# Data Visualization - 3.

# Make Some Graphs

Kieran Healy
Code Horizons

December 10, 2023

# Make Some Graphs

# Load our libraries

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

```
── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
✔ dplyr     1.1.4     ✔ readr     2.1.4
✔ forcats   1.0.0     ✔ stringr   1.5.1
✔ ggplot2   3.4.4     ✔ tibble    3.2.1
✔ lubridate 1.9.3     ✔ tidyr     1.3.0
✔ purrr     1.0.2
── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
✖ dplyr::filter() masks stats::filter()
✖ dplyr::lag()    masks stats::lag()
ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become
errors
```

```r
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

# Feed ggplot tidy data

# What is tidy data?

| gdp | lifexp | pop | continent |
|---|---|---|---|
| 340 | 65 | 31 | Euro |
| 227 | 51 | 200 | Amer |
| 909 | 81 | 80 | Euro |

# What is tidy data?

| gdp | lifexp | pop | continent |
|---|---|---|---|
| 340 | 65 | 31 | Euro |
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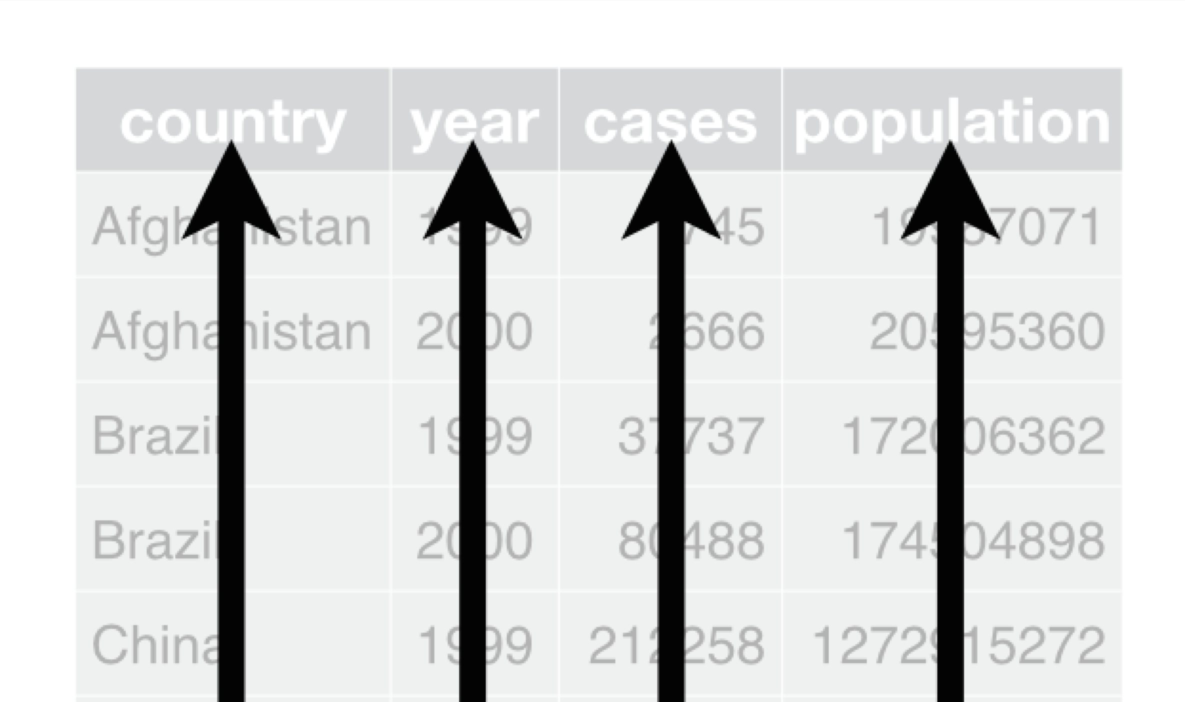
# Every column is a single variable



# Every row is a single observation

# Every cell is a single value

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

# 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:

```
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 |

# 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 |

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| 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 |
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| 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% | |

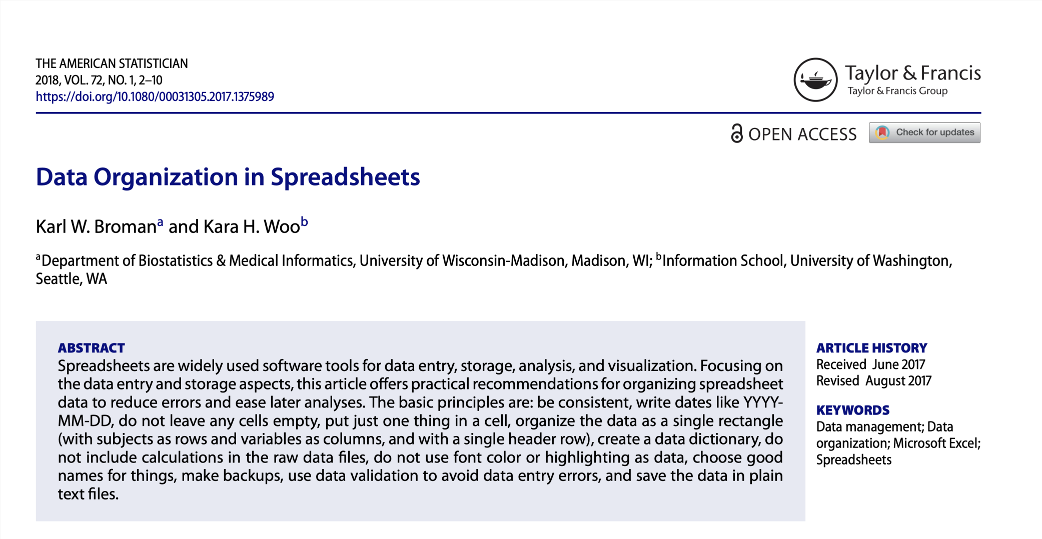
- 😠 More than one header row
- 😡 Mixed data types in some columns
- 💀 Color and typography used to encode variables and their values

# 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]

[a]Department of Biostatistics & Medical Informatics, University of Wisconsin-Madison, Madison, WI; [b]Information School, University of Washington, Seattle, WA

**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:

```r
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.

```
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.

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

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

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

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

```
/Users/kjhealy/Documents/courses/data_visualization
├── LICENSE
├── Makefile
├── README.md
├── README.qmd
├── _extensions
├── _freeze
├── _quarto.yml
├── _site
├── _targets
├── _targets.R
├── code
├── course_notes.qmd
├── data
├── data_visualization.Rproj
├── deploy.sh
├── figures
├── html
├── pdf_slides
└── slides
```

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. Also, I'm on a Mac, but you may not be.

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

So:

```
## Load the file relative to the path from the top of the project, without separators, etc
organs <- read_csv(file = here("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: `,`

```
organans ← read_csv(file = here("data", "organdonation.csv"))
```

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

```
# 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.

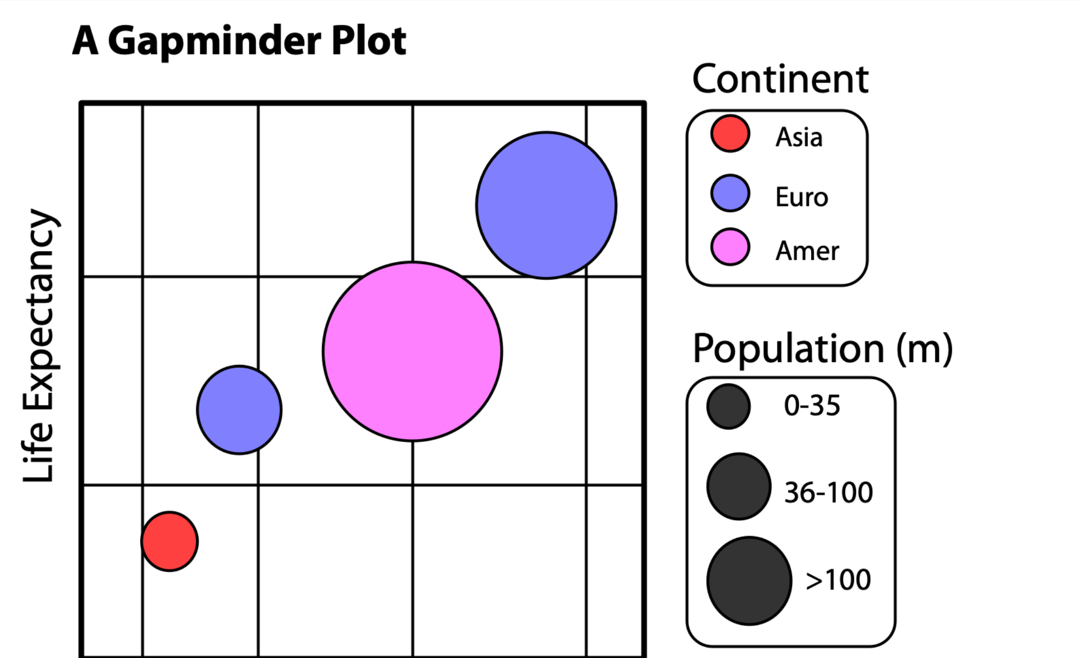
(Be careful what you download from remote locations!)

```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**;

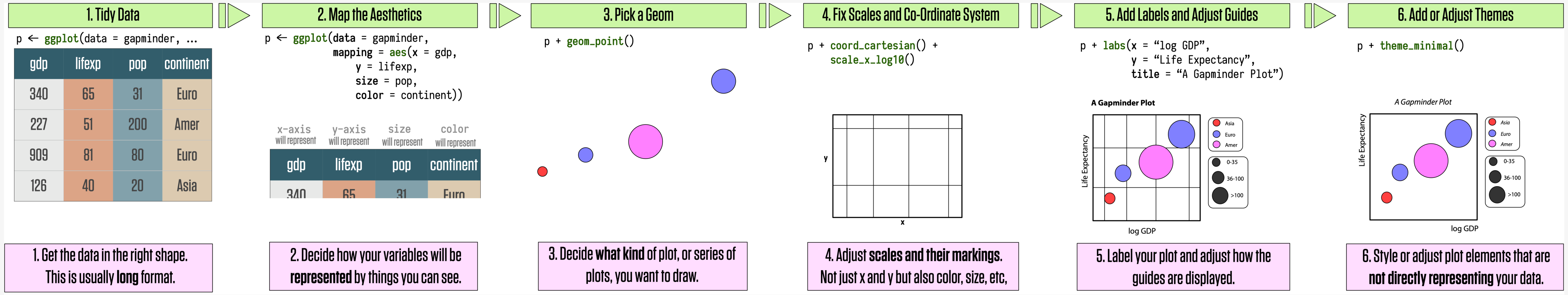
With the plot itself also **titled** and labeled.

# How does ggplot

# do this?

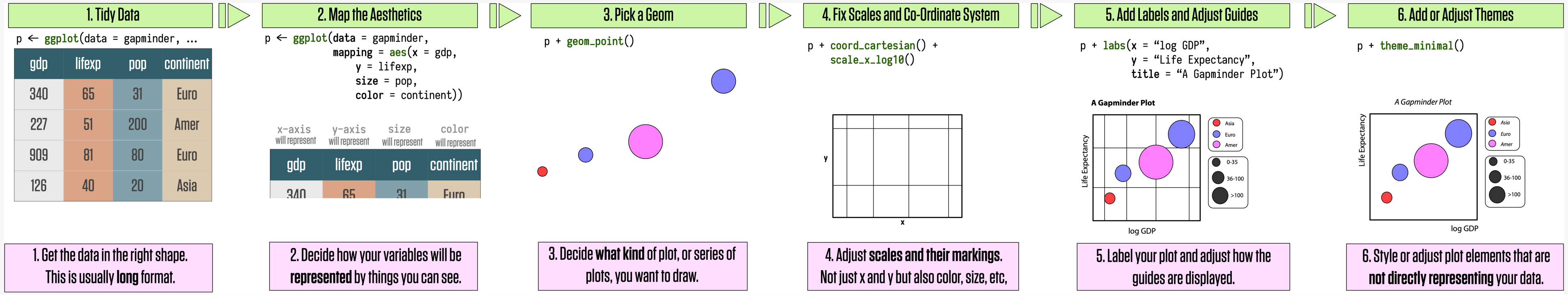
# `ggplot`'s flow of action

# Here's the whole thing, start to finish




Flow of action

# We'll go through it step by step

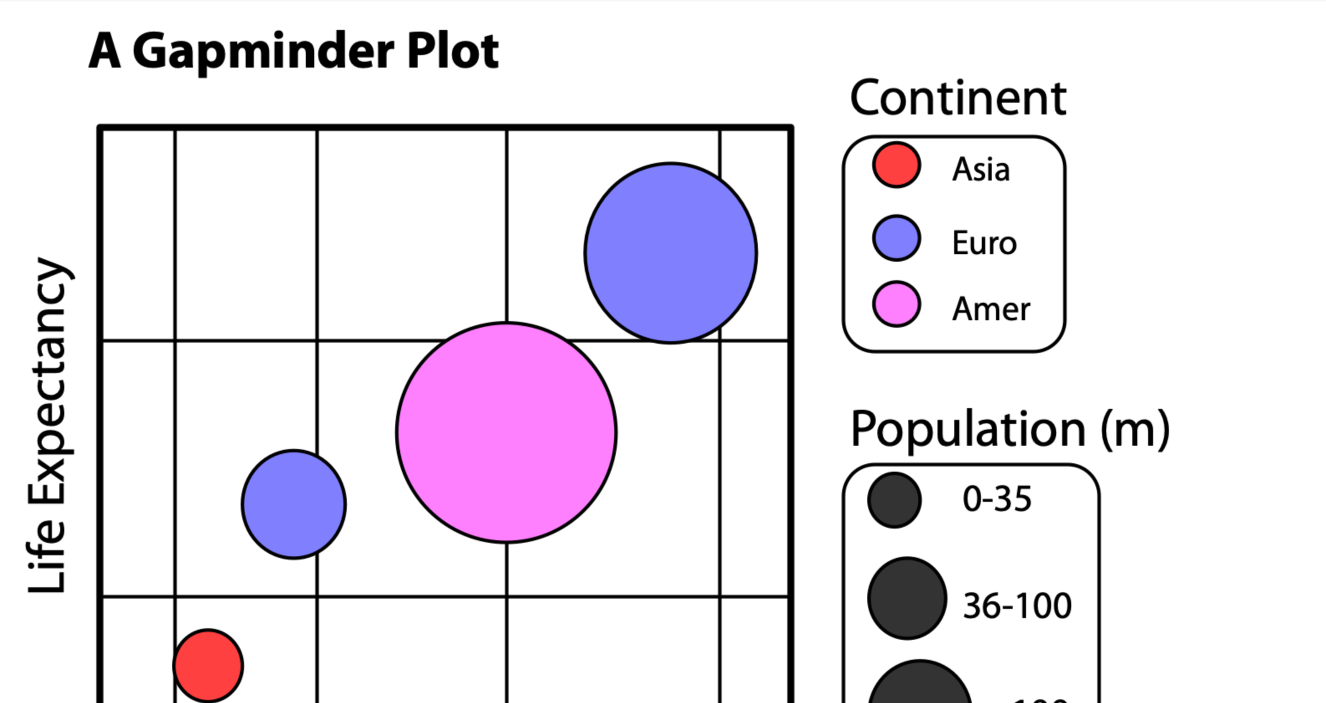



Flow of action

# `ggplot`'s flow of action

| gdp | lifexp | pop | continent |
|---|---|---|---|
| 340 | 65 | 31 | Euro |
| 227 | 51 | 200 | Amer |
| 909 | 81 | 80 | Euro |

# `ggplot`'s flow of action



# 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 |

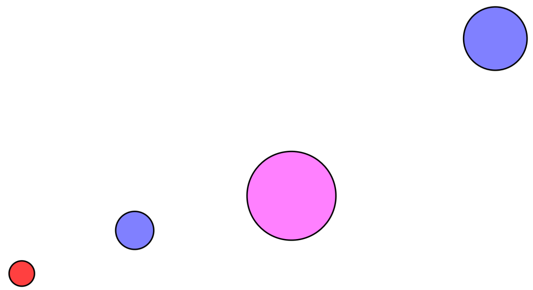
## 2. Map the Aesthetics

```
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 |

## 3. Pick a Geom

```
p + geom_point()
```



1. Get the data in the right shape.

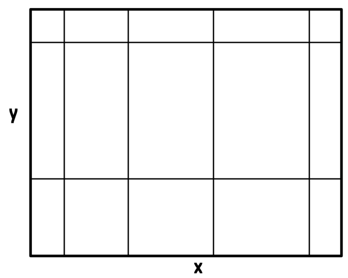
2. Decide how your variables will be

3. Decide **what kind** of plot, or series of

# ggplot's flow of action

## 4. Fix Scales and Co-Ordinate System

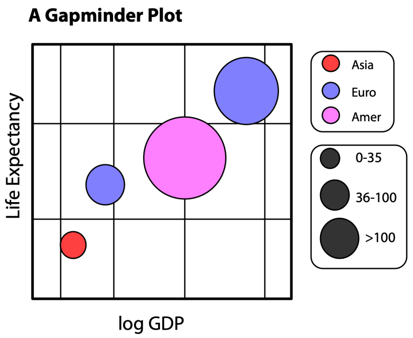
```
p + coord_cartesian() +
    scale_x_log10()
```




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

## 5. Add Labels and Adjust Guides

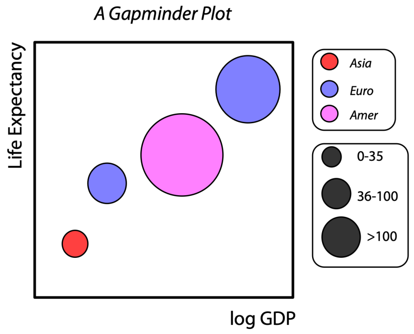
```
p + labs(x = "log GDP",
         y = "Life Expectancy",
         title = "A Gapminder Plot")
```




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.

# 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 |

# ggplot's flow of action: required

## 2. Map the Aesthetics

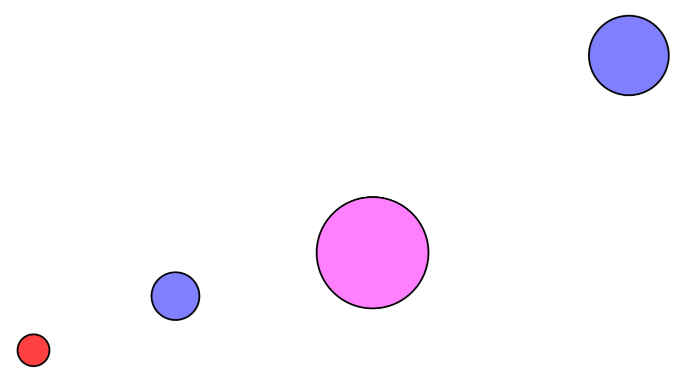
```
p <- ggplot(data = gapminder,
            mapping = aes(x = gdp,
                y = lifexp,
                size = pop,
                color = continent))
```

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

# ggplot's flow of action: required

### 3. Pick a Geom

```
p + geom_point()
```



# Let’s go piece by piece

# Start with the data

```
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
```

```
dim(gapminder)
```

```
[1] 1704    6
```

# Create a plot object

Data is the `gapminder` tibble.

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

# Map variables to aesthetics

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

```
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

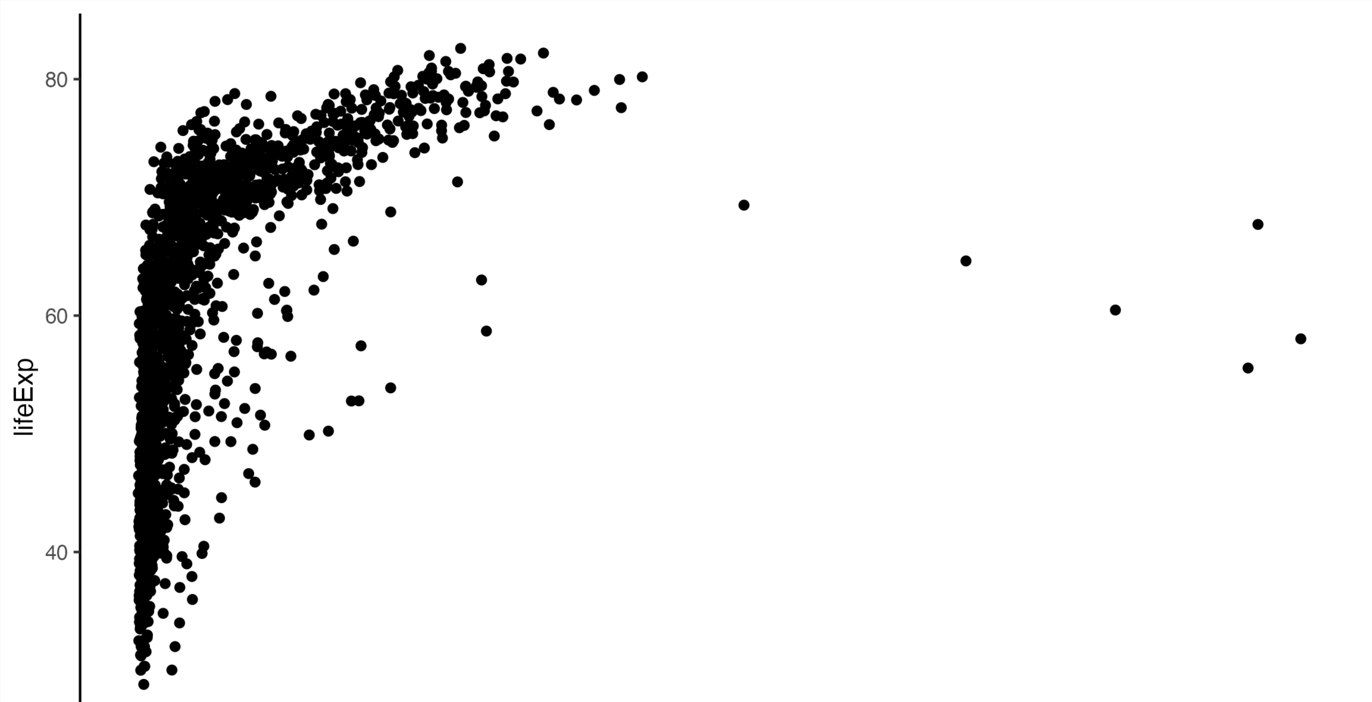
represented by *which visible elements* on the plot.

# p has data and mappings but no geom

```
p
```

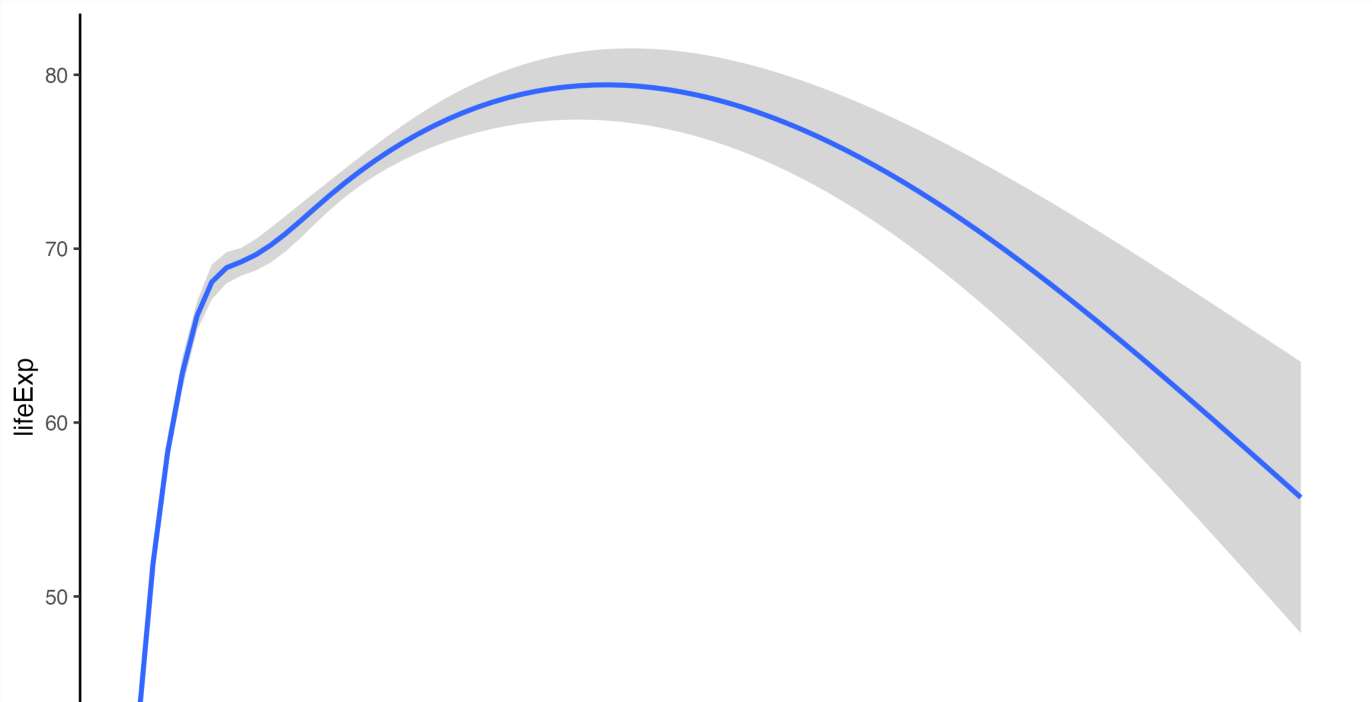
# Add a geom

```
p + geom_point()
```



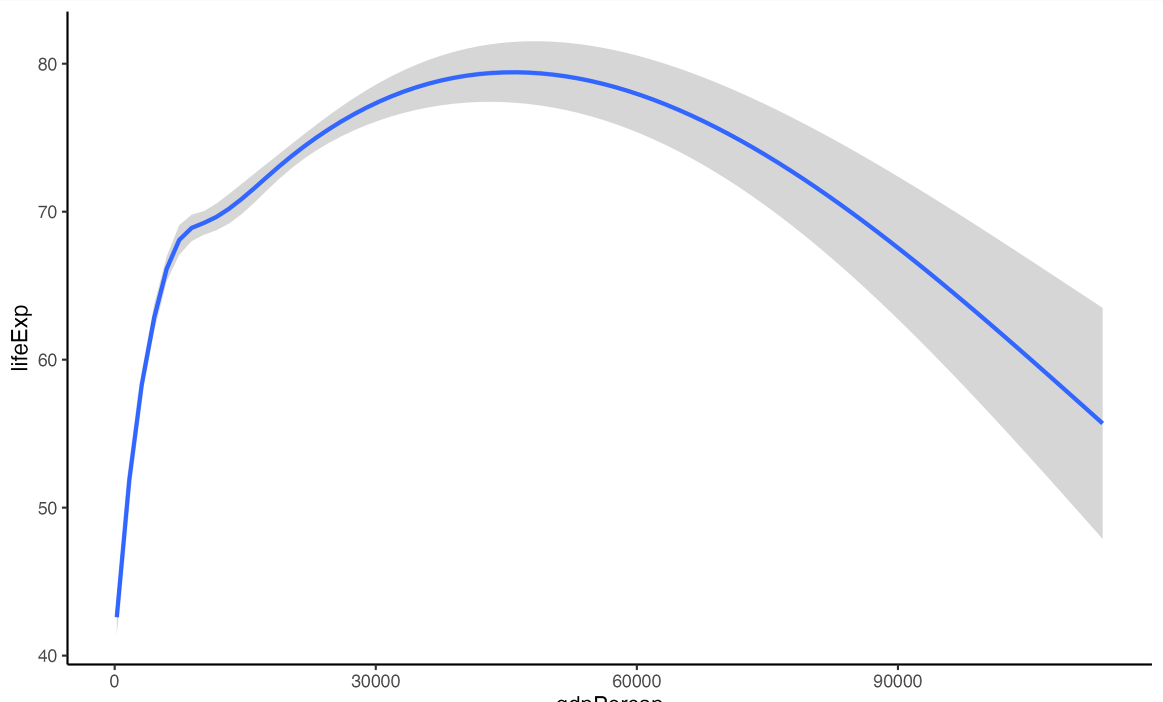
# Try a different geom

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



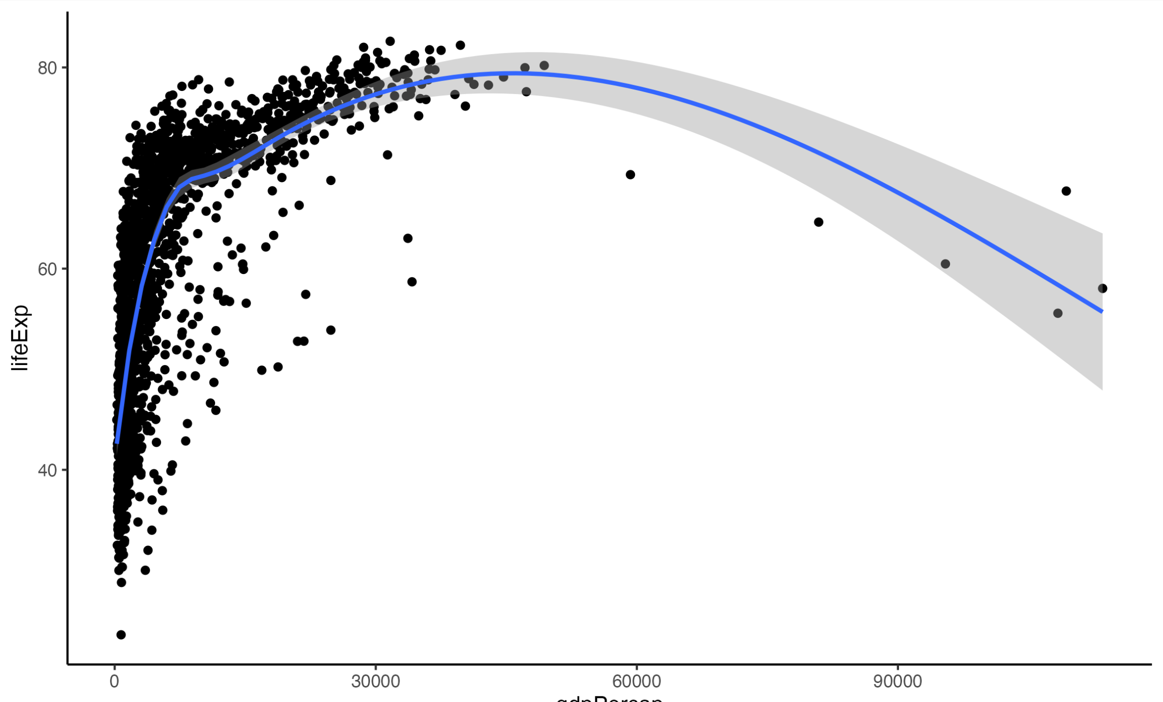
# Build your plots layer by layer

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



# This process is additive

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

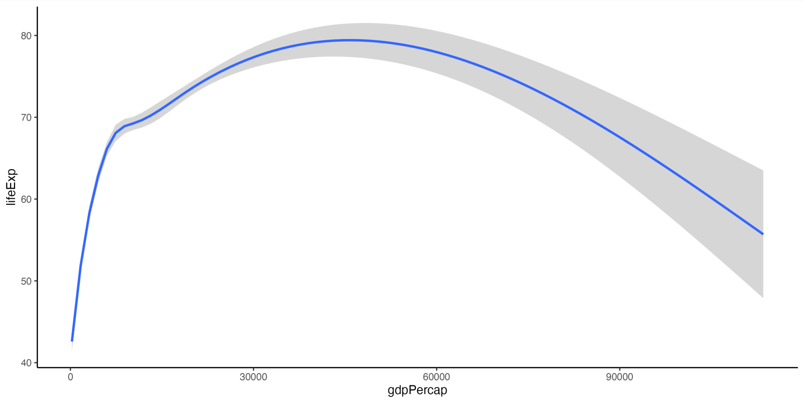


# This process is additive

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

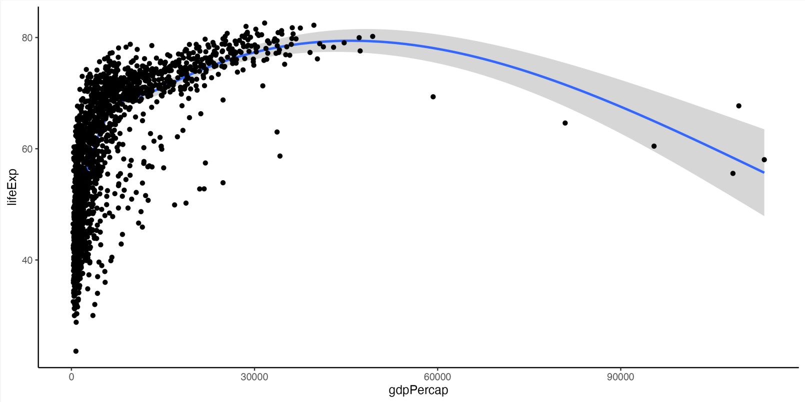
# This process is additive

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



# This process is additive

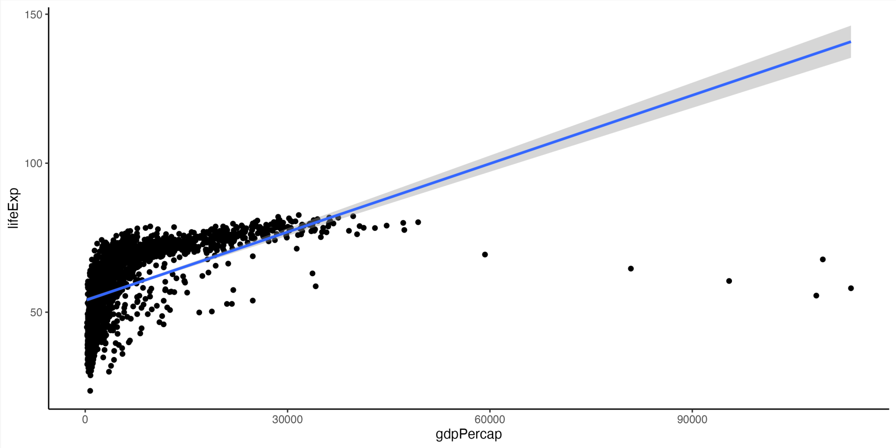
```
p <- ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y=lifeExp))
p + geom_smooth() +
  geom_point()
```



# 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")
```

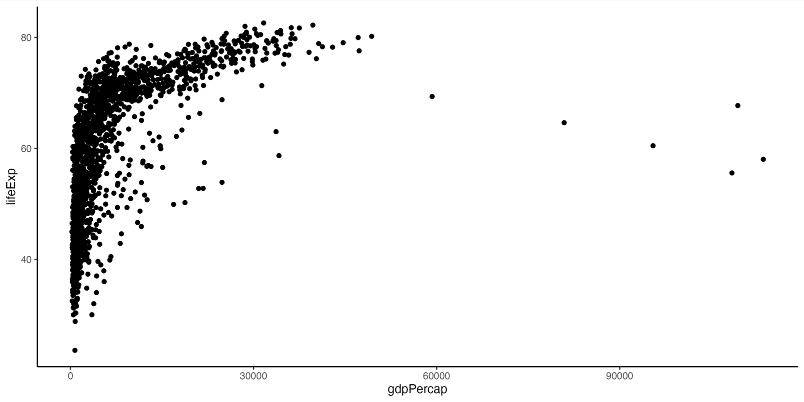


# Keep Layering

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

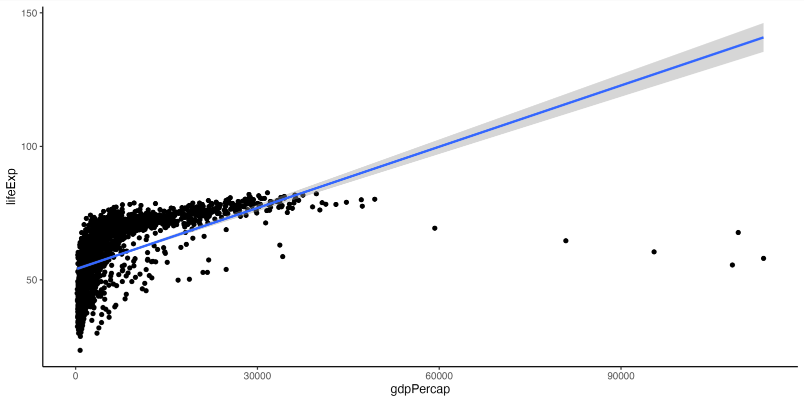
# Keep Layering

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



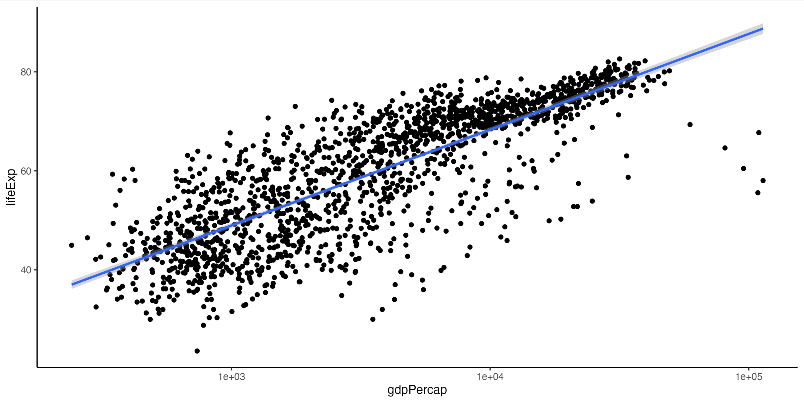
# Keep Layering

```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()
```

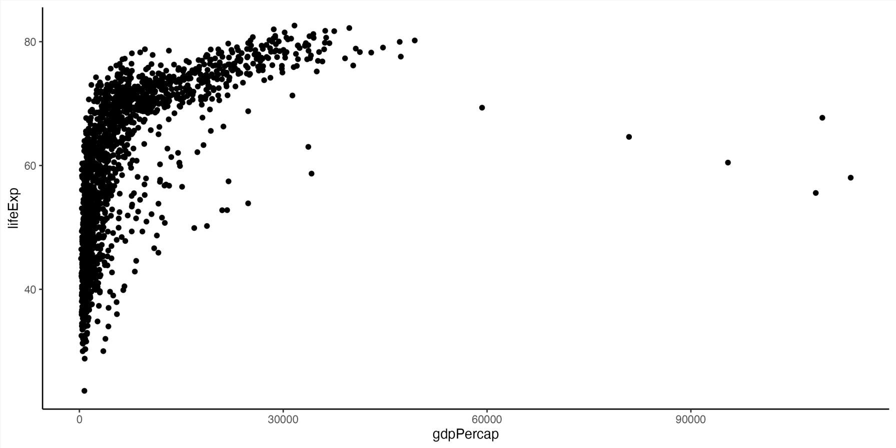


# Fix the labels

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

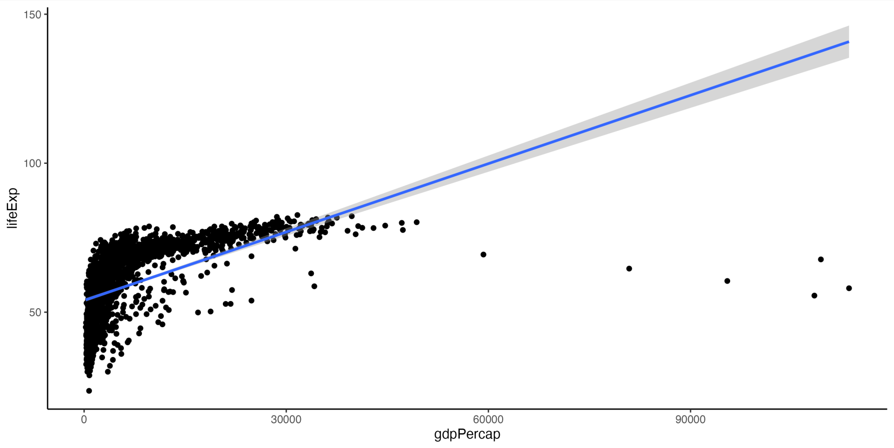
# Fix the labels

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



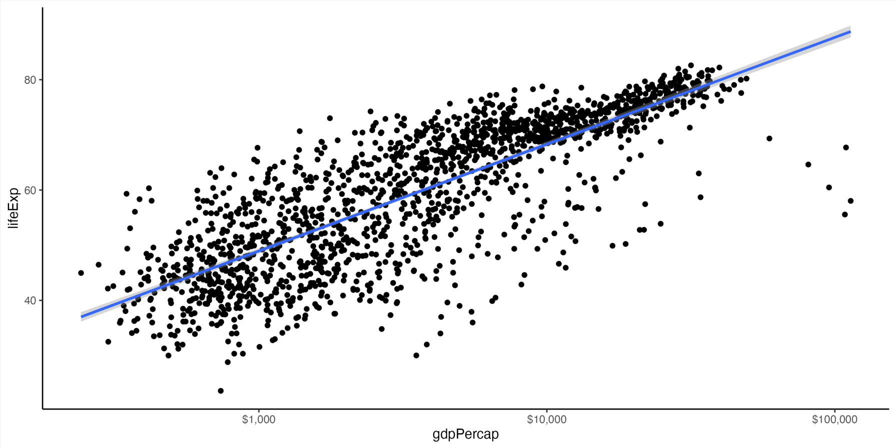
# Fix the labels

```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_do
```



# 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

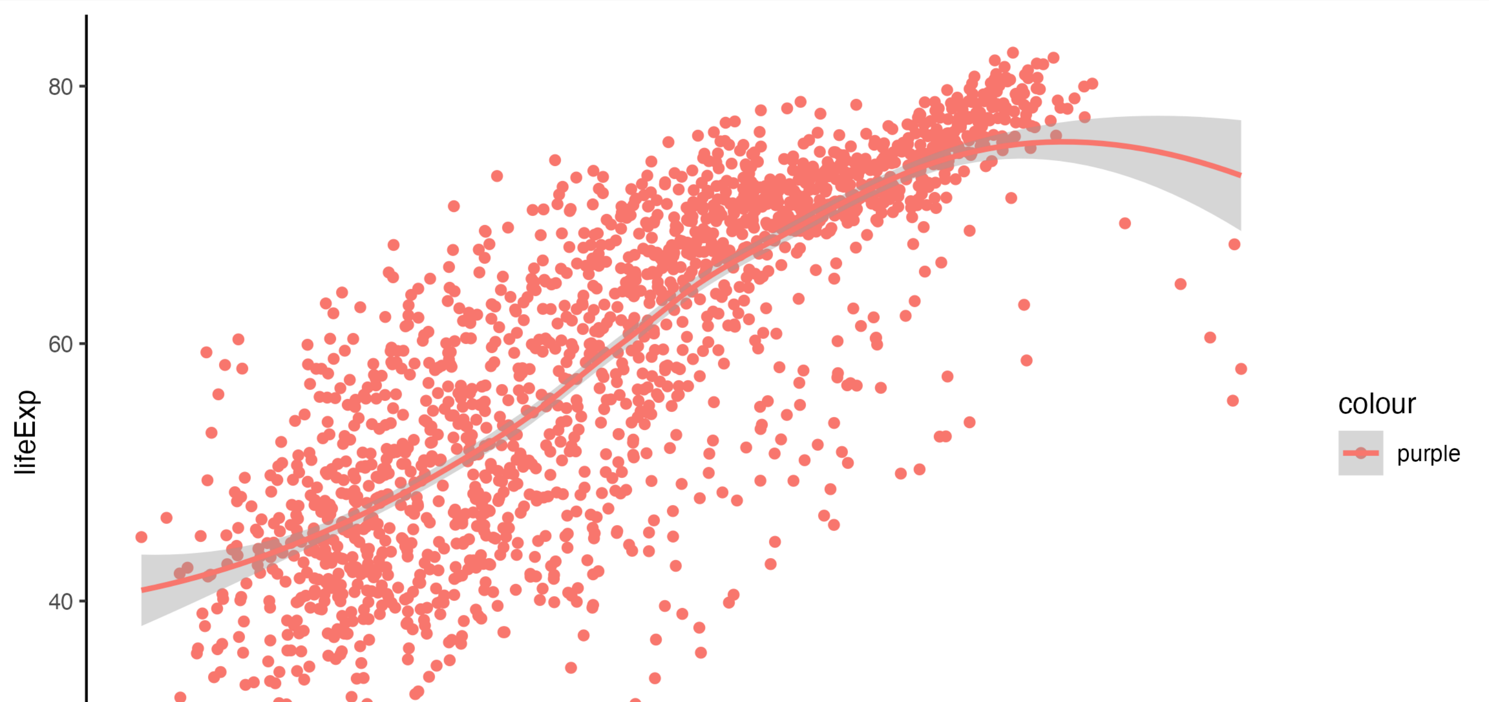
# “Can I change the color of the points?”

```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
```



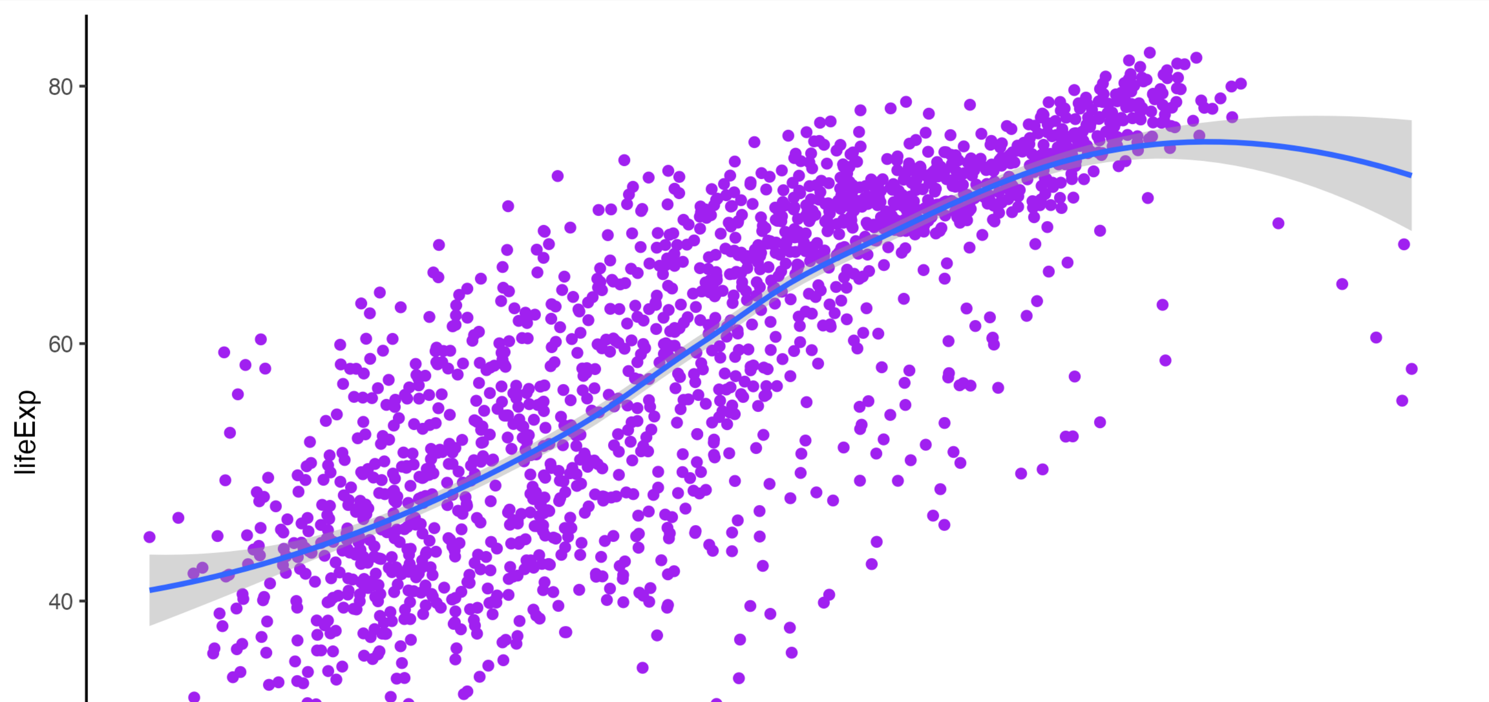
# Try again

```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.

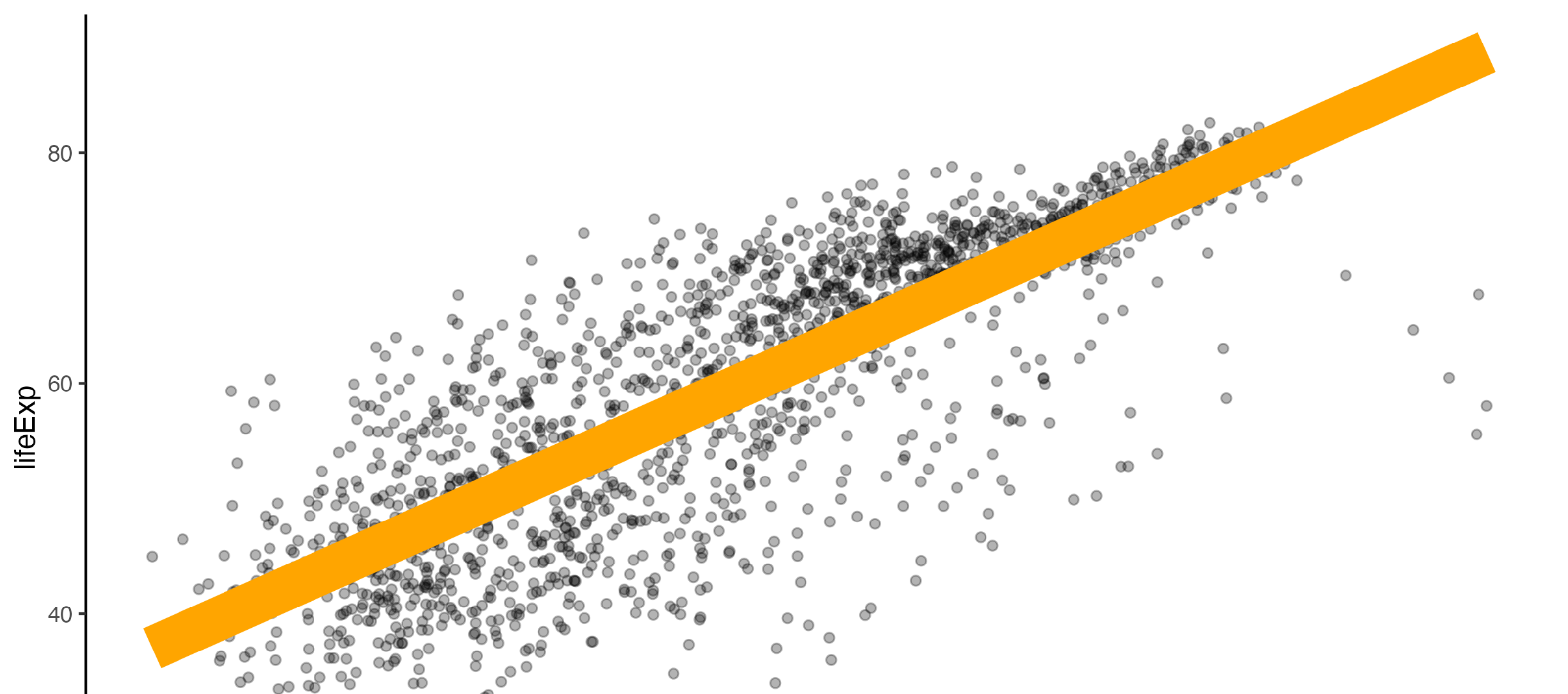
We also give non-default values to some other arguments

```
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.")
```

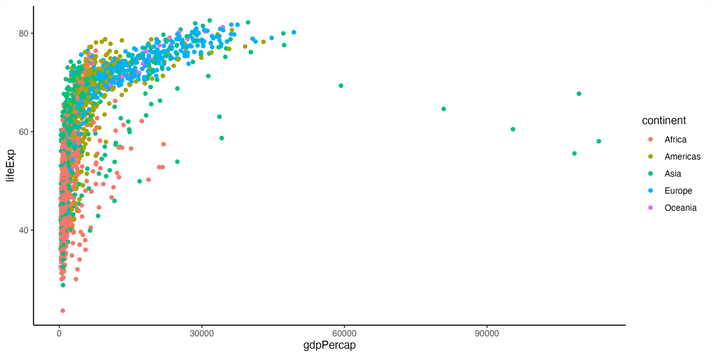
# Map or Set values
# per geom

# Geoms can take their own mappings

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

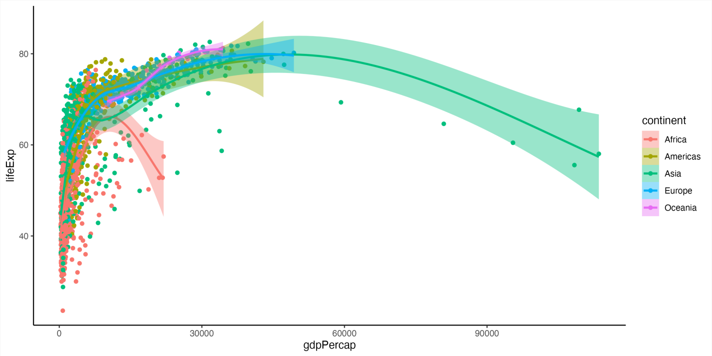
# Geoms can take their own mappings

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



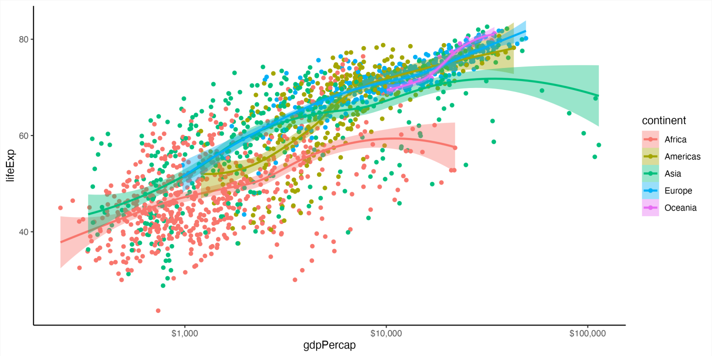
# Geoms can take their own mappings

```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())
```

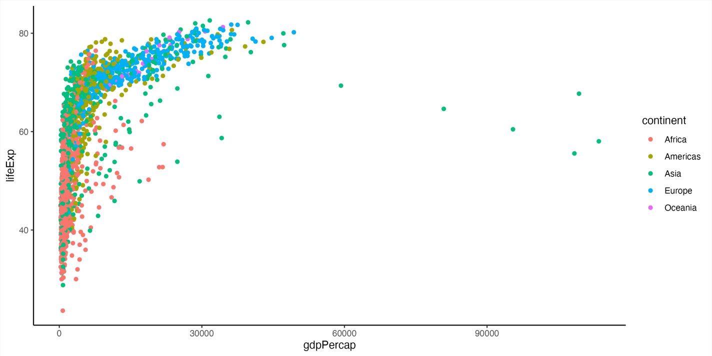


# Geoms can take their own mappings

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

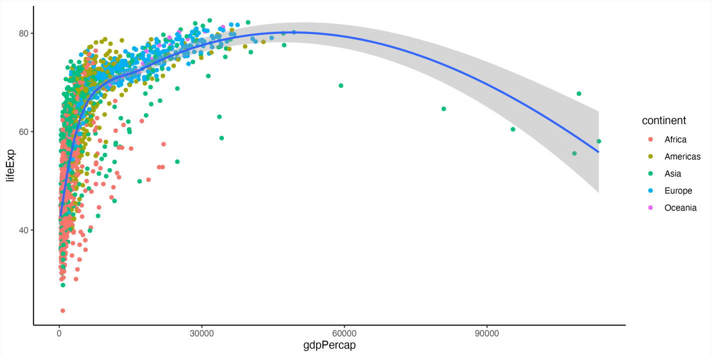
# Geoms can take their own mappings

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



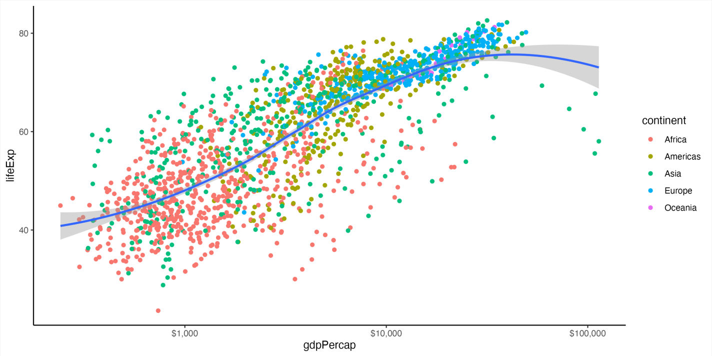
# Geoms can take their own mappings

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



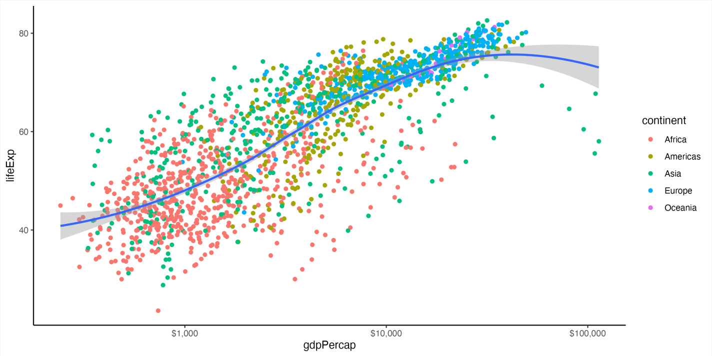
# Geoms can take their own mappings

```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:

## RMarkdown Style

`{r, fig.height=8, fig.width=5, fig.show = "hold", fig.cap="A caption"}`

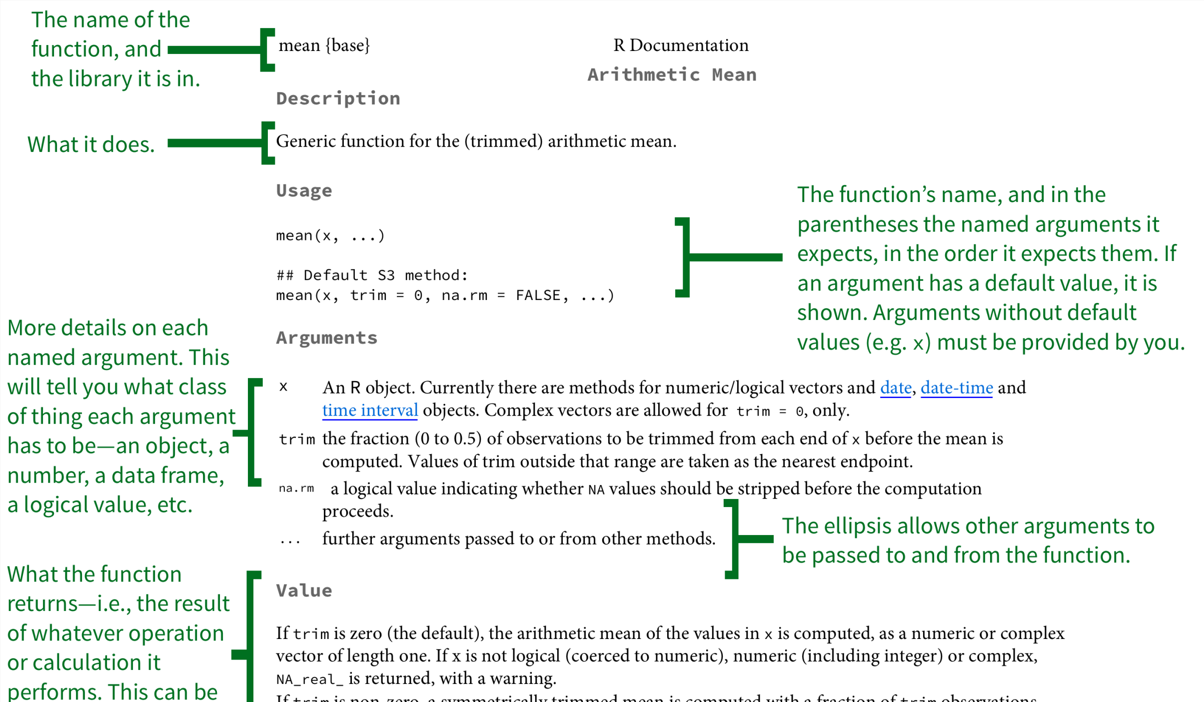
## Quarto Style

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

# Or for the whole document:

```r
knitr::opts_chunk$set(warning = TRUE,
                      message = TRUE,
                      fig.retina = 3,
                      fig.align = "center",
                      fig.asp = 0.7,
                      dev = c("png", "pdf"))
```

# Getting Help



mean {base} R Documentation

**Arithmetic Mean**

**Description**

Generic function for the (trimmed) arithmetic mean.

**Usage**

```
mean(x, ...)

## Default S3 method:
mean(x, trim = 0, na.rm = FALSE, ...)
```

**Arguments**

`x` An R object. Currently there are methods for numeric/logical vectors and date, date-time and time interval objects. Complex vectors are allowed for `trim = 0`, only.

`trim` the fraction (0 to 0.5) of observations to be trimmed from each end of `x` before the mean is computed. Values of trim outside that range are taken as the nearest endpoint.

`na.rm` a logical value indicating whether `NA` values should be stripped before the computation proceeds.

`...` further arguments passed to or from other methods.

**Value**

If `trim` is zero (the default), the arithmetic mean of the values in `x` is computed, as a numeric or complex vector of length one. If x is not logical (coerced to numeric), numeric (including integer) or complex, `NA_real_` is returned, with a warning.

If `trim` is non-zero, a symmetrically trimmed mean is computed with a fraction of `trim` observations

The name of the function, and the library it is in.

mean {base}

R Documentation

**Arithmetic Mean**

## Description

What it does.

Generic function for the (trimmed) arithmetic mean.

## Usage

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mean {base} R Documentation

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## Default S3 method:
mean(x, trim = 0, na.rm = FALSE, ...)
```

The function's name, and in the parentheses the named arguments it expects, in the order it expects them. If an argument has a default value, it is shown. Arguments without default values (e.g. x) must be provided by you

### Arguments

What it does.

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```
mean(x, ...)

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```

The function’s name, and in the parentheses the named arguments it expects, in the order it expects them. If an argument has a default value, it is shown. Arguments without default values (e.g. x) must be provided by you.

More details on each named argument. This will tell you what class of thing each argument has to be—an object, a number, a data frame, a logical value, etc.

**Arguments**

| | |
|---|---|
| `x` | An R object. Currently there are methods for numeric/logical vectors and date, date-time and time interval objects. Complex vectors are allowed for `trim = 0`, only. |
| `trim` | the fraction (0 to 0.5) of observations to be trimmed from each end of `x` before the mean is computed. Values of trim outside that range are taken as the nearest endpoint. |
| `na.rm` | a logical value indicating whether `NA` values should be stripped before the computation proceeds. |

object such as a list, a data frame, a plot, or a model.

**References**

Becker, R. A., Chambers, J. M. and Wilks, A. R. (1988) *The New S Language*. Wadsworth & Brooks/Cole.

**See Also**

weighted.mean, mean.POSIXct, colMeans for row and column means.

Other related functions

**Examples**

```
x <- c(0:10, 50)
xm <- mean(x)
c(xm, mean(x, trim = 0.10))
```

Self-contained examples that you can run at the console. These may use built-in datasets or other R functions.

[Package *base* version 3.4.3 Index]

Visit the package's Index page to look for Demos and Vignettes detailing how it works.