

Make Some Graphs

Data Visualization: Session 3

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Code Horizons, May 2022

A composite image featuring two distinct scenes. On the left, a man in a dark suit and tie stands in a doorway, looking towards the right. He is positioned next to a large potted plant. On the right, a massive alligator is shown in close-up, its mouth wide open, revealing its teeth and tongue. The alligator's skin is textured and patterned.

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

country	year	cases	population
Afghanistan	1999	745	16567071
Afghanistan	2000	2666	20595360
Brazil	1999	31737	172006362
Brazil	2000	80488	174504898
China	1999	212258	1272915272
China	2000	21166	128028583

variables

Every row is a single observation

country	year	cases	population
Iran (Islamic Republic of)	1993	743	195870
Iran (Islamic Republic of)	2000	2000	205500
Brazil	1993	87787	172000000
Brazil	2000	80400	174500000
China	1993	212200	12720102
China	2000	210700	128042000

observations

Every cell is a single value

country	year	cases	population
Afghanistan	99	745	19981071
Afghanistan	2000	2686	20599360
Brasil	99	37737	172009362
Brasil	2000	80483	174504898
China	99	212253	127291272
China	2000	213766	1280421583

values

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																		
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																		
Compiled by: David Wasserman & Ally Flinn, Cook Political Report. @Redistrict/@CookPolitical. <i>Italics</i> 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	<i>Ann Kirkpatrick</i>	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	<i>Greg Stanton</i>	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	<i>Tom McClintock</i>	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%				

It's also common 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	2016 Prez Swing vs. 2016	Raw Votes vs. 2016	Final?	
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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

The screenshot shows a digital journal article page. At the top left, it displays 'THE AMERICAN STATISTICIAN' and '2018, VOL. 72, NO. 1, 2-10'. Below this is the DOI: <https://doi.org/10.1080/00031305.2017.1375989>. On the right side, there is a logo for 'Taylor & Francis' and 'Taylor & Francis Group'. Below the header, the title 'Data Organization in Spreadsheets' is centered. Underneath the title, the authors are listed as 'Karl W. Broman^a and Kara H. Woo^b'. A note below the authors indicates: ^aDepartment of Biostatistics & Medical Informatics, University of Wisconsin-Madison, Madison, WI; ^bInformation School, University of Washington, Seattle, WA. To the right of the authors, there are two buttons: 'OPEN ACCESS' and 'Check for updates'. Further down the page, under the heading 'ABSTRACT', there is a detailed description of the article's content. To the right of the abstract, under 'ARTICLE HISTORY', it says 'Received: June 2017' and 'Revised: August 2017'. Below that, under 'KEYWORDS', are the terms 'Data management; Data organization; Microsoft Excel; Spreadsheets'.

The most common `tidyverse` operation

Pivoting:

```
edu

## # A tibble: 366 × 11
##   age   sex   year total elem4 elem8   hs3   hs4 coll3 coll4 median
##   <chr> <chr> <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!

Reading in CSV files

CSV is not really a proper format at all!

Base R has `read.csv()`

Reading in CSV files

CSV is not really a proper format at all!

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")
```

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

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

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

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

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

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

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

```
here() # this path will be different for you  
## [1] "/Users/kjhealy/Documents/courses/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
##   └── keynote
##   └── package-lock.json
##   └── 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
##   <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
## # ... with 228 more rows, and 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()` 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!)

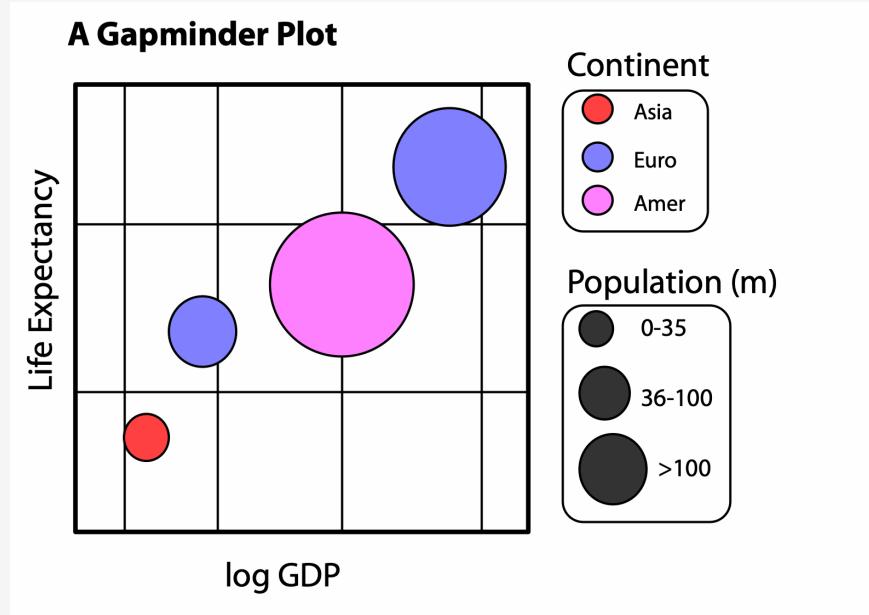
```
organ_remote <- read_csv("http://kjhealy.co/organdonation.csv")

organ_remote

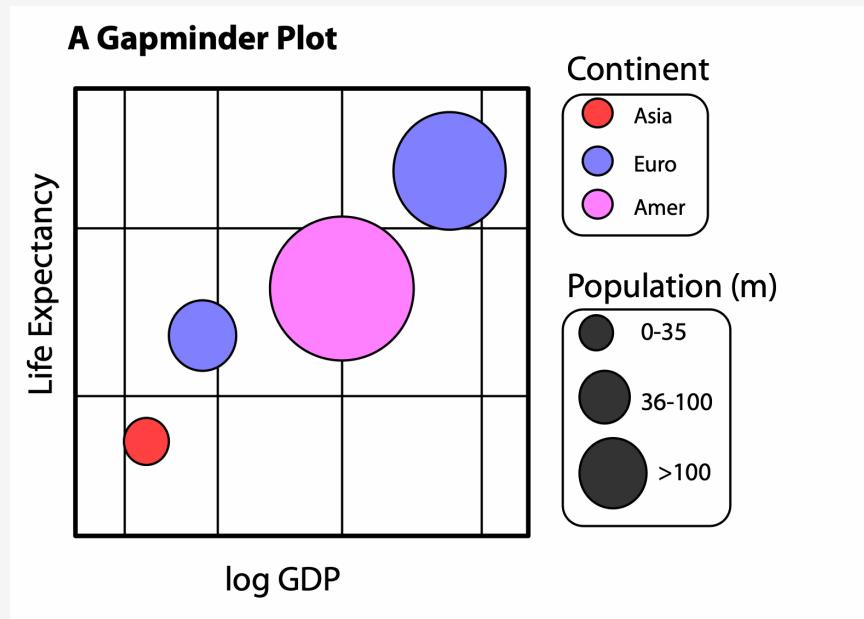
## # A tibble: 238 × 21
##   country year donors   pop pop.dens    gdp gdp.lag health health.lag pubhealth
##   <chr>   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 Austra... NA     17065 0.220 16774 16591 1300 1224 4.8
## 2 Austra... 1991 12.1 17284 0.223 17171 16774 1379 1300 5.4
## 3 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
## # ... with 228 more rows, and 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

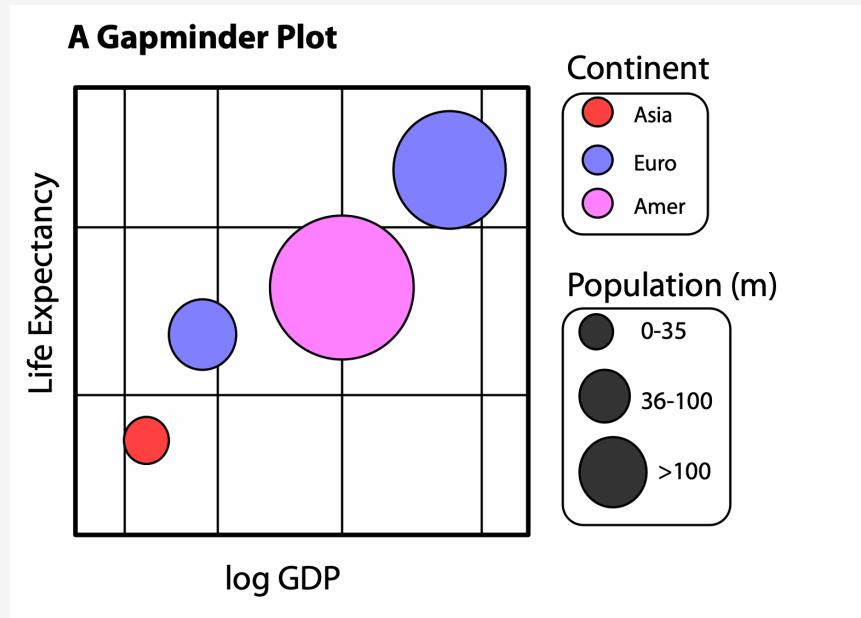


What we need our code to make



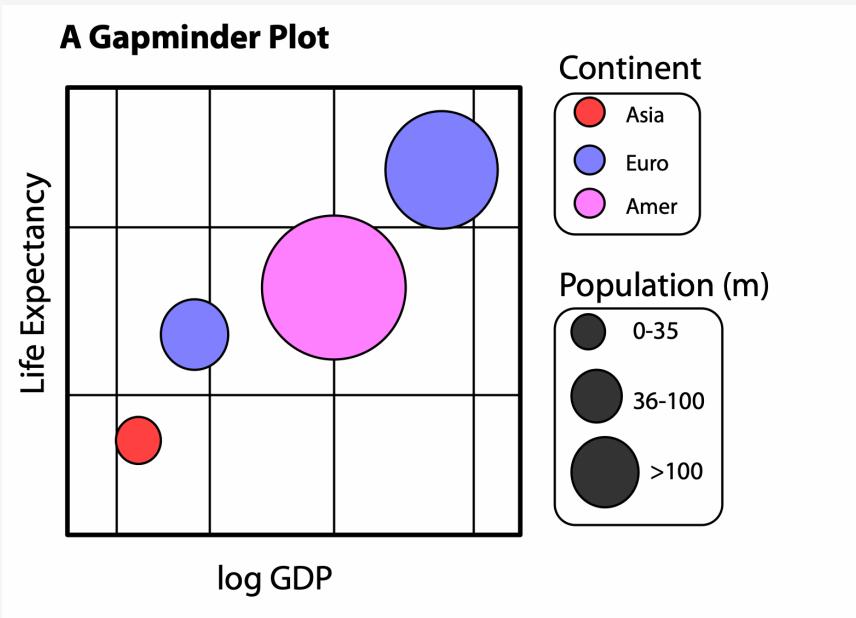
Data **represented** by visual elements,

What we need our code to make



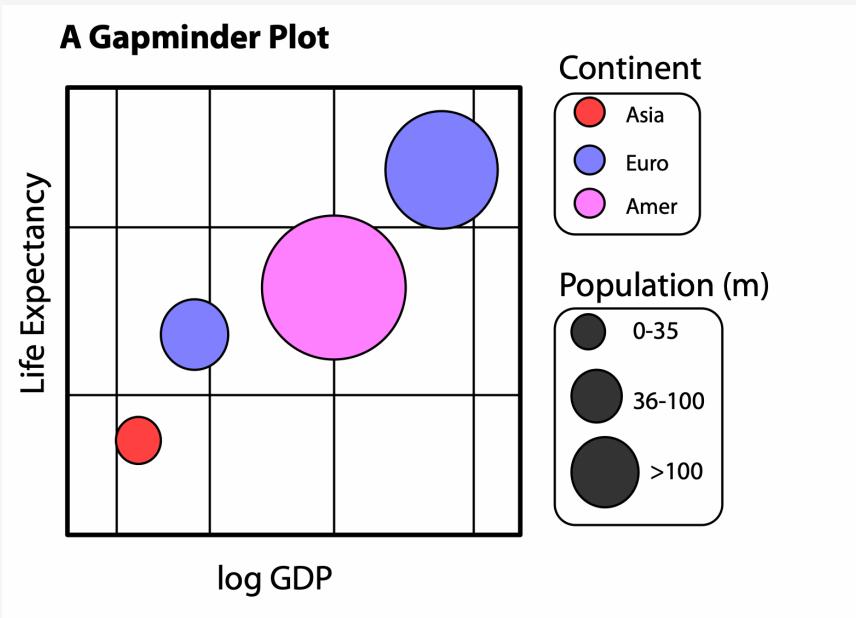
Data **represented** by visual elements, like *position, length, color, and size*,

What we need our code to make



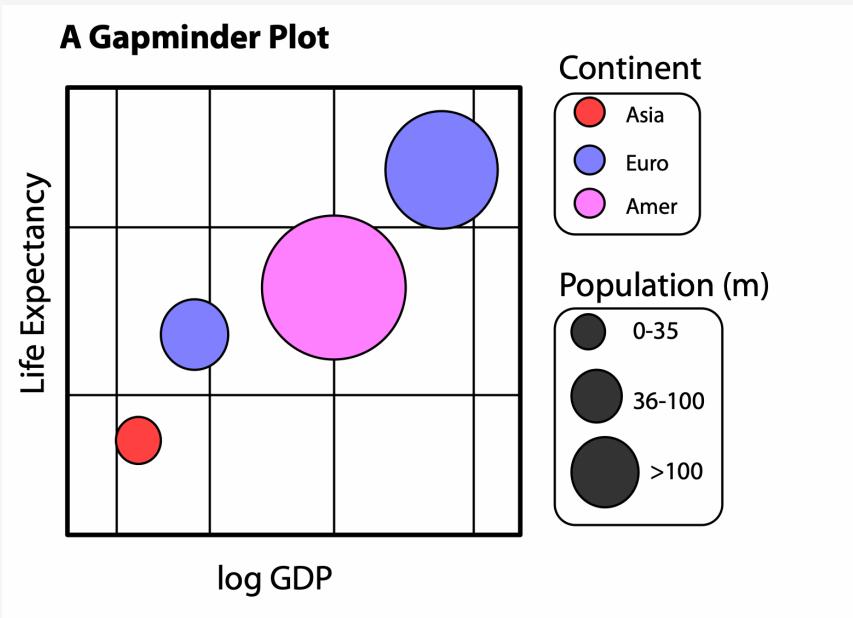
Data **represented** by visual elements,
like *position*, *length*, *color*, and *size*,
Each measured on some **scale**,

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**,

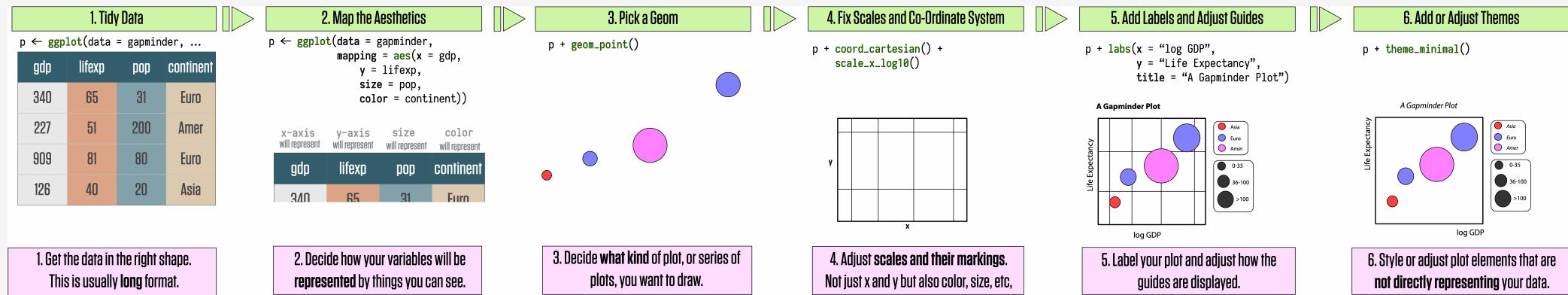
What we need our code to make



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

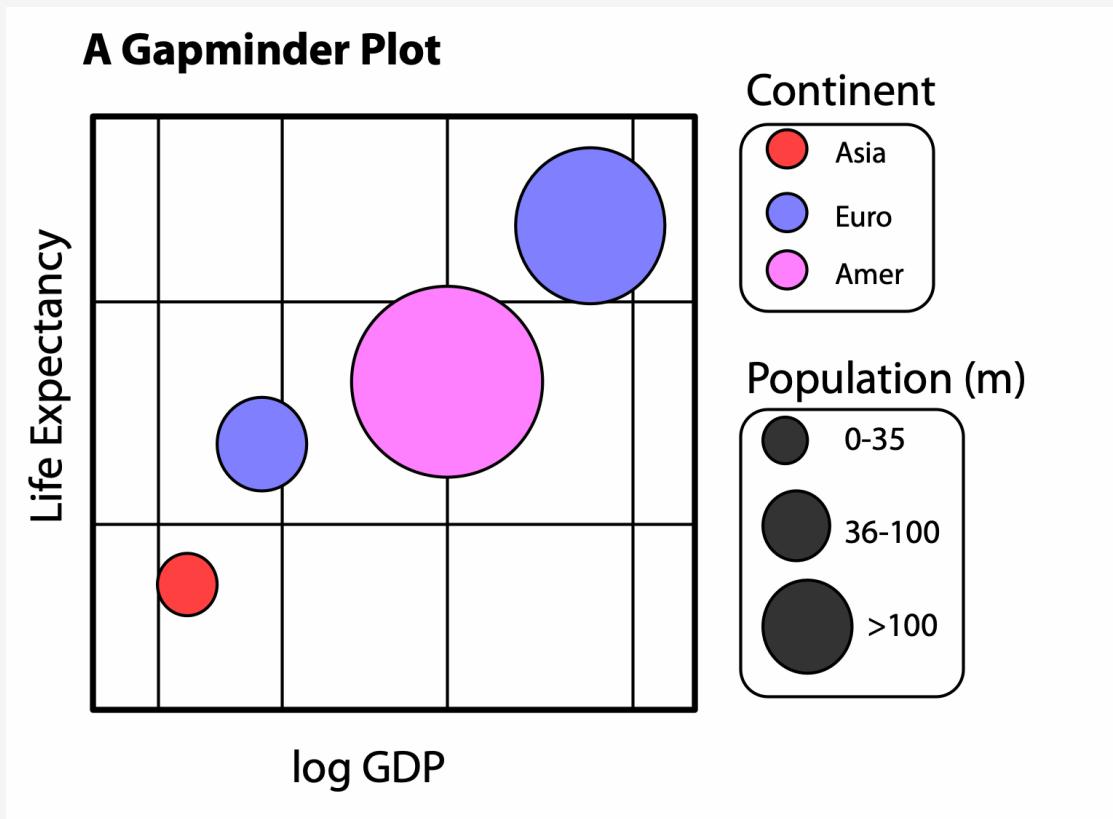
ggplot's flow of action



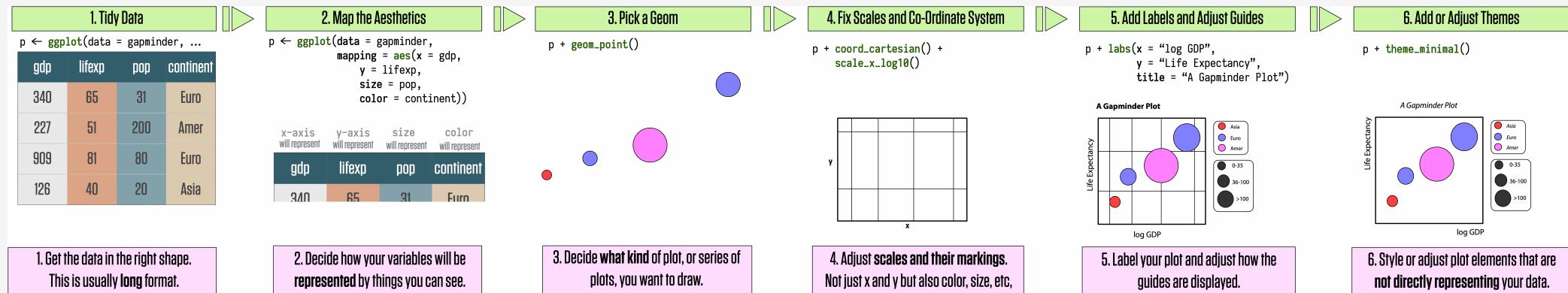
ggplot's flow of action

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



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

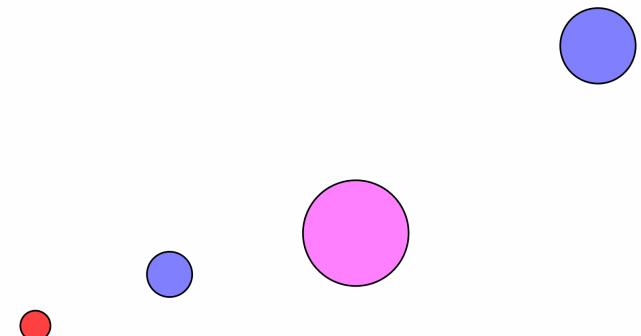
2. Map the Aesthetics

```
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.
This is usually **long** format.

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

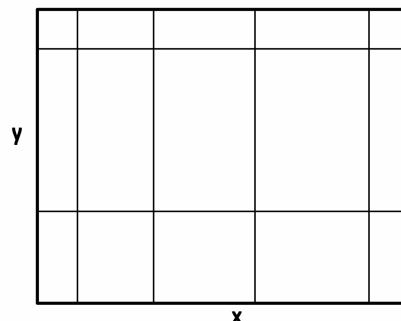
3. Decide what kind of plot, or series of plots, you want to draw.

ggplot's flow of action



4. Fix Scales and Co-Ordinate System

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

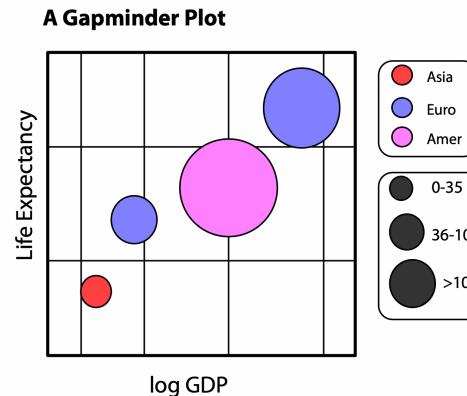


4. Adjust scales and their markings.
Not just x and y but also color, size, etc,



5. Add Labels and Adjust Guides

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

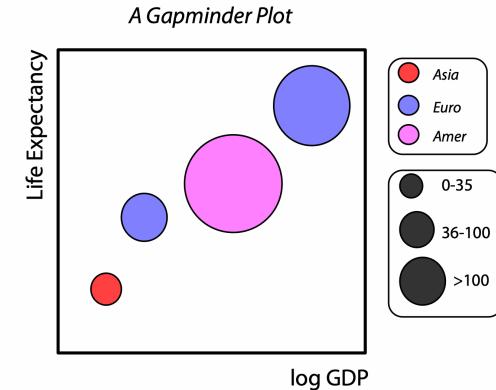


5. Label your plot and adjust how the guides are displayed.



6. Add or Adjust Themes

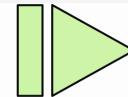
```
p + theme_minimal()
```



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

ggplot's flow of action: **required**

1. Tidy Data



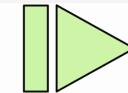
```
p ← ggplot(data = gapminder, ...)
```

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.

ggplot's flow of action: **required**

2. Map the Aesthetics



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

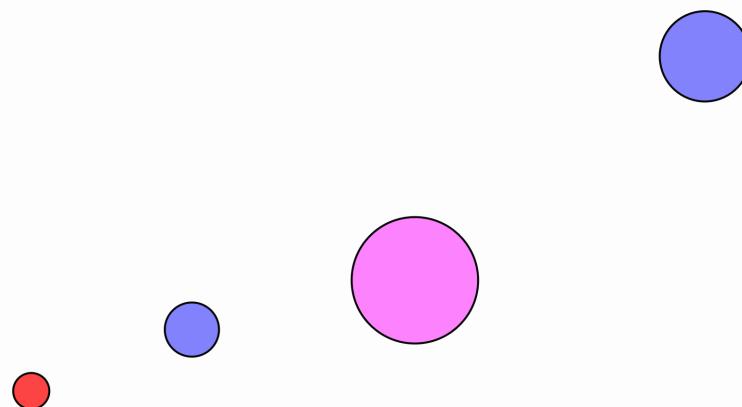
x-axis will represent	y-axis will represent	size will represent	color will represent
gdp	lifexp	pop	continent
340	65	31	Euro

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.

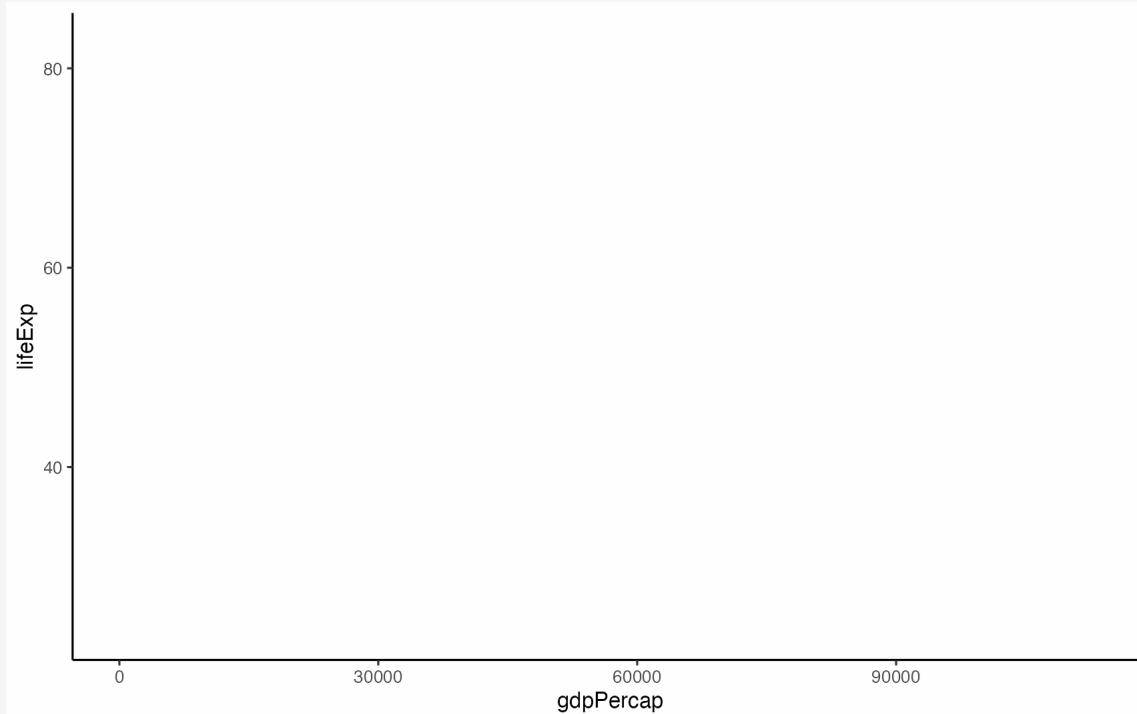
`x` and `y` represent the quantities determining position on the `x` and `y` axes.

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

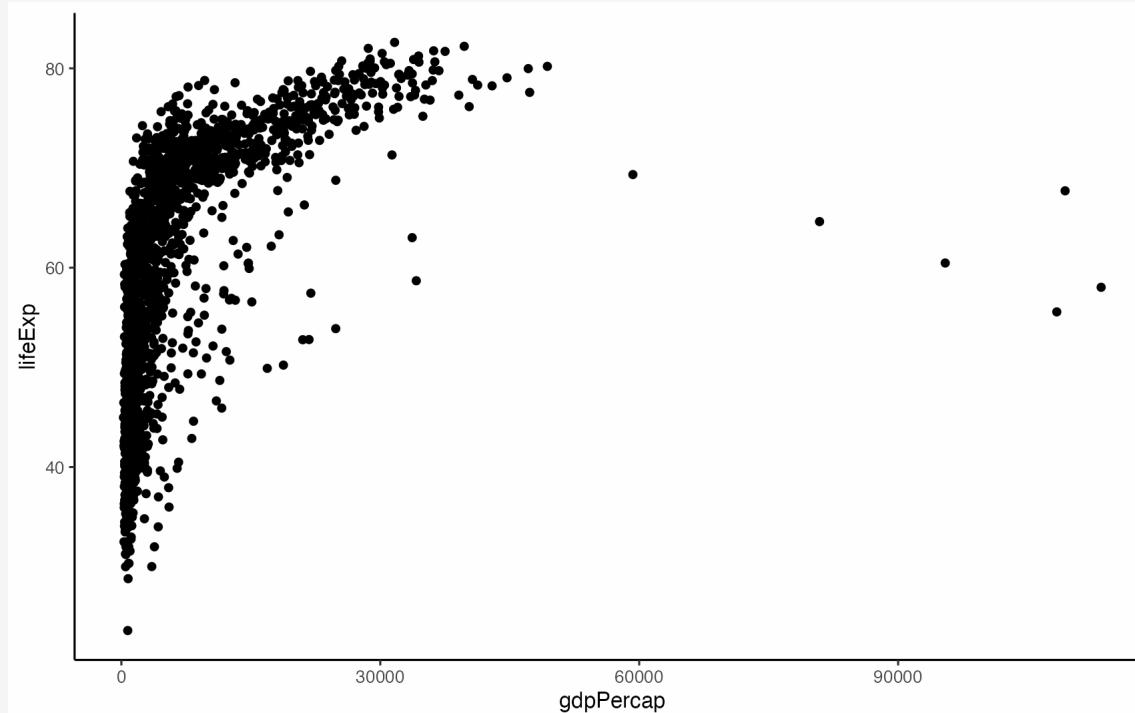
p



This empty plot has no geoms.

Add a geom

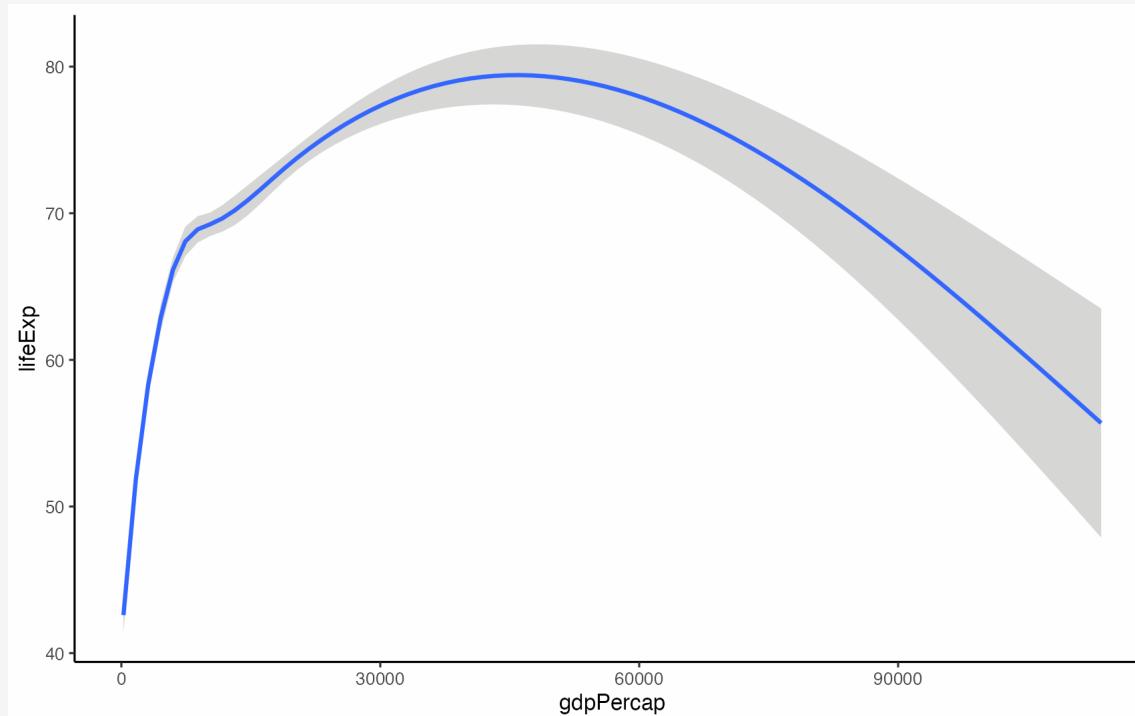
```
p + geom_point()
```



A scatterplot of Life Expectancy vs GDP

Try a different geom

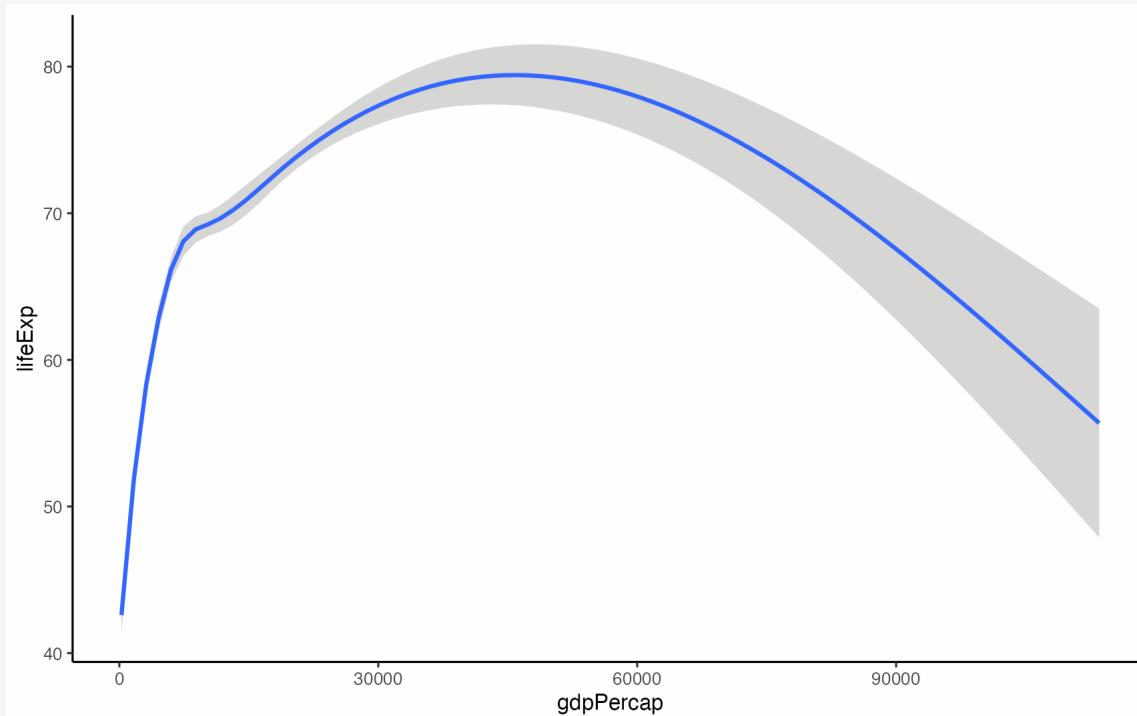
```
p + geom_smooth()
```



A scatterplot of Life Expectancy vs GDP

Build your plots layer by layer

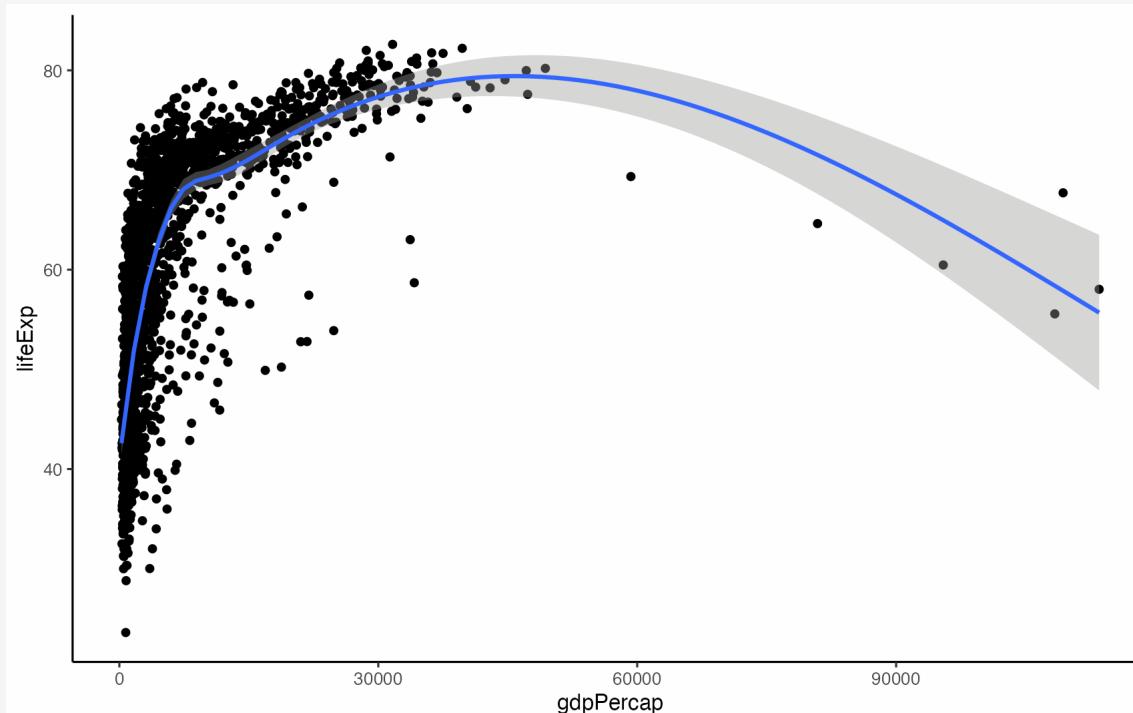
```
p <- ggplot(data = gapminder,  
             mapping = aes(x = gdpPercap,  
                            y=lifeExp))  
p + geom_smooth()
```



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()
```



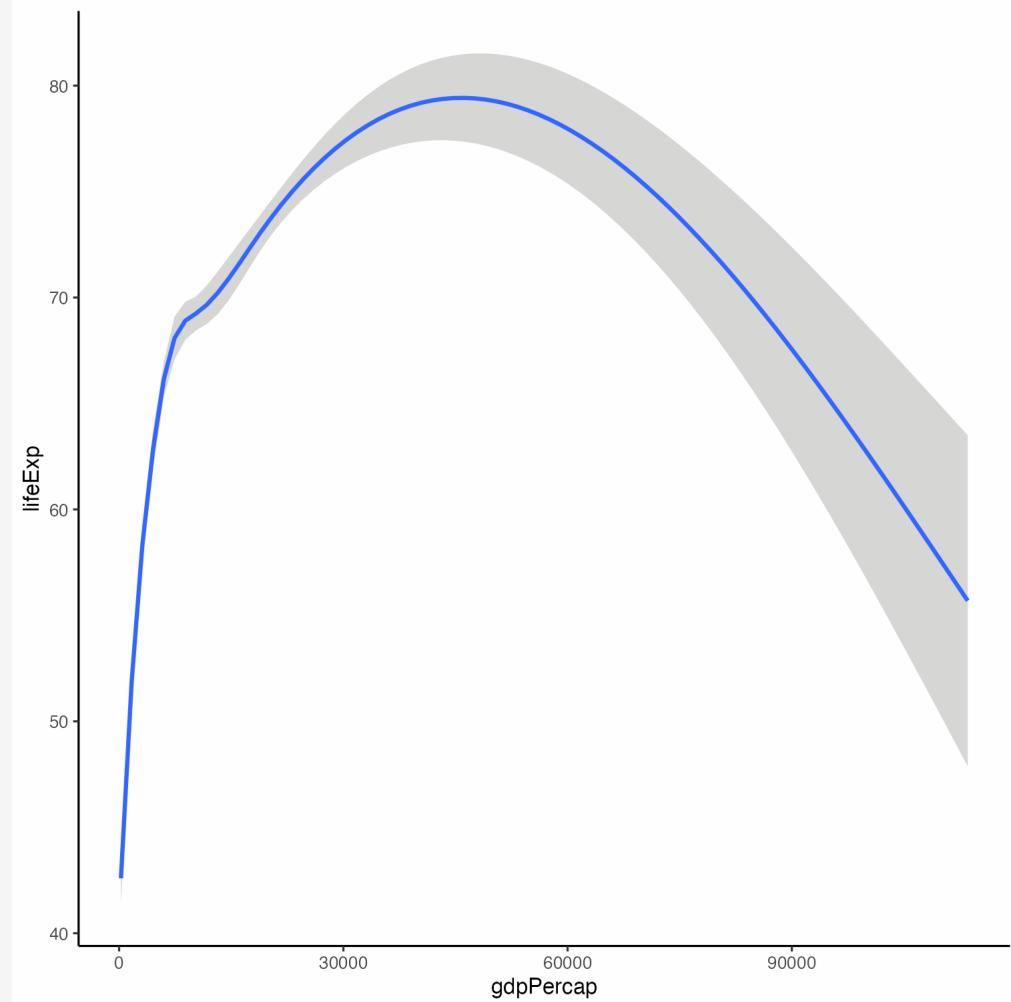
Life Expectancy vs GDP, using a smoother.

This process is additive

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

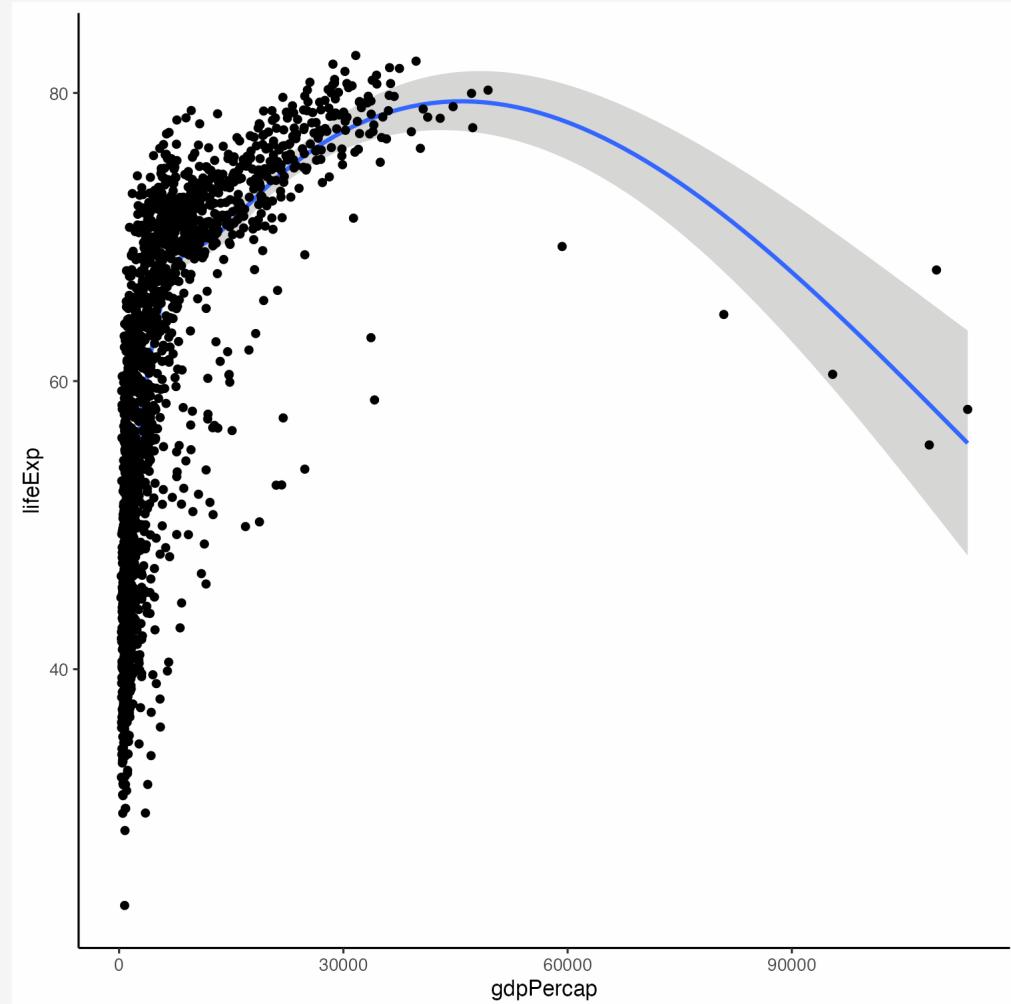
This process is additive

```
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

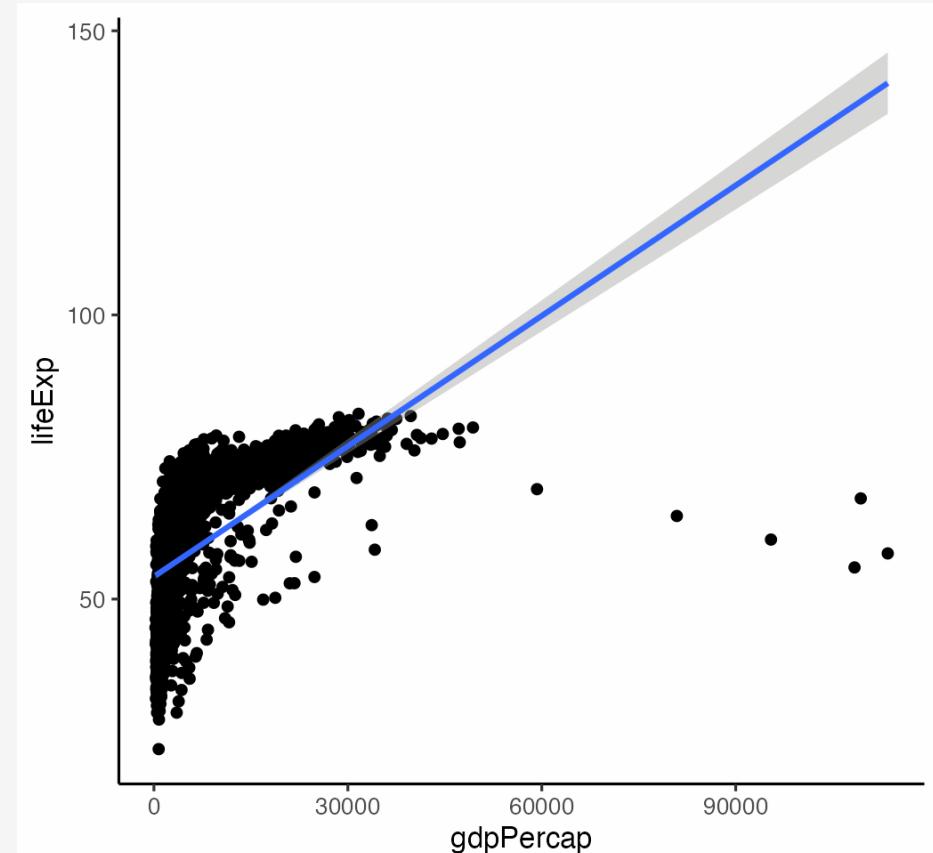
Functions take arguments

```
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")
```

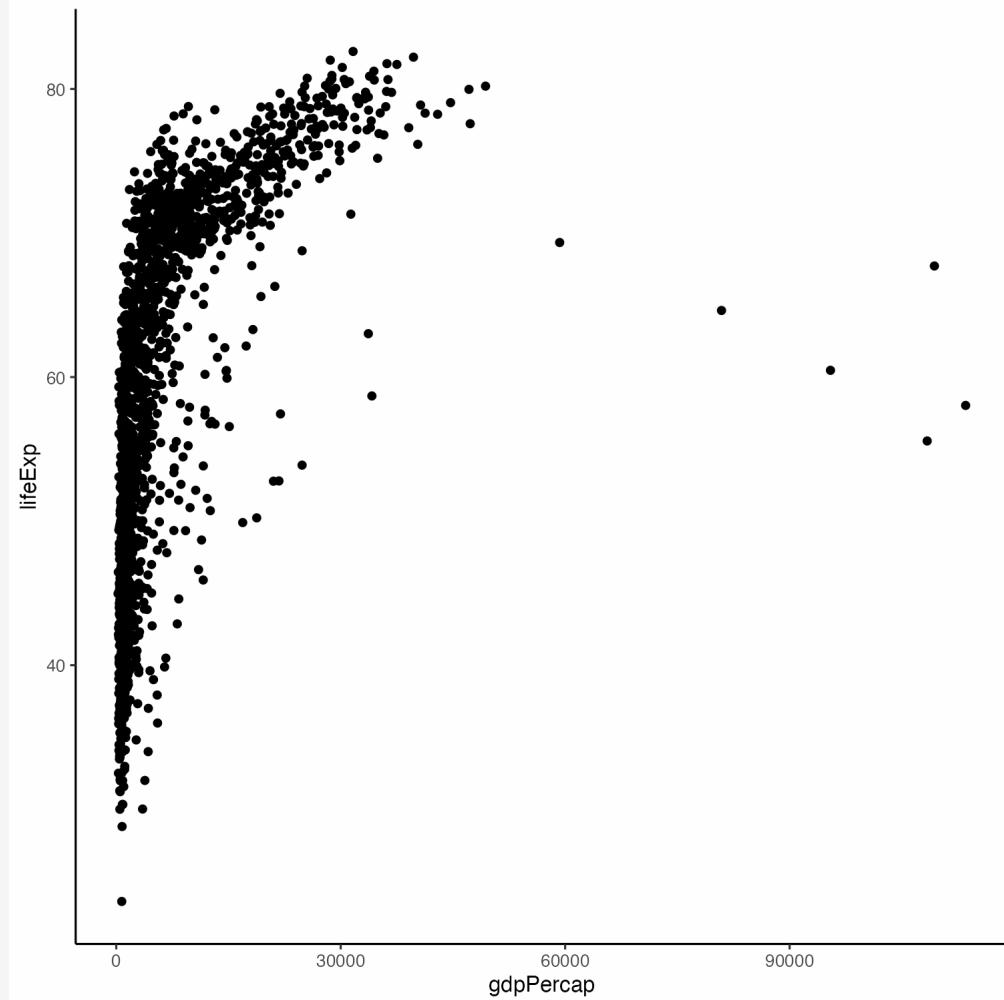


Keep Layering

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

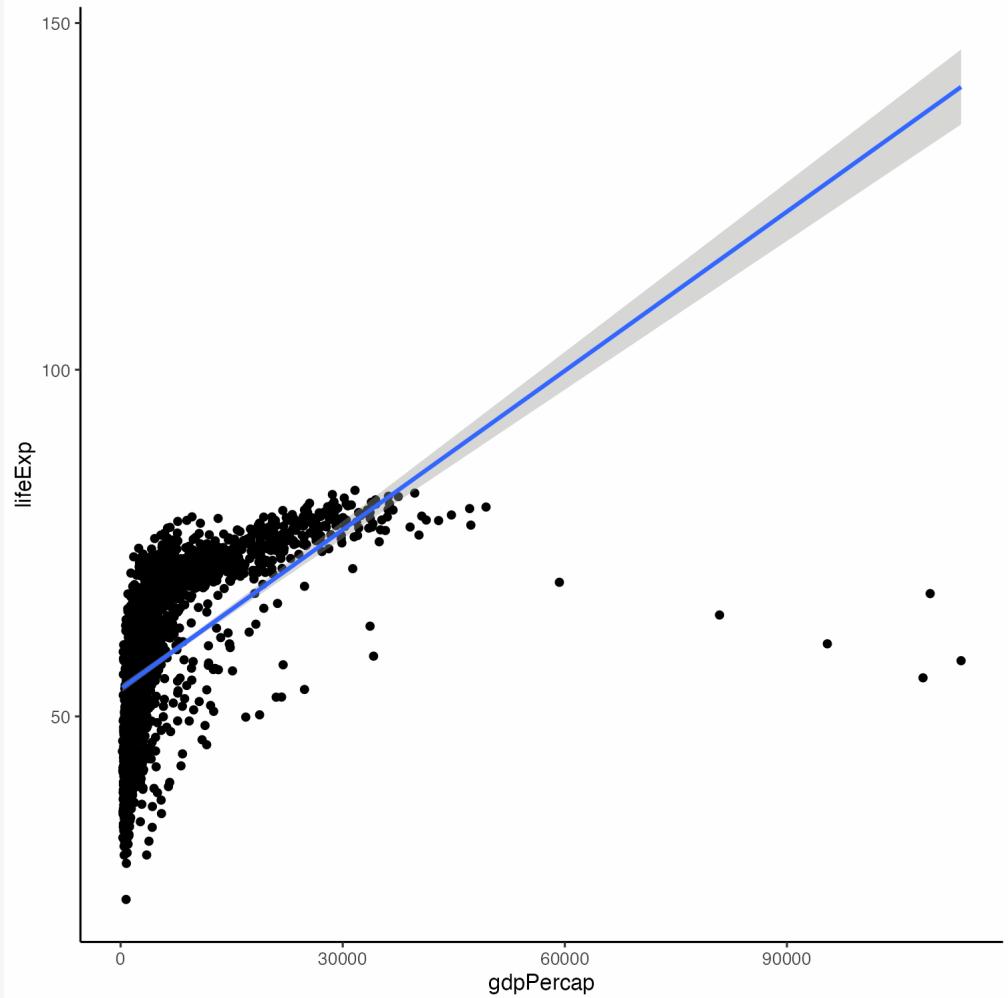
Keep Layering

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



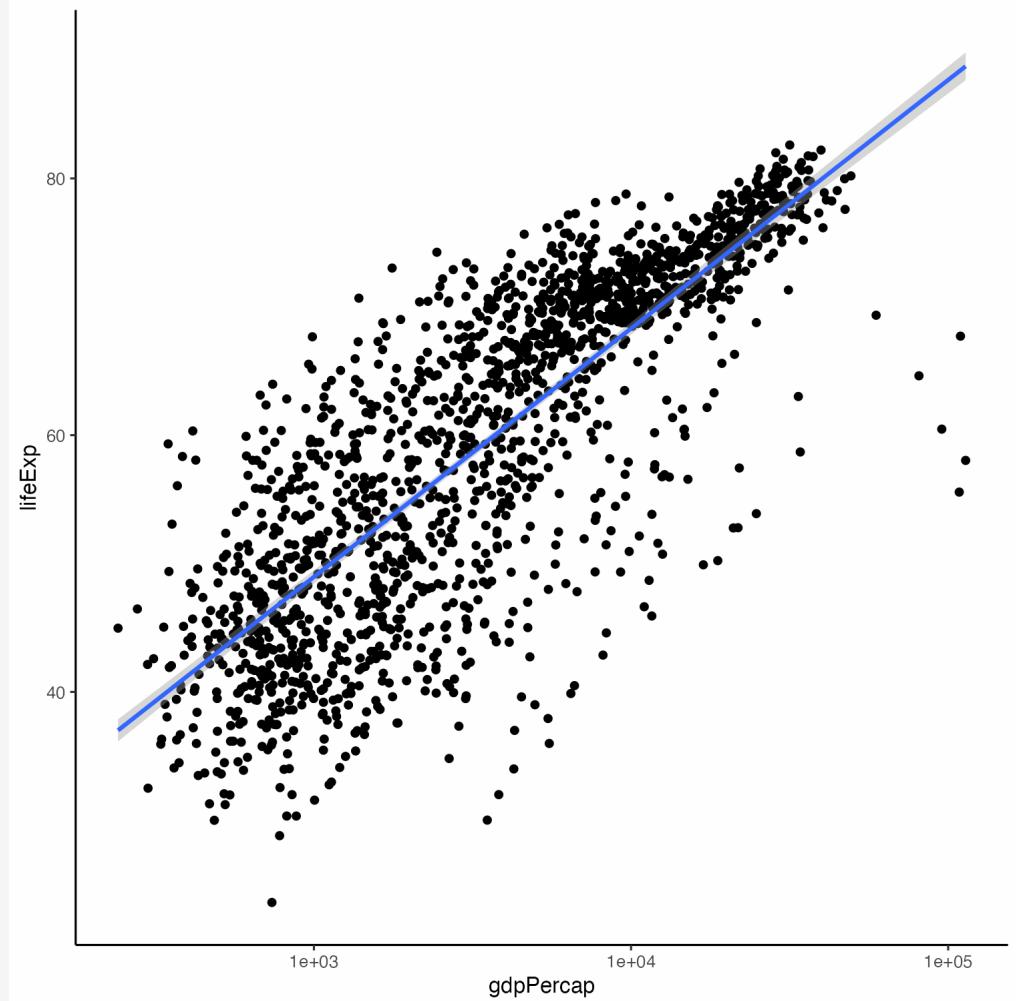
Keep Layering

```
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()
```

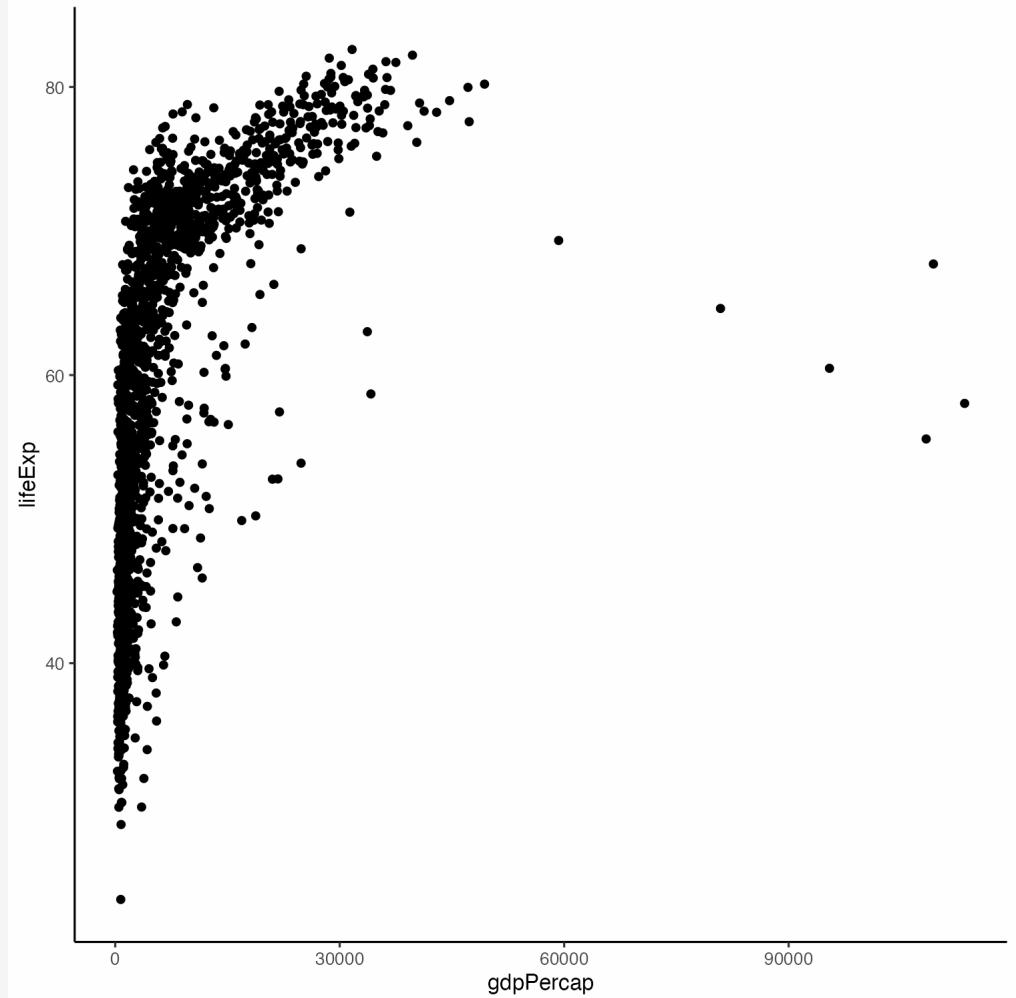


Fix the labels

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

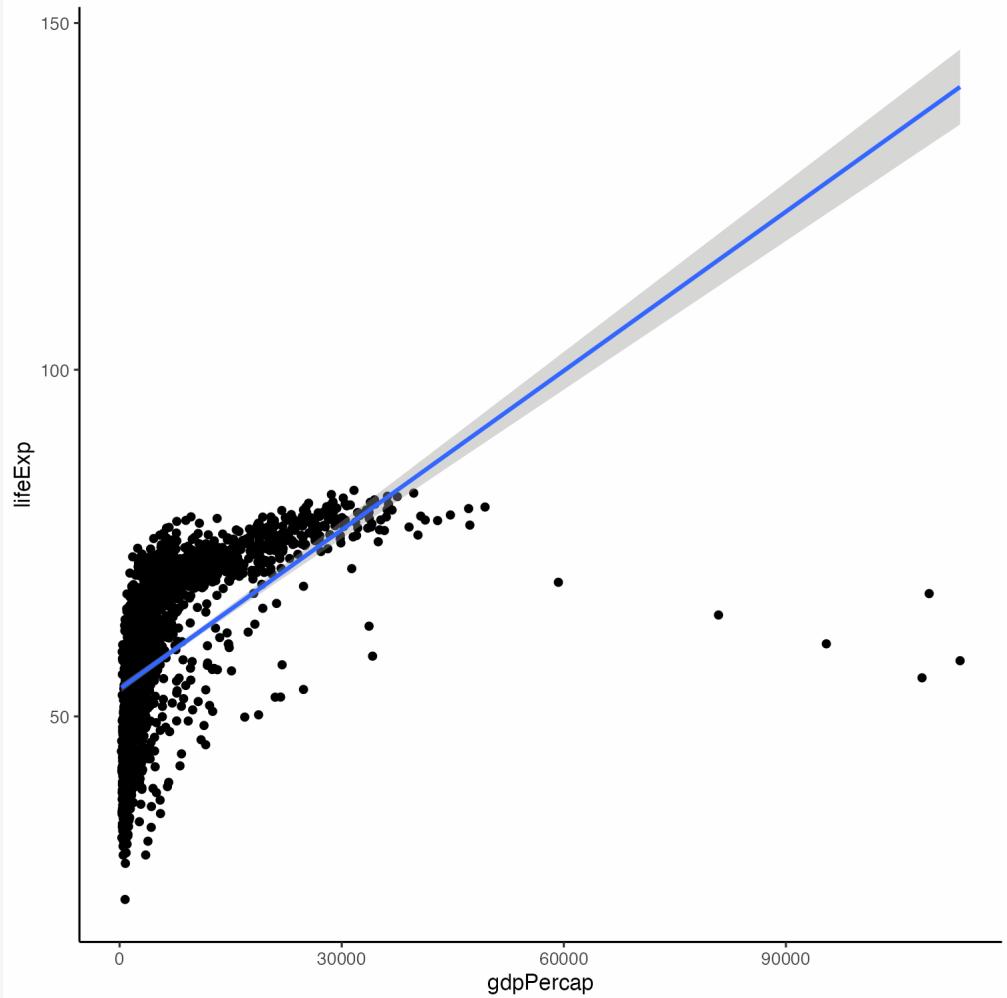
Fix the labels

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



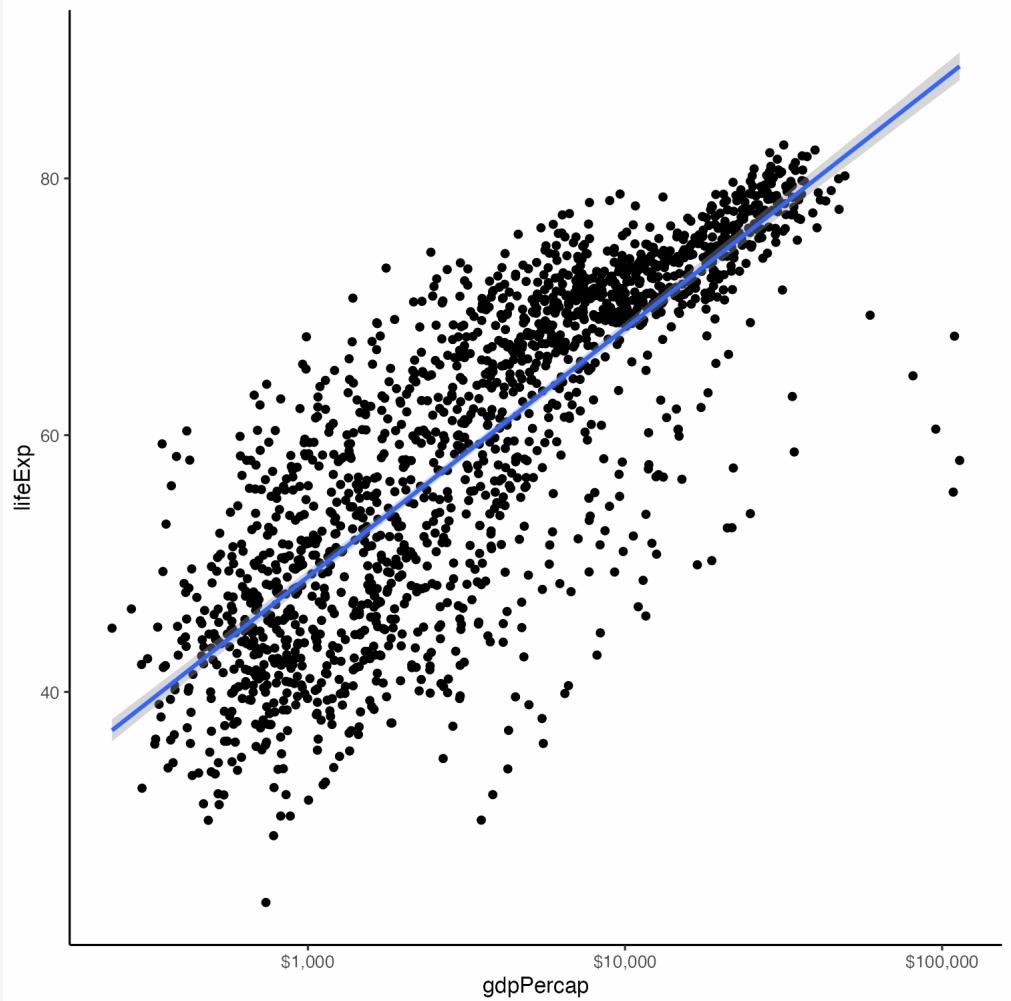
Fix the labels

```
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())
```

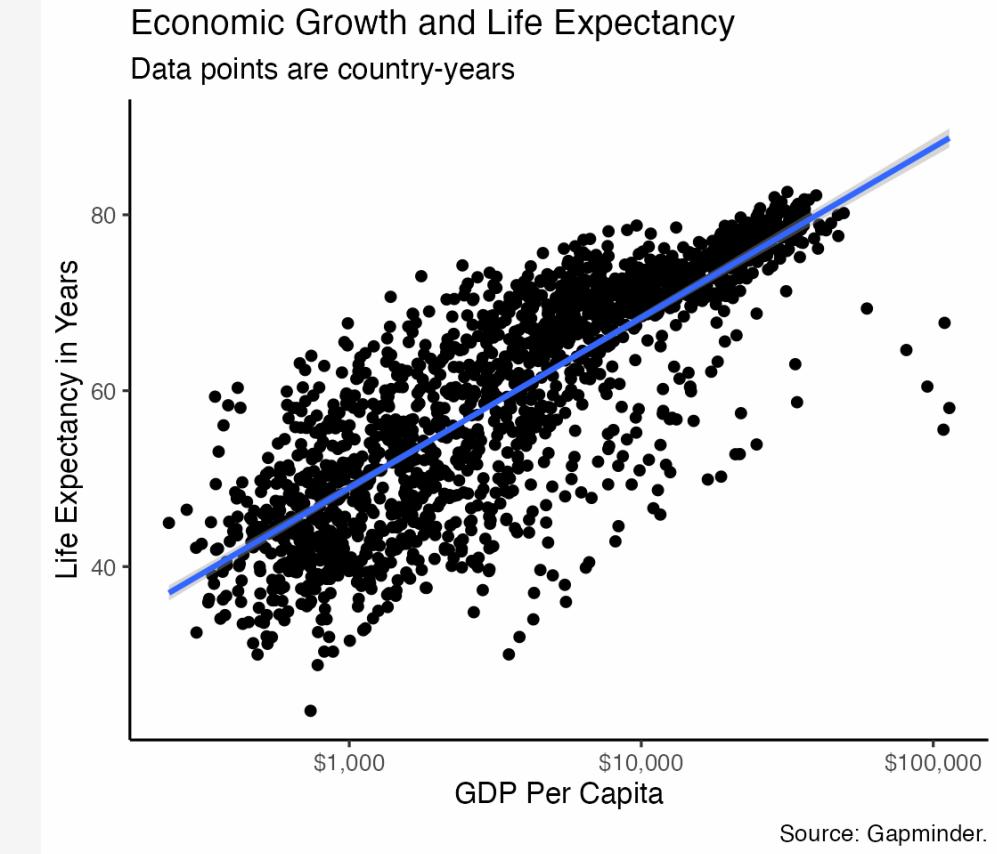


Add labels, title, and caption

```
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.")
```



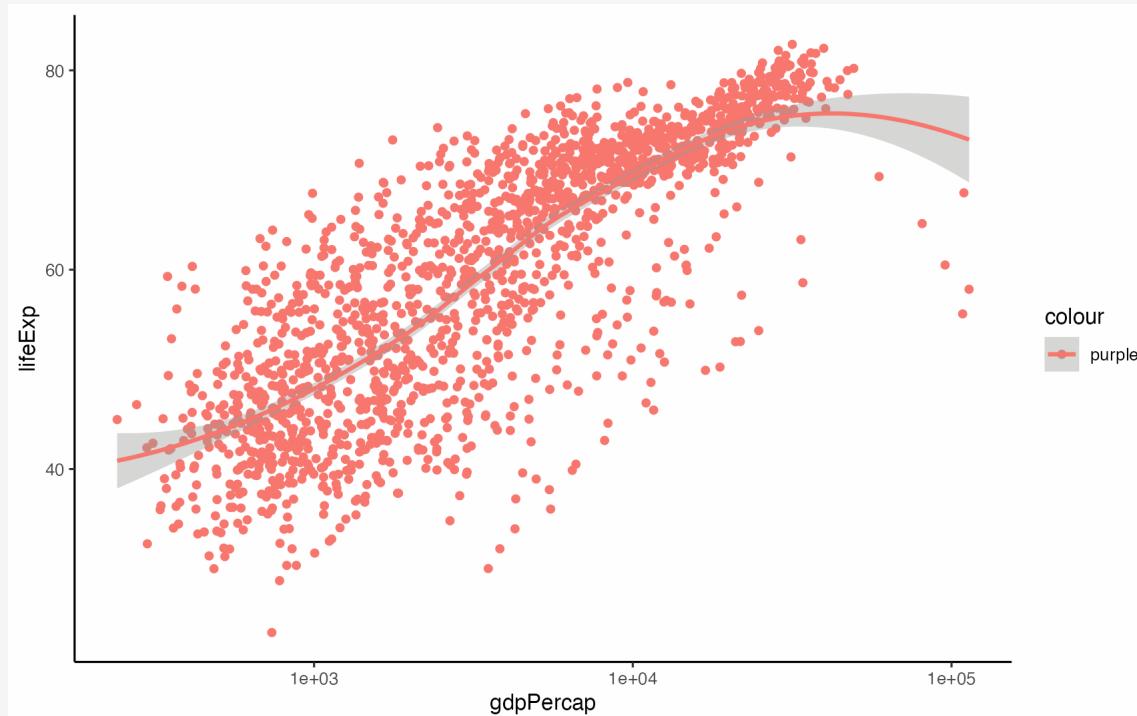
Mapping vs Setting your plot's aesthetics

"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

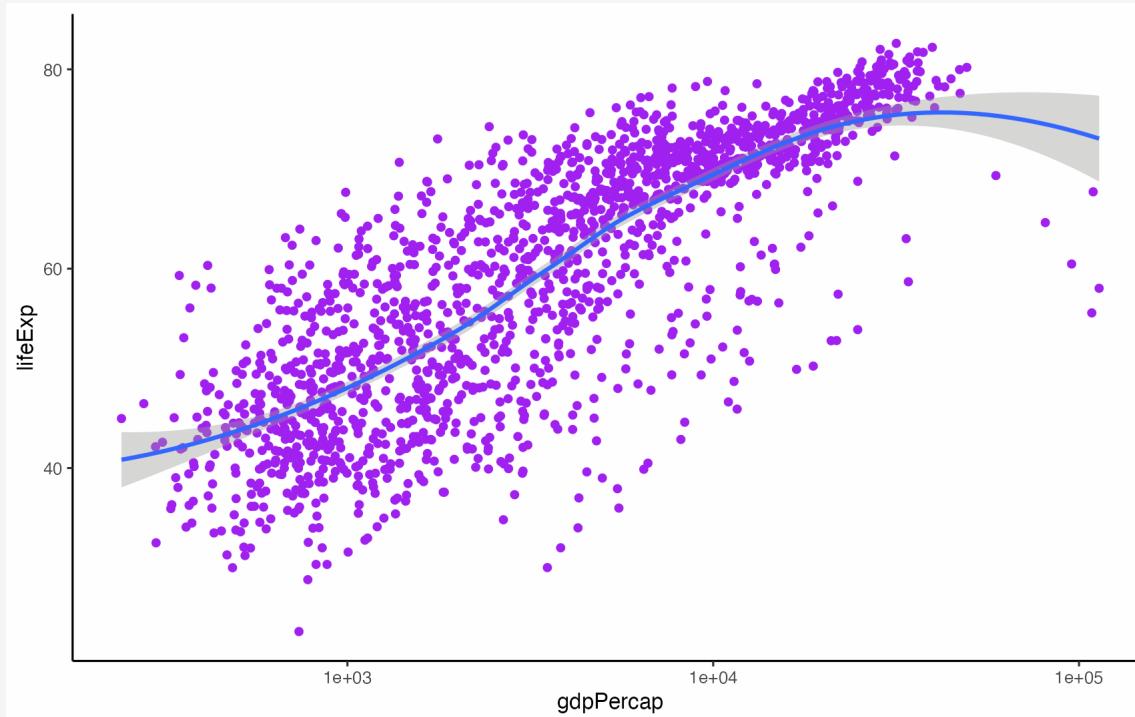


Try again

```
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

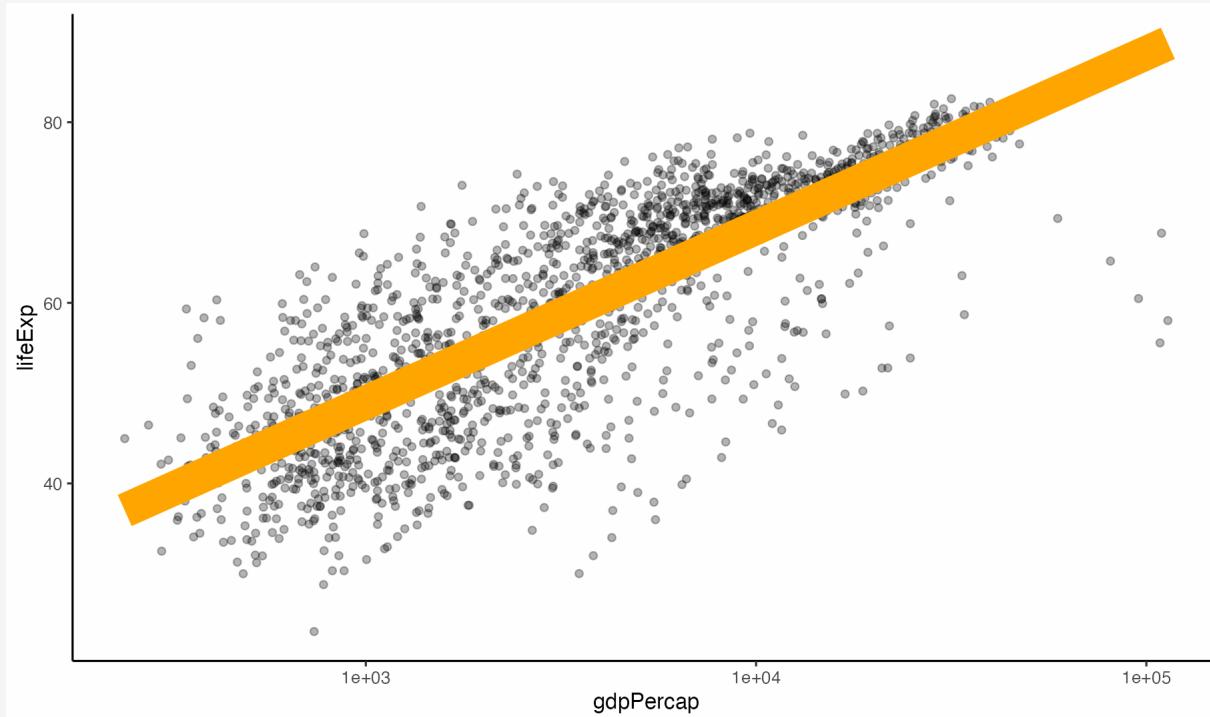
Here we **set** color, size, and alpha. Meanwhile x and y are **mapped**.

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



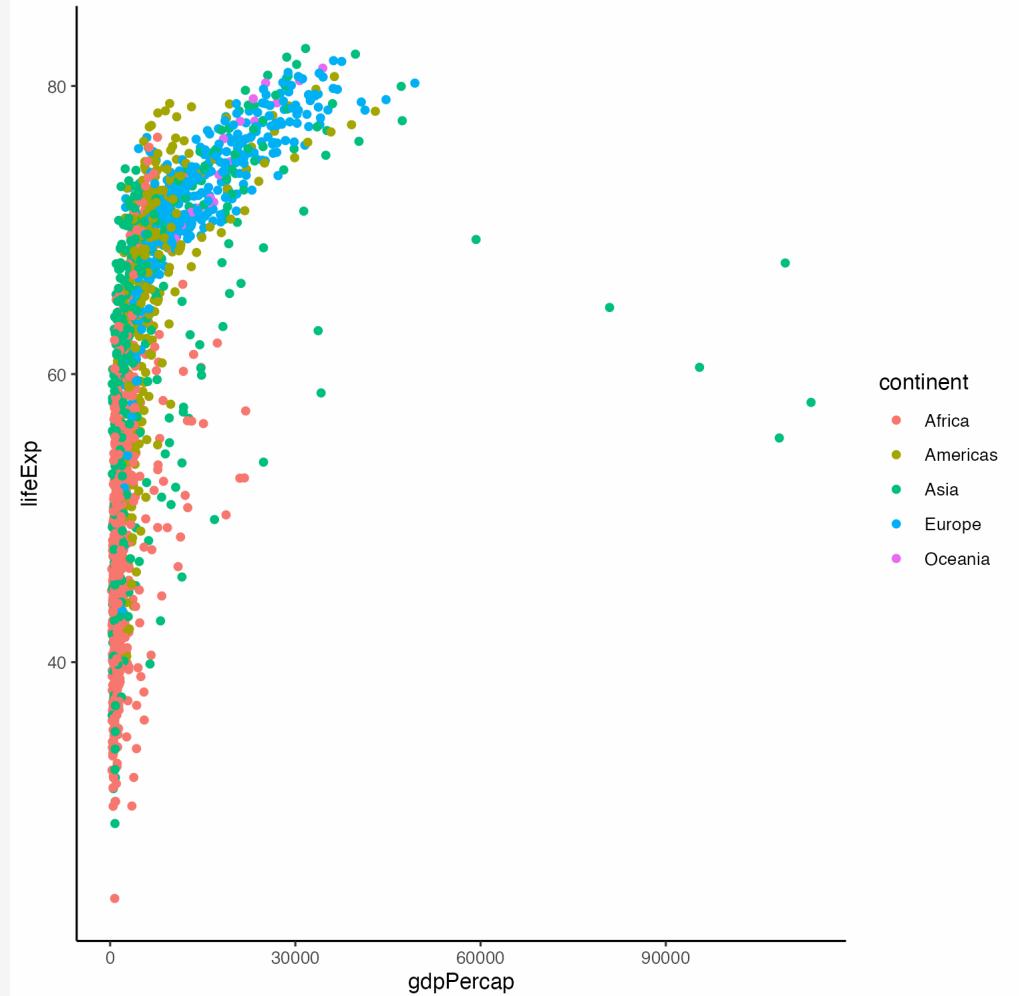
**Map or Set values
per geom**

Geoms can take their own mappings

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

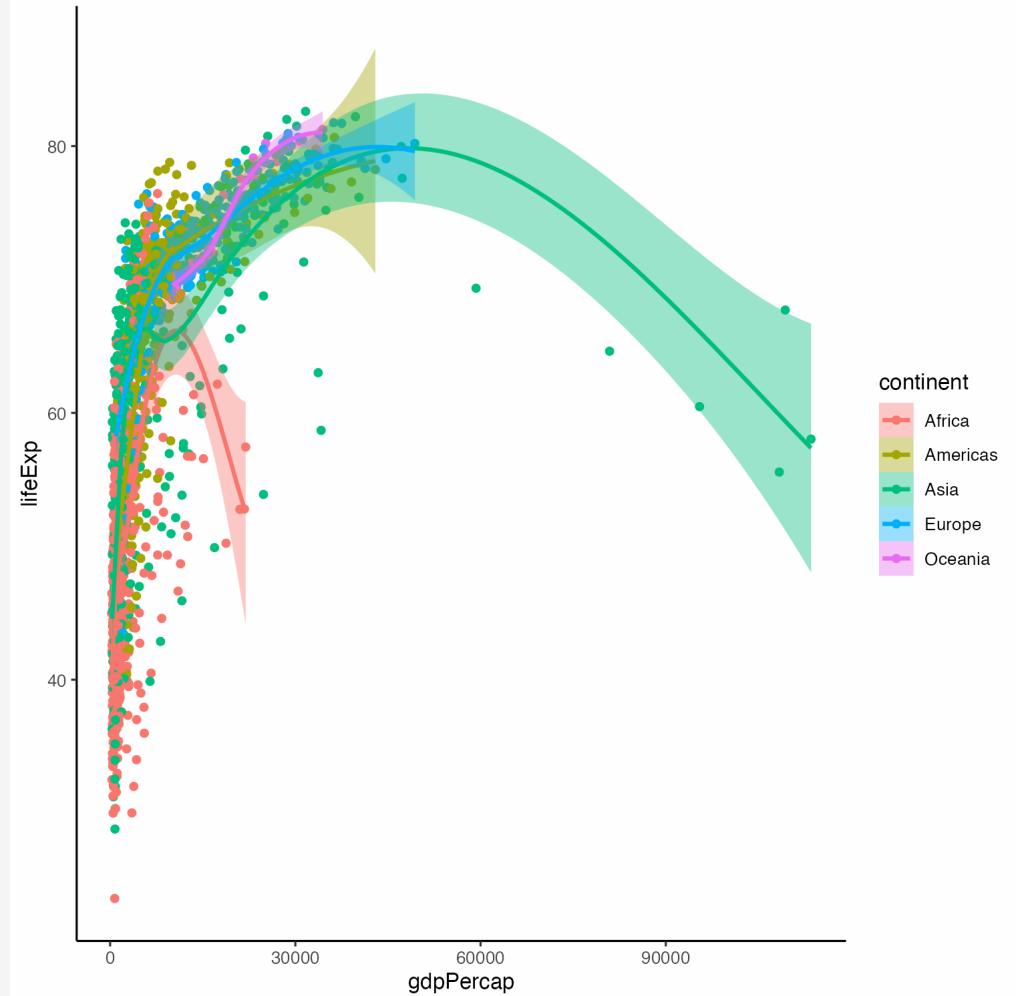
Geoms can take their own mappings

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



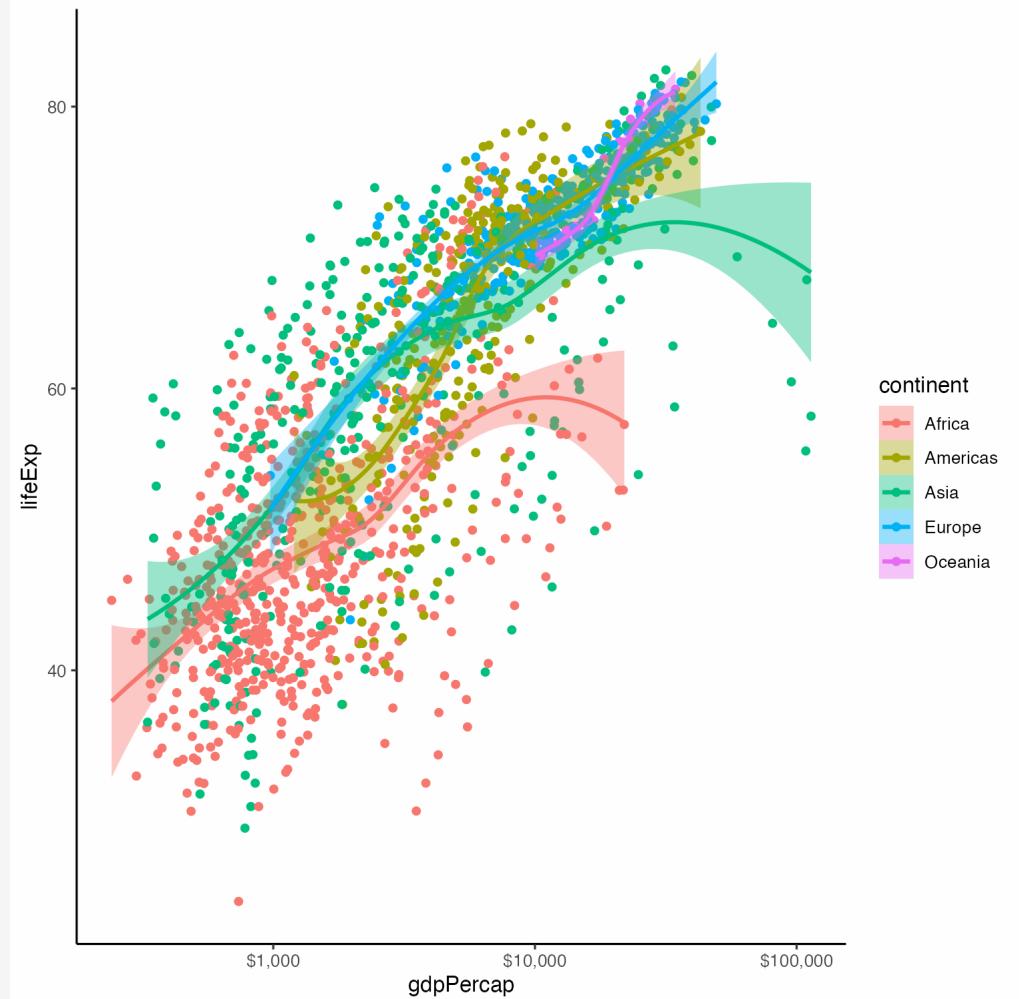
Geoms can take their own mappings

```
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())
```

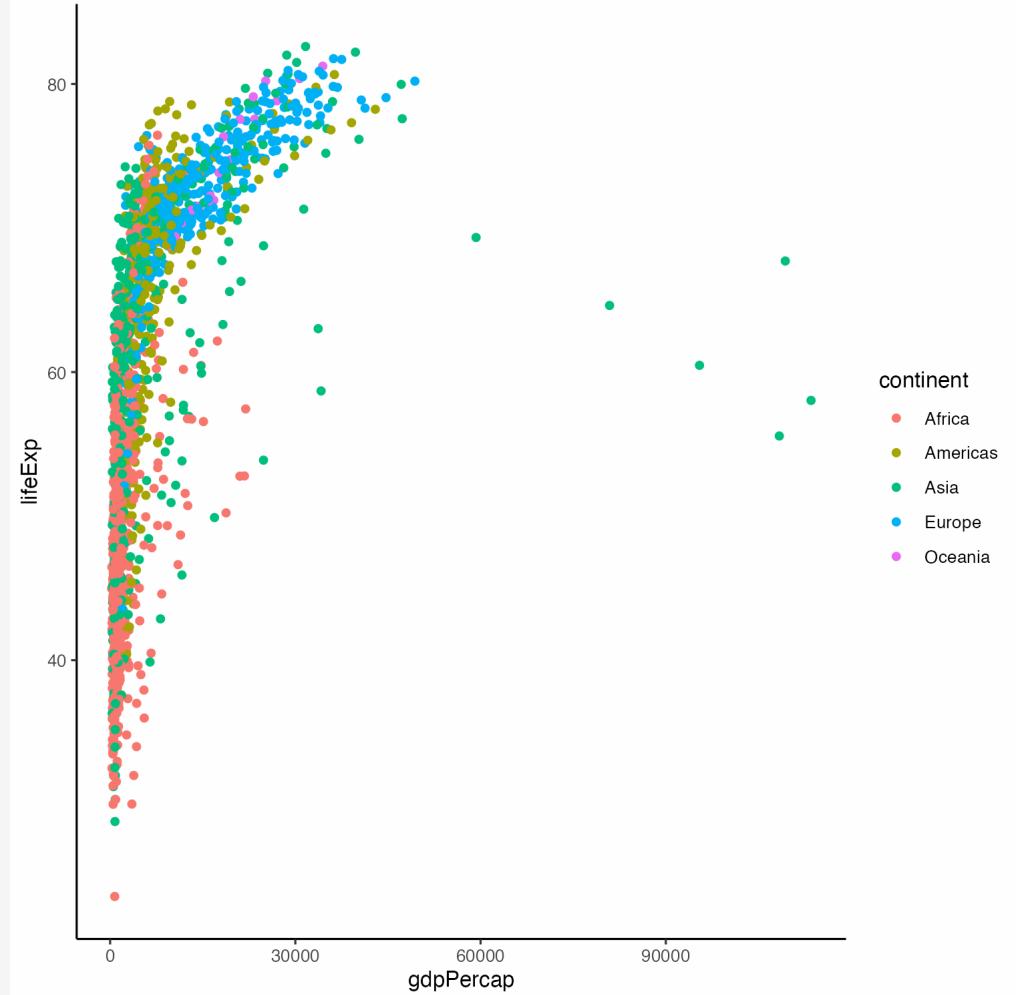


Geoms can take their own mappings

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

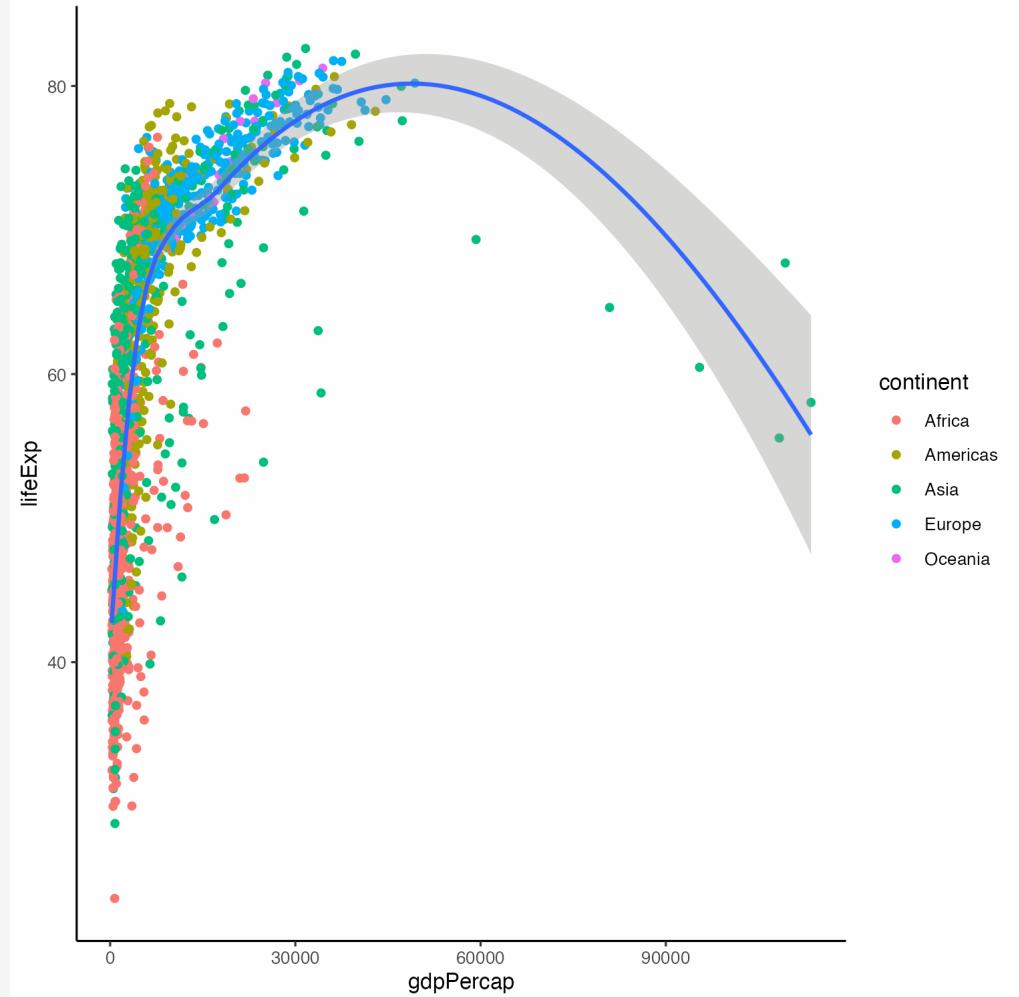
Geoms can take their own mappings

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



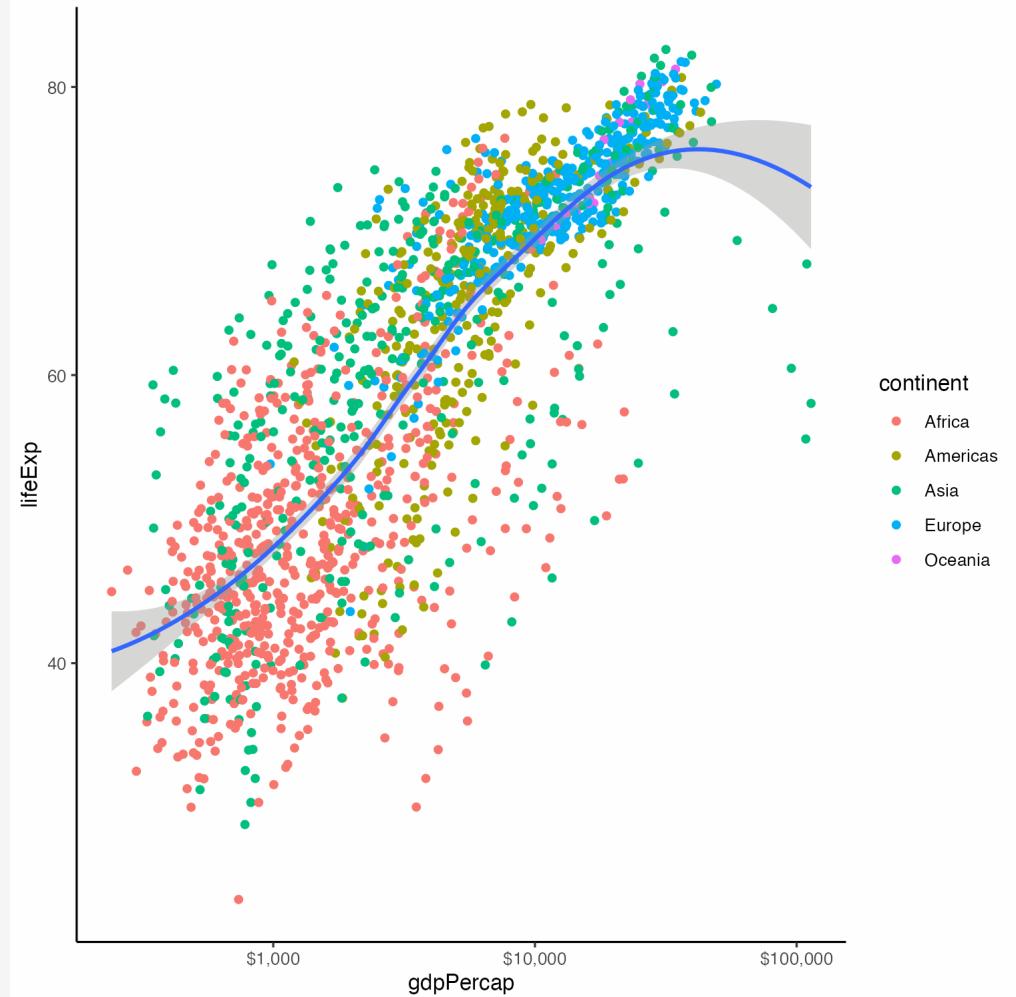
Geoms can take their own mappings

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



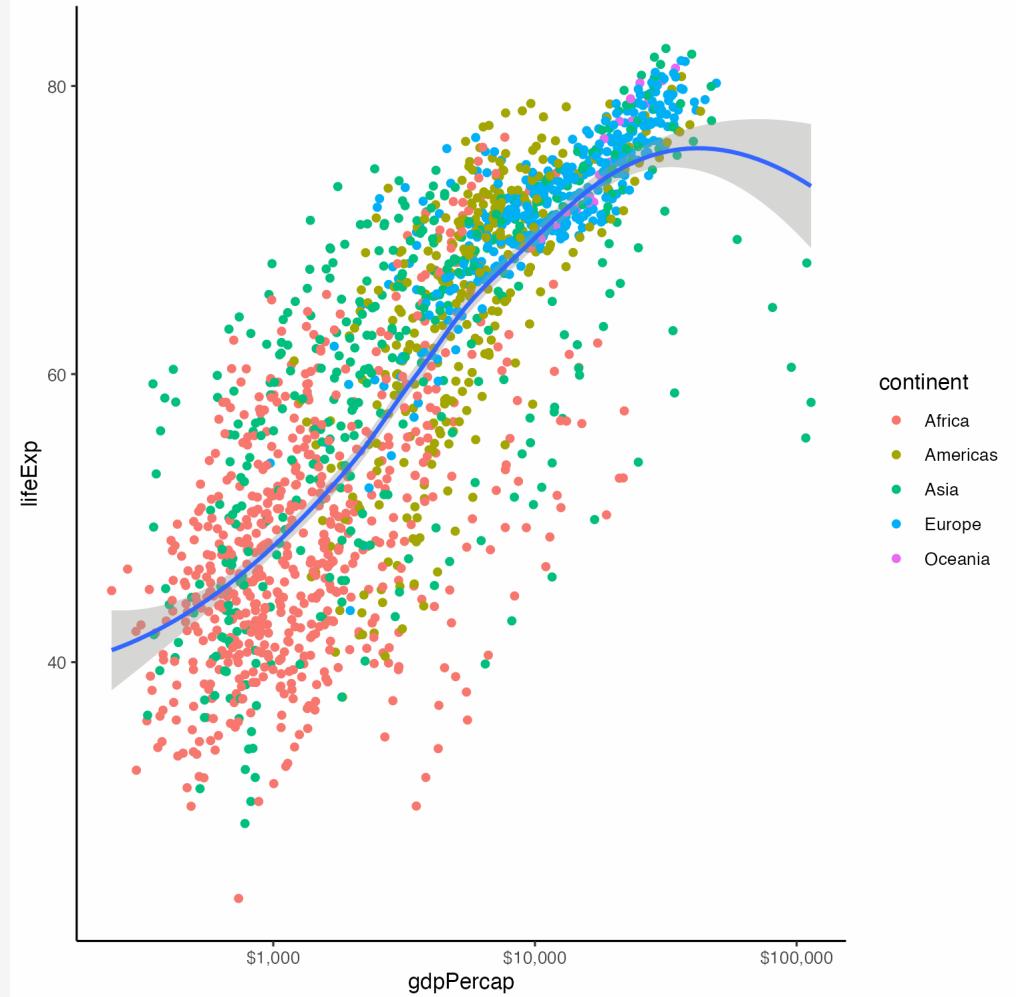
Geoms can take their own mappings

```
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)
```

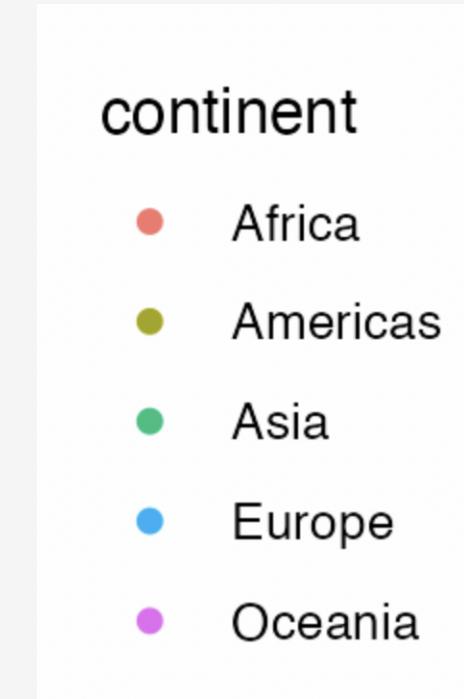


Guides and scales reflect `aes()` mappings

```
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

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

What it does.

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.

What the function returns—i.e., the result of whatever operation or calculation it performs. This can be a single number, as here, or a multi-part object such as a list, a data frame, a plot, or a model.

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 deleted from each end before the mean is computed.

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.

Examples

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

Other related functions

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.

How to read an R Help page

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

mean {base}

R Documentation

Arithmetic Mean

What it does.

Description

Generic function for the (trimmed) arithmetic mean.

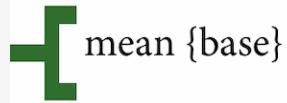
Usage

```
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.

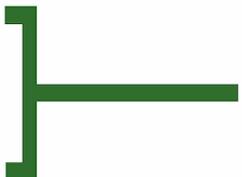
Usage

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

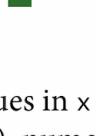
Arguments



- 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



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.

Description	
What it does.	Generic function for the (trimmed) arithmetic mean.
Usage	 <p>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. <code>x</code>) must be provided by you.</p>
<pre data-bbox="641 333 834 469"> mean(x, ...) ## Default S3 method: mean(x, trim = 0, na.rm = FALSE, ...) </pre>	 <p>An R object. Currently there are methods for numeric/logical vectors and date, date-time and time interval objects. Complex vectors are allowed for <code>trim = 0</code>, only.</p>
Arguments	<p><code>trim</code> the fraction (0 to 0.5) of observations to be trimmed from each end of <code>x</code> before the mean is computed. Values of <code>trim</code> outside that range are taken as the nearest endpoint.</p> <p><code>na.rm</code> a logical value indicating whether <code>NA</code> values should be stripped before the computation proceeds.</p> <p><code>...</code> further arguments passed to or from other methods.</p>
Value	 <p>The ellipsis allows other arguments to be passed to and from the function.</p> <p>If <code>trim</code> is zero (the default), the arithmetic mean of the values in <code>x</code> is computed, as a numeric or complex vector of length one. If <code>x</code> is not logical (coerced to numeric), numeric (including integer) or complex, <code>NA_real_</code> is returned, with a warning.</p> <p>If <code>trim</code> is non-zero, a symmetrically trimmed mean is computed with a fraction of <code>trim</code> observations deleted from each end before the mean is computed.</p>

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

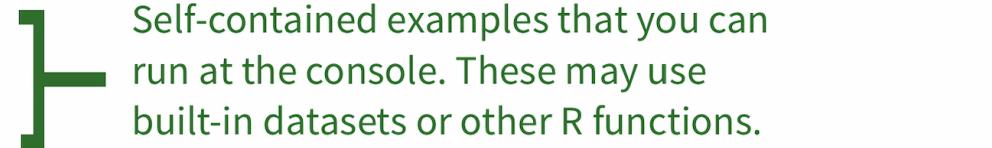
[weighted.mean](#), [mean.POSIXct](#), [colMeans](#) for row and column means.

Examples

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

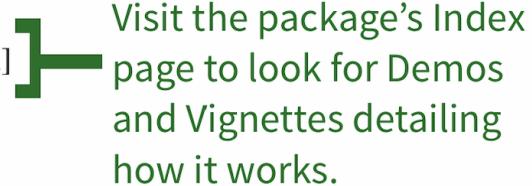


Other related functions



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.