Date Science and Applications with R

Tidy data

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Data wrangling: dplyr

> Data scientists, according to interviews and expert estimates, spend from 50 percent to 80 percent of their time mired in the mundane labor of collecting and preparing data, before it can be explored for useful information. - NYTimes (2014)

What are some common things you like to do with your data? Maybe remove rows or columns, do calculations and maybe add new columns? This is called **data wrangling**. It's not data management or data manipulation: you **keep the raw data raw** and do these things programatically in R with the tidyverse.

We are going to introduce you to data wrangling in R first with the tidyverse. The tidyverse is a suite of packages that match a philosophy of data science developed by Hadley Wickham and the RStudio team. I find it to be a more straight-forward way to learn R. We will also show you by comparison what code will look like in "Base R".

Objectives

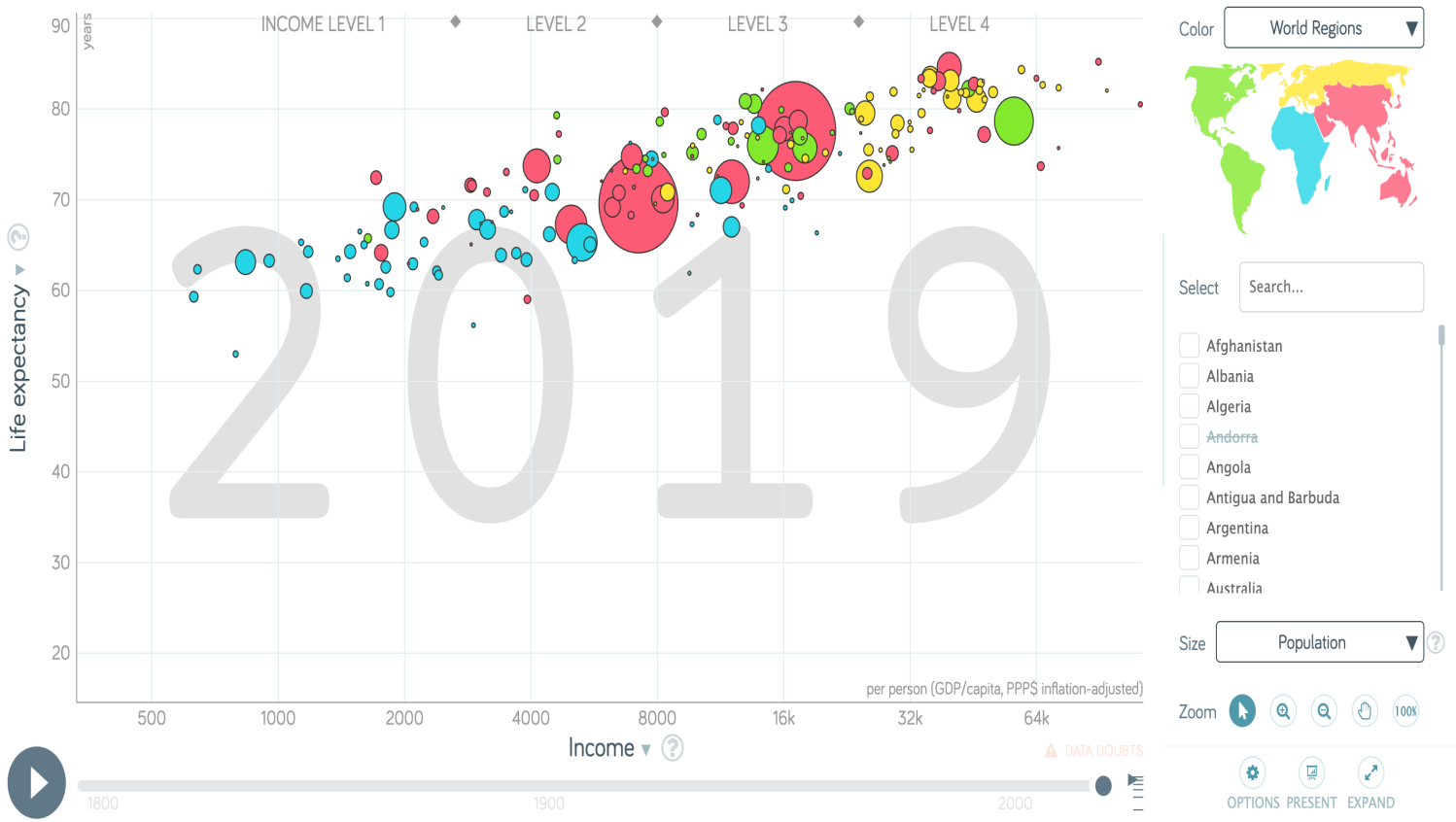
- discuss tidy data
- read data from online into R
- explore gapminder data with base-R functions
- wrangle gapminder data with dplyr tidyverse functions
- practice RStudio-GitHub workflow

Data and packages

Gapminder data

We'll be using Gapminder data, which represents the health and wealth of nations. It was pioneered by Hans Rosling, who is famous for describing the prosperity of nations over time through famines, wars and other historic events with this beautiful data visualization in his 2006 TED Talk: The best stats you've ever seen:

Gapminder Motion Chart



We'll use the package `dplyr`, which is bundled within the `tidyverse` package. Please install the `tidyverse` ahead of time:

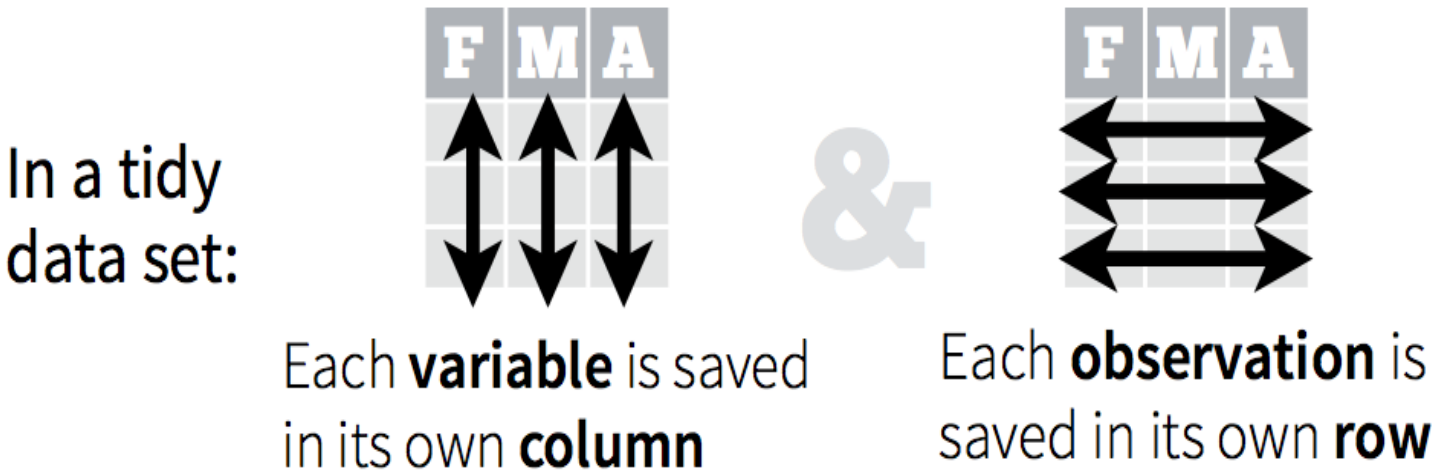
```
install.packages("tidyverse")
```

Tidy Data

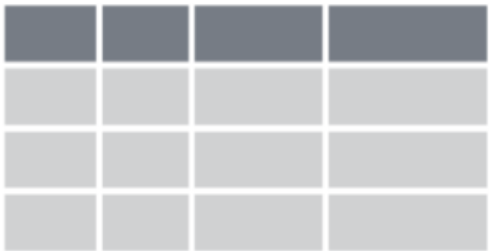
Let's start off discussing Tidy Data.

Hadley Wickham, RStudio's Chief Scientist, and his team have been building R packages for data wrangling and visualization based on the idea of tidy data.

Tidy data has a simple convention: put variables in the columns and observations in the rows.

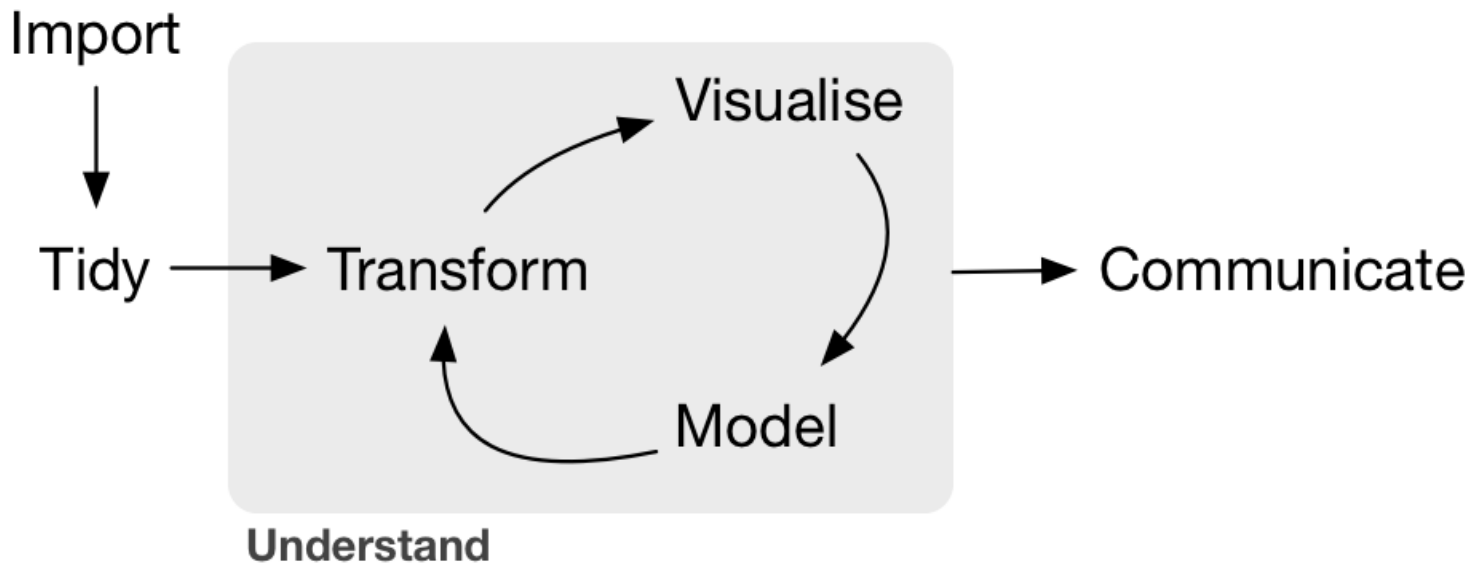


When data are tidy, you are set up to work with it for your analyses, plots, etc.



region	state	code	park_name	type	visitors	year
PW	CA	CHIS	Channel Islands National Park	National Park	1200	1963
PW	CA	CHIS	Channel Islands National Park	National Park	1500	1964
PW	CA	CHIS	Channel Islands National Park	National Park	1600	1965
PW	CA	CHIS	Channel Islands National Park	National Park	300	1966
PW	CA	CHIS	Channel Islands National Park	National Park	15700	1967
PW	CA	CHIS	Channel Islands National Park	National Park	31000	1968
PW	CA	CHIS	Channel Islands National Park	National Park	33100	1969
PW	CA	CHIS	Channel Islands National Park	National Park	32000	1970

Right now we are going to use `dplyr` to wrangle this tidy-ish data set (the transform part of the cycle), and then come back to tidying messy data using `tidyr` once we've had some fun wrangling. These are both part of the `tidyverse` package that we've already installed.



Conceptually, making data tidy first is really critical. Instead of building your analyses around whatever (likely weird) format your data are in, take deliberate steps to make your data tidy. When your data are tidy, you can use a growing assortment of powerful analytical and visualization tools instead of inventing home-grown ways to accommodate your data. This will save you time since you aren't reinventing the wheel, and will make your work more clear and understandable to your collaborators (most importantly, Future You).

Setup

We'll do this in a new RMarkdown file.

Here's what to do:

Clear your workspace (Session > Restart R)

1. New File > R Markdown
2. Save as `gapminder-wrangle.Rmd`
3. Delete the irrelevant text and write a little note to yourself about how we'll be wrangling gapminder data using `dplyr`. You can edit the title too if you need to.

load `tidyverse` (which has `dplyr` inside)

In your R Markdown file, let's make sure we've got our libraries loaded. Write the following:

```
library(tidyverse)      ## install.packages("tidyverse")
```

This is becoming standard practice for how to load a library in a file, and if you get an error that the library doesn't exist, you can install the package easily by running the code within the comment (highlight `install.packages("tidyverse")` and run it).

Explore the gapminder data.frame

read data with `readr::read_csv()`

In our R Markdown, let's read this csv file and name the variable "gapminder". We will use the `read_csv()` function from the `readr` package (part of the tidyverse, so it's already installed!).

Let's inspect:

```
View(gapminder)
```

Let's use head and tail:

```
head(gapminder) # shows first 6
```

```
## # A tibble: 6 x 6
##   country      year      pop continent lifeExp gdpPercap
##   <chr>       <dbl>    <dbl> <chr>       <dbl>     <dbl>
## 1 Afghanistan  1952  8425333 Asia         28.8      779.
## 2 Afghanistan  1957  9240934 Asia         30.3      821.
## 3 Afghanistan  1962 10267083 Asia         32.0      853.
## 4 Afghanistan  1967 11537966 Asia         34.0      836.
## 5 Afghanistan  1972 13079460 Asia         36.1      740.
## 6 Afghanistan  1977 14880372 Asia         38.4      786.
```

```
tail(gapminder) # shows last 6
```

```
## # A tibble: 6 x 6
##   country   year      pop continent lifeExp gdpPercap
##   <chr>    <dbl>    <dbl> <chr>       <dbl>     <dbl>
## 1 Zimbabwe  1982  7636524 Africa       60.4      789.
## 2 Zimbabwe  1987  9216418 Africa       62.4      706.
## 3 Zimbabwe  1992 10704340 Africa       60.4      693.
## 4 Zimbabwe  1997 11404948 Africa       46.8      792.
## 5 Zimbabwe  2002 11926563 Africa       40.0      672.
## 6 Zimbabwe  2007 12311143 Africa       43.5      470.
```

```
head(gapminder, 10) # shows first X that you indicate
```

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

`str()` will provide a sensible description of almost anything: when in doubt, inspect using str() on some of the recently created objects to get some ideas about what to do next.

```
str(gapminder) # ?str - displays the structure of an object
```

```
## spec_tbl_df [1,704 × 6] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ country  : chr [1:1704] "Afghanistan" "Afghanistan" "Afghanistan" "Af
##  $ year     : num [1:1704] 1952 1957 1962 1967 1972 ...
##  $ pop      : num [1:1704] 8425333 9240934 10267083 11537966 13079460 ..
##  $ continent: chr [1:1704] "Asia" "Asia" "Asia" "Asia" ...
##  $ lifeExp  : num [1:1704] 28.8 30.3 32 34 36.1 ...
##  $ gdpPercap: num [1:1704] 779 821 853 836 740 ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   country = col_character(),
##   ..   year = col_double(),
##   ..   pop = col_double(),
##   ..   continent = col_character(),
##   ..   lifeExp = col_double(),
##   ..   gdpPercap = col_double()
##   .. )
```

`gapminder` is a `data.frame`. It is also a `tibble`, a modern extended structure based on data.frame.

- Tibbles are data.frames but modify some older behaviours to make life a little easier
- Preferred data format in the tidyverse
- No need to worry about this!

`dplyr` basics

There are five `dplyr` functions that you will use to do the vast majority of data manipulations:

- `filter()`: pick observations by their values
- `select()`: pick variables by their names
- `mutate()`: create new variables with functions of existing variables
- `summarise()`: collapse many values down to a single summary
- `arrange()`: reorder the rows

These can all be used in conjunction with `group_by()` which changes the scope of each function from operating on the entire dataset to operating on it group-by-group. These six functions provide the verbs for a language of data manipulation.

All verbs work similarly:

1. The first argument is a data frame.
2. The subsequent arguments describe what to do with the data frame. You can refer to columns in the data frame directly without using `$`.
3. The result is a new data frame.

Together these properties make it easy to chain together multiple simple steps to achieve a complex result.

`filter()` subsets data row-wise (observations)

You will want to isolate bits of your data; maybe you want to only look at a single country or a few years. R calls this subsetting.

`filter()` is a function in dplyr that takes logical expressions and returns the rows for which all are TRUE.

Visually, we are doing this (thanks RStudio for your cheatsheet):

Remember your logical expressions? Conditional operators accepted in filter: `==, <, >, <=, >=, is.na(), !is.na(), %in%, !, |, &, xor()`

```
filter(gapminder, lifeExp < 29)
```

```
## # A tibble: 2 x 6
##   country      year     pop continent lifeExp gdpPercap
##   <chr>       <dbl>   <dbl> <chr>       <dbl>     <dbl>
## 1 Afghanistan  1952 8425333 Asia         28.8      779.
## 2 Rwanda       1992 7290203 Africa       23.6      737.
```

You can say this out loud: “Filter the gapminder data for life expectancy less than 29”. Notice that when we do this, all the columns are returned, but only the rows that have the life expectancy less than 29. We’ve subsetted by row.

Let's try another: "Filter the gapminder data for the country Mexico".

```
filter(gapminder, country == "Mexico")
```

```
## # A tibble: 12 x 6
##    country  year      pop continent lifeExp gdpPercap
##    <chr>   <dbl>    <dbl> <chr>       <dbl>     <dbl>
##  1 Mexico   1952  30144317 Americas     50.8     3478.
##  2 Mexico   1957  35015548 Americas     55.2     4132.
##  3 Mexico   1962  41121485 Americas     58.3     4582.
##  4 Mexico   1967  47995559 Americas     60.1     5755.
##  5 Mexico   1972  55984294 Americas     62.4     6809.
##  6 Mexico   1977  63759976 Americas     65.0     7675.
##  7 Mexico   1982  71640904 Americas     67.4     9611.
##  8 Mexico   1987  80122492 Americas     69.5     8688.
##  9 Mexico   1992  88111030 Americas     71.5     9472.
## 10 Mexico   1997  95895146 Americas     73.7     9767.
## 11 Mexico   2002 102479927 Americas     74.9    10742.
## 12 Mexico   2007 108700891 Americas     76.2    11978.
```

How about if we want two country names? We can't use the == operator here, because it can only operate on one thing at a time. We will use the `%in%` operator:

```
filter(gapminder, country %in% c("Mexico", "Peru"))
```

```
## # A tibble: 24 x 6
##    country  year      pop continent lifeExp gdpPercap
##    <chr>   <dbl>    <dbl> <chr>       <dbl>     <dbl>
##  1 Mexico   1952 30144317 Americas     50.8     3478.
##  2 Mexico   1957 35015548 Americas     55.2     4132.
##  3 Mexico   1962 41121485 Americas     58.3     4582.
##  4 Mexico   1967 47995559 Americas     60.1     5755.
##  5 Mexico   1972 55984294 Americas     62.4     6809.
##  6 Mexico   1977 63759976 Americas     65.0     7675.
##  7 Mexico   1982 71640904 Americas     67.4     9611.
##  8 Mexico   1987 80122492 Americas     69.5     8688.
##  9 Mexico   1992 88111030 Americas     71.5     9472.
## 10 Mexico   1997 95895146 Americas     73.7     9767.
## # … with 14 more rows
```

How about if we want Mexico in 2002? You can pass filter different criteria:

```
filter(gapminder, country == "Mexico", year == 2002)
```

```
## # A tibble: 1 x 6
##   country  year       pop continent lifeExp gdpPercap
##   <chr>   <dbl>     <dbl> <chr>       <dbl>     <dbl>
## 1 Mexico   2002 102479927 Americas     74.9    10742.
```

Exercise

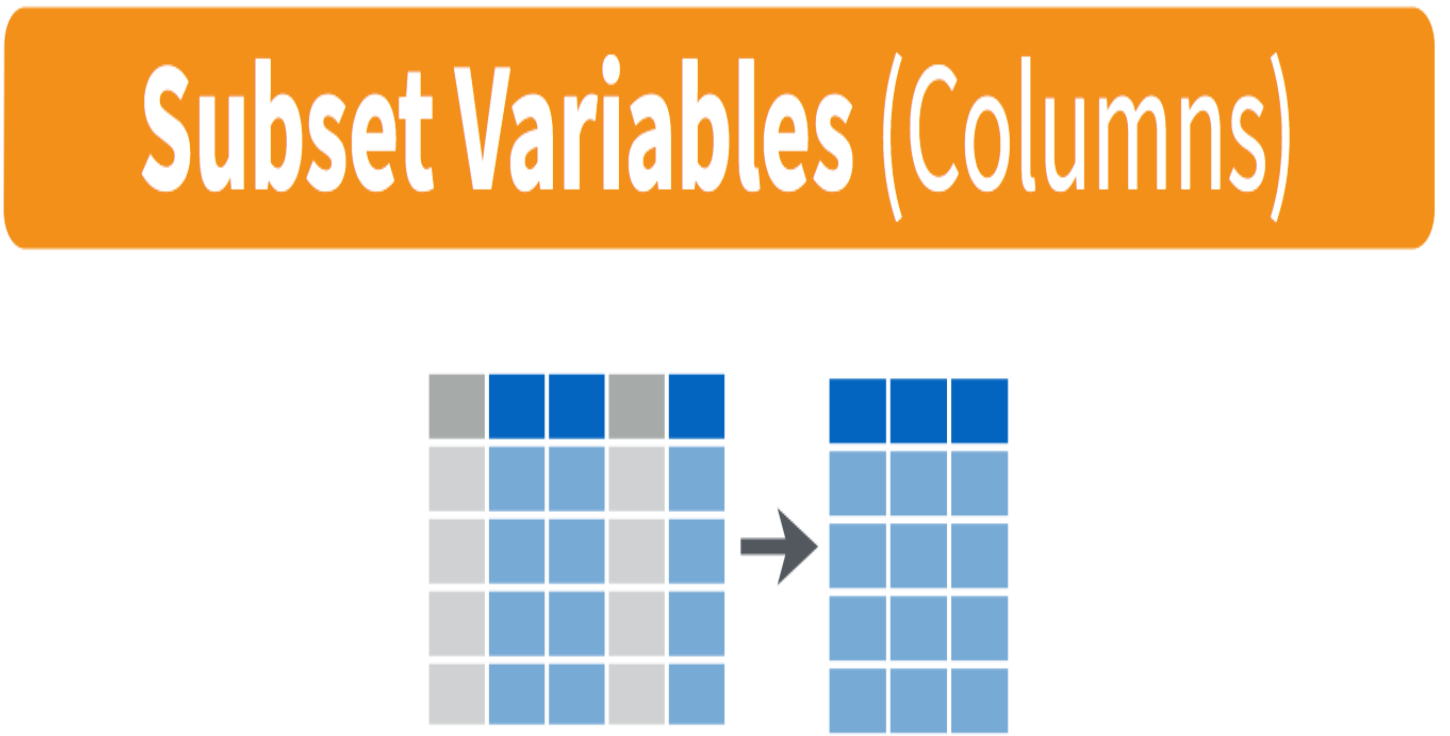
What was the average life expectency in Brazil between 1987 and 2007? Hint: do this in 2 steps by assigning a variable and then using the `mean()` function.

Then, sync to Github.com (pull, stage, commit, push).

`select()` subsets data column-wise (variables)

We use `select()` to subset the data on variables or columns.

Visually, we are doing this (thanks RStudio for your cheatsheet):



- We can select multiple columns with a comma, after we specify the data frame (gapminder).

```
gap1 <- dplyr::select(gapminder, year, country, lifeExp)
head(gap1, 3)
```

```
## # A tibble: 3 x 3
##    year country     lifeExp
##   <dbl> <chr>         <dbl>
## 1  1952 Afghanistan    28.8
## 2  1957 Afghanistan    30.3
## 3  1962 Afghanistan    32.0
```

- We can select a range of variables with a semicolon.

```
gap2 <- dplyr::select(gapminder, year:lifeExp)
head(gap2, 3)
```

```
## # A tibble: 3 x 4
##    year      pop continent lifeExp
##   <dbl>    <dbl> <chr>       <dbl>
## 1  1952  8425333 Asia         28.8
## 2  1957  9240934 Asia         30.3
## 3  1962 10267083 Asia         32.0
```

- We can select columns with indices.

```
gap3 <- dplyr::select(gapminder, 1, 2, 4)
head(gap3, 3)
```

```
## # A tibble: 3 x 3
##   country      year continent
##   <chr>       <dbl> <chr>
## 1 Afghanistan  1952 Asia
## 2 Afghanistan  1957 Asia
## 3 Afghanistan  1962 Asia
```

- We can also use – to deselect columns

```
gap4 <- dplyr::select(gapminder, -continent, -lifeExp) # you can us
head(gap4, 3)
```

```
## # A tibble: 3 x 4
##   country      year      pop gdpPercap
##   <chr>       <dbl>    <dbl>     <dbl>
## 1 Afghanistan  1952  8425333      779.
## 2 Afghanistan  1957  9240934      821.
## 3 Afghanistan  1962 10267083      853.
```

Use `select()` and `filter()` together

Let's filter for Cambodia and remove the continent and lifeExp columns. We'll save this as a variable. Actually, as two temporary variables, which means that for the second one we need to operate on `gap_cambodia`, not `gapminder`.

```
gap_cambodia  <- filter(gapminder, country == "Cambodia")
gap_cambodia2 <- dplyr::select(gap_cambodia, -continent, -lifeExp)
```

We also could have called them both `gap_cambodia` and overwritten the first assignment. Either way, naming them and keeping track of them gets super cumbersome, which means more time to understand what's going on and opportunities for confusion or error.

Meet the new pipe %>% operator

Before we go any further, we should explore the new pipe operator that `dplyr` imports from the `magrittr` package by Stefan Bache. This is going to **change your life**. You no longer need to enact multi-operation commands by nesting them inside each other. And we won't need to make temporary variables like we did in the Cambodia example above. This new syntax leads to code that is much easier to write and to read: it actually tells the story of your analysis.

Here's what it looks like: `%>%`. The RStudio keyboard shortcut: Ctrl + Shift + M (Windows), Cmd + Shift + M (Mac).

Let's demo then I'll explain:

```
gapminder %>% head(3)
```

```
## # A tibble: 3 x 6
##   country      year      pop continent lifeExp gdpPercap
##   <chr>       <dbl>    <dbl> <chr>       <dbl>     <dbl>
## 1 Afghanistan  1952  8425333 Asia         28.8      779.
## 2 Afghanistan  1957  9240934 Asia         30.3      821.
## 3 Afghanistan  1962 10267083 Asia         32.0      853.
```

This is equivalent to `head(gapminder, 3)`. This pipe operator takes the thing on the left-hand-side and **pipes** it into the function call on the right-hand-side. It literally drops it in as the first argument.

You should think "and then" whenever you see the pipe operator, `%>%`.

One of the most awesome things about this is that you START with the data before you say what you're doing to DO to it. So above: "take the gapminder data, and then give me the first three entries".

This means that instead of this:

```
## instead of this...
gap_cambodia  <- filter(gapminder, country == "Cambodia")
gap_cambodia2 <- dplyr::select(gap_cambodia, -continent, -lifeExp)

## ...we can do this
gap_cambodia  <- gapminder %>% filter(country == "Cambodia")
gap_cambodia2 <- gap_cambodia %>% dplyr::select(-continent, -lifeEx
```

So you can see that we'll start with gapminder in the first example line, and then `gap_cambodia` in the second. This makes it a bit easier to see what data we are starting with and what we are doing to it.

But, we still have those temporary variables so we're not truly that better off. But get ready to be majorly impressed:

Revel in the convenience

We can use the pipe to chain those two operations together:

```
gap_cambodia  <- gapminder %>%
  filter(country == "Cambodia") %>%
  dplyr::select(-continent, -lifeExp)
```

What's happening here? In the second line, we were able to delete `gap_cambodia2 <- gap_cambodia`, and put the pipe operator above. This is possible since we wanted to operate on the `gap_cambodia` data anyways. And we weren't truly excited about having a second variable named `gap_cambodia2` anyways, so we can get rid of it. This is huge, because most of your data wrangling will have many more than 2 steps, and we don't want a `gap_cambodia14`!

By using multiple lines I can actually read this like a story and there aren't temporary variables that get super confusing. In my head:

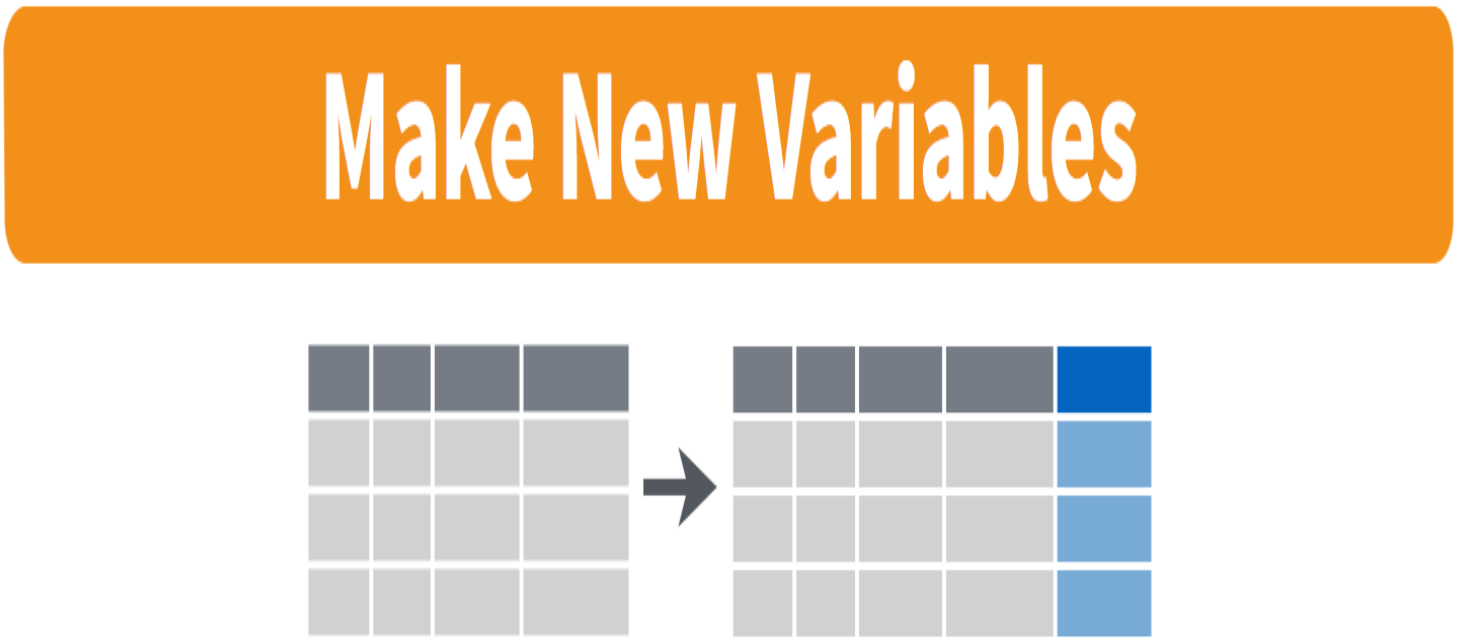
> "start with the gapminder data, and then filter for Cambodia, and then drop the variables continent and lifeExp."

Being able to read a story out of code like this is really game-changing. We'll continue using this syntax as we learn the other dplyr verbs.

`mutate()` adds new variables

Let's say we needed to add an index column so we know which order these data came in. Let's not make a new variable, let's add a column to our gapminder data frame. How do we do that? With the ·mutate()· function.

Visually, we are doing this (thanks RStudio for your cheatsheet):



Imagine we want to know each country's annual GDP. We can multiply pop by gdpPercap to create a new column named gdp.

```
gapminder %>%
  mutate(gdp = pop * gdpPercap)
```

```
## # A tibble: 1,704 x 7
##    country      year      pop continent lifeExp gdpPercap          gdp
##    <chr>       <dbl>    <dbl> <chr>       <dbl>     <dbl>        <dbl>
##  1 Afghanistan  1952  8425333 Asia         28.8      779.  6567086330.
##  2 Afghanistan  1957  9240934 Asia         30.3      821.  7585448670.
##  3 Afghanistan  1962 10267083 Asia         32.0      853.  8758855797.
##  4 Afghanistan  1967 11537966 Asia         34.0      836.  9648014150.
##  5 Afghanistan  1972 13079460 Asia         36.1      740.  9678553274.
##  6 Afghanistan  1977 14880372 Asia         38.4      786. 11697659231.
##  7 Afghanistan  1982 12881816 Asia         39.9      978. 12598563401.
##  8 Afghanistan  1987 13867957 Asia         40.8      852. 11820990309.
##  9 Afghanistan  1992 16317921 Asia         41.7      649. 10595901589.
## 10 Afghanistan  1997 22227415 Asia         41.8      635. 14121995875.
## # … with 1,694 more rows
```

Your turn

> Calculate the population in thousands for all Asian countries in the year 2007 and add it as a new column.
>
> Then, sync to Github.com (pull, stage, commit, push).

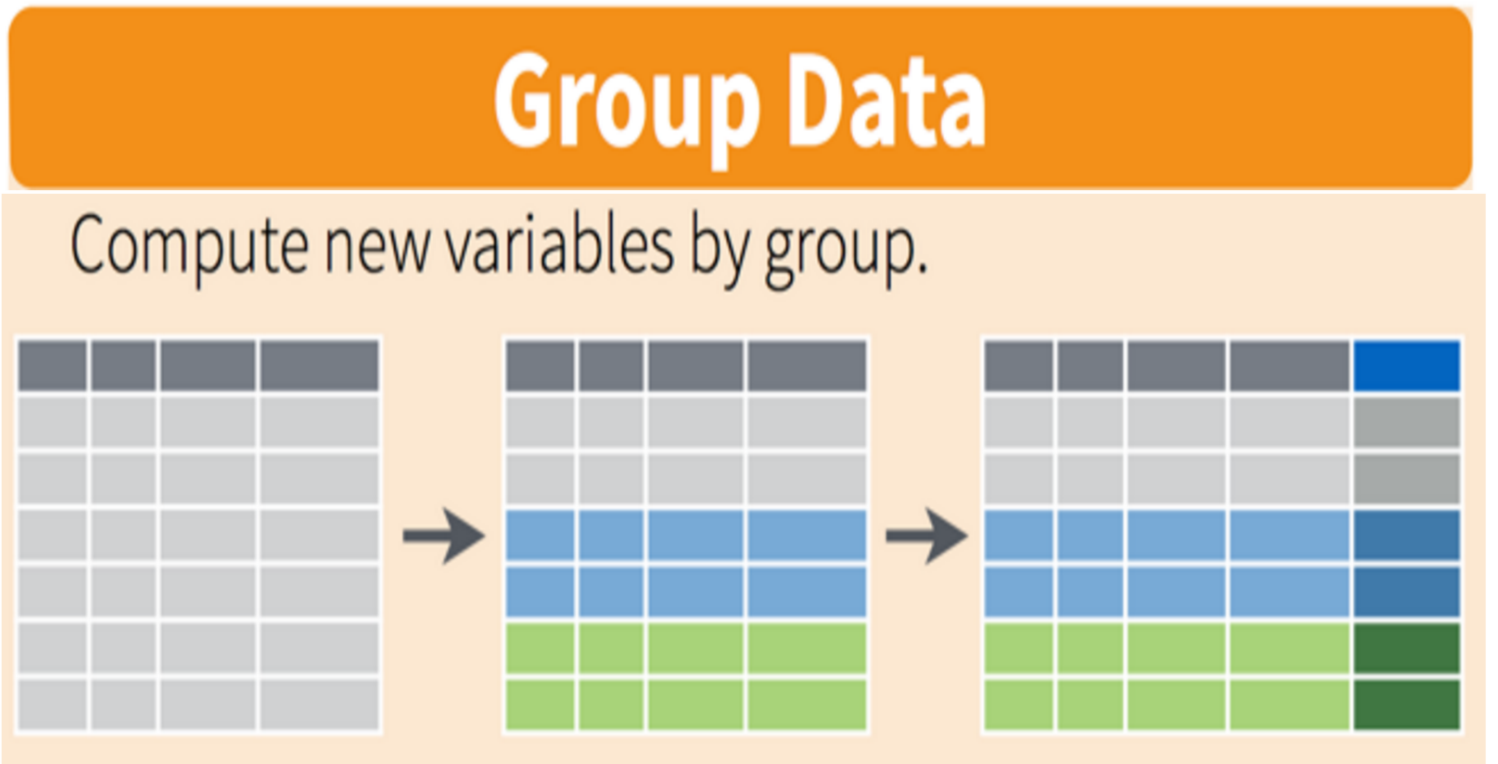
Functions in `mutate()`

- arithmetic operators: `+`, `-`, `*`, `/`, `^`
- modular arithmetic: `%/%`, `%%`
- logs: `log()`, `log2()`, `log10()`
- offsets: `lead()`, `lag()`
- cumulative and rolling aggregates: `cumsum()`, `cumprod()`, `cummin()`, `cummax()`, `cummean()`
- logical comparisons: `<`, `<=`, `>`, `>=`, `!=`
- ranking: `min_rank()`, `row_number()`, `dense_rank()`, `percent_rank()`, `cume_dist()`, `ntile()`
- Any R or custom function that returns a **vector** with the same length as the number of rows

`group_by()` operates on groups

What if we wanted to know the total population on each continent in 2002? Answering this question requires a **grouping variable**.

Visually, we are doing this (thanks RStudio for your cheatsheet):



By using `group_by()` we can set our grouping variable to `continent` and create a new column called `cont_pop` that will add up all country populations by their associated continents.

```
gapminder %>%
  filter(year == 2002) %>%
  group_by(continent) %>%
  mutate(cont_pop = sum(pop))
```

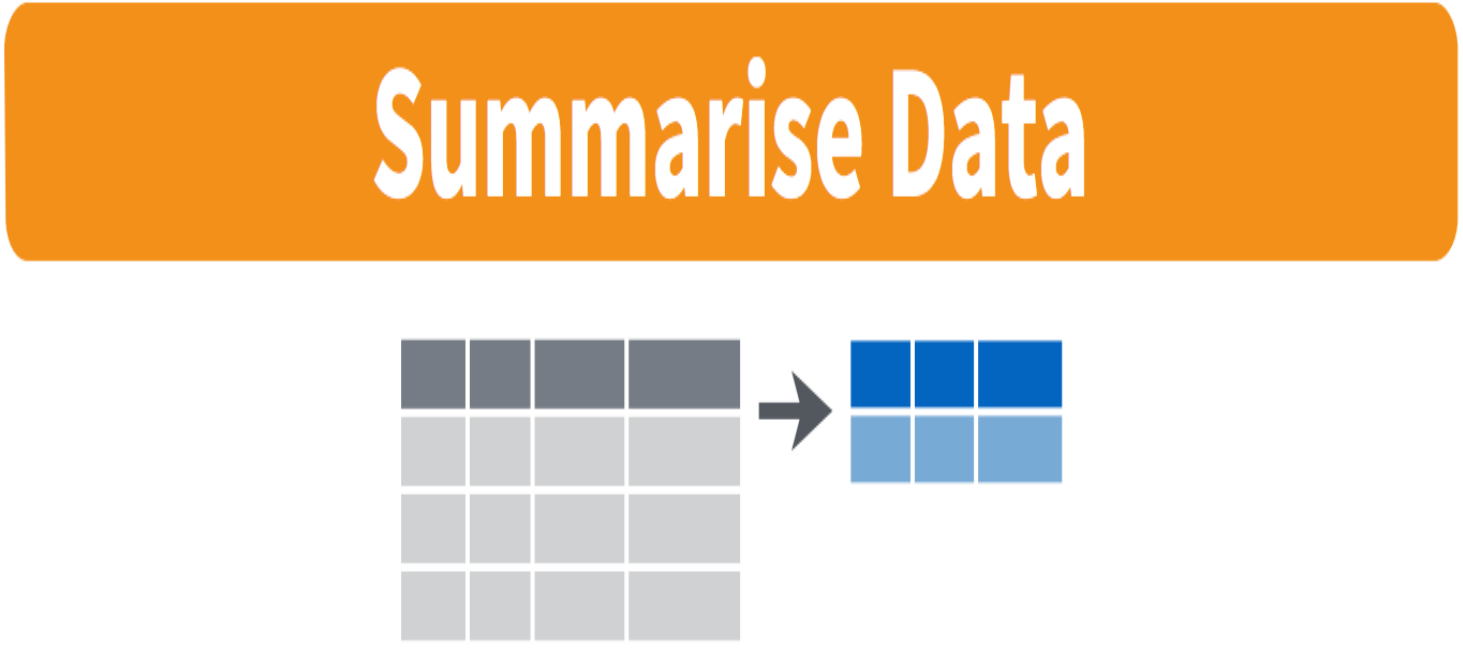
```
## # A tibble: 142 x 7
## # Groups:   continent [5]
##    country      year       pop continent lifeExp gdpPercap   cont_pop
##    <chr>       <dbl>     <dbl> <chr>       <dbl>     <dbl>      <dbl>
##  1 Afghanistan  2002  25268405 Asia         42.1      727. 3601802203
##  2 Albania      2002   3508512 Europe       75.7     4604.  578223869
##  3 Algeria      2002  31287142 Africa       71.0     5288.  833723916
##  4 Angola       2002  10866106 Africa       41.0     2773.  833723916
##  5 Argentina    2002  38331121 Americas     74.3     8798.  849772762
##  6 Australia    2002  19546792 Oceania      80.4    30688.   23454829
##  7 Austria      2002   8148312 Europe       79.0    32418.  578223869
##  8 Bahrain      2002    656397 Asia         74.8    23404. 3601802203
##  9 Bangladesh   2002 135656790 Asia         62.0     1136. 3601802203
## 10 Belgium      2002  10311970 Europe       78.3    30486.  578223869
## # … with 132 more rows
```

What if we don't care about the other columns and we only want each continent and their population in 2002? Here's the next function:

`summarize()` with `group_by()`

We want to operate on a group, but actually collapse or distill the output from that group. The `summarize()` function will do that for us.

Visually, we are doing this (thanks RStudio for your cheatsheet):



Here we go:

```
gapminder %>%
  group_by(continent) %>%
  summarize(cont_pop = sum(pop)) %>%
  ungroup()
```

```
## # A tibble: 5 x 2
##   continent    cont_pop
##   <chr>           <dbl>
## 1 Africa     6187585961
## 2 Americas   7351438499
## 3 Asia      30507333902
## 4 Europe     6181115304
## 5 Oceania     212992136
```

`summarize()` will actually only keep the columns that are `grouped_by` or summarized. So if we wanted to keep other columns, we'd have to do have a few more steps. `ungroup()` removes the grouping and it's good to get in the habit of using it after a `group_by()`.

We can use more than one grouping variable. Let's get total populations by continent and year.

```
gapminder %>%
  group_by(continent, year) %>%
  summarize(cont_pop = sum(pop))
```

```
## `summarise()` has grouped output by 'continent'. You can override using t
```

```
## # A tibble: 60 x 3
## # Groups:   continent [5]
##    continent  year  cont_pop
##    <chr>     <dbl>     <dbl>
##  1 Africa     1952 237640501
##  2 Africa     1957 264837738
##  3 Africa     1962 296516865
##  4 Africa     1967 335289489
##  5 Africa     1972 379879541
##  6 Africa     1977 433061021
##  7 Africa     1982 499348587
##  8 Africa     1987 574834110
##  9 Africa     1992 659081517
## 10 Africa     1997 743832984
## # … with 50 more rows
```

Functions in `summarise()`

- location: `mean(x)`, `median(x)`
- spread: `sd(x)`, `IQR(x)`, `mad(x)`
- rank: `min(x)`, `quantile(x, 0.25)`, `max(x)`
- position: `first(x)`, `nth(x, 2)`, `last(x)`
- count: `n(x)`, `sum(!is.na(x))`, `n_distinct(x)`
- any base R or custom function that returns **one summary value**

arrange() orders columns

This is ordered alphabetically, which is cool. But let's say we wanted to order it in ascending order for year. The dplyr function is arrange().

```
gapminder %>%
  group_by(continent, year) %>%
  summarize(cont_pop = sum(pop)) %>%
  arrange(year)
```

```
## # A tibble: 60 x 3
## # Groups:   continent [5]
##    continent  year    cont_pop
##    <chr>     <dbl>       <dbl>
##  1 Africa     1952  237640501
##  2 Americas   1952  345152446
##  3 Asia       1952 1395357352.
##  4 Europe     1952  418120846
##  5 Oceania    1952   10686006
##  6 Africa     1957  264837738
##  7 Americas   1957  386953916
##  8 Asia       1957 1562780599
##  9 Europe     1957  437890351
## 10 Oceania    1957   11941976
## # … with 50 more rows
```

- Use `desc(var)` to arrange in decreasing order
- Possible to use multiple variables (categorical)

Exercise

> What is the maximum GDP per continent across all years?

Your turn

> 1. arrange your data frame in descending order (opposite of what we've done). Expect that this is possible: ?arrange
> 2. save your data frame as a variable
> 3. find the maximum life expectancy for countries in Asia. What is the earliest year you encounter? The latest? Hint: you can use or `base::max` and `dplyr::arrange()`
> 4. Knit your RMarkdown file, and sync it to GitHub (pull, stage, commit, push)

All together now

We have done a pretty incredible amount of work in a few lines. Our whole analysis is this. Imagine the possibilities from here. It's very readable: you see the data as the first thing, it's not nested. Then, you can read the verbs. This is the whole thing, with explicit package calls from `readr::` and `dplyr::`:

```
## load libraries
library(tidyverse) ## install.packages('tidyverse')

## read in data
gapminder <- readr::read_csv('data/gapminder.csv')

## summarize
gap_max_life_exp <- gapminder %>%
  dplyr::select(-continent, -lifeExp) %>% # or select(country, year
  dplyr::group_by(country) %>%
  dplyr::mutate(gdp = pop * gdpPercap) %>%
  dplyr::summarize(max_gdp = max(gdp)) %>%
  dplyr::ungroup()
```

Compare to base R

Instead of calculating the max for each country like we did with dplyr above, here we will calculate the max for one country, Mexico.

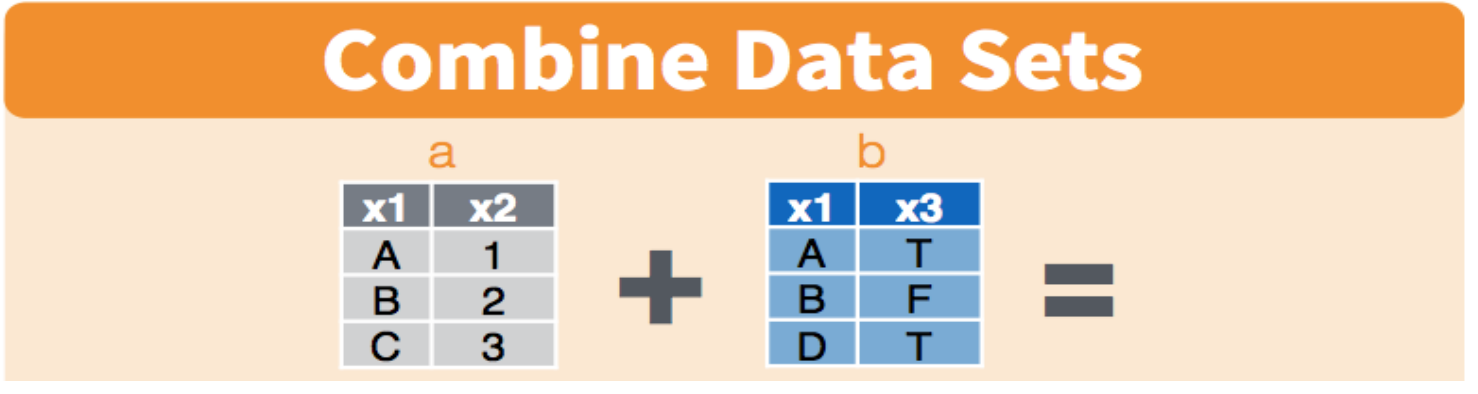
```
gapminder <- read.csv('data/gapminder.csv', stringsAsFactors = FALS
x1  <- gapminder[ , c('country', 'year', 'pop', 'gdpPercap') ]# sub
mex <- x1[x1$country == "Mexico", ] # subset rows
mex$gdp <- mex$pop * mex$gdpPercap # add new columns
mex$max_gdp <- max(mex$gdp)
```

Note too that the chain operator `%>%` that we used with the `tidyverse` lets us get away from the temporary variable `x1`.

Joining datasets

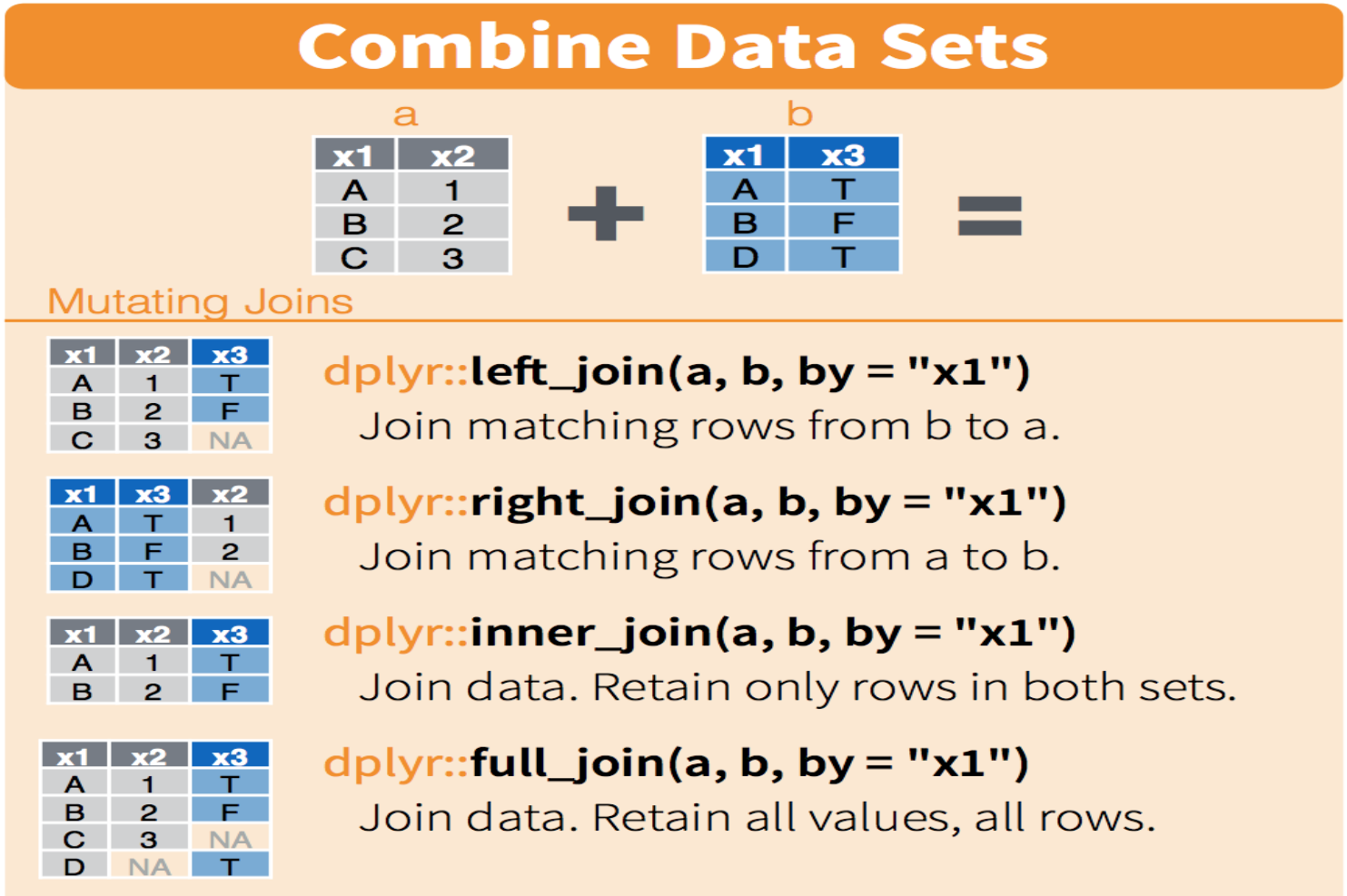
Most of the time you will have data coming from different places or in different files, and you want to put them together so you can analyze them. Datasets you'll be joining can be called relational data, because it has some kind of relationship between them that you'll be acting upon. In the `tidyverse`, combining data that has a relationship is called "joining".

From the RStudio cheatsheet (note: this is an earlier version of the cheatsheet but I like the graphics):



Let’s have a look at this and pretend that the x1 column is a study site and x2 is the variables we’ve recorded (like species count) and x3 is data from an instrument (like temperature data). Notice how you may not have exactly the same observations in the two datasets: in the x1 column, observations A and B appear in both datasets, but notice how the table on the left has observation C, and the table on the right has observation D.

If you wanted to combine these two tables, how would you do it? There are some decisions you'd have to make about what was important to you. The cheatsheet visualizes it for us:



We will only talk about this briefly here, but you can refer to this more as you have your own datasets that you want to join. This describes the figure above:

- `left_join` keeps everything from the left table and matches as much as it can from the right table. In R, the first thing that you type will be the left table (because it's on the left)
- `right_join` keeps everything from the right table and matches as much as it can from the left table
- `inner_join` only keeps the observations that are similar between the two tables
- `full_join` keeps all observations from both tables.

Let's play with these CO2 emissions data to illustrate:

```
## read in the data. (same URL as yesterday, with co2.csv instead o
co2 <- read_csv("data/co2.csv")

## explore
co2 %>% head()
```

```
## # A tibble: 6 x 2
##   country        co2_2007
##   <chr>             <dbl>
## 1 Afghanistan      2938.
## 2 Albania          4218.
## 3 Algeria        105838.
## 4 American Samoa     18.4
## 5 Angola          17405.
## 6 Anguilla           12.4
```

```
co2 %>% dim() # 12
```

```
## [1] 12  2
```

```r
## create new variable that is only 2007 data
gap_2007 <- gapminder %>%
  filter(year == 2007)
gap_2007 %>% dim() # 142
```

```
## [1] 142   6
```

```r
## left_join gap_2007 to co2
lj <- left_join(gap_2007, co2, by = "country")

## explore
lj %>% dim() #142
```

```
## [1] 142   7
```

```r
lj %>% head(3) # lots of NAs in the co2_2017 columm
```

```
## # A tibble: 3 x 7
##   country      year      pop continent lifeExp gdpPercap co2_2007
##   <chr>       <dbl>    <dbl> <chr>       <dbl>     <dbl>    <dbl>
## 1 Afghanistan  2007 31889923 Asia         43.8      975.    2938.
## 2 Albania      2007  3600523 Europe       76.4     5937.    4218.
## 3 Algeria      2007 33333216 Africa       72.3     6223.  105838.
```

```r
## right_join gap_2007 and co2
rj <- right_join(gap_2007, co2, by = "country")

## explore
rj %>% dim() # 12
```

```
## [1] 12  7
```

```r
rj %>% head(3)
```

```
## # A tibble: 3 x 7
##   country      year      pop continent lifeExp gdpPercap co2_2007
##   <chr>       <dbl>    <dbl> <chr>       <dbl>     <dbl>    <dbl>
## 1 Afghanistan  2007 31889923 Asia         43.8      975.    2938.
## 2 Albania      2007  3600523 Europe       76.4     5937.    4218.
## 3 Algeria      2007 33333216 Africa       72.3     6223.  105838.
```

Key Points

Data manipulation functions in `dplyr` allow you to `filter()` by rows and `select()` by columns, create new columns with `mutate()`, and `group_by()` unique column values to apply `summarize()` for new columns that define aggregate values across groupings. The "then" operator `%>%` allows you to chain successive operations without needing to define intermediary variables for creating the most parsimonious, easily read analysis.

Error: unexpected SPECIAL in "%>%"

If you get this error, it is probably because you have a line that starts with a pipe. The pipe should be at the end of the previous line, not the start of the current line.

Yes:

```
gap_cambodia  <- gapminder %>% filter(country == "Cambodia") %>%
  select(-continent, -lifeExp)
```

No:

```
gap_cambodia  <- gapminder %>% filter(country == "Cambodia")
  %>% select(-continent, -lifeExp)
# Error: unexpected SPECIAL in "  %>%"
```

Data Wrangling: `tidyr`

Now you have some experience working with tidy data and seeing the logic of wrangling when data are structured in a tidy way. But 'real' data often don't start off in a tidy way, and require some reshaping to become tidy. The `tidyr` package is for reshaping data. You won't use `tidyr` functions as much as you use dplyr functions, but it is incredibly powerful when you need it.

Why is this important? Well, if your data are formatted in a standard way, you will be able to use analysis tools that operate on that standard way. Your analyses will be streamlined and you won't have to reinvent the wheel every time you see data in a different.

Data are often entered in a *wide* format where each row is often a site/subject/patient and you have multiple observation variables containing the same type of data.

An example of data in a *wide* format is the `AirPassengers` dataset which provides information on monthly airline passenger numbers from 1949-1960. You'll notice that each row is a single year and the columns are each month Jan - Dec.

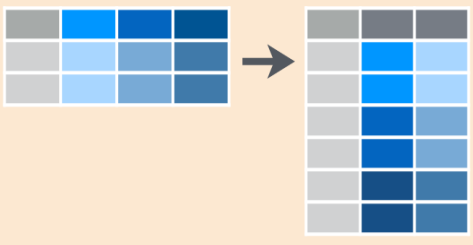
```
AirPassengers
```

```
##      Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
## 1949 112 118 132 129 121 135 148 148 136 119 104 118
## 1950 115 126 141 135 125 149 170 170 158 133 114 140
## 1951 145 150 178 163 172 178 199 199 184 162 146 166
## 1952 171 180 193 181 183 218 230 242 209 191 172 194
## 1953 196 196 236 235 229 243 264 272 237 211 180 201
## 1954 204 188 235 227 234 264 302 293 259 229 203 229
## 1955 242 233 267 269 270 315 364 347 312 274 237 278
## 1956 284 277 317 313 318 374 413 405 355 306 271 306
## 1957 315 301 356 348 355 422 465 467 404 347 305 336
## 1958 340 318 362 348 363 435 491 505 404 359 310 337
## 1959 360 342 406 396 420 472 548 559 463 407 362 405
## 1960 417 391 419 461 472 535 622 606 508 461 390 432
```

This format is intuitive for data entry, but less so for data analysis. If you wanted to calculate the monthly mean, where would you put it? As another row?

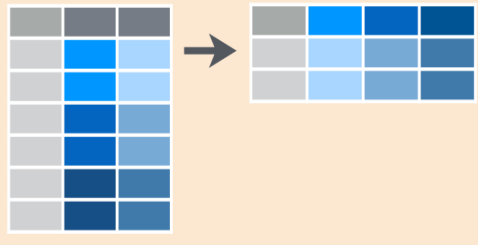
Often, data must be reshaped for it to become tidy data. What does that mean? There are four main verbs we'll use, which are essentially pairs of opposites:

- turn columns into rows (`gather()`),
- turn rows into columns (`spread()`),
- turn a character column into multiple columns (`separate()`),
- turn multiple character columns into a single column (`unite()`)



tidyr::**gather(cases, "year", "n", 2:4)**

Gather columns into rows.

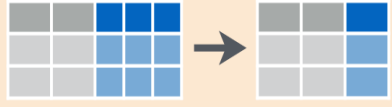


tidyr::**spread(pollution, size, amount)**

Spread rows into columns.

tidyr::**separate(storms, date, c("y", "m", "d"))**

Separate one column into several.



tidyr::**unite(data, col, ..., sep)**

Unite several columns into one.

Explore gapminder dataset

First have a look at the *wide* format data.

You can see there are a lot more columns than the version we looked at before. This format is pretty common, because it can be a lot more intuitive to enter data in this way.

continent	country	gdpPercap_1952	gdpPercap_1957	gdpPercap_1962	gdpPercap_1967	gdpPercap_1972	gdpPercap_1977
Africa	Algeria	2449.008185	3013.976023	2550.81688	3246.991771	4182.663766	4910.416756
Africa	Angola	3520.610273	3827.940465	4269.276742	5522.776375	5473.288005	3008.647355
Africa	Benin	1062.7522	959.6010805	949.4990641	1035.831411	1085.796879	1029.161251
Africa	Botswana	851.2411407	918.2325349	983.6539764	1214.709294	2263.611114	3214.857818
Africa	Burkina Faso	543.2552413	617.1834648	722.5120206	794.8265597	854.7359763	743.3870368
Africa	Burundi	339.2964587	379.5646281	355.2032273	412.9775136	464.0995039	556.1032651
Africa	Cameroon	1172.667655	1313.048099	1399.607441	1508.453148	1684.146528	1783.432873
Africa	Central African Republic	1071.310713	1190.844328	1193.068753	1136.056615	1070.013275	1109.374338
Africa	Chad	1178.665927	1308.495577	1389.817618	1196.810565	1104.103987	1133.98495
Africa	Comoros	1102.990936	1211.148548	1406.648278	1876.029643	1937.577675	1172.603047
Africa	Congo Dem. Rep.	780.5423257	905.8602303	896.3146335	861.5932424	904.8960685	795.757282
Africa	Congo Rep.	2125.621418	2315.056572	2464.783157	2677.939642	3213.152683	3259.178978
Africa	Cote d'Ivoire	1388.594732	1500.895925	1728.869428	2052.050473	2378.201111	2517.736547

Setup

We'll learn `tidyr` in an RMarkdown file within a GitHub repository so we can practice what we've learned so far. You can either continue from the same RMarkdown as yesterday, or begin a new one.

Here's what to do:

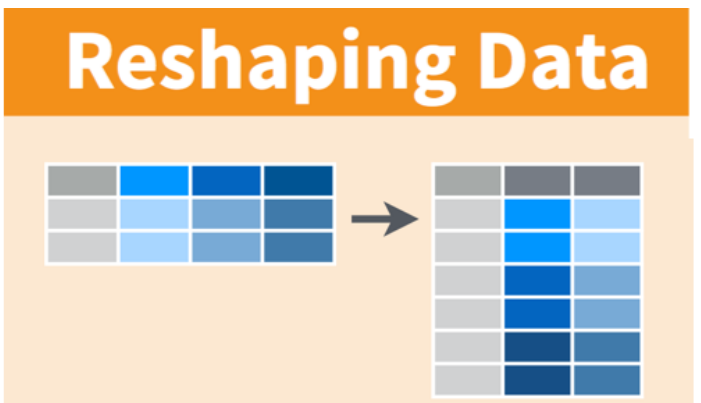
1. Clear your workspace (Session > Restart R)
2. New File > R Markdown..., save as something other than `gapminder-wrangle.Rmd` and delete irrelevant info, or just continue using `gapminder-wrangle.Rmd`

load `tidyverse` (which has `tidyr` inside)

First load `tidyr` in an R chunk. You already have installed the tidyverse, so you should be able to just load it like this (using the comment so you can run `install.packages("tidyverse")` easily if need be):

```
library(tidyverse) # install.packages("tidyverse")
```

`gather()` data from wide to long format



Read in the data. Let's also read in the gapminder data from yesterday so that we can use it to compare later on.

```
## wide format
gap_wide <- readr::read_csv('data/gapminder_wide.csv')
gapminder <- readr::read_csv('data/gapminder.csv')
```

Let's have a look:

```
#head(gap_wide)
str(gap_wide)
```

```
## spec_tbl_df [142 × 38] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ continent     : chr [1:142] "Africa" "Africa" "Africa" "Africa" ...
##  $ country       : chr [1:142] "Algeria" "Angola" "Benin" "Botswana" ...
##  $ gdpPercap_1952: num [1:142] 2449 3521 1063 851 543 ...
##  $ gdpPercap_1957: num [1:142] 3014 3828 960 918 617 ...
##  $ gdpPercap_1962: num [1:142] 2551 4269 949 984 723 ...
##  $ gdpPercap_1967: num [1:142] 3247 5523 1036 1215 795 ...
##  $ gdpPercap_1972: num [1:142] 4183 5473 1086 2264 855 ...
##  $ gdpPercap_1977: num [1:142] 4910 3009 1029 3215 743 ...
##  $ gdpPercap_1982: num [1:142] 5745 2757 1278 4551 807 ...
##  $ gdpPercap_1987: num [1:142] 5681 2430 1226 6206 912 ...
##  $ gdpPercap_1992: num [1:142] 5023 2628 1191 7954 932 ...
##  $ gdpPercap_1997: num [1:142] 4797 2277 1233 8647 946 ...
##  $ gdpPercap_2002: num [1:142] 5288 2773 1373 11004 1038 ...
##  $ gdpPercap_2007: num [1:142] 6223 4797 1441 12570 1217
```

While wide format is nice for data entry, it's not nice for calculations. Some of the columns are a mix of variable (e.g. "gdpPercap") and data ("1952"). What if you were asked for the mean population after 1990 in Algeria? Possible, but ugly. But we know it doesn't need to be so ugly. Let's tidy it back to the format we've been using.

> Question: let's talk this through together. If we're trying to turn the `gap_wide` format into `gapminder` format, what structure does it have that we like? And what do we want to change?

- We like the continent and country columns. We won't want to change those.
- We want 1 column identifying the variable name (`tidyr` calls this a **'key'**), and 1 column for the data (`tidyr` calls this the **'value'**).
- We actually want 3 different columns for variable: `gdpPercap`, `lifeExp`, and `pop`.
- We would like year as a separate column.

Let's get it to long format. We'll have to do this in 2 steps. The first step is to take all of those column names (e.g. `lifeExp_1970`) and make them a variable in a new column, and transfer the values into another column.

> Question: What is our **key-value pair**?

We need to name two new variables in the key-value pair, one for the key, one for the value. It can be hard to wrap your mind around this, so let's give it a try. Let's name them `obstype_year` and `obs_values`.

Here's the start of what we'll do:

```
gap_long <- gap_wide %>%
  gather(key   = obstype_year,
         value = obs_values)
```

Let's inspect our work.

```
str(gap_long)
```

```
## tibble [5,396 × 2] (S3: tbl_df/tbl/data.frame)
##  $ obstype_year: chr [1:5396] "continent" "continent" "continent" "conti
##  $ obs_values  : chr [1:5396] "Africa" "Africa" "Africa" "Africa" ...
```

```
head(gap_long)
```

```
## # A tibble: 6 x 2
##   obstype_year obs_values
##   <chr>        <chr>
## 1 continent    Africa
## 2 continent    Africa
## 3 continent    Africa
## 4 continent    Africa
## 5 continent    Africa
## 6 continent    Africa
```

```
tail(gap_long)
```

```
## # A tibble: 6 x 2
##   obstype_year obs_values
##   <chr>        <chr>
## 1 pop_2007     9031088
## 2 pop_2007     7554661
## 3 pop_2007     71158647
## 4 pop_2007     60776238
## 5 pop_2007     20434176
## 6 pop_2007     4115771
```

We have reshaped our dataframe but this new format isn't really what we wanted.

What went wrong? Notice that it didn't know that we wanted to keep `continent` and `country` untouched; we need to give it more information about which columns we want reshaped. We can do this in several ways.

One way is to identify the columns is by name. Listing them explicitly can be a good approach if there are just a few. But in our case we have 30 columns. I'm not going to list them out here since there is way too much potential for error if I tried to list `gdpPercap_1952`, `gdpPercap_1957`, `gdpPercap_1962` and so on. But we could use some of `dplyr`'s awesome helper functions — because we expect that there is a better way to do this!

```
gap_long <- gap_wide %>%
  gather(key   = obstype_year,
         value = obs_values,
         dplyr::starts_with('pop'),
         dplyr::starts_with('lifeExp'),
         dplyr::starts_with('gdpPercap'))  #here i'm listing all th
str(gap_long)
```

```
## tibble [5,112 × 4] (S3: tbl_df/tbl/data.frame)
##  $ continent   : chr [1:5112] "Africa" "Africa" "Africa" "Africa" ...
##  $ country     : chr [1:5112] "Algeria" "Angola" "Benin" "Botswana" ...
##  $ obstype_year: chr [1:5112] "pop_1952" "pop_1952" "pop_1952" "pop_1952"
##  $ obs_values  : num [1:5112] 9279525 4232095 1738315 442308 4469979 ...
```

```
head(gap_long)
```

```
## # A tibble: 6 x 4
##   continent country      obstype_year obs_values
##   <chr>     <chr>        <chr>              <dbl>
## 1 Africa    Algeria      pop_1952         9279525
## 2 Africa    Angola       pop_1952         4232095
## 3 Africa    Benin        pop_1952         1738315
## 4 Africa    Botswana     pop_1952          442308
## 5 Africa    Burkina Faso pop_1952         4469979
## 6 Africa    Burundi      pop_1952         2445618
```

```
tail(gap_long)
```

```
## # A tibble: 6 x 4
##   continent country        obstype_year   obs_values
##   <chr>     <chr>          <chr>                <dbl>
## 1 Europe    Sweden         gdpPercap_2007     33860.
## 2 Europe    Switzerland    gdpPercap_2007     37506.
## 3 Europe    Turkey         gdpPercap_2007      8458.
## 4 Europe    United Kingdom gdpPercap_2007     33203.
## 5 Oceania   Australia      gdpPercap_2007     34435.
## 6 Oceania   New Zealand    gdpPercap_2007     25185.
```

Success! And there is another way that is nice to use if your columns don't follow such a structured pattern: you can exclude the columns you don't want.

```
gap_long <- gap_wide %>%
  gather(key   = obstype_year,
         value = obs_values,
         -continent, -country)

str(gap_long)
```

```
## tibble [5,112 × 4] (S3: tbl_df/tbl/data.frame)
##  $ continent   : chr [1:5112] "Africa" "Africa" "Africa" "Africa" ...
##  $ country     : chr [1:5112] "Algeria" "Angola" "Benin" "Botswana" ...
##  $ obstype_year: chr [1:5112] "gdpPercap_1952" "gdpPercap_1952" "gdpPerca
##  $ obs_values  : num [1:5112] 2449 3521 1063 851 543 ...
```

```
head(gap_long, 3)
```

```
## # A tibble: 3 x 4
##   continent country obstype_year   obs_values
##   <chr>     <chr>   <chr>               <dbl>
## 1 Africa    Algeria gdpPercap_1952      2449.
## 2 Africa    Angola  gdpPercap_1952      3521.
## 3 Africa    Benin   gdpPercap_1952      1063.
```

To recap:

Inside `gather()` we first name the new column for the new ID variable (`obstype_year`), the name for the new amalgamated observation variable (`obs_value`), then the names of the old observation variable. We could have typed out all the observation variables, but as in the `select()` function (see `dplyr` lesson), we can use the `starts_with()` argument to select all variables that starts with the desired character string. Gather also allows the alternative syntax of using the - symbol to identify which variables are not to be gathered (i.e. ID variables).

OK, but we're not done yet. `obstype_year` actually contains two pieces of information, the observation type (`pop`,`lifeExp`, or `gdpPercap`) and the year. We can use the `separate()` function to split the character strings into multiple variables.

`?separate` –> the main arguments are `separate(data, col, into, sep ...)`. So we need to specify which column we want separated, name the new columns that we want to create, and specify what we want it to separate by. Since the `obstype_year` variable has observation types and years separated by a _, we'll use that.

```
gap_long <- gap_wide %>%
  gather(key   = obstype_year,
         value = obs_values,
         -continent, -country) %>%
  separate(obstype_year,
           into = c('obs_type','year'),
           sep = "_",
           convert = TRUE) #this ensures that the year column is an
str(gap_long)
```

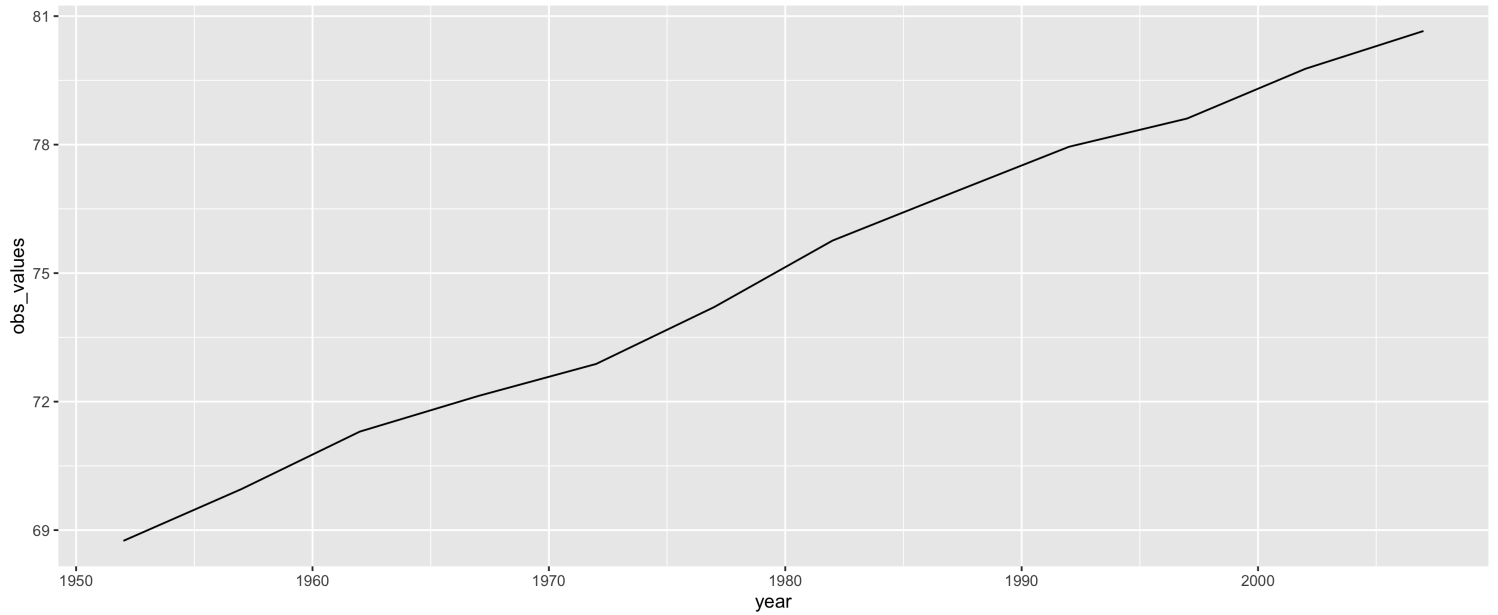
```
## tibble [5,112 × 5] (S3: tbl_df/tbl/data.frame)
##  $ continent : chr [1:5112] "Africa" "Africa" "Africa" "Africa" ...
##  $ country   : chr [1:5112] "Algeria" "Angola" "Benin" "Botswana" ...
##  $ obs_type  : chr [1:5112] "gdpPercap" "gdpPercap" "gdpPercap" "gdpPerca
##  $ year      : int [1:5112] 1952 1952 1952 1952 1952 1952 1952 1952 1952
##  $ obs_values: num [1:5112] 2449 3521 1063 851 543 ...
```

Excellent. This is long format: every row is a unique observation.

Plot long format data

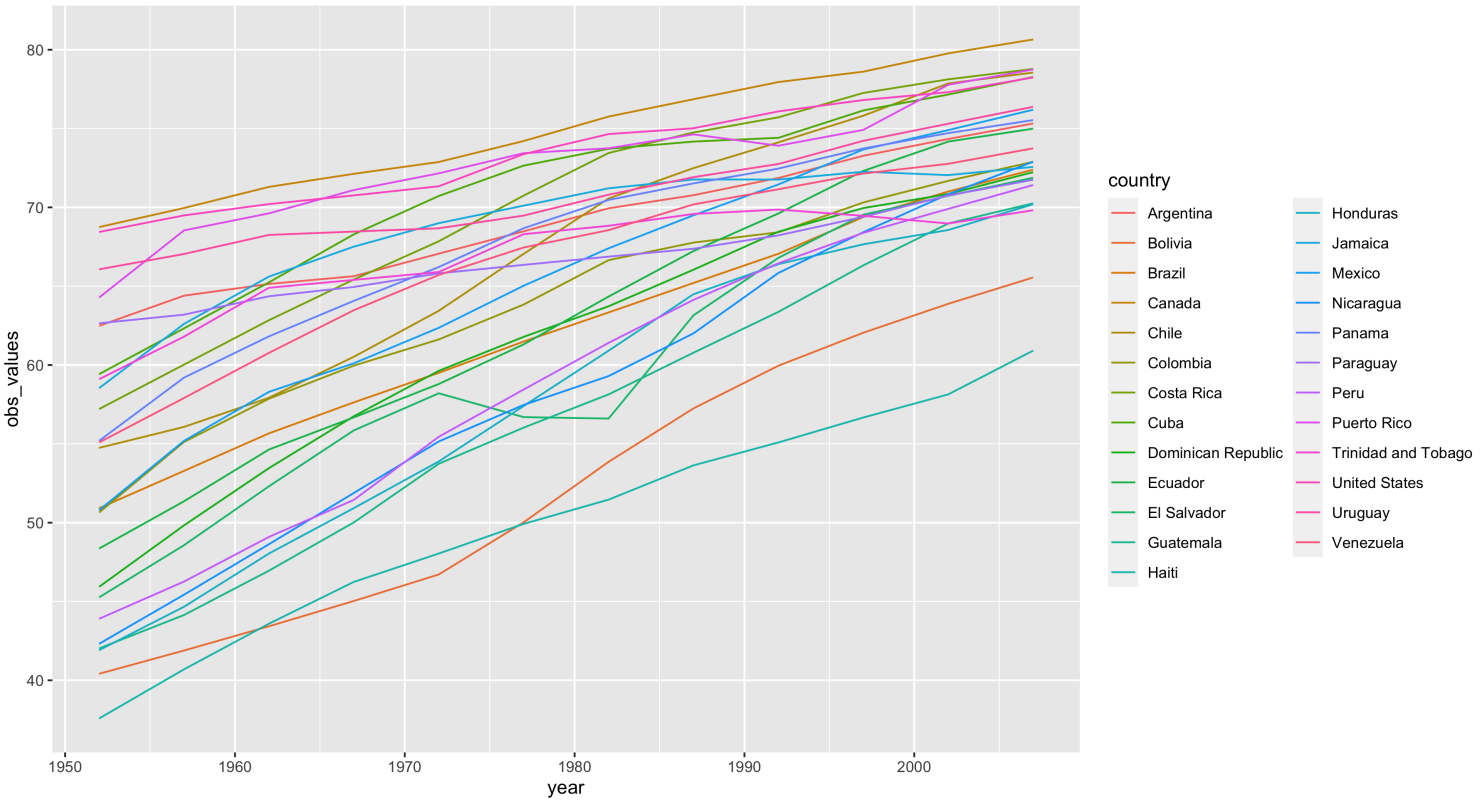
The long format is the preferred format for plotting with `ggplot2`. Let's look at an example by plotting just Canada's life expectancy.

```
canada_df <- gap_long %>%
  filter(obs_type == "lifeExp",
         country == "Canada")
ggplot(canada_df, aes(x = year, y = obs_values)) +
  geom_line()
```



We can also look at all countries in the Americas:

```
life_df <- gap_long %>%
  filter(obs_type == "lifeExp",
         continent == "Americas")
ggplot(life_df, aes(x = year, y = obs_values, color = country)) +
  geom_line()
```



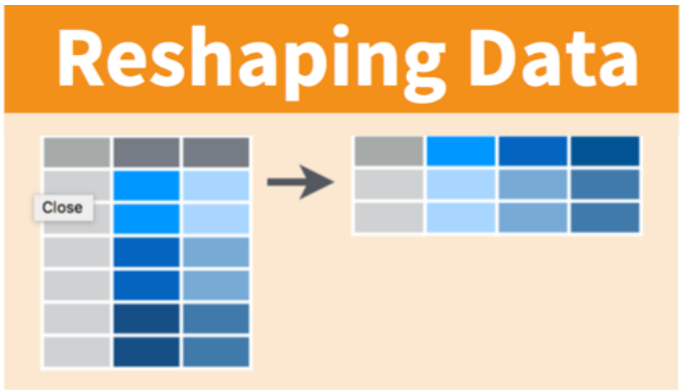
Exercise

Using `gap_long`, calculate and plot the the mean life expectancy for each continent over time from 1982 to 2007. Give your plot a title and assign x and y labels. Hint: do this in two steps. First, do the logic and calculations using `dplyr::group_by()` and `dplyr::summarize()`. Second, plot using `ggplot()`.

spread()

The function `spread()` is used to transform data from long to wide format

Alright! Now just to double-check our work, let's use the opposite of `gather()` to spread our observation variables back to the original format with the aptly named `spread()`. You pass `spread()` the key and value pair, which is now `obs_type` and `obs_values`.




```
gap_normal <- gap_long %>%
  spread(obs_type, obs_values)
```

```
dim(gap_normal)
```

```
## [1] 1704    6
```

```
dim(gapminder)
```

```
## [1] 1704    6
```

```
names(gap_normal)
```

```
## [1] "continent" "country"   "year"      "gdpPercap" "lifeExp"   "pop"
```

```
names(gapminder)
```

```
## [1] "country"   "year"      "pop"       "continent" "lifeExp"   "gdpPerca
```

Now we've got a dataframe `gap_normal` with the same dimensions as the original `gapminder`.

Exercise

1. Convert `gap_long` all the way back to `gap_wide`. Hint: Do this in 2 steps. First, create appropriate labels for all our new variables (variable_year combinations) with the opposite of separate: `tidyr::unite()`. Second, `spread()` that variable_year column into wider format.

2. Knit the R Markdown file and sync to Github (pull, stage, commit, push)

clean up and save your .Rmd

Spend some time cleaning up and saving `gapminder-wrangle.Rmd` Restart R. In RStudio, use *Session* > *Restart R*. Otherwise, quit R with `q()` and re-launch it.

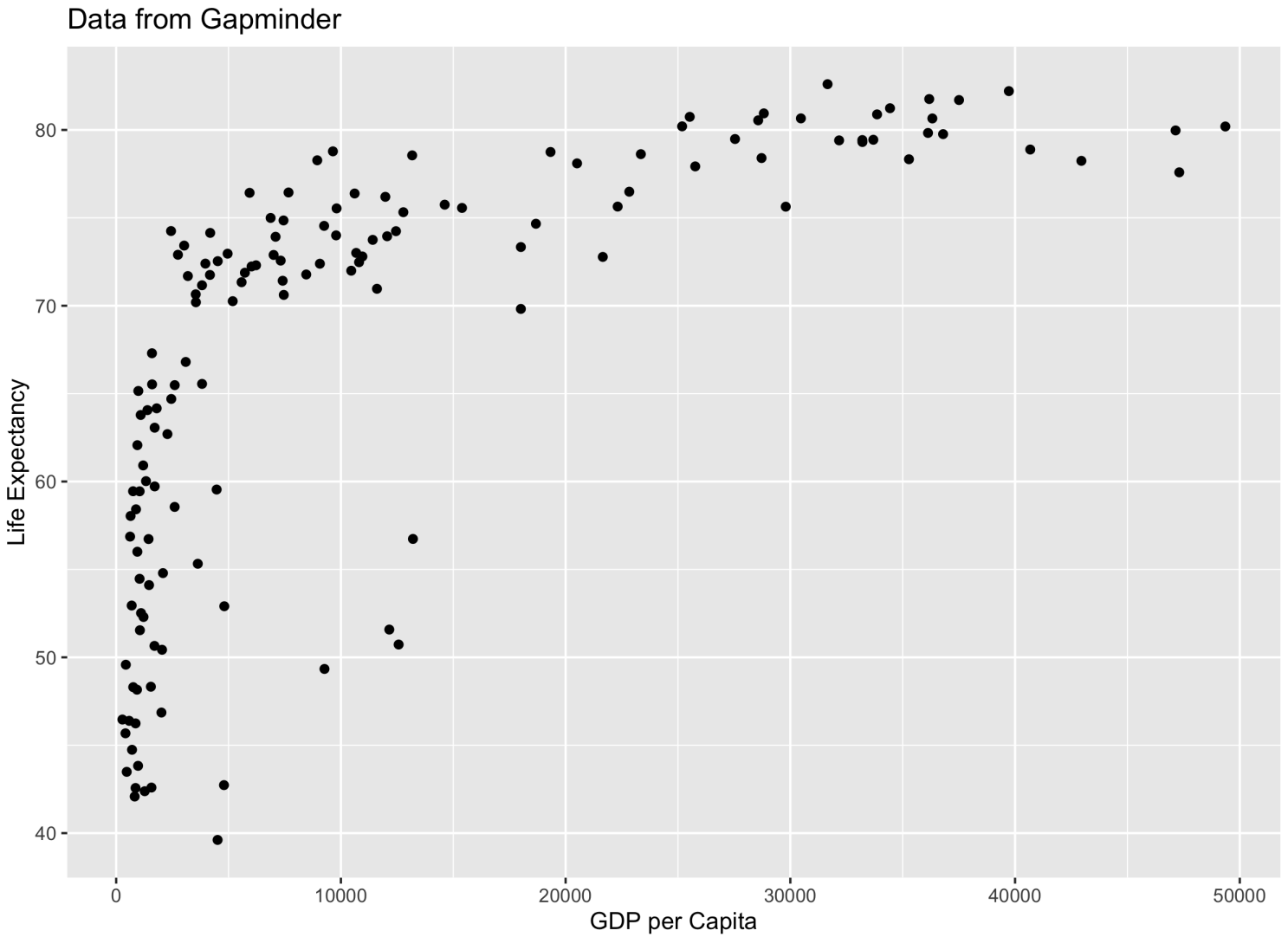
Is there a relationship between life expectancy and GDP per capita?

Let's use the gapminder data to answer this question. To try and answer it we will make a scatterplot. We will do this for the latest entry in the dataset which is:

```
max( gapminder$year )
```

```
## [1] 2007
```

```
gapminder %>% filter(year==2007) %>%
  ggplot(aes(x = gdpPercap, y = lifeExp))+
  geom_point()+
  labs(x = "GDP per Capita",
       y = "Life Expectancy",
       title = "Data from Gapminder")
```

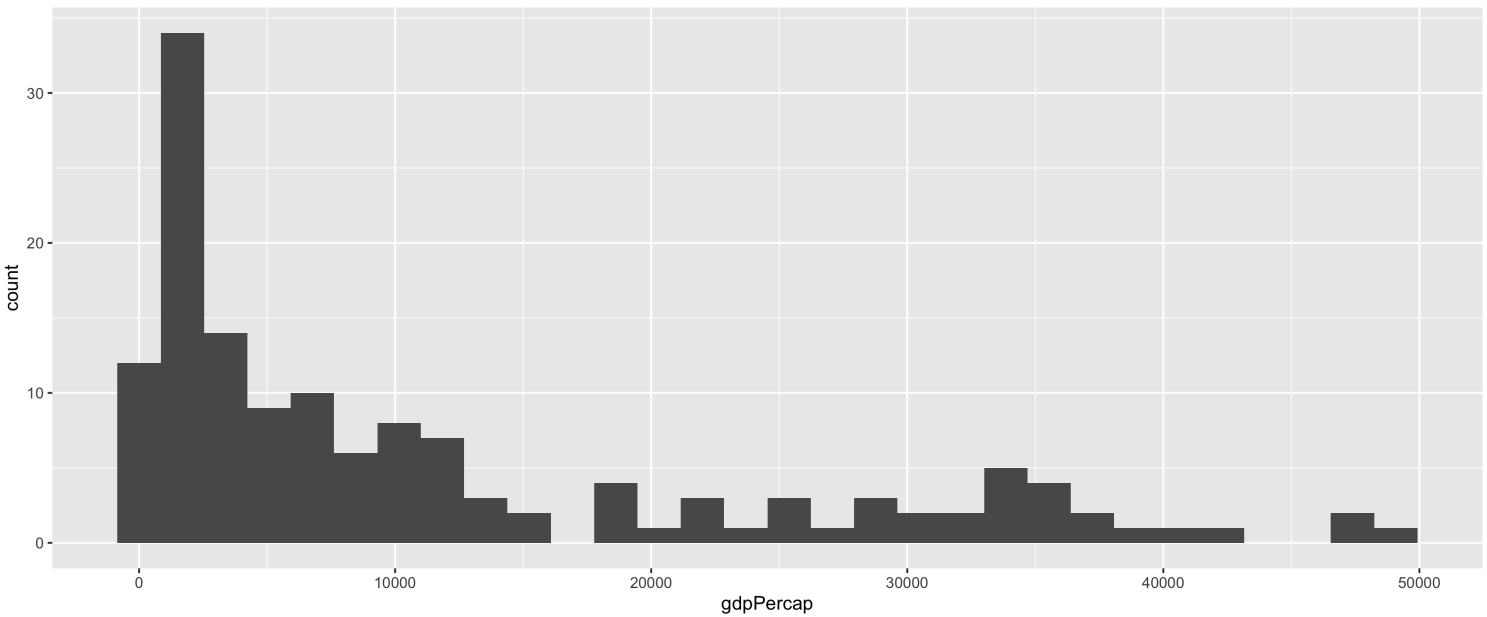

Data from Gapminder
Life Expectancy
80
70
60
50
40
0
10000
20000
30000
40000
50000
GDP per Capita

From this plot, we see that there is a wide variability in life expectancy for the lower income countries and then somewhat of a positive trend. However, there are many countries with incomes below 5,000 dollars per person and it is hard to see differences between these.

We can examine just this variable with a histogram.

```
gapminder %>%
    filter(year==2007) %>%
    ggplot(aes(x=gdpPercap)) + geom_histogram()
```

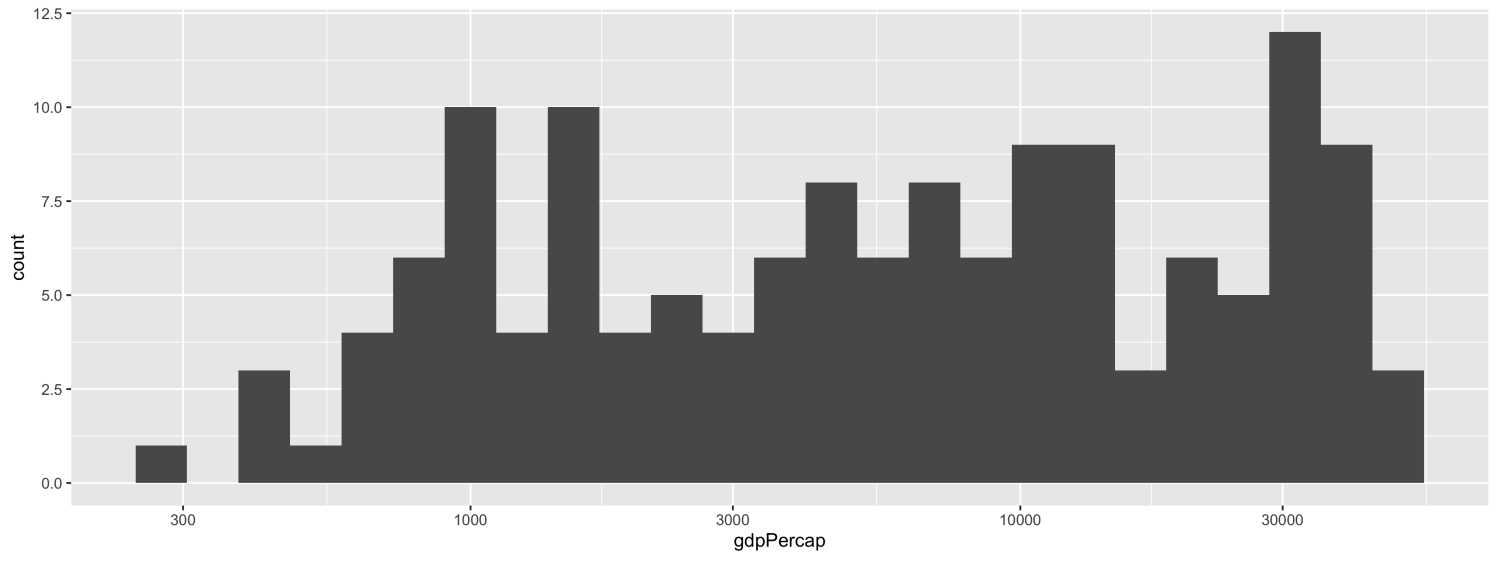
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



The histogram shows very large tails. We may do better by transforming the data. For data like this, the log transformation seems to work well. It also has a nice economic interpretation related to percent growth: in $\log_{10}$ a change of 1 means the country is 10 times richer.

So how do we make the x-axis in the log scale? It is convenient to have this cheat sheet around when using `ggplot2`. From there we see that `scale_x_log10` does what we want.

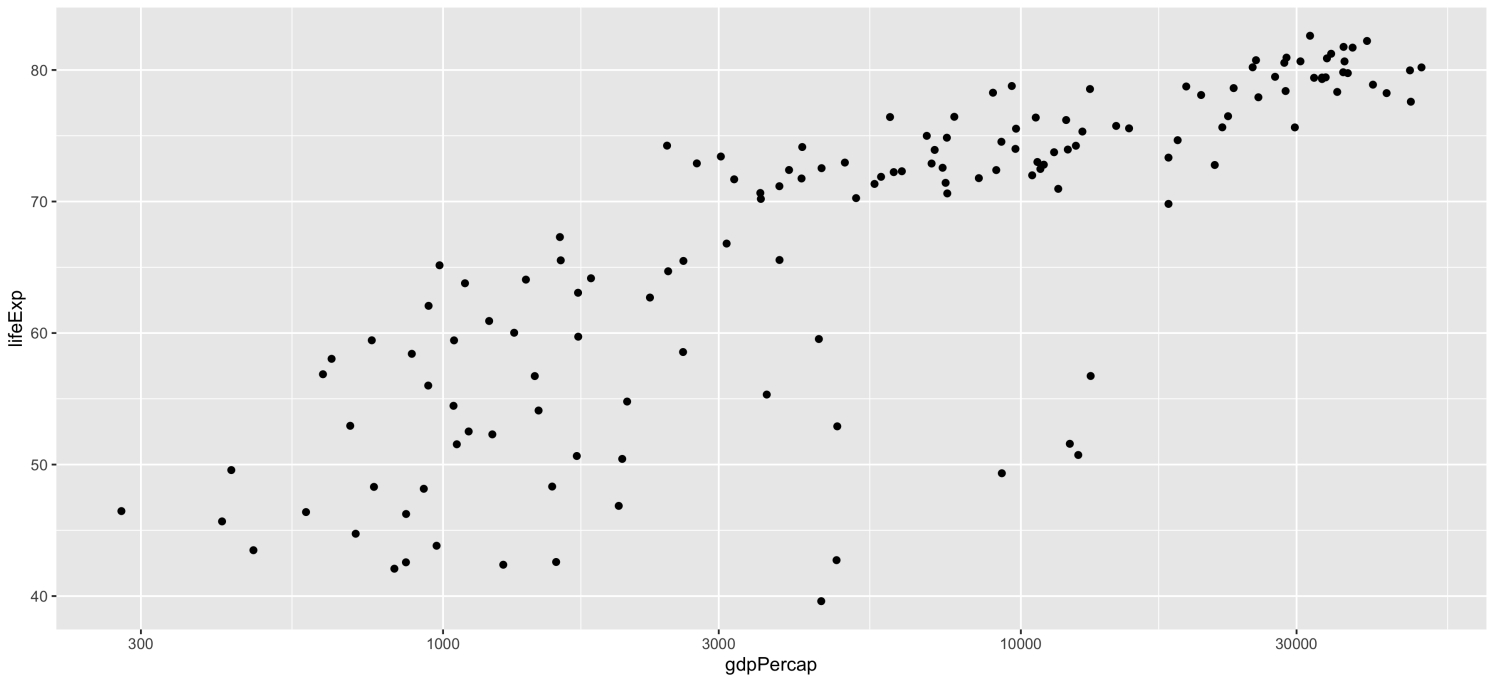
```
gapminder %>%
    filter(year==2007) %>%
    ggplot(aes(x=gdpPercap)) +
    geom_histogram(bins=25) + scale_x_log10()
```



We no longer see extreme tails. The scatter plot now looks much more informative:

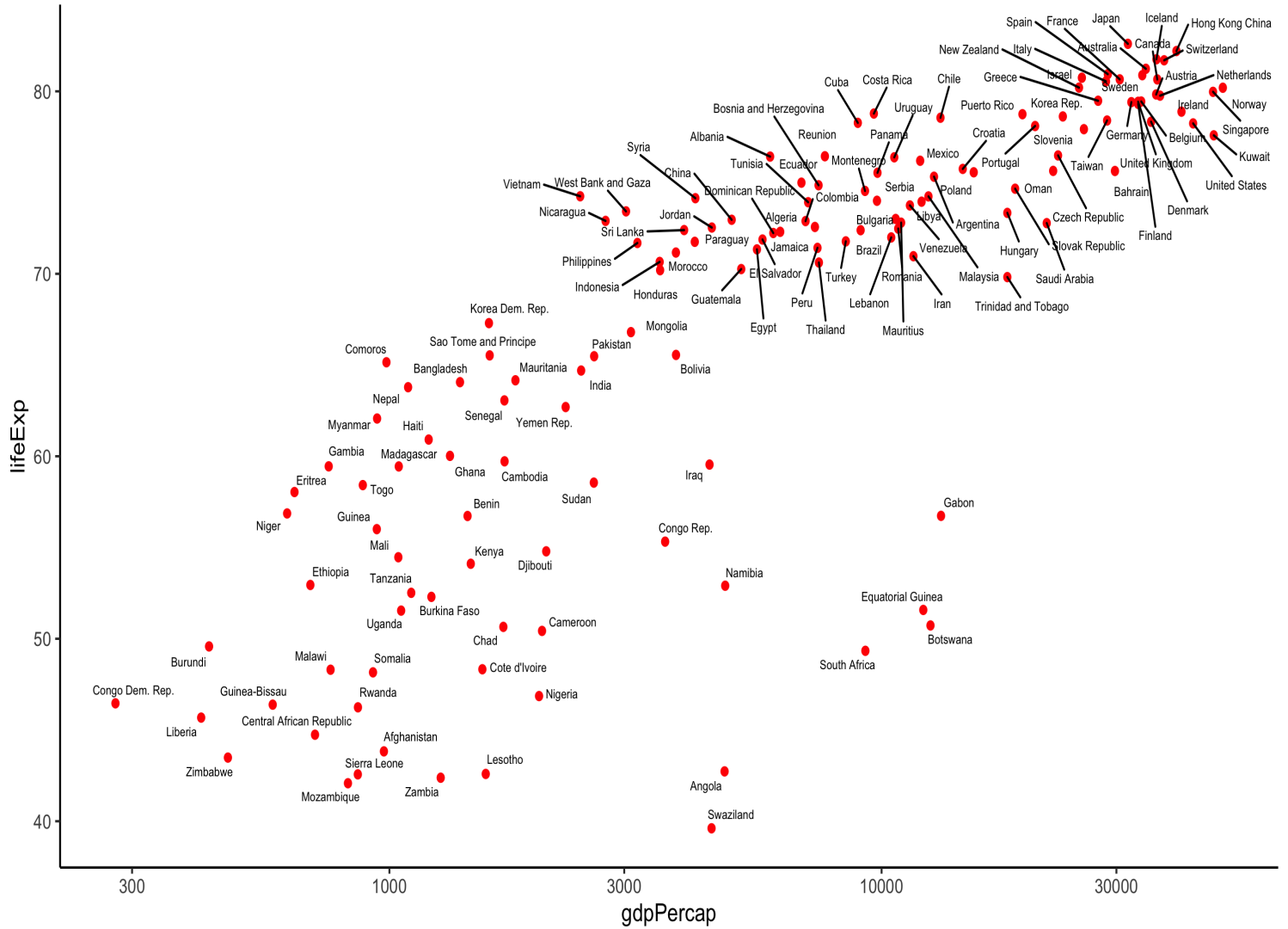
Now we can remake the scatter plot but now make sure the x-axis is in a log-scale.

```
gapminder %>%
    filter(year==2007) %>%
    ggplot(aes(x=gdpPercap, y = lifeExp)) +
    geom_point() + scale_x_log10()
```



We can also use other really great packages, such as `ggrepel`:

```
library(ggrepel)
gapminder %>%
    filter(year==2007) %>%
    ggplot(aes(x=gdpPercap, y = lifeExp)) +
    geom_point(color = 'red',) + scale_x_log10() +
    geom_text_repel(aes(label = country), size = 2) +
  theme_classic()
```


lifeExp
gdpPercap
80
70
60
50
40
300
1000
3000
10000
30000
Spain
France
Japan
Iceland
Hong Kong China
Australia
Canada
Switzerland
New Zealand
Italy
Israel
Sweden
Greece
Austria
Netherlands
Cuba
Costa Rica
Chile
Puerto Rico
Korea Rep.
Ireland
Norway
Bosnia and Herzegovina
Uruguay
Reunion
Panama
Croatia
Slovenia
Germany
Belgium
Singapore
Albania
Syria
Tunisia
Ecuador
Montenegro
Mexico
Portugal
Taiwan
United Kingdom
Kuwait
China
Vietnam
West Bank and Gaza
Dominican Republic
Colombia
Serbia
Poland
Oman
Bahrain
United States
Nicaragua
Jordan
Algeria
Libya
Argentina
Czech Republic
Denmark
Sri Lanka
Paraguay
Bulgaria
Finland
Philippines
Jamaica
Brazil
Venezuela
Hungary
Slovak Republic
Morocco
El Salvador
Turkey
Romania
Malaysia
Saudi Arabia
Indonesia
Honduras
Guatemala
Peru
Lebanon
Iran
Trinidad and Tobago
Egypt
Thailand
Mauritius
Korea Dem. Rep.
Mongolia
Comoros
Sao Tome and Principe
Pakistan
Bangladesh
Mauritania
Bolivia
India
Nepal
Senegal
Yemen Rep.
Myanmar
Haiti
Gambia
Madagascar
Ghana
Cambodia
Iraq
Eritrea
Togo
Sudan
Gabon
Benin
Niger
Guinea
Congo Rep.
Mali
Kenya
Djibouti
Namibia
Ethiopia
Tanzania
Equatorial Guinea
Burkina Faso
Uganda
Cameroon
Botswana
Chad
Burundi
Malawi
Somalia
South Africa
Cote d'Ivoire
Congo Dem. Rep.
Guinea-Bissau
Rwanda
Nigeria
Liberia
Central African Republic
Afghanistan
Zimbabwe
Sierra Leone
Lesotho
Angola
Mozambique
Zambia
Swaziland