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## Prelude to Part IV

Part IV of the book is by far the most theoretical, focusing as it does on the theory of statistical inference. Over the next three chapters my goal is to give you an introduction to probability theory (Chapter 6), sampling and estimation (Chapter 7) and statistical hypothesis testing (Chapter 8). Before we get started though, I want to say something about the big picture. Statistical inference is primarily about *learning from data*. The goal is no longer merely to describe our data but to use the data to draw conclusions about the world. To motivate the discussion I want to spend a bit of time talking about a philosophical puzzle known as the *riddle of induction*, because it speaks to an issue that will pop up over and over again throughout the book: statistical inference relies on *assumptions*. This sounds like a bad thing. In everyday life people say things like “you should never make assumptions”, and psychology classes often talk about assumptions and biases as bad things that we should try to avoid. From bitter personal experience I have learned never to say such things around philosophers!

### On the limits of logical reasoning

*The whole art of war consists in getting at what is on the other side of the hill, or, in other words, in learning what we do not know from what we do.*

– Arthur Wellesley, 1st Duke of Wellington

I am told that quote above came about as a consequence of a carriage ride across the countryside.<sup>2</sup> He and his companion, J. W. Croker, were playing a guessing game, each trying to predict what would be on the other side of each hill. In every case it turned out that Wellesley was right and Croker was wrong. Many years later when Wellesley was asked about the game he explained that “the whole art of war consists in getting at what is on the other side of the hill”. Indeed, war is not special in this respect. All of life is a guessing game of one form or another, and getting by on a day to day basis requires us to make good guesses. So let’s play a guessing game of our own.

Suppose you and I are observing the Wellesley-Croker competition and after every three hills you and I have to predict who will win the next one, Wellesley or Croker. Let’s say that W refers to a Wellesley victory and C refers to a Croker victory. After three hills, our data set looks like this:

WWW

Our conversation goes like this:

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<sup>2</sup>Source: <http://www.bartleby.com/344/400.html>.

you: Three in a row doesn't mean much. I suppose Wellesley might be better at this than Croker, but it might just be luck. Still, I'm a bit of a gambler. I'll bet on Wellesley.

me: I agree that three in a row isn't informative and I see no reason to prefer Wellesley's guesses over Croker's. I can't justify betting at this stage. Sorry. No bet for me.

Your gamble paid off: three more hills go by and Wellesley wins all three. Going into the next round of our game the score is 1-0 in favour of you and our data set looks like this:

WWW WWW

I've organised the data into blocks of three so that you can see which batch corresponds to the observations that we had available at each step in our little side game. After seeing this new batch, our conversation continues:

you: Six wins in a row for Duke Wellesley. This is starting to feel a bit suspicious. I'm still not certain, but I reckon that he's going to win the next one too.

me: I guess I don't see that. Sure, I agree that Wellesley has won six in a row, but I don't see any logical reason why that means he'll win the seventh one. No bet.

you: Do you really think so? Fair enough, but my bet worked out last time and I'm okay with my choice.

For a second time you were right, and for a second time I was wrong. Wellesley wins the next three hills, extending his winning record against Croker to 9-0. The data set available to us is now this:

WWW WWW WWW

And our conversation goes like this:

you: Okay, this is pretty obvious. Wellesley is way better at this game. We both agree he's going to win the next hill, right?

me: Is there really any logical evidence for that? Before we started this game, there were lots of possibilities for the first 10 outcomes, and I had no idea which one to expect. WWW WWW WWW W was one possibility, but so was WCC CWC WWC C and WWW WWW WWW C or even CCC CCC CCC C. Because I had no idea what would happen so I'd have said they were all equally likely. I assume you would have too, right? I mean, that's what it *means* to say you have "no idea", isn't it?

you: I suppose so.

me: Well then, the observations we've made logically rule out all possibilities except two: WWW WWW WWW C or WWW WWW WWW W. Both of these are perfectly consistent with the evidence we've encountered so far, aren't they?

you: Yes, of course they are. Where are you going with this?

me: So what's changed then? At the start of our game, you'd have agreed with me that these are equally plausible and none of the evidence that we've encountered has discriminated between these two possibilities. Therefore, both of these possibilities remain equally plausible and I see no logical reason to prefer one over the other. So yes, while I agree with you that Wellesley's run of 9 wins in a row is remarkable, I can't think of a good reason to think he'll win the 10th hill. No bet.

you: I see your point, but I'm still willing to chance it. I'm betting on Wellesley.

Wellesley's winning streak continues for the next three hills. The score in the Wellesley-Crocker game is now 12-0, and the score in our game is now 3-0. As we approach the fourth round of our game, our data set is this:

WWW WWW WWW WWW

and the conversation continues:

you: Oh yeah! Three more wins for Wellesley and another victory for me. Admit it, I was right about him! I guess we're both betting on Wellesley this time around, right?

me: I don't know what to think. I feel like we're in the same situation we were in last round, and nothing much has changed. There are only two legitimate possibilities for a sequence of 13 hills that haven't already been ruled out, WWW WWW WWW WWW C and WWW WWW WWW WWW W. It's just like I said last time. If all possible outcomes were equally sensible before the game started, shouldn't these two be equally sensible now given that our observations don't rule out either one? I agree that it feels like Wellesley is on an amazing winning streak, but where's the logical evidence that the streak will continue?

you: I think you're being unreasonable. Why not take a look at *our* scorecard, if you need evidence? You're the expert on statistics and you've been using this fancy logical analysis, but the fact is you're losing. I'm just relying on common sense and I'm winning. Maybe you should switch strategies.

me: Hmm, that is a good point and I don't want to lose the game, but I'm afraid I don't see any logical evidence that your strategy is better than mine. It seems to me that if there were someone else watching our game, what they'd have observed is a run of three wins to you. Their data would look like this: YYY.

Logically, I don't see that this is any different to our first round of watching Wellesley and Croker. Three wins to you doesn't seem like a lot of evidence, and I see no reason to think that your strategy is working out any better than mine. If I didn't think that WWW was good evidence then for Wellesley being better than Croker at *their* game, surely I have no reason now to think that YYY is good evidence that you're better at *ours*?

you: Okay, now I think you're being a jerk.

me: I don't see the logical evidence for that.

### **Learning without making assumptions is a myth**

There are lots of different ways in which we could dissect this dialogue, but since this is a statistics book pitched at psychologists and not an introduction to the philosophy and psychology of reasoning, I'll keep it brief. What I've described above is sometimes referred to as the riddle of induction. It seems entirely *reasonable* to think that a 12-0 winning record by Wellesley is pretty strong evidence that he will win the 13th game, but it is not easy to provide a proper logical justification for this belief. On the contrary, despite the *obviousness* of the answer, it's not actually possible to justify betting on Wellesley without relying on some assumption that you don't have any logical justification for.

The riddle of induction is most associated with the philosophical work of David Hume and more recently Nelson Goodman, but you can find examples of the problem popping up in fields as diverse as literature (Lewis Carroll) and machine learning (the "no free lunch" theorem). There really is something weird about trying to "learn what we do not know from what we do know". The critical point is that assumptions and biases are unavoidable if you want to learn anything about the world. There is no escape from this, and it is just as true for statistical inference as it is for human reasoning. In the dialogue I was taking aim at your perfectly sensible inferences as a human being, but the common sense reasoning that you relied on is no different to what a statistician would have done. Your "common sense" half of the dialog relied on an implicit *assumption* that there exists some difference in skill between Wellesley and Croker, and what you were doing was trying to work out what that difference in skill level would be. My "logical analysis" rejects that assumption entirely. All I was willing to accept is that there are sequences of wins and losses and that I did not know which sequences would be observed. Throughout the dialogue I kept insisting that all logically possible data sets were equally plausible at the start of the Wellesley-Croker game, and the only way in which I ever revised my beliefs was to eliminate those possibilities that were factually inconsistent with the observations.

That sounds perfectly sensible on its own terms. In fact, it even sounds like the hallmark of good deductive reasoning. Like Sherlock Holmes, my approach was to rule out that which is impossible in the hope that what would be left is the truth. Yet as we saw, ruling out the impossible *never* led me to make a prediction. On its own terms everything I said in my half of the dialogue was entirely correct. An inability to make any predictions is the logical consequence of making "no assumptions". In the end I lost our game because you did make some assumptions and those assumptions turned out to

be right. Skill is a real thing, and because you believed in the existence of skill you were able to learn that Wellesley had more of it than Croker. Had you relied on a less sensible assumption to drive your learning you might not have won the game.

Ultimately there are two things you should take away from this. First, as I've said, you cannot avoid making assumptions if you want to learn anything from your data. But second, once you realise that assumptions are necessary it becomes important to make sure you *make the right ones!* A data analysis that relies on few assumptions is not necessarily better than one that makes many assumptions, it all depends on whether those assumptions are good ones for your data. As we go through the rest of this book I'll often point out the assumptions that underpin a particular statistical technique, and how you can check whether those assumptions are sensible.



## 6. Introduction to probability

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*[God] has afforded us only the twilight . . . of Probability.*

– John Locke

Up to this point in the book we've discussed some of the key ideas in experimental design, and we've talked a little about how you can summarise a data set. To a lot of people this is all there is to statistics: collecting all the numbers, calculating averages, drawing pictures, and putting them all in a report somewhere. Kind of like stamp collecting but with numbers. However, statistics covers much more than that. In fact, descriptive statistics is one of the smallest parts of statistics and one of the least powerful. The bigger and more useful part of statistics is that it provides information that lets you make inferences about data.

Once you start thinking about statistics in these terms, that statistics is there to help us draw inferences from data, you start seeing examples of it everywhere. For instance, here's a tiny extract from a newspaper article in the Sydney Morning Herald (30 Oct 2010):

"I have a tough job," the Premier said in response to a poll which found her government is now the most unpopular Labor administration in polling history, with a primary vote of just 23 per cent.

This kind of remark is entirely unremarkable in the papers or in everyday life, but let's have a think about what it entails. A polling company has conducted a survey, usually a pretty big one because they can afford it. I'm too lazy to track down the original survey so let's just imagine that they called 1000 New South Wales (NSW) voters at random, and 230 (23%) of those claimed that they intended to vote for the Australian Labor Party (ALP). For the 2010 Federal election the Australian Electoral Commission reported 4,610,795 enrolled voters in NSW, so the opinions of the remaining 4,609,795 voters (about 99.98% of voters) remain unknown to us. Even assuming that no-one lied to the polling company the only thing we can say with 100% confidence is that the true ALP primary vote is somewhere between  $230/4610795$  (about 0.005%) and  $4610025/4610795$  (about 99.83%). So, on what basis is it legitimate for the polling company, the newspaper, and the readership to conclude that the ALP primary vote is only about 23%?

The answer to the question is pretty obvious. If I call 1000 people at random, and 230 of them say they intend to vote for the ALP, then it seems very unlikely that these are the *only* 230 people

out of the entire voting public who actually intend to vote ALP. In other words, we assume that the data collected by the polling company is pretty representative of the population at large. But how representative? Would we be surprised to discover that the true ALP primary vote is actually 24%? 29%? 37%? At this point everyday intuition starts to break down a bit. No-one would be surprised by 24%, and everybody would be surprised by 37%, but it's a bit hard to say whether 29% is plausible. We need some more powerful tools than just looking at the numbers and guessing.

**Inferential statistics** provides the tools that we need to answer these sorts of questions, and since these kinds of questions lie at the heart of the scientific enterprise, they take up the lions share of every introductory course on statistics and research methods. However, the theory of statistical inference is built on top of **probability theory**. And it is to probability theory that we must now turn. This discussion of probability theory is basically background detail. There's not a lot of statistics per se in this chapter, and you don't need to understand this material in as much depth as the other chapters in this part of the book. Nevertheless, because probability theory does underpin so much of statistics, it's worth covering some of the basics.

## 6.1

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### How are probability and statistics different?

Before we start talking about probability theory, it's helpful to spend a moment thinking about the relationship between probability and statistics. The two disciplines are closely related but they're not identical. Probability theory is "the doctrine of chances". It's a branch of mathematics that tells you how often different kinds of events will happen. For example, all of these questions are things you can answer using probability theory:

- What are the chances of a fair coin coming up heads 10 times in a row?
- If I roll a six sided dice twice, how likely is it that I'll roll two sixes?
- How likely is it that five cards drawn from a perfectly shuffled deck will all be hearts?
- What are the chances that I'll win the lottery?

Notice that all of these questions have something in common. In each case the "truth of the world" is known and my question relates to the "what kind of events" will happen. In the first question I *know* that the coin is fair so there's a 50% chance that any individual coin flip will come up heads. In the second question I *know* that the chance of rolling a 6 on a single die is 1 in 6. In the third question I *know* that the deck is shuffled properly. And in the fourth question I *know* that the lottery follows specific rules. You get the idea. The critical point is that probabilistic questions start with a known **model** of the world, and we use that model to do some calculations. The underlying model can be quite simple. For instance, in the coin flipping example we can write down the model like this:

$$P(\text{heads}) = 0.5$$

which you can read as “the probability of heads is 0.5”. As we’ll see later, in the same way that percentages are numbers that range from 0% to 100%, probabilities are just numbers that range from 0 to 1. When using this probability model to answer the first question I don’t actually know exactly what’s going to happen. Maybe I’ll get 10 heads, like the question says. But maybe I’ll get three heads. That’s the key thing. In probability theory the *model* is known but the *data* are not.

So that’s probability. What about statistics? Statistical questions work the other way around. In statistics we do not know the truth about the world. All we have is the data and it is from the data that we want to *learn* the truth about the world. Statistical questions tend to look more like these:

- If my friend flips a coin 10 times and gets 10 heads are they playing a trick on me?
- If five cards off the top of the deck are all hearts how likely is it that the deck was shuffled?
- If the lottery commissioner’s spouse wins the lottery how likely is it that the lottery was rigged?

This time around the only thing we have are data. What I *know* is that I saw my friend flip the coin 10 times and it came up heads every time. And what I want to **infer** is whether or not I should conclude that what I just saw was actually a fair coin being flipped 10 times in a row, or whether I should suspect that my friend is playing a trick on me. The data I have look like this:

H H H H H H H H H H

and what I’m trying to do is work out which “model of the world” I should put my trust in. If the coin is fair then the model I should adopt is one that says that the probability of heads is 0.5, that is  $P(\text{heads}) = 0.5$ . If the coin is not fair then I should conclude that the probability of heads is *not* 0.5, which we would write as  $P(\text{heads}) \neq 0.5$ . In other words, the statistical inference problem is to figure out which of these probability models is right. Clearly, the statistical question isn’t the same as the probability question, but they’re deeply connected to one another. Because of this, a good introduction to statistical theory will start with a discussion of what probability is and how it works.

## 6.2

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### **What does probability mean?**

Let’s start with the first of these questions. What is “probability”? It might seem surprising to you but while statisticians and mathematicians (mostly) agree on what the *rules* of probability are, there’s much less of a consensus on what the word really *means*. It seems weird because we’re all very comfortable using words like “chance”, “likely”, “possible” and “probable”, and it doesn’t seem like it should be a very difficult question to answer. But if you’ve ever had that experience in real life you might walk away from the conversation feeling like you didn’t quite get it right, and that (like many everyday concepts) it turns out that you don’t *really* know what it’s all about.

So I’ll have a go at it. Let’s suppose I want to bet on a soccer game between two teams of robots, *Arduino Arsenal* and *C Milan*. After thinking about it, I decide that there is an 80% probability of *Arduino Arsenal* winning. What do I mean by that? Here are three possibilities:

- They're robot teams so I can make them play over and over again, and if I did that *Arduino Arsenal* would win 8 out of every 10 games on average.
- For any given game, I would agree that betting on this game is only "fair" if a \$1 bet on *C Milan* gives a \$5 payoff (i.e. I get my \$1 back plus a \$4 reward for being correct), as would a \$4 bet on *Arduino Arsenal* (i.e., my \$4 bet plus a \$1 reward).
- My subjective "belief" or "confidence" in an *Arduino Arsenal* victory is four times as strong as my belief in a *C Milan* victory.

Each of these seems sensible. However, they're not identical and not every statistician would endorse all of them. The reason is that there are different statistical ideologies (yes, really!) and depending on which one you subscribe to, you might say that some of those statements are meaningless or irrelevant. In this section I give a brief introduction the two main approaches that exist in the literature. These are by no means the only approaches, but they're the two big ones.

### 6.2.1 The frequentist view

The first of the two major approaches to probability, and the more dominant one in statistics, is referred to as the **frequentist view** and it defines probability as a **long-run frequency**. Suppose we were to try flipping a fair coin over and over again. By definition this is a coin that has  $P(H) = 0.5$ . What might we observe? One possibility is that the first 20 flips might look like this:

T, H, H, H, H, T, T, H, H, H, H, T, H, H, T, T, T, T, T, H

In this case 11 of these 20 coin flips (55%) came up heads. Now suppose that I'd been keeping a running tally of the number of heads (which I'll call  $N_H$ ) that I've seen, across the first  $N$  flips, and calculate the proportion of heads  $N_H/N$  every time. Here's what I'd get (I did literally flip coins to produce this!):

number of flips	1	2	3	4	5	6	7	8	9	10
number of heads	0	1	2	3	4	4	4	5	6	7
proportion	.00	.50	.67	.75	.80	.67	.57	.63	.67	.70
number of flips	11	12	13	14	15	16	17	18	19	20
number of heads	8	8	9	10	10	10	10	10	10	11
proportion	.73	.67	.69	.71	.67	.63	.59	.56	.53	.55

Notice that at the start of the sequence the *proportion* of heads fluctuates wildly, starting at .00 and rising as high as .80. Later on, one gets the impression that it dampens out a bit, with more and more of the values actually being pretty close to the "right" answer of .50. This is the frequentist definition of probability in a nutshell. Flip a fair coin over and over again, and as  $N$  grows large

(approaches infinity, denoted  $N \rightarrow \infty$ ) the proportion of heads will converge to 50%. There are some subtle technicalities that the mathematicians care about, but qualitatively speaking that's how the frequentists define probability. Unfortunately, I don't have an infinite number of coins or the infinite patience required to flip a coin an infinite number of times. However, I do have a computer and computers excel at mindless repetitive tasks. So I asked my computer to simulate flipping a coin 1000 times and then drew a picture of what happens to the proportion  $N_H/N$  as  $N$  increases. Actually, I did it four times just to make sure it wasn't a fluke. The results are shown in Figure 6.1. As you can see, the *proportion of observed heads* eventually stops fluctuating and settles down. When it does, the number at which it finally settles is the true probability of heads.

The frequentist definition of probability has some desirable characteristics. First, it is objective. The probability of an event is *necessarily* grounded in the world. The only way that probability statements can make sense is if they refer to (a sequence of) events that occur in the physical universe.<sup>1</sup> Secondly, it is unambiguous. Any two people watching the same sequence of events unfold, trying to calculate the probability of an event, must inevitably come up with the same answer.

However, it also has undesirable characteristics. First, infinite sequences don't exist in the physical world. Suppose you picked up a coin from your pocket and started to flip it. Every time it lands it impacts on the ground. Each impact wears the coin down a bit. Eventually the coin will be destroyed. So, one might ask whether it really makes sense to pretend that an "infinite" sequence of coin flips is even a meaningful concept, or an objective one. We can't say that an "infinite sequence" of events is a real thing in the physical universe, because the physical universe doesn't allow infinite anything. More seriously, the frequentist definition has a narrow scope. There are lots of things out there that human beings are happy to assign probability to in everyday language, but cannot (even in theory) be mapped onto a hypothetical sequence of events. For instance, if a meteorologist comes on TV and says "the probability of rain in Adelaide on 2 November 2048 is 60%" we humans are happy to accept this. But it's not clear how to define this in frequentist terms. There's only one city of Adelaide, and only one 2 November 2048. There's no infinite sequence of events here, just a one-off thing. Frequentist probability genuinely *forbids* us from making probability statements about a single event. From the frequentist perspective it will either rain tomorrow or it will not. There is no "probability" that attaches to a single non-repeatable event. Now, it should be said that there are some very clever tricks that frequentists can use to get around this. One possibility is that what the meteorologist means is something like "There is a category of days for which I predict a 60% chance of rain, and if we look only across those days for which I make this prediction, then on 60% of those days it will actually rain". It's very weird and counterintuitive to think of it this way, but you do see frequentists do this sometimes. And it *will* come up later in this book (see Section 7.5).

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<sup>1</sup>This doesn't mean that frequentists can't make hypothetical statements, of course. It's just that if you want to make a statement about probability then it must be possible to redescribe that statement in terms of a sequence of potentially observable events, together with the relative frequencies of different outcomes that appear within that sequence.

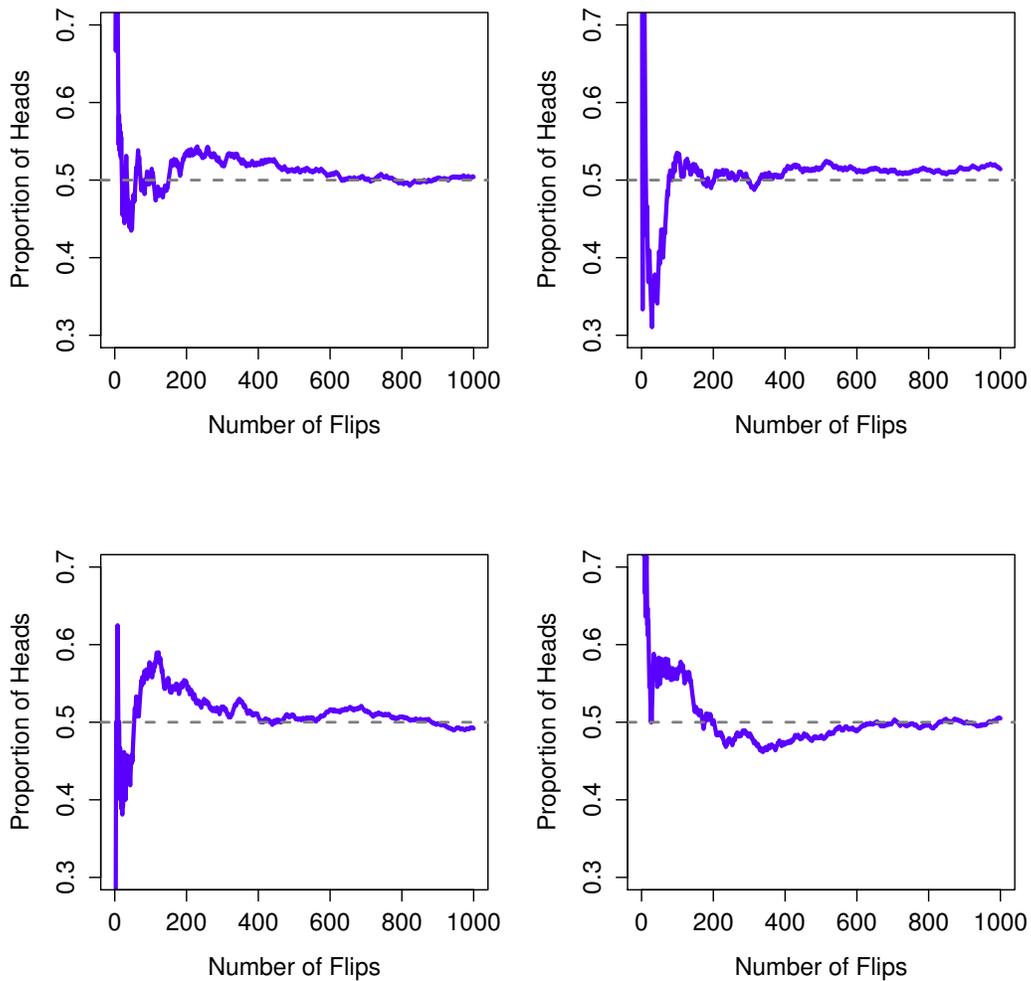


Figure 6.1: An illustration of how frequentist probability works. If you flip a fair coin over and over again the proportion of heads that you've seen eventually settles down and converges to the true probability of 0.5. Each panel shows four different simulated experiments. In each case we pretend we flipped a coin 1000 times and kept track of the proportion of flips that were heads as we went along. Although none of these sequences actually ended up with an exact value of .5, if we'd extended the experiment for an infinite number of coin flips they would have.

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### 6.2.2 The Bayesian view

The **Bayesian view** of probability is often called the subjectivist view, and although it has been a minority view among statisticians it has been steadily gaining traction for the last several decades. There are many flavours of Bayesianism, making it hard to say exactly what “the” Bayesian view is. The most common way of thinking about subjective probability is to define the probability of an event as the **degree of belief** that an intelligent and rational agent assigns to that truth of that event. From that perspective, probabilities don’t exist in the world but rather in the thoughts and assumptions of people and other intelligent beings.

However, in order for this approach to work we need some way of operationalising “degree of belief”. One way that you can do this is to formalise it in terms of “rational gambling”, though there are many other ways. Suppose that I believe that there’s a 60% probability of rain tomorrow. If someone offers me a bet that if it rains tomorrow then I win \$5, but if it doesn’t rain I lose \$5. Clearly, from my perspective, this is a pretty good bet. On the other hand, if I think that the probability of rain is only 40% then it’s a bad bet to take. So we can operationalise the notion of a “subjective probability” in terms of what bets I’m willing to accept.

What are the advantages and disadvantages to the Bayesian approach? The main advantage is that it allows you to assign probabilities to any event you want to. You don’t need to be limited to those events that are repeatable. The main disadvantage (to many people) is that we can’t be purely objective. Specifying a probability requires us to specify an entity that has the relevant degree of belief. This entity might be a human, an alien, a robot, or even a statistician. But there has to be an intelligent agent out there that believes in things. To many people this is uncomfortable, it seems to make probability arbitrary. Whilst the Bayesian approach requires that the agent in question be rational (i.e., obey the rules of probability), it does allow everyone to have their own beliefs. I can believe the coin is fair and you don’t have to, even though we’re both rational. The frequentist view doesn’t allow any two observers to attribute different probabilities to the same event. When that happens then at least one of them must be wrong. The Bayesian view does not prevent this from occurring. Two observers with different background knowledge can legitimately hold different beliefs about the same event. In short, where the frequentist view is sometimes considered to be too narrow (forbids lots of things that that we want to assign probabilities to), the Bayesian view is sometimes thought to be too broad (allows too many differences between observers).

### 6.2.3 What’s the difference? And who is right?

Now that you’ve seen each of these two views independently it’s useful to make sure you can compare the two. Go back to the hypothetical robot soccer game at the start of the section. What do you think a frequentist and a Bayesian would say about these three statements? Which statement would a frequentist say is the correct definition of probability? Which one would a Bayesian opt for? Would some of these statements be meaningless to a frequentist or a Bayesian? If you’ve understood the two perspectives you should have some sense of how to answer those questions.

Okay, assuming you understand the difference then you might be wondering which of them is

*right?* Honestly, I don't know that there is a right answer. As far as I can tell there's nothing mathematically incorrect about the way frequentists think about sequences of events, and there's nothing mathematically incorrect about the way that Bayesians define the beliefs of a rational agent. In fact, when you dig down into the details Bayesians and frequentists actually agree about a lot of things. Many frequentist methods lead to decisions that Bayesians agree a rational agent would make. Many Bayesian methods have very good frequentist properties.

For the most part, I'm a pragmatist so I'll use any statistical method that I trust. As it turns out, that makes me prefer Bayesian methods for reasons I'll explain towards the end of the book. But I'm not fundamentally opposed to frequentist methods. Not everyone is quite so relaxed. For instance, consider Sir Ronald Fisher, one of the towering figures of 20th century statistics and a vehement opponent to all things Bayesian, whose paper on the mathematical foundations of statistics referred to Bayesian probability as "an impenetrable jungle [that] arrests progress towards precision of statistical concepts" (Fisher 1922b, p. 311). Or the psychologist Paul Meehl, who suggests that relying on frequentist methods could turn you into "a potent but sterile intellectual rake who leaves in his merry path a long train of ravished maidens but no viable scientific offspring" (Meehl 1967, p. 114). The history of statistics, as you might gather, is not devoid of entertainment.

In any case, whilst I personally prefer the Bayesian view, the majority of statistical analyses are based on the frequentist approach. My reasoning is pragmatic. The goal of this book is to cover roughly the same territory as a typical undergraduate stats class in psychology, and if you want to understand the statistical tools used by most psychologists you'll need a good grasp of frequentist methods. I promise you that this isn't wasted effort. Even if you end up wanting to switch to the Bayesian perspective, you really should read through at least one book on the "orthodox" frequentist view. Besides, I won't completely ignore the Bayesian perspective. Every now and then I'll add some commentary from a Bayesian point of view, and I'll revisit the topic in more depth in Chapter 14.

## 6.3

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### **Basic probability theory**

Ideological arguments between Bayesians and frequentists notwithstanding, it turns out that people mostly agree on the rules that probabilities should obey. There are lots of different ways of arriving at these rules. The most commonly used approach is based on the work of Andrey Kolmogorov, one of the great Soviet mathematicians of the 20th century. I won't go into a lot of detail, but I'll try to give you a bit of a sense of how it works. And in order to do so I'm going to have to talk about my trousers.

#### **6.3.1 Introducing probability distributions**

One of the disturbing truths about my life is that I only own 5 pairs of trousers. Three pairs of jeans, the bottom half of a suit, and a pair of tracksuit pants. Even sadder, I've given them names: I call

them  $X_1$ ,  $X_2$ ,  $X_3$ ,  $X_4$  and  $X_5$ . I really have, that's why they call me Mister Imaginative. Now, on any given day, I pick out exactly one of pair of trousers to wear. Not even I'm so silly as to try to wear two pairs of trousers, and thanks to years of training I never go outside without wearing trousers anymore. If I were to describe this situation using the language of probability theory, I would refer to each pair of trousers (i.e., each  $X$ ) as an **elementary event**. The key characteristic of elementary events is that every time we make an observation (e.g., every time I put on a pair of trousers) then the outcome will be one and only one of these events. Like I said, these days I always wear exactly one pair of trousers so my trousers satisfy this constraint. Similarly, the set of all possible events is called a **sample space**. Granted, some people would call it a "wardrobe", but that's because they're refusing to think about my trousers in probabilistic terms. Sad.

Okay, now that we have a sample space (a wardrobe), which is built from lots of possible elementary events (trousers), what we want to do is assign a **probability** of one of these elementary events. For an event  $X$ , the probability of that event  $P(X)$  is a number that lies between 0 and 1. The bigger the value of  $P(X)$ , the more likely the event is to occur. So, for example, if  $P(X) = 0$  it means the event  $X$  is impossible (i.e., I never wear those trousers). On the other hand, if  $P(X) = 1$  it means that event  $X$  is certain to occur (i.e., I always wear those trousers). For probability values in the middle it means that I sometimes wear those trousers. For instance, if  $P(X) = 0.5$  it means that I wear those trousers half of the time.

At this point, we're almost done. The last thing we need to recognise is that "something always happens". Every time I put on trousers, I really do end up wearing trousers (crazy, right?). What this somewhat trite statement means, in probabilistic terms, is that the probabilities of the elementary events need to add up to 1. This is known as the **law of total probability**, not that any of us really care. More importantly, if these requirements are satisfied then what we have is a **probability distribution**. For example, this is an example of a probability distribution:

Which trousers?	Label	Probability
Blue jeans	$X_1$	$P(X_1) = .5$
Grey jeans	$X_2$	$P(X_2) = .3$
Black jeans	$X_3$	$P(X_3) = .1$
Black suit	$X_4$	$P(X_4) = 0$
Blue tracksuit	$X_5$	$P(X_5) = .1$

Each of the events has a probability that lies between 0 and 1, and if we add up the probability of all events they sum to 1. Awesome. We can even draw a nice bar graph to visualise this distribution, as shown in Figure 6.2. And, at this point, we've all achieved something. You've learned what a probability distribution is, and I've finally managed to find a way to create a graph that focuses entirely on my trousers. Everyone wins!

The only other thing that I need to point out is that probability theory allows you to talk about **non elementary events** as well as elementary ones. The easiest way to illustrate the concept is with an example. In the trousers example it's perfectly legitimate to refer to the probability that I wear jeans. In this scenario, the "Dan wears jeans" event is said to have happened as long as the elementary event that actually did occur is one of the appropriate ones. In this case "blue jeans", "black jeans"

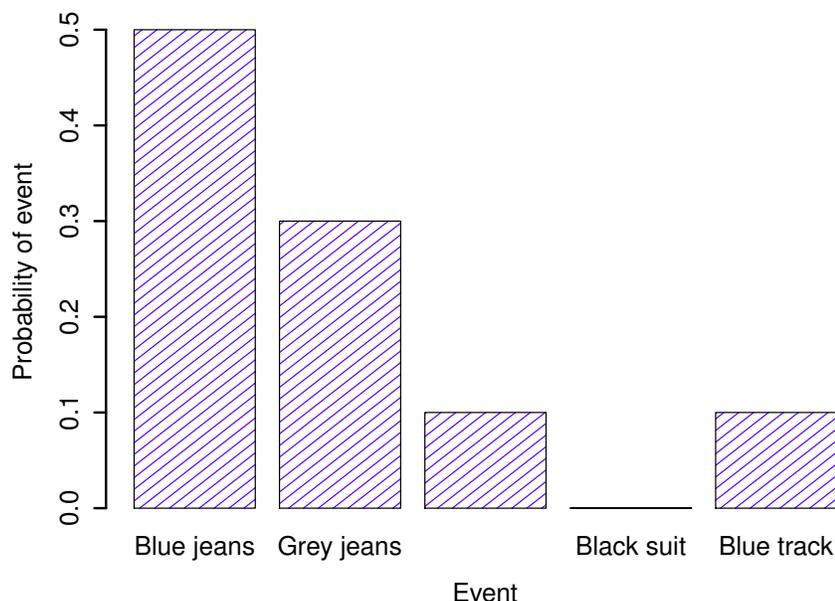


Figure 6.2: A visual depiction of the “trousers” probability distribution. There are five “elementary events”, corresponding to the five pairs of trousers that I own. Each event has some probability of occurring: this probability is a number between 0 to 1. The sum of these probabilities is 1.

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or “grey jeans”. In mathematical terms we defined the “jeans” event  $E$  to correspond to the set of elementary events  $(X_1, X_2, X_3)$ . If any of these elementary events occurs then  $E$  is also said to have occurred. Having decided to write down the definition of the  $E$  this way, it’s pretty straightforward to state what the probability  $P(E)$  is: we just add everything up. In this particular case

$$P(E) = P(X_1) + P(X_2) + P(X_3)$$

and, since the probabilities of blue, grey and black jeans respectively are .5, .3 and .1, the probability that I wear jeans is equal to .9.

At this point you might be thinking that this is all terribly obvious and simple and you’d be right. All we’ve really done is wrap some basic mathematics around a few common sense intuitions. However, from these simple beginnings it’s possible to construct some extremely powerful mathematical tools. I’m definitely not going to go into the details in this book, but what I will do is list, in Table 6.1, some of the other rules that probabilities satisfy. These rules can be derived from the simple assumptions that I’ve outlined above, but since we don’t actually use these rules for anything in this book I won’t do so here.

Table 6.1: Some basic rules that probabilities must satisfy. You don't really need to know these rules in order to understand the analyses that we'll talk about later in the book, but they are important if you want to understand probability theory a bit more deeply.

English	Notation	Formula
not $A$	$P(\neg A)$	$= 1 - P(A)$
$A$ or $B$	$P(A \cup B)$	$= P(A) + P(B) - P(A \cap B)$
$A$ and $B$	$P(A \cap B)$	$= P(A B)P(B)$

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## 6.4

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### The binomial distribution

As you might imagine, probability distributions vary enormously and there's an enormous range of distributions out there. However, they aren't all equally important. In fact, the vast majority of the content in this book relies on one of five distributions: the binomial distribution, the normal distribution, the  $t$  distribution, the  $\chi^2$  ("chi-square") distribution and the  $F$  distribution. Given this, what I'll do over the next few sections is provide a brief introduction to all five of these, paying special attention to the binomial and the normal. I'll start with the binomial distribution since it's the simplest of the five.

#### 6.4.1 Introducing the binomial

The theory of probability originated in the attempt to describe how games of chance work, so it seems fitting that our discussion of the **binomial distribution** should involve a discussion of rolling dice and flipping coins. Let's imagine a simple "experiment". In my hot little hand I'm holding 20 identical six-sided dice. On one face of each die there's a picture of a skull, the other five faces are all blank. If I proceed to roll all 20 dice, what's the probability that I'll get exactly 4 skulls? Assuming that the dice are fair, we know that the chance of any one die coming up skulls is 1 in 6. To say this another way, the skull probability for a single die is approximately .167. This is enough information to answer our question, so let's have a look at how it's done.

As usual, we'll want to introduce some names and some notation. We'll let  $N$  denote the number of dice rolls in our experiment, which is often referred to as the **size parameter** of our binomial distribution. We'll also use  $\theta$  to refer to the the probability that a single die comes up skulls, a

Table 6.2: Formulas for the binomial and normal distributions. We don't really use these formulas for anything in this book, but they're pretty important for more advanced work, so I thought it might be best to put them here in a table, where they can't get in the way of the text. In the equation for the binomial,  $X!$  is the factorial function (i.e., multiply all whole numbers from 1 to  $X$ ), and for the normal distribution "exp" refers to the exponential function. If these equations don't make a lot of sense to you, don't worry too much about them.

Binomial	Normal
$P(X   \theta, N) = \frac{N!}{X!(N-X)!} \theta^X (1-\theta)^{N-X}$	$p(X   \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(X-\mu)^2}{2\sigma^2}\right)$

quantity that is usually called the **success probability** of the binomial.<sup>2</sup> Finally, we'll use  $X$  to refer to the results of our experiment, namely the number of skulls I get when I roll the dice. Since the actual value of  $X$  is due to chance we refer to it as a **random variable**. In any case, now that we have all this terminology and notation we can use it to state the problem a little more precisely. The quantity that we want to calculate is the probability that  $X = 4$  given that we know that  $\theta = .167$  and  $N = 20$ . The general "form" of the thing I'm interested in calculating could be written as

$$P(X | \theta, N)$$

and we're interested in the special case where  $X = 4$ ,  $\theta = .167$  and  $N = 20$ . There's only one more piece of notation I want to refer to before moving on to discuss the solution to the problem. If I want to say that  $X$  is generated randomly from a binomial distribution with parameters  $\theta$  and  $N$ , the notation I would use is as follows:

$$X \sim \text{Binomial}(\theta, N)$$

Yeah, yeah. I know what you're thinking: notation, notation, notation. Really, who cares? Very few readers of this book are here for the notation, so I should probably move on and talk about how to use the binomial distribution. I've included the formula for the binomial distribution in Table 6.2, since some readers may want to play with it themselves, but since most people probably don't care that much and because we don't need the formula in this book, I won't talk about it in any detail. Instead, I just want to show you what the binomial distribution looks like.

To that end, Figure 6.3 plots the binomial probabilities for all possible values of  $X$  for our dice rolling experiment, from  $X = 0$  (no skulls) all the way up to  $X = 20$  (all skulls). Note that this is basically a bar chart, and is no different to the "trousers probability" plot I drew in Figure 6.2. On the horizontal axis we have all the possible events, and on the vertical axis we can read off the probability of each of those events. So, the probability of rolling 4 skulls out of 20 is about 0.20 (the actual

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<sup>2</sup>Note that the term "success" is pretty arbitrary and doesn't actually imply that the outcome is something to be desired. If  $\theta$  referred to the probability that any one passenger gets injured in a bus crash I'd still call it the success probability, but that doesn't mean I want people to get hurt in bus crashes!

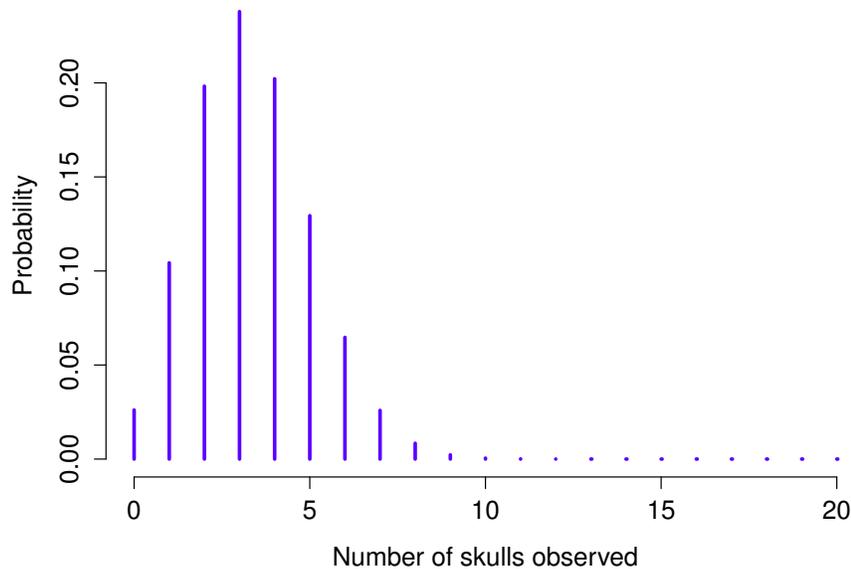


Figure 6.3: The binomial distribution with size parameter of  $N = 20$  and an underlying success probability of  $\theta = 1/6$ . Each vertical bar depicts the probability of one specific outcome (i.e., one possible value of  $X$ ). Because this is a probability distribution, each of the probabilities must be a number between 0 and 1, and the heights of the bars must sum to 1 as well.

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answer is 0.2022036, as we'll see in a moment). In other words, you'd expect that to happen about 20% of the times you repeated this experiment.

To give you a feel for how the binomial distribution changes when we alter the values of  $\theta$  and  $N$ , let's suppose that instead of rolling dice I'm actually flipping coins. This time around, my experiment involves flipping a fair coin repeatedly and the outcome that I'm interested in is the number of heads that I observe. In this scenario, the success probability is now  $\theta = 1/2$ . Suppose I were to flip the coin  $N = 20$  times. In this example, I've changed the success probability but kept the size of the experiment the same. What does this do to our binomial distribution? Well, as Figure 6.4a shows, the main effect of this is to shift the whole distribution, as you'd expect. Okay, what if we flipped a coin  $N = 100$  times? Well, in that case we get Figure 6.4b. The distribution stays roughly in the middle but there's a bit more variability in the possible outcomes.

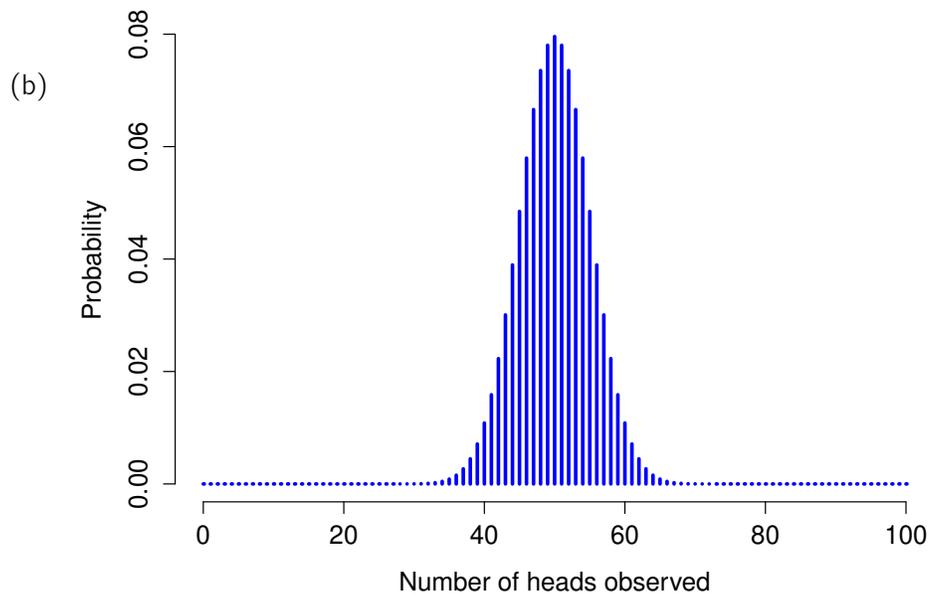
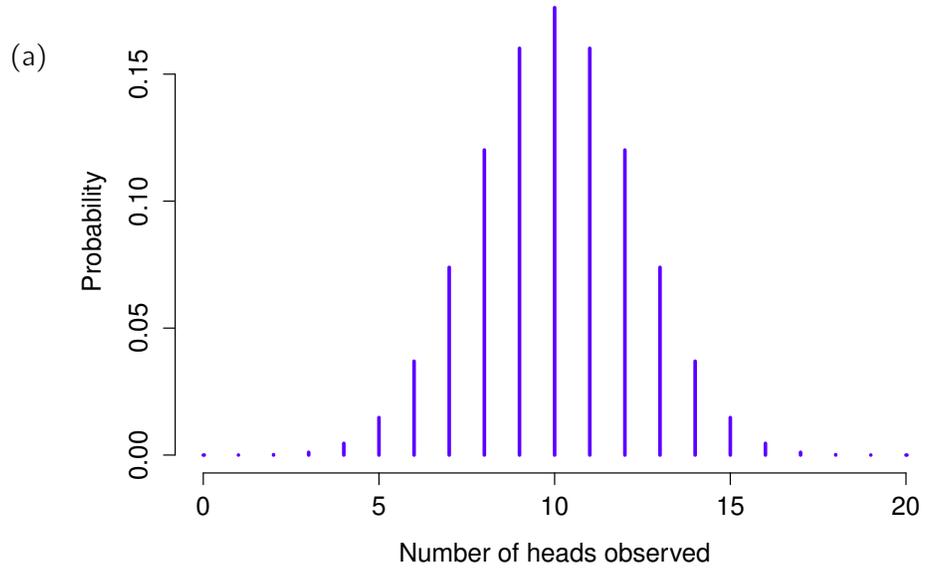


Figure 6.4: Two binomial distributions, involving a scenario in which I'm flipping a fair coin, so the underlying success probability is  $\theta = 1/2$ . In panel (a), we assume I'm flipping the coin  $N = 20$  times. In panel (b) we assume that the coin is flipped  $N = 100$  times.

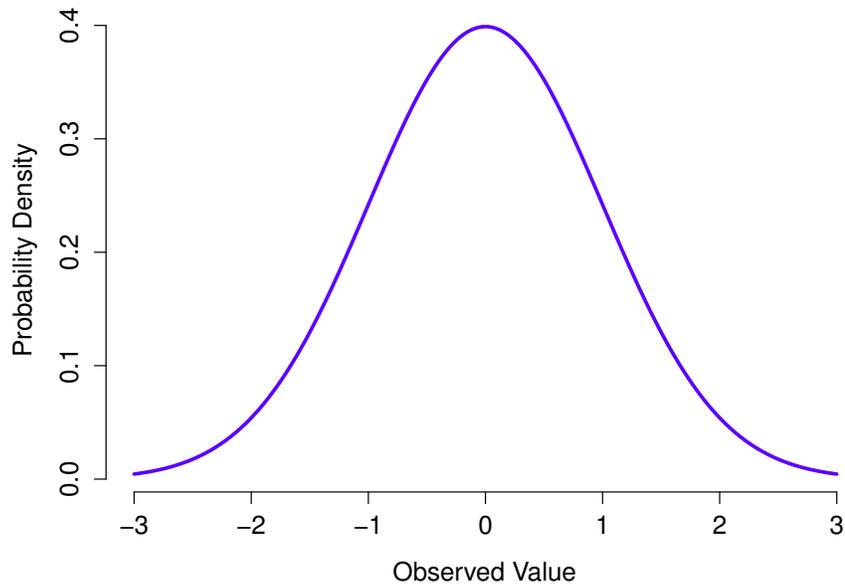


Figure 6.5: The normal distribution with mean  $\mu = 0$  and standard deviation  $\sigma = 1$ . The  $x$ -axis corresponds to the value of some variable, and the  $y$ -axis tells us something about how likely we are to observe that value. However, notice that the  $y$ -axis is labelled “Probability Density” and not “Probability”. There is a subtle and somewhat frustrating characteristic of continuous distributions that makes the  $y$  axis behave a bit oddly: the height of the curve here isn’t actually the probability of observing a particular  $x$  value. On the other hand, it *is* true that the heights of the curve tells you which  $x$  values are more likely (the higher ones!). (see Section 6.5.1 for all the annoying details)

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## 6.5

### The normal distribution

While the binomial distribution is conceptually the simplest distribution to understand, it’s not the most important one. That particular honour goes to the **normal distribution**, also referred to as “the bell curve” or a “Gaussian distribution”. A normal distribution is described using two parameters: the mean of the distribution  $\mu$  and the standard deviation of the distribution  $\sigma$ .

The notation that we sometimes use to say that a variable  $X$  is normally distributed is as follows:

$$X \sim \text{Normal}(\mu, \sigma)$$

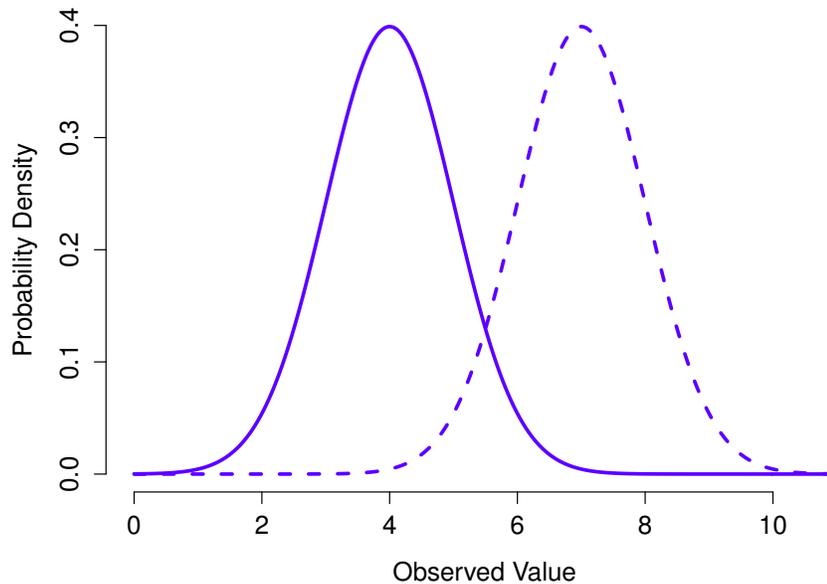


Figure 6.6: An illustration of what happens when you change the mean of a normal distribution. The solid line depicts a normal distribution with a mean of  $\mu = 4$ . The dashed line shows a normal distribution with a mean of  $\mu = 7$ . In both cases, the standard deviation is  $\sigma = 1$ . Not surprisingly, the two distributions have the same shape, but the dashed line is shifted to the right.

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Of course, that's just notation. It doesn't tell us anything interesting about the normal distribution itself. As was the case with the binomial distribution, I have included the formula for the normal distribution in this book, because I think it's important enough that everyone who learns statistics should at least look at it, but since this is an introductory text I don't want to focus on it, so I've tucked it away in Table 6.2.

Instead of focusing on the maths, let's try to get a sense for what it means for a variable to be normally distributed. To that end, have a look at Figure 6.5 which plots a normal distribution with mean  $\mu = 0$  and standard deviation  $\sigma = 1$ . You can see where the name "bell curve" comes from; it looks a bit like a bell. Notice that, unlike the plots that I drew to illustrate the binomial distribution, the picture of the normal distribution in Figure 6.5 shows a smooth curve instead of "histogram-like" bars. This isn't an arbitrary choice, the normal distribution is continuous whereas the binomial is discrete. For instance, in the die rolling example from the last section it was possible to get 3 skulls or 4 skulls, but impossible to get 3.9 skulls. The figures that I drew in the previous section reflected this fact. In Figure 6.3, for instance, there's a bar located at  $X = 3$  and another one at  $X = 4$  but

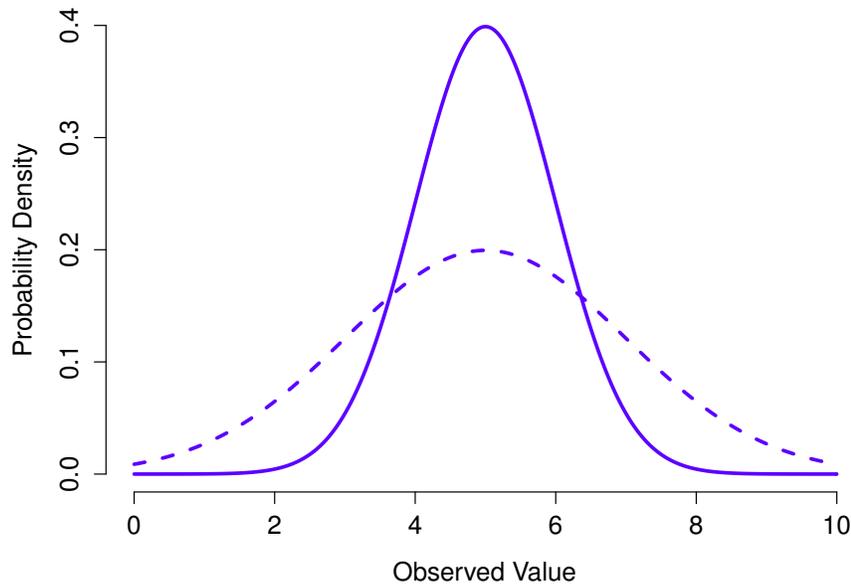


Figure 6.7: An illustration of what happens when you change the the standard deviation of a normal distribution. Both distributions plotted in this figure have a mean of  $\mu = 5$ , but they have different standard deviations. The solid line plots a distribution with standard deviation  $\sigma = 1$ , and the dashed line shows a distribution with standard deviation  $\sigma = 2$ . As a consequence, both distributions are “centred” on the same spot, but the dashed line is wider than the solid one.

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there’s nothing in between. Continuous quantities don’t have this constraint. For instance, suppose we’re talking about the weather. The temperature on a pleasant Spring day could be 23 degrees, 24 degrees, 23.9 degrees, or anything in between since temperature is a continuous variable. And so a normal distribution might be quite appropriate for describing Spring temperatures.<sup>3</sup>

With this in mind, let’s see if we can’t get an intuition for how the normal distribution works. First, let’s have a look at what happens when we play around with the parameters of the distribution. To that end, Figure 6.6 plots normal distributions that have different means but have the same standard deviation. As you might expect, all of these distributions have the same “width”. The only difference between them is that they’ve been shifted to the left or to the right. In every other respect they’re identical. In contrast, if we increase the standard deviation while keeping the mean constant, the

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<sup>3</sup>In practice, the normal distribution is so handy that people tend to use it even when the variable isn’t actually continuous. As long as there are enough categories (e.g., Likert scale responses to a questionnaire), it’s pretty standard practice to use the normal distribution as an approximation. This works out much better in practice than you’d think.

peak of the distribution stays in the same place but the distribution gets wider, as you can see in Figure 6.7. Notice, though, that when we widen the distribution the height of the peak shrinks. This has to happen, in the same way that the heights of the bars that we used to draw a discrete binomial distribution have to *sum* to 1, the total *area under the curve* for the normal distribution must equal 1. Before moving on, I want to point out one important characteristic of the normal distribution. Irrespective of what the actual mean and standard deviation are, 68.3% of the area falls within 1 standard deviation of the mean. Similarly, 95.4% of the distribution falls within 2 standard deviations of the mean, and 99.7% of the distribution is within 3 standard deviations. This idea is illustrated in Figure 6.8.

### 6.5.1 Probability density

There's something I've been trying to hide throughout my discussion of the normal distribution, something that some introductory textbooks omit completely. They might be right to do so. This "thing" that I'm hiding is weird and counter-intuitive even by the admittedly distorted standards that apply in statistics. Fortunately, it's not something that you need to understand at a deep level in order to do basic statistics. Rather, it's something that starts to become important later on when you move beyond the basics. So, if it doesn't make complete sense, don't worry too much, but try to make sure that you follow the gist of it.

Throughout my discussion of the normal distribution there's been one or two things that don't quite make sense. Perhaps you noticed that the  $y$ -axis in these figures is labelled "Probability Density" rather than density. Maybe you noticed that I used  $p(X)$  instead of  $P(X)$  when giving the formula for the normal distribution.

As it turns out, what is presented here isn't actually a probability, it's something else. To understand what that something is you have to spend a little time thinking about what it really *means* to say that  $X$  is a continuous variable. Let's say we're talking about the temperature outside. The thermometer tells me it's 23 degrees, but I know that's not really true. It's not *exactly* 23 degrees. Maybe it's 23.1 degrees, I think to myself. But I know that that's not really true either because it might actually be 23.09 degrees. But I know that... well, you get the idea. The tricky thing with genuinely continuous quantities is that you never really know exactly what they are.

Now think about what this implies when we talk about probabilities. Suppose that tomorrow's maximum temperature is sampled from a normal distribution with mean 23 and standard deviation 1. What's the probability that the temperature will be *exactly* 23 degrees? The answer is "zero", or possibly "a number so close to zero that it might as well be zero". Why is this? It's like trying to throw a dart at an infinitely small dart board. No matter how good your aim, you'll never hit it. In real life you'll never get a value of exactly 23. It'll always be something like 23.1 or 22.99998 or suchlike. In other words, it's completely meaningless to talk about the probability that the temperature is exactly

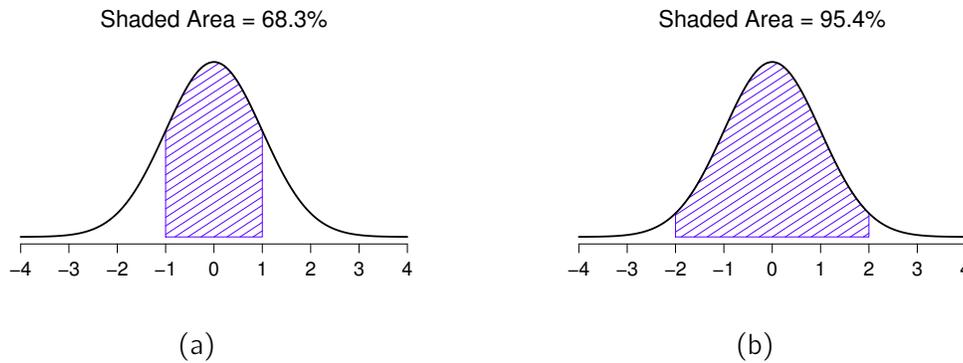


Figure 6.8: The area under the curve tells you the probability that an observation falls within a particular range. The solid lines plot normal distributions with mean  $\mu = 0$  and standard deviation  $\sigma = 1$ . The shaded areas illustrate “areas under the curve” for two important cases. In panel a, we can see that there is a 68.3% chance that an observation will fall within one standard deviation of the mean. In panel b, we see that there is a 95.4% chance that an observation will fall within two standard deviations of the mean.

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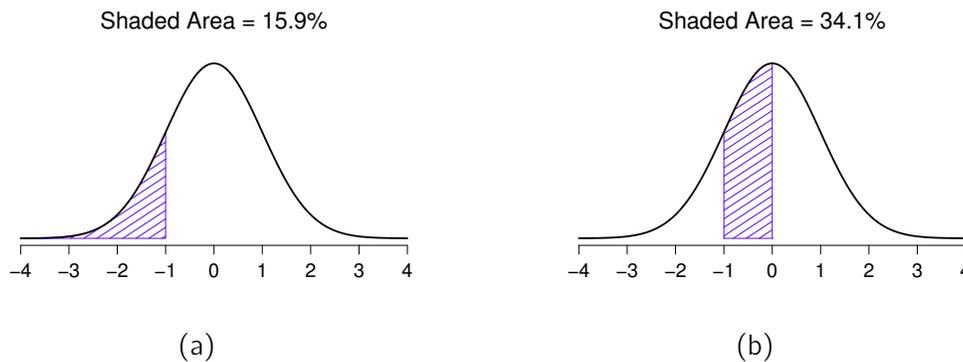


Figure 6.9: Two more examples of the “area under the curve idea”. There is a 15.9% chance that an observation is one standard deviation below the mean or smaller (panel a), and a 34.1% chance that the observation is somewhere between one standard deviation below the mean and the mean (panel b). Notice that if you add these two numbers together you get  $15.9\% + 34.1\% = 50\%$ . For normally distributed data, there is a 50% chance that an observation falls below the mean. And of course that also implies that there is a 50% chance that it falls above the mean.

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23 degrees. However, in everyday language if I told you that it was 23 degrees outside and it turned out to be 22.9998 degrees you probably wouldn't call me a liar. Because in everyday language "23 degrees" usually means something like "somewhere between 22.5 and 23.5 degrees". And while it doesn't feel very meaningful to ask about the probability that the temperature is exactly 23 degrees, it does seem sensible to ask about the probability that the temperature lies between 22.5 and 23.5, or between 20 and 30, or any other range of temperatures.

The point of this discussion is to make clear that when we're talking about continuous distributions it's not meaningful to talk about the probability of a specific value. However, what we *can* talk about is the probability that the value lies within a particular range of values. To find out the probability associated with a particular range what you need to do is calculate the "area under the curve". We've seen this concept already, in Figure 6.8 the shaded areas shown depict genuine probabilities (e.g., in Figure 6.8a it shows the probability of observing a value that falls within 1 standard deviation of the mean).

Okay, so that explains part of the story. I've explained a little bit about how continuous probability distributions should be interpreted (i.e., area under the curve is the key thing). But what does the formula for  $p(x)$  that I described earlier actually mean? Obviously,  $p(x)$  doesn't describe a probability, but what is it? The name for this quantity  $p(x)$  is a **probability density**, and in terms of the plots we've been drawing it corresponds to the *height* of the curve. The densities themselves aren't meaningful in and of themselves, but they're "rigged" to ensure that the *area* under the curve is always interpretable as genuine probabilities. To be honest, that's about as much as you really need to know for now.<sup>4</sup>

## 6.6

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### Other useful distributions

The normal distribution is the distribution that statistics makes most use of (for reasons to be discussed shortly), and the binomial distribution is a very useful one for lots of purposes. But the world of statistics is filled with probability distributions, some of which we'll run into in passing. In particular, the three that will appear in this book are the  $t$  distribution, the  $\chi^2$  distribution and the  $F$  distribution. I won't give formulas for any of these, or talk about them in too much detail, but I will show you some pictures.

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<sup>4</sup>For those readers who know a little calculus, I'll give a slightly more precise explanation. In the same way that probabilities are non-negative numbers that must sum to 1, probability densities are non-negative numbers that must integrate to 1 (where the integral is taken across all possible values of  $X$ ). To calculate the probability that  $X$  falls between  $a$  and  $b$  we calculate the definite integral of the density function over the corresponding range,  $\int_a^b p(x) dx$ . If you don't remember or never learned calculus, don't worry about this. It's not needed for this book.

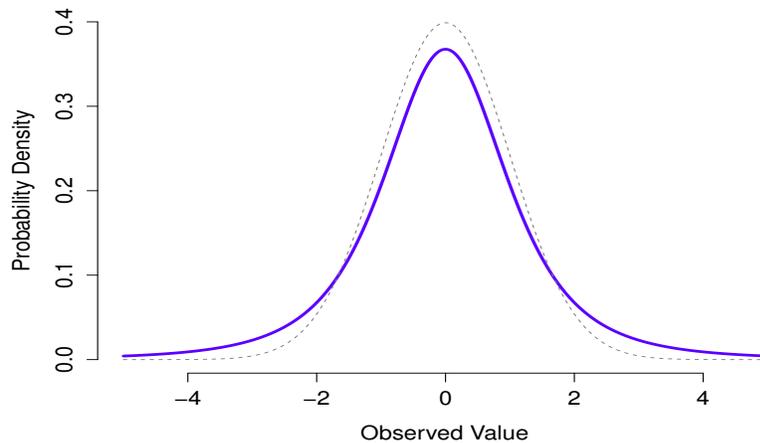


Figure 6.10: A  $t$  distribution with 3 degrees of freedom (solid line). It looks similar to a normal distribution, but it's not quite the same. For comparison purposes I've plotted a standard normal distribution as the dashed line.

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- The  **$t$  distribution** is a continuous distribution that looks very similar to a normal distribution, see Figure 6.10. Note that the “tails” of the  $t$  distribution are “heavier” (i.e., extend further outwards) than the tails of the normal distribution). That's the important difference between the two. This distribution tends to arise in situations where you think that the data actually follow a normal distribution, but you don't know the mean or standard deviation. We'll run into this distribution again in Chapter 10.
  - The  **$\chi^2$  distribution** is another distribution that turns up in lots of different places. The situation in which we'll see it is when doing categorical data analysis (Chapter 9), but it's one of those things that actually pops up all over the place. When you dig into the maths (and who doesn't love doing that?), it turns out that the main reason why the  $\chi^2$  distribution turns up all over the place is that if you have a bunch of variables that are normally distributed, square their values and then add them up (a procedure referred to as taking a “sum of squares”), this sum has a  $\chi^2$  distribution. You'd be amazed how often this fact turns out to be useful. Anyway, here's what a  $\chi^2$  distribution looks like: Figure 6.11.
  - The  **$F$  distribution** looks a bit like a  $\chi^2$  distribution, and it arises whenever you need to compare two  $\chi^2$  distributions to one another. Admittedly, this doesn't exactly sound like something that any sane person would want to do, but it turns out to be very important in real world data analysis. Remember when I said that  $\chi^2$  turns out to be the key distribution when we're taking a “sum of squares”? Well, what that means is if you want to compare two different “sums of

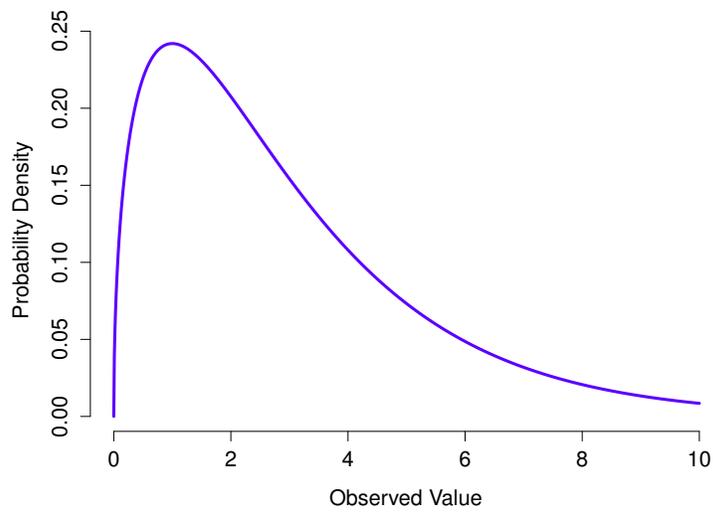


Figure 6.11: A  $\chi^2$  distribution with 3 degrees of freedom. Notice that the observed values must always be greater than zero, and that the distribution is pretty skewed. These are the key features of a chi-square distribution.

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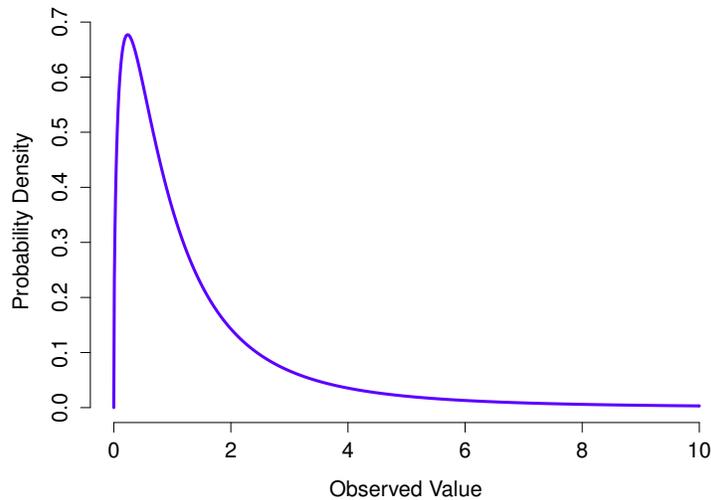


Figure 6.12: An  $F$  distribution with 3 and 5 degrees of freedom. Qualitatively speaking, it looks pretty similar to a chi-square distribution, but they're not quite the same in general.

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squares", you're probably talking about something that has an  $F$  distribution. Of course, as yet I still haven't given you an example of anything that involves a sum of squares, but I will in Chapter 12. And that's where we'll run into the  $F$  distribution. Oh, and there's a picture in Figure 6.12.

Okay, time to wrap this section up. We've seen three new distributions:  $\chi^2$ ,  $t$  and  $F$ . They're all continuous distributions, and they're all closely related to the normal distribution. The main thing for our purposes is that you grasp the basic idea that these distributions are all deeply related to one another, and to the normal distribution. Later on in this book we're going to run into data that are normally distributed, or at least assumed to be normally distributed. What I want you to understand right now is that, if you make the assumption that your data are normally distributed, you shouldn't be surprised to see  $\chi^2$ ,  $t$  and  $F$  distributions popping up all over the place when you start trying to do your data analysis.

## Summary

In this chapter we've talked about probability. We've talked about what probability means and why statisticians can't agree on what it means. We talked about the rules that probabilities have to obey. And we introduced the idea of a probability distribution and spent a good chunk of the chapter talking about some of the more important probability distributions that statisticians work with. The section by section breakdown looks like this:

- Probability theory versus statistics (Section [6.1](#))
- Frequentist versus Bayesian views of probability (Section [6.2](#))
- Basics of probability theory (Section [6.3](#))
- Binomial distribution (Section [6.4](#)), normal distribution (Section [6.5](#)), and others (Section [6.6](#))

As you'd expect, my coverage is by no means exhaustive. Probability theory is a large branch of mathematics in its own right, entirely separate from its application to statistics and data analysis. As such, there are thousands of books written on the subject and universities generally offer multiple classes devoted entirely to probability theory. Even the "simpler" task of documenting standard probability distributions is a big topic. I've described five standard probability distributions in this chapter, but sitting on my bookshelf I have a 45-chapter book called "Statistical Distributions" ([Evans, Hastings, and Peacock 2011](#)) that lists a *lot* more than that. Fortunately for you, very little of this is necessary. You're unlikely to need to know dozens of statistical distributions when you go out and do real world data analysis, and you definitely won't need them for this book, but it never hurts to know that there's other possibilities out there.

Picking up on that last point, there's a sense in which this whole chapter is something of a digression. Many undergraduate psychology classes on statistics skim over this content very quickly (I know mine did), and even the more advanced classes will often "forget" to revisit the basic foundations of the field. Most academic psychologists would not know the difference between probability and density, and until recently very few would have been aware of the difference between Bayesian and frequentist probability. However, I think it's important to understand these things before moving onto the applications. For example, there are a lot of rules about what you're "allowed" to say when doing statistical inference and many of these can seem arbitrary and weird. However, they start to make sense if you understand that there is this Bayesian/frequentist distinction. Similarly, in Chapter [10](#) we're going to talk about something called the *t*-test, and if you really want to have a grasp of the mechanics of the *t*-test it really helps to have a sense of what a *t*-distribution actually looks like. You get the idea, I hope.