

# Data Science Visualization

The textbook for the Data Science course series is [freely available online](#).

## Learning Objectives

- Data visualization principles to better communicate data-driven findings
- How to use ggplot2 to create custom plots
- The weaknesses of several widely used plots and why you should avoid them

## Course Overview

### Section 1: Introduction to Data Visualization and Distributions

You will get started with data visualization and distributions in R.

### Section 2: Introduction to ggplot2

You will learn how to use ggplot2 to create plots.

### Section 3: Summarizing with dplyr

You will learn how to summarize data using dplyr.

### Section 4: Gapminder

You will see examples of ggplot2 and dplyr in action with the Gapminder dataset.

### Section 5: Data Visualization Principles

You will learn general principles to guide you in developing effective data visualizations.

## Section 1 Overview

Section 1 introduces you to Data Visualization and Distributions.

After completing Section 1, you will:

- understand the importance of data visualization for communicating data-driven findings.
- be able to use distributions to summarize data.
- be able to use the average and the standard deviation to understand the normal distribution.
- be able to assess how well a normal distribution fits the data using a quantile-quantile plot.
- be able to interpret data from a boxplot.

## Introduction to Data Visualization

The textbook for this section is available [here](#)

### Key points

- Plots of data easily communicate information that is difficult to extract from tables of raw values.
- Data visualization is a key component of exploratory data analysis (EDA), in which the properties of data are explored through visualization and summarization techniques.
- Data visualization can help discover biases, systematic errors, mistakes and other unexpected problems in data before those data are incorporated into potentially flawed analysis.
- This course covers the basics of data visualization and EDA in R using the **ggplot2** package and motivating examples from world health, economics and infectious disease.

### Code

```
if(!require(dslabs)) install.packages("dslabs")
```

```
## Loading required package: dslabs
```

```
library(dslabs)
data(murders)
head(murders)
```

```
##      state abb region population total
## 1  Alabama  AL  South   4779736    135
## 2   Alaska  AK   West    710231     19
## 3  Arizona  AZ   West   6392017    232
## 4  Arkansas AR  South   2915918     93
## 5 California CA  West  37253956   1257
## 6   Colorado CO   West   5029196     65
```

## Introduction to Distributions

The textbook for this section is available [here](#)

### Key points

- The most basic statistical summary of a list of objects is its distribution.
- We will learn ways to visualize and analyze distributions in the upcoming videos.
- In some cases, data can be summarized by a two-number summary: the average and standard deviation. We will learn to use data visualization to determine when that is appropriate.

## Data Types

The textbook for this section is available [here](#)

### Key points

- Categorical data are variables that are defined by a small number of groups.
  - Ordinal categorical data have an inherent order to the categories (mild/medium/hot, for example).

- Non-ordinal categorical data have no order to the categories.
- Numerical data take a variety of numeric values.
  - Continuous variables can take any value.
  - Discrete variables are limited to sets of specific values.

## Assessment - Data Types

1. The type of data we are working with will often influence the data visualization technique we use.

We will be working with two types of variables: categorical and numeric. Each can be divided into two other groups: categorical can be ordinal or not, whereas numerical variables can be discrete or continuous.

We will review data types using some of the examples provided in the `dslabs` package. For example, the `heights` dataset.

```
library(dslabs)
data(heights)
```

```
data(heights)
names(heights)
```

```
## [1] "sex"    "height"
```

2. We saw that `sex` is the first variable. We know what values are represented by this variable and can confirm this by looking at the first few entries:

```
head(heights)
```

```
##      sex height
## 1  Male     75
## 2  Male     70
## 3  Male     68
## 4  Male     74
## 5  Male     61
## 6 Female     65
```

What data type is the `sex` variable?

- ☐ A. Continuous
- ☒ B. Categorical
- ☐ C. Ordinal
- ☐ D. None of the above

3. Keep in mind that discrete numeric data can be considered ordinal.

Although this is technically true, we usually reserve the term ordinal data for variables belonging to a small number of different groups, with each group having many members.

The `height` variable could be ordinal if, for example, we report a small number of values such as short, medium, and tall. Let's explore how many unique values are used by the `heights` variable. For this we can use the `unique` function:

```
x <- c(3, 3, 3, 3, 4, 4, 2)
unique(x)
```

```
x <- heights$height
length(unique(x))
```

```
## [1] 139
```

4. One of the useful outputs of data visualization is that we can learn about the distribution of variables.

For categorical data we can construct this distribution by simply computing the frequency of each unique value. This can be done with the function `table`. Here is an example:

```
x <- c(3, 3, 3, 3, 4, 4, 2)
table(x)
```

```
x <- heights$height
tab <- table(x)
```

5. To see why treating the reported heights as an ordinal value is not useful in practice we note how many values are reported only once.

In the previous exercise we computed the variable `tab` which reports the number of times each unique value appears. For values reported only once `tab` will be 1. Use logicals and the function `sum` to count the number of times this happens.

```
tab <- table(heights$height)
sum(tab==1)
```

```
## [1] 63
```

6. Since there are a finite number of reported heights and technically the height can be considered ordinal, which of the following is true:
- ☒ A. It is more effective to consider heights to be numerical given the number of unique values we observe and the fact that if we keep collecting data even more will be observed.
  - ☐ B. It is actually preferable to consider heights ordinal since on a computer there are only a finite number of possibilities.
  - ☐ C. This is actually a categorical variable: tall, medium or short.
  - ☐ D. This is a numerical variable because numbers are used to represent it.

## Describe Heights to ET

The textbook for this section is available:

- [Case Study describing student heights](#)
- [Distribution Function](#)
- [CDF Intro](#)
- [Histograms](#)

## Key points

- A distribution is a function or description that shows the possible values of a variable and how often those values occur.
- For categorical variables, the distribution describes the proportions of each category.
- A *frequency table* is the simplest way to show a categorical distribution. Use `prop.table` to convert a table of counts to a frequency table. *Barplots* display the distribution of categorical variables and are a way to visualize the information in frequency tables.
- For continuous numerical data, reporting the frequency of each unique entry is not an effective summary as many or most values are unique. Instead, a distribution function is required.
- The *cumulative distribution function (CDF)* is a function that reports the proportion of data below a value  $a$  for all values of  $a$ :  $F(a) = Pr(x \leq a)$ .
- The proportion of observations between any two values  $a$  and  $b$  can be computed from the CDF as  $F(b) - F(a)$ .
- A *histogram* divides data into non-overlapping bins of the same size and plots the counts of number of values that fall in that interval.

## Code

```
# load the dataset
library(dslabs)
data(heights)
```

```
# make a table of category proportions
prop.table(table(heights$sex))
```

```
##
##      Female      Male
## 0.2266667 0.7733333
```

## Smooth Density Plots

The textbook for this section is available [here](#)

## Key points

- *Smooth density plots* can be thought of as histograms where the bin width is extremely or infinitely small. The smoothing function makes estimates of the true continuous trend of the data given the available sample of data points.
- The degree of smoothness can be controlled by an argument in the plotting function. (We will learn functions for plotting later.)
- While the histogram is an assumption-free summary, the smooth density plot is shaped by assumptions and choices you make as a data analyst.
- The y-axis is scaled so that the area under the density curve sums to 1. This means that interpreting values on the y-axis is not straightforward. To determine the proportion of data in between two values, compute the area under the smooth density curve in the region between those values.
- An advantage of smooth densities over histograms is that densities are easier to compare visually.

**A further note on histograms:** note that the choice of binwidth has a determinative effect on shape. There is no “true” choice for binwidth, and you can sometimes gain insights into the data by experimenting with binwidths.

## Assessment - Distributions

1. You may have noticed that numerical data is often summarized with the average value.

For example, the quality of a high school is sometimes summarized with one number: the average score on a standardized test. Occasionally, a second number is reported: the standard deviation. So, for example, you might read a report stating that scores were 680 plus or minus 50 (the standard deviation). The report has summarized an entire vector of scores with just two numbers. Is this appropriate? Is there any important piece of information that we are missing by only looking at this summary rather than the entire list? We are going to learn when these 2 numbers are enough and when we need more elaborate summaries and plots to describe the data.

Our first data visualization building block is learning to summarize lists of factors or numeric vectors. The most basic statistical summary of a list of objects or numbers is its distribution. Once a vector has been summarized as distribution, there are several data visualization techniques to effectively relay this information. In later assessments we will practice to write code for data visualization. Here we start with some multiple choice questions to test your understanding of distributions and related basic plots.

In the murders dataset, the region is a categorical variable and on the right you can see its distribution. To the closest 5%, what proportion of the states are in the North Central region?

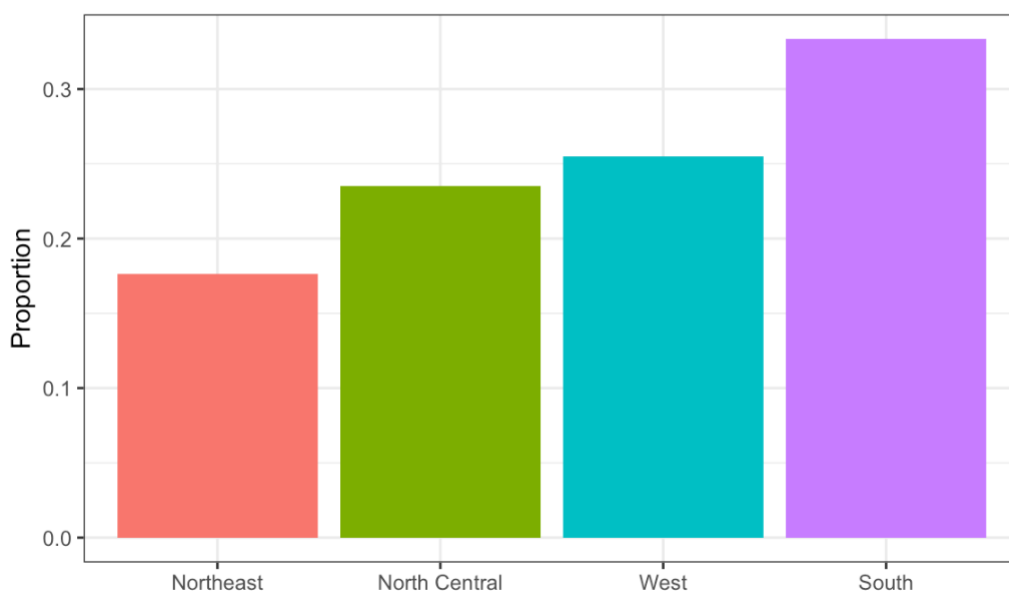


Figure 1: Region vs. Proportion

- ☐ A. 75%
- ☐ B. 50%
- ☒ C. 20%
- ☐ D. 5%

2. In the murders dataset, the region is a categorical variable and to the right is its distribution.

Which of the following is true:

- ☐ A. The graph above is a histogram.

- ☒ B. The graph above shows only four numbers with a bar plot.
- ☐ C. Categories are not numbers, so it does not make sense to graph the distribution.
- ☐ D. The colors, not the height of the bars, describe the distribution.

3. The plot shows the eCDF for male heights.

Based on the plot, what percentage of males are shorter than 75 inches?

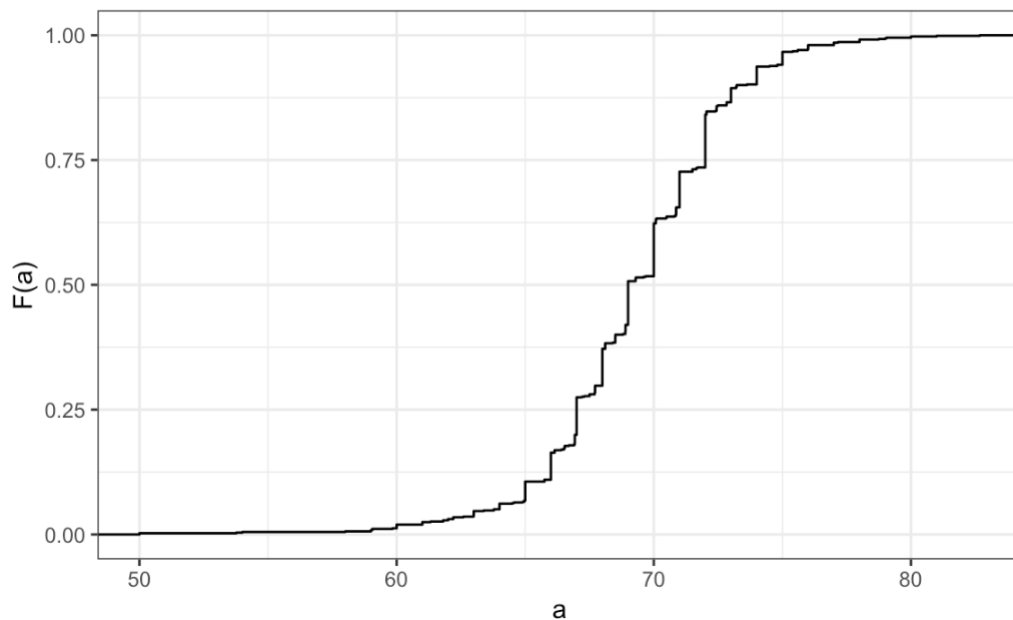


Figure 2: eCDF for male heights

- ☐ A. 100%
- ☒ B. 95%
- ☐ C. 80%
- ☐ D. 72 inches

4. To the closest inch, what height  $m$  has the property that  $1/2$  of the male students are taller than  $m$  and  $1/2$  are shorter?

- ☐ A. 61 inches
- ☐ B. 64 inches
- ☒ C. 69 inches
- ☐ D. 74 inches

5. Here is an eCDF of the murder rates across states.

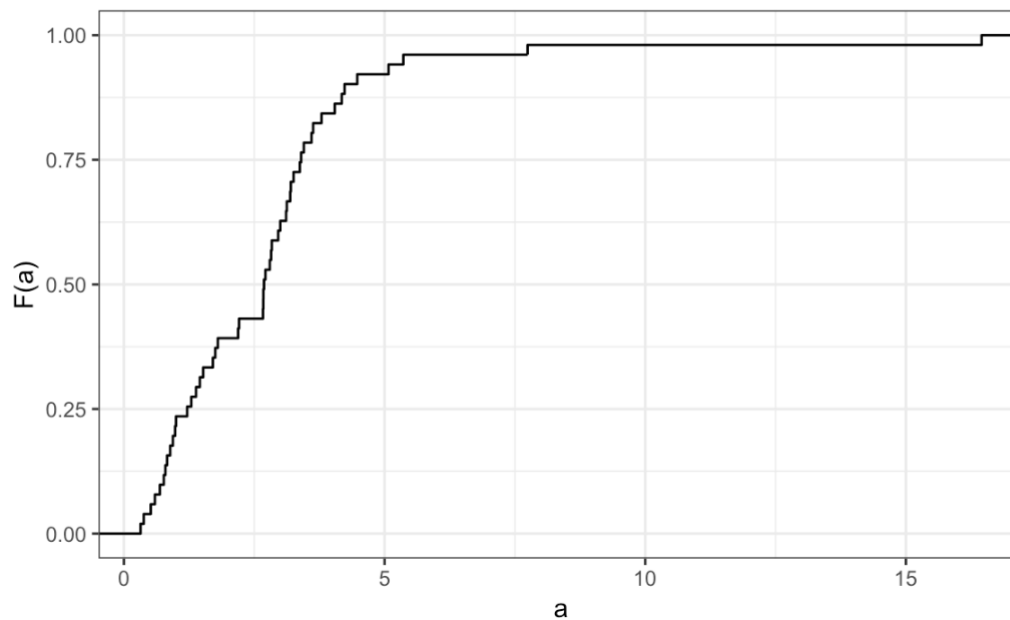


Figure 3: eCDF of the murder rates across states

Knowing that there are 51 states (counting DC) and based on this plot, how many states have murder rates larger than 10 per 100,000 people?

- ☒ A. 1
- ☐ B. 5
- ☐ C. 10
- ☐ D. 50

6. Based on the eCDF above, which of the following statements are true.

- ☐ A. About half the states have murder rates above 7 per 100,000 and the other half below.
- ☐ B. Most states have murder rates below 2 per 100,000.
- ☐ C. All the states have murder rates above 2 per 100,000.
- ☒ D. With the exception of 4 states, the murder rates are below 5 per 100,000.



7. Here is a histogram of male heights in our `heights` dataset.

Based on this plot, how many males are between 62.5 and 65.5?

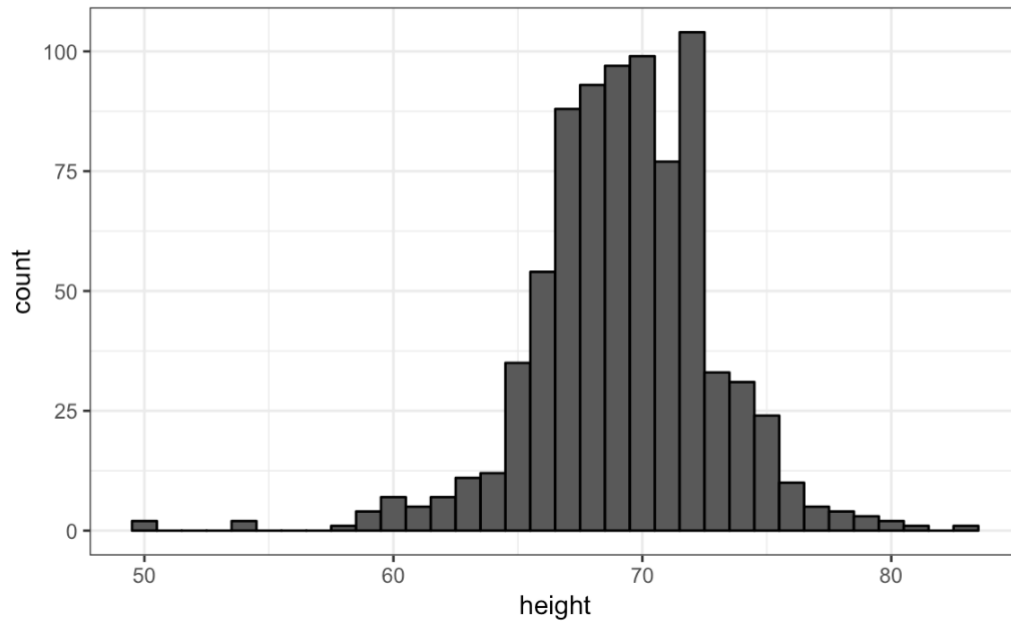


Figure 4: Histogram of male heights

- ☐ A. 11
- ☐ B. 29
- ☒ C. 58
- ☐ D. 99

8. About what percentage are shorter than 60 inches?

- ☒ A. 1%
- ☐ B. 10%
- ☐ C. 25%
- ☐ D. 50%

9. Based on this density plot, about what proportion of US states have populations larger than 10 million?

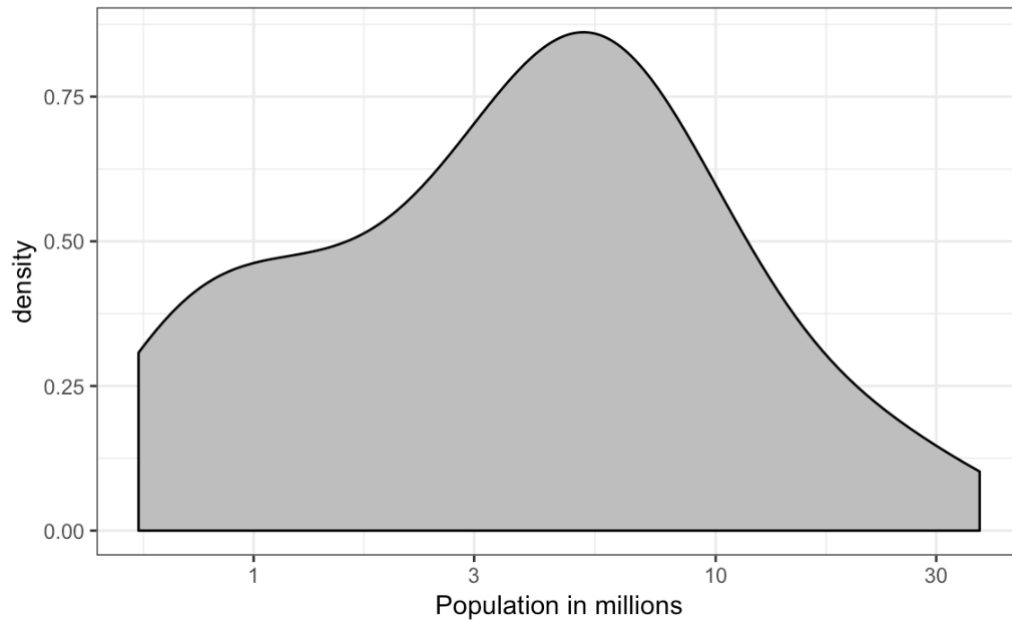


Figure 5: Density plot population

- ☐ A. 0.02
- ☒ B. 0.15
- ☐ C. 0.50
- ☐ D. 0.55

10. Below are three density plots. Is it possible that they are from the same dataset?

Which of the following statements is true?

- ☐ A. It is impossible that they are from the same dataset.
- ☐ B. They are from the same dataset, but the plots are different due to code errors.
- ☐ C. They are the same dataset, but the first and second plot undersmooth and the third oversmooths.
- ☒ D. They are the same dataset, but the first is not in the log scale, the second undersmooths and the third oversmooths.

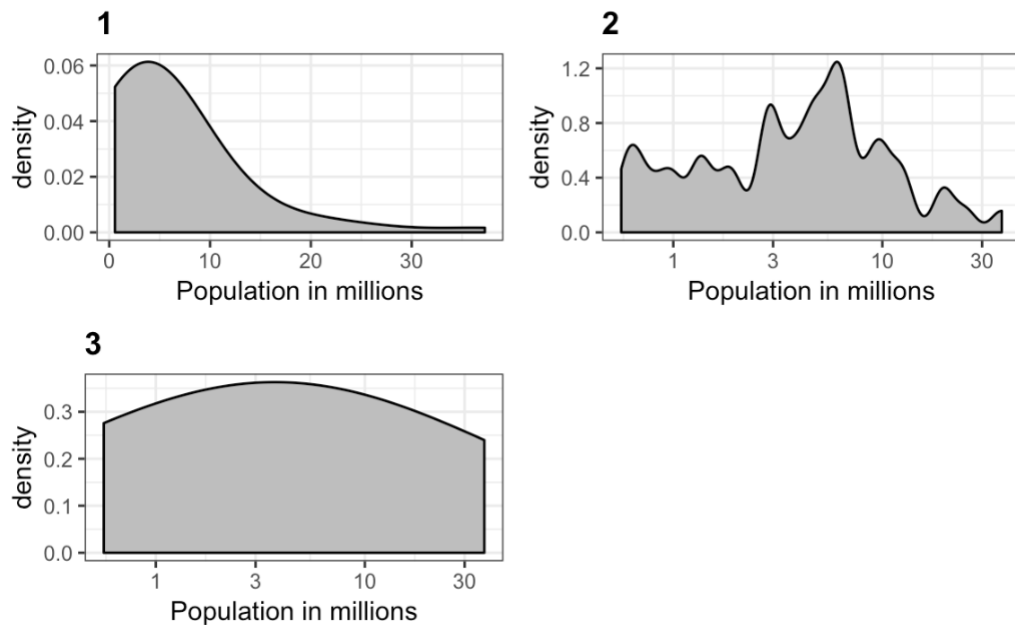


Figure 6: Three density plots

## Normal Distribution

The textbook for this section is available [here](#)

### Key points

- The normal distribution:
  - Is centered around one value, the *mean*
  - Is symmetric around the mean
  - Is defined completely by its mean ( $\mu$ ) and standard deviation ( $\sigma$ )
  - Always has the same proportion of observations within a given distance of the mean (for example, 95% within  $2\sigma$ )
- The standard deviation is the average distance between a value and the mean value.
- Calculate the mean using the `mean` function.
- Calculate the standard deviation using the `sd` function or manually.
- Standard units describe how many standard deviations a value is away from the mean. The z-score, or number of standard deviations an observation  $x$  is away from the mean ( $\mu$ ):
 
$$Z = \frac{x - \mu}{\sigma}$$
- Compute standard units with the `scale` function.
- **Important:** to calculate the proportion of values that meet a certain condition, use the `mean` function on a logical vector. Because TRUE is converted to 1 and FALSE is converted to 0, taking the mean of this vector yields the proportion of TRUE.

## Equation for the normal distribution

The normal distribution is mathematically defined by the following formula for any mean  $\mu$  and standard deviation  $\sigma$ :

$$Pr(a < x < b) = \int_a^b \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx$$

Code

```
if(!require(tidyverse)) install.packages("tidyverse")

## Loading required package: tidyverse

## -- Attaching packages -----

## v ggplot2 3.3.2      v purrr  0.3.4
## v tibble  3.0.3      v dplyr  1.0.0
## v tidyr   1.1.0      v stringr 1.4.0
## v readr   1.3.1      v forcats 0.5.0

## -- Conflicts -----
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

# define x as vector of male heights
library(tidyverse)
index <- heights$sex=="Male"
x <- heights$height[index]

# calculate the mean and standard deviation manually
average <- sum(x)/length(x)
SD <- sqrt(sum((x - average)^2)/length(x))

# built-in mean and sd functions - note that the audio and printed values disagree
average <- mean(x)
SD <- sd(x)
c(average = average, SD = SD)

##      average      SD
## 69.314755  3.611024

# calculate standard units
z <- scale(x)

# calculate proportion of values within 2 SD of mean
mean(abs(z) < 2)

## [1] 0.9495074
```

**Note about the sd function:** The built-in R function `sd` calculates the standard deviation, but it divides by `length(x)-1` instead of `length(x)`. When the length of the list is large, this difference is negligible and you can use the built-in `sd` function. Otherwise, you should compute  $\sigma$  by hand. For this course series, assume that you should use the `sd` function unless you are told not to do so.

## Assessment - Normal Distribution

1. Histograms and density plots provide excellent summaries of a distribution.

But can we summarize even further? We often see the average and standard deviation used as summary statistics: a two number summary! To understand what these summaries are and why they are so widely used, we need to understand the normal distribution.

The normal distribution, also known as the bell curve and as the Gaussian distribution, is one of the most famous mathematical concepts in history. A reason for this is that approximately normal distributions occur in many situations. Examples include gambling winnings, heights, weights, blood pressure, standardized test scores, and experimental measurement errors. Often data visualization is needed to confirm that our data follows a normal distribution.

Here we focus on how the normal distribution helps us summarize data and can be useful in practice.

One way the normal distribution is useful is that it can be used to approximate the distribution of a list of numbers without having access to the entire list. We will demonstrate this with the heights dataset.

Load the height data set and create a vector `x` with just the male heights:

```
library(dslabs)
data(heights)
x <- heights$height[heights$sex == "Male"]
```

What proportion of the data is between 69 and 72 inches (taller than 69 but shorter or equal to 72)? A proportion is between 0 and 1.

```
x <- heights$height[heights$sex == "Male"]
mean(x > 69 & x <= 72)
```

```
## [1] 0.3337438
```

2. Suppose all you know about the height data from the previous exercise is the average and the standard deviation and that its distribution is approximated by the normal distribution.

We can compute the average and standard deviation like this:

```
library(dslabs)
data(heights)
x <- heights$height[heights$sex=="Male"]
avg <- mean(x)
stdev <- sd(x)
```

Suppose you only have `avg` and `stdev` below, but no access to `x`, can you approximate the proportion of the data that is between 69 and 72 inches?

Given a normal distribution with a mean `mu` and standard deviation `sigma`, you can calculate the proportion of observations less than or equal to a certain value with `pnorm(value, mu, sigma)`. Notice that this is the CDF for the normal distribution. We will learn much more about `pnorm` later in the course series, but you can also learn more now with `?pnorm`.

```
x <- heights$height[heights$sex=="Male"]
avg <- mean(x)
stdev <- sd(x)
pnorm(72, avg, stdev) - pnorm(69, avg, stdev)
```

```
## [1] 0.3061779
```

3. Notice that the approximation calculated in the second question is very close to the exact calculation in the first question.

The normal distribution was a useful approximation for this case. However, the approximation is not always useful. An example is for the more extreme values, often called the “tails” of the distribution. Let’s look at an example. We can compute the proportion of heights between 79 and 81.

```
library(dslabs)
data(heights)
x <- heights$height[heights$sex == "Male"]
mean(x > 79 & x <= 81)
```

```
x <- heights$height[heights$sex == "Male"]
avg <- mean(x)
stdev <- sd(x)
exact <- mean(x > 79 & x <= 81)
approx <- pnorm(81, avg, stdev) - pnorm(79, avg, stdev)
exact
```

```
## [1] 0.004926108
```

```
approx
```

```
## [1] 0.003051617
```

```
exact/approx
```

```
## [1] 1.614261
```

4. Someone asks you what percent of seven footers are in the National Basketball Association (NBA). Can you provide an estimate? Let’s try using the normal approximation to answer this question.

First, we will estimate the proportion of adult men that are 7 feet tall or taller.

Assume that the distribution of adult men in the world is normally distributed with an average of 69 inches and a standard deviation of 3 inches.

```
# use pnorm to calculate the proportion over 7 feet (7*12 inches)
1 - pnorm(7*12, 69, 3)
```

```
## [1] 2.866516e-07
```

5. Now we have an approximation for the proportion, call it  $p$ , of men that are 7 feet tall or taller.

We know that there are about 1 billion men between the ages of 18 and 40 in the world, the age range for the NBA.

Can we use the normal distribution to estimate how many of these 1 billion men are at least seven feet tall?

```
p <- 1 - pnorm(7*12, 69, 3)
round(p*10^9)
```

```
## [1] 287
```

6. There are about 10 National Basketball Association (NBA) players that are 7 feet tall or higher.

```
p <- 1 - pnorm(7*12, 69, 3)
N <- round(p*10^9)
10/N
```

```
## [1] 0.03484321
```

7. In the previous exercise we estimated the proportion of seven footers in the NBA using this simple code:

```
p <- 1 - pnorm(7*12, 69, 3)
N <- round(p * 10^9)
10/N
```

Repeat the calculations performed in the previous question for LeBron James' height: 6 feet 8 inches. There are about 150 players, instead of 10, that are at least that tall in the NBA.

```
## Change the solution to previous answer
p <- 1 - pnorm(7*12, 69, 3)
N <- round(p * 10^9)
10/N
```

```
## [1] 0.03484321
```

```
p <- 1 - pnorm(6*12+8, 69, 3)
N <- round(p * 10^9)
150/N
```

```
## [1] 0.001220842
```

8. In answering the previous questions, we found that it is not at all rare for a seven footer to become an NBA player.

What would be a fair critique of our calculations?

- ☐ A. Practice and talent are what make a great basketball player, not height.
- ☐ B. The normal approximation is not appropriate for heights.
- ☒ C. As seen in exercise 3, the normal approximation tends to underestimate the extreme values. It's possible that there are more seven footers than we predicted.
- ☐ D. As seen in exercise 3, the normal approximation tends to overestimate the extreme values. It's possible that there are less seven footers than we predicted.

## Quantile-Quantile Plots

The textbook for this section is available [here](#)

### Key points

- Quantile-quantile plots, or QQ-plots, are used to check whether distributions are well-approximated by a normal distribution.
- Given a proportion  $p$ , the quantile  $q$  is the value such that the proportion of values in the data below  $q$  is  $p$ .
- In a QQ-plot, the sample quantiles in the observed data are compared to the theoretical quantiles expected from the normal distribution. If the data are well-approximated by the normal distribution, then the points on the QQ-plot will fall near the identity line (sample = theoretical).
- Calculate sample quantiles (observed quantiles) using the `quantile` function.
- Calculate theoretical quantiles with the `qnorm` function. `qnorm` will calculate quantiles for the standard normal distribution ( $\mu = 0, \sigma = 1$ ) by default, but it can calculate quantiles for any normal distribution given mean and `sd` arguments. We will learn more about `qnorm` in the probability course.
- Note that we will learn alternate ways to make QQ-plots with less code later in the series.

### Code

```
# define x and z
index <- heights$sex=="Male"
x <- heights$height[index]
z <- scale(x)

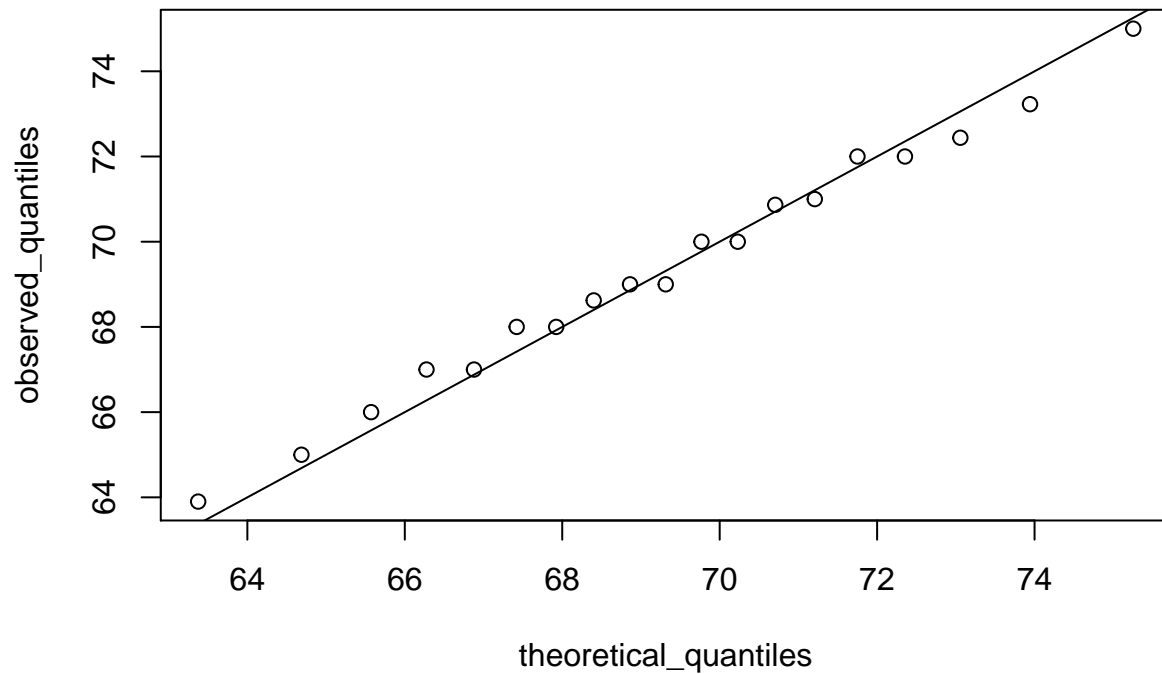
# proportion of data below 69.5
mean(x <= 69.5)
```

```
## [1] 0.5147783
```

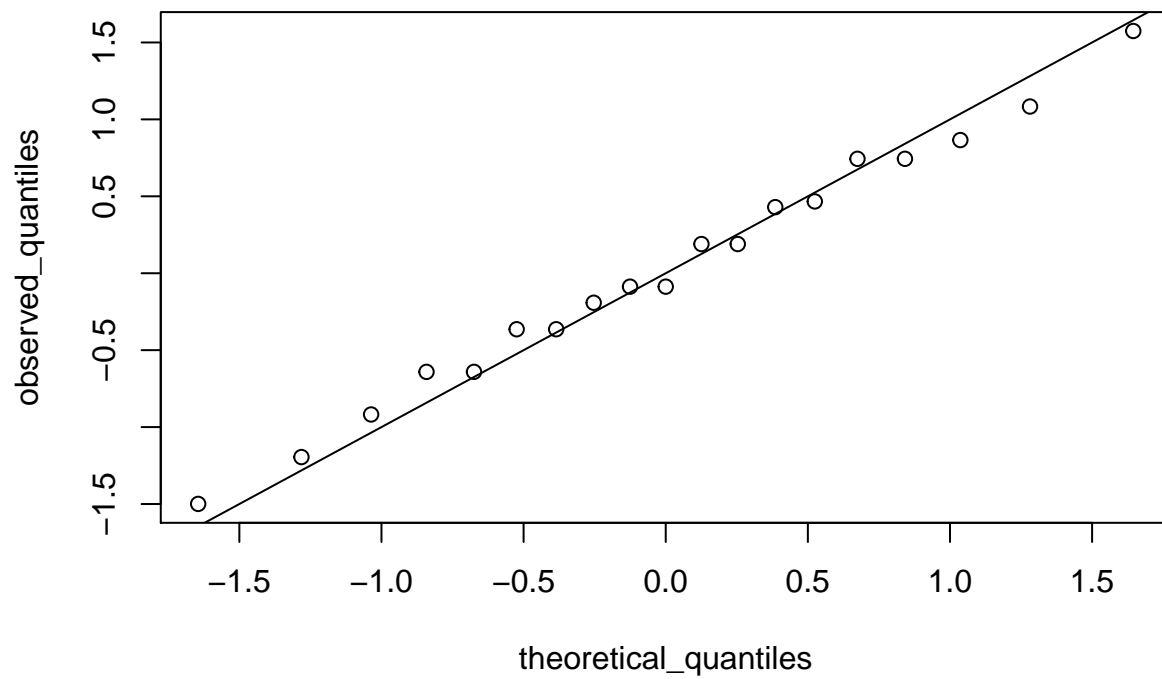
```
# calculate observed and theoretical quantiles
p <- seq(0.05, 0.95, 0.05)
observed_quantiles <- quantile(x, p)
theoretical_quantiles <- qnorm(p, mean = mean(x), sd = sd(x))

# make QQ-plot
plot(theoretical_quantiles, observed_quantiles)
abline(0,1)
```





```
# make QQ-plot with scaled values
observed_quantiles <- quantile(z, p)
theoretical_quantiles <- qnorm(p)
plot(theoretical_quantiles, observed_quantiles)
abline(0,1)
```



## Percentiles

The textbook for this section is available [here](#)

## Key points

- *Percentiles* are the quantiles obtained when defining  $p$  as 0.01, 0.02, ..., 0.99. They summarize the values at which a certain percent of the observations are equal to or less than that value.
- The 50th percentile is also known as the *median*.
- The *quartiles* are the 25th, 50th and 75th percentiles.

## Boxplots

The textbook for this section is available [here](#)

## Key points

- When data do not follow a normal distribution and cannot be succinctly summarized by only the mean and standard deviation, an alternative is to report a five-number summary: range (ignoring outliers) and the quartiles (25th, 50th, 75th percentile).
- In a *boxplot*, the box is defined by the 25th and 75th percentiles and the median is a horizontal line through the box. The whiskers show the range excluding outliers, and outliers are plotted separately as individual points.
- The *interquartile* range is the distance between the 25th and 75th percentiles.
- Boxplots are particularly useful when comparing multiple distributions.
- We discuss outliers later.

## Assessment - Quantiles, percentiles, and boxplots

1. When analyzing data it's often important to know the number of measurements you have for each category.

```
male <- heights$height[heights$sex=="Male"]
female <- heights$height[heights$sex=="Female"]
length(male)
```

```
## [1] 812
```

```
length(female)
```

```
## [1] 238
```

2. Suppose we can't make a plot and want to compare the distributions side by side. If the number of data points is large, listing all the numbers is impractical. A more practical approach is to look at the percentiles. We can obtain percentiles using the `quantile` function like this

```
library(dslabs)
data(heights)
quantile(heights$height, seq(.01, 0.99, 0.01))
```

```
male <- heights$height[heights$sex=="Male"]
female <- heights$height[heights$sex=="Female"]
female_percentiles <- quantile(female, seq(0.1, 0.9, 0.2))
male_percentiles <- quantile(male, seq(0.1, 0.9, 0.2))
df <- data.frame(female = (female_percentiles), male = (male_percentiles))
df
```

```
##      female    male
## 10% 61.00000 65.00000
## 30% 63.00000 68.00000
## 50% 64.98031 69.00000
## 70% 66.46417 71.00000
## 90% 69.00000 73.22751
```

3. Study the boxplots summarizing the distributions of populations sizes by country.

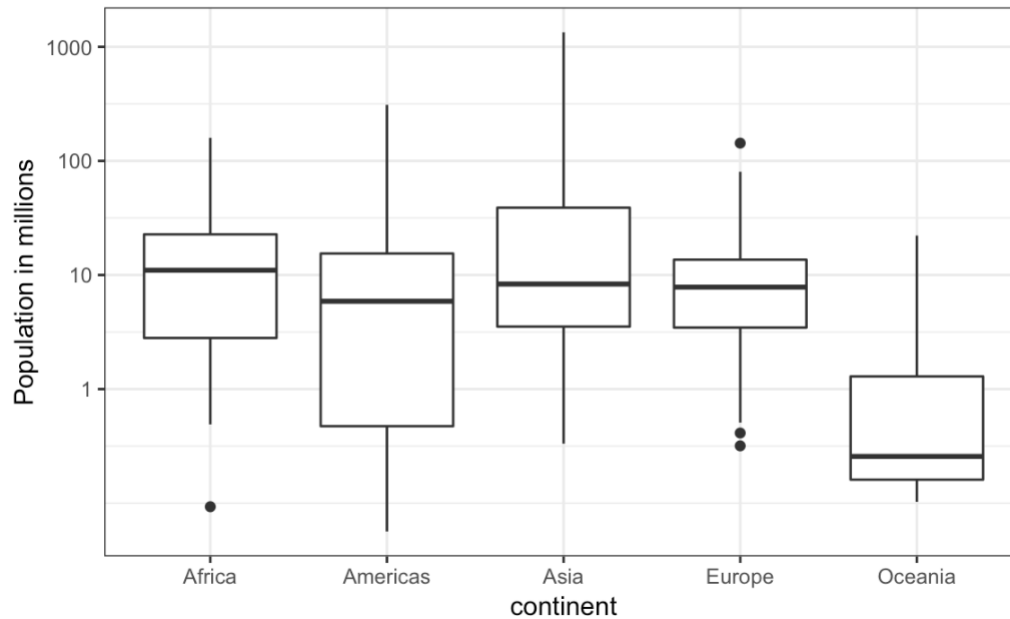


Figure 7: Continent vs Population

Which continent has the country with the largest population size?

- ☐ A. Africa
- ☐ B. Americas
- ☒ C. Asia
- ☐ D. Europe
- ☐ E. Oceania

4. Study the boxplots summarizing the distributions of populations sizes by country.

Which continent has median country with the largest population?

- ☒ A. Africa
- ☐ B. Americas
- ☐ C. Asia
- ☐ D. Europe
- ☐ E. Oceania

5. Again, look at the boxplots summarizing the distributions of populations sizes by country.

To the nearest million, what is the median population size for Africa?

- ☐ A. 100 million
- ☐ B. 25 million
- ☒ C. 10 million
- ☐ D. 5 million
- ☐ E. 1 million

6. Examine the following boxplots and report approximately what proportion of countries in Europe have populations below 14 million?

- ☒ A. 0.75
- ☐ B. 0.50
- ☐ C. 0.25
- ☐ D. 0.01

7. Based on the boxplot, if we use a log transformation, which continent shown below has the largest interquartile range?

- ☐ A. Africa
- ☒ B. Americas
- ☐ C. Asia
- ☐ D. Europe
- ☐ E. Oceania

## Distribution of Female Heights

The textbook for this section is available [here](#)

### Key points

- If a distribution is not normal, it cannot be summarized with only the mean and standard deviation. Provide a histogram, smooth density or boxplot instead.
- A plot can force us to see unexpected results that make us question the quality or implications of our data.

## Assessment - Robust Summaries With Outliers

1. For this chapter, we will use height data collected by Francis Galton for his genetics studies. Here we just use height of the children in the dataset:

```
library(HistData)
data(Galton)
x <- Galton$child
```

```
if(!require(HistData)) install.packages("HistData")
```

```
## Loading required package: HistData
```

```
## Warning: package 'HistData' was built under R version 4.0.2
```

```
library(HistData)
data(Galton)
x <- Galton$child
mean(x)
```

```
## [1] 68.08847
```

```
median(x)
```

```
## [1] 68.2
```

2. Now for the same data compute the standard deviation and the median absolute deviation (MAD).

```
x <- Galton$child
sd(x)
```

```
## [1] 2.517941
```

```
mad(x)
```

```
## [1] 2.9652
```

3. In the previous exercises we saw that the mean and median are very similar and so are the standard deviation and MAD. This is expected since the data is approximated by a normal distribution which has this property.

Now suppose that Galton made a mistake when entering the first value, forgetting to use the decimal point. You can imitate this error by typing:

```
library(HistData)
data(Galton)
x <- Galton$child
x_with_error <- x
x_with_error[1] <- x_with_error[1]*10
```

The data now has an outlier that the normal approximation does not account for. Let's see how this affects the average.

```
x <- Galton$child
x_with_error <- x
x_with_error[1] <- x_with_error[1]*10
gem <- mean(x)
gem_error <- mean(x_with_error)
gem_error - gem
```

```
## [1] 0.5983836
```

4. In the previous exercise we saw how a simple mistake in 1 out of over 900 observations can result in the average of our data increasing more than half an inch, which is a large difference in practical terms.

Now let's explore the effect this outlier has on the standard deviation.

```
x_with_error <- x
x_with_error[1] <- x_with_error[1]*10
sd(x_with_error) - sd(x)
```

```
## [1] 15.6746
```

5. In the previous exercises we saw how one mistake can have a substantial effect on the average and the standard deviation.

Now we are going to see how the median and MAD are much more resistant to outliers. For this reason we say that they are *robust* summaries.

```
x_with_error <- x
x_with_error[1] <- x_with_error[1]*10
mediaan <- median(x)
mediaan_error <- median(x_with_error)
mediaan_error - mediaan
```

```
## [1] 0
```

6. We saw that the median barely changes. Now let's see how the MAD is affected.

We saw that the median barely changes. Now let's see how the MAD is affected.

```
x_with_error <- x
x_with_error[1] <- x_with_error[1]*10
mad_normal <- mad(x)
mad_error <- mad(x_with_error)
mad_error - mad_normal
```

```
## [1] 0
```

7. How could you use exploratory data analysis to detect that an error was made?

- ☐ A. Since it is only one value out of many, we will not be able to detect this.
- ☐ B. We would see an obvious shift in the distribution.
- ☒ C. A boxplot, histogram, or qq-plot would reveal a clear outlier.
- ☐ D. A scatter plot would show high levels of measurement error.

8. We have seen how the average can be affected by outliers.

But how large can this effect get? This of course depends on the size of the outlier and the size of the dataset.

To see how outliers can affect the average of a dataset, let's write a simple function that takes the size of the outlier as input and returns the average.

```
x <- Galton$child
error_avg <- function(k){
  x[1] = k
  mean(x)
}
error_avg(10000)
```

```
## [1] 78.79784
```

```
error_avg(-10000)
```

```
## [1] 57.24612
```

## Section 2 Overview

In Section 2, you will learn how to create data visualizations in R using ggplot2.

After completing Section 2, you will:

- be able to use ggplot2 to create data visualizations in R.
- be able to explain what the data component of a graph is.
- be able to identify the geometry component of a graph and know when to use which type of geometry.
- be able to explain what the aesthetic mapping component of a graph is.
- be able to understand the scale component of a graph and select an appropriate scale component to use.

Note that it can be hard to memorize all of the functions and arguments used by ggplot2, so we recommend that you have a [cheat sheet](#) handy to help you remember the necessary commands.

## ggplot

The textbook for this section is available [here](#)

### Key points

- Throughout the series, we will create plots with the **ggplot2** package. ggplot2 is part of the tidyverse, which you can load with `library(tidyverse)`.
- Note that you can also load ggplot2 alone using the command `library(ggplot2)`, instead of loading the entire tidyverse.
- ggplot2 uses a *grammar of graphics* to break plots into building blocks that have intuitive syntax, making it easy to create relatively complex and aesthetically pleasing plots with relatively simple and readable code.
- ggplot2 is designed to work exclusively with tidy data (rows are observations and columns are variables).

## Graph Components

The textbook for this section is available [here](#)

### Key points

- Plots in ggplot2 consist of 3 main components:
  - Data: The dataset being summarized
  - Geometry: The type of plot (scatterplot, boxplot, barplot, histogram, qqplot, smooth density, etc.)
  - Aesthetic mapping: Variables mapped to visual cues, such as x-axis and y-axis values and color
- There are additional components:
  - Scale
  - Labels, Title, Legend
  - Theme/Style

## Creating a New Plot

The textbook for this section is available [here](#)

### Key points

- You can associate a dataset `x` with a `ggplot` object with any of the 3 commands:
  - `ggplot(data = x)`
  - `ggplot(x)`
  - `x %>% ggplot()`
- You can assign a `ggplot` object to a variable. If the object is not assigned to a variable, it will automatically be displayed.
- You can display a `ggplot` object assigned to a variable by printing that variable.

### Code

```
ggplot(data = murders)
```

```
murders %>% ggplot()
```

```
p <- ggplot(data = murders)
class(p)
```

```
## [1] "gg"      "ggplot"
```

```
print(p)    # this is equivalent to simply typing p
```

The functions above render a plot, in this case a blank slate since no geometry has been defined. The only style choice we see is a grey background.

## Layers

The textbook for this section is available:

- [Geometries](#)
- [Aesthetic mappings](#)
- [Layers](#)

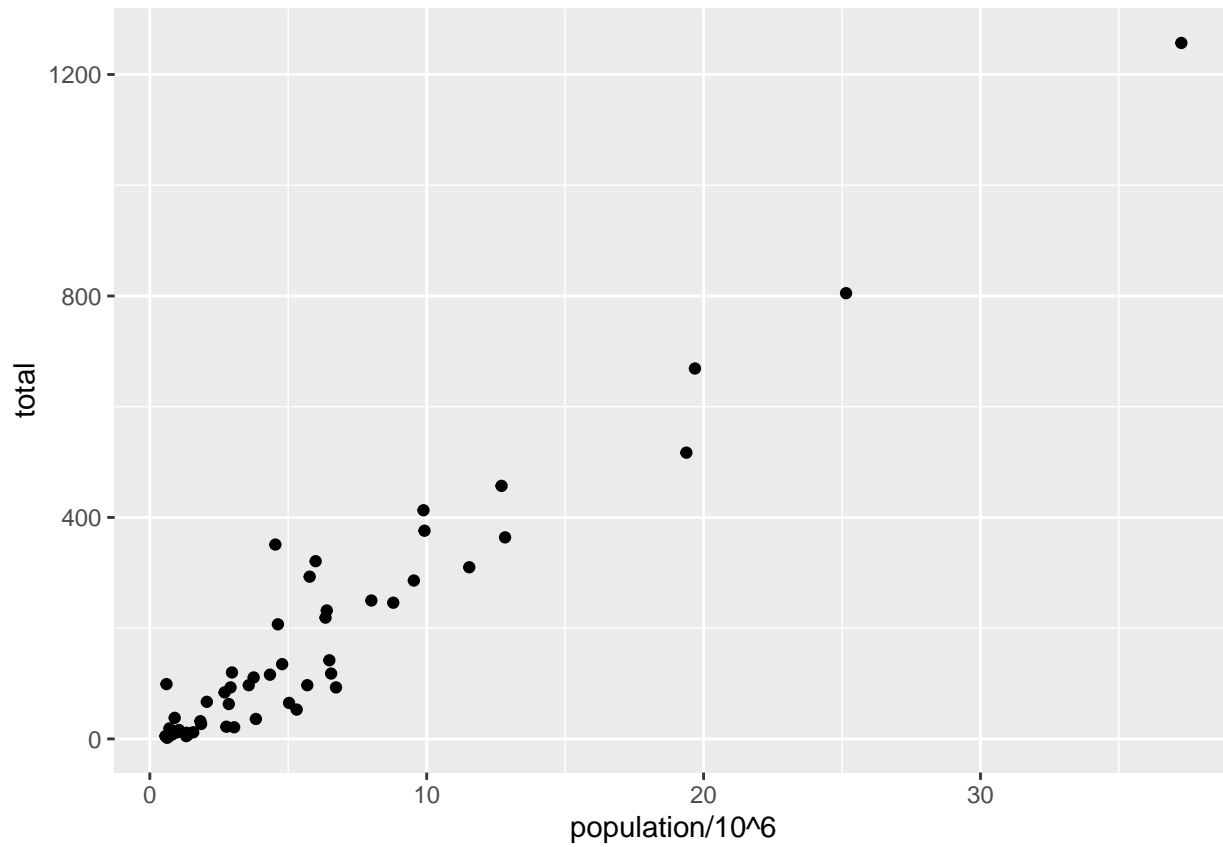
### Key points

- In `ggplot2`, graphs are created by adding *layers* to the `ggplot` object: `DATA %>% ggplot() + LAYER_1 + LAYER_2 + ... + LAYER_N`
- The *geometry layer* defines the plot type and takes the format `geom_X` where `X` is the plot type.
- *Aesthetic mappings* describe how properties of the data connect with features of the graph (axis position, color, size, etc.) Define aesthetic mappings with the `aes` function.
- `aes` uses variable names from the object component (for example, `total` rather than `murders$total`).
- `geom_point` creates a scatterplot and requires `x` and `y` aesthetic mappings.
- `geom_text` and `geom_label` add text to a scatterplot and require `x`, `y`, and label aesthetic mappings.
- To determine which aesthetic mappings are required for a geometry, read the help file for that geometry.
- You can add layers with different aesthetic mappings to the same graph.

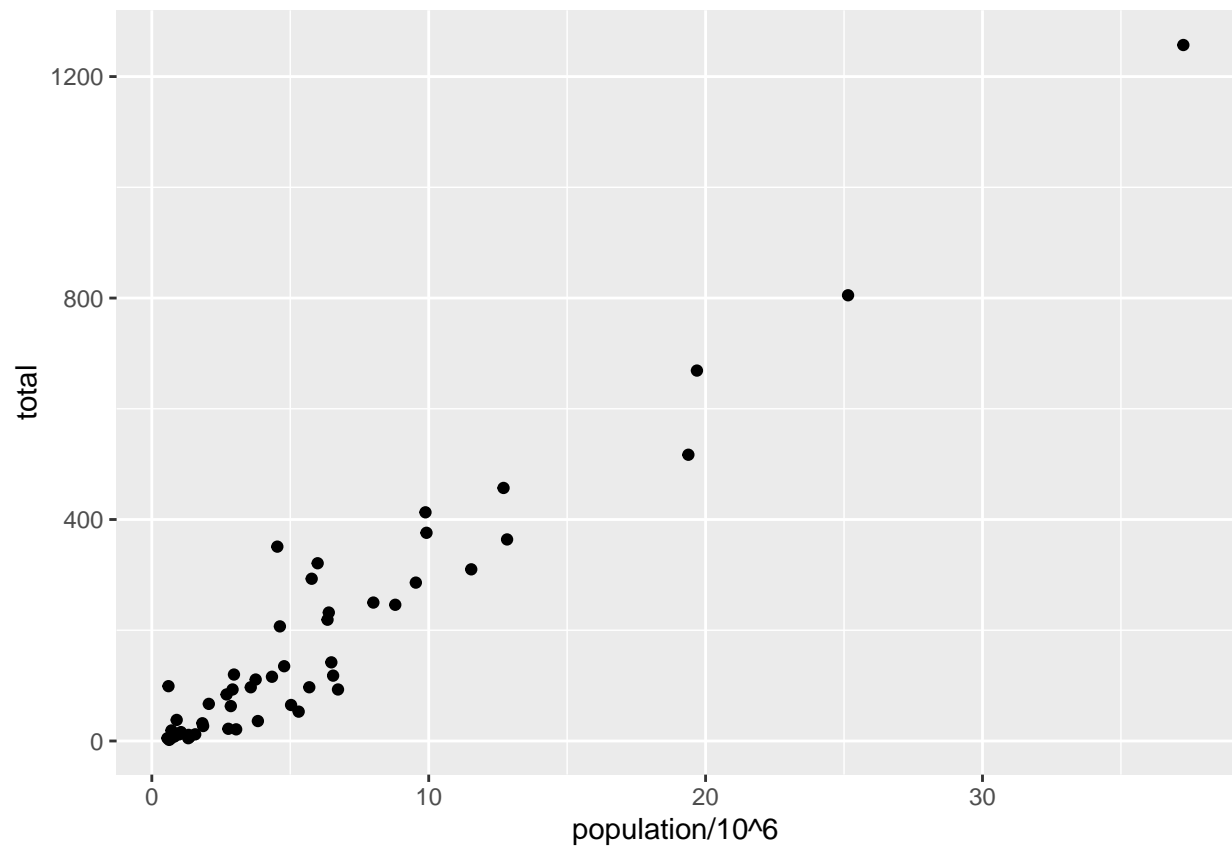


Code: Adding layers to a plot

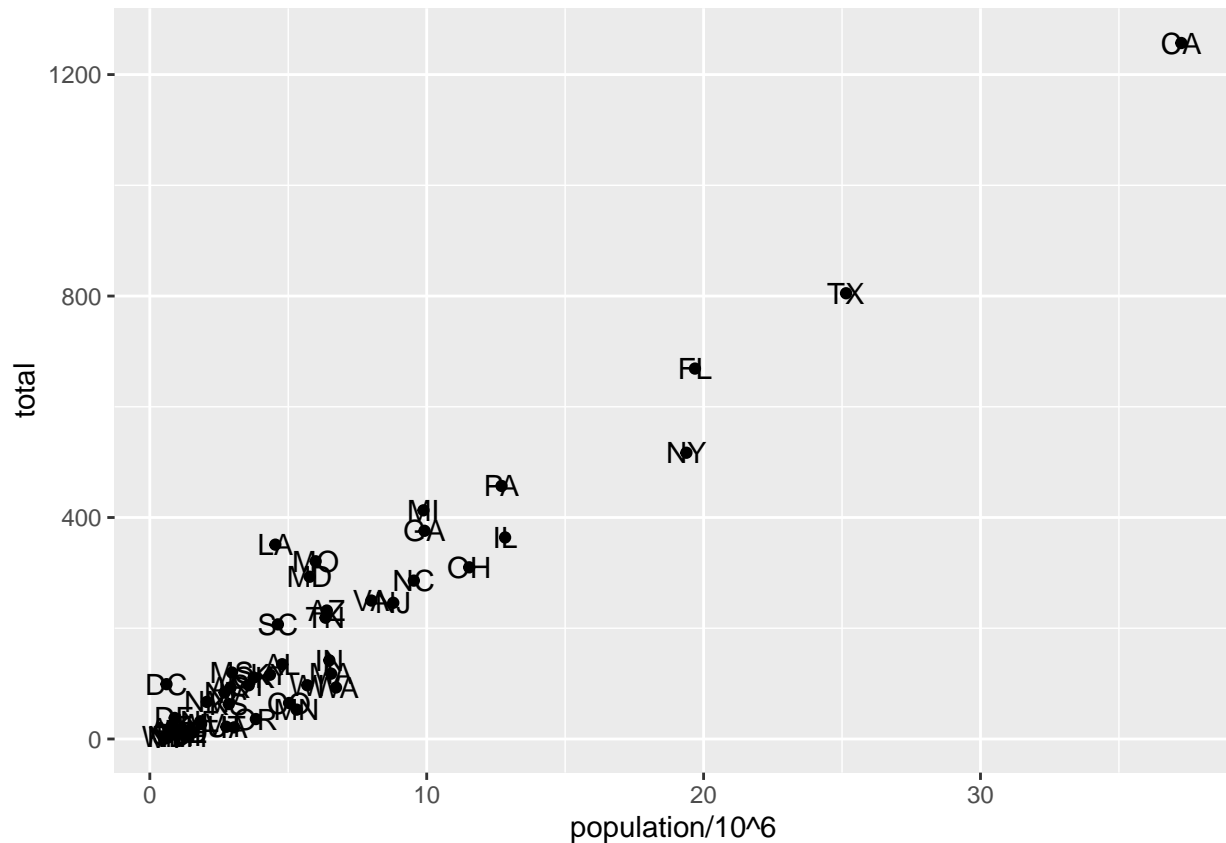
```
murders %>% ggplot() +  
  geom_point(aes(x = population/106, y = total))
```



```
# add points layer to predefined ggplot object  
p <- ggplot(data = murders)  
p + geom_point(aes(population/106, total))
```



```
# add text layer to scatterplot
p + geom_point(aes(population/10^6, total)) +
  geom_text(aes(population/10^6, total, label = abb))
```



Code: Example of *aes* behavior

```
# no error from this call
p_test <- p + geom_text(aes(population/10^6, total, label = abb))
```

```
# error - "abb" is not a globally defined variable and cannot be found outside of aes
p_test <- p + geom_text(aes(population/10^6, total), label = abb)
```

## Tinkering

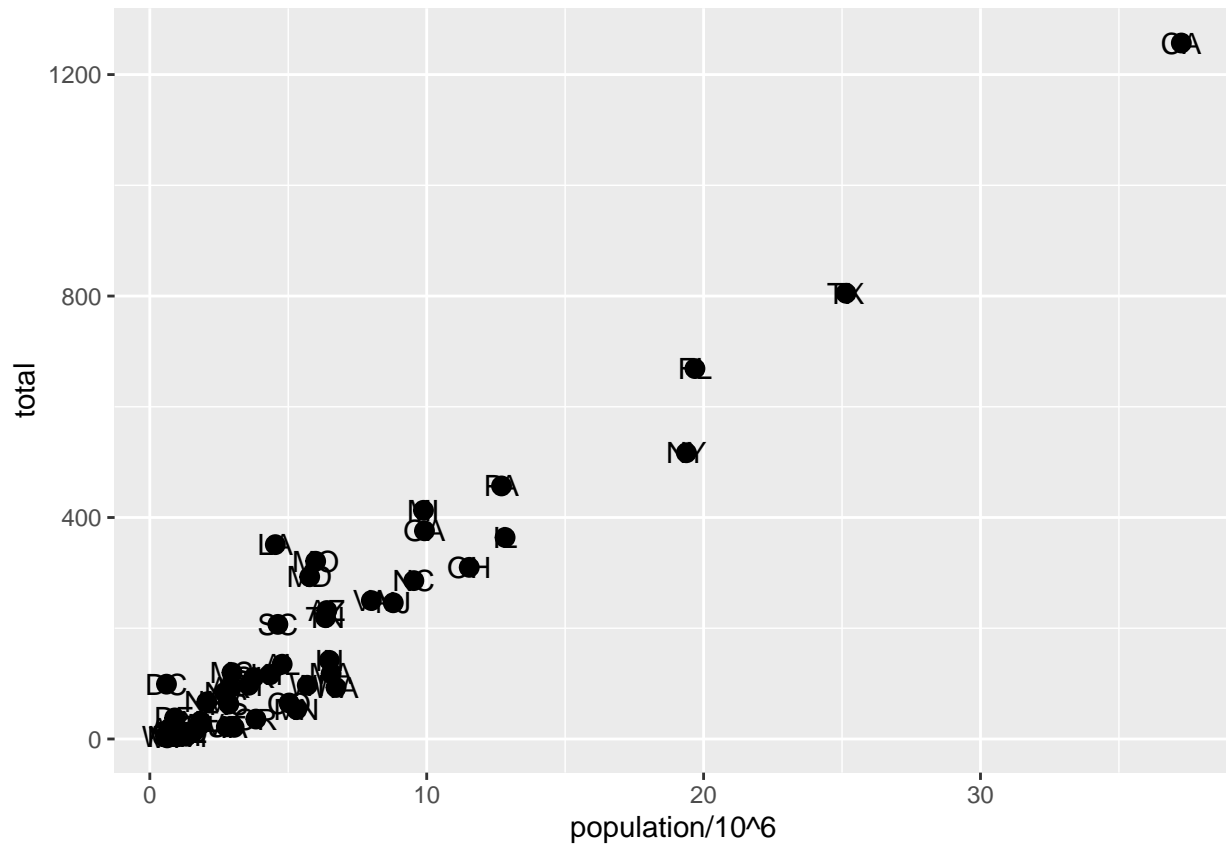
The textbook for this section is available [here](#) and [here](#)

### Key points

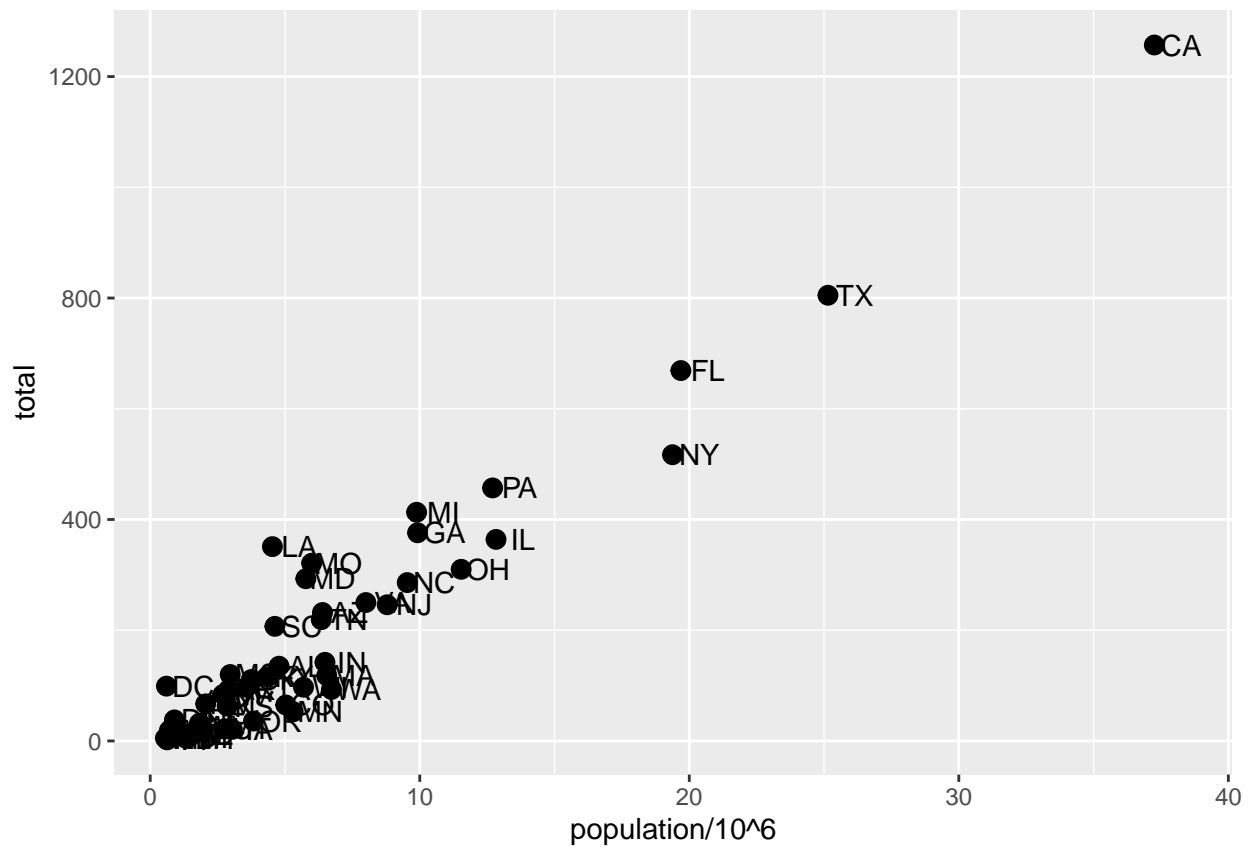
- You can modify arguments to geometry functions other than *aes* and the data. Additional arguments can be found in the documentation for each geometry.
- These arguments are not aesthetic mappings: they affect all data points the same way.
- *Global aesthetic mappings* apply to all geometries and can be defined when you initially call *ggplot*. All the geometries added as layers will default to this mapping. Local aesthetic mappings add additional information or override the default mappings.

Code

```
# change the size of the points
p + geom_point(aes(population/10^6, total), size = 3) +
  geom_text(aes(population/10^6, total, label = abb))
```

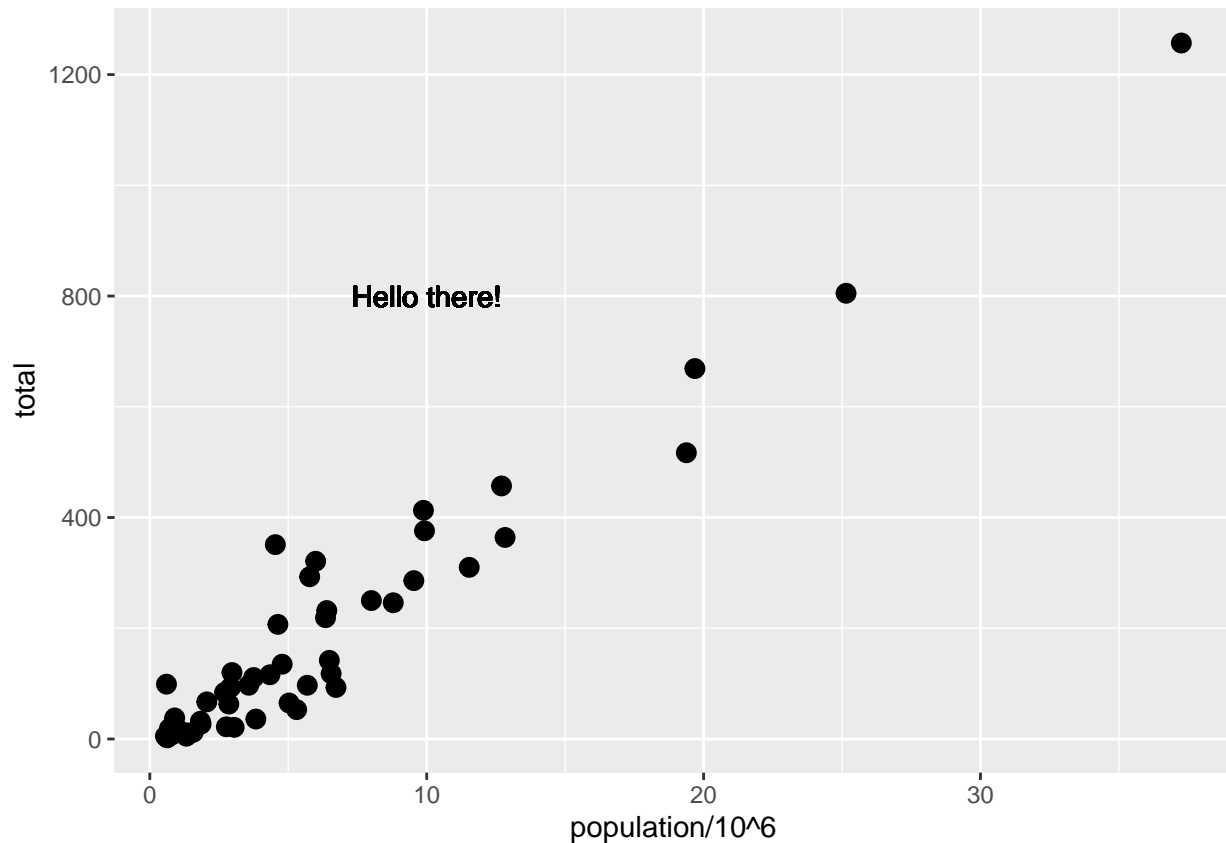


```
# move text labels slightly to the right
p + geom_point(aes(population/10^6, total), size = 3) +
  geom_text(aes(population/10^6, total, label = abb), nudge_x = 1)
```



```
# simplify code by adding global aesthetic
p <- murders %>% ggplot(aes(population/10^6, total, label = abb))
p + geom_point(size = 3) +
  geom_text(nudge_x = 1.5)
```





## Scales, Labels, and Colors

The textbook for this section is available:

- [Scales](#)
- [Labels and titles](#)
- [Categories as colors](#)
- [Annotation, shapes and adjustments](#)

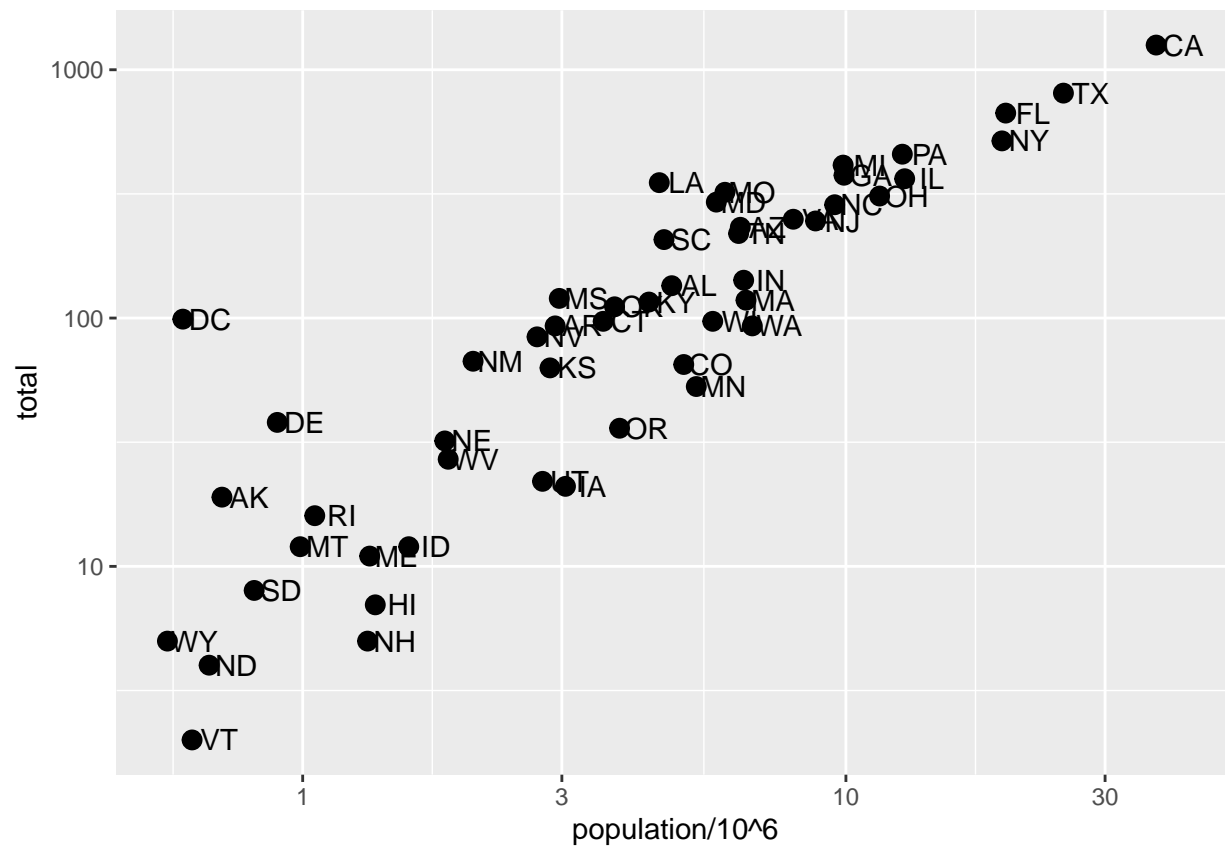
### Key points

- Convert the x-axis to log scale with `scale_x_continuous(trans = "log10")` or `scale_x_log10`. Similar functions exist for the y-axis.
- Add axis titles with `xlab` and `ylab` functions. Add a plot title with the `ggtitle` function.
- Add a color mapping that colors points by a variable by defining the `col` argument within `aes`. To color all points the same way, define `col` outside of `aes`.
- Add a line with the `geom_abline` geometry. `geom_abline` takes arguments `slope` (default = 1) and `intercept` (default = 0). Change the color with `col` or `color` and line type with `lty`.
- Placing the line layer after the point layer will overlay the line on top of the points. To overlay points on the line, place the line layer before the point layer.
- There are many additional ways to tweak your graph that can be found in the ggplot2 documentation, cheat sheet, or on the internet. For example, you can change the legend title with `scale_color_discrete`.

*Code: Log-scale the x- and y-axis*

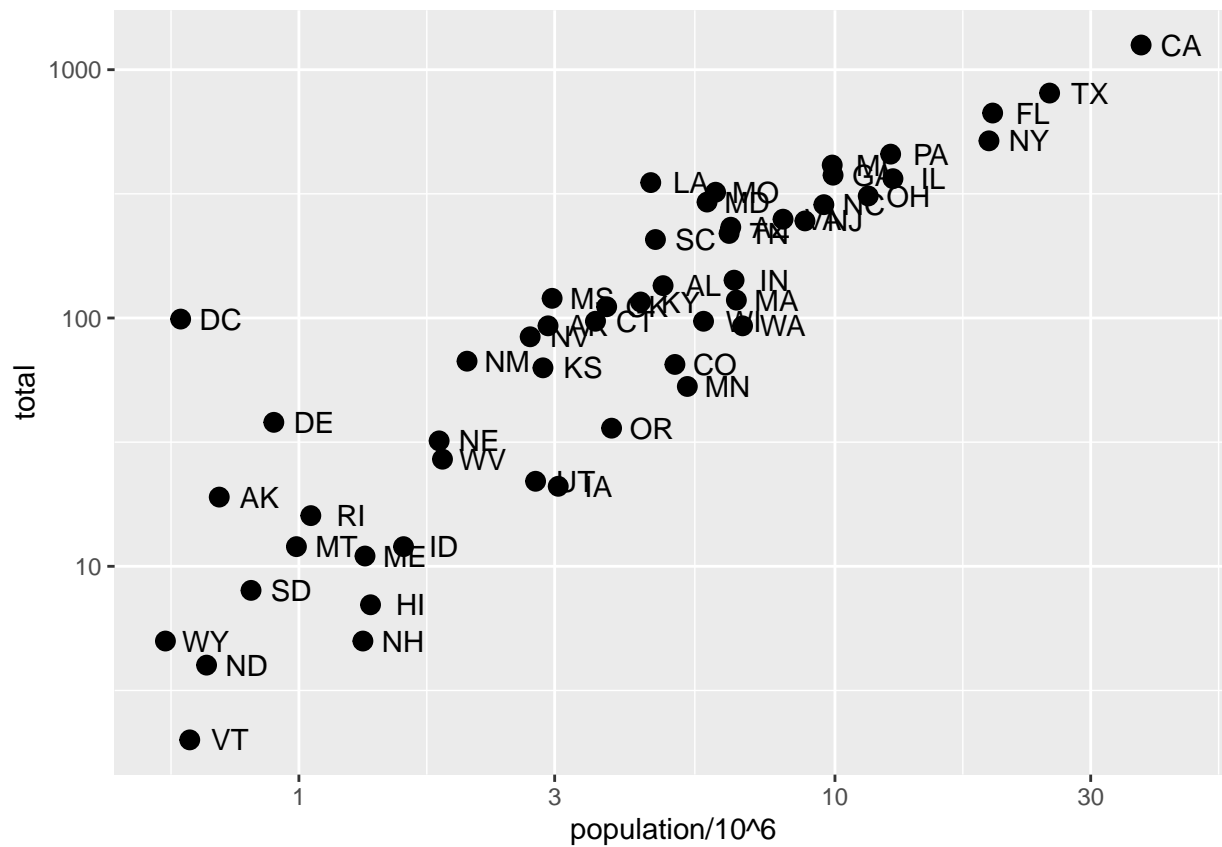
```
# define p
p <- murders %>% ggplot(aes(population/10^6, total, label = abb))

# log base 10 scale the x-axis and y-axis
p + geom_point(size = 3) +
  geom_text(nudge_x = 0.05) +
  scale_x_continuous(trans = "log10") +
  scale_y_continuous(trans = "log10")
```



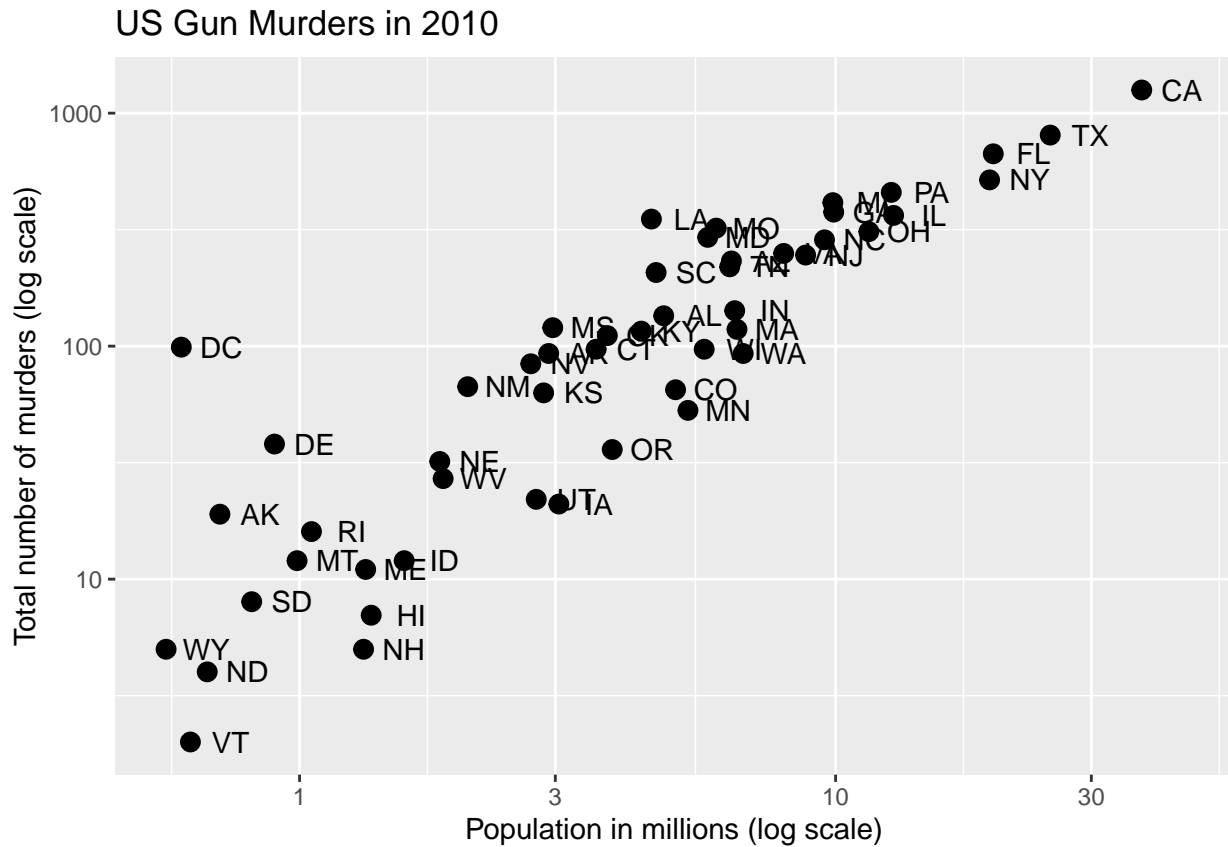
```
# efficient log scaling of the axes
p + geom_point(size = 3) +
  geom_text(nudge_x = 0.075) +
  scale_x_log10() +
  scale_y_log10()
```





Code: Add labels and title

```
p + geom_point(size = 3) +
  geom_text(nudge_x = 0.075) +
  scale_x_log10() +
  scale_y_log10() +
  xlab("Population in millions (log scale)") +
  ylab("Total number of murders (log scale)") +
  ggtitle("US Gun Murders in 2010")
```

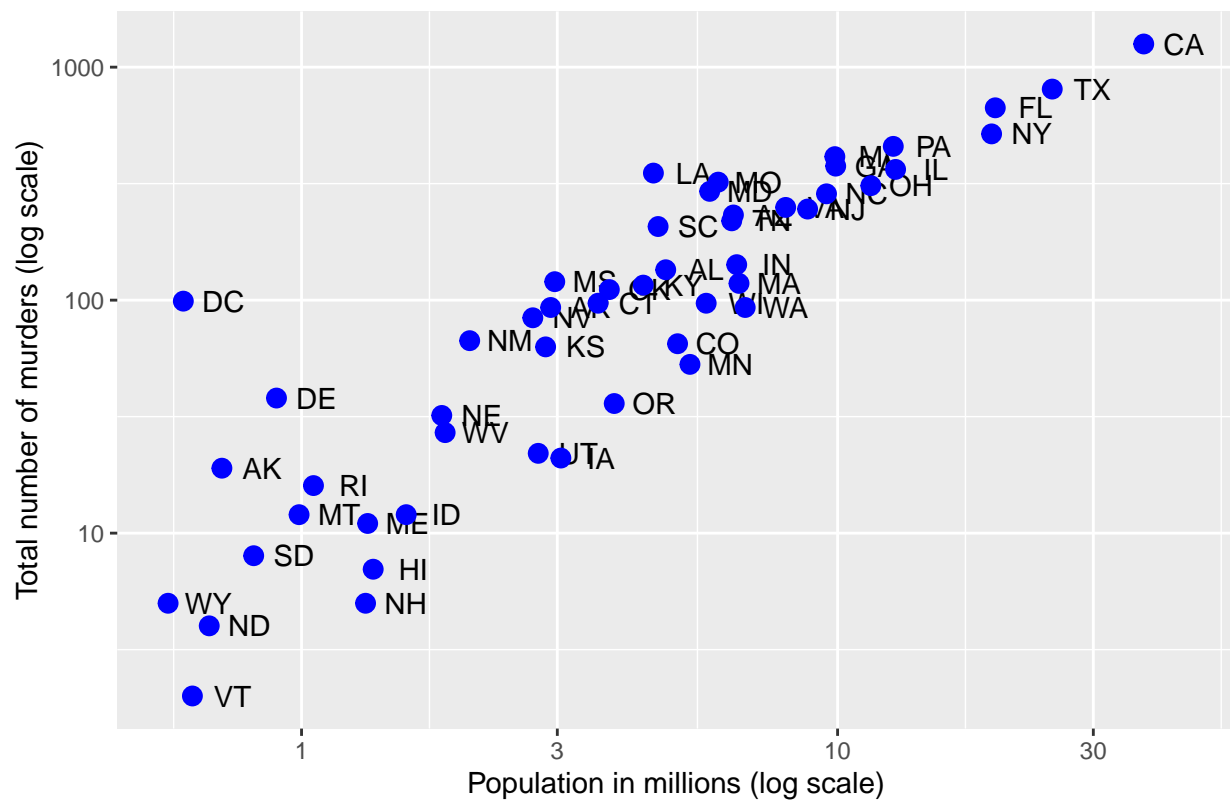


Code: Change color of the points

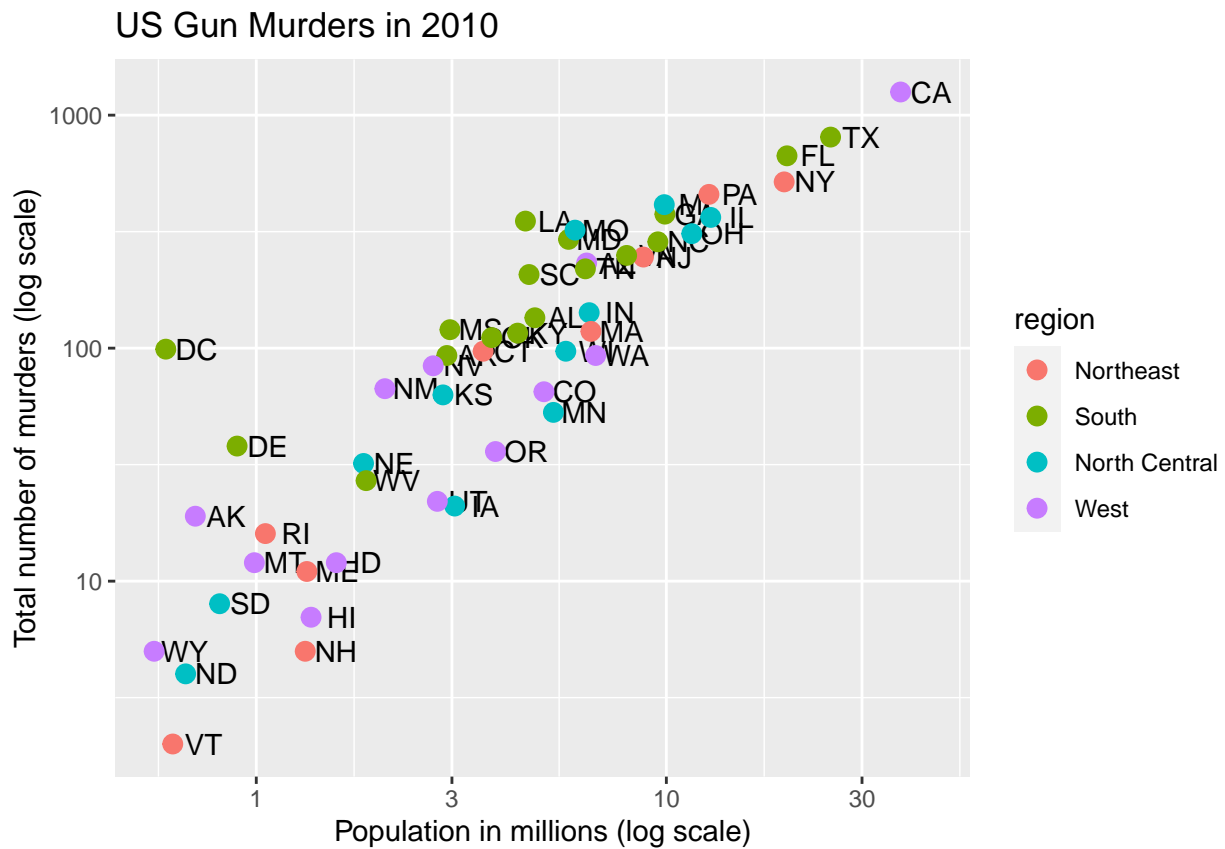
```
# redefine p to be everything except the points layer
p <- murders %>%
  ggplot(aes(population/106, total, label = abb)) +
  geom_text(nudge_x = 0.075) +
  scale_x_log10() +
  scale_y_log10() +
  xlab("Population in millions (log scale)") +
  ylab("Total number of murders (log scale)") +
  ggtitle("US Gun Murders in 2010")

# make all points blue
p + geom_point(size = 3, color = "blue")
```

US Gun Murders in 2010



```
# color points by region
p + geom_point(aes(col = region), size = 3)
```



Code: Add a line with average murder rate

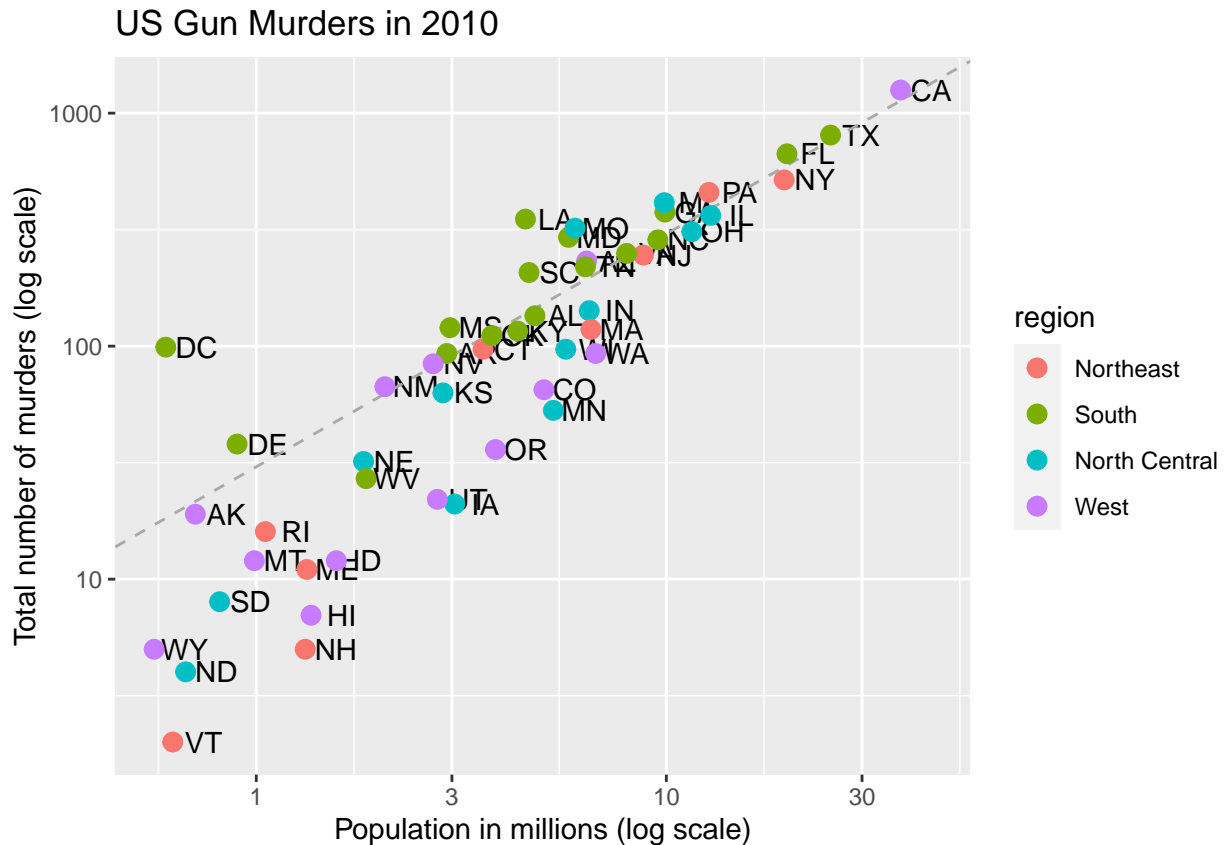
```
# define average murder rate
r <- murders %>%
  summarize(rate = sum(total) / sum(population) * 10^6) %>%
  pull(rate)

# basic line with average murder rate for the country
p + geom_point(aes(col = region), size = 3) +
  geom_abline(intercept = log10(r)) # slope is default of 1
```

Scatter plot showing the relationship between the number of days in the year with a temperature above 50°F (X-axis) and the number of days with a temperature below 32°F (Y-axis) for various US states. The data points are colored by region: West (purple), Midwest (green), Northeast (red), and South (cyan). A positive linear trend line is shown.

State	Days Above 50°F (X)	Days Below 32°F (Y)	Region
CA	280	20	West
TX	250	30	Midwest
FL	240	40	Midwest
NY	230	50	Northeast
PA	220	60	Northeast
IL	210	70	Midwest
OH	200	80	Midwest
IN	190	90	Midwest
MA	180	100	Northeast
VA	170	110	South
WA	160	120	West
CO	150	130	West
MN	140	140	Midwest
OR	130	150	West
UT	120	160	West
NE	110	170	Midwest
WV	100	180	Midwest
AK	90	190	West
RI	80	200	Northeast
MT	70	210	West
ME	60	220	Northeast
SD	50	230	Midwest
HI	40	240	Midwest
NH	30	250	Northeast
VT	20	260	Northeast
WY	10	270	West
ND	0	280	Midwest
DC	20	290	Midwest
DE	50	300	Midwest
LA	150	310	Midwest
MO	160	320	Midwest
MS	170	330	Midwest
AL	180	340	Midwest
SC	190	350	Midwest
GA	200	360	Midwest
NC	210	370	Midwest
TN	220	380	Midwest
OK	230	390	Midwest
KS	240	400	Midwest
NM	250	410	West

```
p +  
  geom_abline(intercept = log10(r), lty = 2, color = "darkgrey") +  
  geom_point(aes(col = region), size = 3)
```



Code: Change legend title

```
p <- p + scale_color_discrete(name = "Region") # capitalize legend title
```

## Add-on Packages

The textbook for this section is available [here](#) and [here](#)

### Key points

- The style of a ggplot graph can be changed using the `theme` function.
- The **ggthemes** package adds additional themes.
- The **ggrepel** package includes a geometry that repels text labels, ensuring they do not overlap with each other: `geom_text_repel`.

Code: Adding themes

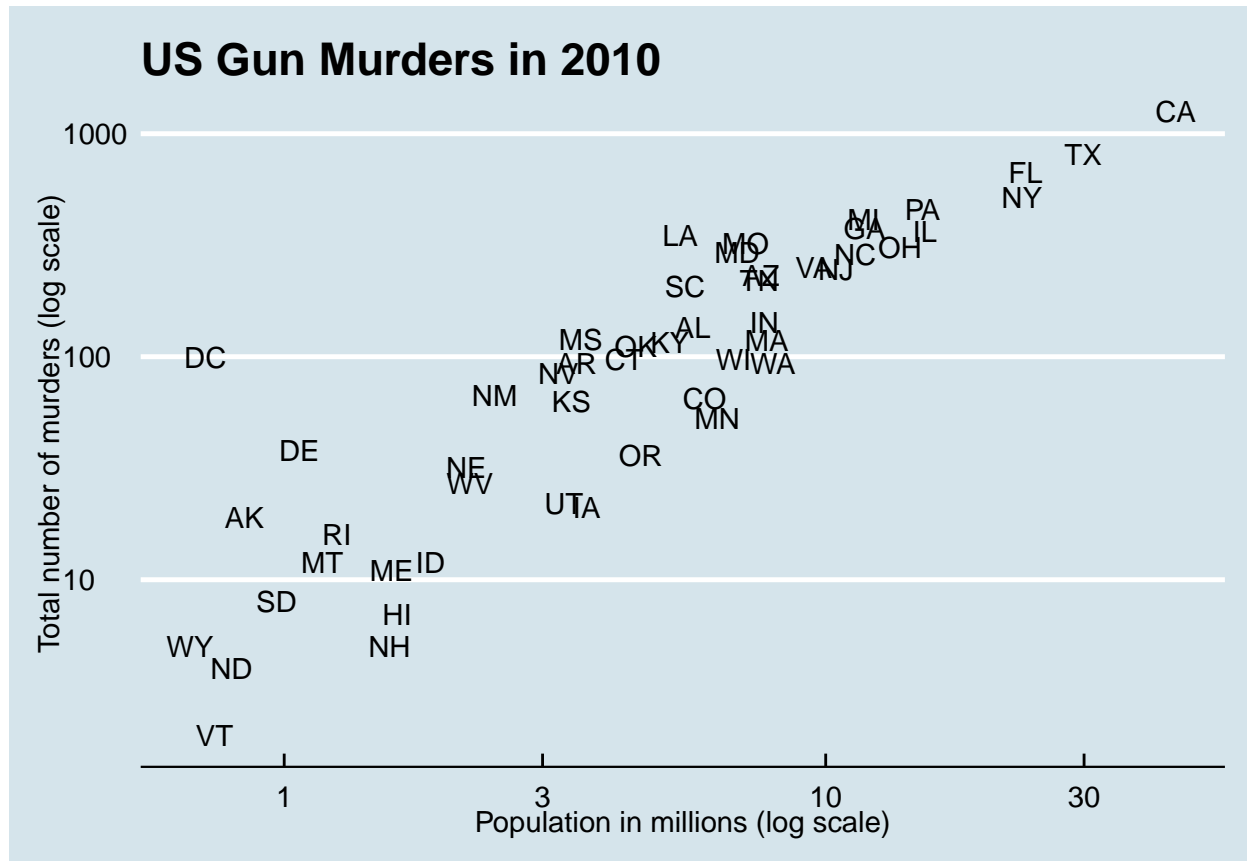
```
if(!require(ggthemes)) install.packages("ggthemes")
```

```
## Loading required package: ggthemes
```

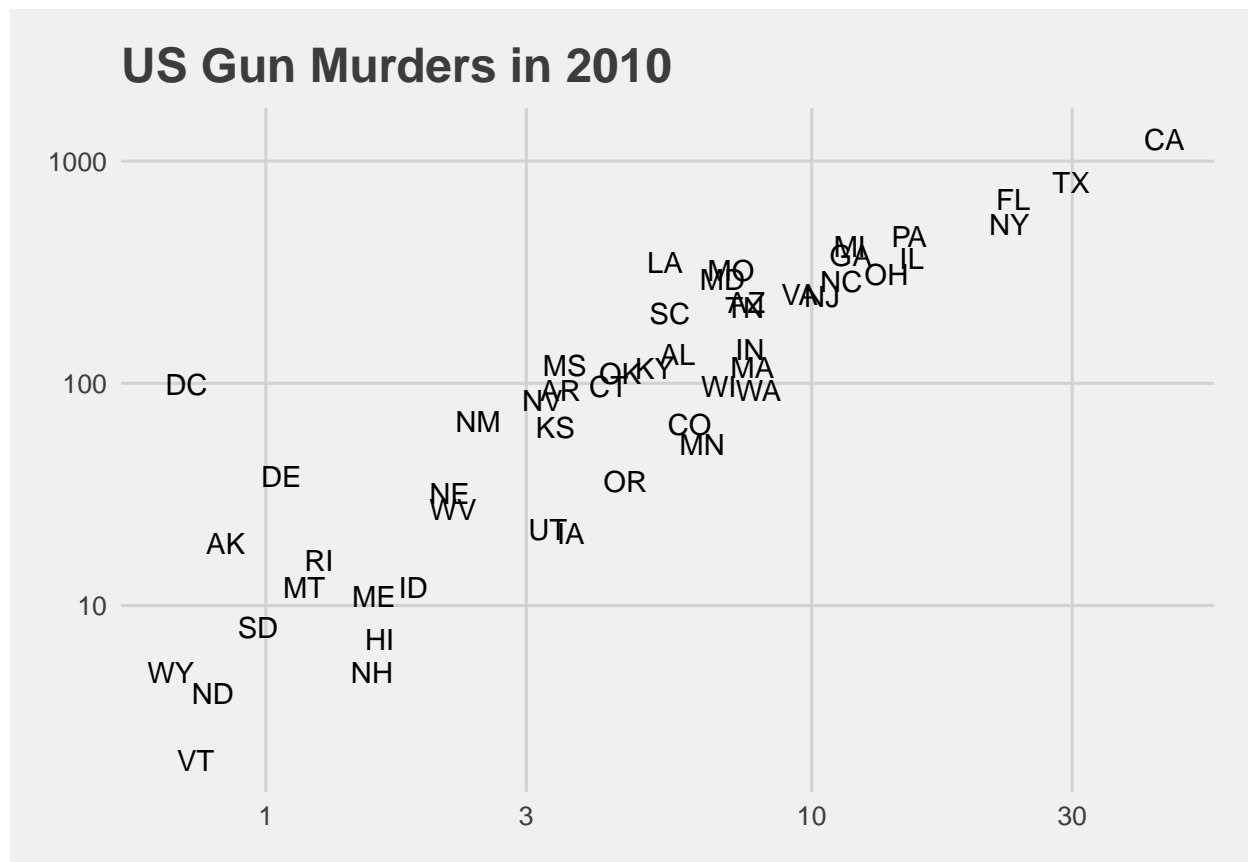
```
## Warning: package 'ggthemes' was built under R version 4.0.2
```

```
# theme used for graphs in the textbook and course
ds_theme_set()

# themes from ggthemes
library(ggthemes)
p + theme_economist()    # style of the Economist magazine
```



```
p + theme_fivethirtyeight()    # style of the FiveThirtyEight website
```



Code: Putting it all together to assemble the plot

```
if(!require(ggrepel)) install.packages("ggrepel")
```

```
## Loading required package: ggrepel
```

```
## Warning: package 'ggrepel' was built under R version 4.0.2
```

```
# load libraries
```

```
library(ggplot2)
```

```
# define the intercept
```

```
r <- murders %>%
```

```
  summarize(rate = sum(total) / sum(population) * 10^6) %>%
```

```
  .$rate
```

```
# make the plot, combining all elements
```

```
murders %>%
```

```
  ggplot(aes(population/10^6, total, label = abb)) +
```

```
  geom_abline(intercept = log10(r), lty = 2, color = "darkgrey") +
```

```
  geom_point(aes(col = region), size = 3) +
```

```
  geom_text_repel() +
```

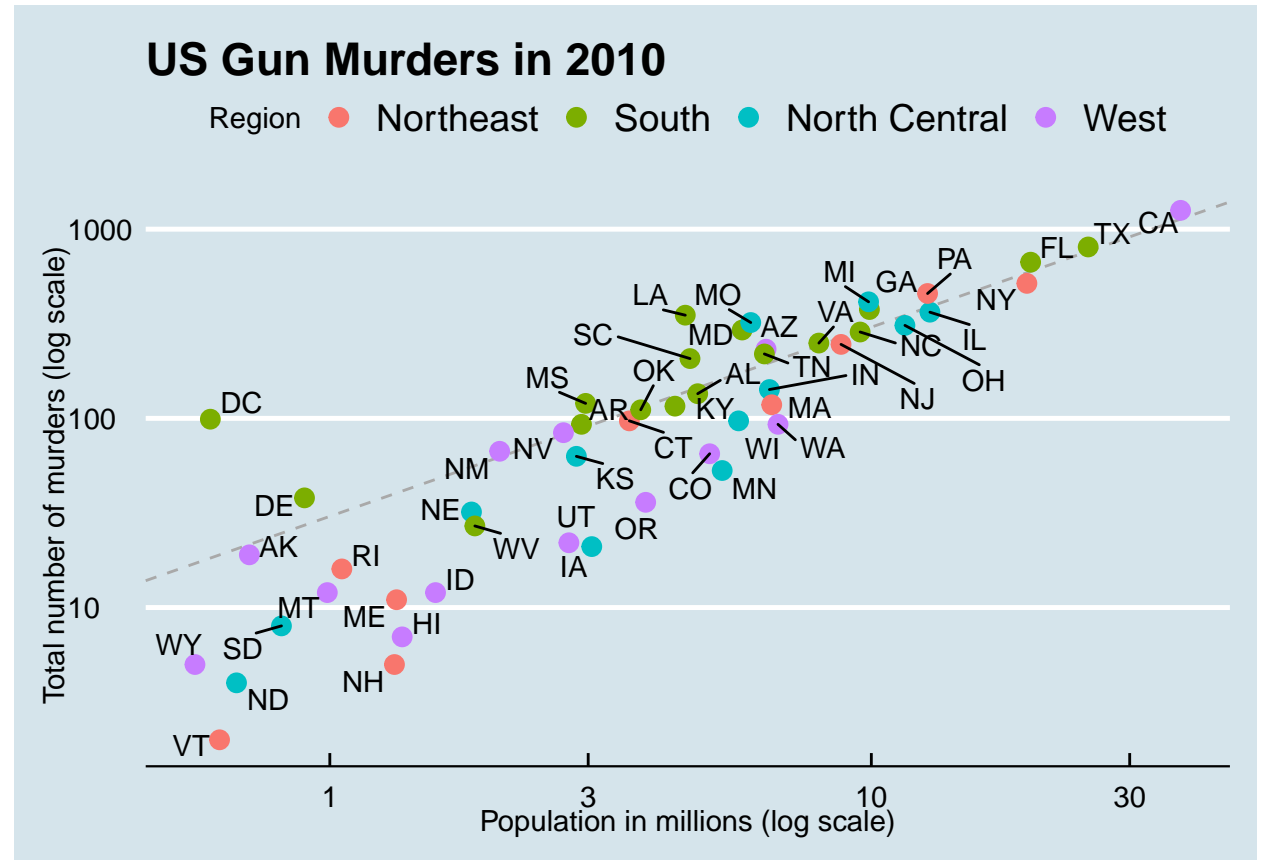
```
  scale_x_log10() +
```

```
  scale_y_log10() +
```

```
  xlab("Population in millions (log scale)") +
```



```
ylab("Total number of murders (log scale)") +
ggtitle("US Gun Murders in 2010") +
scale_color_discrete(name = "Region") +
theme_economist()
```



## Other Examples

The textbook for this section is available:

- Histograms
- Density plots
- QQ-plots
- Grids of plots

## Key points

- `geom_histogram` creates a histogram. Use the `binwidth` argument to change the width of bins, the `fill` argument to change the bar fill color, and the `col` argument to change bar outline color.
- `geom_density` creates smooth density plots. Change the fill color of the plot with the `fill` argument.
- `geom_qq` creates a quantile-quantile plot. This geometry requires the `sample` argument. By default, the data are compared to a standard normal distribution with a mean of 0 and standard deviation of 1. This can be changed with the `dparams` argument, or the sample data can be scaled.

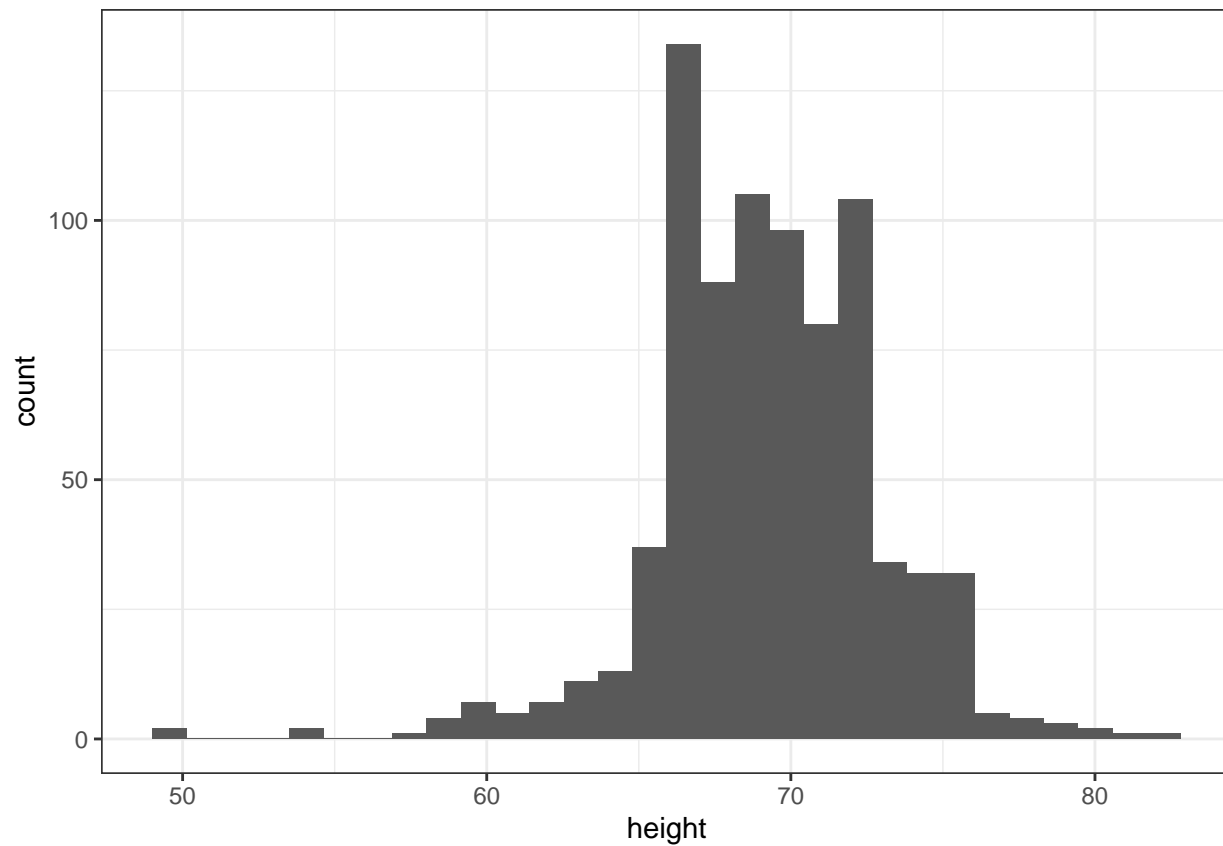
- Plots can be arranged adjacent to each other using the `grid.arrange` function from the `gridExtra` package. First, create the plots and save them to objects (`p1`, `p2`, ...). Then pass the plot objects to `grid.arrange`.

Code: Histograms in ggplot2

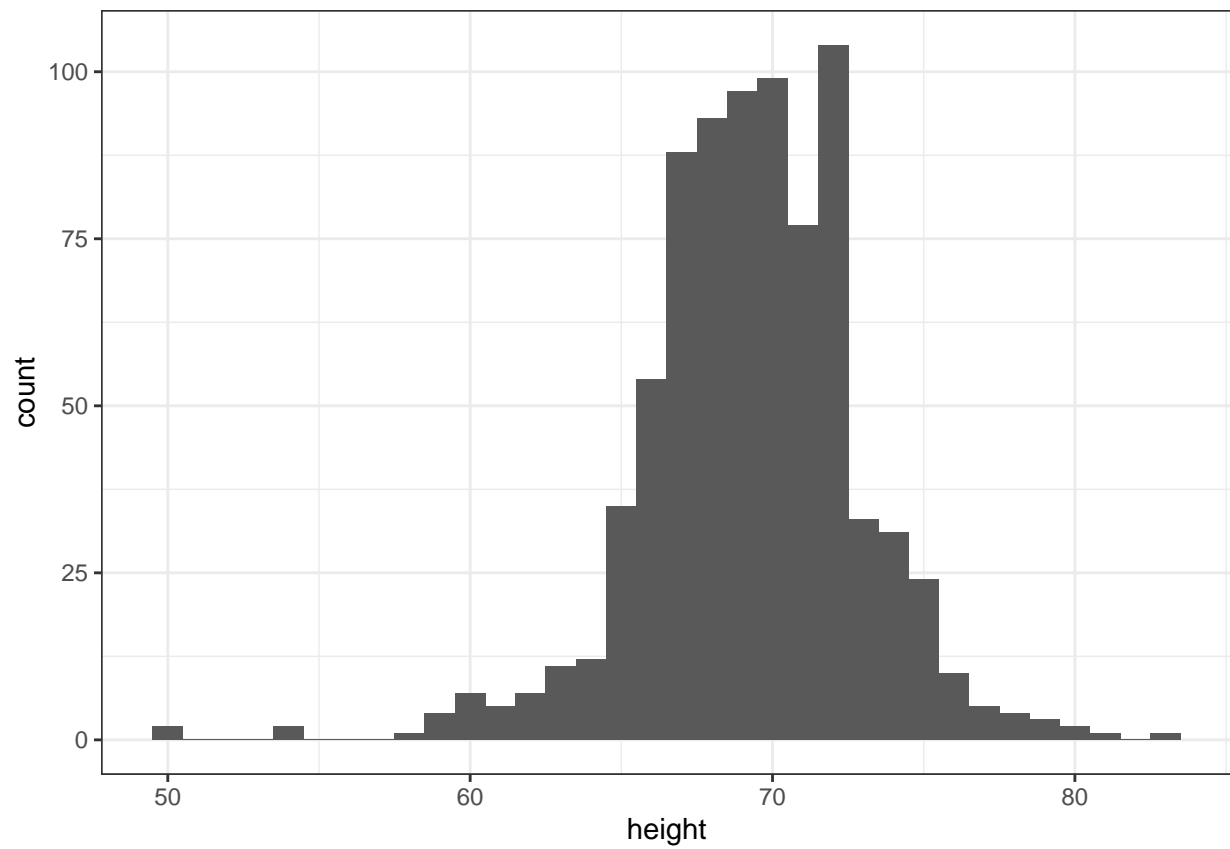
```
# define p
p <- heights %>%
  filter(sex == "Male") %>%
  ggplot(aes(x = height))

# basic histograms
p + geom_histogram()
```

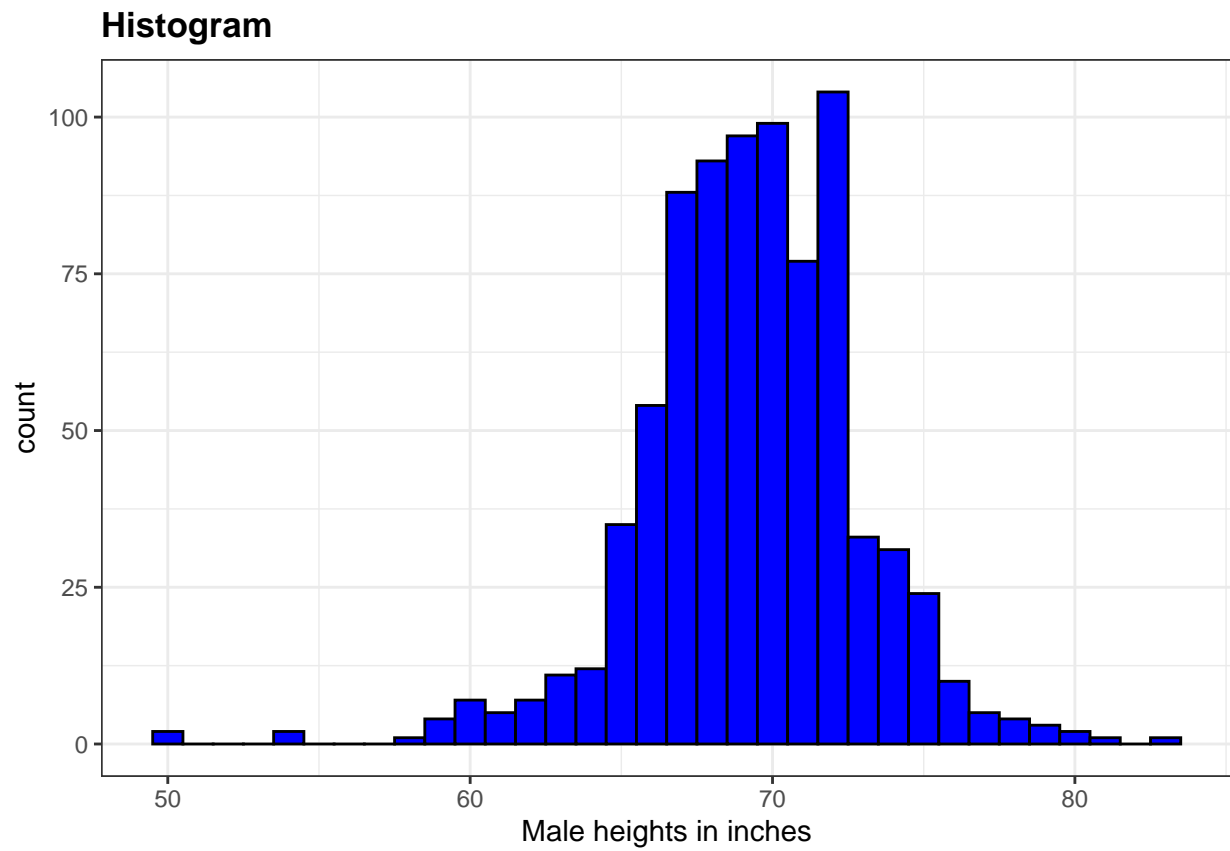
## ``stat_bin()`` using ``bins = 30``. Pick better value with ``binwidth``.



```
p + geom_histogram(binwidth = 1)
```

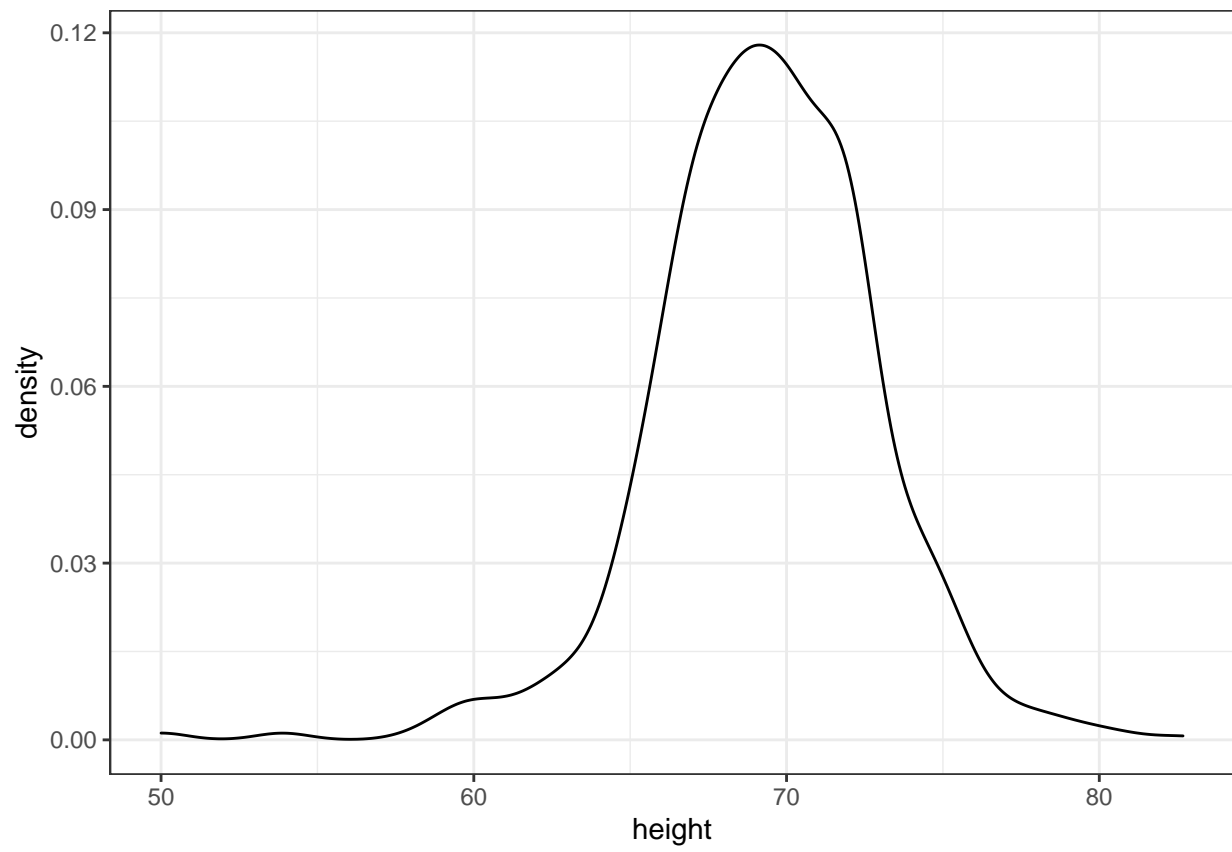


```
# histogram with blue fill, black outline, labels and title
p + geom_histogram(binwidth = 1, fill = "blue", col = "black") +
  xlab("Male heights in inches") +
  ggtitle("Histogram")
```

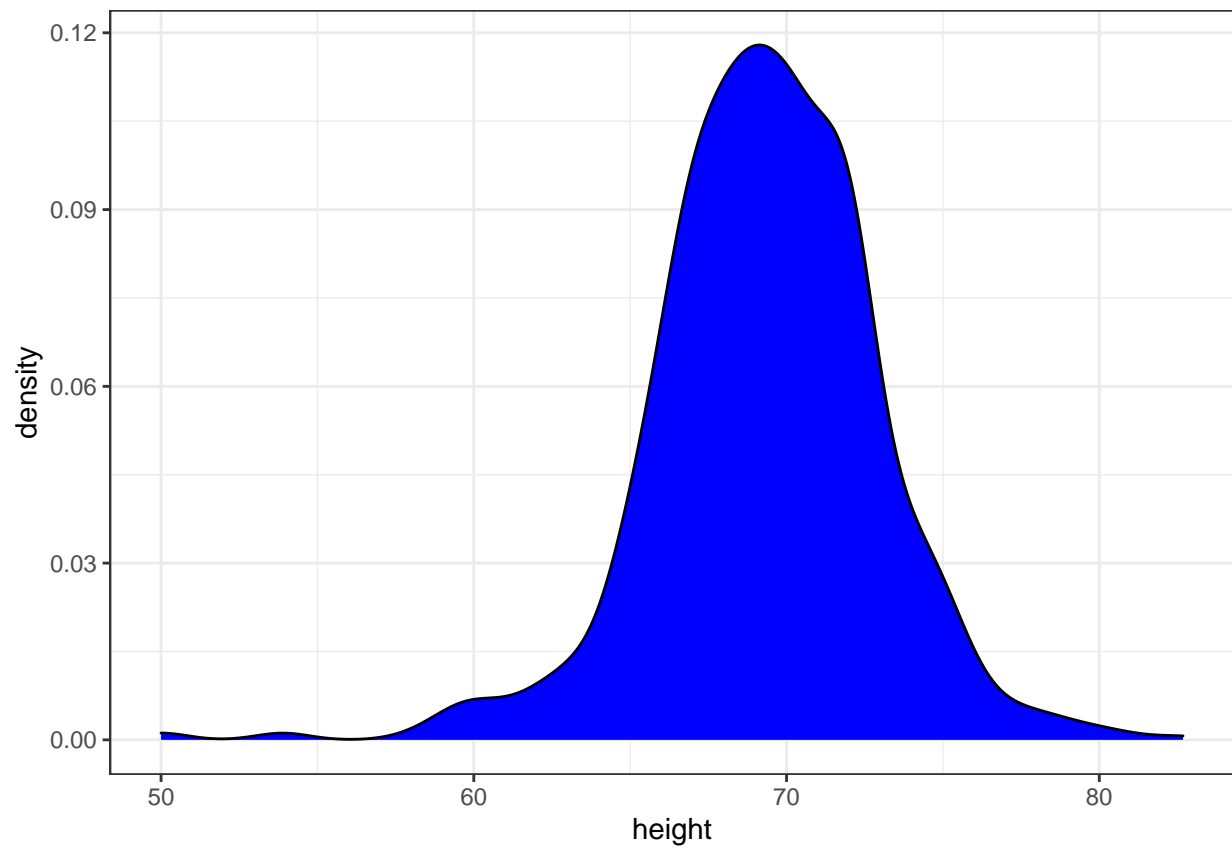


Code: Smooth density plots in ggplot2

```
p + geom_density()
```

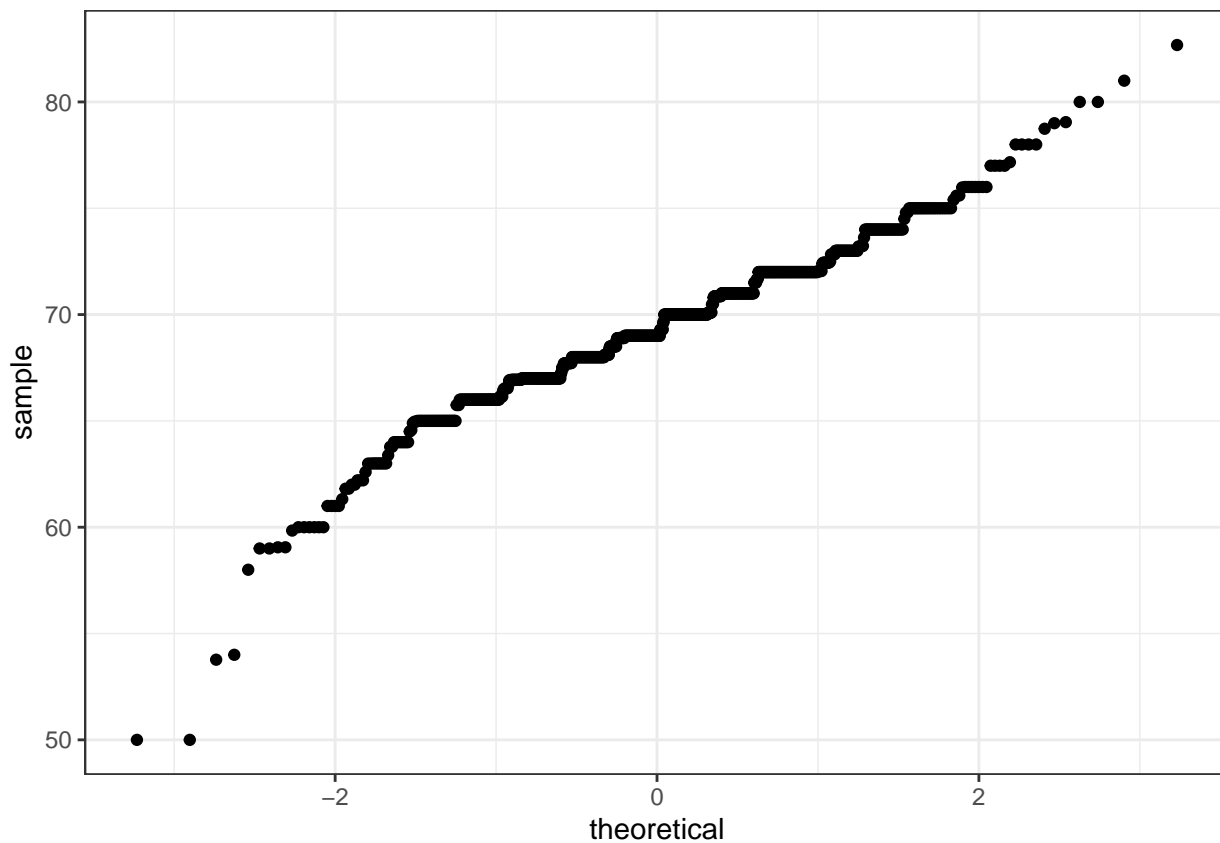


```
p + geom_density(fill = "blue")
```

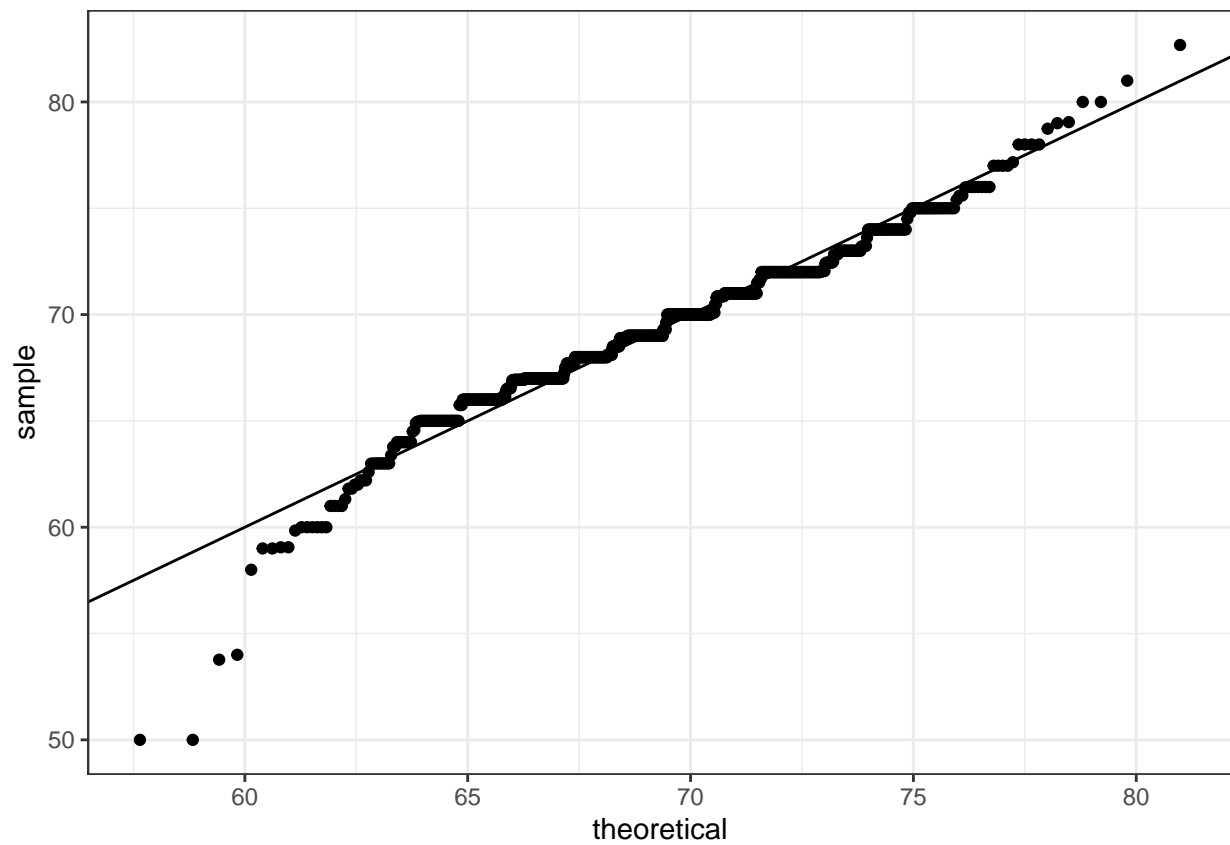


*Code: Quantile-quantile plots in ggplot2*

```
# basic QQ-plot  
p <- heights %>% filter(sex == "Male") %>%  
  ggplot(aes(sample = height))  
p + geom_qq()
```

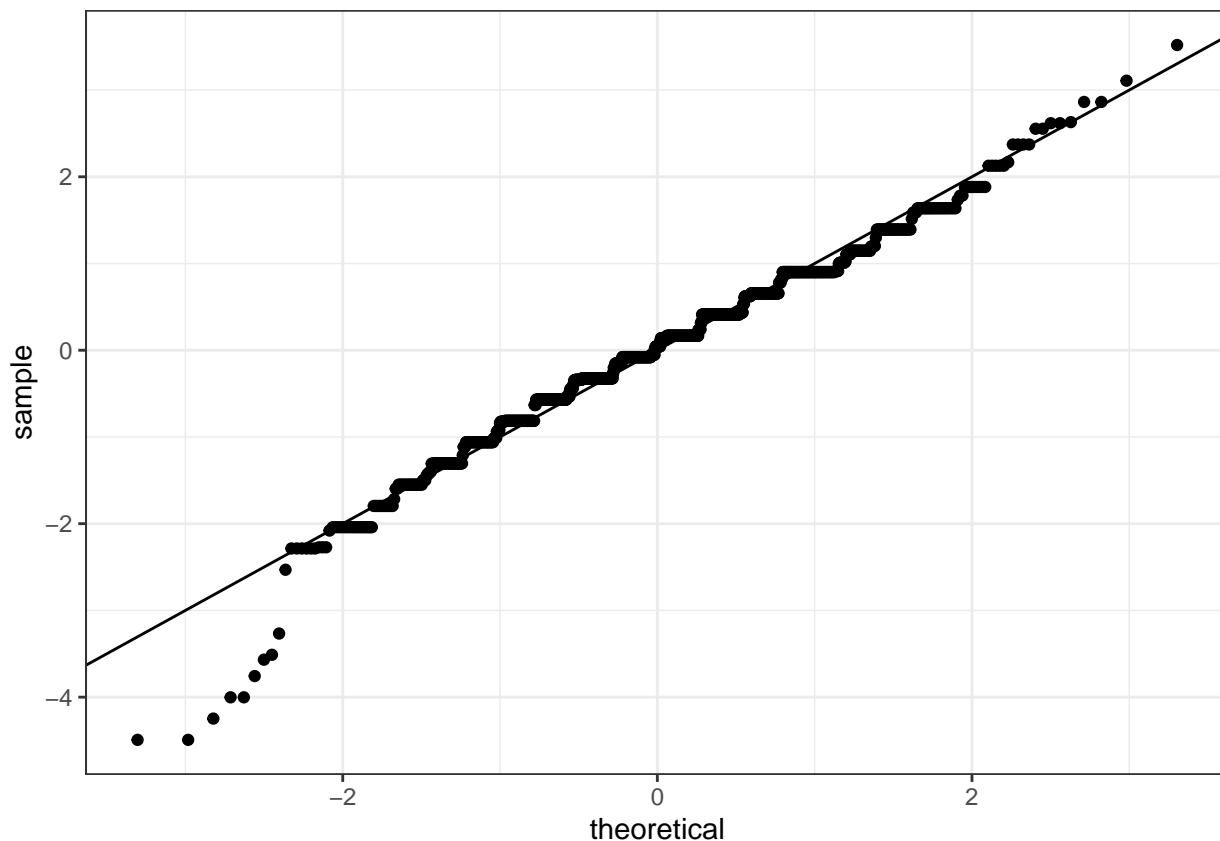


```
# QQ-plot against a normal distribution with same mean/sd as data
params <- heights %>%
  filter(sex == "Male") %>%
  summarize(mean = mean(height), sd = sd(height))
p + geom_qq(dparams = params) +
  geom_abline()
```



```
# QQ-plot of scaled data against the standard normal distribution
heights %>%
  ggplot(aes(sample = scale(height))) +
  geom_qq() +
  geom_abline()
```





Code: Grids of plots with the *grid.extra* package

```
if(!require(gridExtra)) install.packages("gridExtra")
```

```
## Loading required package: gridExtra
```

```
##
```

```
## Attaching package: 'gridExtra'
```

```
## The following object is masked from 'package:dplyr':
```

```
##
```

```
##      combine
```

```
# define plots p1, p2, p3
```

```
p <- heights %>% filter(sex == "Male") %>% ggplot(aes(x = height))
```

```
p1 <- p + geom_histogram(binwidth = 1, fill = "blue", col = "black")
```

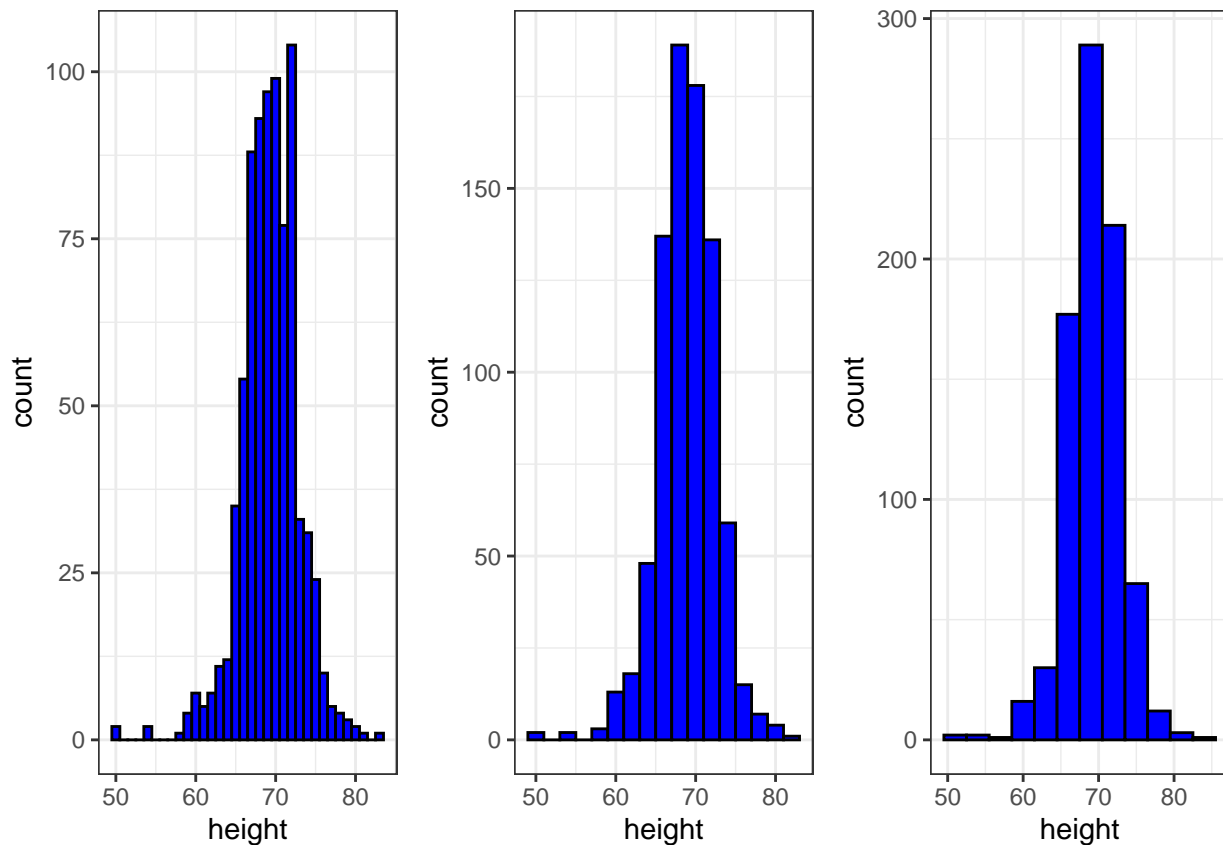
```
p2 <- p + geom_histogram(binwidth = 2, fill = "blue", col = "black")
```

```
p3 <- p + geom_histogram(binwidth = 3, fill = "blue", col = "black")
```

```
# arrange plots next to each other in 1 row, 3 columns
```

```
library(gridExtra)
```

```
grid.arrange(p1, p2, p3, ncol = 3)
```



## Assessment - ggplot2

1. Start by loading the dplyr and ggplot2 libraries as well as the murders data.

```
library(dplyr)
library(ggplot2)
library(dslabs)
data(murders)
```

Note that you can load both dplyr and ggplot2, as well as other packages, by installing and loading the tidyverse package.

With ggplot2 plots can be saved as objects. For example we can associate a dataset with a plot object like this

```
p <- ggplot(data = murders)
```

Because `data` is the first argument we don't need to spell it out. So we can write this instead:

```
p <- ggplot(murders)
```

or, if we load dplyr, we can use the pipe:

```
p <- murders %>% ggplot()
```

Remember the pipe sends the object on the left of %>% to be the first argument for the function the right of %>%.

Now let's get an introduction to ggplot.

```
if(!require(dplyr)) install.packages("dplyr")

library(dplyr)
p <- ggplot(murders)
class(p)
```

```
## [1] "gg"      "ggplot"
```

2. Remember that to print an object you can use the command `print` or simply type the object. For example, instead of

```
x <- 2
print(x)
```

you can simply type

```
x <-2
x
```

Print the object `p` defined in exercise one

```
p <- ggplot(murders)
```

and describe what you see.

- ☐ A. Nothing happens.
- ☒ B. A blank slate plot.
- ☐ C. A scatter plot.
- ☐ D. A histogram.

3. Now we are going to review the use of pipes by seeing how they can be used with ggplot.

```
# define ggplot object called p like in the previous exercise but using a pipe
p <- heights %>% ggplot()
p # a blank slate plot
```



4. Now we are going to add layers and the corresponding aesthetic mappings. For the murders data, we plotted total murders versus population sizes in the videos.

Explore the `murders` data frame to remind yourself of the names for the two variables (total murders and population size) we want to plot and select the correct answer.

- ☐ A. state and abb.
- ☐ B. total\_murders and population\_size.
- ☒ C. total and population.
- ☐ D. murders and size.

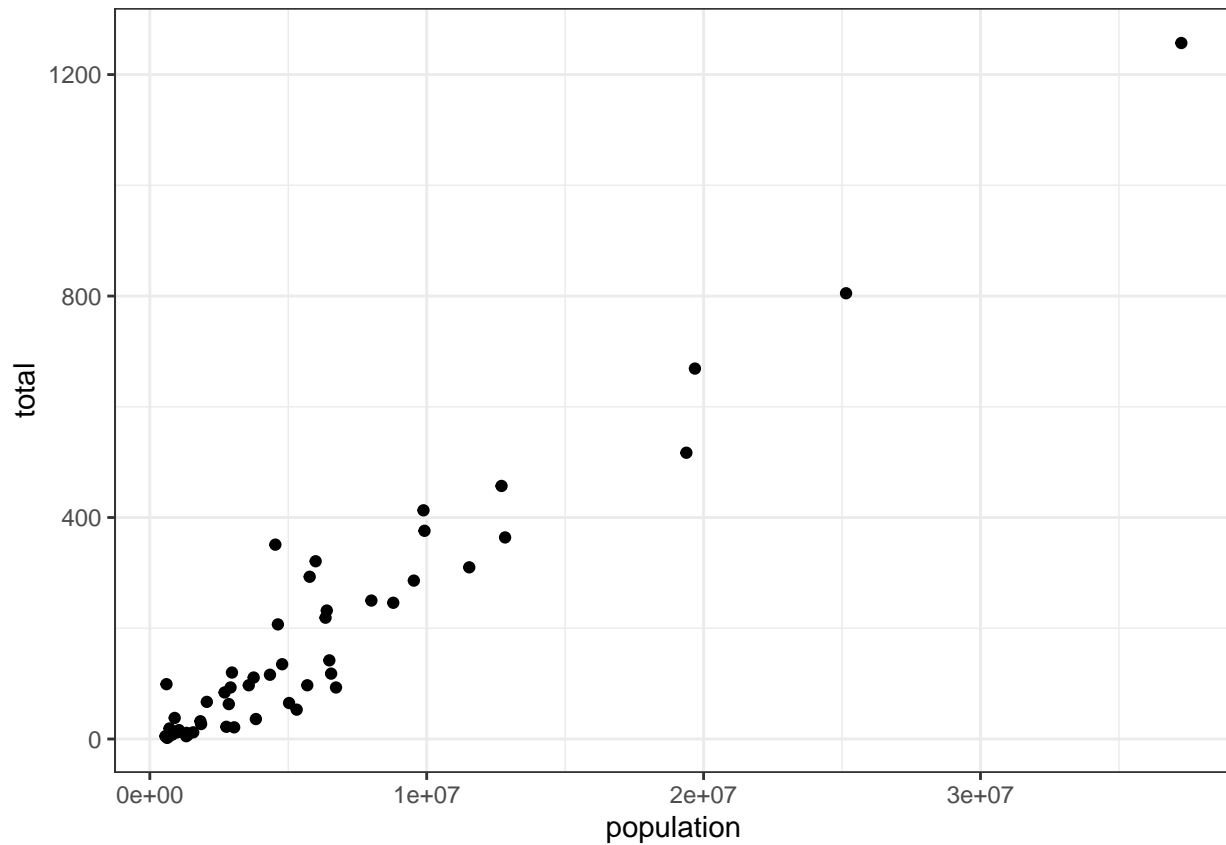
5. To create a scatter plot, we add a layer with the function `geom_point`.

The aesthetic mappings require us to define the x-axis and y-axis variables respectively. So the code looks like this:

```
murders %>% ggplot(aes(x = , y = )) +  
  geom_point()
```

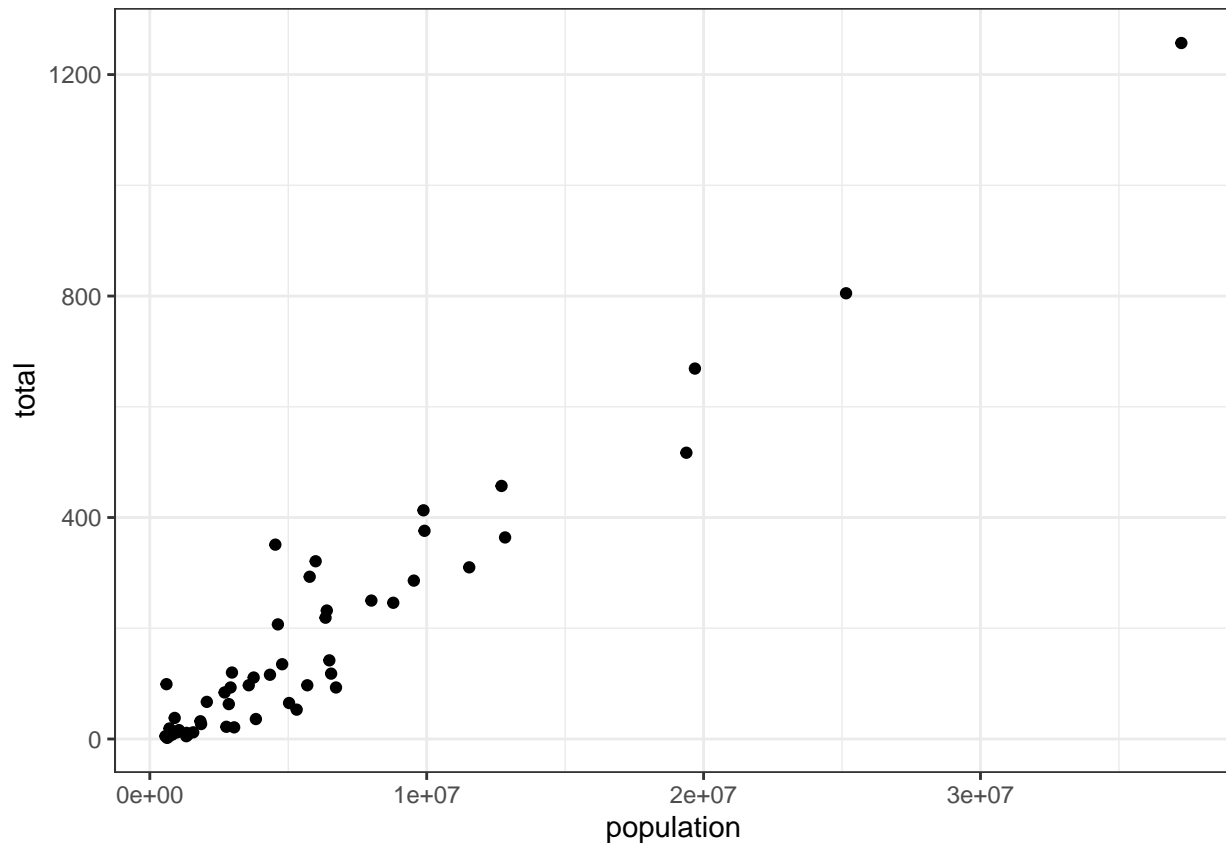
except we have to fill in the blanks to define the two variables `x` and `y`.

```
## Fill in the blanks  
murders %>% ggplot(aes(x =population , y =total )) +  
  geom_point()
```



6. Note that if we don't use argument names, we can obtain the same plot by making sure we enter the variable names in the desired order.

```
murders %>% ggplot(aes(population, total)) +  
  geom_point()
```



7. If instead of points we want to add text, we can use the `geom_text()` or `geom_label()` geometries.

However, note that the following code

```
murders %>% ggplot(aes(population, total)) +  
  geom_label()
```

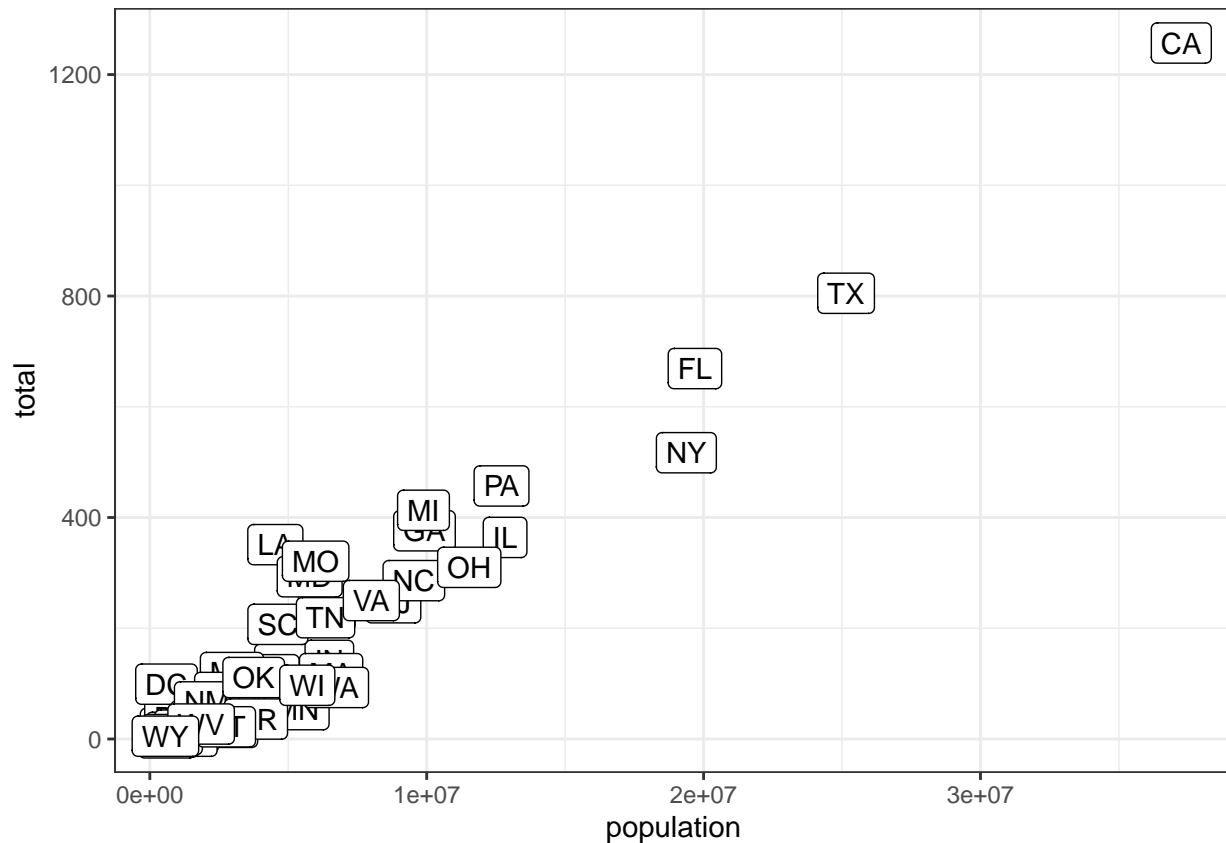
will give us the error message: `Error: geom_label requires the following missing aesthetics: label`

Why is this?

- ☒ A. We need to map a character to each point through the `label` argument in `aes`.
- ☐ B. We need to let `geom_label` know what character to use in the plot.
- ☐ C. The `geom_label` geometry does not require x-axis and y-axis values.
- ☐ D. `geom_label` is not a ggplot2 command.

8. You can also add labels to the points on a plot.

```
## edit the next line to add the label  
murders %>% ggplot(aes(population, total, label = abb)) + geom_label()
```



9. Now let's change the color of the labels to blue. How can we do this?

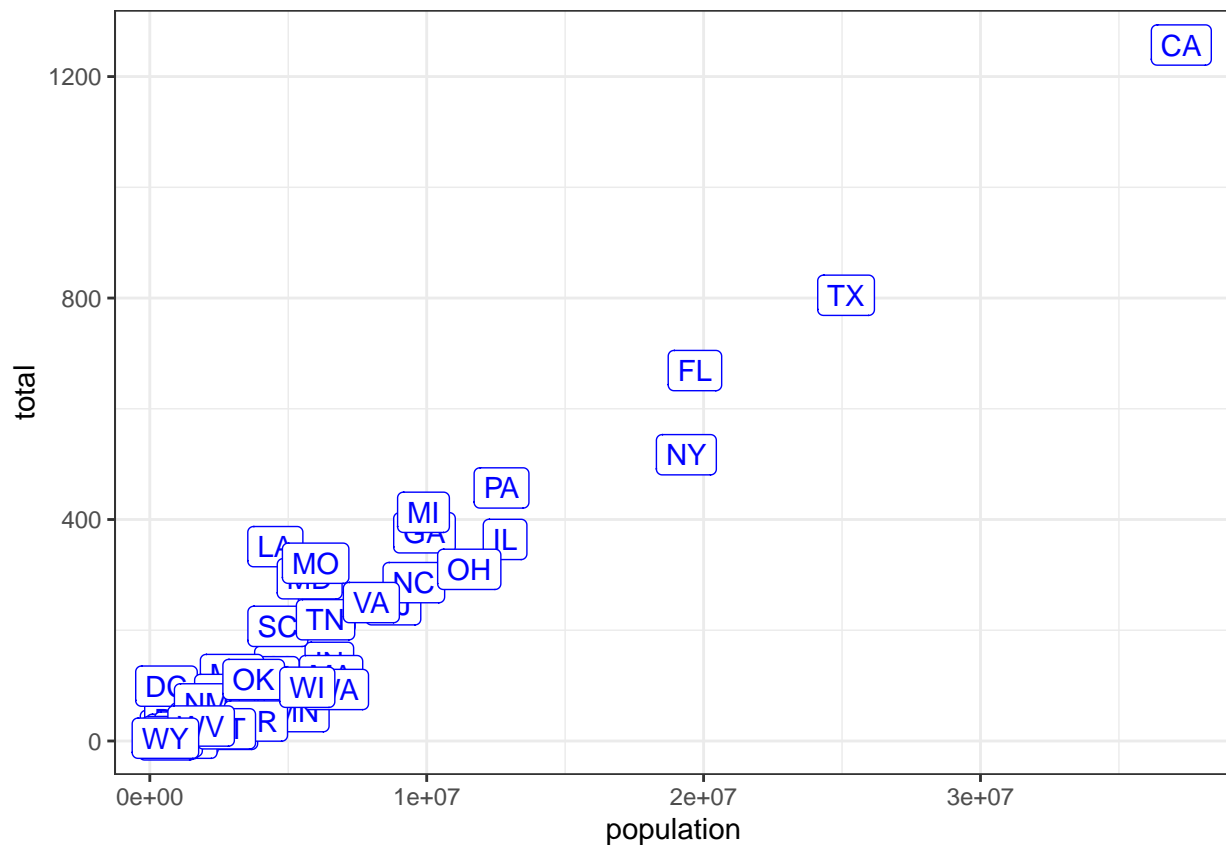
- ☐ A. By adding a column called blue to murders
- ☐ B. By mapping the colors through aes because each label needs a different color
- ☐ C. By using the color argument in ggplot
- ☒ D. By using the color argument in geom\_label because we want all colors to be blue so we do not need to map colors

10. Now let's go ahead and make the labels blue. We previously wrote this code to add labels to our plot:

```
murders %>% ggplot(aes(population, total, label= abb)) +  
  geom_label()
```

Now we will edit this code.

```
murders %>% ggplot(aes(population, total, label= abb)) +  
  geom_label(color="blue")
```



11. Now suppose we want to use color to represent the different regions.

So the states from the West will be one color, states from the Northeast another, and so on.

In this case, which of the following is most appropriate:

- ☐ A. Adding a column called color to murders with the color we want to use
- ☒ B. Mapping the colors through the color argument of aes because each label needs a different color
- ☐ C. Using the color argument in ggplot
- ☐ D. Using the color argument in geom\_label because we want all colors to be blue so we do not need to map colors

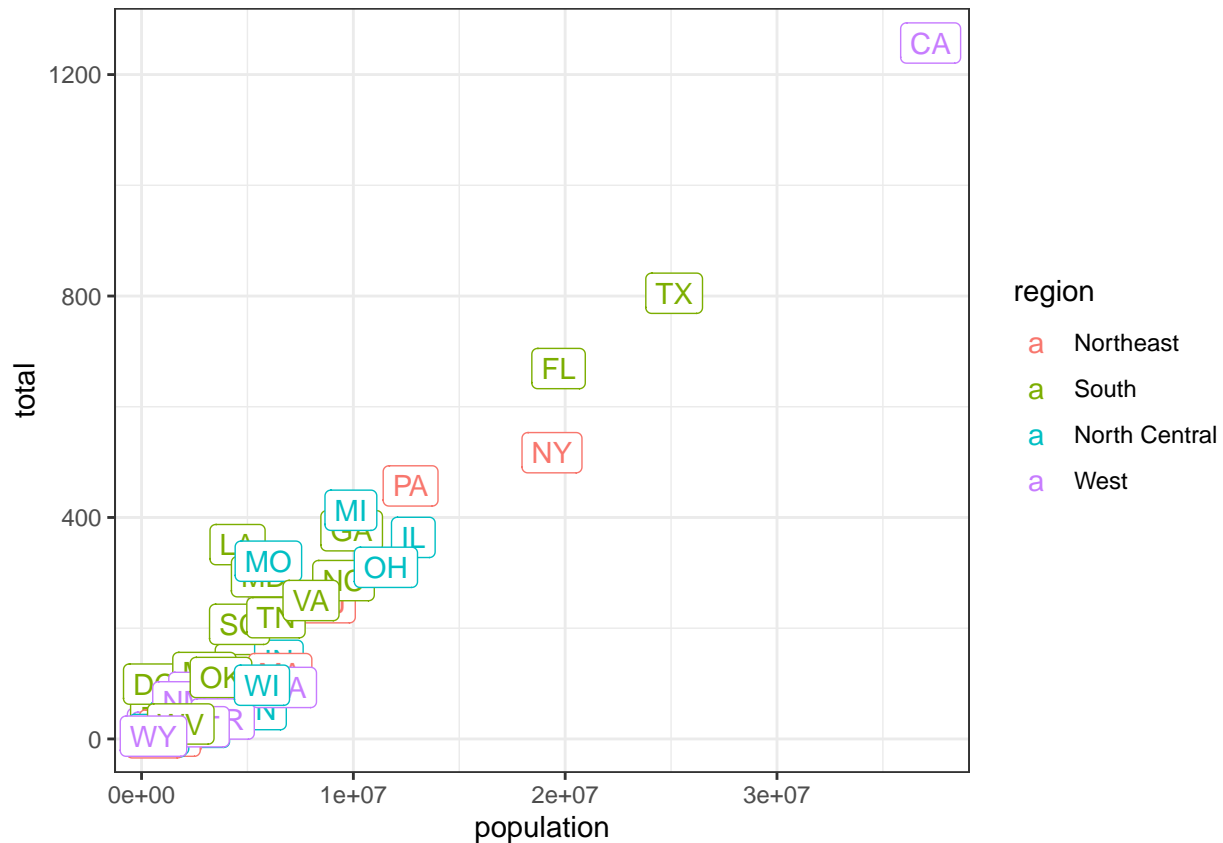
12. We previously used this code to make a plot using the state abbreviations as labels:

```
murders %>% ggplot(aes(population, total, label = abb)) +  
  geom_label()
```

We are now going to add color to represent the region.

```
## edit this code  
murders %>% ggplot(aes(population, total, label = abb, color=region)) +  
  geom_label()
```





13. Now we are going to change the axes to log scales to account for the fact that the population distribution is skewed.

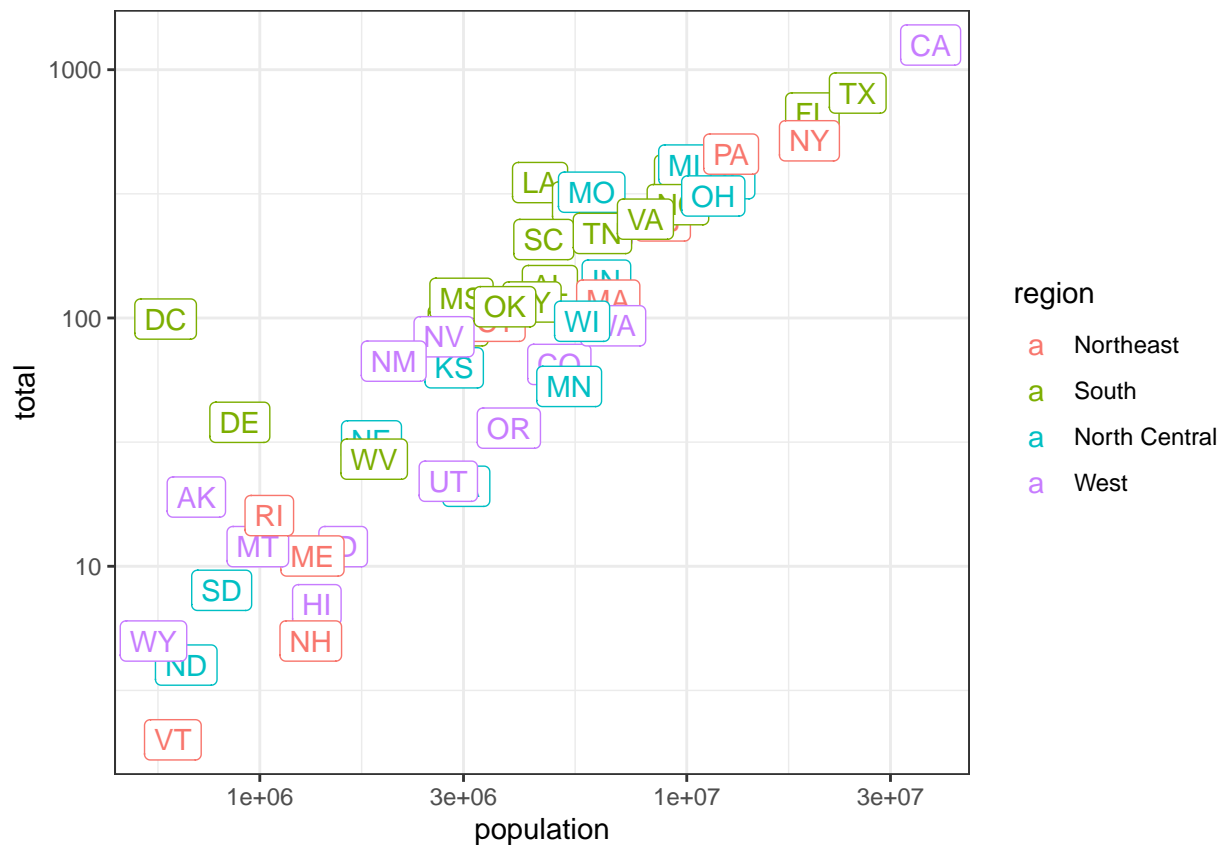
Let's start by defining an object `p` that holds the plot we have made up to now:

```
p <- murders %>% ggplot(aes(population, total, label = abb, color = region)) +  
  geom_label()
```

To change the x-axis to a log scale we learned about the `scale_x_log10()` function. We can change the axis by adding this layer to the object `p` to change the scale and render the plot using the following code:

```
p + scale_x_log10()
```

```
p <- murders %>% ggplot(aes(population, total, label = abb, color = region)) + geom_label()
## add layers to p here
p + scale_x_log10() + scale_y_log10()
```

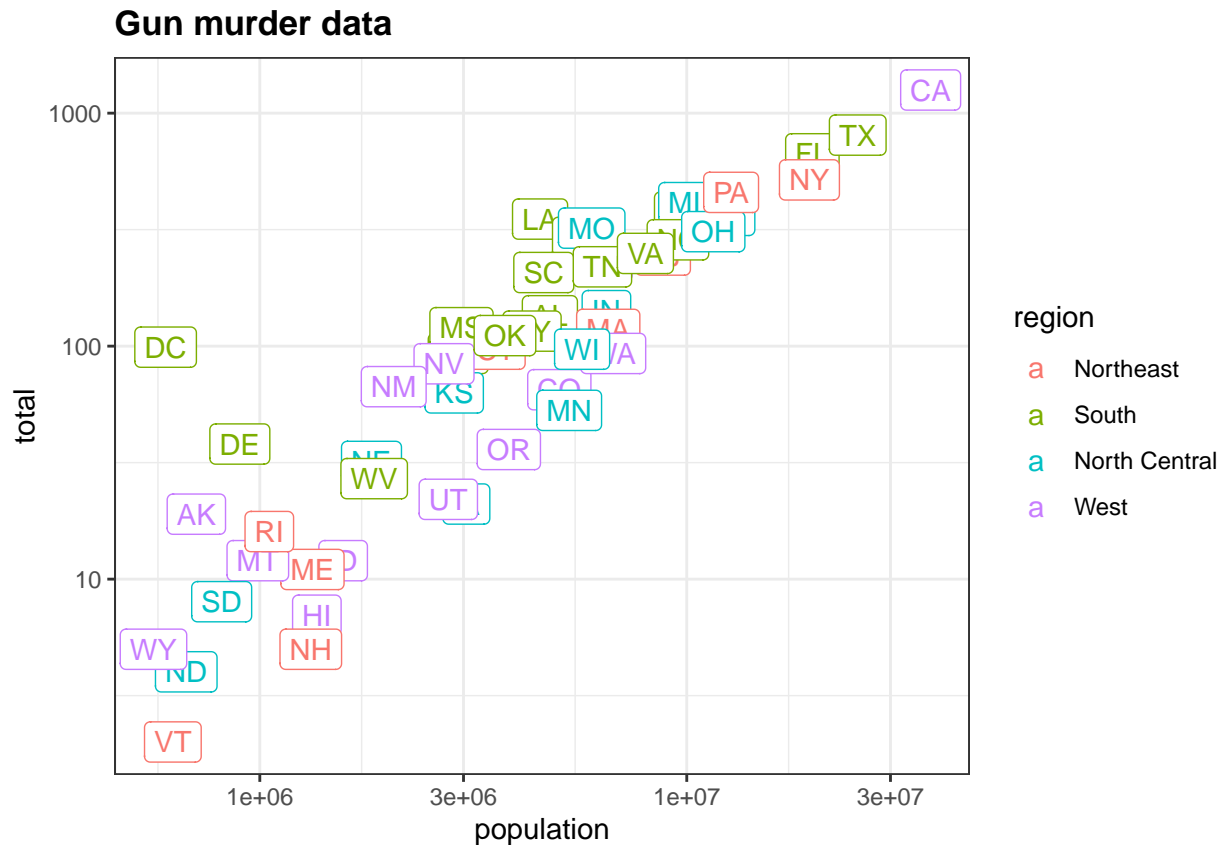


14. In the previous exercises we created a plot using the following code:

```
library(dplyr)
library(ggplot2)
library(dslabs)
data(murders)
p<- murders %>% ggplot(aes(population, total, label = abb, color = region)) +
  geom_label()
p + scale_x_log10() + scale_y_log10()
```

We are now going to add a title to this plot. We will do this by adding yet another layer, this time with the function `ggtitle`.

```
p <- murders %>% ggplot(aes(population, total, label = abb, color = region)) + geom_label()
# add a layer to add title to the next line
p + scale_x_log10() + scale_y_log10() + ggtitle("Gun murder data")
```



15. We are going to shift our focus from the `murders` dataset to explore the `heights` dataset.

We use the `geom_histogram` function to make a histogram of the heights in the `heights` data frame. When reading the documentation for this function we see that it requires just one mapping, the values to be used for the histogram.

What is the variable containing the heights in inches in the `heights` data frame?

- ☐ A. sex
- ☐ B. heights
- ☒ C. height
- ☐ D. heights\$height

16. We are now going to make a histogram of the heights so we will load the `heights` dataset.

The following code has been pre-run for you to load the `heights` dataset:

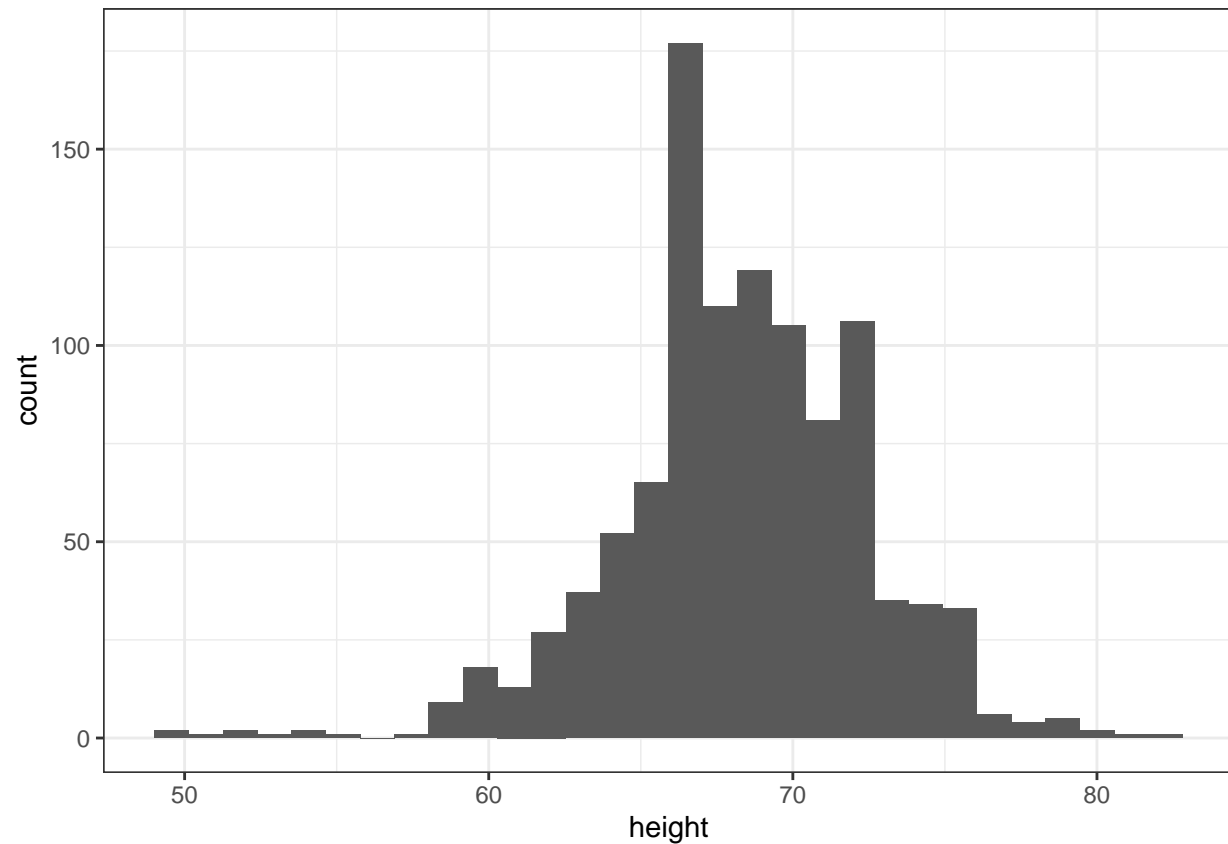
```
library(dplyr)
library(ggplot2)
library(dslabs)
data(heights)
```

```
# define p here
p <- heights %>% ggplot(aes(height))
```

17. Now we are ready to add a layer to actually make the histogram.

```
p <- heights %>%
  ggplot(aes(height))
## add a layer to p
p + geom_histogram()
```

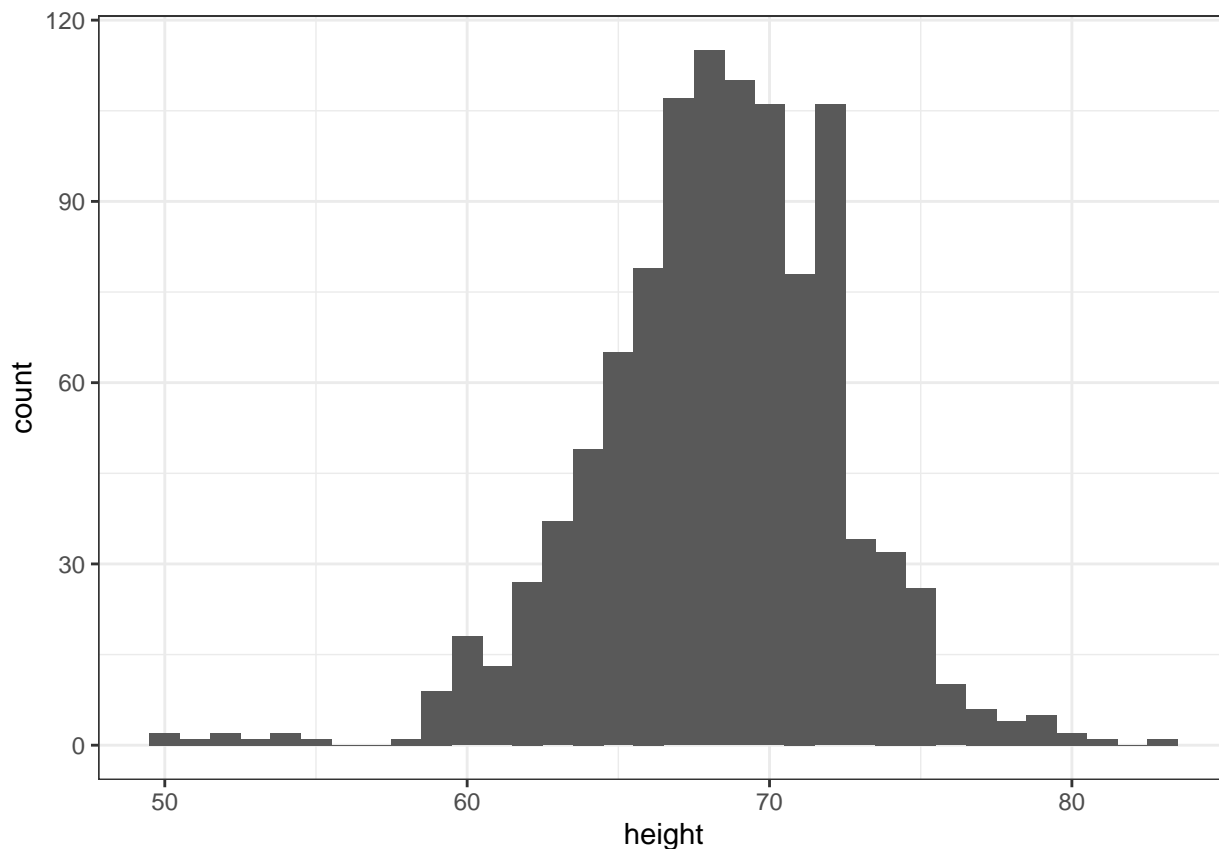
`## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.`



18. Note that when we run the code from the previous exercise we get the following warning:

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

```
p <- heights %>%
  ggplot(aes(height))
## add the geom_histogram layer but with the requested argument
p + geom_histogram(binwidth = 1)
```

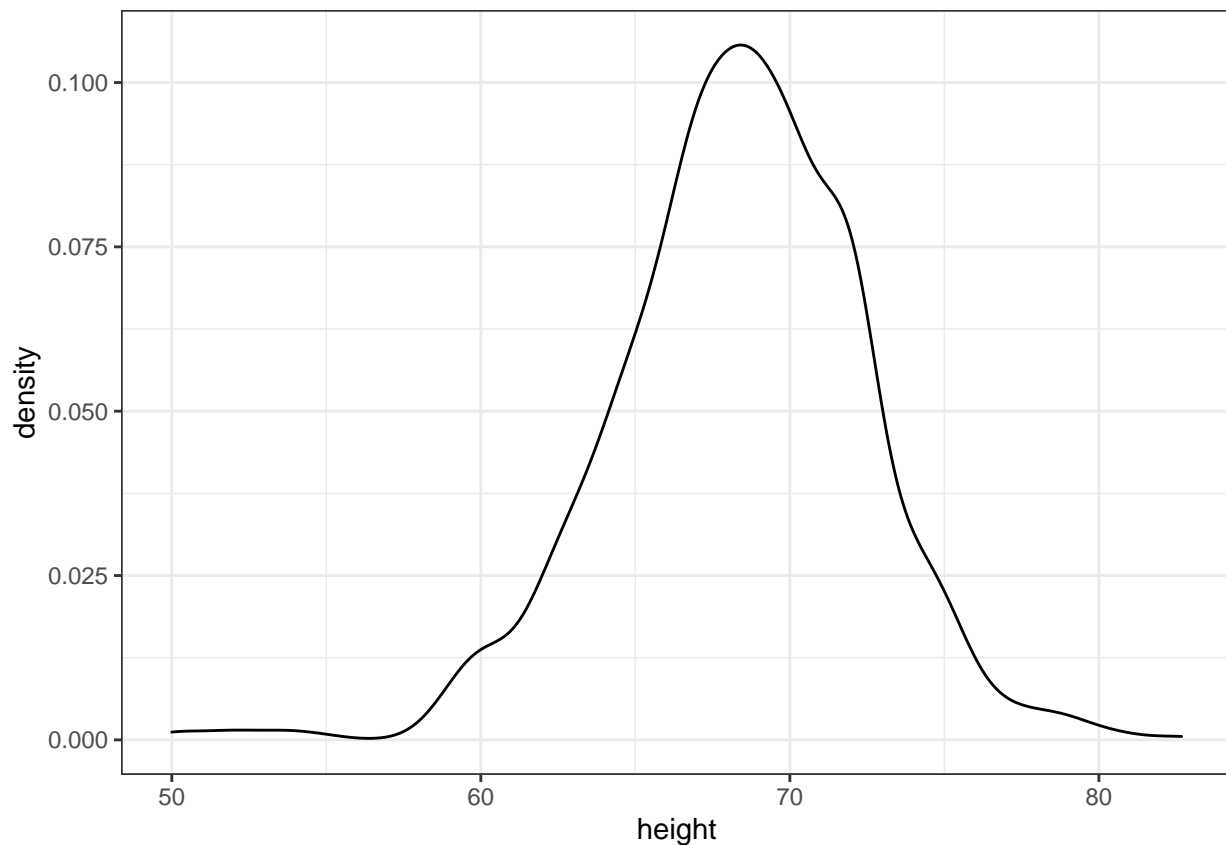


19. Now instead of a histogram we are going to make a smooth density plot.

In this case, we will not make an object `p`. Instead we will render the plot using a single line of code. In the previous exercise, we could have created a histogram using one line of code like this:

```
heights %>%  
  ggplot(aes(height)) +  
  geom_histogram()
```

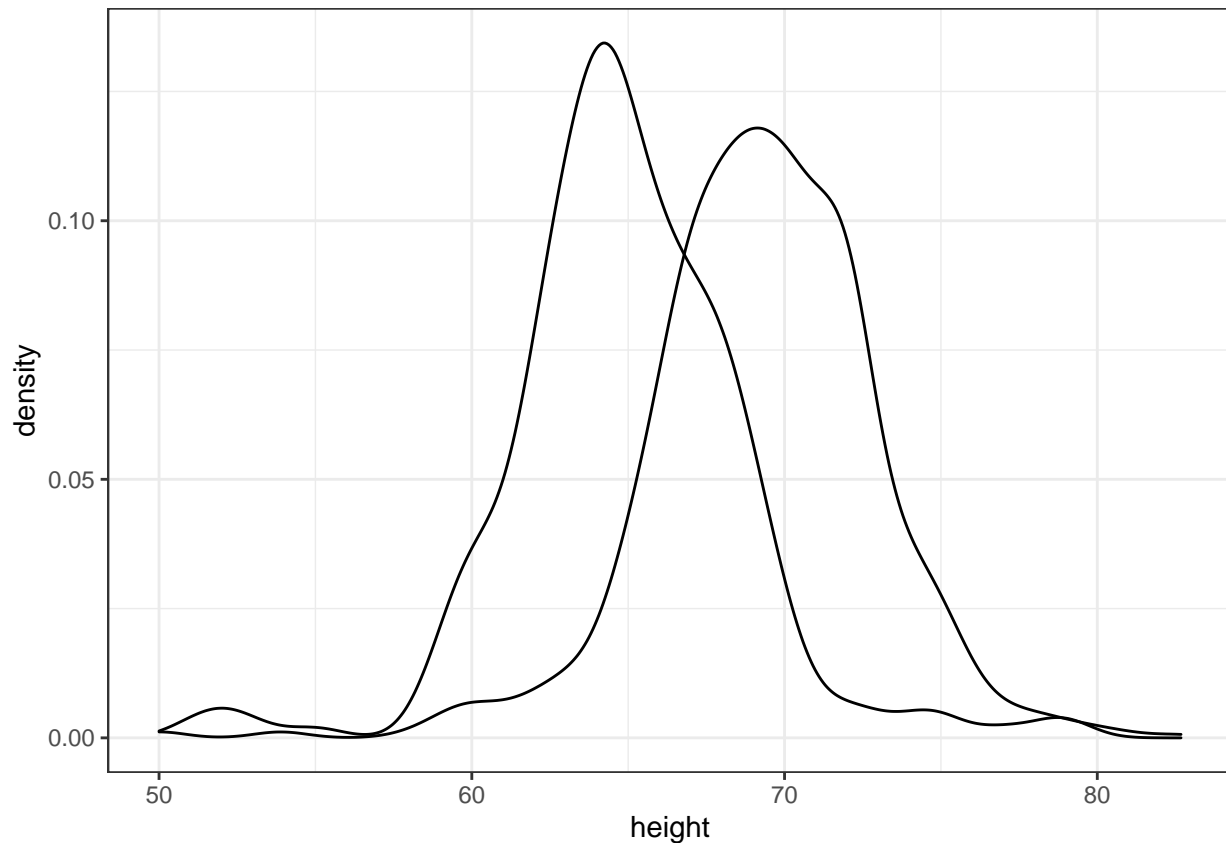
```
## add the correct layer using +  
heights %>%  
  ggplot(aes(height)) + geom_density()
```



20. Now we are going to make density plots for males and females separately.

We can do this using the `group` argument within the `aes` mapping. Because each point will be assigned to a different density depending on a variable from the dataset, we need to map within `aes`.

```
## add the group argument then a layer with +  
heights %>%  
  ggplot(aes(height, group = sex)) + geom_density()
```

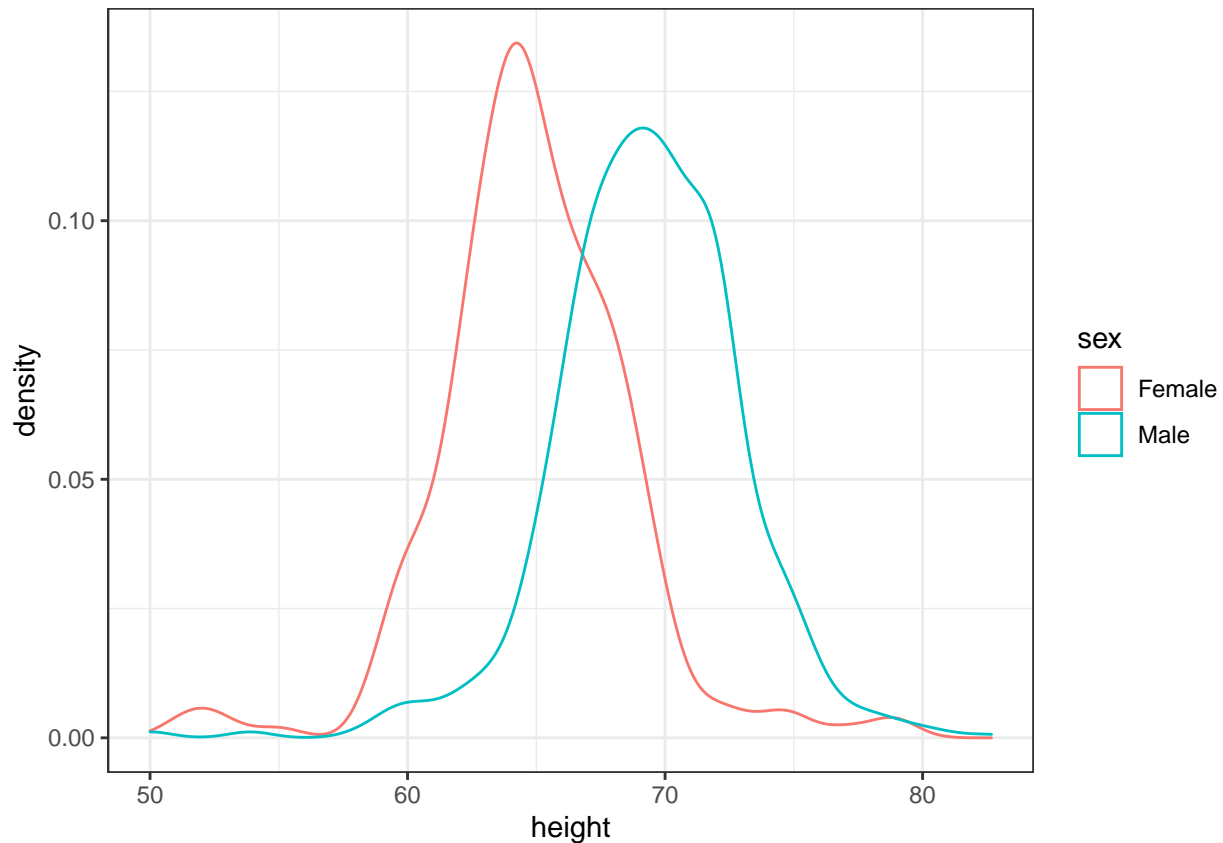


21. In the previous exercise we made the two density plots, one for each sex, using:

```
heights %>%  
  ggplot(aes(height, group = sex)) +  
  geom_density()
```

We can also assign groups through the `color` or `fill` argument. For example, if you type `color = sex` ggplot knows you want a different color for each sex. So two densities must be drawn. You can therefore skip the `group = sex` mapping. Using `color` has the added benefit that it uses color to distinguish the groups. Change the density plots from the previous exercise to add color.

```
## edit the next line to use color instead of group then add a density layer  
heights %>%  
  ggplot(aes(height, color = sex)) + geom_density()
```



22. We can also assign groups using the `fill` argument.

When using the `geom_density` geometry, `color` creates a colored line for the smooth density plot while `fill` colors in the area under the curve.

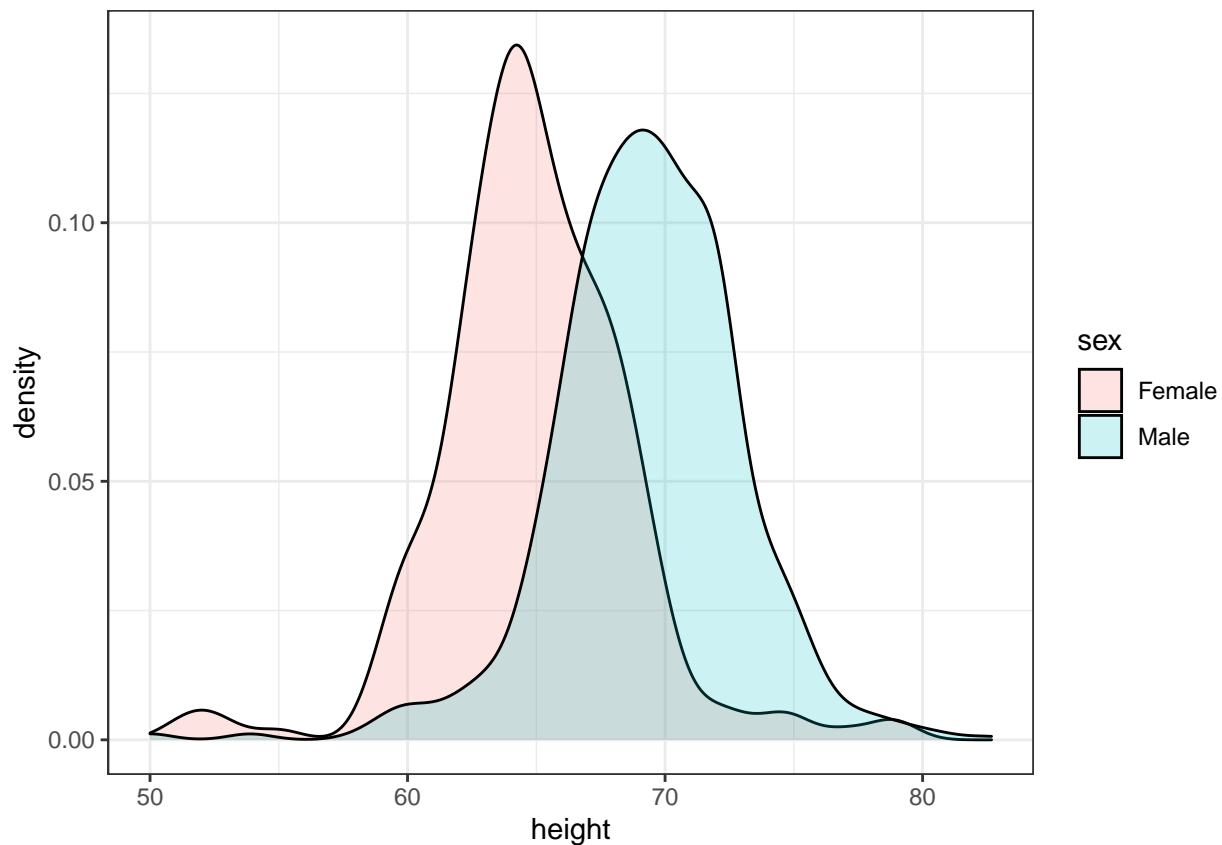
We can see what this looks like by running the following code:

```
heights %>%  
  ggplot(aes(height, fill = sex)) +  
  geom_density()
```

However, here the second density is drawn over the other. We can change this by using something called *alpha blending*.

```
heights %>%  
  ggplot(aes(height, fill = sex)) +  
  geom_density(alpha=0.2)
```





## Section 3 Overview

Section 3 introduces you to summarizing with dplyr.

After completing Section 3, you will:

- understand the importance of summarizing data in exploratory data analysis.
- be able to use the “summarize” verb in dplyr to facilitate summarizing data.
- be able to use the “group\_by” verb in dplyr to facilitate summarizing data.
- be able to access values using the dot placeholder.
- be able to use “arrange” to examine data after sorting.

## dplyr

The textbook for this section is available [here](#)

### Key points

- **summarize** from the dplyr/tidyverse package computes summary statistics from the data frame. It returns a data frame whose column names are defined within the function call.
- **summarize** can compute any summary function that operates on vectors and returns a single value, but it cannot operate on functions that return multiple values.
- Like most dplyr functions, **summarize** is aware of variable names within data frames and can use them directly.

Code

```
# compute average and standard deviation for males
s <- heights %>%
  filter(sex == "Male") %>%
  summarize(average = mean(height), standard_deviation = sd(height))

# access average and standard deviation from summary table
s$average
```

```
## [1] 69.31475
```

```
s$standard_deviation
```

```
## [1] 3.611024
```

```
# compute median, min and max
heights %>%
  filter(sex == "Male") %>%
  summarize(median = median(height),
            minimum = min(height),
            maximum = max(height))
```

```
##   median minimum maximum
## 1      69      50 82.67717
```

```
# alternative way to get min, median, max in base R
quantile(heights$height, c(0, 0.5, 1))
```

```
##      0%      50%     100%
## 50.00000 68.50000 82.67717
```

```
# generates an error: summarize can only take functions that return a single value
heights %>%
  filter(sex == "Male") %>%
  summarize(range = quantile(height, c(0, 0.5, 1)))
```

## The Dot Placeholder

The textbook for this section is available [here](#)

Note that a common replacement for the dot operator is the pull function. Here is the [textbook section on the pull function](#).

### Key points

- The dot operator allows you to access values stored in data that is being piped in using the %>% character. The dot is a placeholder for the data being passed in through the pipe.
- The dot operator allows dplyr functions to return single vectors or numbers instead of only data frames.
- `us_murder_rate %>% .$rate` is equivalent to `us_murder_rate$rate`.

- Note that an equivalent way to extract a single column using the pipe is `us_murder_rate %>% pull(rate)`. The `pull` function will be used in later course material.

Code

```
murders <- murders %>% mutate(murder_rate = total/population*100000)
summarize(murders, mean(murder_rate))
```

```
##      mean(murder_rate)
## 1          2.779125
```

```
# calculate US murder rate, generating a data frame
us_murder_rate <- murders %>%
  summarize(rate = sum(total) / sum(population) * 100000)
us_murder_rate
```

```
##      rate
## 1 3.034555
```

```
# extract the numeric US murder rate with the dot operator
us_murder_rate %>% .$rate
```

```
## [1] 3.034555
```

```
# calculate and extract the murder rate with one pipe
us_murder_rate <- murders %>%
  summarize(rate = sum(total) / sum(population * 100000)) %>%
  .$rate
```

## Group By

The textbook for this section is available [here](#)

### Key points

- The `group_by` function from **dplyr** converts a data frame to a grouped data frame, creating groups using one or more variables.
- `summarize` and some other **dplyr** functions will behave differently on grouped data frames.
- Using `summarize` on a grouped data frame computes the summary statistics for each of the separate groups.

Code

```
# compute separate average and standard deviation for male/female heights
heights %>%
  group_by(sex) %>%
  summarize(average = mean(height), standard_deviation = sd(height))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## # A tibble: 2 x 3
##   sex      average standard_deviation
##   <fct>    <dbl>          <dbl>
## 1 Female    64.9            3.76
## 2 Male     69.3            3.61

# compute median murder rate in 4 regions of country
murders <- murders %>%
  mutate(murder_rate = total/population * 100000)
murders %>%
  group_by(region) %>%
  summarize(median_rate = median(murder_rate))

## `summarise()` ungrouping output (override with `.groups` argument)

## # A tibble: 4 x 2
##   region      median_rate
##   <fct>          <dbl>
## 1 Northeast      1.80
## 2 South          3.40
## 3 North Central  1.97
## 4 West           1.29
```

## Sorting Data Tables

The textbook for this section is available [here](#)

### Key points

- The **arrange** function from **dplyr** sorts a data frame by a given column.
- By default, **arrange** sorts in ascending order (lowest to highest). To instead sort in descending order, use the function **desc** inside of **arrange**.
- You can **arrange** by multiple levels: within equivalent values of the first level, observations are sorted by the second level, and so on.
- The **top\_n** function shows the top results ranked by a given variable, but the results are not ordered. You can combine **top\_n** with **arrange** to return the top results in order.

### Code

```
# set up murders object
murders <- murders %>%
  mutate(murder_rate = total/population * 100000)

# arrange by population column, smallest to largest
murders %>% arrange(population) %>% head()
```

```
##           state abb      region population total murder_rate
## 1      Wyoming  WY      West    563626      5   0.8871131
## 2 District of Columbia DC      South    601723     99  16.4527532
## 3      Vermont  VT      Northeast    625741      2   0.3196211
## 4   North Dakota ND North Central    672591      4   0.5947151
## 5        Alaska AK      West     710231     19   2.6751860
## 6   South Dakota SD North Central    814180      8   0.9825837
```

```
# arrange by murder rate, smallest to largest
murders %>% arrange(murder_rate) %>% head()
```

```
##           state abb      region population total murder_rate
## 1      Vermont  VT      Northeast     625741      2    0.3196211
## 2 New Hampshire NH      Northeast    1316470      5    0.3798036
## 3       Hawaii  HI          West    1360301      7    0.5145920
## 4 North Dakota ND North Central     672591      4    0.5947151
## 5        Iowa  IA North Central    3046355     21    0.6893484
## 6       Idaho  ID          West    1567582     12    0.7655102
```

```
# arrange by murder rate in descending order
murders %>% arrange(desc(murder_rate)) %>% head()
```

```
##           state abb      region population total murder_rate
## 1 District of Columbia DC      South     601723     99  16.452753
## 2       Louisiana LA      South    4533372    351   7.742581
## 3       Missouri MO North Central    5988927    321   5.359892
## 4       Maryland MD      South    5773552    293   5.074866
## 5 South Carolina SC      South    4625364    207   4.475323
## 6       Delaware DE      South     897934     38   4.231937
```

```
# arrange by region alphabetically, then by murder rate within each region
murders %>% arrange(region, murder_rate) %>% head()
```

```
##           state abb      region population total murder_rate
## 1      Vermont  VT Northeast     625741      2    0.3196211
## 2 New Hampshire NH Northeast    1316470      5    0.3798036
## 3        Maine  ME Northeast    1328361     11    0.8280881
## 4 Rhode Island RI Northeast    1052567     16    1.5200933
## 5 Massachusetts MA Northeast    6547629    118    1.8021791
## 6     New York  NY Northeast    19378102    517    2.6679599
```

```
# show the top 10 states with highest murder rate, not ordered by rate
murders %>% top_n(10, murder_rate)
```

```
##           state abb      region population total murder_rate
## 1       Arizona  AZ          West     6392017    232   3.629527
## 2       Delaware DE          South     897934     38   4.231937
## 3 District of Columbia DC      South     601723     99  16.452753
## 4       Georgia GA          South    9920000    376   3.790323
## 5       Louisiana LA          South    4533372    351   7.742581
## 6       Maryland MD          South    5773552    293   5.074866
## 7       Michigan MI North Central    9883640    413   4.178622
## 8       Mississippi MS          South    2967297    120   4.044085
## 9       Missouri MO North Central    5988927    321   5.359892
## 10 South Carolina SC          South    4625364    207   4.475323
```

```
# show the top 10 states with highest murder rate, ordered by rate
murders %>% arrange(desc(murder_rate)) %>% top_n(10)
```

```
## Selecting by murder_rate
```

```
##           state abb      region population total murder_rate
## 1 District of Columbia DC      South      601723      99 16.452753
## 2      Louisiana LA      South    4533372     351  7.742581
## 3      Missouri MO North Central    5988927     321  5.359892
## 4      Maryland MD      South    5773552     293  5.074866
## 5 South Carolina SC      South    4625364     207  4.475323
## 6      Delaware DE      South     897934      38  4.231937
## 7      Michigan MI North Central    9883640     413  4.178622
## 8      Mississippi MS      South    2967297     120  4.044085
## 9      Georgia GA      South    9920000     376  3.790323
## 10     Arizona AZ      West     6392017     232  3.629527
```

## Assessment - Summarizing with dplyr

To practice our dplyr skills we will be working with data from the survey collected by the United States National Center for Health Statistics (NCHS). This center has conducted a series of health and nutrition surveys since the 1960's.

Starting in 1999, about 5,000 individuals of all ages have been interviewed every year and then they complete the health examination component of the survey. Part of this dataset is made available via the NHANES package which can be loaded this way:

```
if(!require(NHANES)) install.packages("NHANES")
```

```
## Loading required package: NHANES
```

```
## Warning: package 'NHANES' was built under R version 4.0.2
```

```
library(NHANES)
data(NHANES)
```

The NHANES data has many missing values. Remember that the main summarization function in R will return NA if any of the entries of the input vector is an NA. Here is an example:

```
data(na_example)
mean(na_example)
```

```
## [1] NA
```

```
sd(na_example)
```

```
## [1] NA
```

To ignore the NAs, we can use the `na.rm` argument:

```
mean(na_example, na.rm = TRUE)
```

```
## [1] 2.301754
```

```
sd(na_example, na.rm = TRUE)
```

```
## [1] 1.22338
```

Try running this code, then let us know you are ready to proceed with the analysis.

1. Let's explore the NHANES data. We will be exploring blood pressure in this dataset.

First let's select a group to set the standard. We will use 20-29 year old females. Note that the category is coded with 20-29, with a space in front of the 20! The `AgeDecade` is a categorical variable with these ages.

To know if someone is female, you can look at the `Gender` variable.

```
## fill in what is needed
tab <- NHANES %>% filter(AgeDecade == " 20-29" & Gender == "female")
head(tab)
```

```
## # A tibble: 6 x 76
##       ID SurveyYr Gender   Age AgeDecade AgeMonths Race1 Race3 Education
##   <int> <fct>   <fct> <int> <fct>         <int> <fct> <fct> <fct>
## 1 51710 2009_10 female   26 " 20-29"         319 White <NA> College ~
## 2 51731 2009_10 female   28 " 20-29"         346 Black <NA> High Sch~
## 3 51741 2009_10 female   21 " 20-29"         253 Black <NA> Some Col~
## 4 51741 2009_10 female   21 " 20-29"         253 Black <NA> Some Col~
## 5 51760 2009_10 female   27 " 20-29"         334 Hisp~ <NA> 9 - 11th~
## 6 51764 2009_10 female   29 " 20-29"         357 White <NA> College ~
## # ... with 67 more variables: MaritalStatus <fct>, HHIIncome <fct>,
## #   HHIIncomeMid <int>, Poverty <dbl>, HomeRooms <int>, HomeOwn <fct>,
## #   Work <fct>, Weight <dbl>, Length <dbl>, HeadCirc <dbl>, Height <dbl>,
## #   BMI <dbl>, BMICatUnder20yrs <fct>, BMI_WHO <fct>, Pulse <int>,
## #   BPSysAve <int>, BPDiaAve <int>, BPSys1 <int>, BPDia1 <int>, BPSys2 <int>,
## #   BPDia2 <int>, BPSys3 <int>, BPDia3 <int>, Testosterone <dbl>,
## #   DirectChol <dbl>, TotChol <dbl>, UrineVol1 <int>, UrineFlow1 <dbl>,
## #   UrineVol2 <int>, UrineFlow2 <dbl>, Diabetes <fct>, DiabetesAge <int>,
## #   HealthGen <fct>, DaysPhysHlthBad <int>, DaysMentHlthBad <int>,
## #   LittleInterest <fct>, Depressed <fct>, nPregnancies <int>, nBabies <int>,
## #   Age1stBaby <int>, SleepHrsNight <int>, SleepTrouble <fct>,
## #   PhysActive <fct>, PhysActiveDays <int>, TVHrsDay <fct>, CompHrsDay <fct>,
## #   TVHrsDayChild <int>, CompHrsDayChild <int>, Alcohol12PlusYr <fct>,
## #   AlcoholDay <int>, AlcoholYear <int>, SmokeNow <fct>, Smoke100 <fct>,
## #   Smoke100n <fct>, SmokeAge <int>, Marijuana <fct>, AgeFirstMarij <int>,
## #   RegularMarij <fct>, AgeRegMarij <int>, HardDrugs <fct>, SexEver <fct>,
## #   SexAge <int>, SexNumPartnLife <int>, SexNumPartYear <int>, SameSex <fct>,
## #   SexOrientation <fct>, PregnantNow <fct>
```

2. Now we will compute the average and standard deviation for the subgroup we defined in the previous exercise (20-29 year old females), which we will use reference for what is typical.

You will determine the average and standard deviation of systolic blood pressure, which are stored in the `BPSysAve` variable in the NHANES dataset.

```
## complete this line of code.
ref <- NHANES %>% filter(AgeDecade == " 20-29" & Gender == "female") %>% summarize(average = mean(BPSysAve),
ref
```

```
## # A tibble: 1 x 2
##   average standard_deviation
##   <dbl>          <dbl>
## 1    108.          10.1
```

3. Now we will repeat the exercise and generate only the average blood pressure for 20-29 year old females.

For this exercise, you should review how to use the place holder . in dplyr or the pull function.

```
## modify the code we wrote for previous exercise.
ref_avg <- NHANES %>%
  filter(AgeDecade == " 20-29" & Gender == "female") %>%
  summarize(average = mean(BPSysAve, na.rm = TRUE),
            standard_deviation = sd(BPSysAve, na.rm=TRUE)) %>% .$average
ref_avg
```

```
## [1] 108.4224
```

4. Let's continue practicing by calculating two other data summaries: the minimum and the maximum.

Again we will do it for the BPSysAve variable and the group of 20-29 year old females.

```
## complete the line
NHANES %>%
  filter(AgeDecade == " 20-29" & Gender == "female") %>% summarize(minbp = min(BPSysAve, na.rm = TRUE),
  maxbp = max(BPSysAve, na.rm=TRUE))
```

```
## # A tibble: 1 x 2
##   minbp maxbp
##   <int> <int>
## 1     84   179
```

5. Now let's practice using the group\_by function.

What we are about to do is a very common operation in data science: you will split a data table into groups and then compute summary statistics for each group.

We will compute the average and standard deviation of systolic blood pressure for females for each age group separately. Remember that the age groups are contained in AgeDecade.

```
##complete the line with group_by and summarize
NHANES %>%
  filter(Gender == "female") %>% group_by(AgeDecade) %>% summarize(average = mean(BPSysAve, na.rm = TRUE),
  standard_deviation = sd(BPSysAve, na.rm=TRUE))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```



```
## # A tibble: 9 x 3
##   AgeDecade average standard_deviation
##   <fct>      <dbl>          <dbl>
## 1 " 0-9"      100.            9.07
## 2 " 10-19"   104.            9.46
## 3 " 20-29"   108.           10.1
## 4 " 30-39"   111.           12.3
## 5 " 40-49"   115.           14.5
## 6 " 50-59"   122.           16.2
## 7 " 60-69"   127.           17.1
## 8 " 70+"     134.           19.8
## 9 <NA>      142.           22.9
```

6. Now let's practice using `group_by` some more.

We are going to repeat the previous exercise of calculating the average and standard deviation of systolic blood pressure, but for males instead of females.

This time we will not provide much sample code. You are on your own!

```
NHANES %>%
  filter(Gender == "male") %>% group_by(AgeDecade) %>% summarize(average = mean(BPSysAve, na.rm = TRUE),
    standard_deviation = sd(BPSysAve, na.rm=TRUE))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## # A tibble: 9 x 3
##   AgeDecade average standard_deviation
##   <fct>      <dbl>          <dbl>
## 1 " 0-9"      97.4            8.32
## 2 " 10-19"   110.            11.2
## 3 " 20-29"   118.            11.3
## 4 " 30-39"   119.            12.3
## 5 " 40-49"   121.            14.0
## 6 " 50-59"   126.            17.8
## 7 " 60-69"   127.            17.5
## 8 " 70+"     130.            18.7
## 9 <NA>      136.            23.5
```

7. We can actually combine both of these summaries into a single line of code.

This is because `group_by` permits us to group by more than one variable.

We can use `group_by(AgeDecade, Gender)` to group by both age decades and gender.

```
NHANES %>% group_by(AgeDecade, Gender) %>% summarize(average = mean(BPSysAve, na.rm = TRUE),
  standard_deviation = sd(BPSysAve, na.rm=TRUE))
```

```
## `summarise()` regrouping output by 'AgeDecade' (override with `.groups` argument)
```

```
## # A tibble: 18 x 4
## # Groups:   AgeDecade [9]
```

```
##   AgeDecade Gender average standard_deviation
##   <fct>      <fct>      <dbl>          <dbl>
## 1 " 0-9"     female    100.           9.07
## 2 " 0-9"     male      97.4           8.32
## 3 " 10-19"   female    104.           9.46
## 4 " 10-19"   male      110.           11.2
## 5 " 20-29"   female    108.           10.1
## 6 " 20-29"   male      118.           11.3
## 7 " 30-39"   female    111.           12.3
## 8 " 30-39"   male      119.           12.3
## 9 " 40-49"   female    115.           14.5
## 10 " 40-49"  male      121.           14.0
## 11 " 50-59"  female    122.           16.2
## 12 " 50-59"  male      126.           17.8
## 13 " 60-69"  female    127.           17.1
## 14 " 60-69"  male      127.           17.5
## 15 " 70+"    female    134.           19.8
## 16 " 70+"    male      130.           18.7
## 17 <NA>      female    142.           22.9
## 18 <NA>      male      136.           23.5
```

8. Now we are going to explore differences in systolic blood pressure across races, as reported in the `Race1` variable.

We will learn to use the `arrange` function to order the outcome according to one variable.

Note that this function can be used to order any table by a given outcome. Here is an example that arranges by systolic blood pressure.

```
NHANES %>% arrange(BPSysAve)
```

If we want it in descending order we can use the `desc` function like this:

```
NHANES %>% arrange(desc(BPSysAve))
```

In this example, we will compare systolic blood pressure across values of the `Race1` variable for males between the ages of 40-49.

```
NHANES %>% filter(AgeDecade == " 40-49" & Gender == "male") %>% group_by(Race1) %>% summarize(average =
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## # A tibble: 5 x 3
##   Race1      average standard_deviation
##   <fct>      <dbl>          <dbl>
## 1 White      120.           13.4
## 2 Other      120.           16.2
## 3 Hispanic   122.           11.1
## 4 Mexican    122.           13.9
## 5 Black      126.           17.1
```

## Section 4 Overview

In Section 4, you will look at a case study involving data from the [Gapminder Foundation](#) about trends in world health and economics.

After completing Section 4, you will:

- understand how Hans Rosling and the Gapminder Foundation use effective data visualization to convey data-based trends.
- be able to apply the ggplot2 techniques from the previous section to answer questions using data.
- understand how fixed scales across plots can ease comparisons.
- be able to modify graphs to improve data visualization.

## Case Study: Trends in World Health and Economics

The textbook for this section is available [here](#)

### More about Gapminder

The original Gapminder TED talks are available and we encourage you to watch them.

- [The Best Stats You've Ever Seen](#)
- [New Insights on Poverty](#)

You can also find more information and raw data (in addition to what we analyze in class) [at](#).

### Key points

- Data visualization can be used to dispel common myths and educate the public and contradict sensationalist or outdated claims and stories.
- We will use real data to answer the following questions about world health and economics:
  - Is it still fair to consider the world as divided into the West and the developing world?
  - Has income inequality across countries worsened over the last 40 years?

## Gapminder Dataset

The textbook for this section is available [here](#)

### Key points

- A selection of world health and economics statistics from the Gapminder project can be found in the **dslabs** package as `data(gapminder)`.
- Most people have misconceptions about world health and economics, which can be addressed by considering real data.

### Code

```
# load and inspect gapminder data
data(gapminder)
head(gapminder)
```

```
##          country year infant_mortality life_expectancy fertility
## 1      Albania 1960          115.40          62.87          6.19
## 2      Algeria 1960          148.20          47.50          7.65
## 3      Angola 1960          208.00          35.98          7.32
## 4 Antigua and Barbuda 1960          NA          62.97          4.43
## 5      Argentina 1960          59.87          65.39          3.11
## 6      Armenia 1960          NA          66.86          4.55
## population      gdp continent      region
## 1    1636054      NA    Europe Southern Europe
## 2    11124892 13828152297    Africa Northern Africa
## 3     5270844      NA    Africa  Middle Africa
## 4      54681      NA  Americas    Caribbean
## 5    20619075 108322326649  Americas    South America
## 6     1867396      NA     Asia    Western Asia
```

```
# compare infant mortality in Sri Lanka and Turkey
gapminder %>%
  filter(year == 2015 & country %in% c("Sri Lanka", "Turkey")) %>%
  select(country, infant_mortality)
```

```
##      country infant_mortality
## 1 Sri Lanka          8.4
## 2   Turkey         11.6
```

## Life Expectancy and Fertility Rates

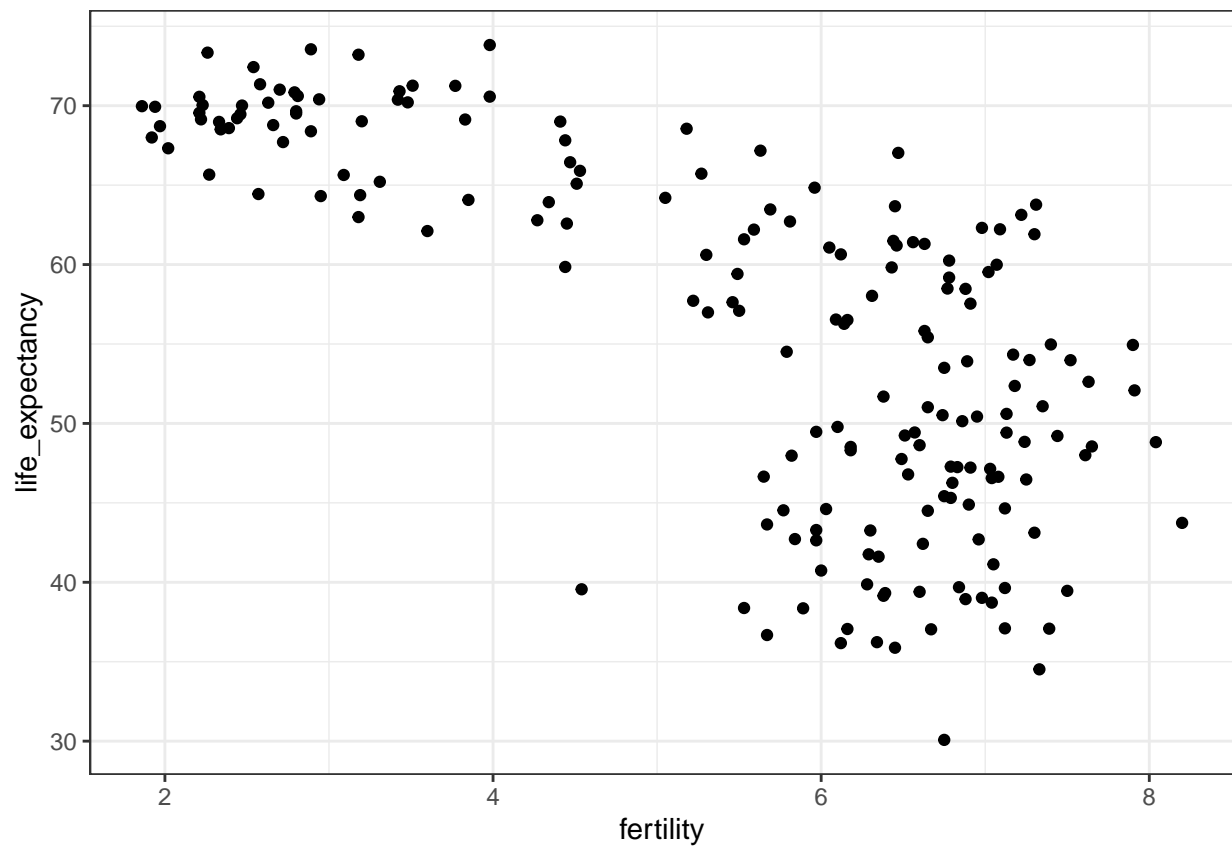
The textbook for this section is available [here](#)

### Key points

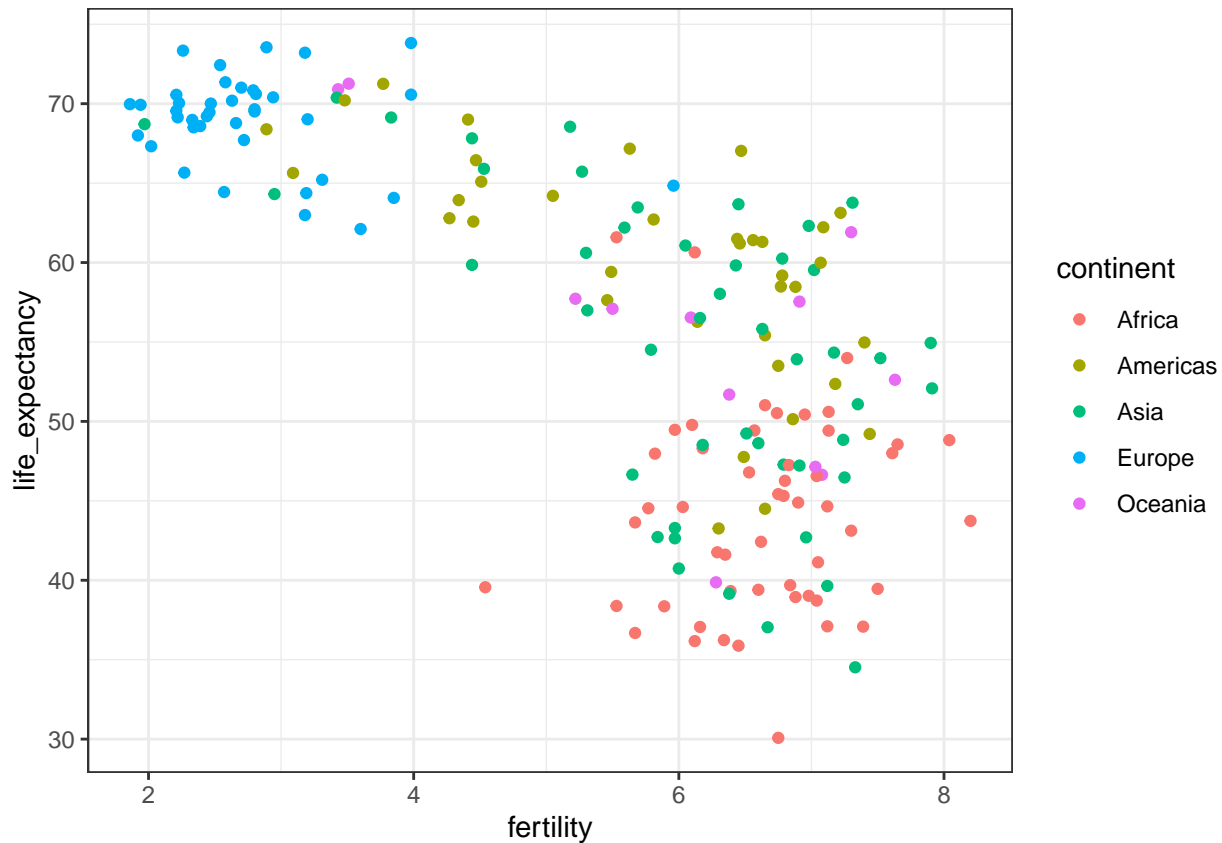
- A prevalent worldview is that the world is divided into two groups of countries:
  - Western world: high life expectancy, low fertility rate
  - Developing world: lower life expectancy, higher fertility rate
- Gapminder data can be used to evaluate the validity of this view.
- A scatterplot of life expectancy versus fertility rate in 1962 suggests that this viewpoint was grounded in reality 50 years ago. Is it still the case today?

### Code

```
# basic scatterplot of life expectancy versus fertility
ds_theme_set() # set plot theme
filter(gapminder, year == 1962) %>%
  ggplot(aes(fertility, life_expectancy)) +
  geom_point()
```



```
# add color as continent
filter(gapminder, year == 1962) %>%
  ggplot(aes(fertility, life_expectancy, color = continent)) +
  geom_point()
```



## Faceting

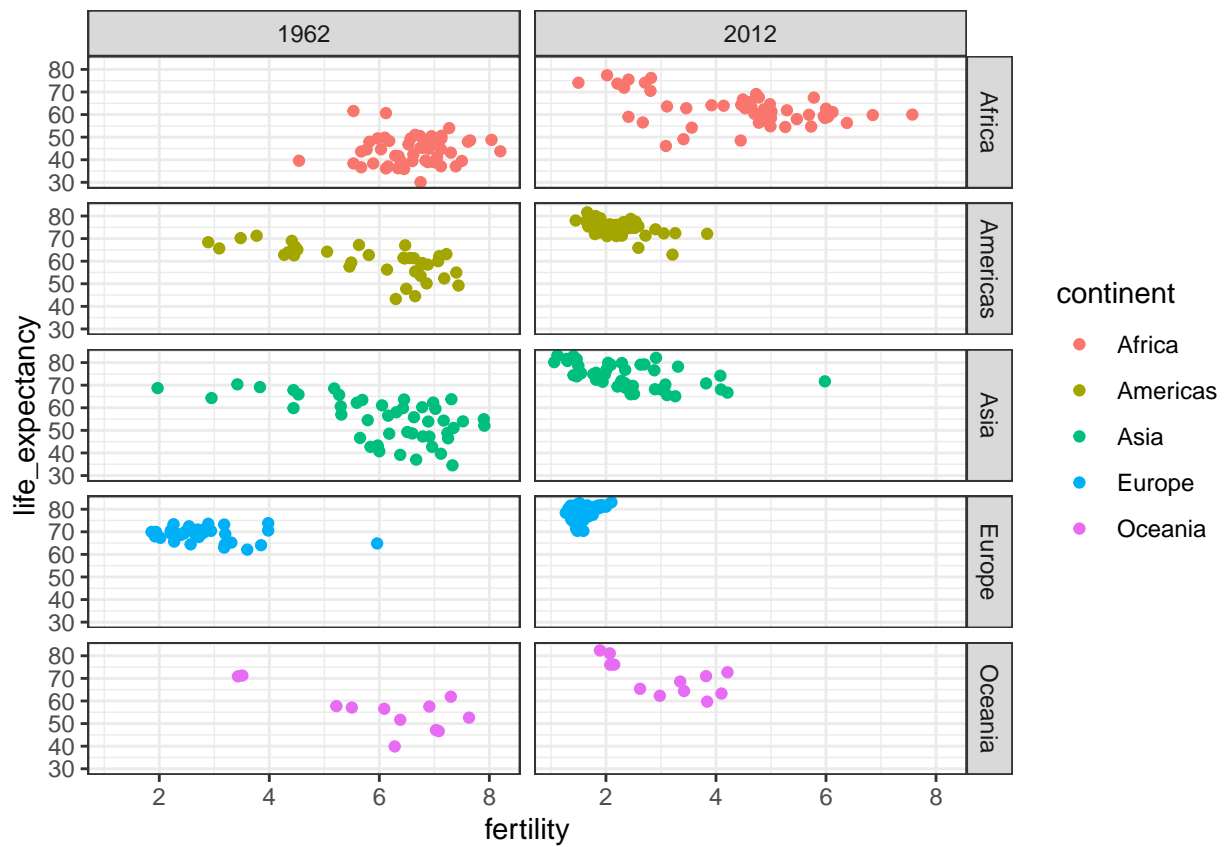
The textbook for this section is available [here](#)

### Key points

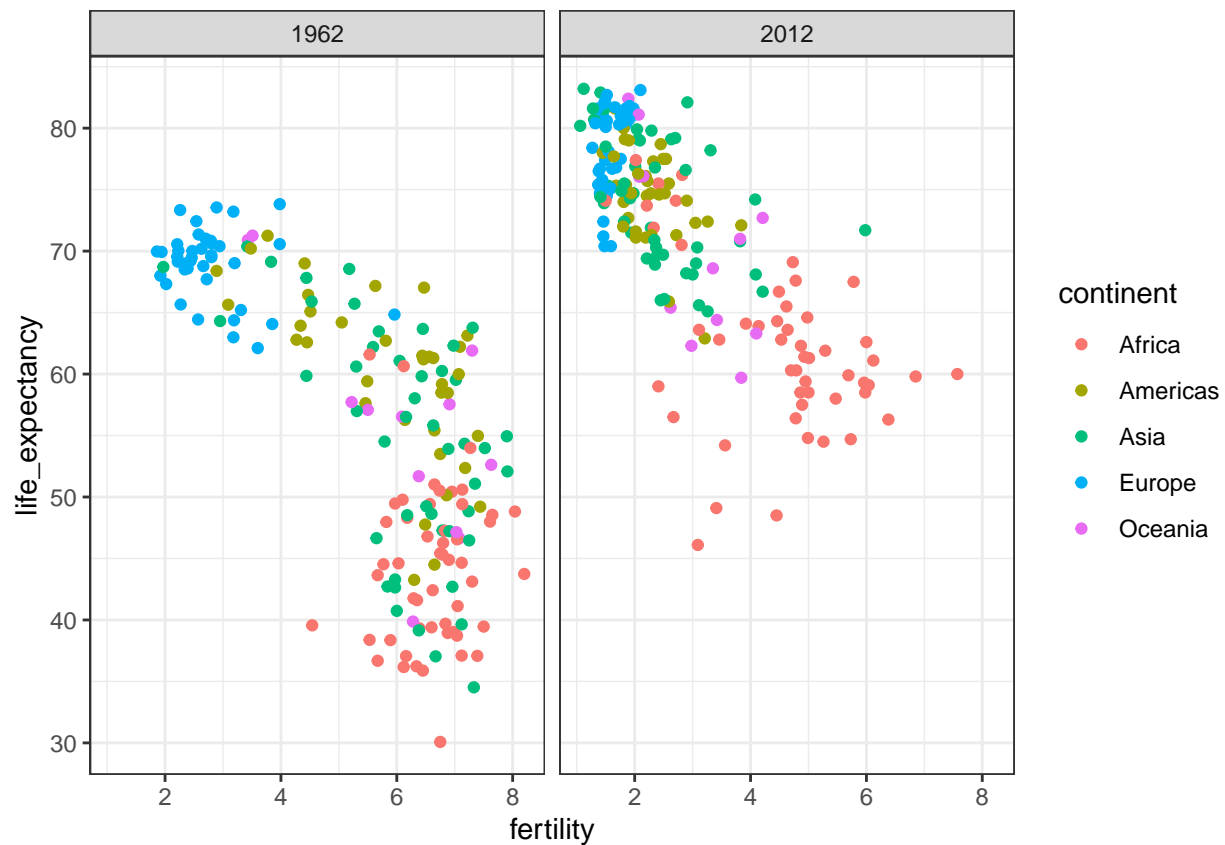
- Faceting makes multiple side-by-side plots stratified by some variable. This is a way to ease comparisons.
- The `facet_grid` function allows faceting by up to two variables, with rows faceted by one variable and columns faceted by the other variable. To facet by only one variable, use the dot operator as the other variable.
- The `facet_wrap` function facets by one variable and automatically wraps the series of plots so they have readable dimensions.
- Faceting keeps the axes fixed across all plots, easing comparisons between plots.
- The data suggest that the developing versus Western world view no longer makes sense in 2012.

### Code

```
# facet by continent and year
filter(gapminder, year %in% c(1962, 2012)) %>%
  ggplot(aes(fertility, life_expectancy, col = continent)) +
  geom_point() +
  facet_grid(continent ~ year)
```

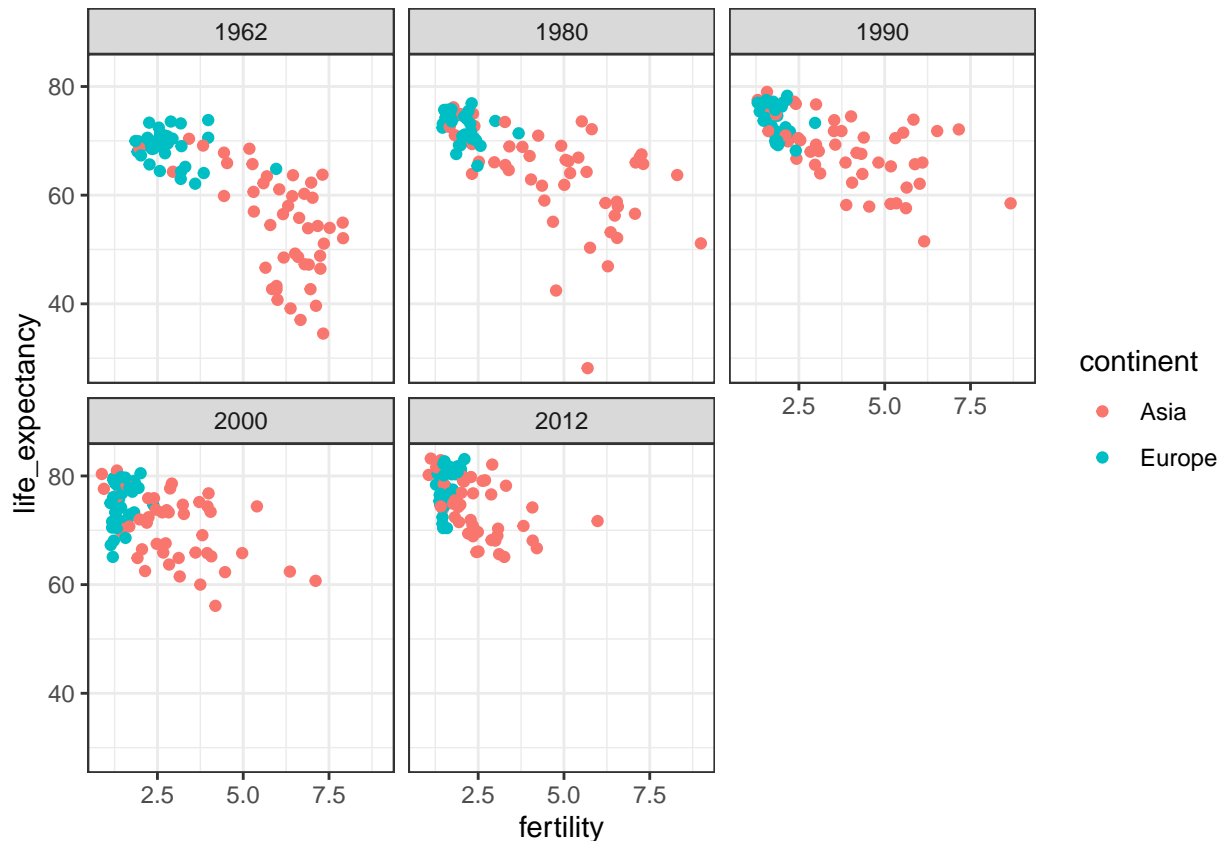


```
# facet by year only
filter(gapminder, year %in% c(1962, 2012)) %>%
  ggplot(aes(fertility, life_expectancy, col = continent)) +
  geom_point() +
  facet_grid(. ~ year)
```



```
# facet by year, plots wrapped onto multiple rows
years <- c(1962, 1980, 1990, 2000, 2012)
continents <- c("Europe", "Asia")
gapminder %>%
  filter(year %in% years & continent %in% continents) %>%
  ggplot(aes(fertility, life_expectancy, col = continent)) +
  geom_point() +
  facet_wrap(~year)
```





## Time Series Plots

The textbook for this section is available [here](#)

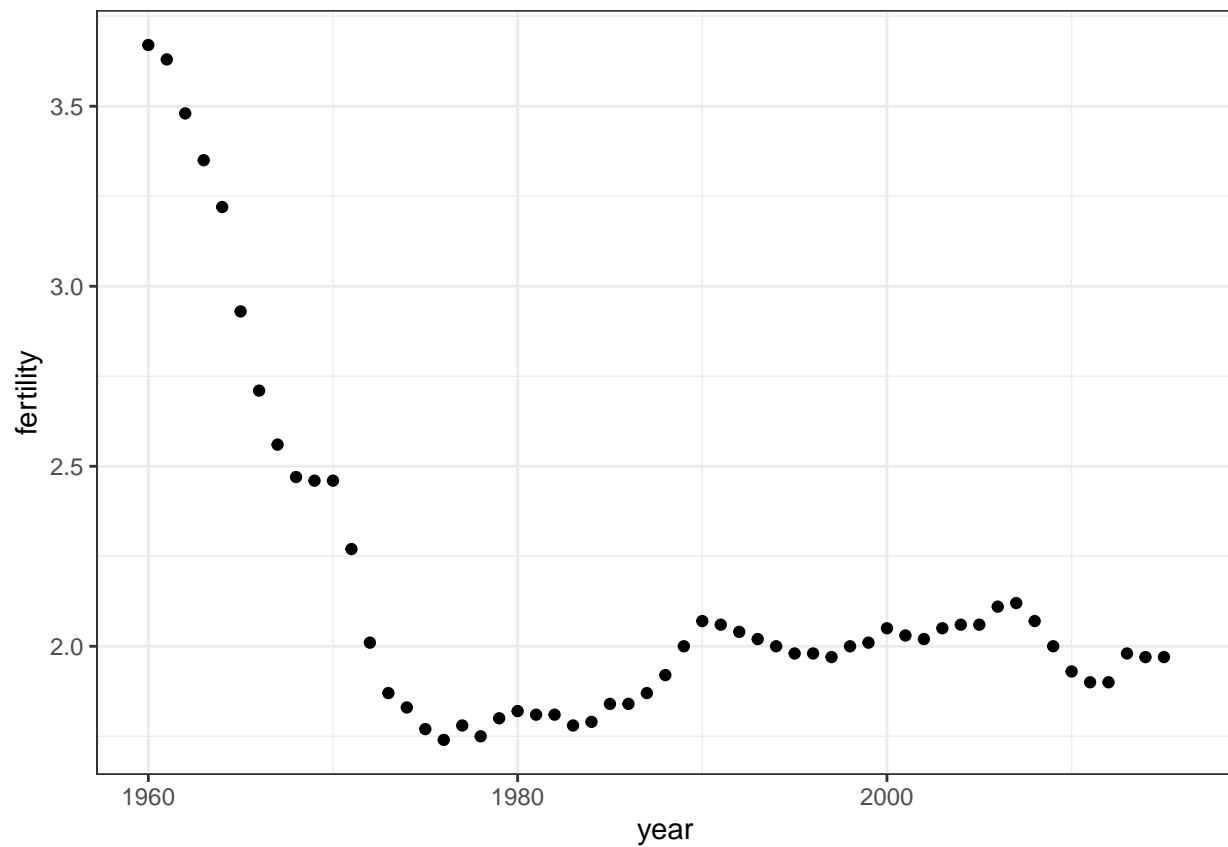
### Key points

- Time series plots have time on the x-axis and a variable of interest on the y-axis.
- The `geom_line` geometry connects adjacent data points to form a continuous line. A line plot is appropriate when points are regularly spaced, densely packed and from a single data series.
- You can plot multiple lines on the same graph. Remember to group or color by a variable so that the lines are plotted independently.
- Labeling is usually preferred over legends. However, legends are easier to make and appear by default. Add a label with `geom_text`, specifying the coordinates where the label should appear on the graph.

*Code: Single time series*

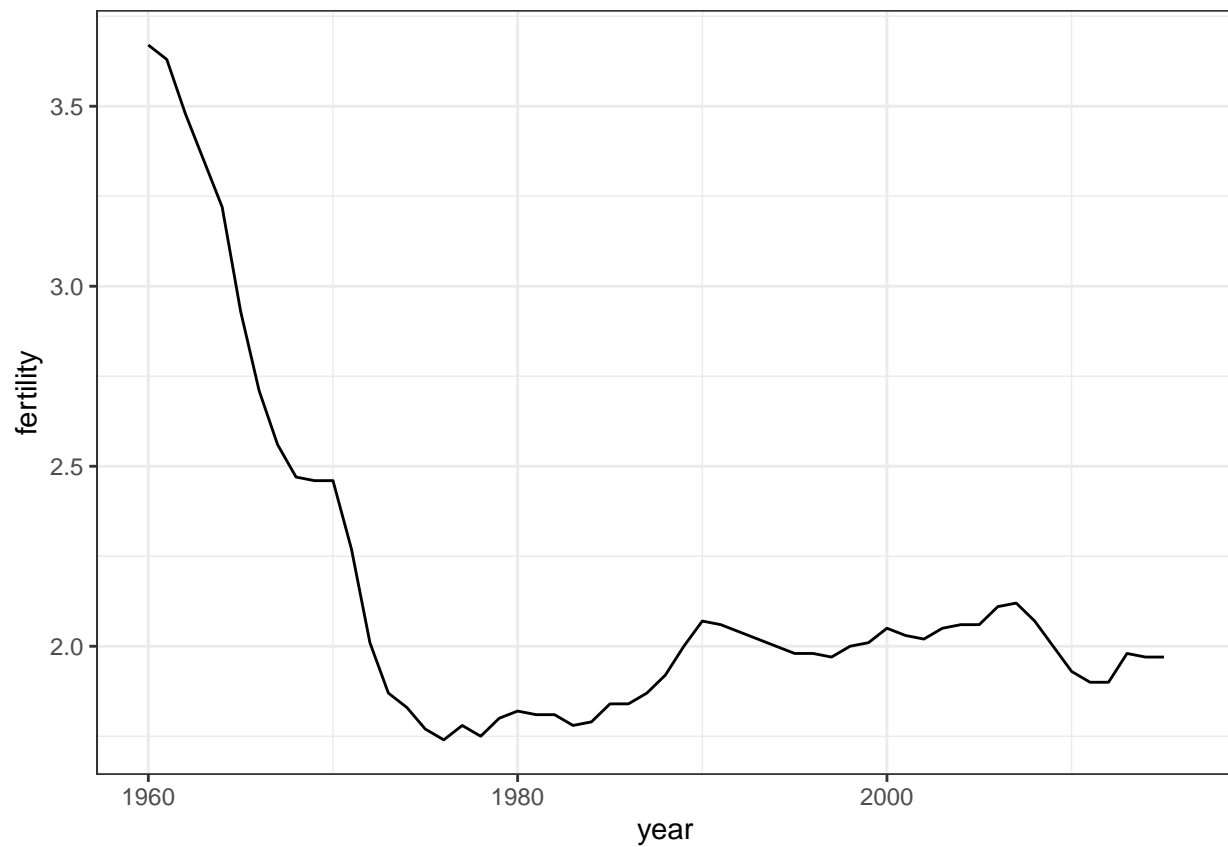
```
# scatterplot of US fertility by year
gapminder %>%
  filter(country == "United States") %>%
  ggplot(aes(year, fertility)) +
  geom_point()
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```



```
# line plot of US fertility by year
gapminder %>%
  filter(country == "United States") %>%
  ggplot(aes(year, fertility)) +
  geom_line()
```

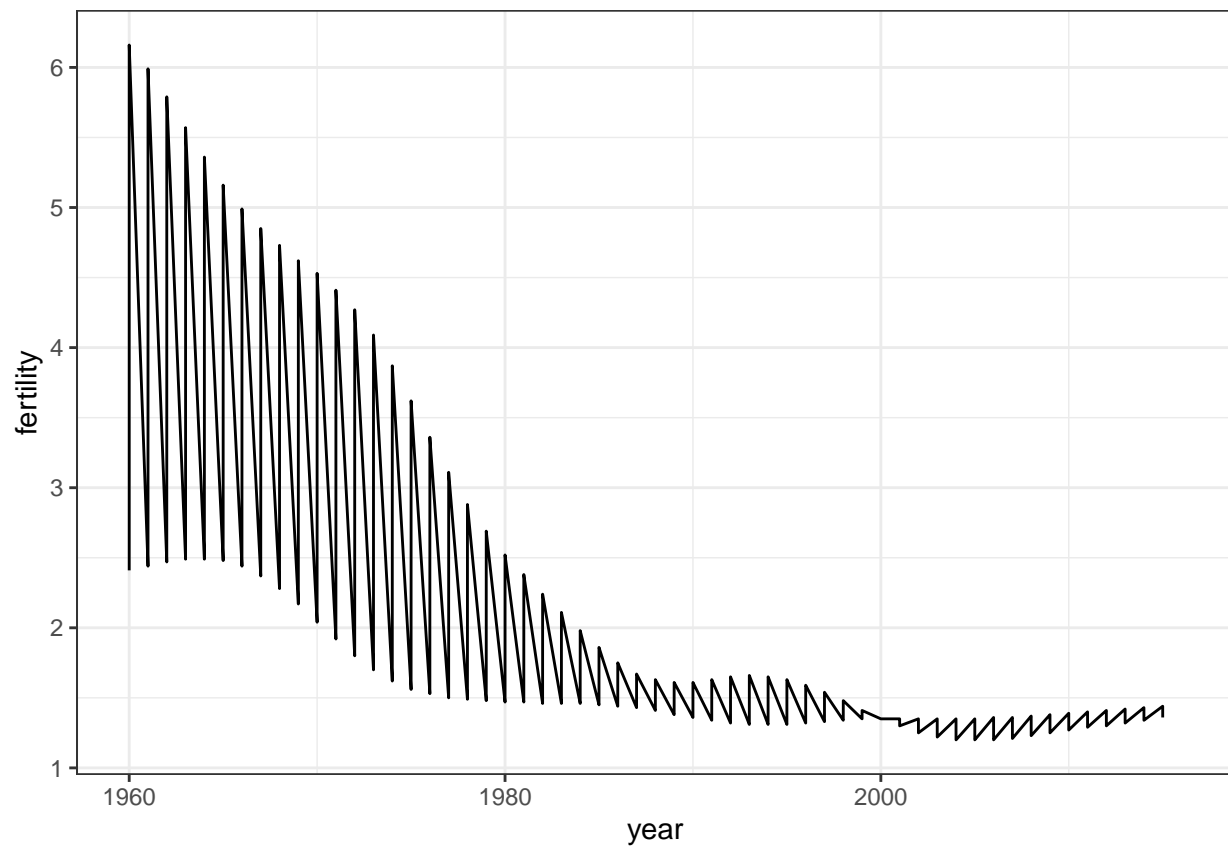
```
## Warning: Removed 1 row(s) containing missing values (geom_path).
```



*Code: Multiple time series*

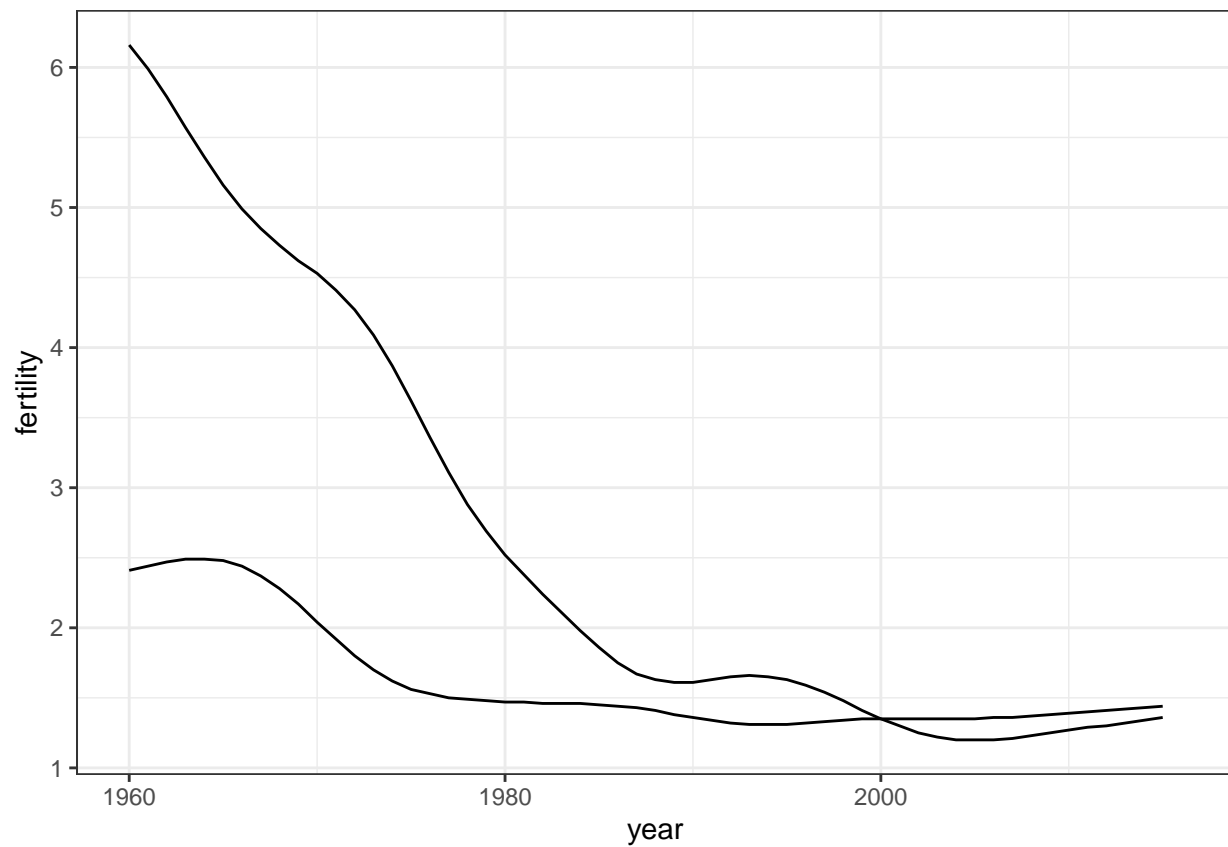
```
# line plot fertility time series for two countries- only one line (incorrect)
countries <- c("South Korea", "Germany")
gapminder %>% filter(country %in% countries) %>%
  ggplot(aes(year, fertility)) +
  geom_line()
```

```
## Warning: Removed 2 row(s) containing missing values (geom_path).
```



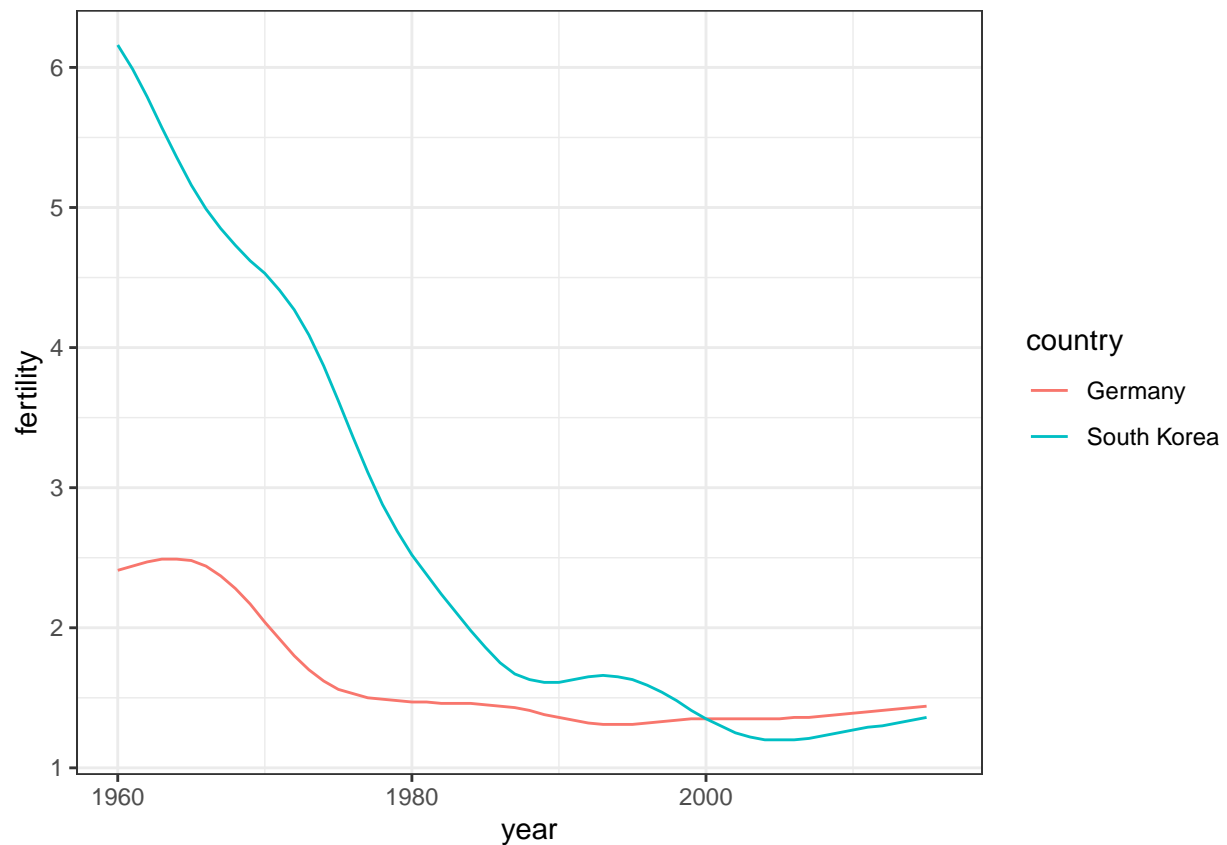
```
# line plot fertility time series for two countries - one line per country  
gapminder %>% filter(country %in% countries) %>%  
  ggplot(aes(year, fertility, group = country)) +  
  geom_line()
```

```
## Warning: Removed 2 row(s) containing missing values (geom_path).
```



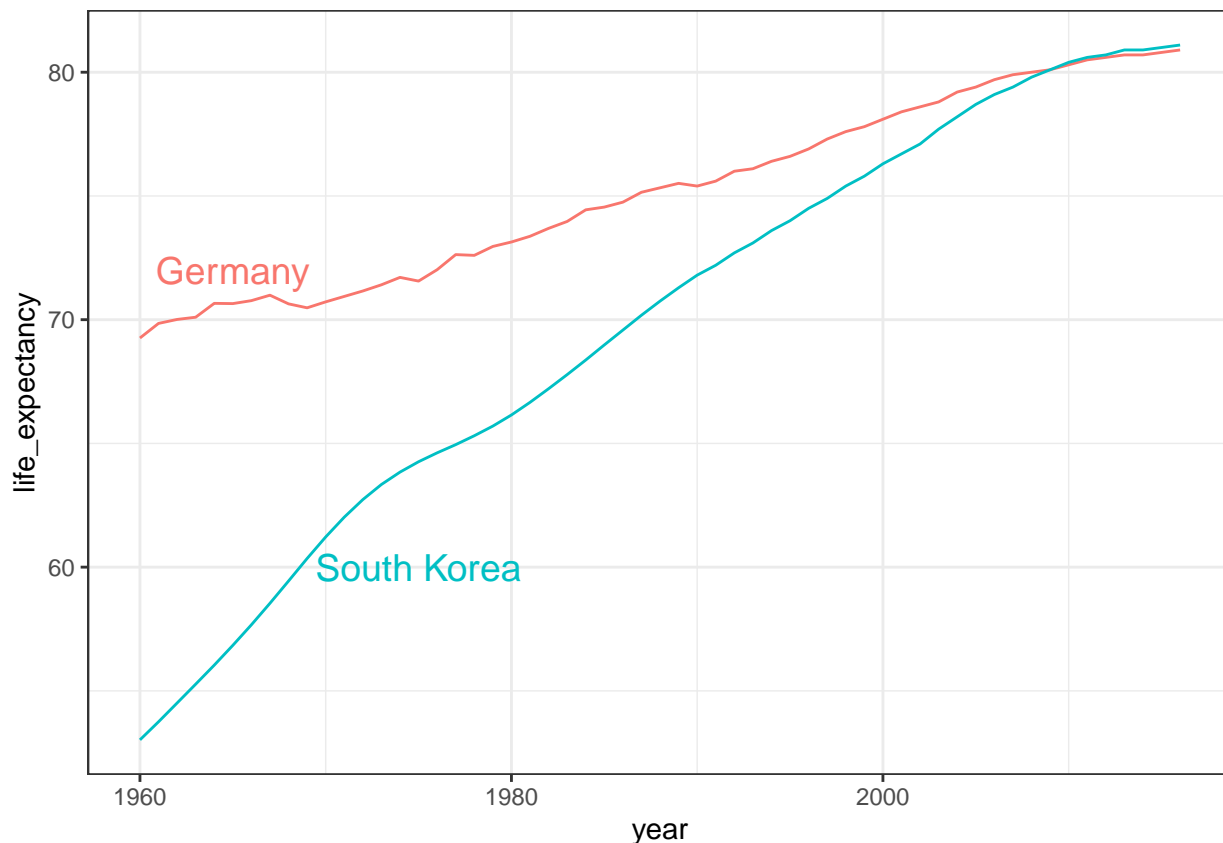
```
# fertility time series for two countries - lines colored by country
gapminder %>% filter(country %in% countries) %>%
  ggplot(aes(year, fertility, col = country)) +
  geom_line()
```

```
## Warning: Removed 2 row(s) containing missing values (geom_path).
```



Code: Adding text labels to a plot

```
# life expectancy time series - lines colored by country and labeled, no legend
labels <- data.frame(country = countries, x = c(1975, 1965), y = c(60, 72))
gapminder %>% filter(country %in% countries) %>%
  ggplot(aes(year, life_expectancy, col = country)) +
  geom_line() +
  geom_text(data = labels, aes(x, y, label = country), size = 5) +
  theme(legend.position = "none")
```



## Transformations

The textbook for this section is available [here](#) and [here](#)

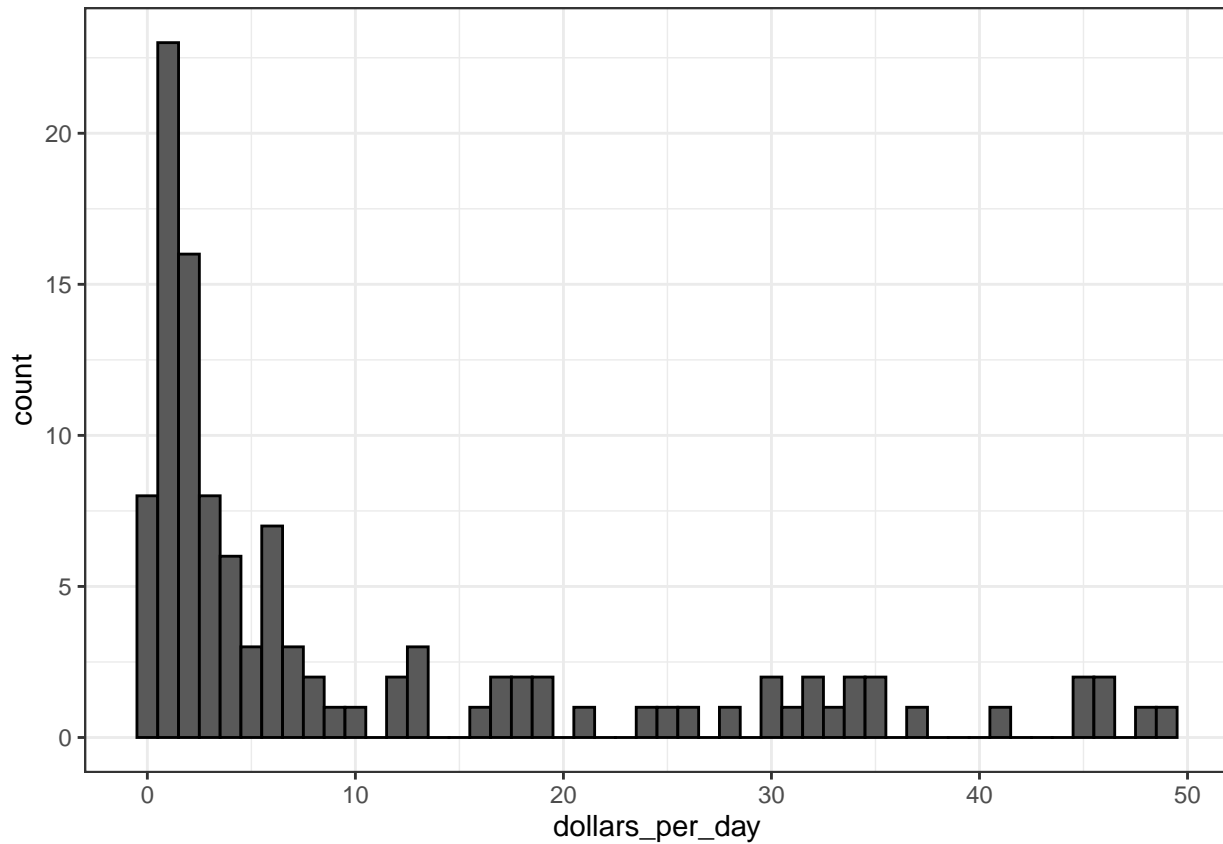
### Key points

- We use GDP data to compute income in US dollars per day, adjusted for inflation.
- Log transformations convert multiplicative changes into additive changes.
- Common transformations are the log base 2 transformation and the log base 10 transformation. The choice of base depends on the range of the data. The natural log is not recommended for visualization because it is difficult to interpret.
- The mode of a distribution is the value with the highest frequency. The mode of a normal distribution is the average. A distribution can have multiple local modes.
- There are two ways to use log transformations in plots: transform the data before plotting or transform the axes of the plot. Log scales have the advantage of showing the original values as axis labels, while log transformed values ease interpretation of intermediate values between labels.
- Scale the x-axis using `scale_x_continuous` or `scale_x_log10` layers in `ggplot2`. Similar functions exist for the y-axis.
- In 1970, income distribution is bimodal, consistent with the dichotomous Western versus developing worldview.

### Code

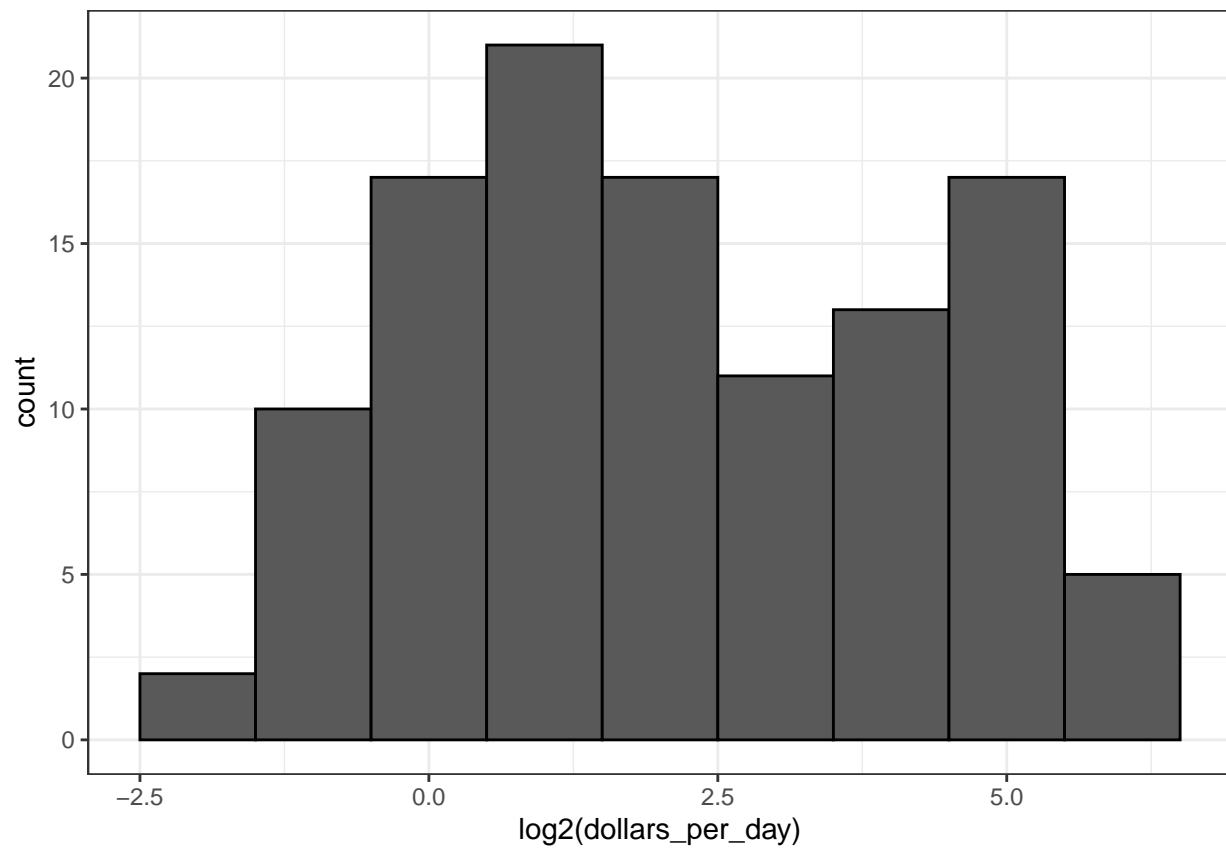
```
# add dollars per day variable
gapminder <- gapminder %>%
  mutate(dollars_per_day = gdp/population/365)
```

```
# histogram of dollars per day
past_year <- 1970
gapminder %>%
  filter(year == past_year & !is.na(gdp)) %>%
  ggplot(aes(dollars_per_day)) +
  geom_histogram(binwidth = 1, color = "black")
```

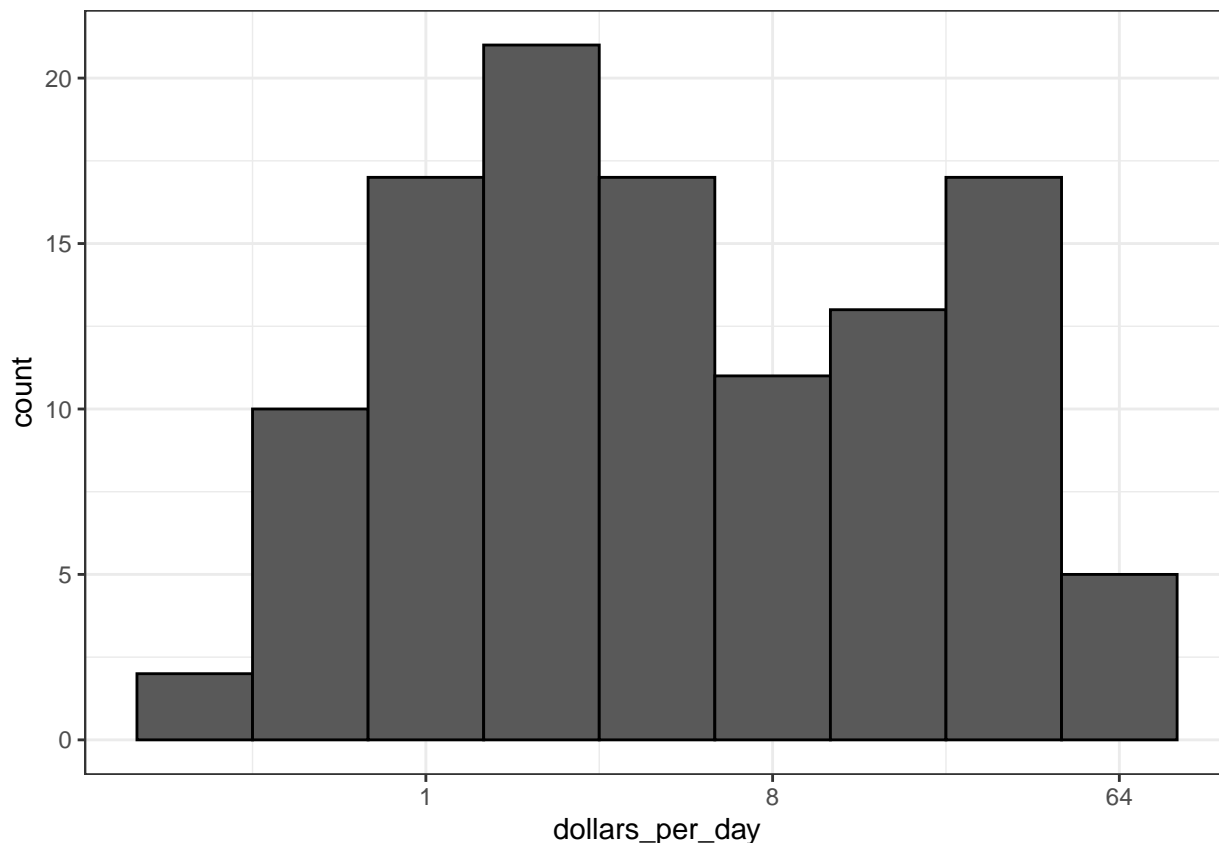


```
# repeat histogram with log2 scaled data
gapminder %>%
  filter(year == past_year & !is.na(gdp)) %>%
  ggplot(aes(log2(dollars_per_day))) +
  geom_histogram(binwidth = 1, color = "black")
```





```
# repeat histogram with log2 scaled x-axis
gapminder %>%
  filter(year == past_year & !is.na(gdp)) %>%
  ggplot(aes(dollars_per_day)) +
  geom_histogram(binwidth = 1, color = "black") +
  scale_x_continuous(trans = "log2")
```



## Stratify and Boxplot

The textbook for this section is available [here](#). Note that many boxplots from the video are instead dot plots in the textbook and that a different boxplot is constructed in the textbook. Also read that section to see an example of grouping factors with the `case_when` function.

### Key points

- Make boxplots stratified by a categorical variable using the `geom_boxplot` geometry.
- Rotate axis labels by changing the theme through `element_text`. You can change the angle and justification of the text labels.
- Consider ordering your factors by a meaningful value with the `reorder` function, which changes the order of factor levels based on a related numeric vector. This is a way to ease comparisons.
- Show the data by adding data points to the boxplot with a `geom_point` layer. This adds information beyond the five-number summary to your plot, but too many data points it can obfuscate your message.

*Code: Boxplot of GDP by region*

```
# add dollars per day variable
gapminder <- gapminder %>%
  mutate(dollars_per_day = gdp/population/365)

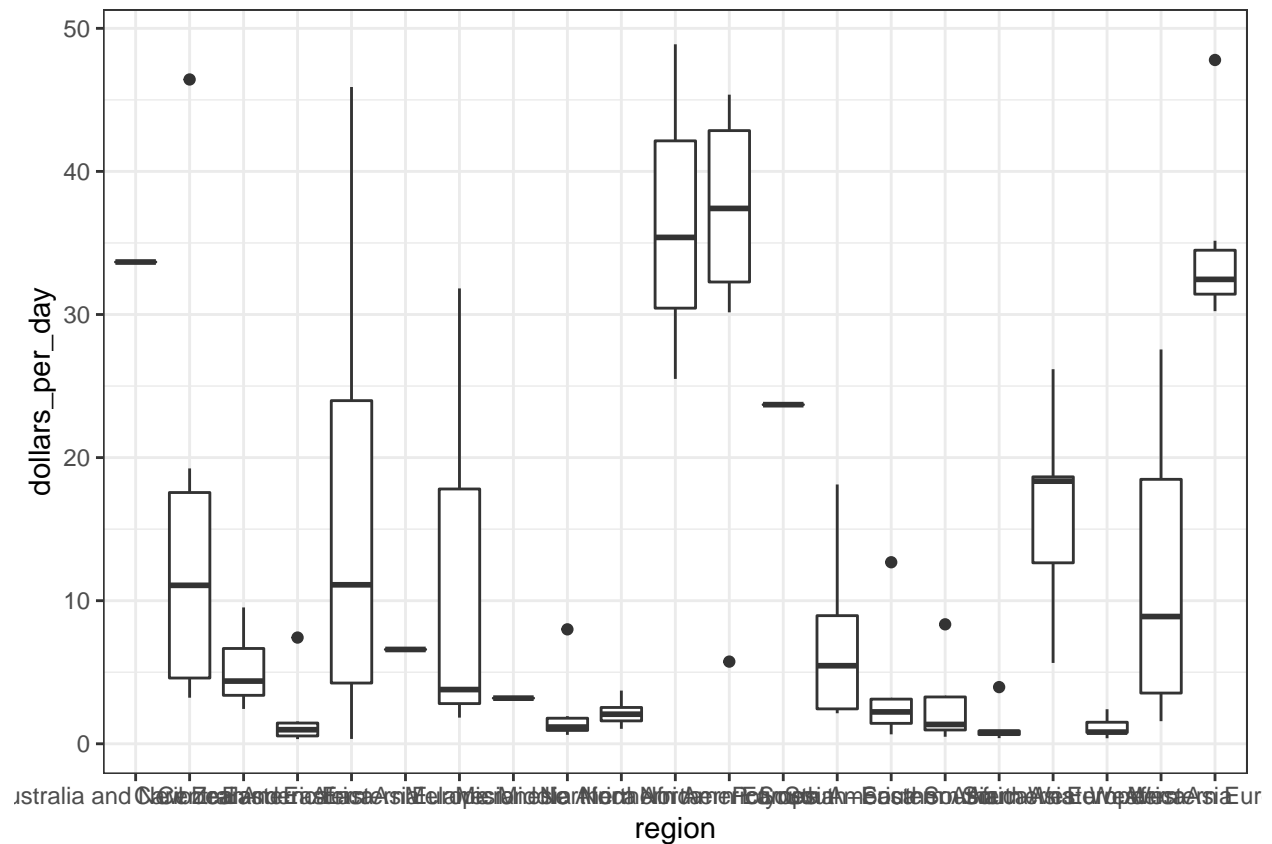
# number of regions
length(levels(gapminder$region))
```

```
## [1] 22
```

```

# boxplot of GDP by region in 1970
past_year <- 1970
p <- gapminder %>%
  filter(year == past_year & !is.na(gdp)) %>%
  ggplot(aes(region, dollars_per_day))
p + geom_boxplot()

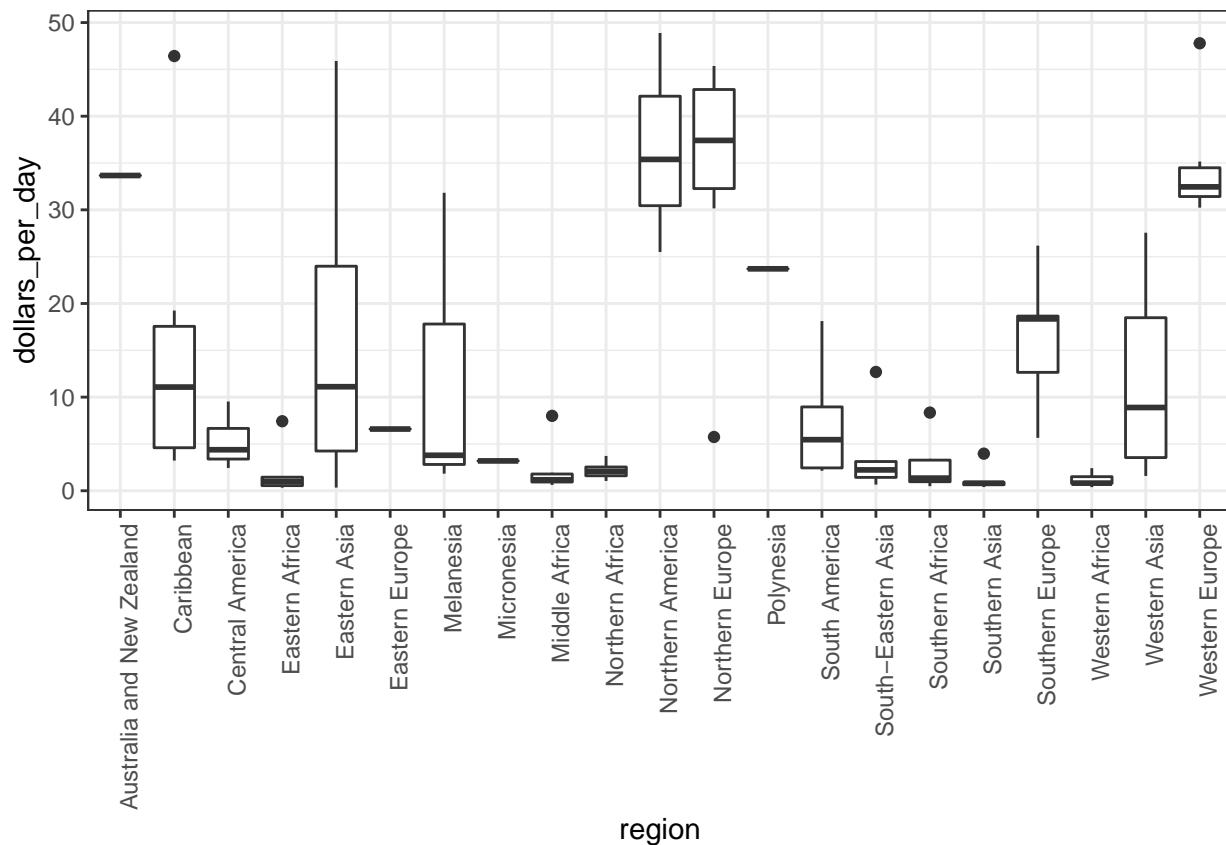
```



```

# rotate names on x-axis
p + geom_boxplot() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))

```



Code: The reorder function

```
# by default, factor order is alphabetical
fac <- factor(c("Asia", "Asia", "West", "West", "West"))
levels(fac)
```

```
## [1] "Asia" "West"
```

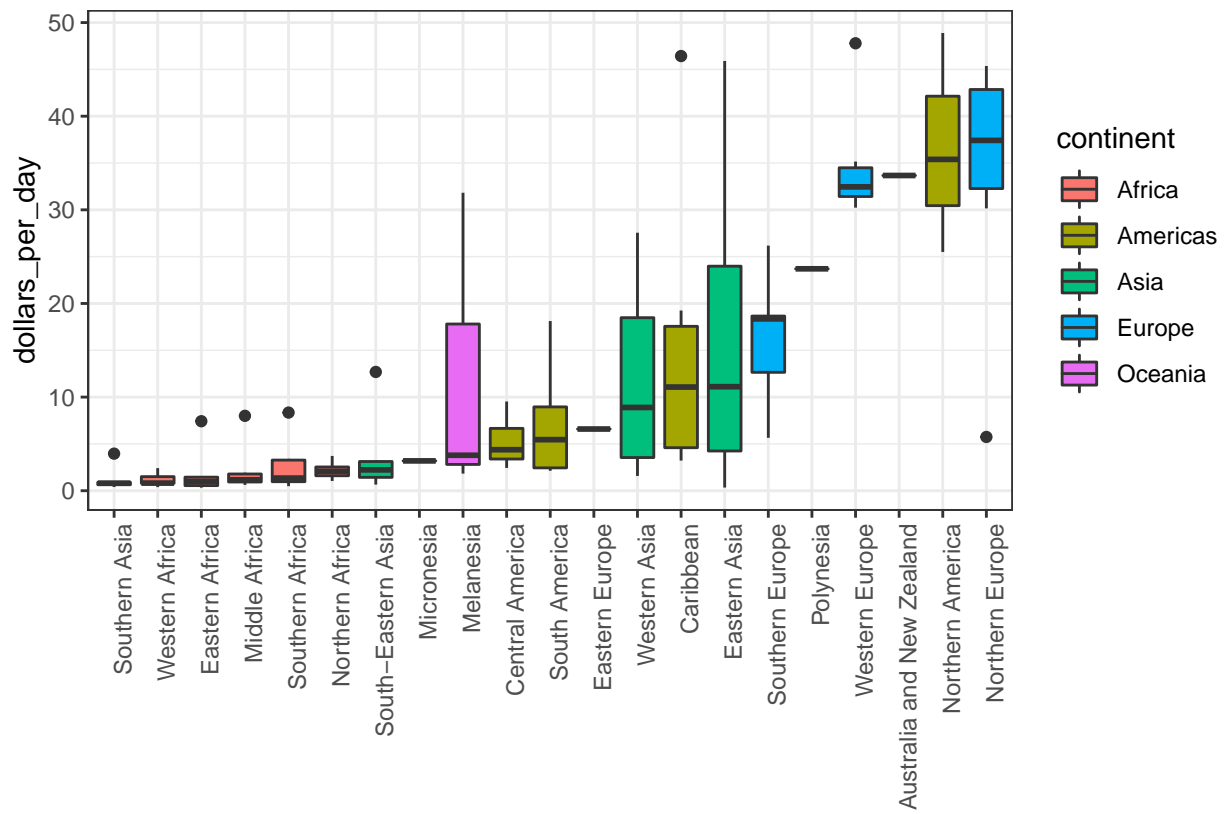
```
# reorder factor by the category means
value <- c(10, 11, 12, 6, 4)
fac <- reorder(fac, value, FUN = mean)
levels(fac)
```

```
## [1] "West" "Asia"
```

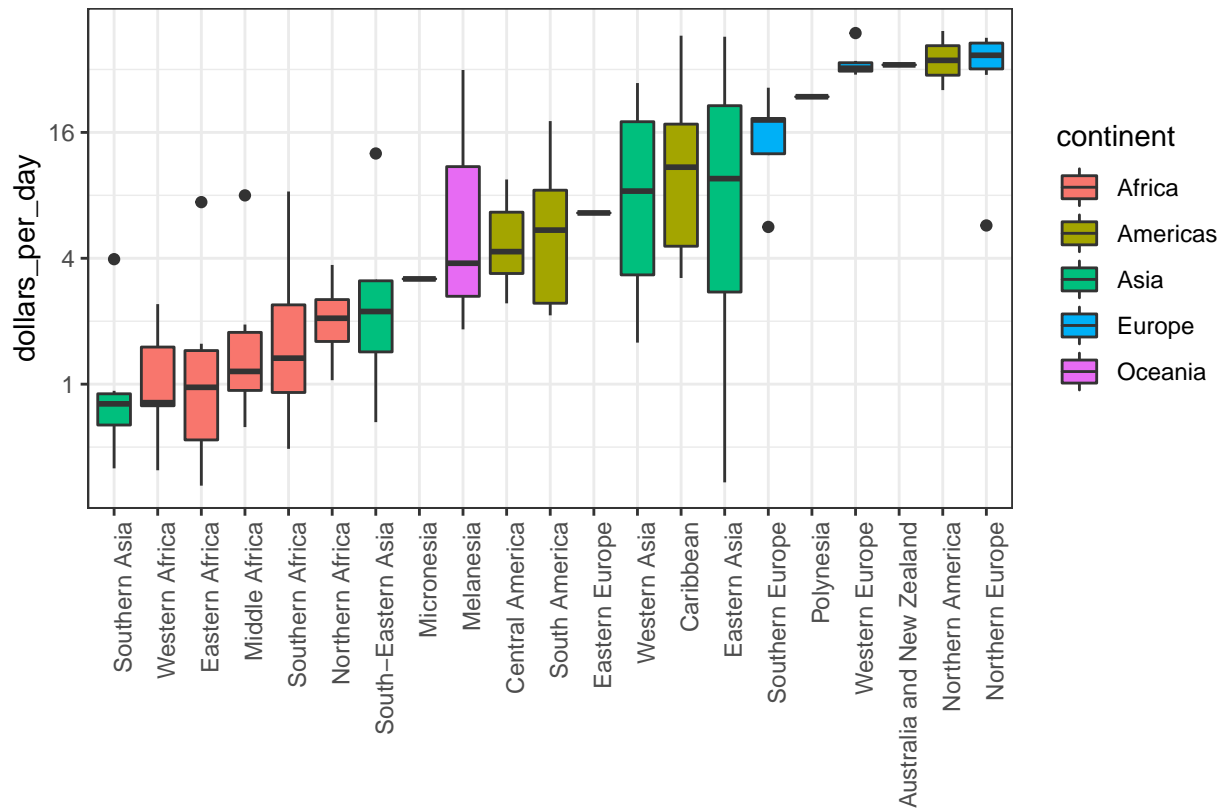
Code: Enhanced boxplot ordered by median income, scaled, and showing data

```
# reorder by median income and color by continent
p <- gapminder %>%
  filter(year == past_year & !is.na(gdp)) %>%
  mutate(region = reorder(region, dollars_per_day, FUN = median)) %>% # reorder
  ggplot(aes(region, dollars_per_day, fill = continent)) + # color by continent
  geom_boxplot() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
  xlab("")
```

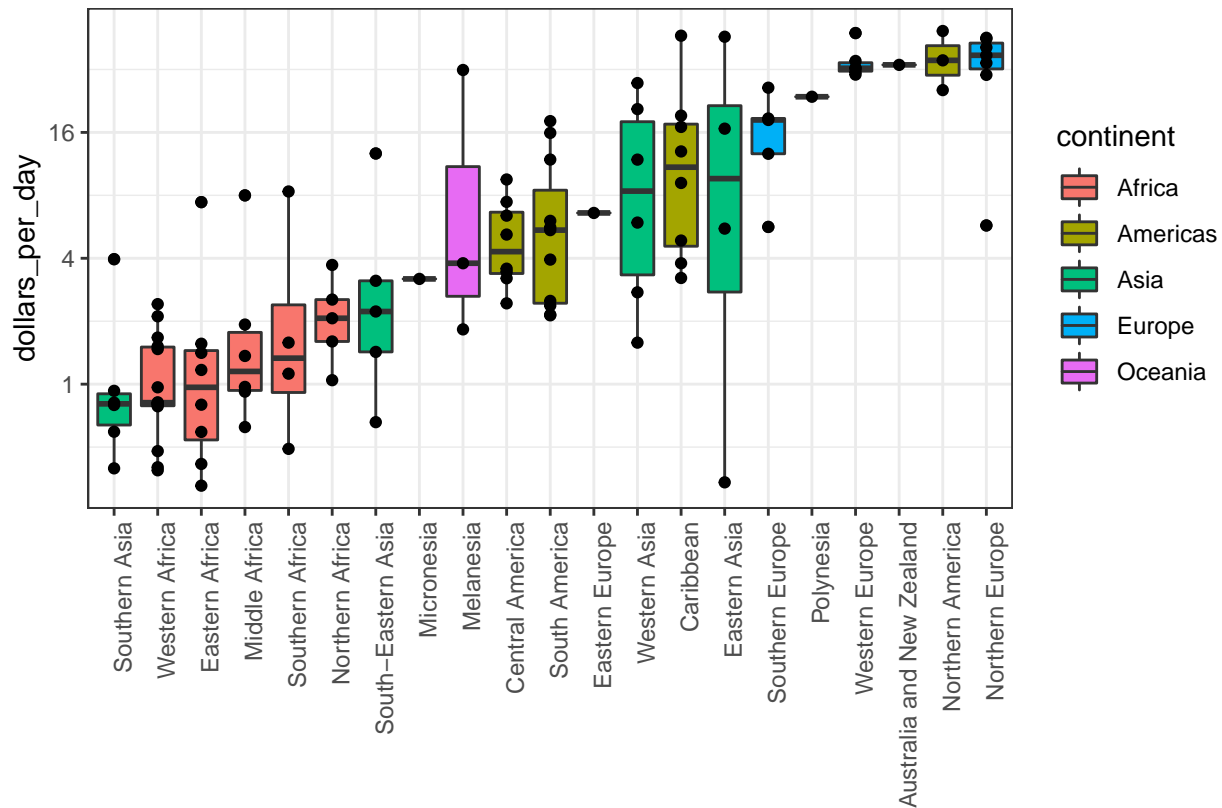
p



```
# log2 scale y-axis
p + scale_y_continuous(trans = "log2")
```



```
# add data points
p + scale_y_continuous(trans = "log2") + geom_point(show.legend = FALSE)
```



## Comparing Distributions

The textbook for this section is available [here](#). Note that the boxplots are slightly different.

### Key points

- Use `intersect` to find the overlap between two vectors.
- To make boxplots where grouped variables are adjacent, color the boxplot by a factor instead of faceting by that factor. This is a way to ease comparisons.
- The data suggest that the income gap between rich and poor countries has narrowed, not expanded.

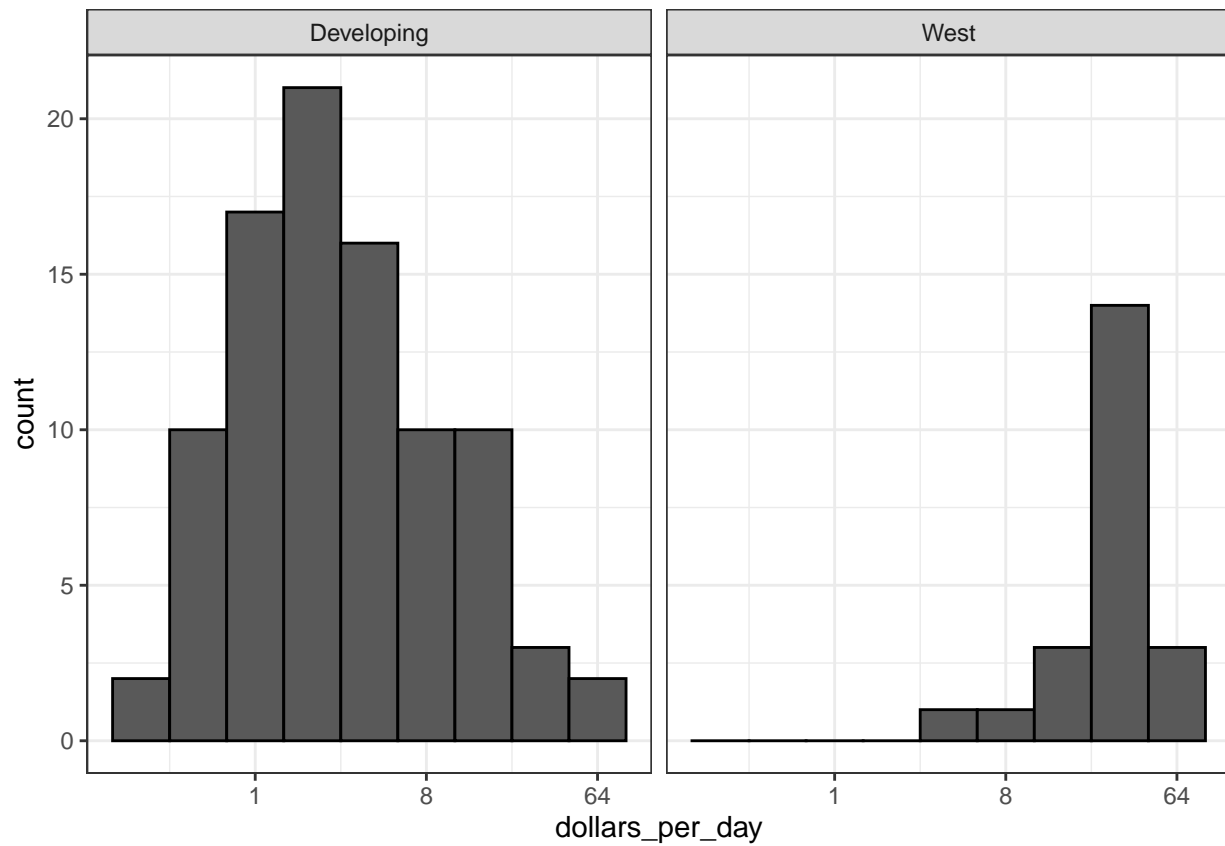
Code: Histogram of income in West versus developing world, 1970 and 2010

```
# add dollars per day variable and define past year
gapminder <- gapminder %>%
  mutate(dollars_per_day = gdp/population/365)
past_year <- 1970

# define Western countries
west <- c("Western Europe", "Northern Europe", "Southern Europe", "Northern America", "Australia and New Zealand")

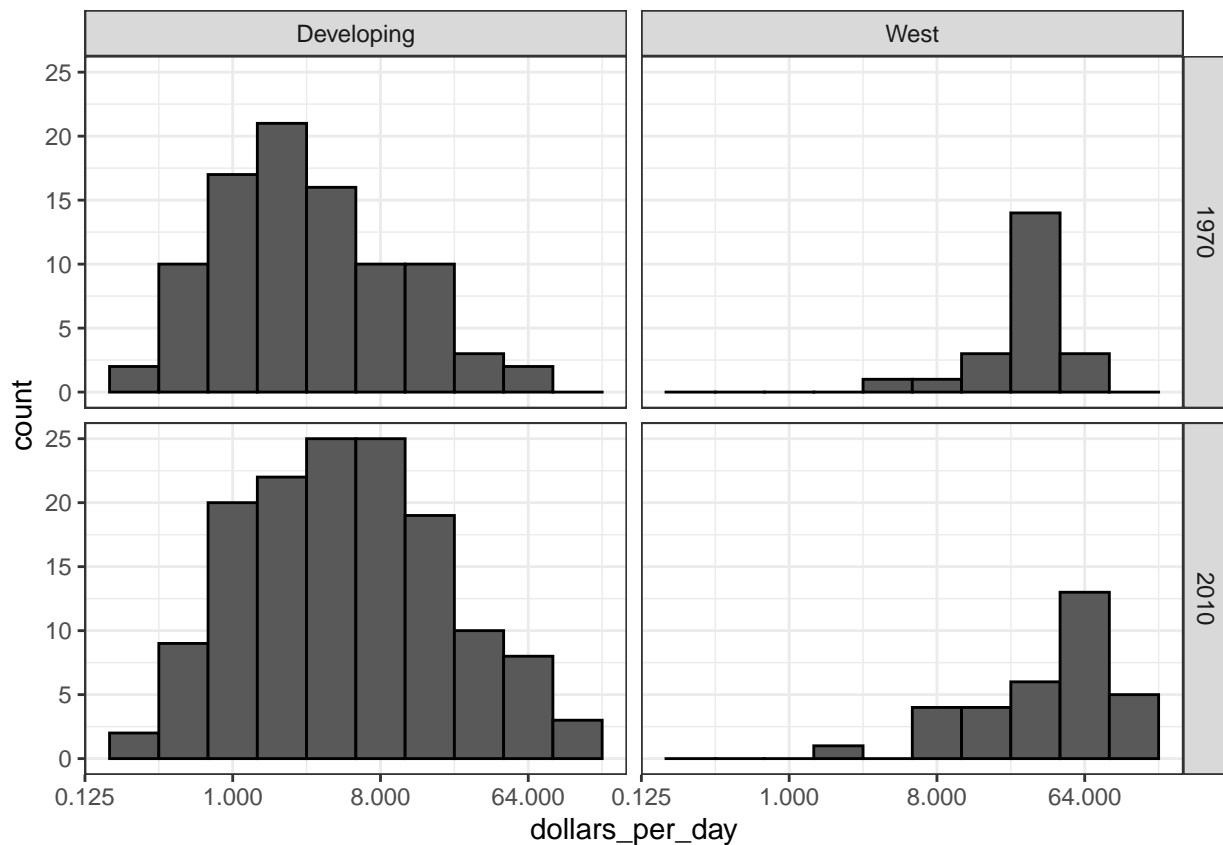
# facet by West vs developing
gapminder %>%
  filter(year == past_year & !is.na(gdp)) %>%
  mutate(group = ifelse(region %in% west, "West", "Developing")) %>%
  ggplot(aes(dollars_per_day)) +
  geom_histogram(binwidth = 1, color = "black") +
```

```
scale_x_continuous(trans = "log2") +  
facet_grid(. ~ group)
```



```
# facet by West/developing and year  
present_year <- 2010  
gapminder %>%  
  filter(year %in% c(past_year, present_year) & !is.na(gdp)) %>%  
  mutate(group = ifelse(region %in% west, "West", "Developing")) %>%  
  ggplot(aes(dollars_per_day)) +  
  geom_histogram(binwidth = 1, color = "black") +  
  scale_x_continuous(trans = "log2") +  
  facet_grid(year ~ group)
```

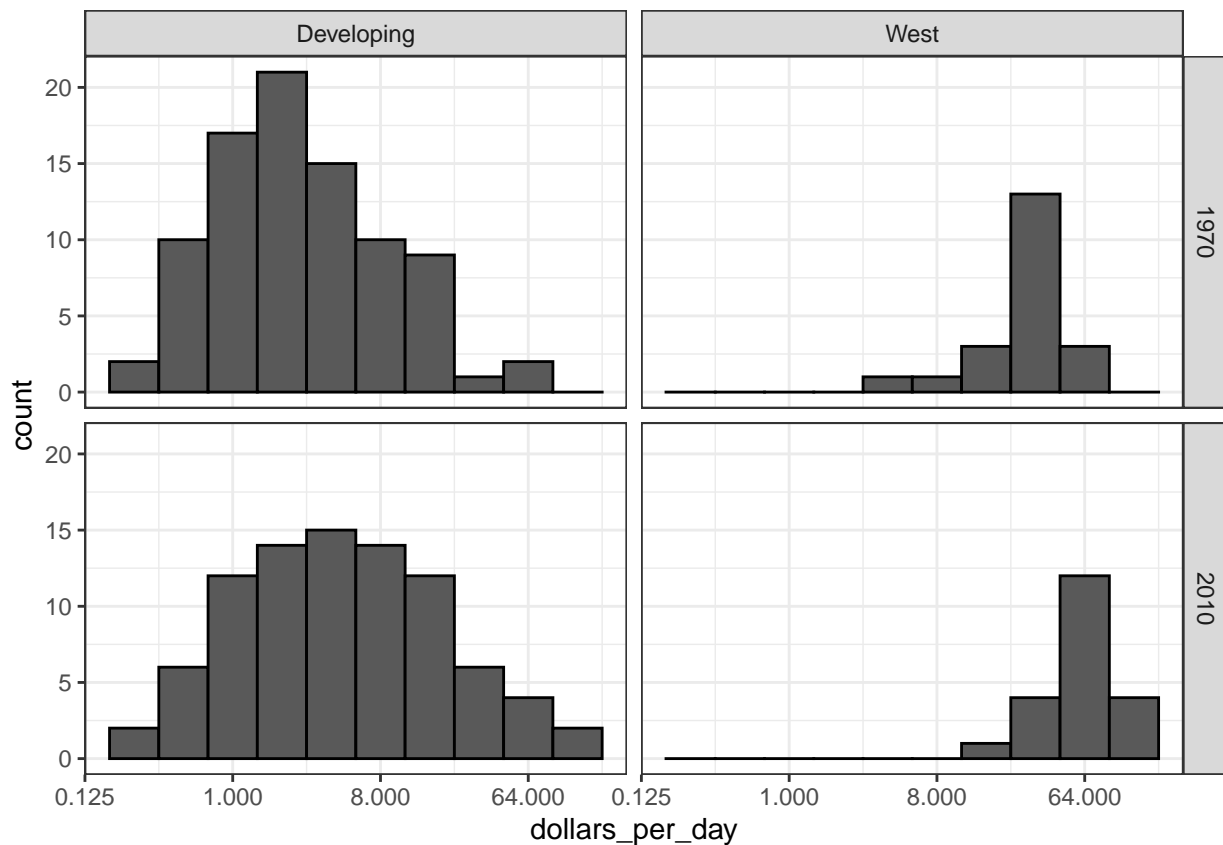




Code: Income distribution of West versus developing world, only countries with data

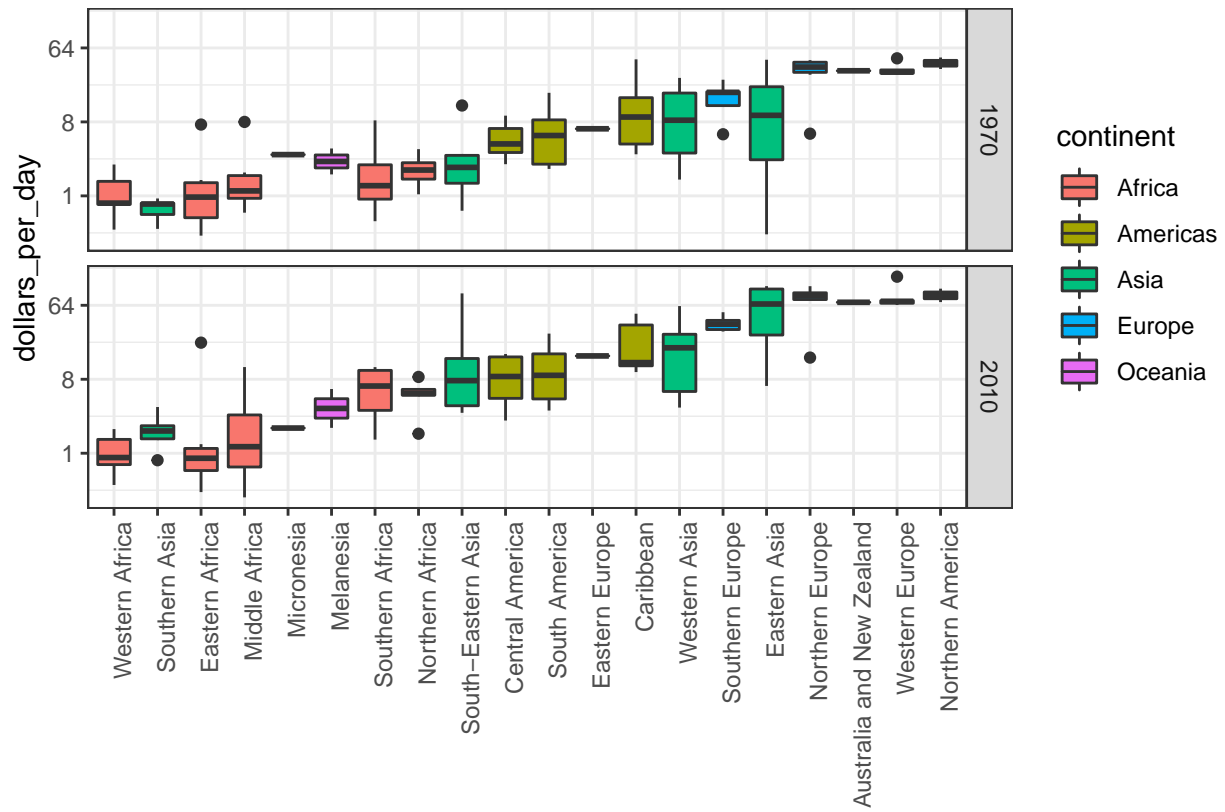
```
# define countries that have data available in both years
country_list_1 <- gapminder %>%
  filter(year == past_year & !is.na(dollars_per_day)) %>% .$country
country_list_2 <- gapminder %>%
  filter(year == present_year & !is.na(dollars_per_day)) %>% .$country
country_list <- intersect(country_list_1, country_list_2)

# make histogram including only countries with data available in both years
gapminder %>%
  filter(year %in% c(past_year, present_year) & country %in% country_list) %>% # keep only selected
  mutate(group = ifelse(region %in% west, "West", "Developing")) %>%
  ggplot(aes(dollars_per_day)) +
  geom_histogram(binwidth = 1, color = "black") +
  scale_x_continuous(trans = "log2") +
  facet_grid(year ~ group)
```

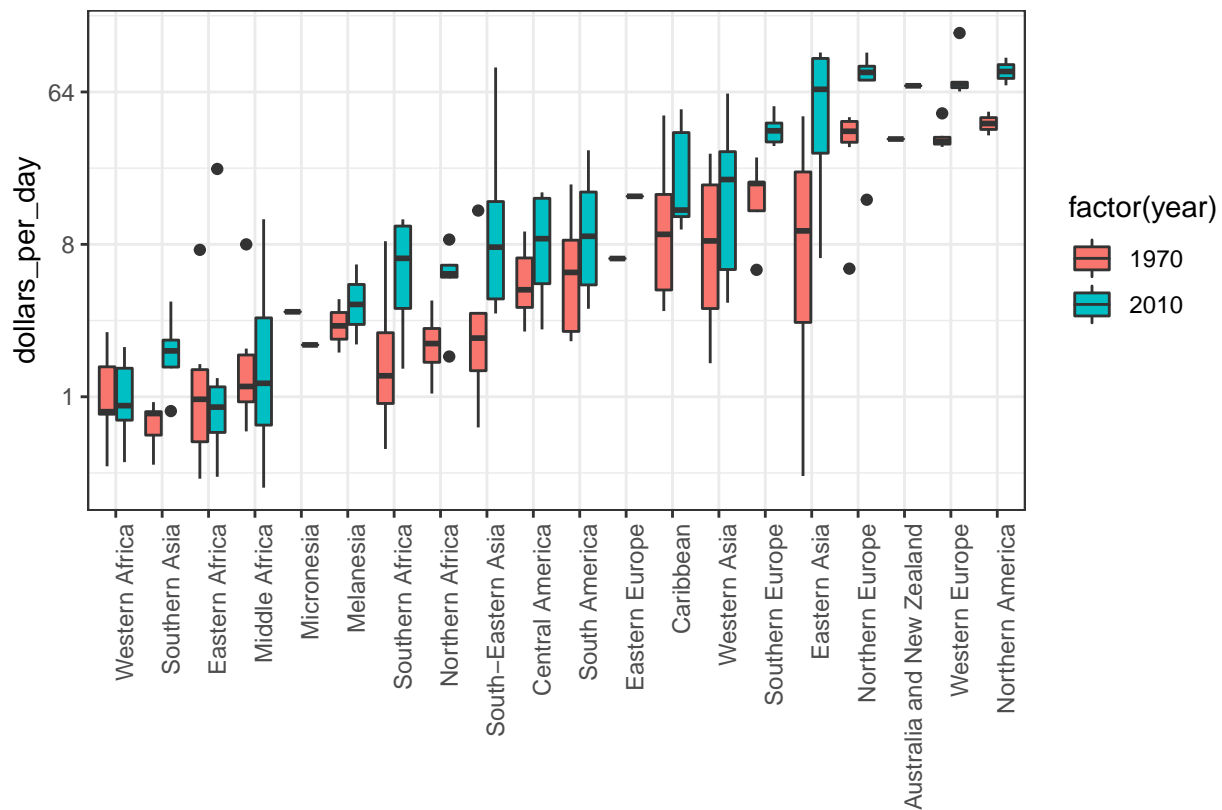


Code: Boxplots of income in West versus developing world, 1970 and 2010

```
p <- gapminder %>%
  filter(year %in% c(past_year, present_year) & country %in% country_list) %>%
  mutate(region = reorder(region, dollars_per_day, FUN = median)) %>%
  ggplot() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
  xlab("") + scale_y_continuous(trans = "log2")
p + geom_boxplot(aes(region, dollars_per_day, fill = continent)) +
  facet_grid(year ~ .)
```



```
# arrange matching boxplots next to each other, colored by year
p + geom_boxplot(aes(region, dollars_per_day, fill = factor(year)))
```



## Density Plots

The textbook for this section is available:

- [1970 versus 2010 income distributions](#)
- [Accessing computed variables](#)
- [Weighted densities](#)

### Key points

- Change the y-axis of density plots to variable counts using `..count..` as the y argument.
- The `case_when` function defines a factor whose levels are defined by a variety of logical operations to group data.
- Plot stacked density plots using `position="stack"`.
- Define a weight `aesthetic` mapping to change the relative weights of density plots - for example, this allows weighting of plots by population rather than number of countries.

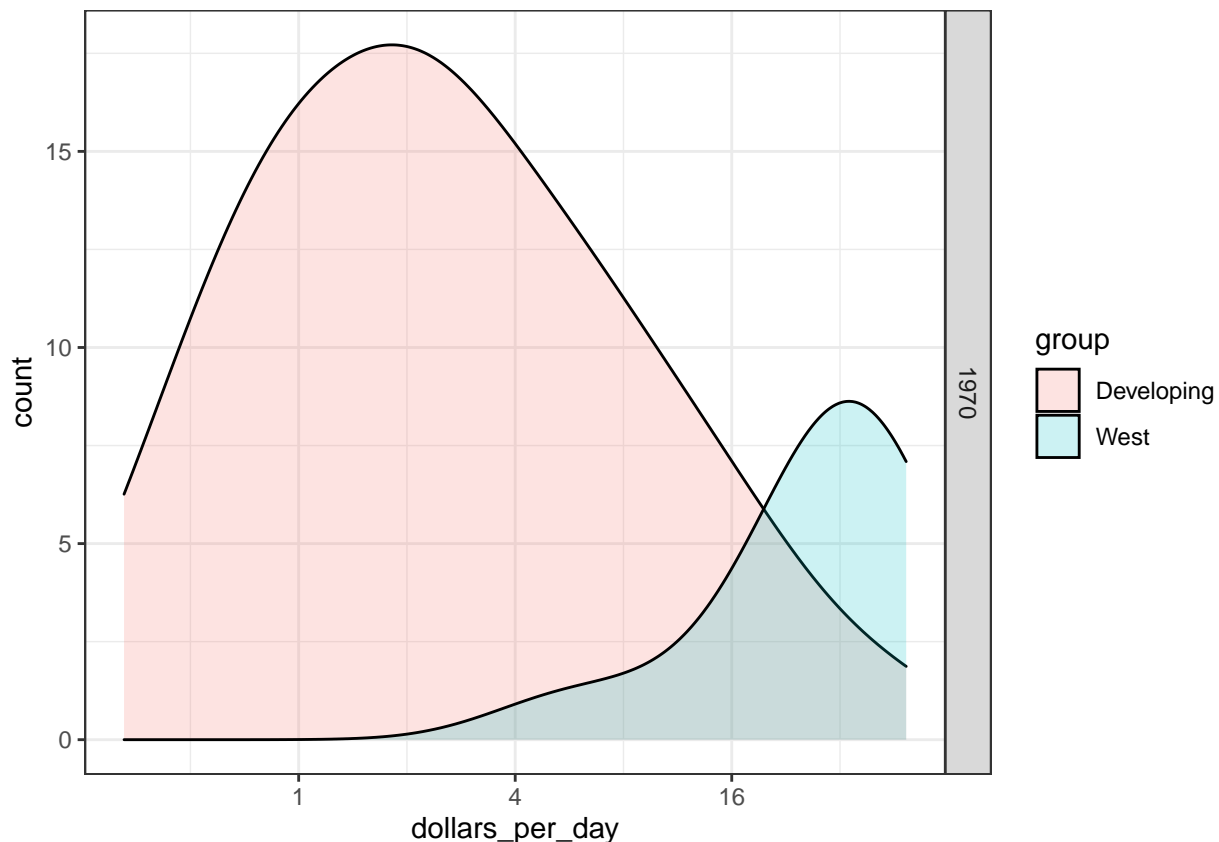
Code: *Faceted smooth density plots*

```
# smooth density plots - area under each curve adds to 1
gapminder %>%
  filter(year == past_year & country %in% country_list) %>%
  mutate(group = ifelse(region %in% west, "West", "Developing")) %>% group_by(group) %>%
  summarize(n = n()) %>% knitr::kable()
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

group	n
Developing	87
West	21

```
# smooth density plots - variable counts on y-axis
p <- gapminder %>%
  filter(year == past_year & country %in% country_list) %>%
  mutate(group = ifelse(region %in% west, "West", "Developing")) %>%
  ggplot(aes(dollars_per_day, y = ..count.., fill = group)) +
  scale_x_continuous(trans = "log2")
p + geom_density(alpha = 0.2, bw = 0.75) + facet_grid(year ~ .)
```



Code: Add new region groups with `case_when`

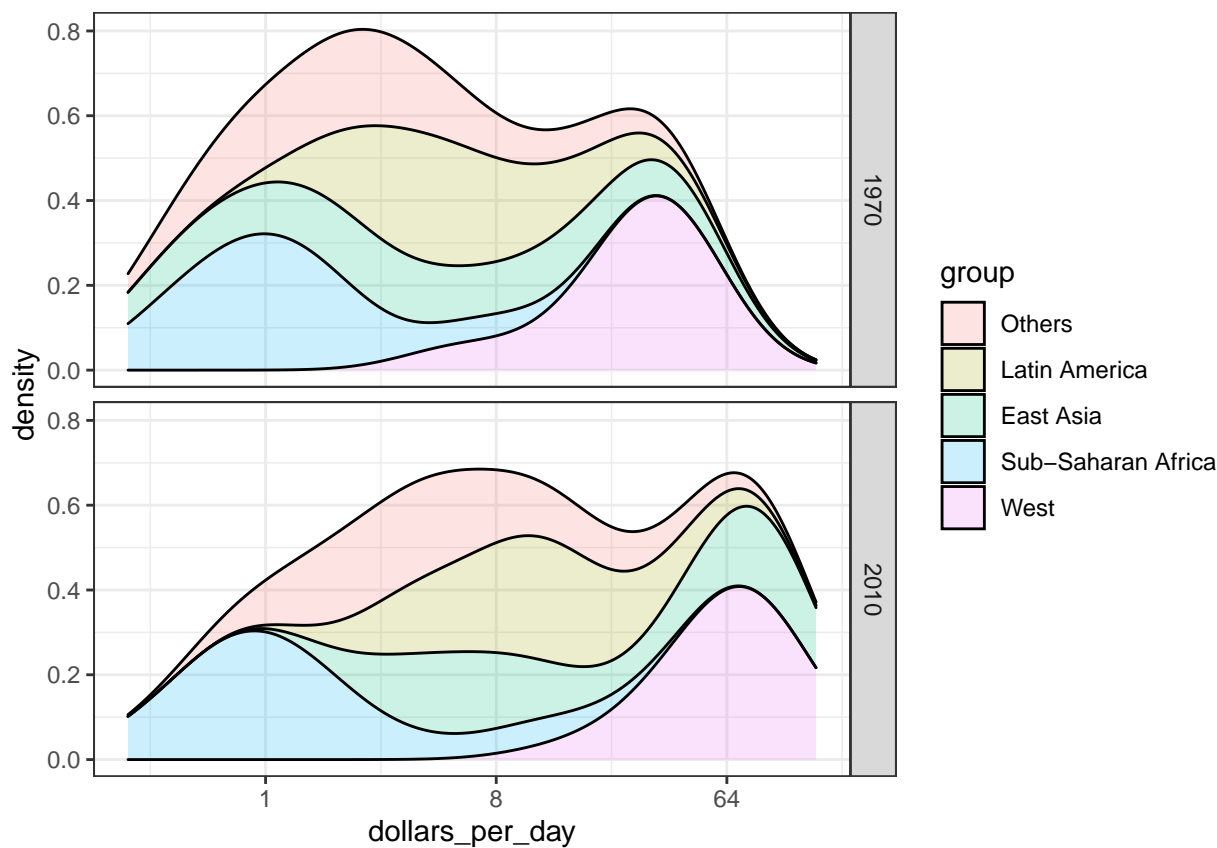
```
# add group as a factor, grouping regions
gapminder <- gapminder %>%
  mutate(group = case_when(
    .$region %in% west ~ "West",
    .$region %in% c("Eastern Asia", "South-Eastern Asia") ~ "East Asia",
    .$region %in% c("Caribbean", "Central America", "South America") ~ "Latin America",
    .$continent == "Africa" & .$region != "Northern Africa" ~ "Sub-Saharan Africa",
    TRUE ~ "Others"))

# reorder factor levels
gapminder <- gapminder %>%
  mutate(group = factor(group, levels = c("Others", "Latin America", "East Asia", "Sub-Saharan Africa")))
```

Code: Stacked density plot

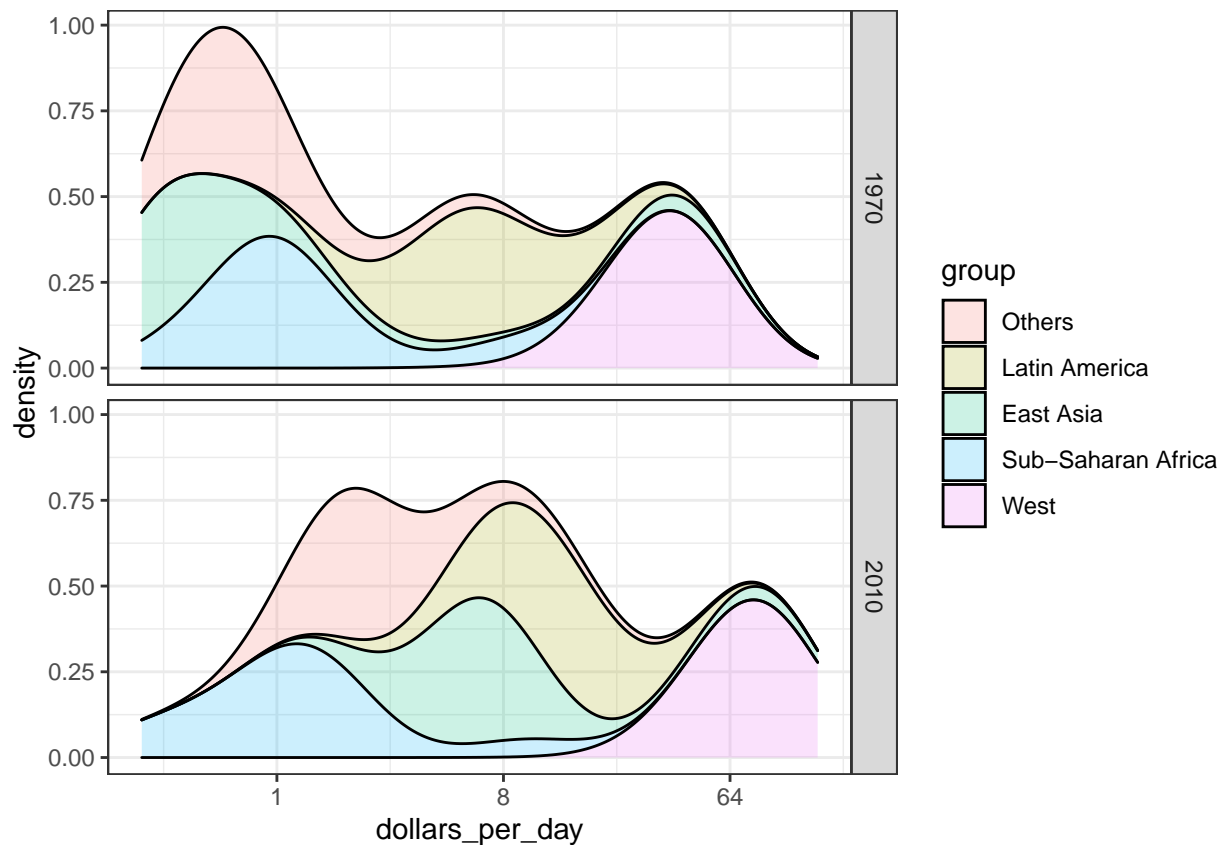
```
# note you must redefine p with the new gapminder object first
p <- gapminder %>%
  filter(year %in% c(past_year, present_year) & country %in% country_list) %>%
  ggplot(aes(dollars_per_day, fill = group)) +
  scale_x_continuous(trans = "log2")

# stacked density plot
p + geom_density(alpha = 0.2, bw = 0.75, position = "stack") +
  facet_grid(year ~ .)
```



Code: Weighted stacked density plot

```
# weighted stacked density plot
gapminder %>%
  filter(year %in% c(past_year, present_year) & country %in% country_list) %>%
  group_by(year) %>%
  mutate(weight = population/sum(population*2)) %>%
  ungroup() %>%
  ggplot(aes(dollars_per_day, fill = group, weight = weight)) +
  scale_x_continuous(trans = "log2") +
  geom_density(alpha = 0.2, bw = 0.75, position = "stack") + facet_grid(year ~ .)
```



## Ecological Fallacy

The textbook for this section is available [here](#)

### Key points

- The *breaks* argument allows us to set the location of the axis labels and tick marks.
- The *logistic* or *logit* transformation is defined as  $f(p) = \log \frac{p}{1-p}$ , or the log of odds. This scale is useful for highlighting differences near 0 or near 1 and converts fold changes into constant increases.
- The *ecological fallacy* is assuming that conclusions made from the average of a group apply to all members of that group.

### Code

```
# add additional cases
gapminder <- gapminder %>%
  mutate(group = case_when(
    .$region %in% west ~ "The West",
    .$region %in% "Northern Africa" ~ "Northern Africa",
    .$region %in% c("Eastern Asia", "South-Eastern Asia") ~ "East Asia",
    .$region == "Southern Asia" ~ "Southern Asia",
    .$region %in% c("Central America", "South America", "Caribbean") ~ "Latin America",
    .$continent == "Africa" & .$region != "Northern Africa" ~ "Sub-Saharan Africa",
    .$region %in% c("Melanesia", "Micronesia", "Polynesia") ~ "Pacific Islands"))

# define a data frame with group average income and average infant survival rate
```

```

surv_income <- gapminder %>%
  filter(year %in% present_year & !is.na(gdp) & !is.na(infant_mortality) & !is.na(group)) %>%
  group_by(group) %>%
  summarize(income = sum(gdp)/sum(population)/365,
            infant_survival_rate = 1 - sum(infant_mortality/1000*population)/sum(population))

```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
surv_income %>% arrange(income)
```

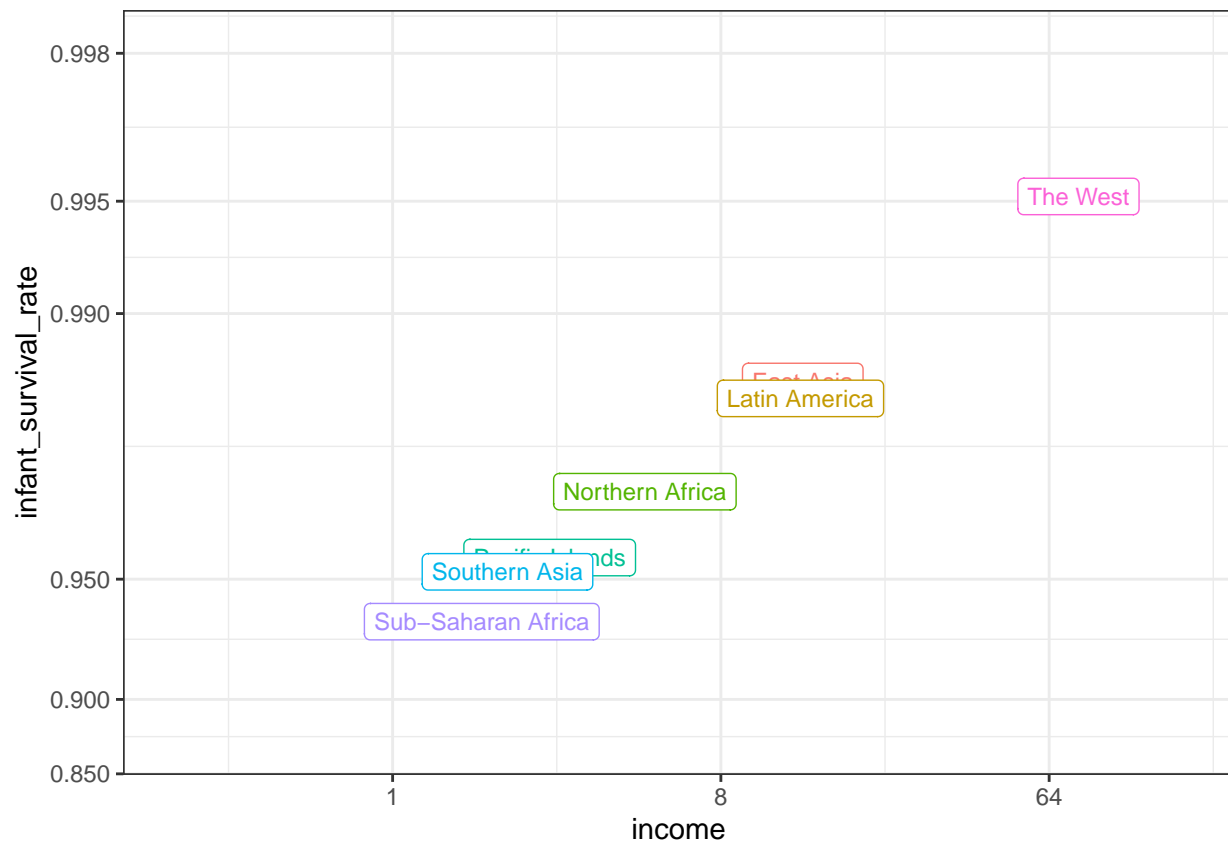
```
## # A tibble: 7 x 3
##   group          income infant_survival_rate
##   <chr>          <dbl>             <dbl>
## 1 Sub-Saharan Africa  1.76             0.936
## 2 Southern Asia      2.07             0.952
## 3 Pacific Islands    2.70             0.956
## 4 Northern Africa    4.94             0.970
## 5 Latin America     13.2             0.983
## 6 East Asia         13.4             0.985
## 7 The West          77.1             0.995
```

```

# plot infant survival versus income, with transformed axes
surv_income %>% ggplot(aes(income, infant_survival_rate, label = group, color = group)) +
  scale_x_continuous(trans = "log2", limit = c(0.25, 150)) +
  scale_y_continuous(trans = "logit", limit = c(0.875, .9981),
                    breaks = c(.85, .90, .95, .99, .995, .998)) +
  geom_label(size = 3, show.legend = FALSE)

```

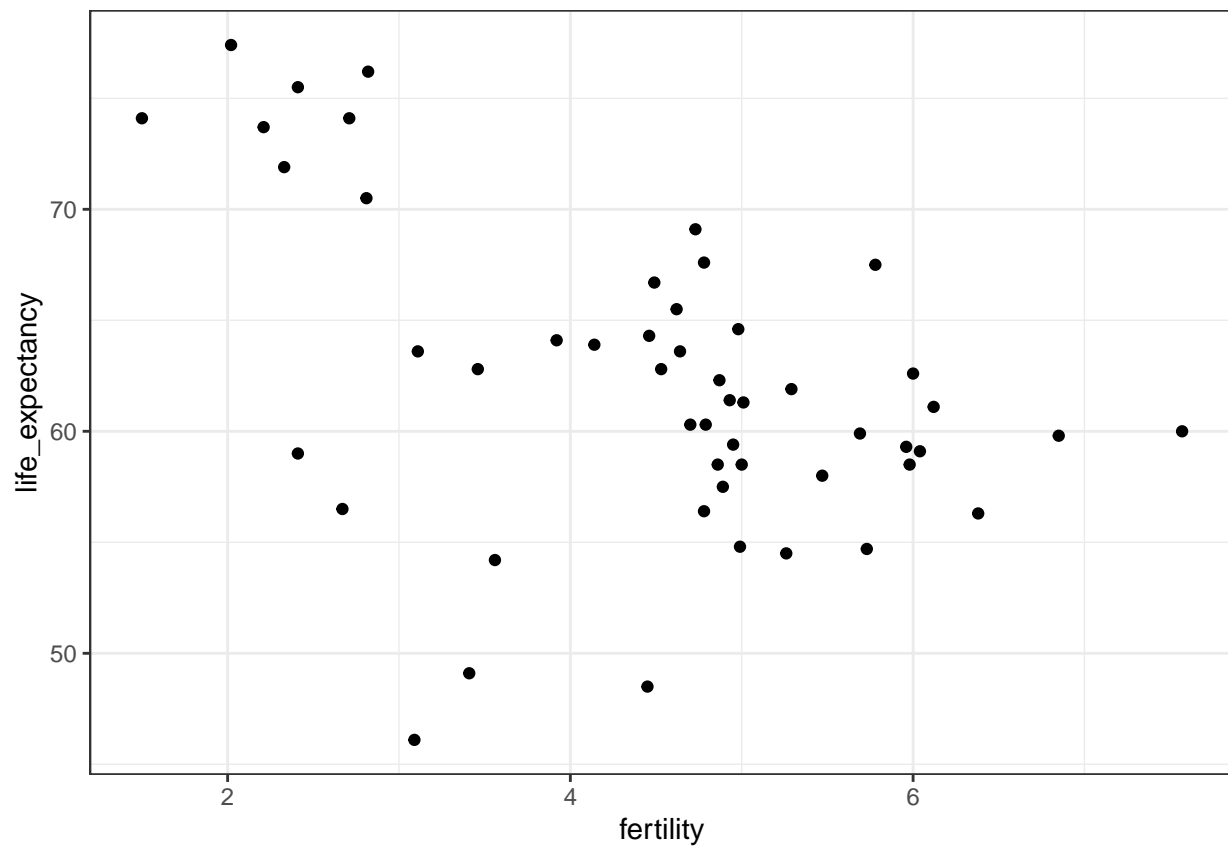




## Assessment - Exploring the Gapminder Dataset

1. The [Gapminder Foundation](#) is a non-profit organization based in Sweden that promotes global development through the use of statistics that can help reduce misconceptions about global development.

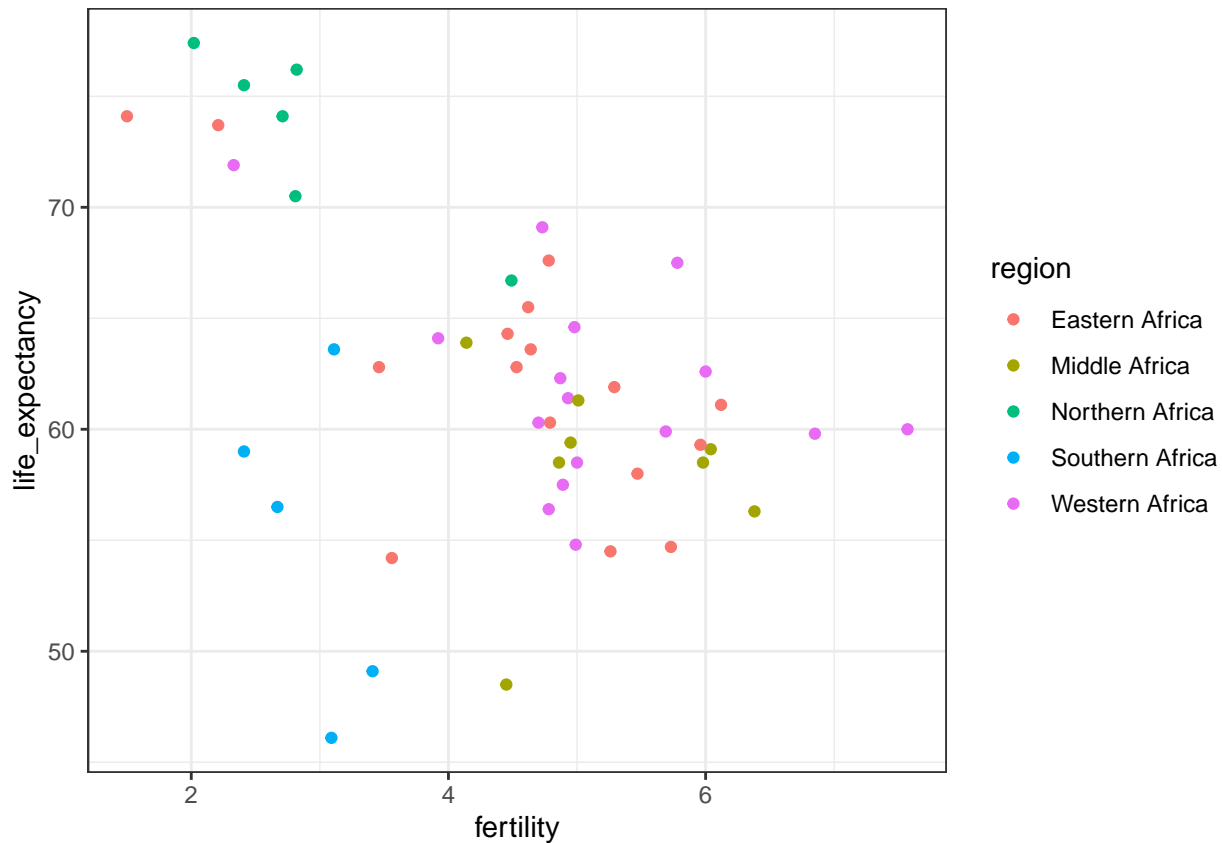
```
## fill out the missing parts in filter and aes
gapminder %>% filter(year == 2012 & continent == "Africa") %>%
  ggplot(aes(fertility, life_expectancy)) +
  geom_point()
```



2. Note that there is quite a bit of variability in life expectancy and fertility with some African countries having very high life expectancies.

There also appear to be three clusters in the plot.

```
gapminder %>% filter(year == 2012 & continent == "Africa") %>%
  ggplot(aes(fertility, life_expectancy, color = region)) +
  geom_point()
```



3. While many of the countries in the high life expectancy/low fertility cluster are from Northern Africa, three countries are not.

```
df <- gapminder %>% filter(year == 2012 & continent == "Africa", fertility <= 3 & life_expectancy >= 70)
df
```

```
##      country      region
## 1   Algeria Northern Africa
## 2 Cape Verde Western Africa
## 3    Egypt Northern Africa
## 4    Libya Northern Africa
## 5 Mauritius Eastern Africa
## 6  Morocco Northern Africa
## 7 Seychelles Eastern Africa
## 8  Tunisia Northern Africa
```

4. The Vietnam War lasted from 1955 to 1975.

Do the data support war having a negative effect on life expectancy? We will create a time series plot that covers the period from 1960 to 2010 of life expectancy for Vietnam and the United States, using color to distinguish the two countries. In this start we start the analysis by generating a table.

```
tab <- gapminder %>% filter(year >= 1960 & year <= 2010 & country%in%c("Vietnam", "United States"))
tab
```

##	country	year	infant_mortality	life_expectancy	fertility	population
## 1	United States	1960	25.9	69.91	3.67	186176524
## 2	Vietnam	1960	75.6	58.52	6.35	32670623
## 3	United States	1961	25.4	70.32	3.63	189077076
## 4	Vietnam	1961	72.6	59.17	6.39	33666768
## 5	United States	1962	24.9	70.21	3.48	191860710
## 6	Vietnam	1962	69.9	59.82	6.43	34684164
## 7	United States	1963	24.4	70.04	3.35	194513911
## 8	Vietnam	1963	67.3	60.42	6.45	35722092
## 9	United States	1964	23.8	70.33	3.22	197028908
## 10	Vietnam	1964	61.7	60.95	6.46	36780984
## 11	United States	1965	23.3	70.41	2.93	199403532
## 12	Vietnam	1965	60.7	61.32	6.48	37860014
## 13	United States	1966	22.7	70.43	2.71	201629471
## 14	Vietnam	1966	59.9	61.36	6.49	38959335
## 15	United States	1967	22.0	70.76	2.56	203713082
## 16	Vietnam	1967	59.0	61.06	6.49	40074695
## 17	United States	1968	21.3	70.42	2.47	205687611
## 18	Vietnam	1968	58.2	60.45	6.49	41195833
## 19	United States	1969	20.6	70.66	2.46	207599308
## 20	Vietnam	1969	57.3	59.63	6.49	42309662
## 21	United States	1970	19.9	70.92	2.46	209485807
## 22	Vietnam	1970	56.4	58.78	6.47	43407291
## 23	United States	1971	19.1	71.24	2.27	211357912
## 24	Vietnam	1971	55.5	58.17	6.42	44485910
## 25	United States	1972	18.3	71.34	2.01	213219515
## 26	Vietnam	1972	54.7	58.00	6.35	45549487
## 27	United States	1973	17.5	71.54	1.87	215092900
## 28	Vietnam	1973	53.8	58.35	6.25	46604726
## 29	United States	1974	16.7	72.08	1.83	217001865
## 30	Vietnam	1974	52.8	59.23	6.13	47661770
## 31	United States	1975	16.0	72.68	1.77	218963561
## 32	Vietnam	1975	51.8	60.54	5.97	48729397
## 33	United States	1976	15.2	72.99	1.74	220993166
## 34	Vietnam	1976	50.9	62.07	5.80	49808071
## 35	United States	1977	14.5	73.38	1.78	223090871
## 36	Vietnam	1977	49.8	63.58	5.61	50899504
## 37	United States	1978	13.8	73.58	1.75	225239456
## 38	Vietnam	1978	48.8	64.86	5.42	52015279
## 39	United States	1979	13.2	74.03	1.80	227411604
## 40	Vietnam	1979	47.8	65.84	5.23	53169674
## 41	United States	1980	12.6	73.93	1.82	229588208
## 42	Vietnam	1980	46.8	66.49	5.05	54372518
## 43	United States	1981	12.1	74.36	1.81	231765783
## 44	Vietnam	1981	45.8	66.86	4.87	55627743
## 45	United States	1982	11.7	74.65	1.81	233953874
## 46	Vietnam	1982	44.8	67.10	4.69	56931822
## 47	United States	1983	11.2	74.71	1.78	236161961
## 48	Vietnam	1983	43.9	67.30	4.52	58277391
## 49	United States	1984	10.9	74.81	1.79	238404223
## 50	Vietnam	1984	43.0	67.51	4.36	59653092
## 51	United States	1985	10.6	74.79	1.84	240691557
## 52	Vietnam	1985	42.0	67.77	4.21	61049370
## 53	United States	1986	10.4	74.87	1.84	243032017

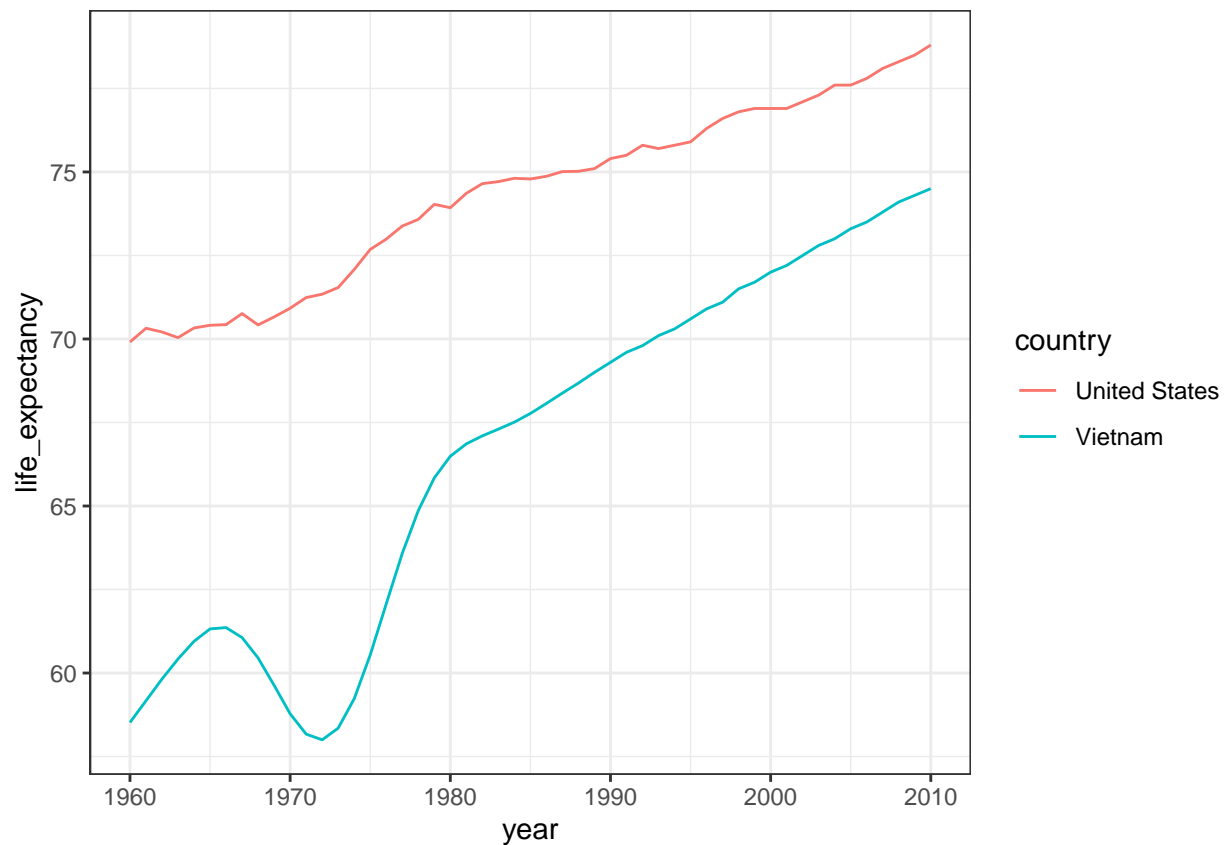
## 54	Vietnam	1986	41.0	68.07	4.06	62459557
## 55	United States	1987	10.2	75.01	1.87	245425409
## 56	Vietnam	1987	40.0	68.38	3.93	63881296
## 57	United States	1988	10.0	75.02	1.92	247865202
## 58	Vietnam	1988	38.9	68.68	3.81	65313709
## 59	United States	1989	9.7	75.10	2.00	250340795
## 60	Vietnam	1989	37.7	69.00	3.68	66757401
## 61	United States	1990	9.4	75.40	2.07	252847810
## 62	Vietnam	1990	36.6	69.30	3.56	68209604
## 63	United States	1991	9.1	75.50	2.06	255367160
## 64	Vietnam	1991	35.4	69.60	3.42	69670620
## 65	United States	1992	8.8	75.80	2.04	257908206
## 66	Vietnam	1992	34.3	69.80	3.26	71129537
## 67	United States	1993	8.5	75.70	2.02	260527420
## 68	Vietnam	1993	33.1	70.10	3.07	72558986
## 69	United States	1994	8.2	75.80	2.00	263301323
## 70	Vietnam	1994	32.0	70.30	2.88	73923849
## 71	United States	1995	8.0	75.90	1.98	266275528
## 72	Vietnam	1995	30.9	70.60	2.68	75198975
## 73	United States	1996	7.7	76.30	1.98	269483224
## 74	Vietnam	1996	29.9	70.90	2.48	76375677
## 75	United States	1997	7.5	76.60	1.97	272882865
## 76	Vietnam	1997	28.9	71.10	2.31	77460429
## 77	United States	1998	7.3	76.80	2.00	276354096
## 78	Vietnam	1998	27.9	71.50	2.17	78462888
## 79	United States	1999	7.2	76.90	2.01	279730801
## 80	Vietnam	1999	27.0	71.70	2.06	79399708
## 81	United States	2000	7.1	76.90	2.05	282895741
## 82	Vietnam	2000	26.1	72.00	1.98	80285563
## 83	United States	2001	7.0	76.90	2.03	285796198
## 84	Vietnam	2001	25.3	72.20	1.94	81123685
## 85	United States	2002	6.9	77.10	2.02	288470847
## 86	Vietnam	2002	24.6	72.50	1.92	81917488
## 87	United States	2003	6.8	77.30	2.05	291005482
## 88	Vietnam	2003	23.9	72.80	1.91	82683039
## 89	United States	2004	6.9	77.60	2.06	293530886
## 90	Vietnam	2004	23.2	73.00	1.90	83439812
## 91	United States	2005	6.8	77.60	2.06	296139635
## 92	Vietnam	2005	22.6	73.30	1.90	84203817
## 93	United States	2006	6.7	77.80	2.11	298860519
## 94	Vietnam	2006	22.0	73.50	1.89	84979667
## 95	United States	2007	6.6	78.10	2.12	301655953
## 96	Vietnam	2007	21.4	73.80	1.88	85770717
## 97	United States	2008	6.5	78.30	2.07	304473143
## 98	Vietnam	2008	20.8	74.10	1.86	86589342
## 99	United States	2009	6.4	78.50	2.00	307231961
## 100	Vietnam	2009	20.3	74.30	1.84	87449021
## 101	United States	2010	6.3	78.80	1.93	309876170
## 102	Vietnam	2010	19.8	74.50	1.82	88357775
##	gdp	continent	region	dollars_per_day	group	
## 1	2.479391e+12	Americas	Northern America	36.4860841	The West	
## 2	NA	Asia	South-Eastern Asia		NA East Asia	
## 3	2.536417e+12	Americas	Northern America	36.7526728	The West	
## 4	NA	Asia	South-Eastern Asia		NA East Asia	

## 5	2.691139e+12	Americas	Northern America	38.4288283	The West
## 6	NA	Asia	South-Eastern Asia	NA	East Asia
## 7	2.809549e+12	Americas	Northern America	39.5724576	The West
## 8	NA	Asia	South-Eastern Asia	NA	East Asia
## 9	2.972502e+12	Americas	Northern America	41.3332358	The West
## 10	NA	Asia	South-Eastern Asia	NA	East Asia
## 11	3.162743e+12	Americas	Northern America	43.4548382	The West
## 12	NA	Asia	South-Eastern Asia	NA	East Asia
## 13	3.368321e+12	Americas	Northern America	45.7684897	The West
## 14	NA	Asia	South-Eastern Asia	NA	East Asia
## 15	3.452529e+12	Americas	Northern America	46.4328711	The West
## 16	NA	Asia	South-Eastern Asia	NA	East Asia
## 17	3.618250e+12	Americas	Northern America	48.1945141	The West
## 18	NA	Asia	South-Eastern Asia	NA	East Asia
## 19	3.730416e+12	Americas	Northern America	49.2309826	The West
## 20	NA	Asia	South-Eastern Asia	NA	East Asia
## 21	3.737877e+12	Americas	Northern America	48.8852142	The West
## 22	NA	Asia	South-Eastern Asia	NA	East Asia
## 23	3.867133e+12	Americas	Northern America	50.1276977	The West
## 24	NA	Asia	South-Eastern Asia	NA	East Asia
## 25	4.080668e+12	Americas	Northern America	52.4338121	The West
## 26	NA	Asia	South-Eastern Asia	NA	East Asia
## 27	4.321881e+12	Americas	Northern America	55.0495657	The West
## 28	NA	Asia	South-Eastern Asia	NA	East Asia
## 29	4.299437e+12	Americas	Northern America	54.2819231	The West
## 30	NA	Asia	South-Eastern Asia	NA	East Asia
## 31	4.291009e+12	Americas	Northern America	53.6901599	The West
## 32	NA	Asia	South-Eastern Asia	NA	East Asia
## 33	4.523528e+12	Americas	Northern America	56.0796900	The West
## 34	NA	Asia	South-Eastern Asia	NA	East Asia
## 35	4.733337e+12	Americas	Northern America	58.1289879	The West
## 36	NA	Asia	South-Eastern Asia	NA	East Asia
## 37	4.999656e+12	Americas	Northern America	60.8138968	The West
## 38	NA	Asia	South-Eastern Asia	NA	East Asia
## 39	5.157035e+12	Americas	Northern America	62.1290351	The West
## 40	NA	Asia	South-Eastern Asia	NA	East Asia
## 41	5.142220e+12	Americas	Northern America	61.3632291	The West
## 42	NA	Asia	South-Eastern Asia	NA	East Asia
## 43	5.272896e+12	Americas	Northern America	62.3314167	The West
## 44	NA	Asia	South-Eastern Asia	NA	East Asia
## 45	5.168479e+12	Americas	Northern America	60.5256797	The West
## 46	NA	Asia	South-Eastern Asia	NA	East Asia
## 47	5.401886e+12	Americas	Northern America	62.6675327	The West
## 48	NA	Asia	South-Eastern Asia	NA	East Asia
## 49	5.790542e+12	Americas	Northern America	66.5445377	The West
## 50	1.145347e+10	Asia	South-Eastern Asia	0.5260311	East Asia
## 51	6.028651e+12	Americas	Northern America	68.6224765	The West
## 52	1.188938e+10	Asia	South-Eastern Asia	0.5335622	East Asia
## 53	6.235265e+12	Americas	Northern America	70.2908174	The West
## 54	1.222101e+10	Asia	South-Eastern Asia	0.5360622	East Asia
## 55	6.432743e+12	Americas	Northern America	71.8098149	The West
## 56	1.265894e+10	Asia	South-Eastern Asia	0.5429137	East Asia
## 57	6.696490e+12	Americas	Northern America	74.0182447	The West
## 58	1.330898e+10	Asia	South-Eastern Asia	0.5582742	East Asia

## 59	6.935219e+12	Americas	Northern America	75.8989379	The West
## 60	1.428912e+10	Asia	South-Eastern Asia	0.5864260	East Asia
## 61	7.063943e+12	Americas	Northern America	76.5411775	The West
## 62	1.501800e+10	Asia	South-Eastern Asia	0.6032171	East Asia
## 63	7.045491e+12	Americas	Northern America	75.5880837	The West
## 64	1.591320e+10	Asia	South-Eastern Asia	0.6257703	East Asia
## 65	7.285373e+12	Americas	Northern America	77.3915942	The West
## 66	1.728906e+10	Asia	South-Eastern Asia	0.6659299	East Asia
## 67	7.494650e+12	Americas	Northern America	78.8143037	The West
## 68	1.868476e+10	Asia	South-Eastern Asia	0.7055104	East Asia
## 69	7.803020e+12	Americas	Northern America	81.1926662	The West
## 70	2.033630e+10	Asia	South-Eastern Asia	0.7536931	East Asia
## 71	8.001917e+12	Americas	Northern America	82.3322348	The West
## 72	2.227648e+10	Asia	South-Eastern Asia	0.8115996	East Asia
## 73	8.304875e+12	Americas	Northern America	84.4322774	The West
## 74	2.435711e+10	Asia	South-Eastern Asia	0.8737312	East Asia
## 75	8.679071e+12	Americas	Northern America	87.1373006	The West
## 76	2.634272e+10	Asia	South-Eastern Asia	0.9317253	East Asia
## 77	9.061073e+12	Americas	Northern America	89.8298924	The West
## 78	2.786124e+10	Asia	South-Eastern Asia	0.9728441	East Asia
## 79	9.502248e+12	Americas	Northern America	93.0664656	The West
## 80	2.919122e+10	Asia	South-Eastern Asia	1.0072573	East Asia
## 81	9.898800e+12	Americas	Northern America	95.8657062	The West
## 82	3.117252e+10	Asia	South-Eastern Asia	1.0637548	East Asia
## 83	1.000703e+13	Americas	Northern America	95.9303301	The West
## 84	3.332183e+10	Asia	South-Eastern Asia	1.1253518	East Asia
## 85	1.018996e+13	Americas	Northern America	96.7782269	The West
## 86	3.568108e+10	Asia	South-Eastern Asia	1.1933517	East Asia
## 87	1.045007e+13	Americas	Northern America	98.3841464	The West
## 88	3.830049e+10	Asia	South-Eastern Asia	1.2690975	East Asia
## 89	1.081371e+13	Americas	Northern America	100.9317862	The West
## 90	4.128394e+10	Asia	South-Eastern Asia	1.3555482	East Asia
## 91	1.114630e+13	Americas	Northern America	103.1195945	The West
## 92	4.476905e+10	Asia	South-Eastern Asia	1.4566432	East Asia
## 93	1.144269e+13	Americas	Northern America	104.8978847	The West
## 94	4.845303e+10	Asia	South-Eastern Asia	1.5621152	East Asia
## 95	1.166093e+13	Americas	Northern America	105.9078868	The West
## 96	5.255039e+10	Asia	South-Eastern Asia	1.6785876	East Asia
## 97	1.161905e+13	Americas	Northern America	104.5511719	The West
## 98	5.586668e+10	Asia	South-Eastern Asia	1.7676470	East Asia
## 99	1.120919e+13	Americas	Northern America	99.9574489	The West
## 100	5.884079e+10	Asia	South-Eastern Asia	1.8434472	East Asia
## 101	1.154791e+13	Americas	Northern America	102.0991582	The West
## 102	6.283222e+10	Asia	South-Eastern Asia	1.9482502	East Asia

5. Now that you have created the data table in Exercise 4, it is time to plot the data for the two countries.

```
p <- tab %>% ggplot(aes(year,life_expectancy,color=country)) + geom_line()
p
```

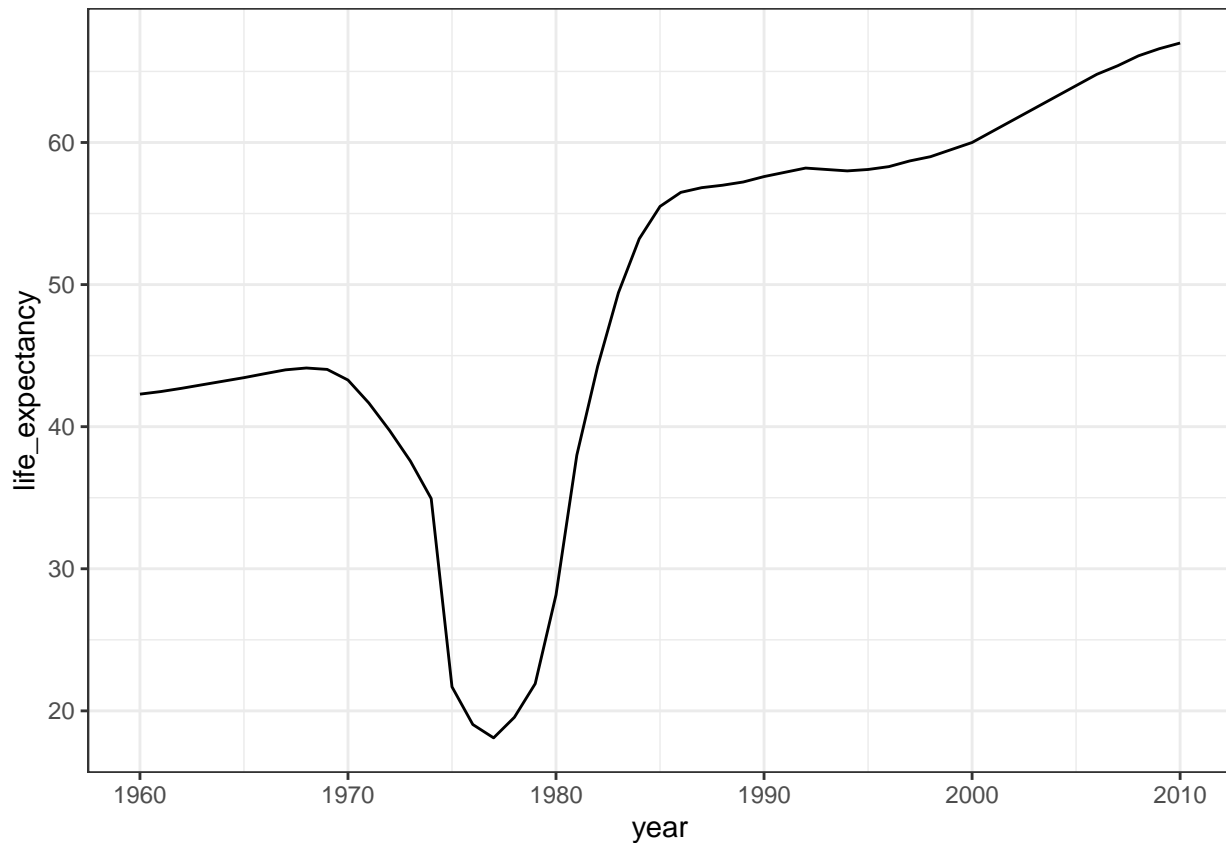


6. Cambodia was also involved in this conflict and, after the war, Pol Pot and his communist Khmer Rouge took control and ruled Cambodia from 1975 to 1979.

He is considered one of the most brutal dictators in history. Do the data support this claim?

```
p <- gapminder %>% filter(year >= 1960 & year <= 2010 & country == "Cambodia") %>% ggplot(aes(year, life_exp))
p
```





7. Now we are going to calculate and plot dollars per day for African countries in 2010 using GDP data.

In the first part of this analysis, we will create the dollars per day variable.

```
daydollars <- gapminder %>%
mutate(dollars_per_day = gdp/population/365) %>% filter(continent == "Africa" & year == 2010 & !is.na(g
daydollars
```

##	country	year	infant_mortality	life_expectancy	fertility
## 1	Algeria	2010	23.5	76.0	2.82
## 2	Angola	2010	109.6	57.6	6.22
## 3	Benin	2010	71.0	60.8	5.10
## 4	Botswana	2010	39.8	55.6	2.76
## 5	Burkina Faso	2010	69.7	59.0	5.87
## 6	Burundi	2010	63.8	60.4	6.30
## 7	Cameroon	2010	66.2	57.8	5.02
## 8	Cape Verde	2010	23.3	71.1	2.43
## 9	Central African Republic	2010	101.7	47.9	4.63
## 10	Chad	2010	93.6	55.8	6.60
## 11	Comoros	2010	63.1	67.7	4.92
## 12	Congo, Dem. Rep.	2010	84.8	58.4	6.25
## 13	Congo, Rep.	2010	42.2	60.4	5.07
## 14	Cote d'Ivoire	2010	76.9	56.6	4.91
## 15	Egypt	2010	24.3	70.1	2.88
## 16	Equatorial Guinea	2010	78.9	58.6	5.14
## 17	Eritrea	2010	39.4	60.1	4.97

## 18	Ethiopia	2010	50.8	62.1	4.90
## 19	Gabon	2010	42.8	63.0	4.21
## 20	Gambia	2010	51.7	66.5	5.80
## 21	Ghana	2010	50.2	62.9	4.05
## 22	Guinea	2010	71.2	57.9	5.17
## 23	Guinea-Bissau	2010	73.4	54.3	5.12
## 24	Kenya	2010	42.4	62.9	4.62
## 25	Lesotho	2010	75.2	46.4	3.21
## 26	Liberia	2010	65.2	60.8	5.02
## 27	Madagascar	2010	42.1	62.4	4.65
## 28	Malawi	2010	57.5	55.4	5.64
## 29	Mali	2010	82.9	59.2	6.84
## 30	Mauritania	2010	70.1	68.6	4.84
## 31	Mauritius	2010	13.3	73.4	1.52
## 32	Morocco	2010	28.5	73.7	2.58
## 33	Mozambique	2010	71.9	54.4	5.41
## 34	Namibia	2010	37.5	61.4	3.23
## 35	Niger	2010	66.1	59.2	7.58
## 36	Nigeria	2010	81.5	61.2	6.02
## 37	Rwanda	2010	43.8	65.1	4.84
## 38	Senegal	2010	46.7	64.2	5.05
## 39	Seychelles	2010	12.2	73.1	2.26
## 40	Sierra Leone	2010	107.0	55.0	4.94
## 41	South Africa	2010	38.2	54.9	2.47
## 42	Sudan	2010	53.3	66.1	4.64
## 43	Swaziland	2010	59.1	46.4	3.56
## 44	Tanzania	2010	42.4	61.4	5.43
## 45	Togo	2010	59.3	58.7	4.79
## 46	Tunisia	2010	14.9	77.1	2.04
## 47	Uganda	2010	49.5	57.8	6.16
## 48	Zambia	2010	52.9	53.1	5.81
## 49	Zimbabwe	2010	55.8	49.1	3.72
##	population	gdp continent	region	dollars_per_day	
## 1	36036159	79164339611	Africa Northern Africa	6.0186382	
## 2	21219954	26125663270	Africa Middle Africa	3.3731063	
## 3	9509798	3336801340	Africa Western Africa	0.9613161	
## 4	2047831	8408166868	Africa Southern Africa	11.2490111	
## 5	15632066	4655655008	Africa Western Africa	0.8159650	
## 6	9461117	1158914103	Africa Eastern Africa	0.3355954	
## 7	20590666	13986616694	Africa Middle Africa	1.8610130	
## 8	490379	971606715	Africa Western Africa	5.4283242	
## 9	4444973	1054122016	Africa Middle Africa	0.6497240	
## 10	11896380	3369354207	Africa Middle Africa	0.7759594	
## 11	698695	247231031	Africa Eastern Africa	0.9694434	
## 12	65938712	6961485000	Africa Middle Africa	0.2892468	
## 13	4066078	5067059617	Africa Middle Africa	3.4141881	
## 14	20131707	11603002049	Africa Western Africa	1.5790537	
## 15	82040994	160258746162	Africa Northern Africa	5.3517764	
## 16	728710	5979285835	Africa Middle Africa	22.4802803	
## 17	4689664	771116883	Africa Eastern Africa	0.4504905	
## 18	87561814	18291486355	Africa Eastern Africa	0.5723232	
## 19	1541936	6343809583	Africa Middle Africa	11.2717391	
## 20	1693002	1217357172	Africa Western Africa	1.9700066	
## 21	24317734	8779397392	Africa Western Africa	0.9891194	

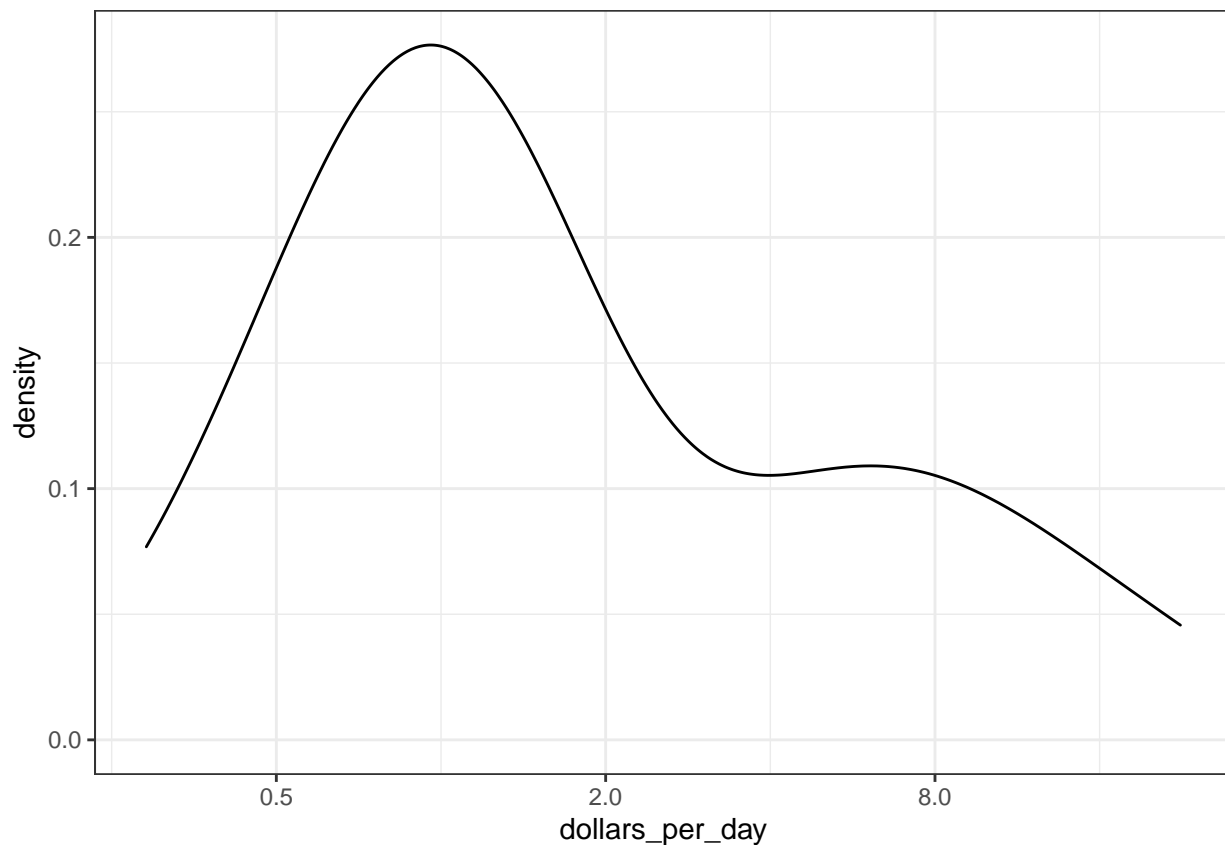
## 22	11012406	5493989673	Africa	Western Africa	1.3668245
## 23	1634196	244395463	Africa	Western Africa	0.4097285
## 24	40328313	18988282813	Africa	Eastern Africa	1.2899794
## 25	2010586	1076239050	Africa	Southern Africa	1.4665377
## 26	3957990	1040653199	Africa	Western Africa	0.7203416
## 27	21079532	5026822443	Africa	Eastern Africa	0.6533407
## 28	14769824	2758392725	Africa	Eastern Africa	0.5116676
## 29	15167286	4199858651	Africa	Western Africa	0.7586368
## 30	3591400	2107593972	Africa	Western Africa	1.6077936
## 31	1247951	6636426093	Africa	Eastern Africa	14.5694737
## 32	32107739	59908047776	Africa	Northern Africa	5.1119027
## 33	24321457	8972305823	Africa	Eastern Africa	1.0106985
## 34	2193643	6155469329	Africa	Southern Africa	7.6878050
## 35	16291990	2781188119	Africa	Western Africa	0.4676957
## 36	159424742	85581744176	Africa	Western Africa	1.4707286
## 37	10293669	3583713093	Africa	Eastern Africa	0.9538282
## 38	12956791	6984284544	Africa	Western Africa	1.4768337
## 39	93081	760361490	Africa	Eastern Africa	22.3803157
## 40	5775902	1574302614	Africa	Western Africa	0.7467505
## 41	51621594	187639624489	Africa	Southern Africa	9.9586457
## 42	36114885	22819076998	Africa	Northern Africa	1.7310873
## 43	1193148	1911603442	Africa	Southern Africa	4.3894552
## 44	45648525	19965679449	Africa	Eastern Africa	1.1982970
## 45	6390851	1595792895	Africa	Western Africa	0.6841085
## 46	10639194	33161453137	Africa	Northern Africa	8.5394905
## 47	33149417	12701095116	Africa	Eastern Africa	1.0497174
## 48	13917439	5587389858	Africa	Eastern Africa	1.0999091
## 49	13973897	4032423429	Africa	Eastern Africa	0.7905980
##	group				
## 1	Northern Africa				
## 2	Sub-Saharan Africa				
## 3	Sub-Saharan Africa				
## 4	Sub-Saharan Africa				
## 5	Sub-Saharan Africa				
## 6	Sub-Saharan Africa				
## 7	Sub-Saharan Africa				
## 8	Sub-Saharan Africa				
## 9	Sub-Saharan Africa				
## 10	Sub-Saharan Africa				
## 11	Sub-Saharan Africa				
## 12	Sub-Saharan Africa				
## 13	Sub-Saharan Africa				
## 14	Sub-Saharan Africa				
## 15	Northern Africa				
## 16	Sub-Saharan Africa				
## 17	Sub-Saharan Africa				
## 18	Sub-Saharan Africa				
## 19	Sub-Saharan Africa				
## 20	Sub-Saharan Africa				
## 21	Sub-Saharan Africa				
## 22	Sub-Saharan Africa				
## 23	Sub-Saharan Africa				
## 24	Sub-Saharan Africa				
## 25	Sub-Saharan Africa				

```
## 26 Sub-Saharan Africa
## 27 Sub-Saharan Africa
## 28 Sub-Saharan Africa
## 29 Sub-Saharan Africa
## 30 Sub-Saharan Africa
## 31 Sub-Saharan Africa
## 32 Northern Africa
## 33 Sub-Saharan Africa
## 34 Sub-Saharan Africa
## 35 Sub-Saharan Africa
## 36 Sub-Saharan Africa
## 37 Sub-Saharan Africa
## 38 Sub-Saharan Africa
## 39 Sub-Saharan Africa
## 40 Sub-Saharan Africa
## 41 Sub-Saharan Africa
## 42 Northern Africa
## 43 Sub-Saharan Africa
## 44 Sub-Saharan Africa
## 45 Sub-Saharan Africa
## 46 Northern Africa
## 47 Sub-Saharan Africa
## 48 Sub-Saharan Africa
## 49 Sub-Saharan Africa
```

8. Now we are going to calculate and plot dollars per day for African countries in 2010 using GDP data.

In the second part of this analysis, we will plot the smooth density plot using a log (base 2) x axis.

```
p <- daydollars %>% ggplot(aes(dollars_per_day)) +
  scale_x_continuous(trans = "log2") + geom_density()
p
```



9. Now we are going to combine the plotting tools we have used in the past two exercises to create density plots for multiple years.

```
daydollars <- gapminder %>%
mutate(dollars_per_day = gdp/population/365) %>% filter(continent == "Africa" & year%in%c(1970,2010) &
daydollars
```

##	country	year	infant_mortality	life_expectancy	fertility
## 1	Algeria	1970	146.0	52.41	7.64
## 2	Benin	1970	157.1	43.93	6.75
## 3	Botswana	1970	85.3	54.30	6.64
## 4	Burkina Faso	1970	149.3	40.27	6.62
## 5	Burundi	1970	146.4	42.76	7.31
## 6	Cameroon	1970	126.2	48.97	6.21
## 7	Central African Republic	1970	137.0	43.36	5.95
## 8	Chad	1970	135.9	45.72	6.53
## 9	Congo, Dem. Rep.	1970	149.0	48.13	6.21
## 10	Congo, Rep.	1970	88.5	52.85	6.26
## 11	Cote d'Ivoire	1970	161.0	45.38	7.91
## 12	Egypt	1970	162.0	52.54	5.94
## 13	Gabon	1970	NA	45.55	5.08
## 14	Gambia	1970	126.0	43.31	6.09
## 15	Ghana	1970	120.1	50.08	6.95
## 16	Guinea-Bissau	1970	NA	45.50	6.07
## 17	Kenya	1970	91.3	53.83	8.08
## 18	Lesotho	1970	131.6	49.67	5.81

## 19	Liberia 1970	191.3	40.10	6.70
## 20	Madagascar 1970	93.2	47.77	7.33
## 21	Malawi 1970	207.7	41.62	7.30
## 22	Mali 1970	195.7	34.51	6.90
## 23	Mauritania 1970	108.5	49.77	6.78
## 24	Morocco 1970	120.8	54.34	6.69
## 25	Niger 1970	137.6	38.24	7.42
## 26	Nigeria 1970	168.9	41.79	6.47
## 27	Rwanda 1970	129.4	45.58	8.23
## 28	Senegal 1970	121.7	39.59	7.34
## 29	Seychelles 1970	54.1	64.62	5.76
## 30	Sierra Leone 1970	191.0	43.15	6.70
## 31	South Africa 1970	NA	52.77	5.59
## 32	Sudan 1970	94.7	54.26	6.89
## 33	Swaziland 1970	119.3	48.79	6.88
## 34	Togo 1970	132.8	47.72	7.08
## 35	Tunisia 1970	122.2	52.94	6.44
## 36	Zambia 1970	109.3	53.88	7.44
## 37	Zimbabwe 1970	72.4	57.22	7.42
## 38	Algeria 2010	23.5	76.00	2.82
## 39	Angola 2010	109.6	57.60	6.22
## 40	Benin 2010	71.0	60.80	5.10
## 41	Botswana 2010	39.8	55.60	2.76
## 42	Burkina Faso 2010	69.7	59.00	5.87
## 43	Burundi 2010	63.8	60.40	6.30
## 44	Cameroon 2010	66.2	57.80	5.02
## 45	Cape Verde 2010	23.3	71.10	2.43
## 46	Central African Republic 2010	101.7	47.90	4.63
## 47	Chad 2010	93.6	55.80	6.60
## 48	Comoros 2010	63.1	67.70	4.92
## 49	Congo, Dem. Rep. 2010	84.8	58.40	6.25
## 50	Congo, Rep. 2010	42.2	60.40	5.07
## 51	Cote d'Ivoire 2010	76.9	56.60	4.91
## 52	Egypt 2010	24.3	70.10	2.88
## 53	Equatorial Guinea 2010	78.9	58.60	5.14
## 54	Eritrea 2010	39.4	60.10	4.97
## 55	Ethiopia 2010	50.8	62.10	4.90
## 56	Gabon 2010	42.8	63.00	4.21
## 57	Gambia 2010	51.7	66.50	5.80
## 58	Ghana 2010	50.2	62.90	4.05
## 59	Guinea 2010	71.2	57.90	5.17
## 60	Guinea-Bissau 2010	73.4	54.30	5.12
## 61	Kenya 2010	42.4	62.90	4.62
## 62	Lesotho 2010	75.2	46.40	3.21
## 63	Liberia 2010	65.2	60.80	5.02
## 64	Madagascar 2010	42.1	62.40	4.65
## 65	Malawi 2010	57.5	55.40	5.64
## 66	Mali 2010	82.9	59.20	6.84
## 67	Mauritania 2010	70.1	68.60	4.84
## 68	Mauritius 2010	13.3	73.40	1.52
## 69	Morocco 2010	28.5	73.70	2.58
## 70	Mozambique 2010	71.9	54.40	5.41
## 71	Namibia 2010	37.5	61.40	3.23
## 72	Niger 2010	66.1	59.20	7.58

## 73	Nigeria	2010	81.5	61.20	6.02
## 74	Rwanda	2010	43.8	65.10	4.84
## 75	Senegal	2010	46.7	64.20	5.05
## 76	Seychelles	2010	12.2	73.10	2.26
## 77	Sierra Leone	2010	107.0	55.00	4.94
## 78	South Africa	2010	38.2	54.90	2.47
## 79	Sudan	2010	53.3	66.10	4.64
## 80	Swaziland	2010	59.1	46.40	3.56
## 81	Tanzania	2010	42.4	61.40	5.43
## 82	Togo	2010	59.3	58.70	4.79
## 83	Tunisia	2010	14.9	77.10	2.04
## 84	Uganda	2010	49.5	57.80	6.16
## 85	Zambia	2010	52.9	53.10	5.81
## 86	Zimbabwe	2010	55.8	49.10	3.72
##	population	gdp	continent	region	dollars_per_day
## 1	14550033	19741305571	Africa	Northern Africa	3.7172265
## 2	2907769	831774871	Africa	Western Africa	0.7837057
## 3	693021	283867117	Africa	Southern Africa	1.1222144
## 4	5624597	795164207	Africa	Western Africa	0.3873223
## 5	3457113	524049198	Africa	Eastern Africa	0.4153035
## 6	6770967	3372153343	Africa	Middle Africa	1.3644693
## 7	1828710	647622869	Africa	Middle Africa	0.9702518
## 8	3644911	829387598	Africa	Middle Africa	0.6234157
## 9	20009902	6728080745	Africa	Middle Africa	0.9211988
## 10	1335090	939633199	Africa	Middle Africa	1.9282127
## 11	5241914	4619775632	Africa	Western Africa	2.4145607
## 12	34808599	20331718433	Africa	Northern Africa	1.6002752
## 13	590119	1722664256	Africa	Middle Africa	7.9977566
## 14	447283	247459869	Africa	Western Africa	1.5157568
## 15	8596977	2549677064	Africa	Western Africa	0.8125434
## 16	711828	104038537	Africa	Western Africa	0.4004297
## 17	11252466	3276361787	Africa	Eastern Africa	0.7977215
## 18	1032240	184783955	Africa	Southern Africa	0.4904454
## 19	1419728	1094083642	Africa	Western Africa	2.1113125
## 20	6576301	2807129955	Africa	Eastern Africa	1.1694670
## 21	4603739	549382768	Africa	Eastern Africa	0.3269426
## 22	5949043	1038617256	Africa	Western Africa	0.4783167
## 23	1148908	700627427	Africa	Western Africa	1.6707406
## 24	16039600	12097898528	Africa	Northern Africa	2.0664435
## 25	4497355	1343819364	Africa	Western Africa	0.8186360
## 26	56131844	19793025795	Africa	Western Africa	0.9660732
## 27	3754546	809941587	Africa	Eastern Africa	0.5910217
## 28	4217754	2266115562	Africa	Western Africa	1.4720005
## 29	52364	141888524	Africa	Eastern Africa	7.4237202
## 30	2514151	739785784	Africa	Western Africa	0.8061610
## 31	22502502	68558449204	Africa	Southern Africa	8.3471326
## 32	10232758	3901968151	Africa	Northern Africa	1.0447158
## 33	445844	257078586	Africa	Southern Africa	1.5797564
## 34	2115521	618863063	Africa	Western Africa	0.8014646
## 35	5060393	4688590613	Africa	Northern Africa	2.5384301
## 36	4185378	2384401746	Africa	Eastern Africa	1.5608166
## 37	5206311	2682438620	Africa	Eastern Africa	1.4115843
## 38	36036159	79164339611	Africa	Northern Africa	6.0186382
## 39	21219954	26125663270	Africa	Middle Africa	3.3731063

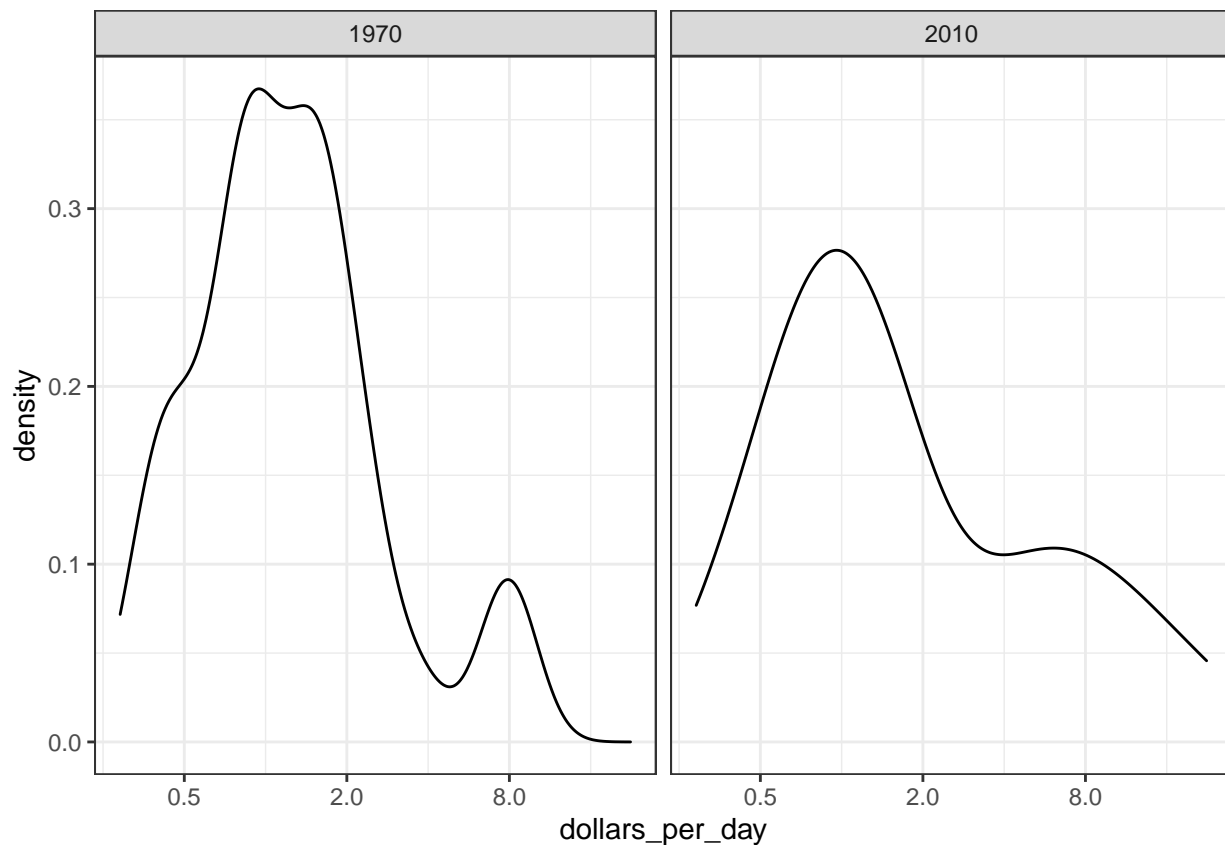
## 40	9509798	3336801340	Africa	Western Africa	0.9613161
## 41	2047831	8408166868	Africa	Southern Africa	11.2490111
## 42	15632066	4655655008	Africa	Western Africa	0.8159650
## 43	9461117	1158914103	Africa	Eastern Africa	0.3355954
## 44	20590666	13986616694	Africa	Middle Africa	1.8610130
## 45	490379	971606715	Africa	Western Africa	5.4283242
## 46	4444973	1054122016	Africa	Middle Africa	0.6497240
## 47	11896380	3369354207	Africa	Middle Africa	0.7759594
## 48	698695	247231031	Africa	Eastern Africa	0.9694434
## 49	65938712	6961485000	Africa	Middle Africa	0.2892468
## 50	4066078	5067059617	Africa	Middle Africa	3.4141881
## 51	20131707	11603002049	Africa	Western Africa	1.5790537
## 52	82040994	160258746162	Africa	Northern Africa	5.3517764
## 53	728710	5979285835	Africa	Middle Africa	22.4802803
## 54	4689664	771116883	Africa	Eastern Africa	0.4504905
## 55	87561814	18291486355	Africa	Eastern Africa	0.5723232
## 56	1541936	6343809583	Africa	Middle Africa	11.2717391
## 57	1693002	1217357172	Africa	Western Africa	1.9700066
## 58	24317734	8779397392	Africa	Western Africa	0.9891194
## 59	11012406	5493989673	Africa	Western Africa	1.3668245
## 60	1634196	244395463	Africa	Western Africa	0.4097285
## 61	40328313	18988282813	Africa	Eastern Africa	1.2899794
## 62	2010586	1076239050	Africa	Southern Africa	1.4665377
## 63	3957990	1040653199	Africa	Western Africa	0.7203416
## 64	21079532	5026822443	Africa	Eastern Africa	0.6533407
## 65	14769824	2758392725	Africa	Eastern Africa	0.5116676
## 66	15167286	4199858651	Africa	Western Africa	0.7586368
## 67	3591400	2107593972	Africa	Western Africa	1.6077936
## 68	1247951	6636426093	Africa	Eastern Africa	14.5694737
## 69	32107739	59908047776	Africa	Northern Africa	5.1119027
## 70	24321457	8972305823	Africa	Eastern Africa	1.0106985
## 71	2193643	6155469329	Africa	Southern Africa	7.6878050
## 72	16291990	2781188119	Africa	Western Africa	0.4676957
## 73	159424742	85581744176	Africa	Western Africa	1.4707286
## 74	10293669	3583713093	Africa	Eastern Africa	0.9538282
## 75	12956791	6984284544	Africa	Western Africa	1.4768337
## 76	93081	760361490	Africa	Eastern Africa	22.3803157
## 77	5775902	1574302614	Africa	Western Africa	0.7467505
## 78	51621594	187639624489	Africa	Southern Africa	9.9586457
## 79	36114885	22819076998	Africa	Northern Africa	1.7310873
## 80	1193148	1911603442	Africa	Southern Africa	4.3894552
## 81	45648525	19965679449	Africa	Eastern Africa	1.1982970
## 82	6390851	1595792895	Africa	Western Africa	0.6841085
## 83	10639194	33161453137	Africa	Northern Africa	8.5394905
## 84	33149417	12701095116	Africa	Eastern Africa	1.0497174
## 85	13917439	5587389858	Africa	Eastern Africa	1.0999091
## 86	13973897	4032423429	Africa	Eastern Africa	0.7905980
##	group				
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```

```
p <- daydollars %>% ggplot(aes(dollars_per_day)) +
  scale_x_continuous(trans = "log2") + geom_density() + facet_grid(.~year)
p
```



10. Now we are going to edit the code from Exercise 9 to show stacked histograms of each region in Africa.

```
daydollars <- gapminder %>%
mutate(dollars_per_day = gdp/population/365) %>% filter(continent == "Africa" & year%in%c(1970,2010) &
daydollars
```

##	country	year	infant_mortality	life_expectancy	fertility
## 1	Algeria	1970	146.0	52.41	7.64
## 2	Benin	1970	157.1	43.93	6.75
## 3	Botswana	1970	85.3	54.30	6.64
## 4	Burkina Faso	1970	149.3	40.27	6.62
## 5	Burundi	1970	146.4	42.76	7.31
## 6	Cameroon	1970	126.2	48.97	6.21
## 7	Central African Republic	1970	137.0	43.36	5.95
## 8	Chad	1970	135.9	45.72	6.53
## 9	Congo, Dem. Rep.	1970	149.0	48.13	6.21
## 10	Congo, Rep.	1970	88.5	52.85	6.26
## 11	Cote d'Ivoire	1970	161.0	45.38	7.91
## 12	Egypt	1970	162.0	52.54	5.94
## 13	Gabon	1970	NA	45.55	5.08
## 14	Gambia	1970	126.0	43.31	6.09
## 15	Ghana	1970	120.1	50.08	6.95
## 16	Guinea-Bissau	1970	NA	45.50	6.07
## 17	Kenya	1970	91.3	53.83	8.08
## 18	Lesotho	1970	131.6	49.67	5.81
## 19	Liberia	1970	191.3	40.10	6.70

## 20	Madagascar 1970	93.2	47.77	7.33
## 21	Malawi 1970	207.7	41.62	7.30
## 22	Mali 1970	195.7	34.51	6.90
## 23	Mauritania 1970	108.5	49.77	6.78
## 24	Morocco 1970	120.8	54.34	6.69
## 25	Niger 1970	137.6	38.24	7.42
## 26	Nigeria 1970	168.9	41.79	6.47
## 27	Rwanda 1970	129.4	45.58	8.23
## 28	Senegal 1970	121.7	39.59	7.34
## 29	Seychelles 1970	54.1	64.62	5.76
## 30	Sierra Leone 1970	191.0	43.15	6.70
## 31	South Africa 1970	NA	52.77	5.59
## 32	Sudan 1970	94.7	54.26	6.89
## 33	Swaziland 1970	119.3	48.79	6.88
## 34	Togo 1970	132.8	47.72	7.08
## 35	Tunisia 1970	122.2	52.94	6.44
## 36	Zambia 1970	109.3	53.88	7.44
## 37	Zimbabwe 1970	72.4	57.22	7.42
## 38	Algeria 2010	23.5	76.00	2.82
## 39	Angola 2010	109.6	57.60	6.22
## 40	Benin 2010	71.0	60.80	5.10
## 41	Botswana 2010	39.8	55.60	2.76
## 42	Burkina Faso 2010	69.7	59.00	5.87
## 43	Burundi 2010	63.8	60.40	6.30
## 44	Cameroon 2010	66.2	57.80	5.02
## 45	Cape Verde 2010	23.3	71.10	2.43
## 46	Central African Republic 2010	101.7	47.90	4.63
## 47	Chad 2010	93.6	55.80	6.60
## 48	Comoros 2010	63.1	67.70	4.92
## 49	Congo, Dem. Rep. 2010	84.8	58.40	6.25
## 50	Congo, Rep. 2010	42.2	60.40	5.07
## 51	Cote d'Ivoire 2010	76.9	56.60	4.91
## 52	Egypt 2010	24.3	70.10	2.88
## 53	Equatorial Guinea 2010	78.9	58.60	5.14
## 54	Eritrea 2010	39.4	60.10	4.97
## 55	Ethiopia 2010	50.8	62.10	4.90
## 56	Gabon 2010	42.8	63.00	4.21
## 57	Gambia 2010	51.7	66.50	5.80
## 58	Ghana 2010	50.2	62.90	4.05
## 59	Guinea 2010	71.2	57.90	5.17
## 60	Guinea-Bissau 2010	73.4	54.30	5.12
## 61	Kenya 2010	42.4	62.90	4.62
## 62	Lesotho 2010	75.2	46.40	3.21
## 63	Liberia 2010	65.2	60.80	5.02
## 64	Madagascar 2010	42.1	62.40	4.65
## 65	Malawi 2010	57.5	55.40	5.64
## 66	Mali 2010	82.9	59.20	6.84
## 67	Mauritania 2010	70.1	68.60	4.84
## 68	Mauritius 2010	13.3	73.40	1.52
## 69	Morocco 2010	28.5	73.70	2.58
## 70	Mozambique 2010	71.9	54.40	5.41
## 71	Namibia 2010	37.5	61.40	3.23
## 72	Niger 2010	66.1	59.20	7.58
## 73	Nigeria 2010	81.5	61.20	6.02

## 74	Rwanda	2010	43.8	65.10	4.84
## 75	Senegal	2010	46.7	64.20	5.05
## 76	Seychelles	2010	12.2	73.10	2.26
## 77	Sierra Leone	2010	107.0	55.00	4.94
## 78	South Africa	2010	38.2	54.90	2.47
## 79	Sudan	2010	53.3	66.10	4.64
## 80	Swaziland	2010	59.1	46.40	3.56
## 81	Tanzania	2010	42.4	61.40	5.43
## 82	Togo	2010	59.3	58.70	4.79
## 83	Tunisia	2010	14.9	77.10	2.04
## 84	Uganda	2010	49.5	57.80	6.16
## 85	Zambia	2010	52.9	53.10	5.81
## 86	Zimbabwe	2010	55.8	49.10	3.72
##	population	gdp	continent	region	dollars_per_day
## 1	14550033	19741305571	Africa	Northern Africa	3.7172265
## 2	2907769	831774871	Africa	Western Africa	0.7837057
## 3	693021	283867117	Africa	Southern Africa	1.1222144
## 4	5624597	795164207	Africa	Western Africa	0.3873223
## 5	3457113	524049198	Africa	Eastern Africa	0.4153035
## 6	6770967	3372153343	Africa	Middle Africa	1.3644693
## 7	1828710	647622869	Africa	Middle Africa	0.9702518
## 8	3644911	829387598	Africa	Middle Africa	0.6234157
## 9	20009902	6728080745	Africa	Middle Africa	0.9211988
## 10	1335090	939633199	Africa	Middle Africa	1.9282127
## 11	5241914	4619775632	Africa	Western Africa	2.4145607
## 12	34808599	20331718433	Africa	Northern Africa	1.6002752
## 13	590119	1722664256	Africa	Middle Africa	7.9977566
## 14	447283	247459869	Africa	Western Africa	1.5157568
## 15	8596977	2549677064	Africa	Western Africa	0.8125434
## 16	711828	104038537	Africa	Western Africa	0.4004297
## 17	11252466	3276361787	Africa	Eastern Africa	0.7977215
## 18	1032240	184783955	Africa	Southern Africa	0.4904454
## 19	1419728	1094083642	Africa	Western Africa	2.1113125
## 20	6576301	2807129955	Africa	Eastern Africa	1.1694670
## 21	4603739	549382768	Africa	Eastern Africa	0.3269426
## 22	5949043	1038617256	Africa	Western Africa	0.4783167
## 23	1148908	700627427	Africa	Western Africa	1.6707406
## 24	16039600	12097898528	Africa	Northern Africa	2.0664435
## 25	4497355	1343819364	Africa	Western Africa	0.8186360
## 26	56131844	19793025795	Africa	Western Africa	0.9660732
## 27	3754546	809941587	Africa	Eastern Africa	0.5910217
## 28	4217754	2266115562	Africa	Western Africa	1.4720005
## 29	52364	141888524	Africa	Eastern Africa	7.4237202
## 30	2514151	739785784	Africa	Western Africa	0.8061610
## 31	22502502	68558449204	Africa	Southern Africa	8.3471326
## 32	10232758	3901968151	Africa	Northern Africa	1.0447158
## 33	445844	257078586	Africa	Southern Africa	1.5797564
## 34	2115521	618863063	Africa	Western Africa	0.8014646
## 35	5060393	4688590613	Africa	Northern Africa	2.5384301
## 36	4185378	2384401746	Africa	Eastern Africa	1.5608166
## 37	5206311	2682438620	Africa	Eastern Africa	1.4115843
## 38	36036159	79164339611	Africa	Northern Africa	6.0186382
## 39	21219954	26125663270	Africa	Middle Africa	3.3731063
## 40	9509798	3336801340	Africa	Western Africa	0.9613161

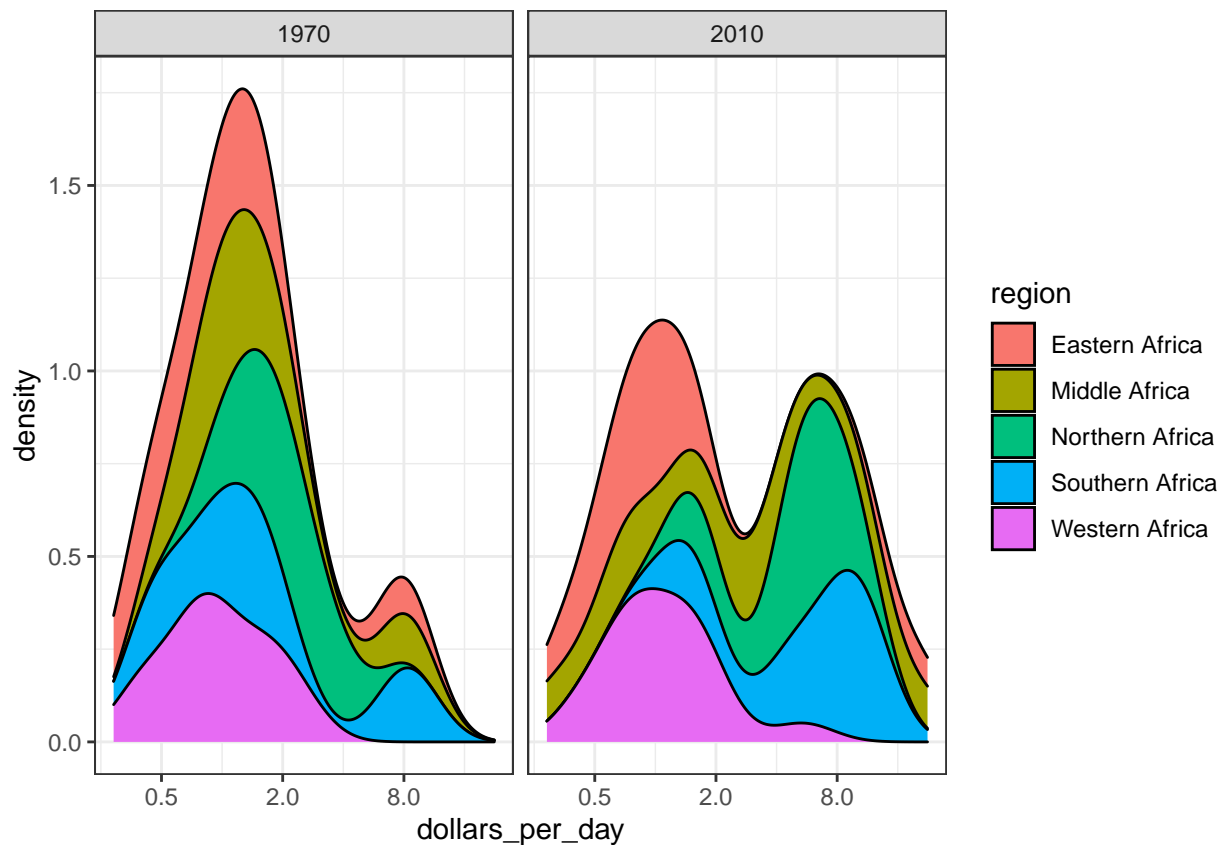
## 41	2047831	8408166868	Africa Southern Africa	11.2490111
## 42	15632066	4655655008	Africa Western Africa	0.8159650
## 43	9461117	1158914103	Africa Eastern Africa	0.3355954
## 44	20590666	13986616694	Africa Middle Africa	1.8610130
## 45	490379	971606715	Africa Western Africa	5.4283242
## 46	4444973	1054122016	Africa Middle Africa	0.6497240
## 47	11896380	3369354207	Africa Middle Africa	0.7759594
## 48	698695	247231031	Africa Eastern Africa	0.9694434
## 49	65938712	6961485000	Africa Middle Africa	0.2892468
## 50	4066078	5067059617	Africa Middle Africa	3.4141881
## 51	20131707	11603002049	Africa Western Africa	1.5790537
## 52	82040994	160258746162	Africa Northern Africa	5.3517764
## 53	728710	5979285835	Africa Middle Africa	22.4802803
## 54	4689664	771116883	Africa Eastern Africa	0.4504905
## 55	87561814	18291486355	Africa Eastern Africa	0.5723232
## 56	1541936	6343809583	Africa Middle Africa	11.2717391
## 57	1693002	1217357172	Africa Western Africa	1.9700066
## 58	24317734	8779397392	Africa Western Africa	0.9891194
## 59	11012406	5493989673	Africa Western Africa	1.3668245
## 60	1634196	244395463	Africa Western Africa	0.4097285
## 61	40328313	18988282813	Africa Eastern Africa	1.2899794
## 62	2010586	1076239050	Africa Southern Africa	1.4665377
## 63	3957990	1040653199	Africa Western Africa	0.7203416
## 64	21079532	5026822443	Africa Eastern Africa	0.6533407
## 65	14769824	2758392725	Africa Eastern Africa	0.5116676
## 66	15167286	4199858651	Africa Western Africa	0.7586368
## 67	3591400	2107593972	Africa Western Africa	1.6077936
## 68	1247951	6636426093	Africa Eastern Africa	14.5694737
## 69	32107739	59908047776	Africa Northern Africa	5.1119027
## 70	24321457	8972305823	Africa Eastern Africa	1.0106985
## 71	2193643	6155469329	Africa Southern Africa	7.6878050
## 72	16291990	2781188119	Africa Western Africa	0.4676957
## 73	159424742	85581744176	Africa Western Africa	1.4707286
## 74	10293669	3583713093	Africa Eastern Africa	0.9538282
## 75	12956791	6984284544	Africa Western Africa	1.4768337
## 76	93081	760361490	Africa Eastern Africa	22.3803157
## 77	5775902	1574302614	Africa Western Africa	0.7467505
## 78	51621594	187639624489	Africa Southern Africa	9.9586457
## 79	36114885	22819076998	Africa Northern Africa	1.7310873
## 80	1193148	1911603442	Africa Southern Africa	4.3894552
## 81	45648525	19965679449	Africa Eastern Africa	1.1982970
## 82	6390851	1595792895	Africa Western Africa	0.6841085
## 83	10639194	33161453137	Africa Northern Africa	8.5394905
## 84	33149417	12701095116	Africa Eastern Africa	1.0497174
## 85	13917439	5587389858	Africa Eastern Africa	1.0999091
## 86	13973897	4032423429	Africa Eastern Africa	0.7905980
##	group			
## 1	Northern Africa			
## 2	Sub-Saharan Africa			
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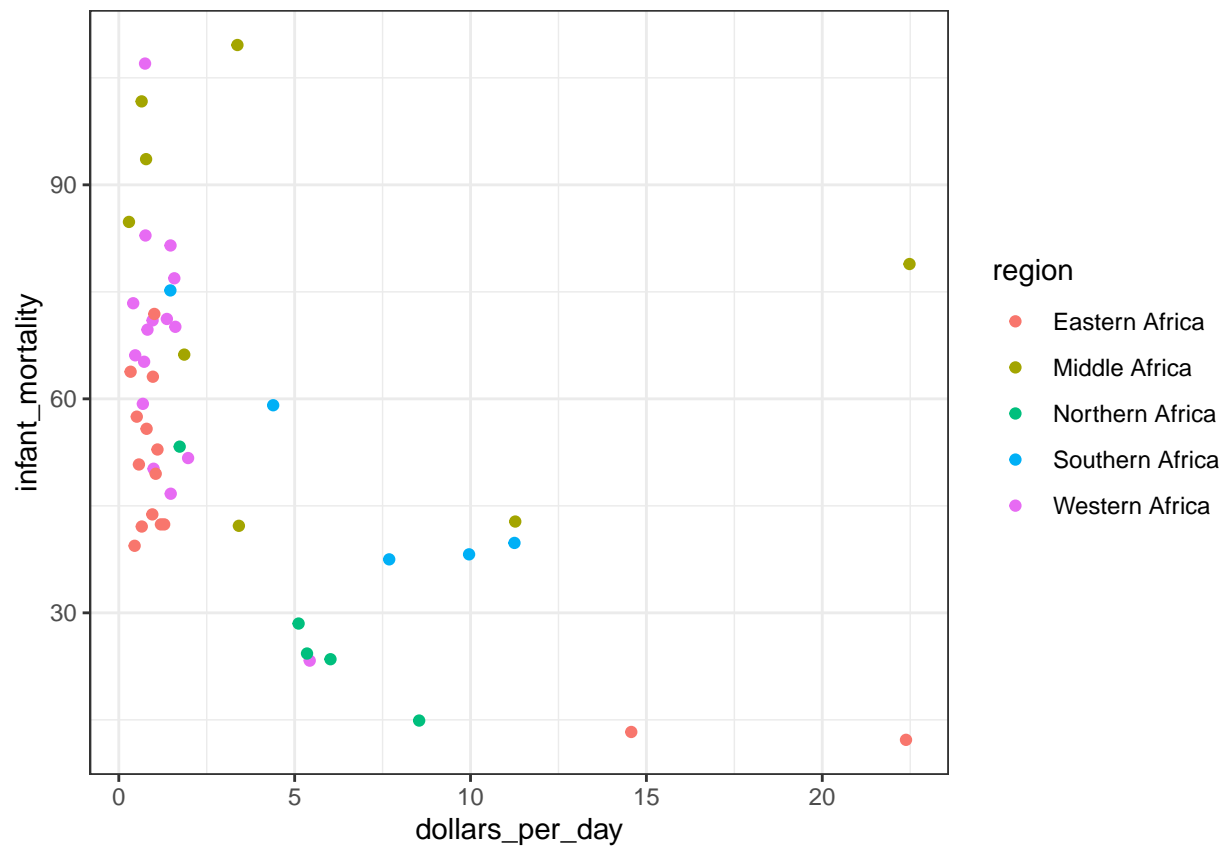
```
daydollars %>% ggplot(aes(dollars_per_day, fill = region)) +
  scale_x_continuous(trans = "log2") + geom_density(bw = 0.5, position = "stack") + facet_grid(.~year)
```

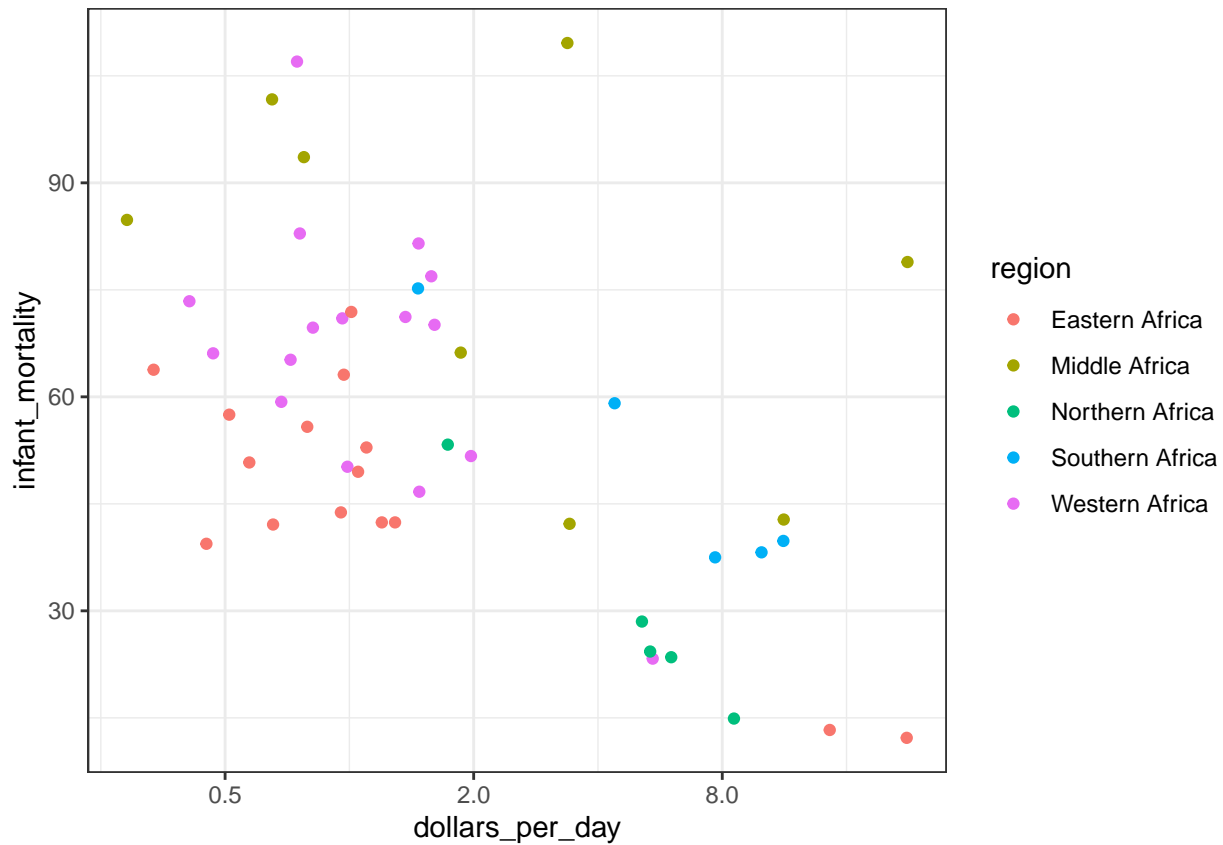




11. We are going to continue looking at patterns in the gapminder dataset by plotting infant mortality rates versus dollars per day for African countries.

```
gapminder_Africa_2010 <- gapminder %>%
mutate(dollars_per_day = gdp/population/365) %>% filter(continent == "Africa" & year == 2010 & !is.na(g
# now make the scatter plot
gapminder_Africa_2010 %>% ggplot(aes(dollars_per_day, infant_mortality, color = region)) + geom_point()
```



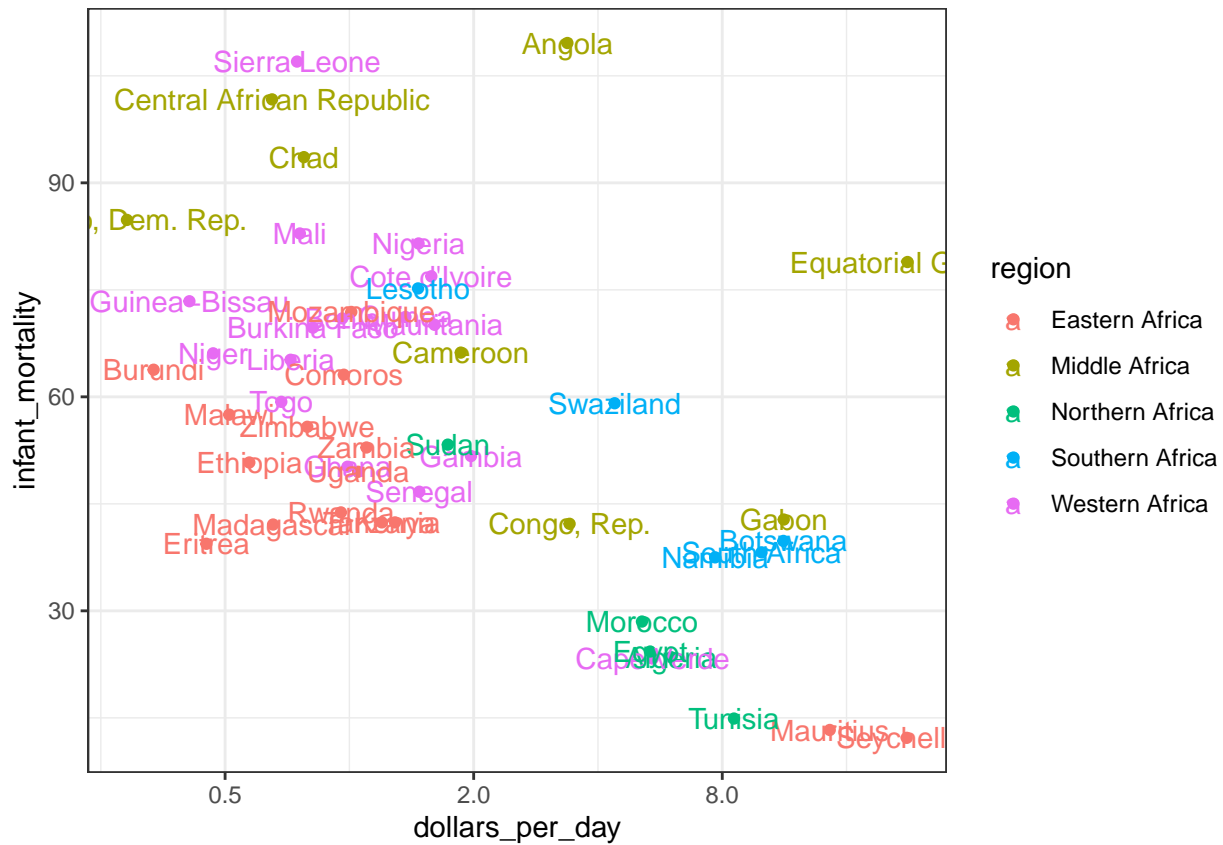


13. Note that there is a large variation in infant mortality and dollars per day among African countries.

As an example, one country has infant mortality rates of less than 20 per 1000 and dollars per day of 16, while another country has infant mortality rates over 10% and dollars per day of about 1.

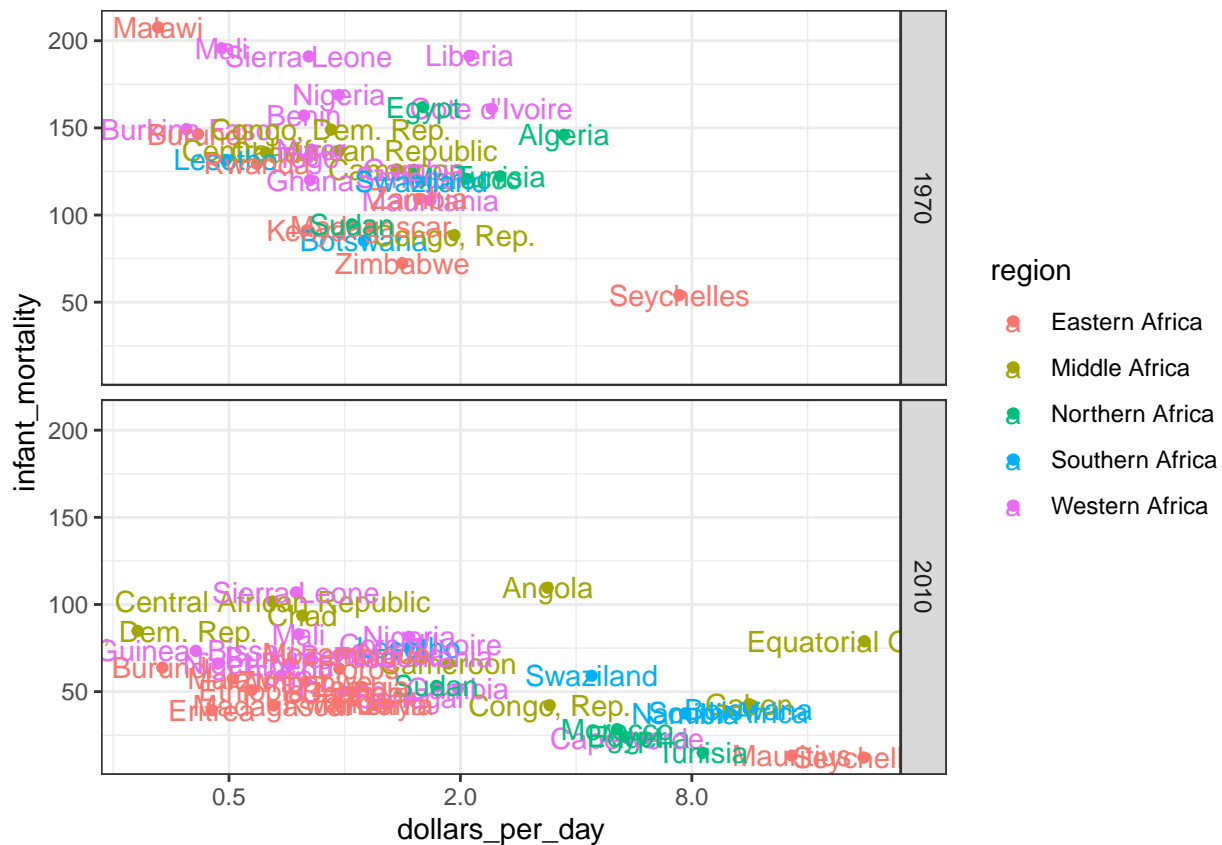
In this exercise, we will remake the plot from Exercise 12 with country names instead of points so we can identify which countries are which.

```
gapminder_Africa_2010 %>% ggplot(aes(dollars_per_day, infant_mortality, color = region, label = country))
```



14. Now we are going to look at changes in the infant mortality and dollars per day patterns African countries between 1970 and 2010.

```
gapminder_Africa_1970_2019 <- gapminder %>% mutate(dollars_per_day = gdp/population/365) %>% filter(cont
gapminder_Africa_1970_2019 %>% ggplot(aes(dollars_per_day, infant_mortality, color = region, label = co
```



## Section 5 Overview

Section 5 covers some general principles that can serve as guides for effective data visualization.

After completing Section 5, you will:

- understand basic principles of effective data visualization.
- understand the importance of keeping your goal in mind when deciding on a visualization approach.
- understand principles for encoding data, including position, aligned lengths, angles, area, brightness, and color hue.
- know when to include the number zero in visualizations.
- be able to use techniques to ease comparisons, such as using common axes, putting visual cues to be compared adjacent to one another, and using color effectively.

## Introduction to Data Visualization Principles

The textbook for this section is available [here](#)

### Key points

- We aim to provide some general guidelines for effective data visualization.
- We show examples of plot styles to avoid, discuss how to improve them, and use these examples to explain research-based principles for effective visualization.
- When choosing a visualization approach, keep your goal and audience in mind.

## Encoding Data Using Visual Cues

The textbook for this section is available [here](#)

You can learn more about barplots in the textbook section on [barplots](#)

### Key points

- Visual cues for encoding data include position, length, angle, area, brightness and color hue.
- Position and length are the preferred way to display quantities, followed by angles, which are preferred over area. Brightness and color are even harder to quantify but can sometimes be useful.
- Pie charts represent visual cues as both angles and area, while donut charts use only area. Humans are not good at visually quantifying angles and are even worse at quantifying area. Therefore pie and donut charts should be avoided - use a bar plot instead. If you must make a pie chart, include percentages as labels.
- Bar plots represent visual cues as position and length. Humans are good at visually quantifying linear measures, making bar plots a strong alternative to pie or donut charts.

## Know When to Include Zero

The textbook for this section is available [here](#)

### Key points

- When using bar plots, always start at 0. It is deceptive not to start at 0 because bar plots imply length is proportional to the quantity displayed. Cutting off the y-axis can make differences look bigger than they actually are.
- When using position rather than length, it is not necessary to include 0 (scatterplot, dot plot, boxplot).

## Do Not Distort Quantities

The textbook for this section is available [here](#)

### Key points

- Make sure your visualizations encode the correct quantities.
- For example, if you are using a plot that relies on circle area, make sure the area (rather than the radius) is proportional to the quantity.

## Order by a Meaningful Value

The textbook for this section is available [here](#)

### Key points

- It is easiest to visually extract information from a plot when categories are ordered by a meaningful value. The exact value on which to order will depend on your data and the message you wish to convey with your plot.
- The default ordering for categories is alphabetical if the categories are strings or by factor level if factors. However, we rarely want alphabetical order.

## Assessment - Data Visualization Principles, Part 1

1: Pie charts are appropriate:

- ☐ A. When we want to display percentages.
- ☐ B. When ggplot2 is not available.
- ☐ C. When I am in a bakery.
- ☒ D. Never. Barplots and tables are always better.

2. What is the problem with this plot?

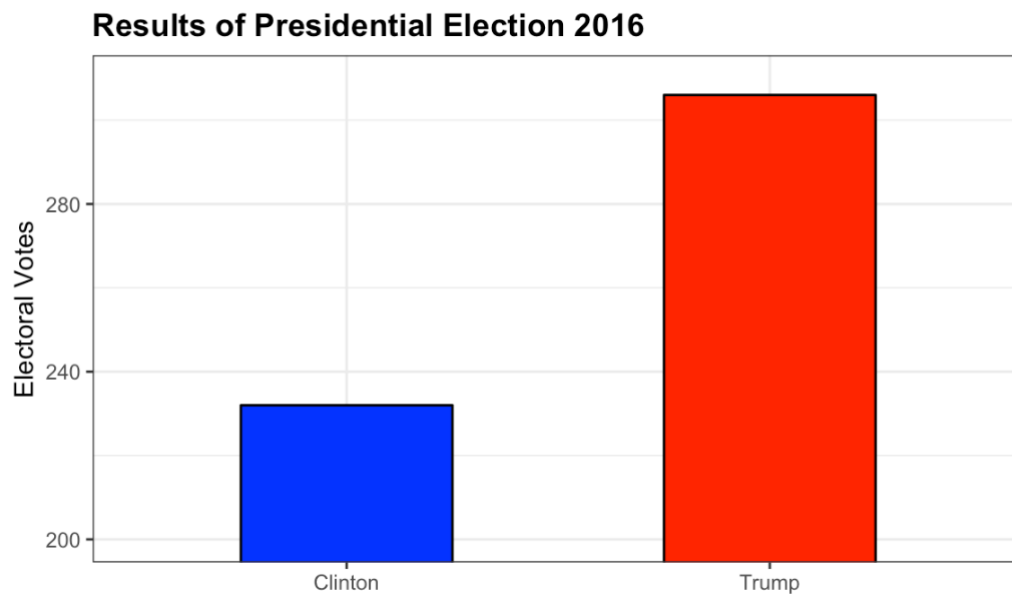


Figure 8: Result of Presidential Election 2016

- ☐ A. The values are wrong. The final vote was 306 to 232.
- ☒ B. The axis does not start at 0. Judging by the length, it appears Trump received 3 times as many votes when in fact it was about 30% more.
- ☐ C. The colors should be the same.
- ☐ D. Percentages should be shown as a pie chart.

3. Take a look at the following two plots. They show the same information: rates of measles by state in the United States for 1928.

- ☐ A. Both plots provide the same information, so they are equally good.
- ☐ B. The plot on the left is better because it orders the states alphabetically.
- ☒ C. The plot on the right is better because it orders the states by disease rate so we can quickly see the states with highest and lowest rates.
- ☐ D. Both plots should be pie charts instead.

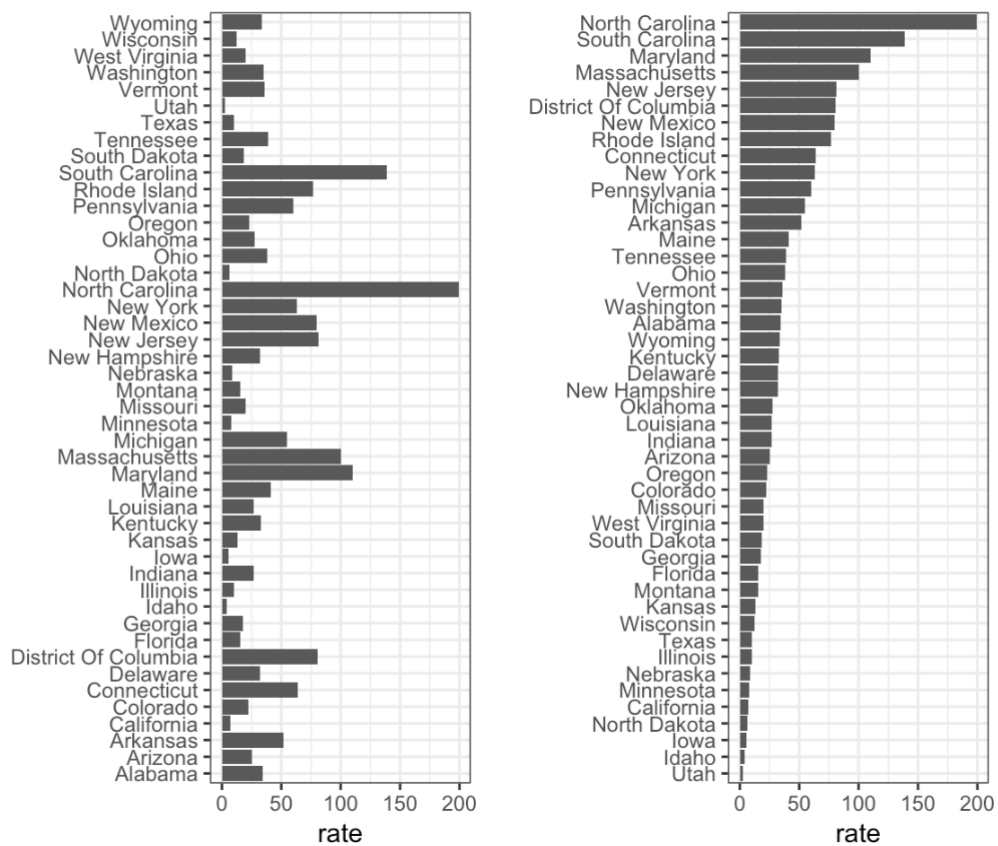


Figure 9: Rates of measles in the US for 1928



## Show the Data

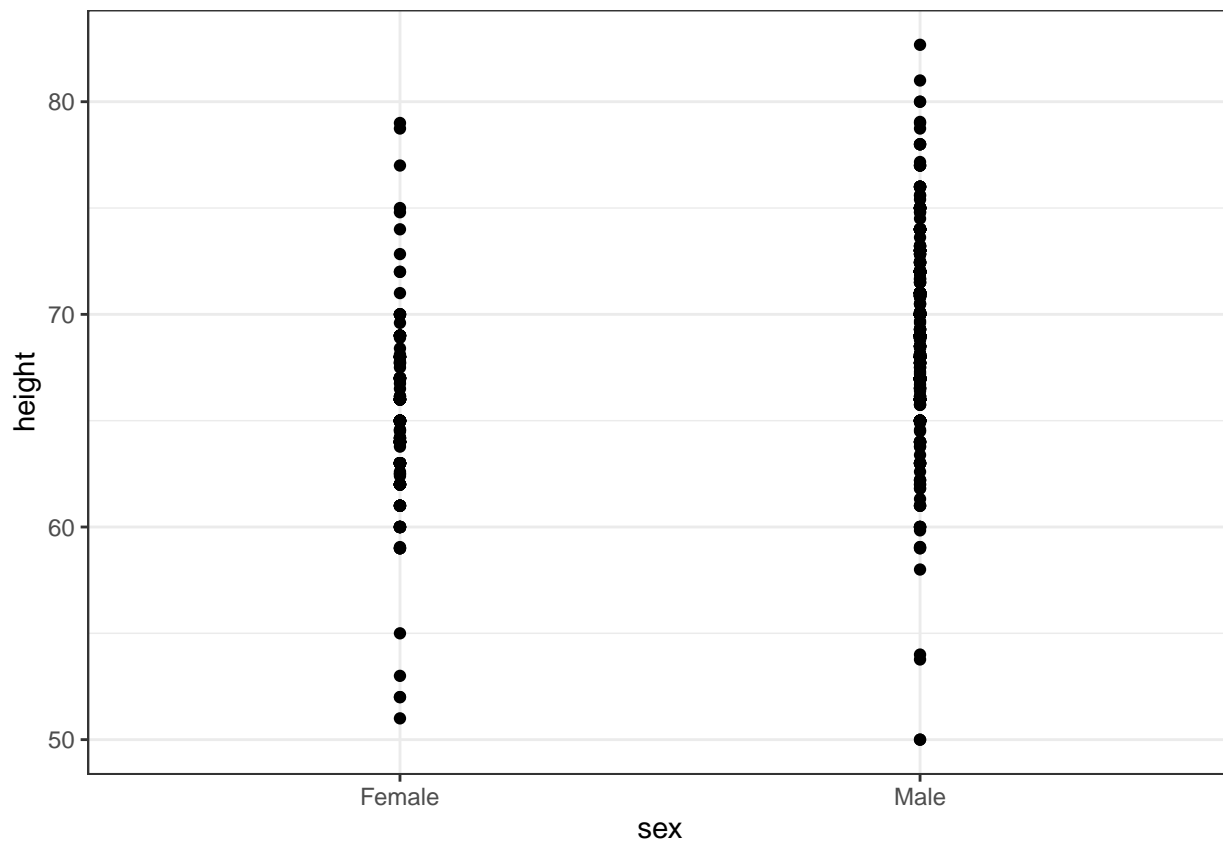
The textbook for this section is available [here](#)

### Key points

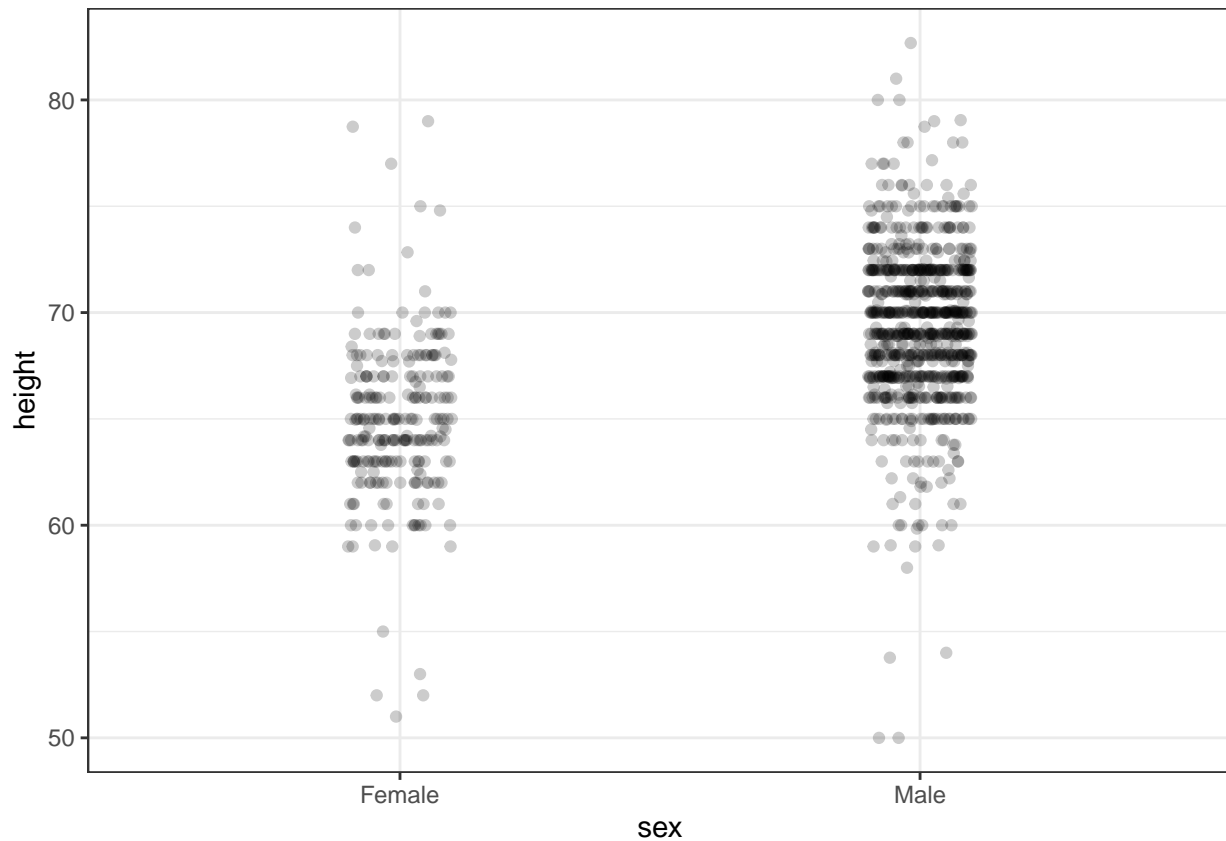
- A dynamite plot - a bar graph of group averages with error bars denoting standard errors - provides almost no information about a distribution.
- By showing the data, you provide viewers extra information about distributions. Jitter is adding a small random shift to each point in order to minimize the number of overlapping points. To add jitter, use the `geom_jitter` geometry instead of `geom_point`.
- Alpha blending is making points somewhat transparent, helping visualize the density of overlapping points. Add an `alpha` argument to the geometry.

### Code

```
# dot plot showing the data
heights %>% ggplot(aes(sex, height)) + geom_point()
```



```
# jittered, alpha blended point plot
heights %>% ggplot(aes(sex, height)) + geom_jitter(width = 0.1, alpha = 0.2)
```



## Ease Comparisons: Use Common Axes

The textbook for this section is available [here](#)

### Key points

- Ease comparisons by keeping axes the same when comparing data across multiple plots.
- Align plots vertically to see horizontal changes. Align plots horizontally to see vertical changes.
- Bar plots are useful for showing one number but not useful for showing distributions.

## Consider Transformations

The textbook for this section is available [here](#)

### Key points

- Use transformations when warranted to ease visual interpretation.
- The log transformation is useful for data with multiplicative changes. The logistic transformation is useful for fold changes in odds. The square root transformation is useful for count data.
- We learned how to apply transformations earlier in the course.

## Ease Comparisons: Compared Visual Cues Should Be Adjacent

The textbook for this section is available:

- Compared visual cues being adjacent
- Using color
- Considering the color blind

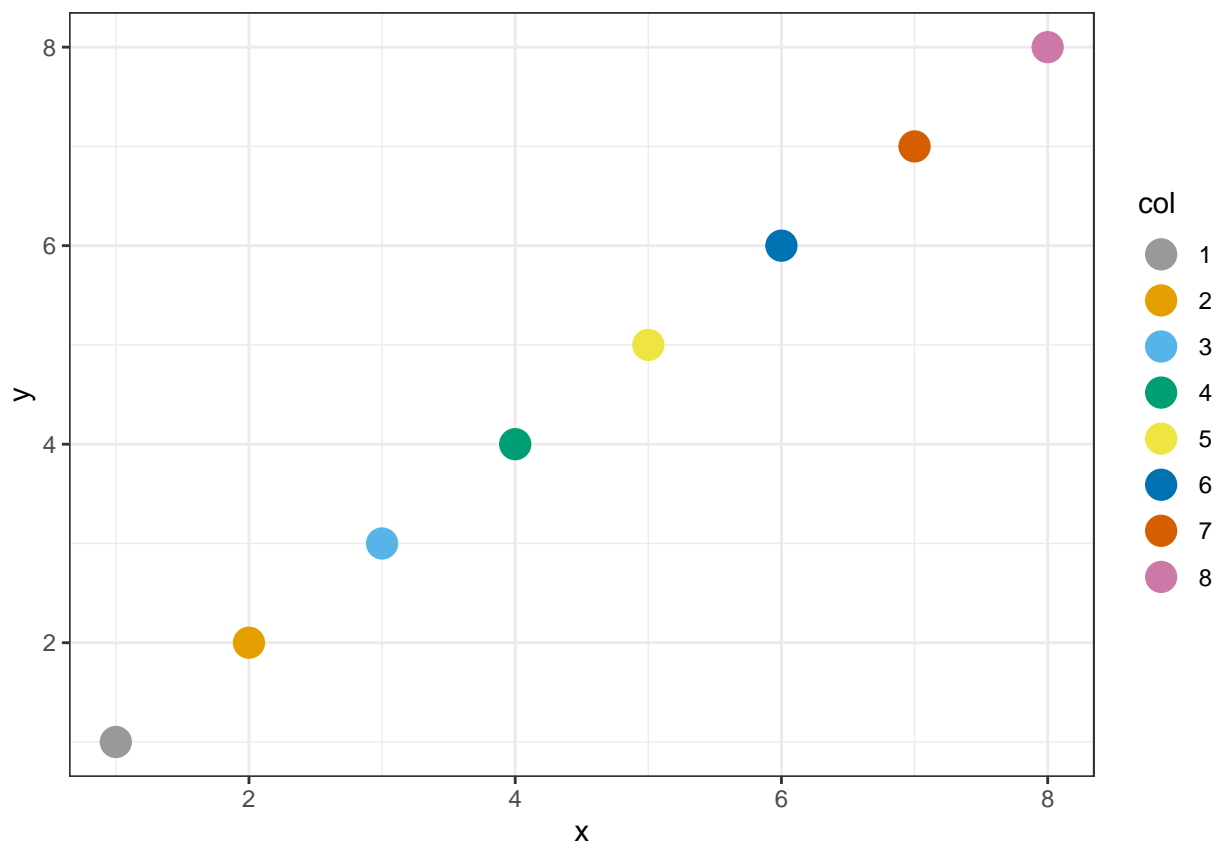
### Key points

- When two groups are to be compared, it is optimal to place them adjacent in the plot.
- Use color to encode groups to be compared.
- Consider using a color blind friendly palette.

### Code

```
color_blind_friendly_cols <- c("#999999", "#E69F00", "#56B4E9", "#009E73", "#F0E442", "#0072B2", "#D55E00", "#D55E00")

p1 <- data.frame(x = 1:8, y = 1:8, col = as.character(1:8)) %>%
  ggplot(aes(x, y, color = col)) +
  geom_point(size = 5)
p1 + scale_color_manual(values = color_blind_friendly_cols)
```



## Assessment - Data Visualization Principles, Part 2

1. To make the plot on the right in the exercise from the last set of assessments, we had to reorder the levels of the states' variables.

```

dat <- us_contagious_diseases %>%
  filter(year == 1967 & disease=="Measles" & !is.na(population)) %>% mutate(rate = count / population * 10000)
state <- dat$state
rate <- dat$count/(dat$population/10000)*(52/dat$weeks_reporting)
state = reorder(state, rate)
levels(state)

```

```

## [1] "Georgia"           "District Of Columbia" "Connecticut"
## [4] "Minnesota"         "Louisiana"           "New Hampshire"
## [7] "Maryland"          "Kansas"               "New York"
## [10] "Pennsylvania"      "Rhode Island"        "Massachusetts"
## [13] "Missouri"          "New Jersey"          "South Dakota"
## [16] "Vermont"           "Delaware"            "Ohio"
## [19] "Illinois"          "Michigan"             "Indiana"
## [22] "North Carolina"    "South Carolina"      "Hawaii"
## [25] "Maine"             "California"           "Florida"
## [28] "Iowa"              "Mississippi"          "Oklahoma"
## [31] "Nebraska"          "Utah"                 "Alabama"
## [34] "Kentucky"          "Wisconsin"            "Montana"
## [37] "Virginia"          "Alaska"               "Tennessee"
## [40] "Idaho"             "New Mexico"           "Arizona"
## [43] "Nevada"            "Arkansas"             "Wyoming"
## [46] "Colorado"          "West Virginia"        "Oregon"
## [49] "Texas"             "North Dakota"         "Washington"

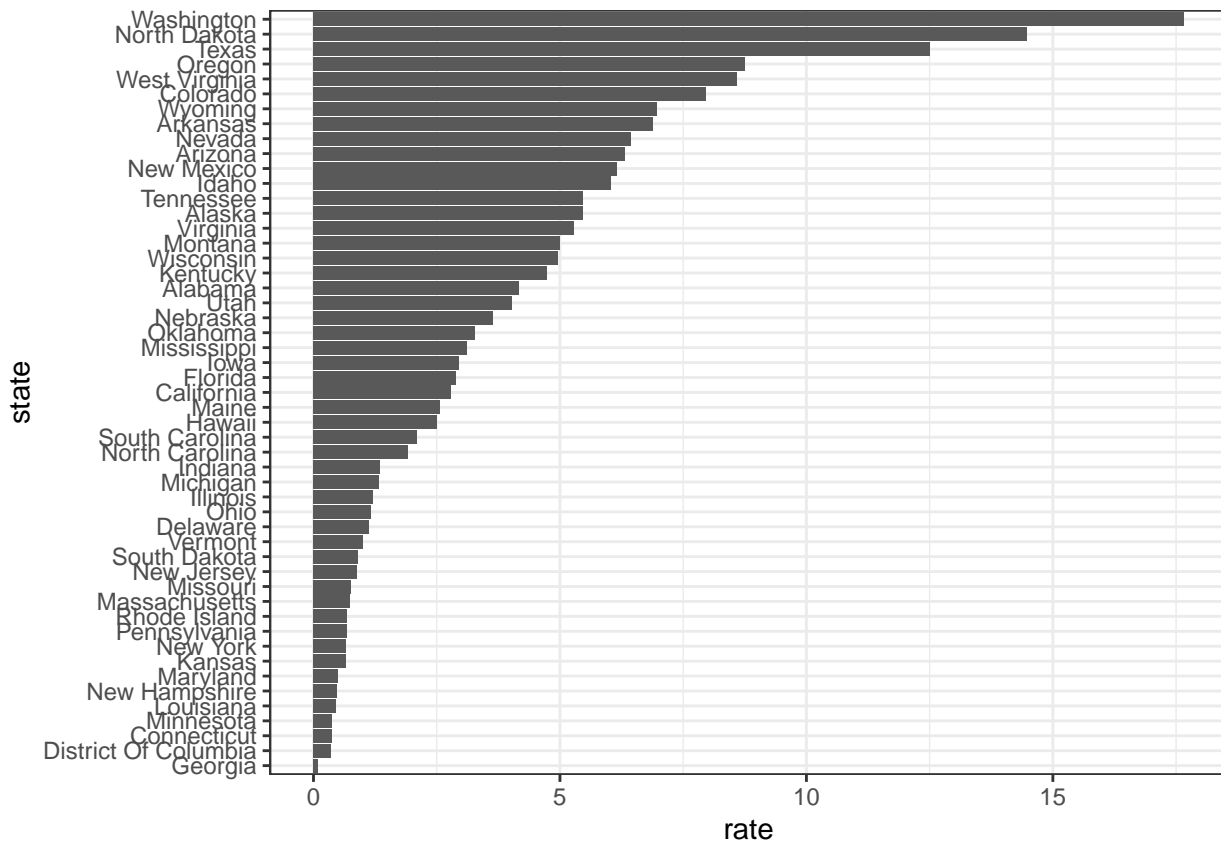
```

2. Now we are going to customize this plot a little more by creating a rate variable and reordering by that variable instead.

```

dat <- us_contagious_diseases %>% filter(year == 1967 & disease=="Measles" & count>0 & !is.na(population))
  mutate(rate = count / population * 10000 * 52 / weeks_reporting)
dat %>% mutate(state = reorder(state, rate)) %>% ggplot(aes(state, rate)) +
  geom_bar(stat="identity") +
  coord_flip()

```



3. Say we are interested in comparing gun homicide rates across regions of the US.

We see this plot and decide to move to a state in the western region.

What is the main problem with this interpretation?

```
library(dplyr)
library(ggplot2)
library(dslabs)
data("murders")
murders %>% mutate(rate = total/population*100000) %>%
  group_by(region) %>%
  summarize(avg = mean(rate)) %>%
  mutate(region = factor(region)) %>%
  ggplot(aes(region, avg)) +
  geom_bar(stat="identity") +
  ylab("Murder Rate Average")
```

- ☐ A. The categories are ordered alphabetically.
- ☐ B. The graph does not show standard errors.
- ☒ C. It does not show all the data. We do not see the variability within a region and it's possible that the safest states are not in the West.
- ☐ D. The Northeast has the lowest average.

4. To further investigate whether moving to the western region is a wise decision, let's make a box plot of murder rates by region, showing all points.

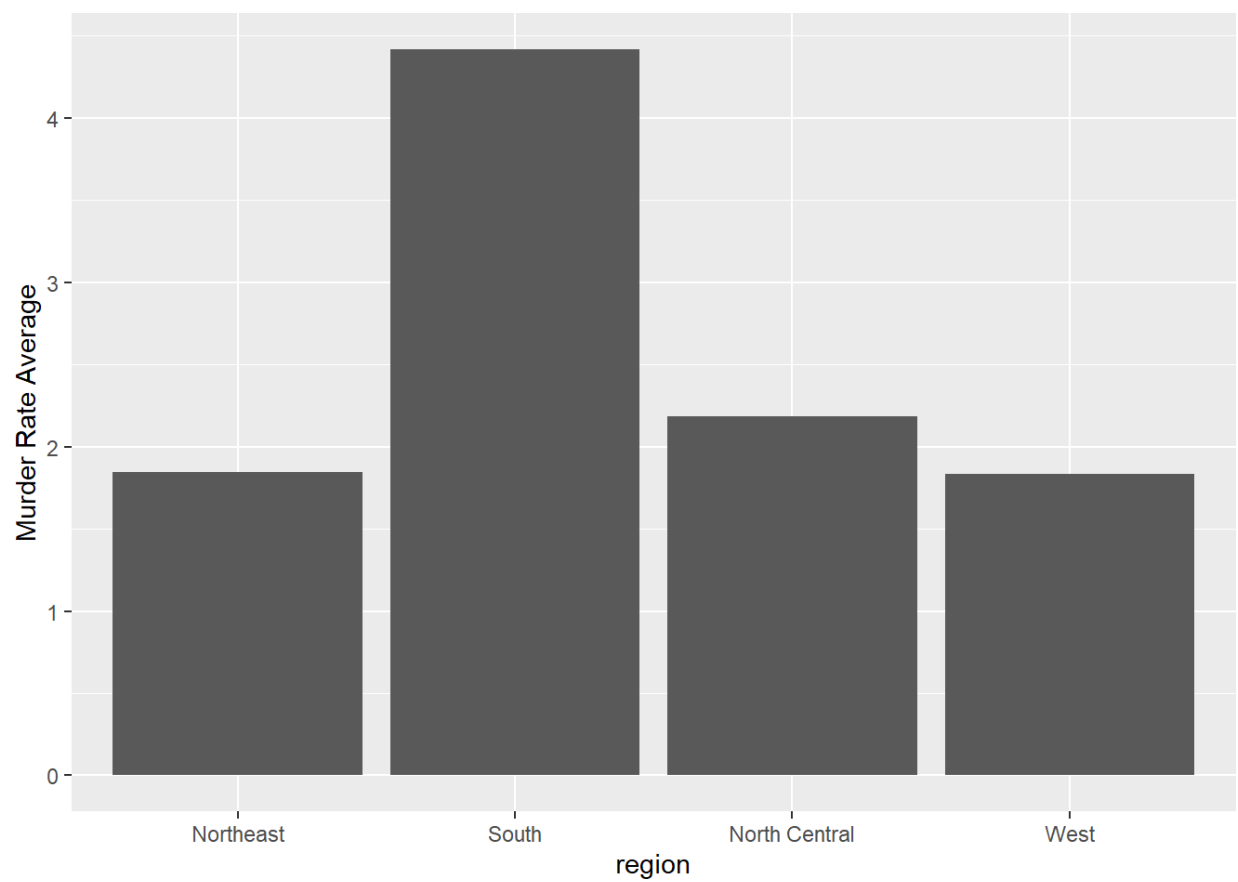
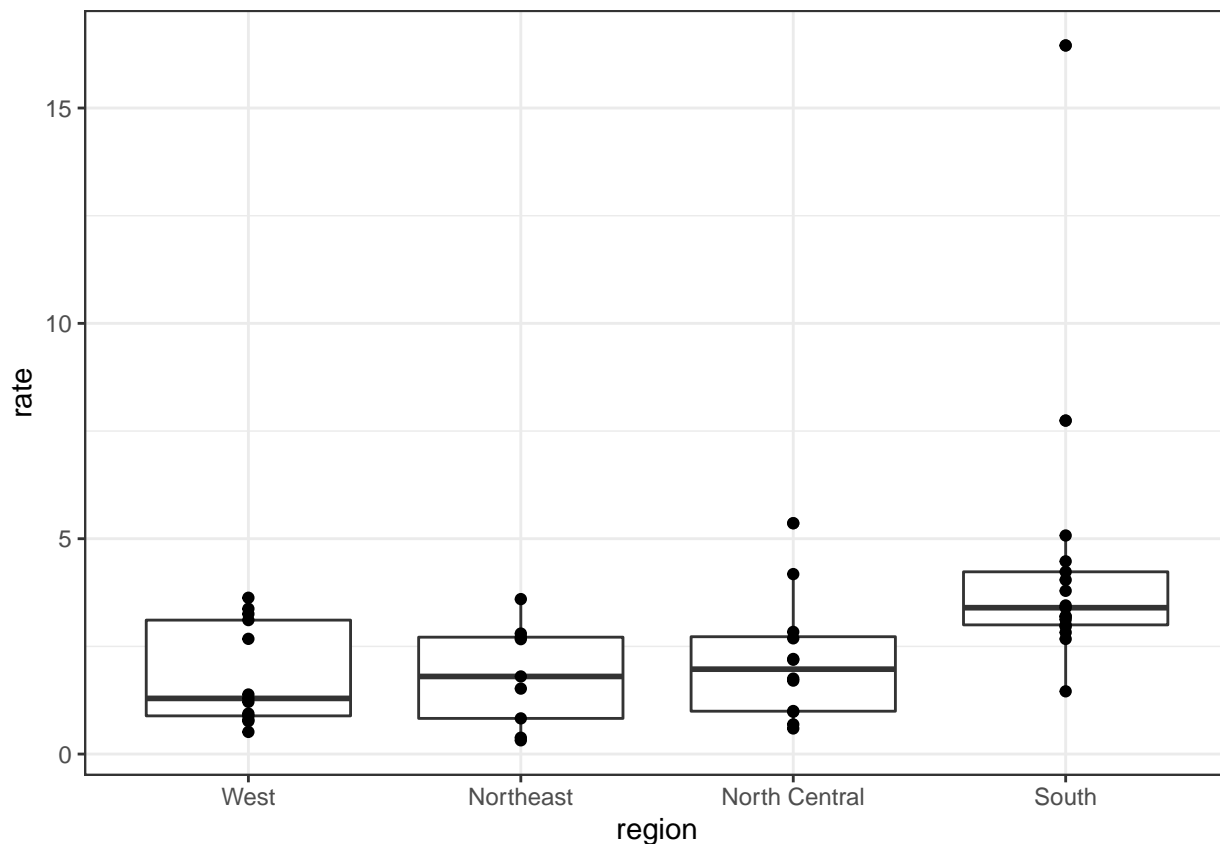


Figure 10: Rates of measles in the US for 1928

```
murders %>% mutate(rate = total/population*100000) %>% mutate(region = reorder(region, rate, FUN = median))
```



## Slope Charts

The textbook for this section is available [here](#)

### Key points

- Consider using a slope chart or Bland-Altman plot when comparing one variable at two different time points, especially for a small number of observations.
- Slope charts use angle to encode change. Use `geom_line` to create slope charts. It is useful when comparing a small number of observations.
- The Bland-Altman plot (Tukey mean difference plot, MA plot) graphs the difference between conditions on the y-axis and the mean between conditions on the x-axis. It is more appropriate for large numbers of observations than slope charts.

*Code: Slope chart*

```
west <- c("Western Europe", "Northern Europe", "Southern Europe", "Northern America", "Australia and New Zealand")

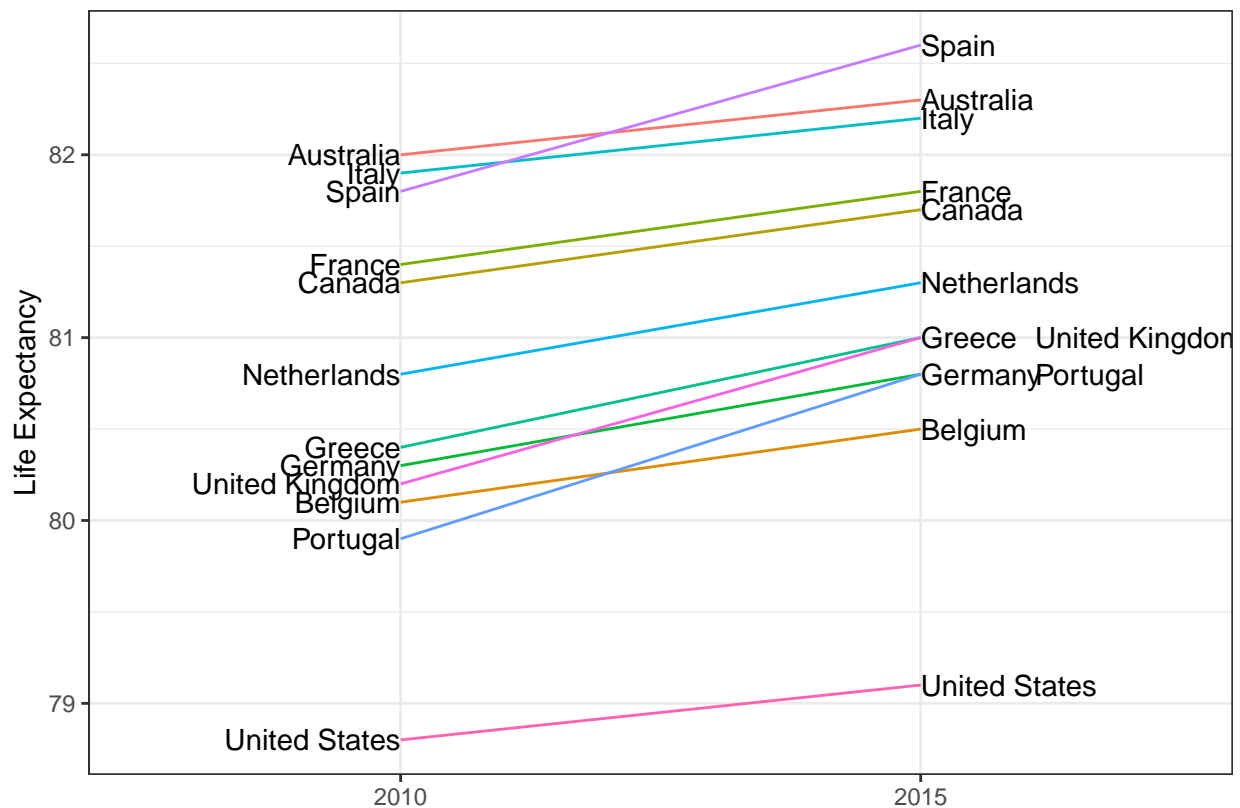
dat <- gapminder %>%
  filter(year %in% c(2010, 2015) & region %in% west & !is.na(life_expectancy) & population > 10^7)

dat %>%
  mutate(location = ifelse(year == 2010, 1, 2),
```

```

location = ifelse(year == 2015 & country %in% c("United Kingdom", "Portugal"), location + 10, location)
hjust = ifelse(year == 2010, 1, 0)) %>%
mutate(year = as.factor(year)) %>%
ggplot(aes(year, life_expectancy, group = country)) +
geom_line(aes(color = country), show.legend = FALSE) +
geom_text(aes(x = location, label = country, hjust = hjust), show.legend = FALSE) +
xlab("") +
ylab("Life Expectancy")

```



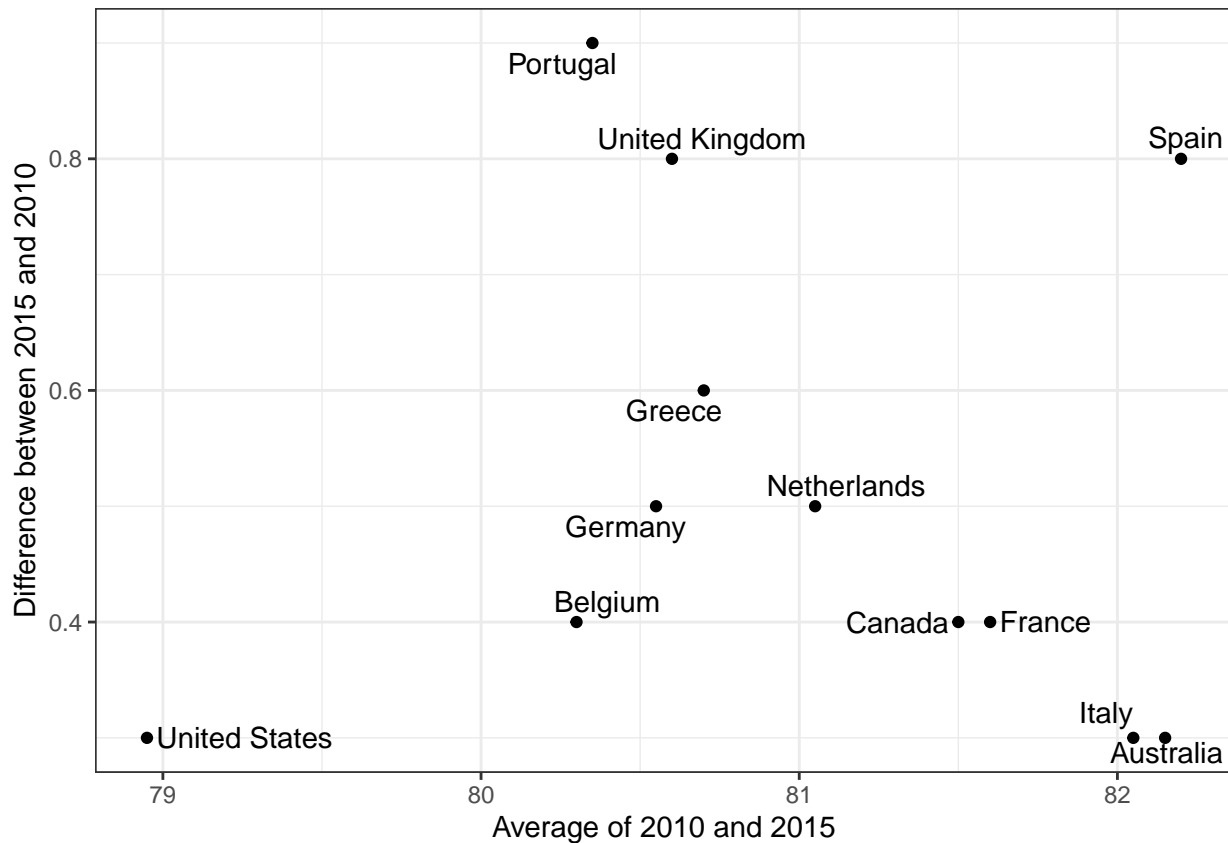
Code: Bland-Altman plot

```

dat %>%
mutate(year = paste0("life_expectancy_", year)) %>%
select(country, year, life_expectancy) %>% spread(year, life_expectancy) %>%
mutate(average = (life_expectancy_2015 + life_expectancy_2010)/2,
difference = life_expectancy_2015 - life_expectancy_2010) %>%
ggplot(aes(average, difference, label = country)) +
geom_point() +
geom_text_repel() +
geom_abline(lty = 2) +
xlab("Average of 2010 and 2015") +
ylab("Difference between 2015 and 2010")

```





## Encoding a Third Variable

The textbook for this section is available [here](#)

### Key points

- Encode a categorical third variable on a scatterplot using color hue or shape. Use the shape argument to control shape.
- Encode a continuous third variable on a using color intensity or size.

## Case Study: Vaccines

The textbook for this section is available [here](#). Information on color palettes can be found in the textbook section [on encoding a third variable](#)

### Key points

- Vaccines save millions of lives, but misinformation has led some to question the safety of vaccines. The data support vaccines as safe and effective. We visualize data about measles incidence in order to demonstrate the impact of vaccination programs on disease rate.
- The **RColorBrewer** package offers several color palettes. Sequential color palettes are best suited for data that span from high to low. Diverging color palettes are best suited for data that are centered and diverge towards high or low values.
- The **geom\_tile** geometry creates a grid of colored tiles.
- Position and length are stronger cues than color for numeric values, but color can be appropriate sometimes.

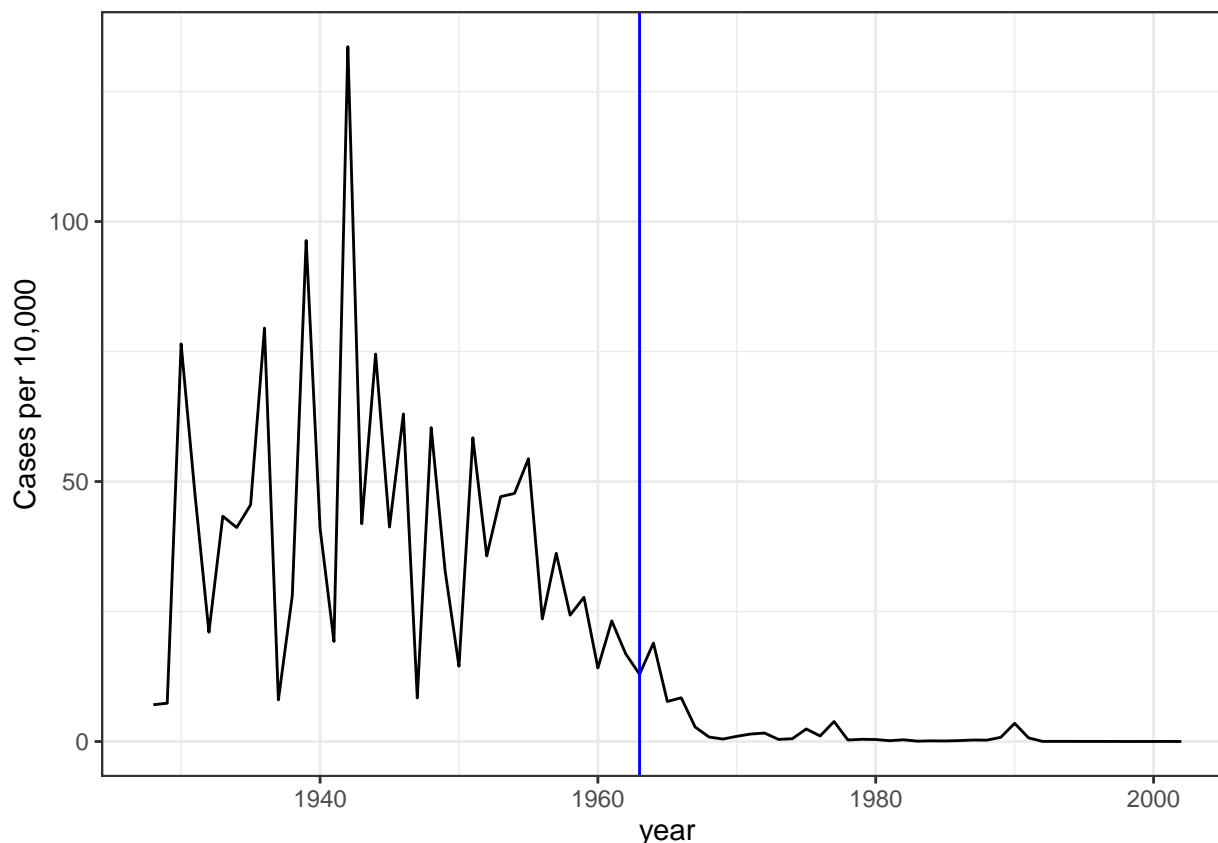
Code: Tile plot of measles rate by year and state

```
# import data and inspect
str(us_contagious_diseases)
```

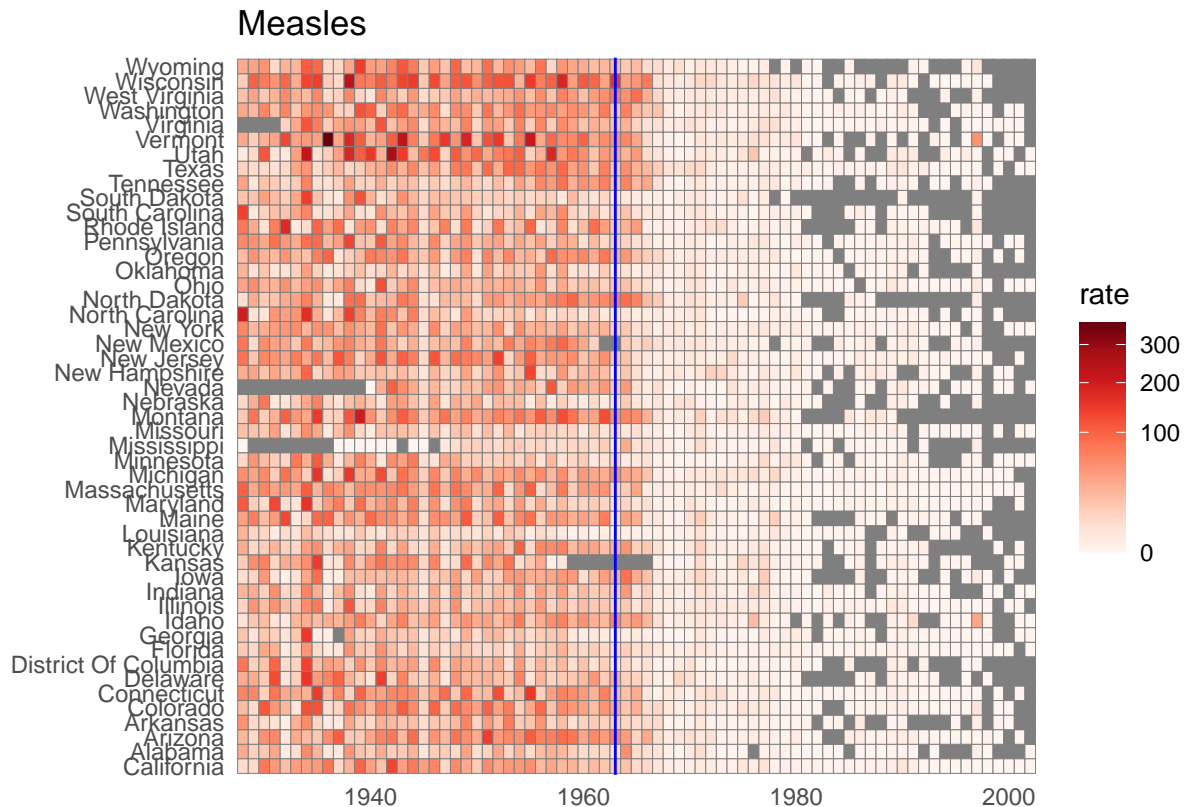
```
## 'data.frame': 16065 obs. of 6 variables:
## $ disease      : Factor w/ 7 levels "Hepatitis A",...: 1 1 1 1 1 1 1 1 1 ...
## $ state        : Factor w/ 51 levels "Alabama","Alaska",...: 1 1 1 1 1 1 1 1 1 ...
## $ year         : num 1966 1967 1968 1969 1970 ...
## $ weeks_reporting: num 50 49 52 49 51 51 45 45 45 46 ...
## $ count        : num 321 291 314 380 413 378 342 467 244 286 ...
## $ population   : num 3345787 3364130 3386068 3412450 3444165 ...
```

```
# assign dat to the per 10,000 rate of measles, removing Alaska and Hawaii and adjusting for weeks reported
the_disease <- "Measles"
dat <- us_contagious_diseases %>%
  filter(!state %in% c("Hawaii", "Alaska") & disease == the_disease) %>%
  mutate(rate = count / population * 10000 * 52/weeks_reporting) %>%
  mutate(state = reorder(state, rate))
```

```
# plot disease rates per year in California
dat %>% filter(state == "California" & !is.na(rate)) %>%
  ggplot(aes(year, rate)) +
  geom_line() +
  ylab("Cases per 10,000") +
  geom_vline(xintercept=1963, col = "blue")
```



```
# tile plot of disease rate by state and year
dat %>% ggplot(aes(year, state, fill=rate)) +
  geom_tile(color = "grey50") +
  scale_x_continuous(expand = c(0,0)) +
  scale_fill_gradientn(colors = RColorBrewer::brewer.pal(9, "Reds"), trans = "sqrt") +
  geom_vline(xintercept = 1963, col = "blue") +
  theme_minimal() + theme(panel.grid = element_blank()) +
  ggtitle(the_disease) +
  ylab("") +
  xlab("")
```



Code: Line plot of measles rate by year and state

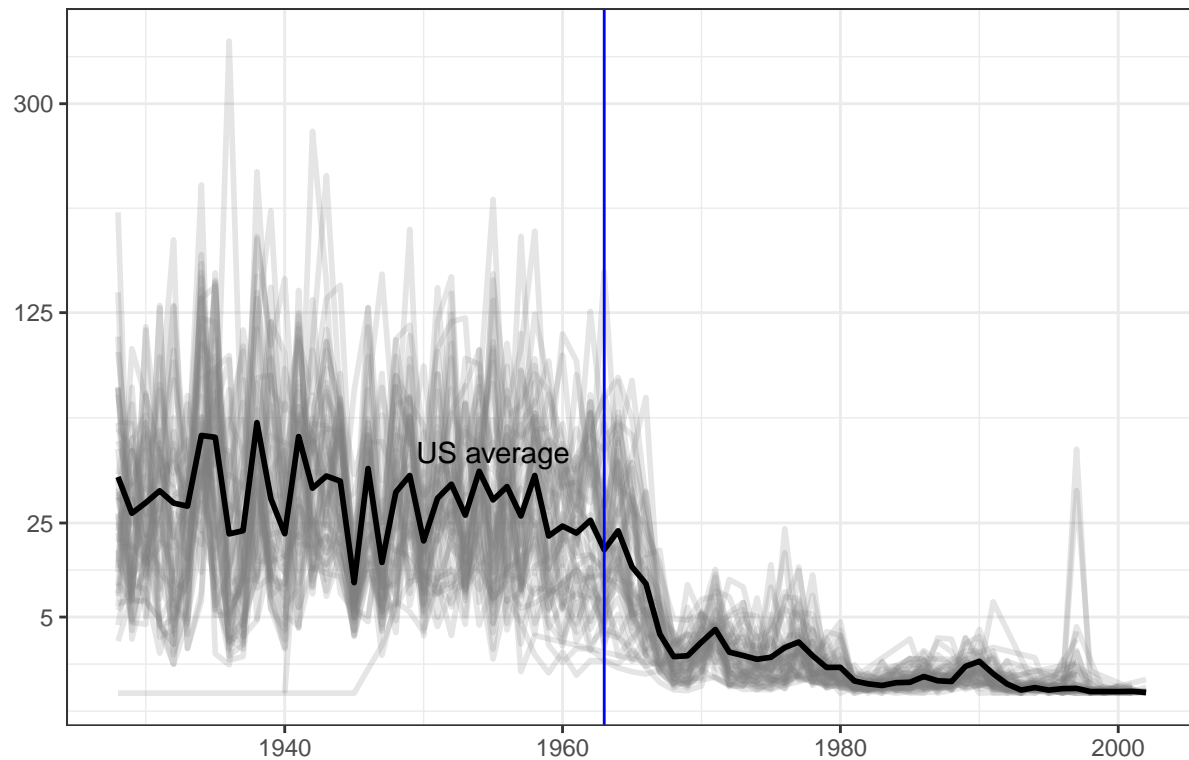
```
# compute US average measles rate by year
avg <- us_contagious_diseases %>%
  filter(disease == the_disease) %>% group_by(year) %>%
  summarize(us_rate = sum(count, na.rm = TRUE)/sum(population, na.rm = TRUE)*10000)
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
# make line plot of measles rate by year by state
dat %>%
  filter(!is.na(rate)) %>%
  ggplot() +
  geom_line(aes(year, rate, group = state), color = "grey50",
    show.legend = FALSE, alpha = 0.2, size = 1) +
  geom_line(mapping = aes(year, us_rate), data = avg, size = 1, col = "black") +
```

```
scale_y_continuous(trans = "sqrt", breaks = c(5, 25, 125, 300)) +
ggtitle("Cases per 10,000 by state") +
xlab("") +
ylab("") +
geom_text(data = data.frame(x = 1955, y = 50),
  mapping = aes(x, y, label = "US average"), color = "black") +
geom_vline(xintercept = 1963, col = "blue")
```

## Cases per 10,000 by state



## Avoid Pseudo and Gratuitous 3D Plots

The textbook for this section is available [here](#)

### Key point

In general, pseudo-3D plots and gratuitous 3D plots only add confusion. Use regular 2D plots instead.

## Avoid Too Many Significant Digits

The textbook for this section is available [here](#)

### Key points

- In tables, avoid using too many significant digits. Too many digits can distract from the meaning of your data.
- Reduce the number of significant digits globally by setting an option. For example, `options(digits = 3)` will cause all future computations that session to have 3 significant digits.
- Reduce the number of digits locally using `round` or `signif`.

## Assessment - Data Visualization Principles, Part 3

1. The sample code given creates a tile plot showing the rate of measles cases per population. We are going to modify the tile plot to look at smallpox cases instead.

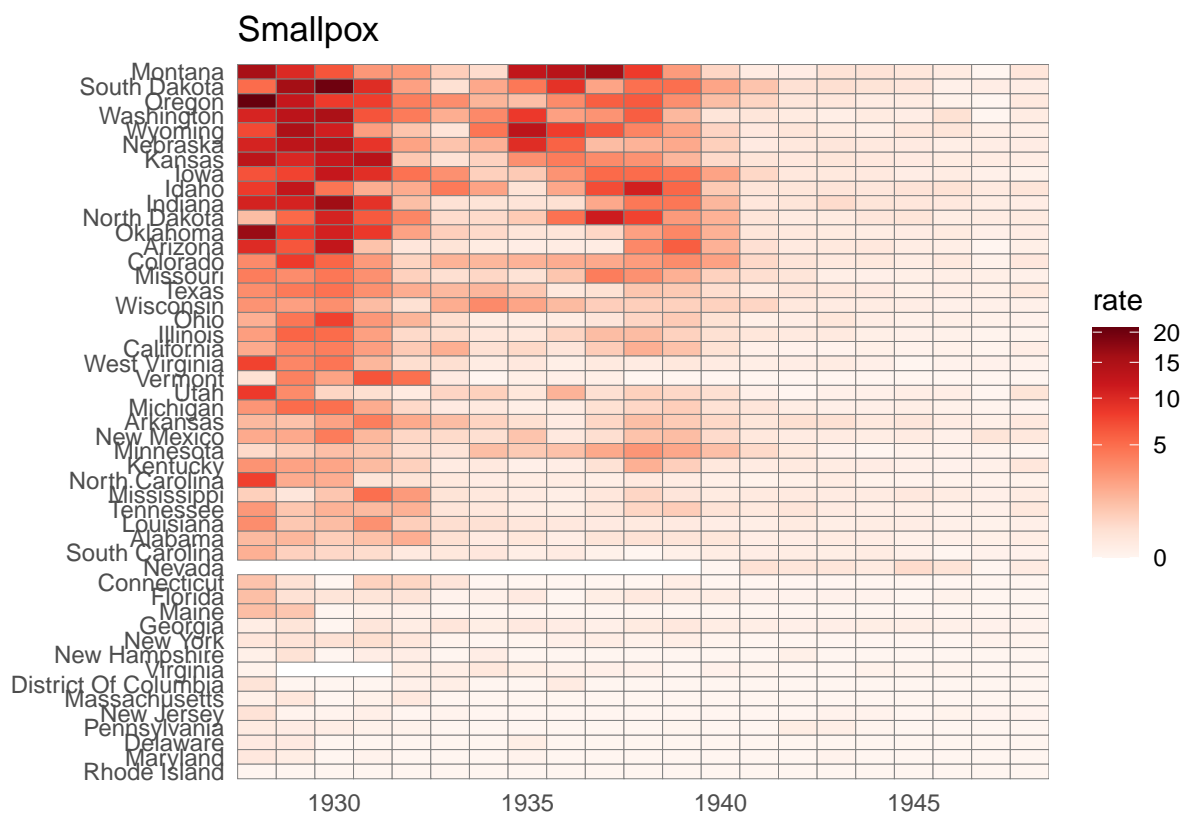
```
if(!require(RColorBrewer)) install.packages("RColorBrewer")

## Loading required package: RColorBrewer

library(RColorBrewer)

the_disease = "Smallpox"
dat <- us_contagious_diseases %>%
  filter(!state%in%c("Hawaii","Alaska") & disease == the_disease & weeks_reporting >= 10) %>%
  mutate(rate = count / population * 10000) %>%
  mutate(state = reorder(state, rate))

dat %>% ggplot(aes(year, state, fill = rate)) +
  geom_tile(color = "grey50") +
  scale_x_continuous(expand=c(0,0)) +
  scale_fill_gradientn(colors = brewer.pal(9, "Reds"), trans = "sqrt") +
  theme_minimal() +
  theme(panel.grid = element_blank()) +
  ggtitle(the_disease) +
  ylab("") +
  xlab("")
```



2. The sample code given creates a time series plot showing the rate of measles cases per population by state.

We are going to again modify this plot to look at smallpox cases instead.

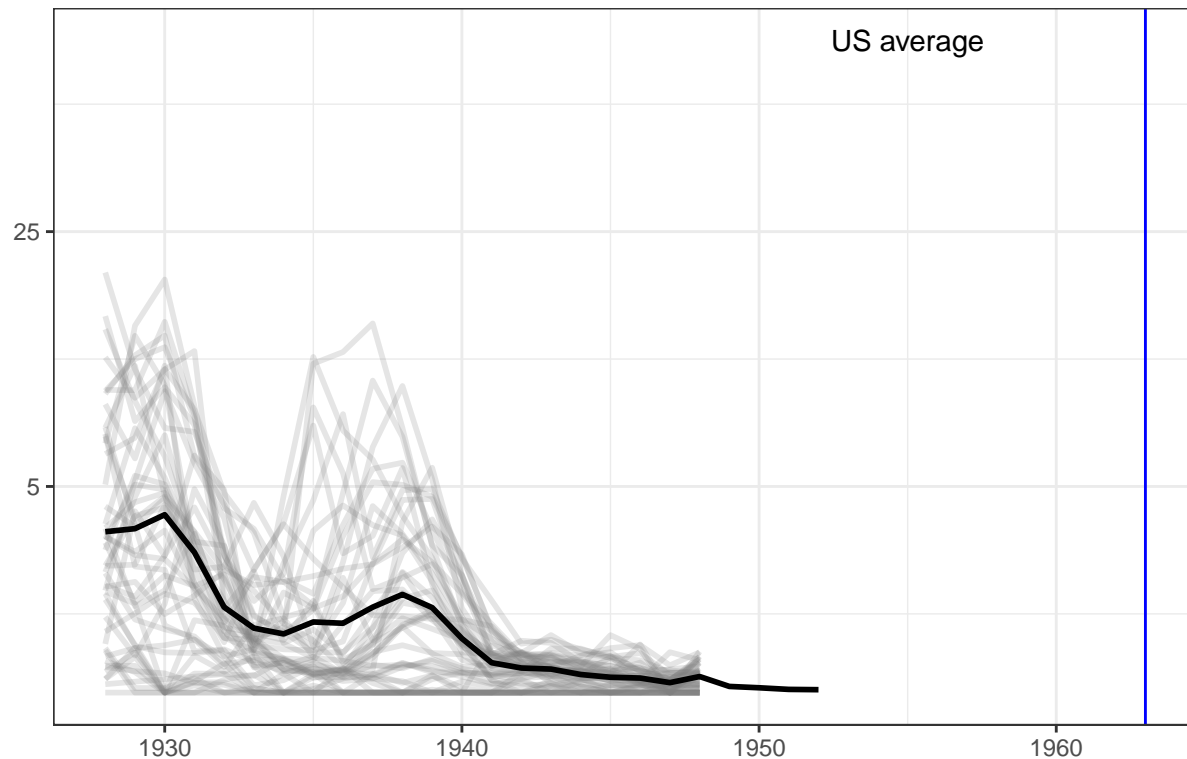
```
the_disease = "Smallpox"
dat <- us_contagious_diseases %>%
  filter(!state%in%c("Hawaii","Alaska") & disease == the_disease & weeks_reporting >= 10) %>%
  mutate(rate = count / population * 10000) %>%
  mutate(state = reorder(state, rate))

avg <- us_contagious_diseases %>%
  filter(disease==the_disease) %>% group_by(year) %>%
  summarize(us_rate = sum(count, na.rm=TRUE)/sum(population, na.rm=TRUE)*10000)

## `summarise()` ungrouping output (override with `.groups` argument)

dat %>% ggplot() +
  geom_line(aes(year, rate, group = state), color = "grey50",
            show.legend = FALSE, alpha = 0.2, size = 1) +
  geom_line(mapping = aes(year, us_rate), data = avg, size = 1, color = "black") +
  scale_y_continuous(trans = "sqrt", breaks = c(5,25,125,300)) +
  ggtitle("Cases per 10,000 by state") +
  xlab("") +
  ylab("") +
  geom_text(data = data.frame(x=1955, y=50), mapping = aes(x, y, label="US average"), color="black") +
  geom_vline(xintercept=1963, col = "blue")
```

### Cases per 10,000 by state

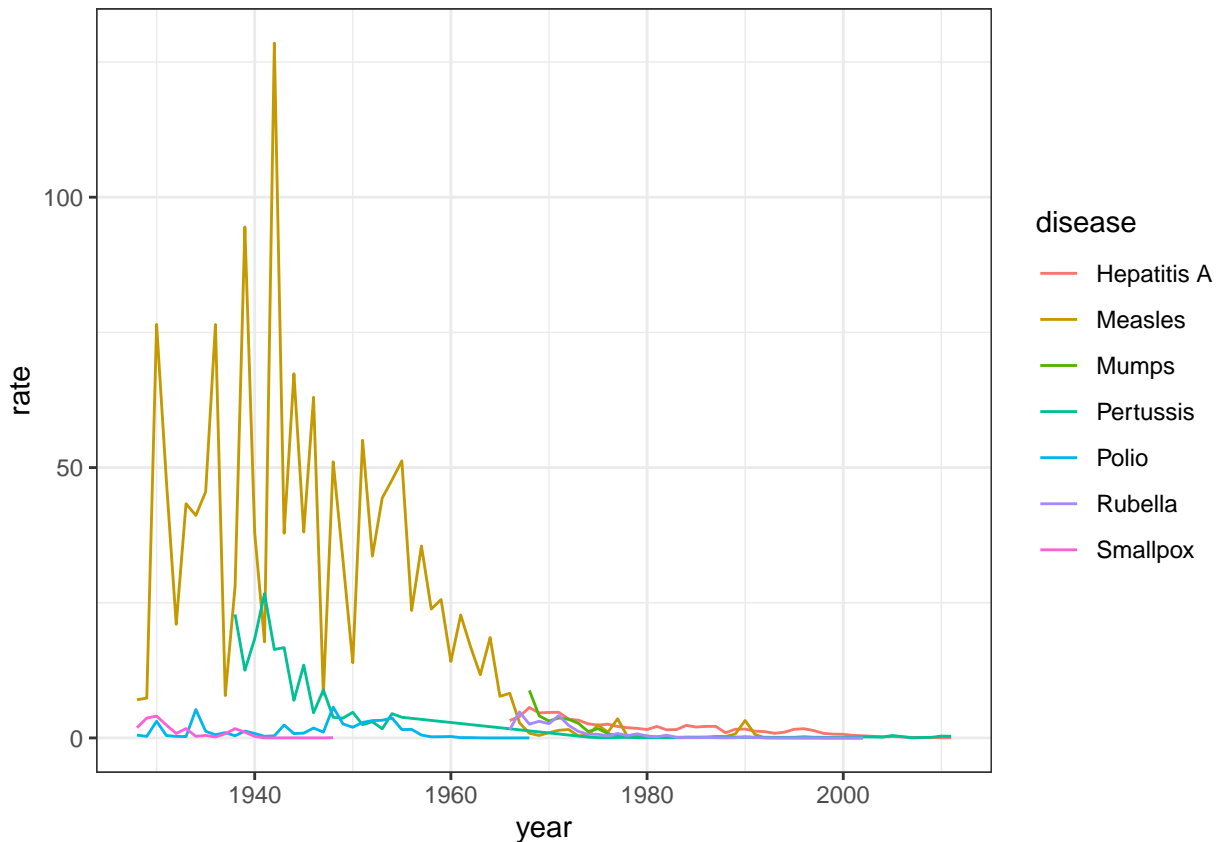


3. Now we are going to look at the rates of all diseases in one state.

Again, you will be modifying the sample code to produce the desired plot.

```
us_contagious_diseases %>% filter(state=="California" & weeks_reporting >= 10) %>%  
  group_by(year, disease) %>%  
  summarize(rate = sum(count)/sum(population)*10000) %>%  
  ggplot(aes(year, rate, color = disease)) +  
  geom_line()
```

```
## `summarise()` regrouping output by 'year' (override with `.groups` argument)
```

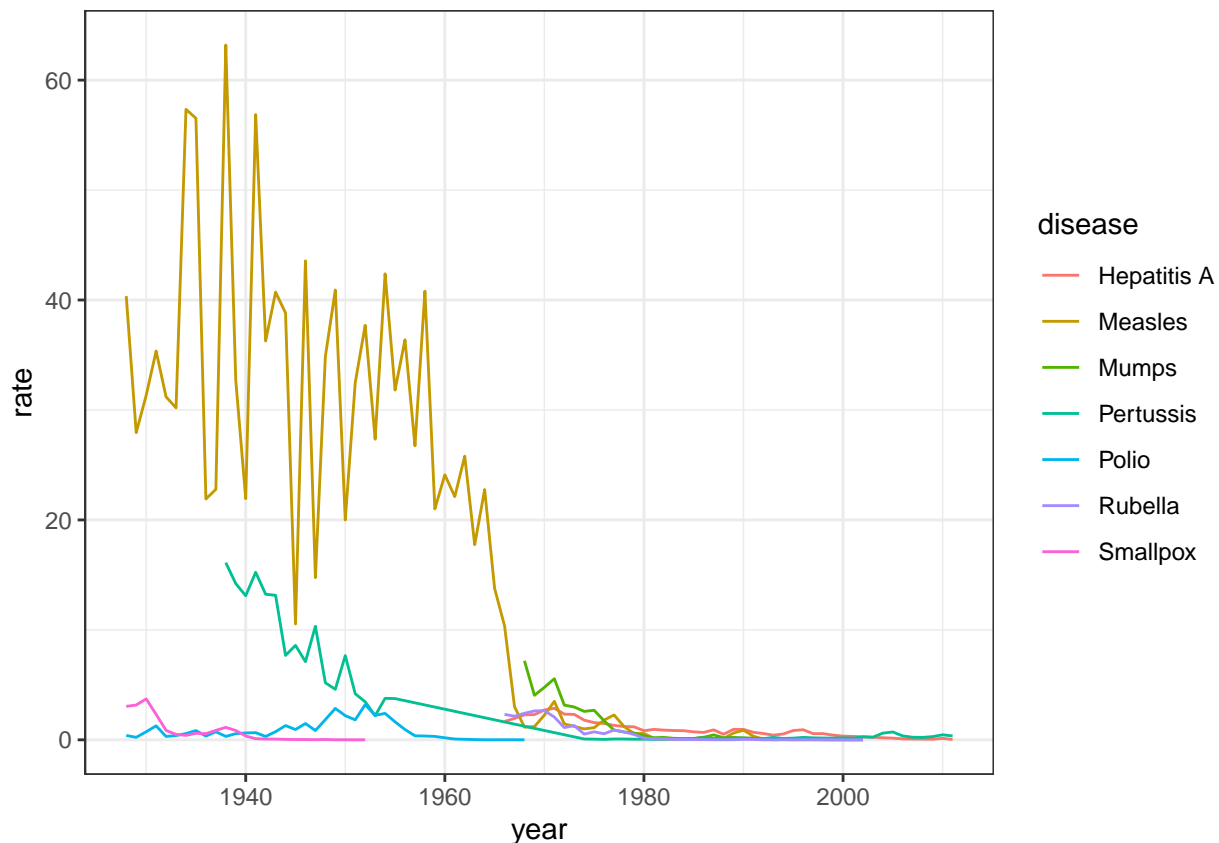


4. Now we are going to make a time series plot for the rates of all diseases in the United States.

For this exercise, we have provided less sample code - you can take a look at the previous exercise to get you started.

```
us_contagious_diseases %>% filter(!is.na(population)) %>%  
  group_by(year, disease) %>%  
  summarize(rate = sum(count)/sum(population)*10000) %>%  
  ggplot(aes(year, rate, color = disease)) +  
  geom_line()
```

```
## `summarise()` regrouping output by 'year' (override with `.groups` argument)
```



## Titanic Survival Exercises

Put all your new skills together to perform exploratory data analysis on a classic machine learning dataset: Titanic survival!

### Background

The Titanic was a British ocean liner that struck an iceberg and sunk on its maiden voyage in 1912 from the United Kingdom to New York. More than 1,500 of the estimated 2,224 passengers and crew died in the accident, making this one of the largest maritime disasters ever outside of war. The ship carried a wide range of passengers of all ages and both genders, from luxury travelers in first-class to immigrants in the lower classes. However, not all passengers were equally likely to survive the accident. We use real data about a selection of 891 passengers to learn who was on the Titanic and which passengers were more likely to survive.

### Libraries, Options, and Data

Define the titanic dataset starting from the **titanic** library with the following code:

```
if(!require(titanic)) install.packages("titanic")
```

```
## Loading required package: titanic
```

```
## Warning: package 'titanic' was built under R version 4.0.2
```

```
options(digits = 3)      # report 3 significant digits
library(tidyverse)
library(titanic)
```



```
titanic <- titanic_train %>%
  select(Survived, Pclass, Sex, Age, SibSp, Parch, Fare) %>%
  mutate(Survived = factor(Survived),
         Pclass = factor(Pclass),
         Sex = factor(Sex))
```

## 1. Variable Types

Inspect the data and also use `?titanic_train` to learn more about the variables in the dataset. Match these variables from the dataset to their variable type. There is at least one variable of each type (ordinal categorical, non-ordinal categorical, continuous, discrete).

- `Survived` non-ordinal categorical
- `Pclass` ordinal categorical
- `Sex` non-ordinal categorical
- `SibSp` discrete
- `Parch` discrete
- `Fare` continuous

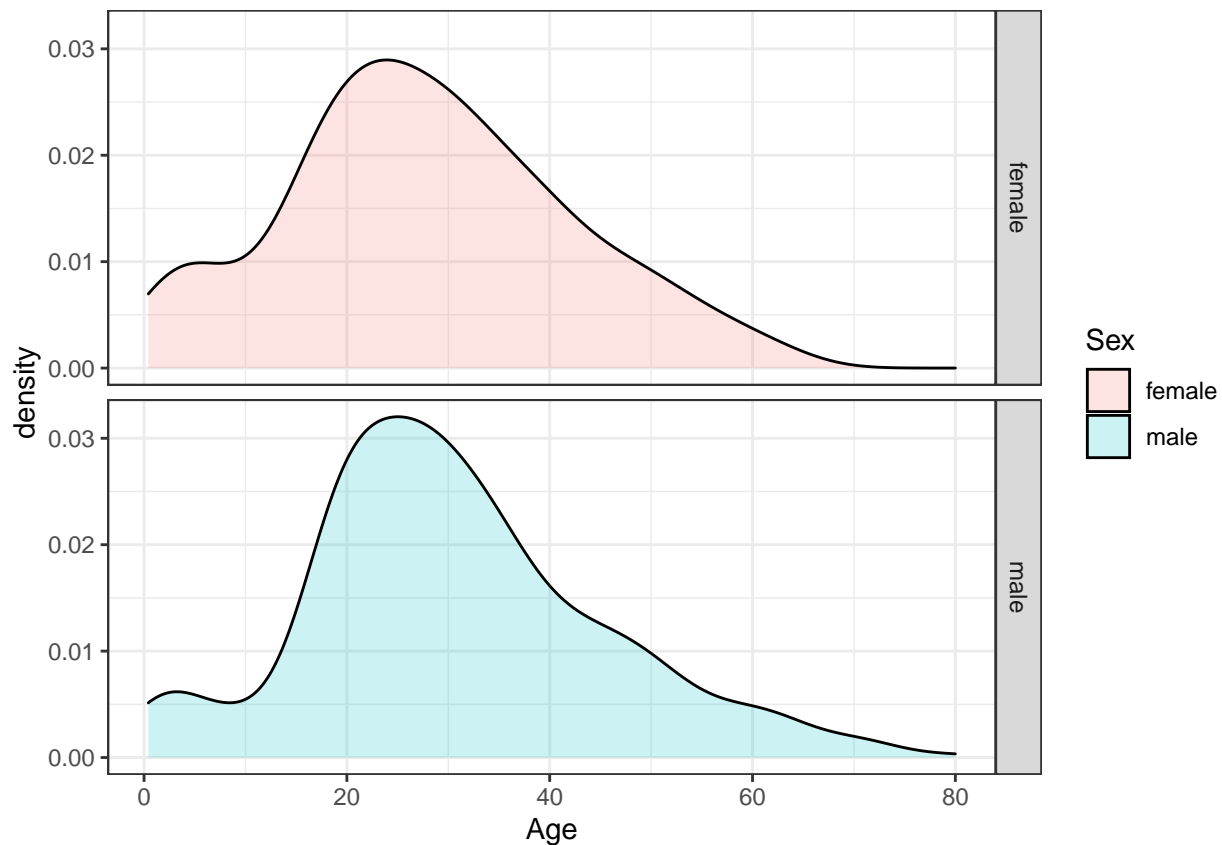
## 2. Demographics of Titanic Passengers

Make density plots of age grouped by sex. Try experimenting with combinations of faceting, alpha blending, stacking and using variable counts on the y-axis to answer the following questions. Some questions may be easier to answer with different versions of the density plot.

A faceted plot is useful for comparing the distributions of males and females for A. Each sex has the same general shape with two modes at the same locations, though proportions differ slightly across ages and there are more males than females.

```
titanic %>%
  ggplot(aes(Age, fill = Sex)) +
  geom_density(alpha = 0.2) +
  facet_grid(Sex ~ .)
```

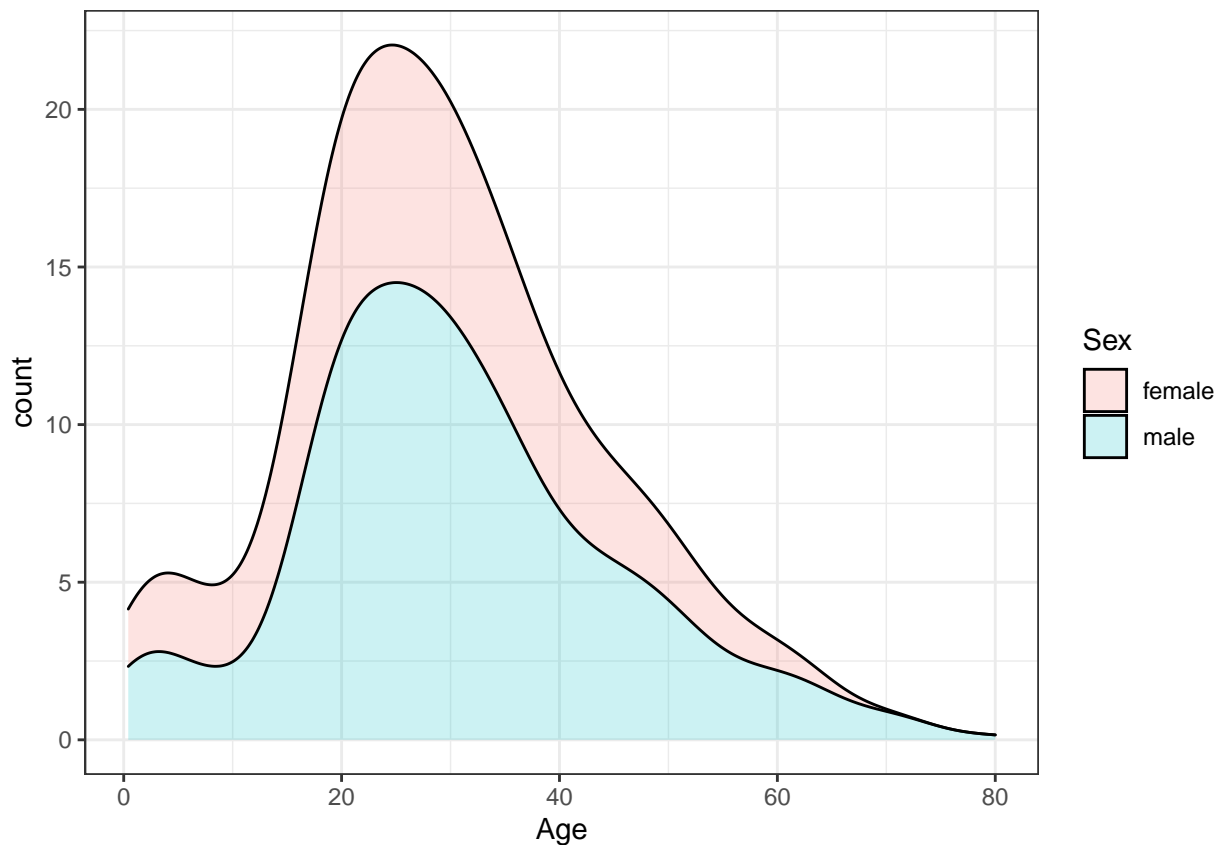
```
## Warning: Removed 177 rows containing non-finite values (stat_density).
```



A stacked density plot with count on the y-axis is useful for answering B, C and D. The main mode is around age 25 and a second smaller mode is around age 4-5. There are more males than females as indicated by a higher total area and higher counts at almost all ages. With count on the y-axis, it is clear that more males than females are age 40.

```
titanic %>%
  ggplot(aes(Age, y = ..count.., fill = Sex)) +
  geom_density(alpha = 0.2, position = "stack")
```

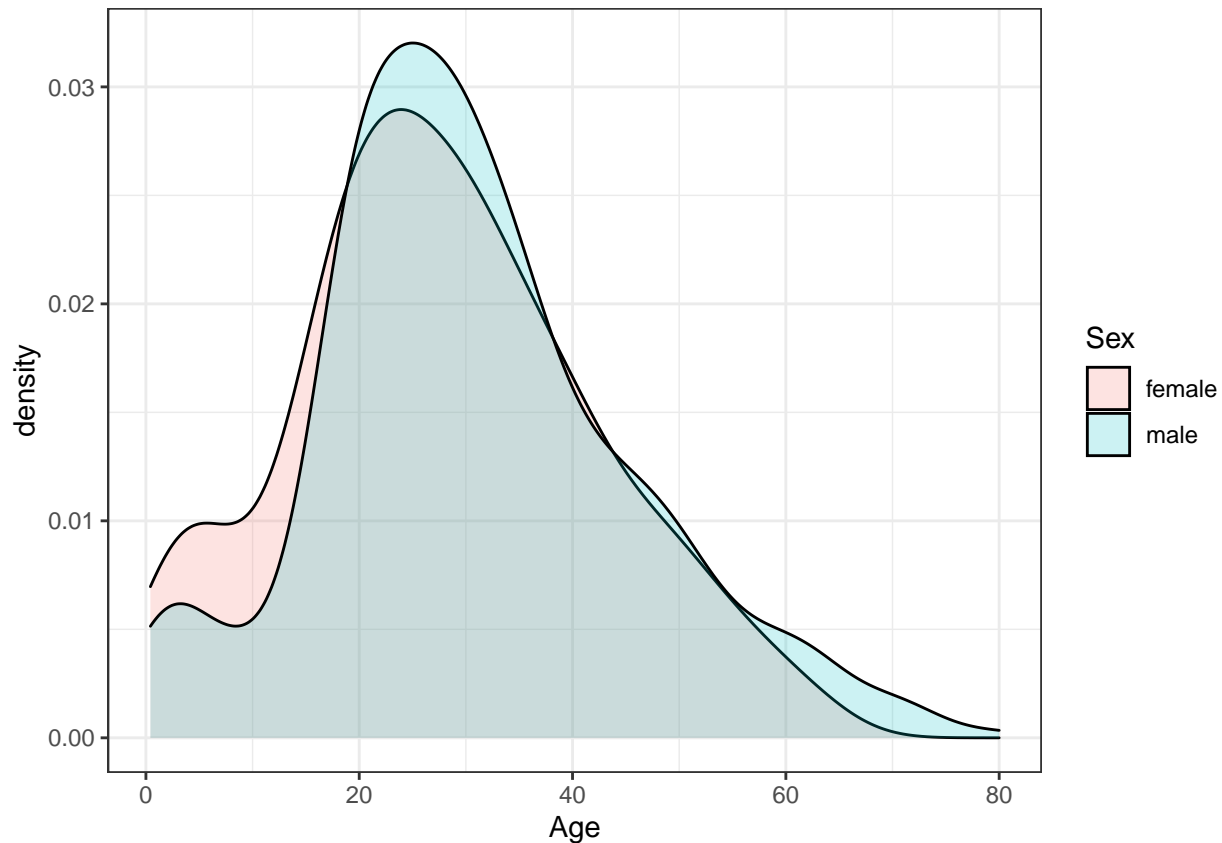
```
## Warning: Removed 177 rows containing non-finite values (stat_density).
```



A plot filled by sex with alpha blending helps reveal the answers to E, F and G. There is a higher proportion of females than males below age 17, a higher proportion of males than females for ages 18-35, approximately the same proportion of males and females age 35-55, and a higher proportion of males over age 55. The oldest individuals are male.

```
titanic %>%  
  ggplot(aes(Age, fill = Sex)) +  
  geom_density(alpha = 0.2)
```

```
## Warning: Removed 177 rows containing non-finite values (stat_density).
```



Which of the following are true? Select all correct answers.

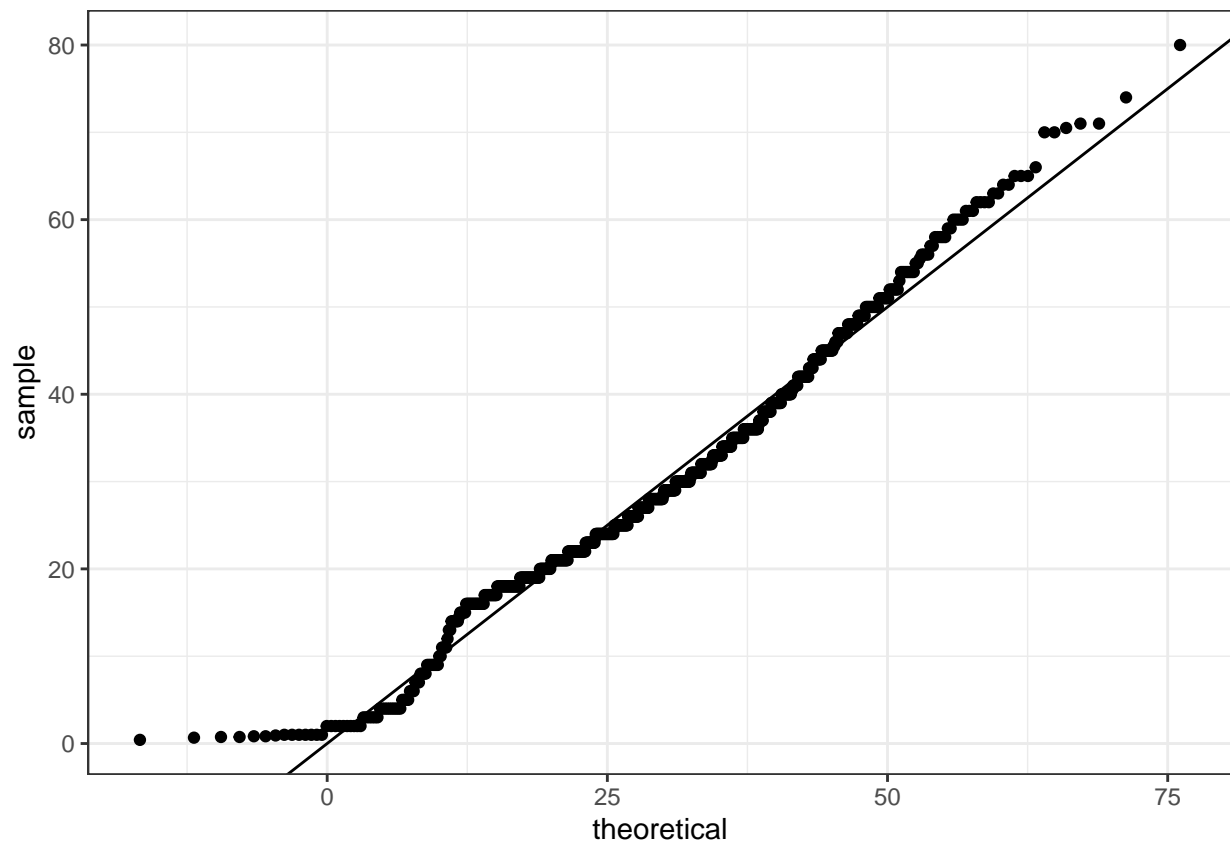
- ☒ A. Females and males had the same general shape of age distribution.
- ☒ B. The age distribution was bimodal, with one mode around 25 years of age and a second smaller mode around 5 years of age.
- ☐ C. There were more females than males.
- ☒ D. The count of males of age 40 was higher than the count of females of age 40.
- ☒ E. The proportion of males age 18-35 was higher than the proportion of females age 18-35.
- ☒ F. The proportion of females under age 17 was higher than the proportion of males under age 17.
- ☐ G. The oldest passengers were female.

### 3. QQ-plot of Age Distribution

Use `geom_qq` to make a QQ-plot of passenger age and add an identity line with `geom_abline`. Filter out any individuals with an age of NA first. Use the following object as the `dparams` argument in `geom_qq`:

```
params <- titanic %>%
  filter(!is.na(Age)) %>%
  summarize(mean = mean(Age), sd = sd(Age))

titanic %>%
  filter(!is.na(Age)) %>%
  ggplot(aes(sample = Age)) +
  geom_qq(dparams = params) +
  geom_abline()
```



What is the correct plot according to the instructions above? QQ-plot C

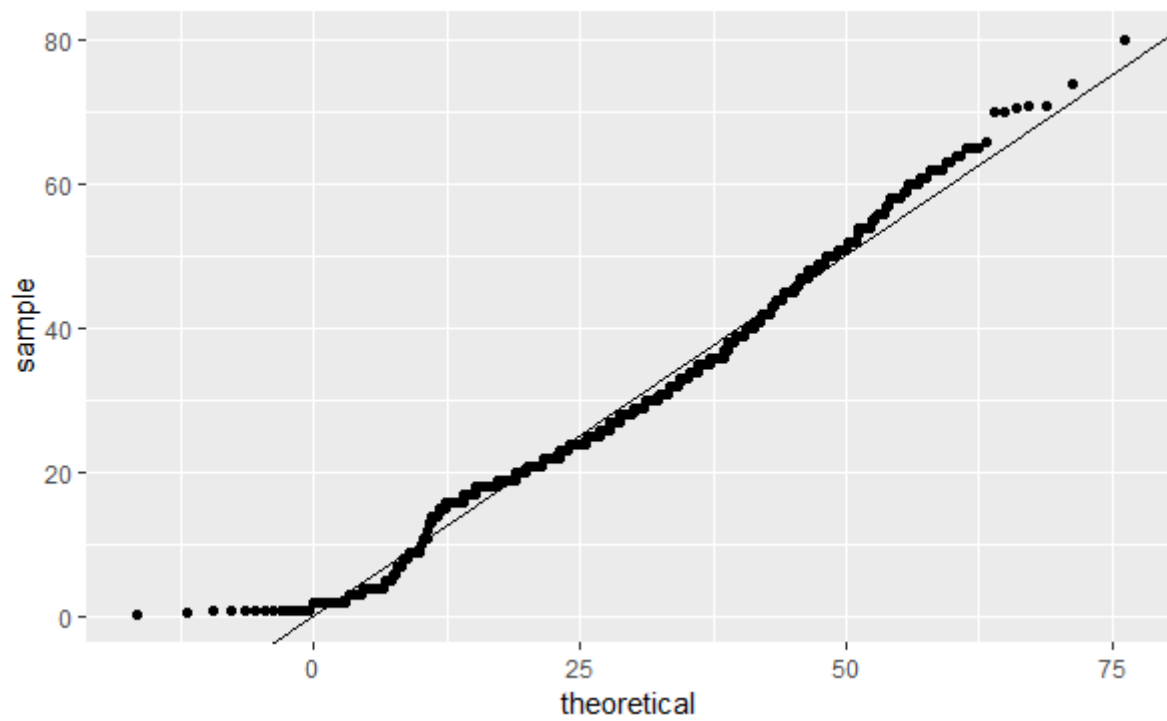


Figure 11: QQ-plot C

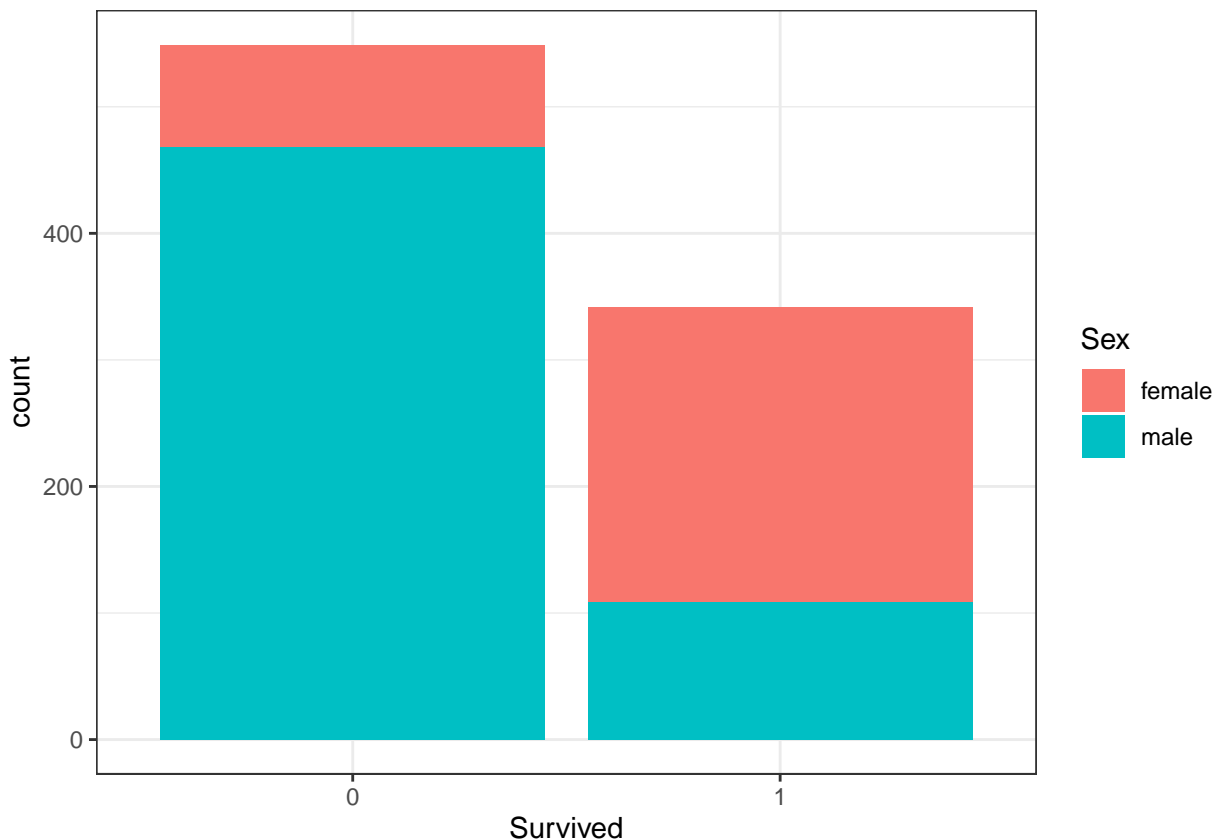
#### 4. Survival by Sex

To answer the following questions, make barplots of the **Survived** and **Sex** variables using `geom_bar`. Try plotting one variable and filling by the other variable. You may want to try the default plot, then try adding `position = position_dodge()` to `geom_bar` to make separate bars for each group.

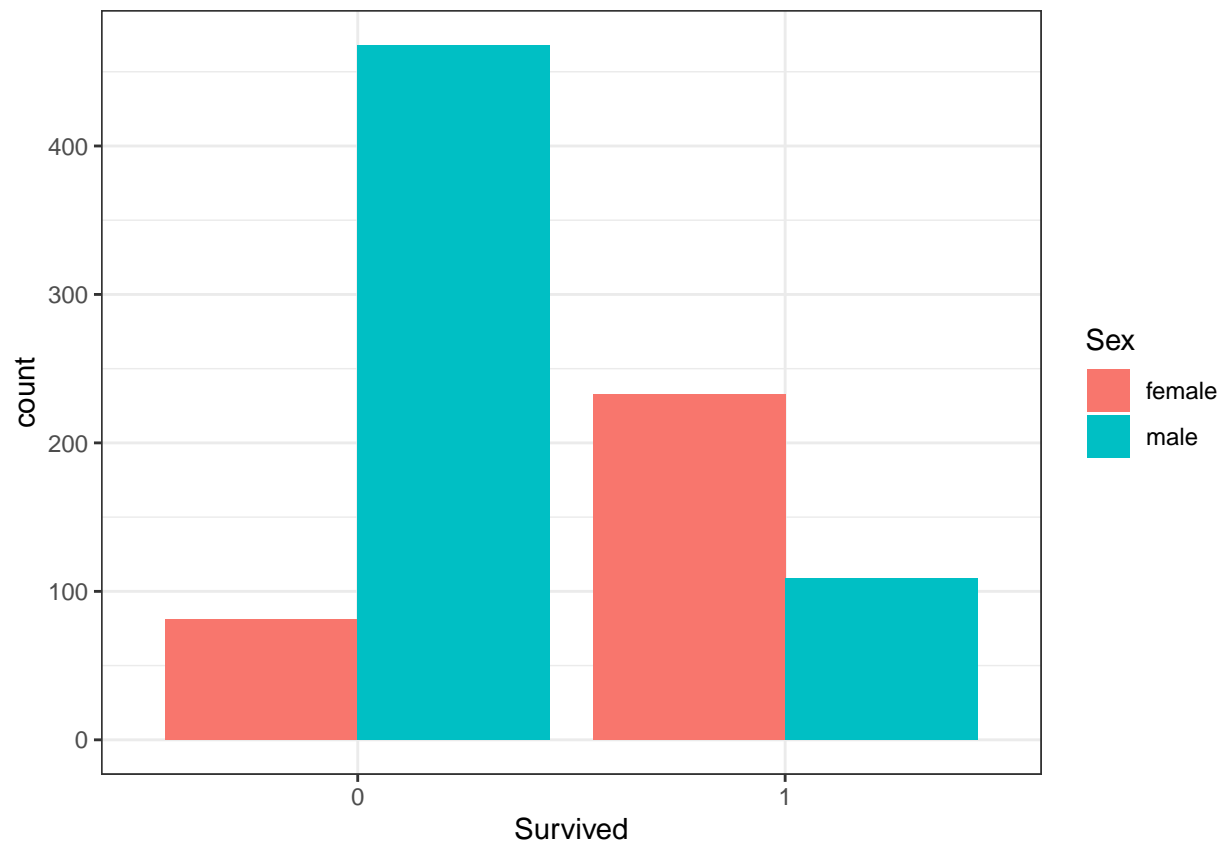
You can read more about making barplots in the textbook section on [ggplot2 geometries](#).

A and B can be clearly seen in the barplot of survival status filled by sex. The count of survivors is lower than the count of non-survivors. The bar of survivors is more than half filled by females. Alternatively, the bars can be split by sex with `position_dodge`, showing the “Female, Survived” bar has a greater height than the “Male, survived” bar. C and D are more clearly seen in the barplot of sex filled by survival status, though they can also be determined from the first barplot. Most males did not survive, but most females did survive.

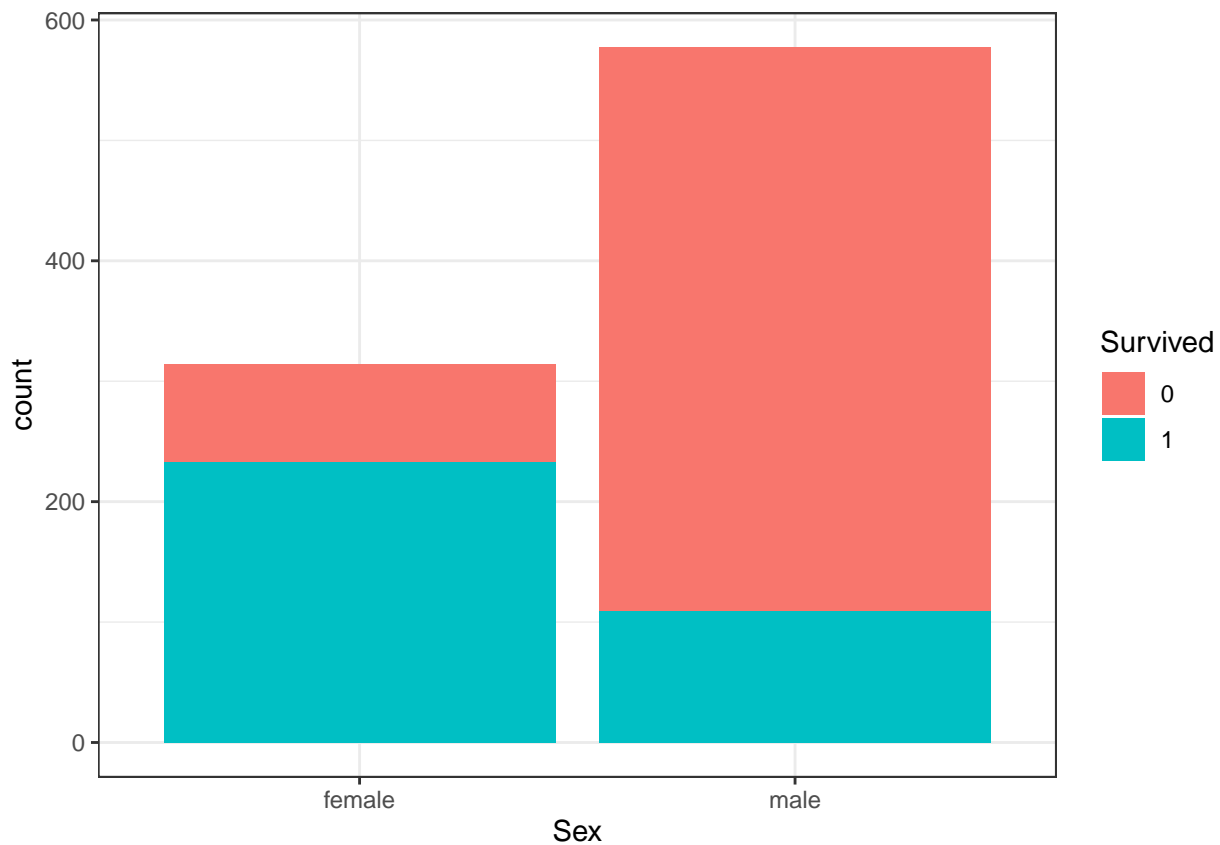
```
#plot 1 - survival filled by sex
titanic %>%
  ggplot(aes(Survived, fill = Sex)) +
  geom_bar()
```



```
# plot 2 - survival filled by sex with position_dodge
titanic %>%
  ggplot(aes(Survived, fill = Sex)) +
  geom_bar(position = position_dodge())
```



```
#plot 3 - sex filled by survival  
titanic %>%  
  ggplot(aes(Sex, fill = Survived)) +  
  geom_bar()
```



Which of the following are true? Select all correct answers.

- ☒ A. Less than half of passengers survived.
- ☒ B. Most of the survivors were female.
- ☐ C. Most of the males survived.
- ☒ D. Most of the females survived.

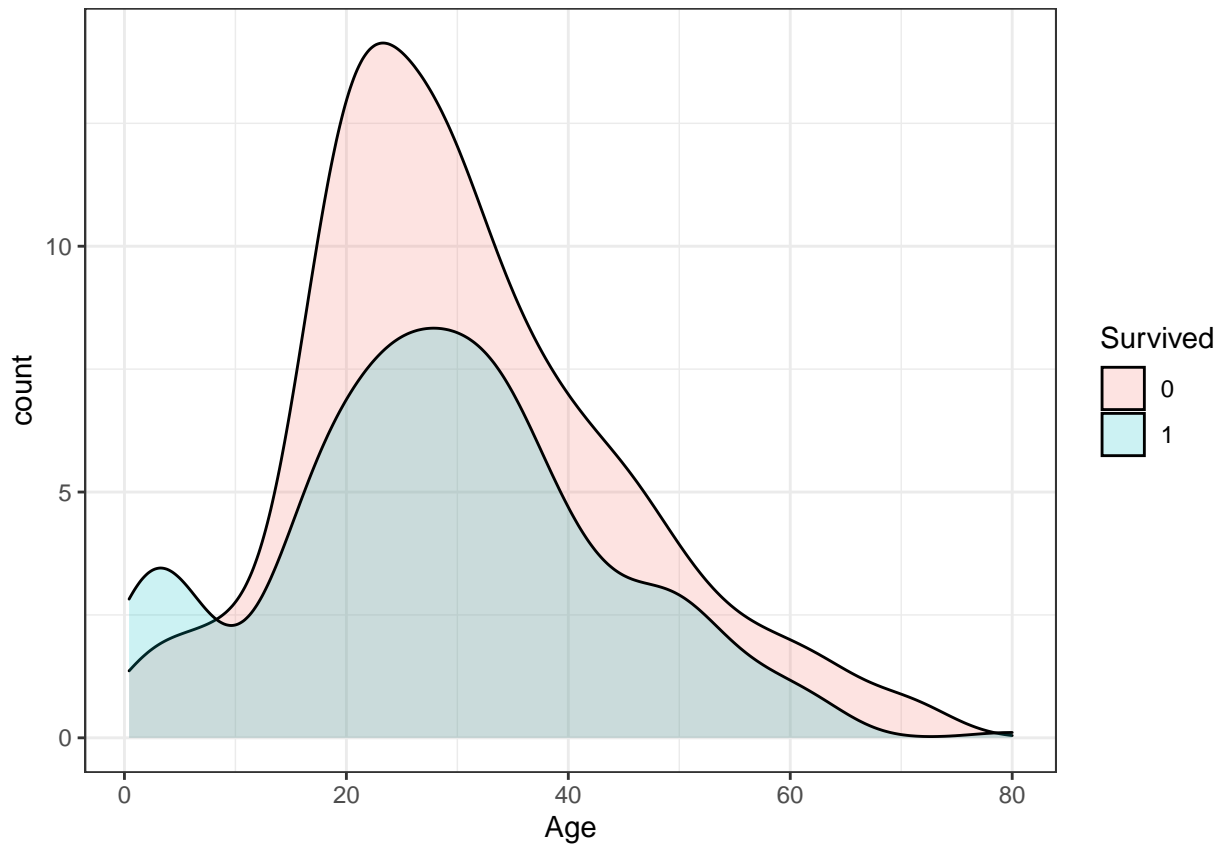
#### 5. Survival by Age

Make a density plot of age filled by survival status. Change the y-axis to count and set `alpha = 0.2`.

```
titanic %>%
  ggplot(aes(Age, y = ..count.., fill = Survived)) +
  geom_density(alpha = 0.2)
```

```
## Warning: Removed 177 rows containing non-finite values (stat_density).
```





Which age group is the only group more likely to survive than die?

- ☒ A. 0-8
- ☐ B. 10-18
- ☐ C. 18-30
- ☐ D. 30-50
- ☐ E. 50-70
- ☐ F. 70-80

Which age group had the most deaths?

- ☐ A. 0-8
- ☐ B. 10-18
- ☒ C. 18-30
- ☐ D. 30-50
- ☐ E. 50-70
- ☐ F. 70-80

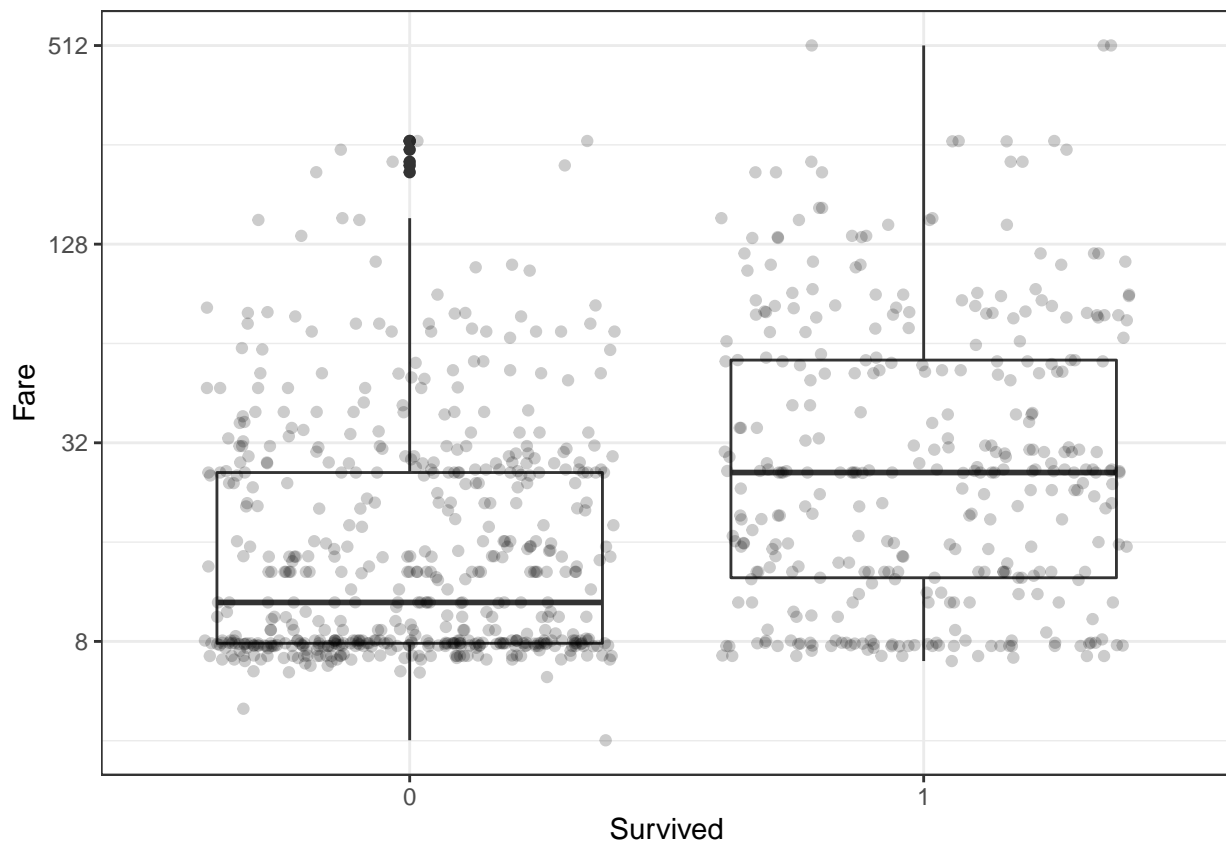
Which age group had the highest proportion of deaths?

- ☐ A. 0-8
- ☐ B. 10-18
- ☐ C. 18-30
- ☐ D. 30-50
- ☐ E. 50-70
- ☒ F. 70-80

## 6. Survival by Fare

Filter the data to remove individuals who paid a fare of 0. Make a boxplot of fare grouped by survival status. Try a log2 transformation of fares. Add the data points with jitter and alpha blending.

```
titanic %>%  
  filter(Fare > 0) %>%  
  ggplot(aes(Survived, Fare)) +  
  geom_boxplot() +  
  scale_y_continuous(trans = "log2") +  
  geom_jitter(alpha = 0.2)
```



Which of the following are true? Select all correct answers.

- ☒ A. Passengers who survived generally paid higher fares than those who did not survive.
- ☐ B. The interquartile range for fares was smaller for passengers who survived.
- ☒ C. The median fare was lower for passengers who did not survive.
- ☐ D. Only one individual paid a fare around \$500. That individual survived.
- ☒ E. Most individuals who paid a fare around \$8 did not survive.

7.

## Properties of Stars Exercises

### Background

Astronomy is one of the oldest data-driven sciences. In the late 1800s, the director of the Harvard College

Observatory hired women to analyze astronomical data, which at the time was done using photographic glass plates. These women became known as the Harvard Computers. They computed the position and luminosity of various astronomical objects such as stars and galaxies. (If you are interested, you can learn more about the Harvard Computers). Today, astronomy is even more of a data-driven science, with an inordinate amount of data being produced by modern instruments every day.

In the following exercises we will analyze some actual astronomical data to inspect properties of stars, their absolute magnitude (which relates to a star's luminosity, or brightness), temperature and type (spectral class).

## Libraries and Options

```
#update.packages()
library(tidyverse)
library(dslabs)
data(stars)
options(digits = 3)  # report 3 significant digits
```

### Question 1

Load the stars data frame from dslabs. This contains the name, absolute magnitude, temperature in degrees Kelvin, and spectral class of selected stars. Absolute magnitude (shortened in these problems to simply “magnitude”) is a function of star luminosity, where negative values of magnitude have higher luminosity.

```
# What is the mean magnitude?
mean(stars$magnitude)
```

```
## [1] 4.26
```

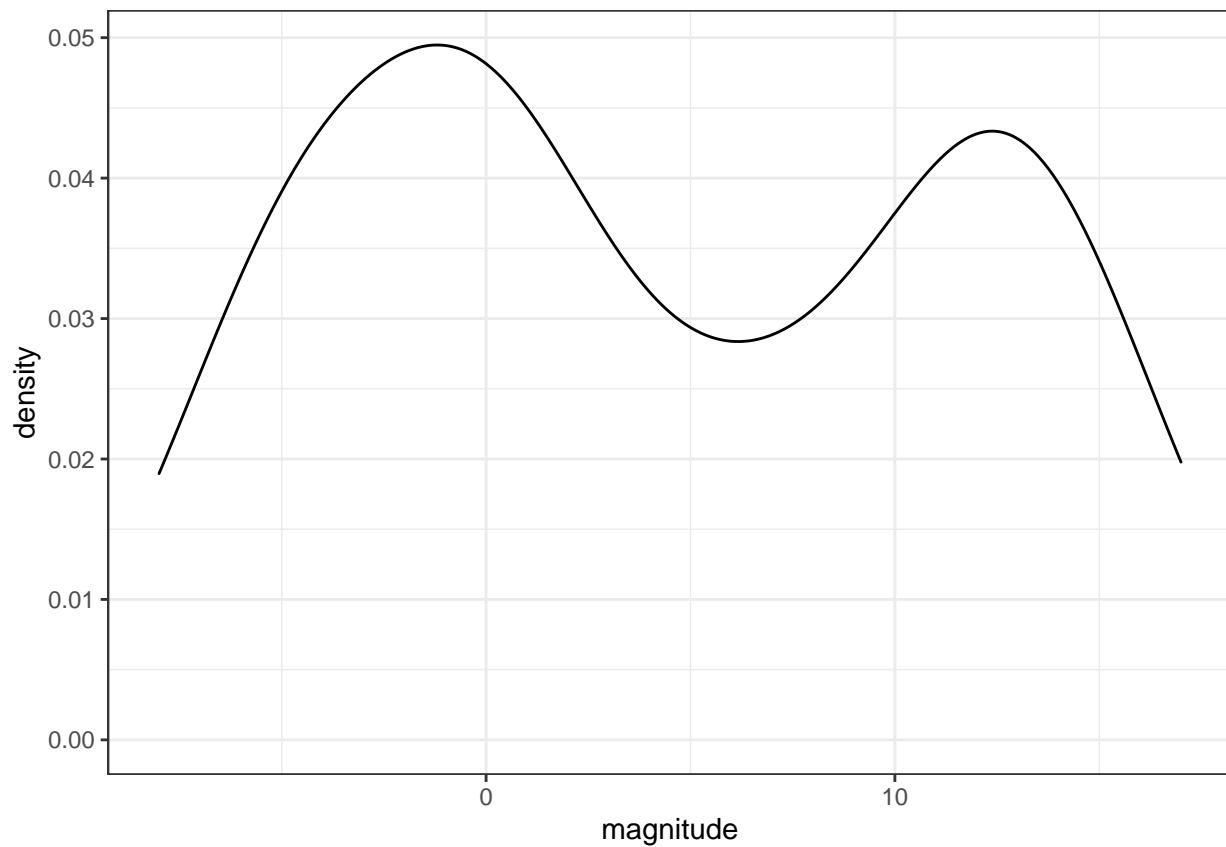
```
# What is the standard deviation of magnitude?
sd(stars$magnitude)
```

```
## [1] 7.35
```

### Question 2

Make a density plot of the magnitude.

```
stars %>%
  ggplot(aes(magnitude)) +
  geom_density()
```

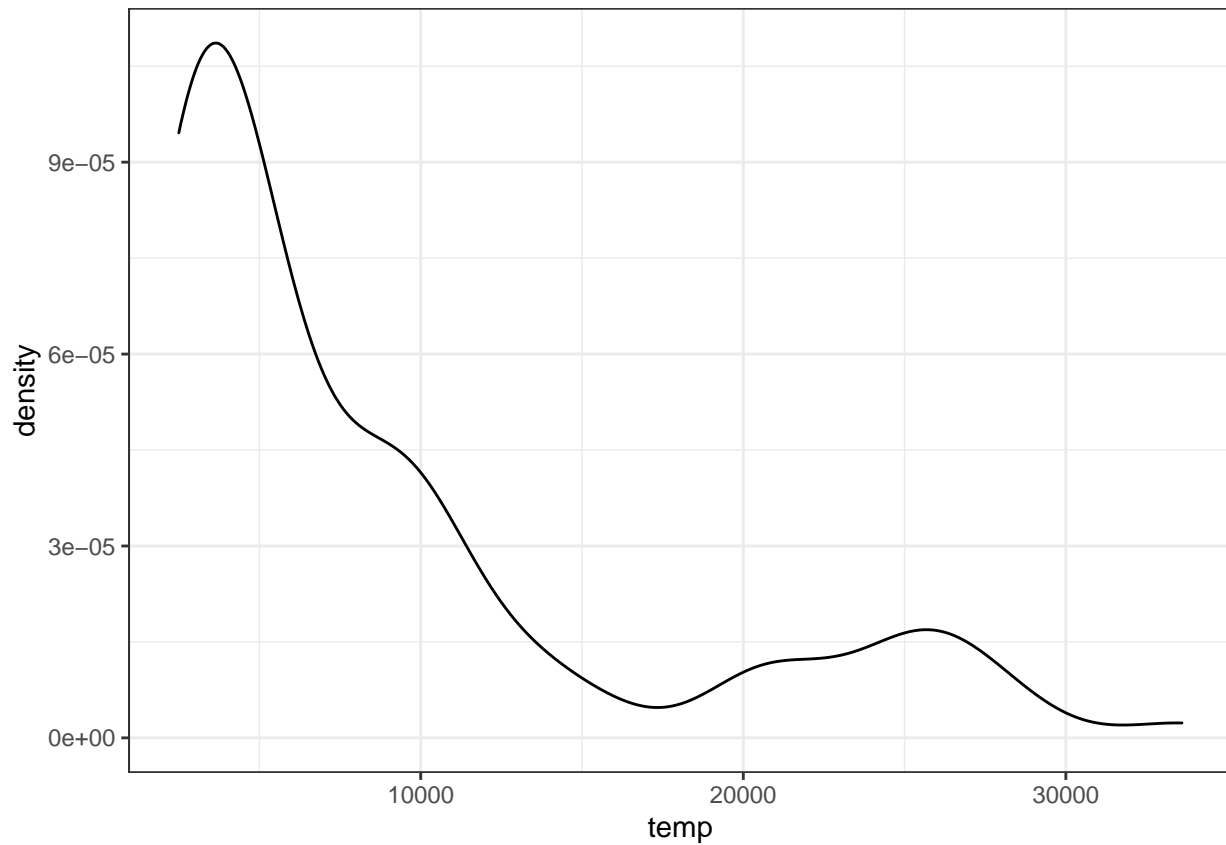


```
# How many peaks are there in the data?  
# A: 2
```

### Question 3

Examine the distribution of star temperature. Which of these statements best characterizes the temperature distribution?

```
stars %>%  
  ggplot(aes(temp)) +  
  geom_density()
```

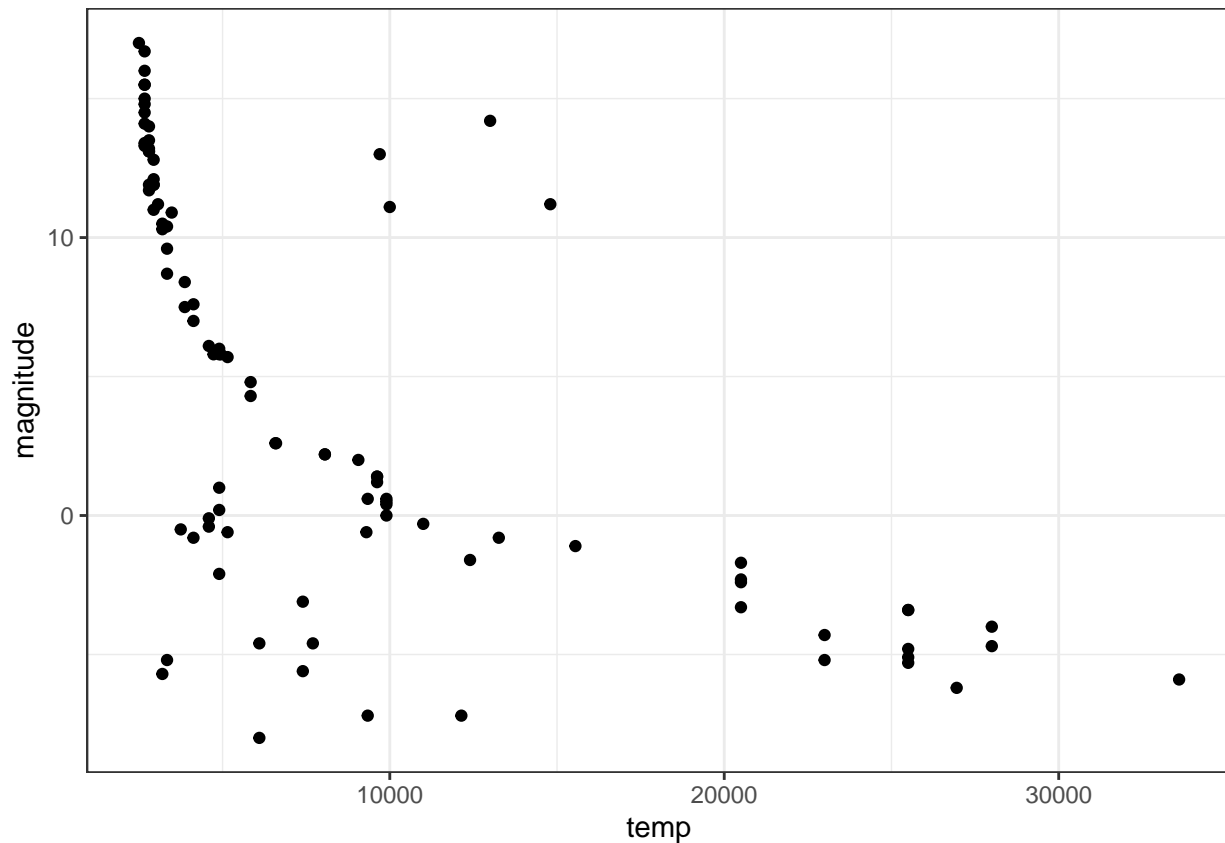


```
# How many peaks are there in the data?  
# A: 2
```

#### Question 4

Make a scatter plot of the data with temperature on the x-axis and magnitude on the y-axis and examine the relationship between the variables. Recall that lower magnitude means a more luminous (brighter) star.

```
stars %>%  
  ggplot(aes(x=temp, y=magnitude)) +  
  geom_point()
```



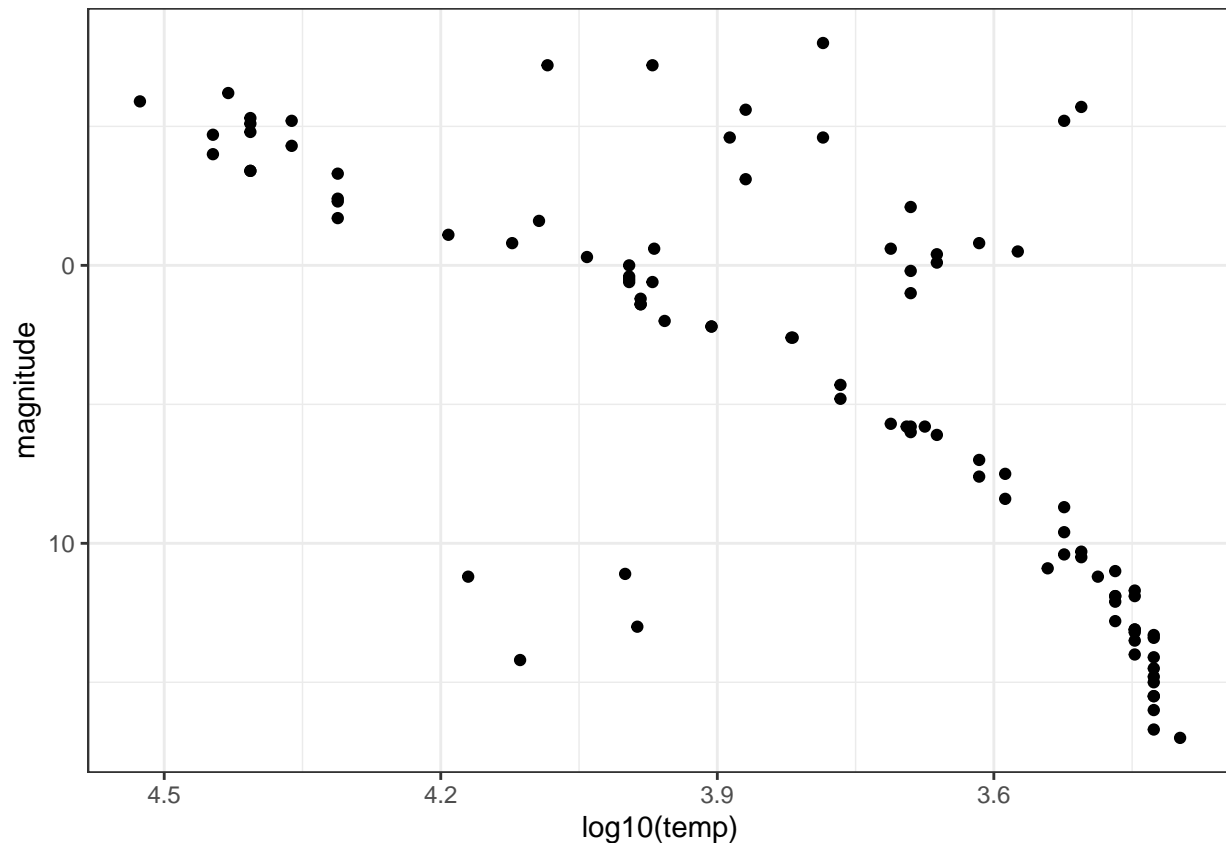
### Question 5

For various reasons, scientists do not always follow straight conventions when making plots, and astronomers usually transform values of star luminosity and temperature before plotting. Flip the y-axis so that lower values of magnitude are at the top of the axis (recall that more luminous stars have lower magnitude) using `scale_y_reverse()`. Take the log base 10 of temperature and then also flip the x-axis.

Fill in the blanks in the statements below to describe the resulting plot:

The brightest, highest temperature stars are in the \_\_\_\_\_ corner of the plot.

```
stars %>%
  ggplot(aes(x=log10(temp), y=magnitude)) +
  scale_y_reverse() +
  scale_x_reverse() +
  geom_point()
```



### Question 6

The trends you see allow scientists to learn about the evolution and lifetime of stars. The primary group of stars to which most stars belong (see question 4) we will call the main sequence stars. Most stars belong to this main sequence, however some of the more rare stars are classified as old and evolved stars. These stars tend to be hotter stars, but also have low luminosity, and are known as white dwarfs.

How many white dwarfs are there in our sample?

A: 4

### Question 7

Consider stars which are not part of the Main Group but are not old/evolved (white dwarf) stars. These stars must also be unique in certain ways and are known as giants. Use the plot from Question 5 to estimate the average temperature of a giant.

Which of these temperatures is closest to the average temperature of a giant?: A: 5000K

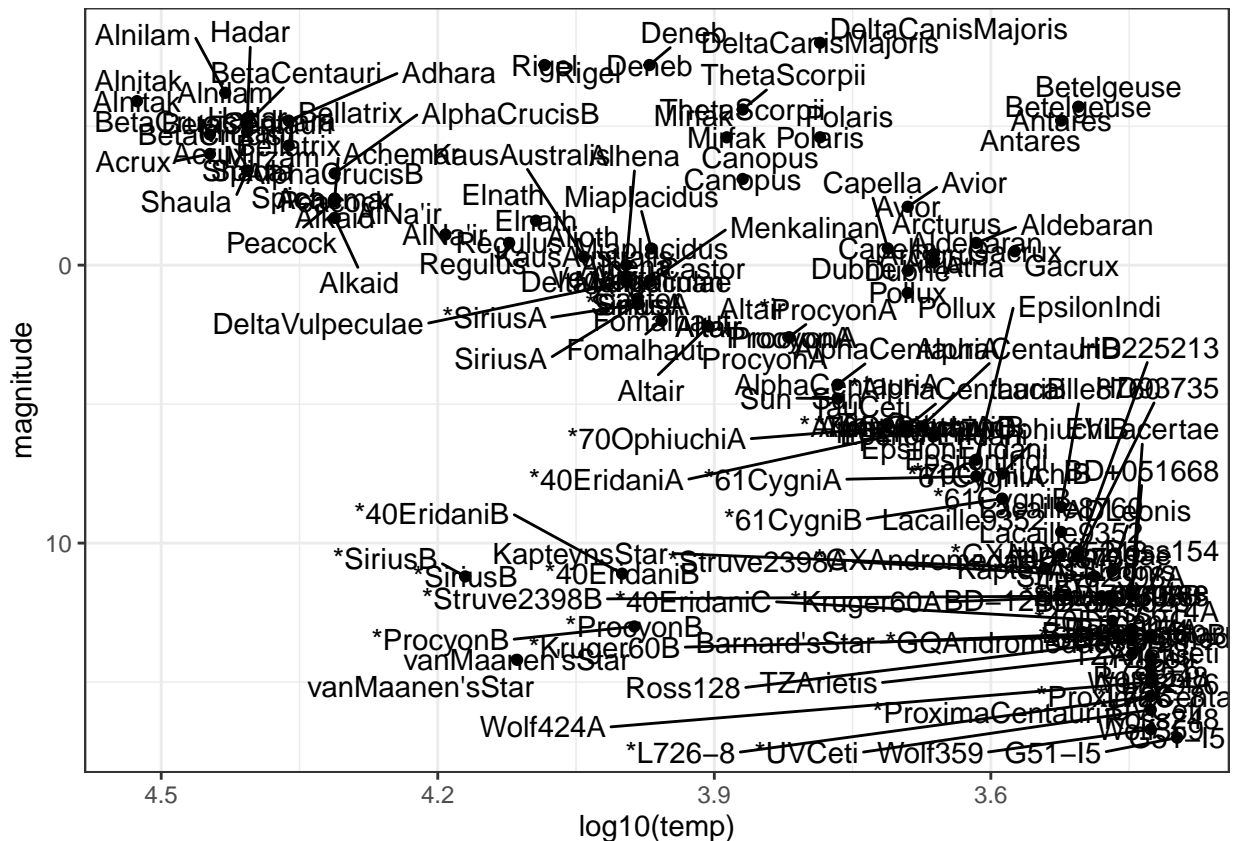
### Question 8

We can now identify whether specific stars are main sequence stars, red giants or white dwarfs. Add text labels to the plot to answer these questions. You may wish to plot only a selection of the labels, repel the labels, or zoom in on the plot in RStudio so you can locate specific stars.

Fill in the blanks in the statements below:

```
library(ggrepel)
stars %>%
  ggplot(aes(x=log10(temp), y=magnitude, label=star)) +
  scale_y_reverse() +
  scale_x_reverse() +
  geom_point() +
  geom_text(aes(label=star)) +
```

```
geom_text_repel()
```



```
# The least luminous star in the sample with a surface temperature over 5000K is -----.
```

```
# A: van Maanens Star
```

```
# The two stars with lowest temperature and highest luminosity are known as supergiants. The two superg
```

```
# A: Betelgeuse and Antares
```

```
# The Sun is a -----.
```

```
# A: main sequence star
```

```
stars %>%
  filter(star=='Sun') %>%
  select_all()
```

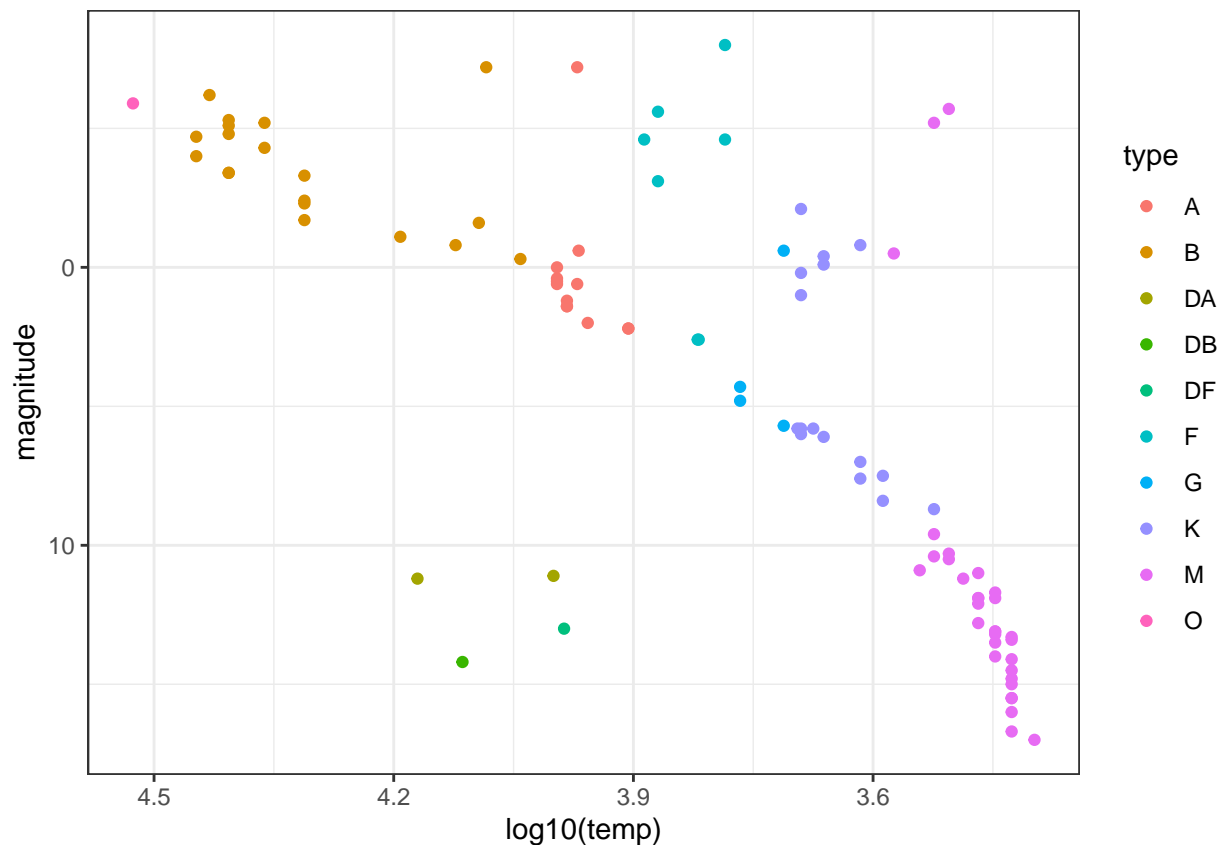
```
##   star magnitude temp type
## 1  Sun         4.8 5840   G
```

### Question 9

Remove the text labels and color the points by star type. This classification describes the properties of the star's spectrum, the amount of light produced at various wavelengths.

```
stars %>%
  ggplot(aes(x=log10(temp), y=magnitude, color=type)) +
  scale_y_reverse() +
  scale_x_reverse() +
  geom_point()
```





```
# Which star type has the lowest temperature?
```

## Climate Change Exercises

### Background

The planet's surface temperature is increasing due to human greenhouse gas emissions, and this global warming and carbon cycle disruption is wreaking havoc on natural systems. Living systems that depend on current temperature, weather, currents and carbon balance are jeopardized, and human society will be forced to contend with widespread economic, social, political and environmental damage as the temperature continues to rise. Although most countries recognize that global warming is a crisis and that humans must act to limit its effects, little action has been taken to limit or reverse human impact on the climate.

One limitation is the spread of misinformation related to climate change and its causes, especially the extent to which humans have contributed to global warming. In these exercises, we examine the relationship between global temperature changes, greenhouse gases and human carbon emissions using time series of actual atmospheric and ice core measurements from the National Oceanic and Atmospheric Administration (NOAA) and Carbon Dioxide Information Analysis Center (CDIAC).

### Libraries and Options

```
#update.packages()
library(tidyverse)
library(dslabs)
data(temp_carbon)
data(greenhouse_gases)
data(historic_co2)
```

### Question 1

Load the `temp_carbon` dataset from `dslabs`, which contains annual global temperature anomalies (difference from 20th century mean temperature in degrees Celsius), temperature anomalies over the land and ocean, and global carbon emissions (in metric tons). Note that the date ranges differ for temperature and carbon emissions.

Which of these code blocks return the latest year for which carbon emissions are reported?

```
str(temp_carbon)
```

```
## 'data.frame': 268 obs. of 5 variables:
## $ year      : num  1880 1881 1882 1883 1884 ...
## $ temp_anomaly : num  -0.11 -0.08 -0.1 -0.18 -0.26 -0.25 -0.24 -0.28 -0.13 -0.09 ...
## $ land_anomaly : num  -0.48 -0.4 -0.48 -0.66 -0.69 -0.56 -0.51 -0.47 -0.41 -0.31 ...
## $ ocean_anomaly : num  -0.01 0.01 0 -0.04 -0.14 -0.17 -0.17 -0.23 -0.05 -0.02 ...
## $ carbon_emissions: num  236 243 256 272 275 277 281 295 327 327 ...
```

```
temp_carbon %>%
  .$year %>%
  max()
```

```
## [1] 2018
```

```
temp_carbon %>%
  filter(!is.na(carbon_emissions)) %>%
  pull(year) %>%
  max()
```

```
## [1] 2014
```

```
#temp_carbon %>%
#   filter(!is.na(carbon_emissions)) %>%
#   max(year)
temp_carbon %>%
  filter(!is.na(carbon_emissions)) %>%
  .$year %>%
  max()
```

```
## [1] 2014
```

```
temp_carbon %>%
  filter(!is.na(carbon_emissions)) %>%
  select(year) %>%
  max()
```

```
## [1] 2014
```

```
#temp_carbon %>%
#   filter(!is.na(carbon_emissions)) %>%
#   max(.$year)
```

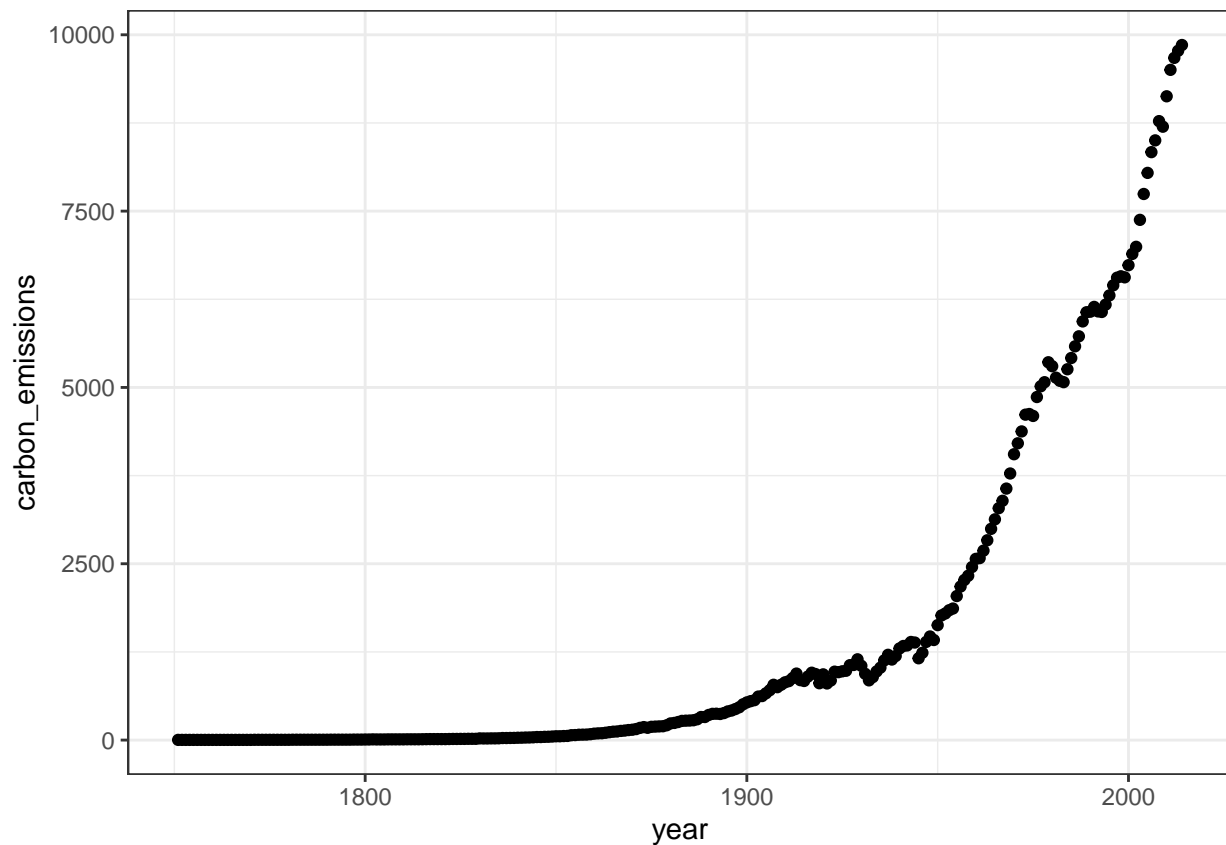
## Question 2

Inspect the difference in carbon emissions in temp\_carbon from the first available year to the last available year.

```
# What is the first year for which carbon emissions (carbon_emissions) data are available?
year_min <- temp_carbon %>%
  filter(!is.na(carbon_emissions)) %>%
  .$year %>%
  min()
# What is the last year for which carbon emissions data are available?
year_max <- temp_carbon %>%
  filter(!is.na(carbon_emissions)) %>%
  .$year %>%
  max()
# How many times larger were carbon emissions in the last year relative to the first year?
ratio <- temp_carbon %>%
  filter(year %in% c(year_min, year_max)) %>%
  .$carbon_emissions
#A:
ratio[1] / ratio[2]
```

```
## [1] 3285
```

```
# Scatter plot
temp_carbon %>%
  filter(!is.na(carbon_emissions)) %>%
  ggplot(aes(x=year, y=carbon_emissions)) +
  geom_point()
```



### Question 3

Inspect the difference in temperature in temp\_carbon from the first available year to the last available year.

```
# What is the first year for which global temperature anomaly (temp_anomaly) data are available?
year_min <- temp_carbon %>%
  filter(!is.na(temp_anomaly)) %>%
  .$year %>%
  min()
year_min
```

```
## [1] 1880
```

```
# What is the last year for which global temperature anomaly data are available?
year_max <- temp_carbon %>%
  filter(!is.na(temp_anomaly)) %>%
  .$year %>%
  max()
year_max
```

```
## [1] 2018
```

```
# How many degrees Celsius has temperature increased over the date range?
diff <- temp_carbon %>%
  filter(year %in% c(year_min, year_max)) %>%
  .$temp_anomaly
#A:
diff
```

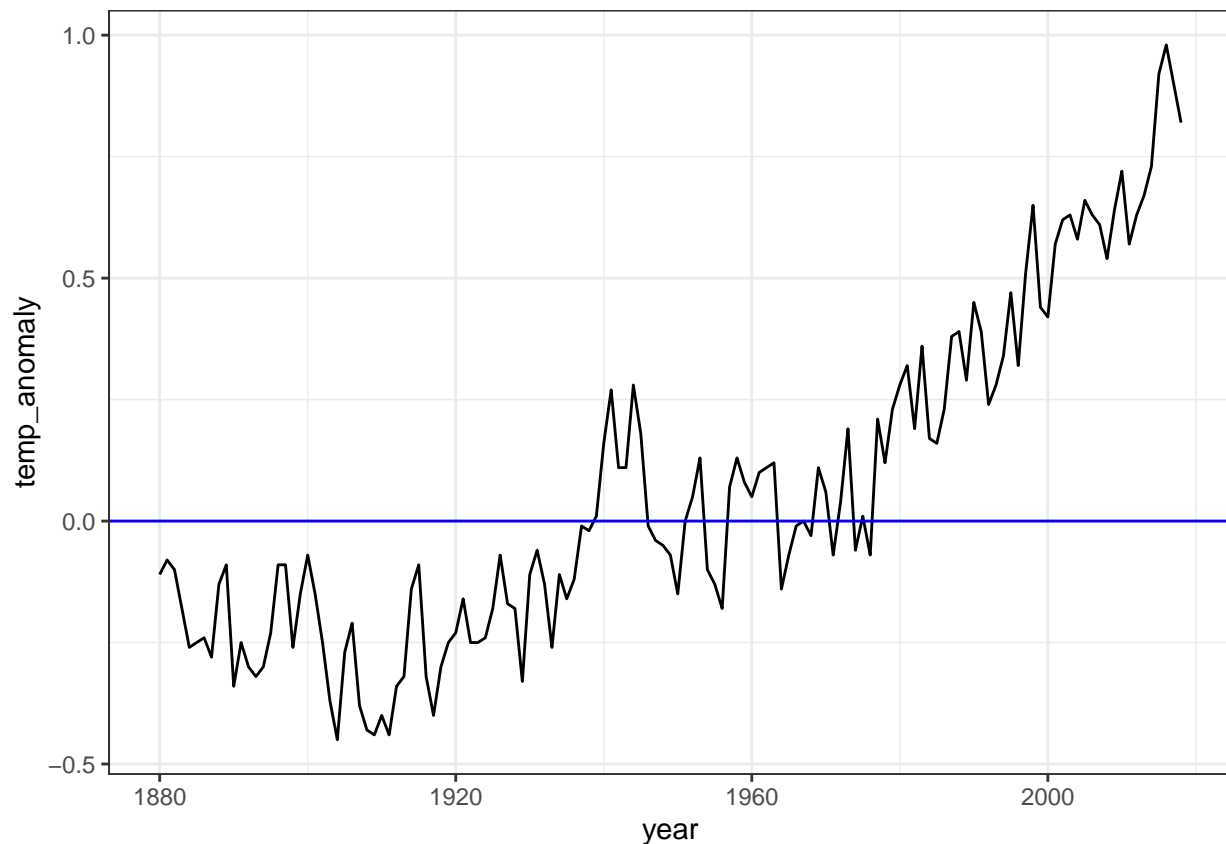
```
## [1] -0.11  0.82
```

```
diff[1] - diff[2]
```

```
## [1] -0.93
```

**Question 4** Create a time series line plot of the temperature anomaly. Only include years where temperatures are reported. Save this plot to the object p. Which command adds a blue horizontal line indicating the 20th century mean temperature?

```
p <- temp_carbon %>%  
  filter(!is.na(temp_anomaly)) %>%  
  ggplot(aes(year, temp_anomaly)) +  
  geom_line() +  
  geom_hline(aes(yintercept=0), color='blue')  
p
```

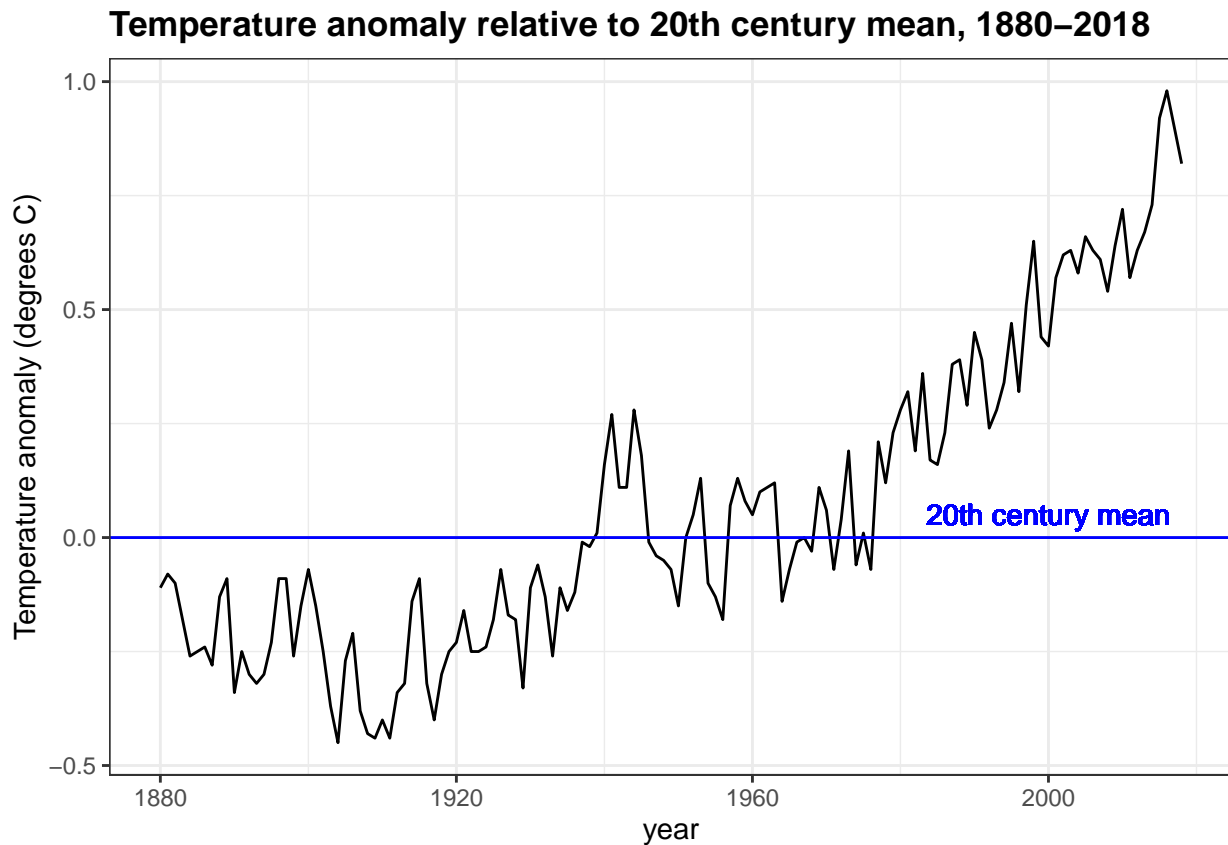


**Question 5**

Continue working with p, the plot created in the previous question.

Change the y-axis label to be “Temperature anomaly (degrees C)”. Add a title, “Temperature anomaly relative to 20th century mean, 1880-2018”. Also add a text layer to the plot: the x-coordinate should be 2000, the y-coordinate should be 0.05, the text should be “20th century mean”, and the text color should be blue.

```
q <- temp_carbon %>%
  filter(!is.na(temp_anomaly)) %>%
  ggplot(aes(year, temp_anomaly)) +
  geom_line() +
  geom_hline(aes(yintercept=0), color='blue') +
  ylab("Temperature anomaly (degrees C)") +
  ggtitle("Temperature anomaly relative to 20th century mean, 1880–2018") +
  geom_text(aes(x=2000, y=0.05, label="20th century mean"), col='blue')
q
```



### Question 6

When was the earliest year with a temperature above the 20th century mean?

```
year_min <- temp_carbon %>%
  filter(!is.na(temp_anomaly) & temp_anomaly>0) %>%
  .$year %>%
  min()
year_min
```

```
## [1] 1939
```

When was the last year with an average temperature below the 20th century mean?

```

year_max <- temp_carbon %>%
  filter(!is.na(temp_anomaly) & temp_anomaly<0) %>%
  .$year %>%
  max()
year_max

```

```
## [1] 1976
```

In what year did the temperature anomaly exceed 0.5 degrees Celsius for the first time?

```

year_ <- temp_carbon %>%
  filter(!is.na(temp_anomaly) & temp_anomaly>0.5) %>%
  .$year %>%
  min()
year_

```

```
## [1] 1997
```

**Question 7** Add layers to the previous plot to include line graphs of the temperature anomaly in the ocean (ocean\_anomaly) and on land (land\_anomaly). Assign different colors to the lines. Compare the global temperature anomaly to the land temperature anomaly and ocean temperature anomaly.

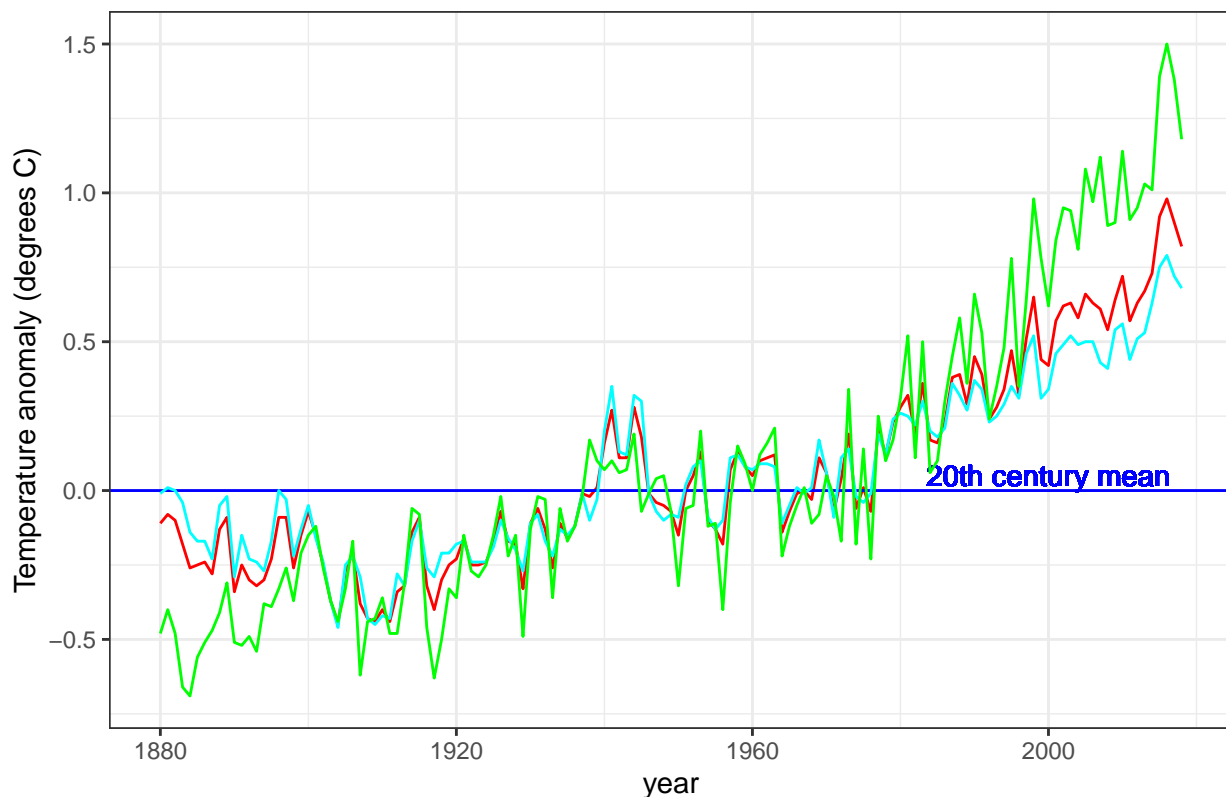
Which region has the largest 2018 temperature anomaly relative to the 20th century mean?

```

temp_carbon %>%
  filter(!is.na(temp_anomaly)) %>%
  ggplot(aes(year, temp_anomaly)) +
  geom_line(col='red') +
  geom_hline(aes(yintercept=0), color='blue') +
  xlim(c(1880, 2018)) +
  ylab("Temperature anomaly (degrees C)") +
  ggtitle("Temperature anomaly relative to 20th century mean, 1880-2018") +
  geom_text(aes(x=2000, y=0.05, label="20th century mean"), col='blue') +
  geom_line(aes(year, ocean_anomaly), col='cyan') +
  geom_line(aes(year, land_anomaly), col='green')

```

## Temperature anomaly relative to 20th century mean, 1880–2018



**Question 8** A major determinant of Earth's temperature is the greenhouse effect. Many gases trap heat and reflect it towards the surface, preventing heat from escaping the atmosphere. The greenhouse effect is vital in keeping Earth at a warm enough temperature to sustain liquid water and life; however, changes in greenhouse gas levels can alter the temperature balance of the planet.

The `greenhouse_gases` data frame from `dslabs` contains concentrations of the three most significant greenhouse gases: carbon dioxide ( `CO2` , abbreviated in the data as `co2`), methane ( `CH4` , `ch4` in the data), and nitrous oxide ( `N2O` , `n2o` in the data). Measurements are provided every 20 years for the past 2000 years.

```
str(greenhouse_gases)
```

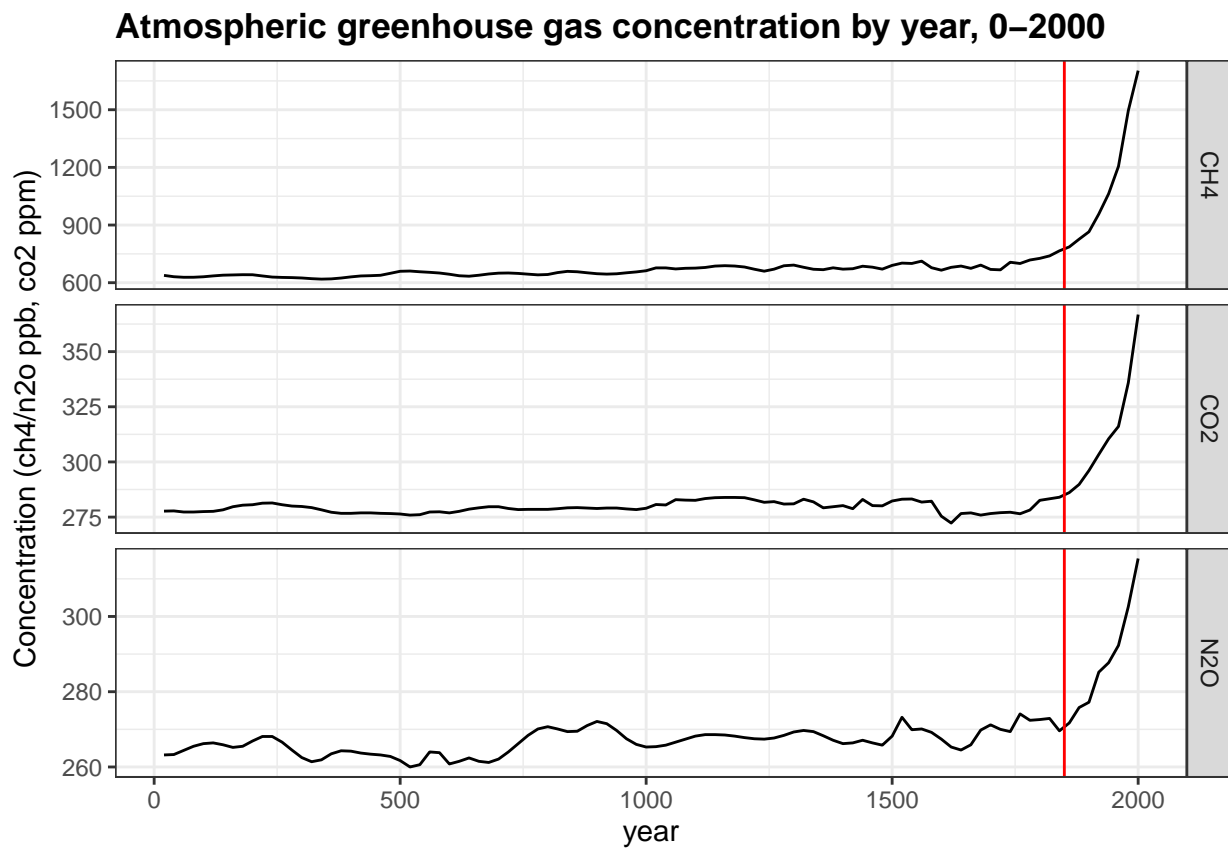
```
## 'data.frame':   300 obs. of  3 variables:
##  $ year      : num  20 40 60 80 100 120 140 160 180 200 ...
##  $ gas       : chr  "CO2" "CO2" "CO2" "CO2" ...
##  $ concentration: num  278 278 277 277 278 ...
```

Complete the code outline below to make a line plot of concentration on the y-axis by year on the x-axis. Facet by gas, aligning the plots vertically so as to ease comparisons along the year axis. Add a vertical line with an x-intercept at the year 1850, noting the unofficial start of the industrial revolution and widespread fossil fuel consumption. Note that the units for `ch4` and `n2o` are ppb while the units for `co2` are ppm.

```
greenhouse_gases %>%
  ggplot(aes(year, concentration)) +
  geom_line() +
  facet_grid(gas ~ ., scales = "free") +
  geom_vline(xintercept = 1850, col='red') +
```

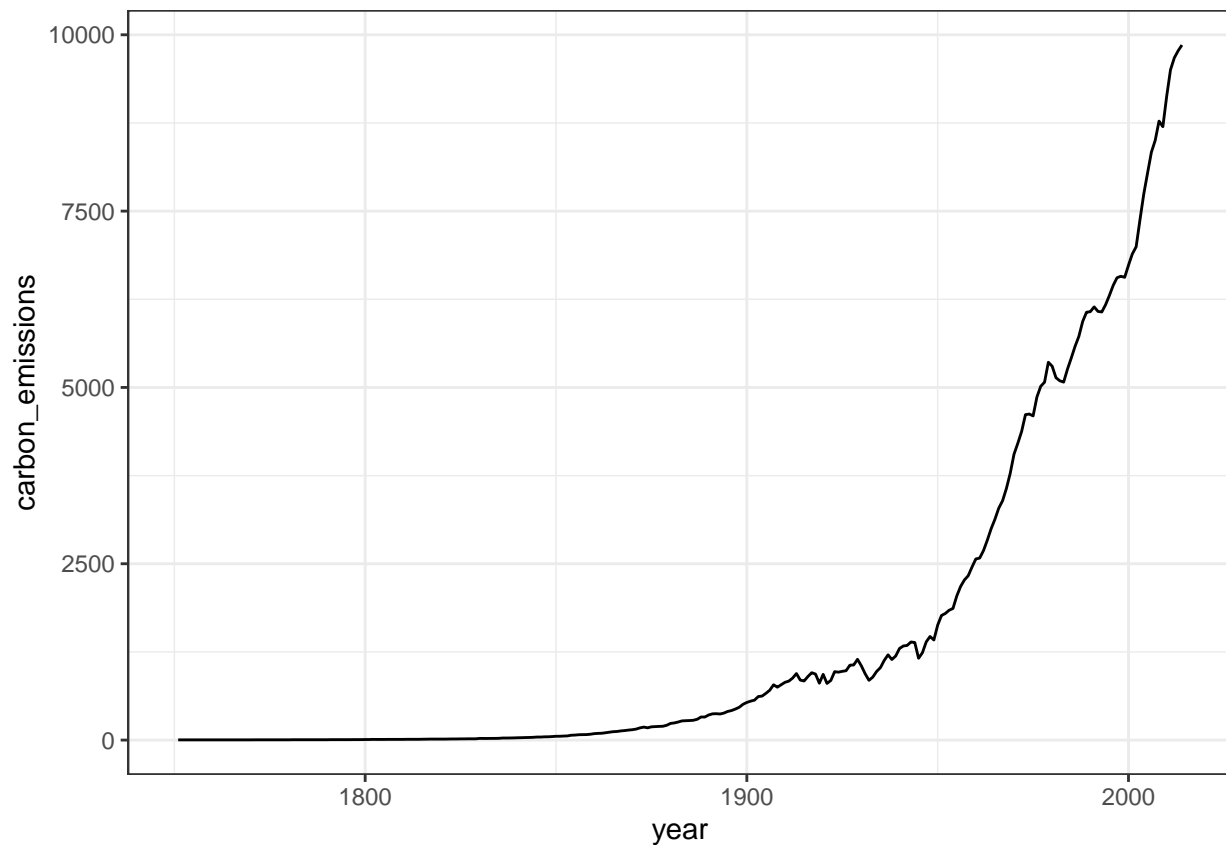


```
ylab("Concentration (ch4/n2o ppb, co2 ppm)") +
ggtitle("Atmospheric greenhouse gas concentration by year, 0-2000")
```



**Question 10** Make a time series line plot of carbon emissions (carbon\_emissions) from the temp\_carbon dataset. The y-axis is metric tons of carbon emitted per year.

```
temp_carbon %>%
  filter(!is.na(carbon_emissions)) %>%
  ggplot(aes(year, carbon_emissions)) +
  geom_line()
```



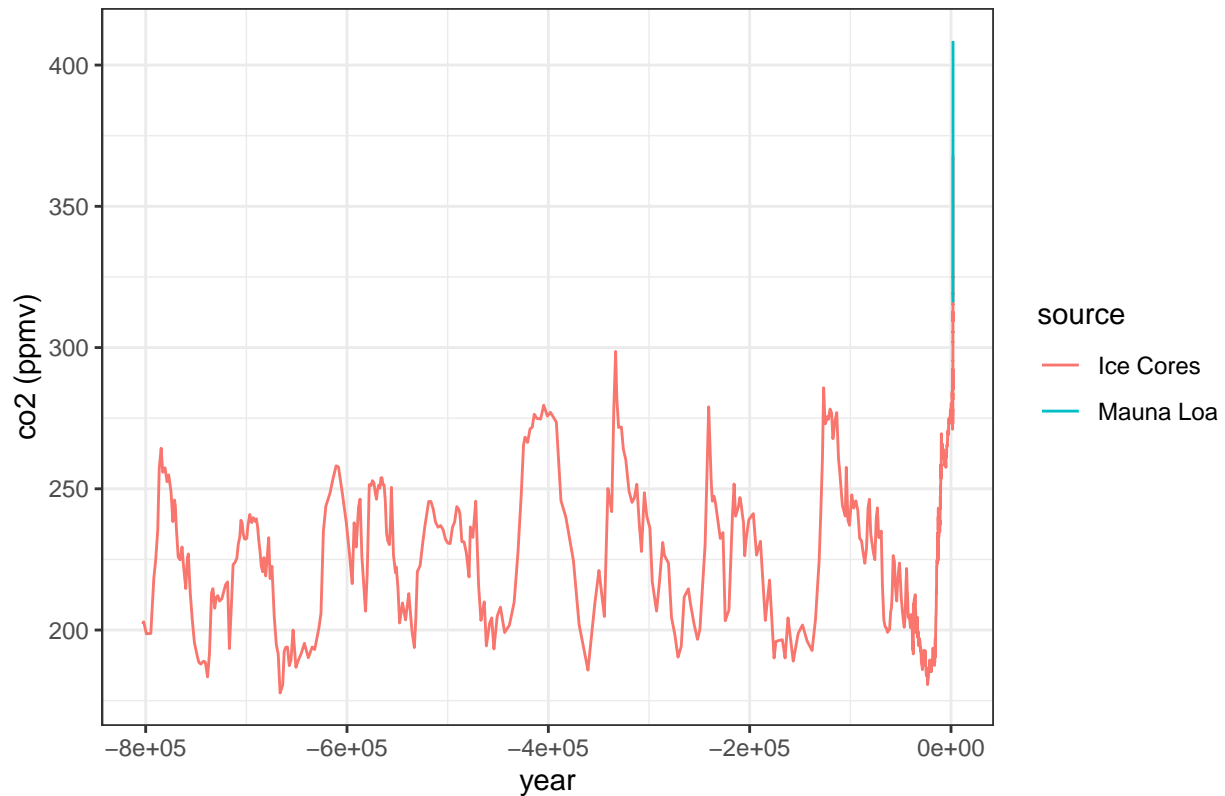
### Question 11

We saw how greenhouse gases have changed over the course of human history, but how has CO<sub>2</sub> (co2 in the data) varied over a longer time scale? The `historic_co2` data frame in `dslabs` contains direct measurements of atmospheric co2 from Mauna Loa since 1959 as well as indirect measurements of atmospheric co2 from ice cores dating back 800,000 years.

Make a line plot of co2 concentration over time (year), coloring by the measurement source (source). Save this plot as `co2_time` for later use.

```
co2_time <- historic_co2 %>%
  filter(!is.na(co2)) %>%
  ggplot(aes(year, co2, col=source)) +
  geom_line() +
  ggtitle("Atmospheric CO2 concentration, -800,000 BC to today") +
  ylab("co2 (ppmv)")
co2_time
```

### Atmospheric CO<sub>2</sub> concentration, –800,000 BC to today



#### Question 12

One way to differentiate natural co<sub>2</sub> oscillations from today's manmade co<sub>2</sub> spike is by examining the rate of change of co<sub>2</sub>. The planet is affected not only by the absolute concentration of co<sub>2</sub> but also by its rate of change. When the rate of change is slow, living and nonliving systems have time to adapt to new temperature and gas levels, but when the rate of change is fast, abrupt differences can overwhelm natural systems. How does the pace of natural co<sub>2</sub> change differ from the current rate of change?

Use the co<sub>2</sub>\_time plot saved above. Change the limits as directed to investigate the rate of change in co<sub>2</sub> over various periods with spikes in co<sub>2</sub> concentration.