



The tidyverse

ARGH meeting
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tidyverse

Import

readr
readxl
haven
httr
jsonlite
DBI
rvest
xml2

Tidy

tibble
tidyr

Program

purrr
magrittr

Transform

dplyr
forcats
hms
lubridate
stringr

Visualise

ggplot2

Model

broom
modelr



Import



Tidy → **Transform**

Visualise

Model

Program

Communicate



Big Data Borat
@BigDataBorat

In Data Science, 80% of time spent prepare data, 20% of time spent complain about need for prepare data.

II **Stat Fact**
@StatFact

Data cleaning code cannot be clean. It's a sort of sin eater.

Transform

dplyr

forcats

hms

lubridate

stringr

A language for data manipulation

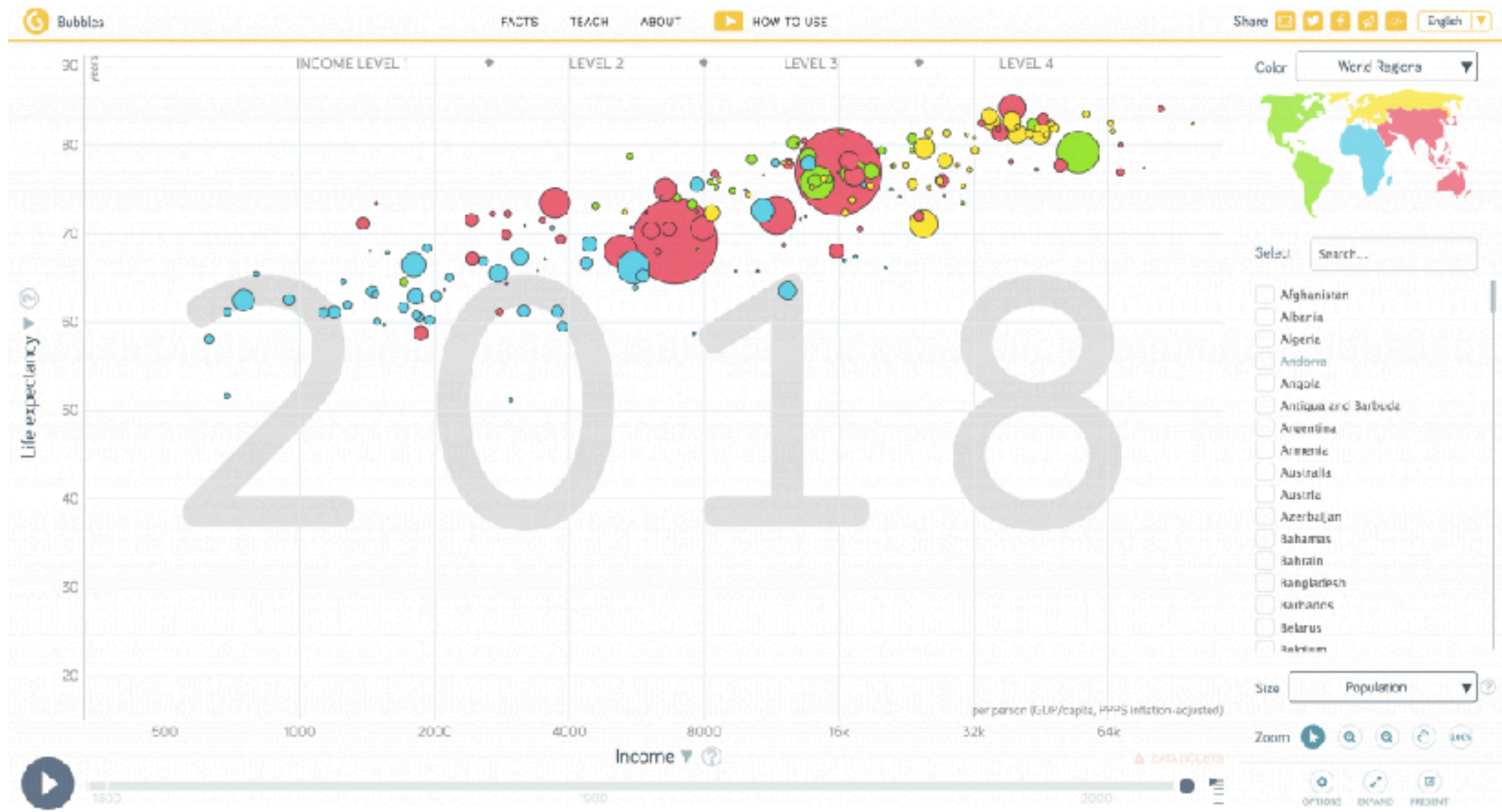
- Six functions for data manipulation:
 - `select()`
 - `filter()`
 - `summarize()`
 - `group_by()`
 - `mutate()`
 - `arrange()`
- These functions provide the verbs for a language of data manipulation.

Operating principles

- Each function uses consistent principles:
 - The first argument is a data frame.
 - The subsequent arguments describe what to do with the data frame.
- Each function returns a data frame.

gapminder package

- Provides an excerpt from the Gapminder data.



```
library(gapminder)
```


> gapminder

A tibble: 1,704 x 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.

```
library(tidyverse)
```

select()

- Lets you extract a subset of **columns** from a data frame

data frame

column names

- `select(gapminder, year, country, gdpPercap)`



- `gapminder[c('year', 'country', 'gdpPercap')]`



- Select all but one variable:

- `select(gapminder, -year)`

filter()

- Lets you extract a subset of **rows** from a data frame.

- `filter(gapminder, continent == "Europe")`

- Filtering a data frame and then selecting specific variables:

- `filter(gapminder, continent == "Europe") %>%
 select(year, country, gdpPercap)`

“then”



```
# A tibble: 360 x 3
  year country gdpPercap
  <int> <fct>      <dbl>
1  1952 Albania    1601.
2  1957 Albania    1942.
3  1962 Albania    2313.
4  1967 Albania    2760.
5  1972 Albania    3313.
6  1977 Albania    3533.
7  1982 Albania    3631.
8  1987 Albania    3739.
9  1992 Albania    2497.
10 1997 Albania    3193.
# ... with 350 more rows
```



%>%

CTRL + SHIFT + M (or CMD + SHIFT + M for OSX)

```
filter(gapminder, continent == "Europe") %>%  
  select(year, country, gdpPercap)
```

```
gapminder %>%  
  filter(continent=="Europe") %>%  
  select(year, country, gdpPercap)
```

Challenge 1

- Use filter and select to produce a data frame that has only the columns lifeExp, country and year for the countries of Africa. How many rows does your data frame have?

Challenge 1 solution


```
gapminder %>%  
  filter(continent == "Africa") %>%  
  select(year, country, lifeExp)
```

summarize()

- Collapse a data frame down to a summary statistic.

- `summarize(gapminder,
 mean_gdpPercap = mean(gdpPercap))`

New variable name



Summary operation



- `gapminder %>%
 summarize(mean_gdpPercap = mean(gdpPercap))`
- What if we wanted the mean gdpPercap for each continent?

group_by()

- Adds an grouping structure to a data frame
- Subsequent functions operate on each group.
- `group_by(gapminder, continent)`

```
# A tibble: 1,704 x 6
```

```
# Groups:   continent [5]
```

	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	16317021	640.

group_by()

- gapminder %>%
 group_by(continent) %>%
 summarize(mean_gdpPercap = mean(gdpPercap))

```
# A tibble: 5 x 2
  continent mean_gdpPercap
  <fct>         <dbl>
1 Africa      2194.
2 Americas   7136.
3 Asia       7902.
4 Europe    14469.
5 Oceania   18622.
```

```
gapminder %>%
```

```
  group_by(continent, year) %>%
```

```
  summarize(mean_gdpPercap = mean(gdpPercap),  
            sd_gdpPercap = sd(gdpPercap),  
            mean_pop = mean(pop),  
            sd_pop = sd(pop))
```

```
# A tibble: 60 x 6
```

```
# Groups:   continent [?]
```

	continent	year	mean_gdpPercap	sd_gdpPercap	mean_pop	sd_pop
	<fct>	<int>	<dbl>	<dbl>	<dbl>	<dbl>
1	Africa	1952	1253.	983.	4570010.	6317450.
2	Africa	1957	1385.	1135.	5093033.	7076042.
3	Africa	1962	1598.	1462.	5702247.	7957545.
4	Africa	1967	2050.	2848.	6447875.	8985505.
5	Africa	1972	2340.	3287.	7305376.	10130833.
6	Africa	1977	2586.	4142.	8328097.	11585184.
7	Africa	1982	2482.	3243.	9602857.	13456243.
8	Africa	1987	2283.	2567.	11054502.	15277484.
9	Africa	1992	2282.	2644.	12674645.	17562719.

Challenge 2

- Calculate the average life expectancy for each country in the gapminder data frame.
- Bonus: Use the `arrange()` function to find out which country has the highest life expectancy?

Challenge 2 solution

```
gapminder %>%  
  group_by(country) %>%  
  summarize(mean_lifeExp = mean(lifeExp)) %>%  
  arrange(desc(mean_lifeExp))
```

mutate()

- Create new variables.
- `mutate(gapminder,
 gdp_billion = gdpPercap*pop/10^9)`
- `gapminder %>%
 mutate(gdp_billion = gdpPercap*pop/10^9)`

A tibble: 1,704 x 7

country	continent	year	lifeExp	pop	gdpPercap	gdp_billion
<fct>	<fct>	<int>	<dbl>	<int>	<dbl>	<dbl>
Afghanistan	Asia	1952	28.8	8425333	779.	6.57
Afghanistan	Asia	1957	30.3	9240934	821.	7.59
Afghanistan	Asia	1962	32.0	10267083	853.	8.76
Afghanistan	Asia	1967	34.0	11537966	836.	9.65
Afghanistan	Asia	1972	36.1	13079460	740.	9.68
Afghanistan	Asia	1977	38.4	14880372	786.	11.7
Afghanistan	Asia	1982	39.9	12881816	978.	12.6
Afghanistan	Asia	1987	40.8	13867957	852.	11.8
Afghanistan	Asia	1992	41.7	16317921	649.	10.6
Afghanistan	Asia	1997	41.8	22227415	635.	14.1

```
gapminder %>%
  mutate(gdp_billion=gdpPercap*pop/10^9) %>%
  group_by(continent, year) %>%
  summarize(mean_gdp_billion = mean(gdp_billion),
            sd_gdp_billion = sd(gdp_billion))
```

```
# A tibble: 60 x 4
# Groups:   continent [?]
  continent year mean_gdp_billion sd_gdp_billion
  <fct>      <int>          <dbl>          <dbl>
1 Africa    1952           5.99           11.4
2 Africa    1957           7.36           14.5
3 Africa    1962           8.78           17.2
4 Africa    1967          11.4           23.2
5 Africa    1972          15.1           30.4
6 Africa    1977          18.7           38.1
7 Africa    1982          22.0           46.6
8 Africa    1987          24.1           51.4
9 Africa    1992          26.3           55.1
10 Africa   1997          30.0           63.0
```

Advanced Challenge

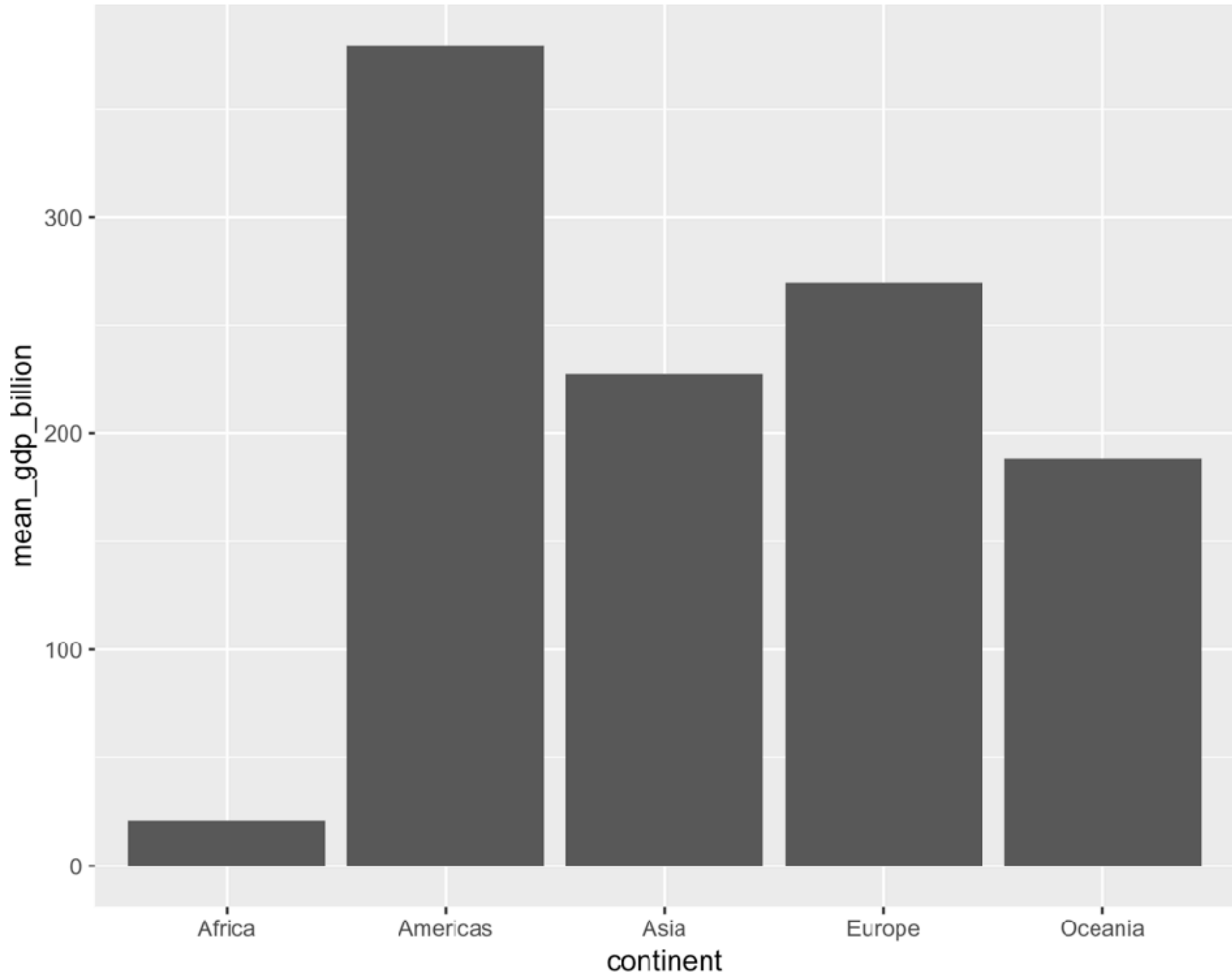
- Calculate the average life expectancy in 2002 of 2 randomly selected countries from each continent. Then arrange this data so that it is ordered by mean lifeExp (highest to lowest).
- Hint: Use the functions `sample_n()` and `arrange()`; they have similar syntax to other dplyr functions.

Advanced Challenge Solution

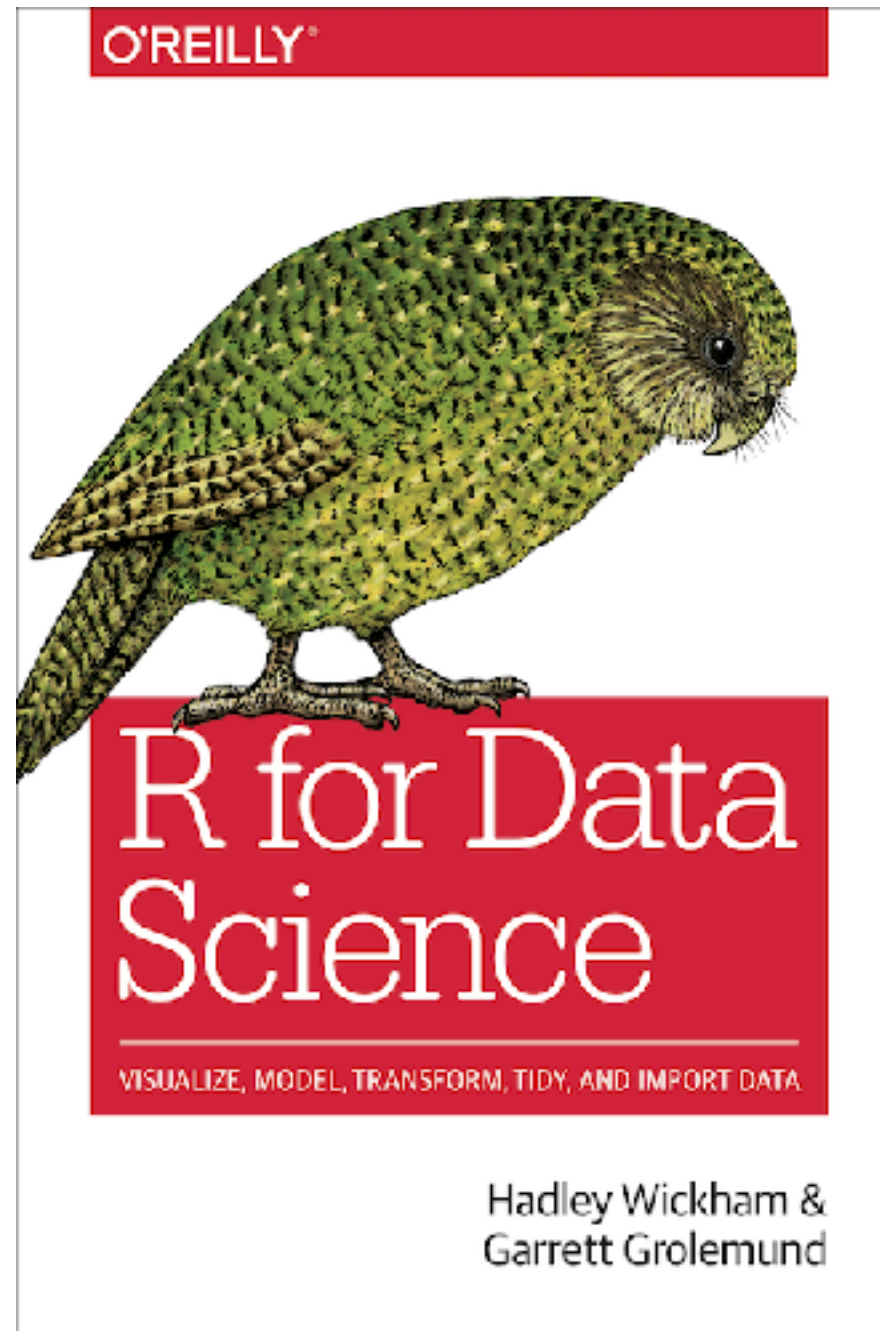
```
gapminder %>%  
  filter(year==2002) %>%  
  group_by(continent) %>%  
  sample_n(2) %>%  
  summarize(mean_lifeExp=mean(lifeExp)) %>%  
  arrange(desc(mean_lifeExp))
```

Where you can go

```
gapminder %>%  
  mutate(gdp_billion=gdpPercap*pop/10^9) %>%  
  group_by(continent) %>%  
  summarize(mean_gdp_billion=mean(gdp_billion)) %>%  
  ggplot(aes(x=continent, y = mean_gdp_billion)) +  
  geom_col()
```



Learning more



<http://r4ds.had.co.nz>



Journal of Statistical Software

MMMMMM YYYY, Volume VV, Issue II.

<http://www.jstatsoft.org/>

Tidy Data

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RStudio

Abstract

A huge amount of effort is spent cleaning data to get it ready for analysis, but there has been little research on how to make data cleaning as easy and effective as possible. This paper tackles a small, but important, component of data cleaning: data tidying. Tidy datasets are easy to manipulate, model and visualise, and have a specific structure: each variable is a column, each observation is a row, and each type of observational unit is a table. This framework makes it easy to tidy messy datasets because only a small set of tools are needed to deal with a wide range of un-tidy datasets. This structure also makes it easier to develop tidy tools for data analysis, tools that both input and output tidy datasets. The advantages of a consistent data structure and matching tools are demonstrated with a case study free from mundane data manipulation chores.

<http://rpubs.com/aelhabr/tidyverse-basics>

People to follow on twitter

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- Jenny Bryan: @JennyBryan
- David Robinson: @drob
- Mara Averick: @dataandme
- Julia Silge: @juliasilge

Thanks for listening!