

# Chapter 8

## Chapter 8 Visualizing data distributions

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. 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?

Our first data visualization building block is learning to summarize lists of factors or numeric vectors. More often than not, the best way to share or explore this summary is through data visualization. The most basic statistical summary of a list of objects or numbers is its distribution. Once a vector has been summarized as a distribution, there are several data visualization techniques to effectively relay this information.

In this chapter, we first discuss properties of a variety of distributions and how to visualize distributions using a motivating example of student heights. We then discuss the `ggplot2` geometries for these visualizations in Section 8.16.

### 8.1 Variable types

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.

When each entry in a vector comes from one of a small number of groups, we refer to the data as categorical data. Two simple examples are sex (male or female) and regions (Northeast, South, North Central, West). Some categorical data can be ordered even if they are not numbers per se, such as spiciness (mild, medium, hot). In statistics textbooks, ordered categorical data are referred to as ordinal data.

Examples of numerical data are population sizes, murder rates, and heights. Some numerical data can be treated as ordered categorical. We can further divide numerical data into continuous and discrete. Continuous variables are those that can take any value, such as heights, if measured with enough precision. For example, a pair of twins may be 68.12 and 68.11 inches, respectively. Counts, such as population sizes, are discrete because they have to be round numbers.

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. In contrast, when we have many groups with few cases in each group, we typically refer to them as discrete numerical variables. So, for example, the number of packs of cigarettes a person smokes a day, rounded to the closest pack, would be considered ordinal, while the actual number of cigarettes would be considered a numerical variable. But, indeed, there are examples that can be considered both numerical and ordinal when it comes to visualizing data.

### 8.2 Case study: describing student heights

Here we introduce a new motivating problem. It is an artificial one, but it will help us illustrate the concepts needed to understand distributions.

Pretend that we have to describe the heights of our classmates to ET, an extraterrestrial that has never seen humans. As a first step, we need to collect data. To do this, we ask students to report their heights in inches. We ask them to provide sex information because we know there are two different distributions by sex. We collect the data and save it in the heights data frame:

```
library(tidyverse)

## -- Attaching packages ----- tidyverse 1.3.1 --

## v ggplot2 3.3.5      v purrr 0.3.4
## v tibble 3.1.5       v dplyr 1.0.7
## v tidyr 1.1.4        v stringr 1.4.0
## v readr 2.0.2        v forcats 0.5.1

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

library(dslabs)
data(heights)
```

One way to convey the heights to ET is to simply send him this list of 1050 heights. But there are much more effective ways to convey this information, and understanding the concept of a distribution will help. To simplify the explanation, we first focus on male heights. We examine the female height data in Section 8.14.

### 8.3 Distribution function

It turns out that, in some cases, the average and the standard deviation are pretty much all we need to understand the data. We will learn data visualization techniques that will help us determine when this two number summary is appropriate. These same techniques will serve as an alternative for when two numbers are not enough.

The most basic statistical summary of a list of objects or numbers is its distribution. The simplest way to think of a distribution is as a compact description of a list with many entries. This concept should not be new for readers of this book. For example, with categorical data, the distribution simply describes the proportion of each unique category. The sex represented in the heights dataset is:

```
#>
#> Female Male
#> 0.227 0.773
```

This two-category frequency table is the simplest form of a distribution. We don't really need to visualize it since one number describes everything we need to know: 23% are females and the rest are males. When there are more categories, then a simple barplot describes the distribution. Here is an example with US state regions:

This particular plot simply shows us four numbers, one for each category. We usually use barplots to display a few numbers. Although this particular plot does not provide much more insight than a frequency table itself, it is a first example of how we convert a vector into a plot that succinctly summarizes all the information in the vector. When the data is numerical, the task of displaying distributions is more challenging.

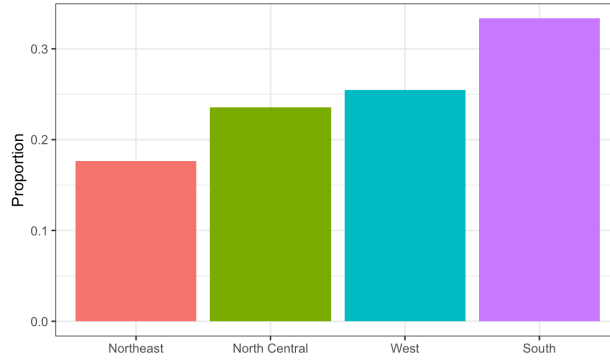


Figure 1: Distribution of Us state region

## 8.4 Cumulative distribution function

Numerical data that are not categorical also have distributions. In general, when data is not categorical, reporting the frequency of each entry is not an effective summary since most entries are unique. In our case study, while several students reported a height of 68 inches, only one student reported a height of 68.503937007874 inches and only one student reported a height 68.8976377952756 inches. We assume that they converted from 174 and 175 centimeters, respectively.

Statistics textbooks teach us that a more useful way to define a distribution for numeric data is to define a function that reports the proportion of the data below  $a$  for all possible values of  $a$ . This function is called the cumulative distribution function (CDF). In statistics, the following notation is used:

$$F(a) = \Pr(x \leq a)$$

Here is a plot of  $F$  for the male height data:

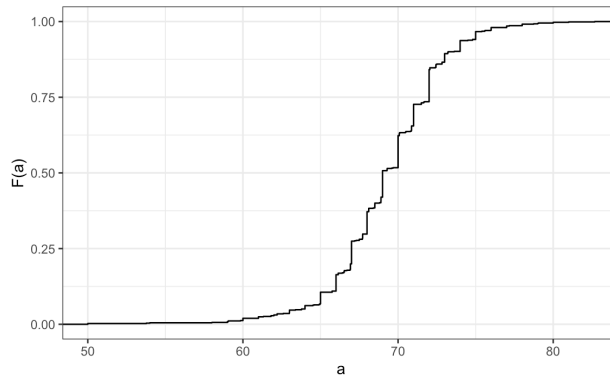


Figure 2: distribution of male height

Similar to what the frequency table does for categorical data, the CDF defines the distribution for numerical data. From the plot, we can see that 16% of the values are below 65, since  $F(66) = 0.164$ , or that 84% of the values are below 72, since  $F(72) = 0.841$ , and so on. In fact, we can report the proportion of values between any two heights, say  $a$  and  $b$ , by computing  $F(b) - F(a)$ . This means that if we send this plot above to ET, he will have all the information needed to reconstruct the entire list. Paraphrasing the expression “a picture is worth a thousand words,” in this case, a picture is as informative as 812 numbers.

A final note: because CDFs can be defined mathematically the word empirical is added to make the distinction when data is used. We therefore use the term empirical CDF (eCDF).

## 8.5 Histograms

Although the CDF concept is widely discussed in statistics textbooks, the plot is actually not very popular in practice. The main reason is that it does not easily convey characteristics of interest such as: at what value is the distribution centered? Is the distribution symmetric? What ranges contain 95% of the values? Histograms are much preferred because they greatly facilitate answering such questions. Histograms sacrifice just a bit of information to produce plots that are much easier to interpret.

The simplest way to make a histogram is to divide the span of our data into non-overlapping bins of the same size. Then, for each bin, we count the number of values that fall in that interval. The histogram plots these counts as bars with the base of the bar defined by the intervals. Here is the histogram for the height data splitting the range of values into one inch intervals:

$(49.5, 50.5], (50.5, 51.5], (51.5, 52.5], (52.5, 53.5], \dots, (82.5, 83.5]$

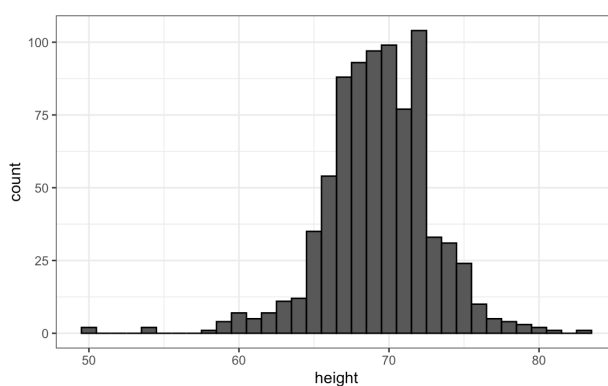


Figure 3: Histogram of height

## 8.6 Smoothed density

Smooth density plots are aesthetically more appealing than histograms. Here is what a smooth density plot looks like for our heights data:

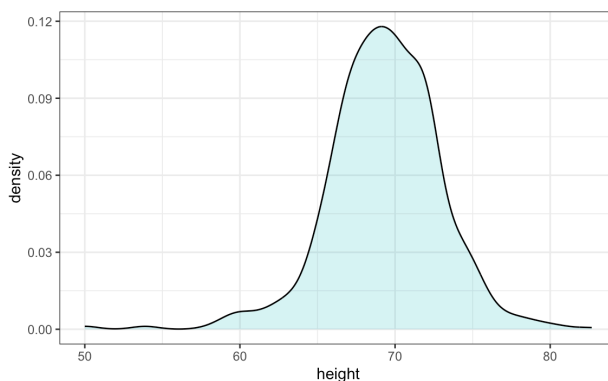


Figure 4: smooth density of height

In this plot, we no longer have sharp edges at the interval boundaries and many of the local peaks have been removed. Also, the scale of the y-axis changed from counts to density.

To understand the smooth densities, we have to understand estimates, a topic we don't cover until later. However, we provide a heuristic explanation to help you understand the basics so you can use this useful data visualization tool.

The main new concept you must understand is that we assume that our list of observed values is a subset of a much larger list of unobserved values. In the case of heights, you can imagine that our list of 812 male students comes from a hypothetical list containing all the heights of all the male students in all the world measured very precisely. Let's say there are 1,000,000 of these measurements. This list of values has a distribution, like any list of values, and this larger distribution is really what we want to report to ET since it is much more general. Unfortunately, we don't get to see it.

However, we make an assumption that helps us perhaps approximate it. If we had 1,000,000 values, measured very precisely, we could make a histogram with very, very small bins. The assumption is that if we show this, the height of consecutive bins will be similar. This is what we mean by smooth: we don't have big jumps in the heights of consecutive bins. Below we have a hypothetical histogram with bins of size 1:

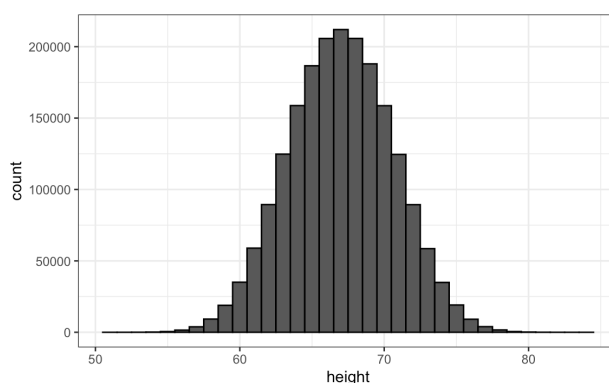


Figure 5: histogram

The smaller we make the bins, the smoother the histogram gets. Here are the histograms with bin width of 1, 0.5, and 0.1:

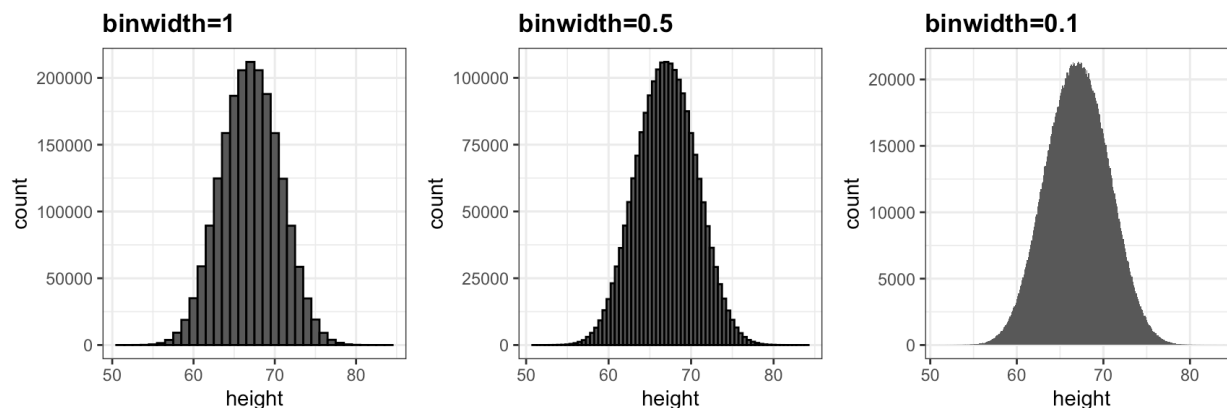


Figure 6: histogram

The smooth density is basically the curve that goes through the top of the histogram bars when the bins are very, very small. To make the curve not depend on the hypothetical size of the hypothetical list, we compute the curve on frequencies rather than counts:

Now, back to reality. We don't have millions of measurements. Instead, we have 812 and we can't make a histogram with very small bins.

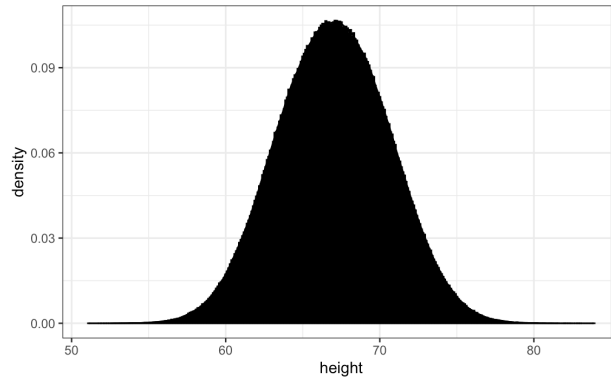


Figure 7: curve

We therefore make a histogram, using bin sizes appropriate for our data and computing frequencies rather than counts, and we draw a smooth curve that goes through the tops of the histogram bars. The following plots demonstrate the steps that lead to a smooth density:

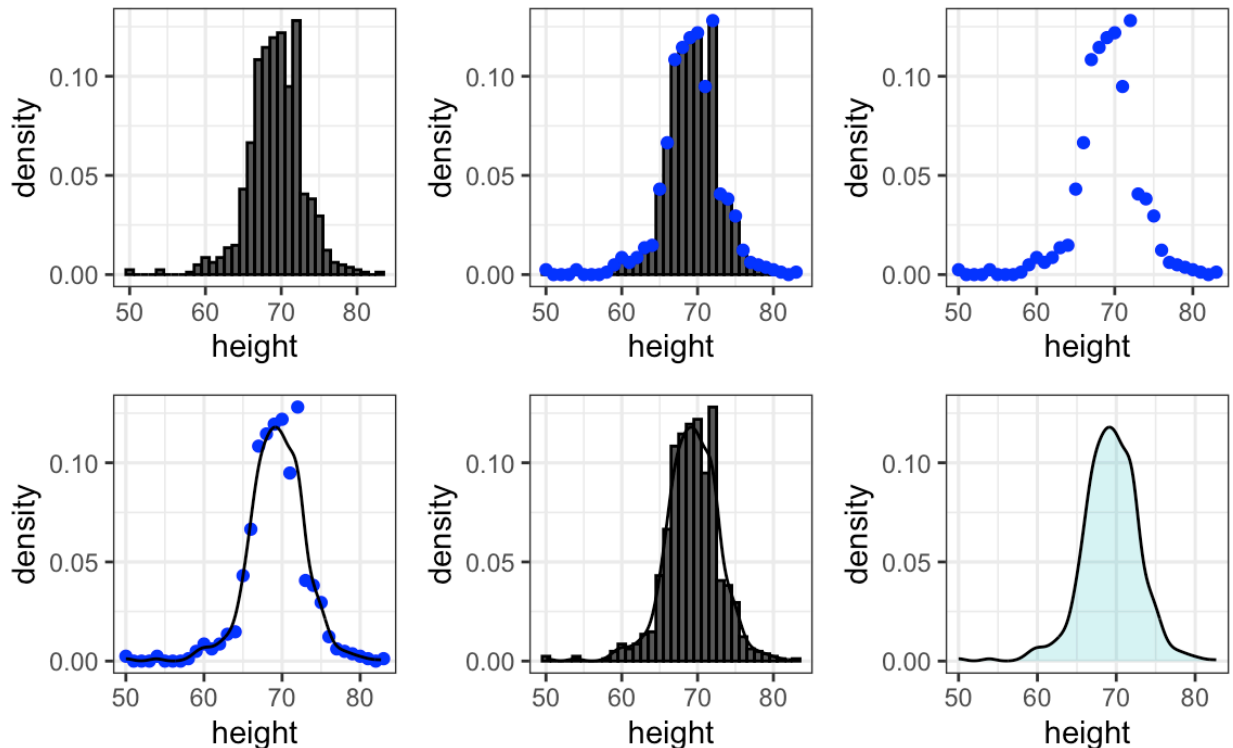


Figure 8: step that lead to smooth density

However, remember that smooth is a relative term. We can actually control the smoothness of the curve that defines the smooth density through an option in the function that computes the smooth density curve. Here are two examples using different degrees of smoothness on the same histogram:

We need to make this choice with care as the resulting visualizations can change our interpretation of the data. We should select a degree of smoothness that we can defend as being representative of the underlying data. In the case of height, we really do have reason to believe that the proportion of people with similar heights should be the same. For example, the proportion that is 72 inches should be more similar to the

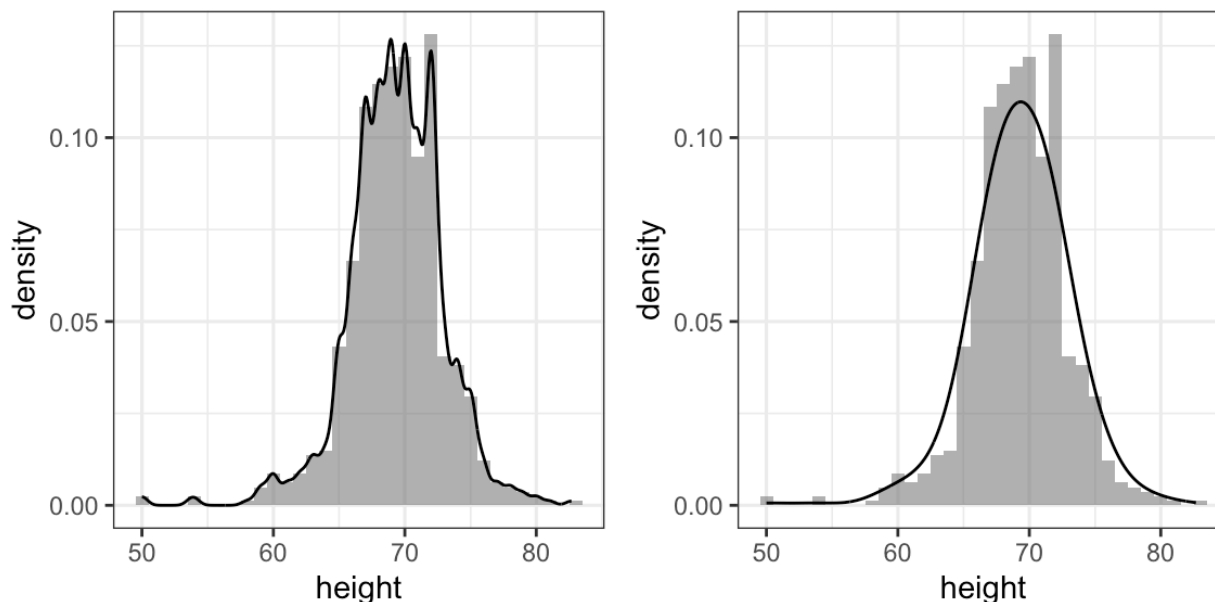


Figure 9: different degrees of smoothness on the same histogram

proportion that is 71 than to the proportion that is 78 or 65. This implies that the curve should be pretty smooth; that is, the curve should look more like the example on the right than on the left.

While the histogram is an assumption-free summary, the smoothed density is based on some assumptions.

### 8.6.1 Interpreting the y-axis

Note that interpreting the y-axis of a smooth density plot is not straightforward. It is scaled so that the area under the density curve adds up to 1. If you imagine we form a bin with a base 1 unit in length, the y-axis value tells us the proportion of values in that bin. However, this is only true for bins of size 1. For other size intervals, the best way to determine the proportion of data in that interval is by computing the proportion of the total area contained in that interval. For example, here are the proportion of values between 65 and 68:

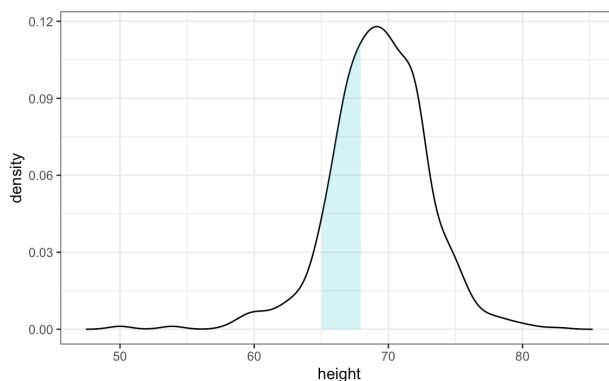


Figure 10: smooth density plot

The proportion of this area is about 0.3, meaning that about 30% of male heights are between 65 and 68 inches.

By understanding this, we are ready to use the smooth density as a summary. For this dataset, we would feel quite comfortable with the smoothness assumption, and therefore with sharing this aesthetically pleasing figure with ET, which he could use to understand our male heights data: **Figure 8**

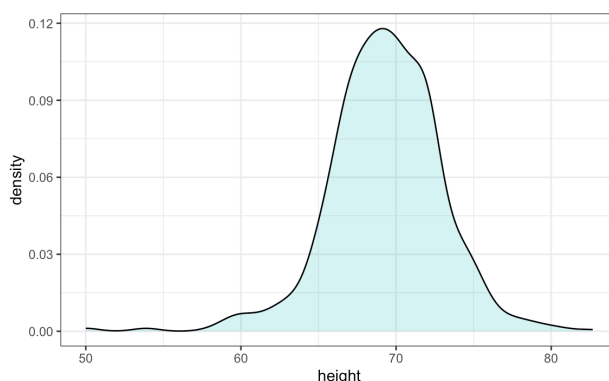


Figure 11: smooth density of height

### 8.6.2 Densities permit stratification

As a final note, we point out that an advantage of smooth densities over histograms for visualization purposes is that densities make it easier to compare two distributions. This is in large part because the jagged edges of the histogram add clutter. Here is an example comparing male and female heights:

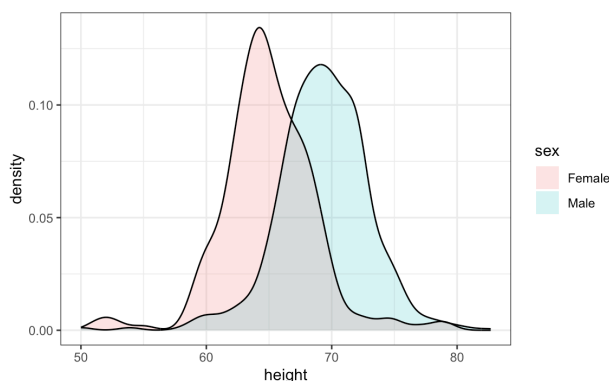


Figure 12: smooth density of male and female height

With the right argument, ggplot automatically shades the intersecting region with a different color. We will show examples of ggplot2 code for densities in Section 9 as well as Section 8.16.

## 8.7 Exercises

1. In the murders dataset, the region is a categorical variable and the following is its distribution:

To the closest 5%, what proportion of the states are in the North Central region?

# 25%

2. Which of the following is true:



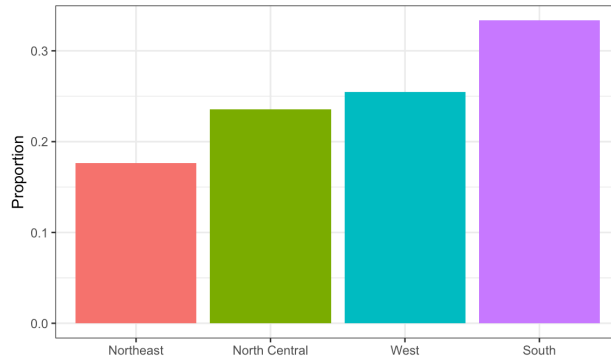


Figure 13: Distribution of Us state region

# b is answer.

3. The plot below shows the eCDF for male heights:

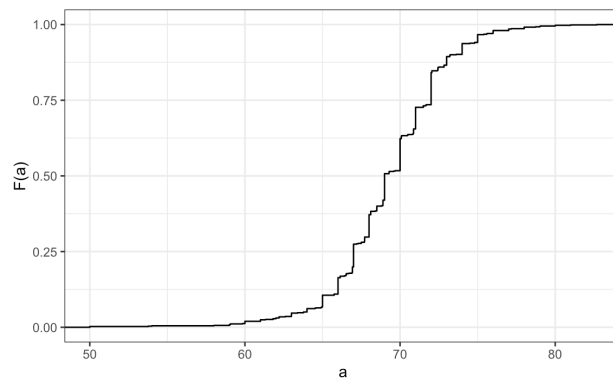


Figure 14: distribution of male height

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

# b 95% is answers

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?

# c is answer

5. Here is an 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?

# d(50) is answer

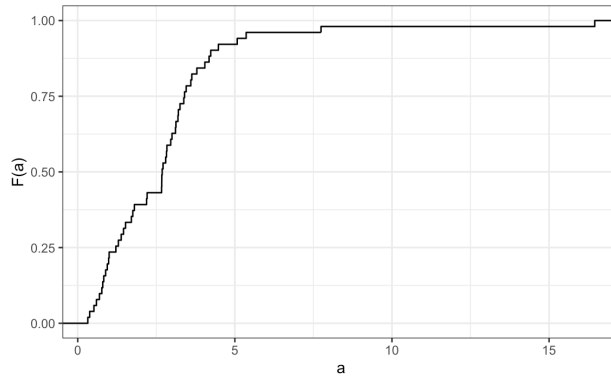


Figure 15: eCDF of murder rates

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

*# d is answer*

7. Below is a histogram of male heights in our heights dataset:

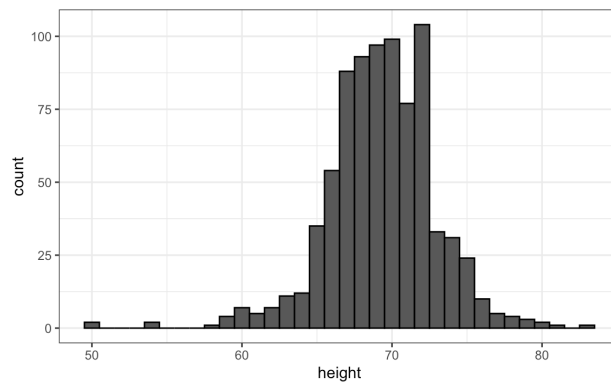


Figure 16: height histogram

Based on this plot, how many males are between 63.5 and 65.5?

*# Maybe no answer...*

*# It looks about 47 males are between 63.5 and 65.5*

8. About what percentage are shorter than 60 inches?

*# a is answer*

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

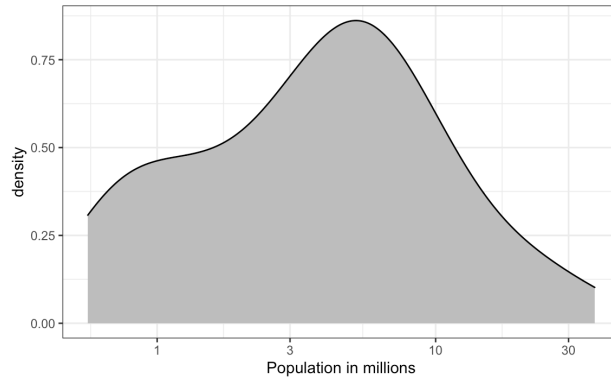


Figure 17: density plot

# b is answer

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

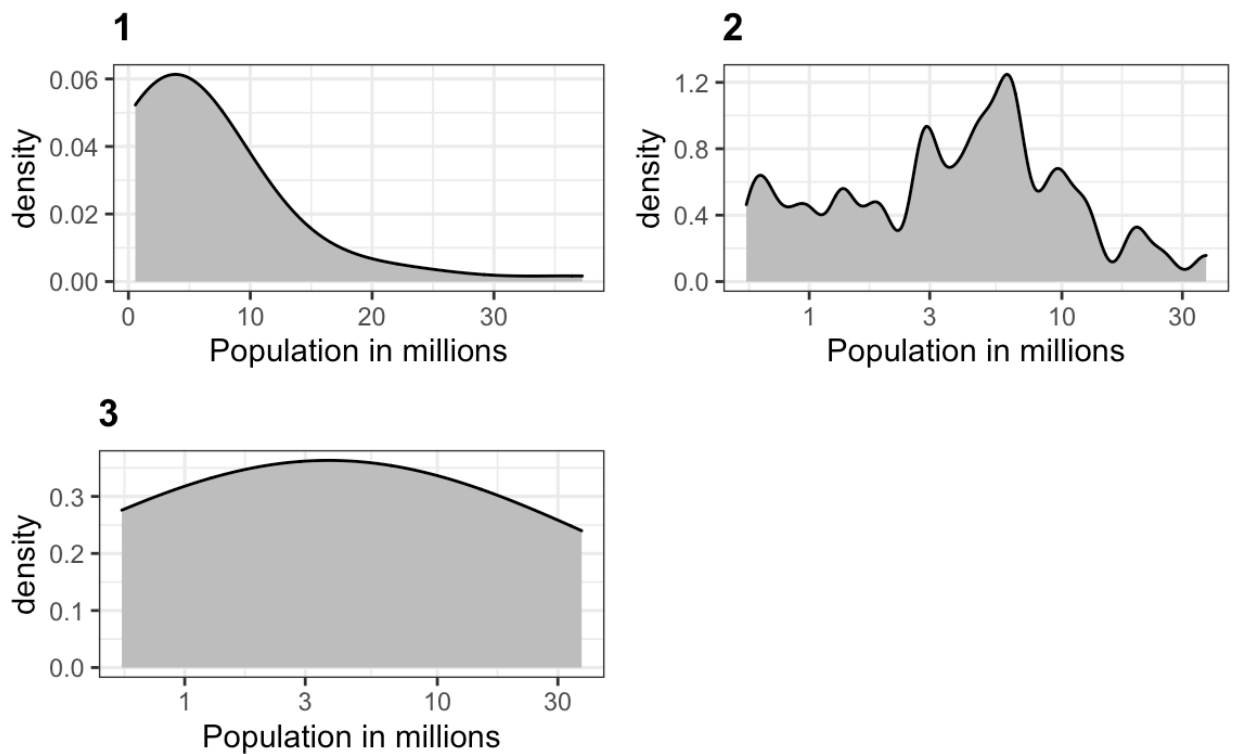


Figure 18: density plot

Which of the following statements is true:

# d is answer They are the same dataset, but the first is not in the log scale,  
# the second undersmooths, and the third oversmooths.

## 8.8 The normal distribution

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, including gambling winnings, heights, weights, blood pressure, standardized test scores, and experimental measurement errors. There are explanations for this, but we describe these later. Here we focus on how the normal distribution helps us summarize data.

Rather than using data, the normal distribution is defined with a mathematical formula. For any interval  $(a, b)$ , the proportion of values in that interval can be computed using this formula:

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

You don't need to memorize or understand the details of the formula. But note that it is completely defined by just two parameters:

$m$  and  $s$ . The rest of the symbols in the formula represent the interval ends that we determine,  $a$  and  $b$ , and known mathematical constants  $\pi$  and  $e$ . These two parameters,  $m$  and  $s$ , are referred to as the average (also called the mean) and the standard deviation (SD) of the distribution, respectively.

The distribution is symmetric, centered at the average, and most values (about 95%) are within 2 SDs from the average. Here is what the normal distribution looks like when the average is 0 and the SD is 1:

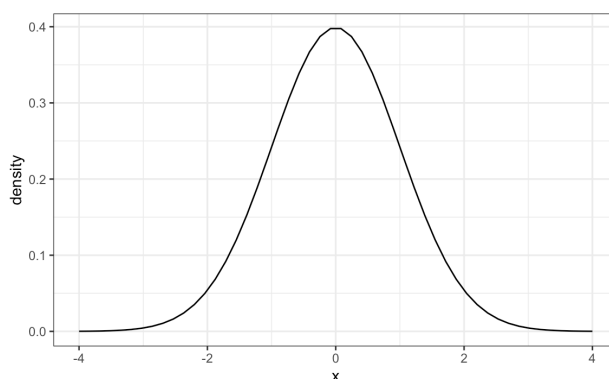


Figure 19: image

The fact that the distribution is defined by just two parameters implies that if a dataset is approximated by a normal distribution, all the information needed to describe the distribution can be encoded in just two numbers: the average and the standard deviation. We now define these values for an arbitrary list of numbers.

For a list of numbers contained in a vector  $x$ , the average is defined as:

```
# m <- sum(x)/length(x)
```

and the SD is defined as:

```
# s <- sqrt(sum((x-m)^2) / length(x))
```

which can be interpreted as the average distance between values and their average.

Let's compute the values for the height for males which we will store in the object x:

```
index<-heights$sex=="Male"  
x <- heights$height[index]
```

The pre-built functions mean and sd (note that for reasons explained in Section 16.2, sd divides by  $\text{length}(x)-1$  rather than  $\text{length}(x)$ ) can be used here:

```
m <- mean(x)  
s <- sd(x)  
c(average=m, sd=s)
```

```
##   average      sd  
## 69.314755  3.611024
```

Here is a plot of the smooth density and the normal distribution with mean = 69.3 and SD = 3.6 plotted as a black line with our student height smooth density in blue:

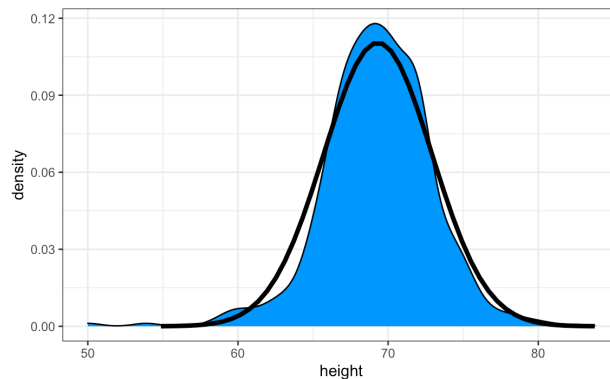


Figure 20: nd and smooth density

The normal distribution does appear to be quite a good approximation here. We now will see how well this approximation works at predicting the proportion of values within intervals.

## 8.9 Standard units

For data that is approximately normally distributed, it is convenient to think in terms of standard units. The standard unit of a value tells us how many standard deviations away from the average it is. Specifically, for a value  $x$  from a vector  $X$ , we define the value of  $x$  in standard units as  $z = (x - m)/s$  with  $m$  and  $s$  the average and standard deviation of  $X$ , respectively. Why is this convenient?

First look back at the formula for the normal distribution and note that what is being exponentiated is  $-z^2/2$  with  $z$  equivalent to  $x$  in standard units. Because the maximum of  $e^{-z^2/2}$  is when  $z = 0$ , this explains why the maximum of the distribution occurs at the average. It also explains the symmetry since  $-z^2/2$  is symmetric around 0. Second, note that if we convert the normally distributed data to standard units, we can quickly know if, for example, a person is about average ( $z = 0$ ), one of the largest ( $z \approx 2$ ),

one of the smallest ( $z \approx -2$ ), or an extremely rare occurrence ( $z > 3$  or  $z < -3$ ). Remember that it does not matter what the original units are, these rules apply to any data that is approximately normal.

In R, we can obtain standard units using the function `scale`:

```
z <- scale(x)
```

Now to see how many men are within 2 SDs from the average, we simply type:

```
mean(abs(z)<2)
```

```
## [1] 0.9495074
```

The proportion is about 95%, which is what the normal distribution predicts! To further confirm that, in fact, the approximation is a good one, we can use quantile-quantile plots.

## 8.10 Quantile-quantile plots

A systematic way to assess how well the normal distribution fits the data is to check if the observed and predicted proportions match. In general, this is the approach of the quantile-quantile plot (QQ-plot).

First let's define the theoretical quantiles for the normal distribution. In statistics books we use the symbol  $\Phi(x)$  to define the function that gives us the probability of a standard normal distribution being smaller than  $x$ . So, for example,  $\Phi(-1.96) = 0.025$  and  $\Phi(1.96) = 0.975$ . In R, we can evaluate  $\Phi$  using the `pnorm` function:

```
pnorm(-1.96)
```

```
## [1] 0.0249979
```

The inverse function  $\Phi^{-1}(x)$  gives us the theoretical quantiles for the normal distribution. So, for example,  $\Phi^{-1}(0.975) = 1.96$ . In R, we can evaluate the inverse of  $\Phi$  using the `qnorm` function.

```
qnorm(0.975)
```

```
## [1] 1.959964
```

Note that these calculations are for the standard normal distribution by default (mean = 0, standard deviation = 1), but we can also define these for any normal distribution. We can do this using the `mean` and `sd` arguments in the `pnorm` and `qnorm` function. For example, we can use `qnorm` to determine quantiles of a distribution with a specific average and standard deviation

```
qnorm(0.975, mean=5, sd=2)
```

```
## [1] 8.919928
```

For the normal distribution, all the calculations related to quantiles are done without data, thus the name theoretical quantiles. But quantiles can be defined for any distribution, including an empirical one. So if we have data in a vector  $x$ , we can define the quantile associated with any proportion  $p$  as the  $q$  for which the proportion of values below  $q$  is  $p$ . Using R code, we can define  $q$  as the value for which  $\text{mean}(x \leq q) = p$ . Notice that not all  $p$  have a  $q$  for which the proportion is exactly  $p$ . There are several ways of defining the best  $q$  as discussed in the help for the quantile function.

To give a quick example, for the male heights data, we have that:

```
mean(x<=69.5)
```

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

So about 50% are shorter or equal to 69 inches. This implies that if  $p = 0.50$  then  $q = 69.5$ .

The idea of a QQ-plot is that if your data is well approximated by normal distribution then the quantiles of your data should be similar to the quantiles of a normal distribution. To construct a QQ-plot, we do the following:

1. Define a vector of  $m$  proportions  $p_1, p_2, \dots, p_m$ .
2. Define a vector of quantiles  $q_1, q_2, \dots, q_m$  for your data for the proportions  $p_1, p_2, \dots, p_m$ . We refer to these as the sample quantiles.
3. Define a vector of theoretical quantiles for the proportions  $p_1, p_2, \dots, p_m$  for a normal distribution with the same average and standard deviation as the data.
4. Plot the sample quantiles versus the theoretical quantiles.

Let's construct a QQ-plot using R code. Start by defining the vector of proportions.

```
p <- seq(0.05,0.95,0.05)
```

To obtain the quantiles from the data, we can use the quantile function like this:

```
sample_quantiles <- quantile(x,p)
sample_quantiles
```

```
##      5%      10%      15%      20%      25%      30%      35%      40%
## 63.90079 65.00000 66.00000 67.00000 67.00000 68.00000 68.00000 68.62236
##      45%      50%      55%      60%      65%      70%      75%      80%
## 69.00000 69.00000 70.00000 70.00000 70.86614 71.00000 72.00000 72.00000
##      85%      90%      95%
## 72.44000 73.22751 75.00000
```

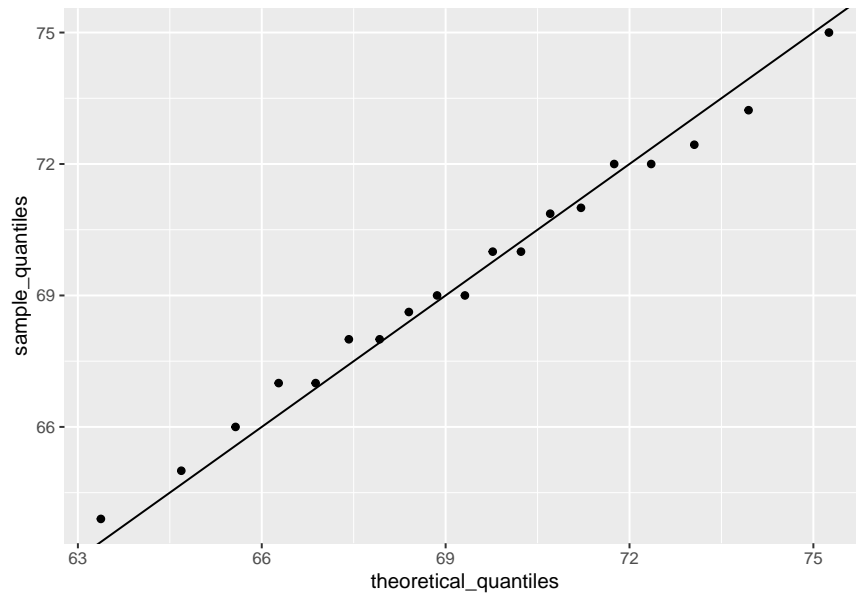
To obtain the theoretical normal distribution quantiles with the corresponding average and SD, we use the qnorm function:

```
theoretical_quantiles <- qnorm(p, mean=mean(x),sd=sd(x))
theoretical_quantiles
```

```
## [1] 63.37515 64.68704 65.57217 66.27564 66.87916 67.42113 67.92335 68.39991
## [9] 68.86099 69.31475 69.76852 70.22960 70.70616 71.20838 71.75035 72.35387
## [17] 73.05734 73.94247 75.25436
```

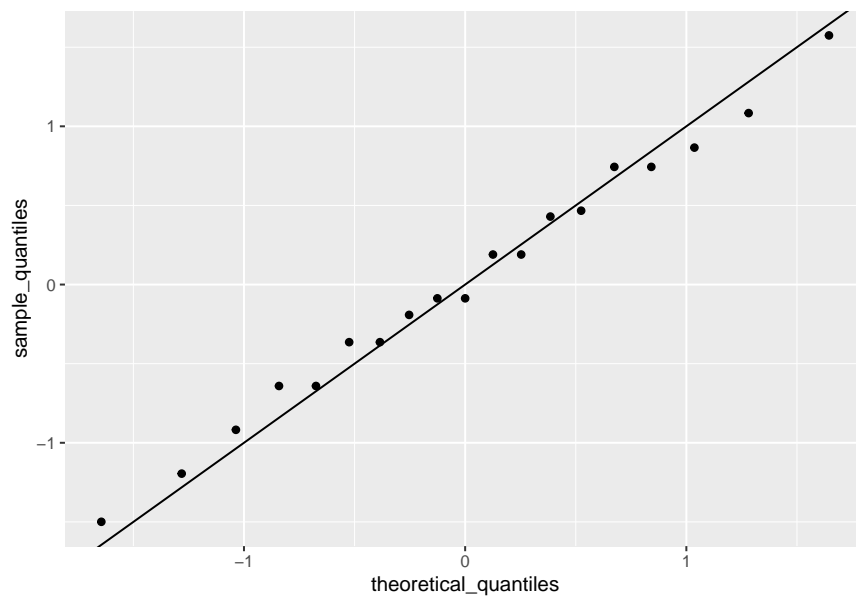
To see if they match or not, we plot them against each other and draw the identity line:

```
qplot(theoretical_quantiles, sample_quantiles) + geom_abline()
```



Notice that this code becomes much cleaner if we use standard units:

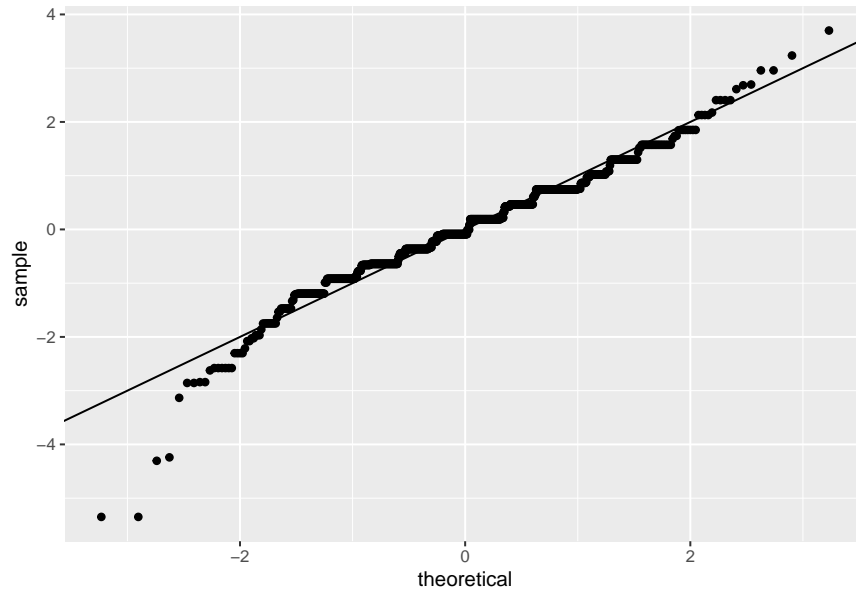
```
sample_quantiles <- quantile(z, p)
theoretical_quantiles <- qnorm(p)
qplot(theoretical_quantiles, sample_quantiles) + geom_abline()
```



The above code is included to help describe Q-Q-plots. However, in practice it is easier to use the ggplot2 code described in Section 8.16:

```
heights %>% filter(sex == "Male") %>%
  ggplot(aes(sample=scale(height))) +
  geom_qq() +
  geom_abline()
```





While for the illustration above we used 20 quantiles, the default from the `geom_qq` function is to use as many quantiles as data points.

## 8.11 Percentiles

Before we move on, let's define some terms that are commonly used in exploratory data analysis.

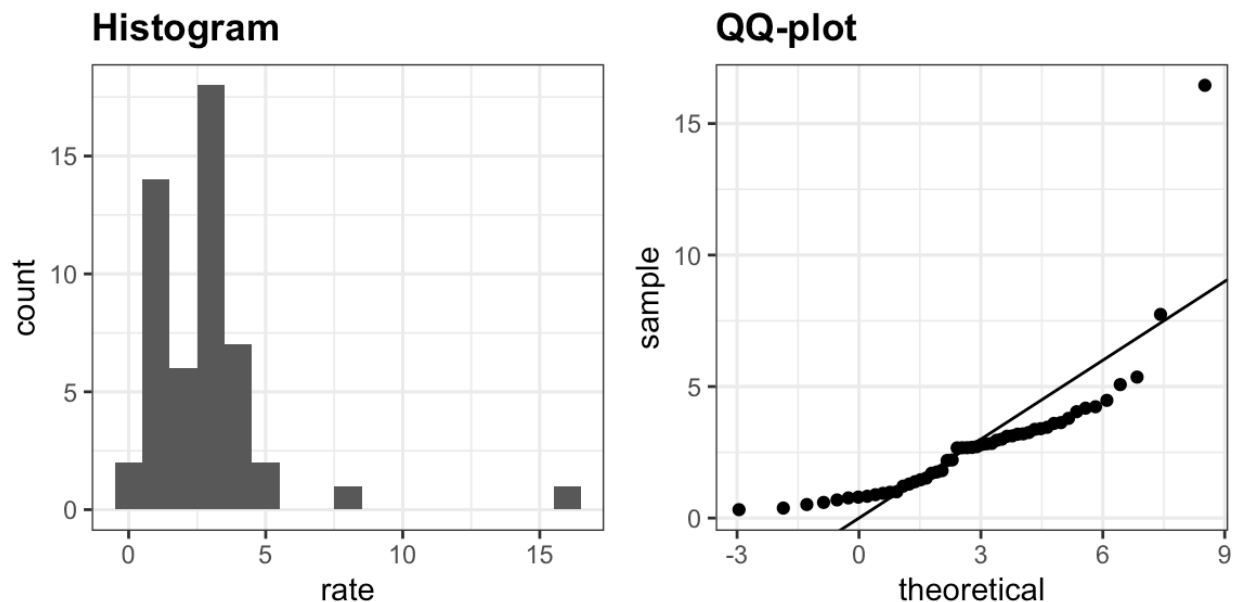
Percentiles are special cases of quantiles that are commonly used. The percentiles are the quantiles you obtain when setting the  $p$  at 0.01, 0.02, ..., 0.99. We call, for example, the case of  $p = 0.25$  the 25th percentile, which gives us a number for which 25% of the data is below. The most famous percentile is the 50th, also known as the median.

For the normal distribution the median and average are the same, but this is generally not the case.

Another special case that receives a name are the quartiles, which are obtained when setting  $p = 0.25, 0.50$ , and  $0.75$ .

## 8.12 Boxplots

To introduce boxplots we will go back to the US murder data. Suppose we want to summarize the murder rate distribution. Using the data visualization technique we have learned, we can quickly see that the normal approximation does not apply here:



In this case, the histogram above or a smooth density plot would serve as a relatively succinct summary.

Now suppose those used to receiving just two numbers as summaries ask us for a more compact numerical summary.

Here Tukey offered some advice. Provide a five-number summary composed of the range along with the quartiles (the 25th, 50th, and 75th percentiles). Tukey further suggested that we ignore outliers when computing the range and instead plot these as independent points. We provide a detailed explanation of outliers later. Finally, he suggested we plot these numbers as a “box” with “whiskers” like this:

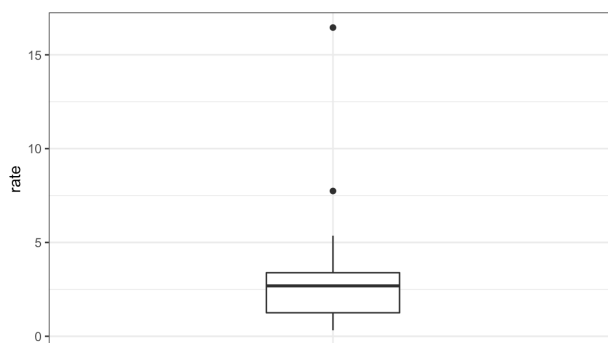


Figure 21: boxplot

with the box defined by the 25% and 75% percentile and the whiskers showing the range. The distance between these two is called the interquartile range. The two points are outliers according to Tukey’s definition. The median is shown with a horizontal line. Today, we call these boxplots.

From just this simple plot, we know that the median is about 2.5, that the distribution is not symmetric, and that the range is 0 to 5 for the great majority of states with two exceptions.

We discuss how to make boxplots in Section 8.16.

## 8.13 Stratification

In data analysis we often divide observations into groups based on the values of one or more variables associated with those observations. For example in the next section we divide the height values into groups based on a sex variable: females and males. We call this procedure stratification and refer to the resulting groups as strata.

Stratification is common in data visualization because we are often interested in how the distribution of variables differs across different subgroups. We will see several examples throughout this part of the book. We will revisit the concept of stratification when we learn regression in Chapter 17 and in the Machine Learning part of the book.

## 8.14 Case study: describing student heights(continued)

Using the histogram, density plots, and QQ-plots, we have become convinced that the male height data is well approximated with a normal distribution. In this case, we report back to ET a very succinct summary: male heights follow a normal distribution with an average of 69.3 inches and a SD of 3.6 inches. With this information, ET will have a good idea of what to expect when he meets our male students. However, to provide a complete picture we need to also provide a summary of the female heights.

We learned that boxplots are useful when we want to quickly compare two or more distributions. Here are the heights for men and women:

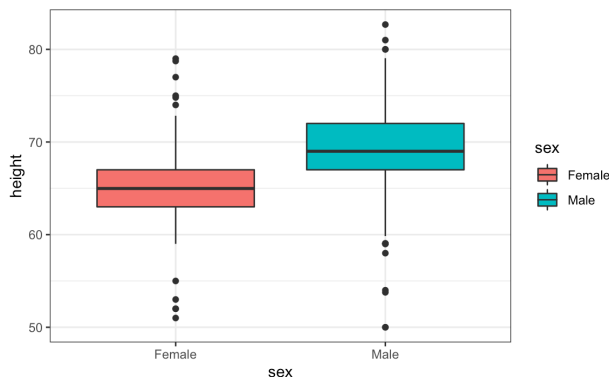
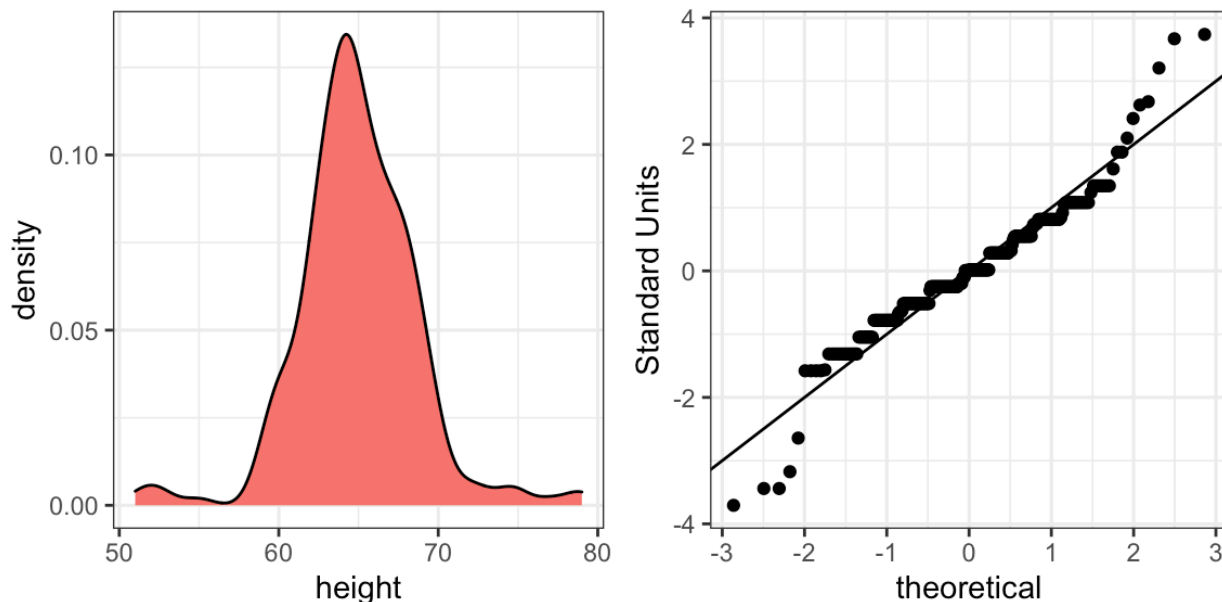


Figure 22: boxplot

The plot immediately reveals that males are, on average, taller than females. The standard deviations appear to be similar. But does the normal approximation also work for the female height data collected by the survey? We expect that they will follow a normal distribution, just like males. However, exploratory plots reveal that the approximation is not as useful:



We see something we did not see for the males: the density plot has a second “bump.” Also, the QQ-plot shows that the highest points tend to be taller than expected by the normal distribution. Finally, we also see five points in the QQ-plot that suggest shorter than expected heights for a normal distribution. When reporting back to ET, we might need to provide a histogram rather than just the average and standard deviation for the female heights.

However, go back and read Tukey’s quote. We have noticed what we didn’t expect to see. If we look at other female height distributions, we do find that they are well approximated with a normal distribution. So why are our female students different? Is our class a requirement for the female basketball team? Are small proportions of females claiming to be taller than they are? Another, perhaps more likely, explanation is that in the form students used to enter their heights, FEMALE was the default sex and some males entered their heights, but forgot to change the sex variable. In any case, data visualization has helped discover a potential flaw in our data.

Regarding the five smallest values, note that these values are:

```
heights %>% filter(sex == "Female") %>%
  top_n(5, desc(height)) %>%
  pull(height)
```

```
## [1] 51 53 55 52 52
```

Because these are reported heights, a possibility is that the student meant to enter 5’1“, 5’2“, 5’3” or 5’5”.

## 8.15 Exercises

1. Define variables containing the heights of males and females like this:

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

How many measurements do we have for each?

```
length(male) #812
```

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

```
length(female) #238
```

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

2. Suppose we can't make a plot and want to compare the distributions side by side. We can't just list all the numbers. Instead, we will look at the percentiles. Create a five row table showing female\_percentiles and male\_percentiles with the 10th, 30th, 50th, 70th, & 90th percentiles for each sex. Then create a data frame with these two as columns.

```
percentiles <- seq(0.1,0.9,0.2)
female_percentiles <- quantile(female,percentiles)
male_percentiles <- quantile(male, percentiles)

data.frame(female_percentiles,male_percentiles)
```

```
##      female_percentiles male_percentiles
## 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 following boxplots showing population sizes by country:

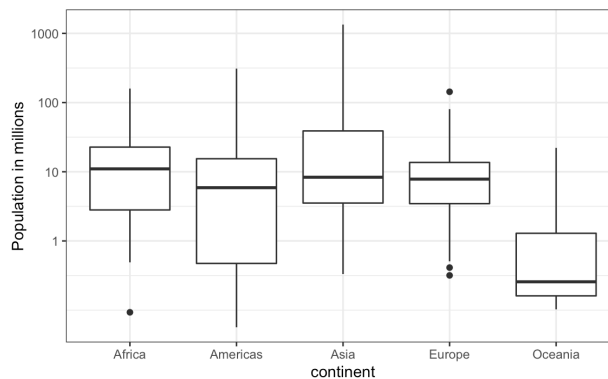


Figure 23: boxplots

Which continent has the country with the biggest population size?

```
#Asia
```

4. What continent has the largest median population size?

```
#Africa
```

5. What is median population size for Africa to the nearest million?

```
#10
```

6. What proportion of countries in Europe have populations below 14 million?

```
#b. 0.75
```

7. If we use a log transformation, which continent shown above has the largest interquartile range?

```
#Asia
```

8. 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)? Hint: use a logical operator and mean.

```
mean(69<x & x<=72)
```

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

```
# 33.3%
```

9. Suppose all you know about the data is the average and the standard deviation. Use the normal approximation to estimate the proportion you just calculated. Hint: start by computing the average and standard deviation. Then use the pnorm function to predict the proportions.

```
pnorm(72,mean=mean(x),sd=sd(x))-pnorm(69,mean=mean(x),sd=sd(x))
```

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

10. Notice that the approximation calculated in question nine is very close to the exact calculation in the first question. Now perform the same task for more extreme values. Compare the exact calculation and the normal approximation for the interval (79,81]. How many times bigger is the actual proportion than the approximation?
11. Approximate the distribution of adult men in the world as normally distributed with an average of 69 inches and a standard deviation of 3 inches. Using this approximation, estimate the proportion of adult men that are 7 feet tall or taller, referred to as seven footers. Hint: use the pnorm function.
12. There are about 1 billion men between the ages of 18 and 40 in the world. Use your answer to the previous question to estimate how many of these men (18-40 year olds) are seven feet tall or taller in the world?
13. There are about 10 National Basketball Association (NBA) players that are 7 feet tall or higher. Using the answer to the previous two questions, what proportion of the world's 18-to-40-year-old seven footers are in the NBA?
14. Repeat the calculations performed in the previous question for LeBron James' height: 6 feet 8 inches. There are about 150 players that are at least that tall.