DANIELLE NAVARRO
RÓBERT FODOR

LEARNING STATISTICS WITH COGSTAT

A tutorial for psychology students and other beginners

First Revised Edition. CogStat version 2.3

Learning Statistics with CogStat

A tutorial for psychology students and other beginners

Danielle Navarro[1] Róbert Fodor[2]

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[1]Danielle Navarro – Github | 0000-0001-7648-6578

[2]Róbert Fodor – Github | 0000-0001-8470-335X

Contents

About this book **3**

Author's note for the *First Edition* 3

Changes in the *Revised Edition* 4

INTRODUCTIONS **7**

1 Why do we learn statistics? **7**

1.1 The curse of belief bias 7

1.2 The Simpson's paradox 9

1.3 Statistics in psychology 10

1.4 There's more to research methods than statistics 12

2 Introduction to research design **13**

2.1 Introduction to psychological measurement 13

2.2 Measurement levels 16

2.3 The "role" of variables: predictors and outcomes 22

2.4 Reliability 22

2.5 Experimental and non-experimental research 23

2.6 Validity 25

2.7 Confounds, artefacts and other threats to validity 28

2.8 Summary 37

3 Introduction to automatic statistical analysis **39**

4 Introduction to CogStat **41**

DESCRIPTIVE STATISTICS **45**

5 Exploring a single variable **45**

5.1 Measures of central tendency 46

5.2 Measures of variability 54
5.3 Skewness and kurtosis 62
5.4 Standard scores (z-score) 64
5.5 Summary: descriptives 66

6 Exploring a variable pair 67

6.1 The strength and direction of a relationship 69
6.2 The correlation coefficient 70
6.3 Interpreting a correlation 72
6.4 Spearman's rank correlations 74
6.5 Missing values in pairwise calculations 76
6.6 Summary 79

About this book

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The online version of the book is updated regularly. The date of the last update is shown on the title page. The book features screenshots based on CogStat version 2.3.

- *First edition* was published on 27 September 2022 (electronic).
- Critical fixes applied (typos and minor errors) on 5 November 2022.
- *Revised Edition* was published on XX January 2023 (electronic).

Author's note for the *First Edition*

This book is intended for psychology students and other beginners who are interested in learning statistics and want to use CogStat to perform their analyses. CogStat is a statistics software written in Python by Attila Krajcsi[1] and developed with the help of supporters. Its distinct advantage is automatic hypothesis test selection and chart creation with an APA-style output to suit the needs of psychology researchers and students.

Learning Statistics with CogStat is a book which covers the contents of an introductory statistics class. It is an adaptation made by Róbert Fodor based on Danielle Navarro's original *(Learning Statistics with R)*[2] (Version 0.6[3]). While the theory laid out in the original book is still valid, this book focuses on the practical application of statistical methods in CogStat. The book is not intended to be a comprehensive guide to either CogStat or statistical theory, though. One of the key challenges of the adaptation was to balance between a fully applied approach (like how CogStat handles analysis) and a theoretical one (like the fantastic textbook it is based on). Danielle's original content, while making up a massive chunk of the material, has been revised, reorganised, redacted, expanded on and rewritten to fit the new purpose.

This book will always be a living thing. As CogStat expands and evolves, so will this book. If you have any suggestions, comments or questions, please feel free to reach out to me on GitHub.

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[1] Attila Krajcsi – Website | 0000-0001-9792-9091

[2] https://learningstatisticswithr.com

[3] This book is compiled from scratch in bookdown but some code snippets rely on Emily Kothe's bookdown adaptation of the original material (e.g. some knitr plots and tables appear in the source code without alteration), numbered as version 0.6.1

– Robert

Changes in the *Revised Edition*

Author's note

This edition brings in plenty of changes, well beyond 10% of the book, which should warrant, per publishing standards, for it to be called "Second Edition" instead of a "Revised Edition" of the first one. However, it sounds quite conceited considering I've done some of the work that really should've gone into the original edition in the first place. The main drive behind these edits was reflections on the material's usefulness and *accuracy*, since some explanations and wordings needed to be more robust to withstand scientific scrutiny, which Attila Krajcsi provided. I must thank him for his helpful notes as consulting editor for this version, not due to sheer obligation but on account of genuine appreciation. His feedback was essential, and while I spent quite some time defending most of my earlier decisions (some of which I still do), I had to accept that I simply couldn't have got it quite right the first time, and I shouldn't be too attached to the source material. I loved that the original was accessible and the opposite of stuffy, but I decided to cut down some of the chattiness and informality while aiming to make it scientifically more accurate and still accessible to students and other audiences. I consulted some open textbooks on the web and the textbooks I am studying at Ulster University. I hope that this version is a step in the right direction.

– Robert

Changelog

- Chapters 3 and 4 were amended and slightly expanded, and now they follow Chapter 2, so that the reader can better appreciate automatic statistical analysis.
- Chapter 2 was largely revised to make explanations and examples more accurate.
- Chapter 5 was largely revised to tie to other statistics textbooks, also focusing on differentiating between population and sample measures.
- New: callout boxes added throughout the chapters to explain chart types and other concepts.
- New: definitions and examples are now presented markedly in the text.
- New: explanatory charts were added to the text.
- Typos and minor errors were fixed all throughout the book.

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INTRODUCTIONS

Chapter 1

Why do we learn statistics?

To the surprise of many students, statistics is a fairly significant part of a psychological education. To the surprise of no-one, statistics is very rarely the *favourite* part of one's psychological education. Not surprisingly, there's a pretty large proportion of the student base that isn't happy about the fact that psychology has so much statistics in it. A big part of this issue at hand relates to the very idea of statistics.

> *Why do you do statistics? Why don't scientists just use* ***common sense?***

Humans are susceptible to all kinds of biases, temptations and frailties, and much of statistics is basically a safeguard. Using "common sense" to evaluate evidence means trusting gut instincts, relying on verbal arguments and on using the raw power of human reason to come up with the right answer, which is not scientific at all.

1.1 The curse of belief bias

Psychologists have shown over the years is that we really do find it hard to be neutral, to evaluate evidence impartially and without being swayed by pre-existing biases. A good example of this is the ***belief bias effect*** in logical reasoning: if you ask people to decide whether a particular argument is logically valid (i.e., conclusion would be true if the premises were true), we tend to be influenced by the believability of the conclusion, even when we shouldn't. For instance, here's a valid argument where the conclusion is believable:

> No cigarettes are inexpensive (Premise 1)
> Some addictive things are inexpensive (Premise 2)
> Therefore, some addictive things are not cigarettes (Conclusion)

And here's a valid argument where the conclusion is not believable:

> No addictive things are inexpensive (Premise 1)
> Some cigarettes are inexpensive (Premise 2)
> Therefore, some cigarettes are not addictive (Conclusion)

The logical *structure* of argument #2 is identical to the structure of argument #1, and they're both valid. However, in the second argument, there are good reasons to think that premise

1 is incorrect, and as a result it's probably the case that the conclusion is also incorrect. But that's entirely irrelevant to the topic at hand: an argument is deductively valid if the conclusion is a logical consequence of the premises. That is, a valid argument doesn't have to involve true statements.

On the other hand, here's an invalid argument that has a believable conclusion:

> No addictive things are inexpensive (Premise 1)
> Some cigarettes are inexpensive (Premise 2)
> Therefore, some addictive things are not cigarettes (Conclusion)

And finally, an invalid argument with an unbelievable conclusion:

> No cigarettes are inexpensive (Premise 1)
> Some addictive things are inexpensive (Premise 2)
> Therefore, some cigarettes are not addictive (Conclusion)

Now, suppose that people really are perfectly able to set aside their pre-existing biases about what is true and what isn't, and purely evaluate an argument on its logical merits. We'd expect 100% of people to say that the valid arguments are valid, and 0% of people to say that the invalid arguments are valid. So if you ran an experiment looking at this, you'd expect to see data like this:

	conclusion feels true	conclusion feels false
argument is valid	100% say "valid"	100% say "valid"
argument is invalid	0% say "valid"	0% say "valid"

If the psychological data looked like this (or even a good approximation to this), we might feel safe in just trusting our gut instincts. That is, it'd be perfectly okay just to let scientists evaluate data based on their common sense, and not bother with all this murky statistics stuff.

In a classic study, Evans et al. (1983) ran an experiment looking at exactly this. What they found is that when pre-existing biases (i.e., beliefs) were in agreement with the structure of the data, everything went the way you'd hope:

	conclusion feels true	conclusion feels false
argument is valid	92% say "valid"	
argument is invalid		8% say "valid"

Not perfect, but that's pretty good. But look what happens when our intuitive feelings about the truth of the conclusion run against the logical structure of the argument:

	conclusion feels true	conclusion feels false
argument is valid	92% say "valid"	**46% say "valid"**
argument is invalid	**92% say "valid"**	8% say "valid"

Apparently, when people are presented with a strong argument that contradicts our pre-existing beliefs, we find it pretty hard to even perceive it to be a strong argument

(people only did so 46% of the time). Even worse, when people are presented with a weak argument that agrees with our pre-existing biases, almost no-one can see that the argument is weak.

It's just *too easy* for us to "believe what we want to believe"; so if we want to "believe in the data" instead, we're going to need a bit of help to keep our personal biases under control. That's what statistics does: it helps keep us honest.

1.2 The Simpson's paradox

In 1973, the University of California, Berkeley, had some worries about the gender breakdown of student admissions into postgraduate courses. Given that there were nearly 13,000 applicants, a difference of 9 percentage points in admission rates between males and females is just way too big to be a coincidence.

	Number of applicants	Percent admitted
Males	8442	46%
Females	4321	35%

When people started looking more carefully at the admissions data (Bickel et al., 1975) on a department by department basis, it turned out that most of the departments actually had a slightly *higher* success rate for female applicants than for male applicants.

	Male		Female	
Department	Applicants	Percent Admitted	Applicants	Percent Admitted
A	825	62%	108	82%
B	560	63%	25	68%
C	325	37%	593	34%
D	417	33%	375	35%
E	191	28%	393	24%
F	272	6%	341	7%

Yet the overall rate of admission across the university for females was *lower* than for males. How can both of these statements be true at the same time?

Firstly, notice that the departments are *not* equal to one another in terms of their admission percentages: some departments (e.g., engineering, chemistry) tended to admit a high percentage of the qualified applicants, whereas others (e.g., English) tended to reject most of the candidates, even if they were high quality. So, among the six departments shown above, notice that department A is the most generous, followed by B, C, D, E and F in that order. Next, notice that males and females tended to apply to different departments. If we rank the departments in terms of the total number of male applicants, we get **A**>**B**>D>C>F>E (the "easy" departments are in bold). On the whole, males tended to apply to the departments that had high admission rates. Now compare this to how the female applicants distributed themselves. Ranking the departments in terms of the total number of female applicants produces a quite different ordering: C>E>D>F>**A**>**B**. In other words, what this data seems to be suggesting is that the female applicants tended to apply to "harder" departments. And in fact, if we look at Figure 1.1, we see that this trend is systematic, and quite striking. This effect is known as Simpson's paradox. It's not

Figure 1.1: The Berkeley 1973 college admission rate for the 85 departments that had at least one female applicant based on Bickel et al. (1975). Circles plot departments with more than 40 applicants; the area of the circle is proportional to the total number of applicants. The crosses plot department with fewer than 40 applicants.

common, but it does happen in real life, and most people are very surprised by it when they first encounter it, and many people refuse to even believe that it's real. It is very real.

When doing research, there are *lots* of subtle, counterintuitive traps lying in wait for the unwary. Truth is sometimes cunningly hidden in the nooks and crannies of complicated data. Statistics only solves *part* of the problem.

Remember that we started, we looked at the "aggregated" data, and it did seem like the university was discriminating against women, but when we "disaggregated" and looked at the individual behaviour of all the departments, it turned out that the actual departments were, if anything, slightly biased in favour of women. The gender bias in total admissions was caused by the fact that women tended to self-select for harder departments. If you're interested in the overall structural effects of subtle gender biases, then you probably want to look at *both* the aggregated and disaggregated data. If you're interested in the decision making process at Berkeley itself then you're probably only interested in the disaggregated data.

In short there are a lot of critical questions that you can't answer with statistics, but the answers to those questions will have a huge impact on how you analyse and interpret data. And this is the reason why you should always think of statistics as a *tool* to help you learn about your data, no more and no less. It's a powerful tool to that end, but there's no substitute for careful thought.

1.3 Statistics in psychology

We hope that the discussion above helped explain why science in general is so focused on statistics. But we're guessing that you have a lot more questions about what role statistics plays in psychology, and specifically why psychology classes always devote so many lectures to stats. So here's an attempt to answer a few of them…

Why does psychology have so much statistics?

The most important reason is that psychology is a statistical science. There's a saying used sometimes in physics, to the effect that "if your experiment needs statistics, you should have

done a better experiment".

The "things" that we study are *people*. Real, complicated, gloriously messy people. The "things" of physics include object like electrons, and while there are all sorts of complexities that arise in physics, electrons don't have minds of their own. They don't have opinions, they don't differ from each other in weird and arbitrary ways, they don't get bored in the middle of an experiment, and they don't get angry at the experimenter and then deliberately try to sabotage the data set.[1]

We teach statistics to you as psychologists because you need to be better at stats than physicists. They have the luxury of being able to say that because their objects of study are simple in comparison to the vast mess that confronts social scientists.

Can't someone else do the statistics?

To some extent, but not completely. It's true that you don't need to become a fully trained statistician just to do psychology, but you do need to reach a certain level of statistical competence. There's three reasons that every psychological researcher ought to be able to do basic statistics:

- Firstly, there's the fundamental reason: statistics is deeply intertwined with research design. If you want to be good at designing psychological studies, you need to at least understand the basics of stats.
- Secondly, if you want to be good at the psychological side of the research, then you need to be able to understand the psychological literature, right? But almost every paper in the psychological literature reports the results of statistical analyses. So if you really want to understand the psychology, you need to be able to understand what other people did with their data. And that means understanding a certain amount of statistics.
- Thirdly, there's a big practical problem with being dependent on other people to do all your statistics: statistical analysis is *expensive*. In almost any real life situation where you want to do psychological research, the cruel facts will be that you don't have enough money to afford a statistician. So the economics of the situation mean that you have to be self-sufficient.

Note that a lot of these reasons generalise beyond researchers. If you want to be a practicing psychologist and stay on top of the field, it helps to be able to read the scientific literature, which relies pretty heavily on statistics.

I don't care about jobs, research, or clinical work. Do I need statistics?

Statistics should matter to you in the same way that statistics should matter to *everyone*: we live in the 21st century, and data are *everywhere*. Frankly, given the world in which we live these days, a basic knowledge of statistics is pretty damn close to a survival tool! Which is the topic of the next section…

[1] Some may argue that natural science experiments still struggle with data quality, noise etc. But to the best of my knowledge, there's no evidence of electron producing response bias in the lab due to over- or undercompliance. – Robert

1.4 There's more to research methods than statistics

Most research methods courses will cover a lot of topics that relate much more to the pragmatics of research design, and in particular the issues that you encounter when trying to do research with humans. Most student fears relate to the statistics part of the course. Hopefully you are convinced that statistics matters, and more importantly, that it's not to be feared.

Introductory classes focus a lot on the statistics because you almost always find yourself needing statistics before you need the other research methods training. Why? Because almost all of your assignments in other classes will rely on statistical training, to a much greater extent than they rely on other methodological tools. It's not common for undergraduate assignments to require you to design your own study from the ground up (in which case you would need to know a lot about research design), but it is common for assignments to ask you to analyse and interpret data that were collected in a study that someone else designed (in which case you need statistics). In that sense, from the perspective of allowing you to do well in all your other classes, the statistics is more urgent.

But note that "urgent" is different from "important" – they both matter. We really do want to stress that research design is just as important as data analysis, and this book does spend a fair amount of time on it. However, while statistics has a kind of universality, and provides a set of core tools that are useful for most types of psychological research, the research methods side isn't quite so universal. There are some general principles that everyone should think about, but a lot of research design is very idiosyncratic, and is specific to the area of research that you want to engage in. To the extent that it's the details that matter, those details don't usually show up in an introductory stats and research methods class.

Chapter 2

Introduction to research design

In this chapter, we'll start thinking about the basic ideas for designing a study, collecting data, checking whether your data collection works, and so on. It won't give you enough information to design studies of your own, but it will provide you with a lot of the essential tools you need to assess the studies done by other people. Since this book focuses more on data analysis than data collection, this only gives a very brief overview.

2.1 Introduction to psychological measurement

First, data collection can be thought of as a kind of **measurement**. That is, what we're trying to do here is measure something about human behaviour or the human mind. What do we mean by "measurement"?

Measurement as a concept comes down to finding some way of assigning numbers, labels, or other well-defined descriptions to phenomena. So, any of the following would count as a psychological measurement:

- Danielle's **age** is *33 years*.
- She *does not* **like anchovies**.
- Her **chromosomal gender** is *male*.
- Her **self-identified gender** is *female*.

In the short list above, the **bolded part** is "the thing to be measured", and the *italicised part* is "the measurement itself". We can expand on this a little bit by thinking about the set of possible measurements that could have arisen in each case:

- **Age** (in years) could have been *1, 2, 3 ... years*, etc. The upper bound on what the age could be is a bit fuzzy, but in practice, you'd be safe in saying that the largest possible age is *150* since no human has ever lived that long. And age doesn't really have a true zero, but that is not important just yet.
- When asked if someone **likes anchovies**, they might say *I do*, *I do not*, *I have no opinion*, or *I sometimes do*.
- **Chromosomal gender** is almost certainly going to be *male (XY)* or *female (XX)*, but there are a few other possibilities: with *Klinefelter's syndrome (XXY)*, it is more similar to male than to female. And there are other possibilities, too.
- **Self-identified gender** is also very likely to be *male* or *female*, *transgender*, *nonbinary*, *queer* etc.

As you can see, for some things, like age, it seems pretty apparent what the set of possible measurements should be, whereas, for other things, it gets a bit tricky. But even regarding someone's age, it's a bit more subtle. For instance, if you're a developmental psychologist, measuring in *years* is way too crude, and so you often measure age in *years and months* (if a child is 2 years and 11 months, this is usually written as "2;11"). If you're interested in newborns, you might want to measure age in *days since birth*, or maybe even *hours since birth*.

Looking at this a bit more closely, you might also realise that the concept of "age" isn't all that precise. Generally, when we say "age", we implicitly mean "the length of time since birth". But that's not always the right way to do it.

Suppose you're interested in how newborn babies control their eye movements. If Baby Alice is born 3 weeks premature and Baby Bianca is born 1 week late, would it really make sense to say that they are the "same age" if we encountered them "2 hours after birth"? In a sense, yes. By social convention, we use birth as our reference point for talking about age in everyday life since it defines the amount of time the person has been operating as an independent entity in the world. But from a scientific perspective, that's not the only thing we care about. You might want to measure age from conception, and voilà, you're already thinking about all the potential problems with analysis and comparisons. When we think about the biology of human beings, it's often helpful to think of ourselves as organisms that have been growing and maturing since conception. From that perspective, Alice and Bianca aren't the same age at all. So you might want to define the concept of "age" in two different ways: the length of time since conception and the length of time since birth. It won't make much difference when dealing with adults, but when dealing with newborns, it might. In other words, how you specify the allowable measurement values is important.

Still, there's the question of methodology. What specific measurement **method** will you use to find out someone's age? There are several options:

- You could just ask people, "how old are you?" The method of *self-report* is fast, cheap and easy, but it only works with people old enough to understand the question, and some people lie about their age.
- You could ask an authority (e.g. a parent), "how old is your child?" This method is fast, and it's not all that hard when dealing with kids since the parent is almost always around. It doesn't work as well if you want to know "age since conception" since a lot of parents can't say for sure when conception took place. You might need a different authority (e.g. an obstetrician).
- You could look up official records, like birth certificates. This is time-consuming and annoying, but it has its uses (e.g. if the person is now dead).

All of the ideas discussed in the previous section relate to the concept of **operationalisation**. To be a bit more precise about the idea, operationalisation is the process by which we take a meaningful but somewhat vague concept and turn it into an accurate measurement. The method of operationalisation can involve several different things:

- For instance, does "age" mean "time since birth" or "time since conception" in the context of your research?
- Will you use self-report to measure age, ask a parent, or look up an official record? If you're using self-report, how will you phrase the question?
- Defining the set of allowable values that the measurement can take. Note that these values don't always have to be numerical, though they often are. When measuring

age, the values are numerical, but we still need to think carefully about what numbers are allowed. Do we want age in years, years and months, days, or hours? The values aren't numerical for other types of measurements (e.g. gender). But, as before, we need to consider what values are allowed. If we're asking people to self-report their gender, what options do we allow them to choose from? Is it enough to allow only "male" or "female"? Do you need an "other" option? Or should we not give people any specific options and let them answer in their own words? And if you open up the set of possible values to include all verbal responses, how will you interpret their answers?

Operationalisation is tricky, and there's no "one, true way" to do it. How you operationalise the informal concept of "age" or "gender" into a formal measurement depends on what you need to use the measurement for. You'll often find that the community of scientists who work in your area have some well-established ideas for how to go about it. Tip: when working on your dissertation, consult your supervisor and the literature to see what the community has settled on.

In other words, operationalisation needs to be thought through case-by-case. Nevertheless, while there are a lot of issues that are specific to each individual research project, there are some aspects to it that are pretty general.

Let's take a moment to clear up our terminology and, in the process, introduce one more term. Here are four different things that are closely related to each other:

- *A clear construct*. This is the concept that you're trying to measure, like "age", "gender", or an "opinion".
- *A measure*. The measure refers to the method or instrument used to make your observations. A question in a survey, a behavioural observation or a brain scan could all count as a measure.
- *Operationalisation*. This is the logical connection between the measure and the theoretical construct: a definition of how you assign value to the concept (calculation, range, level of measurement etc.).
- ***A variable***. Finally, a new term. A variable is the outcome of the measurement process.

Here's an example:

- Construct: attitude towards Prince Harry the Duke of Sussex (the underlying concept)
- Measure: 5-point Likert scale in a self-report survey (instrument)
- Operationalisation: survey a sample of UK online newsreaders and ask them to rate their level of agreement on a 5-point Likert scale with the following statement: "I personally find Prince Harry the Duke of Sussex an agreeable person". (A statement operationalised the concept - whether it's the right sentence to use is a different question. Is this really the tangible representation of the concept you want to measure?)
- Variable: the numerical value of the response to the question, e.g., 5: "strongly agree"...

2.2 Measurement levels

As the previous section indicates, the outcome of a psychological measurement is called a variable. But not all variables are of the same qualitative type, and it's handy to understand what types there are. A very useful concept for distinguishing between different types of variables is what's known as **scales of measurement**, or in CogStat terminology, **measurement levels**.

2.2.1 Nominal categories

Definition 2.1 (Nominal scale variable)**.** A **nominal scale variable** (also referred to as a **categorical variable**) is the results of a *qualitative* measurement, where the number of possible values are limited and fixed; they represent a name, a label, a classification, or non-overlapping categories; and there is no order, hierarchy or ranking between the categories. E.g. eye colour, place of residence, gender.

For these kinds of variables, it doesn't make any sense to say that one of them is "bigger' or"better" than any other one, and it doesn't make any sense to average them. The classic example for this is "eye colour". Eyes can be blue, green and brown, among other possibilities, but none of them is any "better" than any other one. As a result, it would feel bizarre to talk about an "average eye colour". Similarly, gender is nominal too: *male* isn't better or worse than *female*, neither does it make sense to try to talk about an "average gender". In short, nominal scale variables are those for which the only thing you can say about the different possibilities is that they are different. That's it.

Note that sometimes nominal variables will have numbers coded to them usually for technical reasons (e.g., in survey data outputs). E.g., 1: male, 2: female, 3: nonbinary... This is a common practice, but the variable is still nominal: the numbers are just a way of representing the categories, and you should never, ever, ever (!) analyse them as if they were numerical/score measurements.

Example 2.1 (Nominal scale variable example)**.** Suppose we were researching how people commute to and from work. One variable we would have to measure would be what kind of transportation people use to get to work. This "transport type" variable could have quite a few possible values, including: "train", "bus", "car", "bicycle", etc. For now, let's suppose that these four are the only possibilities, and suppose that when we ask 100 people how they got to work today, we get this:

Transportation	Number of people
Train	12
Bus	30
Car	48
Bicycle	10

So, what's the *average transportation type*? Obviously, the answer here is that there isn't one. You can say that travel by car is the *most popular method*, and travel by train is the *least popular method*, but that's about all. That is based

on the *frequency* of the occurence (i.e., count). Similarly, notice that the order in which the options are listed isn't very exciting. We could have chosen to display the data like this:

Transportation	Number of people
Car	48
Train	12
Bicycle	10
Bus	30

– and nothing really changes.

2.2.2 Ordinal scale and rank

Definition 2.2 (Ordinal scale variable)**.** An **ordinal scale variable** or **rank** is the results of a measurement, where there is a natural, meaningful way to order or rank the different outcome possibilities. E.g. finishing position in a race, education status.

The *quantitative* difference between the outcomes might be unknown or uneven. E.g. education status: finishing elementary school takes 8 years in Europe, while an undergraduate degree is usually 3 years long; or you *can* say that the person who finished first was faster than the person who finished second, but you don't know the exact difference (unless you had a "finished at" timestamp data, which in turn is no longer an ordinal variable anymore). The important thing is that there is a natural, meaningful way to *order the outcomes*, but we don't *quantify* the difference between them.

Note that you can have a numeric code assigned to an ordinal variable. However, do not process these numbers as if they were meaningful beyond them representing an order. E.g., if you have a variable that measures the level of education, and you code it as 1: elementary school, 2: high school, 3: undergraduate degree, 4: graduate degree, but the variable still represents an order (i.e., level): you cannot add, subtract, divide or multiply these numbers.

Example 2.2 (Ordinal scale variable example)**.** Suppose we're interested in people's attitudes to climate change, and we ask them to pick one of these four statements that most closely matches their beliefs:

(1) Temperatures are rising because of human activity
(2) Temperatures are rising, but we don't know why
(3) Temperatures are rising, but not because of humans
(4) Temperatures are not rising

Notice that these four statements actually do have a natural ordering in terms of "the extent to which they agree with the current science". Statement 1 is a close match, statement 2 is a suitable match, statement 3 isn't a perfect match, and statement 4 strongly opposes science. So, in terms of the thing we're interested in (the extent to which people endorse the science), we can order the items as $1 > 2 > 3 > 4$. Since this ordering exists, it would be peculiar to list the options like this:

(3) Temperatures are rising, but not because of humans
(4) Temperatures are rising because of human activity
(5) Temperatures are not rising
(6) Temperatures are rising, but we don't know why

– because it seems to violate the natural "structure" of the question.
So, let's suppose I asked 100 people these questions and got the following answers:

Response	Number
(1) Temperatures are rising because of human activity	51
(2) Temperatures are rising, but we don't know why	20
(3) Temperatures are rising, but not because of humans	10
(4) Temperatures are not rising	19

When analysing these data, it seems quite reasonable to try to group (1), (2) and (3) together and say that 81 of 100 people were willing to *at least partially* endorse the science. And it's *also* quite reasonable to group (2), (3) and (4) together and say that 49 of 100 people registered *at least some disagreement* with the dominant scientific view. However, it would be entirely bizarre to try to group (1), (2) and (4) together and say that 90 of 100 people said what? There's nothing sensible that allows you to group those responses together at all.
That said, notice that while we *can* use the natural ordering of these items to construct sensible groupings, what we *can't* do is average them. For instance, in our simple example here, the "average" response to the question is 1.97. We would love to know if someone can tell us what that means.

2.2.3 Interval scale

Definition 2.3 (Interval scale variable)**.** An (equal-)**interval scale variable** is the results of a *quantitative* measurement, where the difference between the outcomes is meaningful, but *no true zero* value can be assigned to our variable. E.g. temperature in Celsius or Fahrenheit etc.

In contrast to nominal and ordinal scale variables, the *differences* between the numbers are interpretable: *addition* and *subtraction* make sense for interval scale variables. The intervals are same-sized, but a measurement value of 0 does not mean "nothing"/"none at all" on the Celsius scale: 0° means "the temperature at which water freezes", it's a, useful, but arbitrary label, not a true zero. As a consequence, it becomes pointless to try to multiply and divide temperatures. It is wrong to claim that 20° is *negative two times as hot as* −10°.

Example 2.3 (Interval scale variable example)**.** Suppose we're interested in looking at how the attitudes of first-year university students have changed over time, and we need to capture the *year they started*. This is an interval scale variable. A student who started in 2003 did arrive 5 years before a student who started in 2008. However, it would be completely insane to divide 2008

by 2003 and say that the second student started "1.0024 times later" than the first one.

2.2.4 Ratio scale

Definition 2.4 (Ratio scale variable)**.** A **ratio scale variable** is the results of a *quantitative* measurement, where both the difference between the outcomes and the ratio of the outcomes are meaningful, and the variable has a true zero value. E.g. distance in meters, heart rate, mass, temperature on the Kelvin scale etc.

The fourth and final type of variable to consider is a ratio scale variable, in which zero really means zero, and it's okay to multiply and divide on top of addition and subtraction. You can have a heart rate of zero, or in other words, "no heart rate at all" (an absolute zero), but that sadly means that you are likely dead. Kelvin is a ratio scale variable, because it has a true zero (absolute zero), and 100 K means truly twice as much energy as 50 K.

Example 2.4 (Ratio scale variable example)**.** A psychological example would be the result of a short-term working memory capacity test[a], where we ask respondents to remember a set of 5-letter words and recall them. Let's make our variable the number of words that they successfully recall. Person A is able to recall 12 words, and Person B can recall 6 words, Person C cannot recall a single word (i.e., 0 words), and Person D can recall 7 words. We can set an *order* between them: Person A > Person D > Person B > Person C; there is equal distance between the possible units, so subtraction is meaningful (*interval*); furthermore, there is a true zero (Person C). It also makes sense to say Person B made twice as many errors as Person A.

[a] One of the most famous ones is a digit span test (Miller, 1956), but the original article is not without its faults (Cowan, 2015).

2.2.5 The special case of the Likert scale

The humble Likert scale is all survey designs' bread and butter tool. You have filled out hundreds, maybe thousands of them, and odds are you've even used one yourself. Suppose we have a survey question that looks like this:

> Which of the following best describes your opinion of the statement that "all pirates are awesome" ...

and then, the options presented to the participant are these:

(1) Strongly disagree
(2) Disagree
(3) Neither agree nor disagree
(4) Agree
(5) Strongly agree

This set of items is an example of a 5-point Likert scale: people are asked to choose among one of several (in this case, 5) clearly ordered possibilities, generally with a verbal descriptor given in each case. However, it's not necessary that all items be explicitly described. This is a perfect example of a 5-point Likert scale too:

(1) Strongly disagree
(2)
(3)
(4)
(5) Strongly agree

Likert scales are convenient, if somewhat limited, tools. The question is, what kind of variable are they? They're obviously discrete since you can't give a response of 2.5. They're obviously not nominal scale since the items are ordered, and they're not ratio scale either since there's no natural zero[1].

But are they ordinal scale or interval scale? One argument says that we can't prove that the difference between "strongly agree" and "agree" is of the same size as the difference between "agree" and "neither agree nor disagree". In fact, in everyday life, it's pretty apparent they're not the same. So this suggests that we ought to treat Likert scales as ordinal variables. On the other hand, we can argue that some participants will take the whole "on a scale from 1 to 5" part seriously, and they tend to act as if the differences between the five response options were equidistant. While theoretically it is not an interval scale, researchers treat it as a **quasi-interval scale**.

2.2.6 Continuous versus discrete variables

There's a second kind of distinction that you need to be aware of regarding what types of variables you can run into. This is the distinction between *continuous* and *discrete* data types.

Definition 2.5 (Continuous variables)**.** A **continuous variable** can take on any value on a spectrum, and it's logically possible to have a value in between.

Definition 2.6 (Discrete variables)**.** A **discrete variable** can take on a limited number of distinct values; there is no possible value in between.

Example 2.5 (Continuous variable example)**.** These definitions probably seem a bit abstract, but they're pretty simple once you see some examples. For instance, response time is continuous. If Alan takes 3.1 seconds and Ben takes 2.3 seconds to respond to a question, then Cameron's response time can lie in between by taking 3.0 seconds. And, of course, it would also be possible for David to take 3.031 seconds to respond, meaning that his RT would lie in between Cameron's and Alan's. And while in practice, it might be impossible to measure RT that precisely, it's certainly possible in principle. Because we can always find a new value for RT in between any two other ones, we say that RT is continuous.

[1] And you can't cheat. You can code your Likert scale from 0 to 4 instead of 1 to 5, but these are arbitrary, just like deciding that the freezing temperature is labelled as 0.

Example 2.6 (Discrete variable example)**.** Discrete variables occur when this rule is violated. For example, nominal scale variables are always discrete: there isn't a type of transportation that falls "in-between" trains and bicycles, not in the strict mathematical way that 2.3 falls in between 2 and 3. So transportation type is discrete. Similarly, ordinal scale variables are always discrete: although "2nd place" does fall between "1st place" and "3rd place", there's nothing that can logically fall in between "1st place" and "2nd place". Interval scale and ratio scale variables can go either way. Temperature in degrees Celsius (an interval scale variable) is also continuous; however, the year you went to school (an interval scale variable) is discrete. There's no year between 2002 and 2003. The number of questions you get right on a true-or-false test (a ratio scale variable) is also discrete: since a true-or-false question doesn't allow you to be "partially correct", there's nothing in between 5/10 and 6/10.

Note that some people might say "discrete variable" when they mean "nominal scale variable". While all nominal scale variables are discrete, not all discrete variables are nominal.

2.2.7 A summary guide for levels of measurement

Variable types	Nominal	Ordinal	Interval	Ratio
Data types				
Discrete	✓ gender, birthplace	✓ education, finishing position	✓ year of enrolment to university	✓ number of questions answered correctly
Continuous			✓ attitude	✓ height, weight, heart rate, distance
Properties				
Can be ordered or ranked		✓	✓	✓
Equidistant units			✓	✓
Has a meaningful, true zero				✓
Valid operations				
+ addition, − subtraction			✓	✓
× multiplication, ÷ division			✓	✓
Central tendency measures				
Mode	✓	✓	✓	✓
Median		✓	✓	✓
Mean			✓	✓

2.3 The "role" of variables: predictors and outcomes

Usually, when we do some research, we end up with lots of different variables. Then, when we analyse our data, we often try to explain some of the variables in terms of the other variables. It's essential to keep the two roles, "thing doing the explaining" and "thing being explained", distinct. So let's be clear about this now. Firstly, we might as well get used to the idea of using mathematical symbols to describe variables since it's going to happen repeatedly. Let's denote the "to be explained" variable Y, and the variables "doing the explaining" as X_1, X_2, etc.

Now, when we are doing analysis, we have different names for X and Y, since they play different roles. The classical names for these roles are **independent variable** (IV) and **dependent variable** (DV). The IV is the variable you use to explain (i.e., X) and the DV is the variable being explained (i.e., Y). The logic behind these names goes like this: if there is a relationship between X and Y, then we can say that Y depends on X, and if we have designed our study "properly", then X isn't dependent on anything else. However, those names are horrible: they're hard to remember, and they're highly misleading because (a) the IV is never actually "independent of everything else" and (b) if there's no relationship, then the DV doesn't actually depend on the IV. And, because we're not the only people who think that IV and DV are just awful names, there are several alternatives that some find more appealing. The terms used in these notes are ***predictors*** and ***outcomes***. The idea here is that you're trying to use X (the predictors) to make guesses about Y (the outcomes). This is summarised in Table 2.1.

Table 2.1: The terminology used to distinguish between different roles that a variable can play when analysing a data set

role of the variable	classical name	modern name
to be explained	dependent variable (DV)	outcome
to do the explaining	independent variable (IV)	predictor

Note:
This book will tend to avoid the classical terminology in favour of the newer names.

2.4 Reliability

At this point, we've thought a little bit about how to operationalise a theoretical construct and thereby create a psychological measure. We've seen that by applying psychological measures we end up with variables, which can come in many different types. At this point, we should start discussing the obvious question: is the measurement any good? We'll do this in terms of two related ideas: *reliability* and *validity*. Put simply, the **reliability** of a measure tells you how *precisely* and *consistenly* you are measuring something (i.e. you are measuring the precise thing you inted to measure, and if you repeat the measurement on other samples or on the same sample some time later, you are still measuring the same variable). Whereas the **validity** of a measure tells you how *accurate* the measure is (i.e. the measurement is measuring the thing they are meant to measure and they do that exactly). See more in Chapter 2.6.

Let's think about the different ways in which we might measure reliability:

- ***Test-retest reliability***. This relates to consistency over time: if we repeat the

measurement at a later date, do we get the same answer?

- ***Inter-rater reliability***. This relates to consistency across people: if someone else repeats the measurement (e.g. someone else rates our intelligence), will they produce the same answer?
- ***Parallel forms reliability***. This relates to consistency across theoretically-equivalent measurements: if we use a different set of bathroom scales to measure our weight, does it give the same answer?
- ***Internal consistency reliability***. Suppose a measurement is constructed from many different parts that perform similar functions (e.g. a personality questionnaire result is added up across several questions). Do the individual parts tend to give similar answers?

Not all measurements need to possess all forms of reliability. For instance, educational assessment can be thought of as a form of measurement. One of the subjects that Danielle teaches, *Computational Cognitive Science*, has an assessment structure that has a research component and an exam component (plus other things). The exam component is *intended* to measure something different from the research component, so the assessment as a whole has low internal consistency. However, within the exam, several questions are intended to (approximately) measure the same things, and those tend to produce similar outcomes, so the exam on its own has a relatively high internal consistency, which is as it should be. You should only demand reliability when you want to measure the same thing!

2.5 Experimental and non-experimental research

One of the big distinctions that you should be aware of is the distinction between "experimental research" and "non-experimental research". When we make this distinction, what we're really talking about is the degree of control that the researcher exercises over the people and events in the study.

2.5.1 Experimental research

The key feature of **experimental research** is that the researcher controls specific aspects of the study. In particular, the researcher manipulates or varies the predictor variables (IVs) and then allows the outcome variable (DV) to vary naturally. The idea here is to deliberately vary the predictors (IVs) to see if they have any causal effects on the outcomes. Moreover, in order to ensure that there's no chance that something other than the predictor variables is causing the outcomes, everything else is kept constant or is in some other way "balanced" to ensure that they have no effect on the results. In practice, it's almost impossible to *think* of everything else that might have an influence on the outcome of an experiment, much less keep it constant.

Let's consider a very simple, completely unrealistic and grossly unethical example. Suppose you wanted to find out if smoking causes lung cancer. One way to do this would be to find people who smoke and people who don't smoke and look to see if smokers have a higher rate of lung cancer. This is *not* a proper experiment since the researcher doesn't have a lot of control over who is and isn't a smoker. And this really matters: for instance, it might be that people who choose to smoke cigarettes also tend to have poor diets, or maybe they tend to work in asbestos mines, or whatever. The point here is that the groups (smokers and non-smokers) actually differ on lots of things, not *just* smoking. So it might be that the higher incidence of lung cancer among smokers is caused by something else, not by smoking

per se. In technical terms, these other things (e.g. diet) are called "confounds", and we'll talk about those in just a moment.

In the meantime, let's now consider what a good experiment might look like. Recall that our concern was that smokers and non-smokers might differ in lots of ways. The solution, as long as you have no ethics, is to *control* who smokes and who doesn't. Specifically, suppose we randomly divide participants into two groups and force half of them to become smokers. In that case, it's doubtful that the groups will differ in any respect other than half of them smoke. That way, if our smoking group gets cancer at a higher rate than the non-smoking group, we can feel pretty confident that (a) smoking does cause cancer and (b) we're murderers.

2.5.2 Non-experimental research

In **non-experimental research**, the researcher doesn't have quite as much control over a specific variable as they do in an experiment. Control is something that scientists like to have, but as the previous example illustrates, there are many situations in which you can't or shouldn't try to obtain that control. Since it's grossly unethical (and almost undoubtedly criminal) to force people to smoke to find out if they get cancer, this is an excellent example of a situation where you shouldn't try to obtain experimental control. But there are other reasons too. Even leaving aside the ethical issues, our "smoking experiment" does have a few other issues. For instance, when we suggested that we "force" half of the people to become smokers, we must have been talking about *starting* with a sample of non-smokers and then forcing them to become smokers. While this sounds like the kind of solid, evil experimental design that a mad scientist would love, it might not be a very sound way of investigating the effect in the real world. For instance, suppose that smoking only causes lung cancer when people have poor diets and also suppose that people who usually smoke do tend to have poor diets. However, since the "smokers" in our experiment aren't "natural" smokers (i.e. we forced non-smokers to become smokers; they didn't take on all of the other normal, real-life characteristics that smokers might tend to possess), they probably have better diets. As such, in this silly example, they wouldn't get lung cancer, and our experiment will fail because it violates the structure of the "natural" world (the technical name for this is an "artefactual" result; see later).

One distinction worth making between two types of non-experimental research is the difference between ***quasi-experimental research*** and ***case studies***. The example from earlier – in which we wanted to examine the incidence of lung cancer among smokers and non-smokers without trying to control who smokes and who doesn't – is a quasi-experimental design. That is, it's the same as an experiment, but we don't control the predictors (IVs). We can still use statistics to analyse the results – it's just that we have to be a lot more careful.

The alternative approach, case studies, aims to provide a very detailed description of one or a few instances. In general, you can't use statistics to analyse the results of case studies, and it's usually very hard to draw any general conclusions about "people in general" from a few isolated examples. However, case studies are very useful in some situations. Firstly, there are situations where you don't have any alternative: neuropsychology has this issue a lot. Sometimes, you just can't find a lot of people with brain damage selectively in a specific area, so the only thing you can do is describe those cases that you do have in as much detail and with as much care as you can. Case studies can complement the more statistically-oriented approaches that you see in experimental and quasi-experimental designs. We won't talk much about case studies in these lectures, but they are nevertheless very valuable tools.

2.6 Validity

More than any other thing, a scientist wants their research to be "valid". The conceptual idea behind **validity** is very simple: can you trust the results of your study? If not, the study is invalid. However, while it's easy to state, in practice, it's much harder to check validity than to check reliability. And in all honesty, there's no precise, clearly agreed-upon notion of what validity actually is. In fact, there are lots of different kinds of validity, each of which raises its own issues, and not all forms of validity are relevant to all studies. Let's talk about five different types:

- Internal validity
- External validity
- Construct validity
- Face validity
- Ecological validity

To give you a quick guide as to what matters here:

(1) Internal and external validity are the most important since they tie directly to the fundamental question of whether your study really works.

(2) Construct validity asks whether you're actually measuring what you think you are.

(3) Face validity isn't terribly important except insofar as you care about "appearances".

(4) Ecological validity is a special case of face validity that corresponds to a kind of appearance that you might care about a lot.

2.6.1 Internal validity

Internal validity refers to the extent to which you are able to draw the correct conclusions about the causal relationships between variables. It's called "internal" because it refers to the relationships between things "inside" the study. Let's illustrate the concept with a simple example. Suppose you're interested in finding out whether a university education makes you write better. To do so, you get a group of first-year students, ask them to write a 1000-word essay, and count the number of spelling and grammatical errors they make. Then you find some third-year students, who obviously have had more university education than the first-years, and repeat the exercise. And let's suppose it turns out that the third-year students produce fewer errors. And so you conclude that a university education improves writing skills. Right? Except – the big problem that you have with this experiment is that the third-year students are older, and they've had more experience with writing things. So it's hard to know for sure what the causal relationship is: Do older people write better? Or people who have had more writing experience? Or people who have had more education? Which of the above is the true *cause* of the superior performance of the third-years? Age? Experience? Education? You can't tell. This is an example of a failure of internal validity because your study doesn't properly tease apart the *causal* relationships between the different variables.

2.6.2 External validity

External validity relates to the **generalisability** of your findings. That is, to what extent do you expect to see the same pattern of results in "real life" as you saw in your study? To put it a bit more precisely, any study that you do in psychology will involve a fairly specific set of questions or tasks, will occur in a specific environment, and will involve participants that are drawn from a particular subgroup. So, if it turns out that the results don't actually generalise to people and situations beyond the ones that you studied, then what you've got is a lack of external validity.

The classic example of this issue is the fact that a very large proportion of studies in psychology will use undergraduate psychology students as participants. However, the researchers don't care *only* about psychology students; they care about people in general. Given that, a study that uses only psych students as participants always risks lacking external validity. That is, if there's something "special" about psychology students that makes them different to the general populace in some *relevant* respect, then we may start worrying about a lack of external validity.

That said, it is absolutely critical to realise that a study that uses only psychology students does not necessarily have a problem with external validity. The choice of population threatens the external validity: if (a) the population from which you sample your participants is very narrow (e.g. psych students), and (b) the narrow population that you sampled from is systematically different from the general population, *in some respect that is relevant to the psychological phenomenon that you intend to study*. The italicised part is the bit that many people forget: psychology undergraduates indeed differ from the general population in many ways, so a study that uses only psych students *may* have problems with external validity. However, if those differences aren't very relevant to the phenomenon you're studying, there's nothing to worry about. To make this a bit more concrete, here are two extreme examples:

- You want to measure "attitudes of the general public towards psychotherapy", but all of your participants are psychology students. This study would almost certainly have a problem with external validity.
- You want to measure the effectiveness of a visual illusion, and your participants are all psychology students. This study is very unlikely to have a problem with external validity

Having just spent the last couple of paragraphs focusing on the choice of participants (since that's the big issue that everyone tends to worry most about), it's worth remembering that external validity is a broader concept. The following are also examples of things that might pose a threat to external validity, depending on what kind of study you're doing:

- People might answer a "psychology questionnaire" in a manner that doesn't reflect what they would do in real life.
- Your lab experiment on (say) "human learning" has a different structure to the learning problems people face in real life.

2.6.3 Construct validity

Construct validity is a question of whether you're measuring what you want to be measuring. A measurement has good construct validity if it is actually measuring the correct theoretical construct and inadequate construct validity if it doesn't. To give a very simple (if ridiculous) example, suppose we're trying to investigate the rates with which university students cheat on their exams. And the way we attempt to measure it is by asking the cheating students to stand up in the lecture theatre so that we can count them. When we do this with a class of 300 students, 0 people claim to be cheaters. So we, therefore, conclude that the proportion of cheaters is 0%. Clearly, this is a bit ridiculous. But the point here is not that this is a very deep methodological example, but rather to explain construct validity. The problem with the measure is that while we're *trying* to measure "the proportion of people who cheat", we're actually measuring "the proportion of people stupid enough to own up to cheating, or bloody-minded enough to pretend that they do". Obviously, these aren't the same thing! So our study has gone wrong because our measurement has very poor construct validity.

2.6.4 Face validity

Face validity simply refers to whether or not a measure "looks like" it's doing what it's supposed to, nothing more. If you design a test of intelligence, and people look at it and say, "no, that test doesn't measure intelligence", then the measure lacks face validity. It's as simple as that. Obviously, face validity isn't very important from a purely scientific perspective. After all, what we care about is whether or not the measure *actually* does what it's supposed to do, not whether it *looks like* it does what it's supposed to do. Consequently, we generally don't care much about face validity. That said, the concept of face validity serves three useful pragmatic purposes:

- Sometimes, an experienced scientist will have a "hunch" that a particular measure won't work. While these hunches have no strict evidentiary value, it's often worth paying attention to them. Because oftentimes people know they can't quite verbalise, there might be something to worry about even if you can't quite say why. In other words, when someone you trust criticises the face validity of your study, it's worth taking the time to think more carefully about your design to see if you can think of reasons why it might go awry. If you don't find any reason for concern, you should probably not worry: after all, face validity doesn't matter much.
- (Very) often, completely uninformed people will also have a "hunch" that your research is bollocks. And they'll criticise it on the internet or something. On close inspection, you'll often notice that these criticisms are focused entirely on how the study "looks", but not on anything more profound. The concept of face validity is useful for gently explaining to people that they need to substantiate their arguments further.
- Expanding on the last point, if the beliefs of untrained people are critical (e.g. this is often the case for applied research where you actually want to convince policymakers of something or other), then you *have* to care about face validity. Simply because – whether you like it or not – a lot of people will use face validity as a proxy for real validity. If you want the government to change a law on scientific, psychological grounds, then it won't matter how good your studies "really" are. If they lack face validity, you'll find that politicians ignore you. Of course, it's somewhat unfair that policy often depends more on appearance than fact, but that's how things go.

2.6.5 Ecological validity

Ecological validity is a different notion of validity, similar to external validity but less important. The idea is that, to be ecologically valid, the entire study set-up should closely approximate the real-world scenario being investigated. In a sense, ecological validity is a kind of face validity – it relates mostly to whether the study "looks" right, but with a bit more rigour to it. To be ecologically valid, the study has to look right in a fairly specific way. The idea behind it is the intuition that a study that is ecologically valid is more likely to be externally valid. It's no guarantee, of course. But the nice thing about ecological validity is that it's much easier to check whether a study is ecologically valid than it is to check whether a study is externally valid. A simple example would be eyewitness identification studies. Most of these studies tend to be done in a university setting, often with a fairly simple array of faces to look at rather than a lineup. The length of time between seeing the "criminal" and being asked to identify the suspect in the "line up" is usually shorter. The "crime" isn't real, so there's no chance that the witness is scared, and there are no police officers present, so there's not as much chance of feeling pressured. These things all mean that the study *definitely* lacks ecological validity. They might (but might not) mean that it also lacks external validity.

2.7 Confounds, artefacts and other threats to validity

If we look at the issue of validity in the most general fashion, the two biggest worries that we have are *confounds* and *artefacts*. These two terms are defined in the following way:

- **Confound**: A confound is an additional, often unmeasured variable[2] that turns out to be related to both the predictors and the outcomes. The existence of confounds threatens the internal validity of the study because you can't tell whether the predictor causes the outcome, if the confounding variable causes it, etc.
- **Artefact**: A result is said to be "artefactual" if it only holds in the special situation you tested in your study. The possibility that your result is an artefact describes a threat to your external validity, because it raises the possibility that you can't generalise your results to the actual population you care about.

As a general rule, confounds are a more significant concern for non-experimental studies precisely because they're not proper experiments. By definition, you're leaving lots of things uncontrolled, so there's a lot of scope for confounds working their way into your study. Experimental research tends to be much less vulnerable to confounds: the more control you have over what happens during the study, the more you can prevent confounds from appearing.

However, there are always swings and roundabouts, and when we start thinking about artefacts rather than confounds, the shoe is very firmly on the other foot. For the most part, artefactual results tend to be a concern for experimental studies than for non-experimental studies. To see this, it helps to realise that the reason that a lot of studies are non-experimental is precisely because what the researcher is trying to do is examine human behaviour in a more naturalistic context. By working in a more real-world context,

[2]The reason why we say that it's unmeasured is that if you *have* measured it, then you can use some fancy statistical tricks to deal with the confound. Because of the existence of these statistical solutions to the problem of confounds, we often refer to a confound that we have measured and dealt with as a *covariate*. Dealing with covariates is a topic for a more advanced course, but it's comforting to know that it exists.

you lose experimental control (making yourself vulnerable to confounds). Still, because you tend to be studying human psychology "in the wild", you reduce the chances of getting an artefactual result. Or, to put it another way, when you take psychology out of the wild and bring it into the lab (which we usually have to do to gain our experimental control), you always run the risk of accidentally studying something different than you wanted to study: which is more or less the definition of an artefact.

Be warned though: the above is a rough guide only. It's absolutely possible to have confounds in an experiment, and to get artefactual results with non-experimental studies. This can happen for all sorts of reasons, not least of which is researcher error. In practice, it's really hard to think everything through ahead of time, and even very good researchers make mistakes. But other times it's unavoidable, simply because the researcher has ethics (e.g. see 2.7.5).

Okay. There's a sense in which almost any threat to validity can be characterised as a confound or an artefact: they're pretty vague concepts. So let's have a look at some of the most common examples...

2.7.1 History effects

History effects refers to the possibility that specific events may occur during the study itself that might influence the outcomes. For instance, something might happen between a pre-test and a post-test. Or in between testing participant 23 and participant 24. Alternatively, it might be that you're looking at an older study, which was perfectly valid for its time, but the world has changed enough since then that the conclusions are no longer trustworthy. Examples of things that would count as history effects:

- You're interested in how people think about risk and uncertainty. You started your data collection in December 2010. But finding participants and collecting data takes time, so you were still finding new people in February 2011. Unfortunately for you (and even more unfortunately for others), the Queensland floods occurred in January 2011, causing billions of dollars of damage and killing many people. Not surprisingly, the people tested in February 2011 expressed quite different beliefs about handling risk than the people tested in December 2010. Which (if any) of these reflects the "true" beliefs of participants? I think the answer is probably both: the Queensland floods genuinely changed the beliefs of the Australian public, though possibly only temporarily. The key thing here is that the "history" of the people tested in February is quite different to people tested in December.
- You're testing the psychological effects of a new anti-anxiety drug. So what you do is measure anxiety before administering the drug (e.g. by self-report, and taking physiological measures, let's say), then you administer the drug, and then you take the same measures afterwards. In the middle, however, because your labs are in Los Angeles, there's an earthquake, which increases the anxiety of the participants.

2.7.2 Maturation effects

As with history effects, **maturational effects** are fundamentally about change over time. However, maturation effects aren't in response to specific events. Instead, they relate to how people change on their own over time: we get older, we get tired, we get bored, etc. Some examples of maturation effects:

- When doing developmental psychology research, you need to be aware that children grow up quite rapidly. So, suppose that you want to find out whether some educational trick helps with vocabulary size among 3-year-olds. One thing you need to be aware of is that the vocabulary size of children that age is growing at an incredible rate (multiple words per day), all on its own. If you design your study without taking this maturational effect into account, you won't be able to tell if your educational trick works.
- When running a very long experiment in the lab (say, something that goes for 3 hours), it's very likely that people will begin to get bored and tired and that this maturational effect will cause performance to decline, regardless of anything else going on in the experiment

2.7.3 Repeated testing effects

An important type of history effect is the effect of **repeated testing**. Suppose I want to take two measurements of some psychological construct (e.g. anxiety). One thing I might be worried about is if the first measurement has an effect on the second measurement. In other words, this is a history effect in which the "event" that influences the second measurement is the first measurement itself! This is not at all uncommon. Examples of this include:

- *Learning and practice*: e.g. "intelligence" at time 2 might appear to go up relative to time 1 because participants learned the general rules of how to solve "intelligence-test-style" questions during the first testing session.
- *Familiarity with the testing situation*: e.g. if people are nervous at time 1, this might make the performance go down; after sitting through the first testing situation, they might calm down a lot precisely because they've seen what the testing looks like.
- *Auxiliary changes caused by testing*: e.g. if a questionnaire assessing mood is boring, then mood at measurement at time 2 is more likely to become "bored", precisely because of the boring measurement made at time 1.

2.7.4 Selection bias

Selection bias is a pretty broad term. Suppose you're running an experiment with two groups of participants, where each group gets a different "treatment", and you want to see if the different treatments lead to different outcomes. However, suppose that, despite your best efforts, you've ended up with a gender imbalance across groups (say, group A has 80% females and group B has 50% females). It might sound like this could never happen, but trust me, it can. This is an example of a selection bias, in which the people "selected into" the two groups have different characteristics. If any of those characteristics turn out to be relevant (say, your treatment works better on females than males), then you're in a lot of trouble.

2.7.5 Differential attrition

One quite subtle danger to be aware of is called **differential attrition**, which is a kind of selection bias that is caused by the study itself. Suppose that, for the first time ever in the history of psychology, we manage to find a perfectly balanced and representative sample of people. We start running "our incredibly long and tedious experiment" on our perfect sample, but then, because our study is incredibly long and tedious, lots of people start dropping out. We can't stop this: as we'll discuss later in the chapter on research ethics, participants absolutely have the right to stop doing any experiment, any time, for whatever reason they feel like, and as researchers, we are morally (and professionally) obliged to remind people that they do have this right. So, suppose that "our incredibly long and tedious experiment" has a very high dropout rate. What do you suppose the odds are that this dropout is random? Answer: zero. Almost certainly, the people who remain are more conscientious, more tolerant of boredom etc., than those that leave. To the extent that (say) conscientiousness is relevant to the psychological phenomenon that we care about, this attrition can decrease the validity of our results.

When thinking about the effects of differential attrition, it is sometimes helpful to distinguish between two different types. The first is **homogeneous attrition**, in which the attrition effect is the same for all groups, treatments or conditions. In the example above, the differential attrition would be homogeneous if (and only if) the easily bored participants are dropping out of all the conditions in our experiment at about the same rate. The main effect of homogeneous attrition is likely to be that it makes your sample unrepresentative. As such, the biggest worry you'll have is that the generalisability of the results decreases: in other words, you lose external validity.

The second type of differential attrition is **heterogeneous attrition**, in which the attrition effect is different for different groups. This is a much bigger problem: not only do you have to worry about your external validity, but you also have to worry about your internal validity too. To see why this is the case, let's consider a very dumb study in which I want to see if insulting people makes them act more obediently. So, we design our experiment with two conditions. In the "treatment" condition, the experimenter insults the participant and then gives them a questionnaire designed to measure obedience. In the "control" condition, the experimenter engages in a bit of pointless chitchat and then gives them the questionnaire. Leaving aside the questionable scientific merits and dubious ethics of such a study, let's have a think about what might go wrong here. As a general rule, when someone insults me to my face, I tend to get much less cooperative. So, there's a pretty good chance that a lot more people are going to drop out of the treatment condition than the control condition. And this dropout isn't going to be random. The people most likely to drop out would probably be those who don't care all that much about the importance of obediently sitting through the experiment. Since the most bloody-minded and disobedient people all left the treatment group but not the control group, we've introduced a confound: the people who actually took the questionnaire in the treatment group were *already* more likely to be dutiful and obedient than the people in the control group. In short, in this study, insulting people doesn't make them more obedient: it makes the more disobedient people leave the experiment! The internal validity of this experiment is completely shot.

2.7.6 Non-response bias

Non-response bias is closely related to selection bias and to differential attrition. The simplest version of the problem goes like this. You mail out a survey to 1000 people, and only 300 reply. The 300 people who replied are almost certainly not a random subsample. People who respond to surveys are systematically different to people who don't. This introduces a problem when trying to generalise from those 300 people who replied, to the population at large; since you now have a very non-random sample. The issue of non-response bias is more general than this, though. Among the (say) 300 people that did respond to the survey, you might find that not everyone answered every question. If (say) 80 people chose not to answer one of your questions, does this introduce problems? As always, the answer is maybe. If the question that wasn't answered was on the last page of the questionnaire, and those 80 surveys were returned with the last page missing, there's a good chance that the missing data isn't a big deal: probably the pages just fell off. However, if the question that 80 people didn't answer was the most confrontational or invasive personal question in the questionnaire, then almost certainly you've got a problem. In essence, what you're dealing with here is what's called the problem of ***missing data***. If the data that is missing was "lost" randomly, then it's not a big problem. If it's missing systematically, then it can be a big problem.

2.7.7 Regression to the mean

Regression to the mean is a curious variation on selection bias. It refers to any situation where you select data based on an extreme value on some measure. Because the measure has natural variation, it almost certainly means that when you take a subsequent measurement, that later measurement will be less extreme than the first one, purely by chance.

Here's an example. Say we're interested in whether a psychology education has an adverse effect on very smart kids. To do this, I find the 20 psych I students with the best high school grades and look at how well they're doing at university. It turns out that they're doing a lot better than average, but they're not topping the class at university, even though they did top their classes at high school. What's going on? The natural first thought is that this must mean that the psychology classes must be having an adverse effect on those students. However, while that might very well be the explanation, it's more likely that what you're seeing is an example of "regression to the mean". To see how it works, let's take a moment to think about what is required to get the best mark in a class, regardless of whether that class be at high school or at university. When you've got a big class, there are going to be *lots* of very smart people enrolled. To get the best mark, you have to be very smart, work very hard, and be a bit lucky. The exam has to ask just the right questions for your unique skills, and you have to not make any dumb mistakes (we all do that sometimes) when answering them. And that's the thing: intelligence and hard work are transferrable from one class to the next. Luck isn't. The people who got lucky in high school won't be the same as the people who get lucky at university. That's the very definition of "luck". The consequence of this is that when you select people at the very extreme values of one measurement (the top 20 students), you're selecting for hard work, skill and luck. But because the luck doesn't transfer to the second measurement (only the skill and work), these people will all be expected to drop a little bit when you measure them a second time (at university). So their scores fall back a little bit, back towards everyone else. This is regression to the mean.

Regression to the mean is surprisingly common. For instance, if two very tall people have kids, their children will tend to be taller than average but not as tall as the parents. The reverse happens with very short parents: two very short parents will tend to have short

children, but nevertheless, those kids will tend to be taller than the parents. It can also be extremely subtle. For instance, there have been studies done that suggest that people learn better from negative feedback than from positive feedback. However, the way that people tried to show this was to give people positive reinforcement whenever they did good and negative reinforcement when they did bad. And what you see is that after the positive reinforcement, people tended to do worse, but after the negative reinforcement, they tended to do better. But! Notice that there's a selection bias here: when people do very well, you're selecting for "high" values, and so you should *expect* (because of regression to the mean) that performance on the next trial should be worse, regardless of whether reinforcement is given. Similarly, after a bad trial, people will tend to improve all on their own. The apparent superiority of negative feedback is an artefact caused by regression to the mean (see Kahneman & Tversky, 1973 for discussion).

2.7.8 Experimenter bias

Experimenter bias can come in multiple forms. The basic idea is that the experimenter, despite the best of intentions, can accidentally influence the experiment results by subtly communicating the "right answer" or the "desired behaviour" to the participants. Typically, this occurs because the experimenter has special knowledge that the participant does not – either the right answer to the questions being asked or knowledge of the expected performance pattern for the condition the participant is in, and so on. The classic example of this happening is the case study of "Clever Hans", which dates back to 1907 (Hothersall, 2004; Pfungst, 1911). Clever Hans was a horse that apparently was able to read and count and perform other human-like feats of intelligence. After Clever Hans became famous, psychologists started examining his behaviour more closely. It turned out that – not surprisingly – Hans didn't know how to do maths. Rather, Hans was responding to the human observers around him. Because they did know how to count, and the horse had learned to change its behaviour when people changed theirs.

The general solution to the problem of experimenter bias is to engage in double-blind studies, where neither the experimenter nor the participant knows which condition the participant is in or knows what the desired behaviour is. This provides a good solution to the problem, but it's essential to recognise that it's not quite ideal and hard to pull off perfectly. For instance, the obvious way that we could try to construct a double-blind study is to have one of the PhD students (one who doesn't know anything about the experiment) run the study. That feels like it should be enough. The only person (us) who knows all the details (e.g. correct answers to the questions, assignments of participants to conditions) has no interaction with the participants, and the person who does all the talking to people (the PhD student) doesn't know anything. Except, that last part is improbable. For the PhD student to run the study effectively, they need to have been briefed by us, the researcher. And as it happens, the PhD student also knows a bit about our general beliefs about people and psychology. As a result of all this, it's almost impossible for the experimenter to avoid learning a little bit about what expectations we have. And even a little knowledge can have an effect: suppose the experimenter accidentally conveys that the participants are expected to do well in this task. Well, there's a thing called the "Pygmalion effect": if you expect great things of people, they'll rise to the occasion; but if you expect them to fail, they'll do that too. In other words, the expectations become a self-fulfilling prophecy.

2.7.9 Demand effects and reactivity

When talking about experimenter bias, the worry is that the experimenter's knowledge or desires for the experiment are communicated to the participants and that these affect people's behaviour (Rosenthal, 1966). However, even if you manage to stop this from happening, it's almost impossible to stop people from knowing that they're part of a psychological study. And the mere fact of knowing that someone is watching/studying you can have a pretty big effect on behaviour. This is generally referred to as ***reactivity*** or ***demand effects***. The Hawthorne effect captures the idea that people alter their performance because of the attention that the study focuses on them. The effect takes its name from the "Hawthorne Works" factory outside of Chicago (see Adair, 1984). A study done in the 1920s looking at the effects of lighting on worker productivity at the factory turned out to be an effect of the fact that the workers knew they were being studied rather than the lighting.

To get a bit more specific about how the mere fact of being in a study can change how people behave, it helps to think like a social psychologist and look at some of the *roles* that people might adopt during an experiment. Still, it might not adopt if the corresponding events were occurring in the real world:

- The *good participant* tries to be too helpful to the researcher: he or she seeks to figure out the experimenter's hypotheses and confirm them.
- The *negative participant* does the exact opposite of the good participant: he or she seeks to break or destroy the study or the hypothesis in some way.
- The *faithful participant* is unnaturally obedient: he or she seeks to follow instructions perfectly, regardless of what might have happened in a more realistic setting.
- The *apprehensive participant* gets nervous about being tested or studied, so much so that his or her behaviour becomes highly unnatural or overly socially desirable.

2.7.10 Placebo effects

The **placebo effect** is a specific type of demand effect that we worry a lot about. It refers to the situation where the mere fact of being treated causes an improvement in outcomes. The classic example comes from clinical trials: if you give people a completely chemically inert drug and tell them that it's a cure for a disease, they will tend to get better faster than people who aren't treated at all. In other words, it is people believing that they are being treated that causes the improved outcomes, not the drug.

2.7.11 Situation, measurement and subpopulation effects

In some respects, these terms are a catch-all term for "all other threats to external validity". They refer to the fact that the choice of the subpopulation from which you draw your participants, the location, timing and manner in which you run your study (including who collects the data) and the tools that you use to make your measurements might all be influencing the results. Specifically, the worry is that these things might be influencing the results in such a way that the results won't generalise to a wider array of people, places and measures.

2.7.12 Fraud, deception and self-deception

Textbooks assessing the validity of a study often seem to make the assumption that the researcher is honest. I find this hilarious. While the vast majority of scientists are honest, in my experience at least, some are not.[3] Not only that, but scientists are not immune to belief bias – it's easy for a researcher to end up deceiving themselves into believing the wrong thing, which can lead them to conduct subtly flawed research, and then hide those flaws when they write it up. So you need to consider not only the (probably unlikely) possibility of outright fraud, but also the (probably quite common) possibility that the research is unintentionally "slanted". Here's a list of a few ways in which these issues can arise:

- **Data fabrication**. Sometimes, people just make up the data. This is occasionally done with "good" intentions. For instance, the researcher believes that the fabricated data do reflect the truth and may actually reflect "slightly cleaned up" versions of actual data. On other occasions, the fraud is deliberate and malicious. Some high-profile examples where data fabrication has been alleged or shown include Cyril Burt (a psychologist who is thought to have fabricated some of his data), Andrew Wakefield (who has been accused of fabricating his data connecting the MMR vaccine to autism) and Hwang Woo-suk (who falsified a lot of his data on stem cell research).
- **Hoaxes**. Hoaxes share many similarities with data fabrication, but they differ in the intended purpose. A hoax is often a joke, and many of them are intended to be (eventually) discovered. Often, the point of a hoax is to discredit someone or some field. There are quite a few well-known scientific hoaxes that have occurred over the years (e.g. Piltdown man). Some were deliberate attempts to discredit particular fields of research (e.g. the Sokal affair).
- **Data misrepresentation**. While fraud gets most of the headlines, it's much more common in my experience to see data misrepresented. Often the data doesn't say what the researchers think it says. This isn't the result of deliberate dishonesty, but it's due to a lack of sophistication in the data analysis. For instance, think back to the example of Simpson's paradox. It's very common to see people present "aggregated" data of some kind, and sometimes, when you dig deeper and find the raw data yourself, you find that the aggregated data tell a different story to the disaggregated data. Alternatively, you might find that some aspect of the data is being hidden because it tells an inconvenient story (e.g. the researcher might choose not to refer to a particular variable). There are a lot of variants on this, many of which are very hard to detect.
- **Study "misdesign"**. Okay, this one is subtle. The issue here is that a researcher designs a study with built-in flaws, which are never reported in the paper. The data reported are authentic and are correctly analysed, but they are produced by a study that is actually quite wrongly put together. The researcher really wants to find a particular effect, and so the study is set up in such a way as to make it "easy" to (artefactually) observe that effect. One sneaky way to do this – in case you're feeling like dabbling in a bit of fraud yourself – is to design an experiment in which it's obvious to the participants what they're "supposed" to be doing and then let reactivity work its magic for you. If you want, you can add all the trappings of double-blind experimentation etc. It won't make a difference since the study materials are subtly

[3] Some people might argue that if you're not honest then you're not a real scientist. That does have some truth, but that's disingenuous (google the "No true Scotsman" fallacy). The fact is that there are lots of people who are employed ostensibly as scientists, and whose work has all of the trappings of science, but who are outright fraudulent. Pretending that they don't exist by saying that they're not scientists is just childish.

telling people what you want them to do. When you write up the results, the fraud won't be obvious to the reader: what's obvious to the participant when they're in the experimental context isn't always obvious to the person reading the paper. Of course, the way we've described this makes it sound like it's always fraud: probably there are cases where this is done deliberately, but the bigger concern has been unintentional misdesign. The researcher *believes*. And so the study just happens to end up with a built-in flaw, and that flaw then magically erases itself when the study is written up for publication.

- **Data mining & post hoc hypothesising**. Another way in which the authors of a study can more or less lie about what they found is by engaging in what's referred to as "data mining". As we'll discuss later in the class, if you keep trying to analyse your data in lots of different ways, you'll eventually find something that "looks" like a real effect but isn't. This is referred to as "data mining". It used to be quite rare because data analysis used to take weeks, but now that everyone has very powerful statistical software on their computers, it's becoming very common. Data mining per se isn't "wrong", but the more that you do it, the bigger the risk you're taking. The wrong thing is *unacknowledged* data mining. That is, the researcher runs every possible analysis known to humanity, finds the one that works, and then pretends that this was the only analysis that they ever conducted. Worse yet, they often "invent" a hypothesis after looking at the data to cover up the data mining. To be clear: it's not wrong to change your beliefs after looking at the data and to reanalyse it using your new "post hoc" hypotheses. What is wrong is failing to acknowledge that you've done so. If you acknowledge that you did it, then other researchers are able to take your behaviour into account. If you don't, then they can't. And that makes your behaviour deceptive.
- **Publication bias & self-censoring**. Finally, a pervasive bias is the "non-reporting" of negative results. This is almost impossible to prevent. Journals don't publish every article submitted to them: they prefer to publish articles that find "something". So, if 20 people run an experiment looking at whether reading *Finnegans Wake* causes insanity in humans, and 19 of them find that it doesn't, which one do you think is going to get published? Obviously, it's the one study that did find that *Finnegans Wake* causes insanity [4]. This is an example of a *publication bias*: since no one ever published the 19 studies that didn't find an effect, a naive reader would never know that they existed. Worse yet, most researchers "internalise" this bias and end up *self-censoring* their research. Knowing that negative results aren't going to be accepted for publication, they never even try to report them. As a friend of Danielle's says, "for every experiment that you get published, you also have ten failures". And she's right. The catch is, while some (maybe most) of those studies are failures for boring reasons (e.g. you stuffed something up), others might be genuine "null" results that you ought to acknowledge when you write up the "good" experiment – and telling which is which, is often hard to do. A good place to start is a paper by Ioannidis (2005) with the depressing title "Why most published research findings are false". We'd also suggest taking a look at work by Kühberger et al. (2014) presenting statistical evidence that this actually happens in psychology.

There's probably a lot more issues like this to think about, but that'll do to start with. It's the obvious truth that real world science is conducted by actual humans, and only the most gullible of people automatically assumes that everyone else is honest and impartial. Actual scientists aren't usually *that* naive, but for some reason, the world likes to pretend that we are, and the textbooks we usually write seem to reinforce that stereotype.

[4] Clearly, the real effect is that only insane people would even try to read *Finnegans Wake*.

2.8 Summary

This chapter isn't really meant to provide a comprehensive discussion of psychological research methods: it would require another volume just as long as this one does justice to the topic. However, in real life, statistics and study design are tightly intertwined, so discussing some key topics is convenient. In this chapter, we've briefly discussed the following:

- Introduction to psychological measurement. What does it mean to operationalise a theoretical construct? What does it mean to have variables and take measurements?
- Scales of measurement and types of variables. Remember that there are *two* different distinctions here: there's the difference between discrete and continuous data, and there's the difference between the four different scale types (nominal, ordinal, interval and ratio).
- Reliability of a measurement. If I measure the "same" thing twice, should I expect the same result? Only if my measure is reliable. But what does it mean to talk about doing the "same" thing? Well, that's why we have different types of reliability. Make sure you remember what they are.
- Terminology: predictors and outcomes. What roles do variables play in an analysis? Can you remember the difference between predictors and outcomes? Dependent and independent variables? Etc.
- Experimental and non-experimental research designs. What makes an experiment an experiment? Is it a nice white lab coat, or does it have something to do with researcher control over variables?
- Validity and its threats. Does your study measure what you want it to? How might things go wrong?

All this should make clear to you that study design is a critical part of research methodology.

This chapter relies on Stevens (1946) and Howitt & Cramer (2020) for discussing scales of measurement, and on Marks & Yardley (2004) and Campbell & Stanley (1963) for discussing study design.

Chapter 3

Introduction to automatic statistical analysis

In recent years, the reliability of psychological science has been questioned due to the overstated use of *p*-values and effect sizes, and their lower-than-expected replicability (Open Science Collaboration, 2015). This may be a result of the high pressure on researchers to produce a large volume of work with statistically positive results (Krajcsi, 2021).

To produce strong research results, it is important to have good data analysis, which can make or break a research project. In psychological research, this includes: identifying and selecting a good design from many alternative design options, sampling participants appropriately, observing ethical standards in data collection and documentation, controlling for confounding variables, selecting appropriate statistics and replications of analyses, analysing data with appropriate software, assessing the effect sizes of results based on their inferential characteristics, reporting findings accurately in papers – just to name a few. Some of these tasks can be automated to ensure that the appropriate protocol is followed, which is why we have CogStat, and why you are reading this book.

Neglecting early protocols can lead to errors. For example, using a tool designed for *normally distributed* data on a highly *skewed* data set will be inappropriate. In this book, we will cover why this characteristic of our data set matters. Ignoring the foundations of hypothesis testing tools will harm the reliability of the research and, in turn, the reliability and prestige of psychology as a science.

There are several manual statistical programs, such as SPSS, SAS, and Stata, and some programming languages used for data analysis, such as R and Python. These tools can be time-consuming and require multiple steps for simple tasks like creating tables and graphs, not to mention the time spent on learning how to use them. One benefit of automatic statistical software is that it is programmed to follow all necessary steps as part of its protocol. A good automatic statistical software will apply the most appropriate tools based on current statistical consensus.

In this book, you will learn what it means to do normality and heteroscedasticity checks, calculate effect sizes, and performing hypothesis tests etc. We focus on making sure you understand what they are, why they matter, and how to interpret them. We will indulge in presenting mathematical formulas as well, but you won't have to do any of the calculations. To be fair, you don't have to manually calculate the respective metrics in a manual statistical program either, but deciding which tool to pick up first, or which step to take next might be a challenge if statistics is not in your veins. Beyond the anxiety of how to even get started

with manual statistical programs, applying a single tool can take up to tens of steps. In comparison, producing the full analysis with multiple tools with supporting charts and graphs may only take three steps in CogStat.

Researchers often have too little time for rigorous data analysis and interpretation, and at the same time, journals set somewhat arbitrary standards (e.g. specific *p*-values are demanded whether or not they avoid Type I errors – this is one of the topics in this book), so some researchers might just use those as rules of thumb without going deeper into data analysis. By using an automatic procedure, the time spent on data analysis can be redirected towards understanding the implications of the test results for the research question.

For more about the merits of automatic statistical analysis, here are some further reads from Attila Krajcsi, the creator of CogStat:

- Methodological considerations behind CogStat
- Reducing the replication crisis

Chapter 4

Introduction to CogStat

CogStat is a statistical analysis program designed for psychology research, particularly in cognitive science. It is user-friendly and automatic, yet powerful enough to handle a variety of statistical analyses. CogStat is free to download from the CogStat website and runs on Windows, macOS, and Linux.

The main feature of CogStat is its automatic analysis of source data and automatic selection of hypothesis tests, which can be very useful after learning about statistical theory and hypothesis testing. The program will automatically choose the most appropriate statistical test for your data, making it a useful tool for researchers who want to save time on test selection or are unsure of the best fit for their purposes.

CogStat automatically analyzes data based on its scale type, runs necessary pre-checks (such as for normality and heteroscedasticity), and performs the appropriate hypothesis test. The results are presented in a clear format following APA7 guidelines, and the program also generates graphical representations of the results.

To install CogStat, simply download the latest version from the CogStat website. The installation is easy and straightforward, and should only take a few minutes. For help with installation, please visit our GitHub page.

To quickly test CogStat without using your own data, you can use the demo data provided in the program. From the `Data > Open demo data file...` menu, choose a folder and data file, then click `Open`.

To use your own data with CogStat, prepare it in spreadsheet software like Excel, Google Spreadsheet, or LibreOffice Calc, or in statistical software like jamovi, JASP, SPSS, STATA, or SAS. CogStat does not handle data editing tasks, as there are more efficient solutions available. To import your data into CogStat, you can either copy and paste it from your spreadsheet software, or import it as a saved file (.xlsx, .ods, .csv, .jasp, .omv, .rdata etc.). You can also drag and drop the file into the CogStat window.

If your data comes from a spreadsheet software or is a text file, like .csv, make sure of the following:

- The first row of your data should include the variable names without accent characters (áâő...).
- The second row should include the measurement levels: `int` for interval and ratio scales, `ord` for ordinal variables, and `nom` for nominal variables. More on measurement levels (scales) in Chapter 2.2. The remaining rows should include the values of the variables.

To learn more about using CogStat, including how to prepare and load data, refer to the GitHub Wiki page.

DESCRIPTIVE STATISTICS

Chapter 5

Exploring a single variable

Any time you get a new data set to look at, one of the first things you might want to do is find ways of summarising the data in a compact, easily understood fashion. This is what **descriptive statistics** (as opposed to *inferential statistics*) is all about. In fact, to many people, the term "statistics" is synonymous with descriptive statistics.

The first dataset we'll be looking at is real data relating to the Australian Football League (AFL)[1]. To do this, let us load the aflsmall.csv file.

Figure 5.1: Loading 'aflsmall.csv'. This is what you would see after loading the dataset.

CogStat will help you get familiar with some essential aspects of your variable, like:

- measures of central tendency (mean, median)
- measures of variability (range, minimum, maximum, standard deviation, quartiles)
- measures of "distortion" (skewness, kurtosis).

These measures will help you contextualise the results so the conclusions drawn from the variable will be valid.

To start understanding a variable in CogStat, select `Explore variable` so a pop-up appears. Move the name of the data you wish to analyse (in this case: `aflmargins`) from `Available variables` to `Selected variables`, then click `OK` (Figure 5.2).

[1]Note for non-Australians: the AFL is an Australian rules football competition. You don't need to know anything about Australian rules in order to follow this section.

Figure 5.2: ‘Explore variable‘ dialogue.

Figure 5.3: ‘Explore variable results‘ for the ‘aflsmall.csv‘ data set. This is the first chart you will see exploring the raw shape of the data.

The first piece of information here is N, which we will use to refer to the number of observations we're analysing. CogStat (or any other software for that matter) will only use valid data for calculations. Sometimes, when working with survey data, you will have missing data points, the number of which you might have to mention in your report. CogStat will quote these for you:

```
N of valid cases: 176
N of missing cases: 0
```

In the rest of this chapter, we will explore what these measures mean and what they indicate.

5.1 Measures of central tendency

In most situations, the first thing that you'll want to calculate is a measure of ***central tendency***. That is, you'd like to know something about the "average" or "middle" of your data lies.

5.1.1 The mean

The first measure of *central tendency* is the mean, or arithmetic average. It is calculated by adding up all of the values in the data set and then divide the sum by the total number (count) of values.

Definition 5.1 (Mean)**.** The **mean** of a set of observations is the sum of the observations divided by the number of observations.

$$\bar{X} = \frac{\sum_{i=1}^{N} X_i}{N}$$

Example 5.1 (Mean)**.** The first five AFL margins were 56, 31, 56, 8 and 32 (which CogStat will display when loading the data, see Figure 5.1), so the mean of these observations is just:

$$\frac{56 + 31 + 56 + 8 + 32}{5} = \frac{183}{5} = 36.60$$

Of course, this definition of the mean isn't news to anyone: averages (i.e., means) are used so often in everyday life that this is quite familiar.

We used N to denote the number of observations. Now let's attach a label to the observations themselves. It's traditional to use X for this, and to use subscripts to indicate which observation we're actually talking about. That is, we'll use X_1 to refer to the first observation, X_2 to refer to the second observation, and so on, all the way up to X_N for the last one. The following table lists the 5 observations in the `afl.margins` variable, along with the mathematical symbol used to refer to it, and the actual value that the observation corresponds to:

Observation	Symbol	Observed value
winning margin, game 1	X_1	56 points
winning margin, game 2	X_2	31 points
winning margin, game 3	X_3	56 points
winning margin, game 4	X_4	8 points
winning margin, game 5	X_5	32 points

Okay, now let's try to write a formula for the mean. The goal here is to try to make sure that everyone reading this book is clear on the notation that we'll be using throughout the book. By tradition, we use $\bar{X}$ as the notation for the mean, $\sum$ for the idea of summation, X_i for the ith observation, and N for the total number of observations. We're going to be re-using these symbols a fair bit, so you must understand them well enough to be able to "read" the equations and to be able to see what they're really saying.

So the calculation for the mean could be expressed using the following formula:

$$\bar{X} = \frac{X_1 + X_2 + \ldots + X_{N-1} + X_N}{N}$$

This formula is entirely correct, but it's terribly long, so we make use of the summation symbol $\sum$ to shorten it:

$$\sum_{i=1}^{5} X_i$$

Taken literally, this could be read as "the sum, taken over all i values from 1 to 5, of the value X_i". But basically, what it means is "add up the first five observations". In any case, we can use this notation to write out the formula for the mean, which looks like this:

$$\bar{X} = \frac{1}{N} \sum_{i=1}^{N} X_i$$

In all honesty, all this mathematical notation is just a fancy way of laying out the same things said in words: *add all the values up, and then divide by the total number of items.*

Summation symbol: $\sum$ and Product symbol: $\prod$ notations

The summation symbol $\sum$ is used to denote the operation of adding up a sequence of numbers. It is used to write out formulas in a concise way, and is used extensively in mathematics.

$$\sum_{i=1}^{n} X_i = X_1 + X_2 + \ldots + X_{n-1} + X_n$$

where i is the *index of the observation*, which means that the index starts out at the given number, so in this case, at the first observation (X_1). The index is incremented by 1 for each observation (even if $i > 1$), so the next observation is X_2, and so on, until the last observation, which is X_n, as denoted above the symbol.

The choice to use Σ to denote summation isn't arbitrary: it's the Greek upper case letter sigma, which is the analogue of the letter S in that alphabet.

Similarly, there's an equivalent symbol used to denote the multiplication of lots of numbers: because multiplications are also called "products", we use the Π symbol for this; the Greek upper case pi, which is the analogue of the letter P.

Check out more examples of summation notation and product notation on Wikipedia.

CogStat calculates the mean automatically when exploring a variable using all valid data points, not just the first five. It will be part of the `Descriptives for the variable` section, as seen in Figure 5.4. The result for our variable is:

```
afl.margins
Mean 35.3
```

Figure 5.4: Descriptive statistics and histogram for the 'aflsmall.csv' data set. Scrolling down, you'll see CogStat reporting all the descriptive measures while showing you a histogram to understand the shape of your data better. Drawing pictures of the data is an excellent way to convey the gist of what the data is trying to tell you; it's often instrumental to try to condense the data into a few simple summary statistics.

5.1.2 The median

The second measure of *central tendency* people use a lot is the median[2], and it's even easier to describe than the mean.

Definition 5.2 (Median)**.** The **median** is the middle value in a set of observations that has been arranged in ascending or descending order.

Example 5.2 (Median)**.** As before, let's imagine we were interested only in the first 5 AFL winning margins: 56, 31, 56, 8 and 32. To figure out the median, we sort these numbers into ascending order. From inspection, it's evident that the median value of these five observations is 32 since that's the middle one in the sorted list.

[2] *medianus* is Latin for "the one in the middle", originating from the word *medius*, meaning "the middle".

$$8, 31, 32, 56, 56$$

But what should we do if we were interested in the first six games rather than the first 5? Since the sixth game in the season had a winning margin of 14 points, our sorted list is now:

$$8, 14, 31, 32, 56, 56$$

and there are *two* middle numbers, 31 and 32. The median is defined as the average of those two numbers, which is 31.5.

In the data set we loaded to CogStat, there were 176 valid cases, so we ought to have two middle numbers. The result in this case is (as seen in Figure 5.4):

```
afl.margins
Median 30.5
```

5.1.3 Mean or median? What's the difference?

Figure 5.5: An illustration of the difference between how the mean and the median should be interpreted. The mean is basically the "centre of gravity" of the data set: if you imagine that the histogram of the data is a solid object, then the point on which you could balance it (as if on a see-saw) is the mean. In contrast, the median is the middle observation. Half of the observations are smaller, and half of the observations are larger.

Knowing how to calculate means and medians is only a part of the story. You also need to understand what each one is saying about the data, what that implies, and which one to choose. This is illustrated in Figure 5.5; the mean is kind of like the "centre of gravity" of the data set, whereas the median is where you'd cut it in half. What this implies about which one you should use depends a little on what type of data you've got and what you're trying to achieve. As a rough guide:

- If your data are *nominal scale*, you shouldn't be using either the mean or the median. Both the mean and the median rely on the idea that the numbers assigned to values are meaningful (i.e., 1 means 1 of a unit of measure, and not simply a technical coding for "1: men, 2: women, 3: nonbinary ..."). If the numbering scheme is arbitrary, then use the mode (Section 5.1.5) instead.
- If your data are *ordinal scale*, you can to use the median but not the mean. The median only uses the order information in your data (i.e., which numbers are larger) which is the purpose of an ordinal scale. The mean makes use of the precise numeric values

assigned to the observations beyond their order info, so it's not appropriate for ordinal data.

- For *interval* and *ratio scale* data, either one is generally acceptable. Which one you pick depends a bit on what you're trying to achieve. The mean has the advantage of using all the information in the data (which is useful when you don't have a lot of data), but it's very susceptible to extreme values, as we'll see in Chapter 5.1.4.

Let's expand on that last part a little. One consequence is that there are systematic differences between the mean and the median when the histogram is asymmetric (skewed; see Chapter 5.3). This is illustrated in Figure 5.5 notice that the median (right hand side) is located closer to the "body" of the histogram, whereas the mean (left hand side) gets dragged towards the "tail" (where the extreme values are).

Example 5.3 (Mean or median)**.** Suppose Bob (income \$50,000), Kate (income \$60,000) and Jane (income \$65,000) are sitting at a table: the average income at the table is \$58,333 and the median income is \$60,000. Then Bill sits down with them (income \$100,000,000). The average income has now jumped to \$25,043,750 but the median rises only to \$62,500. If you're interested in looking at the overall income at the table, the mean might be the right answer; but if you're interested in what counts as a typical income at the table, the median would be a better choice here.

5.1.4 Trimmed mean

Example 5.4 (Outliers)**.** Consider this rather strange-looking data set:

$$-100, 2, 3, 4, 5, 6, 7, 8, 9, 10$$

If you were to observe this in a real-life data set, you'd probably suspect that there is something odd about the -100 value. It's probably an **outlier**, a value that doesn't belong with the others. You might consider removing it from the data set entirely. In this particular case, it might be the right call. However, you don't always get such cut-and-dried examples. For instance, you might get this instead:

$$-15, 2, 3, 4, 5, 6, 7, 8, 9, 12$$

The -15 looks suspicious, but not as much as that -100 did. In this case, it's a little trickier. It *might* be a legitimate observation; it might not.

When faced with a situation where some of the most extreme-valued observations might not be quite trustworthy, the mean is not necessarily a good measure of central tendency. It is highly sensitive to one or two extreme values and might not be a *robust* measure in all cases. One remedy is to use the median. An alternative solution is to use a **trimmed mean**.

Definition 5.3 (Trimmed mean)**.** A **trimmed mean** is a measure of central tendency, a type of average, that is calculated by discarding a certain percentage of the largest and smallest observations from the data, and then calculating the arithmetic average of the remaining observations.

The goal is to preserve the best characteristics of the mean and the median: just like a median, you aren't highly influenced by extreme outliers. Generally, we describe a trimmed mean in terms of the percentage of observations on either side that are discarded. So, for instance, a 10% trimmed mean discards the largest 10% of the observations *and* the smallest 10% of the observations and then takes the mean of the remaining 80% of the observations. Not surprisingly, the 0% trimmed mean is just the regular mean, and the 50% trimmed mean is the median. In that sense, trimmed means provide a whole family of central tendency measures that span the range from the mean to the median.

Example 5.5. For our toy example above, we have 10 observations. So a 10% trimmed mean is calculated by ignoring the largest value (i.e. 12) and the smallest value (i.e. −15) and taking the mean of the remaining values.

```
Mean: 4.1
Median: 5.5
```

That's a fairly substantial difference. But the mean is being influenced too much by the extreme values at either end of the data set, especially the −15 one. If we take a 10% trimmed mean, we'll drop the extreme values on either side and take the mean of the rest:

```
Mean: 5.5
```

Which, in this case, gives exactly the same answer as the median.

Currently, there is no direct way for you to do that in CogStat, but you can certainly trim those outlying data points in your source file and re-load the data.

5.1.5 Mode

Definition 5.4 (Mode)**.** The **mode** is a measure of central tendency that indicates the value that occurs most frequently in the data set.

Example 5.6 (Mode)**.** Consider the following data set:

0, 1, 1, 2, 3, 5, 8, 13, 21

The mode would be 1, as it's the value the occurs most frequently. A **frequency table** helps you identify the mode in more complex datasets even if it's not calculated automatically.

Value: Frequency (Relative frequency)
0: 1 (11.1%)
1: 2 (22.2%)
2: 1 (11.1%)
3: 1 (11.1%)
5: 1 (11.1%)
8: 1 (11.1%)
13: 1 (11.1%)
21: 1 (11.1%)

In CogStat, you will see a frequency table (Figure 5.6) of the values in your data if you have `Frequencies` ticked in the `Explore variable` dialogue.

Sample properties

Frequencies

Value	Freq	Cum freq	Rel freq	Cum rel freq
0.0	2	2	1.1%	1.1%
1.0	4	6	2.3%	3.4%
2.0	2	8	1.1%	4.5%
3.0	8	16	4.5%	9.1%
4.0	2	18	1.1%	10.2%
5.0	1	19	0.6%	10.8%
6.0	1	20	0.6%	11.4%
7.0	2	22	1.1%	12.5%
8.0	5	27	2.8%	15.3%
9.0	6	33	3.4%	18.8%
10.0	5	38	2.8%	21.6%
11.0	3	41	1.7%	23.3%
12.0	3	44	1.7%	25.0%
13.0	1	45	0.6%	25.6%
14.0	2	47	1.1%	26.7%
15.0	1	48	0.6%	27.3%
16.0	4	52	2.3%	29.5%
18.0	1	53	0.6%	30.1%
19.0	5	58	2.8%	33.0%
20.0	3	61	1.7%	34.7%
21.0	2	63	1.1%	35.8%
22.0	3	66	1.7%	37.5%
23.0	3	69	1.7%	39.2%
24.0	2	71	1.1%	40.3%
25.0	2	73	1.1%	41.5%
26.0	4	77	2.3%	43.7%
27.0	2	79	1.1%	44.9%
28.0	2	81	1.1%	46.0%
29.0	6	87	3.4%	49.4%

Figure 5.6: The frequency table sorts non-nominal values from lowest to highest.

While it's generally true that the mode is most often calculated when you have nominal scale data – because means and medians are useless for those sorts of variables –, there are some situations in which you do want to know the mode of an ordinal, interval or ratio scale variable.

Example 5.7 (Mode for ordinal, interval and ratio scale)**.** Let's look at our `afl.margins` variable we loaded into CogStat. This variable is clearly ratio scale, and so in most situations the mean or the median is the measure of central tendency that you want. But consider that a friend of yours is offering a bet. They pick a football game at random, and without knowing who is playing you have to guess the *exact* margin. If you guess correctly, you win $50. If you don't, you lose $1. There are no consolation prizes for "almost" getting the right answer. You have to guess exactly the right margin[a] For this bet, the mean and the median are completely useless to you. It is the mode that you should bet on. So, we look at the frequency table offered by the result set: the data suggest you should bet on a 3.0 point margin, and since this was observed in 8 of the 176 games (4.5% of games – the *relative frequency*), the odds are firmly in your favour.

[a] This is called a "0-1 loss function", meaning that you either win (1) or you lose (0), with no middle ground.

5.2 Measures of variability

The statistics that we've discussed so far all relate to *central tendency*. They all talk about which values are "in the middle" or "popular" in the data. However, central tendency is not the only type of summary statistic that we want to calculate. The second thing that we really want is a measure of the **variability** (or, *dispersion*) of the data. That is, how "spread out" are the data? How "far" away from the mean or median do the observed values tend to be?

Figure 5.7: Data sets with the same mean but different dispersion.

For now, let's assume that the data are interval or ratio scale, so we'll continue to use the `afl.margins` data. We'll use this data to discuss several different measures of spread, each with different strengths and weaknesses.

5.2.1 Range

Definition 5.5 (Range)**.** As a measure of variability, the **range** of a variable is the difference between the largest and smallest observation in the data set.

$$\text{Range} = \max(x) - \min(x)$$

Example 5.8 (Range)**.** For the AFL winning margins data, the maximum value is 116, and the minimum is 0, so the range is:

$$116 - 0 = 116$$

CogStat automatically calculates all these values (see Figure 5.4), so there is nothing we need to do about this, only to understand what it implies.

Although the range is the simplest way to quantify the notion of variability, it's not a fit-for-all tool. Recall from our discussion of the mean that we want our summary measure to be robust. If the data set has one or two extremely "bad" values in it (i.e., *outliers*), we'd like our statistics not to be unduly influenced by these cases.

Example 5.9 (Range with outliers present)**.** Let us look once again at our toy

example of a data set containing very extreme outliers:

$$-100, 2, 3, 4, 5, 6, 7, 8, 9, 10$$

It is clear that the range is not robust since this has a range of 110, but if the outlier was removed, we would have a range of only 8.

Quantiles

Quantiles are cut points that divide an ordered data set (or a distribution) into equal-sized groups of observations when the data is continuous. Or more generally, they cut a probability distribution to equally probable intervals (see Chapter **??**).

For example, a data set of 40 observations can be divided into 4 equal-sized groups of 10 observations each.

Quantile	Number of observations	Lower bound	Upper bound
1	10	1	10
2	10	11	20
3	10	21	30
4	10	31	40

This is called a ***quartile*** (i.e., 1/4). If we wanted to define in percentages, this would be able to define 25th, 50th and 75th ***percentiles*** of a data set. The *25th percentile* (*1st quartile* or *lower quartile*) holds the value in a distribution that is greater than 25% of the values and less than 75% of the values. The *50th percentile* (*2nd quartile*) is the *median*, and the *75th percentile* (*3rd quartile* or *upper quartile*) is the value that is greater than 75% of the values and less than 25% of the values.

Figure 5.8: The 25th, 50th and 75th percentiles of a cumulative distribution of a normal distribution. (StevenJYang on Wikipedia: Quartile)

The data can be divided into other quantiles as well: e.g. a distribution cut in 5 equal-sized groups are called ***quintiles***, and a distribution cut in 10 equal-sized groups are called ***deciles***, and so on.

There are different methods to cutting discrete data into quantiles, but we're not going to discuss them here.

5.2.2 Interquartile range

The **interquartile range** (IQR) is similar to the range in terms of measuring variability, but instead of calculating the difference between the largest and smallest value, it calculates the difference between the 25th and 75th quantile, hence, somewhat minimising the effect of a few outliers.

Definition 5.6 (Interquartile range)**.** The **interquartile range** (IQR) is the difference between the 25th and 75th quantile of a data set. It is a measure of variability that is less sensitive to outliers than the range.

CogStat provides you with both the 25th (`Lower quartile`) and 75th quantiles (`Upper quartile`) automatically:

```
Upper quartile: 50.5
Lower quartile: 12.8
```

Example 5.10 (Interquartile range)**.** We can see that the interquartile range for the 2010 AFL winning margins data is:

$$50.5 - 12.8 = 37.7$$

While it's obvious how to interpret the range, it's a little less obvious how to interpret the IQR. The simplest way to think about it is like this: the interquartile range is the range spanned by the "middle half" of the data, ignoring any data between $-\infty$ and Q_1, and between Q_3 and $+\infty$. That is, one quarter of the data falls below the 25th percentile, one quarter of the data is above the 75th percentile, leaving the "middle half" of the data lying in between the two. And the IQR is the range covered by this middle half.

Boxplots

Boxplots (or "box and whiskers" plots) are a standardised method to display the distribution of a data set based on a five-number summary:

- the minimum and maximum (i.e., range),
- first quartile and third quartile (i.e., IQR),
- and the median.

Like histograms, they're most suited for interval or ratio scale data. Some boxplots separate out those observations that are "suspiciously" distant from the rest of the data, i.e., the outliers. These are usually displayed with a circle or a dot.

5.2.3 Mean absolute deviation (average absolute deviation)

The two measures we've looked at so far, the range and the interquartile range, both rely on the idea that we can measure the spread of the data by looking at quantiles. However, this isn't the only way to think about the problem. A different approach is to select some meaningful reference point (usually the mean or the median) and then report the "typical" deviations from that. In practice, this leads to two different measures, the "mean absolute deviation" (from the mean) and the "median absolute deviation" (from the median). Irritatingly, "mean absolute deviation" and "median absolute deviation" have the same acronym (i.e., MAD), which leads to a certain amount of ambiguity. What we'll do is use *AAD* (*average absolute deviation*) for *mean absolute deviation*, while *MAD* will stand for *median absolute deviation*.

Definition 5.7 (Average absolute deviation)**.** The **average absolute deviation** (AAD) is a measure of variability calculated as the average of the absolute difference between each observation and the *mean* of the data set.

$$\text{AAD} = \frac{1}{n}\sum_{i=1}^{n} |X_i - \bar{X}|$$

where n is the number of observations, X_i is the ith observation, and $\bar{X}$ is the mean of the data set.

Example 5.11 (Average absolute deviation)**.** Let's think about our AFL winning margins data, and once again we'll start by pretending that there's only 5 games in total, with winning margins of 56, 31, 56, 8 and 32. Our calculations rely on an examination of the deviation from some reference point, in this case, the mean.

1. The first thing we need to look up is the mean, $\bar{X}$. For these five observations, our mean is $\bar{X} = 36.6$.
2. The next step is to convert each of our observations X_i into a deviation score. We do this by calculating the difference between the observation X_i and the mean $\bar{X}$ (i.e., the deviation score: $X_i - \bar{X}$).
3. Then we convert these deviations to absolute deviations. Mathematically, we would denote the absolute value of -3 as $|-3|$, and so we say that $|-3| = 3$. We use the absolute value function here because we don't care whether the value is higher than the mean or lower than the mean; we're just interested in how *close* it is to the mean.

To help make this process as obvious as possible, the table below shows these calculations for all five observations:

Observation	Symbol	Observed value	Deviation score $X_i - \bar{X}$	Absolute d.s. $\lvert X_i - \bar{X}\rvert$
winning margin, game 1	X_1	56 points	56 - 36.6 = 19.4	19.4
winning margin, game 2	X_2	31 points	31 - 36.6 = -5.6	5.6
winning margin, game 3	X_3	56 points	56 - 36.6 = 19.4	19.4
winning margin, game 4	X_4	8 points	8 - 36.6 = -28.6	28.6
winning margin, game 5	X_5	32 points	32 - 36.6 = -4.6	4.6

Now that we have calculated the absolute deviation score for every observation in the data set, we only have to calculate the mean of these scores. Let's do that:

$$\frac{19.4 + 5.6 + 19.4 + 28.6 + 4.6}{5} = 15.52$$

And we're done. The mean absolute deviation for these five scores is 15.52.

Currently, AAD is not calculated in CogStat, but you can calculate this with other statistics software. When this is added, we'll update this section.

5.2.4 Median absolute deviation

The basic idea behind *median absolute deviation* (MAD) is identical to the one behind the mean absolute deviation (Section 5.2.3). The difference is that you use the median. This has a straightforward interpretation: every observation in the data set lies some distance away from the typical value (the median). So the MAD is an attempt to describe a *typical deviation from a typical value* in the data set.

Definition 5.8 (Median absolute deviation)**.** The **median absolute deviation** (MAD) is a measure of variability calculated as the average of the absolute difference between each observation and the *median* of the data set.

$$\text{MAD} = \frac{1}{n}\sum_{i=1}^{n}|X_i - \text{median}(X)|$$

where n is the number of observations, X_i is the ith observation, and median(X) is the median of the data set.

Example 5.12 (Median absolute deviation)**.** Let's think about our AFL winning margins data, and once again we'll start by pretending that there's only 5 games in total, with winning margins of 56, 31, 56, 8 and 32. Our calculations rely on an examination of the deviation from some reference point, in this case, the median. The median for these five observations is median(X) = 32. We'll repeat the same steps as before with the mean absolute deviation, and we'll have the following result:

$$\text{MAD} = \frac{1}{5}(|56-32| + |31-32| + |56-32| + |8-32| + |32-32|) = 19.5$$

5.2.5 Variance

Variance isn't all too different from the mean absolute deviation. The main difference is that we use squared deviations instead of absolute deviations. With squared deviations, we obtain a measure called **variance**.

Definition 5.9 (Variance)**.** **Variance** is a measure of variability calculated as the average of the *squared difference* between each observation and the *mean* of the data set.

$$\text{Var}(X) = \frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2$$

where n is the number of observations, X_i is the ith observation, and $\bar{X}$ is the mean of the data set.

Variances are *additive*. Suppose we have two variables (X and Y), whose variances are Var(X) and Var(Y) respectively. Now imagine we want to define a new variable Z that is the sum of the two, $Z = X + Y$. As it turns out, the variance of Z is equal to Var(X) + Var(Y).

Example 5.13 (Additive property of the variance)**.** Let's use the first five AFL games as our data. If we follow the same approach that we took last time, we end up with the following table:

Which game	Value	Deviation from mean	Absolute squared deviation
i	X_i	$X_i - \bar{X}$	$(X_i - \bar{X})^2$
1	56	19.4	376.36
2	31	-5.6	31.36
3	56	19.4	376.36
4	8	-28.6	817.96
5	32	-4.6	21.16

That last column contains all of our squared deviations, so all we have to do is average them.

$$\frac{(376.36 + 31.36 + 376.36 + 817.96 + 21.16)}{5} = 324.64$$

Let's tackle the burning question you're probably thinking: how do you *interpret* the variance? Unfortunately, the reason why we haven't given you the human-friendly interpretation of the variance is that there really isn't one. It does have some elegant mathematical properties that suggest that it really is a fundamental quantity for expressing variation and spread. The reason for the difficulty is that all the numbers have been squared, and they don't necessarily mean anything in the original units. For example, if you're running an analysis on vitamin D levels in a study about mood disorders, you'll have a base unit of measure of nmol/L or ng/mL. If you square these numbers, you'll end up with a variance in nmol/L-squared or ng/mL-squared. This is a meaningless unit of measure on its own. However, variance is still a good measure to indicate a spread of data, and it's a good measure to use when comparing variances between different groups.

CogStat will not attempt to interpret the variance nor will it give you the raw value.

Population variance versus variance estimate

If you are extremely lucky and have a data set that contains the entire population, then you can calculate the variance as given in Definition 5.9. This is called **population variance**. In this case the variance is denoted σ^2, the mean is denoted as μ.

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n}(X_i - \mu)^2$$

In research, however, you are most likely to have gathered data for merely a *sample* of the population. There is an alternative formula for this case. This is called **variance estimate**, or *estimated variance*, or *sample variance*, or *estimated population variance*, and is denoted s^2. The formula for the variance estimate is:

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2$$

where n is the number of observations in the sample, X_i is the ith observation, and $\bar{X}$ is the mean of the sample. You'll notice the difference is the denominator using $n - 1$ instead of n.

5.2.6 Standard deviation

Suppose you would like to have a measure expressed in the same units as the data itself (i.e. nmol/L, not nmol/L-squared). What should you do? The solution to the problem is obvious: take the square root of the variance, known as the **standard deviation** (usually shortened as *SD* or *Std dev.*), also called the *root mean squared deviation*, or RMSD. This solves our problem with variance fairly neatly: it's much easier to understand "a standard deviation of 18.01 nmol/L" since it's expressed in the original units.

Definition 5.10 (Standard deviation)**.** **Standard deviation** is the *square root* of the average of the *squared difference* between each observation and the *mean* of the data set.

$$\text{SD} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2}$$

So how do we interpret standard deviation? Standard deviation has the same unit of measure as the observations, e.g., nmol/L, but just like variance, it doesn't have a simple interpretation either. The interpretation is based on the scale of the measurement. E.g. 3.5 can be big or small depending on the scale of measurement. For example, a 3.5 nmol/L SD value for vitamin D level suggests a fairly consistent measurement, considering 50-75 nmol/L is adequate, >75 is optimum, and <25 is deficient according to NHS UK guidelines[3] in 2023. But an SD of 3.5 for a 5-level Likert scale is massive, indicating a less consistent data point and high variability.

There are different ways to standardise the SD. One way is to divide the SD by the mean, which gives you the **coefficient of variation** (CV). Another way is by utilizing z-scores which assumes the data are *normally* distributed, which is an important concept discussed in Chapter **??**. We'll discuss z-scores shortly in Chapter 5.4.

Population SD versus estimated SD

Similarly to variance, we can differentiate the formula for a population-based standard deviation and a sample-based standard deviation.

The **population SD** is denoted σ, the mean is denoted as μ.

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \mu)^2}$$

For calculating a population *estimate* based on sample data, we use the **estimated standard deviation** (s) formula.

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2}$$

where n is the number of observations in the sample, X_i is the ith observation, and $\bar{X}$ is the mean of the sample. The denominator is $n - 1$ instead of n.

[3] https://www.southtees.nhs.uk/services/pathology/tests/vitamin-d/

5.2.7 Which measure to use?

We've discussed quite a few measures of spread and hinted at their strengths and weaknesses. Here's a quick summary:

- *Range*. Gives you the full spread of the data. It's very vulnerable to outliers, and as a consequence, it isn't often used unless you have good reasons to care about the extremes in the data.
- *Interquartile range*. Tells you where the "middle half" of the data sits. It's pretty robust and complements the median nicely. This is used a lot.
- *Average absolute deviation*. Tells you how far "on average" the observations are from the mean. It's very interpretable but has a few minor issues that make it less attractive to statisticians than the standard deviation. Used sometimes, but not often.
- *Median absolute deviation*. The typical deviation from the median value.
- *Variance*. Tells you the average squared deviation from the mean. It's mathematically elegant and is probably the "right" way to describe variation around the mean, but it's completely uninterpretable because it doesn't use the same units as the data. Almost never used except as a mathematical tool, but it's buried "under the hood" of a very large number of statistical tools.
- *Standard deviation*. This is the square root of the variance. It's fairly elegant mathematically, and it's expressed in the same units as the data, so it can be interpreted pretty well. In situations where the mean is the measure of central tendency, this is the default. This is by far the most popular measure of variation.

In short, the IQR and the standard deviation are easily the two most common measures used to report the variability of the data. Still, there are situations in which range or other measures are used.

5.3 Skewness and kurtosis

There are two more descriptive statistics that you will likely see reported in the psychological literature, known as **skewness** and **kurtosis**. These are measures of the shape of the distribution of the data.

Figure 5.9: An illustration of skewness. On the left we have a negatively skewed data set (skewness = −.93), in the middle we have a data set with no skew (technically, skewness = −.006), and on the right we have a positively skewed data set (skewness = .93).

Definition 5.11 (Skewness)**.** **Skewness** is a measure of assymetry of a distribution that compares the median and mean to the mode. A negative skew means the median and mean are smaller than the mode, resulting in a long tail on the left. A positive skew means the median and mean are larger than the mode, resulting in a long tail on the right. A skewness of 0 means the median and mean are equal to the mode, resulting in a symmetrical distribution.

$$\text{skewness}(X) = \frac{1}{N\hat{\sigma}^3} \sum_{i=1}^{N} (X_i - \bar{X})^3$$

where N is the number of observations, $\bar{X}$ is the sample mean, and $\hat{\sigma}$ is the standard deviation (the "divide by $N - 1$" version, that is).

As Figure 5.9 illustrates, if the data tend to have a lot of extreme small values (i.e., the lower tail is "longer" than the upper tail) and not so many extremely large values (left panel), then we say that the data are *negatively skewed*. On the other hand, if there are more extremely large values than extremely small ones (right panel) we say that the data are *positively skewed*.

Not surprisingly, it turns out that the AFL winning margins data is fairly skewed: 0.8 (see Figure 5.4 depicting the analysis results from CogStat).

Definition 5.12 (Kurtosis)**.** **Kurtosis** describes the degree of steepness of a distribution. A steep distribution is *leptokurtic* (positive kurtosis) distribution, a flat distribution is *platykurtic* (negative kurtosis), and the normal distribution is *mesokurtic* (kurtosis is 0).

$$\text{kurtosis}(X) = \frac{1}{N\hat{\sigma}^4} \sum_{i=1}^{N} \left(X_i - \bar{X}\right)^4 - 3$$

where N is the number of observations, $\bar{X}$ is the sample mean, and $\hat{\sigma}$ is the standard deviation (the "divide by $N - 1$" version, that is).

Kurtosis, put simply, is a measure of the "pointiness" of a data set, as illustrated in Figure 5.10.

Figure 5.10: An illustration of kurtosis. On the left, we have a "platykurtic" data set (kurtosis = $-.95$), meaning that the data set is "too flat". In the middle we have a "mesokurtic" data set (kurtosis is almost exactly 0), which means that the pointiness of the data is just about right. Finally, on the right, we have a "leptokurtic" data set (kurtosis = 2.12) indicating that the data set is "too pointy". Note that kurtosis is measured with respect to a normal curve (black line)

When reading the automatically calculated kurtosis value from our CogStat result set, we discover that the AFL winning margins data is just pointy enough: 0.1.

5.4 Standard scores (z-score)

Suppose a friend is creating a new questionnaire to measure "grumpiness". The survey has 50 questions, which you can answer in a grumpy way or not. Across a big sample (hypothetically, let's imagine a million people or so!), the data are fairly normally distributed, with the mean grumpiness score being 17 out of 50 questions answered in a grumpy way and the standard deviation is 5. In contrast, when we take the questionnaire, we answer 35 out of 50 questions in a grumpy way. So, how grumpy are we? One way to think about it would be to say that we have a grumpiness of 35/50, so you might say that we're 70% grumpy. But that's a bit weird when you think about it. Suppose our friend had phrased her questions a bit differently. In that case, people might have answered them differently, so the overall distribution of answers could easily move up or down depending on the precise way the questions were asked. So, we're only 70% grumpy *with respect to this set of survey questions*. Even if it's an excellent questionnaire, this isn't a very informative statement.

A simpler way around this is to describe our grumpiness by comparing us to other people. Shockingly, out of a sample of 1,000,000 people, only 159 people were as grumpy as us, suggesting that we're in the top 0.016% of people for grumpiness. This makes much more sense than trying to interpret the raw data. This idea – that we should describe

our grumpiness in terms of the overall distribution of the grumpiness of humans – is the qualitative idea that standardisation attempts to get at. One way to do this is to describe everything in terms of percentiles. However, the problem with doing this is that "it's lonely at the top".

Suppose that our friend had only collected a sample of 1000 people, and this time got a mean of 16 out of 50 with a standard deviation of 5. The problem is that, almost certainly, not a single person in that sample would be as grumpy as us.

However, all is not lost. A different approach is to convert our grumpiness score into a **standard score**, also referred to as a z-score. The standard score is defined as the number of standard deviations above the mean that my grumpiness score lies. To phrase it in "pseudo-maths", the standard score is calculated like this:

$$\text{standard score} = \frac{\text{raw score} - \text{mean}}{\text{standard deviation}}$$

In actual maths, the equation for the z-score is

$$z_i = \frac{X_i - \bar{X}}{\hat{\sigma}}$$

So, going back to the grumpiness data, we can now transform our raw grumpiness into a standardised grumpiness score. If the mean is 17 and the standard deviation is 5 then my standardised grumpiness score would be (in a bit simplistic way, since we haven't discussed estimations yet):

$$z = \frac{35 - 17}{5} = 3.6$$

To interpret this value, recall the rough heuristic from Chapter 5.2.6: 99.7% of values are expected to lie within 3 standard deviations of the mean. So the fact that our grumpiness corresponds to a z score of 3.6 indicates that we're very grumpy indeed. A theoretical percentile rank for grumpiness, would be 0.9998409.[4]

In addition to allowing you to interpret a raw score in relation to a larger population (and thereby allowing you to make sense of variables that lie on arbitrary scales), standard scores serve a second useful function. Standard scores can be compared to one another in situations where the raw scores can't. Suppose our friend also had another questionnaire that measured extraversion using a 24 items questionnaire. The overall mean for this measure turns out to be 13 with a standard deviation 4; and we scored a 2. As you can imagine, it doesn't make a lot of sense to compare this raw score of 2 on the extraversion questionnaire to our raw score of 35 on the grumpiness questionnaire. The raw scores for the two variables are "about" fundamentally different things, so this would be like comparing apples to oranges.

What about the standard scores? Well, this is a little different. If we calculate the standard scores, we get $z = (35 - 17)/5 = 3.6$ for grumpiness and $z = (2 - 13)/4 = -2.75$ for extraversion. These two numbers *can* be compared to each other.[5] We'd be much less extraverted than most people ($z = -2.75$) and much grumpier than most people ($z = 3.6$): but the extent of our unusualness is much more extreme for grumpiness (since 3.6 is a bigger number than 2.75). Because each standardised score is a statement about where an observation falls *relative to its own population*, it *is* possible to compare standardised scores across completely different variables.

[4]Note that this is true given a normal distribution. More on that later.

[5]Though some caution is usually warranted. It's not always the case that one standard deviation on variable A corresponds to the same "kind" of thing as one standard deviation on variable B. Use common sense when trying to determine whether or not the z scores of two variables can be meaningfully compared.

5.5 Summary: descriptives

We have covered some key aspects of how to summarise what we have learned about the data. As a summary, the following table lists the measures that CogStat will calculate for you, with a brief explanation of what they are and how they are used.

Table 5.1: Descriptives for the variable

	afl.margins	Meaning
Mean	35.3	Average – the "centre of gravity" of the data
Standard deviation	26.0	How clustered is the data around the mean (smaller figure means more clustered, larger figure closer to interquartile range means more spread out)
Skewness	0.8	The assymetry of the data compared to a normal distribution (bell curve)
Kurtosis	0.1	Pointiness of the data. Smaller figure means more pointy, larger figure means less pointy
Range	116.0	The spread of the data set between the maximum and minimum values
Maximum	116.0	The highest value in the data set
Upper quartile	50.5	25% of the data points reside at and above this value
Median	30.5	This is the value of the data point in the middle (or the average of the two middle points in case of even number of data points). 50-50% of data points reside at above and below this value
Lower quartile	12.8	25% of the data points reside at and below this value
Minimum	0.0	The lowest value in the data set

We also discussed z-scores as very specific alternatives to percentiles in some cases, which will come in handy later on.

Chapter 6

Exploring a variable pair

Up to this point, we have focused entirely on how to construct descriptive statistics for a single variable. What we have not done is talk about how to describe the relationships *between* variables in the data. To do that, we want to talk mainly about the **correlation** between variables. But first, we need some data.

After watching the AFL data, let's turn to a topic close to every parent's heart: sleep. The following data set (parenthood.csv) is fictitious but based on real events. Suppose we're curious to determine how much a baby's sleeping habits affect the parent's mood. Let's say we can rate parent grumpiness very precisely on a scale from 0 (not at all grumpy) to 100 (very, very grumpy). And let's also assume that we've been measuring parent grumpiness, parent sleeping patterns, and the baby's sleeping patterns for 100 days.

Figure 6.1: This is what you would see after loading the parenthood.csv dataset.

As described in Chapter 5, we can get all the necessary descriptive statistics for all the variables: `parentsleep`, `babysleep` and `grumpiness`. Let's summarise all these into a neat little table (Table 6.1).

Table 6.1: Descriptive statistics for the parenthood data.

	Parent grumpiness	Parent's hours slept	Baby's hours slept
	'parentgrump'	'parentsleep'	'babysleep'
Mean	63.7	6.965	8.049
Standard deviation	10	1.011	2.064
Skewness	0.4	-0.296	-0.024
Kurtosis	0	-0.649	-0.613
Range	50	4.16	8.82
Maximum	91	9	12.07
Upper quartile	71	7.74	9.635
Median	62	7.03	7.95
Lower quartile	57	6.292	6.425
Minimum	41	4.84	3.25

To start understanding the relationship between a pair of variables, select `Explore relation of variable pair` so a pop-up appears. Move the name of the two variables you wish to analyse from `Available variables` to `Selected variables`, then click `OK`. In CogStat, we can run analysis on multiple variables at once by selecting them in the variable list. This will display all analysis results after each other sequentially. We'll be looking at sections called *Sample properties* from the result sets.

6.1 The strength and direction of a relationship

We can draw scatterplots to give us a general sense of how closely related two variables are. Ideally, though, we might want to say a bit more about it than that. For instance, let's compare the relationship between `parentsleep` and `parentgrump` with that between `babysleep` and `parentgrump` (Figure 6.2).

Figure 6.2: Scatterplot drawn by CogStat showing the relationship between 'parentsleep' and 'parentgrump' and between 'babysleep' and 'parentgrump'

When looking at these two plots side by side, it's clear that the relationship is *qualitatively* the same in both cases: more sleep equals less grump! However, it's also obvious that the relationship between `parentsleep` and `parentgrump` is *stronger* than between `babysleep` and `parentgrump`. The plot on the left is "neater" than on the right. It feels like if you want to predict the parent's mood, it will help you a little bit to know how many hours the baby slept, but it'd be *more* helpful to know how many hours the parent slept.

Scatterplots

On a scatterplot graph, each observation is represented by one dot in a coordinate system. The horizontal location of the dot plots the value of the observation on one variable, and the vertical location displays its value on the other variable.

Scatterplots are used often:

- to visualise the relationship between two variables,
- to identify trends, which can be further explored with regression analysis (see Chapter **??**),
- and to detect outliers.

Scatterplots can only be used with *continuous variables*. If you have a *discrete variable*, you can use a boxplot instead.

Figure 6.3: Scatterplot drawn by CogStat showing the relationship between ‘babysleep‘ and ‘parentsleep‘

In contrast, let's consider Figure 6.2 vs. Figure 6.3. If we compare the scatterplot of "`babysleep` v `parentgrump`" to the scatterplot of "“`babysleep` v `parentsleep`", the overall strength of the relationship is the same, but the direction is different. If the baby sleeps more, the parent gets *more* sleep (positive relationship, but if the baby sleeps more, then the parent gets *less* grumpy (negative relationship).

6.2 The correlation coefficient

We can make these ideas a bit more explicit by introducing the idea of a **correlation coefficient** (or, more specifically, **Pearson's correlation coefficient**), which is traditionally denoted by r. The correlation coefficient between two variables X and Y (sometimes denoted r_{XY}), which we'll define more precisely shortly, is a measure that varies from -1 to 1. When $r = -1$, it means that we have a perfect negative relationship, and when $r = 1$, it means we have a perfect positive relationship. When $r = 0$, there's no relationship at all. If you look at Figure 6.4, you can see several plots showing what different correlations visually look like.

Figure 6.4: Illustration of the effect of varying the strength and direction of a correlation

The Pearson's correlation coefficient formula can be written in several ways. The simplest way to write down the formula is to break it into two steps. Firstly, let's introduce the idea of a **covariance**. The covariance between two variables X and Y is a generalisation of the notion of the variance. It is a mathematically simple way of describing the relationship between two variables that isn't terribly informative to humans:

$$\text{Cov}(X, Y) = \frac{1}{N-1} \sum_{i=1}^{N} (X_i - \bar{X})(Y_i - \bar{Y})$$

Because we're multiplying (i.e., taking the "product" of) a quantity that depends on X by a quantity that depends on Y and then averaging[1], you can think of the formula for the covariance as an "average cross product" between X and Y. The covariance has the nice property that, if X and Y are entirely unrelated, the covariance is exactly zero. If the relationship between them is positive (in the sense shown in Figure 6.4), then the covariance is also positive. If the relationship is negative, then the covariance is also

[1]Just like we saw with the variance and the standard deviation, in practice, we divide by $N - 1$ rather than N.

negative. In other words, the covariance captures the basic qualitative idea of correlation. Unfortunately, the raw magnitude of the covariance isn't easy to interpret: it depends on the units in which X and Y are expressed, and worse yet, the actual units in which the covariance is expressed are really weird. For instance, if X refers to the `parentsleep` variable (units: hours) and Y refers to the `parentgrump` variable (units: grumps), then the units for their covariance are "hours × grumps". And I have no freaking idea what that would even mean.

The Pearson correlation coefficient r fixes this interpretation problem by standardising the covariance in the same way that the z-score standardises a raw score: dividing by the standard deviation. However, because we have two variables that contribute to the covariance, the standardisation only works if we divide by both standard deviations.[2] In other words, the correlation between X and Y can be written as follows:

$$r_{XY} = \frac{\text{Cov}(X, Y)}{\hat{\sigma}_X \, \hat{\sigma}_Y}$$

By doing this standardisation, we keep all of the nice properties of the covariance discussed earlier, and the actual values of r are on a meaningful scale: $r = 1$ implies a perfect positive relationship, and $r = -1$ implies a perfect negative relationship.

6.3 Interpreting a correlation

Naturally, in real life, you don't see many correlations of 1. So how should you interpret a correlation of, say $r = .4$? The honest answer is that it really depends on what you want to use the data for, and on how strong the correlations in your field tend to be. A friend of Danielle's in engineering once argued that any correlation less than .95 is completely useless (he may have been exaggerating, even for engineering). On the other hand, there are real cases – even in psychology – where you should expect strong correlations. For instance, one of the benchmark data sets used to test theories of how people judge similarities is so clean that any theory that can't achieve a correlation of at least .9 isn't deemed successful. However, when looking for (say) elementary intelligence correlates (e.g., inspection time, response time), if you get a correlation above .3 you're doing very well. In short, the interpretation of a correlation depends a lot on the context. That said, the rough guide in Table 6.2 is fairly typical.

However, something that can never be stressed enough is that you should *always* look at the scatterplot before attaching any interpretation to the data. A correlation might not mean what you think it means. The classic illustration of this is "Anscombe's Quartet" (Anscombe, 1973), which is a collection of four data sets. Each data set has two variables, an X and a Y. For all four data sets, the mean value for X is 9, and the mean for Y is 7.5. The standard deviations for all X variables are almost identical, as are the standard deviations for the Y variables. And in each case the correlation between X and Y is $r = 0.816$.

You'd think that these four data sets would look pretty similar to one another. They do not. If we draw scatterplots of X against Y for all four variables, as shown in Figure 6.5 we see that all four of these are *spectacularly* different to each other.

[2] This is an oversimplification.

Table 6.2: Rough guide to interpreting correlations

Correlation	Strength	Direction
-1.0 to -0.9	Very strong	Negative
-0.9 to -0.7	Strong	Negative
-0.7 to -0.4	Moderate	Negative
-0.4 to -0.2	Weak	Negative
-0.2 to 0	Negligible	Negative
0 to 0.2	Negligible	Positive
0.2 to 0.4	Weak	Positive
0.4 to 0.7	Moderate	Positive
0.7 to 0.9	Strong	Positive
0.9 to 1.0	Very strong	Positive

Figure 6.5: Anscombe's quartet. All four of these data sets have a Pearson correlation of $r = .816$, but they are qualitatively different from one another.

The lesson here, which so very many people seem to forget in real life, is "*always graph your raw data*".

6.4 Spearman's rank correlations

Figure 6.6: The relationship between hours worked and grade received for a toy data set consisting of only 10 students (each circle corresponds to one student). The dashed line through the middle shows the linear relationship between the two variables. This produces a strong Pearson correlation of $r = .91$. However, the interesting thing to note here is that there's actually a perfect monotonic relationship between the two variables: in this toy example, at least, increasing the hours worked always increases the grade received, as illustrated by the solid line. This is reflected in a Spearman correlation of $rho = 1$. With such a small data set, however, it's an open question as to which version better describes the actual relationship involved.

The Pearson correlation coefficient is useful for many things, but it has shortcomings. One particular issue stands out: what it actually measures is the strength of the *linear* relationship between two variables. In other words, it gives you a measure of the extent to which the data all tend to fall on a single, perfectly straight line. Often, this is a pretty good approximation to what we mean when we say "relationship", and so the Pearson correlation is a good thing to calculate. Sometimes, it isn't.

One very common situation where the Pearson correlation isn't quite the right thing to use arises when an increase in one variable X really is reflected in an increase in another variable Y. However, the nature of the relationship isn't necessarily linear. An example of this might be the relationship between effort and reward when studying for an exam. If you put zero effort (X) into learning a subject, you should expect a grade of 0% (Y). However, a little bit of effort will cause a *massive* improvement: just turning up to lectures means that you learn a fair bit and if you just turn up to classes and scribble a few things down so your grade might rise to 35%, all without a lot of effort. However, you just don't get the same effect at the other end of the scale. As everyone knows, it takes *a lot* more effort to get a grade of 90% than it takes to get a grade of 55%. This means that if I've got data looking at study effort and grades, there's a good chance that Pearson correlations will be misleading.

To illustrate, consider the data plotted in Figure 6.6, showing the relationship between hours worked and grade received for 10 students taking some classes. The curious thing about this – highly fictitious – data set is that increasing your effort *always* increases your grade. It might be by a lot or by a little, but increasing the effort will never decrease your grade.

The data are stored in `effort.csv`. CogStat will calculate a standard Pearson correlation

Student	Rank (hours worked)	Rank (grade received)
student 1	1	1
student 2	10	10
student 3	6	6
student 4	2	2
student 5	3	3
student 6	5	5
student 7	4	4
student 8	8	8
student 9	7	7
student 10	9	9

first[3]. It shows a strong relationship between hours worked and grade received: $r = 0.909$. But this doesn't actually capture the observation that increasing hours worked *always* increases the grade. There's a sense here in which we want to say that the correlation is *perfect* but for a somewhat different notion of a "relationship". What we're looking for is something that captures the fact that there is a perfect **ordinal relationship** here. That is, if student 1 works more hours than student 2, then we can guarantee that student 1 will get a better grade. That's not what a correlation of $r = 0.91$ says at all.

How should we address this? Actually, it's really easy: if we're looking for ordinal relationships, all we have to do is treat the data as if it were an ordinal scale! So, instead of measuring effort in terms of "hours worked", let us rank all 10 of our students in order of hours worked. That is, student 1 did the least work out of anyone (2 hours), so they got the lowest rank (rank = 1). Student 4 was the next laziest, putting in only 6 hours of work over the whole semester, so they got the next lowest rank (rank = 2). Notice that we're using "rank = 1" to mean "low rank". Sometimes in everyday language, we talk about "rank = 1" to mean "top rank" rather than "bottom rank". So be careful: you can rank "from smallest value to largest value" (i.e., small equals rank 1), or you can rank "from largest value to smallest value" (i.e., large equals rank 1). In this case, we're ranking from smallest to largest. But in real life, it's really easy to forget which way you set things up, so you have to put a bit of effort into remembering!

Okay, so let's have a look at our students when we rank them from worst to best in terms of effort and reward:

Hm. These are *identical*. The student who put in the most effort got the best grade, the student with the least effort got the worst grade, etc. We can rank students by hours worked, then rank students by grade received, and these two rankings would be identical. So if we now correlate them, we get a perfect relationship: 1.

We've just re-invented the **Spearman's rank order correlation**, usually denoted ρ (pronounced: rho) to distinguish it from the Pearson correlation r. CogStat will use r_S to denote rank order correlation.

CogStat will automatically calculate both Pearson's correlation and Spearman's rank order correlation for you if your measurement is not set in your source data (Figure 6.7). If you set the measurement type to "ordinal" in your source file, it will omit to calculate Pearson's correlation due to the above reasons.

[3] Unless, of course, you set your measurement level in the second row of the CSV as `"ord"` (*ordinal*), because then you already tell the software that Pearson's r does not make sense to look at.

Figure 6.7: This is what you would see in CogStat after loading the 'effort.csv' dataset.

6.5 Missing values in pairwise calculations

To illustrate the issues, let's open up a data set with missing values, `parenthood_missing.csv`. This file contains the same data as the original parenthood data but with some values deleted. While the original source could contain an empty value or `NA`, CogStat will display `NaN` for these missing values (Figure 6.8).

Figure 6.8: This is what you would see in CogStat after loading the adjusted dataset.

Let's calculate descriptive statistics using the `Explore variable` function (See Chapter: 5):

We can see that there are 9 missing values for `parentsleep` (`N of missing cases: 9`), 11 missing values for `babysleep` (`N of missing cases: 11`), and 8 missing values for `parentgrump` (`N of missing cases: 8`).

Whichever pair you'd like to run (e.g., `parentsleep` vs. `parentgrump`), CogStat will automatically exclude the missing values from the calculation:

Table 6.3: Descriptive statistics for the parenthood data with missing values. We can observe the slight difference in our statistics when we have missing values.

	Parent grumpiness	Parent's hours slept	Baby's hours slept
	'parentgrump'	'parentsleep'	'babysleep'
Mean	63.2	6.977	8.114
Standard deviation	9.8	1.015	2.035
Skewness	0.4	-0.346	-0.096
Kurtosis	-0.2	-0.647	-0.5
Range	48	4.16	8.82
Maximum	89	9	12.07
Upper quartile	70.2	7.785	9.61
Median	61	7.03	8.2
Lower quartile	56	6.285	6.46
Minimum	41	4.84	3.25

Figure 6.9: 17 missing pairs when comparing 'parentsleep' and 'parentgrump'

Figure 6.10: 18 missing pairs when comparing ‘babysleep‘ and ‘parentgrump‘

Figure 6.11: 20 missing pairs when comparing ‘babysleep‘ and ‘parentsleep‘

6.6 Summary

In this chapter, we discussed how to measure the strength of the relationship between two variables. We introduced the concept of correlation and how to calculate it using CogStat. We also discussed the difference between **Pearson's correlation** (Chapter 6.2) and **Spearman's rank order correlation** (Chapter 6.4), and how CogStat will calculate it for you. Finally, we discussed how CogStat handles missing values (Chapter 6.5) in pairwise calculations.

You might have been tempted to look at the regression coefficient, the linear regression formula etc. when exploring the results from CogStat. Don't worry, you'll have a chance to learn about these in Chapter **??**.

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