

STAT 1793: Course Notes

Introduction to Probability and Statistics I

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Preface

What are these notes?

These notes are being written to supplement the Winter 2024 offering of STAT 1793 at the University of New Brunswick on the Saint John campus. These are intended to provide the complete set of notes required to be successful in the course, along with a series of examples. Note that, if you are a student in the offering of STAT 1793, the specific material that we cover and focus on may be a subset of these notes: we will be crafting our path through them together, as a class, and as such, not all material will be equally relevant. It is important to check the course website and to listen in lecture to ensure that you are always aware of what is being emphasized, what will be covered on the assessments, and so forth.

Moreover, it is important to note that these notes are a work-in-progress. As of today (January 5, 2024), the material through to Chapter 5 has been made up-to-date. Further chapters will be added throughout term. Additionally, some of the completed chapters may be revised in an attempt to add clarity, fix mistakes or typos, and to better format or sequence the material. If at any point you have comments, questions, suggestions, or corrections to these notes, please do reach out! They are intended to be a helpful resource to ensure your success in the course, and to help your probability and statistics skills into the future.

One final note is that our coverage of concepts throughout STAT 1793 reflects my personal biases and proclivities towards what is important in a first course in probability and statistics. Compared to others I likely have a larger emphasis on probability, leaving concepts more tied to statistics to a second course (e.g., STAT 2793). This is reflected both in the ordering of material (we start at Probability not at Statistics), and in the weight that each topic will be given. It is my belief that you need to be able to fluently speak the language of probability in order to study statistics, and that is where we will put our focus. However, this does mean that if you have impressions or content from another offering of the course, they may be less well-suited to the specific range of topics we will cover. The material is all the same, and if they help you learn, by all means; it is however important to emphasize that what is highlighted will likely be different.

Using These Notes

These notes are best viewed online. You can access them from anywhere at <https://dylanspicker.github.io/STAT1793-course-notes/index.html>. Viewing online will allow you to take advantage of interactivity (such as through code blocks and solutions hiding), the search feature (visible in the left hand margin), as well as better overall formatting. There is a version of these notes in PDF format available. To download them, press the PDF icon button () next to the note title in the left hand bar. The PDF notes contain all the same content, and will be updated alongside the web notes. The formatting of the PDF document may be less visually appealing compared to the web notes. Though an effort will be made to ensure that everything remains legible, and well-formatted, the aesthetics of these notes will be a lower priority than those available on the web.

To successfully use these notes, I would recommend a several step procedure:

1. Prior to the lecture where the material will be covered, read through the sections that are to be covered. For examples, do not read the solution, and instead try to think of how the example can be solved (perhaps trying to solve it yourself).
2. Attend lecture and be engaged. Our lectures will follow along with the course notes rather closely, including doing as a class many of the example problems. As a result, this will reemphasize what you have read.
 - Note, by reading *before* you come to class you will be seeing the material for a second time, allowing you to better process it.
 - Additionally, this will allow you to better follow the parts that were confusing in the notes, and be more prepared to ask questions of me throughout the lecture.
3. Return to the notes after class to ensure that everything has made sense. At this point try solving the example problems directly without referencing the solutions at all.
 - Only once you've gotten a solution to the problem should you check if it is correct. When checking, only look as far as any mistakes that have been made, and then try the problem again.
 - Note: struggling with problems is a key component of learning in any mathematical discipline. It is only by struggling to understand how the pieces fit together that you will develop a proper understanding for yourself.
 - Looking at solutions will often undermine your own understanding. It is a much different process to look at a solution and understand why it is correct, than it is to determine a solution for yourself.
4. Ask questions, attend office hours, and send emails as is required to ensure you are fully successful in the course!

Throughout the notes there will be references to computer code in a programming language known as R. R is the most common language used for statistics by practicing statisticians, and

it is a great utility for many of the types of problems we will be considering in this course. You are not expected to be able to write R code throughout the course, however, there is plenty of material throughout the notes to ensure that you will be able to read and run R code. This will be required for solving certain problems, and will make the process of statistics far nicer to engage with. If you are using the web notes this code can all be run directly in the browser. If you are using the PDF notes, the code and output is still provided. In either case, I would suggest getting R running on your own device, if possible. It is free to [download and install](#). I would also suggest installing [R Studio](#), which is a program specifically designed for writing and running R code with a lot of nice features.

Some Mathematical Background

These notes (and this course more broadly) require high school mathematics to complete. There is no calculus specifically required. The assumption is that you will be comfortable manipulating mathematical expressions, solving basic equations, using a calculator, and so forth. The following are a handful of topics which will come up throughout the course that are assumed to be known, presented here in brief as a quick reference.

Logarithms and Exponent Rules

Recall that if $a^x = b$, then we can solve for x through the use of logarithms. Specifically, $x = \log_a(b)$, where we read this as “the logarithm with base a of b .” The expression means that “ x is the exponent we put on a to get b .” In this course¹ we use the notation $\log(x)$ to represent the **natural logarithm**. The natural logarithm is $\log_e(x)$, where $e \approx 2.71828$ is Euler’s number. The **exponential function** is given by $e^x = \exp(x)$. Which notation is used depends on the specific setting, but both are equivalent.

¹And in most math courses beyond a certain point.

Recall further the following exponent and log rules:

$$\begin{aligned}a^b \times a^c &= a^{b+c} \\a^b \times c^b &= (ac)^b \\a^{-b} &= \frac{1}{a^b} \\(a^b)^c &= a^{bc} \\a^0 &= 1 \\\log(ab) &= \log(a) + \log(b) \\\log(a^b) &= b \log(a) \\\log(1) &= 0 \\\log(e) &= 1.\end{aligned}$$

Summation and Product Notation

If we wish to add up a series of numbers, x_1, x_2, \dots, x_n then we can use summation notation to record this. Specifically,

$$x_1 + x_2 + \dots + x_n = \sum_{i=1}^n x_i.$$

Here i is an indexing variable just used to keep track of which number we are currently working on. Note that the following quantities will hold

$$\begin{aligned}\sum_{i=1}^n (x_i + y_i) &= \sum_{i=1}^n x_i + \sum_{i=1}^n y_i \\\sum_{i=1}^n (x_i - y_i) &= \sum_{i=1}^n x_i - \sum_{i=1}^n y_i \\\sum_{i=1}^n cx_i &= c \sum_{i=1}^n x_i.\end{aligned}$$

We can also use a similar shorthand to discuss repeated products. That is, if we want to multiply x_1, x_2, \dots, x_n , then we can write

$$x_1 \times x_2 \times \dots \times x_n = \prod_{i=1}^n x_i.$$

Again, i is used as an indexing variable to keep track of what value is currently being multiplied.

The following results hold

$$\prod_{i=1}^n x = x^n$$

$$\prod_{i=1}^n b^{x_i} = b^{\sum_{i=1}^n x_i}$$

$$\prod_{i=1}^n c x_i = c^n \prod_{i=1}^n x_i.$$

Other Important Points

The following are some additional points that are useful to know, but which do not necessarily fit together nicely.

- For any two values x and y , we get $(x + y)^2 = x^2 + 2xy + y^2$.
- The integers are the set of all whole numbers, $\{0, \pm 1, \pm 2, \dots\}$. We will often denote the set of integers using \mathbb{Z} .
- The natural numbers are the set of all counting numbers, either $\{0, 1, 2, 3, \dots\}$ or else $\{1, 2, 3, 4, \dots\}$ depending on the source. We often denote the set using \mathbb{N} .
- The real numbers are the set of all numbers that you think of when thinking of numbers. They include the integers, and any fractions, and anything that cannot be written as a fraction (like π and e) as well. We denote the real numbers as \mathbb{R} .
- Intervals of real numbers are denoted as (a, b) or $[a, b]$ (or a mixture, giving $[a, b)$ or $(a, b]$). A round bracket means that the endpoint is **not** included in the set, where a square bracket means that it is. That is, a value of x is in (a, b) if $a < x < b$, where it is in $[a, b]$ if $a \leq x \leq b$.
- We write “ x is in the interval (a, b) ” mathematically using the \in symbol. Specifically, $x \in (a, b)$.
- Infinity (∞) is not a number. Rather, it is a statement regarding the lack of a bound. When we say that something is infinity, or infinite, we simply mean that it is larger than any of the natural numbers. If you were to be given any number, then infinity will be larger than that.
- **Limits:** note that, while limits are from calculus, they are useful for formally understanding a few concepts in class. The limit of a function, $f(x)$, is simply the value that the function approaches as x approaches a specific point. So, for instance, $\lim_{x \rightarrow a} f(x)$ is the value that $f(x)$ approaches as x approaches a . If $f(a)$ exists then it is simply $f(a)$. However, $f(a)$ may not exist, at which point, we look at where the function is tending to.
- **Infinite Limits:** Of specific importance to us are infinite limits. Specifically,

$$\lim_{x \rightarrow \infty} f(x)$$

captures the behaviour of the function $f(x)$ as x gets larger and larger. In many cases, $f(x)$ will approach some specific value, which we assign to be the limiting value of the function.

Additional Resources

The following are helpful resources which may be used to supplement the material in the class. If you have any suggested resources, please feel free to send them to me, and I will include them here.

1. [Open Intro Statistics](#).
2. [Probability Course](#).
3. [Introduction to R](#).
4. [Learning Statistics with R](#).

Part I

Part 1: Probability

1 Introduction

1.1 What is Probability?

At its core, statistics is the study of uncertainty. Uncertainty permeates the world around us, and in order to make sense of the world, we need to make sense of uncertainty. The language of uncertainty is **probability**. Probability is a concept which we all likely have some intuitive sense of. If there was a 90% probability of rain today, you likely considered grabbing an umbrella. You are not likely to wager your life savings on a game that has only a 1% probability of paying out. We have a sense that probability provides a measure of *likelihood*. Defining probability mathematically is a non-trivial task, and there have been many attempts to formalize it throughout history. While we will spend a good deal of time formalizing notions of probability in this course, we first pause to emphasize the familiarity with probability that you are likely starting with.

Suppose that two friends, Charles and Sadie, meet for coffee once a week. During their meetings they have wide-ranging, deep, philosophical conversations spanning across many important topics.¹ Beyond making progress on some of the most pressing issues of our time, Charles and Sadie each adore probability. As a result, at the end of each of their meetings, they play a game to decide who will pay. The game proceeds by having them flip a coin three times. If two or more heads come up Charles pays, and otherwise Sadie pays.

We can think about the strategy that they are using here and *feel* that this is going to be “fair”. With two or more heads, Charles pays. With two or more tails, Sadie pays. There always has to be either two or more heads *or* two or more tails, and each is equally likely to come up². The outcome of their game is uncertain before it begins, but we know that in the long run neither of the friends is going to be disadvantaged relative to the other. We can say that the probability that either of them pays is equal. It’s 50-50. Everything is balanced.

Now imagine that one day, in the middle of their game, Charles gets a very important phone call³ and leaves abruptly after the first coin has been tossed. The first coin toss showed a heads.

¹For instance they ask “do we all really see green as the same colour?” or “why is it that ‘q’ comes as early in the alphabet as it does? it deserves to be with ‘UVWXYZ’?”

²There has been some recent literature, see Bartoš et al. (2023), which may suggest that a coin is ever so slightly more likely to land on the same side it started on, perhaps undermining this assertion.

³Someone has just pointed out the irony in the fact that there is no synonym for synonym. Technically, there are the words *metonym* and *poecilonym* and *polyonym*, but these are rarely used and Charles would wager that there is a very high probability you have never seen them.

Sadie, recognizing the gravity of the phone call, pays for the both of them, while realizing that Charles was well on the way to having to pay.

Example 1.1 (Basic Probability Enumeration). What is the probability that Sadie would have had to pay in the aforementioned scenario? That is, assuming that the first coin shows a head, what is the probability that at least two heads are shown on the first three coin tosses?

Solution

Sadie figures that any coin toss is equally likely to show heads or tails. because the first coin showed heads, then there are four possible sequences that could have shown up:

1. H, H, H ;
2. H, H, T ;
3. H, T, H ;
4. H, T, T .

In three of these situations ((1) H, H, H , (2) H, H, T , and (3) H, T, H) there are two heads and so Charles would have to pay. In one of them there are two tails, and so Sadie would have to pay. As a result, Charles would have to pay in 3 of the 4 (with probability 0.75) and Sadie in 1 of the 4 (with probability 0.25).

Looking at Example 1.1, we can see that Sadie should likely have not paid. Only one out of every four times would Sadie have had to pay, given the first coin being heads. However, we can not be certain that, had all three tosses been observed, Sadie would *not* have paid. It is possible that we would have observed two tails, making her responsible for the bill. This possibility happens one time out of four, which is more likely than the probability of rolling a four on a six-sided die⁴. Fours are rolled on six-sided dice quite frequently⁵, and so it is not all together unreasonable for her to have paid.

This seemingly simple concept is the core of probability. Probability serves as a method for quantifying uncertainty. It allows us to make numeric statements regarding the set of outcomes that we can observe, by quantifying the frequency with which we expect to observe those outcomes. Probability does not *remove* the uncertainty. We still need to flip the coin or roll the die to know what will happen. All probability gives us is a set of tools to quantify this uncertainty. These tools are critical for decision making in the face of the ever-present uncertainty around us.

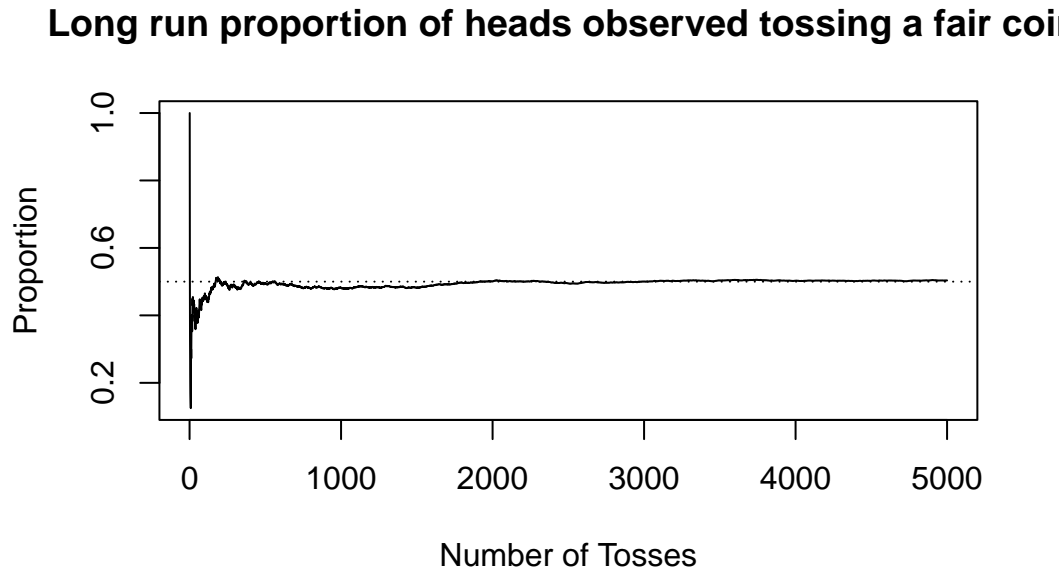
⁴This event happens one time out of every six.

⁵Again, about one out of every six rolls

1.2 How to Interpret Probabilities (like a Frequentist)

We indicated that, intuitively, probability is a measure of the frequency with which a particular outcome occurs. This intuition can be codified exactly with the **Frequentist interpretation** of probability. According to the Frequentist interpretation (or frequentism, as it is often called), probabilities correspond to the proportion of time any event of interest is⁶ actually occurs in the long run. For a Frequentist, you imagine yourself performing the experiment you are running over, and over, and over, and over, and over again. Each time you answer “did the event happen?” and you count up those occurrences. As you do this more and more and more, wherever that proportion lands corresponds to the probability.

Figure 1.1: This plot simulates the repeated tossing of a coin. The x-axis represents the number of coins being tossed, and the y-axis plots the proportion of times that heads has shown up cumulatively over the tosses thus far. We can see in the long run that this proportion tends towards 0.5.



To formalize this mathematically, we first define several important terms.

Definition 1.1 (Experiment). Any action to be performed whose outcome is not (or cannot) be known with certainty, before it is performed.

⁶Be that flipping a heads, rolling a four, or observing rain on a given day.

Definition 1.2 (Event [Informally]). A specified result that may or may not occur when an experiment is performed.

Suppose that an experiment is able to be performed as many times as one likes, limited only by your boredom. If you take k_N to represent the number of times that the event of interest occurs when you perform the experiment N times, then a Frequentist would define the probability of the event as

$$\text{covprobability} = \lim_{N \rightarrow \infty} \frac{k_N}{N}.$$

This course does not assume that you have any familiarity with calculus, and yet, this definition relies on limits, a concept taken directly from calculus. However, we will not actually require the ability to work with limits for this course. Instead, when you see a statement of the form

$$\lim_{x \rightarrow \infty} f(x),$$

simply think “what is happening to the function $f(x)$ as x grows and grows (off to ∞)?”

In practice this means that, in order to interpret probabilities, we think about repeating an experiment many, many times over. As we do that, we observe the proportion of times that any particular outcome occurs, and take that to be the defining relation for probabilities. The reason that we say the probability of flipping a heads is 0.5 is because if we were to sit around and flip a coin⁷ over, and over, and over again, then in the long-run we would observe a head⁸ in 0.5 of cases.

Example 1.2 (Probability Interpretation). How do we interpret the statement “the probability that Sadie would have had to pay, given a head on the first toss, is 0.25”? Recall that in the game, they toss three coins, and Sadie pays if two of them show tails.

Solution

This statement means that, if Sadie were to repeatedly be in the situation where one head has shown and there are two coins left to toss, then in 0.25 of these situations (in the limit, as this is repeated an infinite number of times) will end up showing two tails.

Many situations in the real world are not able to be run over and over again. Think about, for instance, the probability that a particular candidate wins in a particular election. There is uncertainty there, of course, but the election can only be run once. What then? There are several ways through these types of events.

First, we can rely on the **power of imagination**. There is nothing stopping us from envisioning the hypothetical possibility of running the election over, and over, and over, and over again. If we step outside of reality for a moment, we can ask “if we could play the day of the

⁷Our experiment.

⁸Our event.

election many, many, many times, what proportion of those days would end with the candidate being elected?” If we say that the candidate has a 75% chance of being elected, then we mean that in 0.75 of those imagined worlds, the candidate wins. It is crucial to stress that in our imagination here, we need to be thinking about the **exact same day** over and over again. We cannot imagine a different path leading to the election, different speeches being given in advance, or different opposition candidates. If we start from the same place, and play it out many times over, what happens in each of those worlds?

This repeated imagining is not for everyone. As a result, alternative proposals to the interpretation of probability have been made. Most popularly, the **Bayesian interpretation** has recently become prominent. To Bayesians, probability is a measure of subjective belief. To say that there is a 50% chance of a coin coming up is a statement about one’s knowledge of the world. Typically, coins show up heads half the time, so that’s our belief about heads. The Bayesian view, built around subjective confidence in the state of the world, can be formalized mathematically as well. A Bayesian considers the *prior evidence* that they have about the world⁹ and combine this with current observations in order to update their subject beliefs, balancing these two sources of information.

Remark (Bayesian Probabilities and Belief Updating). Suppose that a Bayesian is flipping a coin. Before any flips have been made the Bayesian understandably believes that the coin will come up heads 50% of the time. However, when the coin starts to be flipped, the observations are a string of tails in a row.

After having flipped the coin five times, the individual has observed five tails. Of course, it is totally possible to flip a fair coin five times and see five tails, but there is a level of skepticism growing.

After 10 flips, the Bayesian has still not seen a head. At this point, the subjective belief is that there is likely something unfair about this coin. Even though the experiment started with a baseline assumption that the coin was fair the Bayesian no longer believes that the next flip will be a head.

As this goes on, you can imagine the Bayesian continuing to update their view of the world. To them, the probability is an evolving concept, capturing what was believed and what has been observed.

For the election example, the Bayesian interpretation is somewhat easier to think through. To say that a candidate has a 75% chance of winning the election means that “based on everything that has been observed, and any prior beliefs about the viability of the candidates, the subjective likelihood that the candidate wins the election is 0.75”. If we disagree about prior beliefs, or have experienced different pieces of information, then we may disagree on the probability. That is okay.

⁹Any relevant evidence that has previously been collected.

In this course, we focus on the Frequentist interpretation. This is, in part, because Frequentist probability is an easier introduction to the concepts that are necessary for grasping uncertainty. Additionally, there is some research to suggest that Frequentist interpretations are fairly well understood by the general public ¹⁰. However, it is important to know and recognize that there is a world beyond Frequentist Probability and Statistics, one which can be very powerful once it is unlocked. ¹¹

If probability measures the long term proportion of times that a particular event occurs, how can we go about computing probabilities? Do we require to perform an experiment over and over again? Fortunately, the answer is no. The tools of probability we will cover allow us to make concrete statements about the probabilities of events without the need for repeated experimental runs. However, before dismissing the idea of repeatedly running an experiment at face value, it is worth considering a tool we have at our disposal that renders this more possible than it has ever been: computers.

1.3 R Programming for Probability and Statistics

Throughout this course we will make use of a programming language for statistical computing, called R. Classically, introductory statistics courses involved heavy computation of particular quantities by hand. The use of a programming language (like R) frees us from the tedium of these calculations, allowing for a deeper focus on understanding, explanation, decision-making, and complex problem solving. This is **not** to say we will *never* do problems by hand¹², however, we will emphasize the use of statistical computing often. While you will not be expected to write R programs on your own, you will be expected to read simple scripts, make basic modifications, and to run code that is given to you.

Throughout these course notes, where relevant, R code will be provided to demonstrate the ideas being discussed. It may be useful to have R open alongside the notes to ensure that you can get the same results that are printed throughout. In this section we will cover some of the very basics of using R, and reading R code. If you are interested, there are plenty of resources to becoming a more proficient R programmer. This is a skill that will benefit you not only in this course, but in many courses to come, and far beyond your university training. If you have any programming in your background, R is a fairly simple language to learn; if not, R can be quite beginner friendly.

¹⁰See, for instance Gigerenzer et al. (2005), where they study how people interpret the statement “there is a 30% chance of rain tomorrow.” Interestingly, most people can convert this into a frequency statement (3 out of 10, say), even if the specific meaning is sometimes lost. They conclude that there are other issues in attempting to understanding this statement, issues which we will address later on.

¹¹More on this in later years, if you so desire! Come have a chat, if that sounds interesting.

¹²To the contrary, some amount of by-hand problem solving helps to solidify these concepts.

1.3.1 Basic Introduction to R Programming

When programming, the basic idea is that we are going to write instructions in a **script** which we will tell our computer to execute. These instructions are¹³ performed one-by-one, from the top to the bottom of the script. We can have instructions which operate on their own, or which interact with previous (or future) instructions to add to the complexity. The trick with programming then is to determine which actions you need the computer to perform, in which order, to accomplish the task that you are setting out to do.

To begin, we may consider a very simple R program, one which uses the programming language as a basic calculator.

```
5 + 3 - (10*2) + 8^(25/3)
## [1] 33554420
```

Here, we ask the computer to perform some simple arithmetic operations. We use + for addition, - for subtraction, * for multiplication, / for division, and ^ for exponentiation. With the use of parentheses, any expressions relating to these basic operations can be performed. Note that here the result is simply output after it is computed. Try modifying the exact expressions being computed, allowing you to feel comfortable with these types of mathematical operations.

```
5 + 3 - (10*2) + 8^(25/3)
8 * 5
## [1] 33554420
## [1] 40
```

Here, we have two lines of math running with simple operations. Each is simply output when it is computed. These two results have no ability to interact with one another, and if we were to add more and more lines beneath, the same would continue to happen. If we want different commands to be able to interact with one another, we need a method for storing the results. To do so, we can define **variables**. In R, to define a variable, we use the syntax `variable_name <- variable_value`. We can choose *almost* anything that we want for the variable name¹⁴ and the variable value can also be of many types.¹⁵ The arrow between the two is the **assignment operator** and it simply tells R to assign the `variable_value` to be accessible from the `variable_name`.

¹³Typically. There are some exceptions to this, but if this is your first time programming, you need not worry about that!

¹⁴The variable name must start with a letter and can be a combination of letters, numbers, periods, and underscore.

¹⁵more on this later

```
my_5 <- 5
my_8 <- 8
my_5
my_8
## [1] 5
## [1] 8
```

In this code we assign the variable `my_5` to contain the value 5, and the variable `my_8` to contain the value 8. We can output these as expressions themselves, simply by typing the variable name. Simply outputting these variables is not of particular interest, however, we can use the variables in later statements by simply including the variable name in them.

```
my_5 <- 5
my_8 <- 8
my_5*my_8
## [1] 40
```

Here, instead of simply outputting the variables, we multiply them together. We could have used `5 * 8` in this case for the same result, however, we are afforded a lot more flexibility with this approach. Much of this flexibility comes from our capacity to *change* the values of variables over time. Consider the following script, and try to understand why the output is the way that it is.

```
my_5 <- 5
my_8 <- 8
my_5*my_8

my_5 <- 10
my_5*my_8
## [1] 40
## [1] 80
```

At the top point in the script, before the first `my_5*my_8` call, The variable `my_5` has the value 5. However, after this is called, the value is updated to be 10. Then, when we call `my_5*my_8` again, this is now simplified to `10 * 8`, giving the result. Perhaps more importantly, we can take the value of an expression and assign that to a variable itself.

```
my_5 <- 5
my_8 <- 8
result <- my_5*my_8
result
## [1] 40
```

Here, we define another variable. This time, **result** now contains the result of multiplying our previous two variables. Thus, when we output it, we get the same value. Take a moment to read through the following script, and try to understand what will happen at the end.

```
my_5 <- 5
my_8 <- 8
result <- my_5*my_8

my_5 <- result
my_8 <- my_5
result <- my_5 * my_8

result
```

The result is 1600. Why? We can read through this step-by-step in order to understand this. First we set our variables to have the values of 5 and 8. Then, **result** is made to be the product of our two variables, which in this case is 40. After that, we set the value of **my_5** to be the same as the value of **result**, which gives **my_5** equal to 40. At this point, **result** equals 40, **my_5** equals 40, and **my_8** is equal to 8. The next line updates **my_8** to be the same as the value of **my_5**, which we just clarified was 40. As a result, all of the variables we have defined now take on the value of 40. The final line before output, **result <- my_5 * my_8** updates the value of **result** to be the product of the two variables again, this time giving 40 * 40 which gives 1600.

1.3.2 Function Calls in R

Up until this point we have simply used numerical operations and variable assignment. While this allows R to serve as a very powerful calculator, we often want computers to do much more than arithmetic. As a result, we need to explore **functions** in R. A function is a piece of code which takes in various arguments and outputs some value (or values). Most of the way that we will use R in this course is through the use of function calls.¹⁶ This is exactly analogous to a mathematical function: it is simply some rule which maps input to output. In fact, some of the most basic functions in R are functions which relate to mathematical functions.

```
x <- 10

exp(x)
sqrt(x)
```

①
②

¹⁶Note: when you begin to write programs for yourself, a lot of your time will be spent writing custom functions. If this is of interest to you, I suggest looking into programming more! For this course we will not need to define our own functions, except perhaps ones that will be defined for you.

```
log(x)
## [1] 22026.47
## [1] 3.162278
## [1] 2.302585
```

③

- ① Computes the exponential function applied to x , that is $e^x = e^{10}$.
- ② Computes the square root of x , that is $\sqrt{x} = \sqrt{10}$.
- ③ Computes the natural logarithm of x , that is $\log(x) = \log(10)$.

The basic format of a function call will always be `function_name(param1, param2, ...)`. Each of these functions required only a single parameter, however, there are some functions which take more than one parameter. If we have decimal numbers, for instance, we may wish to round them. To do so, we can use the `round` function in R, which takes two parameters: the number we wish to round, and how many digits we wish to keep.

```
unrounded_value <- 3.141592
rounded_value <- round(unrounded_value, digits = 3)

rounded_value
## [1] 3.142
```

There are a few things to note about this sequence of function calls. First, note that we assign the output of a function to a new variable. This behaves exactly as we saw above with simple numeric calculations. Next, consider that the output of the function¹⁷ has a value of 3.142. That is: we rounded the value to 3 decimal points, exactly as would be expected. The final part to note is that the second parameter passed to the function call is **named**. That is, instead of simply calling `round(unrounded_value, 3)`, we have `round(unrounded_value, digits = 3)`. If you had made the first call this would have worked perfectly.¹⁸ However, R also provides the ability to pass in parameter names alongside the parameter values with the syntax `function_name(param_name = param_value, ...)`. The benefit to doing this is two-fold. First, it is easier to read what is happening, especially for function calls that you have never seen before. Second, it removes the need to have the parameters ordered correctly. It is best practice to **always** include parameter names where you can.

Now, you may be wondering “how do you know what the parameter names should be?” The names are built-in to the different functions that you are working with and so overtime you will become quite familiar with them. However, at any point you can also run the command `?function_name`, replacing `function_name` with the name of a function you are interested in, to open documentation about that function. There you will see not only the names of the different parameters, but useful information regarding what the function does, examples of how to call it, and so forth.

¹⁷Which we have stored in the variable `rounded_value`

¹⁸Try it out to convince yourself!

```
?round
```

When we run this code, we are given *a lot* of information. We can see the function name, the details, how it's called, and so forth. In the **Arguments** section we get a list of all of the arguments we can pass to the function, along with a description of them. In this case we see that **round** can take a parameter called **x** for the number to be rounded, and **digits** (which we have previously seen).

```
unrounded_value <- 3.141592
rounded_value <- round(digits = 3, x = unrounded_value)

rounded_value
## [1] 3.142
```

This code produces the exact same output, where now both parameters are named. Specifically, we could read this function call as “round the value of **x** to have **digits** decimal points.” If you had instead written `round(3, unrounded_value)`, you would get the value 3, since now we are rounding 3 to 3.141592 decimal points.

1.3.3 Moving Beyond Numeric Data

So far, everything that we have looked at has been numeric data. We have seen integers, and decimals. You can have negative results, say by taking `my_var <- -5`. And while numbers are frequently useful, we will require further types of data to write useful computer programs. For this course we will focus on three additional data types: textual data which (referred to as **strings**), true and false binary data (referred to as **booleans**), and lists of the same data type (referred to as **vectors**). They will behave in much the same way as numeric data, with different functions and techniques which can be applied to them.

To define a string of text, we simply encapsulate the text that we are interested in within quotation marks (either single ' or double " quotation marks will work).

```
first_string <- "This is a string."
second_string <- 'This is also a string.'

first_string
## [1] "This is a string."
```

Two commonly used functions which rely on strings are **paste** and **print**. Each will take in strings as input, and they do not need to be named. The function **paste** can take in as many strings as you would like. It will “paste” together all the strings provided, creating a longer

string out of these. The function `print` will display the string that is passed as output. Until now we have been running these programs in a way where all calls are displayed as output: this will not always be the case, and so `print` can come in handy there.

```
my_greeting <- "Hello! Welcome to R programming,"
my_name <- "Dylan"

combined_string <- paste(my_greeting, my_name, "!")
print(combined_string)
## [1] "Hello! Welcome to R programming, Dylan !"
```

Note that `paste` has several additional options which can be investigated in the documentation for `paste`. This is only the simplest use case for it. In general, strings are particularly helpful when we wish to have output from the computer that will be human readable. Where strings are largely for humans, booleans are largely for computers.

Much of what computer programming entails is checking whether certain conditions hold, and then taking different actions depending on what is found. In order to do this, the computer needs a way to represent true and false statements. In R, these are codified with the values `TRUE` and `FALSE`. Note, the capital letters here make a difference. You cannot use `true` or `True` or any other combination thereof. More important than simply being able to specify the values `TRUE` and `FALSE` directly is the ability to detect whether certain statements are `TRUE` or `FALSE`. For this we require comparison operators.

If we think of mathematical comparisons we can state whether two things are equal, or not equal, and whether one thing is less than (or equal to) or greater than (or equal to) another. We can run all of these same checks in R.

- To check whether two quantities are equal you use `quantity_1 == quantity_2`. This statement will be `TRUE` if `quantity_1` and `quantity_2` are exactly the same, and will be `FALSE` otherwise.
- To check whether two quantities are not equal, you can use `quantity_1 != quantity_2`. This statement will be `TRUE` if the quantities differ from one another.
- To check whether one quantity is larger than another, you can use `quantity_1 > quantity_2`. If you want to know whether it is greater than *or* equal to, you can use `quantity_1 >= quantity_2`.
- To check whether one quantity is smaller than another, you can use `quantity_1 < quantity_2`. If you want to know whether it is less than *or* equal to, you can use `quantity_1 <= quantity_2`.

```
5 == 5 # TRUE
5 == 6 # FALSE
```

```

5 != 5 # FALSE
5 != 6 # TRUE

5 > 6 # FALSE
5 > 5 # FALSE

5 >= 6 # FALSE
5 >= 5 # TRUE

5 < 6 # TRUE
5 < 5 # FALSE

5 <= 6 # TRUE
5 <= 5 # TRUE
## [1] TRUE
## [1] FALSE
## [1] FALSE
## [1] TRUE
## [1] FALSE
## [1] FALSE
## [1] FALSE
## [1] TRUE
## [1] TRUE
## [1] FALSE
## [1] TRUE
## [1] TRUE

```

There are two key points to note beyond this. First, we will of course not normally compare two constants to one another. We already know that `5==5` and so we would not need to check it. We can, however, plug-in variables, perhaps with unknown values, and have the same types of statements being made. Second, the checks for equality and inequality also work with other data types (like strings).

```

string1 <- "STRING1"
string2 <- "STRING1"
string3 <- "string1"
string4 <- "5"
string5 <- "5.3421"
num1 <- 5
num2 <- 1
num3 <- 0
bool1 <- TRUE

```

```

bool2 <- FALSE

string1 == string2 # TRUE
string1 == string3 # FALSE
string2 != string3 # TRUE
string1 != string4 # TRUE

string4 == num1      # TRUE
string1 == num2      # FALSE
num1 == string5      # FALSE
num2 == bool1        # TRUE
bool2 == num3        # TRUE
bool2 == num2        # FALSE
## [1] TRUE
## [1] FALSE
## [1] TRUE
## [1] TRUE
## [1] TRUE
## [1] FALSE
## [1] FALSE
## [1] TRUE
## [1] TRUE
## [1] FALSE

```

The final checks may be slightly odd. Here we are comparing across different types of data. When we do this R will automatically try to convert from one type to the other. With strings and numbers this is not too challenging. If they can be converted nicely between types, then they are and the values are compared. Otherwise, R will conclude they are not equal by default. For booleans, it is important to note that `TRUE == 1` and `FALSE == 0`. We will often use these values interchangeably.

The final data type that we will consider are vectors. Vectors store many different values, of the same type, in a single object. Thus, we may have a vector of numeric data, or a vector of strings, or a vector of booleans. The vectors will always contain the same type throughout, but they are stored in a single object (and as such, for instance, can be stored in a single variable). To define a vector we call `c(...)`, where the `...` contains the set of objects we want to store in the vector. The `c` stands for concatenate, as we are *concatenating* together the set of items into a single container.

```

v1 <- c("vector", "of", "strings")
v2 <- c(3, 1, 4, 1, 5)
v3 <- c(TRUE, TRUE, FALSE, TRUE)

```



```

v4 <- c(1==2, 2==2, 3==4)
v1
v2
v3
v4
## [1] "vector" "of"      "strings"
## [1] 3 1 4 1 5
## [1] TRUE TRUE FALSE TRUE
## [1] FALSE TRUE FALSE

```

We see that each of these vectors holds one type of object. Vectors can be of arbitrary and different lengths. It is also possible to combine multiple vectors *of the same type* into one, by using the `c` function again.

```

v1 <- c(3,1,4,1,5)
v2 <- c(9,2,6)
v3 <- c(5)
num1 <- 3

combined_v1 <- c(v1, v2)
combined_v2 <- c(combined_v1, v3)
combined_v3 <- c(combined_v2, num1)

combined_v3
## [1] 3 1 4 1 5 9 2 6 5 3

```

Here we combine different numeric vectors together. We also show, when forming `combined_v3`, how numeric vectors can have single items added onto them. That is, if you have a single number, it can be treated as a vector with one element in it. This becomes very useful when building up vectors within code. In addition to combining multiple vectors together, we can also select elements out of a vector. To do this, we use a set of square brackets after the vector's name, with a number within those square brackets specifying the **index** of the vector we are interested in. The index is simply the element position starting at 1¹⁹ and running to the length of the vector. We can include a vector of indices to select multiple elements at once.

```

alpha_vector <- c("A","B","C","D","E","F","G","H","I",
                  "J","K","L","M","N","O","P","Q","R",

```

¹⁹If you have programmed in the past there is a good chance the language you have learned is “0 indexed” rather than “1 indexed”. In R, all vectors start at position 1 and count up, which is not the case in many languages. Be careful of this.

```

      "S", "T", "U", "V", "W", "X", "Y", "Z")

alpha_vector[4]    # D
alpha_vector[25]   # Y
alpha_vector[12]   # L
alpha_vector[1]    # A
alpha_vector[14]   # N

my_name <- alpha_vector[c(4,25,12,1,14)]

my_name
## [1] "D"
## [1] "Y"
## [1] "L"
## [1] "A"
## [1] "N"
## [1] "D" "Y" "L" "A" "N"

```

Note that, each element is selectable individually, giving a single item of that type (in this case, strings). If you select multiple of the elements together, it will create a vector of that type (in this case, a string vector). Note that in addition to selecting elements in this way by their indices, you can also update the elements in the same way.

```

cur_year <- c(2,0,2,3)
cur_year

# After Midnight on December 31
cur_year[4] <- 4
cur_year
## [1] 2 0 2 3
## [1] 2 0 2 4

```

In this example we are changing the last element of the vector. Sometimes we may not know how long the vector actually is, if for instance, it is being built-up as our code runs. If we ever want to check the length of a vector, we can simply call the function `length` which takes as input only one vector, and outputs the numeric value of its length.

```

v1 <- c(1,2,3,4,5)
length(v1)
## [1] 5

```

1.3.4 Program Control Flow

We have seen different types of data, different ways of manipulating data, functions, and variables so far. In order to bring all of these concepts together into useful programs we need some way to control the flow of our programs. We have seen that, by default, programs execute from the top until the bottom. However, it will often be the case that we want to have certain code running only if certain conditions hold, or that we want to repeat some piece of code many times over. To accomplish these tasks we require **control flow statements**. We will consider only two types of control flow statements now, which will serve well enough to read most of what needs to be read for this course.

The first type of statement is the **conditional statement**. Conditional statements execute only when certain conditions hold. The simplest conditional statement is an **if** statement. The format to define an if statement is `if (condition){ ... }`, where **condition** is some logical condition to be evaluated. If the condition is **TRUE** then the code contained in `{ ... }` is evaluated. If the condition is **FALSE** it is not.

```
my_number <- 5

if(my_number > 0) {
  print("My number is a positive.")
}

if(my_number < 0) {
  print("My number is a negative.")
}
## [1] "My number is a positive."
```

In this case, these simple conditional statement check to see whether the number we entered is larger than zero and whether the number we entered is smaller than zero, respectively. When run, notice that only one of the statements is executed.²⁰ In this case, we know that only one (or neither) of these statements can be true. When that is the case it may make sense to make use of **else** clauses in our conditional logic.

```
my_number <- -5

if(my_number > 0) {
  print("My number is a positive.")
} else {
  print("My number is not a positive.")
}
## [1] "My number is not a positive."
```

²⁰In fact, if `my_number` is set to 0 then none of the statements are executed.

Here, *if* the number is greater than 0, then we run the first block of code, *otherwise* we run the second block of code. Thus, whenever a positive number is entered, we see “My number is a positive”, and whenever a non-positive number is entered, we see “My number is not a positive.” We can extend **else** blocks to be **else if** blocks, where further conditions can be specified.

```
my_number <- 100

if(my_number > 50) {
  print("My number is a large positive value.")
} else if(my_number > 0){
  print("My number is a small positive value.")
} else if(my_number < -50) {
  print("My number is a large negative value.")
} else if(my_number < 0) {
  print("My number is a small negative value.")
} else {
  print("My number is zero.")
}
## [1] "My number is a large positive value."
```

In these case we can simply pass through each conditional statement in order. First, is the number larger than 50? If so, print the statement, otherwise we check the next condition, is the number greater than 0? Note that if we are checking this condition we *know* that the number is less than or equal to 50 since it failed the first check. We continue through the rest of this procedure down until the last else block. This block is run only when all of the other conditions fail: that is, our value is not larger than 50, or larger than 0, or smaller than -50, or smaller than 0. The only value that satisfies this is 0 itself.

Sometimes, we wish to check compound conditions. That is, we want to know whether multiple conditions hold, or perhaps, whether at least one of many conditions hold. These statements can be converted into “and” and “or” statements, respectively. To denote “and” statements we use **&&** and to denote “or” statements we use **||**. Thus, the check `my_val > 0 && my_val < 100` returns true only if `my_val` is both above 0 **and** below 100. The check `my_val < -50 || my_val > 50` returns true whenever **either** `my_val` is less than -50 **or** `my_val` is greater than 50.

```
my_number <- 5

if(my_number < 50 && my_number > 10) {
  print("A moderate, positive number.")
} else if(my_number != 5 && my_number <= 10 && my_number >= 0) {
  print("A positive value which is not 5.")
}
```

```

} else if(my_number == 5 || my_number < 0) {
  print("Either 5 or a negative value.")
}
## [1] "Either 5 or a negative value."

```

Conditional statements can grow to be very complex, however, with these rules you can read through them top-to-bottom, substituting for “and” and “or” where necessary. It is also possible, where required, to place one conditional statement inside the code block for another, and to combine them with any of the other techniques that we have learned thus far.

The final piece of control flow that we will consider for now is the **for** loop. The idea with a **for** loop is that we want to repeat the same action either a certain number of times, or for every item in a set of items. To do so, we use the syntax `for(x in vector){...}`, where the code in ... will be performed once for every single item in the vector. Within the code block specified by ..., the value `x` will take on the current value in the loop.

```

for(x in c(1,2,3)){
  print(x)
}
## [1] 1
## [1] 2
## [1] 3

```

Notice that three values are printed, in order, 1 then 2 then 3. The loop code is run three different times, one for each element in the list. Each time the loop is running the next value from the list gets assigned to the variable `x`. The first time it runs it gets the first element, and so forth. As a result, we can use these values in our calculations in whatever way we need to.

```

for(x in c(1,2,3)){
  x_sq <- x^2
  print(paste("The square of", x, 'is', x_sq))
}
## [1] "The square of 1 is 1"
## [1] "The square of 2 is 4"
## [1] "The square of 3 is 9"

```

Whenever we are trying to form a numeric vector with consecutive elements, as we are in `c(1,2,3)`, we can make this easier on ourselves by simply specifying the upper and lower bounds of the range, separated by a colon. That is `c(1,2,3) == 1:3`. This is often useful when specifying a loop as we very often want to repeat something a set number of times. Note

that we do not ever *need* to use the value of the looping variable. Sometimes, we just want things to repeat, and so the loop is a convenient way to do that.

```
times_to_loop <- 5

for(x in 1:times_to_loop){
  print(paste("This will get printed", times_to_loop, "times."))
}
## [1] "This will get printed 5 times."
## [1] "This will get printed 5 times."
## [1] "This will get printed 5 times."
## [1] "This will get printed 5 times."
## [1] "This will get printed 5 times."
```

1.3.5 Reading Through a More Complex R Program

Take a moment to read through the following R program and try to understand what is happening exactly. There are comments throughout which will assist in the parsing of the script. We have seen comments up until now, without drawing explicit attention to them. In R, anything placed after a `#` on the line is considered a comment. The programming language ignores these and so they are only there to help other individuals who may be reading through. It is good practice to comment your code to help others, and also to help yourself whenever you return to it in the future. In the course notes code will typically be commented. If you are reading the PDF version of the notes often these comments will be annotations beside the code (numbering certain lines) with the comments provided below, for the sake of legibility.

Note, this combines everything that we have learned, and it is entirely understandable if it takes some time to process. Fortunately, you can always try running the script yourself, and playing with different components of it. Remember, if you do not know what a function call does, you can use the documentation²¹ and try playing with it some yourself. To help with the interpretation here, note that this is an implementation of the game that Charles and Sadie have been playing.

```
# Define some variables which dictate how the game runs.
player1 <- "Charles"
player2 <- "Sadie"
num_of_flips <- 3
flip_option1 <- "H"
flip_option2 <- "T"

# Begin with the game setup
```

²¹The internet is also a wonderful resource, one which even very experienced developers make frequent use of.

```

num_to_win <- round(x = num_of_flips / 2, 0)
flip_results <- c()
flip_options <- c(flip_option1, flip_option2)
total_1 <- 0
total_2 <- 0
player_name <- "" # This is an 'empty string'

# Start Playing the Game
for(game_round in 1:num_of_flips) {
  print(paste("Now starting round", game_round))

  # Select a flip of the coin, using the sample function.
  # See more details with ?sample
  flip_result <- sample(x = flip_options, size = 1)

  # See who benefits from this flip
  # Then set player_name to be the player who benefits from the flip,
  # and update their score variable.
  if (flip_result == flip_option1) {
    player_name <- player1
    total_1 <- total_1 + 1
  } else if (flip_result == flip_option2) {
    player_name <- player2
    total_2 <- total_2 + 1
  }

  print(paste("The flip was a", flip_result, "which benefits", player_name))

  # Check to see if either player has won at this point.
  if(total_1 >= num_to_win) {
    print(paste(player1, "has scored enough points to win. "))
  } else if(total_2 >= num_to_win){
    print(paste(player2, "has scored enough points to win. "))
  }
}

# The game is over
# Select the winner based on who scored above the threshold
# and then print out the results.
winner <- player1

if(total_2 >= num_to_win) {

```

```

    winner <- player2
}

# Separate these statements into multiple lines to ensure the text is
# not too wide.
print(paste("After flipping the coin", num_of_flips, "times,", player1,
           "scored a total of", total_1, "points"))
print(paste("while", player2, "scored a total of", total_2, "points."))
print(paste("As a result", winner, "won the game and will not have to pay!"))
## [1] "Now starting round 1"
## [1] "The flip was a H which benefits Charles"
## [1] "Now starting round 2"
## [1] "The flip was a T which benefits Sadie"
## [1] "Now starting round 3"
## [1] "The flip was a T which benefits Sadie"
## [1] "Sadie has scored enough points to win."
## [1] "After flipping the coin 3 times, Charles scored a total of 1 points"
## [1] "while Sadie scored a total of 2 points."
## [1] "As a result Sadie won the game and will not have to pay!"

```

1.3.6 R Programming for Probability Interpretations

Recall that the motivation for the discussion of R was the Frequentist interpretation of probability. One task that computers are very effective at is repeatedly performing some action. As a result, we can use computers to mimic the idea of repeatedly performing an experiment. Consider the simple case of flipping a coin over and over again.

We can use `sample(x, size)` as a function to select `size` realizations from the set contained in `x`. Thus, if we take `sample(x = c("H","T"), size=1)` we can view this as flipping a coin one time. If we use the loop structure we talked before, then we can simulate the experience of repeatedly flipping a coin. Consider the following R code. Note, any time that we are doing something which is randomized in R (such as drawing random samples) we also will make use of the `set.seed()` function. This function takes in an integer value as an argument, and by providing the *same* integer value we can make sure to always get the same random numbers generated.²² This helps to ensure the repeatability of any R analysis, and it is good practice to do. To see what happens without seeding, try modifying the following code without a seed, and running it several times. Then, set the seed (to any number you like) and do the same process.

²²Technically, we cannot use a computer to generate random numbers. We can only generate *pseudo random* numbers, which are close enough for most purposes.


```

set.seed(3141592) ①

number_of_runs <- 1000 ②
tosses <- c() ③

for(idx in 1:number_of_runs){ ④
  toss <- sample(x = c("H","T"), size = 1) ⑤
  if(toss == "H"){ ⑥
    tosses <- c(tosses, 1)
  } else {
    tosses <- c(tosses, 0)
  }
}

mean(tosses) ⑦
## [1] 0.522

```

- ① A seed ensures that the random numbers generated by the program are always the same. This helps to be able to reproduce our work.
- ② This is how many times we want to repeat the experiment.
- ③ This is where we are going to store the results of our tosses. It creates an empty list for us.
- ④ Here we are going to loop over the experiments, one for each run.
- ⑤ This is our coin toss. We are going to sample 1 from either 'H' or 'T'
- ⑥ If the coin toss is heads, then we add a 1 to the list. Otherwise, we add a zero to the list.
- ⑦ Return the mean of all of the tosses.

It is worth adjusting some of the parameters within the simulation, and seeing what happens. What if you ran the experiment only 5 times? Ten thousand times? What if instead of counting the number of heads, we wanted to count the number of tails? What if we wanted to count the number of times that a six-sided die rolled a 4? All of these settings can be investigated with simple modifications to the provided script.

References

2 The Mathematical Foundations of Statistical Experiments

2.1 The Sample Space and Events

While we gave the mathematical formulation for the Frequentist interpretation of probability, we will typically require a more detailed mathematical model to work with probabilities. We want a description, framed in terms of mathematical objects, which will allow us to work out the probabilities of interest. In general, to form such a probability model we need both a list of all possible outcomes that the experiment can produce, as well as the probabilities of these outcomes.

We call the list of outcomes that can occur from an experiment the **sample space** of the experiment. The sample space is denoted \mathcal{S} , and is defined as the set of all possible outcomes from the experiment. For instance, if the experiment is flipping a coin we have $\mathcal{S} = \{covH, covT\}$. If the experiment is rolling a six-sided die then $\mathcal{S} = \{1, 2, 3, 4, 5, 6\}$.

Definition 2.1 (Sample Space). The sample space of a statistical experiment is the set of all possible outcomes that can be realized from that experiment. The sample space is typically denoted \mathcal{S} , or with similar script letters.

Example 2.1 (Enumerating Sample Spaces). Write down the complete sample space, \mathcal{S} for the game that Sadie and Charles play, based on flipping and observing a coin three times in sequence.

Solution

For Sadie and Charles their experiment involves tossing a coin three times in sequence. As a result each outcome is a three-dimensional list of values, given for instance by $(covH, covH, covH)$. As a result, we can write down the full sample space as

$$\mathcal{S} = \{(covH, covH, covH), (covH, covH, covT), (covH, covT, covH), (covH, covT, covT), (covT, covH, covH),$$

With the sample space formally defined, we can revisit Definition 1.2, and formally define the concept of an event.

Definition 2.2 (Event). An event is any collection of outcomes from a sample space for a statistical experiment. Mathematically, an event, E , is a subset of \mathcal{S} , and we write $E \subset \mathcal{S}$.

Take for instance the experiment of a single coin. In this case, $E_1 = \{covH\}$, $E_2 = \{covT\}$, and $E_3 = \{covH, covT\}$ are examples of possible events. Here, E_1 corresponds to the event that a head is observed, E_2 corresponds to the event that a tail is observed, and E_3 corresponds to the event that either a tails or a heads was observed. Note that for each event we have $E_1 \subset \mathcal{S}$, $E_2 \subset \mathcal{S}$, and $E_3 \subseteq \mathcal{S}$.

Example 2.2 (Basic Event Listing). List several events from the game that Charles and Sadie are playing. Indicate why these are events.

Solution

Recall that an event is any subset of the sample space. In Example 2.1 we define \mathcal{S} for this game. As a result we can take sets which contain any combinations of these elements. For instance $E_1 = \{(covH, covH, covH)\}$, or $E_2 = \{(covH, covH, covT), (covH, covT, covH)\}$, or

$E_3 = \{(covH, covH, covH), (covH, covH, covT), (covH, covT, covH), (covH, covT, covT), (covT, covH, covH)\}$

These are all events since $E_1 \subset \mathcal{S}$, $E_2 \subset \mathcal{S}$, and $E_3 \subset \mathcal{S}$.

Example 2.3 (Event Identification). Is “Charles has to pay” an event from the game that Charles and Sadie are playing? Why?

Solution

No. “Charles has to pay” is not an event as it is not a subset of the sample space. This could plausibly be seen as a real-world description of a possible event, but it is not *itself* an event. ¹

Example 2.4 (Defining Events from Real-World Descriptions). What event corresponds to the description “Charles has to pay” in the game that Charles and Sadie are playing? Recall that they flip a coin three times, and Charles will pay if at least two heads come up, while Sadie will pay if at least two tails come up.

¹As time goes on we will become less strict about this language. When speaking to a statistician, they would understand “Charles has to pay” as an event that *can* occur based on the defined sample space, by simply transforming it into the language of the sample space. However, the distinction is important to make: events are always subsets of the sample space. Once this is second nature, it is a rule that can be loosened, as the knowledge can always be fallen back on when needed. Simply put: you need to know the rules in order to break them!

Solution

Charles will have to pay whenever there are two or more heads. As a result we can enumerate the possible outcomes that leads to Charles paying. We have

1. $(covH, covH, covH)$;
2. $(covT, covH, covH)$;
3. $(covH, covT, covH)$;
4. $(covH, covH, covT)$.

Any other outcome will have fewer than two heads, and as a result, Charles will not have to pay. Thus, to form an event, we consider the set with each of these outcomes in it. This gives

$$E = \{(covH, covH, covH), (covT, covH, covH), (covH, covT, covH), (covH, covH, covT)\}.$$

While the events $E_1 = \{covH\}$ and $E_2 = \{covT\}$ each correspond to a simple outcome from the sample space, $E_3 = \{covH, covT\}$ corresponds to a combined event. We call direct outcomes **simple events** and more complex outcomes like E_3 **compound events**.

Definition 2.3 (Simple Event). A simple event is any event which corresponds to exactly one outcome from the sample space. A simple event only has one way of occurring. The size of the set for a simple event will be 1. The sample space, in turn, is made up of a collection of simple events.

Definition 2.4 (Compound Event). A compound event is any event which corresponds to more than one outcome from the sample space. A compound event can occur in multiple different ways. The size of the set for the compound event will be greater than 1.

If we consider rolling a six-sided die, then an example of a simple event is that a four shows up, denoted $\{4\}$. A compound event could be that an even number is rolled, $\{2, 4, 6\}$, or that a number greater than or equal to four is rolled, $\{4, 5, 6\}$.

Example 2.5 (Identifying Simple and Compound Events). List an example of (at least) one simple and one compound event from the game that Charles and Sadie are playing.

Solution

An example of a simple event would be $E_1 = \{(covH, covH, covH)\}$ since it is comprised of exactly one outcome. If three heads are rolled, this event occurs, there is no other way for it to occur. An example of a compound event would be

$$E_2 = \{(covH, covH, covH), (covT, covH, covH), (covH, covT, covH), (covH, covH, covT)\}.$$

Here there are four outcomes that correspond to this event, and if any of those outcomes

are observed the event occurs.

We say that an event “occurs” if any of the outcomes comprising the event occur. As a result we can have more than one event occurring as the result of a run of a statistical experimental. Suppose that we are rolling a fair, six-sided die. Consider the events “an even number was rolled” and “a number greater than or equal to four was rolled.” If a four or a six are rolled, both of these events happen simultaneously. Our goal when working with probability will be to assign probability values to different events. We will talk about how likely, or unlikely, events of interest are, given the underlying statistical experiment.

Above, we defined E_3 to be equal to \mathcal{S} . As a result, we can say that \mathcal{S} is an event since $\mathcal{S} \subseteq \mathcal{S}$. This is the event that any outcome is observed, which is certain to happen. Since it is certain to happen, we know it happens with probability 1. There is another “special” event which is important to consider. We call this the *null event*. Denote \emptyset , the null event is an event that corresponds to “nothing in the sample space”. We know that every time an experiment is run something in the sample space occurs, and so the null event is assigned probability zero.

Definition 2.5 (Null Event). The null event, denoted \emptyset or $\{\}$, is an event from a statistical experiment which corresponds to nothing within the sample space. The null event has probability zero, and it is impossible to observe. Note that, no matter the sample space, $\emptyset \subset \mathcal{S}$.

2.2 Set Operations for Event Manipulation

Ultimately, we think of all events as being sets. These sets are subsets of the sample space, and can contain single or multiple outcomes. Every quantity that we are interested in can be expressed as some set of outcomes of interest. In building up these sets it is common to construct through the use of “and”, “or”, and “not” statements. That is, we may say that our event occurs if some outcome **OR** another outcome occurs, or perhaps our outcomes occurs if some outcome does **NOT** occur.²

Consider the example of drawing cards from a standard 52-card deck. In such a deck there are 13 card ranks, and four card suits, with one of each combination present. If we draw a single card we can think of the outcomes of the experiment as being any of the 52 possible combinations of rank and suit. We are often interested in an event such as “the card is red”, which is the same as saying “the card is a heart **or** the card is a diamond.” Perhaps we want to know whether the card was an ace through ten, this is the same as saying “the card is **not** a

²While both *or* and *not* language is likely clear from the examples we have seen so far, *and* language may be slightly less obvious. While we will explore this in more depth shortly, note that you could not have two simple events occurring simultaneously. If E_1 and E_2 are both simple events, then you can have E_1 **or** E_2 , and you can have **not** E_1 , but you cannot have E_1 **and** E_2 . This is *not* true for compound events.

Jack **or** a Queen **or** a King.” If we are interested in the event that the ace of spades was drawn, this can be expressed by saying that “the card was a spade **and** the card was an ace.”

As you begin to pay attention to the linguistic representation of events that we use, you will notice more and more the use of these words to form compound events in particular. As a result, we give each of them a mathematical operation which allow us to quickly and compactly express these quantities in notation.

Example 2.6 (Description of Events). Describe “Charles has to pay”, based on the game Charles and Sadie are playing, using language revolving around “or”, “and”, and “not” each. That is, describe observing at least two heads, on three flips of a coin, one time using “or”, one time using “and”, and one time using “not”.³

Solution

There are plausibly many possible ways of doing so. Consider the following:

1. **OR**: Two heads are observed **OR** three heads are observed.
2. **AND**: Not two tails are observed **AND** not three tails are observed.
3. **NOT**: Not more than one tails are observed.

We define mathematical operations to encapsulate the use of **or**, **and**, and **not**. These operations apply to any mathematical sets, whether they refer to events or not.

Definition 2.6 (Union). The union encodes the use of “or” in reference to two or more sets. Formally, with two sets A and B , the union of A and B is the set of all elements that are contained in A , or B , or both A and B . We write $A \cup B$ and read that as A union B . When we wish to take the union of many sets, A_1, A_2, \dots, A_n , we write this as

$$\bigcup_{i=1}^n A_i.$$

Definition 2.7 (Intersection). The intersection captures the use of “and” in reference to two or more sets. Formally, the intersection of two sets, A , and B , is the set that contains all elements that belong to both A and B . We write $A \cap B$, and say “ A intersect B .” When we wish to take the union of many sets, A_1, A_2, \dots, A_n , we write

$$\bigcap_{i=1}^n A_i.$$

³It may be helpful to notice that you can mix and match these terms to your hearts content!

Definition 2.8 (Complement). The complement makes formal the concept of “not.” The complement of a set to be the set of all elements which occur in the sample space but are not in the given set. We write this as A^C and say “ A complement.” When dealing with a sample space, \mathcal{S} , the complement of A is the set of all elements in \mathcal{S} that are not in A .

Example 2.7 (Basic Set Operations). For the game being played by Charles and Sadie, take $E_1 = \{(covH, covH, covH)\}$, $E_2 = \{(covH, covH, covH), (covT, covH, covH), (covH, covT, covH)\}$, and $E_3 = \{(covH, covH, covT)\}$. Express the following events.

- $E_1 \cup E_2$;
- $E_1 \cap E_2$;
- E_2^C ;
- $E_2 \cap E_3$;
- $E_1 \cup E_2 \cup E_3$.

Solution

Directly from definitions we can write down each of the following sets:

a.

$$E_1 \cup E_2 = \{(covH, covH, covH), (covT, covH, covH), (covH, covT, covH)\} = E_2.$$

As a result, the union of E_1 and E_2 is simply E_2 .⁴

b.

$$E_1 \cap E_2 = \{(covH, covH, covH)\} = E_1.$$

As a result, the intersection of E_1 and E_2 is simply E_1 .⁵

c.

$$E_2^C = \{(covH, covH, covT), (covH, covT, covT), (covT, covH, covT), (covT, covT, covH), (covT, covT, covT)\}.$$

d. For $E_2 \cap E_3$ note that they share no elements. As a result, the intersection will be empty since there are no elements common to both of them. This gives $E_2 \cap E_3 = \emptyset$.

e.

$$E_1 \cup E_2 \cup E_3 = \{(covH, covH, covH), (covT, covH, covH), (covH, covT, covH), (covH, covH, covT)\}.$$

Definition 2.9 (Disjoint Events). Two events, E_1 and E_2 are said to be disjoint whenever their intersection is the null event. That is, if $E_1 \cap E_2 = \emptyset$ then E_1 and E_2 are disjoint events.

These concepts allow us to more compactly express sets of interest, and in particular, will be quite useful when it comes to assigning probability. The more times you work with the

⁴Note that whenever we have two events, A and B , with $A \subset B$, then $A \cup B = B$.

⁵Note that whenever we have two events, A and B , with $A \subset B$ then $A \cap B = A$.

set operations, the more familiar they will become, and as a result, practice is always useful. Considering rolling a 6-sided die, and take A to be the event that a 6 is rolled, B to be the event that the roll was at least 5, C to be the event that the roll was less than 4, and D to be the event that the roll was odd.

- If we consider D^C this is the event that the roll was even;
- $A \cup C$ is the event that a 6 was rolled or that a number less than 4 was rolled, which is to say anything other than a 4 or a 5;
- If we take $A \cup B$ then this will be the same as B , and $A \cap B$ will be A .
- If we take the event $A \cap C$, notice that no outcomes satisfy both conditions, and so $A \cap C = \emptyset$.
- We can also join together multiple operations. $D^C \cap C$ gives us even numbers less than 4, which is to say the outcome 2.
- Similarly, $(A \cap B)^C$ would represent the event that a number less than 6 is rolled.

Example 2.8 (Set Operations with Decks of Cards). Charles and Sadie are tiring of flipping their coin, and so they wish to start using decks of cards sometimes instead. Before they formalize a game based on decks of cards, they want to make sure that they are both very comfortable working with these. Suppose that the sample space is defined to be the set of 52 standard cards that may be drawn on a single draw. Describe how set operations can be used to form events corresponding to:

- A red card is observed.
- Any card between an ace and a ten is observed.
- The ace of spades is observed.

Solution

First, we define several events. Note, these can be defined in shorthand to prevent needing to write out many different cards. We take D to be the event that a diamond is observed, we take H to be the event that a heart is observed, take S to be the event that a spade is observed⁶ and then take A to be the event that an ace is observed, J to be the event that a Jack is observed, Q to be the event that a Queen is observed, and K to be the event that a King is observed⁷ then we can use unions, intersections, and complements to express the previously mentioned scenarios.

- To represent outcomes corresponding to “the card is red”, we can use $D \cup H$.
- To represent outcomes corresponding to “an ace through ten”, we can use $(J \cup Q \cup K)^C$.
- To represent the outcome “the ace of spades”, we may use $A \cap S$.

⁶Note, these three are compound events with 13 different outcomes contained within them.

⁷Compound events with four different options.

Working with these basic set operations should eventually become second nature. There are often very many ways of expressing the same event using these different operations, and finding the most useful method of representing a particular event can often be the key to solving challenging probability questions. The first step in making sure that these tools are available to you is in ensuring that the basic operations are fully understood, and this comes via practice. Remember, unions represent “ors”, intersections represent “ands”, and complements represent “nots”.

2.2.1 Using R To Represent Sample Spaces and Events and Performing Set Operations

We have seen how R can encode sets of elements using vectors. For instance, we may take `sample_space <- 1:6` to represent the sample space of rolling a six-sided die. We can form events by taking subsets of the relevant quantities, selecting via indices. Fortunately, there are also all of the basic set operations implemented in R. We can use `union(x, y)` to perform the union of `x` and `y`, `intersect(x, y)` to perform the intersection of `x` and `y`, and `setdiff(x = sample_space, y)` to perform the complement of `y` (assuming that `sample_space` contains the full sample space).⁸

```
# Define the Sample Space of Rolling a 20 Sided Die
sample_space <- 1:20

# Define some Events
E1 <- sample_space[2]
E2 <- sample_space[c(1, 3, 5, 7)]
E3 <- sample_space[c(1, 2, 4, 8)]

# Consider Set Operations
union(x = E1, y = E2) # E1 union E2 = {1, 2, 3, 5, 7}
union(x = E1, y = E3) # E1 union E3 = {1, 2, 4, 8}

intersect(x = E1, y = E3) # E1 intersect E3 = {2}
intersect(x = E1, y = E2) # E1 intersect E2 = {}

setdiff(x = sample_space, y = E1) # E1 complement

# (E2 union E3) complement
setdiff(x = sample_space, y = union(E2, E3))
## [1] 2 1 3 5 7
```

⁸R does not implement complements directly, and instead implements the set difference operation. The set difference function, `setdiff(x, y)` returns the set of all elements in `x` which are not in `y`, a sort of subtracting of sets. The complement of a set is defined to be $A^C = \text{covsetdiff}(\mathcal{S}, A)$, indicating why this works!

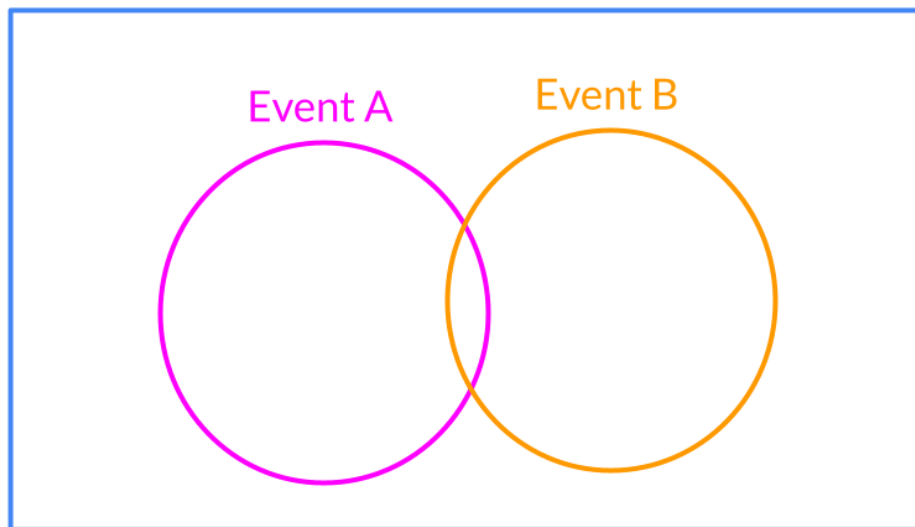
```
## [1] 2 1 4 8
## [1] 2
## integer(0)
## [1] 1 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
## [1] 6 9 10 11 12 13 14 15 16 17 18 19 20
```

2.3 Venn Diagrams

The sample space is partitioned into outcomes, and the outcomes can be grouped together into events. These events are sets and can be manipulated via basic set operations. Sometimes it is convenient to represent this process graphically through the use of Venn diagrams. In a Venn diagram, the sample space is represented by a rectangle with the possible outcomes placed inside, and events are drawn inside of this as circles containing the relevant outcomes.

Figure 2.1: A basic Venn diagram, representing the sample space and two different events. In practice, the sample space would have the possible outcomes written into the rectangle, and the circled events would end up containing the relevant outcomes for those events.

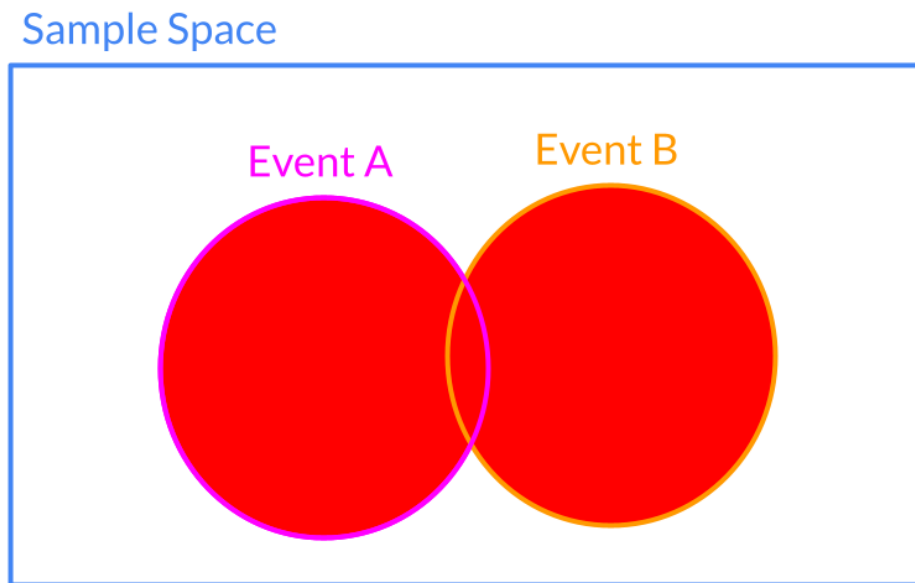
Sample Space



On the Venn diagram then, the overlap between circles represents their intersection, the combined area of two (or more) circles represents their union, and everything outside of a given

circle represents the complement of a set. This can be a fairly useful method for representing sample spaces, and for visualizing the basic set operations that we use to manipulate events inside the sample spaces. A word of caution: Venn diagrams are useful tools, but they are not suitable as proofs themselves. It is possible to convince yourself of false truths if the wrong diagrams are used, and as a result, Venn diagrams should be thought of as aids to understanding, rather than as a rigorous tool in and of themselves.⁹

Figure 2.2: **Union:** The union of events A and B is shaded here in red. The union of two sets is all of the contents of both sets, including the overlap between the two.



⁹This is a general principle in mathematics. Coming up with one example that makes something *seem* true does not form an argument demonstrating that it *is* true. Venn Diagrams should largely be thought of as specific examples of the underlying phenomena, which are great if you're a visual learner!

Figure 2.3: **Intersection:** The intersection of events A and B is shaded here in red. The intersection of two sets is all of the content shared by both sets, given by the overlapping area of the two circles.

Sample Space

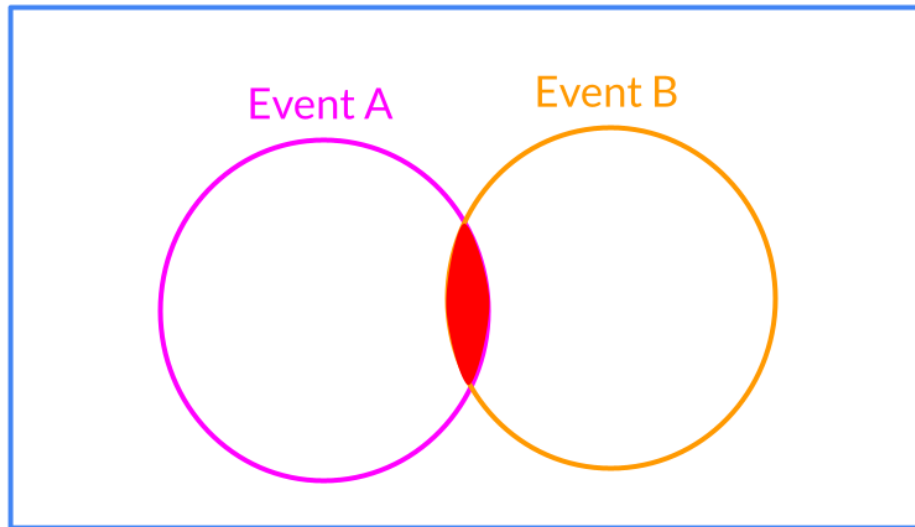
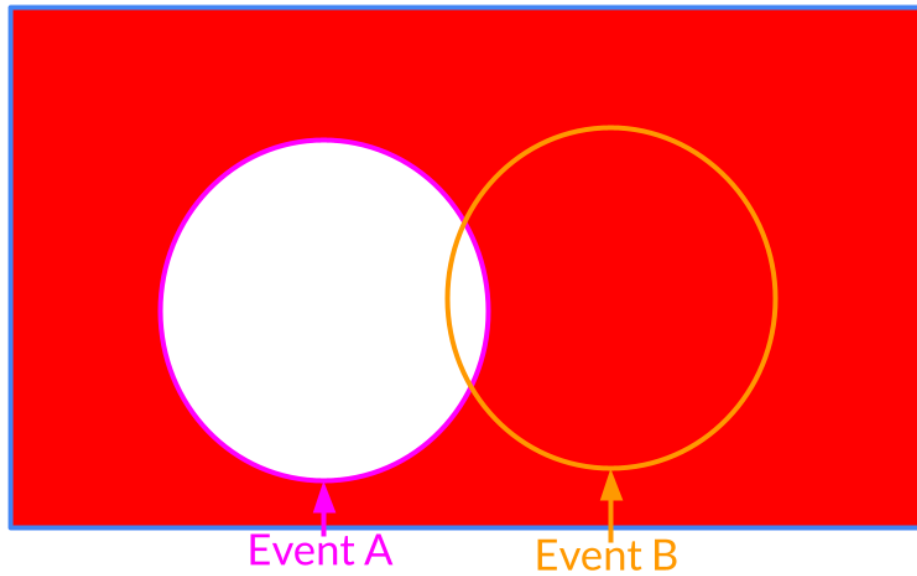


Figure 2.4: **Complement:** The complement of event A is shaded here in red. The complement of a sets is all of area inside of the sample space, not inside of the set. Here we show the complement of Event A, though Event B would be similar.

Sample Space

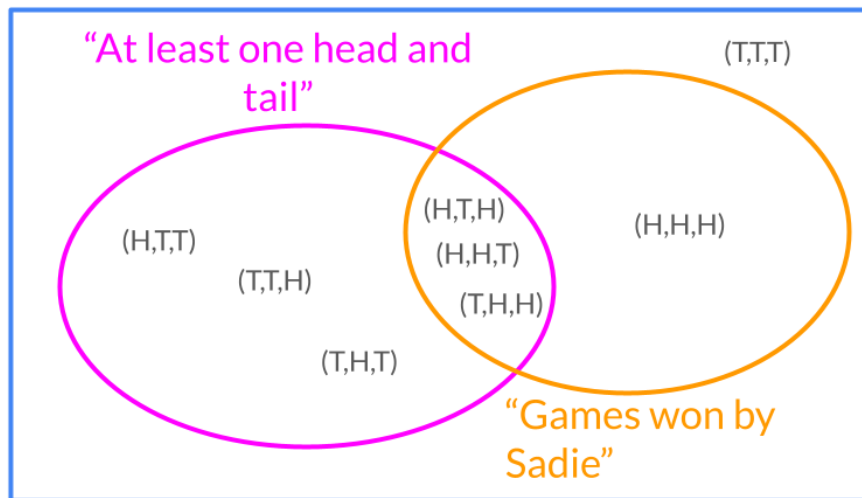


Example 2.9 (Venn Diagram with Defined Events). Draw a Venn diagram representing the original game that Charles and Sadie played. On the diagram draw the events corresponding to “At least one head **and** one tail are observed”, and “Sadie won the game”. Recall that three coins are tossed, and Sadie wins if at least two of them show heads.

Solution

The sample space contains the eight possible options. Only $(covT, covT, covT)$ does not belong to at least one of the events. Both events share $(covH, covH, covT)$, $(covH, covT, covH)$, and $(covT, covH, covH)$.

Sample Space



Sample spaces, events, and the manipulation of these quantities forms a critical component of understanding probability models. In particular, they describe the complete set of occurrences in a statistical experiment that we could be interested in assigning probability values to. To formalize a probability model, however, we also need some rule for assigning probability values.

3 The Core Concepts of Probability

3.1 Assigning Probabilities (and The Equally Likely Outcome Model)

There are a plethora of ways to assign probabilities to different events. At the most basic level any rule that maps from the space of possible events to real numbers between 0 and 1 can be used as rules for probability assignment. That is, probability assignment is simply a set of rules which says “for this event assign this probability.”

Example 3.1 (Coin Toss Probabilities). Suppose that the fair coin used by Charles and Sadie is tossed one time. Write down the probability assignments relating to this experiment.

Solution

In this case we have $\mathcal{S} = \{covH, covT\}$. Thus, the possible events for which we need to assign probabilities are \emptyset , $\{covH\}$, $\{covT\}$, and $\{covH, covT\} = \mathcal{S}$. For any probability model we have $P(\emptyset) = 0$ and $P(\mathcal{S}) = 1$. When we say that a coin is “fair” we are saying that $P(covT) = P(covH)$, and since these are the only two possible outcomes in the sample space, we must have that they each have probability 0.5.

Not every assignment of probability values is going to be valid. Suppose, for instance, that we have a six-sided die, each side labelled with a number from one to six. If I told you that there was a probability of 0.5 that it comes up 1, 0.5 that it comes up 2, 0.5 that it comes up 3, 0.5 that it comes up 4, 0.5 that it comes up 5, and 0.5 that it comes up 6, you would probably call me a liar.¹ If, as we have previously seen, probabilities represent the long run proportion of time that a particular event is observed, we cannot have 6 different outcomes each occurring in half of all cases.

Beyond the requirements that we impose on what constitutes a “valid” probability rule, we have another concern: scalability. It is perfectly acceptable to indicate that in an experiment with 3 outcomes, the first has a probability of 0.25, the second of 0.3, and the third of 0.45. What if the experiment has 100 possible outcomes? Or 1000? It quickly becomes apparent that enumerating the probabilities of each event in the sample space is an efficient way of assigning probabilities in practice. A core focus of our study of probability will be finding techniques

¹Or else conclude that I was mistaken and maybe should not be teaching probability.

that allow us to efficiently encode probability information into manageable objects. Once we have done this we will be in a position where we can manipulate these (comparatively) simple mathematical quantities in order to make statements and conclusions about any of the events of interest, even if they have never been explicitly outlined as having an assigned probability.

While we will consider myriad methods for accomplishing these goals throughout our study of probability, we begin with a very useful model which simplifies probability assignment, without any added complexity, and creates a solid foundation for us to explore the properties of probability models. We start by considering **equally likely outcomes**. As the name suggests, the probability model considering equally likely outcomes assigns an equal probability to every possible outcome of the experiment. This is a probability model that we are already distinctly familiar with: flipping a coin, rolling a die, or drawing a card are all examples of experiments which rely on the equally likely outcomes framework.

Remark (Statisticians and Urn Models). In statistics and probability courses and books you will often have instructors or authors using fairly simple models to illustrate probability concepts. There will often be questions relating to coin tosses, and dice, and decks of cards, and everyone's favourite: urns. It will very frequently be the case that a statistics question will state that there is an urn with some combination of coloured balls within it, from which you will be selecting some number either with or without replacement. The frequency of these types of examples and questions often feels disconnected from the refrain that "uncertainty is all around us" and that "statistics is relevant to every aspect of our world!"² Why is it that we seldom see questions or examples that are directly tied to these wide spread applications of the lessons and techniques being taught?

In part these simple experiments are cleaner to handle than "real world" situations. We can easily assume that a die is fair and that takes care of any unsuspecting wrinkles that will necessarily come along with the "real world". This is not dissimilar to working under the assumption of frictionless surfaces in introductory physics, or assuming that human beings are rational in economics. Another key point is that most of us have deep familiarity with dice, and coins, and cards.³ The same is not going to be true of stories that are derived from different use cases in the real world. A final important point, and this will be something we see in depth in the coming chapters, is that from a statistical point of view: there is no difference. Once we have the tools to work with these quantities, we have the tools to work with any of the quantities. This actually distinguishes the use of these types of examples in statistics and probability from those for other subjects: at no point is anything that we are learning incorrect, or overly simple - we are just focusing on the raw probabilistic nature of the phenomenon. As a result, we will continue to see these simple models in these notes. I would encourage you,

²One of the most famous quotes from a statistician was a thought shared by John Tukey, stating "The best thing about being a statistician is that you get to play in everyone's backyard." This is a common refrain, and one rooted in truth. Statistics is everywhere, across every field of human inquiry, and can help us make sense of everything from the trivial to the deeply important.

³This does not help to explain why we use urns so much, of course. When was the last time any of us drew a ball from an urn?

whenever possible, to hold a topic in mind that matters more to you and start trying to draw the parallels between rolling dice, and whatever it is that you may care about.

Why urns, specifically? Well, whether it be coin flipping or dice rolling or card selection, we can model this equivalently using an urn (with 2, 6, and 52 items, respectively). The urn becomes more flexible to *exactly* dictate what the probability of any selection will be, which is a useful way of moving from equally likely models (each ball is equally likely to be selected) to arbitrary models (we can have however many identical balls in the urn as we would like).

If we have an experiment with a sample space \mathcal{S} which has $|\mathcal{S}| = k$ total elements⁴, then each element of the sample space occurs with probability $\frac{1}{k}$. In the case of the coin toss example, $\mathcal{S} = \{covH, covT\}$, and so $k = 2$ and each outcome occurs with probability $\frac{1}{2}$. In the case of drawing a card at random, there are 52 different outcomes, and so $k = 52$, and the probability of drawing any particular card is $\frac{1}{52}$.

It is critically important to recognize that the equal probability model assigns equal likelihood to the possible outcomes of an experiment, not the possible events of interest. It will not be the case that all events have the same probability. To make this concrete, consider the events A “the ace of spades is drawn” and B “any spade is drawn”. It is clear that B happens more frequently than A , even though we have said that this is an experiment with equally likely outcomes. Remember: an outcome is an observation from a single experimental run, an event is any collection of these possible outcomes.

A core goal is then bridging the gap between the probability of an outcome⁵ and the probability of an event. In order to do so, we will next consider the rules of probability, introducing properties that are required for valid probability assignments, and the techniques for manipulating probabilities to calculate the probabilities of quantities of interest.

3.1.1 Using R for the Equally Likely Probability Model

In the previous chapter we saw how we can codify sample spaces and events using vectors in R. In the introduction we actually saw how can sample from a sample space using the equally likely outcome framework. Specifically, an application of the `sample` function will draw a set number of values from a sample space, giving each value an equal probability to be drawn.⁶

```
# Define the Sample Space of Rolling a 20 Sided Die
sample_space <- 1:20

# Recall that whenever we wish to perform an experiment in R with
```

⁴Note that, when we have a set, using the absolute value symbols $|\cdot|$ stands for the **cardinality** of the set. Cardinality is just a fancy way of saying the size or the number of elements that the set has in it.

⁵A quantity which in the equally likely outcome framework, we know exactly.

⁶The `sample` function can also be used without equally likely events by specifying a vector of probabilities, however, this is a less common use case.

```

# randomness, we should call set.seed
set.seed(31415)

# The sample function takes three main parameters:
#   x: the sample space
#   size: the number of items to draw
#   replace: a boolean representing whether the draws should be
#             with replacement or not.
one_roll <- sample(x = sample_space, size = 1)
ten_rolls_with_replacement <- sample(x = sample_space,
                                     size = 10,
                                     replace = TRUE)
ten_rolls_without_replacement <- sample(x = sample_space,
                                       size = 10,
                                       replace = FALSE)

one_roll
ten_rolls_with_replacement
ten_rolls_without_replacement
## [1] 2
## [1] 19 17 14 3 5 12 2 15 9 3
## [1] 18 8 16 9 7 20 2 19 10 13

```

3.2 The Axioms of Probability

We have previously seen that not every probability assignment can be valid. For instance, assigning 0.5 probability to each outcome on a die leads to a nonsensical scenario. With just a little imagination, we can conjure equally nonsensical scenarios in other ways. For instance, it would make very little sense to discuss the probability of an event being a negative value. What would it mean for an event to occur in a negative proportion of experimental runs? Alternatively, we can consider two events that are nested in one another: say event A is that we draw the ace of spades, and event B is that we draw any spade. Every single time that A happens, we know that B also happens. But there are ways that B can occur where A does not.⁷ If I told you the probability of A was 0.5 and the probability of B was 0.2, this would violate our base instincts. How can it be more likely to draw the ace of spades than it would be to draw any spade at all?⁸

⁷For instance, the Queen of spades being drawn.

⁸This is actually a scenario where our instincts may lead us awry in some situations. Consider the following from Kahneman and Tversky (1972): Linda is 31 years old, single, outspoken, and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in anti-nuclear demonstrations. Which is more probable? (a) Linda is a bank teller, or (b)

Often in mathematics when we have an intuitive set of rules⁹ that particular quantities must obey, we work to add formality through defining properties of these concepts. To this end, we can define the key properties that probabilities must obey in order to be well-defined, valid probabilities. With three fairly basic properties, we can completely specify what must be true in order for a set of probabilities to be “valid”, and to in turn match with our intuitions.

The Axioms of Probability

1. **Unitary:** Every valid set of probabilities must assign a probability of 1 to the full sample space. That is, $P(\mathcal{S}) = 1$. This is an intuitive requirement as every time the experiment is run we observe an outcome in the sample space. As a result, in every experimental run the event \mathcal{S} occurs.
2. **Non-negative:** We require that every probability is non-negative. We can have probabilities of 0, but we can never have a probability less than zero. Again, this is sensible¹⁰ but is important to include in our formalization. Specifically, for every event E , we must have $P(E) \geq 0$.
3. **Additivity:** the final property requires slightly more parsing on first pass. Suppose that we define a sequence of events, E_1, E_2, E_3, \dots such that no two events have any overlap. That is, $E_j \cap E_\ell = \emptyset$ for all $\ell \neq j$. Then, the final property we require for probabilities is that

$$P\left(\bigcup_i E_i\right) = \sum_i P(E_i).$$

That is, the probability of the union of disjoint events is the summation of the probability of these events.

It is worth dwelling slightly on axiom 3. Consider the case of drawing a card at random from a deck of 52 cards. Using the equally likely outcome model for probability we know that the probability that any card is drawn is given by $\frac{1}{52}$. If I were to ask “what is the probability you draw that ace of spades?” under this model you can respond, immediately, with $\frac{1}{52}$. Now, if I were to ask “what is the probability that you draw the ace of spades or the two of spades?” then intuitively you likely figure that this will be $\frac{2}{52}$. Note that the event E_1 , “draw the ace of spades” and the event E_2 “draw the two of spades”, are disjoint events. Moreover, recall that the union is the “or” and so $E_1 \cup E_2$ is the same as E_1 or E_2 . Taken together then,

$$P(E_1 \cup E_2) = P(E_1) + P(E_2).$$

The axiom of additivity simply extends this intuition to an arbitrary number of events.

Linda is a bank teller and is active in the feminist movement. A majority of respondents rate (b) as being more probable, even though (a) is contained in (b).

⁹These rules, which we call “properties” are formally known as “axioms”.

¹⁰What would it mean to have a negative probability? It is perhaps a more interesting question than it seems at first glance. It is a topic that has come up in some pretty strange places and, while it is not presently sensible to call them “probabilities” in a traditional sense, there are interesting results which follow.

Example 3.2 (Basic Additivity). Still unsure of how best to go about using cards to replace their coin game, Charles and Sadie are considering various different events and trying to understand their probabilistic behaviour. They take S , C , H , and D to be the events that a spade, club, heart, or diamond are drawn from a standard deck of cards, respectively. Further, they take C_j to be the event that a card with denomination j is drawn (j ranging from ace with 1 through King with 13). If they consider the union of any two (or more) of these events when can they leverage properties of additivity? When can't they?

Solution

In order to use the properties of additivity it is required that the two events are disjoint. Note that taking any two (or more) of S , C , H , and D will lead to disjoint events. There is no way to draw a card which has two suits on it at once. Similarly, taking any two (or more) of C_j will lead to disjoint events. However, mixing any of the suited events (S , C , H , and D) with any C_j will not be disjoint.

Consider $S \cap C_1$. The ace of spades is in S since it is a spade and it is in C_1 since it is an ace. As a result, $S \cap C_1 = \{\text{ace of Spades}\}$. Because of this we are not able to say that $P(S \cup C_1) = P(S) + P(C_1)$. However, we can say that

$$P(S \cup C \cup H \cup D) = P(S) + P(C) + P(H) + P(D),$$

and could do the same with any subset of these sets. Similarly, we can take

$$P\left(\bigcup_{j=1}^{13} C_j\right) = \sum_{j=1}^{13} P(C_j),$$

or any of the subsets there.

These three axioms fully define valid probabilities. Any mechanism that assigns probability values to events which conforms to these rules will assign valid probabilities. While it may seem counterintuitive that such basic rules fully define our notion of a probability, these rules readily give rise to many other properties that are indispensable when working with probabilities.

3.3 Secondary Properties of Probabilities

Using the previously indicated axioms of probability we are able to derive many useful **secondary properties**. These properties will frequently be used to actually compute different probabilities, and are helpful to become familiar with. All of the following properties follow directly from the axioms, though, some are more clear than others. For the following we take E and E_1, E_2, E_3, \dots to be arbitrary events on some well defined sample space.

1. $P(E^C) = 1 - P(E)$, and equivalently, $P(E) = 1 - P(E^C)$.

2. $P(\emptyset) = 0$.
3. $P(E_1 \cup E_2) = P(E_1) + P(E_2) - P(E_1 \cap E_2)$.
- 4.

$$P(E_1 \cup E_2 \cup E_3) = P(E_1) + P(E_2) + P(E_3) - P(E_1 \cap E_2) - P(E_1 \cap E_3) - P(E_2 \cap E_3) + P(E_1 \cap E_2 \cap E_3).$$

5. If $E_1 \subset E_2$ then $P(E_1) \leq P(E_2)$.

Proofs of the Secondary Properties of Probability

It may be instructive to see how these properties are derived. Doing so generates added familiarity with manipulating probability expressions and helps to encourage deeper understanding.

1. Note that, for any event E , by definition we have $E \cup E^C = \mathcal{S}$ and $E \cap E^C = \emptyset$. As a result, we can apply **additivity** to the sets E and E^C giving $P(E \cup E^C) = P(E) + P(E^C)$. However, since $E \cup E^C = \mathcal{S}$, then we know that $P(E \cup E^C) = P(\mathcal{S}) = 1$ by the **unitary** property. Taken together this tells us that $1 = P(E) + P(E^C)$, and rearranging gives $P(E^C) = 1 - P(E)$, or $P(E) = 1 - P(E^C)$, as required.
2. We know that $\mathcal{S}^C = \emptyset$. Using secondary property (1), $P(E) = 1 - P(E^C)$. Taking $E = \emptyset$ gives $P(\emptyset) = 1 - P(\mathcal{S}) = 1 - 1 = 0$, by the **unitary** property.
3. Here note that $E_1 \cup E_2$ can be written as $E_1 \cup E'_2$ where $E'_2 = E_2 \cap E_1^C$. That is, E'_2 contains the outcomes from E_2 which were not shared by E_1 . Then $E_1 \cap E'_2 = \emptyset$ so we can write $P(E_1 \cup E_2) = P(E_1 \cup E'_2) = P(E_1) + P(E'_2)$, by **additivity**. Now, if we define $E_2^* = E_2 \cap E_1$ then $E_2 = E'_2 \cup E_2^*$, and $E'_2 \cap E_2^* = \emptyset$. Thus, $P(E_2) = P(E'_2 \cup E_2^*) = P(E'_2) + P(E_2^*)$. Rearranging this gives $P(E'_2) = P(E_2) - P(E_2^*)$, and we know that $P(E_2^*) = P(E_1 \cap E_2)$. Thus, plugging into what we found before we get

$$P(E_1 \cup E_2) = P(E_1) + P(E'_2) = P(E_1) + P(E_2) - P(E_1 \cap E_2).$$

4. This follows exactly from the argument for (3). To see, first consider $E_2 \cup E_3$ to be an event itself, say E_4 . Then we can apply the above result to $E_1 \cup E_4$. And then we need only repeat the process for the remaining terms.
5. We can rewrite E_2 as $E_1 \cup (E_2 \cap E_1^C)$. These two sets are disjoint, since the one is E_1 and the other must contain only elements in E_1^C . Then, $P(E_2) = P(E_1) + P(E_2 \cap E_1^C)$ by **additivity**. Then, through the **non-negative** property we know that $P(E_2 \cap E_1^C) \geq 0$, and so rearranging we have $P(E_1) = P(E_2) - P(E_2 \cap E_1^C) \leq P(E_2)$.

These properties are immensely useful when computing probabilities. In fact, these secondary properties will be used with more frequency than the basic axioms when manipulating proba-

bilities in practice. It is worth building comfort with these properties, early and often, as they will assist in manipulating all probability expressions in the future.

While these properties hold in general for all probability models, it is instructive to focus on the equal probability model to begin building familiarity with probability. These properties allow us to take events – whether compound or simple – and combine, rewrite, and manipulate expressions to assist in the handling of the computations. Eventually, however, we require the ability to assign numerical values to these probabilities.

Consider a simple event, A . Recall that a simple event is defined as a possible outcome of an experiment, and so in this case, A corresponds directly to an event that may be observed. If our sample space is k elements large, then $P(A) = \frac{1}{k}$ in this framework. For instance, if A is the event that a two is rolled on a six-sided fair die, then $P(A) = \frac{1}{6}$.

Now, suppose that a compound event is defined, B . By definition, a compound event can be expressed as a set of possible outcomes from the experiment. Suppose that we enumerate these possible events as b_1, b_2, \dots, b_ℓ . Then we know that B occurs if any of b_1, b_2, \dots, b_ℓ occur. Each b_j are elements of the sample space and correspond to possible outcomes of the experiment. As a result, we know that $P(b_j) = \frac{1}{k}$, based on the equal probability assumption. Now, if we take any two distinct events, say b_i and b_j , we know that they must be disjoint: $b_i \cap b_j = \emptyset$. This is because in an experiment run only one outcome can occur. Moreover, we can say that $B = b_1 \cup b_2 \cup \dots \cup b_\ell$.

Using the axioms of probability outlined above we therefore know that $P(B) = \sum_{j=1}^{\ell} P(b_j) = \sum_{j=1}^{\ell} \frac{1}{k} = \frac{\ell}{k}$. This holds in general for any compound event in this setting. If we take B to be the event that an even number is rolled on a six-sided die, then we would have b_1 is the event that a two is rolled, b_2 is the event that a four is rolled, and b_3 is the event that a six is rolled. There are three such events, and so the probability that an even number is rolled must be $\frac{3}{6} = 0.5$, which matches our intuition.

If we consider what this process is doing at its core, we can reframe the calculation as counting up the number of ways that event can happen and dividing by the total number of events. In our previous discussion, there were ℓ ways of B occurring, a total of k outcomes, and so the probability becomes $\frac{\ell}{k}$. In the equal probability model, this will always be the case. The probability of any event A occurring is given by

$$P(A) = \frac{N_A}{k},$$

where N_A is the number of unique ways that A can occur. In other words, N_A is the size of the set A , $|A|$.

As a result of this, computing probabilities largely relies on the counting of possible outcomes corresponding to different events. If we can determine $N_A = |A|$, and the count of the total number of occurrences, k , then we can determine the probability of A . This study of counting is known as **combinatorics**, and it is where we will turn our attention next.

Example 3.3 (Unmatched Six-Sided Dice). Charles and Sadie, not all together content with the progress through decks of cards, are considering games with dice. Suppose that they have two, fair, six-sided dice. They are interested in the probability that the two dice show different numbers when they are rolled. What is this probability?

Solution

Here, the key is to realize that the probability is easier to solve when considering the complement rather than the event itself. Notably, rolling two, fair, six-sided dice gives a total of 36 possible outcomes. Of these, exactly 6 have equal numbers showing on both dice. Thus, the probability that the two dice show the **same** number is going to be $\frac{6}{36} = \frac{1}{6}$. Then, using the fact that $P(E) = 1 - P(E^C)$, and that taking E to refer to the event where the two dice show different numbers, then E^C refers to the event that the two dice show the *same* number. As a result, the probability that we want is $P(E) = 1 - \frac{1}{6} = \frac{5}{6}$.

Example 3.4 (Unmatched Arbitrary Dice). Charles and Sadie, working from their intrigue about dice, have decided that instead of using two six-sided dice, they wish to take two dice of possibly different sizes. Suppose that the first die has d_1 sides and the second has d_2 sides, and that both dice are otherwise fair. They are interested in the probability that the two dice show different numbers when they are rolled. What is this probability?

Solution

This problem is conceptually no different from Example 3.3. There will be a total of $d_1 \times d_2$ possible combinations of the two dice to be rolled.¹¹ Of these, the dice will match in $\min\{d_1, d_2\}$ events.¹² Then, with the same complement trick discussed above, we get

$$P(E) = 1 - P(E^C) = 1 - \frac{\min\{d_1, d_2\}}{d_1 \times d_2}.$$

3.4 Combinatorics

3.4.1 The Product Rule

Fundamentally, counting is a matter of assessing the size of a collection of items. Sometimes, this is very straightforward. If you want to count the number of students in a classroom, you start at 1 and enumerate upwards through the integers. To count the number of days

¹²Note: if this is not yet clear to you, that's okay! In the very next section we begin to discuss how to count the possible combinations in these types of scenarios.

¹²Suppose that $d_1 = 2$ and $d_2 = 4$. Then here, the dice can match when they show either 1 or 2, but if the second die shows 3 or 4 there is no possibility of having a match at all.

until the next Holiday, you do the same thing. If you really need to sleep, perhaps you will count imaginary sleep until you drift off. There is not much to this type of counting, and it is certainly deeply familiar to you all. However, it is also quite limited in its utility.

Imagine that you are interested in determining how many possible ways there are of arranging a deck of 52 cards. You could of course arrange them in a particular order, then count each of those. That would take a tremendous amount of time, so perhaps instead of using an actual deck you just write down the combinations. Still, each combination is going to be 52 cards long, and keeping track of that all will be a tremendous challenge. This seems like an approachable question, and yet, it illustrates how complicated (and large) these types of “counting” problems can become very quickly.

Fortunately for us there are some strategies for simplifying these problems down, some of which you are likely already familiar with. Think about trying to form an outfit where you have 4 different sweaters, 3 pairs of pants, and 2 options for your shoes. Suppose that any combination of these will work well. How many total outfits are there? Well, if you have already picked your sweater and pants, then there are going to be 2 different outfits using these: one with each of the pairs of shoes. This is true for each possible sweater-pant combination, and so we can count 2 for each one these. In other words, to get the total number of outfits we multiply the number of sweater-pant combinations by the number of shoe options. The same rationale can be applied to count the total number of sweater-pant combinations. For each sweater, there are 3 pairs of possible pants, and so to get the total number we can take 3 for each possible sweater, or in other words, 3×4 . Taken together then we have $4 \times 3 \times 2 = 24$ total possible outfits.

Another way of framing this is that we have to make three sequential decisions: which of the 4 sweaters, which of the 3 pants, and which of the 2 shoes are to be worn? When we do this we multiply through the number of alternatives at each decision point to get the total number of combinations. This is known as the **product rule for counting**.

Definition 3.1 (Product Rule for Counting). The product rule for counting states that, when there are a sequence of k decisions to be made, and for each decision $j = 1, \dots, k$, there are n_j options, then the total number of combinations will be

$$N = n_1 \times n_2 \times \dots \times n_k.$$

Example 3.5 (Counting Coffee Orders). When Charles and Sadie are out for coffee, Sadie enjoys ordering the same thing each time: a black coffee and vegan chocolate chip cookie. Charles, on the other hand, has decided to work through the entire menu of the local coffee shop, each day ordering a drink, with one add-in, and a snack. If there are 10 different drinks, 8 possible add-ins, and 12 different snacks, how many trips to the coffee shop will it take until Charles has tried it all?

Solution

This necessitates an application of the product rule for counting. Specifically, we can view this as three sequential decisions, where the first decision is which drink (with $n_1 = 10$), the second decision is which add-in (with $n_2 = 8$), and the third decision is which snack (with $n_3 = 12$). Taking the product gives the total number of combinations as $10 \times 8 \times 12 = 960$. As a result, it will take 960 visits (assuming that nothing on the menu changes!) to try all combinations.

Example 3.6 (Sequence of Dice Rolls). Charles and Sadie have been enjoying playing with dice, but they lost one of the two they had. As a result, they are trying to come up with games revolving around rolling a single die. They decide to try a game called “six is lava”, where they roll a single six-sided die 10 times in a row. If they get 1 or more sixes, they lose the game. They are not sure if 10 is the correct number of rolls to use. What is the probability that they lose on any given set of 10 rolls of the die in this game?

Solution

Once again this is a scenario where using the complement simplifies the problem. If we asked “what is the probability that no 6’s are rolled, on 10 rolls of the die” then we can count the number of possibilities through an application of the product rule. In particular, there are going to be 5 options which are not 6 at each possible step. We can view this as have $n_1 = n_2 = \dots = n_{10} = 5$. Thus, the total number of ways of rolling **no** sixes is $5 \times 5 \times 5 \times \dots \times 5 = 5^{10}$.

Essentially the same process can be used to count the total number of possible rolls, replacing 5 with 6 to get the denominator. This means that there are 6^{10} total sequences of 10 rolls, and 5^{10} which contain no sixes. As a result, taking E to represent the probability that we observe no sixes on 10 rolls of the die, we would get

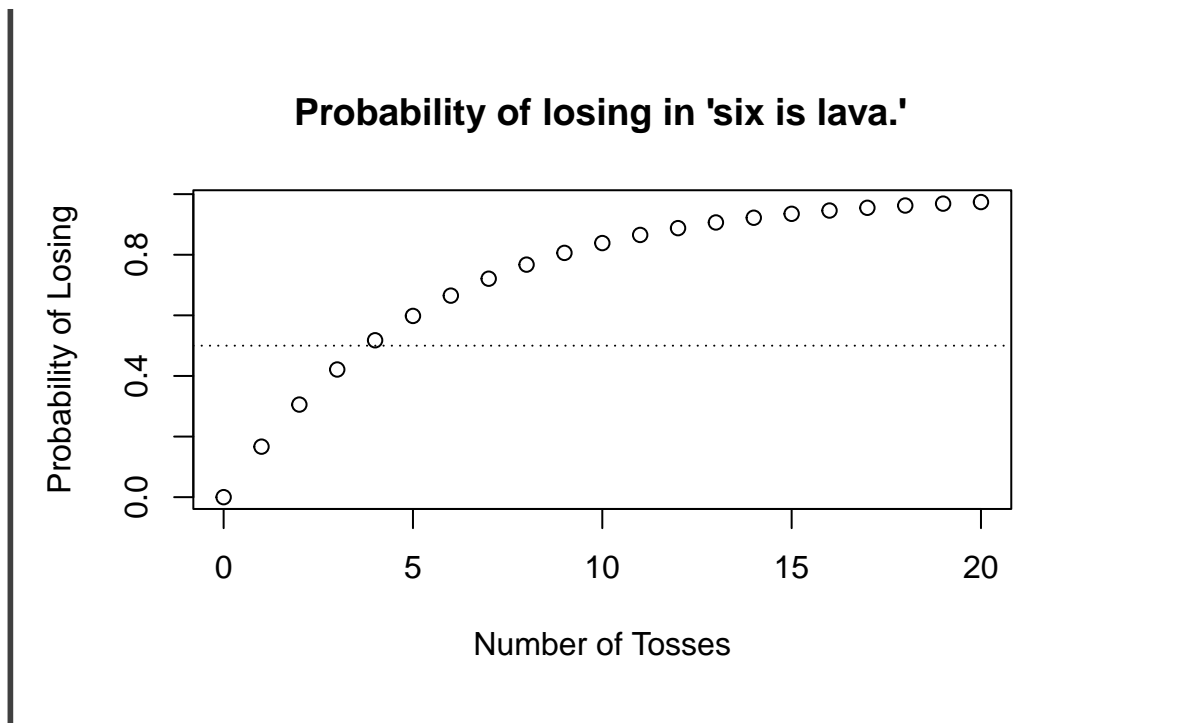
$$P(E) = \frac{5^{10}}{6^{10}}.$$

The question asks for E^C and so we take

$$P(E^C) = 1 - P(E) = 1 - \left(\frac{5}{6}\right)^{10}.$$

This is approximately 0.8385.

Note that if instead of 10 flips they had n flips, the probability would be $1 - (5/6)^n$. We can plot this over various values of n , to see how the number of flips impacts this probability. The probability of 0.5 is marked and we can see that taking 4 tosses gives an ever so slightly greater than 0.5 probability of losing (0.5177).



3.4.2 Tree Diagrams

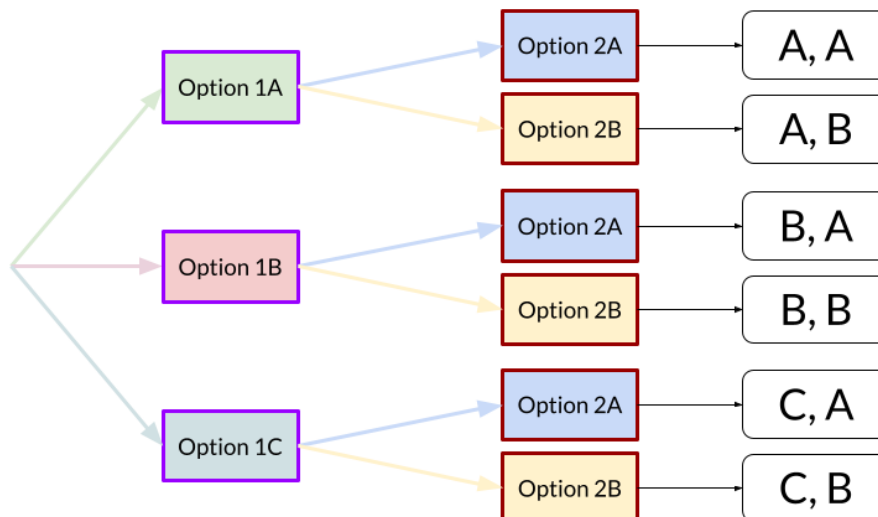
Sometimes it is helpful to express counting rules graphically. To do so we rely on tree diagrams.

Definition 3.2 (Tree Diagram). A tree diagram is a graphical representation for the product rule of counting. Specifically, a tree diagram puts each of the decisions in sequence, and draws a branch for each separate option, starting from the branches drawn at the previous decision step.

To draw a tree diagram, you start with the first choice, drawing one branch for each of the n_1 alternatives, labelling each. Then, at the second choice, you do the same process at the end of each of the branches you drew for choice 1, this time drawing n_2 branches there (so you will have just drawn $n_1 \times n_2$ branches). Then for each of those you draw the n_3 further branches, and so on and so forth until the end.

If you want to know the total number of choices, you simply count the end points at the very end of the diagram. Each branch corresponds to a single option. To determine which combination of choices it corresponds to, you simply read off the branch labels at each branch you take. If you want to know how many possible combinations come with certain options selected, you can look at only those branches which are downstream from the choices that you care about.

Figure 3.1: A generic tree diagram. Here the first choice has three different options and the second choice has two. We can see the six total combinations, labelled on the right of the diagram, and can trace the choices required to get there.



While tree diagrams can be quite useful for visualizing a problem, they often grow to be overly complex. As a result, we need to fall back on the numerical representation afforded to us through the product rule for counting. Counting problems, in general, can very quickly become tremendously large and complex. For this reason, we have several tools to assist us in reducing this complexity based on common types of problems that we would like to count.

3.4.3 The Factorial

The first useful tool for simplifying these problems is the **factorial**. The factorial of an integer, denoted by $x!$ is given by the product of all integers from x to 1.¹³ That is,

$$x! = x(x-1)(x-2)\cdots(2)(1).$$

If we consider the product rule for counting then note that if $n_1 = 1$, $n_2 = 2$, ..., $n_k = k$, then the total number of options is $k \times (k-1) \times \cdots \times 1 = k!$. The most common reason that this comes up is when we want to order a collection of items. Suppose that you have 10 books that you want to place on a shelf. You can view this as making 10 sequential decisions: what book

¹³Factorials are exciting because they always look like they are shouting!

goes first, second, third, and so on. There are 10 options for the first book, then 9 for the second (any except for the first one), and then 8 for the third (any except for the first 2). This continues down to the last book, and so we conclude that there are $10 \times 9 \times 8 \times \cdots \times 1 = 10!$ ways of arranging these books.

Example 3.7 (Seating in a (Full) Coffee Shop). One day Charles and Sadie walk into the coffee shop and find that it is completely full. There are ten seats and ten people sitting in them. They are disappointed that they do not have room to sit themselves, however, they are never ones to pass up an interesting probability question.

- How many different ways could these ten people have sat in these ten seats?
- If there are ten drinks that have been made, and one is to be passed out to each seat, how many different ways can these ten people sit in these ten seats, with each of these ten drinks?
- Alongside the ten drinks, there are ten snacks to be served up as well. How many different ways can these ten people sit in these ten seats, with each of these ten drinks, and each of these ten snacks?

Solution

- Here, we can think about lining up the ten seats in a row, each number 1 through 10. Then, we want to place one patron into each of the seats. This is no different from ordering 10 books, and so the total is $10!$ which is 3,628,800.
- Note that we still have to make the seat choices from part (a), so there are $10!$ ways of getting the 10 people sat in the 10 chairs. Once there, we can think of handing out the drinks to each of the numbered combinations of person-chair. This is no different from passing out the people as well, giving $10!$ ways of doing this. We use the product rule to combine these two choices, with $10! \times 10!$ total combinations of people-chair-drink. This is 13,168,189,440,000.
- Extending the same logic before, there are $10! \times 10!$ ways of getting each person sat in a chair with a drink. Then, there will be an additional $10!$ ways of passing out the snacks to these people. Taken together this gives $10! \times 10! \times 10!$ which is 47,784,725,839,872,000,000.¹⁴

¹⁴It is somewhat interesting to note how large these values get relatively quickly. This is a comparatively small question: only 10 people with 10 drinks and 10 snacks. If you consider any counting problem with a larger number of items, these problems quickly grow to be intensely complex. For instance, a count of my main home book collection reveals 376 of them. To order these would give $376!$ possible orderings. In decimal representation this is

$$4.992244775852435618292576458782762114148884082811840265632 \cdots \times 10^{806}.$$

This is an 807 digit long number. This is an incomprehensibly large number. This number is 8×10^{726} times larger than the number of atoms in the universe. That is, if every atom in the universe were given

Remark ($0!$). Depending on how factorials are thought of, some trouble can come up around a quantity like $0!$. On one hand, if we view factorials as multiplying each number between n and 1 together then $0! = 0 \times 1$ and we get $0! = 0$. On the other hand, if we view factorials as counting the number of ways which we can order a set of n items, then $0!$ is the number of ways we can order 0 items, which is 1.¹⁵ So, which is it?

We take $0!$ to be equal to 1. The ordering argument is perhaps the most convincing. However, if you are algebraically minded you may wonder how we get around the tricky issue of using our algebraic definition. The key insight is to not define $n!$ as the product of the numbers from n to 1, but rather, to define

$$(n-1)! = \frac{n!}{n},$$

and specify that $1! = 1$. Then in this case we get all of the usual requirements for how we have discussed factorials, but we also get that $0! = \frac{(0+1)!}{(0+1)} = 1$. As a result, we will take $0! = 1$.¹⁶

3.4.4 Permutations and Combinations

Sometimes, we want to order items from a collection, but we want to only take a subset of these items. That is, suppose that you have 20 books, only 9 of them will fit on the shelf, and you want to know “how many ways can you put 9 books on the shelf, in order, from your collection of 20?” Using the product rule of counting for this directly, we recognize that there are 20 options for the first, then 19, then 18, and so on until there are 12 choices for the 9th book to place. We can write this out in a seemingly strange way.

$$\begin{aligned} & \frac{(20)(19)(18)(17)(16)(15)(14)(13)(12)(11)(10)(9)(8)(7)(6)(5)(4)(3)(2)(1)}{(11)(10)(9)(8)(7)(6)(5)(4)(3)(2)(1)} \\ &= \frac{(20)(19)(18)(17)(16)(15)(14)(13)(12)\cancel{(11)}\cancel{(10)}\cancel{(9)}\cancel{(8)}\cancel{(7)}\cancel{(6)}\cancel{(5)}\cancel{(4)}\cancel{(3)}\cancel{(2)}\cancel{(1)}}{\cancel{(11)}\cancel{(10)}\cancel{(9)}\cancel{(8)}\cancel{(7)}\cancel{(6)}\cancel{(5)}\cancel{(4)}\cancel{(3)}\cancel{(2)}\cancel{(1)}} \end{aligned}$$

This expression is $20!$ divided by $11!$, and gives the same as our argument from the product rule for counting directly. This is a more general result than our example with books would suggest. If we have n items, and we want to choose k of them taking into account the order those choices, it will always be $n!$ divided by $(n-k)!$. We call this a permutation.

some arrangements of books to hold onto, they would need to hold 8×10^{726} of them in order for all of the arrangements to be held. I point this out because combinatorics *explodes* in this way. Even simple problems grow out of hand very, very quickly. This is where comfort with the algebraic tools is required, rather than a reliance on intuition. There is simply no way to have intuition regarding the scope of these numbers, at least, not without a lot of practice.

¹⁵Imagine I am placing books on my shelf. With 3 books there are $3! = 6$ ways my shelf can look at the end. With 2 books there are $2! = 2$ ways my shelf can look at the end. With 1 book there are $1! = 1$ ways my shelf can look at the end. With 0 books there are $0! = 1$ ways my shelf can look at the end.

¹⁶Note, this does not help us with the factorials of negative numbers, nor of fractional numbers. Factorials *can* be extended to these in sensible ways, but these are not for combinatorial purposes and are no longer “factorials” exactly.

Definition 3.3 (Permutations). If we wish to select k items from a collection of n items, where the ordering of these selections matters, then the total number is referred to as a permutation. Mathematically,

$$P_{n,k} = \frac{n!}{(n-k)!}.$$

Permutations arise when we select ordered subsets from a collection. We often, in combinatorial problems, talk about ordering, though sometimes what we mean by this is slightly more abstract. Suppose that you want to form a committee with 5 different people, each of which occupies a different role: the president, vice president, treasurer, note taker, and critic. If there are 30 people to select for this then there are $P_{30,5}$ total possible committees that can be formed. While there is not a sequential order here, we talk about this as being “ordered” since we can differentiate between the five roles. Instead of labelling them with their names, we could label them 1 through 5 and make the ordering more explicit.

Example 3.8 (Seating in a (Not Full) Coffee Shop). Still haunted by that time when the coffee shop was full, Sadie and Charles enter the coffee shop at a later date and find that, including themselves, there are only 7 patrons in the store, and still the 10 seats to choose from.

- How many different ways can the 7 people sit in the 10 different chairs?
- If there are 10 drinks on the menu, how many different ways can each person choose a chair and a drink?
- If the coffee shop can make only one of each drink, how does the previous total change?

Solution

- In this case we are looking to order subsets from a total collection. If we line up the 7 patrons we then need to select 7 chairs to go with them, and keep these ordered. This is simply

$$P_{10,7} = \frac{10!}{3!} = 604800.$$

- In this part of the question we know that the 7 people have $P_{10,7}$ ways of sitting into seats, we can view this as decision one. Then, for each of these 7 people there is a decision of what drink they will order. For these 7 decisions, $n_2 = \dots = n_8 = 10$. As a result, we get the total number is

$$P_{10,7} \times 10 \times 10 \times \dots \times 10 = P_{10,7} \times 10^7 = 6,048,000,000,000.$$

- This setting, like part (b) starts with a first decision involving $P_{10,7}$ choices. Then, instead of there being 7 more decisions with 10 choices each, we can either view this as 7 more choices with a descending number of options 10 for the first, then 9,

and so on, or we can view this as a single choice where we need to select 7 **ordered** options from the 10 drinks available. This gives

$$P_{10,7} \times P_{10,7} = 365,783,040,000,$$

total choices.

Factorials compute the number of orderings for a set of objects, and permutations compute the number of ordered subsets from a collection of objects. What about when we do not wish to differentiate the order of subsets? Suppose that you still need to form a 5 person committee, but you do not have explicit roles for the different members of the committee. Here we cannot use a permutation directly, as we know that this takes into account the order.

To determine the number of unordered subsets, we will consider a different approach for taking ordered subsets. Suppose that we formulate the ordered committee as a two step procedure. First, we select 5 people without concern for their order. Then we choose which order they will have. If M represents the number of unordered sets of 5 from this population, the product rule for counting tells us that the total number of ordered committees will be $M \times 5!$, since there are $5!$ arrangements of the 5 people. Thus, we can write this down as

$$P_{30,5} = \frac{30!}{25!} = M \times 5! \implies M = \frac{30!}{25!5!}.$$

This will be true far more broadly than our committee example. If we want to select k items from a collection of n , we will have $n!$ divided by the product of $k!$ and $(n - k)!$. We refer to these as combinations.

Definition 3.4 (Combinations). If we wish to select k items from a collection of n items, where the ordering of these selections does not matter, then the total number is referred to as a combination. Mathematically,

$$\binom{n}{k} = \frac{n!}{k!(n - k)!}.$$

We read $\binom{n}{k}$ as “ n choose k ”, which translates to “select k items from a population of n total options, without concern for their order.”

To summarize: factorials allow us to order a complete collection, permutations allow us to select a subset with consideration of the ordering, and combinations allow us to select a subset from the collection without regard to the order. These three techniques can be used in combination with the product rule for counting to allow us to have very complex total summations.

Example 3.9 (Changing the Seating in the Coffee Shop). Some nights, the coffee shop hosts local music acts. Because of the added equipment, the coffee shop owners only keep out the number of seats that are going to be required based on the number of tickets that were sold.

- a. If there are 8 tickets sold, how many different combinations of the 10 chairs can get left out?
- b. Suppose that only 6 people end up showing up. How many different ways can the 6 people sit in the 8 chairs that are being selected from the 10 total possibilities?

Solution

- a. Here, there is no ordering for the 8 chairs that are to be selected. As a result, we are simply looking for how many chairs can be selected from a group of 10 of them. This is

$$\binom{10}{8} = \frac{10!}{8! \cdot 2!} = 45.$$

- b. With the first choice having 45 possible options, the second choice that needs to be made is how 6 people sit into 8 chairs. Here the ordering *does* matter, since the chairs are distinguishable. As a result, this is a permutations question, with there being a total of $P_{8,6} = \frac{8!}{2!}$ ways of having the people select their seats. In total then there are

$$\binom{10}{8} \times P_{8,6} = \frac{10!}{8! \cdot 2!} \cdot \frac{8!}{2!} = 907,200.$$

3.4.5 Less Common Counting Techniques

While most of the problems we address will revolve around permutations and combinations (with heavy use of the product rule), there are additional techniques which are important to know (and recognize when to use). In particular, combinations and permutations each assume that we are sampling from our set **without replacement**. That is, each time you select an item, it is removed from the population. These are the most common situations in these combinatorial problems, however, there are *some* situations which arise where we need to count the number of ordered or unordered subsets *with* replacement.

3.4.5.1 Ordered Subsets with Replacement

Consider, for instance, forming a password using only lowercase numbers and letters. If you decide on a fixed length for the password, then there are going to be 36 choices at each decision point, and you want to take an ordered subset of these. This is forming an **ordered subset with replacement**, and to count how many different ways there are of doing this, we can simply use the product rule. That is, you have 36 choices at each decision point, and so there are $36 \times 36 \times \cdots \times 36 = 36^k$ total decisions, where k is the number of items to select.

In general, if you have n total items and you want to make an ordered set of k of these items **with replacement** you will have n^k total ways of doing this.

3.4.5.2 Unordered Subsets with Replacement

Forming unordered sets with replacement is slightly less intuitive. Consider rolling k dice which are not distinguishable from one another. We know that there are 6 total sides that can show up on each of these dice, but how many different combinations of numbers can show up overall? If the dice can be distinguished we would say that there are 6^k possible ways of doing this. However, some of these combinations are going to be equivalent in the unordered world. Take the simple case of $k = 2$. Here we have the following possibilities:

$$\begin{aligned}(1, 1), (1, 2), (1, 3), (1, 4), (1, 5), (1, 6) \\ (2, 2), (2, 3), (2, 4), (2, 5), (2, 6) \\ (3, 3), (3, 4), (3, 5), (3, 6) \\ (4, 4), (4, 5), (4, 6) \\ (5, 5), (5, 6) \\ (6, 6)\end{aligned}$$

This gives a total of 21 possible combinations, rather than 36.

In general, if we want to find the way of selecting k elements *with replacement* from a total of n , then the number of ways of doing this will be

$$\binom{n+k-1}{k}.$$

In our example this gives $\binom{6+2-1}{2} = 21$.

3.4.5.3 Permutations with Identical Objects

Finally, it is worth understanding how to handle identical objects in combinatorial problems. Suppose that, of the 10 books that we wish to place on a shelf, we have 2 copies of one of them, 3 copies of another one, and the other 5 have one copy each. Supposing that there is no way to tell these identical objects apart, how many ways can we arrange the bookshelf?

First, if we pretend that all of the items are actually able to be differentiated then there are $10!$ ways of placing these books. Now, in any of these permutations, had we swapped the order of the first book (with 2 copies) the ordering would have been indistinguishable. As a result, for every ordering of the 8 other books, we counted that permutation twice (when it should have only been counted once!). So to address the two repeated copies we need to take $10!/2$. Now, a similar argument is going to hold for the book with 3 repeated copies. However, instead of there being 2 permutations which are identical, there are going to be $3! = 6$ permutations which are identical. This is because we can reorder the 3 copies of the book in anyway we

choose, and still wind up with the same overall permutation.¹⁷ As a result, the total number is going to be

$$\frac{10!}{2! \cdot 3!} = 302400.$$

We can see this same result through an alternative construction. First, we select which of the 10 slots should have the first book. We do not care about the order, and so there are $\binom{10}{2}$ ways of doing this. Next, we can select which of the 8 remaining slots should have the second book. Like the first one there will be $\binom{8}{3}$ ways of placing these. Now, there are 5 slots remaining, and 5 books to place, so as a result, we can order those in $5!$ different ways, and then slot them into the remaining places in order. This gives, in total

$$\binom{10}{2} \binom{8}{3} (5!) = \frac{10!}{2!8!} \cdot \frac{8!}{3!5!} \cdot 5! = \frac{10!}{2!3!}.$$

To generalize this, if we want to order n elements, such that there are k distinguishable elements with n_1 of the first type, n_2 of the second, and so forth until n_k of the last type ($n = n_1 + n_2 + \dots + n_k$), then the total number of orderings will be

$$\frac{n!}{n_1! \cdot n_2! \cdots n_k!}.$$

3.5 From Combinatorics to Probability

While combinatorics is a field of study on its own, with many intriguing tools and developments surrounding the enumeration of objects, for the purposes of simple probability models these tools will suffice. Ultimately, we care about counting since in the equal probability model, the probability of any event can be determined by counting the number of ways that the event can occur and dividing by the total number of outcomes that are possible. That is, we use these tools to derive N_A , the total number of ways that A can occur, and N , the total number of experimental outcomes, and then we conclude that

$$P(A) = \frac{N_A}{N}.$$

Example 3.10 (Poker Hand Counts). During one of their conversations, Charles and Sadie were remarking how they never really played poker. As they understand it, in poker you are dealt a hand of 5 cards and you want to use these 5 cards to try to match certain sets of cards, some of which are more rare than others. Charles and Sadie start to get hung-up on discussions regarding “straights” and “flushes”.

A straight is any sequence of 5 cards in ascending order (where aces can be low, or high). For instance, 7, 8, 9, 10, *covJ* of any suit. A flush, is any set of 5 cards belonging to the same suit. Charles just *feels* that straights have to be more rare than flushes.

¹⁷In fact, the reason that there are 2 ways of doing this with the book with 2 copies is since $2! = 2$.

- How many different straights are there from a standard deck of cards?
- How many different flushes are there from a standard deck of cards?
- If dealt 5 cards at random, what is the probability of a flush? What is the probability of a straight?
- A straight flush occurs when you have 5 cards in order, of the same suit. What is the probability of a straight flush?
- If straight flushes were not counted as flushes, and not counted as straights, how do the probabilities of either hand change?

Solution

- A straight necessitates drawing five cards in order, with each of any suit. Just as with the straight flush, there are 10 possible starting values for the straight. Once we have selected the starting value, then for each of the five cards we can pick any of the four suits, resulting in 4 choices each. That gives

$$N_A = 10 \times 4 \times 4 \times 4 \times 4 \times 4 = 10 \times 4^5 = 10240.$$

- A flush necessitates drawing **any** five cards from the same suit. If we had a suit fixed, there would be $\binom{13}{5}$ ways of doing this, since we do not care about ordering. If we think about first choosing the suit, we have 4 ways of doing that, resulting in

$$N_A = 4 \times \binom{13}{5} = 5148.$$

- To find the probabilities of each of these, we need to know the total number of 5 card hands. We do not consider order, and so $N = \binom{52}{5} = 2598960$. Then, the probability is simply the number of combinations (calculated above) divided by the number of hands. This gives, for straights,

$$P(A) = \frac{10240}{2598960} = \frac{128}{32487} \approx 0.00394,$$

and for flushes,

$$P(A) = \frac{5148}{2598960} = \frac{33}{16660} \approx 0.00198.$$

As a result, we see that straights are roughly twice as common as flushes are.¹⁸

- Note that to form a straight flush, we first have to fix a suit. There are $\binom{4}{1} = 4$ total ways of doing this. Next, we need to pick which starting value we will use. Once a card has been selected as a starting value, the remaining cards are fixed. The start value ranges from A through to 10. Correspondingly, we have

$$N_A = \binom{4}{1} \binom{10}{1} = 4 \times 10 = 40.$$

As a result, we get that

$$P(A) = \frac{40}{2598960} = \frac{1}{64974}.$$

- e. From (d) exactly 40 of the straights and 40 of the flushes are also straight flushes. We can thus remove 40 from the totals of each of these, giving $\frac{10200}{2598960}$ for straights and $\frac{5108}{2598960}$ for flushes.

References

¹⁸This is *still* a deeply unintuitive result to me. To me it feels like it should be harder to get a nice ordering of cards all in a row than it is to find ones of the same suit. And yet, it is about twice as likely to have the straights. Now, if you think about this deeply, it makes a lot of sense: there is a lot more leeway in selecting the straight than the flush. However, my brain refuses to accept this as intuitive. This is something that can often occur in probability questions where the true results can be far from what we would expect. An interesting question is how long does a straight have to be to be less likely than a flush of the same length. Note that the number of ways of choosing a flush will always be $4 \times \binom{13}{k}$, and the number of ways of forming a straight will always be 10×4^k . If we consider k from 1 to 13, we can take the ratios of these to see just how much more (or less) likely a straight is. Doing this gives: $k=1$ gives 0.769. $k=2$ gives 0.513. $k=3$ gives 0.559. $k=4$ gives 0.895. $k=5$ gives 1.989. $k=6$ gives 5.967. $k=7$ gives 23.869. $k=8$ gives 127.304. $k=9$ gives 916.587. $k=10$ gives 9165.874. $k=11$ gives 134432.821. $k=12$ gives 3226387.692. $k=13$ gives 167772160. Up to (and including) 4 cards the straight is indeed harder to achieve. However, this does not last long!

4 Probabilities with More than One Event

4.1 Marginal and Joint Probabilities

Up until this point we have primarily focused on assigning probabilities to particular events. If we have some event of interest, A , then $P(A)$ is the probability that A occurs in any manner. If we are using our equally likely probability model, then $P(A) = \frac{N_A}{N}$. This is the probability of the event A where nothing else is known at all. If we smooth over anything which could alter the likelihood, if we have no additional information, if we want the best guess for the likelihood of occurrence in a vacuum, this is the probability of interest. We refer to such quantities as marginal probabilities.

Definition 4.1 (Marginal Probability). The marginal probability of a single event, A , is the probability that the event happens without considering any information. This is simply the probability that the event happens, denoted $P(A)$.

It is useful to specifically call these marginal probabilities to differentiate them from probabilities which depend on two or more events. Specifically, we can think about taking the intersection of two events, say $A \cap B$. In words this is the event that A occurs **and** B occurs. Until this point we have thought about solving for probabilities related to intersections as a two-step procedure: first, find an event $C = A \cap B$, and then second solve for the marginal probability of C . While this is a useful technique for calculation, sometimes it is more useful to think of the probability of the intersection as the probability of A and B occurring simultaneously. We call this the joint probability of A and B .

Definition 4.2 (Joint Probability). The joint probability of two events, A and B , is given by the probability of their intersection. That is, $P(A \cap B)$. This is sometimes denoted $P(A, B)$ and corresponds to the probability that both A and B occur. The joint probability of more than two events extends in the same way. Suppose there exists a sequence of events, A_1, \dots, A_n , then the joint probability of these events is

$$P(A_1, A_2, \dots, A_n) = P\left(\bigcap_{i=1}^n A_i\right).$$

4.2 What are Conditional Probabilities?

Marginal probabilities are often of interest, and frequently are the best tool for summarizing the overall state of the world, or our knowledge regarding the state of the world. Joint probabilities can be useful when working with compound events, or thinking of complex outcomes that we wish to consider. However, there are many scenarios which are not covered by either the joint or marginal probabilities we have seen. In practice we know that sometimes information that we have will change our understanding of the probability of an event. Suppose the event A corresponds to the event that it snows tomorrow, in some particular city. It is possible to think about how often it snows on average, and report a value related to that as $P(A)$. Now, what if we know that it is currently the middle of summer? In this case, while $P(A)$ does not shrink to 0, it becomes far less likely than if we did not have that information. Similarly, if we know that it is winter, the likelihood that it snows tomorrow increases. In order to formally capture this we can introduce the idea of conditional probability.

Definition 4.3 (Conditional Probability). The conditional probability of an event A given an event B , is the probability that A occurs assuming that we know that B occurs. The conditional probability takes into account additional information codified through the occurrence of an additional event. We write this quantity as $P(A|B)$, and will read this as “the probability of A given B .”

Unlike in the case of marginal probabilities, conditional probabilities allow us to *condition* on extra pieces of information. Instead of asking “what is the probability of this event”, we instead ask, “given that we know this piece of information, what is the probability of this event?” Joint probabilities ask “what is the probability that both of these events occur simultaneously” which is distinct in that we do not have any additional information about the state of the world when working with joint probabilities. The subtle distinction becomes quite powerful, both in terms of manipulating and working with probabilities, but also in terms of expressing the correct events of interest for ourselves.

To make use of conditional probabilities, we will think of the process of *conditioning* on one or more events. We will talk of the probability of A conditional on B , where A and B are two events of interest. Intuitively, this is the probability of A happening, supposing that we know that B has already happened.

Example 4.1 (Six from the Sum). Charles and Sadie are playing a new game using two dice. In the game they each take turns rolling the two dice into a container that the other player cannot see. They add up the dice and then report this sum to the other player. The other player then has to guess whether or not there is a six showing.

- a. On one round, Charles does not hear the sum that Sadie reports as he was not paying attention. Sadie is strict and insists that she will not repeat herself. What should Charles guess?

- b. Determine a strategy which optimizes the likelihood that the guessing player will be correct.

Solution

- a. In this case we want the **marginal probability** of a six showing up on the roll of two dice. Take E to represent the event wherein at least one six is showing on the roll of two dice. Thus, E^C is the event that no sixes are showing. There are $5 \times 5 = 25$ (using the product rule for counting) ways of *not* rolling a 6, meaning that $P(E^C) = \frac{25}{36} \Rightarrow P(E) = 1 - \frac{25}{36} = \frac{11}{36}$. Thus, Charles should guess that there is no 6 as the probability is only $11/36 \approx 0.31$.
- b. Here we wish to determine conditional probabilities. We take E to be the event that at least one 6 is showing, and then S to be a variable representing the sum of the two dice. For $s = 1, \dots, 12$ we wish to find $P(E|\{S = s\})$. Notice that for $s = 2, \dots, 6$ $P(E|S = s) = 0$. If the sum is 2 we know that there could not have been a 6. Moreover, for $s = 11, 12$ we know that $P(E|S = s) = 1$ since the only way to form 11 is a five and a six, and the only way to form 12 is to have two sixes. This leaves $s = 7, \dots, 10$ to check. The following table gives the set of values, the possible combinations to reach the value, and then the combinations that end up involving a 6.

Value	Combinations	Involving 6
7	(1,6) (2,5) (3, 4) (4, 3) (5, 2) (6, 1)	(1, 6) (6, 1)
8	(2,6) (3,5) (4, 4) (5, 3) (6, 2)	(2, 6) (6, 2)
9	(3,6) (4,5) (5, 4) (6, 3)	(2, 6) (6, 2)
10	(4, 6) (5, 5) (6, 4)	(4, 6) (6, 4)

Referencing from this table we can read off the following probabilities

$$\begin{aligned}
 P(E|S = 7) &= \frac{2}{6} = \frac{1}{3} \\
 P(E|S = 8) &= \frac{2}{5} \\
 P(E|S = 9) &= \frac{2}{4} \\
 P(E|S = 10) &= \frac{2}{3}.
 \end{aligned}$$

As a result, the best strategy is to guess “yes” when a 10, 11, or 12 is rolled and to be indifferent to the guess when a 9 is rolled. Otherwise, guess “no.”

Recall that A and B , as events, are merely subsets of the sample space, \mathcal{S} . Each item in either

A or B is one of the possible outcomes from the experiment or process that we are observing. Suppose that we know that B has occurred. What this means is that, one of the outcomes in the set B was the observed outcome from the experiment. Now, if we want to know $P(A|B)$, we want to know the probability, working from the assumption that B has happened, that A also happens. That is, knowing that B has happened, what is the probability that A and B both happen.

The event that A and B both happen is denoted by the intersection, $A \cap B$. This corresponds to the set of events inside the set B which also belong to the set A . Now, instead of considering the joint probability directly, we need to acknowledge that for $A|B$, only the events in B were possible. That is, instead of being divided by the whole space, we can only divide by the space of B . In some sense, we can view conditioning on B as treating B as though it is the full sample space, and finding probabilities within that. In general, B will be smaller than \mathcal{S} , and so $P(B) < 1$. Instead of the conditional probability being “out of” 1, it will instead be “out of” $P(B)$, which gives $P(A|B) = \frac{P(A \cap B)}{P(B)}$.

Computing Conditional Probabilities

For an event A , and an event B with probability $P(B) > 0$, the conditional probability of A given B is

$$P(A|B) = \frac{P(A \cap B)}{P(B)}.$$

To make this more clear, let's consider a simple example. Suppose that we take A to be the event that a 2 is rolled on a fair, six-sided die, and B to be the event that an even number was rolled. This is an equal probability model, and so each outcome gets $\frac{1}{6}$ probability. The original sample space is $\mathcal{S} = \{1, 2, 3, 4, 5, 6\}$, the event A is $\{2\}$, and the event B is $\{2, 4, 6\}$. In order for both A and B to occur, we note that we need $A \cap B = \{2\}$. If we know that B has occurred, then we know that either a 2, 4, or 6 has been rolled, with equal probability for each. Thus, intuitively, we can view B as the new sample space, and say that rolling a 2 has a $\frac{1}{3}$ probability, given that there are 3 outcomes and 1 of them is the event of interest. Another way to consider this is to note that $P(B) = \frac{1}{2}$, and so we need to scale each event by $\frac{1}{1/2}$ in order to make sure that the total probability of our reduced sample space equals 1. Then $P(A \cap B) = \frac{1}{6}$, so

$$P(A|B) = \frac{1/6}{1/2} = \frac{1}{3}.$$

Suppose that, instead of a fair die, it was weighted so that 6 comes up more frequently than the other options. Consider the probability of observing a six to be 0.5, with the other five values each coming up with probability 0.10. If A and B are the same events as above, then $P(B) = 0.7$. If we know that B has occurred then the new sample space is $\{2, 4, 6\}$ where $P(2) = \frac{0.1}{0.7} = \frac{1}{7}$, $P(4) = \frac{0.1}{0.7}$, and $P(6) = \frac{0.5}{0.7} = \frac{5}{7}$. Note that these three probabilities sum to 1 still, which constitutes a valid probability model, and so $P(A|B) = \frac{1}{7}$.

Example 4.2 (Six from the Sum - Revisited). Sadie sees the solution worked out for the best strategy in the dice game above, but is having trouble understanding it in the context of conditional probability more broadly. For the sums 7, 8, 9, and 10, describe the process of limiting the sample space to get the correct conditional probability, and use the formula to show that the probabilities worked out in Example 4.1 are correct.

Solution

The relevant table of solutions is copied from above.

Value	Combinations	Involving 6
7	(1,6) (2,5) (3, 4) (4, 3) (5, 2) (6, 1)	(1, 6) (6, 1)
8	(2,6) (3,5) (4, 4) (5, 3) (6, 2)	(2, 6) (6, 2)
9	(3,6) (4,5) (5, 4) (6, 3)	(2, 6) (6, 2)
10	(4, 6) (5, 5) (6, 4)	(4, 6) (6, 4)

Here, given a sum, we **know** that one of the events listed under “combinations” has occurred. As a result, once we have conditioned on what the sum is, we are able to treat the “combinations” column as the full sample space of possible outcomes. Each of these in this case is equally likely, and so we can divide the number which contain a 6, by the total number in the reduced sample space.

To do this algebraically, we first note that

$$\begin{aligned}P(S = 7) &= \frac{6}{36} \\P(S = 8) &= \frac{5}{36} \\P(S = 9) &= \frac{4}{36} \\P(S = 10) &= \frac{3}{36}.\end{aligned}$$

Now, suppose we consider the event $E \cap \{S = 7\}$. This is the set $\{(1, 6), (6, 1)\}$ and so $P(E \cap \{S = 7\}) = 2/36$. In fact, the same holds true for all of the joint events. As a result, we get

$$\begin{aligned}P(E|S = 7) &= \frac{\frac{2}{36}}{\frac{6}{36}} = \frac{2}{6} \\P(E|S = 8) &= \frac{\frac{2}{36}}{\frac{5}{36}} = \frac{2}{5} \\P(E|S = 9) &= \frac{\frac{2}{36}}{\frac{4}{36}} = \frac{2}{4} \\P(E|S = 10) &= \frac{\frac{2}{36}}{\frac{3}{36}} = \frac{2}{3}.\end{aligned}$$

This corresponds exactly to the values we found before.

Sometimes, we wish to condition on more than one event. To do so, the same process extends naturally. For instance, suppose we want to know the probability of A given B and C . This would be written

$$P(A|B, C) = \frac{P(A \cap B \cap C)}{P(B \cap C)} = \frac{P(A, B, C)}{P(B, C)}.$$

Moving beyond two events occurs in the expected way.

4.3 Using Conditional Probabilities

Conditional probability is a mechanism for capturing our knowledge of the world, and using that to update our sense of the uncertainties at play. For instance, suppose that we are interested in drawing a random card from a deck of 52, and we want to know the probability that it is a heart. Without any additional knowledge, the probability of this event is $\frac{1}{4}$. Now, suppose that you know that it is a red card. In this case, we now know that it is either a heart or a diamond, and there are equal numbers of each, meaning that the new probability is 0.5. We can work this out directly

$$P(\text{covHeart}|\text{covRed}) = \frac{P(\text{covHeart}, \text{covRed})}{P(\text{covRed})} = \frac{P(\text{covHeart})}{1/2} = \frac{1/4}{1/2} = 0.5.$$

Suppose instead that we had been told that the card was an ace. Here we now know that there are four possible outcomes that correspond to an ace, and only one of these is a heart, meaning the probability is $\frac{1}{4}$. In this case, $P(A|B) = P(A)$, and our beliefs did not update.

What if instead we had considered the second event to be “the card was a spade.” In this case if we want to know $P(A|B)$ then, given a spade being drawn, we know that the probability of drawing a heart is 0.

Example 4.3 (Charles’s Mismatched Urn Mishap). Charles’s love of probability prompts a spontaneous decision: buy an urn and some coloured balls to fill it up with. Unfortunately, the supplier of the balls misunderstood the request and sent over an assortment of different shapes rather than just spheres. There are some spheres, some cubes, some pyramids, and some cones. There are also five different colours present, red, blue, green, yellow, and black. Charles is slightly dismayed as, when reaching into the urn, it is very easy to feel what shape you are pulling out before you see the object, and the distribution of colour-shape combinations is not even. Despite the dismay, Charles shows Sadie, who is deeply excited, explaining how this mismatched urn is perfect for understanding conditional probabilities deeply. The distribution of shapes and colours is presented in the following table.

Colour	Sphere	Cube	Pyramid	Cone
Red	2	3	2	0
Blue	1	0	0	6
Green	2	2	1	2
Yellow	0	4	2	1
Black	3	1	1	2

- What is the probability of drawing each colour, if items are selected at random, without knowledge of the shape?
- Assuming that the shape is known, what is the probability of selecting each colour?

Solution

- a. Note that there are $2 + 3 + 2 = 7$ red, $1 + 6 = 7$ blue, $2 + 2 + 1 + 2 = 7$ green, $4 + 2 + 1 = 7$ yellow, and $3 + 1 + 1 + 2 = 7$ black objects. As a result, each colour is going to be equally likely, with a probability of 0.2.
- b. Take S, C, P, Cn to be the events that a sphere, cube, pyramid, or cone are drawn, respectively. Take R, B, G, Y, Bk to be the events that a red, blue, green, yellow, or black object is drawn, respectively. We want the probability of each colour, given the corresponding shape. There are a total of 20 conditional probabilities to solve for here. We walk through, in full, the first conditional probability calculation. Afterwards, the same process follows to get the (provided) answer.

First note that there are 8 spheres, 10 cubes, 6 pyramids, and 11 cones. Thus, the marginal probabilities are $P(S) = 8/35$, $P(C) = 10/35$, $P(P) = 6/35$, and $P(Cn) = 11/35$. Note further that the joint probability between any colour-shape combination is going to be given by the number of that combination that exist, divided by 35. Thus, suppose we want $P(R|S)$. There are 2 red spheres, so $P(R \cap S) = 2/35$. The marginal probability $P(S) = 8/35$, so taken together this gives

$$P(R|S) = \frac{2/35}{8/35} = \frac{2}{8} = \frac{1}{4}.$$

Applying the same process gives the following probabilities, reported in the table for convenience.

Colour	Sphere	Cube	Pyramid	Cone
Red	$\frac{2}{8} = \frac{1}{4}$	$\frac{3}{10}$	$\frac{1}{3}$	0
Blue	$\frac{1}{8}$	0	0	$\frac{6}{11}$
Green	$\frac{2}{8} = \frac{1}{4}$	$\frac{1}{3}$	$\frac{1}{6}$	$\frac{2}{11}$
Yellow	0	$\frac{2}{10}$	$\frac{1}{6}$	$\frac{1}{11}$
Black	$\frac{3}{8}$	$\frac{5}{10}$	$\frac{3}{6}$	$\frac{1}{11}$

4.3.1 The Multiplication Rule

While sometimes we will want to work out the conditional probability using our knowledge of the joint and marginal probabilities, there are other times where it is easier to determine the conditional probability directly. In these settings we may wish to understand the marginal or joint probabilities. That is, we may know $P(A|B)$, but we want to make statements regarding $P(A)$ or $P(A, B)$.

To do so, we can simply rearrange the defining relationship of conditional probability, to solve

for the quantities of interest. Because of the importance of this procedure, we actually give this mostly straightforward rearrangement a special name.

Multiplication Rule

The multiplication rule states that, for two events A and B where $P(B) > 0$,

$$P(A \cap B) = P(A|B)P(B).$$

Note that, by multiplying both sides of the definition of $P(A|B)$ by $P(B)$ gives the result. In words it states that we can solve for the joint probability of A and B by multiplying the conditional probability of A given B , by the marginal probability of B . This is symmetric in A and B so that

$$P(A \cap B) = P(B|A)P(A).$$

This is useful as sometimes it is easier to determine B given A .

Example 4.4 (Package Delivery Times). To thank Sadie for the help in seeing the silver lining with the urn mishap, Charles decides to order a small gift online, sending it direct to Sadie. Unfortunately, the website does not list which delivery company each package is sent out with. After some sleuthing, Charles determines that there are two different companies that it may have been sent with. Looking at online reviews it appears as though company A is late 75% of the time while company B is late 15% of the time.

If the store that Charles ordered from sends out 10% of packages with company A , and the rest with company B , which is more likely: that the package is late and was sent with A , or that the package was late and sent with B ?

Solution

We will take L to correspond to the events where the package is late, A to the events where the package was sent with A and B to be the events where the package was sent with B . We wish to compare $P(L, A)$ and $P(L, B)$. We know that $P(A) = 0.1$ and $P(B) = 0.9$, and we know that $P(L|A) = 0.75$ and $P(L|B) = 0.15$. As a result, we can use the multiplication rule to find the joint probabilities. First, $P(L, A) = P(L|A)P(A) = (0.75)(0.1) = 0.075$. Additionally, $P(L, B) = P(L|B)P(B) = (0.15)(0.9) = 0.135$. As a result it is more likely to have the package late and sent with B than the package late and sent with A .¹

¹Note, this is another result which seems to (on the surface) defy expectations. We will see this again later on in this chapter in a slightly different context. It seems strange that company A is more likely to be late, and yet, we are more likely to see a late package that is sent by company B than a late package that is sent by company A . The reason for this is that company B is used much more frequently than company A , which overcomes the added likelihood of company A being late.

4.3.2 Partitions and the Law of Total Probability

While the multiplication rule gives us the capacity to solve for joint probabilities, often we wish to make statements regarding marginal probabilities. Fortunately, we can extend this process outlined in the multiplication rule to solve directly for marginal probabilities as well. To do so, we first introduce the concept of a partition.

Definition 4.4 (Partition). A partition is a collection of sets which divide up the sample space such that all of the sets are disjoint from one another, and the sample space is given by the union of all of the sets. That is, A_1, \dots, A_n is a partition of \mathcal{S} if:

1. $A_i \cap A_j = \emptyset$ for all $i \neq j$, and
- 2.

$$\bigcup_{i=1}^n A_i = \mathcal{S}.$$

For instance, if the sample space were all the positive integers, we could partition this space into all the even numbers as one set and all the odd numbers as a second. We could also partition this into the set of numbers which are less than 10, the set of numbers that are greater than 10, and then 10. In both examples we have sets whose union forms the full sample space with no overlap. Note that we could not partition the set into multiples of 2 and multiples of 3, since (i) not all values are contained between these two sets,² and (ii) there is overlap between these two sets.³

Example 4.5 (Partitions of the Coin Game). Charles and Sadie are thinking back with fondness to their original coin flipping game, where they would toss a coin three times in a row. If two or more heads showed up, Charles would pay. Otherwise, Sadie would.

To help them reminisce, Write down three different partitions of the sample space, each with a different number of partitioning sets. Describe your partitions using words.

Solution

There are many possible partitions to write down. The following are examples.

1. We can partition the space into games where Charles pays and games where Sadie pays. This gives

$$B_1 = \{(covH, covH, covH), (covH, covH, covT), (covH, covT, covH), (covT, covH, covH)\}$$

$$B_2 = \{(covT, covT, covT), (covT, covT, covH), (covT, covH, covT), (covH, covT, covT)\}.$$

²For instance, 5 is neither a multiple of 2 nor of 3.

³For instance, 6 is a multiple of both 2 and 3.

2. We can partition the space into those with 0, 1, 2, or 3 heads. This gives

$$B_1 = \{(covH, covH, covH)\}$$

$$B_2 = \{(covT, covT, covH), (covT, covH, covT), (covH, covT, covT)\}$$

$$B_3 = \{(covH, covH, covT), (covH, covT, covH), (covT, covH, covH)\}$$

$$B_4 = \{(covH, covH, covH)\}.$$

3. We can partition the space into the number of times the sequence switches between heads and tails. There will be either 0 switches, 1 switch, or 2 switches. This gives

$$B_1 = \{(covH, covH, covH), (covH, covH, covH)\}$$

$$B_2 = \{(covT, covT, covH), (covH, covT, covT), (covH, covH, covT), (covT, covH, covH)\}$$

$$B_3 = \{(covT, covH, covT), (covH, covT, covH)\}.$$

Partitions allow us to move from discussions regarding the joint probability of events to the marginal probability of an event. Suppose that we have a partition given by B_1, B_2, \dots . This means that our full sample space can be cut up into these various non-overlapping sets, and every single outcome belongs to exactly one of them. Now, suppose we are interested in some other event A . We can ask: how can A occur, in terms of the events B_1, B_2, \dots ? Since every single event in the sample space belongs to exactly one of our partitioning sets, then it **must** be the case that every single event in A belongs to exactly one of our partitioning sets. This means that if we consider $A \cap B_j$, for all j , then every single event in A must belong to exactly one of these. In other words, it must be the case that

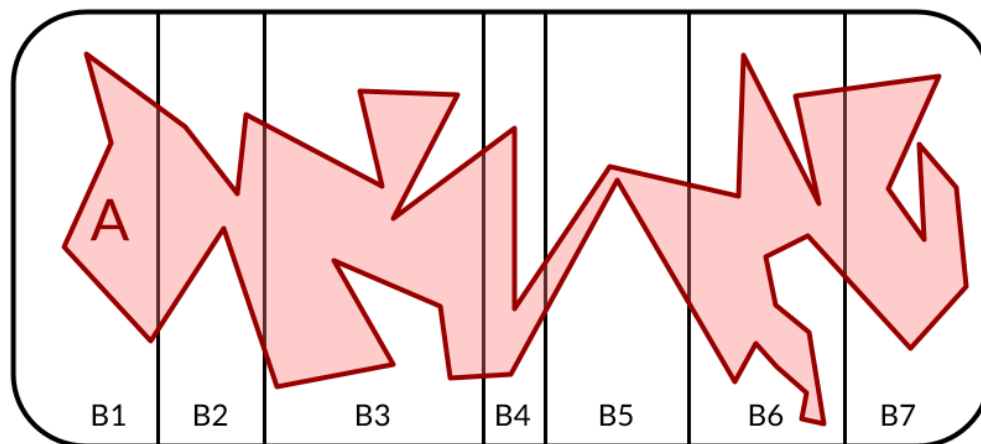
$$A = \bigcup_j A \cap B_j,$$

for any partition B_1, B_2, \dots . Moreover, every single $A \cap B_j$ is disjoint from every other $A \cap B_\ell$, whenever $\ell \neq j$. This means that we can use the axiom of additivity to give

$$P(A) = P\left(\bigcup_j A \cap B_j\right) = \sum_j P(A \cap B_j).$$

In other words: the marginal probability of A can be found by summing over **all** joint probabilities between A and sets that form a partition. This argument gives the law of total probability.

Figure 4.1: This graphic shows the argument that summing over the joint probabilities between an event and a partition gives the full marginal probability. Note that B_1, \dots, B_7 forms a partition of the space where every possible outcome is contained in exactly one of these sets. Then, if we take an arbitrary event A , we can divide A into the components that intersect with each partitioning set, namely $A \cap B_1$, $A \cap B_2$, and so forth.



The Law of Total Probability

Given a partition, B_1, B_2, \dots , and an event A , the law of total probability states that

$$P(A) = \sum_i P(A, B_i) = \sum_i P(A|B_i)P(B_i).$$

Intuitively, since the whole sample space is divided into the different B_i s, this rule breaks down the calculation of A happening into manageable chunks. Each term in the summation is “the probability that A happens, given B_i happening” weighted by how likely it is that B_i happens. Then by summing over all possible B_i , we know that we must be capturing all possible ways that A can occur since all parts of the sample space are contained in exactly one of the sets of our partition. The law of total probability is an indispensable tool for computing probabilities in practice.

Example 4.6 (Sadie’s Possibly Late Package). Sadie has still not received the package that Charles had ordered. While it is not late yet, Charles decides to figure out the probability

that the package will end up being late. Recall that company A is late 75% of the time while company B is late 15% of the time, and the store that Charles ordered from sends out 10% of packages with company A , and the rest with company B , which is more likely.

What is the probability that the package is late?

Solution

Note that A, B forms a partition of the sample space as every package is either sent with A or with B , and no package can be sent with both. Further, if L represents the event that the package is late, then we know that $P(L|A) = 0.75$ and $P(L|B) = 0.15$. Since $P(A) = 0.1$ and $P(B) = 0.9$, an application of the law of total probability gives

$$P(L) = P(L|A)P(A) + P(L|B)P(B) = (0.75)(0.1) + (0.15)(0.9) = 0.21.$$

As a result, knowing nothing else, the package has a probability of 0.21 of being late.

Example 4.7 (Charles' Many Urns). While shopping at some garage sales one Sunday morning, Charles and Sadie stumble across a wonderful find! They see three urns which are **exactly** identical to the one that Charles had already purchased to store the different balls which turned out to not be balls at all. Realizing the opportunity they splurge and purchase them all, and then divide the various objects between the four urns, placing all the spheres in one container, all the cubes in another, all the pyramids in a third, and all the cones in a fourth.

Once done, they use a different selection mechanism. First, they pick an urn at random. Next, they random grab one of the items from within it. The distribution of colours and shapes is included in the following table.

Colour	Sphere (Urn 1)	Cube (Urn 2)	Pyramid (Urn 3)	Cone (Urn 4)
Red	2	3	2	0
Blue	1	0	0	6
Green	2	2	1	2
Yellow	0	4	2	1
Black	3	1	1	2

- What is the probability that they select any of the five colours under this sampling scheme?
- How does this change if the probability that each urn is selected is proportional to the number of items in it? (Thus, urn 1 is selected with probability $8/35$, and so forth).

Solution

- Let R , B , G , Y , and Bk be the events that a red, blue, green, yellow, or black ball are selected. Further, let U_1 , U_2 , U_3 , and U_4 be the events that the first, second,

third, or fourth urn are selected. Then note that, according to the law of total probability,

$$P(R) = P(R, U_1) + P(R, U_2) + P(R, U_3) + P(R, U_4) = \sum_{j=1}^4 P(R|U_j)P(U_j).$$

An equivalent argument holds for each of the other colours. Now,

$$P(R|U_j) = \frac{N_{R \cap U_j}}{N_{U_j}},$$

where $N_{R \cap U_j}$ is the number of red objects in urn j and N_{U_j} is the total number in urn j . Plugging this in and simplifying we get

$$P(R) = \sum_{j=1}^4 P(R|U_j) \left(\frac{1}{4} \right) = \frac{1}{4} \left\{ \frac{2}{8} + \frac{3}{10} + \frac{2}{6} \right\} = \frac{53}{240}.$$

We can apply analogous arguments to the other colours giving

$$\begin{aligned} P(B) &= \frac{1}{4} \left\{ \frac{1}{8} + \frac{6}{11} \right\} = \frac{59}{352} \\ P(G) &= \frac{1}{4} \left\{ \frac{2}{8} + \frac{2}{10} + \frac{1}{6} + \frac{2}{11} \right\} = \frac{527}{2640} \\ P(Y) &= \frac{1}{4} \left\{ \frac{4}{10} + \frac{2}{6} + \frac{1}{11} \right\} = \frac{34}{165} \\ P(Bk) &= \frac{1}{4} \left\{ \frac{3}{8} + \frac{1}{10} + \frac{1}{6} + \frac{2}{11} \right\} = \frac{1087}{5280}. \end{aligned}$$

Note that these probabilities sum to 1. In decimal these simplify to approximately 0.221, 0.168, 0.2, 0.206, 0.206.

b. Using the same setup as before, we have

$$P(R) = P(R, U_1) + P(R, U_2) + P(R, U_3) + P(R, U_4) = \sum_{j=1}^4 P(R|U_j)P(U_j).$$

Now $P(U_1) = 8/35$, $P(U_2) = 10/35$, $P(U_3) = 6/35$, and $P(U_4) = 11/35$. Moreover, the conditional probabilities themselves do not change, and so instead we have

$$P(R) = \left\{ \frac{2}{8} \cdot \frac{8}{35} + \frac{3}{10} \cdot \frac{10}{35} + \frac{2}{6} \cdot \frac{6}{35} + \frac{0}{11} \cdot \frac{11}{35} \right\} = \frac{N_R}{35}.$$

Note that when multiplying by the marginal probability of the urn, the denominator will always cancel. As a result, we end up with the total number of reds over 35, which leads to $P(R) = \frac{1}{5}$. The same will be true for the other colours, and as a result, if we choose the urn based on a weighted selection, this will result in equal probability once more.

4.3.3 Bayes' Theorem

We have seen the direct computation of marginal probabilities (while using an equally likely outcome model), the computation of conditional probabilities, the use of the multiplication rule for joint probabilities, and the use of the law of total probability to indirectly calculate marginal probabilities through conditioning arguments. Throughout these discussions we have been primarily concerned with keeping events A and B arbitrary. Everything that we have indicated for $P(A)$ holds for $P(B)$, as does $P(A|B)$ and $P(B|A)$. In reality, it will often be the case that conditioning on one of the events will be natural, while conditioning on the other will be more tricky. In these events, it can be useful to be able to transform statements regarding $P(A|B)$ into statements regarding $P(B|A)$, and vice versa.

Note that because the definitions are symmetric,

$$P(A|B)P(B) = P(A, B) = P(B|A)P(A).$$

This is an application of the multiplication rule in two different orientations. If we divide both sides of the equality by $P(B)$, assuming that it is not 0, then we get

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}.$$

Now, if we form a partition, say A, A_2, A_3, \dots , then we can rewrite $P(B)$ using the law of total probability as

$$P(B) = P(B|A)P(A) + P(B|A_2)P(A_2) + \dots = P(B|A)P(A) + \sum_{i=2} P(B|A_i)P(A_i),$$

which can replace $P(B)$. Taken together this gives a result known as Bayes' Theorem.⁴

Bayes' Theorem

Suppose that there are two events, A and B , with $P(B) > 0$. Moreover, suppose that A taken with A_2, A_3, \dots forms a partition. Then Bayes' Theorem states that

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} = \frac{P(B|A)P(A)}{P(B|A)P(A) + \sum_{i=2} P(B|A_i)P(A_i)}.$$

Bayes' Theorem allows us to convert statements regarding $P(B|A)$ into statements regarding $P(A|B)$. Note that, as we derived above, Bayes' Theorem is an application of the multiplication

⁴Bayes' Theorem is named in the same way that the Bayesian interpretation of probability is, and that Bayesian statistics is more broadly. The connections are more than merely surface: Bayes' Theorem can be viewed as the primary technique with which we can update subjective beliefs about the world. Importantly, however, even those who use a Frequentist view of statistics accept the math of Bayes' Theorem, and use it frequently.

rule and an application of the law of total probability.⁵ Sometimes we may have $P(B)$ directly, rendering the law of total probability in the denominator unnecessary.

Often, the natural partition to select when we do need the law of total probability is to take A and A^C . Note that any set with its complement forms a partition, since by definition they occupy the entire space and are non-overlapping. When this is done we get the slightly more compact relationship of

$$P(A|B) = \frac{P(B|A)P(A)}{P(B|A)P(A) + P(B|A^C)P(A^C)}.$$

Bayes' Theorem differs from our previous relationships as it allows us to translate one set of conditional probabilities into another. Every other relationship we have looked at has moved between types of probabilities, whereas Bayes' Theorem deals directly with conditional relationships.

The most commonly cited example application is in medical testing. Suppose that we know the performance characteristics of a particular medical test: it is 99% accurate for positive cases, and 95% accurate for negative cases. That is, with probability 0.99 it correctly returns positive when an individual is infected, and with probability 0.95 it returns negative when an individual is not infected. These are both statements of conditional probability. If we take A to be the event that the test returns positive, and B to be the event that the patient is infected,⁶ then we are saying that $P(A|B) = 0.99$ and $P(A^C|B^C) = 0.95$ which means that $P(A|B^C) = 0.05$. Suppose that we know that, across the entire population, one in a thousand individuals is likely to be infected. This means that $P(B) = 0.001$.

Now if a random individual goes into a doctor's office and tests positive for the disease, how likely are they to actually be infected? In this case we want to know the probability of them being infected given that they have tested positive. In notation, this is $P(B|A)$. We do not know this quantity directly, but given an application of Bayes' Theorem, we can find it. Using the natural partition of B and B^C , we get

$$P(B|A) = \frac{P(A|B)P(B)}{P(A|B)P(B) + P(A|B^C)P(B^C)} = \frac{(0.99)(0.001)}{(0.99)(0.001) + (0.05)(0.999)} \approx 0.019.$$

⁵In fact, I would go as far as to suggest that learning Bayes' Theorem by itself is less important than fully grasping the definition of conditional probability alongside the multiplication rule and the law of total probability. I myself do not remember Bayes' Theorem directly, but can write it down directly from these definitions without any thought.

⁶It is worth drawing attention to the language that we have started to use at this point in the notes regarding "events". In this case our sample space would actually be formed using pairs of information. In particular, we might have

$$\mathcal{S} = \{(covPos.Test, covIllness), (covNeg.Test, covIllness), (covPos.Test, covNoIllness), (covNeg.Test, covNoIllness)\}.$$

Then the event A here is actually $A = \{(covPos.Test, covIllness), (covPos.Test, covNoIllness)\}$ and B is $\{(covPos.Test, covIllness), (covNeg.Test, covIllness)\}$. It is far more clunky to make explicit these events, and so we move towards using more natural language. Until you feel confident that you can identify the specific outcomes associated with the events of interest, it is worth writing these out in full.

That is, despite the fact that this test is exceptionally effective at detecting this disease, a positive test still means that an individual has a probability of only 0.019 of actually having the illness.⁷

Example 4.8 (Sadie’s Late Package). Sadie eventually received the package that Charles had sent, but it arrived very late. Sadie was not home when the package was delivered and there no obvious markings on the box to indicate which of the two delivery companies had sent it.

Given this information, and knowing that company A is late 75% of the time while company B is late 15% of the time, and the store that Charles ordered from sends out 10% of packages with company A , and the rest with company B , what is the probability that the package was delivered by each of the two companies?

Solution

We want to determine $P(A|L)$ and $P(B|L)$. We know that $P(L|A) = 0.75$ and $P(L|B) = 0.15$. Moreover, we know that $P(A) = 0.1$ and $P(B) = 0.9$. Applying Bayes’ Theorem directly we get

$$P(A|L) = \frac{P(L|A)P(A)}{P(L|A)P(A) + P(L|B)P(B)} = \frac{(0.75)(0.10)}{(0.75)(0.10) + (.10)(0.90)} = \frac{5}{11}.$$

Similarly, we get

$$P(B|L) = \frac{P(L|B)P(B)}{P(L|A)P(A) + P(L|B)P(B)} = \frac{(0.15)(0.90)}{(0.75)(0.10) + (.10)(0.90)} = \frac{6}{11}.$$

Note, we could have also used the fact that $P(A|L) + P(B|L) = 1$ to determine this. As a result, it is more likely that B delivered the package than A .⁸

Bayes’ Theorem highlights a key lesson when considering conditional probabilities, and it’s a common mistake to make which should be avoided at all costs. Namely, we cannot interchange $P(A|B)$ with $P(B|A)$. These probabilities are not necessarily highly correlated with

⁷This counter intuitive fact was an intensely frustrating reality for statisticians everywhere during the height of the COVID-19 pandemic, when politicians and the population at large turned away from testing owing to its perceived “ineffectiveness”. The quantity of interest for knowing how good a test is is $P(A|B)$ and $P(A^C|B^C)$. However, if a disease is sufficiently rare, with $P(B)$ sufficiently small, then no matter how effective the tests are you will likely have $P(B|A)$ to be low. Note that $P(B|A) \gg P(B)$ in the example, and this will also be true in general. A single test cannot say with certainty, however, they are an incredibly effective tool at reducing our uncertainty.

⁸Note that this is another example of a counterintuitive result. Here, A is far more likely to be late, but it is more likely that B delivered a late package to us than A because of the **base rates**. That is, $P(B)$ is much higher to begin than $P(A)$, and so that is hard to overcome. It is worth noting, however, that originally $P(B)$ is 9 times more likely than $P(A)$, and after knowing that package is late it is $\frac{6}{5} = 1.2$ times more likely. This major reduction in the relative likelihood is owed to how much more likely A is to deliver late packages than B .

one another, and it is important to distinguish clearly which is the probability of interest.⁹ The stakes of these types of confusion can be quite high, and it is tremendously important to ensure that you are conditioning on the correct events. Fortunately, Bayes' Theorem allows us to translate between events for conditioning, giving a mechanism from translating between the two.¹⁰

4.4 Independence

We have seen that, in most cases, conditioning on an event changes the probability of that event. For instance, if we want to know the probability it is raining, if we condition on knowing that it is a day full of gray skies, the conditional probability is likely higher than the marginal probability. By considering how the marginal and conditional probabilities differ, we are in effect indicating a dependence of the events on one another. In terms of probability, this dependence is captured by an influence on the degree of uncertainty present depending on what we know.

It is totally possible that two events do not influence one another at all. The weather outside today is likely not influenced by your favourite sports team's performance last night.¹¹ In this case, we would have $P(A|B) = P(A)$.

We saw an example of this previously when we wanted to know the probability of a randomly selected card being a heart (A) given that it was an ace (B). We found that this was $\frac{1}{4}$, exactly the same as the probability if we did not know that it was an ace. Thus here we have $P(A|B) = P(A)$. We could have also said that $P(B|A) = P(B) = \frac{1}{13}$. The symmetry of these events makes it somewhat more convenient to express this relationship differently.

Instead of writing $P(A|B) = P(A)$ and $P(B|A) = P(B)$, we can multiply the first relationship by $P(B)$ on both sides, or the second by $P(A)$ on both sides. The multiplication rule gives

⁹Mixing up $P(B|A)$ and $P(A|B)$ is often called *confusion of the inverse*, and it can lead to very faulty conclusions when ignored. In the medical testing example above, it is important to not confuse “the probability that the test returns positive, assuming you have the illness” with “the probability that you have the illness, given that the test returns positive.” This type of faulty logic has long been used to justify discriminatory behaviour in medicine, the law, and so on. A thorough understanding of statistics and probability helps to ensure that these types of errors are not made, and gives you the tools to push-back on the spots where people are making these arguments incorrectly, particularly when the stakes are high or harm is being done.

¹⁰When discussing Bayes' Theorem we introduced two frequently occurring sources of error when reasoning about probabilities, and showed how to remedy them. *Confusion of the inverse* occurs when you mix up $P(A|B)$ with $P(B|A)$, and can lead to disastrous consequences. The *base rate fallacy* occurs when you fail to take into account the rareness of the marginal events and instead only consider the conditionals (such as seeing that delivery company A was more likely to be late than B , without considering that B was more likely to be used than A). These are both examples of the challenges at the heart of probability and statistics: namely, the subjects are fairly unintuitive once moving beyond the basics. As a result, we need to rely on building up our intuitions over time by making use of the formal rules that we are able to derive.

¹¹Though, perhaps the world will freeze over if (*insert-your-least-favourite-team-here*) wins the (*insert-the-name-of-the-championship-for-the-league-you-care-about-here*)?

$P(A|B)P(B) = P(A, B)$, and so the first relationship becomes $P(A, B) = P(A)P(B)$. The second follows exactly the same. Any two events that satisfy this relationship are said to be independent.

Definition 4.5 (Independence). Any two events, A and B , which satisfy $P(A, B) = P(A)P(B)$ are said to be independent. If A and B are independent we write $A \perp B$, and read “ A is independent of B ”. Any events which are not independent are said to be dependent, and we write $A \not\perp B$.

Note that independence is always a symmetric property: if A is independent of B , then B is independent of A . To check whether two events are independent, we check whether their joint probability is equal to the product of their marginal probabilities.

Properties of Independence

Note that if $A \perp B$, then $A^C \perp B$, $A^C \perp B^C$, and vice versa. To see this note

$$P(A^C, B) + P(A, B) = P(B),$$

by the Law of Total Probability. Then, by independence of A and B this gives

$$\begin{aligned} P(A^C, B) + P(A)P(B) &= P(B) \\ \implies P(A^C, B) &= P(B) - P(A)P(B) \\ &= P(B)(1 - P(A)) \\ &= P(B)P(A^C), \end{aligned}$$

as is required. The other combinations follow in the same manner.

If $P(A) \neq 0$, then we can divide both sides by $P(A)$ to give $P(B|A) = P(B)$. Similarly, if $P(B) \neq 0$, then we can divide both sides by $P(B)$ to give $P(A|B) = P(A)$. This expression in terms of conditional probabilities is the more intuitive expression of independence. It directly captures the idea that “knowing B does not change our belief about A ”. However, we must be careful. This conditional argument is only valid when the event that is being conditioned on is not probability 0, where the defining relationship, $P(A, B) = P(A)P(B)$, will hold for all events. Recall that, in general, $P(A \cap B) = P(A) + P(B) - P(A \cup B)$. It is only when assuming independence that this simplifies further.

Example 4.9 (Independence and Board Games). Charles and Sadie are invited over to a friends house, Garth, to play some board games. Both of them are quite excited by this prospect as board games feel like the next logical step for the two of them, being as into probability and games as they are! Garth has a large board game collection, and begins to explain the games to Charles and Sadie across a variety of axes:

- Whether the games are competitive or cooperative.
- How many players the games play best at ($\{1, 2, 3, 4+\}$).
- How “heavy” the games tend to be (friendly for everyone, moderately involved, or very heavy).

While Garth continues on about several other topics including the themes, the mechanics, or the rating on BoardGameGeek, Charles drifts off wondering whether the traits listed are independent in Garth’s collection. Suppose that Garth has 100 games, of which:

- 25 are cooperative.
 - 5 are best played at one player, 20 at two, and 55 at three.
 - 10 are friendly for everyone and 45 are moderately involved.
- If 5 games are best played at two players and are cooperative, are these events independent?
 - If 20 games are heavy and best played with 4+ players, are these events independent?
 - If 0 games are both moderately involved and cooperative, are these events independent?
 - Charles figures that competitive games and two player games are independent. How many competitive two player games are there?
 - Is it possible that competitive games are independent of heavy games?

Solution

- We are suggesting that $P(A, B) = 0.05$, where A is “two player” and B is “cooperative”. We know that $P(B) = 0.25$ and $P(A) = 0.20$. Calculating $P(A)P(B) = (0.20)(0.25) = 0.05 = P(A, B)$, and so these traits **are** independent.
- We have $P(A, B) = 0.2$ where A is “heavy” and B is “4+ players. We know that $P(A) = 0.45$ and $P(B) = 0.20$, and so $P(A)P(B) = (0.45)(0.20) = 0.09 \neq P(A, B)$. As a result, these traits are **not** independent.
- We know that $P(A) > 0$ and $P(B) > 0$ for A being moderately involved and B being cooperative. As a result, $P(A)P(B) > 0$, and so if $P(A, B) = 0$, they must **not** be independent.
- Taking A to be “competitive” we have $P(A) = 0.75$. Taking B to be “two player” we have $P(B) = 0.20$. As a result, if $A \perp B$ then $P(A, B) = P(A)P(B) = (0.75)(0.20) = 0.15$. Thus, there must be 15 competitive, two player games.
- Taking A to be “competitive” we have $P(A) = 0.75$. Taking B to be “heavy” we have $P(B) = 0.45$. Thus, if they were independent, we would have $P(A, B) = P(A)P(B) = (0.75)(0.45) = 0.3375$. This would require 33.75 games to be heavy, competitive games and so we must conclude that they are **not** independent.

4.4.0.1 Mutually Exclusive Events

Importantly, if $A \perp B$, then $A \cap B \neq \emptyset$ unless either $A = \emptyset$, $B = \emptyset$, or both. To see this recall that $P(\emptyset) = 0$, and so if $A \cap B = \emptyset$ then $P(A \cap B) = P(A)P(B) = P(\emptyset) = 0$. This only holds if either $P(A) = 0$ or $P(B) = 0$. This may seem to be a rather technical point, however, it is the source of much confusion regarding independence. In particular, it is common to mistake independent events for mutually exclusive events.

Definition 4.6 (Mutually Exclusive Events). Two events, A and B are said to be mutually exclusive if they are disjoint. In particular, if $P(A, B) = 0$ then A and B are mutually exclusive. If A and B are mutually exclusive events, with $P(A) > 0$ and $P(B) > 0$, then $A \perp\!\!\!\perp B$.

Whenever only one event from a set of events can happen, we refer to the events as being mutually exclusive. If one happens, we know that the others did not. Mutually exclusive events are always dependent since knowing that A occurs dramatically shifts our belief about B, C , and D .¹²

The primary concern with mutually exclusive and independent events is a linguistic one. We often use words like independent to mean unrelated, and in a sense, mutually exclusive events are unrelated in that one has nothing to do with another. However, in statistics and probability, when we discuss independence, it is not an independence of the events themselves but rather an independence relating to our beliefs regarding the uncertainty associated with the events. In this sense, mutually exclusive events are very informative regarding the uncertainty associated with them.

Example 4.10 (Charles and Sadie Cooking Dinner). Suppose that Charles and Sadie always eat dinner together. It will either be the case that Charles cooks at home, that Sadie cooks at home, that the two of them order in, or that they go out to eat. If we take these to be four events, A , B , C , and D , then are any of these events independent? Mutually exclusive? Explain.

Solution

Assuming, as it seems reasonable given the information in the question, that only one of the possible tasks occurs for dinner in a night, then we *know* that

$$P(A, B) = P(A, C) = P(A, D) = P(B, C) = P(B, D) = P(C, D) = 0.$$

As a result, all of the events described are mutually exclusive, and correspondingly, are *not* independent.

¹²Namely, we know that all of the others are then impossible.

Table 4.6: Frequency and corresponding proportions of enrolment by faculty in a university.

Faculty	Enrolment	Proportion
Arts	1266	0.2182382
Computer Science	749	0.1291157
Education	786	0.1354939
Engineering	1315	0.2266851
Law	266	0.0458542
Nursing	543	0.0936046
Science	876	0.1510084
Total	5801	1.0000000

4.5 Contingency Tables

Through to this point we have discussed probabilities in the abstract, either through an enumeration of equally likely outcomes, or else by directly specifying the likelihood of various events. While these are useful in many regards, we are often looking for more concise manners of summarizing information of interest. One tool for accomplishing this is a contingency table.

Definition 4.7 (Contingency Table). A contingency table is a tabular summary of information which summarizes the joint probabilities of two or more variables. Typically a contingency table will take one factor for the columns and a secondary factor for the rows, where each cell then represents the frequency with which observations occur in the two corresponding categories simultaneously.

To begin, you could imagine constructing a frequency table relaying the frequency with which undergraduate students are enrolled in various faculties at a particular university. This tells you, of the whole population of students at the university, what is the faculty breakdown. By dividing the number in each faculty by the total number of students, you convert the frequencies to proportions, and these proportions can be viewed as probabilities. (See Table 4.6.¹³) The interpretation of proportions as probabilities implies a very specific statistical experiment. In particular, the proportion represents the probability that an individual selected at random from the entire population has the given trait. This is frequently a probability of interest, which makes these summary tables a useful tool.¹⁴

When a single trait is displayed we refer to these tabular summaries as frequency tables or frequency distributions. A contingency table instead plots two or more traits on the same

¹³Note, the values in this table are *roughly* inspired by a subset of the [Fall 2022 University of New Brunswick Enrolment Numbers](#).

¹⁴This provides further emphasis for the utility of urn models. If you imagine an urn that has balls with two or more traits (say like those in Example 4.3), then randomly selecting a single ball from this population has an analogous probability distribution.

Table 4.7: Frequency of enrolment by faculty and year of study in a university.

	Year 1	Year 2	Year 3	Year 4	Year 5+	
Arts	222	276	273	225	270	1266
Comp. Sci.	164	87	164	90	244	749
Education	100	136	184	128	238	786
Engineering	189	290	354	298	184	1315
Law	54	50	58	37	67	266
Nursing	55	90	154	112	132	543
Science	242	114	206	183	131	876
	1026	1043	1393	1073	1266	5801

table, with each cell representing the frequency of both traits occurring simultaneously in the population. Extending the university example, we may further include the student's current year of study to see the breakdown of both faculty and year of study, in one table.

By including two (or more) factors in the table we are able to capture not only the marginal probabilities for the population, but also the joint probabilities for the population, and in turn, the conditional probabilities for the population. Being able to concisely summarize all of these concepts regarding traits in a population of interest renders contingency tables immensely useful in the study of uncertainty broadly.

Consider the two-way contingency table, Table 4.7. Each cell consists of frequency with which a combination of the two traits occurs in the population.¹⁵ If we take events corresponding to each of the levels of the two variables of interest, then these central cells represent the frequency of joint events. That is, each interior cell gives the total number of observations with a set level for variable one¹⁶ AND a set level for variable two¹⁷. For instance, there are 50 individuals who are in Law and studying in Year 2.

Each row is then summed, with the total number following into the corresponding row recorded in the right hand margin. each column is summed, with the total number corresponding to the given column recorded in the bottom margin. For instance there are a total of 786 students in Education and a total of 1393 in Year 3. Then the margin totals are summed and the total is recorded in the lower right margin space (in this case, 5801). Whether the rows or columns are summed, they should sum to the same total, which is the total of the population under consideration. This is the same as simply adding all of the observed interior frequencies. To turn a frequency into a probability, you need only divide the correct frequency by the correct total.

For the standard joint probabilities, you take the interior cell count and divide by the population total. Here we are saying that some fixed number, m , of the N total individuals have

¹⁵That is, the number of students who are enrolled in that faculty, in that year of study.

¹⁶Faculty.

¹⁷Year of study.

Table 4.8: Proportions of enrolment by faculty and year of study in a university.

	Year 1	Year 2	Year 3	Year 4	Year 5+	
Arts	0.0382693	0.0475780	0.0470609	0.0387864	0.0465437	0.2182382
Comp. Sci.	0.0282710	0.0149974	0.0282710	0.0155146	0.0420617	0.1291157
Education	0.0172384	0.0234442	0.0317187	0.0220652	0.0410274	0.1354939
Engineering	0.0325806	0.0499914	0.0610240	0.0513705	0.0317187	0.2266851
Law	0.0093087	0.0086192	0.0099983	0.0063782	0.0115497	0.0458542
Nursing	0.0094811	0.0155146	0.0265471	0.0193070	0.0227547	0.0936046
Science	0.0417169	0.0196518	0.0355111	0.0315463	0.0225823	0.1510084
	0.1768661	0.1797966	0.2401310	0.1849681	0.2182382	1.0000000

both traits under consideration. For instance, the joint probability that a student is in Law and studying in Year 2 is 0.0086192.¹⁸ If instead you wish to find a marginal probability, you have to consider the value in the corresponding margin: this is the total number of individuals with the given trait, ignoring the level of the other variable. These marginal values are also divided by the total population size. For instance, there is a 0.1354939 probability of observing a student in Education and a probability 0.240131 of observing a student in Year 3.

Outside of joint and marginal probabilities, we can also find conditional probabilities. To do so, we restrict our focus to either only one row, or one column. Then, we can take the joint cell and divide by the value in the margin, which gives the conditional probability of interest. Note, this works with *either* the contingency table directly **or** with the propensity table. The reasoning is that the propensity table divided by the same totals in the numerator and the denominator. Suppose we take some cell, $A \cap B$, which has $N_{A,B}$ in the contingency table. Then,

$$P(A \cap B) = \frac{N_{A,B}}{N} \quad \text{covand} \quad P(B) = \frac{N_B}{N}.$$

If we consider then forming $P(A|B)$ we get

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{N_{A \cap B}/\mathcal{N}}{N_B/\mathcal{N}} = \frac{N_{A,B}}{N_B}.$$

Thus, given that we know a student is in Education, then the probability that they are in Year 3 is approximately 0.2341.

Note that these procedures are exactly in line with what we had seen before. The conditional probability is defined as the joint probability divided by the marginal probability. The process of computing the marginal can be seen as an application of the law of total probability. As

¹⁸It is worth reemphasizing what this probability actually means. If we were to randomly sample, with equal probability, individuals from this population then the probability that an individual selected has both the faculty and year specified is given by the joint probability. That is to say, if we did this over and over again (with replacement) in the long-term, these probabilities represent proportion of time those combinations would be observed.

a result, contingency tables can be a useful, tangible tool for investigating the techniques we have been discussing: they are not a substitute for direct manipulation of the mathematical objects, but they can present insight into the underlying processes where it may be hard to derive that insight otherwise.

The Law of Total Probability: Contingency Table's Version

Recall that the law of total probability states that, if B_1, \dots, B_n forms a partition of the sample space, then

$$P(A) = \sum_{i=1}^n P(A|B_i)P(B_i) = \sum_{i=1}^n P(A, B_i)$$

. In a contingency table it is easier to see how either of the two factors at play (either those in the rows or the columns) forms a partition of the space. Every observation has to fall in exactly one row and exactly one column. Thus, if we want to know the marginal frequency of a single trait (say represented by some row of the table), then one way to find this total is to sum up every observation in each of the corresponding columns. This is *precisely* the same process as the law of total probability. Note that, denoting each column as B_i , and supposing there are k total columns, then the total number in a row is taken to be

$$N_A = \sum_{i=1}^k N_{A, B_i},$$

simply as the summation of the corresponding row. By definition, $P(A) = \frac{N_A}{N}$, and so dividing both sides by N gives

$$P(A) = \frac{N_A}{N} = \frac{1}{N} \sum_{i=1}^k N_{A, B_i} = \sum_{i=1}^k \frac{N_{A, B_i}}{N} = \sum_{i=1}^k P(A \cap B_i).$$

It is important to note that there is redundant information within a contingency table. For instance, the margins need not be listed explicitly, as they can be directly calculated from the interior points. Same goes for interior points, given the margins of the table (assuming *some* interior points are also presented). This can be useful for a compact representation of the information, and manipulating these tables – being able to find the required information in many places – should become familiar to you as you continue to work with them more and more.

Example 4.11 (The Evolving Contents of Charles's Urns). After learning of contingency tables, Sadie points out to Charles that with the whole urn debacle they went through, the two of them actually ended up using a contingency table to summarize the information. How neat! In the interim, there has been some development in the contents of Charles's urns, and armed with the new knowledge of contingency tables, the following summary is produced.

	Cone	Cube	Pyramid	Sphere	
Black	2	A	1	3	10
Blue	1	2	1	1	5
Green	3	3	B	5	15
Red	2	C	3	2	D
Yellow	5	3	4	1	13
	13	E	13	12	50

Sadly, Charles does not have the best writing and Sadie cannot make out what values were written in for the cells marked A , B , C , D , and E .

- What are the values for the missing values?
- What is the probability that a black cube is drawn?
- What is the probability that a red object is drawn?
- What is the probability that a cube is drawn?
- Given that the drawn object was a pyramid, what is the probability that it is green?
- Given that the object is green, what is the probability that it is a pyramid.

Solution

- We start by filling in the missing cells, in order.
 - For A we can note that $2 + A + 1 + 3 = 10$, which gives that $A = 4$. We could have also tried a column sum, however, this would involve 3 unknowns and so would not have given a numeric result.
 - For B either a row sum or column sum would produce the correct answer. We either take $3 + 3 + B + 5 = 15$ giving $B = 4$ or $1 + 1 + B + 3 + 4 = 13$ giving $B = 4$.
 - C is more challenging as we either have that $2 + C + 3 + 2 = D$ or $4 + 2 + 3 + C + 3 = E$ ¹⁹ As a result, for this technique we will need to find either D or E first. There is an alternative technique to use, which would be to note that we have *all* the internal points specified at this point, and we know that these sum to 50. As a result, we could note that $C = 50 - 10 - 5 - 15 - 13 - 2 - 3 - 2 = 0$ or that $C = 50 - 13 - 13 - 12 - 4 - 2 - 3 - 3 = 0$.
 - We can find D either by subtracting from the total, $D = 50 - 10 - 5 - 15 - 13 = 7$, or by adding along the row, $2 + 0 + 3 + 2 = 7$.²⁰ Note that with $D = 7$, had we not found $C = 0$ above, we could now take $2 + C + 3 + 2 = 7$ and find $C = 0$.
 - Like D , we have two options for working this out. Either $E = 50 - 13 - 13 - 12 = 12$ or $E = 4 + 2 + 3 + 0 + 3 = 12$.²¹ Like with D , had we solved for E first, then we could find C via $4 + 2 + 3 + C + 3 = 12$.
- Here we want $P(\text{covBlack}, \text{covCube})$. This is given by the frequency of black cubes

divided by 50. Thus,

$$P(\text{covBlack}, \text{covCube}) = \frac{A}{50} = \frac{4}{50} = 0.08.$$

- c. Here we want $P(\text{covRed})$. This is given by the marginal frequency of red objects divided by 50. Thus,

$$P(\text{covRed}) = \frac{D}{50} = \frac{7}{50} = 0.14.$$

- d. Here we want $P(\text{covCube})$. This is given by the marginal frequency of cubes divided by 50. Thus,

$$P(\text{covCube}) = \frac{E}{50} = \frac{12}{50} = 0.24.$$

- e. Here we want $P(\text{covGreen}|\text{covPyramid})$. This is given by the frequency of green pyramids divided by the marginal frequency of pyramids. Thus

$$P(\text{covGreen}|\text{covPyramid}) = \frac{B}{13} = \frac{4}{13} \approx 0.308.$$

- f. Here we want $P(\text{covPyramid}|\text{covGreen})$. This is given by the frequency of green pyramids divided by the marginal frequency of green objects.²² Thus

$$P(\text{covPyramid}|\text{covGreen}) = \frac{B}{15} = \frac{4}{15} \approx 0.267.$$

It is also important to recognize that independence and mutually exclusive events can be codified via the table as well. Zeros on the interior points indicate events which are mutually exclusive: if we know that one of them occurred, we also know that the other one did not. For independence, it requires a degree of solving proportions. We can either check that the joint probability ($N_{A,B}/N$) is equal to the product of the two marginal probabilities, ($N_A N_B / N^2$), or else (assuming that the events are all non-zero), that the conditional probability ($N_{A,B}/N_A$) equals the marginal probability N_B/N . Either way this is represented by $N \times N_{A,B} = N_A N_B$, and when this holds, we can conclude that the events are independent.

²²Note here, $A = 4$ has been filled in.

²²We have filled in $C = 0$ here.

²²This uses $A = 4$ and $C = 0$.

²²Note, we could also apply Bayes' Theorem to find the result here. We know that $P(\text{covGreen}|\text{covPyramid}) = 4/13$, that $P(\text{covGreen}) = 15/50$ and that $P(\text{covPyramid}) = 13/50$. Thus, Bayes' Theorem gives

$$P(\text{covPyramid}|\text{covGreen}) = \frac{(4/13)(13/50)}{15/50} = \frac{4}{15},$$

exactly as in the direct derivation.

Example 4.12 (Independent or Mutually Exclusive Urn Shapes). After helping Charles *neatly* fill in the contingency table, Sadie begins to wonder about whether there are any shape-colour combinations which are independent, or if any are mutually exclusive.

	Cone	Cube	Pyramid	Sphere	
Black	2	4	1	3	10
Blue	1	2	1	1	5
Green	3	3	4	5	15
Red	2	0	3	2	7
Yellow	5	3	4	1	13
	13	12	13	12	50

- Are there any events represented in the contingency table which are mutually exclusive?
- Are there any events represented in the contingency table which are independent?

Solution

- Mutually exclusive events are codified via a 0 frequency. We can see then that cov_{Cube} and cov_{Red} are mutually exclusive. That is, if we know that an object is red, we also know that it is not a cube. And if we know that an object is a cube, then we know that it is not red.
- Independence is more cumbersome to check. We require the product of marginal counts to be equal to the total times by the joint counts. As a result, the easiest way to check is to consider the product of each marginal value in the columns by each marginal value in the row, divided by 50. If this value corresponds to the value in that row/column pairing, then we know that those features are independent. Note that immediately we can rule out any products which are not divisible by 50, since we know that $N_{A,B}$ is an integer for all A, B and $N_{A,B} = N_A N_B / 50$ if there is independence. To this end, we only need to check the product of each of the row totals with each of 12 and 13 (as those are the only two unique column totals). This gives, in order 120, 130, 60, 65, 180, 195, 84, 91, 156, and 169. None of these values are divisible by 50 and as a result we know that there is **no independence** codified in this table.

4.5.0.1 Contingency Tables and Data Frames in R

In R we can use the `table` and `prop.table` to calculate the (interior) of a contingency table. This will return a `table` type object in R, which can be thought of as a matrix of sorts. On it, we can use the functions `rowSums` and `colSums` to get the summation of the rows and columns, respectively. Typically the object we pass to `table` will be a **data frame**. A data frame is another R object type that we have not yet seen. The idea with a data frame is that we have multiple columns with different variables (of possibly different types) represented. Each

row corresponds to a single observation, and then each column is read as a feature of those observations. Data frames are essentially large spreadsheets (or data tables) which indicate the various observations that we have. In practice, data frames are the most commonly used object in an R analysis, and we will see them plenty going forward.

```
# As always, when randomization is to be used, we call
# the set.seed function to ensure that the analysis can be
# replicated.
set.seed(314)

# Begin by Defining the possible shapes and colours for
# the objects in Charles's urns
shapes <- c("Sphere", "Cube", "Pyramid", "Cone")
colours <- c("Red", "Blue", "Green", "Yellow", "Black")

# Use sample to draw 50 different shapes, and 50 different
# colours. We are drawing *with* replacement.
all_shapes <- sample(x = shapes, size = 50, replace = TRUE)
all_colours <- sample(x = colours, size = 50, replace = TRUE)

# Now we form the data frame. This will consist of two columns,
# one called "Colours" and one called "Shapes". The values to
# place here will correspond to the random colours and shapes we
# sampled above.
charles_data <- data.frame("Colours" = all_colours, "Shapes" = all_shapes)

# To get a sense of the data frame we can use the head function
# which will return the first few rows of our data frame.
head(charles_data)
##   Colours  Shapes
## 1  Green    Cube
## 2  Blue     Cone
## 3   Red     Cone
## 4   Red Pyramid
## 5 Yellow    Cone
## 6   Red Pyramid
```

With a data frame specified, we can then use the `table` function called on it to form a contingency table.

```
charles_c_table <- table(charles_data)
```

```

charles_c_table
##           Shapes
## Colours  Cone Cube Pyramid Sphere
##   Black    2   4     1     3
##   Blue     1   2     1     1
##   Green    3   3     4     5
##   Red      2   0     3     2
##   Yellow   5   3     4     1

```

Then, to get the totals, we can either use `rowSums` or `colSums` to return a vector with the corresponding row or column sums.

```

marginal_shapes <- colSums(charles_c_table)
marginal_colours <- rowSums(charles_c_table)

marginal_shapes
marginal_colours
##      Cone      Cube Pyramid  Sphere
##      13      12      13      12
## Black  Blue  Green   Red Yellow
##      10      5      15      7      13

```

Finally, we can take our formed contingency table, and use `prop.table` on it, in order to return a table with the proportions (rather than the frequencies).

```

charles_p_table <- prop.table(charles_c_table)

charles_p_table
##           Shapes
## Colours  Cone Cube Pyramid Sphere
##   Black 0.04 0.08  0.02  0.06
##   Blue  0.02 0.04  0.02  0.02
##   Green 0.06 0.06  0.08  0.10
##   Red   0.04 0.00  0.06  0.04
##   Yellow 0.10 0.06  0.08  0.02

```

5 Summarizing Statistical Experiments with Random Variables

5.1 The Need for Random Variables

When introducing probability originally we worked from a sample space and then corresponding events. This is a very general framework which allows us to effectively analyze any statistical experiment. Sample spaces are not restricted to be numeric, for instance, and events are simply subsets of the sample space. As a result, this framework provides the tools for capturing uncertainty quantification in almost any setting. Still, the need to enumerate sample spaces and events over complex sets of arbitrary items is cumbersome and may prevent succinct representations of the underlying phenomena. Often, rather than caring about the entire space of outcomes from an experiment of interest, we are primarily concerned with a summary of the experiment. When we can summarize the experiment using a numerical quantity, we are able to define a random variable.

Definition 5.1 (Random Variable). A random variable is a numeric quantity whose specific value depends on chance through the outcome of a statistical experiment. Formally, a random variable is a mapping from the result of an experiment to a set of numbers.

By reporting the numeric value of the random variable, we are able to summarize the key part of the experiment, succinctly. For instance, suppose that we are repeatedly tossing a coin. If we toss the coin 100 times, then the sample space is going to consist of 2^{100} total possible outcomes, each of which is a sequence of 100 heads and tails.¹ Instead, it may be more convenient to assign a random variable to be the number of heads that show up on the 100 tosses of the coin. In this case, the random variable takes on a non-negative integer between 0 and 100. In many situations, such a summary may be all that is relevant from the experiment.

It is important to recognize that information *is* lost when we define this random variable. If X summarizes the number of heads in 100 tosses of a coin, then provided X you are not able to answer the question “what was the 23rd toss of the coin?” As a result, random variables smooth over the unnecessary information, summarizing the parts of the statistical experiment that we care for. For any statistical experiment, however, we need to carefully define the

¹Recall our discussions of combinatorics.

random variables which are truly of interest to us. For instance, if the 23rd toss of the coin was integral to our decision-making, then perhaps we define a random variable Y which counts the number of heads that show up on the 100 tosses of the coin, but does so with negative numbers if the 23rd toss was a tail, and with positive numbers if it was a head. Then, provided Y you can answer “how many heads showed up in the tosses of the coin?” by calculating $|Y|$, and you can answer “what was the 23rd toss of the coin?” by looking at $\text{covsign}(Y)$.

Example 5.1 (Random Variables at the Coffee Shop). Back at their favourite coffee shop, Charles and Sadie are sitting in their favourite chairs, discussing random variables and watching the cash register for the inevitable sequence of customers who will arrive there. Charles suggests playing a game together, which is creatively called “how many random variables can we name that have to do with the statistical experiment of watching for customers at a cash register?” Seeing as how catchy the name is, Sadie is excited to play along, and so they start.

Name several distinct random variables which could be observed via the described statistical experiment.

Solution

There are essentially countless different random variables that could be named here, depending on what is of interest. The important concept is that each random variable needs to be a numeric quantity which is calculable from the statistical experiment. For instance:

- The number of people who arrive at the cashier in the next hour.
- The length of time until the next customer arrives at the cashier.
- The amount of money that the next customer spends when paying at the cashier.
- A value of 1 if the next customer is wearing a hat, and a value of 0 otherwise.
- The number of different items that are ordered by all customers over the next hour.
- The number of words that the cashier says to the next customer, prior to payment.
- A count of the number of red items of clothing that can be seen being worn by the next 15 customers.

Because of their ability to summarize effectively and flexibly the pertinent components of a statistical experiment, random variables are the default paradigm for discussing randomness. When discussing a random variable we will typically use capital letters, such as X , to represent the random quantity with an unknown value. In the event that an experiment is actually performed, and a value is realized for the random variable, we will record this value as a lower case letter, such as x . For instance, the number of heads showing in 100 flips of a coin is an unknown quantity depending on chance which we call X . Once we have flipped the coin 100 times and observed 57 heads, we denote this as $x = 57$.

The importance of this notation is merely to emphasize what values are unknown and random, and what values are known numeric quantities. Because x is a known value taking on some

set number we will not often speak of probabilities involving x .² Instead, we wish to translate the language of probability that we have built to statements regarding the random variable X .

The random variable X has a corresponding “sample space” of possible values that it can take on. We will typically refer to this as the *support* of the random variable, though borrowing other terms from math courses (such as *range*) will work also. This support, which we can think of as directly analogous to the sample space of arbitrary elements from before, will depend on the possible realizations from the underlying experiment. We typically will denote the support of a random variable X as \mathcal{X} . After the experiment has been performed the random variable will take on a single value from this set.³ We can sometimes compactly describe the set of possible values for a random variable, for instance, by stating all of the integers, or integers between 5 and 10, or even values less than 1000. This allows for compact descriptions of \mathcal{X} even when the set \mathcal{S} is challenging to describe. The probability of realizing any outcome in \mathcal{X} is dictated by the underlying probability model.

When introducing the concepts of probability we indicated that probability was assigned to events. With random variables, this remains true. As a result we need to define events in terms of random variables. When we have a random variable, X , an event is defined as any set of values that it can take on. For instance, we may have the event $X = 4$, or the event $X \geq 18$, or the event $2 \leq X \leq 93$, or the event $X \in \{2, 4, 6, 8, 10\}$. In each case these are subsets of the possible values that the random variable can take on, based on the outcome of the experiment.⁴

Just as before these events can be simple events (comprised of a single outcome) or compound events (comprising of multiple outcomes). The event $\{X = 5\}$ is a simple event, whereas the event $\{X \geq 25\}$ is a compound event. With events defined in this way, we can translate the other concepts from the explicit event-based probability. Specifically, we think of the experiment producing a numerical outcome, and then use the same sets of tools as before applied to numeric events.

Example 5.2 (Expanding on Random Variables at the Coffee Shop). After tiring of their game of “how many random variables can we name that have to do with the statistical experiment of watching for customers at a cash register?”, Charles and Sadie fall into a deeper discussion of some of the some of their favourite random variables named during the play through. They

²We can actually discuss probabilities revolving around x , but they are all deeply uninteresting. Every probability will either be 1, or 0. If I tell you that $x = 5$, then $P(x = 5) = 1$ and $P(x = 2) = 0$. While this is not a particularly *interesting* probability statement, it is true, and somewhat surprisingly, can arise in meaningful ways.

³The support of a random variable is directly analogous to the sample space from the statistical experiment. That is, it is the set of possible observations which can be made of the random variable. As a result, it is *sometimes* permissible to call the support the “sample space of the random variable”, in an informal manner. The informality here is important. Formally, a random variable X is a function which maps from the sample space to its support, which is to say $X: \mathcal{S} \rightarrow \mathcal{X}$.

⁴That is to say, events in the case of random variables are subsets of \mathcal{X} .

take turns describing the support of a chosen random variable, as well as listing examples of simple and compound events that can be translated into the language of random variables.

Choose a random variable identified in Example 5.1 and indicate its support, as well as possible simple and compound events that could be observed in terms of it.

Solution

Suppose that we take X to be a random variable representing “The number of people who arrive at the cashier in the next hour.” The support of this random variable is likely best select as the non-negative integers. That is, we take

$$\mathcal{X} = \mathbb{N} = \{0, 1, 2, \dots\}.$$

There may be a reasonable maximal value for the random quantity (such as knowing the number of people who are within an hour radius of the coffee shop, or else knowing the number of people who are presently alive), however, the simpler “all non-negative integers” will likely suffice.

For simple events we may consider $\{X = 0\}$ or $\{X = 10\}$ or $\{X = 31415\}$. In every case, the simple event takes the form $\{X = x\}$.

For compound events we could consider $\{X > 0\}$, representing the event that at least one customer arises, we could consider $\{X \leq 10\}$, the event where no more than 10 customers show up, or we could consider something a little more abstract, like $X \in \{0, 3, 5, 9, 19, 25\}$ or X is an even number. In all these cases the key point is that compound events have more than one way of being satisfied (in that they correspond to more than one event).

When considering random variables there is a key distinction between two types of random variables, discrete and continuous.

Definition 5.2 (Discrete Random Variable). A discrete random variable is any random variable whose support is either finite or else countably infinite.

Definition 5.3 (Continuous Random Variable). A continuous random variable is any random variable whose support is uncountably infinite.

Countable and Uncountable Sets

We say that a set is **countable** whenever we can enumerate the elements of the set using the positive integers. If we have a set with a finite number of elements in it, then we say that it is countable because each element in the set can get assigned an integer value (just using 1 through to the cardinality of the set).

If we take a set like the positive integers, $\{1, 2, 3, \dots\}$, then this is an infinitely large set. However, it is still countable because we can assign each element of the set an integer

value (just use the same integer it is corresponding to!). What if we have the set of positive, even integers ($\{2, 4, 6, 8, \dots\}$)? Each of these is just 2 times one of the counting numbers, in order, and so these too are countable.

What if we took the set of real numbers⁵ in the interval $[0, 1]$? In this case there is **no way** to map each of these values to the values $\{1, 2, 3, 4, \dots\}$ and as a result the interval $[0, 1]$ is **not countable**. It is infinitely large, but it remains infinitely large even after we have enumerated an infinite set of the items in it.

A key difference between countable and uncountable sets is that, with a countable set, we can⁶ sum over the elements of the set. We cannot sum over the elements of an uncountable set, as there would be no way to actually order and enumerate the items. In this course the detailed mathematics of countable versus non-countable sets is tangential to the main point which is in distinguishing between discrete and continuous random variables.

Typically, discrete random variables will take on some collection of the integers, where continuous random variables will be defined on some interval (or set of intervals). That is, we may take discrete random variables to be defined on $\{0, 1, 2, 3, \dots, 100\}$ or $\{0, 1, 2, 3, \dots\}$ or \mathbb{Z} ⁷. For continuous random variables we may take $X \in [0, 1]$ or $X \in (0, \infty)$ or $X \in (-\infty, 129]$.

Example 5.3 (The Countability of Coffee Shop Random Variables). Charles and Sadie have been discussing the features of all of the random variables they identified at the coffee shop for a long time when Sadie points out that they have not been differentiating between discrete and continuous random variables. Charles thinks “how could we have overlooked this?” and seeks to remedy the situation, immediately!

List at least one discrete and one continuous random variable that could arise via the statistical experiment of watching the cashier at a coffee shop over time (as described in Example 5.1).

Solution

For this we categorize the random variables originally defined in the solution to Example 5.1.

- “The number of people who arrive at the cashier in the next hour.”
- “The number of different items that are ordered by all customers over the next hour.”
- “The number of words that the cashier says to the next customer, prior to payment.”
- “A count of the number of red items of clothing that can be seen being worn by the next 15 customers.”

⁵Recall that “real numbers” are just all of the standard numbers that we think of (decimals, whole numbers, fractions, negative values, etc.).

⁶(in principle)

⁷This notation refers to the set of all integers

These are all **discrete** random variables, as the only values they can take on are the counting integer values.

- “The length of time until the next customer arrives at the cashier.” This is a **continuous** random variable, as it can take on any value over an interval (say, the interval $(0, 28800)$ if the store is open for 8 hours and the customer were there the whole time).
- “The amount of money that the next customer spends when paying at the cashier.” This is a **discrete** random variable, as it must take a finite set of values. One way to make this clear is to count the value in cents, and then it will be only integer values.
- “A value of 1 if the next customer is wearing a hat, and a value of 0 otherwise.” This is a **discrete** random variable as it can only be from $\{0, 1\}$.

5.2 Probability Distributions and Probability Mass Functions

We will discuss continuous random variables later. For now, we turn our focus to discrete random variables. One of the major utilities of random variables is that they provide a shorthand for summarizing the results of a statistical experiment. To this end, there are several tools which have been developed centered on random variables which help to expedite the analysis of the corresponding probabilities. Chief among these tools is the concept of a probability distribution.

Definition 5.4 (Probability Distribution). A probability distribution is a mathematical statement describing the probabilistic behaviour of a random variable.

Distributions capture the underlying random behaviour of the random variables of interest, and in so doing, summarize information regarding the experiment or process that is being considered. When concerned with discrete random variables, we typically summarize probability distributions through the use of a probability mass function.

Definition 5.5 (Probability Mass Function). A probability mass function is a function, $p(x)$, which maps possible values for a discrete random variable (the set \mathcal{X}) to the probabilities corresponding to those events.⁸

If a random variable X has support $\mathcal{X} = \{x_1, x_2, \dots, x_k\}$, then a probability mass function is a function $p(x)$ such that $p(x_1) = P(X = x_1)$, $p(x_2) = P(X = x_2)$, and so on through

⁸That is, $p(x)$ is a function, $p: \mathcal{X} \rightarrow [0, 1]$.

to $p(x_k) = P(X = x_k)$. Once a probability mass function is known, all of the probabilistic behaviour of the random variable is fully described.

Example 5.4 (The Coin Game for Three). Sometimes Charlie and Sadie are joined by their friend Garth on their trips to the coffee shop. Also a probability aficionado, Garth contently joins in the game with Charles and Sadie where three coins are flipped, and depending on the results, one friend pays for the group. Garth's order is typically less than Charles and Sadie and so Sadie proposes the following modified game.

A fair coin is tossed three times. If all tosses of the coin show the same symbol, Garth pays. Otherwise, if there are more heads than tails, Charles pays. Finally, if there are more tails than heads, Sadie pays.

Help to simplify this statistical experiment by first defining a random variable, X which can be used to encode this game and then record the probability mass function of X .

Solution

One choice of X is to allow X to coin the number of heads that show on three tosses of the coin. In this case we have $\mathcal{X} = \{0, 1, 2, 3\}$. If $x = 0$ or $x = 3$ is observed then Garth pays. If $x = 2$ is observed then Charles pays. Finally, if $x = 1$ is observed, Sadie pays. Thus writing down the probability mass function for X also provides an easy way for computing the probability of each player having to pay.

In order for $X = 0$, we must have all tails come up. There are $2^3 = 8$ total possible sequences of 3 coin tosses, and only 1 of these results in $X = 0$, therefore $P(X = 0) = p(0) = \frac{1}{8}$. The same logic applies to $X = 3$ where we need to toss all heads. There are several techniques for finding $p(1)$ and $p(2)$.⁹ The most direct way is to recognize that there are exactly 3 ways of observing 1 head (it can be in the first, second, or third toss). Thus, $p(1) = \frac{3}{8}$. For $p(2)$, the same logic applies except we ask "where is the one tail?" to give $p(2) = \frac{3}{8}$. Then, taken together, this results in

$$p(x) = \begin{cases} \frac{1}{8} & x \in \{0, 3\} \\ \frac{3}{8} & x \in \{1, 2\} \\ 0 & \text{otherwise.} \end{cases}$$

We can also read off from this result that Garth pays $\frac{1}{4}$ of the time in the long run, while Sadie and Charles each pay $\frac{3}{8}$ of the time.¹⁰

¹⁰One particularly elegant technique is to realize that $p(1)$ and $p(2)$ must be the same by interchanging the roles of heads and tails. Thus, we have $p(1) + p(2) + 0.25 = 1$ by the unitary property of probability, and rearranging gives $p(1) = p(2) = 0.375$.

¹⁰We can actually write down this probability mass function more succinctly as $p(x) = \binom{3}{x} \frac{1}{8}$. You can check this holds for yourself, and we will understand why later on!

The previously outlined conditions for probabilities must still hold when using probability mass functions. As a result, we know that probabilities are all between 0 and 1, and so we must have $0 \leq p(x) \leq 1$, for all $x \in \mathcal{X}$. Moreover, we saw previously that summing the probabilities over the full sample space gave a value of 1. Correspondingly, we must have that

$$\sum_{x \in \mathcal{X}} p(x) = 1.$$

These two properties are often used to define a *valid* probability mass function, and we can use these properties to both check whether a given mass function is valid and to turn a given function into a valid probability mass function.

Example 5.5 (Charles's Messy Writing Strikes Again). Charles is reading through some notes regarding a new game under development which, like most good games, relies at least a little bit on chance. In the notes there is a probability mass function written down, which, the best Charles can make out, reads

$$p(x) = \begin{cases} 3c & x = 0 \\ 0.6 & x = 1 \\ 7c & x = 2. \end{cases}$$

Frustrated with the illegibility, Charles brings the problem to Sadie who points out, if it really is $p(0) = 3c$ and $p(2) = 7c$, they actually have all the information required to solve the problem.

What is the probability mass function, assuming Charles is reading it correctly.

Solution

We know that two properties must be true of all probability mass functions. First $0 \leq p(x) \leq 1$. Second, $\sum_{x \in \mathcal{X}} p(x) = 1$. The first property tells us that $0 < 3c < 1$ and that $0 < 7c < 1$. This means that $c > 0$, and that $c < 1/3$ and $c < 1/7$. Using the second property we get that

$$1 = 3c + 0.6 + 7c \implies 0.4 = 10c.$$

This tells us that $c = 0.04$, which satisfies all of the previous properties. Taking $c = 0.04$ gives a probability mass function of

$$p(x) = \begin{cases} 0.12 & x = 0 \\ 0.6 & x = 1 \\ 0.28 & x = 2. \end{cases}$$

When solving questions related to probabilities using a probability mass function, the same secondary properties apply. Notably, if we want to know $P(X \in A)$, for some set of possible values A , then we can write

$$P(X \in A) = \sum_{x \in A} p(x).$$

This can be particularly helpful, for instance, if we want to know $P(X \leq c)$ for some constant value c . In this case we know that the possible values range from the smallest value X can take on, through to c , giving for instance,

$$P(X \leq c) = \sum_{x=0}^c p(x),$$

if $X \geq 0$. Rules regarding the complements of events continue to hold as well, where for instance, $P(X > c) = 1 - P(X \leq c)$, giving a useful avenue for simplifying probability calculations.

Example 5.6 (Charles and Sadie: Amateur Ornithologists). Charles and Sadie watched a documentary about birds together, which had Sadie become quite interested in bird watching. Charles is skeptical¹¹ but agrees to go along with Sadie, supposing that there is a high enough probability of something interesting happening. Sadie scours the scholarly literature and determines that, in the area, the probability of seeing x rare birds over a five hour birding session has a probability mass function given by

$$p(x) = \frac{e^{-3}3^x}{x!},$$

where $x \geq 0$.¹²

What is the probability that during their bird watching adventure, Charles and Sadie see at least 1 rare bird?

Solution

We are interested in the probability $P(X \geq 1)$, which we can write down explicitly as

$$P(X \geq 1) = \sum_{x=1}^{\infty} \frac{e^{-3}3^x}{x!}.$$

While, strictly speaking, it is possible to solve this infinite summation, it is an infinite summation and we would rather not. Instead we can realize that, if we take the event $A = \{X \geq 1\}$ then A^C is the event $\{X < 1\} = \{X = 0\}$. As a result, using our elementary rules of probability we get that

$$P(X \geq 1) = 1 - P(X = 0) = 1 - \frac{e^{-3}3^0}{0!} = 1 - e^{-3} \approx 0.95.$$

As a result, there is an approximately 0.95 probability that they see a rare bird while bird watching for five hours.

¹¹Charles is still not entirely sure if birds are even real, let alone worth watching.

¹²How Sadie found such a concrete answer, I will never know.

With events defined in terms of random variables, we can talk about events as being independent of each other or mutually exclusive using the familiar definitions. On a related note, we can talk of joint and conditional probabilities, relating to multiple events. With joint probabilities, it is often easiest to combine the event into a single, compound event, and find the marginal probability of that event. For instance, if you have the events X is even and $X \leq 15$, then the intersection of these events is $X \in \{2, 4, 6, 8, 10, 12, 14\}$ (supposing $X > 0$).

Example 5.7 (Charles: The Ornithological Photographer). After a single time bird watching Charles is hooked! The next time that they go out, Charles brings a camera to snag some beautiful memories of the majesty they are witnessing. The only trouble is that Charles is not particularly good at taking photographs of stills, let alone of creatures that can fly. Charles is not yet certain, but suspects that every time a photograph is snapped, there is a 0.1 probability that it turns out good. Because the camera is a film camera, the number of photos taken is a key metric, and Charles works out that, if X is the number of bad photographs taken for every good photograph, the probability mass function for X is given by

$$p(x) = (0.1) \times (0.9)^x,$$

where $x \geq 0$ is an integer.

- What is the probability that Charles takes exactly three bad photos before the first good one?
- If A is the event that Charles takes three bad photos before the first good one, and B is the event that Charles takes more than four photos before the first good one, what is $P(A, B)$? What does this mean about A and B ?
- Suppose that Charles has taken 2 photos, both of which are bad. What is the probability that at least two more bad photos are taken before a good one?
- What is the probability that at least 2 bad photos are taken?
- Do the results of (c) and (d) suggest an independence?
- List two events, not previously described, which are independent of one another.

Solution

- Here, we want $p(3) = (0.1) \times (0.9)^3 = 0.0729$.
- Considering $A \cap B$ we have $\{X = 3\} \cap \{X \geq 4\} = \emptyset$. As a result, $P(A, B) = 0$ since there is no overlap between A and B . As a result, these events are mutually exclusive.
- Here, we can frame this probability as

$$P(X \geq 4 | X \geq 2)$$

This can be directly computed using the definition of conditional probability,

$$\begin{aligned}
 P(X \geq 4 | X \geq 2) &= \frac{P(X \geq 4, X \geq 2)}{P(X \geq 2)} \\
 &= \frac{P(X \geq 4)}{1 - P(X < 2)} \\
 &= \frac{1 - P(X < 4)}{1 - (0.1 + 0.1 \times 0.9)} \\
 &= \frac{1 - (0.1 + 0.1 \times 0.9 + 0.1 \times 0.9^2 + 0.1 \times 0.9^3)}{1 - (0.1 + 0.1 \times 0.9)} \\
 &= 0.81.
 \end{aligned}$$

d. Through direct calculation we get

$$P(X \geq 2) = 1 - P(X < 2) = 1 - (0.1 + 0.1 \times 0.9) = 0.81.$$

e. Combining (c) and (d) we find that the probability that an additional two photos are required, given that two have already been taken, is the same as the probability that two photos are required, without knowing that any have been taken. While this feels like an independence type of property, it is not precisely independence. Note that the event $\{X \geq 4\}$ immediately gives the event $\{X \geq 2\}$ and so they cannot be independent of one another.¹³ For this to be independent we would require $P(A, B) = P(A)P(B)$ which is not true of any of the events discussed.

f. One option is to consider the event $X \geq 0$ with any other event. Because $\{X \geq 0\} = \mathcal{X}$, no information can be gained conditioning on this event.

5.3 Multiple Random Variables and Joint Probability Mass Functions

While we can discuss independence, joint probabilities, and conditional probabilities relating to events on the same random variable, it is often of interest to combine multiple random variables. Sometimes these random variables will be multiple versions coming from the same distribution, and other times they will be coming from multiple different distributions. In either event, frequently our main concern is in summarizing the probabilistic behaviour of two or more random quantities.

¹³Instead of independence, we may describe this distribution as being “memoryless”. If you know that you have been waiting a certain amount of time for something to happen (a good picture to get taken) that does not change your belief about how much longer you have to wait; the process “forgets” that it has been ongoing for sometime.

A Discussion of Distributional Language

Note that when we talk of a random variable “following” a particular distribution, we are saying that the probability mass function of the random variable is described by that distribution’s mass function. Thus, if two random variables “share a distribution”, we just mean that their probabilistic behaviour is described by the same underlying mass function.

For instance, if I flip a coin 10 times, and you flip a different coin 10 times, and we each count the number of heads that show up, we can say that the random quantity for the number of heads I observe will have the **same distribution** as the random quantity for the number of heads that you observe.

These two quantities are not equal, in general, but they are described by the same random processes.

When we describe the distribution of a particular random variable, we are implicitly describing the marginal probabilities associated with that quantity. Just as before, the marginal probabilities describe the behaviour of the random variable alone. What happens when we want to be able to describe multiple components of an experiment, together? For this we require extending the idea of a joint probability beyond the concept of events.

Suppose that we roll two six-sided fair dice. Let X denote the sum of the two dice, and let Y denote the maximum value showing on the two dice. X is a discrete random variable taking on values between 2 and 12, while Y is a discrete random variable taking on values between 1 and 6. The supports for the two random variables are different from one another and so immediately we know that their probabilistic behaviour must be different, despite the fact that both random variables summarize the same statistical experiment.

We can also immediately see that the two random variables, while not equal to each other, are dependent. For instance, if you know that $Y = 1$ then you know that $X = 2$, and if you know that $Y = 3$, then you know that $X \leq 6$. To begin to capture the joint behaviour of X and Y we introduce the joint distribution and joint probability mass function.

Definition 5.6 (Joint Distribution). A joint probability distribution describes the joint probabilistic behaviour of two or more random variables, simultaneously.

Definition 5.7 (Joint Probability Mass Function). A joint probability mass function describes the behaviour of the joint distribution of multiple random variables. For a set of random variables, X_1, \dots, X_n , the joint probability mass function assigns a probability value for every *tuple* of values that (X_1, \dots, X_n) can take on.

The joint probability mass function is analogous to the marginal probability mass function, only it considers joint events rather than marginal ones. Suppose that you have two random variables, X and Y . The joint probability mass function assigns a probability value for every

pair of values that (X, Y) can take on. That is, $p_{X,Y}(x, y) = P(X = x, Y = y)$. Then, once you know the joint behaviour of X and Y , you can fully summarize the combined behaviour of the underlying experiment.

Example 5.8 (Charles and Sadie’s Bird Outings). Charles and Sadie have both gotten deeply into their ornithological adventures. They go on trips together, Sadie is responsible for spotting the rare birds, and then Charles for snapping the photos. Charles has settled on a camera setup that allows for 10 pictures to be taken before changing the film. The strategy that they follow is to go out and look for a rare bird. When one is spotted, Charles takes 10 photos, trying to get as many good photos as possible. Then, the film is replaced and they repeat the process.

If X is a random variable representing the number of good photos that are taken, and Y is the number of birds that are seen on the trip, then the joint probability mass function of X and Y is

$$p_{X,Y}(x, y) = \binom{10y}{x} \times (0.25)^x \times (0.75)^{10y-x} \times \frac{e^{-3}3^y}{y!},$$

with $0 \leq x \leq 10y$, and $y \geq 0$.

- What is the probability that one bird is seen and there are no good photos taken?
- What is the probability that there is one or fewer good photos taken and two birds seen?

Solution

- Here we want $Y = 1$ and $X = 0$. Thus, we compute

$$p_{X,Y}(0, 1) = \binom{10(1)}{0} \times (0.25)^0 \times (0.75)^{10(1)-0} \times \frac{e^{-3}3^1}{1!} \approx 0.008411.$$

- Here we want $\{X \leq 1\}$ and $Y = 2$. This is the same as $X = 0$ with $Y = 2$ or $X = 1$ with $Y = 2$. Thus,

$$\begin{aligned} p_{X,Y}(0, 2) + p_{X,Y}(1, 2) &= \binom{10(2)}{0} \times (0.25)^0 \times (0.75)^{10(2)-0} \times \frac{e^{-3}3^2}{2!} \\ &\quad + \binom{10(2)}{1} \times (0.25)^1 \times (0.75)^{10(2)-1} \times \frac{e^{-3}3^2}{2!} \\ &\approx 0.00547. \end{aligned}$$

5.3.1 Joint Probability Distributions as Contingency Tables

In practice, joint probability mass functions can be thought of as analogous to the contingency tables we previously saw. If the first variable represents the first random variable being con-

sidered, and the second variable represents the second random variable, then each cell of the contingency table assigns a probability to one of the joint events that could be observed in the experiment. Joint distributions are a useful generalization of contingency tables as they allow us to compactly represent not only two different random variables, but sometimes many more. All of the definitions used for the case of two random variables extend naturally to three, four, and beyond.

Example 5.9 (Charles and Sadie: Rock-Paper-Scissors Experimentation). Charles and Sadie were once asked if rock-paper-scissors may be an easier way to solve their “who pays for coffee” dilemmas. Though both of them rejected the description of their coffee games as a “dilemma”, they had never really given it much thought. One day while bird watching, during a particularly long break with no birds, they begin to think through whether this could work or not. To this end, the friends play 1000 games, recording the results of each game into a contingency table. They suspect that this provides the true long run proportion of occurrences. To encode these games numerically, they take $X = -1$, $X = 0$, and $X = 1$ to represent Charles playing rock, paper, and scissors respectively, and they take $Y = -1$, $Y = 0$, and $Y = 1$ to represent the same events from Sadie.

	$Y = -1$	$Y = 0$	$Y = 1$
$X = -1$	400	100	50
$X = 0$	10	200	40
$X = 1$	50	50	100

What is the joint probability mass function that corresponds to this contingency table?

Solution

We can explicitly enumerate the possibilities to define the joint probability mass function. That is

$$p_{X,Y}(x,y) = \begin{cases} 0.4 & x = -1, y = -1 \\ 0.1 & x = -1, y = 0 \\ 0.05 & x = -1, y = 1 \\ 0.01 & x = 0, y = -1 \\ 0.2 & x = 0, y = 0 \\ 0.04 & x = 0, y = 1 \\ 0.05 & x = 1, y = -1 \\ 0.05 & x = 1, y = 0 \\ 0.1 & x = 1, y = 1. \end{cases}$$

While it may be possible to express this in a more compact way, this fits the criteria for a joint probability mass function.

5.4 Independence of Random Variables

If we continue to consider the case of a bivariate (two variable) joint distribution, we can use this setting to introduce the independence of random variables. Recall that the joint probability mass function of X and Y is a function, $p_{X,Y}(x, y) = P(X = x, Y = y)$. We have also introduced the marginal mass functions, $p_X(x) = P(X = x)$ and $p_Y(y) = P(Y = y)$. Further, we have said that two events, A and B , are independent if their joint probability is equal to the product of their marginal probabilities, that is $P(A, B) = P(A)P(B)$.

If we take $A = \{X = x'\}$ and $B = \{Y = y'\}$, then if $A \perp B$ we can write $p_{X,Y}(x', y') = p_X(x')p_Y(y')$. If this holds for every possible x' and every possible y' , then we say that X and Y are independent random variables, and we write $X \perp Y$.

Definition 5.8 (Independent Random Variables). Two random variables, X and Y are said to be independent random variables if their joint probability mass function is given by the product of their marginal probability mass functions,

$$p_{X,Y}(x, y) = p_X(x)p_Y(y).$$

We write $X \perp Y$, and read: X is independent of Y .

In words, two random variables are independent whenever all possible combinations of events between them are independent.

Example 5.10 (Charles the Sports Fan). Charles is a major sports fan and has been particularly fond of *hurling* ever since a trip to Ireland. Each week, Charles watches with deep investment, becoming very attached to the outcome. Because of this attachment, Charles is willing to do just about anything to help out from behind the television set, which mostly consists of wearing the right coloured clothing. Charles's theory is that by increasing the number of articles of green clothing that are worn, the number of scores in the game will also increase.

Let X represent the number of articles of green clothing that Charles is wearing, with $X \in \{0, 1, 2, 3, 4\}$, and Y is the number of scores in the game. Suppose that

$$p_X(x) = \frac{(x-2)^2}{10},$$

and that

$$p_Y(y) = \frac{e^{-45} \times 45^y}{y!}.$$

- What is the joint probability mass function for X and Y , assuming that they are independent?
- If it is determined that, assuming Charles wears no green clothing, the probability of 50 scores is 0.01, are these random variables independent?

Solution

- a. If $X \perp Y$, then the joint probability mass function is the product of the two, which is to say

$$p_{X,Y}(x, y) = \frac{(x-2)^2}{10} \cdot \frac{e^{-45} \times 45^y}{y!} = \frac{e^{-45}}{10} \times (x-2)^2 \times \frac{45^y}{y!}.$$

- b. Using the joint probability mass function found in (a),

$$p_{X,Y}(0, 15) = \frac{e^{-45}}{10} \times (0-2)^2 \times \frac{45^{50}}{(50)!} \approx 0.017.$$

This is not equal to 0.01, and so it must be the case that $X \not\perp Y$.

Example 5.11 (The Independence Argument). Charles and Sadie are having a disagreement about the nature of the probabilities on their bird outings. Charles claims that, without knowing the marginal probability mass functions of the number of good pictures taken, and the number of rare birds that are seen, there is no way to tell whether the two random quantities are independent or not. Sadie cannot say exactly why this argument feels wrong, but insists that the two quantities must not be independent.

Who is correct, and why? Recall that

$$p_{X,Y}(x, y) = \binom{10y}{x} \times (0.25)^x \times (0.75)^{10y-x} \times \frac{e^{-3} 3^y}{y!},$$

with $0 \leq x \leq 10y$, and $y \geq 0$

Solution

In this case Sadie is correct. The most clear way of seeing this is by noting that the support set for X depends on Y . The question to ask yourself is: how could two functions which are independent of one another multiply together so that one's support depends on the other's? It cannot happen. Put differently: we know that these cannot be independent as, if $Y = 0$ then $P(X = 0) = 1$ as Charles will not take any pictures.

Equivalent Definition of Independence

There is an equivalence between the described definition, and a slightly more intuitive definition for independence.

Whenever $X \perp Y$ any two events corresponding to X and Y , say $X \in A$ and $Y \in B$ are independent. The subtle distinction is that in our previous definition, we were only

concerned with simple events of the form $X = x'$ or $Y = y'$. Here we allow any two arbitrary events.

Note that if we have the above definition holding for simple events, then

$$\begin{aligned}
 P(X \in A, Y \in B) &= \sum_{x \in A} P(X = x, Y \in B) \\
 &= \sum_{x \in A} \sum_{y \in B} P(X = x, Y = y) \\
 &= \sum_{x \in A} \sum_{y \in B} p_X(x) p_Y(y) \\
 &= \left(\sum_{x \in A} p_X(x) \right) \left(\sum_{y \in B} p_Y(y) \right) \\
 &= P(X \in A) P(Y \in B).
 \end{aligned}$$

Even by only making the assumption for simple events, the conclusion regarding compound events follows naturally. Whenever any two random variables are known to be independent we know that any two events corresponding to these random variables will be independent. Moreover, we can directly write down the joint probability mass function by taking the product of the two marginals.

5.5 Conditional Probability Distributions

When introducing events, we discussed how the concepts of independence and dependence could be understood more intuitively through the use of conditional probabilities. The same is true for random variables.

Definition 5.9 (Conditional Distributions). A conditional distribution of a random variable captures the probabilistic behaviour of a random variable, given information regarding another (or several other) random variables.

Definition 5.10 (Conditional Probability Mass Function). A conditional probability mass function assigns probability values associated with any conditional event between multiple random variables. For instance, if there are two random variables X and Y , the conditional probability mass function of X given Y characterizes events of the form X given $Y = y$. Mathematically, the conditional mass function is

$$p_{X|Y}(x|y) = \frac{p_{X,Y}(x,y)}{p_Y(y)}.$$

This definition is analogous to the formula for conditional probabilities more generally, give by the joint distribution over the marginal distribution. To determine the probability of any event (for X) given some information about Y , you plug-in $X = x$ and $Y = y$ into the conditional probability mass function. If you want to condition on more than one random variable, the quantities extend in exactly the same way, where for instance

$$P(X = x|Y = y, Z = z) = \frac{P(X = x, Y = y, z = z)}{P(Y = y, Z = z)}.$$

Example 5.12 (Charles Accepts the Argument). After some convincing, Charles accepts the argument that the number of good pictures taken and the number of rare birds seen cannot be independent events. What really makes this clear, however, is when Sadie points out that the marginal probability mass function for the number of rare birds seen is given by

$$p_Y = \frac{e^{-3}3^y}{y!}.$$

Taken together with the fact that

$$p_{X,Y}(x, y) = \binom{10y}{x} \times (0.25)^x \times (0.75)^{10y-x} \times \frac{e^{-3}3^y}{y!},$$

with $0 \leq x \leq 10y$, and $y \geq 0$, Charles realizes that the conditional distribution of $X|Y$ can be computed.

- What is the conditional probability mass function of X given Y ?
- Given that 2 birds are seen, what is the probability that any good photos are taken?

Solution

- For the conditional probability mass function we take $p_{X,Y}(x, y)/p_Y(y)$. This gives

$$p_{X|Y}(x|y) = \frac{\binom{10y}{x} \times (0.25)^x \times (0.75)^{10y-x} \times \frac{e^{-3}3^y}{y!}}{\frac{e^{-3}3^y}{y!}} = \binom{10y}{x} \times (0.25)^x \times (0.75)^{10y-x}.$$

- To represent this, we want $P(X \geq 1|Y = 2)$. From properties of probability, we know that $P(X \geq 1|Y = 2) = 1 - P(X < 1|Y = 2) = P(X = 0|Y = 2)$, and so using the conditional probability mass function found previously, this gives

$$P(X = 0|Y = 2) = \binom{20}{0} (0.25)^0 \times (0.75)^{20} = 0.75^{20}.$$

As a result, the probability of interest is $1 - 0.75^{20} \approx 0.9968$, which is the probability that Charles takes at least one good picture if two birds are seen.

As was discussed, the joint probability mass function of two independent random variables is given by the product of the marginals. If $X \perp Y$, then $p_{X,Y}(x,y) = p_X(x)p_Y(y)$. Combined with the expression for the conditional probability mass function this results in $p_{X|Y}(x|y) = p_X(x)$. That is, whenever two variables are independent, the conditional probability mass function is exactly equal to the marginal probability mass function.

We saw that this was true for events, and the same reasoning applies here. This result gives an intuitive method for interpreting the independence of random variables. Two random variables are independent whenever any information about the one does not provide information about the other; when they are completely uninformative for one another. With this intuitive description it is easier to infer when independence of random variables is reasonable. Doing so is a useful skill for manipulating probability expressions.

Example 5.13 (Charles Exploration of Independence). A little shaken after the previous independence mishap, Charles is committed to better understanding independence at an intuitive level. As a result, every time a pair of random quantities are seen together Charles has taken to deciding whether or not the underlying random variables would be independent.

For each of the following, indicate whether the pairs of random quantities are likely to be independent (and why).

- Charles is buying a butternut squash, and is considering the length of the squash (X) and the weight of the squash (Y) as the most relevant measurements.
- Charles is sitting at an intersection which has a separated bike path in front of it, and a lane of vehicular traffic. Take X to be the number of bikes passing by over a length of time, and Y to be the number of cars passing by over a certain time.
- As the weekend comes around Charles prepares for the hurling match, once again considering whether the number of green items of clothing worn (X) has an impact on the number of scores (Y).
- Charles and Sadie are playing battle dice, where Charles rolls a die and compares the result (X) to the result of a separate die rolled by Sadie (Y).

Solution

- The length of a butternut squash and its weight are likely dependent. The longer a squash is, all else equal, the more likely it will be heavier, and vice versa. Both of these measure the size of the squash, and as a result, will be connected.
- This is an interesting example which likely could be argued either way. On one hand, if cars and bikes do not mix, then the traffic of one will not likely impact the traffic on another. However, there are plenty of reasons why a larger number of bikes may suggest a certain number of cars: (1) perhaps more people bike on the weekends and fewer people drive on the weekends; (2) perhaps a city with more bikers has more cars; (3) perhaps more bikes represents a busy time of the day,

which would also lead to more cars. It is challenging to know precisely where the impact stems from, it seems likely that there would be some relationship.

- c. There is likely no impact of what Charles is doing and what is happening in a sporting match being watched on the TV. As a result, these two quantities should be independent.
- d. The die roll from Charles has no impact on the die roll from Sadie, and vice versa. As a result, these two random variables will almost certainly be independent.

5.6 Manipulating Probabilities with Random Variables

Seeing as the joint, marginal, and conditional probability mass functions are exactly analogous to the corresponding concepts when they were introduced regarding events, it is reasonable to assume that we can extend the multiplication rule, the law of total probability, and Bayes' theorem to the framework of probability functions. Indeed, each of these relationships continues to hold for random variables in much the way that would be expected.

Multiplication Rule (with Probability Mass Functions)

Translating the multiplication rule to use probability mass functions gives

$$p_{X,Y}(x,y) = p_{X|Y}(x|y)p_Y(y) = p_{Y|X}(y|x)p_X(x).$$

This can be seen by rearranging the relationship defining the conditional probabilities.

Bayes' Theorem (with Probability Mass Functions)

Bayes' Theorem can be rewritten using probability mass functions as well. Specifically,

$$p_{Y|X}(y|x) = \frac{p_{X|Y}(x|y)p_Y(y)}{p_X(x)}.$$

This follows directly from the definition of conditional probabilities, as well as the multiplication rule.

These rules give the ability to compute the joint distribution and the other conditional information, when we have information regarding some of the marginals and some of the conditionals. These properties are used less *explicitly* when dealing with probability mass functions directly. Instead, they almost become absorbed into the fabric of the defining relationships themselves. That is to say, you are less likely to see Bayes' theorem invoked directly when moving between conditional distributions; however, moving between conditional distributions *is* an important

skill, and requires the use of Bayes' Theorem.

Example 5.14 (Charles and the Chores). Charles has decided to take a break from having paid employment, instead taking time to help ensure that Sadie's house runs smoothly as Sadie has been busy trying to write a novel. Unfortunately, sometimes chores are not done in a timely manner, despite Charles's best efforts. While Sadie has been nothing but supportive, Charles decides to turn to probability to ease uncertainties.

Define $X = 1$ if a given chore was done by Charles, with $X = 0$ if it was done by Sadie. Let $Y = 1$ denote a chore being done on time with $Y = 0$ if it was late. Suppose that

$$p_{Y|X}(y|x) = (0.5 + 0.4x)^y \times (0.5 - 0.4x)^{1-y},$$

$$p_X(x) = 0.85^x \times (0.15)^{1-x},$$

$$p_Y(y) = .85 \times (0.9)^y(0.1)^{1-y} + 0.075.$$

- What is the probability that a chore is late and done by Charles?
- What is the probability that, given a chore was done by Charles, it was done late? What about with Sadie?
- What is the probability that, given a chore was late, it was done by Charles? What about with Sadie?
- Explain how the results of (b) and (c) may result in Charles feeling responsible for the late chores. Is that accurate?

Solution

- For this question, we require the joint probability mass function we apply the product rule. That is,

$$p_{X,Y}(x,y) = p_{Y|X}(y|x)p_X(x) = (0.5 + 0.4x)^y \times (0.5 - 0.4x)^{1-y} \times 0.85^x \times (0.15)^{1-x}.$$

Then, to find the probability that a chore is late and done by Charles we take $p_{X,Y}(1,0) = 0.1 \times 0.85 = 0.085$.

- For Charles, we want $P(Y = 0|X = 1)$, which can be solved for directly using the provided conditional probability mass function. That is,

$$p_{Y|X}(0|1) = (0.5 + 0.4)^0 \times (0.5 - 0.4)^1 = 0.1.$$

For Sadie, we want $P(Y = 0|X = 0)$. This gives

$$p_{Y|X}(0|0) = (0.5)^0 \times (0.5)^1 = 0.5.$$

- Here we require the alternative conditional distribution, $P(X|Y)$. For this we can leverage Bayes' Theorem. Specifically,

$$p_{X|Y} = \frac{p_{Y|X}(y|x)p_X(x)}{p_Y(y)} = \frac{(0.5 + 0.4x)^y \times (0.5 - 0.4x)^{1-y} \times 0.85^x \times (0.15)^{1-x}}{.85 \times (0.9)^y(0.1)^{1-y} + 0.075}.$$

Then, the probability that Charles did the chore, given it was late, is $p_{X|Y}(1|0) = 0.53125$ and the probability that Sadie did the chore, given it was late, is $p_{X|Y}(0|0) = 0.46875$.

- d. Two things are true with the given probabilities. First, if a chore was done late, it was more likely done by Charles than Sadie. Second, Sadie is more likely to do chores late than Charles. This explains why Charles may feel responsibility for the late chores: a higher proportion of late chores are Charles's chores. However, that is only because Charles does so many more chores to begin (the probability that Charles does a chore is 0.85).¹⁴

Unlike the multiplication rule and Bayes' theorem, the extension of the law of total probability is frequently cited when manipulating probability mass functions. It is a process which is important enough so as to warrant its own name: marginalization.

Marginalization

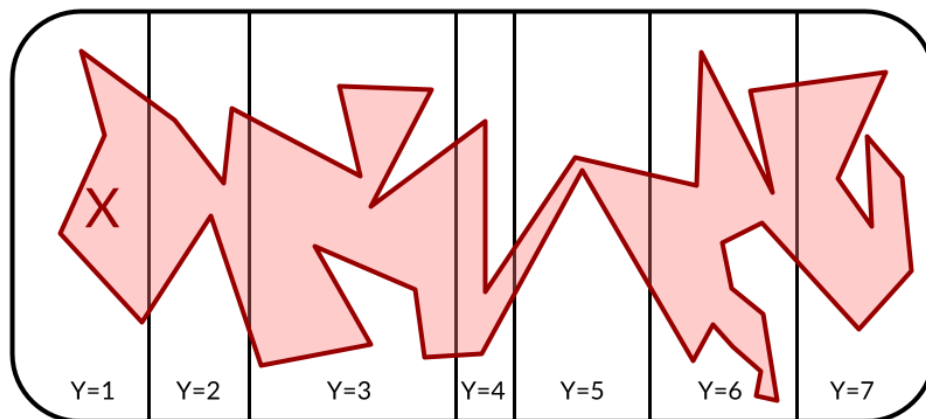
The idea with marginalization is that we are going to take a joint probability mass function and *marginalize it*, turning it into a marginal distribution. This is analogous to the law of total probability.

When dealing with a random variable, Y , there is some set of numeric values that Y can take on, namely the support of Y , which we denote \mathcal{Y} . A natural partition of the space is to then take each possible value for Y as the event, and simply enumerate through the elements of \mathcal{Y} .

Using this partition, we can ask about the ways that X can take on any particular value. In order for X to be some specific value, x' , we know that Y must be one of the values, $y' \in \mathcal{Y}$. Thus, if we add up all the possible combinations, $(X = x', Y = y_1)$, $(X = x', Y = y_2)$, and so forth, we will have covered every possible way of making $X = x'$. This is the exact same process we used when looking at contingency tables, where we summed a row or column to get the marginal probabilities.

¹⁴This is another example of *confusion of the inverse*.

Figure 5.1: This graphic shows the partitioning of the sample space using a random variable. It is entirely analogous to Figure 4.1, where in place of many different events, we partition over the set of values for Y . Here, $\mathcal{Y} = \{1, 2, 3, 4, 5, 6, 7\}$.



Taking this argument and encoding it with mathematical notation we get that

$$P(X = x) = \sum_{y \in \mathcal{Y}} P(X = x, Y = y) \implies p_X(x) = \sum_{y \in \mathcal{Y}} p_{X,Y}(x, y).$$

The process of marginalization involves summing over one of the random variables in a joint distribution, leaving behind only the marginal of the other. This is often a very effective way of determining a marginal distribution when information about two random variables is easier to discern than information about only one.

To complete the analogy to the law of total probability, recall that the multiplication rule tells us that $p_{X,Y}(x, y) = p_{X|Y}(x|y)p_Y(y)$, and so we may also marginalize by taking

$$p_X(x) = \sum_{y \in \mathcal{Y}} p_{X|Y}(x|y)p_Y(y).$$

This makes it clear that marginalization is often accomplished via arguments based on conditioning.

When confronted with questions from statistics and probability, it will often be the case that the natural answer to the question is “it depends.” For instance, if asked “what is the probability that a student passes their next exam?” the likely response is “it depends.” One very useful

technique for solving these questions in a satisfactory way is to continue that line of thought and explicitly specify “on what.” In the previous example, you may say “it depends on how much they study.” The conceit here is that, if you knew how much the student studied, then you would better understand the outcomes of the student’s exam.

In mathematical terms this means you have a firm belief about the conditional distribution between the random quantities of *exam performance* and *study time*. The process of marginalization, and the law of total probability before that, provide useful ways of being able to translate these “it depends” statements into concrete beliefs about the marginal probabilities. Recall that marginal distributions are distributions which do not depend on any other quantity, and instead, they capture the overall behaviour of a random variable. They have, in some sense, averaged out all other factors and give you the beliefs which do not depend on anything else at all. The technique for accomplishing this is marginalization.¹⁵

Example 5.15 (Photos and Bird Sightings on their Own). Recall that when Charles and Sadie go on their bird watching adventures, Charles takes photos hoping for as many good ones as possible, and Sadie spots the birds. We take X to be the number of good photos taken on these trips, and Y to be the number of rare birds that are seen. We noted that

$$p_{X,Y}(x, y) = \binom{10y}{x} \times (0.25)^x \times (0.75)^{10y-x} \times \frac{e^{-3}3^y}{y!},$$

with $0 \leq x \leq 10y$, and $y \geq 0$.

- Write down an expression for the marginal probability mass function of Y .
- Write down an expression for the marginal probability mass function of X .
- Challenge:** solve for the marginal probability mass function of Y .

Solution

- To find $p_Y(y)$, we marginalize over X . That is, we sum the joint probability distribution function over all values for X . This gives

$$p_Y(y) = \sum_{x=0}^{10y} p_{X,Y}(x, y) = \sum_{x=0}^{10y} \binom{10y}{x} \times (0.25)^x \times (0.75)^{10y-x} \times \frac{e^{-3}3^y}{y!}.$$

- To find $p_X(x)$, we marginalize over Y . That is, we sum the joint probability distribution function over all values for Y . This gives

$$p_X(x) = \sum_{y=0}^{\infty} p_{X,Y}(x, y) = \sum_{y=0}^{\infty} \binom{10y}{x} \times (0.25)^x \times (0.75)^{10y-x} \times \frac{e^{-3}3^y}{y!}.$$

¹⁵We shall see other forms of these “conditioning arguments” in the next chapter, where we try to summarize the behaviour of a random variable.

- c. Note, that you will generally not be expected to manipulate these types of sums, however, it is possible to do. First, for $p_Y(y)$,

$$\begin{aligned} p_Y(y) &= \sum_{x=0}^{10y} \binom{10y}{x} \times (0.25)^x \times (0.75)^{10y-x} \times \frac{e^{-3} 3^y}{y!} \\ &= \frac{e^{-3} 3^y}{y!} \underbrace{\sum_{x=0}^{10y} \binom{10y}{x} \times (0.25)^x \times (0.75)^{10y-x}}_{=1} \\ &= \frac{e^{-3} 3^y}{y!}. \end{aligned}$$

5.7 Independent and Identically Distributed: A Framework for Interpretation

A very common assumption when addressing questions in statistics and in probability is that we have a set of random variables which are independent and identically distributed (often written iid). We now have the tools to understand concretely what this means.

Definition 5.11 (Independent and Identically Distributed (iid)). A set of random variables, X_1, X_2, \dots, X_n are said to be independent and identically distributed (denoted iid) whenever:

- i. every subset of random variables in the collection is independent of every other subset of random variables in the collection; and
- ii. the marginal distribution for each of the random variables are exactly the same.

The assumption of iid random quantities will often come up when we are repeating a process many times over, and thinking about what observations will arise from this. Suppose that X_1 is a random variable that takes the value 1 if a flipped coin comes up heads, and 0 otherwise. If we imagine flipping this coin 100 times then it is reasonable to assume that each sequential coin flip will be independent of each other coin flip, since the result on one flip of a coin should not influence the result of any other flip of a coin. Moreover, every time the coin is flipped, it is reasonable to assume that the probability it shows up heads remains the same. As a result, these 100 random quantities, $(X_1, X_2, \dots, X_{100})$, are said to be iid.

Example 5.16 (Reframing the Bird Photos). Charles and Sadie had, to this point, been considering their bird photo taking adventures in terms of the joint and conditional distributions. After learning of independent and identically distributed random variables, Charles thinks that there is another way to frame the setup, and describes the following to Sadie:

Suppose it is known that there will be y birds seen on any given day. Then, the total number of good pictures of birds can be viewed as the sum of the number of good pictures of each bird. Thus, we can take a set of iid random variables, say X_1, \dots, X_y which represent the number of good pictures taken of each bird.

- Is this an accurate description? In reality, do we think that this will hold?
- Supposing that this description is accurate, and that the probability mass function for each X_j is given by

$$p_X(x) = \binom{10}{x} (0.25)^x (0.75)^{10-x},$$

what is the joint probability mass function of (X_1, \dots, X_y) ?

Solution

- Yes, this is a reasonable explanation. In this case, if Charles is willing to assume that good photos for one bird do not impact the chances of good photos of another bird, then this is a perfectly valid way to frame the setting. Note that in this case, $Y = y$ is still random, so this whole description is conditioning on knowing $Y = y$. In the real world, it is likely that photos may not actually be independent. If Charles takes some really bad photos of one bird, that may impact the chances of taking good photos of the next. However, it is likely close enough to correct in order to be true.
- Recall that for independent random variables, the joint probability mass function is given by the product of the marginal probability mass functions. To simplify the notation, we will define $T(X) = \sum_{i=1}^y x_i$. Thus the probability mass function of X_1, \dots, X_y is given by

$$\begin{aligned} p_{X_1, X_2, \dots, X_y}(x_1, \dots, x_y) &= \prod_{i=1}^y \binom{10}{x_i} (0.25)^{x_i} (0.75)^{10-x_i} \\ &= \left(\prod_{i=1}^y \binom{10}{x_i} \right) \times (0.25)^{\sum_{i=1}^y x_i} (0.75)^{10y - \sum_{i=1}^y x_i} \\ &= \left(\prod_{i=1}^y \frac{10!}{x_i! (10 - x_i)!} \right) \times 0.25^{T(X)} \times 0.75^{10y - T(X)} \\ &= \left(\frac{(10!)^y}{\prod_{i=1}^y x_i! (10 - x_i)!} \right) \times 0.25^{T(X)} \times 0.75^{10y - T(X)}. \end{aligned}$$

While we will use the assumption of iid random variables explicitly at a later point, the iid assumption also provides an intuitive method for interpreting probability functions and distributions.

Suppose that we were to take a probability mass function, $p_X(x)$. If we were able to generate independent and identically distributed realizations from this probability mass function, then the function $p_X(x)$ describes the behaviour for these repeated realizations. Specifically, $p_X(x)$ will give the long-run proportion of realizations of the iid random variables which take the value x .

This type of statement is always the flavour of interpretation statements that are made with respect to probability and statistics. It is always be the case that, in order to understand what is meant by a statement of probability, we consider the repetition of some statistical experiment over and over again. When we were discussing sample spaces and experiments directly, we talked about repeating the experiment over and over again. When we begin to work with random variables instead, it becomes more natural to think about the replication procedures coming through the use of independent and identically distributed random variables.

As your study of probability progresses, you will begin to work with random quantities in a strictly theoretical sense. In introductory level problems, we are often holding in mind very concrete examples to illustrate the procedures and concepts. In this setting it is easy enough to hold in mind the experiment of interest: for instance, we may have a random variable representing the result of a coin toss, and you can envision repeatedly tossing a coin. As the concepts become less concrete, more abstract, and harder to draw direct parallels to tangible scenarios, it becomes more and more important to rely on the interpretations rooted in a series of independent and identically distributed random variables.

A large component of statistics as an area of study is making explicit the assumptions we are working with, and doing our best to ensure that these are reasonable. By interpreting probability mass functions as the proportion of independent and identically distributed random variables that take on a particular value when we repeatedly take realizations of these random variables, this philosophy is made clear and explicit.

6 The Expected Value and Location Summaries

6.1 Summarizing the Location of a Distribution

Until this point in our discussions of probability we have relied upon characterizing the behaviour of a random variable via the use of probability mass functions. In some sense, a probability mass function captures all of the probabilistic behaviour of a discrete random variable. Using the mass function you are able to characterize how often, in the long run, any particular value will be observed, and answer any questions associated with this. As a result, the mass function remains a critical area of focus for understanding how random quantities behave.

However, these functions need to be explored and manipulated in order for useful information to be extracted from them. They do not summarize this behaviour effectively, as they are not intended to be a summary tool. We may wish to have numeric quantities which are able to *concisely* express the behaviour of a distribution. Put differently, provided with a probability mass function it is hard to immediately answer “what do we expect to happen with this random variable?” despite the fact that this is a very obvious first question.

To address questions related to our expectations, we turn towards the statistical concept of central tendency or location.

Definition 6.1 (Location (Central Tendency)). The location of a distribution is a measure of a typical value, or a central value, for that distribution. A measure of location may also be referred to as a measure of central tendency.

With measures of location we are trying to capture, with one single number, what value is expected when we make observations from the random quantity. There are many ways one might think to describe our expectations, and it is worth exploring these concepts in some detail. In particular, we want to explore how we might think to define the **expected value** of a distribution.¹

¹As a general rule when learning it is often helpful to consider exercises of discovery. That is, try to determine *why* particular definitions are the way that they are, or where they have from.

6.2 Deriving the Expected Value

6.2.1 The Mode

One way that we may think to define our expected value is by asking what value is the most probable. This is a question which can be directly answered using the probability mass function. The process for this requires looking at the function and determining which value for x corresponds to the highest probability. This is the value that we are most likely to see. Sometimes this procedure is fairly straightforward, sometimes it is quite complicated. Regardless of the complexity of the specific scenario, the most probable value has a straightforward interpretation. As intuitive as this may seem, this is not the value that will be used as *the* expected value generally. Instead, this quantity is referred to as the mode.

Definition 6.2 (Mode). The mode of a distribution is the most probable value of that distribution. Specifically, if X is a discrete random variable with mass function $p_X(x)$, then the mode is the value of x such that $p_X(x)$ is maximized.

Example 6.1 (Charles and Sadie Investigate Cupcake Sprinkles). Charles and Sadie have noticed that their favourite coffee shop has been experiencing less foot traffic ever since *Probability Patisserie: Cupcake Conundrums* has opened up next door.² This cupcake shop has been attracting many of the regular customers, though, Charles and Sadie think that it has more to do with fancy marketing than with a better product. To this end, they go into the store and workout the probability mass function for X , the number of sprinkles on top of the cupcakes. They find the following

$$p_X(x) = \begin{cases} 0.25 & x = 0 \\ 0.3 & x = 1 \\ 0.1 & x = 2 \\ 0.05 & x \in \{3, 4, 5, 6, 7, 8, 9\} \\ 0 & \text{otherwise.} \end{cases}$$

What is the mode for the number of sprinkles on the cupcakes?

Solution

The mode is the value x such that $p_X(x)$ is a maximum. In this case the maximum occurs when $x = 1$, with $p_X(1) = 0.3$, and so the mode of the number of sprinkles is 1.

²You should picture the owner of this fictitious cupcake store as a giant, multinational, faceless corporation. A corporation that seems to take pleasure in stepping on the local businesses. That way, as Charles and Sadie try to fight back, we can remain on their side!

While the mode is a useful quantity, and for some decisions will be the most relevant summary value, there are some major issues with it as a general measure of location. For starters, consider that our most common probability model considered until this point has been that of equally likely outcomes. Here, there is no well-defined mode.³ While the case of equally likely outcomes is a fairly strong example highlighting the issues with the mode, it need not be so dramatic to undermine its utility. It is possible for a distribution to have several modes which are quite distinct from one another, even if it's not all values in the support.

Moreover, it is quite common for the modal value to be not particularly likely itself. Consider a random variable that can take on a million different values. If all of the probabilities are approximately 0.000001 then presenting the mode as the most probable value does not translate to saying that the mode is particularly probable.

Example 6.2 (Charles and Sadie Investigate Cupcake Happiness). After realizing that the cupcake shop did not provide very many sprinkles, Charles and Sadie decided to turn to the marketing material. In it, *Cupcake Conundrums* claims that, on a scale from 0 to 100,000 happiness points, most of their customers experience the maximum happiness after eating their cupcakes. Charles and Sadie are well aware of the ways in which these types of reports can be misleading, and so they investigate, finding the following probability mass function for the number of happiness points.

$$p_X(x) = \begin{cases} \frac{x}{5,000,050,000} & x \in \{1, \dots, 100000\} \\ 0 & \text{otherwise.} \end{cases}$$

- a. Is the mode reported by the company correct?
- b. Is the mode an accurate depiction of the distribution in this setting?

Solution

- a. Yes. Note that $p_X(x)$ is increasing in x . As a result, the mode of the distribution is the highest value that the distribution can take on, which in this case is $x = 100,000$.
- b. The mode is likely not a good indication of the distribution. Note that the maximal value happens only $100000/5000050000$ of the time, which is a very very small value. If you look at the probability that a customer is only halfway happy, this is $50000/5000050000$. This value is half the likelihood of the modal value, but the difference between these two probabilities is also only $50000/5000050000 \approx 0.000001$. That is, it is only 1 in 100,000 more likely to observe perfect happiness compared with half happiness. By extension, it is only about 2 in 100,000 more likely to observe perfect happiness compared with no happiness. The mode simply is not a good indicator of behaviour in this setting.

³When multiple modes exist, convention tends to report the set of all of the modes. In the equally likely outcome model, this is the entire support for the random variable, and as a result, the mode is exactly the probability mass function. There is no summary provided.

6.2.2 The Median

If the mode has these shortcomings, what else might work? Another intuitive concept is to try to select the “middle” of the distribution. One way to define the middle would be to select the value such that, in the long run, half of observations from the distribution are beneath it and half are above it. That way, when you are told this value, you immediately know that it is equally likely to observe values on either side of this mark. This is also a particularly intuitive definition for expected value, and is important enough to be named, the median.

Definition 6.3 (Median). The median of a distribution is the value m which attempts to have $P(X \leq m) = 0.5$ and $P(X \geq m) = 0.5$. This value may not always exist, and so formally for discrete random variables, the median m is any value such that $P(X \leq m) \geq 0.5$ and $P(X \geq m) \geq 0.5$.

The median is the midpoint of a distribution and is very important for describing the behaviour of random variables. Medians are often the most helpful single value to report to indicate the typical behaviour of a distribution, and they are frequently used. When people interpret averages it is often the median that they are actually interpreting. It is very intuitive to be given a value and know that half of all realizations are above that point, and half of all realizations are below that point.

Example 6.3 (Charles and Sadie Investigate Cupcake Sprinkles (Again)). After seeing how the cupcake shop used the mode to misrepresent the happiness of its customers, Charles and Sadie worry that they may have been unfair with using the mode. As a result, they turn back to the cupcake sprinkle distribution and try to summarize it differently. Recall that the probability mass function for X , the number of sprinkles on top of the cupcakes, is

$$p_X(x) = \begin{cases} 0.25 & x = 0 \\ 0.3 & x = 1 \\ 0.1 & x = 2 \\ 0.05 & x \in \{3, 4, 5, 6, 7, 8, 9\} \\ 0 & \text{otherwise.} \end{cases}$$

What is the median number of sprinkles on the cupcakes?

Solution

Note that we are looking for a value, m , such that $P(X \geq m) \geq 0.5$ and $P(X \leq m) \geq 0.5$. To find this we can consider the cumulative probability sums. We know that $P(X \leq k) = \sum_{x=0}^k p_X(x)$, and as a result, stopping this value at the first time that the sum goes beyond 0.5 satisfies the second condition. In this case our cumulative sums are 0.25 then 0.55. As a result, $P(X \leq 1) = 0.55 > 0.5$. If we check $P(X \geq 1) = 1 - P(X <$

$1) = 1 - P(X = 0) = 0.75 > 0.5$. As a result, $m = 1$ satisfies the required conditions and is a median.

Despite the advantages of medians, they have their own drawbacks. For starters, the median can be exceptionally challenging to compute in certain settings. As a result, even when a median is appropriate, it may not be desirable if it is too challenging to determine.

Beyond the difficulties in computation, medians have a feature which is simultaneously a major benefit and a major drawback. Specifically, medians are less influenced by extreme values in the probability distribution. Consider two different distributions. The first is equally likely to take any value between 1 and 10. The second is equally likely to take any value between 1 and 9 or 1,000,000. In both of these settings, the median is 5 since $P(X \leq 5) = 0.5$ and $P(X \geq 5) = 0.5$. However, in the second setting we may observe a value as high as 1,000,000. Moreover, this value will be observed as often as the median will be.

The median, in some sense, ignores the extreme value in the probability distribution. In certain settings, this can be very desirable.⁴ Consider the distribution of household incomes. There are a few households that earn an incredibly large amount, compared to the remaining households. If you are interested in understanding the “average household”, the median may be a more appropriate measure, as those households with extreme incomes would otherwise distort the picture provided by most families. In this sense, the median’s robustness to extreme values is a positive feature of it in terms of a summary measure for distributional behaviour.

Suppose instead that you work for an insurance company and are concerned with understanding the value of insurance claims that your company will need to pay out. The distribution will look quite similar to the income distribution. Most of the probability will be assigned to fairly small claims, with a small chance of a very large one. As an insurance company, if you use the median this large claim behaviour will be smoothed over, perhaps leaving you unprepared for the possibility of extremely large payouts. In this setting, the extreme values are informative and important, and as a result the median’s robustness becomes a hindrance to correctly describing the important behaviour.⁵

Example 6.4 (Charles and Sadie Investigate Cupcake Public Relations). Charles and Sadie feel as though they may be finally catching a break when word gets around that the cupcake shop was using spoiled ingredients, making the patrons sick! The cupcake shop, in hearing this, sent their massive public relations team into damage control mode. They claimed that the median number of illnesses per week associated with the cupcake store was the same as

⁴You will find many introductory sources that say that you should always use the median when you are concerned with extreme values. This is a great oversimplification of the truth, and points to a general rule in Statistics: there are very few general rules. The guidance comes from the fact that often extreme values skew our perceptions of the underlying truth. While this may be true in general, it is not true often enough to warrant being given as universal guidance.

⁵An insurance company ignoring these massive claims would almost certainly go out of business very, very quickly.

most local food services businesses. Doing some digging, Charles and Sadie find the following two probability mass functions, for X and Y , where X is the number of weekly illnesses at the cupcake shop, and Y is the number from a local business that has been around for a while.

$$p_X(x) = \begin{cases} 0.1 & x = 0 \\ 0.1 & x = 1 \\ 0.35 & x = 2 \\ 0.05 & x = 3 \\ 0.4 & x = 25 \\ 0 & \text{otherwise;} \end{cases}$$

$$p_Y(y) = \begin{cases} 0.45 & x = 0 \\ 0.04 & x = 1 \\ 0.5 & x = 2 \\ 0.01 & x = 3 \end{cases}.$$

- What is the median of X ?
- What is the median of Y ?
- Is the claim made by the public relations team an accurate depiction of the world? Why or why not?

Solution

- We can consider cumulative sums here again. In order we get, 0.1, 0.2, 0.55. This suggests that $x = 2$ is a candidate. If we check $P(X \geq 2) = 1 - 0.2 = 0.8$, and so $x = 2$ is a median.
- Using cumulative sums we get 0.45, 0.49, 0.99. Again, this gives $x = 2$ as a candidate. If we check $P(X \geq 2) = 1 - 0.49 = 0.51$, and so $x = 2$ is a median.
- The claim is accurate in that the median number for both establishments is 2. However, here the median is a bad representation for X . The probability that more than 2 cases occur in a week at the cupcake shop is 0.8, compared with 0.51 at the local business. What's more, the probability that X is as high as 25 is 0.4, where Y is *never* higher than 3.

Between the median and the mode we have two measures which capture some sense of expected value, each with their own set of strengths and drawbacks. Neither capture what it is that is referred to as *the* expected value. For this, we need to take inspiration from the median, and consider another way that we may think to find the center of the distribution.

6.2.3 The Mean

If the median gives the middle reading along the values sequentially, we may also wish to think about trying to find the *center of gravity* of the numbers. Suppose you take a pen, or marker, or small box of chocolates, and you wish to balance this object on a finger or an arm. To do so, you do not place the item so that half of its length sits on one side of the appendage and half on the other. You adjust the location so that half of the *mass* sits on either side of the appendage.

Throughout our discussion of discrete random variables we have referred to probability as *mass*. We use the *probability mass function* to generate our probability values. This metaphor can be extended when we try to find the center of the distribution. If we imagine placing a mass with weight equal to the probability mass at each value that a random variable can take on, we may ask, “where would we have to place a fulcrum to have this number line be balanced?” The answer to this question serves as another possible measure of center. It turns out that this notion of center is the one that we are all most familiar with, the simple average, or mean.

Definition 6.4 (Mean). The mean of a distribution is the center of mass of the distribution. For a random variable, X with support \mathcal{X} , and probability mass function $p_X(x)$, the mean of X is given by

$$\sum_{x \in \mathcal{X}} xp_X(x).$$

It is this measure of location which ends up being called the **expected value** in statistics. We will use average, expected value, mean, and expectation interchangeably. In terms of notation, the expected value of a random variable X is denoted $E[X]$. Mathematically, the expected value is desirable for many reasons, some of which we will study in more depth later on. One of these desirable features, which stands in contrast with the median, is the comparative ease with which expected values can be computed. The summation for the expected value is easy to write down, and typically can be solved (either analytically, or readily with a computer).

Example 6.5 (Charles and Sadie Investigate Cupcake Sprinkles (One Last Time)). While the median and mode number of sprinkles on the cupcakes were the same, Charles and Sadie realize that this does not end up connecting well with the total number of sprinkles given out. Perhaps customers like the possibility of getting a large number of sprinkles, if they get lucky. As a result, they decide to round out the summary of the distribution by considering the mean number of sprinkles as well. Recall that the probability mass function for X , the number of sprinkles on top of the cupcakes, is

$$p_X(x) = \begin{cases} 0.25 & x = 0 \\ 0.3 & x = 1 \\ 0.1 & x = 2 \\ 0.05 & x \in \{3, 4, 5, 6, 7, 8, 9\} \\ 0 & \text{otherwise.} \end{cases}$$

What is the mean number of sprinkles?

Solution

Recall that the mean of a distribution is given by $E[X] = \sum_{x \in \mathcal{X}} xP_X(x)$. In this case, this results in

$$\begin{aligned} & \sum_{x=0}^9 xp_X(x) \\ &= 0(0.25) + 1(0.3) + 2(0.1) + (3 + 4 + 5 + 6 + 7 + 8 + 9)(0.05) \\ &= 2.6. \end{aligned}$$

As a result, the mean number of sprinkles used is 2.6. This is higher than the median and mode, but is still not particularly high.

In the case of an equally likely probability model, the expected value becomes the standard average that is widely used. Suppose that there are n options in the support with $\mathcal{X} = \{x_1, \dots, x_n\}$. We can write

$$E[X] = \sum_{i=1}^n x_i \frac{1}{n} = \frac{1}{n} \sum_{i=1}^n x_i.$$

This is the formula for the average that is most commonly applied. When the probability models are more complex, the formula is not precisely the standard average – instead, it becomes a weighted average, where the weights are the probabilities.⁶ The frequency with which expected values are used make them attractive as a quick summary for the center of a distribution.

6.2.4 How is the Mean “Expected”?

While the mean provides a useful, intuitive measure of center of the distribution, it is perhaps counterintuitive to name it the “expected value.” To understand the naming convention it is easiest to consider the application which has likely spurred more development of statistics and probability than any other: gambling.

Suppose that there is some game of chance that can pay out different amounts with different probabilities. A critical question for a gambler in deciding whether or not to play such a game is “how much can I expect to earn, if I play?” This is crucial to understanding, for instance, how much you should be willing to pay to participate, or if you are the one running the game, how much you should charge to ensure that you make a profit.

⁶While less commonly applied than the simple average, a weighted average is familiar to most students for a crucial purpose: grade calculations. If you view the weight of each item in a course as a probability mass, and the grade you scored as the value, then your final grade in the course is exactly the expected value of this distribution.

If you want to understand what you expect to earn, the intuitive way of accomplishing this is to weight each possible outcome by how likely it is to occur. This is exactly the expected value formula that has been provided, and so the expected value can be thought of as the expected payout of a game of chance where the outcomes are payouts corresponding to each probability.

Cost for a Game of Chance

Suppose that a game of chance is being run. It will cost $\$m$ to play, and the game will pay out values from \mathcal{X} , according to a random variable X with probability mass function $p_X(x)$. The question that we want to know is what should the value be for m , such that, in the long term, a player playing the game will earn no money?

Note that if $X = x$ then a player playing the game will earn $x - m$ for that play, and this will happen with probability $p_X(x)$. Thus, in the long run, in $p_X(x)$ proportion of games the player earns $x - m$. If the player plays N games, then as $N \rightarrow \infty$, the total contribution from these winnings will be $(x - m) \cdot N \cdot p_X(x)$. If we add up this contribution for all possible results, x , we get

$$\begin{aligned} \sum_{x \in \mathcal{X}} N(x - m)p_X(x) &= N \left[\sum_{x \in \mathcal{X}} xp_X(x) - \sum_{x \in \mathcal{X}} mp_X(x) \right] \\ &= N \left[\sum_{x \in \mathcal{X}} xp_X(x) - m \sum_{x \in \mathcal{X}} p_X(x) \right] \\ &= N [E[X] - m]. \end{aligned}$$

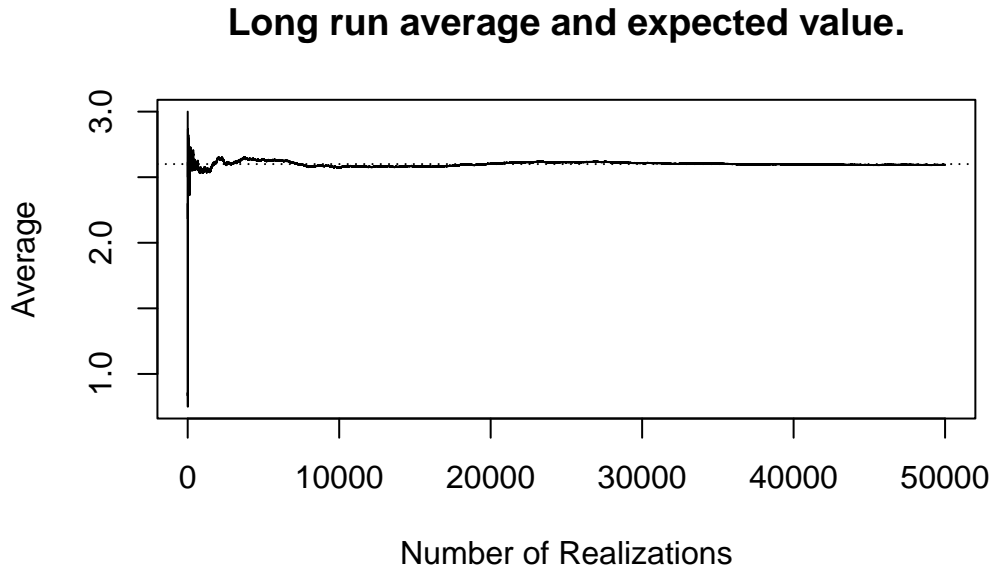
Thus, in the long run, the total that the player wins, as $N \rightarrow \infty$ will be $N(E[X] - m)$. Thus, in order for the long run earnings to be zero, m should be set to be equal to $E[X]$. If m is set to be 0, then per game the player *expects* to earn $E[X]$. This also represents the cost at which a rational actor should be willing to pay to participate. If a game of chance costs more than the expected value to play, in the long run you will lose money. If a game of chance costs less than the expected value, in the long run you will earn money. It is hard to overstate the utility of gambling in developing probability theory, and as such these types of connections are expected.

To interpret the expected value of a random variable, one possibility is using the intuition that we used to derive the result. Notably, the expected value is the center of mass of the distribution, where the masses correspond to probabilities. This means that it is not necessarily an actual central number over the range, but rather that it sits in the weighted middle. While this interpretation is useful in many situations, there are times where the point of balance is a less intuitive description. For these, it can sometimes be useful to frame the expected value as the long term simple average from the distribution.

If we imagine observing many independent and identically distributed random variables, then

as the number of samples tends to infinity, the expected value of X and the simple average will begin to coincide with one another. That is the distance between $E[X]$ and $\frac{1}{n} \sum_{i=1}^n X_i$ will shrink to 0. As a result, we can view the expected value as the average over repeated experiments. This interpretation coincides nicely with the description based on games of chance. Specifically, if you were to repeatedly play the same game of chance, the average payout per game will be equal to the expected value, if you play for long enough.

Figure 6.1: This plot produces 50000 realizations of the random variable described in Example 6.5. As computed in the example, the expected value is 2.6. As many repeated observations are averaged, the empirical average converges to this computed value.



6.3 Which Measure of Central Tendency Should be Used?

Where the median demonstrated robustness against extreme values in the distribution, the mean does not. For instance, if we consider the distribution of incomes across a particular region, the mean will be much higher than the median, since those families with exceptionally high incomes will not be smoothed over as they were with medians. In this case, the lack of robustness for the expected value will render the mean a less representative summary for the true behaviour of the random quantity.

To see this concretely consider a random variable which with equal probability takes a value between 1 and 9. This will have $E[X] = 5$. Now, if the 9 is made to be 1,000,000, the expected

value will now be $E[X] = 111115.\dot{1}$. This is a far cry from the median which does not change from 5 in either case. This lack of robustness is desirable in the event of the insurance example from the median discussion, but will be less desirable in other settings.

The mean, median, and mode are the three standard measures of central tendency. They are single values which describe the standard behaviour of a random quantity. Each of the three has merits as a measure, and each has drawbacks for certain settings. The question of which to use and when depends primarily on the question of interest under consideration, rather than on features of the data alone.⁷ Often, presenting more than one measure can give a better sense of the distributional behaviour that any one individual will.

Example 6.6 (Charles and Sadie Reflect on the Cupcake Adventures). Charles and Sadie decide it is worth stepping back and summarizing all that has happened with regards to their cupcake adventures, trying to ensure that distributions are always summarized fairly.

- a. For the number of sprinkles per cupcake is the mean, median, or mode the best measure of central tendency?
- b. For the amount happiness in customers, is the mean, median, or mode the best measure of central tendency?
- c. For the number of customers who become ill eating at establishments, is the mean, median, or mode the best measure of central tendency?

Solution

- a. There is an argument that any of the measures here could work the best, it would depend on the individual's preferences. The mode makes a lot of sense as, if you are a regular customer, the mode is what you will experience day-to-day; most days you will have the modal number of sprinkles. The median may make sense as it provides a benchmark for measuring what constitutes a lot of sprinkles and a little. Half of the time you'll end up with a more sprinkled donut, half the time a less. The mean would be particularly interesting to note for the store owners themselves, since the mean is directly tied to totals: if the store knows that they sell 100 cupcakes per day, most days, then they also can expect to use 100 times the mean number of sprinkles in a day. This is helpful for planning.
- b. The median is likely the most useful measure in this setting. The mode could be useful if happiness were not measured on a 100,000 point scale. The mean is likely a less relevant value here as we are not particularly concerned with the total happiness, and if there was a large skew or major outliers in this distribution, we would want to determine where the majority fall. This is more analogous to the income example rather than the insurance example.

⁷The data is one consideration for which measure to use, but not the only one (and not the most important one).

- c. In this case either the mode or mean are likely the best gauges. Here we do care about totals, and in particular, we do not want to smooth over outliers. It is very relevant if sometimes a lot of individuals become ill after eating an establishment, and the median would hide this information.

Despite the utility of all three measures, the expected value holds a place of more central importance in probability and statistics. A lot of this has to do with further mathematical properties of the mean. Because of its central role, it is worth studying the expected value in some more depth.

6.4 Expected Values of Functions of Random Variables

Sometimes the value of a random variable needs to be mapped through a function to give the value which is most relevant to us. Consider, for instance, a situation wherein the side lengths of boxes being manufactured by a specific supplier are random, due to incorrectly calibrated tolerances in the machines. The resulting boxes are perfect cubes. Suppose we are interested in the volume of the produced box not the side length. If a box has side length x , then its volume will be x^3 , and so we may desire some way of computing $E[X^3]$ rather than $E[X]$.

Generally, for a function $g(X)$, we may want to compute $E[g(X)]$. It is important to recognize that $E[g(X)] \neq g(E[X])$. This is a common mistake.⁸ If we are unable to apply the function to the expected value, then the question of how to compute the expected value remains. Instead of applying the function to overall expected value, instead, we apply the function to *each* value in the defining relationship for the expected value. That is,

$$E[g(X)] = \sum_{x \in \mathcal{X}} g(x)p_X(x).$$

This is sometimes referred to as the “law of the unconscious statistician,” a name which may be aggressive enough to help remember the correct way to compute the expectation.⁹

The Law of the Unconscious Statistician

The law of the unconscious statistician (LOTUS) states that, for a random variable X , if we wish to find $E[g(X)]$, then we compute

$$E[g(X)] = \sum_{x \in \mathcal{X}} g(x)p_X(x).$$

⁸and an attractive one, but a mistake nonetheless.

⁹Some statisticians dislike this name. I find it to be rather cute.

Example 6.7 (The Happiness Scale Inversion). Charles and Sadie have made really great strides working to protect their favourite coffee shop from the new cupcake store. One day when digging through the material more, they realize that the happiness report produced by the company is even less accurate than they had originally reported! The company reported the following probability mass function for happiness points

$$p_X(x) = \begin{cases} \frac{x}{5,000,050,000} & x \in \{1, \dots, 100000\} \\ 0 & \text{otherwise.} \end{cases}$$

Charles and Sadie track down the source of this expression and they find that, in fact, this does not measure happiness points at all. Instead, the number of happiness points is a function of X , specifically, $Z = 1/X$.

- What is the expected value of X ? Note, it may be helpful to recall that $\sum_{x=1}^k x^2 = \frac{k(k+1)(2k+1)}{6}$.
- What is the expected value of Z ?

Solution

- Using directly the formula for $E[X]$ gives

$$\begin{aligned} E[X] &= \sum_{x=1}^{100000} x p_X(x) = \sum_{x=1}^{100000} x \frac{x}{5000050000} \\ &= \frac{1}{5000050000} \sum_{x=1}^{100000} x^2 \\ &= \frac{1}{5000050000} \cdot \frac{100000(100000+1)(2(100000)+1)}{6} \\ &= 66667. \end{aligned}$$

- Applying the law of the unconscious statistician, gives

$$\begin{aligned} E[Z] = E[1/X] &= \sum_{x=1}^{100000} \frac{1}{x} p_X(x) = \sum_{x=1}^{100000} \frac{1}{x} \frac{x}{5000050000} \\ &= \frac{1}{5000050000} \sum_{x=1}^{100000} 1 \\ &= \frac{100000}{5000050000} \\ &= \frac{2}{100001}. \end{aligned}$$

These functions applied to random variables are often thought of as “transformations” of the random quantities. For instance, we *transformed* a side length into a volume. While the law of the unconscious statistician will apply to any transformation for a random variable, we can sometimes use shortcuts to circumvent its application. In particular, when $g(X) = aX + b$, for constant numbers a and b , we can greatly simplify the expected value of the transformation. To see this note

$$\begin{aligned} E[aX + b] &= \sum_{x \in \mathcal{X}} (ax + b)p_X(x) \\ &= \sum_{x \in \mathcal{X}} axp_X(x) + bp_X(x) \\ &= a \sum_{x \in \mathcal{X}} xp_X(x) + b \sum_{x \in \mathcal{X}} p_X(x) \\ &= aE[X] + b. \end{aligned}$$

That is, in general, we have that $E[aX + b] = aE[X] + b$.

This is particularly useful as linear transformations like $aX + b$ arise very commonly. For instance, most unit conversions are simple linear combinations. If a random quantity is measured in one unit then this result can be used to quickly convert expectations to another.

Example 6.8 (Sadie’s Trip to America). Sadie has recently returned from a long trip to America. The trip was long enough that temperatures measured in Fahrenheit started to make sense. When Sadie and Charles begin to talk about the weather, Charles brings up the temperature distribution of a possible summer vacation spot. Unfortunately for Sadie, these temperatures are all in Celsius. The distribution Charles provides is

$$p_X(x) = \begin{cases} 0.1 & x \in \{10, 11, 12, 13, 14\} \\ 0.05 & x \in \{15, 16, 17, 18, 19, 20, 21, 22, 23, 24\} \\ 0 & \text{otherwise} \end{cases}$$

- What is the expected temperature, in Celsius?
- Supposing that the temperature in Fahrenheit is given by $Y = 1.8X + 32$, what is the expected temperature in Fahrenheit?

Solution

- Here we find

$$\begin{aligned} \sum_{x=10}^{24} xp_X(x) &= 0.1 \sum_{x=10}^{14} x + 0.05 \sum_{x=15}^{24} x \\ &= 15.75. \end{aligned}$$

- Since $E[X] = 15.75$ then $E[Y] = E[1.8X + 32] = 1.8E[X] + 32 = 60.35$.

This type of linear transformation also frequently comes up with games of chance and payouts, or with scoring more generally.¹⁰

Measures of central tendency are important to summarize the behaviour of a random quantity. Whether using the mean, median, or mode, these measures of location describe, on average, what to expect from observations of the random quantity. However, understanding a distribution requires understanding far more than simply the measures of location. As was discussed previously, the probability mass function captures the complete probabilistic behaviour of a discrete random variable, it is only intuitive that some information would be lost with a single numeric summary.

Equal Location Across Different Distributions

Consider the following three distributions for three random variables, X , Y , and Z :

$$p_X(x) = \begin{cases} 0.25 & x = -1 \\ 0.5 & x = 0 \\ 0.25 & x = 1 \\ 0 & \text{otherwise.} \end{cases} \quad p_Y(y) = \begin{cases} 0.05 & x = -5 \\ 0.1 & x = -4 \\ 0.1 & x = -3 \\ 0.1 & x = -2 \\ 0.1 & x = -1 \\ 0.15 & x = 0 \\ 0.1 & x = 1 \\ 0.1 & x = 2 \\ 0.1 & x = 3 \\ 0.1 & x = 4 \\ 0.05 & x = 5 \\ 0 & \text{otherwise.} \end{cases} \quad p_Z(z) = \begin{cases} 0.25 & x = -400 \\ 0.5 & x = 0 \\ \frac{1}{3196} & x \in \{1, \dots, 799\} \\ 0 & \text{otherwise.} \end{cases}$$

In each of these distributions we have the mean, median, and mode all equalling 0.¹¹ However, even just from a quick glance, these distributions are all very, very differently behaved. The location summaries here clearly miss much of the important information about these different distributions. Spend some time trying to think of the ways in which they differ from one another, and see if you can determine *what* is missing from relying solely on measures of location.

¹⁰For instance, suppose you are betting a certain amount on the results of a coin toss, or that you are taking a multiple choice test that gives 2 points for a correct answer.

¹¹Try working this out!

Part II

Part 2: Statistics

- Bartoš, František, Alexandra Sarafoglou, Henrik R. Godmann, Amir Sahrani, David Klein Leunk, Pierre Y. Gui, David Voss, et al. 2023. “Fair Coins Tend to Land on the Same Side They Started: Evidence from 350,757 Flips.” <https://arxiv.org/abs/2310.04153>.
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- Kahneman, Daniel, and Amos Tversky. 1972. “Subjective Probability: A Judgment of Representativeness.” *Cognitive Psychology* 3 (3): 430–54.