Introduction to the Tidyverse

Lessons from DataCamp

Neil Yetz

Contents

Introduction

The following documentoutlines the written portion of the lessons from DataCamp's Introduction to the Tidyverse. This works to develop skills within the tidyverse package.

As a note: All text is completely copied and pasted from the course. There are instances where the document refers to the "editor on the right", please note, that in this notebook document all of these instances are noted in the "r-chunks" (areas containing working r-code), which occurs below the text, rather than to the right. Furthermore, This lesson contained instructional videos at the begining of new concepts that are not detailed in this document. However, even without these videos, the instructions are quite clear in indicating what the code is accomplishing.

If you have this document open on "R-Notebook", simply click "run" -> "Run all" (Or just press 'ctrl + alt + r'), let the "r-chunks" run (This might take a bit of time) then click "Preview". There are 5 necessary datasets to run this program, please create an r-project with this data or set a working directory (required files names are available in the "Required data for this session" section)

This document was created by Neil Yetz on 05/17/2018. Please send any questions or concerns in this document to Neil at ndyetz@gmail.com

Course Description

This is an introduction to the programming language R, focused on a powerful set of tools known as the "tidyverse". In the course you'll learn the intertwined processes of data manipulation and visualization through the tools dplyr and ggplot2. You'll learn to manipulate data by filtering, sorting and summarizing a real dataset of historical country data in order to answer exploratory questions. You'll then learn to turn this processed data into informative line plots, bar plots, histograms, and more with the ggplot2 package. This gives a taste both of the value of exploratory data analysis and the power of tidyverse tools. This is a suitable introduction for people who have no previous experience in R and are interested in learning to perform data analysis.

Chapter 1: Data wrangling

In this chapter, you'll learn to do three things with a table: filter for particular observations, arrange the observations in a desired order, and mutate to add or change a column. You'll see how each of these steps lets you answer questions about your data.

Loading the gapminder and dplyr packages

Before you can work with the `gapminder` dataset, you'll need to load two R packages that contain the tools for working with it, then display the `gapminder` dataset so that you can see what it contains.

To your right, you'll see two windows inside which you can enter code: The `script.R` window, and the R Console. All of your code to solve each exercise must go inside `script.R`.

If you hit Submit Answer, your R script is executed and the output is shown in the R Console. DataCamp checks whether your submission is correct and gives you feedback. You can hit Submit Answer as often as you want. If you're stuck, you can ask for a hint or a solution.

You can use the R Console interactively by simply typing R code and hitting Enter. When you work in the console directly, your code will not be checked for correctness so it is a great way to experiment and explore.

INSTRUCTIONS

Use the `library()` function to load the `dplyr` package, just like we've loaded the `gapminder` package for you.

Type `gapminder`, on its own line, to look at the `gapminder` dataset.

```
# Load the gapminder package
#install.packages("gapminder")
library(gapminder)

# Load the dplyr package
#install.packages("dplyr")
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
# Look at the gapminder dataset
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.
## # ... with 1,694 more rows
```

Understanding a data frame

Now that you've loaded the `gapminder` dataset, you can start examining and understanding it.

We've already loaded the `gapminder` and `dplyr` packages. Type `gapminder` in your R terminal, to the lower right, to display the object.

How many observations (rows) are in the dataset?

Possible Answers (Correct Answer is **Bolded**)

1704

6

1694

1952

Filtering for one year

The `filter` verb extracts particular observations based on a condition. In this exercise you'll filter for observations from a particular year.

INSTRUCTIONS

Add a `filter()` line after the pipe (`%>%`) to extract only the observations from the year 1957. Remember that you use `==` to compare two values.

```
library(gapminder)
library(dplyr)
```

```
# Filter the gapminder dataset for the year 1957
gapminder %>%
  filter(year == 1957)
```

```
## # A tibble: 142 x 6
##    country     continent  year lifeExp      pop gdpPercap
##    <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
##  1 Afghanistan Asia       1957    30.3  9240934      821.
##  2 Albania     Europe     1957    59.3  1476505     1942.
##  3 Algeria     Africa     1957    45.7 10270856     3014.
##  4 Angola      Africa     1957    32.0  4561361     3828.
##  5 Argentina   Americas   1957    64.4 19610538     6857.
##  6 Australia   Oceania    1957    70.3  9712569    10950.
##  7 Austria     Europe     1957    67.5  6965860     8843.
##  8 Bahrain     Asia       1957    53.8   138655    11636.
##  9 Bangladesh  Asia       1957    39.3 51365468      662.
## 10 Belgium     Europe     1957    69.2  8989111     9715.
## # ... with 132 more rows
```

Filtering for one country and one year

You can also use the `filter()` verb to set two conditions, which could retrieve a single observation.

Just like in the last exercise, you can do this in two lines of code, starting with `gapminder %>%` and having the `filter()` on the second line. Keeping one verb on each line helps keep the code readable. Note that each time, you'll put the pipe `%>%` at the end of the first line (like `gapminder %>%`); putting the pipe at the beginning of the second line will throw an error.

```
library(gapminder)
library(dplyr)

# Filter for China in 2002
gapminder %>%
  filter(country == "China", year == 2002)
```

```
## # A tibble: 1 x 6
##   country continent  year lifeExp        pop gdpPercap
##   <fct>   <fct>     <int>   <dbl>      <int>     <dbl>
## 1 China   Asia       2002    72.0 1280400000     3119.
```

Arranging observations by life expectancy

You use `arrange()` to sort observations in ascending or descending order of a particular variable. In this case, you'll sort the dataset based on the `lifeExp` variable.

INSTRUCTIONS

Sort the `gapminder` dataset in ascending order of life expectancy (`lifeExp`). Sort the `gapminder` dataset in descending order of life expectancy.

```
library(gapminder)
library(dplyr)

# Sort in ascending order of lifeExp
```

```
gapminder %>%
  arrange(lifeExp)
```

```
## # A tibble: 1,704 x 6
##    country      continent  year lifeExp     pop gdpPercap
##    <fct>        <fct>     <int>   <dbl>   <int>     <dbl>
##  1 Rwanda       Africa     1992    23.6 7290203      737.
##  2 Afghanistan  Asia       1952    28.8 8425333      779.
##  3 Gambia       Africa     1952    30.0  284320      485.
##  4 Angola       Africa     1952    30.0 4232095     3521.
##  5 Sierra Leone Africa     1952    30.3 2143249      880.
##  6 Afghanistan  Asia       1957    30.3 9240934      821.
##  7 Cambodia     Asia       1977    31.2 6978607      525.
##  8 Mozambique   Africa     1952    31.3 6446316      469.
##  9 Sierra Leone Africa     1957    31.6 2295678     1004.
## 10 Burkina Faso Africa     1952    32.0 4469979      543.
## # ... with 1,694 more rows
```

```
# Sort in descending order of lifeExp
gapminder %>%
  arrange(desc(lifeExp))
```

```
## # A tibble: 1,704 x 6
##    country          continent  year lifeExp       pop gdpPercap
##    <fct>            <fct>     <int>   <dbl>     <int>     <dbl>
##  1 Japan            Asia       2007    82.6 127467972    31656.
##  2 Hong Kong, China Asia       2007    82.2   6980412    39725.
##  3 Japan            Asia       2002    82.0 127065841    28605.
##  4 Iceland          Europe     2007    81.8    301931    36181.
##  5 Switzerland      Europe     2007    81.7   7554661    37506.
##  6 Hong Kong, China Asia       2002    81.5   6762476    30209.
##  7 Australia        Oceania    2007    81.2  20434176    34435.
##  8 Spain            Europe     2007    80.9  40448191    28821.
##  9 Sweden           Europe     2007    80.9   9031088    33860.
## 10 Israel           Asia       2007    80.7   6426679    25523.
## # ... with 1,694 more rows
```

Filtering and arranging

You'll often need to use the pipe operator (`%>%`) to combine multiple dplyr verbs in a row. In this case, you'll combine a `filter()` with an `arrange()` to find the highest population countries in a particular year.

INSTRUCTIONS

Use `filter()` to extract observations from just the year 1957, then use `arrange()` to sort in descending order of population (`pop`).

```
library(gapminder)
library(dplyr)

# Filter for the year 1957, then arrange in descending order of population

gapminder %>%
  filter(year == 1957) %>%
  arrange(desc(pop))
```

```
## # A tibble: 142 x 6
##    country        continent  year lifeExp       pop gdpPercap
##    <fct>          <fct>     <int>   <dbl>     <int>     <dbl>
##  1 China          Asia       1957    50.5 637408000      576.
##  2 India          Asia       1957    40.2 409000000      590.
##  3 United States  Americas   1957    69.5 171984000    14847.
##  4 Japan          Asia       1957    65.5  91563009     4318.
##  5 Indonesia      Asia       1957    39.9  90124000      859.
##  6 Germany        Europe     1957    69.1  71019069    10188.
##  7 Brazil         Americas   1957    53.3  65551171     2487.
##  8 United Kingdom Europe     1957    70.4  51430000    11283.
##  9 Bangladesh     Asia       1957    39.3  51365468      662.
## 10 Italy          Europe     1957    67.8  49182000     6249.
## # ... with 132 more rows
```

Using mutate to change or create a column

Suppose we want life expectancy to be measured in months instead of years: you'd have to multiply the existing value by 12. You can use the `mutate()` verb to change this column, or to create a new column that's calculated this way.

INSTRUCTIONS

Use `mutate()` to change the existing `lifeExp` column, by multiplying it by 12: `12 * lifeExp`.

Use `mutate()` to add a new column, called `lifeExpMonths`, calculated as `12 * lifeExp`.

```
library(gapminder)
library(dplyr)

# Use mutate to change lifeExp to be in months
gapminder %>%
  mutate(lifeExp = lifeExp * 12)
```

```
## # A tibble: 1,704 x 6
##    country     continent  year lifeExp      pop gdpPercap
##    <fct>       <fct>     <int>   <dbl>    <int>     <dbl>
##  1 Afghanistan Asia       1952    346.  8425333      779.
##  2 Afghanistan Asia       1957    364.  9240934      821.
##  3 Afghanistan Asia       1962    384. 10267083      853.
##  4 Afghanistan Asia       1967    408. 11537966      836.
##  5 Afghanistan Asia       1972    433. 13079460      740.
##  6 Afghanistan Asia       1977    461. 14880372      786.
##  7 Afghanistan Asia       1982    478. 12881816      978.
##  8 Afghanistan Asia       1987    490. 13867957      852.
##  9 Afghanistan Asia       1992    500. 16317921      649.
## 10 Afghanistan Asia       1997    501. 22227415      635.
## # ... with 1,694 more rows
```

```
# Use mutate to create a new column called lifeExpMonths
gapminder %>%
  mutate(lifeExpMonths = 12 * lifeExp)
```

```
## # A tibble: 1,704 x 7
##    country     continent  year lifeExp      pop gdpPercap lifeExpMonths
##    <fct>       <fct>     <int>   <dbl>    <int>     <dbl>         <dbl>
```

```
##  1 Afghanistan Asia       1952    28.8  8425333      779.          346.
##  2 Afghanistan Asia       1957    30.3  9240934      821.          364.
##  3 Afghanistan Asia       1962    32.0 10267083      853.          384.
##  4 Afghanistan Asia       1967    34.0 11537966      836.          408.
##  5 Afghanistan Asia       1972    36.1 13079460      740.          433.
##  6 Afghanistan Asia       1977    38.4 14880372      786.          461.
##  7 Afghanistan Asia       1982    39.9 12881816      978.          478.
##  8 Afghanistan Asia       1987    40.8 13867957      852.          490.
##  9 Afghanistan Asia       1992    41.7 16317921      649.          500.
## 10 Afghanistan Asia       1997    41.8 22227415      635.          501.
## # ... with 1,694 more rows
```

Combining filter, mutate, and arrange

In this exercise, you'll combine all three of the verbs you've learned in this chapter, to find the countries with the highest life expectancy, in months, in the year 2007.

INSTRUCTIONS

- In one sequence of pipes on the gapminder dataset:
- `filter()` for observations from the year 2007,
- `mutate()` to create a column `lifeExpMonths`, calculated as `12 * lifeExp`, and
- `arrange()` in descending order of that new column

```
library(gapminder)
library(dplyr)

# Filter, mutate, and arrange the gapminder dataset
gapminder %>%
  filter(year == 2007) %>%
  mutate(lifeExpMonths = lifeExp * 12) %>%
  arrange(desc(lifeExpMonths))
```

```
## # A tibble: 142 x 7
##    country          continent  year lifeExp    pop gdpPercap lifeExpMonths
##    <fct>            <fct>     <int>   <dbl>  <int>     <dbl>         <dbl>
##  1 Japan            Asia       2007    82.6 1.27e8    31656.          991.
##  2 Hong Kong, China Asia       2007    82.2 6.98e6    39725.          986.
##  3 Iceland          Europe     2007    81.8 3.02e5    36181.          981.
##  4 Switzerland      Europe     2007    81.7 7.55e6    37506.          980.
##  5 Australia        Oceania    2007    81.2 2.04e7    34435.          975.
##  6 Spain            Europe     2007    80.9 4.04e7    28821.          971.
##  7 Sweden           Europe     2007    80.9 9.03e6    33860.          971.
##  8 Israel           Asia       2007    80.7 6.43e6    25523.          969.
##  9 France           Europe     2007    80.7 6.11e7    30470.          968.
## 10 Canada           Americas   2007    80.7 3.34e7    36319.          968.
## # ... with 132 more rows
```

Chapter 2: Data Visualization

You've already been able to answer some questions about the data through dplyr, but you've engaged with them just as a table (such as one showing the life expectancy in the US each year). Often a better way to

understand and present such data is as a graph. Here you'll learn the essential skill of data visualization, using the ggplot2 package. Visualization and maniuplation are often intertwined, so you'll see how the dplyr and ggplot2 packages work closely together to create informative graphs.

Variable assignment

Throughout the exercises in this chapter, you'll be visualizing a subset of the gapminder data from the year 1952. First, you'll have to load the ggplot2 package, and create a `gapminder_1952` dataset to visualize.

INSTRUCTIONS

Load the `ggplot2` package after the `gapminder` and `dplyr` packages. Filter `gapminder` for observations from the year 1952, and assign it to a new dataset `gapminder_1952` using the assignment operator (`<-`).

```
# Load the ggplot2 package as well
library(gapminder)
library(dplyr)
library(ggplot2)

# Create gapminder_1952
gapminder_1952 <- gapminder %>%
  filter(year == 1952)
```

Comparing population and GDP per capita

In the video you learned to create a scatter plot with GDP per capita on the x-axis and life expectancy on the y-axis (the code for that graph is shown here). When you're exploring data visually, you'll often need to try different combinations of variables and aesthetics.

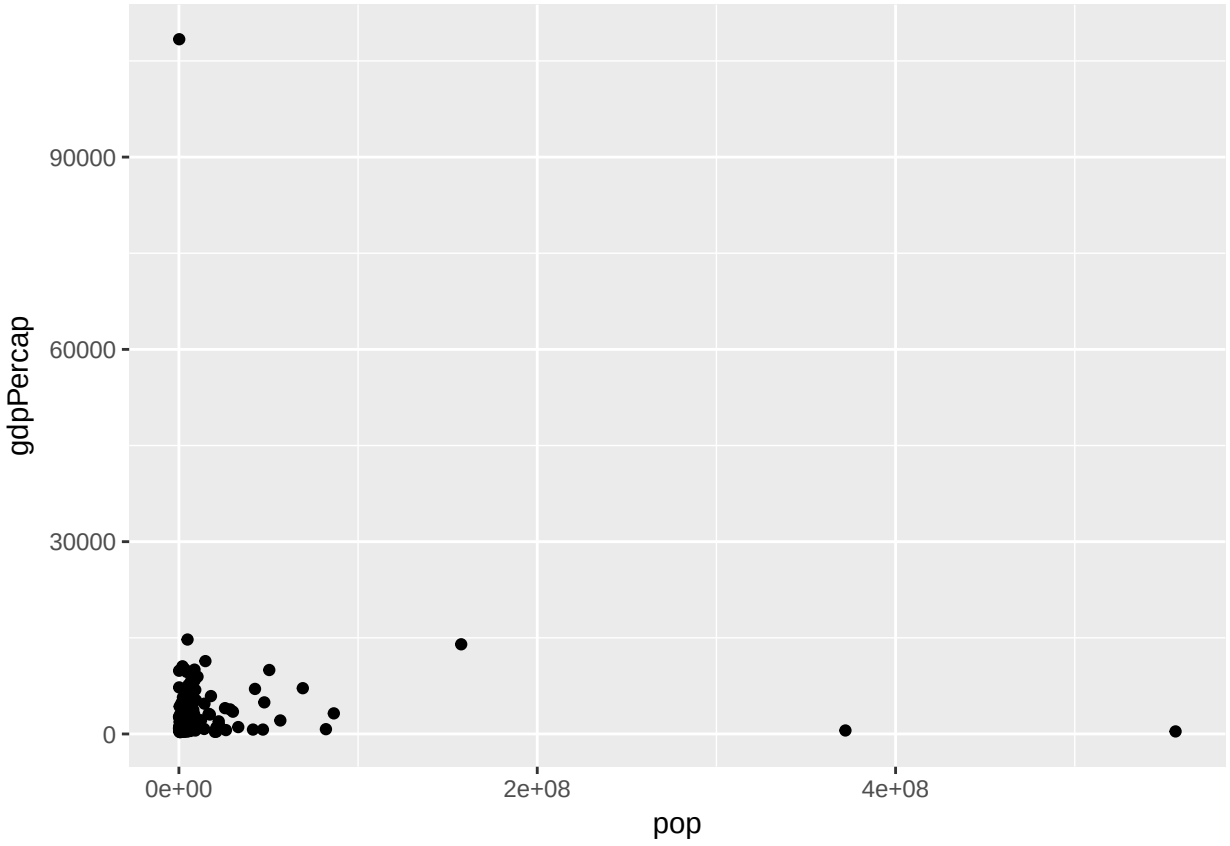
INSTRUCTIONS

Change the scatter plot of `gapminder_1952` so that (`pop`) is on the x-axis and GDP per capita (`gdpPercap`) is on the y-axis.

```
library(gapminder)
library(dplyr)
library(ggplot2)

gapminder_1952 <- gapminder %>%
  filter(year == 1952)

# Change to put pop on the x-axis and gdpPercap on the y-axis
ggplot(gapminder_1952, aes(x = pop, y = gdpPercap)) +
  geom_point()
```



Comparing population and life expectancy

In this exercise, you'll use `ggplot2` to create a scatter plot from scratch, to compare each country's population with its life expectancy in the year 1952.

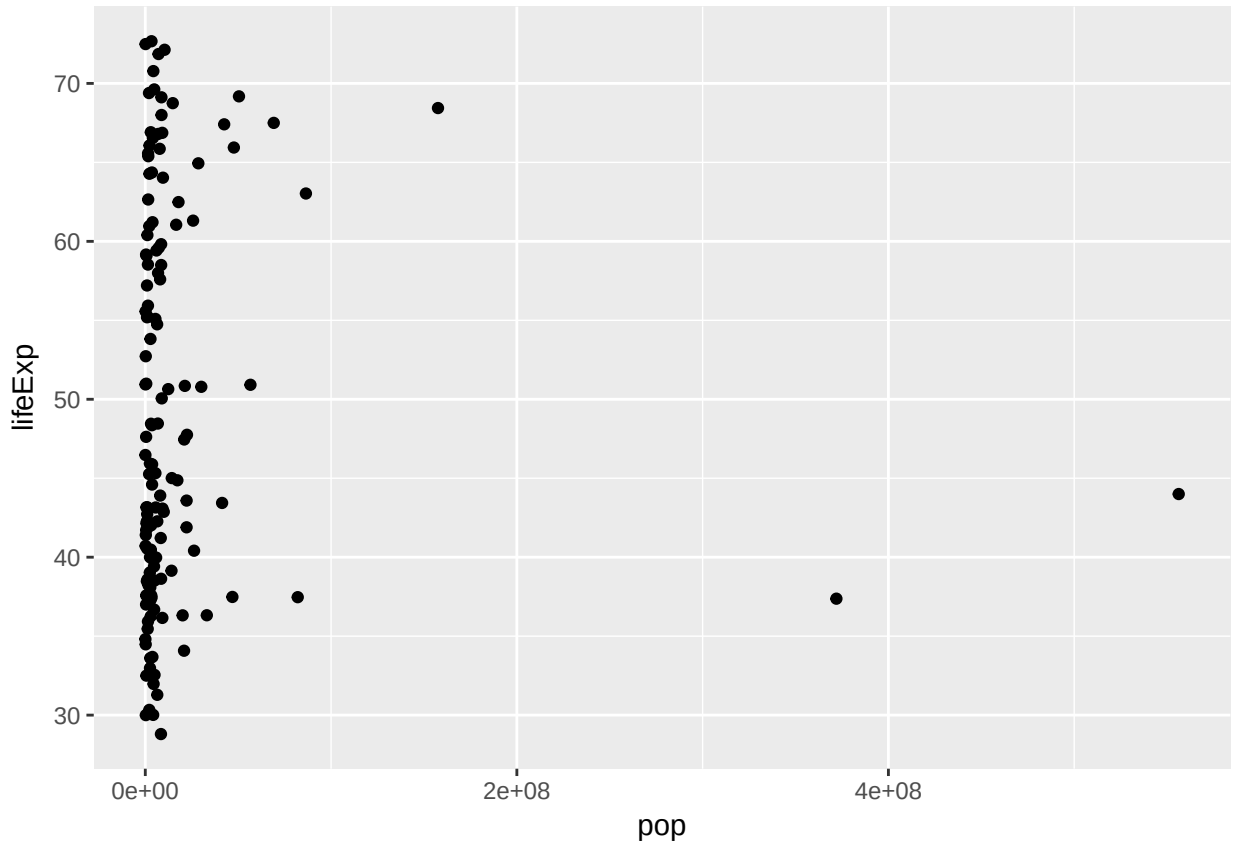
INSTRUCTIONS

Create a scatter plot of `gapminder_1952` with population (`pop`) is on the x-axis and life expectancy (`lifeExp`) on the y-axis.

```
library(gapminder)
library(dplyr)
library(ggplot2)

gapminder_1952 <- gapminder %>%
  filter(year == 1952)

# Create a scatter plot with pop on the x-axis and lifeExp on the y-axis
ggplot(gapminder_1952, aes(x = pop, y = lifeExp)) +
  geom_point()
```



Putting the x-axis on a log scale

You previously created a scatter plot with population on the x-axis and life expectancy on the y-axis. Since population is spread over several orders of magnitude, with some countries having a much higher population than others, it's a good idea to put the x-axis on a log scale.

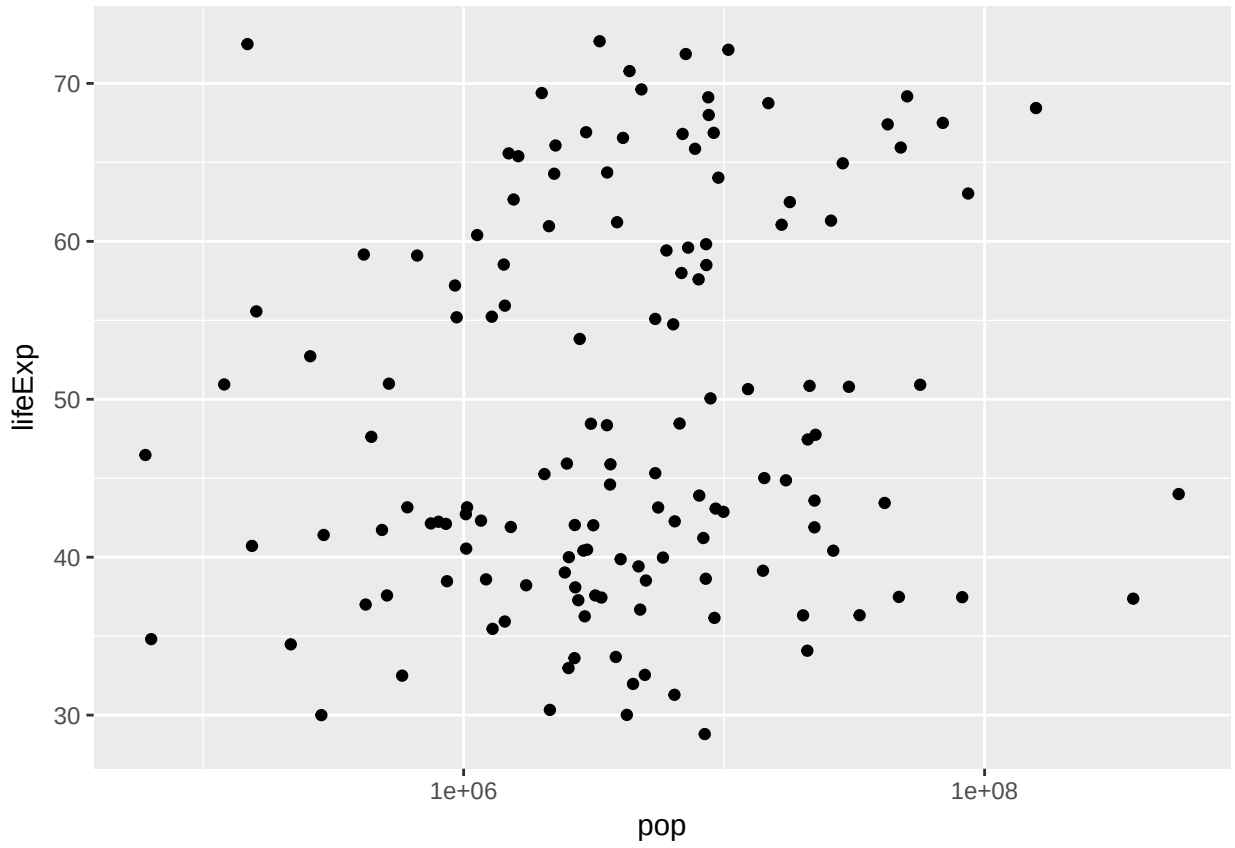
INSTRUCTIONS

Change the existing scatter plot (code provided) to put the x-axis (representing population) on a log scale.

```
library(gapminder)
library(dplyr)
library(ggplot2)

gapminder_1952 <- gapminder %>%
  filter(year == 1952)

# Change this plot to put the x-axis on a log scale
ggplot(gapminder_1952, aes(x = pop, y = lifeExp)) +
  geom_point() +
  scale_x_log10()
```



Putting the x- and y- axes on a log scale

Suppose you want to create a scatter plot with population on the x-axis and GDP per capita on the y-axis. Both population and GDP per-capita are better represented with log scales, since they vary over many orders of magnitude.

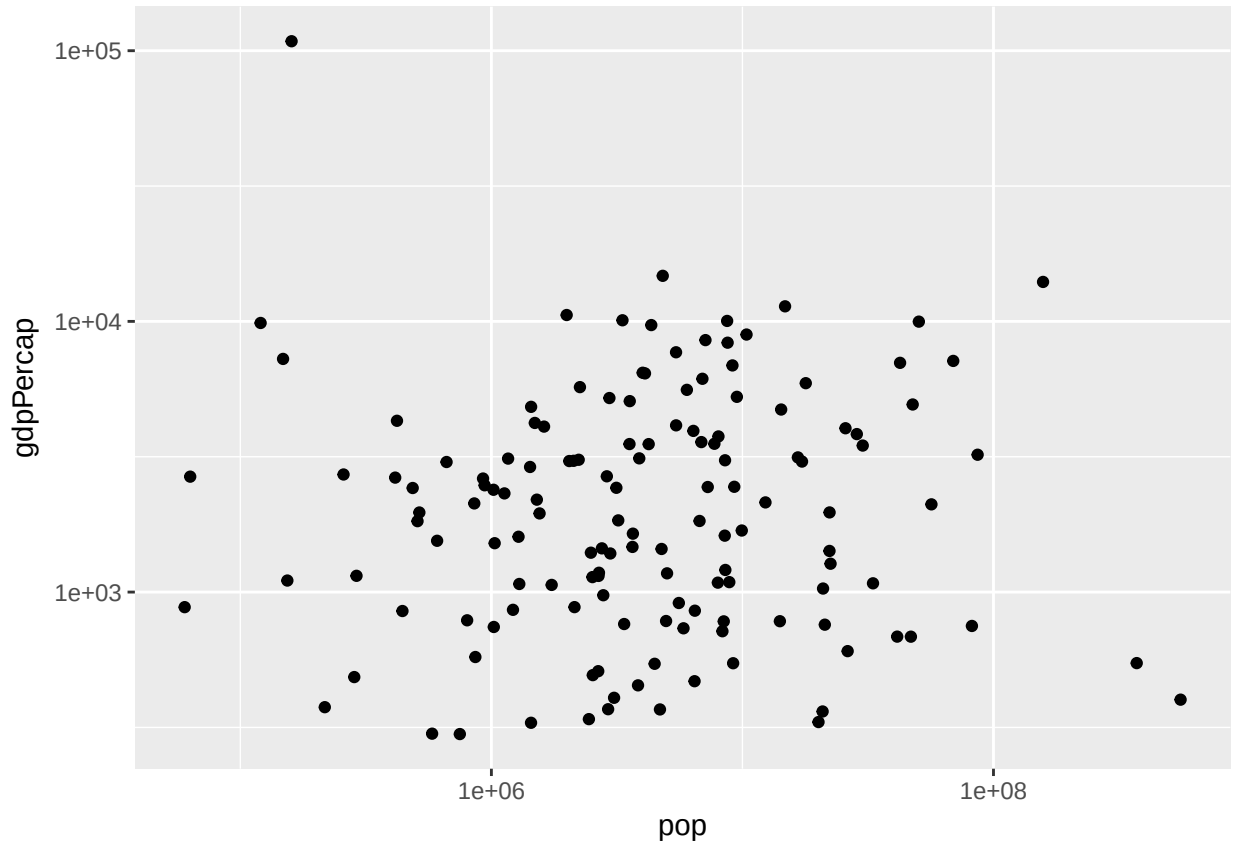
INSTRUCTIONS

Create a scatter plot with population (`pop`) on the x-axis and GDP per capita (`gdpPercap`) on the y-axis. Put both the x- and y- axes on a log scale.

```
library(gapminder)
library(dplyr)
library(ggplot2)

gapminder_1952 <- gapminder %>%
  filter(year == 1952)

# Scatter plot comparing pop and gdpPercap, with both axes on a log scale
ggplot(gapminder_1952, aes(x = pop, y = gdpPercap)) +
  geom_point() +
  scale_x_log10() +
  scale_y_log10()
```



Adding color to a scatter plot

In this lesson you learned how to use the color aesthetic, which can be used to show which continent each point in a scatter plot represents.

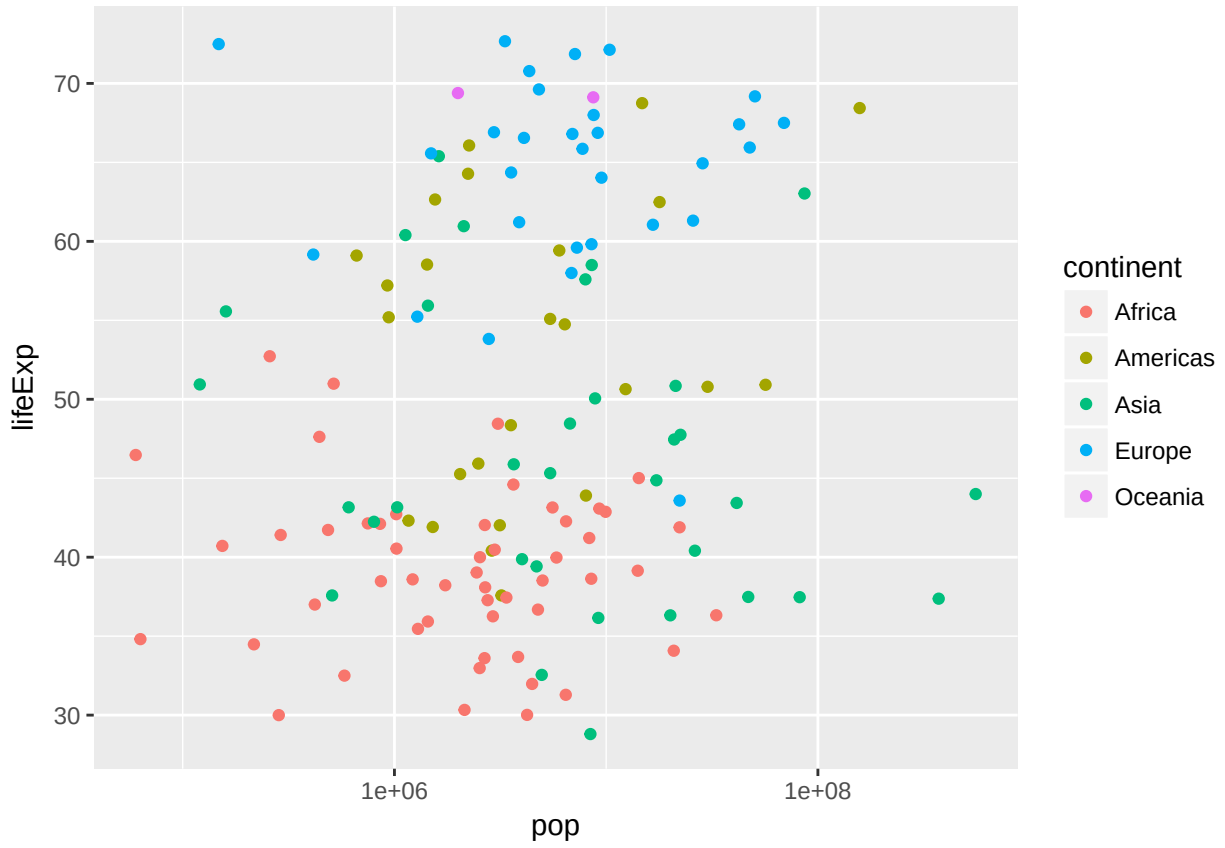
INSTRUCTIONS

Create a scatter plot with population (`pop`) on the x-axis, life expectancy (`lifeExp`) on the y-axis, and with continent (`continent`) represented by the color of the points. Put the x-axis on a log scale.

```
library(gapminder)
library(dplyr)
library(ggplot2)

gapminder_1952 <- gapminder %>%
  filter(year == 1952)

# Scatter plot comparing pop and lifeExp, with color representing continent
ggplot(gapminder_1952, aes(x = pop, y = lifeExp, color = continent)) +
  geom_point() +
  scale_x_log10()
```



Adding size and color to a plot

In the last exercise, you created a scatter plot communicating information about each country's population, life expectancy, and continent. Now you'll use the size of the points to communicate even more.

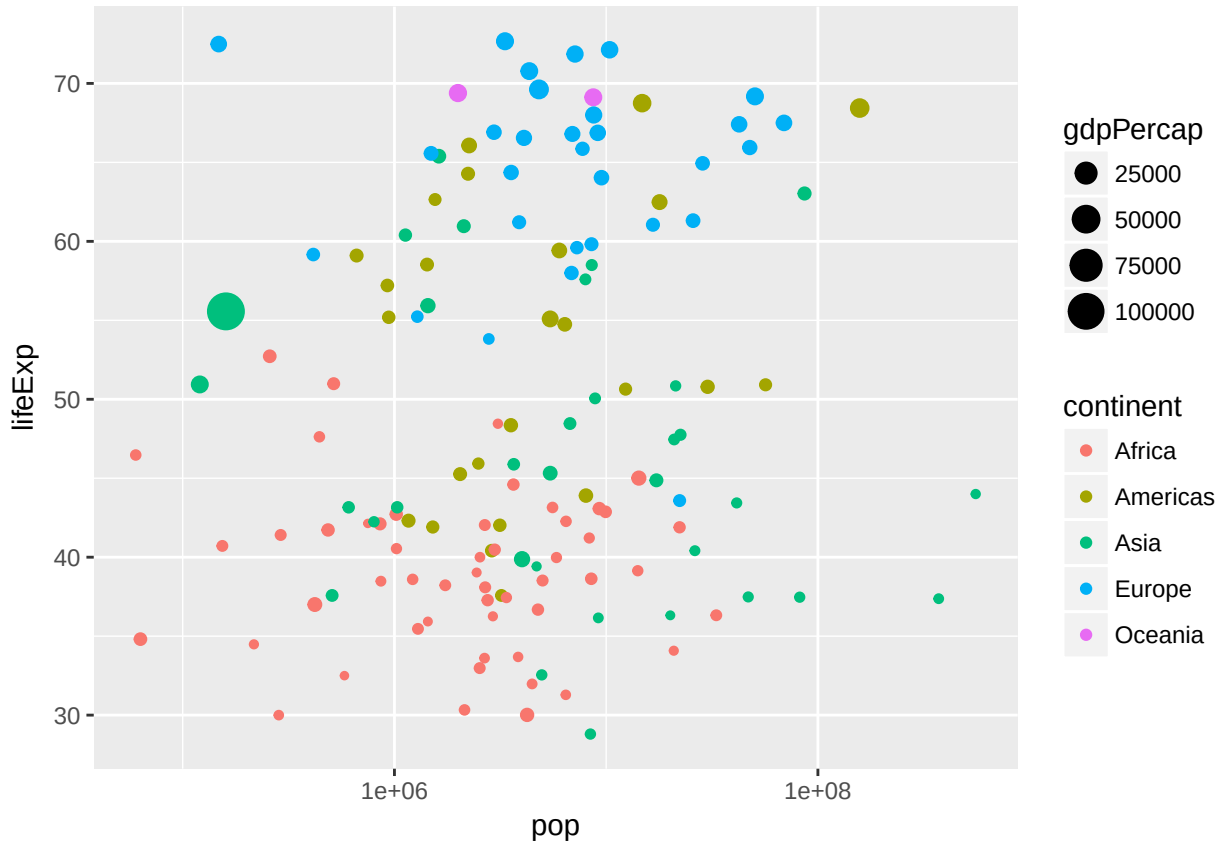
INSTRUCTIONS

Modify the scatter plot so that the size of the points represents each country's GDP per capita (`gdpPercap`).

```
library(gapminder)
library(dplyr)
library(ggplot2)

gapminder_1952 <- gapminder %>%
  filter(year == 1952)

# Add the size aesthetic to represent a country's gdpPercap
ggplot(gapminder_1952, aes(x = pop, y = lifeExp, color = continent,
                           size = gdpPercap)) +
  geom_point() +
  scale_x_log10()
```



Creating a subgraph for each continent

You've learned to use faceting to divide a graph into subplots based on one of its variables, such as the continent.

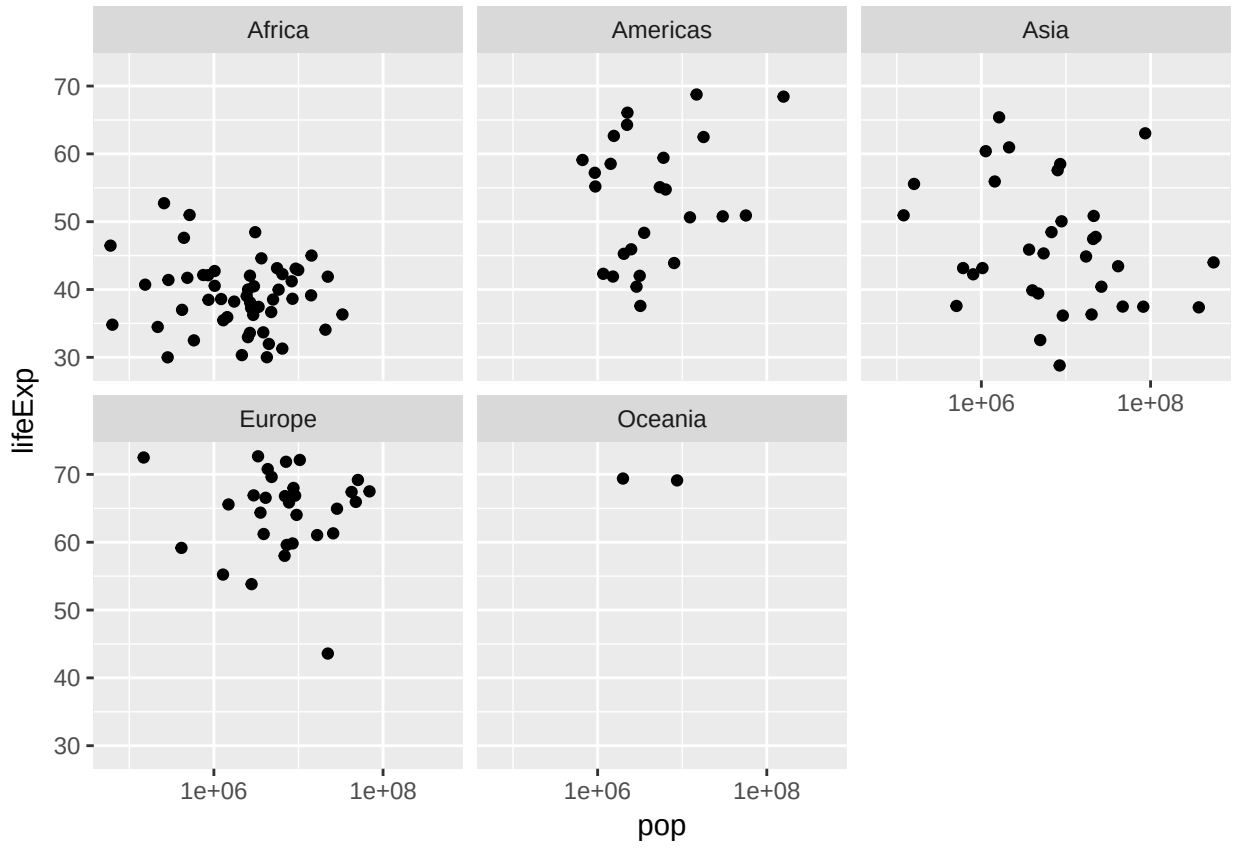
INSTRUCTIONS

Create a scatter plot of `gapminder_1952` with the x-axis representing population (`pop`), the y-axis representing life expectancy (`lifeExp`), and faceted to have one subplot per continent (`continent`). Put the x-axis on a log scale.

```
library(gapminder)
library(dplyr)
library(ggplot2)

gapminder_1952 <- gapminder %>%
  filter(year == 1952)

# Scatter plot comparing pop and lifeExp, faceted by continent
ggplot(gapminder_1952, aes(x = pop, y = lifeExp)) +
  geom_point() +
  scale_x_log10()+
  facet_wrap(~ continent)
```



Faceting by year

All of the graphs in this chapter have been visualizing statistics within one year. Now that you're able to use faceting, however, you can create a graph showing all the country-level data from 1952 to 2007, to understand how global statistics have changed over time.

INSTRUCTIONS

Create a scatter plot of the gapminder data:

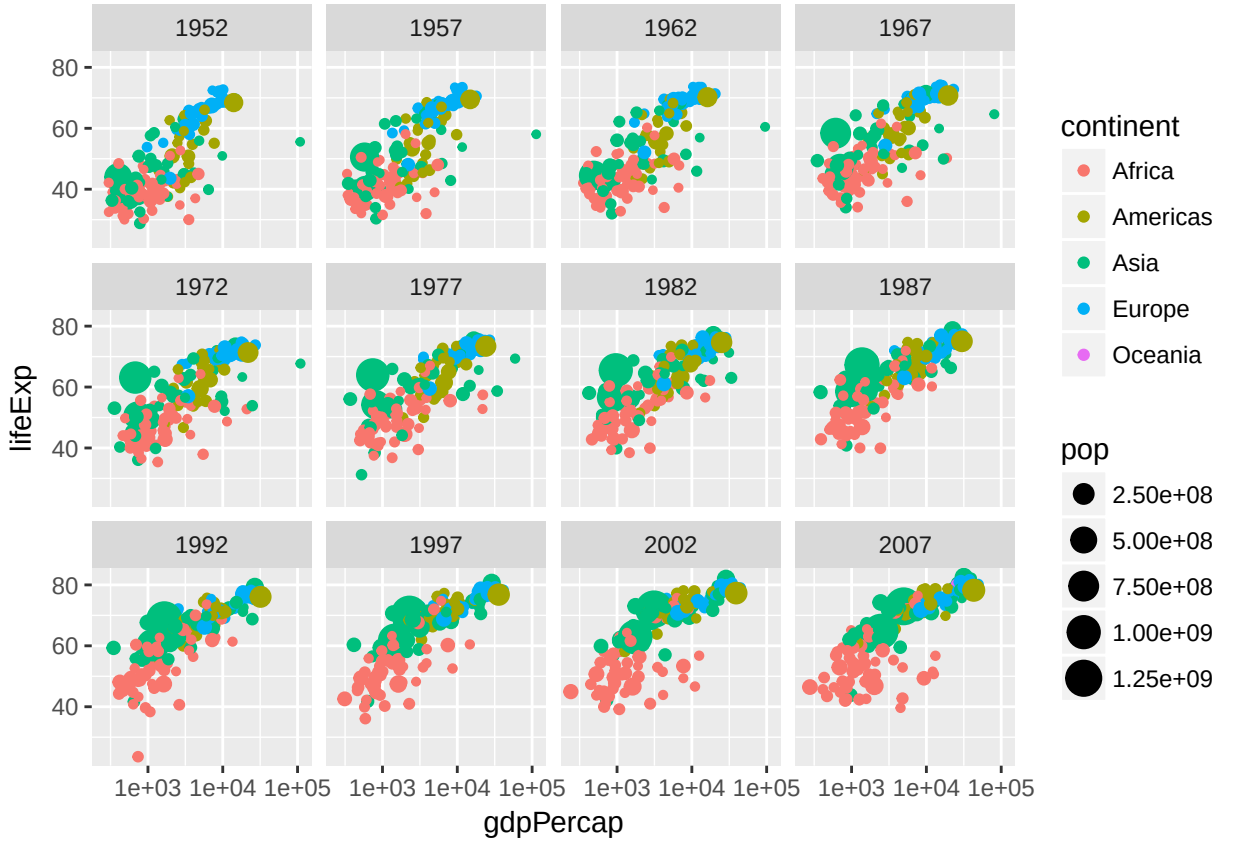
- Put GDP per capita (`gdpPercap`) on the x-axis and life expectancy (`lifeExp`) on the y-axis, with continent (`continent`) represented by color and population (`pop`) represented by size.
- Put the x-axis on a log scale
- Facet by the `year` variable

```
library(gapminder)
library(dplyr)
library(ggplot2)

# Scatter plot comparing gdpPercap and lifeExp, with color representing continent
# and size representing population, faceted by year

ggplot(gapminder, aes(x = gdpPercap, y = lifeExp, color = continent,
                      size = pop)) +
      geom_point() +
```

```
  scale_x_log10() +
  facet_wrap(~ year)
```



Chapter 3: Grouping and summarizing

So far you've been answering questions about individual country-year pairs, but we may be interested in aggregations of the data, such as the average life expectancy of all countries within each year. Here you'll learn to use the group by and summarize verbs, which collapse large datasets into manageable summaries.

Chapter 4: Types of Visualization

You've learned to create scatter plots with ggplot2. In this chapter you'll learn to create line plots, bar plots, histograms, and boxplots. You'll see how each plot needs different kinds of data manipulation to prepare for it, and understand the different roles of each of these plot types in data analysis.