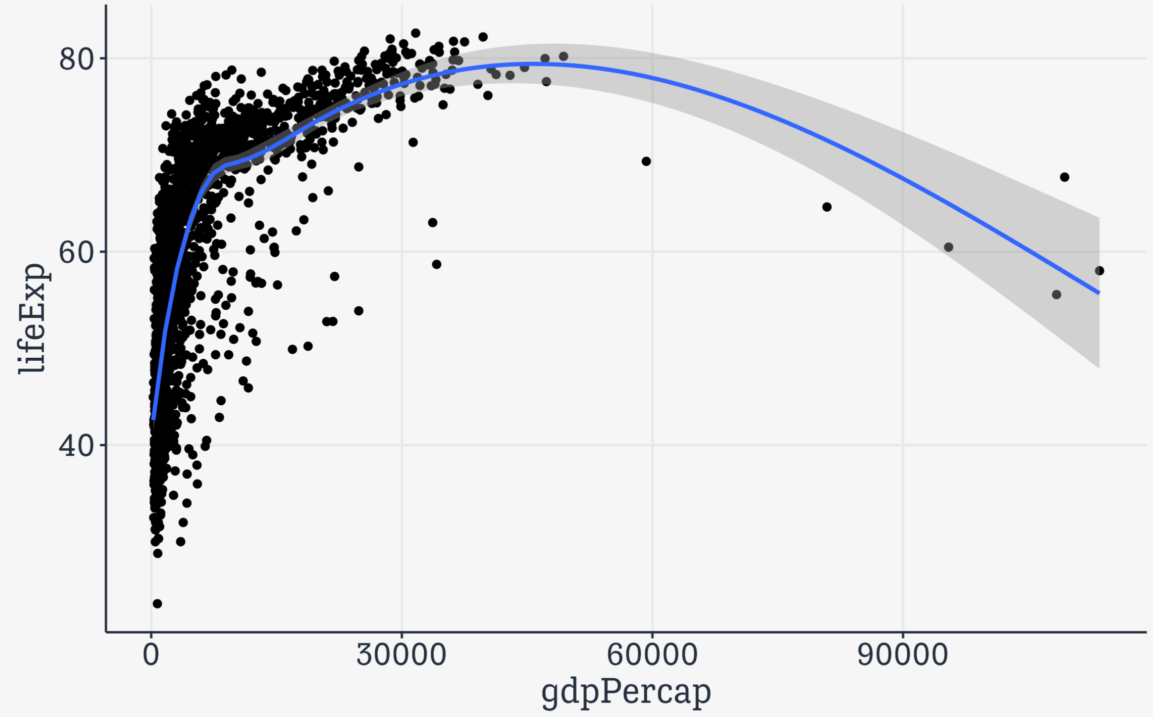
```r
p ← ggplot(data = gapminder,
           mapping = aes(x = gdpPercap,
                         y=lifeExp))
p + geom_smooth()
```



Life Expectancy vs GDP, using a smoother.

This process is additive

```r
p ← ggplot(data = gapminder,
           mapping = aes(x = gdpPercap,
                         y=lifeExp))
p + geom_point() + geom_smooth()
```



Life Expectancy vs GDP, using a smoother.

This process is additive

```r
p ← ggplot(data = gapminder,
           mapping = aes(x = gdpPercap,
                         y=lifeExp))
```

This process is additive

```r
p ← ggplot(data = gapminder,
           mapping = aes(x = gdpPercap,
                         y=lifeExp))
p + geom_smooth()
```

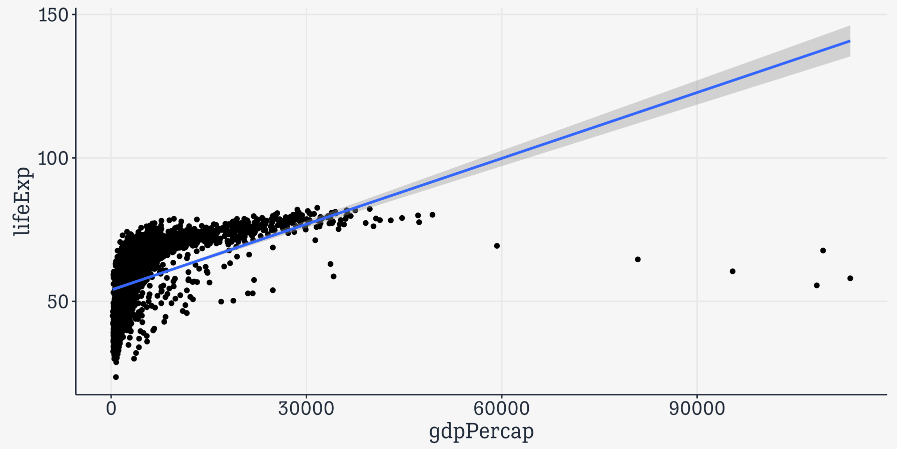
This process is additive

```r
p <- ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y=lifeExp))
p + geom_smooth() +
  geom_point()
```

Every geom is a function

Functions take arguments

```r
p ← ggplot(data = gapminder,
           mapping = aes(x = gdpPercap,
                         y = lifeExp))
p + geom_point() +
  geom_smooth(method = "lm")
```



Keep Layering

```r
p <- ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y=lifeExp))
```

Keep Layering

```r
 p <- ggplot(data = gapminder,
             mapping = aes(x = gdpPercap,
                           y=lifeExp))
p + geom_point()
```

Keep Layering

```r
 p <- ggplot(data = gapminder,
              mapping = aes(x = gdpPercap,
                            y=lifeExp))
p + geom_point() +
    geom_smooth(method = "lm")
```

Keep Layering

```r
 p <- ggplot(data = gapminder,
             mapping = aes(x = gdpPercap,
                           y=lifeExp))
p + geom_point() +
    geom_smooth(method = "lm") +
    scale_x_log10()
```

Fix the labels

```r
p ← ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y=lifeExp))
```

Fix the labels

```r
p ← ggplot(data = gapminder,
           mapping = aes(x = gdpPercap,
                         y=lifeExp))
p + geom_point()
```

Fix the labels

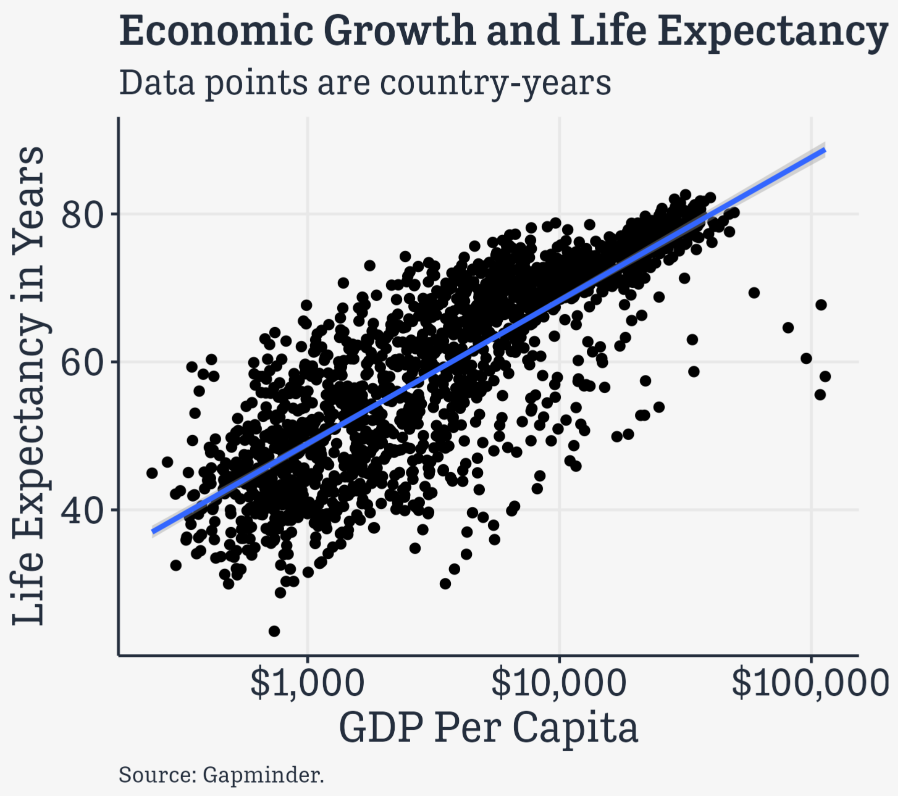
```r
p ← ggplot(data = gapminder,
           mapping = aes(x = gdpPercap,
                         y=lifeExp))
p + geom_point() +
    geom_smooth(method = "lm")
```

Fix the labels

```r
p ← ggplot(data = gapminder,
           mapping = aes(x = gdpPercap,
                         y=lifeExp))
p + geom_point() +
    geom_smooth(method = "lm") +
    scale_x_log10(labels = scales::label_dollar
```

Add labels, title, and caption

```r
p <- ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y = lifeExp))
p + geom_point() +
  geom_smooth(method = "lm") +
    scale_x_log10(labels = scales::label_dollar
    labs(x = "GDP Per Capita",
         y = "Life Expectancy in Years",
         title = "Economic Growth and Life Expe
         subtitle = "Data points are country-ye
         caption = "Source: Gapminder.")
```



Mapping vs Setting your plot’s aesthetics

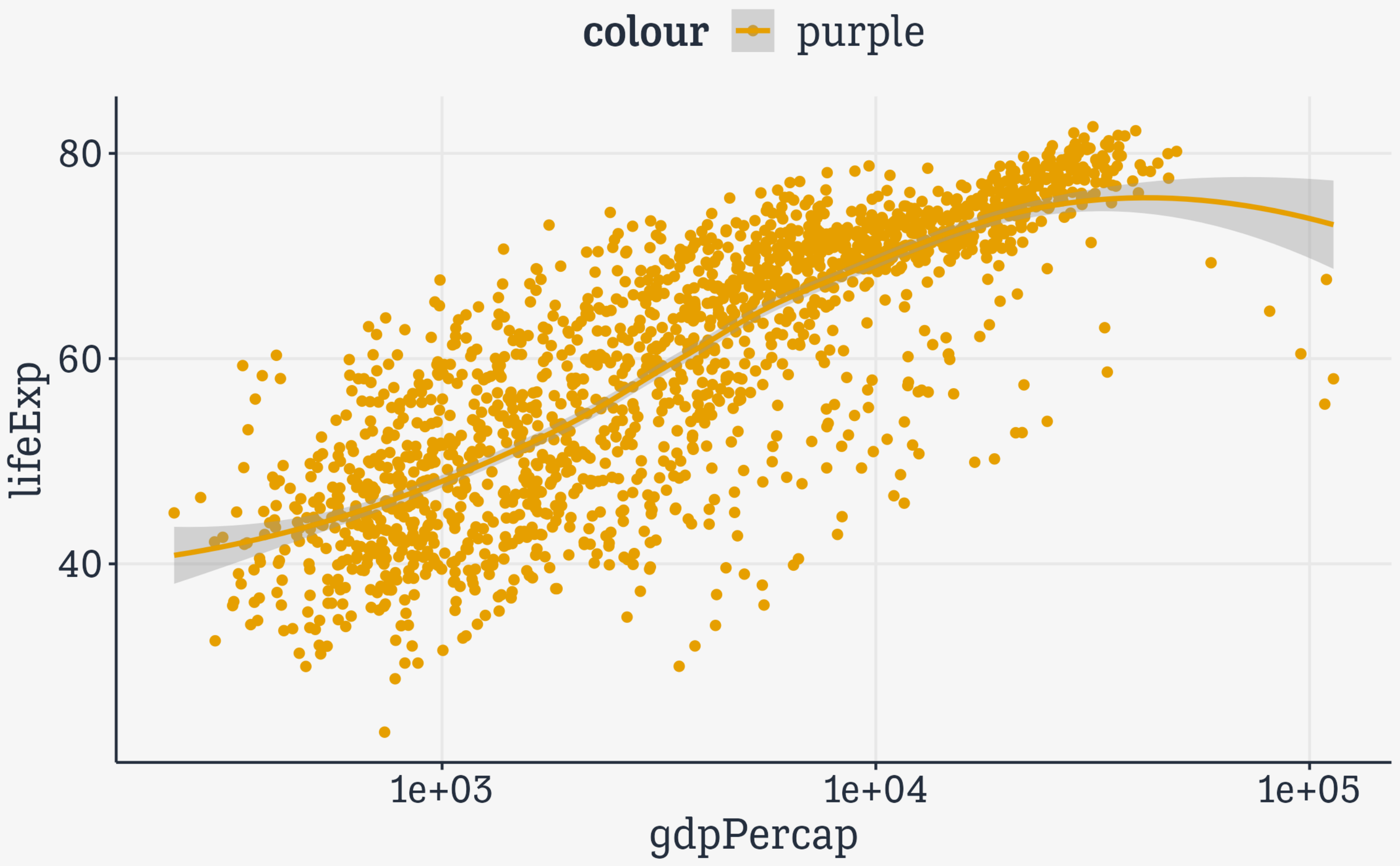
“Can I change the color of the points?”

```r
p <- ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y = lifeExp,
                          color = "purple"))

## Put in an object for convenience
p_out <- p + geom_point() +
    geom_smooth(method = "loess") +
    scale_x_log10()
```

What has gone wrong here?

```
p_out
```



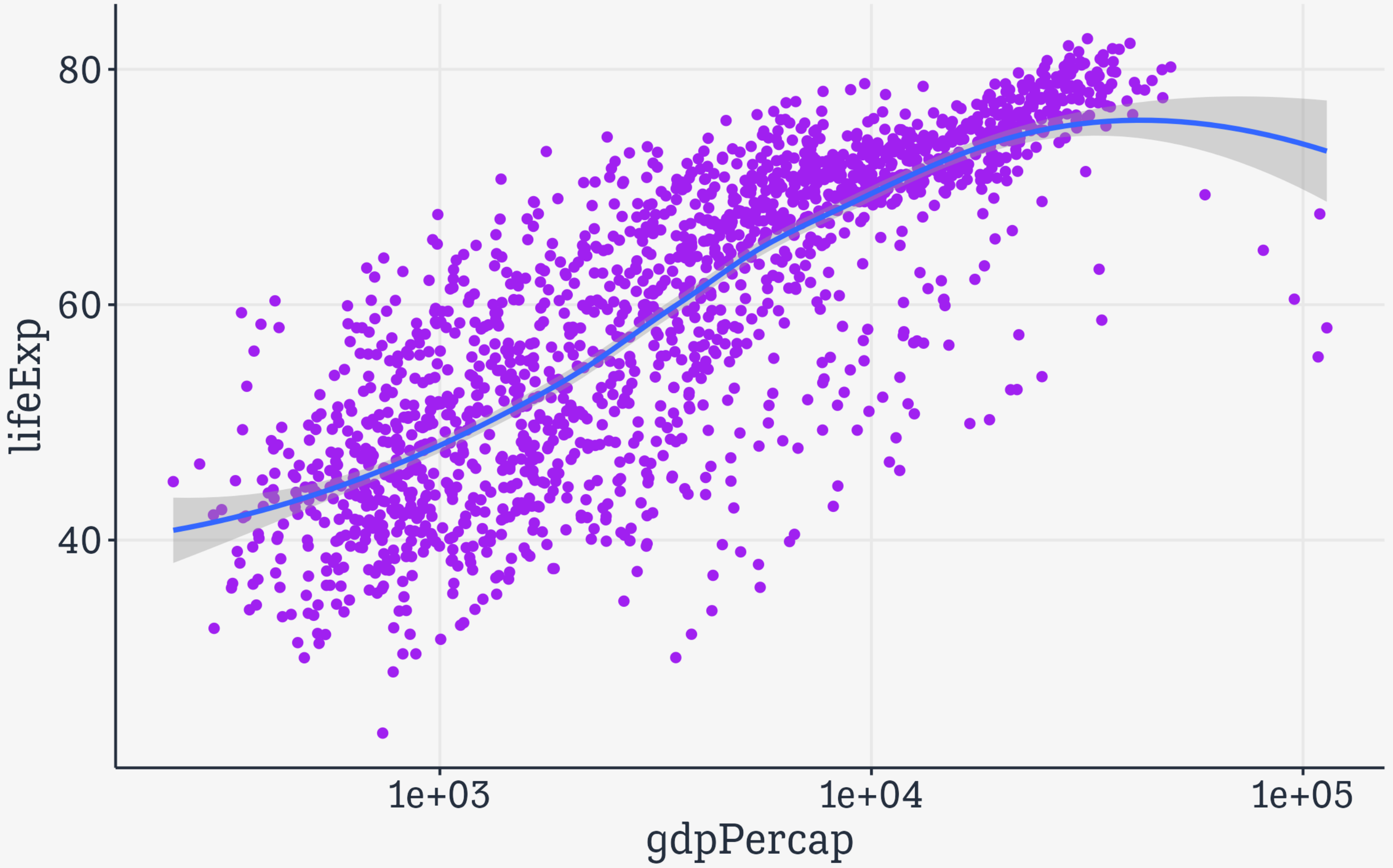
Try again

```r
p ← ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y = lifeExp))

## Put in an object for convenience
p_out ← p + geom_point(color = "purple") +
    geom_smooth(method = "loess") +
    scale_x_log10()
```

Try again

```
p_out
```



Geoms can take many arguments

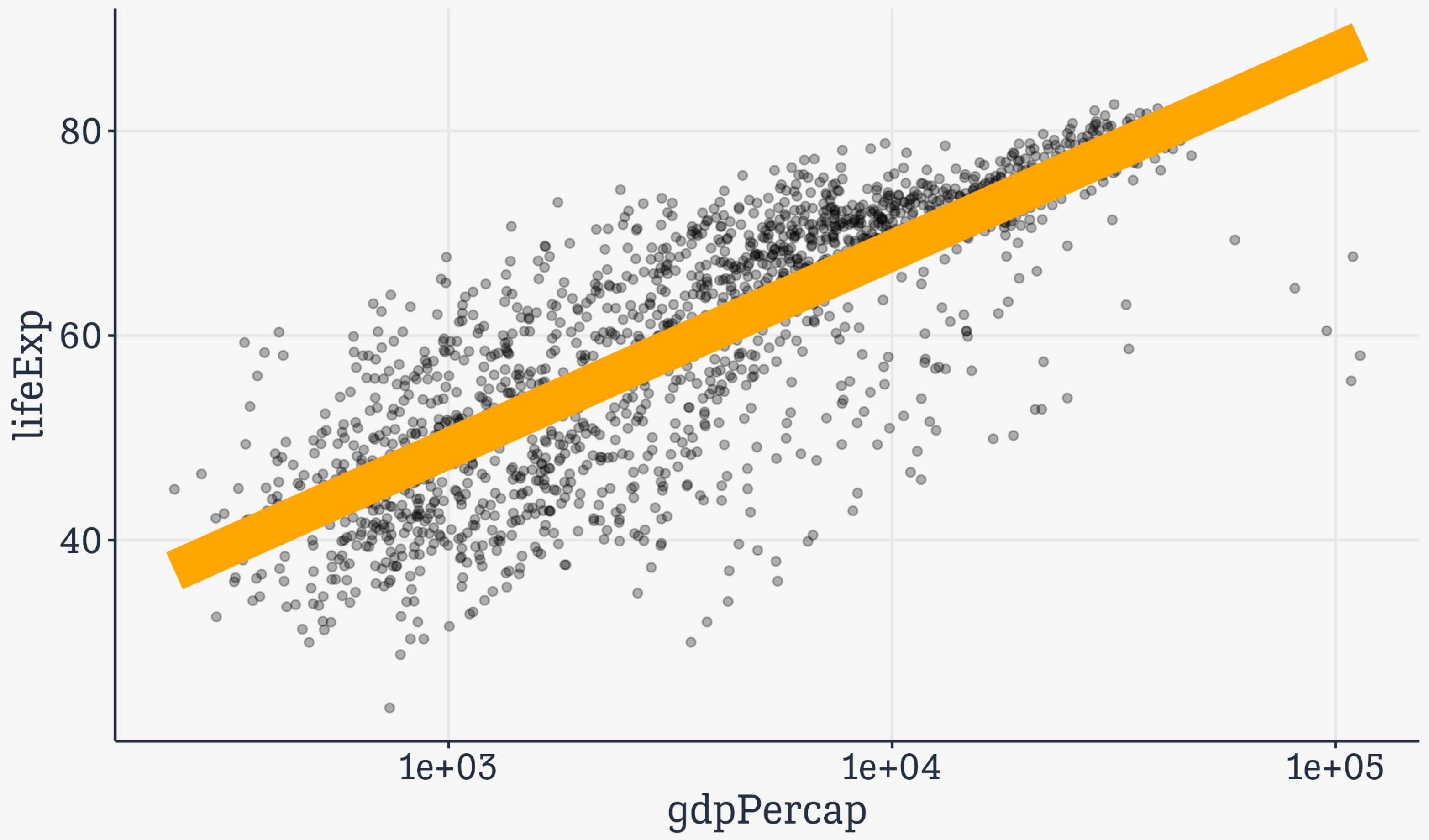
Here we set `color`, `size`, and `alpha`. Meanwhile `x` and `y` are mapped.

We also give non-default values to some other arguments

```r
p <- ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y = lifeExp))
p_out <- p + geom_point(alpha = 0.3) +
    geom_smooth(color = "orange",
                se = FALSE,
                size = 8,
                method = "lm") +
    scale_x_log10()
```

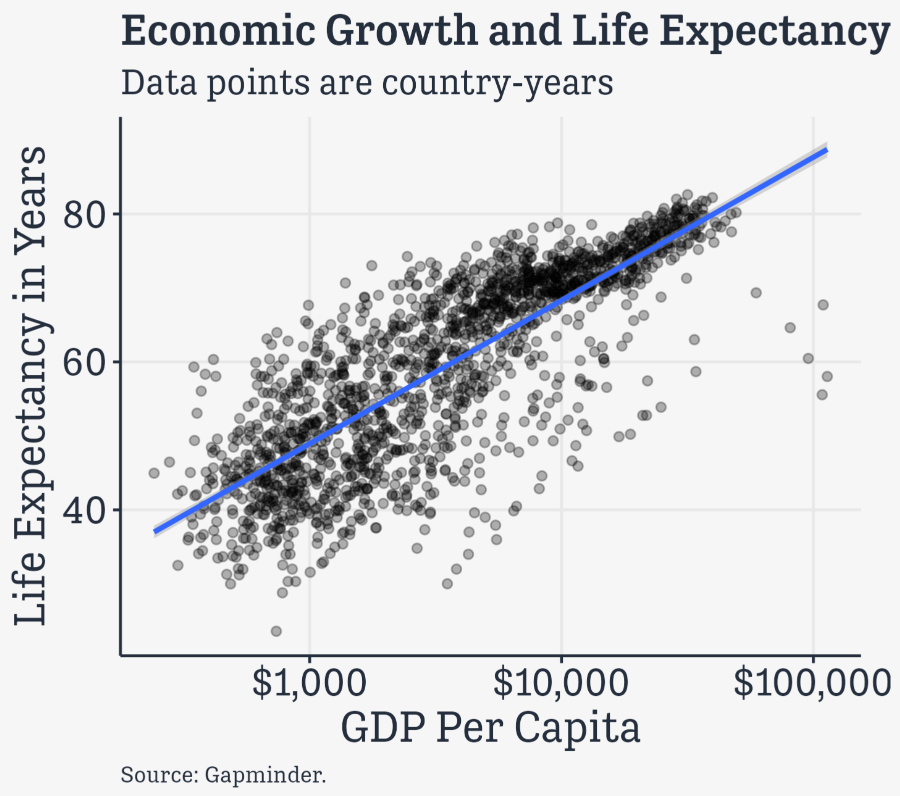
Geoms can take many arguments

```
p_out
```



alpha for overplotting

```r
p <- ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y = lifeExp))
p + geom_point(alpha = 0.3) +
  geom_smooth(method = "lm") +
    scale_x_log10(labels = scales::label_dollar
    labs(x = "GDP Per Capita",
         y = "Life Expectancy in Years",
         title = "Economic Growth and Life Expe
         subtitle = "Data points are country-ye
         caption = "Source: Gapminder.")
```



Map or Set values per geom

Geoms can take their own mappings

```r
p <- ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y = lifeExp,
                          color = continent,
                          fill = continent))
```

Geoms can take their own mappings

```r
p ← ggplot(data = gapminder,
           mapping = aes(x = gdpPercap,
                         y = lifeExp,
                         color = continent,
                         fill = continent))
p + geom_point()
```

Geoms can take their own mappings

```r
p <- ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y = lifeExp,
                          color = continent,
                          fill = continent))
p + geom_point() +
    geom_smooth(method = "loess")
```

Geoms can take their own mappings

```r
p <- ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y = lifeExp,
                          color = continent,
                          fill = continent))
p + geom_point() +
    geom_smooth(method = "loess") +
    scale_x_log10(labels = scales::label_dollar())
```

Geoms can take their own mappings

```
p ← ggplot(data = gapminder,
           mapping = aes(x = gdpPercap,
                         y = lifeExp))
```

Geoms can take their own mappings

```r
p ← ggplot(data = gapminder,
           mapping = aes(x = gdpPercap,
                         y = lifeExp))
p + geom_point(mapping = aes(color = continent))
```

Geoms can take their own mappings

```r
p ← ggplot(data = gapminder,
           mapping = aes(x = gdpPercap,
                         y = lifeExp))
p + geom_point(mapping = aes(color = continent)) +
    geom_smooth(method = "loess")
```

Geoms can take their own mappings

```r
p <- ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y = lifeExp))
p + geom_point(mapping = aes(color = continent)) +
    geom_smooth(method = "loess") +
    scale_x_log10(labels = scales::label_dollar())
```

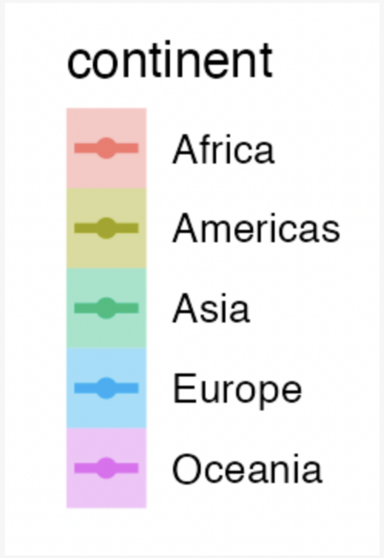
Geoms can take their own mappings

```r
p <- ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y = lifeExp))
p + geom_point(mapping = aes(color = continent)) +
    geom_smooth(method = "loess") +
    scale_x_log10(labels = scales::label_dollar())
```

Pay attention to which scales and guides are drawn, and why

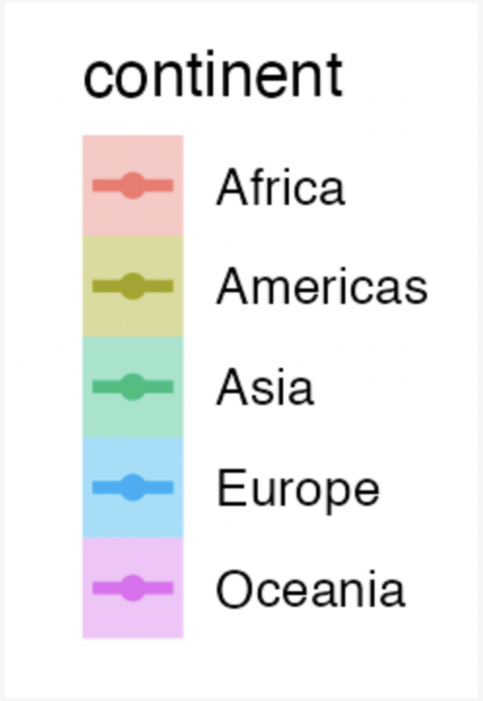
Guides and scales reflect `aes()` mappings

```
mapping = aes(color =
continent, fill = continent)
```

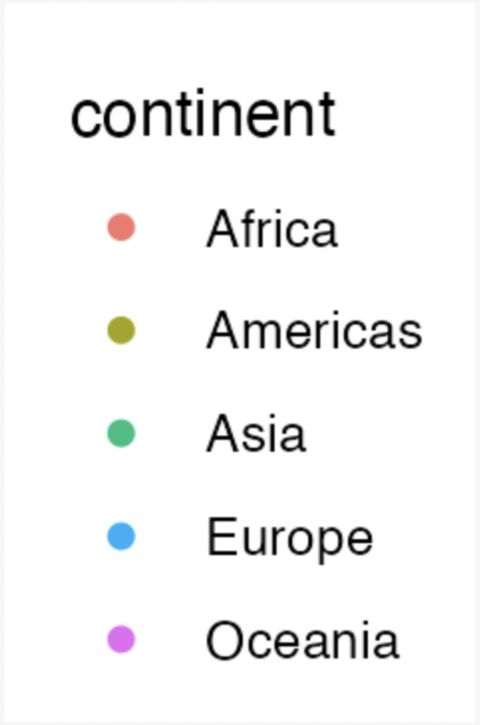


Guides and scales reflect `aes()` mappings

```
mapping = aes(color = continent, fill =
continent)
```



```
mapping = aes(color = continent)
```



Remember: Every mapped variable has a scale

Saving your work

Use ggsave()

```r
## Save the most recent plot
ggsave(filename = "figures/my_figure.png")

## Use here() for more robust file paths
ggsave(filename = here("figures", "my_figure.png"))

## A plot object
p_out <- p + geom_point(mapping = aes(color = log(pop))) +
    scale_x_log10()

ggsave(filename = here("figures", "lifexp_vs_gdp_gradient.pdf"),
       plot = p_out)

ggsave(here("figures", "lifexp_vs_gdp_gradient.png"),
       plot = p_out,
       width = 8,
       height = 5)
```

In code chunks

Set options in any chunk:

```
#| fig-height: 8
#| fig-width: 5
#| fig-show: "hold"
#| fig-cap: "A caption"
```

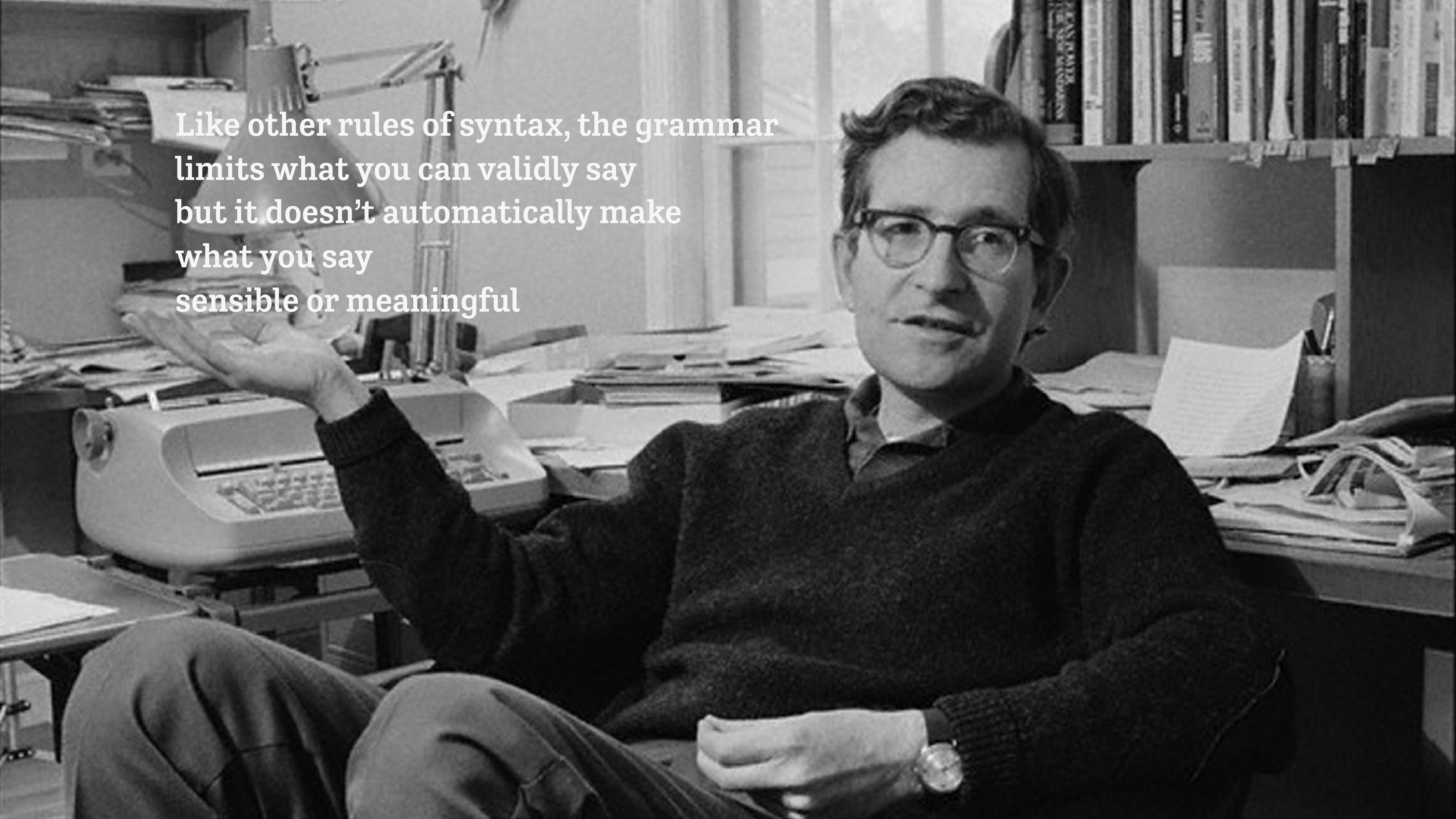
Or for the whole document:

```yaml
---
title: "My Document"
format:
  html:
    fig-width: 8
    fig-height: 6
  pdf:
    fig-width: 7
    fig-height: 5
---
```

`ggplot` implements a grammar of graphics

A grammar of graphics

The grammar is a set of rules for how to .kjh-lblueproduce graphics from data, by *mapping* data to or *representing* it by geometric objects (like points and lines) that have aesthetic attributes (like position, color, size, and shape), together with further rules for transforming data if needed, for adjusting scales and their guides, and for projecting results onto some coordinate system.



Like other rules of syntax, the grammar
limits what you can validly say
but it doesn't automatically make
what you say
sensible or meaningful

Grouped data and the `group` aesthetic

Try to make a lineplot

```
p ← ggplot(data = gapminder,
            mapping = aes(x = year,
                          y = gdpPercap))
```

Try to make a lineplot

```r
p ← ggplot(data = gapminder,
           mapping = aes(x = year,
                         y = gdpPercap)) +
  geom_line()
```

Try to make a lineplot

```r
p <- ggplot(data = gapminder,
            mapping = aes(x = year,
                          y = gdpPercap)) +
  geom_line()

p
```

Try to make a lineplot

```r
p ← ggplot(data = gapminder,
           mapping = aes(x = year,
                         y = gdpPercap))
```

Try to make a lineplot

```r
p <- ggplot(data = gapminder,
            mapping = aes(x = year,
                          y = gdpPercap)) +
  geom_line(mapping = aes(group = country))
```

Try to make a lineplot

```r
p ← ggplot(data = gapminder,
           mapping = aes(x = year,
                         y = gdpPercap)) +
  geom_line(mapping = aes(group = country))

p
```

Try to make a lineplot

```r
p <- ggplot(data = gapminder,
            mapping = aes(x = year,
                          y = gdpPercap)) +
  geom_line(mapping = aes(group = country))

p
```

Facet the plot

```r
gapminder
```

```
# A tibble: 1,704 × 6
   country     continent  year lifeExp      pop
gdpPercap
   <fct>       <fct>     <int>   <dbl>    <int>
<dbl>
 1 Afghanistan Asia       1952    28.8  8425333
779.
 2 Afghanistan Asia       1957    30.3  9240934
821.
 3 Afghanistan Asia       1962    32.0 10267083
853.
 4 Afghanistan Asia       1967    34.0 11537966
836.
 5 Afghanistan Asia       1972    36.1 13079460
740.
 6 Afghanistan Asia       1977    38.4 14880372
786.
 7 Afghanistan Asia       1982    39.9 12881816
978.
```

Facet the plot

```r
gapminder |>
  ggplot(mapping =
           aes(x = year,
           y = gdpPercap))
```

Facet the plot

```r
gapminder |>
  ggplot(mapping =
           aes(x = year,
           y = gdpPercap)) +
  geom_line(mapping = aes(group = country))
```

Facet the plot

```r
gapminder |>
  ggplot(mapping =
           aes(x = year,
           y = gdpPercap)) +
  geom_line(mapping = aes(group = country)) +
  facet_wrap(~ continent)
```

Faceting is very powerful

Faceting

A facet is not a geom; it's a way of arranging repeated geoms by some additional variable

Facets use R's "formula" syntax: `facet_wrap(~ continent)`

Read the `~` as "on" or "by"

Faceting

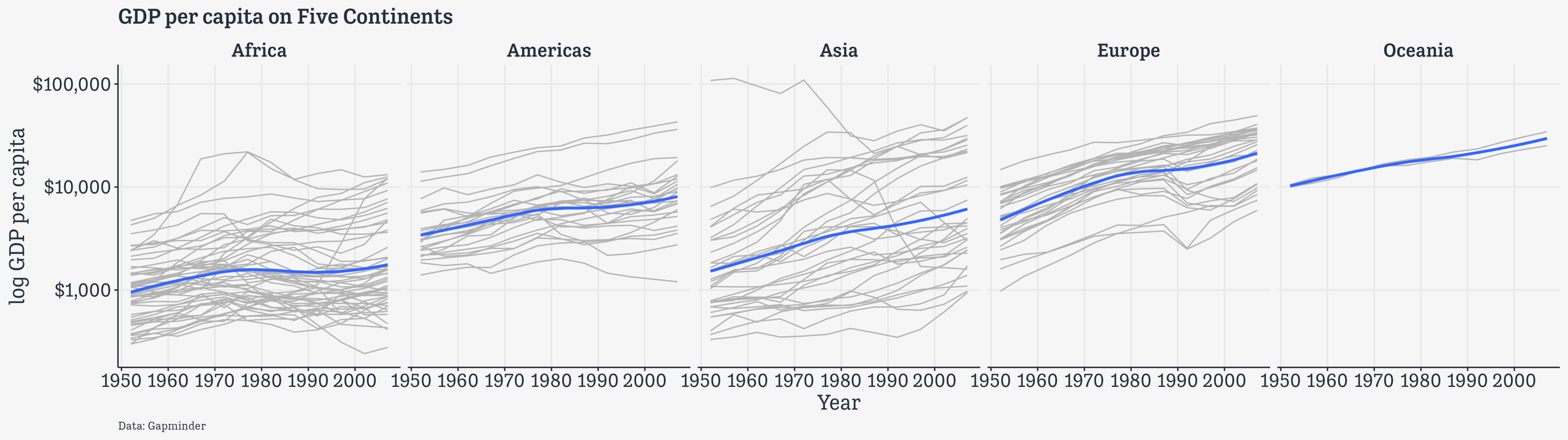
You can also use this syntax: `facet_wrap(vars(continent))`

This is newer, and consistent with other ways of referring to variables within tidyverse functions.

Facets in action

```r
p <- ggplot(data = gapminder,
            mapping = aes(x = year,
                          y = gdpPercap))

p_out <- p + geom_line(color="gray70",
              mapping=aes(group = country)) +
    geom_smooth(size = 1.1,
                method = "loess",
                se = FALSE) +
    scale_y_log10(labels=scales::label_dollar()) +
    facet_wrap(~ continent, ncol = 5) +
    labs(x = "Year",
         y = "log GDP per capita",
         title = "GDP per capita on Five Continents",
         caption = "Data: Gapminder")
```



A more polished faceted plot.

One-variable summaries

The midwest dataset

County-level census data for Midwestern U.S. Counties

```r
midwest
```

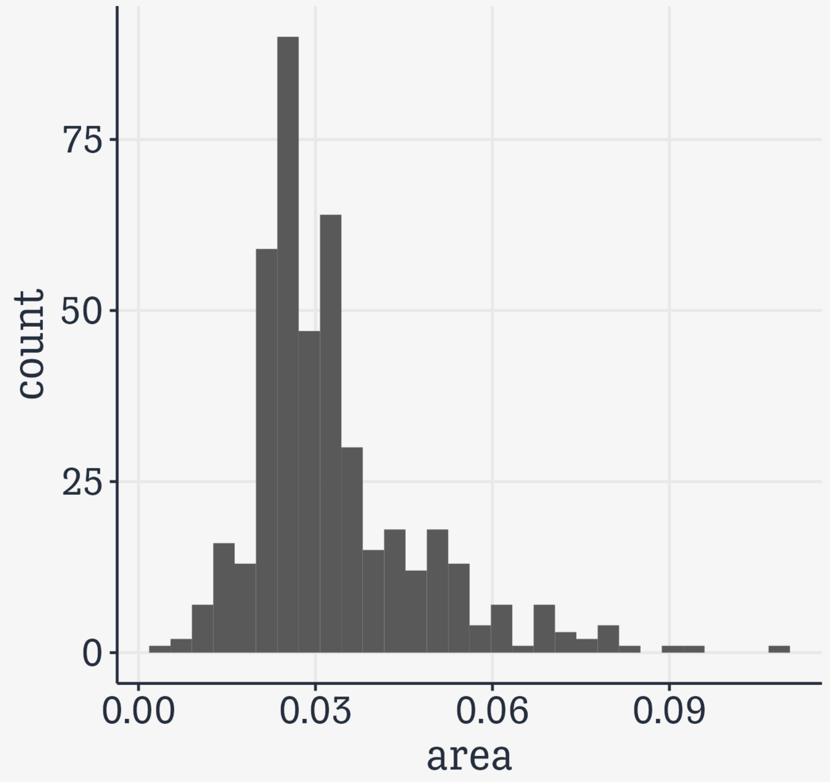
```
# A tibble: 437 × 28
     PID county  state  area poptotal popdensity popwhite popblack popamerindian
   <int> <chr>   <chr> <dbl>    <int>      <dbl>    <int>    <int>         <int>
 1   561 ADAMS   IL    0.052    66090      1271.    63917     1702            98
 2   562 ALEXAN… IL    0.014    10626       759      7054     3496            19
 3   563 BOND    IL    0.022    14991       681.    14477      429            35
 4   564 BOONE   IL    0.017    30806      1812.    29344      127            46
 5   565 BROWN   IL    0.018     5836       324.     5264      547            14
 6   566 BUREAU  IL    0.05     35688       714.    35157       50            65
 7   567 CALHOUN IL    0.017     5322       313.     5298        1             8
 8   568 CARROLL IL    0.027    16805       622.    16519      111            30
 9   569 CASS    IL    0.024    13437       560.    13384       16             8
10   570 CHAMPA… IL    0.058   173025      2983.   146506    16559           331
# ℹ 427 more rows
# ℹ 19 more variables: popasian <int>, popother <int>, percwhite <dbl>,
#   percblack <dbl>, percamerindan <dbl>, percasian <dbl>, percother <dbl>,
#   popadults <int>, perchsd <dbl>, percollege <dbl>, percprof <dbl>,
#   poppovertyknown <int>, percpovertyknown <dbl>, percbelowpoverty <dbl>,
#   percchildbelowpovert <dbl>, percadultpoverty <dbl>,
```

`stat_` functions behind the scenes

```r
p <- ggplot(data = midwest,
            mapping = aes(x = area))

p + geom_histogram()
```

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

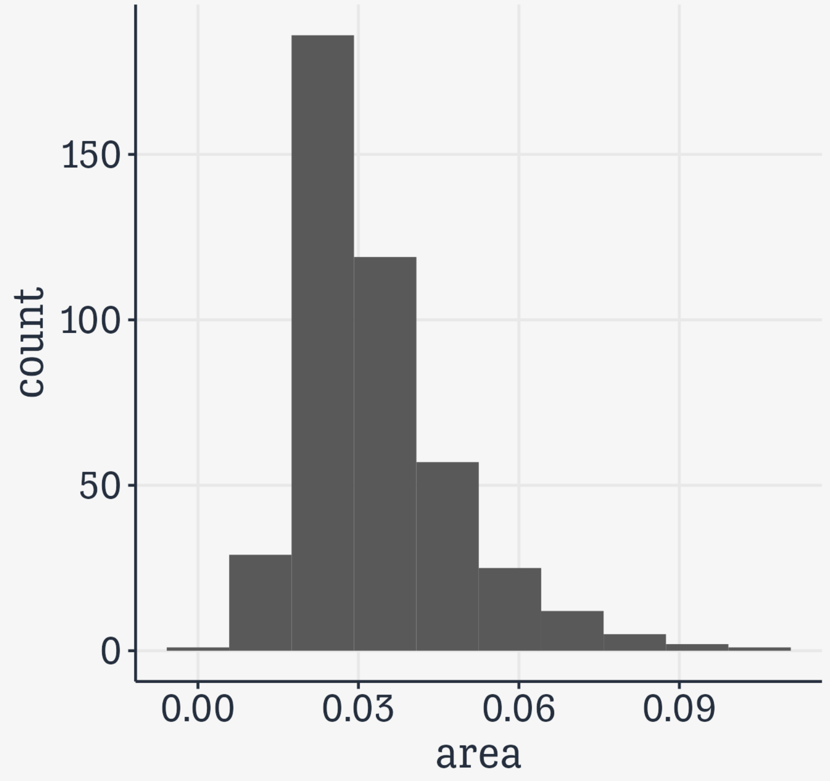


Here the default `stat_` function for this geom has to make a choice. It is

`stat_` functions behind the scenes

```r
p <- ggplot(data = midwest,
            mapping = aes(x = area))

p + geom_histogram(bins = 10)
```

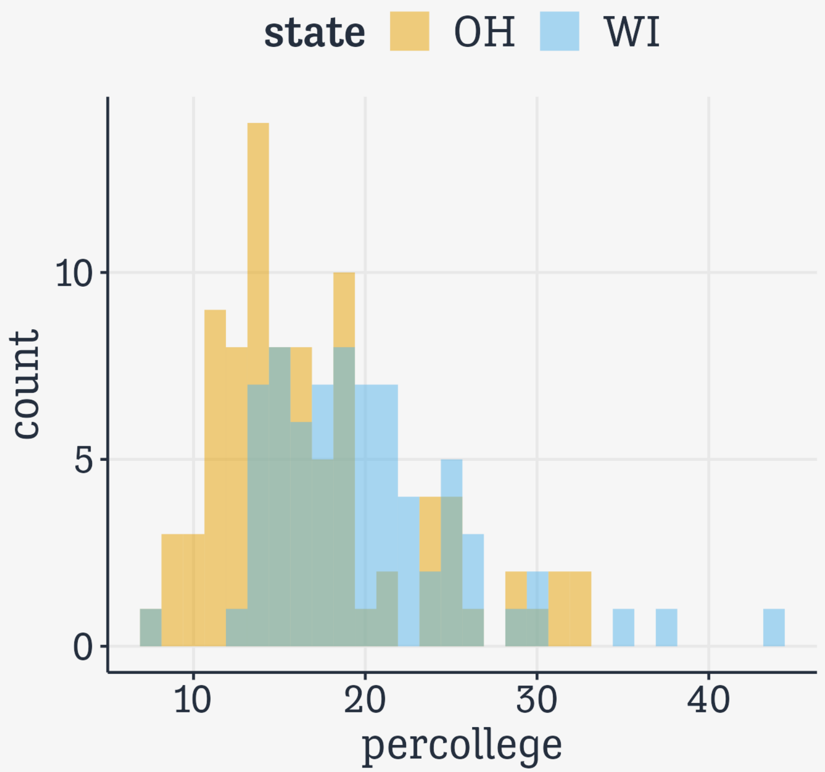


We can choose *either* the number of bins *or* the `binwidth`

Compare two distributions

```r
## Two state codes
oh_wi <- c("OH", "WI")

midwest |>
  filter(state %in% oh_wi) |>
  ggplot(mapping = aes(x = percollege,
                       fill = state)) +
  geom_histogram(alpha = 0.5,
               position = "identity")
```



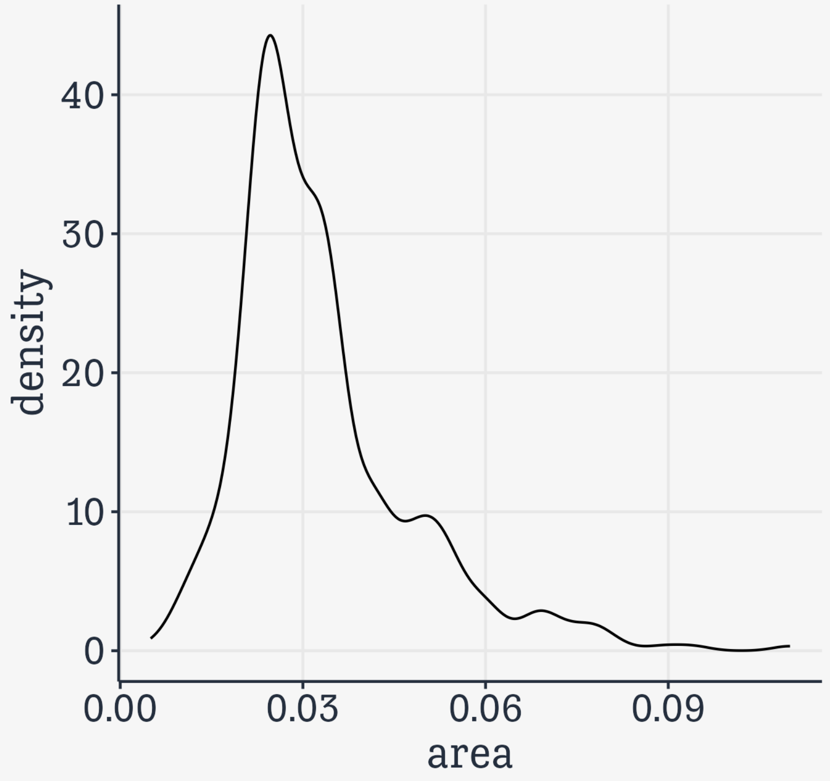
Here we do the whole thing in a pipeline using the pipe and the `dplyr` verb `filter()` to subset rows of the data by some condition.

Experiment with leaving the `position` argument out, or changing it to `"dodge"`.

geom_density()

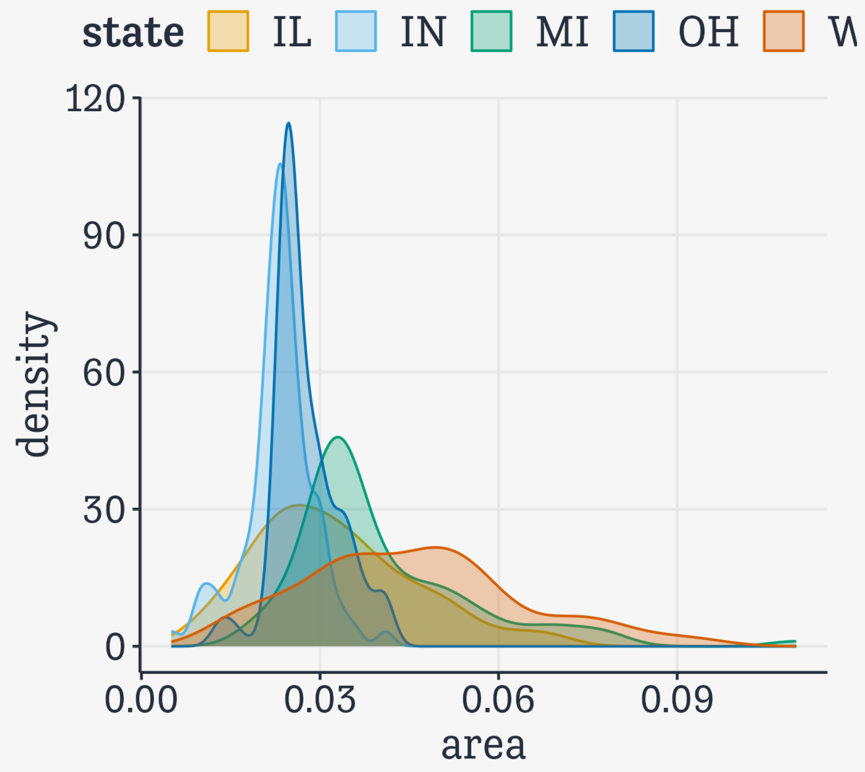
```r
p <- ggplot(data = midwest,
            mapping = aes(x = area))

p + geom_density()
```



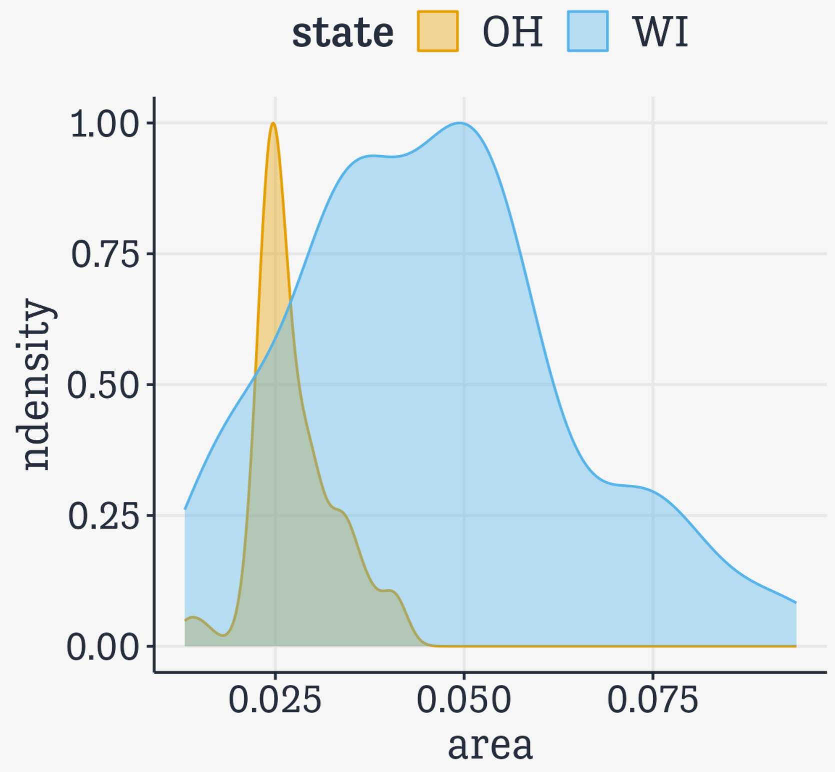
geom_density()

```r
p <- ggplot(data = midwest,
            mapping = aes(x = area,
                          fill = state,
                          color = state))
p + geom_density(alpha = 0.3)
```



geom_density()

```
midwest ▷
  filter(state %in% oh_wi) ▷
  ggplot(mapping = aes(x = area,
                       fill = state,
                       color = state)) +
  geom_density(mapping = aes(y = after_stat(nde
               alpha = 0.4)
```



`ndensity` here is not in our data! It’s *computed*. Histogram and density geoms have default statistics, but you can ask them to do more. The `after_stat` functions can do this work for us.

Avoid counting up,
when necessary

Sometimes no counting is needed

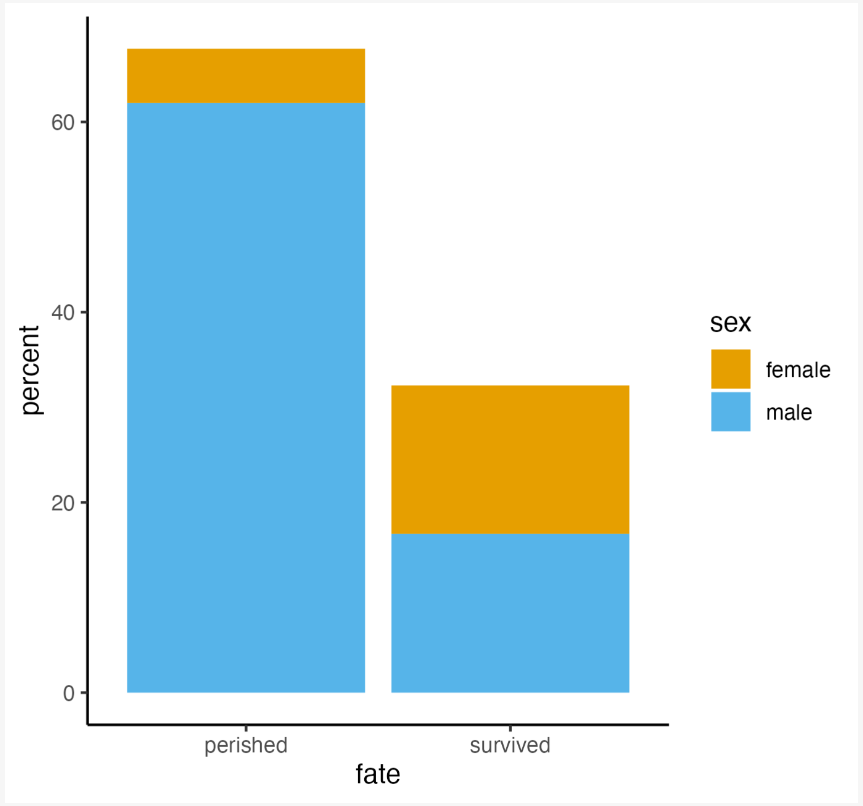
```
titanic
```

```
      fate    sex    n percent
1 perished   male 1364    62.0
2 perished female  126     5.7
3 survived   male  367    16.7
4 survived female  344    15.6
```

Here we just have a summary table and want to plot a few numbers directly in a bar chart.

geom_bar() wants to count up

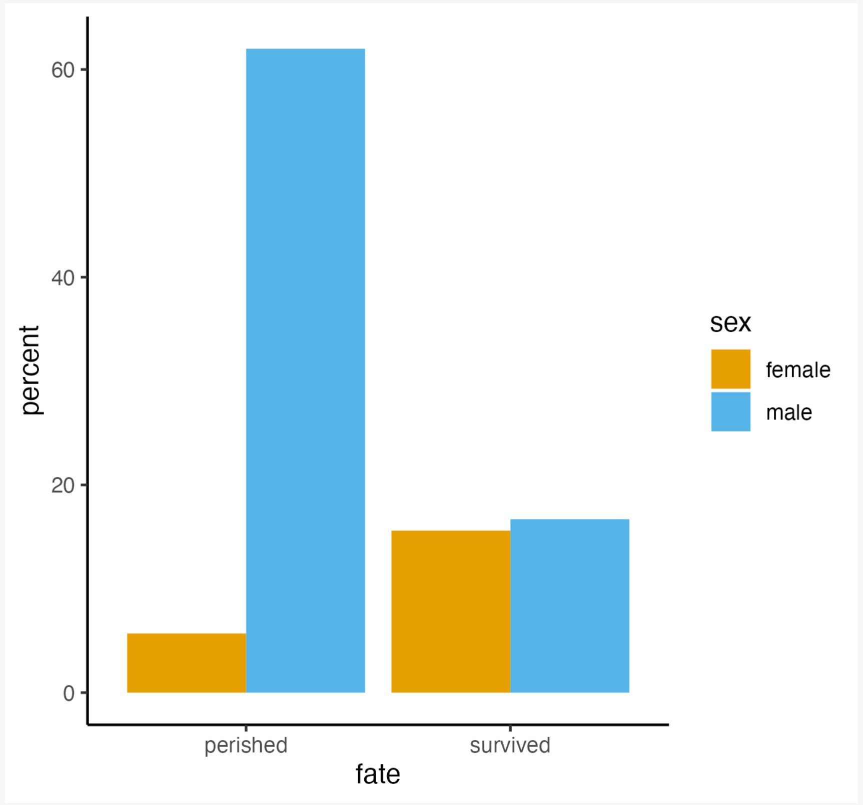
```
p <- ggplot(data = titanic,
            mapping = aes(x = fate,
                          y = percent,
                          fill = sex))
p + geom_bar(stat = "identity")
```



By default `geom_bar()` tries to count up data by category. (Really it's the `stat_count()` function that does this behind the scenes.) By saying `stat="identity"` we explicitly tell it not to do that. This also allows us to use a `y` mapping. Normally this would be the result of the counting up.

geom_bar() stacks bars by default

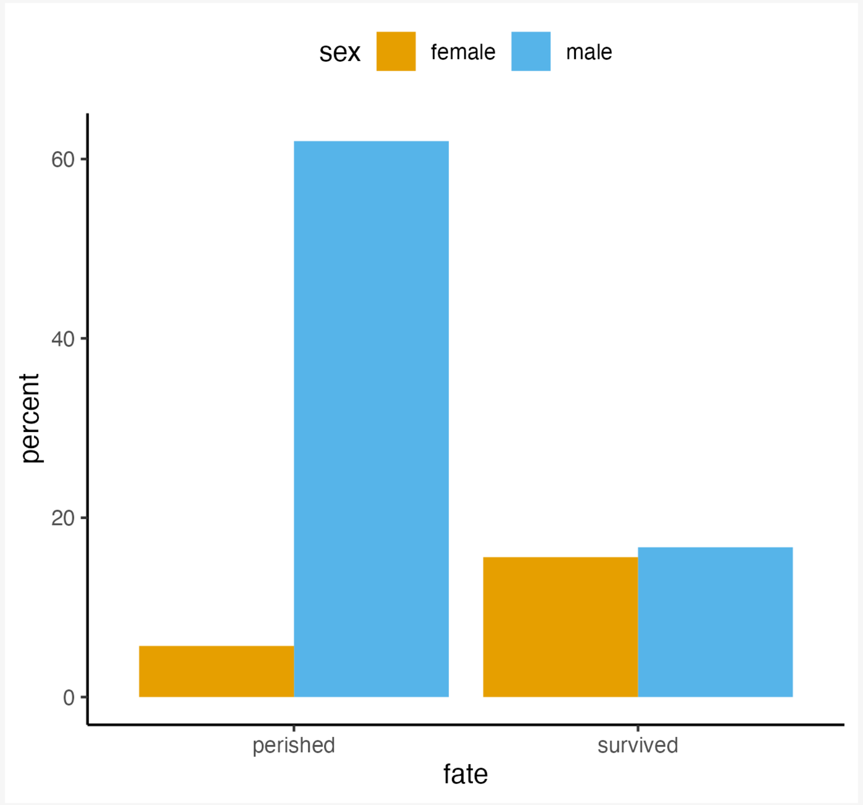
```
p ← ggplot(data = titanic,
           mapping = aes(x = fate,
                         y = percent,
                         fill = sex))
p + geom_bar(stat = "identity",
             position = "dodge")
```



Position arguments adjust whether the things drawn are placed on top of one another (`"stack"`), side-by-side (`"dodge"`), or taken as-is (`"identity"`).

A quick theme() adjustment

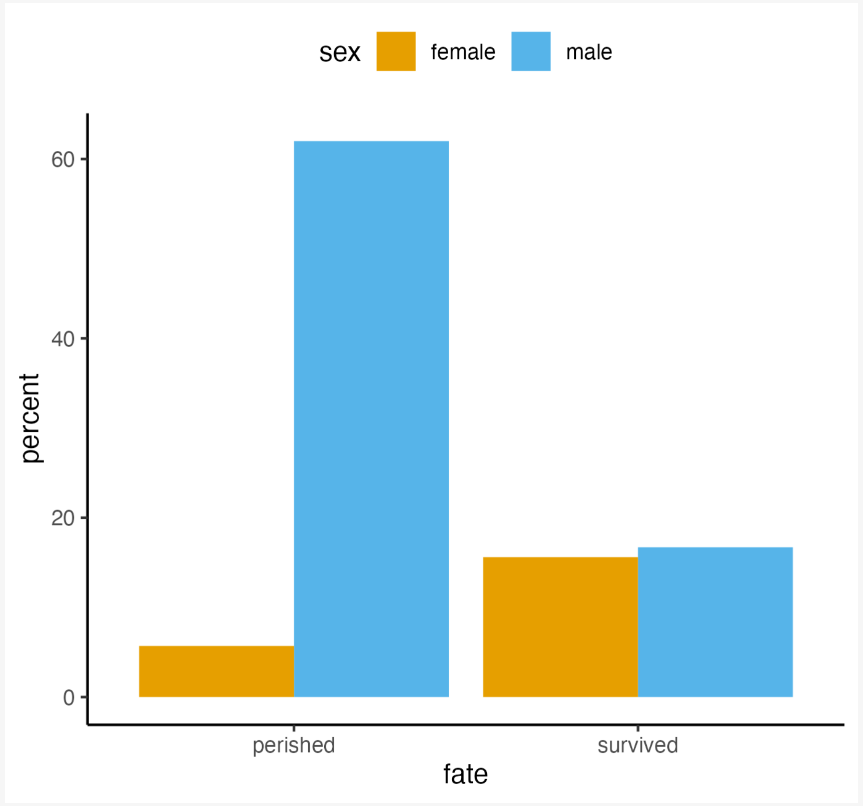
```r
p <- ggplot(data = titanic,
            mapping = aes(x = fate,
                          y = percent,
                          fill = sex))
p + geom_bar(stat = "identity",
             position = "dodge") +
  theme(legend.position = "top")
```



The `theme()` function controls the styling of parts of the plot that don't belong to its "grammatical" structure. That is, that are not contributing to directly representing data.

For convenience, use `geom_col()`

```r
p ← ggplot(data = titanic,
           mapping = aes(x = fate,
                         y = percent,
                         fill = sex))
p + geom_col(position = "dodge") +
  theme(legend.position = "top")
```



`geom_col()` assumes `stat = "identity"` by default. It’s for when you want to directly plot a table of values, rather than create a bar chart by summing over one varible categorized by another.

Using geom_col() for thresholds

```
oecd_sum
```

```
# A tibble: 57 × 5
# Groups:   year [57]
    year other   usa  diff hi_lo
   <int> <dbl> <dbl> <dbl> <chr>
 1  1960  68.6  69.9 1.30  Below
 2  1961  69.2  70.4 1.20  Below
 3  1962  68.9  70.2 1.30  Below
 4  1963  69.1  70   0.900 Below
 5  1964  69.5  70.3 0.800 Below
 6  1965  69.6  70.3 0.700 Below
 7  1966  69.9  70.3 0.400 Below
 8  1967  70.1  70.7 0.600 Below
 9  1968  70.1  70.4 0.300 Below
10  1969  70.1  70.6 0.5   Below
# ℹ 47 more rows
```

Data comparing U.S. average life expectancy to the rest of the OECD average.

`diff` is difference in years with respect to the U.S.

`hi_lo` is a flag saying whether the OECD is above or below the U.S.

Using geom_col() for thresholds

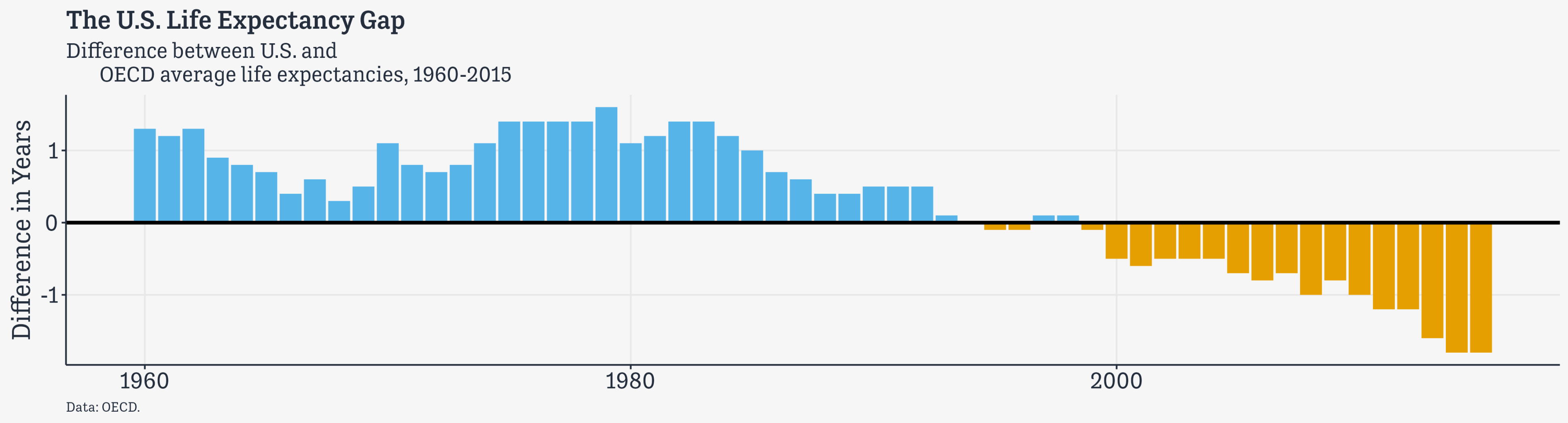
```
p ← ggplot(data = oecd_sum,
           mapping = aes(x = year,
                         y = diff,
                         fill = hi_lo))

p_out ← p + geom_col() +
  geom_hline(yintercept = 0, size = 1.2) +
  guides(fill = "none") +
  labs(x = NULL,
       y = "Difference in Years",
       title = "The U.S. Life Expectancy Ga
       subtitle = "Difference between U.S.
       OECD average life expectancies, 196
       caption = "Data: OECD.")
```

`geom_hline()` doesn't take any data argument. It just draws a horizontal line with a given y-intercept.

`x = NULL` means "Don't label the x-axis (not even with the default value, the variable name).

Using `geom_col()` for thresholds


The U.S. Life Expectancy Gap
Difference between U.S. and
OECD average life expectancies, 1960-2015
Difference in Years
Data: OECD.