Make Some Graphs

Data Visualization: Session 3

Kieran Healy

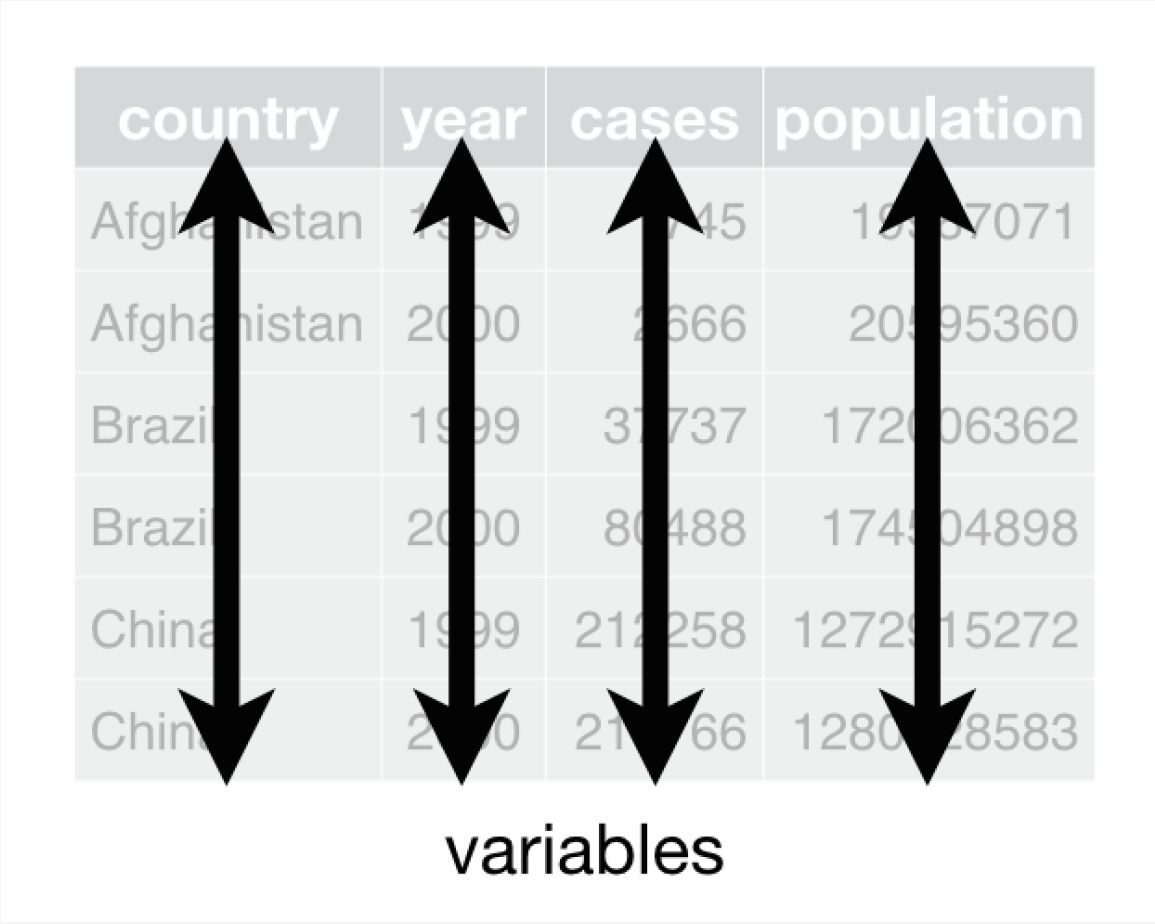
Code Horizons, May 2022


Feed ggplot tidy data
FEED ME

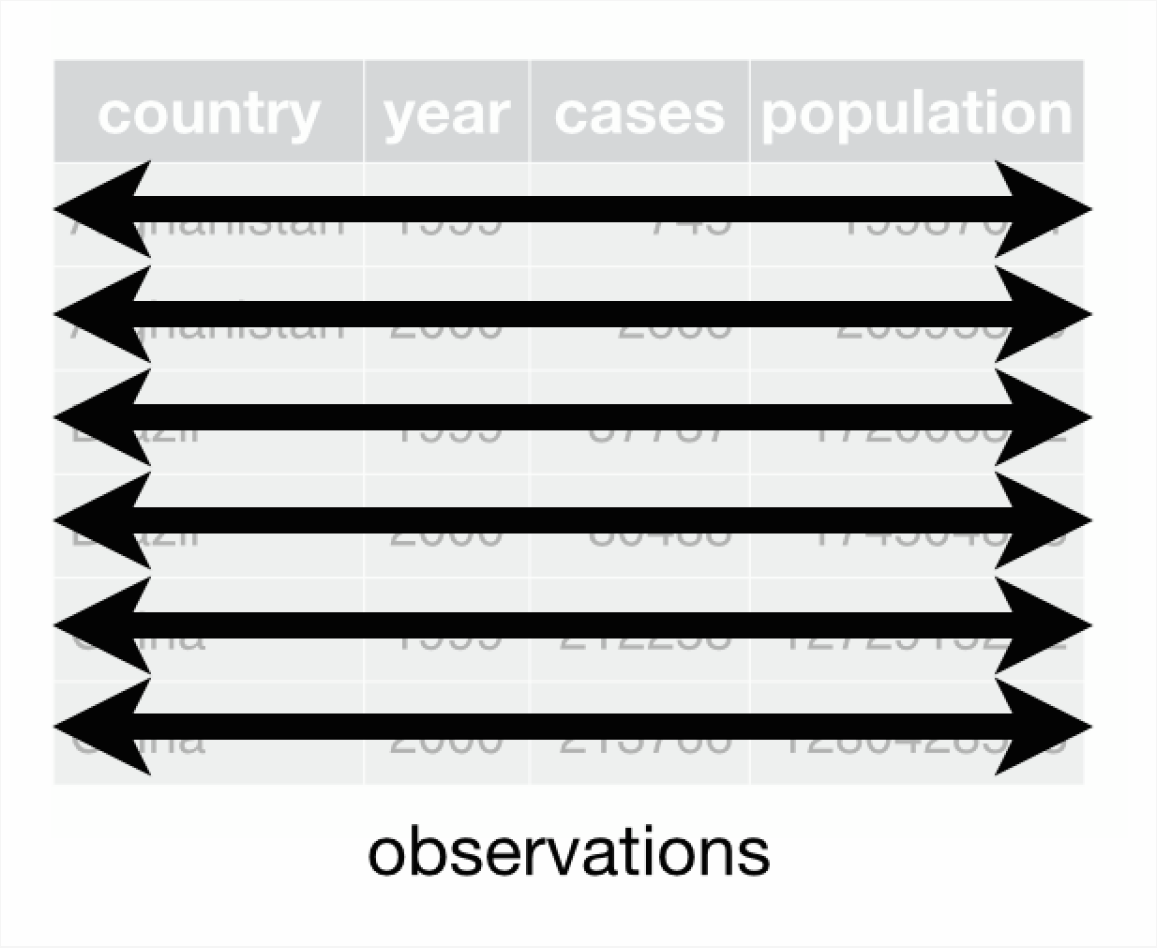
What is tidy data?

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

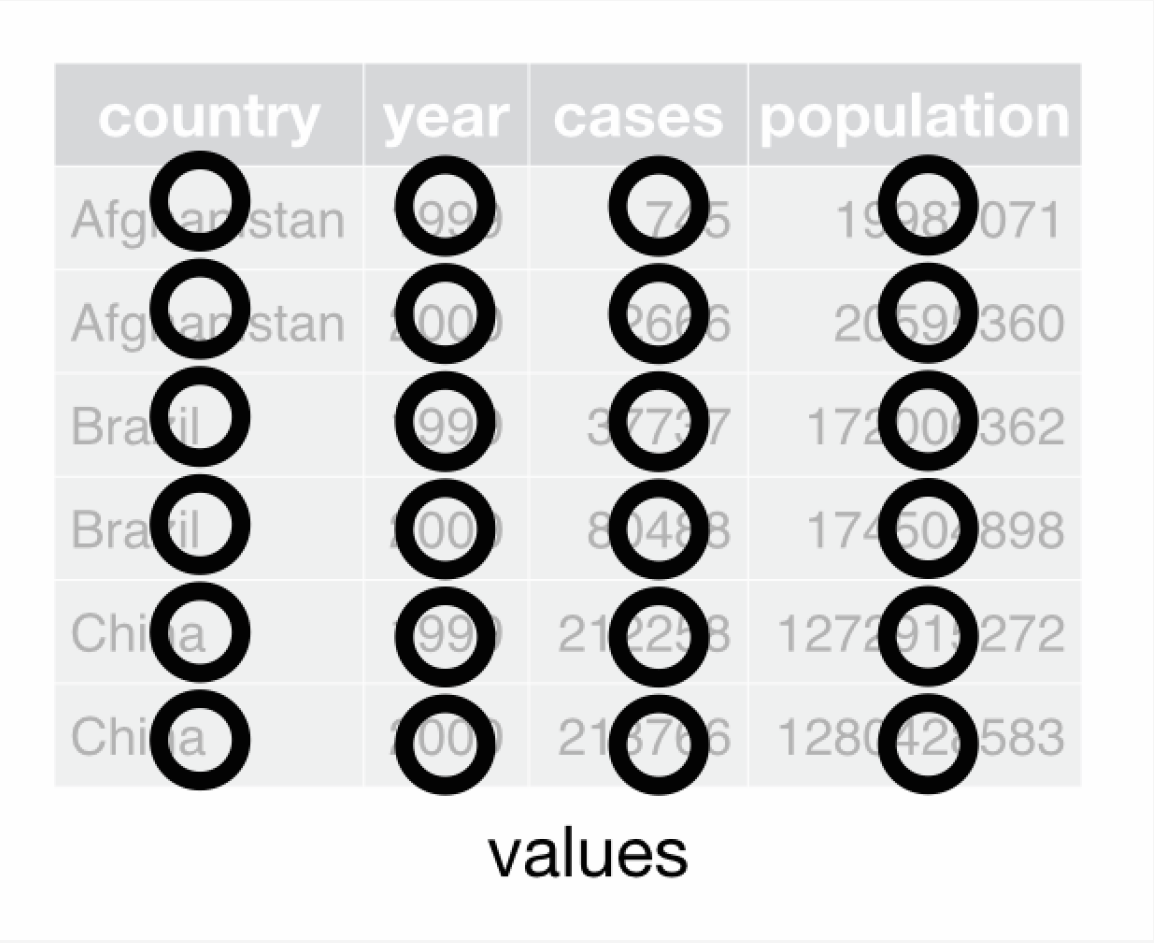
Every column is a single variable



Every row is a single observation



Every cell is a single value



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 is common for good reasons!

Storing data in long format has a lot of *repetition* and *redundancy* in a printed table:

```
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

Untidy data is common for good reasons

Wide form 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

(Again, these tables are made directly in R with the code you see here.)

It's also common for *less* good reasons

State

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%	

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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%	

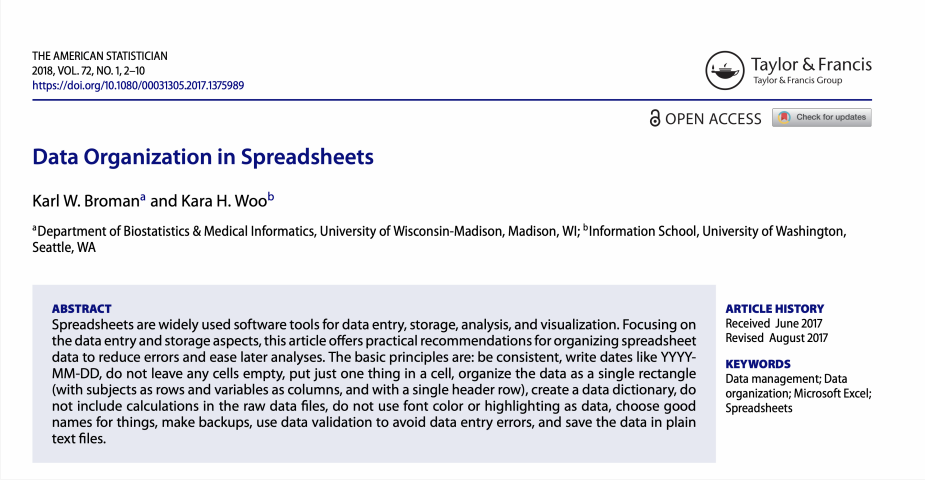
- More than one header row
- Mixed data types in some columns
- Color and typography used to encode variables and their values

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

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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

The most common `tidyr` operation

Pivoting:

```
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
## # … with 356 more rows
```

The "Level of Schooling Attained" measure is spread across the columns, from `elem4` to `coll4`.

This is fine for a compact table, but for us it should be a single measure, say, "education".

From 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
## # … with 2,186 more rows
```

From wide to long with `pivot_longer()`

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

```
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
## # … with 2,186 more rows
```

How to get your own data into R

Reading in CSV files

CSV is not really a proper format at all!

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Base R has `read.csv()`

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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 on our local disk 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")
```

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```
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```

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/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.Rmd
## ├── README.md
## ├── code
## ├── course_notes.Rmd
## ├── data
## ├── data_visualization.Rproj
## ├── figures
## ├── 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()

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"))
```

```
organs
```

```
## # A tibble: 238 × 21
##    country    year donors   pop pop.dens   gdp gdp.lag health health.lag pubhealth roads cerebvas assault external txp.pop world
##    <chr>     <dbl>  <dbl> <dbl>    <dbl> <dbl>   <dbl>  <dbl>      <dbl>     <dbl> <dbl>    <dbl>   <dbl>    <dbl>   <dbl> <chr>
##  1 Australia    NA  NA    17065    0.220 16774   16591   1300       1224       4.8 137.       682      21      444   0.938 Libera
##  2 Australia  1991  12.1  17284    0.223 17171   16774   1379       1300       5.4 122.       647      19      425   0.926 Libera
##  3 Australia  1992  12.4  17495    0.226 17914   17171   1455       1379       5.4 113.       630      17      406   0.915 Libera
##  4 Australia  1993  12.5  17667    0.228 18883   17914   1540       1455       5.4 111.       611      18      376   0.906 Libera
##  5 Australia  1994  10.2  17855    0.231 19849   18883   1626       1540       5.4 108.       631      17      387   0.896 Libera
##  6 Australia  1995  10.2  18072    0.233 21079   19849   1737       1626       5.5 112.       592      16      371   0.885 Libera
##  7 Australia  1996  10.6  18311    0.237 21923   21079   1846       1737       5.6 108.       576      17      395   0.874 Libera
##  8 Australia  1997  10.3  18518    0.239 22961   21923   1948       1846       5.7  95.4      525      17      385   0.864 Libera
##  9 Australia  1998  10.5  18711    0.242 24148   22961   2077       1948       5.9  93.8      516      16      410   0.855 Libera
## 10 Australia  1999   8.67 18926    0.244 25445   24148   2231       2077       6.1  93.2      493      15      409   0.845 Libera
## # … with 228 more rows, and 3 more variables: consent.practice <chr>, consistent <chr>, ccode <chr>
```

And there it is.

`read_csv()` comes in different varieties

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

```
organs <- 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 tidyverse's `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!)

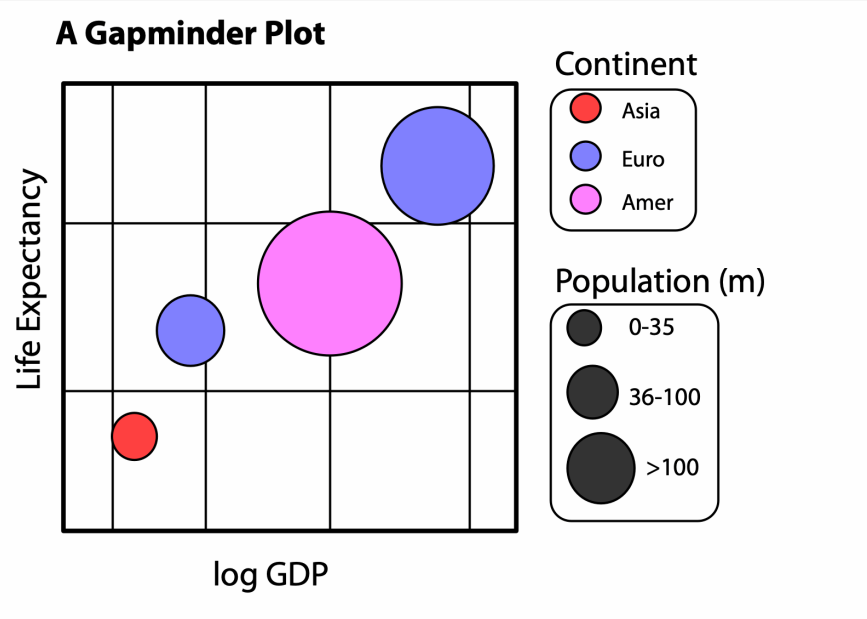
```
organ_remote <- read_csv("http://kjhealy.co/organdonation.csv")

organ_remote
```

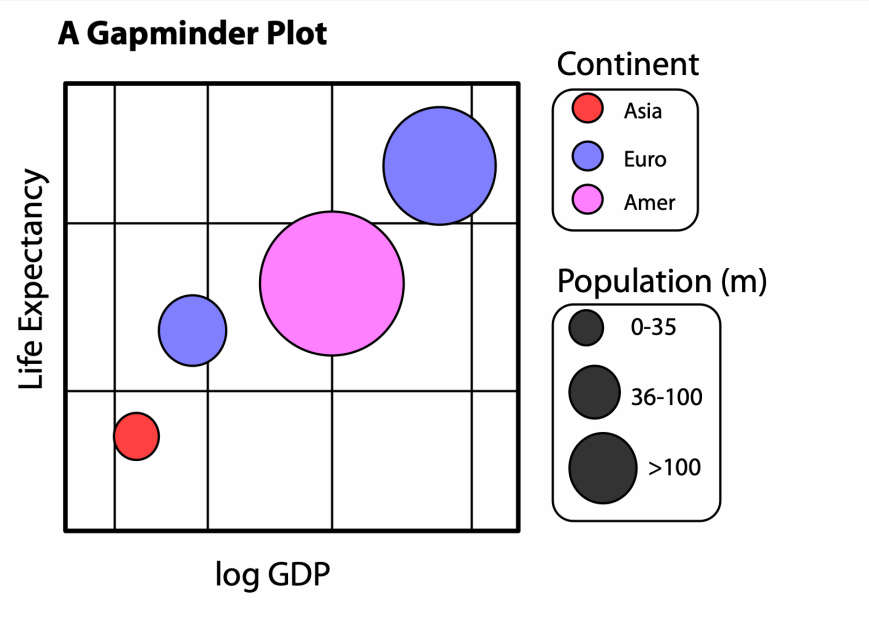
```
## # A tibble: 238 × 21
##    country    year donors   pop pop.dens   gdp gdp.lag health health.lag pubhealth roads cerebvas assault external txp.pop world
##    <chr>     <dbl>  <dbl> <dbl>    <dbl> <dbl>   <dbl>  <dbl>      <dbl>     <dbl> <dbl>    <dbl>   <dbl>    <dbl>   <dbl> <chr>
##  1 Australia    NA   NA    17065    0.220 16774   16591   1300       1224       4.8 137.       682      21      444   0.938 Libera
##  2 Australia  1991   12.1  17284    0.223 17171   16774   1379       1300       5.4 122.       647      19      425   0.926 Libera
##  3 Australia  1992   12.4  17495    0.226 17914   17171   1455       1379       5.4 113.       630      17      406   0.915 Libera
##  4 Australia  1993   12.5  17667    0.228 18883   17914   1540       1455       5.4 111.       611      18      376   0.906 Libera
##  5 Australia  1994   10.2  17855    0.231 19849   18883   1626       1540       5.4 108.       631      17      387   0.896 Libera
##  6 Australia  1995   10.2  18072    0.233 21079   19849   1737       1626       5.5 112.       592      16      371   0.885 Libera
##  7 Australia  1996   10.6  18311    0.237 21923   21079   1846       1737       5.6 108.       576      17      395   0.874 Libera
##  8 Australia  1997   10.3  18518    0.239 22961   21923   1948       1846       5.7  95.4      525      17      385   0.864 Libera
##  9 Australia  1998   10.5  18711    0.242 24148   22961   2077       1948       5.9  93.8      516      16      410   0.855 Libera
## 10 Australia  1999    8.67 18926    0.244 25445   24148   2231       2077       6.1  93.2      493      15      409   0.845 Libera
## # … with 228 more rows, and 3 more variables: consent.practice <chr>, consistent <chr>, ccode <chr>
```

A Plot's Components

What we need our code to make

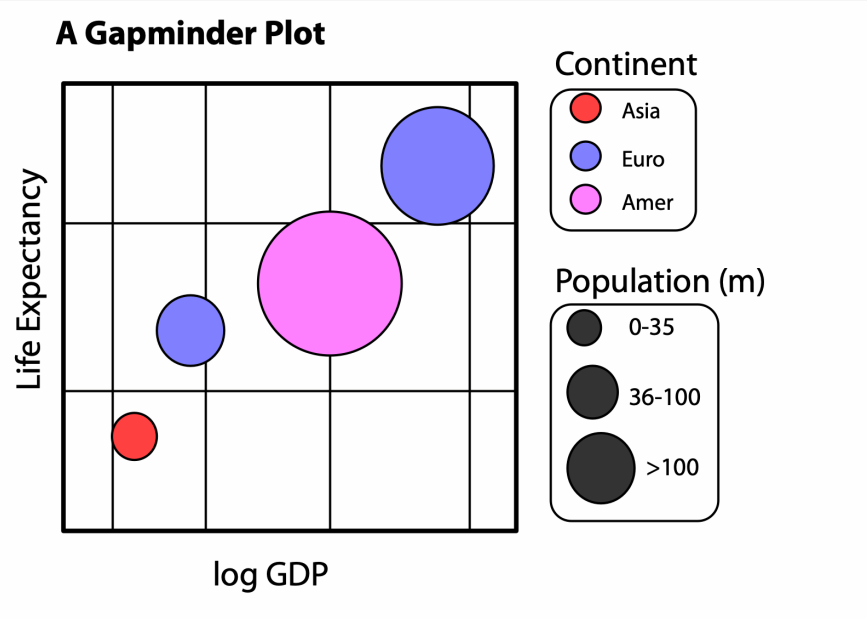


What we need our code to make



Data **represented** by visual elements,

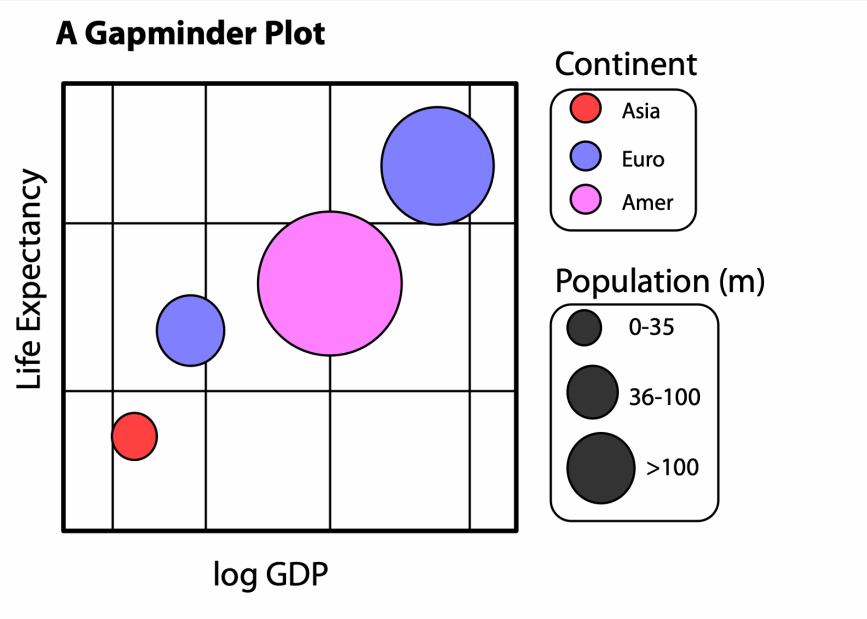
What we need our code to make



Data **represented** by visual elements,

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

What we need our code to make

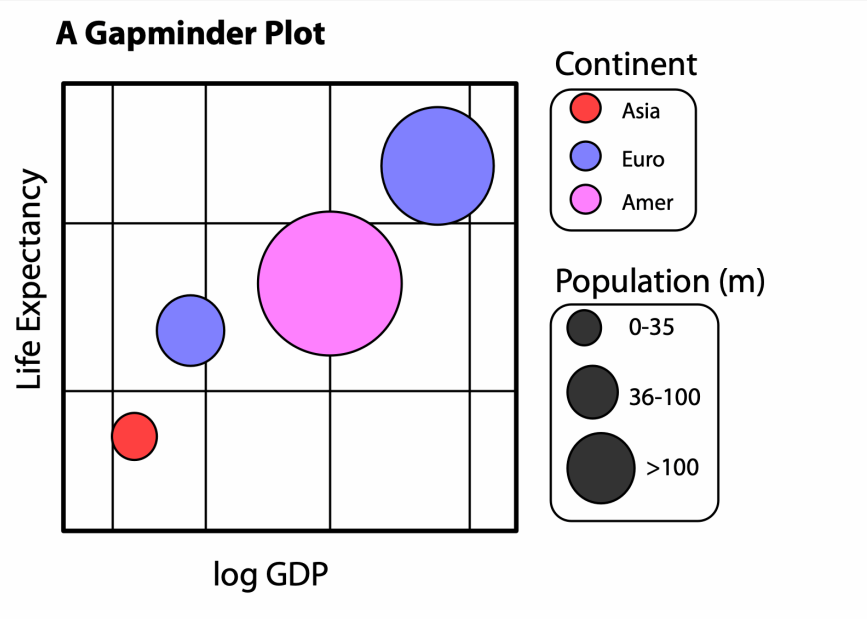


Data **represented** by visual elements,

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

Each measured on some **scale**,

What we need our code to make



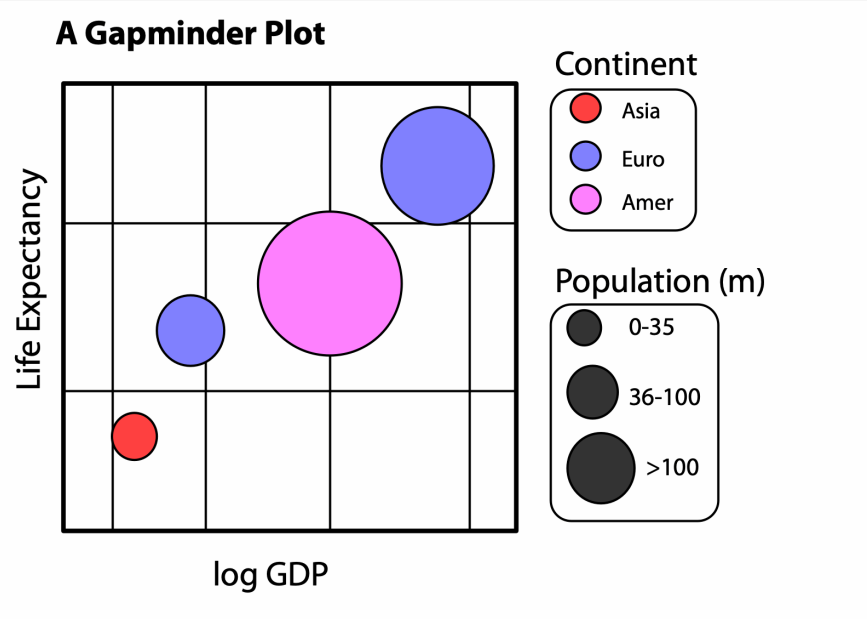
Data **represented** by visual elements,

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

Each measured on some **scale**,

Each scale with a labeled **guide**,

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 ggplot does this

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

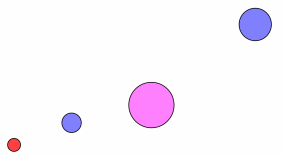
```
p ← ggplot(data = gapminder,
           mapping = aes(x = gdp,
               y = lifexp,
               size = pop,
               color = continent))
```

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

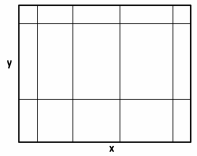
```
p + geom_point()
```



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

4. Fix Scales and Co-Ordinate System

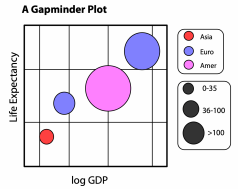
```
p + coord_cartesian() +
    scale_x_log10()
```



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

5. Add Labels and Adjust Guides

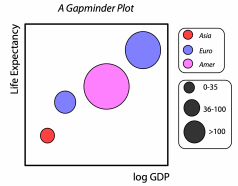
```
p + labs(x = "log GDP",
         y = "Life Expectancy",
         title = "A Gapminder Plot")
```



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

6. Add or Adjust Themes

```
p + theme_minimal()
```

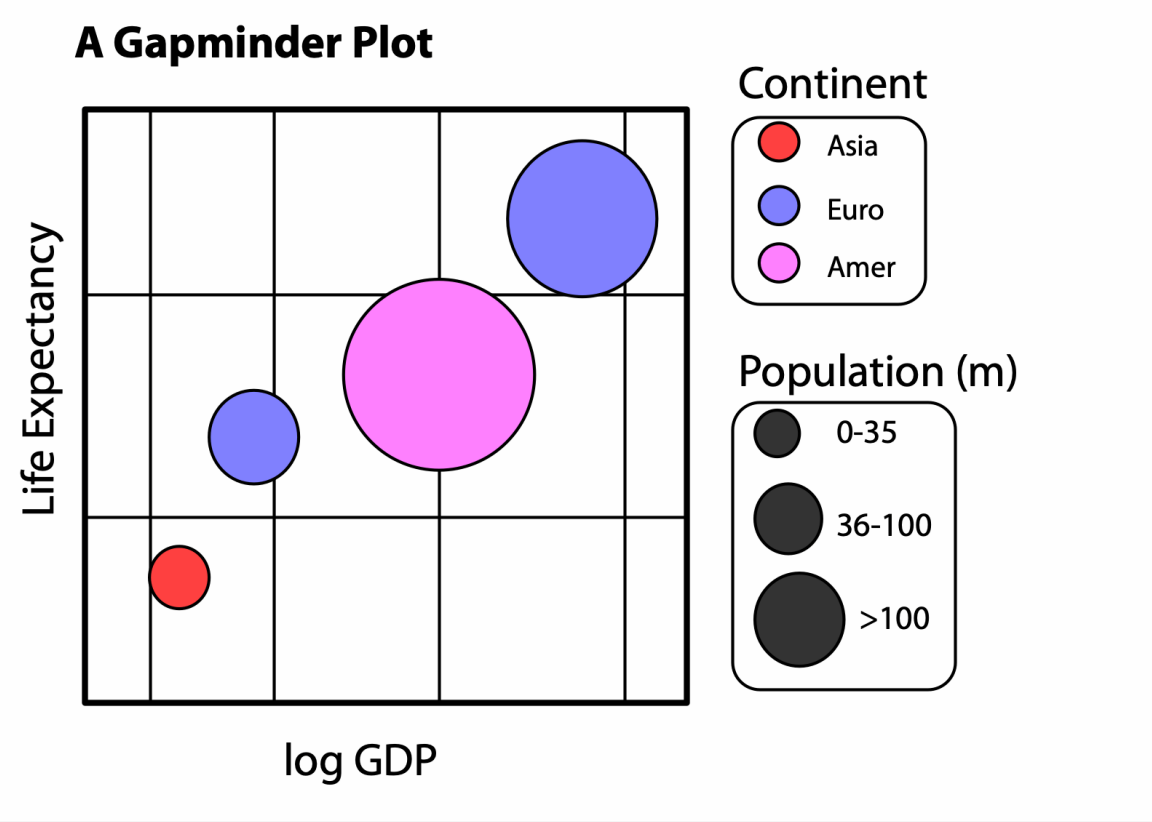


6. Style or adjust plot elements that are **not directly representing** your data.

ggplot's flow of action

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



ggplot's flow of action

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```

gdp	lifexp	pop	continent
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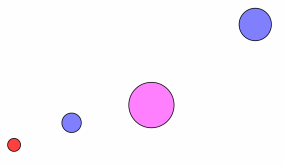
```



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```
p + coord_cartesian() +
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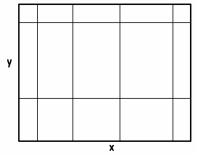

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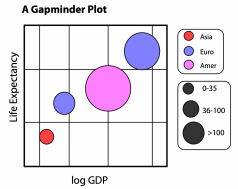
```



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```
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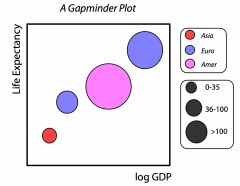
```



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ggplot's flow of action

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```

gdp	lifexp	pop	continent
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126	40	20	Asia

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

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```
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

```
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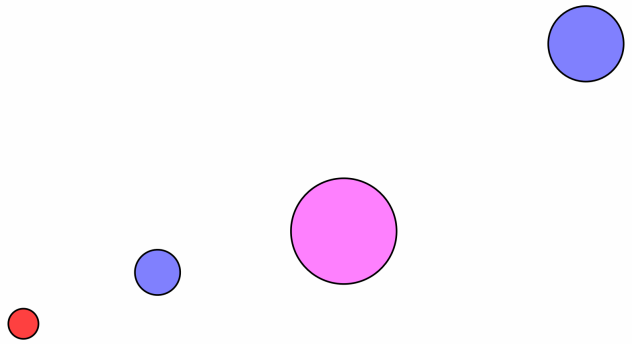
```

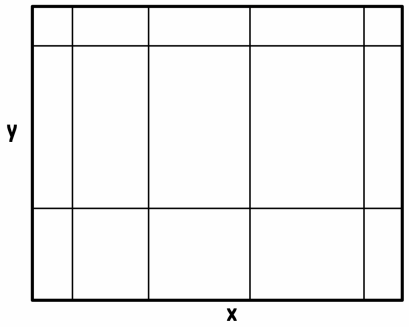


3. Decide **what kind** of plot, or series of plots, you want to draw.

ggplot's flow of action

4. Fix Scales and Co-Ordinate System

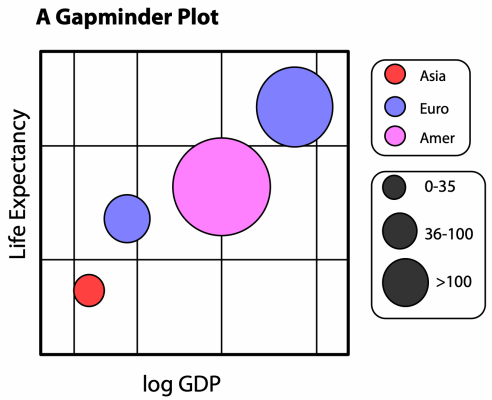
```
p + coord_cartesian() +
    scale_x_log10()
```



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

5. Add Labels and Adjust Guides

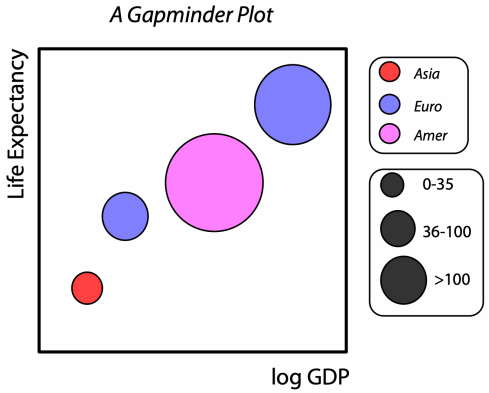
```
p + labs(x = "log GDP",
         y = "Life Expectancy",
         title = "A Gapminder Plot")
```



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

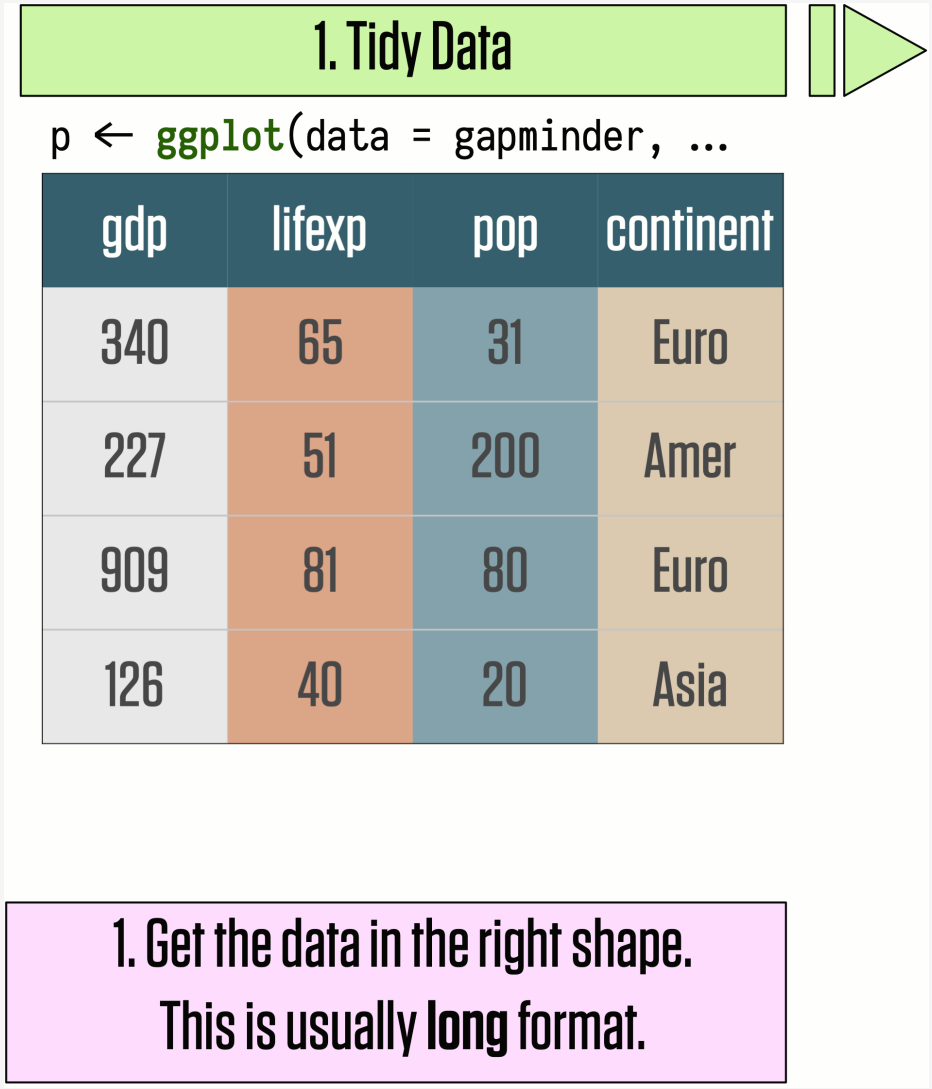
6. Add or Adjust Themes

```
p + theme_minimal()
```



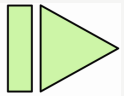
6. Style or adjust plot elements that are **not directly representing** your data.

ggplot's flow of action: required



ggplot's flow of action: required

2. Map the Aesthetics



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

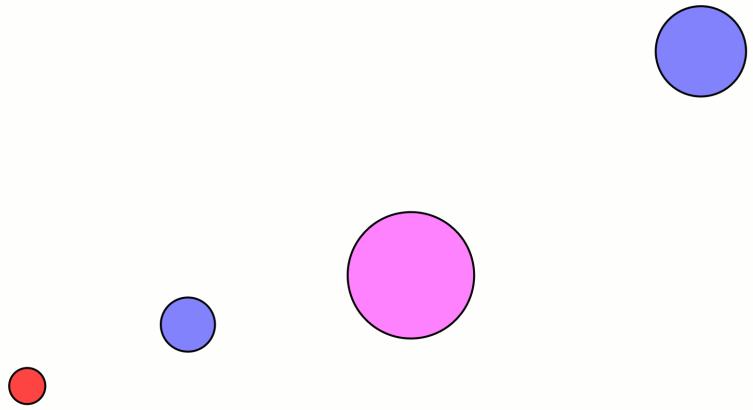
x-axis will represent	y-axis will represent	size will represent	color will represent
gdp	lifexp	pop	continent
340	65	31	Euro

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

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.

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.
## # … with 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.

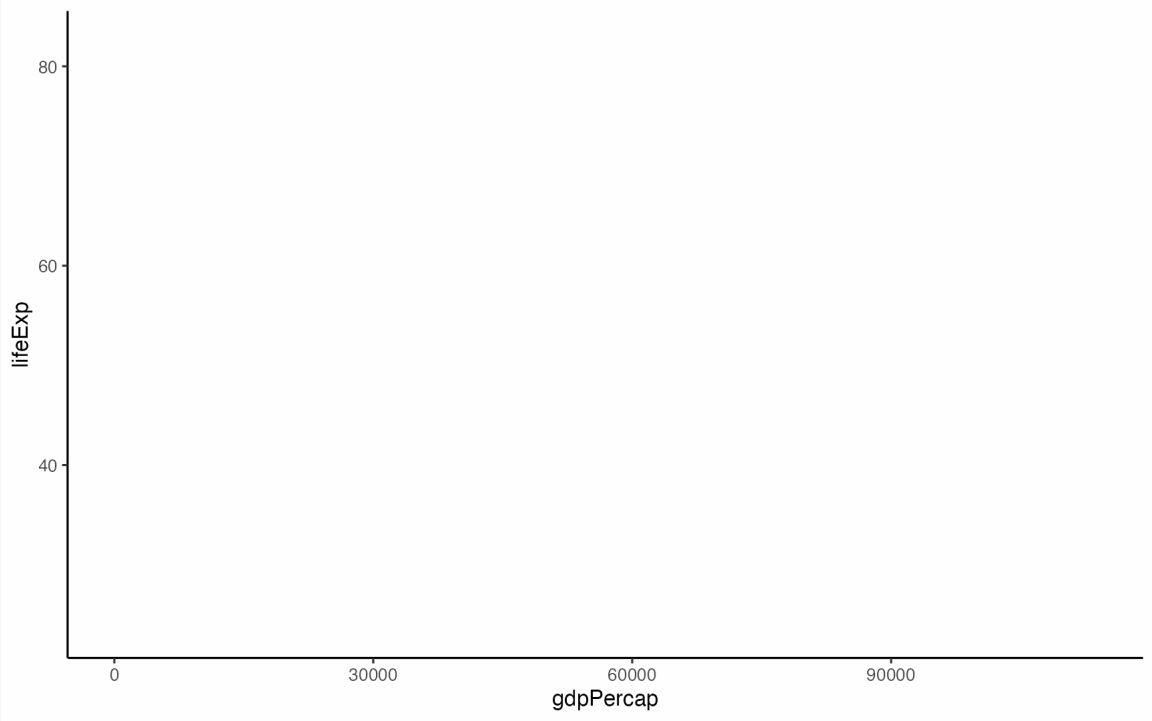
`x` and `y` represent the quantities determining position on the `x` and `y` axes.

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.

Our plot has mappings but no geom

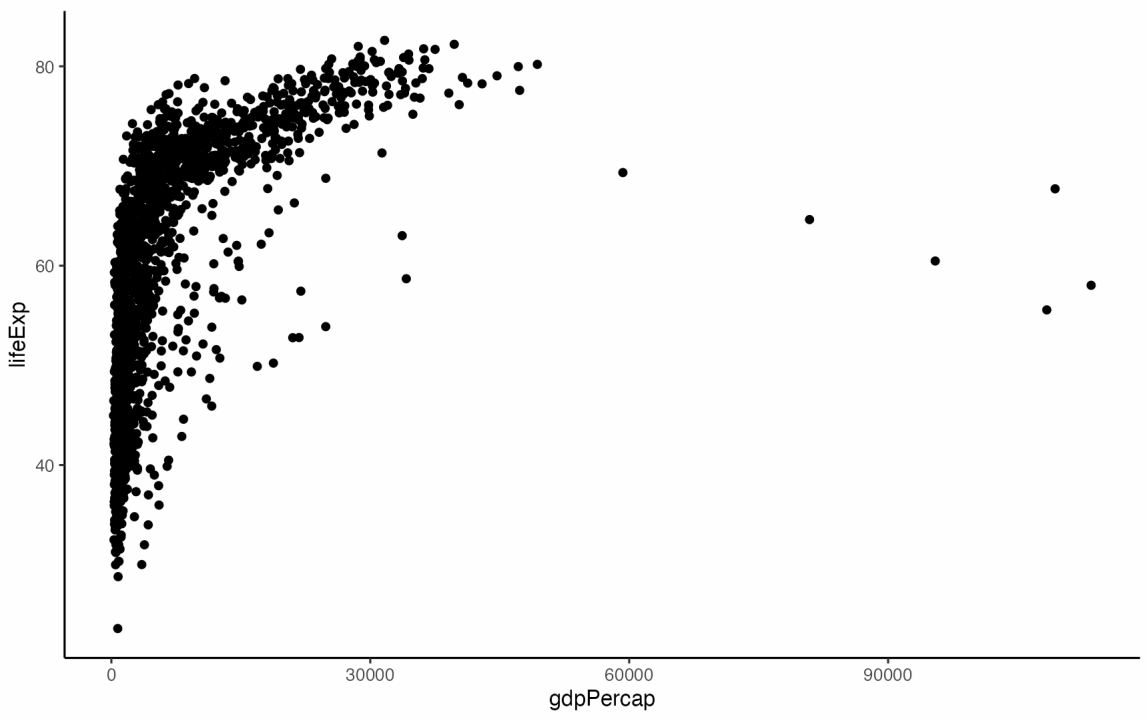
```
p
```



This empty plot has no geoms.

Add a geom

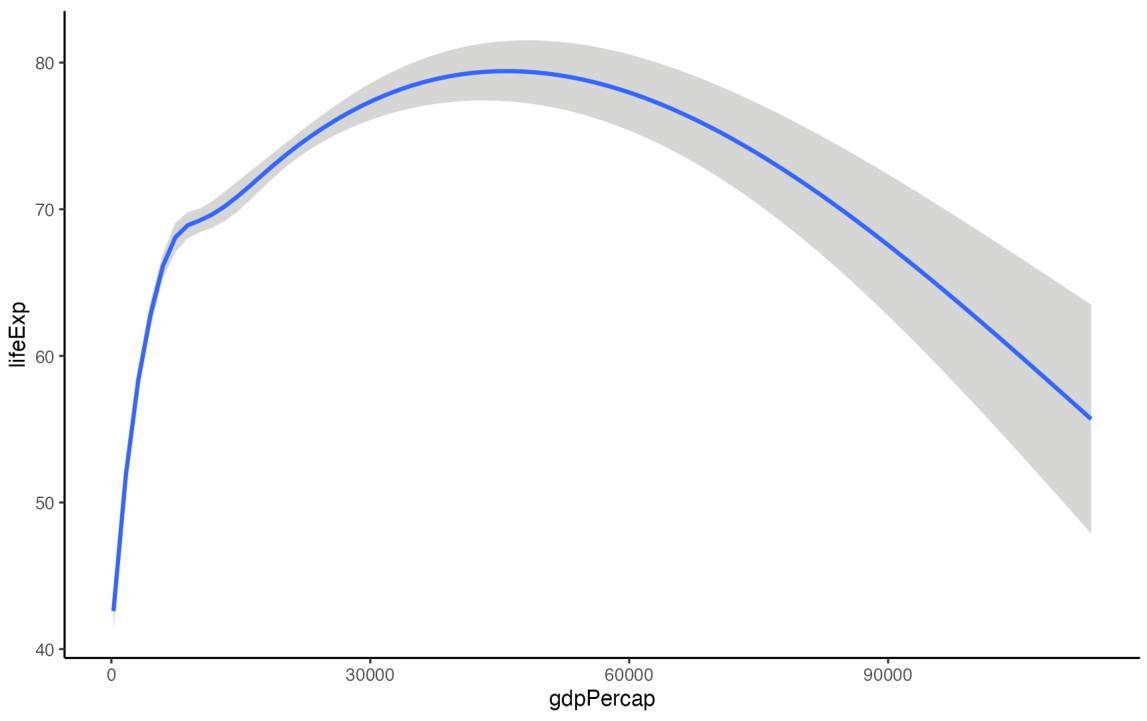
```
p + geom_point()
```



A scatterplot of Life Expectancy vs GDP

Try a different geom

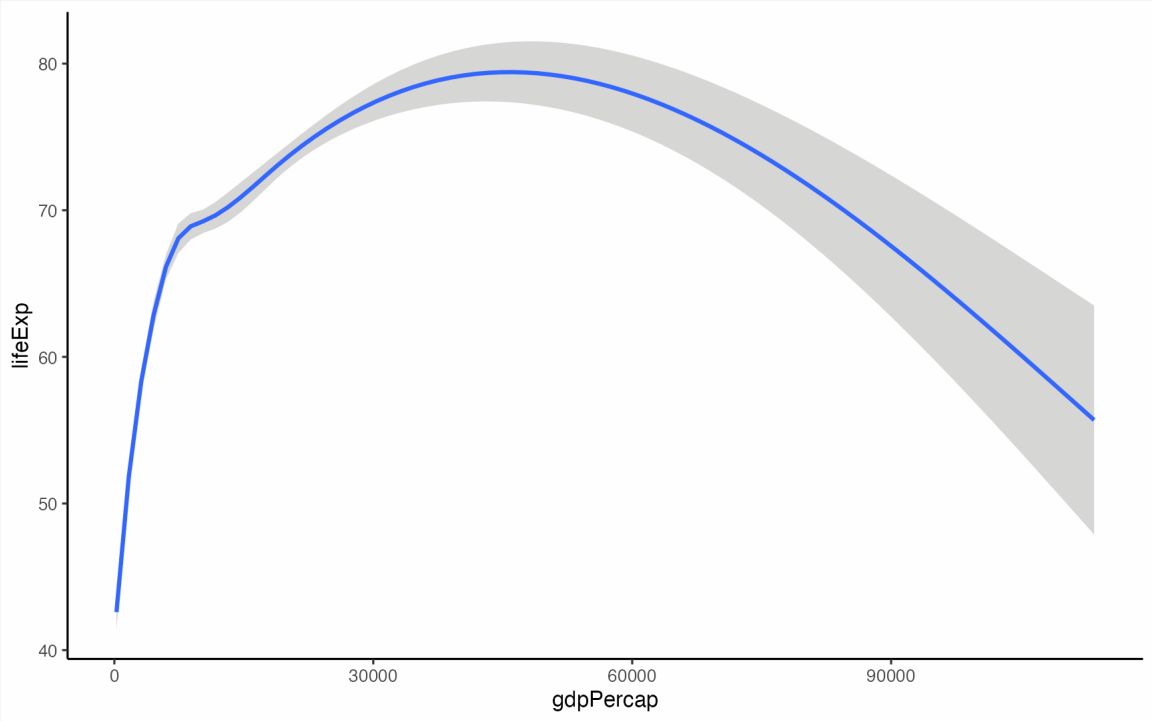
```
p + geom_smooth()
```



A scatterplot of Life Expectancy vs GDP

Build your plots layer by layer

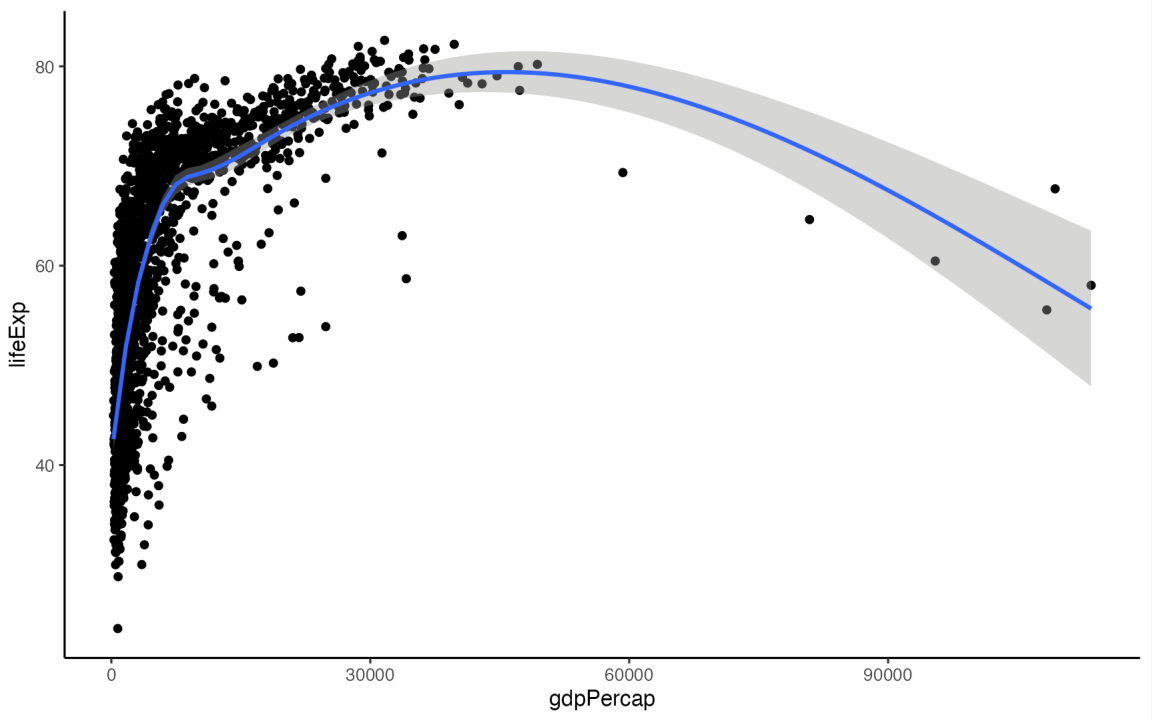
```
p <- ggplot(data = gapminder,
            mapping = aes(x = gdpPercap,
                          y=lifeExp))
p + geom_smooth()
```



Life Expectancy vs GDP, using a smoother.

This process is additive

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



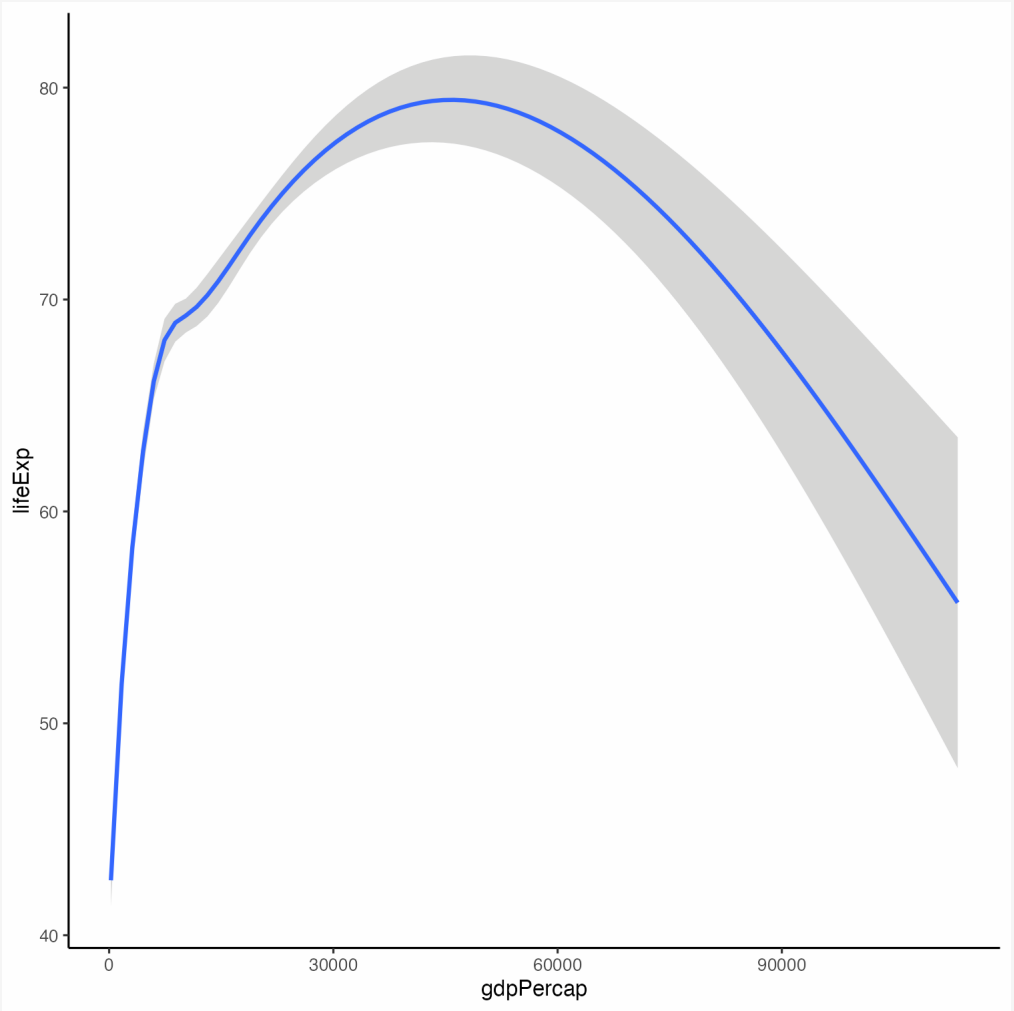
Life Expectancy vs GDP, using a smoother.

This process is additive

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

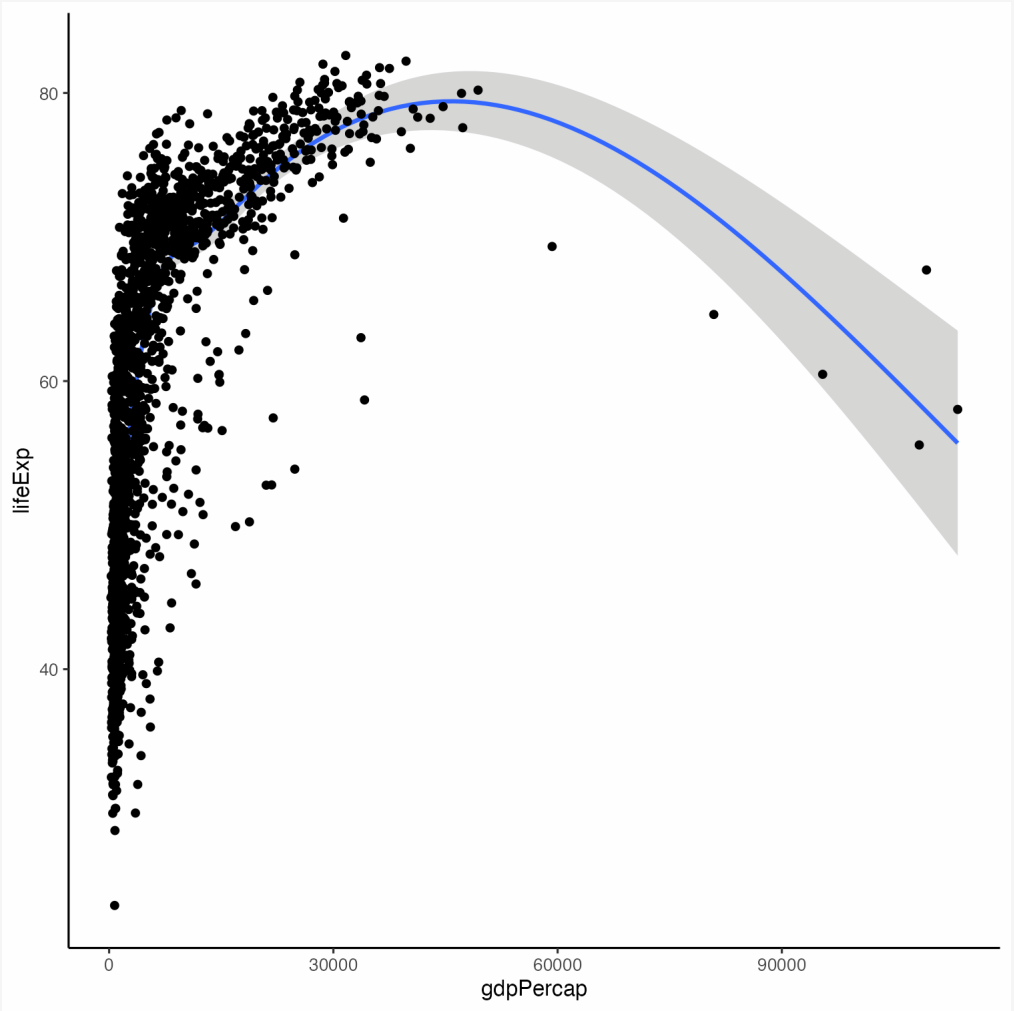
This process is additive

```
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

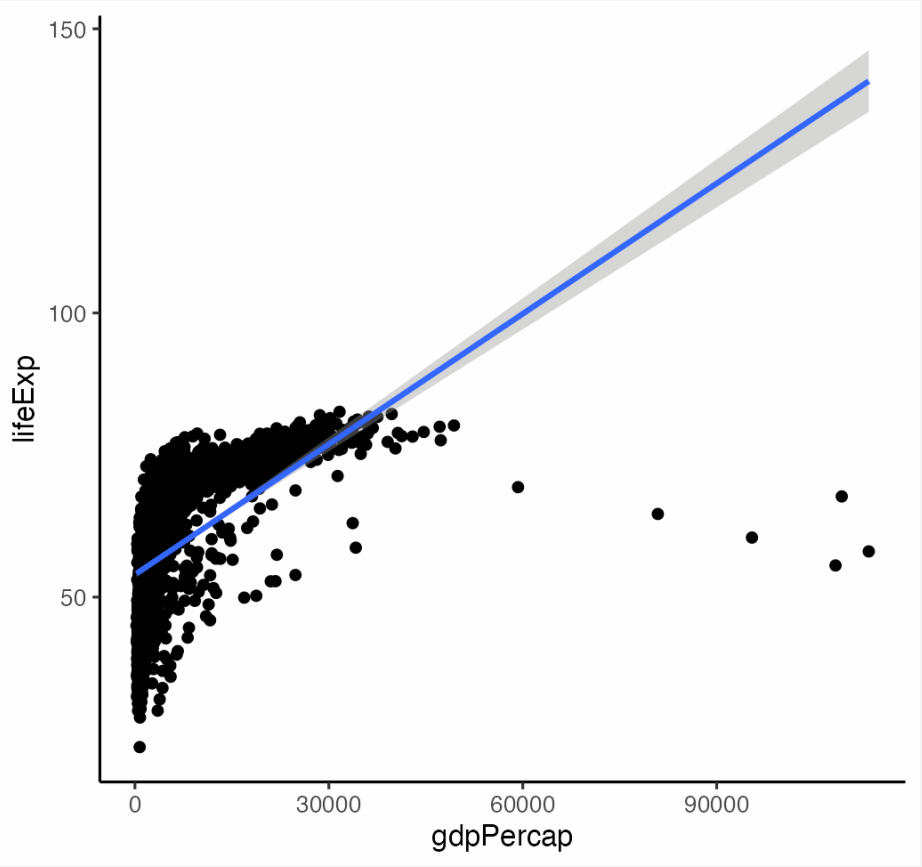
Functions take arguments

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

Every geom is a function

Functions take arguments

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

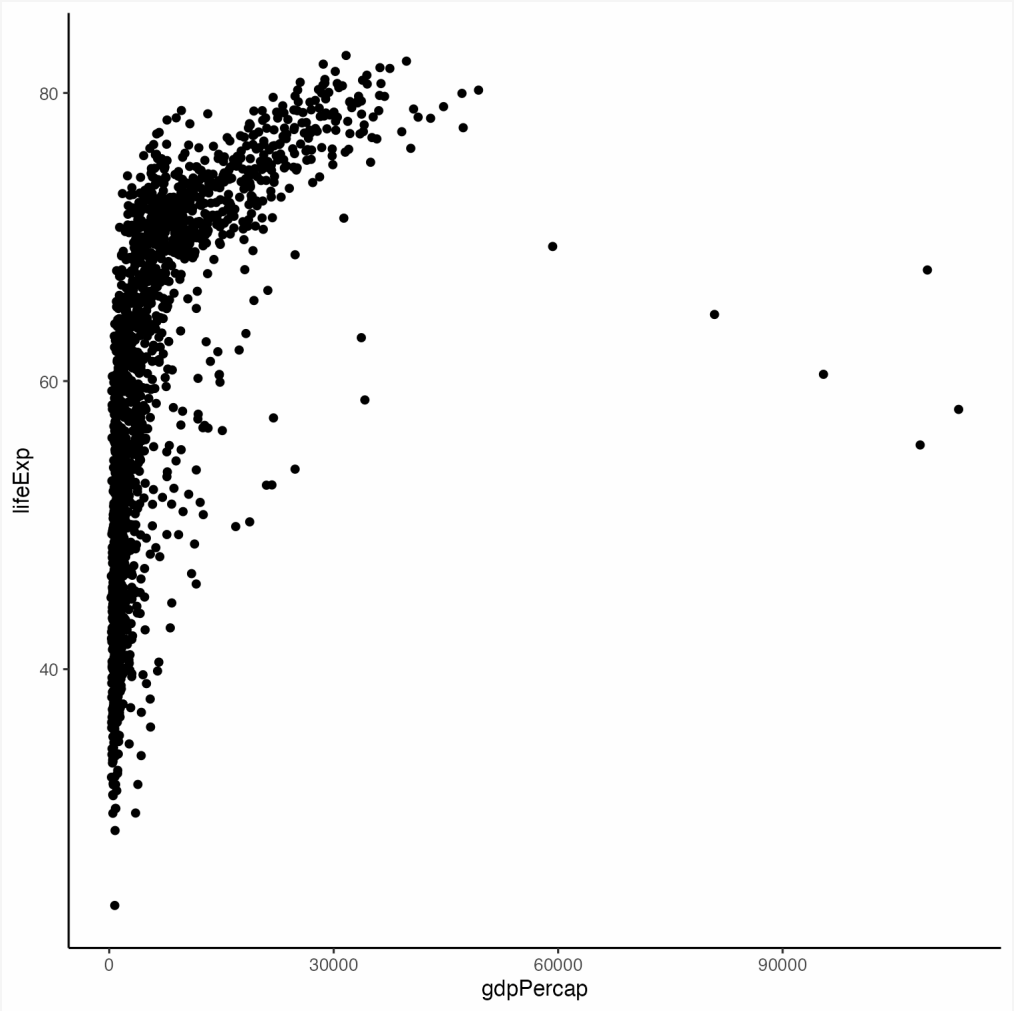


Keep Layering

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

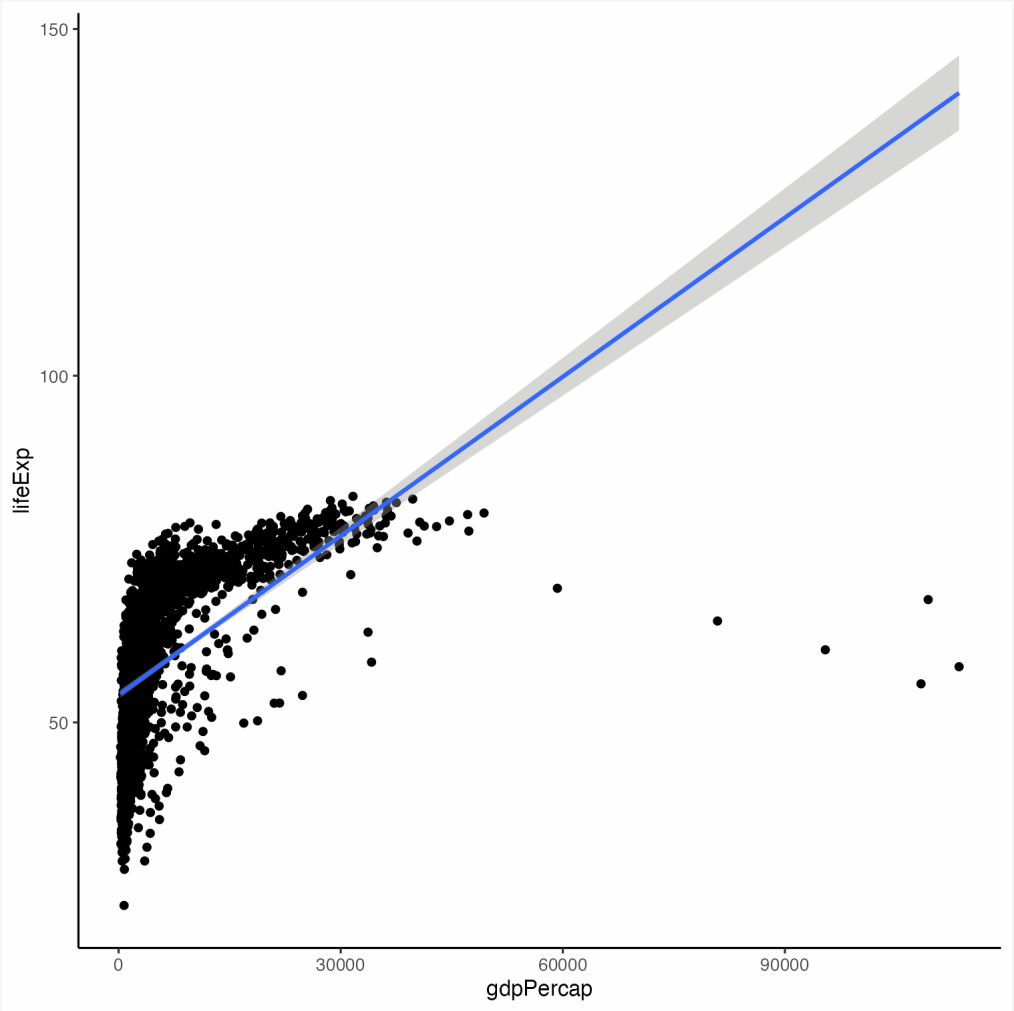
Keep Layering

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



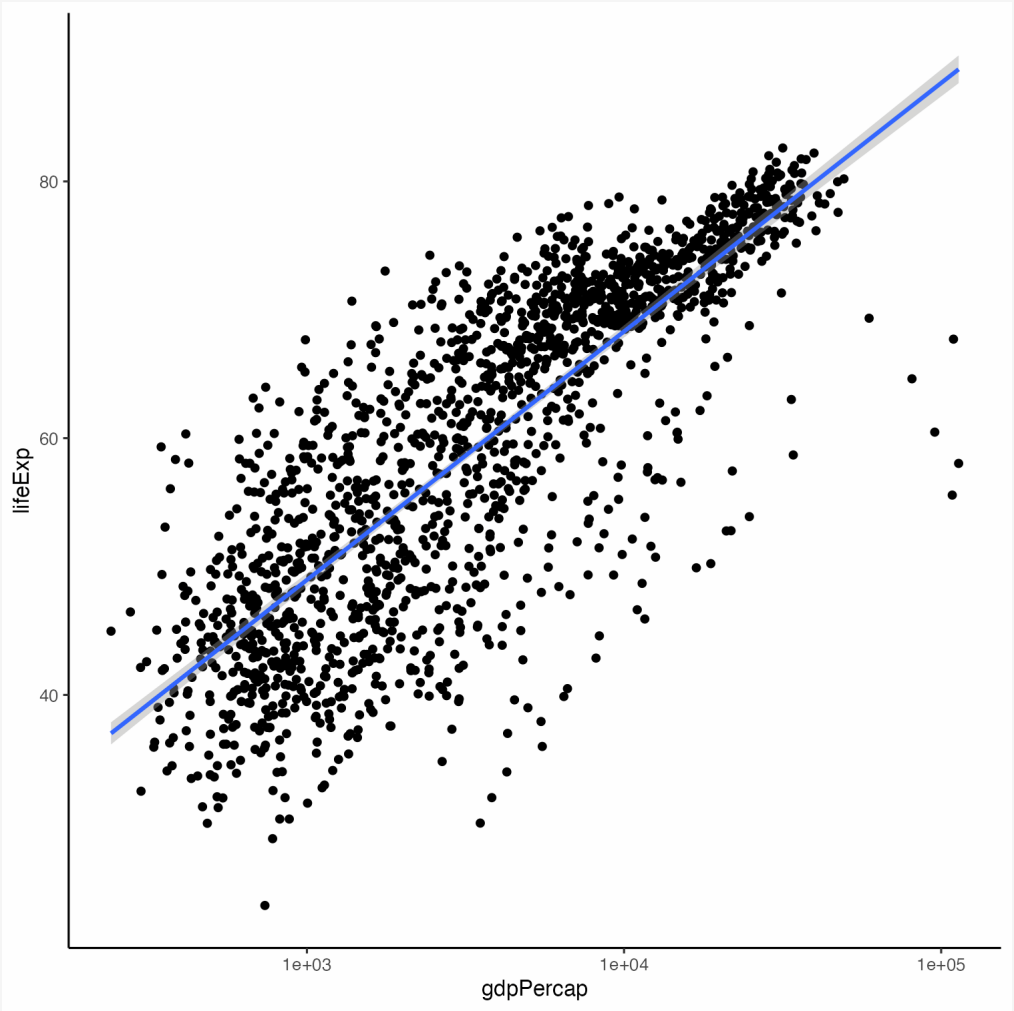
Keep Layering

```
 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))
p + geom_point() +
    geom_smooth(method = "lm") +
    scale_x_log10()
```

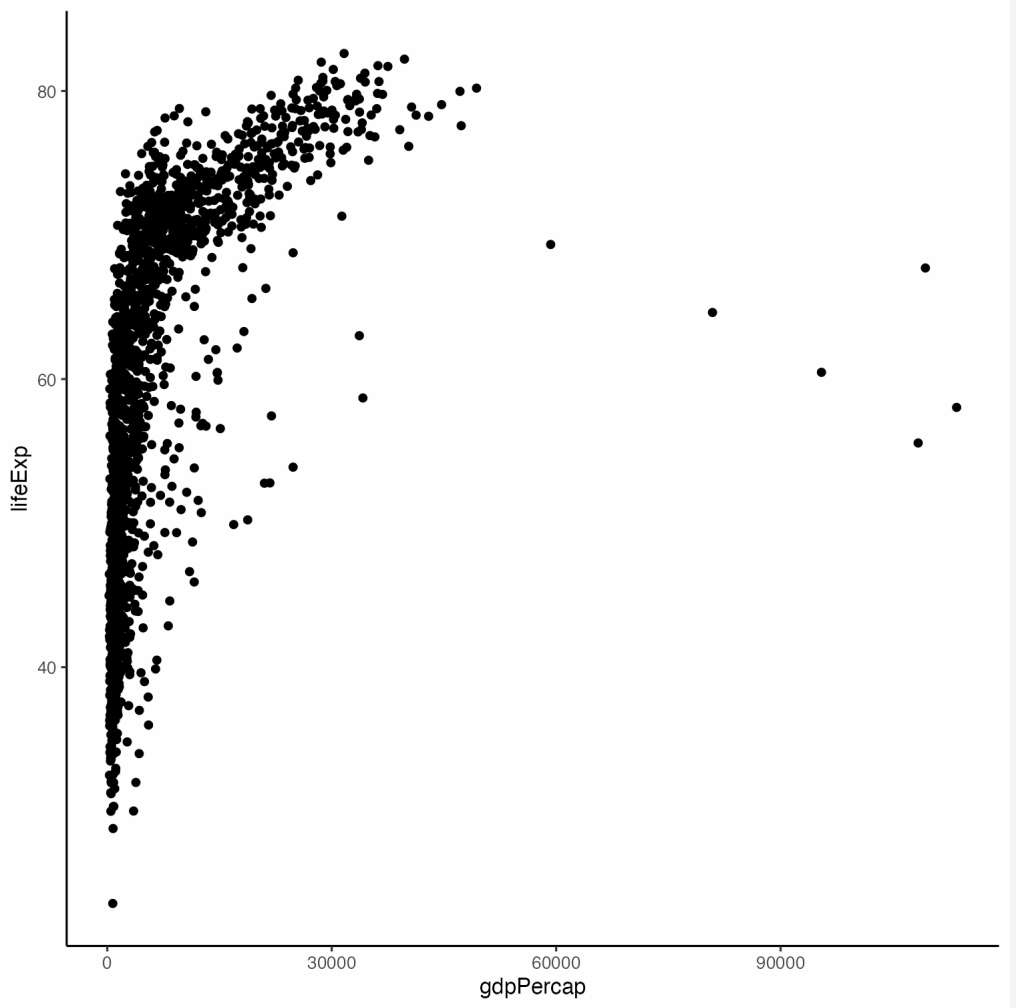


Fix the labels

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

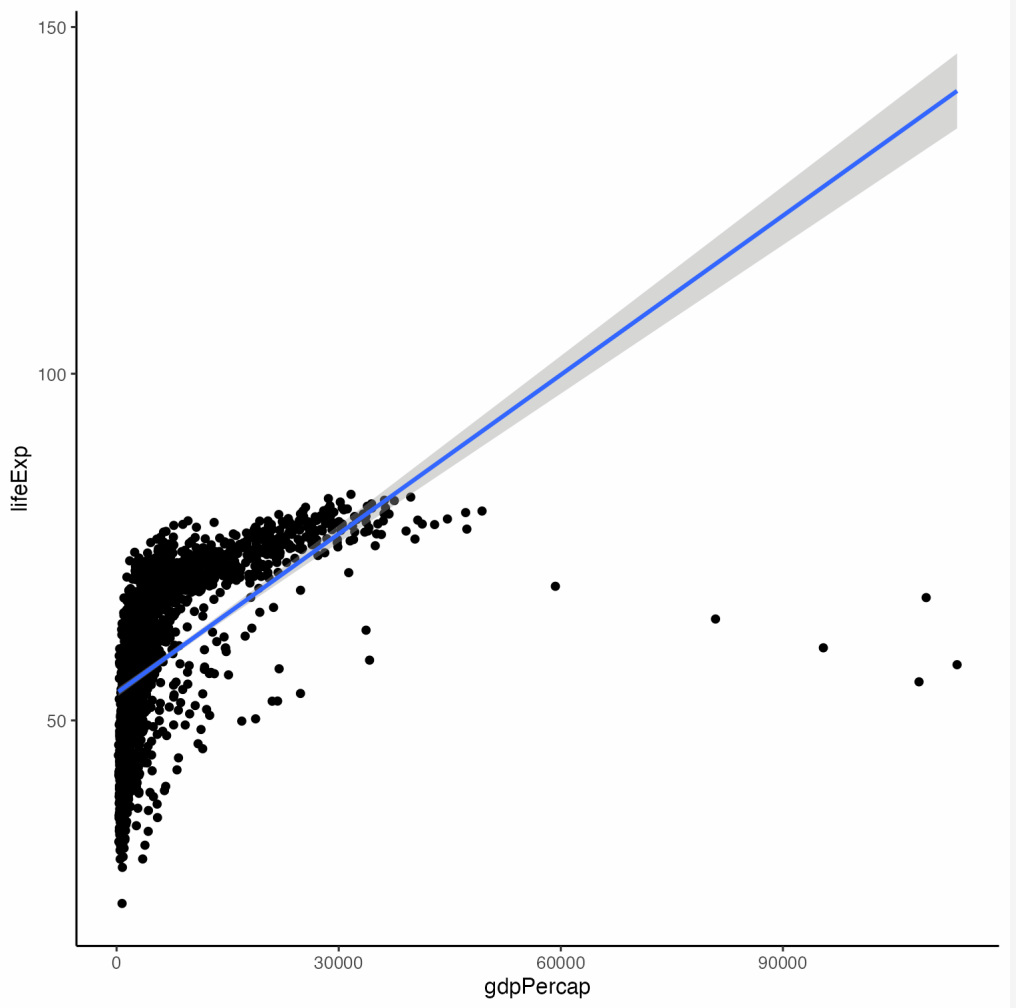
Fix the labels

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



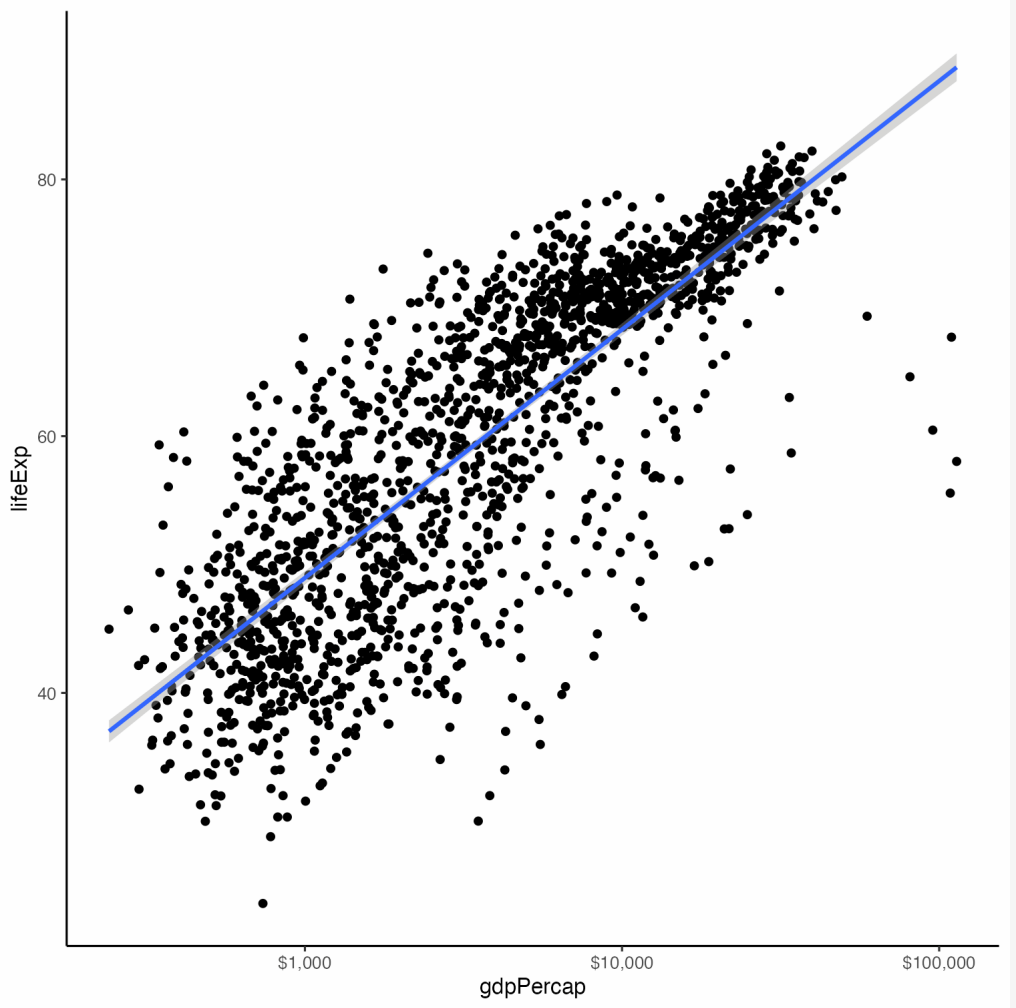
Fix the labels

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



Fix the labels

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

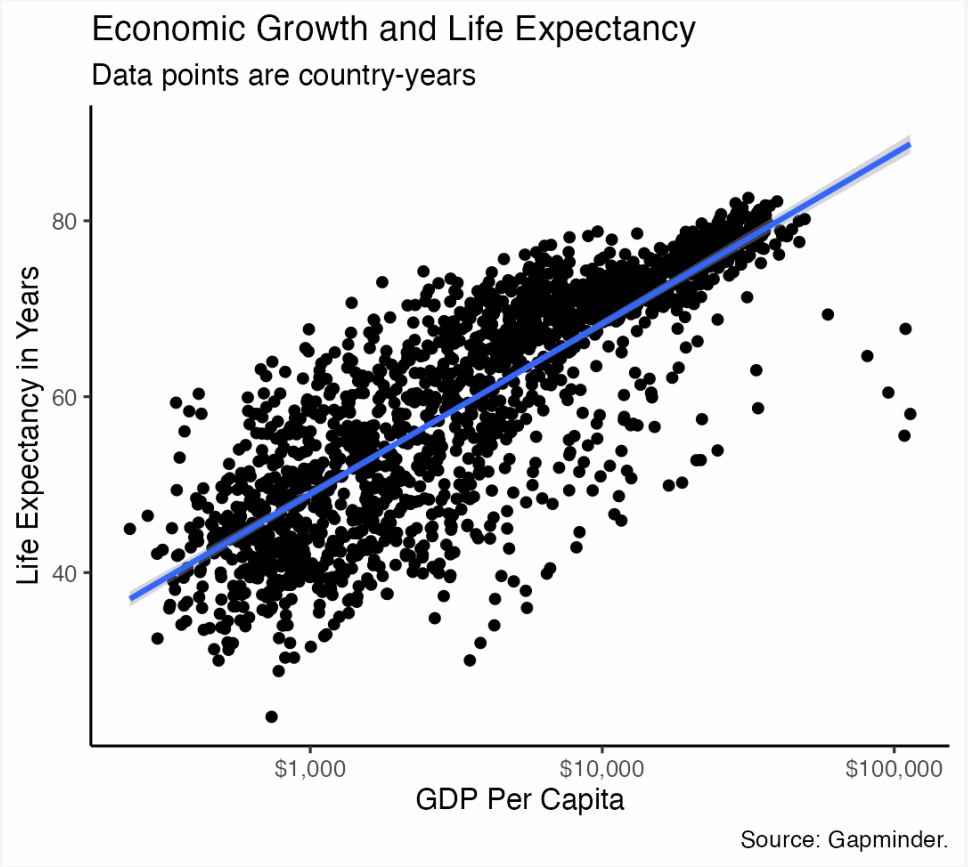


Add labels, title, and caption

```
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 Expectancy",
         subtitle = "Data points are country-years",
         caption = "Source: Gapminder.")
```

Add labels, title, and caption

```
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 Expectancy",
         subtitle = "Data points are country-years",
         caption = "Source: Gapminder.")
```



Mapping vs Setting your plot's aesthetics

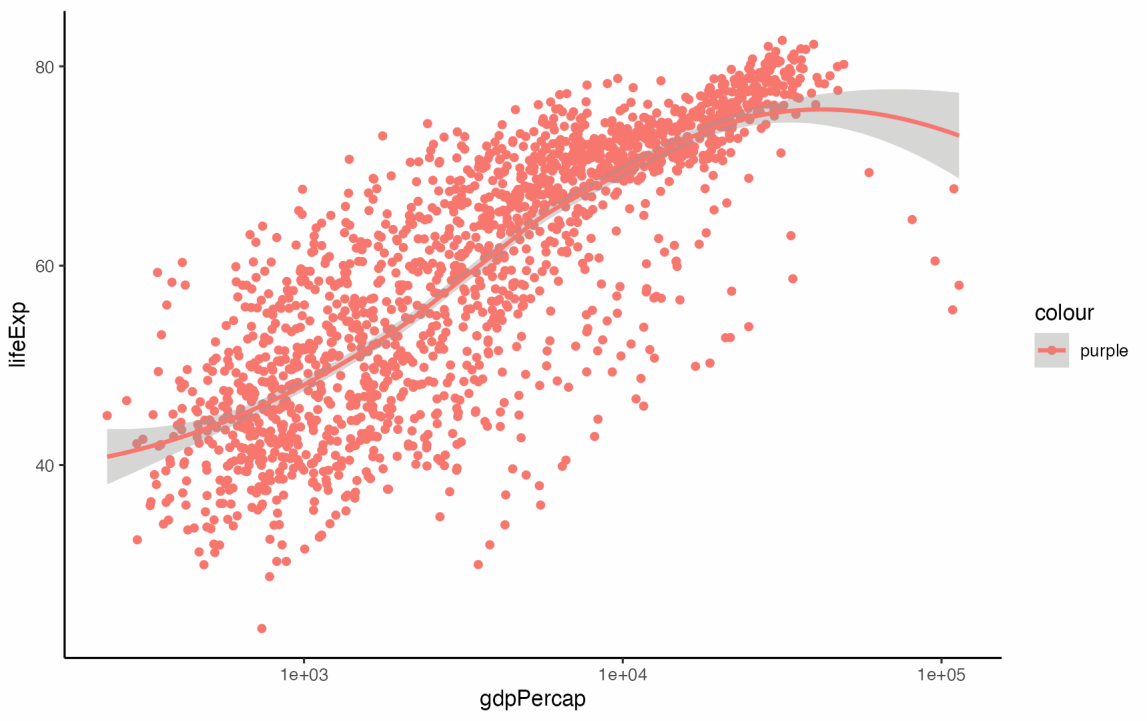
"Can I change the color of the points?"

```
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
```



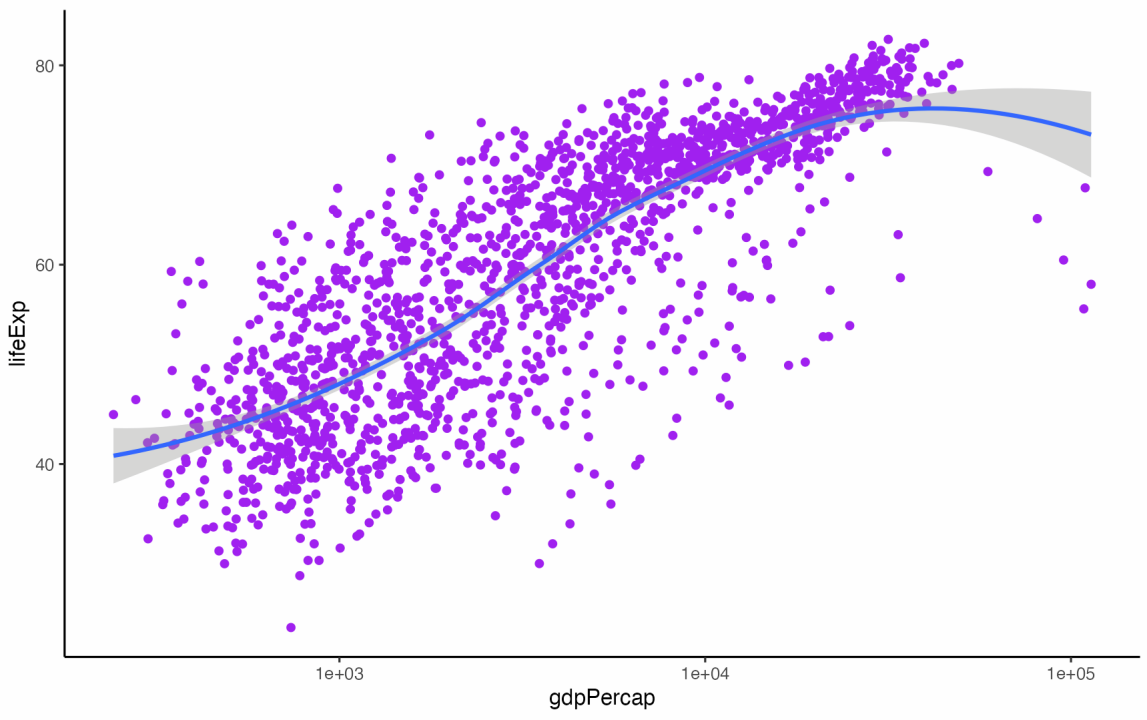
Try again

```
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

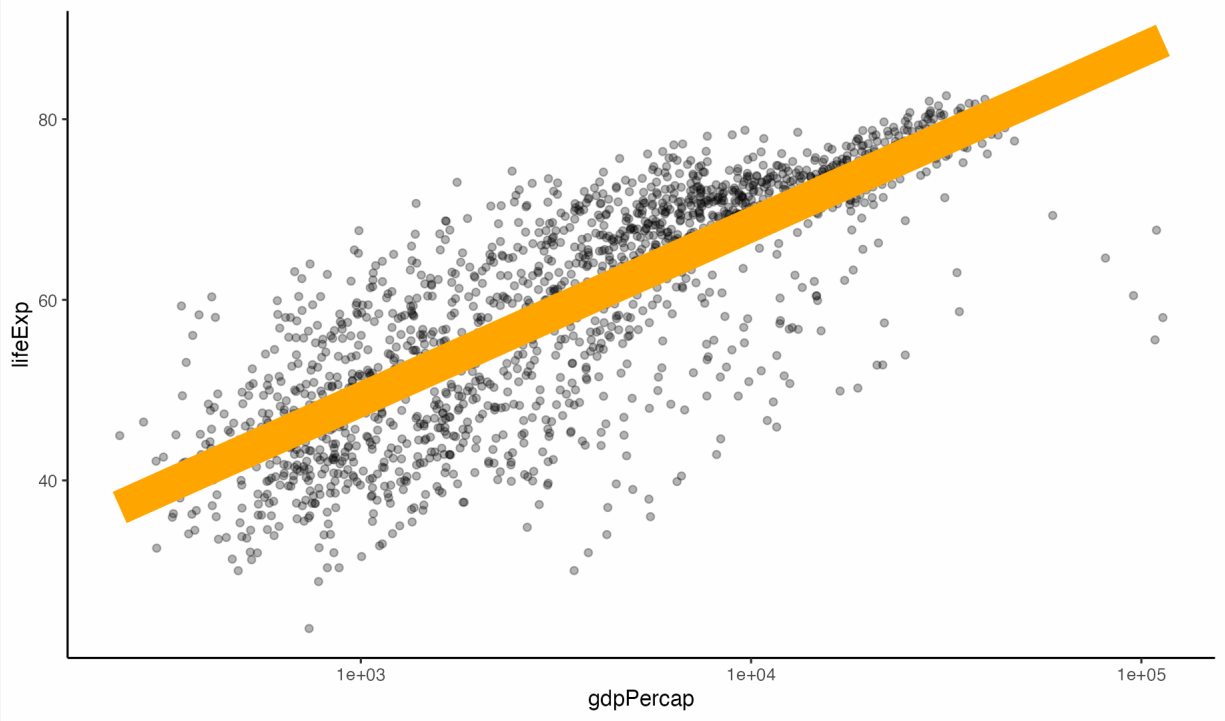
Here we set `color`, `size`, and `alpha`. Meanwhile x and y are mapped.

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
```



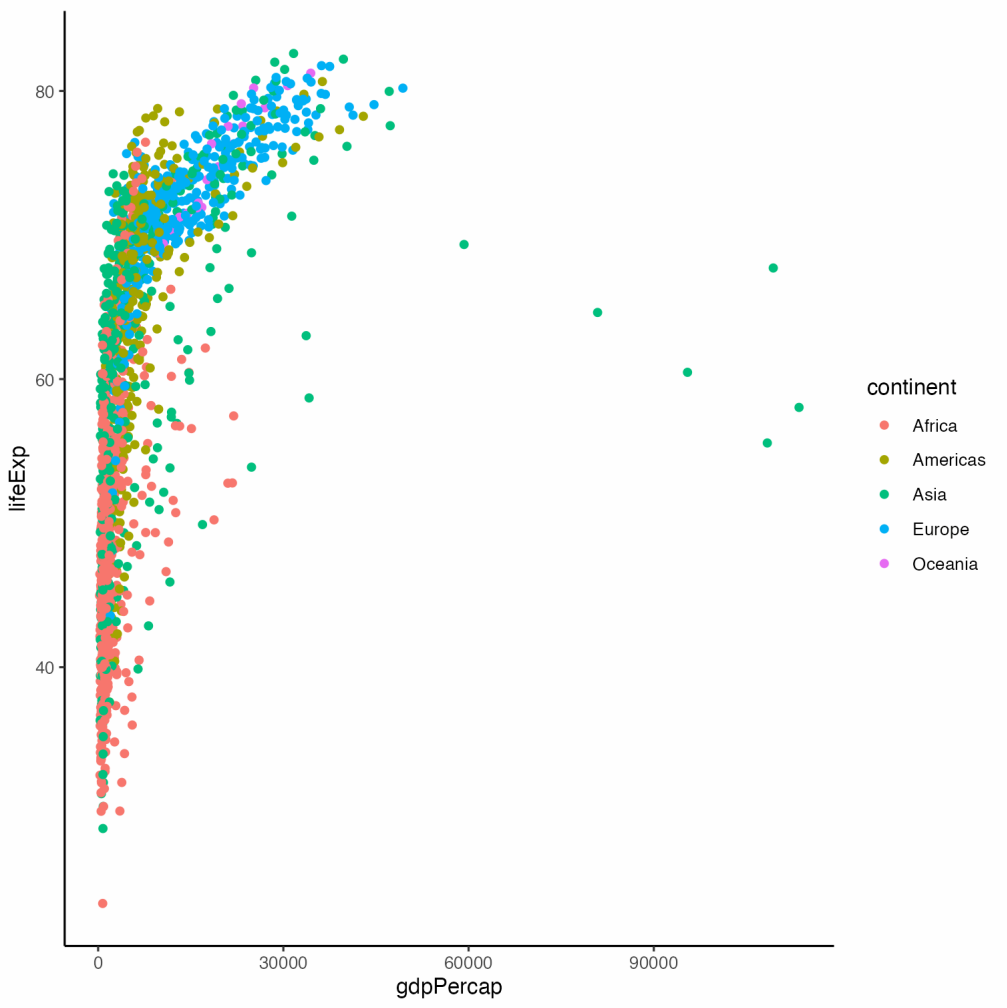
Map or Set values per geom

Geoms can take their own mappings

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

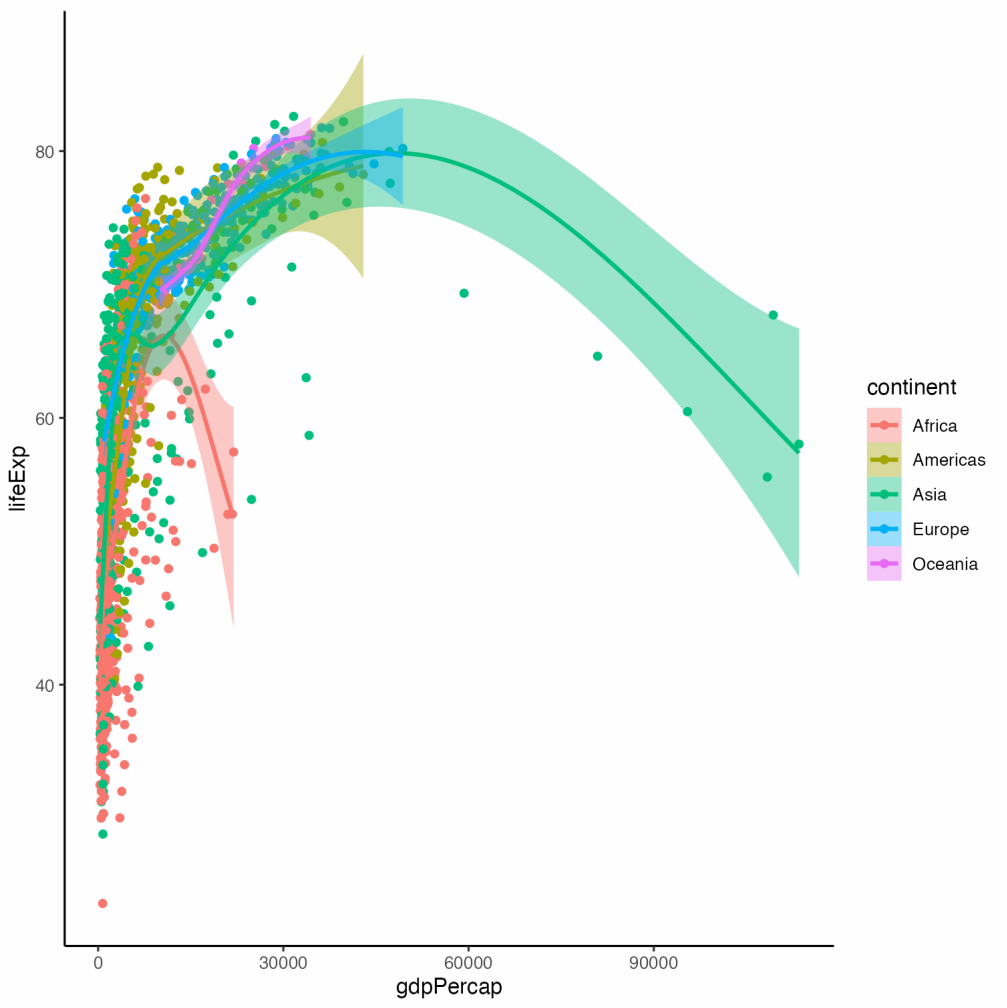
Geoms can take their own mappings

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



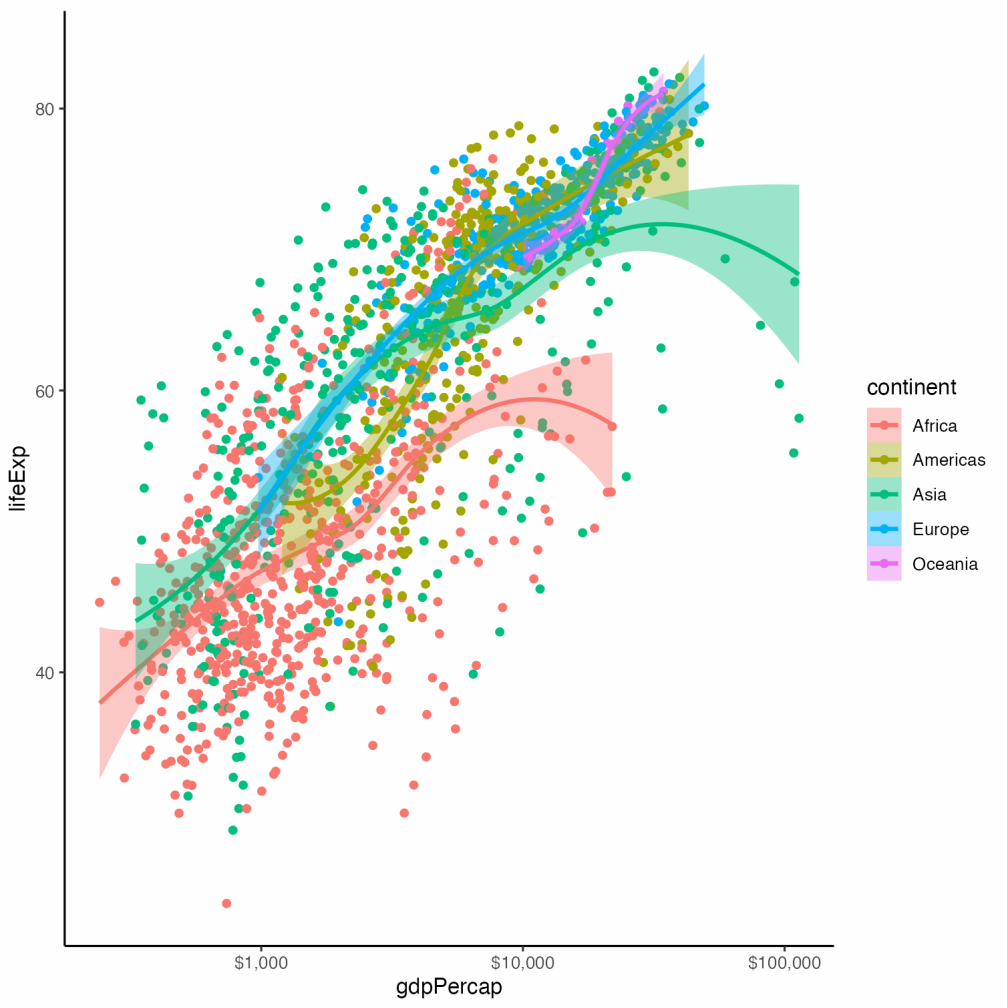
Geoms can take their own mappings

```
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

```
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())
```

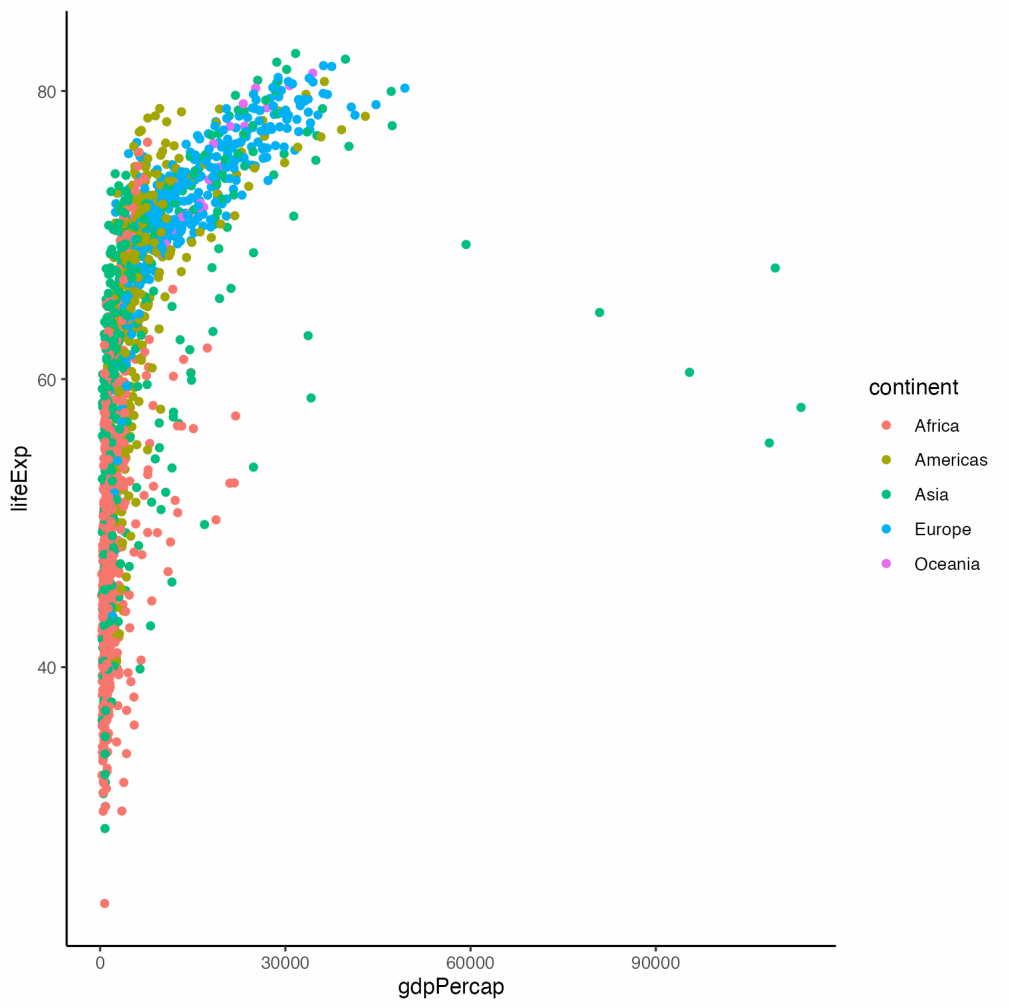


Geoms can take their own mappings

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

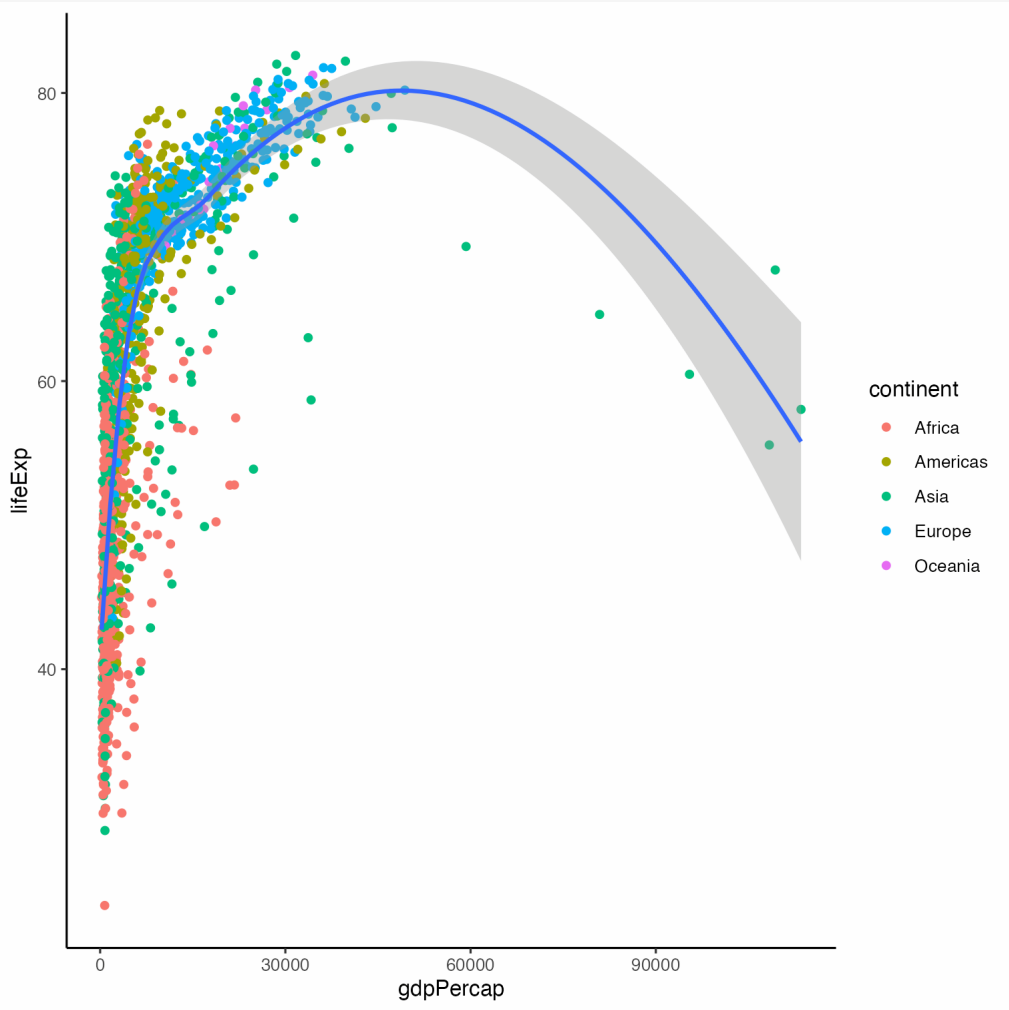
Geoms can take their own mappings

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



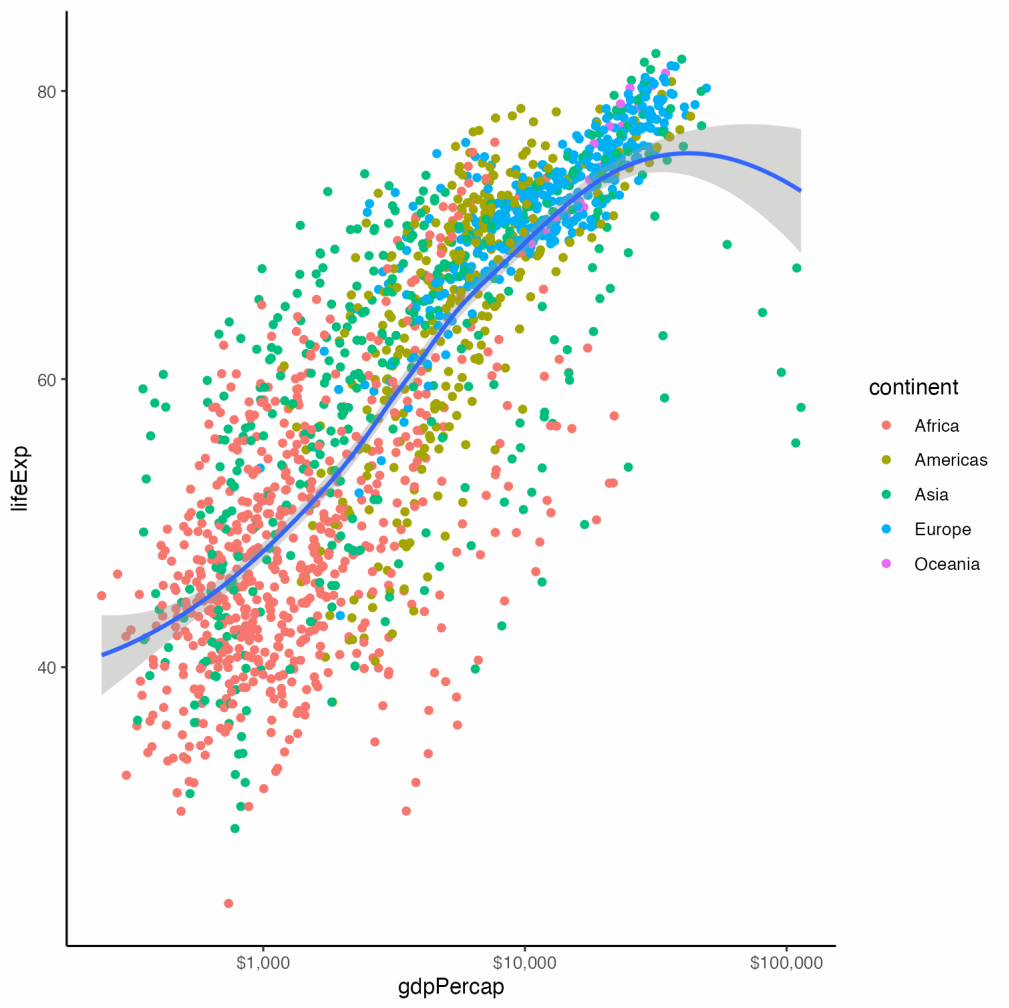
Geoms can take their own mappings

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



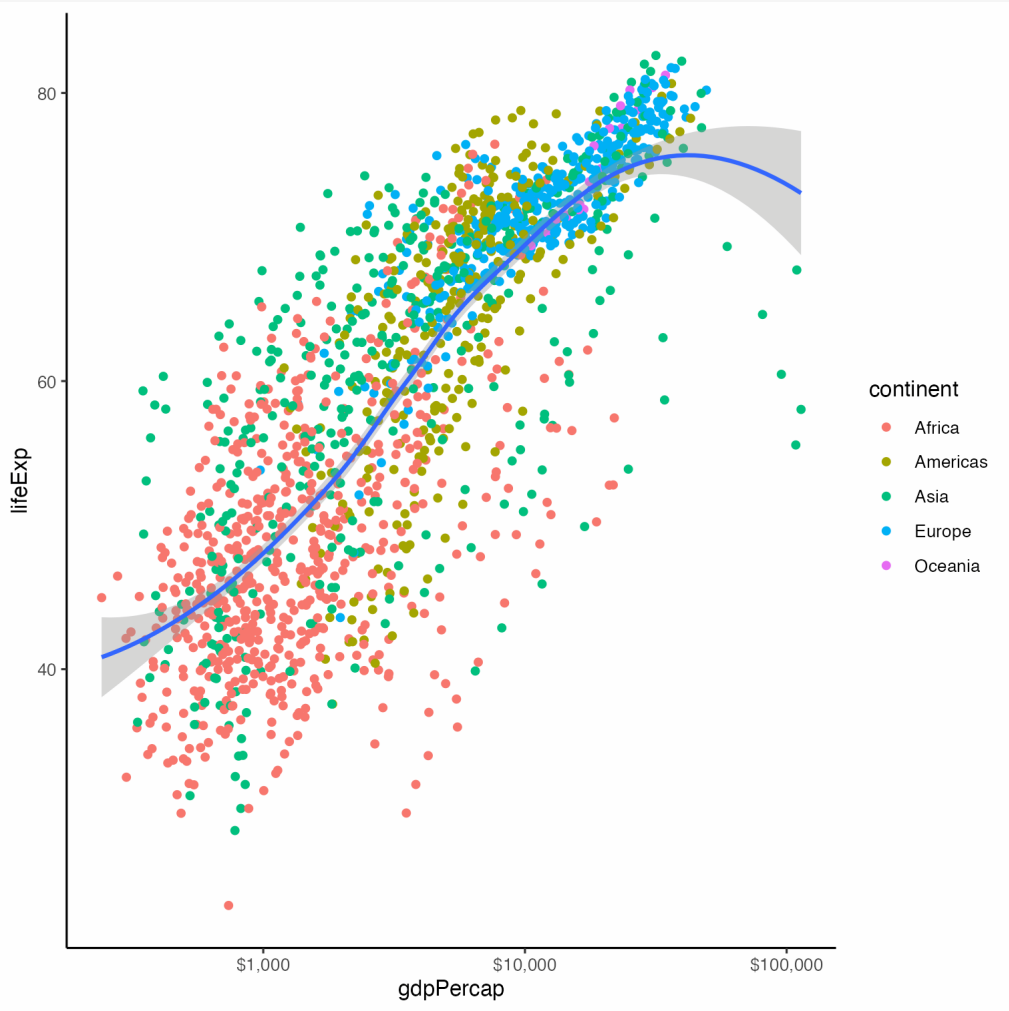
Geoms can take their own mappings

```
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

```
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()

```
## 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

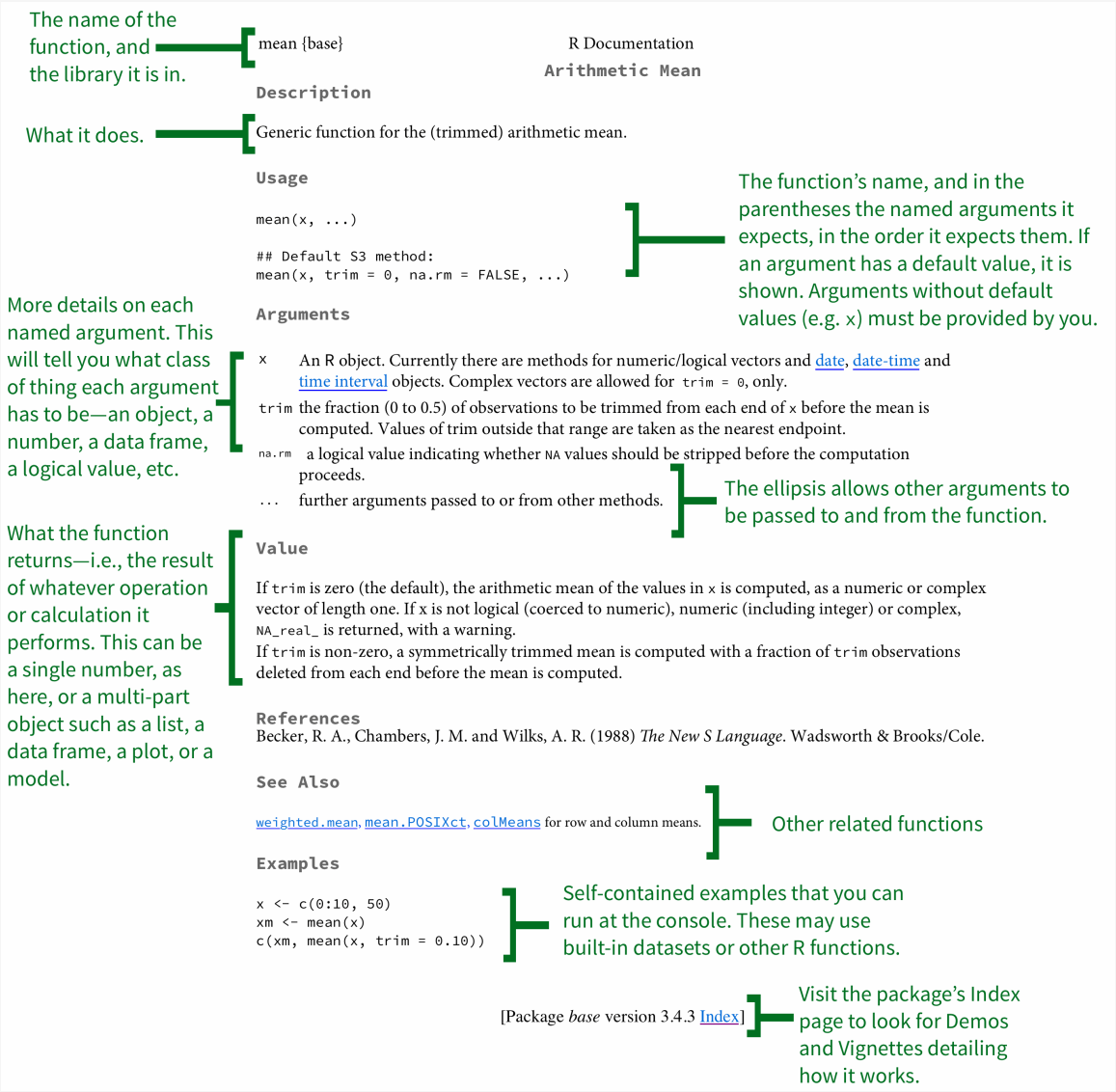
Set options in any chunk header:

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

Or for the whole document:

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

Getting Help



How to read an R Help page

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

```
mean(x, ...)

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

More details on each named argument. This

Arguments

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, ...)
```

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

`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

Description

What it does.

Generic function for the (trimmed) arithmetic mean.

Usage

```
mean(x, ...)

## 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

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.

`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.

The ellipsis allows other arguments to be passed to and from the function.

Value

What the function returns—i.e., the result of whatever operation or calculation it performs. This can be a single number, as

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 deleted from each end before the mean is computed.

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.