

AN ADVENTURE IN STATISTICS

THE REALITY ENIGMA

ANDY FIELD



ILLUSTRATED BY JAMES ILES

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STATISTICS

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SAGE Publications Ltd
1 Oliver's Yard
55 City Road
London EC1Y 1SP

SAGE Publications Inc.
2455 Teller Road
Thousand Oaks, California 91320

SAGE Publications India Pvt Ltd
B 1/I 1 Mohan Cooperative Industrial Area
Mathura Road
New Delhi 110 044

SAGE Publications Asia-Pacific Pte Ltd
3 Church Street
#10-04 Samsung Hub
Singapore 049483

Editor: Mark Kavanagh
Development editor: Robin Lupton
Production editor: Ian Antcliff
Copyeditor: Richard Leigh
Proofreader: Andy Baxter
Indexer: David Rudeforth
Marketing manager: Ben Griffin-Sherwood
Cover design: Wendy Scott
Typeset by: C&M Digitals (P) Ltd, Chennai, India
Printed and bound in Great Britain
by Bell and Bain Ltd, Glasgow

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First published 2016

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Library of Congress Control Number: 2016936610

British Library Cataloguing in Publication data

A catalogue record for this book is available from
the British Library

ISBN 978-1-4462-1044-4
ISBN 978-1-4462-1045-1 (pbk)

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HOW TO USE THIS BOOK

The whole ‘embedding the statistics in a fictional story’ thing makes this book a bit unusual compared to a lot of statistics textbooks. I realize that a lot of students and tutors don’t like ‘unusual’, so here are some questions that I think some people might want to ask.

WHO IS THE BOOK AIMED AT?

The book is aimed at anyone interested in learning statistical methods. It assumes no prior knowledge at all.

HOW DO I TEACH WITH A BOOK THAT HAS A FICTIONAL NARRATIVE?

Fundamentally, I’d teach with it the same way as with any other book. Most of the chapters have a very similar structure: section of story, section of statistics, section of story, section of statistics, section of story. So, in most chapters there are two large sections of statistics that are book-ended by story, and there’s a bit of story in the middle to offer some light relief. As such, it’s fairly easy to ignore the story if you want to. The sections of statistics are all written as conversations between the main character and various people he meets. The academic content is what you’d expect to find but presented as a conversation between a student (the main character) and a teacher (the particular character in the story who is teaching him). This sort of Socratic style is a good tool for teaching because the main character (hopefully) asks the same sorts of questions that students often want to ask. Of course, you should feel free to embrace the story if that suits your teaching style, and I could imagine giving lectures that begin by setting the scene of the story, or which end with the chapter cliff-hangers. I’d *love* to hear of people doing that, but ultimately you have to do what works for your teaching style.

CAN I DIP INTO THE BOOK?

Having a story running through the book means that it works best if you read it from cover to cover. The idea is that once you get into the story it acts as a motivator to read the book, and therefore the statistics parts. One of the major problems in teaching statistics, I think, is that people tend to dip into it without laying the foundations in the correct order. In a sense, the intentions of this book are to encourage you to learn things in a sensible order and build up your knowledge; in doing so you will (hopefully) understand the material better. However, I think you can dip in if you really want to because the chapters are structured in a fairly standard way (see my answer to *How do I teach with a book that has a fictional narrative?*) so you can read the sections relating to statistics without necessarily having to know what's going on in the story. In my ideal world, though, you would start at the beginning and read until the end.

WHAT ONLINE RESOURCES ARE THERE?

This book is supported by SAGE edge, which offers a range of additional resources to support students and lecturers alike. Visit <https://edge.sagepub.com/field-adventures-in-stats>

For students

- **Learning objectives** remind you of the key concepts you will learn in each chapter.
- **Multiple choice quizzes** let you test yourself and prepare for exams.
- **Flashcards** featuring all the statistical terms in this book, as well as a few non statistical ones.
- **Data files** and **R** scripts for each chapter allow you to work through the Check your Brain problems and end of chapter puzzles.
- **Zach's facts** from each chapter have been extracted to help your revision.
- **Answers to end of chapter questions** for you to check your work.
- Links to a videos relevant to this book (as well as others) are available on my YouTube channel, at www.youtube.com/user/ProfAndyField
- **Action plans** highlighting all the resources available on the website.
- A bit of **distraction**. My publisher has created a few theoretically fun quizzes such as *Are You a Chipper or a Clockotorian?* because sometimes you need a break from all the stats.
- For more support and news for this and my other books visit <http://www.discoveringstatistics.com/> or <https://www.facebook.com/ProfAndyField> or follow me @ProfAndyField
- Join the conversation: my publisher will be posting news, competitions and more, follow #StatsAdventure or visit <https://www.facebook.com/DiscoveringStatisticsWithAndyField/>

For lecturers

- A **testbank** based on the most relevant questions from *Discovering Statistics Using SPSS, 4e*, has been adapted to support this book and can be customised for your teaching.
- **PowerPoints** featuring the figures and tables from the book.
- **Datasets** from each chapter in one zip file, so you can download them quickly for your teaching.



This book is dedicated to the three loves of my life: Zoë, Zach and our currently unborn and unnamed (but I'm sure Zoë is working on that) child. I wish memoryBank existed so I could store how I feel when my children are asleep in my arms and re-experience it in years to come when they don't want to sleep in my arms any more. As for my amazing wife Zoë, if she ever mysteriously disappears I will, without hesitation, cross a probability bridge to find her.



PROLOGUE

THE DYING STARS

ADEONA

ELPIS

ANTEVORTA

HERMES CAFE

THE ASHTREE SHRINE

ZACH'S APARTMENT

GENARI'S OFFICE

JANUS

OCCAM'S

DOCTRINE OF CHANCE

POSTVERTA

HALLOWED POINT

PORUS

THE EVIL POCKETS

SECRET PHILANTHROPIC SOCIETY

REPOSITORY

BEIMENI CENTRE OF GENETICS

EGESTES

PROBABILITY BRIDGE

VERITAS

THE 6 BAR

JIGSAW



Zach Slade: the most inspirational, talented, creative musician in Elpis, the city of hope. His band, The Reality Enigma, has done virtual tours of the world to their fanatic followers, but only the people in our hometown, Elpis, get to see them in the flesh. Despite what the ‘Chippers’ will tell you, nothing beats the transcendental experience of a live band, and I have never missed one of their gigs. On stage, this intense, spellbinding man exorcises the souls of his audience with every note he plays, word he sings, and stare from his brooding eyes. Every gig I see a thousand people falling in love with him, but none of them knows the kind, gentle, and self-doubting man with whom I share my life. I can only dream of affecting people with my research like Zach does with his music. Although he barely registers it, Zach has changed thousands of people’s lives, but none as much as mine when he first spoke to me in our college library ten years ago. He took a shy, lonely girl – estranged from the social world – and connected her; but since we met everything has changed.

Zach and I are children of the Reality Revolution: the first generation born after society collapsed. Before then, everyone believed that they were special, talented, and destined for fame. People blamed reality TV, but perhaps we all need to hope for a bright future to keep us sane. Whatever the reason, values of hard work and collective good were eroded and replaced with self-interest and entitlement. History blames Professor Milton Grey for the revolution because it was his invention – the reality prism – that started everything. The reality prism – a transparent pyramid worn on the head – split reality into the part that is objectively true and the part that is subjective experience. The prism went from an expensive prototype to a cheap mass-produced piece of technology almost overnight, and millions bought them.

The reality prism bought honesty to the world: propaganda and media influence became impossible in a world where people could bisect the objective truth from the subjective spin. Religions collapsed, not because the prism proved them wrong but because it exposed the organizations that profited from them. Everyone could know the truth about anything that they could



look at, but the gift of the reality prism was also its curse. Inevitably people looked at themselves in mirrors through the prism. Imagine seeing yourself stripped of the small, harmless tricks that our minds play to make ourselves feel better about who we are. The prism let people see how intelligent, funny, attractive, and talented they really were, and for most people the truth didn't live up to their beliefs. Most of us are ordinary, and there's nothing wrong with that, unless society tells you that ordinary isn't good enough.

People became depressed and purposeless. They lost interest in everything because the media lost their power to hype anything: bands couldn't pretend that their latest album was their best, you couldn't be fooled into thinking the latest Proteus is much better than the previous one, no one believed that a sports event was more important than a game that would be repeated every subsequent season with very little bearing on anything, and everyone knew that cosmetics could not perform the miracles that they claimed. Advertising failed, businesses collapsed, and political parties ceased to function in a world where they couldn't lie. The revolution itself was over in 5 years, but society has taken decades to rebuild. My parents describe the revolution as killing culture: without self-belief there is no creativity, and without creativity there cannot be musicians, artists, or writers. People abandoned these pursuits because the reality prisms made them believe that they had nothing of value to offer. Instead people looked back to the old world: the musicians and bands from the pre-revolution period of the 1970s to 2040s became revered because nobody believed they had the talent to emulate them. Our parents, who lived through the revolution, lost faith, but to Zach and me it was a story from before we were born, we'd never looked through a reality prism so we'd never seen our limitations. Zach absorbed the music of the past but believed he could use it to inspire something new: songs for our world, not a world of the past. He was brilliant at it.

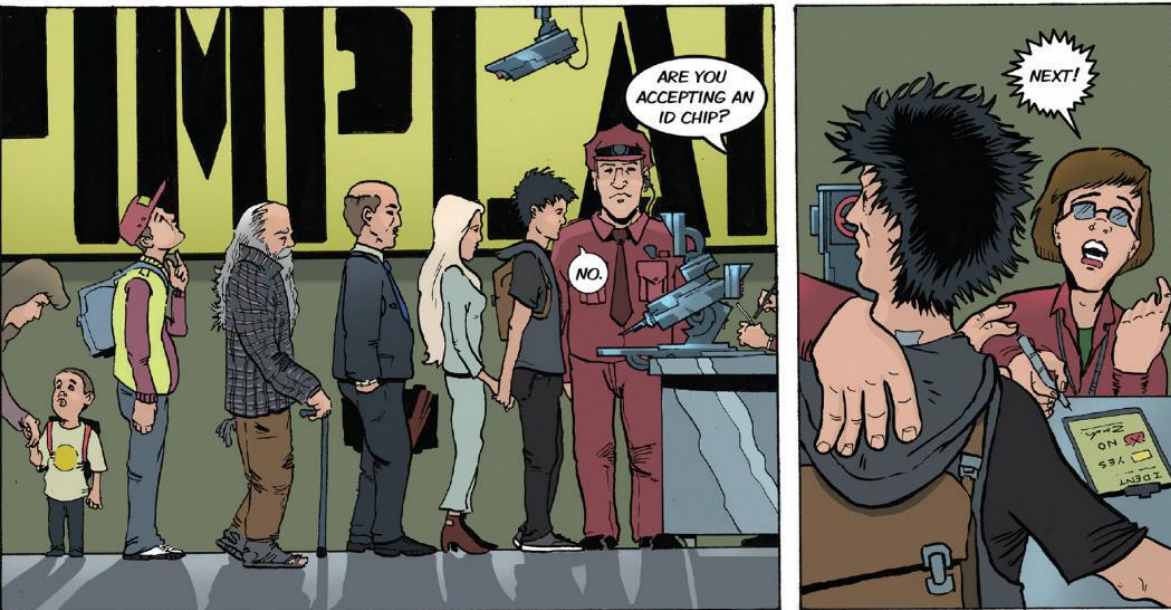
The history I was taught as a child told me that the revolution sent us back to darker times, but I believe it saved us. To me, Milton Grey is a hero, not a villain. In the wake of the revolution, people across the world united in the common goal of rebuilding. Some believed that we should start from where we left off and embrace the technological advances of the pre-revolution, whereas others yearned to return to what they believed were simpler and happier times. As they delved into our cultural past, they fell back in love with the physical experience of books, art and vinyl LPs, all of which were thought obsolete before the revolution. These people were also driven by a desire to reconnect to the Earth through eco-friendly retro-technology: they embraced the pre-21st century culture of clockwork and steam technology. Over time these technologies merged with those of our own generation: clockwork and steam fusion were born.

The World Governance Agency (**WGA**) emerged from the ashes of the revolution: a humanitarian organization that built a new society on foundations of truth. The WGA worked to create order in a fragmented society; their primary goal was to promote community and well-being. It was largely due to their efforts that the different views on the new world were seamlessly merged: under their guidance, scientists developed steam and clockwork technologies to power both retro and modern devices, they built vast repositories to house collections of physical media and provided the space for people to enjoy them. The world became both brave and innovative, but sentimental to its past; it is a strange but beautiful mix of the modern and the antique. Unlike any political party before it, the WGA achieved the impossible: everyone was happy.

That was the utopian world that Zach and I grew up in, it is the backdrop of our early years, but is also an uncomfortable reminder of how things have changed since we met. First, the WGA



started to ‘chip’ people. Small microchips had been implanted in family pets for more than a century, but with technological advancements it became possible to implant WiFi-enabled chips into humans, enabling them to record what they saw, thought and heard in real time. Those who embraced technology raced to be the first to have chips implanted, queuing at the chipping stations to have their minds tagged. We called them ‘Chippers’ and they labelled those refusing the chips as ‘Clocktorians’, a derogatory term to imply that we were backward-looking people stuck in a ‘clockwork, Victorian’ society. Perhaps they were right, but at least we didn’t have chips in our brains.



Next *memoryBank* was launched: a virtual mind where Chippers broadcast their lives to each other as real-time, high-definition streams. With only a thought, Chippers could flag single moments in the video stream as highly significant events (‘highsies’). These events were broadcast directly to the brains of other Chippers in the same network and their emotional reaction to it, their ‘emo’, was automatically recorded and tagged in real time. There was no hiding your feelings on *memoryBank*. Our lives were stored virtually; the pre-revolution idea of the cloud had been taken to a logical conclusion and everyone had a ‘star’: a limitless space to store their digital world. Friends and family could network their stars in constellations; *memoryBank* was the next step – a galaxy of Chippers’ stars.

Clocktorians were ostracized from much of this online world: we had stars, but connected using technology instead of our minds; we retreated into retro-culture. Society was becoming fragmented again, and it felt like a metaphor for Zach and me. As I became more successful in my scientific career I became more reliant on evidence for my beliefs, and understood less his blind acceptance of his gut feelings. The more advanced my work became, the less he understood or even tried to

understand it. The more science drives me towards technology the less I understand why he clings to an old-fashioned world that died more than a century ago. I know that I cannot love anyone as much as I love him so these feelings scare me, but not as much as what's happened in the last few weeks, and that's why I have to leave him. Worse than that, I can't tell him why. I hope he forgets me, and one day forgives me, but never sees how heartbroken I'm about to become.

Dr Alice Nightingale

The Beimeni Centre of Genetics

Elpis

IN THE NEXT CHAPTER, ZACH DISCOVERS ...

The scientific process
How to make a scientific statement
The various research methods
Why we need science
That Alice is acting weird





WHY YOU NEED SCIENCE

THE BEGINNING AND THE END

Will you love me now? #10

How science works #14

The research process #14

Science as a life skill #21

Research methods #21

Correlational research methods #22

Experimental research methods #24

Two methods of data collection #25

Two types of variation #26

Practice, order and randomization #27

Piecing it all together #31

Why we need science #34

Key terms #36

JIG:SAW's puzzles #36



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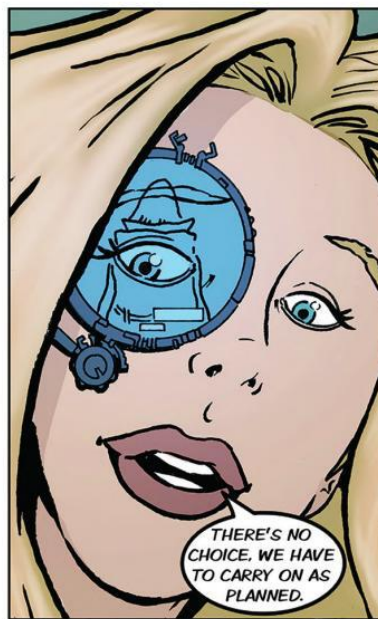
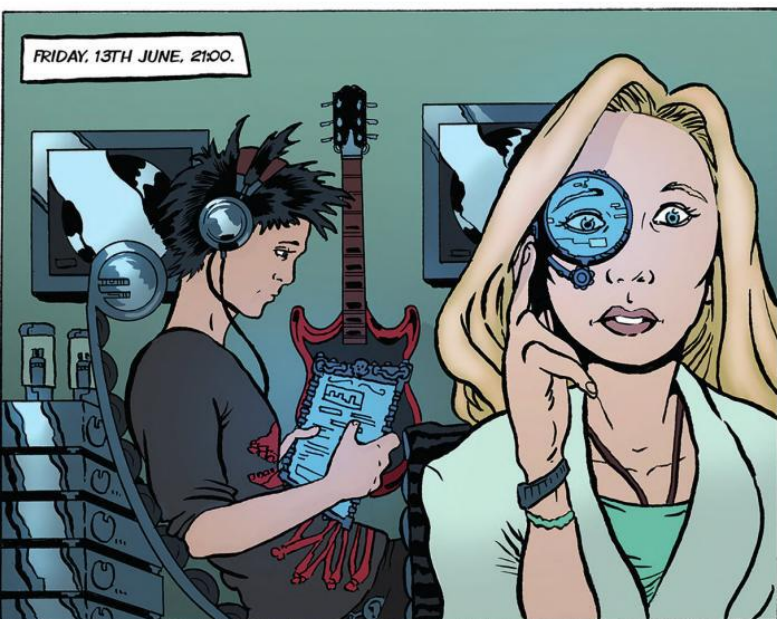
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JIGSAW puzzles #36



Alice had been acting strangely all night. I had returned from band practice to make dinner before she got in from work, but she was already home. Alice never left work early. She was on edge, and had been for weeks, as though she was hiding something. She was playing music too. Nothing strange about that, you might think, and, sure, when we first hooked up music was our shared passion, but Alice had lost interest. She would come to my gigs, but otherwise she seemed to live and work in silence. I worried sometimes that there was too much silence in her life – that she was too disconnected. Tonight, though, our apartment was full of the sound of an album we used to listen to back in the day, an album that transported me back to a time of staying up with her all night talking and avoiding sleep because it meant being apart. The riffs hit me as soon as I opened the door. It was strange not to return to an empty, silent apartment – it made me a little uneasy. I smiled when I registered that Alice was home and recognized the album she was playing: perhaps her world wasn't as silent as I feared, and maybe these songs still meant something to her? These hopes faded as I saw her nervous and distant expression. She barely registered that I was back, and I felt stupid for thinking that the music might be anything other than a random decision. Alice was a scientist, and that seemed to rule out being sentimental. I cooked, we ate, and Alice spoke only to snap at me. This was normal in recent weeks: things between us had become strained; I wasn't sure how we'd got to this place, or how to leave it.

Alice and I are Clocktorians, but I cling to the pre-revolution more than she does. I wish I had lived through those times; the turn of the 21st century sat in the middle of a golden era for music. People would gather in their thousands at events called 'festivals' to watch bands perform, not in virtual reality but in the flesh. Bands travelled the world, had a real, physical connection to their

fans. Of course, my band plays gigs too, but only in our home city. For the rest of the world we are an image in an oculus riff: a multisensory headset for experiencing virtual gigs. For me, the world did so much right a century ago, I couldn't understand how it went so wrong, but people like me were doing our bit to bring back the old ways.

Before the ID chips came in everybody had a Proteus – a device made from programmable matter,¹ which means that it can transform shape and function. In the pre-revolution people had iWatches, iPods, iPhones and the like. The Proteus replaced them all with a single device: it could transform into a touch screen to type text messages, become an earpiece for streamed music, and would happily become a visual screen or project a 3-D image for a video. A Proteus could become whatever you wanted it to be: the owner had only to think of what they wanted it to look like and it would become that thought. You could wear it as a ring, a bracelet, or any design in your imagination. I mainly kept mine in the shape of a slim tombstone, across the top of which was inscribed 'In loving memory of your memory'. I called it my diePad. It was a joke to myself because I think everyone relies so much on technology that our memories have died. Of course Chippers not only don't need a memory, they don't need a Proteus: the chips in their heads relay their thoughts to others via *memoryBank*. This connectivity has made Clocktorians like us outsiders: it's difficult for us to connect to Chippers and they have to resort to a Proteus to get hold of a Clocktorian. It's a pain.

Alice had been on her Proteus most of the evening. She liked to wear hers as an earpiece with a small microphone to pick up her voice and a monocle to see the caller. This meant that I couldn't see who she was talking to or hear the conversation, but I could tell that something wasn't right. I wanted to help, but Alice didn't seem in the mood to talk to me. Fed up with her spiky mood, I put on my headphones to listen back to our rehearsal recordings and picked up my diePad to look at the news. Wearing headphones said a lot about me: Chippers had music transmitted directly to their brains, and even most Clocktorians used their Proteus for listening, but I liked the space and warmth created by dedicated headphones.

1.1 WILL YOU LOVE ME NOW?

As I listened, I found myself distracted by a news story about the Proteus. It claimed that some of the technology in the Proteus had its roots in pre-revolution mobile phones: primitive, inflexible blocks that people used to communicate before the first Proteus, they couldn't change shape or function. They were basically useless. The news story looked at some data from before the revolution that claimed that these old phones caused brain tumours. The journalist argued that the same was likely to be true of the Proteus. Alice spent a lot of time with her Proteus stuck in her ear, and this article worried me: what if she was harming herself? She'd been talking for ages while I'd been engrossed in the story. Now she was pacing around like she was looking for somewhere to offload the weight on her shoulders. I couldn't bear it any more; I took my headphones off and asked her if everything was level. She looked at the floor and reassured me that everything was fine. She always looked at the floor when she was lying.

'Maybe I can help?' I offered.

Alice sighed. It was one of those sighs that made her seem as though she'd become suddenly aware of how little of her lung capacity she normally used. In the Venn diagram of Alice and me

there was a beautiful ellipse containing music, films, literature and a general belief in the goodness of humanity, but outside of it we were poles apart. At times like this Alice made me think the ellipse was shrinking. Her facial expression was a window into our growing differences.

She looked at me as though I'd said something ridiculous. 'It's work stuff, you wouldn't understand,' she said dismissively.

Alice did this a lot since she started working at the Beimeni Centre of Genetics: she assumes I'm stupid and uninterested in her research. She has a point. I don't understand maths and science and I never have. Science is dull, unemotional, uninspiring. It can't break your heart like a good resolution in a song. The mistake she makes is assuming that because I'm not interested in science, I am not interested in *her*. She couldn't be more wrong: I'm in awe of her ability to analyse and evaluate situations. She is the most intelligent person I know, and even other scientists think that she is brilliant: she won the World Science Federation's prestigious Einstein medal when she was 21 for her genetics research. She is a genius, of that I'm certain. I know exactly how brilliant she is, and every day I see a passion for knowledge burning in her every bit as strong as the one I have for music.

For real, the vibe was spooks tonight; I didn't know why, but I felt sure that Alice needed someone, and I wanted that person to be me. She had always taken an interest in my music, perhaps it was time I took an interest in science; it might be enough for her to let me in on whatever was going on.

'Maybe I *could* understand,' I said. 'Try me.'

Alice gave an exasperated sigh. 'It's too late for that, Zach; you can't just make everything better by suddenly showing an interest in me.'

Her directness hurt me, but it also seemed at odds with her vibe. The same album was still playing in the background, as though it comforted her to hear the songs that once were the glue that bonded us. Her eyes too; I couldn't explain, but in her eyes was *something*, the tiniest glint of something, that said 'It's *not* too late Zach, please help me.' Maybe it was nothing, but there was only one way to find out.

'I've been reading this,' I said passing my diePad to her. 'This guy believes that the Proteus might cause brain tumours – for real. It's based on pre-revolution science. He quotes newspaper headlines from last century: the *Daily Express* says "Just a few minutes a day on a mobile phone 'raises cancer risk'";² the *Daily Mail*, "Mobile phones may cause cancer, warn world health chiefs";³ and *US News and World Report*, "Cellphone Use and Cancer: New Study Suggests a Link".⁴ Even the BBC and CBS News report "Mobiles 'may cause brain cancer'".^{5,6} Seems scary to me. You're a scientist, tell me how *you* would know if the cancer thing was true.'

Alice eyed me suspiciously. 'The headlines are there to grab your attention. I'd look at the *evidence*,' she said curtly.

Alice was trying to shut down the conversation, but I wasn't going to give in. I pulled a silver hunter-cased pocket watch from my jacket. On the silver cover was etched 'Be still, and know'. I pressed the winding mechanism to spring open the cover. Laying the watch flat on my palm, we looked at the familiar clockwork mechanism: a beautiful configuration of cogs, hairsprings, and red, yellow and blue jewels positioned equidistant inside the circular edge. The cogs accelerated into a blur of motion, and at the point of critical velocity the three jewels projected each of their colours upwards into a central mist that quickly settled into the shape of an opaque human head. Clockwork fusion never ceased to impress me: how could self-winding springs create the kind of power needed to generate a fully functional artificially intelligent head? The device was a 'reality



checker' and the head within was linked to everything. Of course, you could find things out using a Proteus, or even an ID chip if you had one, but the reality checkers added something that none of these devices could: a brain much better than your own. A reality checker would assimilate data from everywhere, evaluate it, and give you the best answer it could to any question. Gone were the days of believing any nonsense that you uncovered on the internet; a reality checker would filter it all for you. Every head had a personality: for a price you could customize it, or choose one modelled on a favourite celebrity, but at the cheaper end the personalities were randomly generated. If you were as skint as me you bought one of the factory rejects, the ones with such quirky personalities that the manufacturers assumed nobody would want them. Mine was a nice dude, but he certainly was quirky. He refused to respond to any name except for 'The Head', as though he was the definitive model, and he kind of answered questions if he felt like it, and liked to wind me up with false information. Not what you want in a reality checker, but mine was more like an electronic friend. I didn't care about how straight his facts were, I just liked the banter and his beaming smile and deep, hearty laugh. He was pretty handsome too, with a chiselled face, perfect dark skin, an Afro and shades. As vapour-based dudes went, the guy was sick.

'What you got for me, Z?' he said in his cheerful, lispy, North Carolina accent. He was the only person in the world I'd allow to call me *Zee*.

'I was discussing with Alice whether the Proteus causes brain tumours. She told me to look at the evidence. Can you help me out?'

'Hmm, does the Proteus create brain tumours? Let me see ...' The corner of The Head's mouth curled up in a knowing smile. He span around as he checked his database. 'They do ...' he smiled before spinning some more, 'or maybe they don't.' There was more spinning. 'Wait up ... looks like they do ... or don't ... or they *might* ... or not ... but possibly.' He span some more, and when he returned to a static state he had an overly arched, furrowed brow as though he was about to relay some terrible news. 'Bad news, Z. The evidence is contradictory,' he said. He pouted at me to convey the severity of the matter.

'OK ... and the answer is?' I raised my tone expectantly to let him know that his answer didn't fulfil his duty as a reality checker.

'Hmm,' he sulked. 'I *could* assimilate this contradictory evidence for you, but you don't like science, so I'll tell you a story instead. That's more your level.' Like I said, he answered questions when he felt like it. 🍷

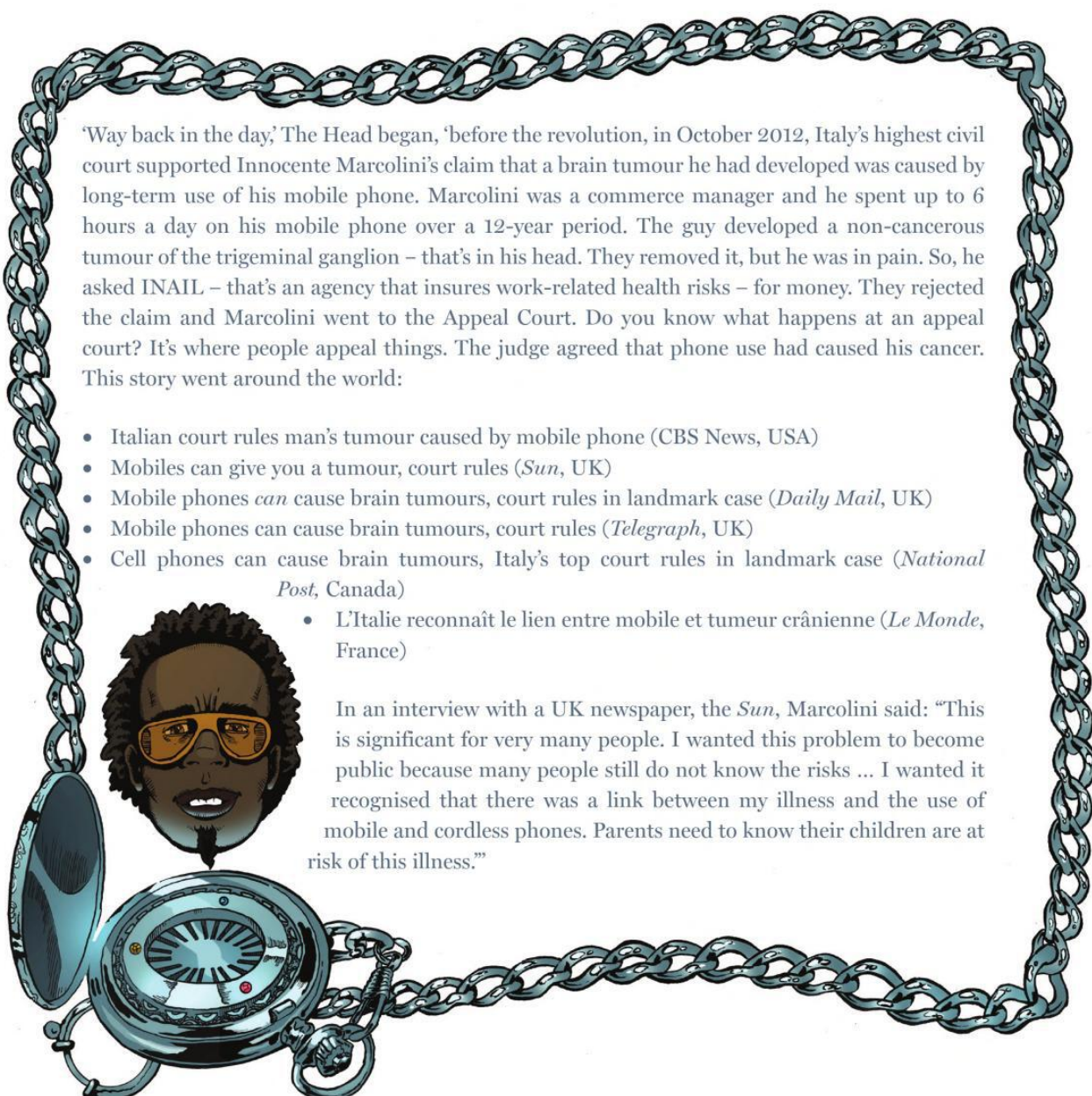
REALITY CHECK 1.1

This was typical of The Head, it was rarely clear if he was being helpful, so I closed his lid, effectively trapping him in a watch. I paused to take in Marcolini's story. Was this evidence the kind that Alice meant? Alice had been flitting nervously around the room, but I suspected she'd heard the story too, so I asked whether Marcolini's story showed that phones gave you cancer. She sat next to me. This *was* a small breakthrough.

'Even if we put aside how old this story is, Zach, it tells us nothing. I feel for Mr Marcolini, but his experience could be unique; in itself, it doesn't prove anything. There could have been a thousand other people back then who used their phones just as often as Mr Marcolini and *didn't* get cancer.'

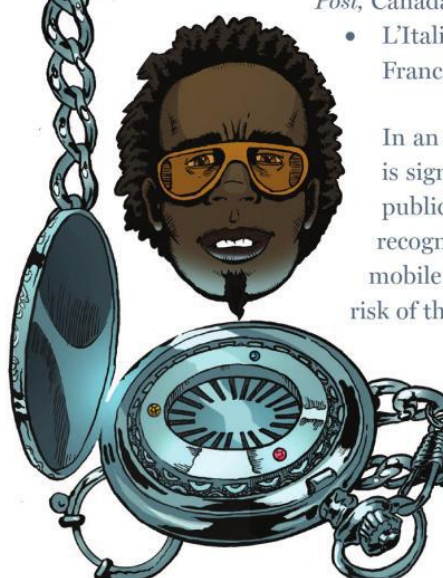
'But the judge agreed, and judges know what they're talking about.'

'Perhaps, but they are not scientists. Science isn't perfect, and it's not the only way to view the world, but it does give us a system for trying to find answers to questions. You asked me to explain science to you, and I've tried, lots of times, but the trouble is that you're scared of it and you refuse to engage with it.'



'Way back in the day,' The Head began, 'before the revolution, in October 2012, Italy's highest civil court supported Innocente Marcolini's claim that a brain tumour he had developed was caused by long-term use of his mobile phone. Marcolini was a commerce manager and he spent up to 6 hours a day on his mobile phone over a 12-year period. The guy developed a non-cancerous tumour of the trigeminal ganglion – that's in his head. They removed it, but he was in pain. So, he asked INAIL – that's an agency that insures work-related health risks – for money. They rejected the claim and Marcolini went to the Appeal Court. Do you know what happens at an appeal court? It's where people appeal things. The judge agreed that phone use had caused his cancer. This story went around the world:

- Italian court rules man's tumour caused by mobile phone (CBS News, USA)
- Mobiles can give you a tumour, court rules (*Sun*, UK)
- Mobile phones *can* cause brain tumours, court rules in landmark case (*Daily Mail*, UK)
- Mobile phones can cause brain tumours, court rules (*Telegraph*, UK)
- Cell phones can cause brain tumours, Italy's top court rules in landmark case (*National Post*, Canada)
- L'Italie reconnaît le lien entre mobile et tumeur crânienne (*Le Monde*, France)



In an interview with a UK newspaper, the *Sun*, Marcolini said: "This is significant for very many people. I wanted this problem to become public because many people still do not know the risks ... I wanted it recognised that there was a link between my illness and the use of mobile and cordless phones. Parents need to know their children are at risk of this illness."

Reality Check 1.1 A case study of subjective beliefs becoming 'facts'

I felt the breakthrough slipping away. We'd been here many times before, and she was right, I was scared that if she explained her world to me it would reveal to her how stupid I am. When I couldn't understand maths and science at school, it made me feel inferior and frustrated, like I wanted to throw my desk out of the window. I was the rad kid with the guitar, so I couldn't ask for

help; I just kept telling myself that music was my thing, and you don't need maths and science to do music. She *had* tried to explain it before, and I *had* refused to engage. Tonight was different, though. Alice looked desperate, and maybe the soundtrack in the background was making me too emotionally charged, but I felt overwhelmed by a need to protect her. I didn't know what to protect her from, but I sensed that, for some reason, she needed me to understand her life, to understand why science was important. I reached for her hand, fixed her gaze and promised that if she tried one more time then I would listen.

1.2 HOW SCIENCE WORKS

1.2.1 The research process

Alice looked sceptical, but her relief was obvious. Her eyes darted as she tried to think of a way to capitalize on my interest. Suddenly her expression changed, and I saw the first smile of the evening. 'I've got it!' she said, looking pleased with herself. 'Do you remember at your last Reality Enigma gig, you gave away a free wristband with every T-shirt? After the show you told me that you'd sold more shirts than the previous gig and you thought it was because of the free wristband. How do you *know* that it was because of the wristbands?' she asked.

I shrugged. 'I don't, it was just a hunch.'

'Exactly – and this is a question that science can answer for you,' she said. 'Do you always sell exactly the same number of T-shirts at concerts?'

'No – it's different at each gig.'

'Which means it could have been the wristband offer that made the difference, or perhaps it was just one of those nights where you happen to sell a lot of T-shirts?' She had a point. 'That's why it's useful to have a system, like science, for trying to find out the true answer to questions.'


Alice took her Proteus and stretched it into a large flat screen. Then she sketched a diagram on it.  'This diagram shows the process of science,' she said. 'Scientists begin with an observation in the real world that they want to understand, and this observation could be based on data, like when you notice more T-shirts sold when you give away a free wristband, or it could be anecdotal, such as Mr Marcolini believing that his tumour was caused by phone use. These "data" could be an isolated observation such as noticing that one person was persuaded into buying a shirt when you offered them a wristband, or based on several, such as you noticing that nine out of ten people who you offered a wristband ended up buying a shirt. From these initial observations, you can generate a research question, such as "Do free gifts help to sell T-shirts?" or "Can a Proteus give you brain cancer?" Having a research question implies that you are trying to generate a **theory**, which is a well-established principle or set of general principles to explain a broad range of observations. For example, you observed more T-shirt sales at one gig compared to another, and your theory might be that people buy things when they believe that they are getting value for money. This theory explains general consumer behaviour. Although you might care only what happens with your band, The Reality Enigma, normally scientists are interested in theories that apply very generally – they want their theories to apply to all entities or situations. An entire set of entities is known as a **population**. A population can be quite diverse (for example, you might want to draw conclusions about the T-shirt sales of every band

FIGURE 1.1

on the planet) but can also be more specific (you might be interested in drawing conclusions only about bands who play a certain style of music, like heavy metal). Different types of scientists might focus on different populations. I work in genetics, so I want my theories to generalize to the population of humans, and this population would also be interesting to psychologists, and epidemiologists too. However, an economist might be interested in the population of “small businesses” or “workers” or “managers”, and biologists might be interested in the population of “cells”. We want theories to be general and apply to the entire population rather than applying only to a specific case within that population; using the T-shirt example, it’s more interesting to be able to say that free gifts, in general, will help any band (the population) to sell T-shirts than it is to conclude that free gifts are effective at increasing T-shirt sales if you happen to be in the band called The Reality Enigma, fronted by Zach Slade.

Alice smiled affectionately at me, and I loved seeing her relax a little. ‘You can use existing theory, to generate a **hypothesis**, which is a proposed explanation of the specific observation that interests you. Based on consumer theory you might hypothesize “T-shirt sales increase because a free gift improves the value for money”. A hypothesis can be tested by operationalizing it as a

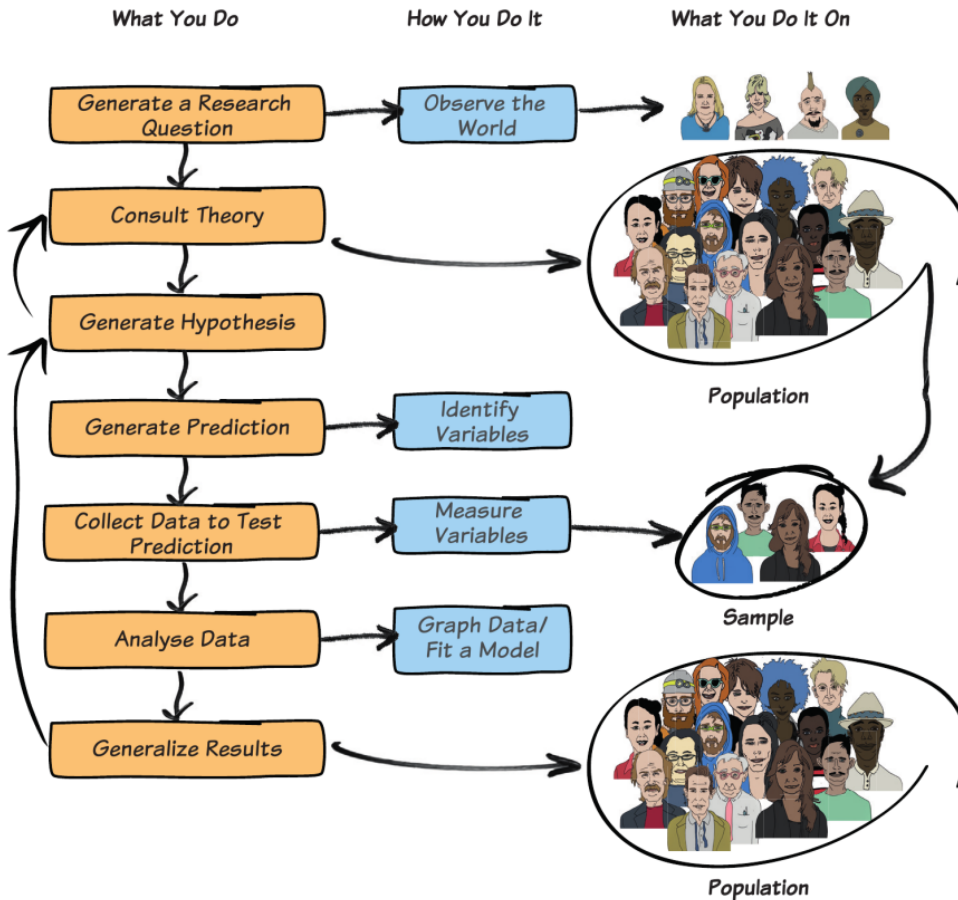


Figure 1.1 The research process

FIGURE 1.1

prediction about what will happen. In this case, we might predict from our hypothesis that “if a band offers a free gift, they will sell more T-shirts”. A prediction should be a scientific statement: a statement that can be verified (or not) using data. That means that you can break the statement down into things that you can measure, known as **variables**. Just now you told me that the number of T-shirts you sold varied from one concert to the next, so “T-shirt sales” is a variable.’

‘You mean that I can count how many T-shirts we sell? I suppose I could also note down whether or not we gave away a free gift with the T-shirt at that gig?’

‘Yes. You can test the hypothesis about free gifts with two variables: how many shirts were sold, and whether or not a free gift was offered with the T-shirt. You will often come across non-scientific statements, though, and these are statements that cannot be verified, often because they refer to things that can’t be measured. For example, “Alice is the best girlfriend in the world” – she threw me a cheeky smile – ‘is not a scientific statement because you probably couldn’t get anyone to agree on a definition of “best”: different people will value different facets of people (some value looks highly, some intelligence, and others kindness or sociability – who’s to say what is “best”?). However, you could turn it into a scientific statement by changing “best” to something that could be measured, such as intelligence. So, “Alice is the cleverest girlfriend” is a scientific statement because we could, in theory, get all of the girlfriends on the planet and measure their intelligence to evaluate this statement.’

‘Right, so “The Reality Enigma are the most influential band in Elpis” would be non-scientific because it would be impossible to measure “influence” but “The Reality Enigma are the most popular band in Elpis” would be scientific because we could measure popularity by, for example, measuring how many nodes on *memoryBank* each band in Elpis has?’



Zach's Facts 1.1 Scientific statements

‘Exactly.’

I unrolled my diePad, touched the screen to activate it and, as Alice continued, I typed what I thought were the important bits. ➤

ZACH'S FACTS 1.1

Alice looked impressed that I made notes. ‘The next step of the process is to collect some data. ➤ The problem here is that you want to draw conclusions about the entire population, but it’s usually impractical to collect data from every entity in the population. It would be quite difficult to get T-shirt sales and information about free gifts from all of the bands in our city, so instead we use a **sample**, which is a smaller set of entities from our population. We want the entities that we choose for our sample to be representative of the wider population, and we can do that by selecting them randomly. In doing so, we should get a group of bands that represent all of the bands in the city. We can use the data in the sample to compute **statistics**, which are values that describe the sample. So, the average number of T-shirts sold in our sample is a statistic. However, we can use this value to estimate what the value would have been if we had collected data from the entire population. The value in the population is known as a **parameter**.’

FIGURE 1.1

‘So, the average number of T-shirts in the sample is called a statistic, but the average number in the population is called a parameter? That’s really confusing, why not call them the same thing – they’re both the average?’

‘The different names remind us that statistics can be computed directly from the actual data we collect, whereas the equivalent “statistic” in the population is something that we can only estimate based on the sample data.’

Alice sensed that I was still confused, and changed tack.

‘It boils down to two things that you might want to do with data. The first is to describe what happened in the sample that you collected. You might draw a graph of the data, or calculate some summary information such as the average T-shirt sales. This is known as **descriptive statistics**. However, because scientists usually want to generalize their findings beyond the data they collected to the entire population, they use the sample data to estimate what the likely values are in the population. This is known as **inferential statistics**. Inferential statistics help us to make generalizations about what is going on in the real world, based on a sample of data that we have collected.’

Something clicked in me. ‘Sweet, so you see whether offering free gifts increases T-shirt sales for, like, 20 bands and then, based on that, you can say whether it will work for every band. That’s sick. *How* can you do that?’

‘Let’s imagine we could get together the whole population of rock bands.’ Alice grabbed my diePad and began to draw. ‘I’ll draw the population as an ellipse and we’ll put some band names in there. Obviously there’s your band, The Reality Enigma, and you play with Chamber of the Damned and Zombie Wrath all the time.’

‘Yeah, those guys are sick! There’s also Hollow, Brain of Morbius, Forest of Trees ...’

‘... and that band with the amazing woman singing,’ Alice added, struggling to think of their name.

‘Ten Plagues,’ I said.

‘Of course ... oh, and Kings of Archea,’ Alice said, getting into the swing of the game.

Before long we’d listed all the bands we could think of. It was great to see Alice dropping her guard a little.

‘Let’s pretend that’s all the bands that exist. That’s our population. ➤ Let’s also say that on average across all of those bands, you expect to sell 35 T-shirts at a show. That’s the magic number that we’d like to find out – the population parameter – but we can’t ordinarily find it out directly because

FIGURE 1.2

we don't have information from the entire population. However, we can estimate it by taking samples. Imagine we took a sample of three bands: Zombie Wrath, The Reality Enigma and Scansion. We work out the average number of T-shirts sold across those three bands and it's 37. This is the sample statistic. This value is slightly different from the population parameter: it is 2 T-shirts bigger. This difference is known as **sampling error**, which is the difference between what the population parameter actually is, and the value estimated from the sample. Imagine we put these bands back into the population and took a different sample; this time we get Odin's Law, Forest of Trees and Habit of Hate. For these bands the average T-shirt sales are 42, which is not only different from the population parameter, but also different from the previous sample. The sampling error is bigger than for the first sample (the sample average is 7 T-shirts more than the population average in the second sample, but it was only 2 T-shirts more for the first). Finally, again pretend we put these bands back and randomly select another three to make up a third sample. In this sample the average T-shirt sales are 28, which underestimates the population value and is again different from the other sample values. This illustrates two important things: (1) statistics vary across different samples, which is known as **sampling variation**; and (2) the sampling error differs across samples.' 🍀

FIGURE 1.2

Amazingly, this made sense to me. You can't get data from everyone, so you take a random sample instead, and use the data in the sample to estimate the value in the population, but the estimate might be wrong because samples will be different from one another, and might be slightly different from the population too. I was feeling pleased with myself. Normally Alice talking about science is a cue for my brain to start thinking about a song I was working on; today,

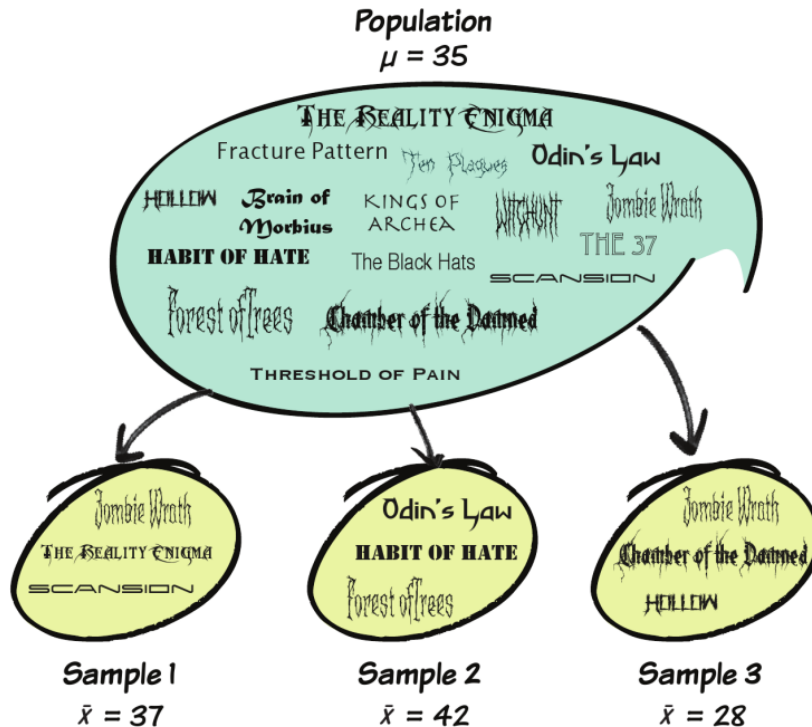
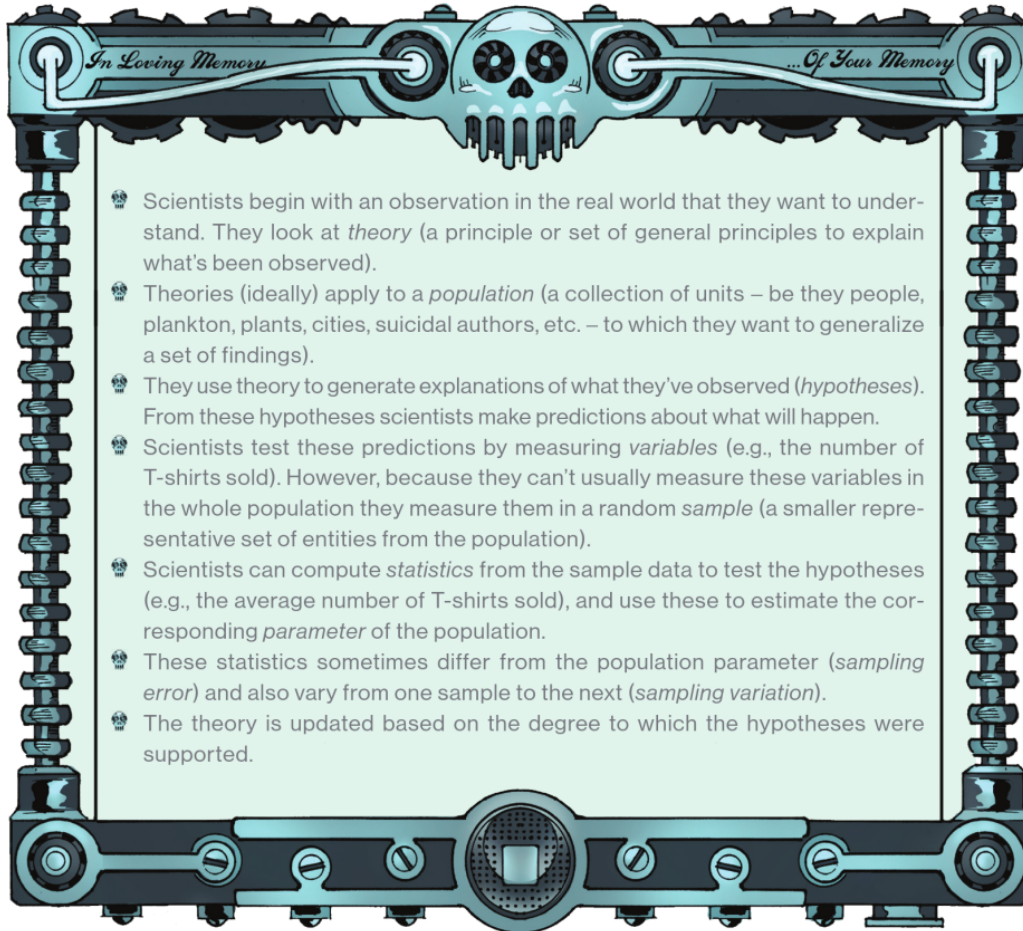


Figure 1.2 Sampling variation

though, she needed me, and I'd listened, and although I did get momentarily side-tracked by remembering that I hadn't seen the guys in *Zombie Wrath* for ages, I more or less understood. 🖤 I was still missing something, though. How did this help us to find out whether a free wristband sells T-shirts?

ZACH'S FACTS 1.2



Zach's Facts 1.2 The scientific process

Alice looked pleased at my question. 'That's the next step. We have to look at how descriptive and inferential statistics work together.' Alice drew me another picture 🖤, and I was reminded of how she'd looked when I used to admire her in our college library. She had that same intensity and purpose right now. 'Imagine we take two samples of bands from the population of bands in Elpis. The bands in one sample we tell to offer a free wristband with every T-shirt, but the other sample of bands we tell not to. After the concert, we count how many T-shirts each band sold. We can then use descriptive statistics to quantify what has happened in each sample. For example, we could calculate the average T-shirts sales. Perhaps we find that the average sales are 37 for those bands that offered a free wristband, and 35 for those that did not. We know that two random samples will

FIGURE 1.3

differ anyway because of sampling variation, so the question is whether our sample averages differ because of sampling variation, or because one sample offered a free wristband with every T-shirt. Inferential statistics helps us to distinguish which explanation is most likely.

FIGURE 1.1

‘Right, so to use the scientific process to find out whether wristbands help T-shirts sales, you start with a theory of why free gifts improve sales. From that you generate a hypothesis that free gifts increase people’s perception of value for money, and that leads to a prediction that when you offer a free wristband more T-shirts will sell than when you don’t. You test that prediction by collecting data – you measured T-shirt sales and whether free gifts were offered in the two samples – then using statistics to compare the samples, you can see whether offering a free wristband, in general, will help to sell band T-shirts.’ For the first time, I understood the use of science. I was impressed, but not as much as Alice was that I’d paid attention.

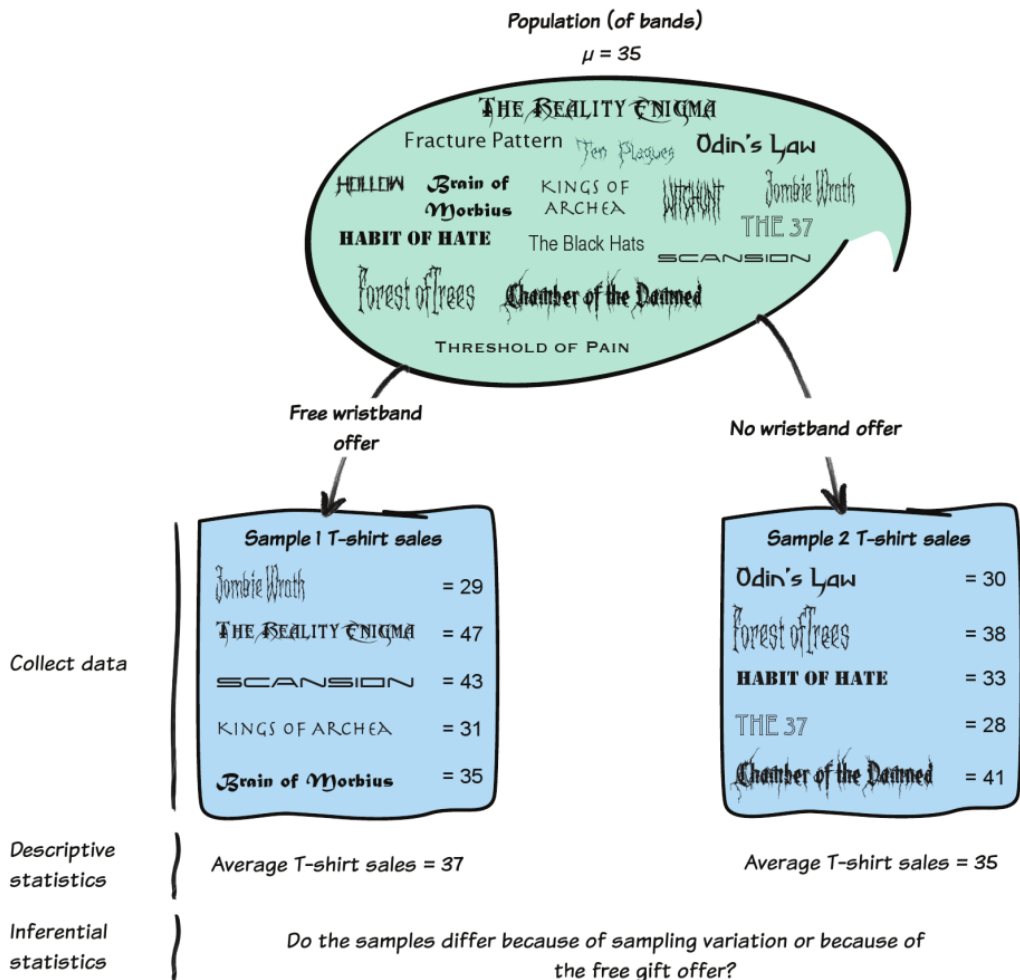


Figure 1.3 Using statistics to answer empirical questions

1.2.2 Science as a life skill

All this talk of T-shirts had got us away from my original question, which was how a scientist would know whether the Proteus device caused cancer. Remembering the article I felt panicky at the possibility that something bad could happen to Alice. I'd say that the thought of life without her was unthinkable, but that would be a lie because I constantly thought about it and it felt like imagining my last breath. I reminded her of our original purpose.

'You can apply everything I have just told you to addressing the question of whether using a Proteus increases your risk of a brain tumour. Rather than rely on the subjective opinion of Mr Marcolini about his phone, or believing a newspaper headline, or what a politician tells you, you can evaluate the objective evidence. Good science should attempt to be objective, and by agreeing a system of discovery like the one I described, we establish standards that promote objectivity. However, scientists are humans and you can never fully get away from some subjectivity. There will always be subjectivity in how data are interpreted, for example. This is why understanding the system of science empowers you, because it enables you to make your own judgements about the evidence. You don't have to believe everything you read in the paper, or what a scientist tells you. You can look at the science for yourself. In this case, you could look at the studies before the revolution that investigated links between mobile phone use and brain tumours, then look at studies that address the same question about the Proteus (if they existed), and make your own judgement about the risk. You won't be relying on a journalist, who might want to spin the data to make a good story, or a politician, who might want to spin the data to make him or herself look better, or a Proteus salesman, who it might suit to play down the risks. You will be using your knowledge and skills to make an informed decision.'

'Wow, so, like, if I was ill and my doctor gave me some pills, rather than just take them I could find out how likely they are to help me first?'

'Yes.'

'Sick. So, how *would* a scientist know if a Proteus causes brain tumours?'

1.3 RESEARCH METHODS

Alice seemed conflicted. Her furrowed brow suggested that she desperately wished that I'd decided to ask her about science at a different time and place, but she also had softness in her face that hadn't been there earlier in the evening. Perhaps I *had* seen something in her that wanted me to help, or perhaps she knew this was a chance to shrink the space that had been growing between us. All that mattered was that she was talking to me rather than shutting me out.

'There are different ways to collect data,' she said, 'and different types of data that we can collect. Broadly speaking, we can test a hypothesis in one of two ways: by observing what naturally happens, or by manipulating some aspect of the environment and observing the effect it has on the variable that interests us.'

'So, just observing what happens to T-shirt sales when bands decided to give away wristbands, or actually making some bands give away wristbands, and preventing others from doing it.'

1.3.1 Correlational research methods

Alice nodded. ‘When you observe what naturally happens in the world without directly interfering with it, it is known as **correlational research**. There are different ways to do this: we could take a snapshot of many variables at a single point in time (a **cross-sectional study**), or measure variables repeatedly at different time points (a **longitudinal study**). To look at the Proteus and cancer, we could measure how often a cross-section of people use the Proteus and how many of them have brain tumours, or we could take a sample of people, follow them over a long period of time and measure their Proteus use and whether they develop tumours over that period. Correlational research gives us a very natural view of the question we’re researching because we’re not influencing what happens and the measures of the variables should not be biased by the researcher being there. This makes it more likely that the study will have **ecological validity**, which means that the results of the study can be applied to real-life situations. There is a price to pay, which is that correlational research tells us nothing about whether one variable causes another. For example, even if we find an association between Proteus use and brain tumours, we cannot conclude that Proteus use causes brain tumours. This is particularly true of cross-sectional research because the variables are measured at the same point in time, so it would be equally valid to conclude that brain tumours cause Proteus use.’

‘Get real! How can a brain tumour cause more Proteus use?’

‘Well, perhaps having a tumour means that you call people more because you need social support, but you’re right that sometimes explaining associations between variables does make more sense one way around than the other. For example, imagine that you discovered that popular people tend to be more attractive.⁷ Although it makes more sense to assume that there’s something about being attractive that makes you popular than it does to conclude that popularity changes your physical appearance, statistically both interpretations are equally valid. With longitudinal research you can make a slightly stronger statement about cause and effect if one variable predicts the other in the future, but not versa; for example, if attractiveness predicted your popularity in two years’ time, but your popularity did not predict your attractiveness in two years’ time. Even here though, you cannot be sure of cause and effect.’

‘Why not?’

Alice sighed – a long, drawn-out sigh that was punctuated by her Proteus ringing. She jumped at the noise and was transported back into a state of tension. She felt inside my pocket and emerged with my reality checker. Her perfectly manicured finger pressed gently on the winder to release the front cover and again the crystals glowed, the cogs whirred and the mist appeared.

‘Doc Nightingale,’ The Head said with a chuckle, ‘this is the most pleasant surprise. We should spend more time together ... two geniuses, just hanging out, talking about genetics.’ He turned to me and feigned surprise. ‘Oh, you’re still on the scene?’ he asked cheekily.


‘I need to take this call, so I need you to give Zach the lowdown on cause and effect please.’ She kissed the top of The Head and he span. Alice’s Proteus fizzed into a vaporous cloud and emerged looking like a strange alien brain. She twisted it into her ear and headed into the next room.

‘Anything for you,’ The Head shouted after her. I didn’t like it when he flirted with Alice.

‘Cause and effect, eh? That’s gonna *cause* me to delve into my database and hope to have an *effect* on your brain.’ The Head chuckled a deep, throaty laugh. 🐛

REALITY CHECK 1.2

→ effect on your brain.’ The Head chuckled a deep, throaty laugh. 🐛



Having finished his chuckle, The Head explained: ‘Most scientific questions imply a causal link between variables. The causal link can be obvious, such as “being physically attractive makes you more popular”, but it can be, you know, subtle, like “physically attractive people are more popular”, which implies that being attractive causes you to be more popular. It doesn’t matter, though: regardless of whether the question mentions cause, most scientific questions break down into a proposed cause (in this case attractiveness) and a proposed outcome (popularity).

‘The cause and the outcome are both variables: they vary. For the cause, some people will be more physically attractive than others. You know, like Alice has a pretty face and you have a ... less pretty one. For the outcome, some people will have more friends than others. You answer the research question by uncovering the relationship between the proposed cause and the proposed outcome: are the more attractive people the more popular ones?’

‘Let’s get philosophical. Hume^{8,9} said that to know about cause and effect: (1) cause and effect must happen at a similar time (which is called contiguity); (2) the cause should happen before the effect; and (3) cause and effect should always co-occur. Let me put it like this: causality can be inferred through *corroborating evidence*. To know that physical attractiveness caused you to be more popular, you would have to show that popularity and physical attractiveness co-occur and that the physical attractiveness emerged before the popularity.

‘Sounds rad. But it isn’t rad enough, because what happens if we find people who are attractive but also unpopular? This finding doesn’t violate Hume’s rules because he doesn’t say anything about the cause happening *without* the effect. We need something else, and Mill¹⁰ gave it to us: all other explanations of the cause–effect relationship must be ruled out. To do this, an effect should be present when the cause is present and absent when the cause is absent. The only way to show causality is to compare two controlled situations: one in which the cause is present and one in which the cause is absent.’



Reality Check 1.2 Cause and effect

I was distracted by the conversation in the next room. I couldn’t make out what Alice was saying over the voice of the jabbering Head, but she was becoming more animated and stressed. As The Head was finishing his jibber-jabber, Alice cut the call, and returned looking worried and distracted. I asked if she was level.

‘I’m not sure ... well, it’ll all be fine.’

She wasn’t making any sense and I wasn’t used to seeing her so indecisive – it made my guts churn.

‘Tell me what’s up.’

‘It’s work stuff. ... I’ve got a big decision to make – it’s hard to explain. Don’t worry.’

I held her hands in mine. ‘I’d do anything for you, Alice. Look, it’s a Friday night and I’m talking to you about science. I’m *trying* really hard to understand. Give me a chance.’

Alice was looking right through me as though I was missing the point, but she squeezed my hands. ‘Maybe you’re right, maybe it might help you one day to understand this stuff.’

What an odd thing to say: I couldn’t imagine any situation between now and my death when I would need to know about statistics, but this was the first time in weeks that Alice was letting me into whatever was going on with her, and I wasn’t going to blow the opportunity. She still looked distracted, so I reminded her what we’d been talking about.

‘Of course ... yes ... the problem with correlational research ... cross-sectional research tells us nothing about the contiguity between different variables: we might find from a questionnaire study that attractive people are also popular, but we wouldn’t know whether the popularity or attractiveness came first. Longitudinal research addresses this issue to some extent, but there is still the problem that other variables that you haven’t measured, called **confounding variables**, might be influencing both variables. For example, perhaps personality affects both how physically attractive a person is perceived to be and also their popularity. People with a nice personality have more friends (because they are nice) but they are also perceived to be more attractive. In this example, a person’s personality would be known as a third variable, or **tertium quid**, which is a variable that explains the apparent relationship between two other variables.’

‘That’s what The Head was talking about: when you do correlational research you can’t know that one variable has caused the other because you haven’t compared a situation where the cause is present and the cause is absent.’ Alice broke into a smile that came across as hiding sadness, and I continued with my epiphany. ‘When we were talking about whether a free wristband would help to sell T-shirts, you used an example of comparing a sample that had been allowed to offer a free wristband with one that had not. Wouldn’t this be comparing when the cause is there (the free gift) and when it is not (no free gift)?’

FIGURE 1.3

1.3.2 Experimental research methods

Alice’s smile transformed into a more genuine one. ‘Zach, that is perfect – *you* are perfect.’ Alice fixed her watery gaze onto my eyes. I wasn’t sure whether it was the call that had made her so emotional, or that I had set the baseline of my ability so low that any vaguely intelligent thing that I said was cause for her to break down. ‘See, you can understand this stuff when you try. I don’t know why you always underestimate yourself.’

‘Come on, we all know who the brains in this relationship is, and it’s not the guy with spiky hair.’

‘True enough,’ said The Head.

Alice ignored him. ‘Look, just because I’ve made some of the most important genetic discoveries of the past 100 years doesn’t mean I don’t struggle with things. Remember what happened when you tried to teach me the guitar?’

That reminded me, I needed to pick my guitar up from the repair shop.

‘I would never have dated you if I didn’t think you were a clever guy.’ Her use of the past tense unnerved me. ‘The trouble is that you play the fool because you’re scared that you will fail; but you’re

spot on with this. Comparing two conditions in a controlled way is at the heart of **experimental methods**: they provide a comparison of situations (usually called *treatments* or *conditions*) in which the proposed cause is present or absent, while controlling for all other variables that might influence the effect in which we're interested. This scenario is an **experiment**. The T-shirt sales example is a good one. Imagine we randomly select some bands, and half of them we asked to give away free gifts with every T-shirt, and the other half gave away nothing. The thing that we have manipulated is the incentive to buy a shirt (the free gift or no gift). This is known as an **independent variable** because it is not affected by the other variables in the experiment. More generally, it is known as a **predictor variable**, because it can be used to predict **scores** of another variable (i.e., we predict T-shirt sales based on whether or not a gift was offered). In this situation it is said to have two *levels*, because it has been manipulated in two ways (i.e., free gift or no free gift). The outcome in which we are interested is T-shirt sales. This variable is called the **dependent variable** because we assume that its value will depend upon whether or not a free gift was offered (the independent variable). More generally, we can refer to it as an **outcome variable**, because it is the variable that we're trying to predict the values of (i.e., we want to know how many T-shirt sales there are). The critical thing is the inclusion of the no-gift group because this is a group in which our proposed cause (an incentive to buy) is absent, and we can compare the outcome in this group against the situation in which the proposed cause is present (a free gift was offered). If the T-shirt sales are different when the free gift is offered (cause is present) compared to when it is not (cause is absent) then this difference can be attributed to the free gift. In other words, the free gift caused a difference in T-shirt sales.'

1.3.2.1 Two methods of data collection

'OK, that makes sense. So, you can infer cause only in experiments where you manipulate the thing that you think is the cause, and not in experiments where you just measure variables cross-sectionally.'

'Sort of, but be careful with your terminology. You can only call something an *experiment* if you have manipulated one variable and looked at the effect it has on another. If you measure variables without manipulating any of them then it is not an experiment, it is a correlational study. Lots of people make that mistake, but it's worth getting it right.'

'What would happen if the same sample of bands wanted to look at their T-shirt sales from one gig to the next when sometimes they use free gifts and sometimes not? Could that tell you anything about cause?'

'Actually it can: we can manipulate variables in experiments in two ways. The first is to manipulate the independent variable using different entities. This is the method we've been discussing – we allocate different bands, or entities, to two different groups – and it's known as a **between-groups**, **between-subjects**, or **independent design**.'

'Seriously? Three terms for the same thing? No wonder this stuff is confusing. Whose stupid idea was it to give the same idea three different names?'

'According to one ancient statistics text,¹¹ it was a character called Confucius who invented a confusion machine, but that story has never been verified. In any case, the second method is to manipulate the independent variable using the *same* entities. This would be similar to what you were suggesting: we tell a group of bands to give out a free gift with every T-shirt sold at one of their concerts and ask them not to use the free gift at the next concert (or vice versa). This is known as a **within-subject**, **related** or **repeated-measures design**.'

'Does everything in science have three different names?' I quipped.

1.3.2.2 Two types of variation

The conversation was going better than I had expected. I found myself becoming really interested in how I could sell more T-shirts. Our T-shirt designs were totally sick, some would say better than our music. I liked seeing people in them because it made me feel like I was doing some good in the world. After the Reality Revolution real music died out, and instead everyone looked to the great bands of the pre-revolution. Bands like mine were trying to recreate that old-school vibe, where music brought people together. There wasn't a soundtrack to the post-revolution, but my generation were trying to create one. When I listen to those old bands it's how I imagine it was for our parents when they wore a reality prism: it brings home how ordinary you are. Maybe you don't need a reality prism to be a victim of reality.

My mind was wandering, and Alice had noticed and stopped talking. She shot me the look that she gives me when I'm ignoring her and tersely suggested that it might be time to stop. I didn't want to stop, because I'd seen glimpses of the old Alice this evening. There had been cracks in her emotional armour that gave me hope that the past few weeks were an aberration. The key was to stay interested and keep her talking. I apologized and tried to reopen the conversation.

'I get that manipulating whether or not bands give away free gifts tells us about cause and effect, but if we do that experiment, and the T-shirt sales are more for the group that gave away gifts than for the group that didn't, then how do we know that is because of the free gift? I mean, earlier on you said that if you took different samples and measured their T-shirt sales they would be slightly different ... erm, look, it's in my notes ... sampling variation ... so how do we know that

ZACH'S FACTS 1.2

→ the difference in the groups' T-shirt sales isn't just because of that?'

'That's a brilliant question,' she said, and she was hooked in again. 'The answer is that you compare different types of variation in scores or T-shirt sales. Let's take a step back and think what would happen if we did *not* introduce an experimental manipulation. Imagine we have a sample of bands and we measure their T-shirt sales at two gigs (i.e., they never give away free gifts). If there is no experimental manipulation then we expect T-shirt sales to be similar in both conditions. In other words, their sales at the first gig should be similar to those at the second. We expect this because external factors such as the T-shirt designs, the price, the music played by the bands, and characteristics of the people at the gigs and what T-shirt designs appeal to them will be the same for both conditions (The Reality Enigma won't play heavy metal one week and break into some improvised jazz the next). A band's T-shirt sales at one concert should be very highly related to their sales at the other. Bands who sell a lot of T-shirts at one concert are likely to sell a lot at the next, and those that have low sales at the first concert are likely to have low sales at the next. However, sales won't be *identical*; there will be small differences in sales created by unmeasured or unknown factors. This variation is known as **unsystematic variation**. If we introduce an experimental manipulation (i.e., provide a free gift at one of the concerts), then we do something different to participants in one condition compared to what we do to them in the other. The *only* difference between the conditions (or concerts) is the manipulation that the experimenter has made (in this case that fans at one concert get a free gift if they buy a T-shirt). Therefore, any difference between the average of the two conditions is probably due to the experimental manipulation. If T-shirt sales are higher at one concert compared to the other then this *has* to be due to the fact that a free gift was offered with every T-shirt at one concert but not the other. Differences in performance created by a specific experimental manipulation are known as **systematic variation**.'

'But what if you had used different bands in the two samples?'

‘In an independent design there are still two conditions, but different bands participate in each condition. Imagine again that we didn’t have an experimental manipulation. If we did nothing to the groups, then we would still find some variation in sales between the groups because they contain different bands that will vary the shirt designs that they have on offer, their prices and other things that might affect sales. The factors that were held constant in the repeated-measures design are free to vary in the independent design. So, the unsystematic variation will be bigger than for a repeated-measures design. As before, if we introduce a manipulation (i.e., a free gift) then we would hope to see additional variation created by this manipulation. As such, in both the repeated-measures design and the independent design there is always systematic and unsystematic variance, it’s just that, other things being equal, the unsystematic variance will be greater in independent designs. We can use statistical models to compare the size of the systematic variance to the unsystematic variance. In effect, we’re looking at the effect of our experimental manipulation against a background of “noise” caused by random, uncontrollable differences between our conditions. In a repeated-measures design this “noise” is kept to a minimum and so the effect of the experiment is more likely to show up. This means that, other things being equal, repeated-measures designs have more power to detect effects than independent designs.’

1.3.3 Practice, order and randomization

‘You said that if we didn’t include an experimental manipulation then we’d expect the two samples to have similar T-shirt sales, but if we were using a, what was it called, you know, the same bands but tested twice ...’

‘A repeated-measured design,’ Alice replied.

‘Yeah, if you were using a repeated-measures design, you might expect fewer T-shirts to be sold at the second gig because if people had bought a shirt at the first gig and then also come to the next one, they won’t buy another shirt.’

‘That’s true, and in reality you would counterbalance the order in which the samples complete each condition. For our example that means that half of the bands would give away a free gift at the first concert and not at the second, but the others would give away the free gift at the second concert but not the first. **Counterbalancing** is a technique used to eliminate sources of systematic variation. One source of systematic variance is **practice effects**. Let’s imagine that you wanted to see whether you could help people to overcome their fear of statistics by getting them to pretend to be someone else.¹² You give participants two comparable statistics tests. One of them they complete as themselves, but the other they complete while pretending to be someone who is really good at statistics. When the same entities participate in more than one experimental condition they are naive during the first experimental condition, but they come to the second experimental condition with prior experience of what is expected of them. For example, when they take the second statistics test they have had some practice at the types of questions that might be asked, they’re familiar with the format of the test and so on. A second source of systematic variation is **boredom effects**, that is, when participants take part in several experimental conditions they are likely to become fatigued. Imagine we asked people to take statistics tests while pretending to be themselves, a student good at statistics, a statistics professor, someone who had never done statistics, and as a watermelon (as a control). They would have to complete five statistics tests. By the fifth test they’d be quite bored ...’

‘Or by the first ...’

FIGURE 1.4

Alice gave me a disapproving look. ‘The point is, the more tests they do, the more their attention is likely to wander as they get bored with the task. If every participant does the tests in the same order then we introduce a systematic bias because by the time they do the test as a watermelon, they are more bored and more practised than when they did it as themselves. So, we can combat these effects by counterbalancing the order in which people complete the tasks, or by having them complete the tasks in a random order. Sometimes people use a **Latin square** counterbalancing method. This is easy to visualize with a drawing.’ Alice started to sketch. ‘Imagine we just had three conditions to our experiment: we asked 30 people to complete the statistics test as a statistics professor (A), as themselves (B), and as an arts professor (C). In a Latin square design with three conditions we’d split the 30 people into three equal groups. The first group would complete the tasks in order A, B, C (i.e., as the statistics professor, as themselves, then as the arts professor). However, the second group would complete it in order C, A, B (i.e., as the arts professor, as the statistics professor, then as themselves). The final group would complete the tasks in order B, C, A (i.e., as themselves, then as the arts professor, and finally as the statistics professor). The important thing is that across the participants each task or condition appears equally as the first task, the second task and the last task. So, a third of the participants do the task as themselves first, a third of them take that task second, and for the final third it is the last task. Therefore, the order of tasks is balanced. You can do the same type of arrangement with more tasks. With 4 tasks you’d need 4 groups who complete the tasks in 4 different orders, and with 5 tasks you’d need 5 groups who complete the tasks in one of 5 different orders. In all cases, though, across all of the groups a particular task is done at every different position in the order of tasks.’

‘That’s mind-blowing. I totally get it.’ I was partly lying: I didn’t get it, but staring at grids of As, Bs and Cs was making me want to blow up my mind.

Alice eyed me suspiciously. ‘You understood all of that perfectly? You’re not just saying that because you’re bored with staring at As and Bs?’

It was frightening how well she knew me. ‘Not at all. Crystal clear.’

‘I’d understand if it’s not – it’s quite confusing, and that’s why sometimes people randomize the order of tasks instead – it does much the same thing. So, we’d choose the first task randomly out of the three, then choose the second task randomly from the remaining two, and that would also leave a task as the final one.’

‘And you do this to minimize the – what did you call it – unsystematic variance?’

‘Yes.’

‘What happens if you have one of those designs in which *different* people do different tasks?’

‘In an independent design you follow a similar logic, it’s just that you don’t need to worry about practice or order effects. Instead you worry about differences in the natural composition of the groups. If we asked different groups of people to take statistics tests with each group pretending to be someone different, then differences between their scores will be caused by us manipulating who they are pretending to be (a professor or themselves) but also by natural variation between the groups. It might be convenient to take students from two different lecturers’ stats classes, and one of these groups completes the test as themselves, and the other as their lecturer. If we find a difference between the groups can we conclude that who the student was pretending to be affected the test?’

‘Yeah, because you’re comparing groups where the cause is present (pretending to be a statistics lecturer) and where it is absent (taking the test as yourself).’

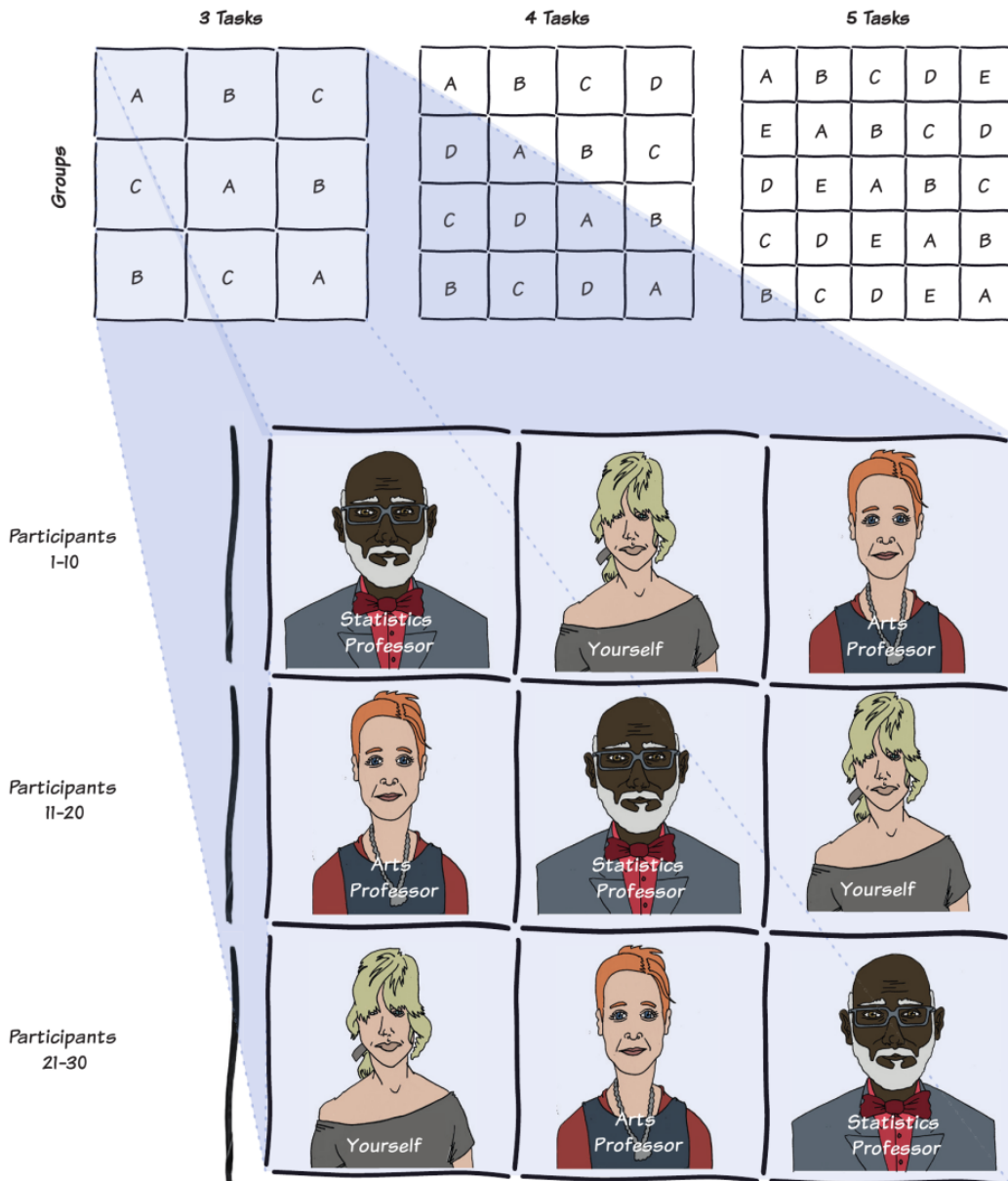


Figure 1.4 Latin square counterbalancing orders

‘No, because the groups have different lecturers, so not only does our manipulation vary across the groups, but so does each group’s background knowledge in statistics. Perhaps one lecturer is much better than the other and produces students better able to do the test?’

‘Maybe, but we don’t know that for sure.’

‘That’s exactly my point. We don’t know whether the group differences are due to the systematic variation created by our manipulation, or the systematic variation created by the lecturers in their

teaching. This is why **randomization** is absolutely crucial in experimental research. If we randomize participants to different conditions, then, providing the randomization works, we should start the study with two groups who are comparable in age, sex and, most important in this example, statistical ability. If we do this randomization then we can be confident that any differences between groups can only have been created by the manipulation that we carried out. Without randomization we can't be sure from where the group differences come. Sometimes though you can't randomize; for example, imagine we wanted to look at the effect of horror movies on children. It wouldn't be ethical to randomize some children into a group that watches a horror movie and others into a group that does not, because some of the children might be very disturbed by the movie. Instead, we would have to compare children who naturally decide to watch horror movies to those who do not. When you don't randomize participants into different groups it is known as a **quasi-experimental design**.



CHECK YOUR BRAIN: Why is randomization important?

A decorative border for a text box, featuring a skull in the center, gears, and the phrases "In Loving Memory" and "...Of Your Memory".

- Collect data using *correlational methods*, in which you observe what naturally goes on in the world without directly interfering with it, or *experimental methods*, in which you systematically manipulate certain variables (*independent variables*) to look at their effect on the so-called *dependent variables*.
- Experimental methods usually enable you to draw conclusions about cause and effect, correlational methods mostly do not.
- In correlational research the relationships between variables can sometimes be explained by a third variable (a *tertium quid*).
- In experimental research you manipulate the independent variable by having different treatment conditions that represent different levels of it. You can either assign different entities to each condition (an *independent design*) or have the same entities take part in all conditions (a *repeated-measures design*).
- In repeated-measures designs, make sure that conditions are completed in different orders by different entities, by using *counterbalancing* or *randomization*. In independent designs, randomize entities to the different conditions so that conditions are comparable on all variables except the one you want to measure.
- The effect of the independent variable is evaluated by comparing how much variation it creates in the outcome variable (*systematic variation*) against the variance created by unknown or unmeasured variables (*unsystematic variation*).

Zach's Facts 1.3 Research methods

1.3.4 Piecing it all together

‘That’s more or less all there is to know about how science works,’ Alice said. ‘Now you know it, how *would* you use science to discover whether Proteus use causes brain tumours?’



CHECK YOUR BRAIN: What are the different ways you could test Alice's hypothesis? What are the pros and cons?

I felt a wave of nausea. I thought I'd been paying attention, I really did, but now that Alice had put me on the spot I could feel my mind emptying. I stuttered, I ummed and ahed, and I caught the growing disappointment in Alice's eyes. She swayed her head from side to side, moving almost imperceptibly as though questioning why she'd believed I was capable of understanding what she'd said. I'd found hope of reaching the old Alice, but that hope drained as I fumbled around in my mind. I needed to get a grip, to find a hook to get me started. I remembered the T-shirts – I'd been interested in the T-shirts. Then the answer hit me.

‘You'd want to compare the people who had used a Proteus to those who hadn't and see how many people in each group had tumours ... erm, oh, yes, but you'd have to randomize people to the groups.’

Alice looked pleased, but she wasn't going to let me off easily. ‘What's the problem with doing that?’ she asked.

‘I guess it's pretty mean to force people to use a Proteus if it might give them a brain tumour.’

‘Yes!’ she exclaimed. ‘It's unethical, but you're right that it would theoretically be the right thing to do. How else could you do it?’

I racked my brain. ‘You could let people decide for themselves whether or not they use a Proteus.’

‘Would it be easy to find people who have never ever used a Proteus?’

‘I guess not ... but you could look at *how much* they use their Proteus.’

‘Could you still draw conclusions about cause and effect?’

I thought Alice was being a bit negative. I was trying my best, but every suggestion she came back with a problem. I guess that's why she is a genius. I thought about the problem some more. The answer could either be yes or no, so I picked one hoping it would be the right choice.

‘No,’ I said.

‘Why?’ she enquired.

‘Batticks!’ I thought. I concentrated more. ‘We're not comparing a situation where the cause, the Proteus use, is absent to one where it is present.’ I felt deflated; she had defeated me because I couldn't think of another way to do it. I was surprised when she smiled warmly at me.

‘Zach, you're brilliant. Everything you've said is right, but I want you to see that research is complicated: there are always trade-offs and compromises. You're right, we can't do a controlled experiment on Proteus use and brain tumours because it's unethical. We can measure Proteus use and tumours longitudinally and see whether Proteus use predicts tumours over time, but we sacrifice the conclusions we can make about cause and effect. However, we gain ecological validity.

So, what some scientists who have researched this have done is to look at cohorts of people, that is, people born at the same time, and followed them over time, making notes of their Proteus use, and using hospital records to see whether they end up with tumours that might be related to Proteus use.'

Alice opened up the reality checker and unleashed The Head.

'Twice in one day, Doc? I am honoured, let me take you on the information highway to knowledge paradise,' he said flirtatiously.

'Sorry, I already booked my ticket for that particular trip, and I'm not allowed to take pets,' she said, cruelly. 'Get me the summary statistics of all the studies that were done on phone use and brain tumours before the revolution. I want point estimates and intervals around the effect sizes.'

'Now you're talking my language,' said The Head with a chuckle.

She certainly wasn't talking *my* language, all I had heard was 'Get me the blah, blah, blah'. Alice and The Head had a weird dynamic where he would flirt with her, she would put him in his place, and yet he carried on flirting. My relationship with him was different: he liked to insult me. I think he just enjoyed any banter he could provoke from people. With Alice he knew that the best way to push her buttons was with sexism, whereas with me it was pretending to think I was an idiot. I wasn't sure Alice liked The Head at all, but despite his goading I did: he liked to talk nonsense, and I liked to fill up hours trying to think up questions that he couldn't answer. I never succeeded. The Head was spewing numbers and names at Alice; she made notes and then started

sketching. 🖍️

FIGURE 1.5

'Zach, here are 23 studies from the pre-revolution that looked at whether mobile phone use is related to brain tumours.¹³ There are no studies that have looked at the Proteus, so this is all we have to go on. I've listed the studies down the side of the picture. For each study, the scientists computed a statistic in the sample that represents the size of the effect that phone use had on brain tumours. This statistic is represented by the dots. Remember that we're interested in the effect of phone use on tumours in the whole population, not just in that particular sample. We could use this statistic as the estimate of the effect in the population. If we do this we are using a **point estimate** because we're using a single value, or point, to estimate the effect in the population. However, we know that there will be sampling error.'

'You mean that the value in the sample won't always be the same as the value in the population?'

'Yes, exactly, so we can instead compute an **interval estimate**, which is a range of values between which we think the population value is likely to fall, based on the amount of sampling error we expect for that sample. Notice for each study that there is a point estimate of the effect of phone use on brain tumours, but I have also drawn a horizontal line sticking out of each side of the point. These are limits: for each study we are estimating the limits between which we think the population value falls.'

'Every study has different limits, so is every study giving us a different answer?'

'Yes, because of sampling variation. The important thing is that when you have lots of studies that have looked at the same question you can look for consistency in the pattern of results. For example, I have drawn a red dotted line at the value that represents "no effect". If the population value is the same as the red line then phone use had no effect whatsoever on brain tumours. Anything to the left of the dotted line means that phone use *decreased* brain tumours, and anything to the right means that phone use *increased* brain tumours. What do you notice about the dots?'



CHECK YOUR BRAIN: Based on the dots (point estimates), how many studies in Figure 1.5 suggest that phone use increases the risk of cancer, and how many suggest it decreases the risk?

I quickly counted the dots on each side of the line. 'About 11 dots are above the dotted line, which means phone use increases cancer, and 12 are below the line suggesting it decreases the risk. That's like half of the studies say one thing and half say the other, and actually a lot of the dots are close to the dotted line that shows no effect.'

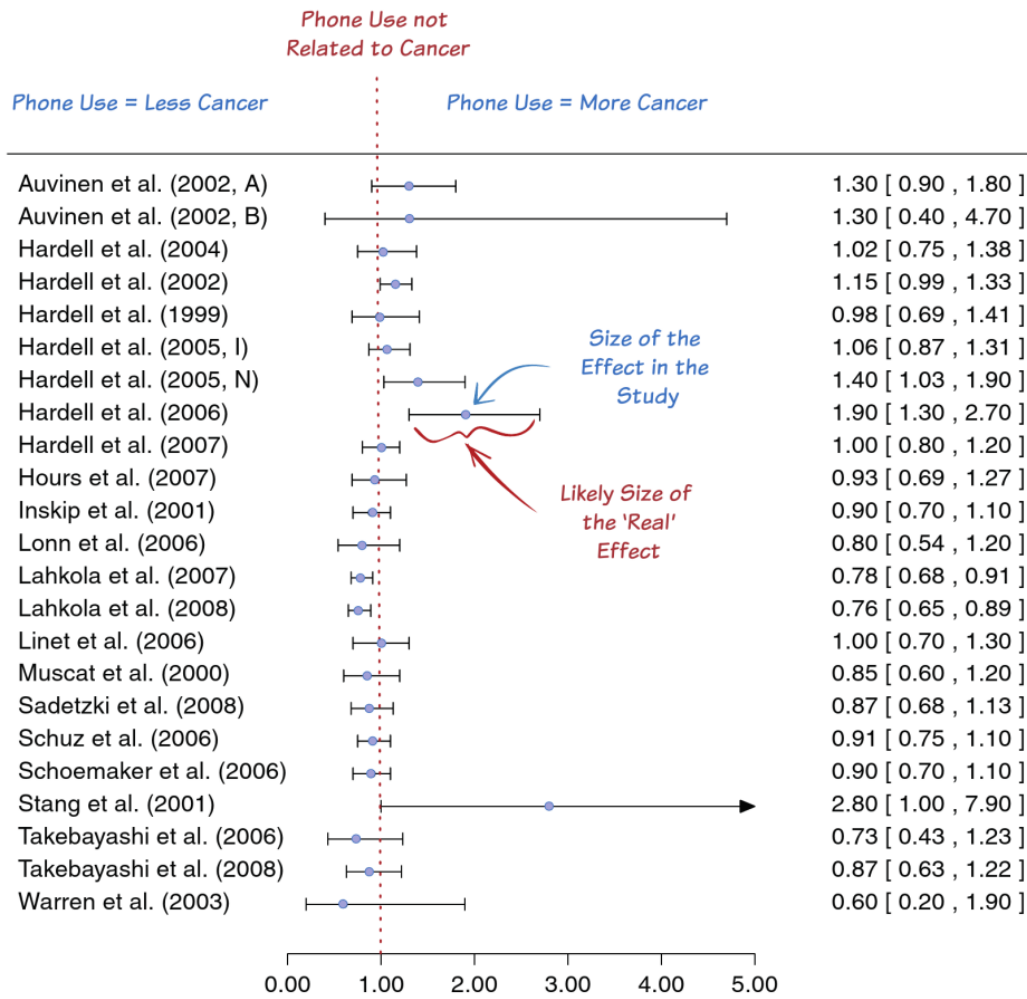


Figure 1.5 Does your mobile phone cause cancer?

‘Let’s look at the interval estimates,’ Alice said. ‘The horizontal bars estimate a range of values that the population value could be, based on the data in each study. If this bar crosses the dotted line, then what do you think that means?’

‘That the population value could be “no effect”?’

‘Exactly. It also means that the population value could be either an increased risk of cancer, or a decreased risk of cancer. In other words, if the bar contains the dotted line it means that there isn’t a lot of evidence one way or another that phone use does anything to cancer risk. What about if the bar is completely on the right of the dotted line?’

‘Would that mean the population value is definitely showing an effect of phone use increasing cancer?’

‘We can’t say “definitely”, because these are estimates and there is a chance they are wrong, but we can say “likely”. What about if the horizontal bars are completely on the left of the dotted line?’

‘The population is *likely* showing an effect of phone use decreasing cancer.’

‘Yes. Based on the interval estimates, how many studies show a likely effect of phone use on cancer and how many show that it likely has no effect?’



CHECK YOUR BRAIN: Based on the horizontal bars (interval estimates), how many studies in Figure 1.5 suggest that phone use increases the risk of cancer (bars are fully to the right of the dotted line), how many suggest it decreases the risk (bars are fully to the left of the dotted line), and how many suggest there is no effect (the bars cross the dotted line)?

‘There are about 4 studies where the bars are fully to the right, suggesting that phone use increases cancer, 2 studies where the bars are fully to the left, suggesting that phone use decreases cancer, but most of them – 17, to be exact – contain the dotted line and so suggest that no effect of phone use on cancer is plausible. That’s unreal: if you look at a particular study you might believe one thing, but then a different study might tell you the opposite, but if you look at them together then you can see a pattern.’

‘Yes, and pulling together the results of lots of studies on the same question is known as a **meta-analysis**. It helps us to get more conclusive answers to questions from a range of studies on the same topic.’

‘Basically, I should ignore the headlines and stop worrying about you getting a brain tumour from using your Proteus,’ I said.

Alice pressed her palm to my cheek and smiled a sad smile.

1.4 WHY WE NEED SCIENCE

As our conversation ended I was struck by why Alice was so ‘scientific’. It gave her power. She was always interested in the news and she always questioned what she read and saw. The news and

politics made me feel helpless and depressed, but it made Alice want to change things. We are constantly bombarded with ‘facts and figures’ from politicians, journalists, and advertisements. Alice would say that throughout history the media would try to sell us remedies for which there’s no evidence, or advise us not to protect our children from diseases based on flawed science.¹⁴ When she heard these claims she would dispute them and find out more, whereas I accepted it all. The media could tell me I’m an intergalactic space frog and I’d probably believe it, but not Alice. It made sense, Alice understood the rules of science, she knew the system for evaluating evidence, and sometimes the jerks in power didn’t play by the rules: they twist the evidence to suit their own needs, or line their own pockets. Science gave Alice the power to see through it all; in a way, she held her own reality prism to the truth.

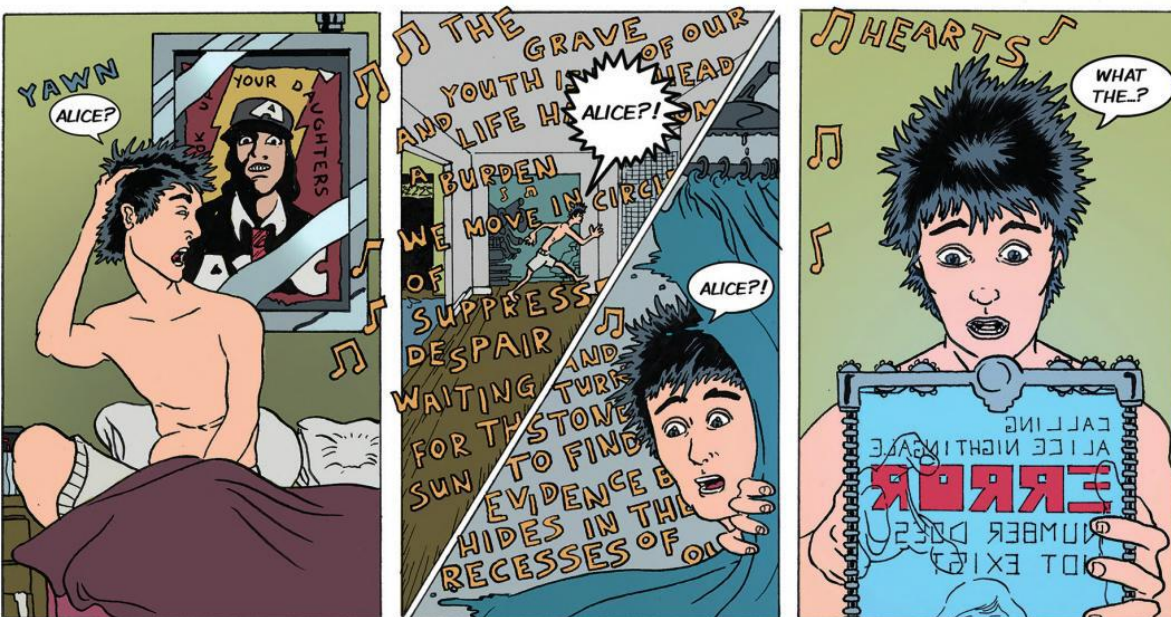
I was reminded of when we first dated, so I told Alice how when we first got together I really admired her passion for the truth, her humanity, and the way that she always wanted to do the right thing. I told her how I now understand that science is a part of that; it’s a system to help us to know what ‘the right thing’ is. It made total sense to me now.

Alice sucked the air out of the room before releasing it in an almighty sigh. Her breath wavered and she trembled as she exhaled. ‘Thank you’, she finally said, ‘... for listening, and for understanding. It makes everything easier.’

What did she mean by everything? Before I could ask she smiled beneath her distracted eyes, announced that she was going to bed, and headed towards the bathroom. That was my cue that the conversation was over.

‘You said you had a big decision to make. ... Can I help?’ I shouted after her.

‘You already have,’ came her reply.



KEY TERMS

Between-groups design	Independent variable	Related design
Between-subjects design	Inferential statistics	Repeated-measures design
Boredom effect	Interval estimate	Sample
Confounding variables	Latin square design	Sampling error
Correlational research	Longitudinal study	Sampling variation
Counterbalancing	Meta-analysis	Scores
Cross-sectional study	Outcome variable	Statistics
Dependent variable	Parameter	Systematic variation
Descriptive statistics	Point estimate	Tertium quid
Ecological validity	Population	Theory
Experiment (research)	Practice effect	Unsystematic variation
Experimental methods	Predictor variable	Variable
Hypothesis (hypotheses)	Quasi-experimental design	Within-subject design
Independent design	Randomization	

JIG:SAW'S PUZZLES

- Zach wanted to impress Alice, so he asked The Head to find him some famous scientific theories. For each one, can you help him to try to generate a hypothesis that might arise from the theory.
 - Galton¹⁵ suggested that intelligence is hereditary (runs in families).
 - Bandura¹⁶ suggested that people learn their behaviours from watching others (observational learning).
 - Paivio¹⁷ suggested that things are easier to remember if you visualize them (dual-coding theory).
 - Piaget¹⁸ suggested that children develop logical thinking skills as they grow older.
- What is the difference between descriptive and inferential statistics?
- What is the difference between a statistic and a parameter?
- What is the difference between sampling variation and sampling error?
- What is the difference between a point and an interval estimate?
- What is the difference between correlational and experimental research?
- What is the difference between systematic and unsystematic variation?
- Zach takes a group of fans of his band and gets them to rate each of five successive gigs according to how good they thought the band were.
 - What kind of design has Zach used?
 - What is the independent variable?
 - What is the dependent variable?
- Zach wants to know which musical instrument makes you the most popular. He looks at the *memoryBank* pages of a random selection of guitarists, drummers, bassists and singers and counts how many 'Hails' they have.
 - What kind of design is this?
 - What is the outcome variable?
 - What is the predictor variable?

- 10 Alice wanted to see what methods were best for getting boyfriends to take an interest in your life. She got her girlfriends to try different techniques on their boyfriends: giving the boyfriends affection whenever they showed an interest in their lives, giving their boyfriends chocolate when they showed an interest, or nagging them when they did not pay attention. Every woman tried each method for one week and counted how often her boyfriend listened to her.
- a How would you implement a Latin square counterbalancing for this study?
 - b What is the outcome variable?
 - c What is the independent variable?
 - d What is the predictor variable?
 - e What is the dependent variable?

IN THE NEXT CHAPTER, ZACH DISCOVERS ...

That his girlfriend doesn't exist
How to report research
Statistical notation
The mysteries of BODMAS
Levels of measurement
Measurement error
Validity and reliability
Never to corner a man who is clutching his sausage





REPORTING RESEARCH, VARIABLES AND MEASUREMENT

BREAKING THE LAW

Writing up research #43

Maths and statistical notation #49

Variables and measurement #55

The conspiracy unfolds #55

Qualitative and quantitative data #57

Levels of measurement #60

Measurement error #66

Validity and reliability #68

Key terms #70

JIG:SAW's puzzles #70



BREAKING THE LAW AND MEASUREMENT REPORTING RESEARCH, VARIABLES



Writing up research # 43

Maths and statistical notation # 44

Variables and measurement # 52

The conspiracy unfolds # 52

Qualitative and quantitative data # 57

Levels of measurement # 60

Measurement error # 66

Validity and reliability # 68

Key terms # 70

JIGSAW puzzles # 70



I woke with a knot in my gut: something wasn't right and my sleeping body sensed it before my waking brain. Alice wasn't in the bed. During the week she was up and out before me, but today was Saturday and she never got up early on the weekend. Perhaps she couldn't sleep and had decided to get up, but the bedroom was a tip: and Alice, even if half asleep, moved within our apartment like a ghost unable to disrupt the objects around her. Alice wouldn't leave the room in this kind of state. I jumped out of bed and rushed around the apartment. It confirmed what I already felt: Alice was gone and something wasn't right. Her clothes were gone, her possessions were gone, and every photo of Alice and me that we beamed from our stars onto the walls of our apartment was gone. Our home had been stripped of everything that made it our home.

I went to call her Proteus, but she wasn't in my contacts and neither were her family or any of her friends. Their details weren't in my history and of course I had no idea what their numbers were: like everything else, I had them stored on my star, never thinking to store them in my own memory. 'In loving memory of my memory indeed,' I thought as I tried in vain to make my diePad take me somewhere where I could find her number. I found the number for the Beimeni Centre of Genetics, where she worked, but they told me that no one by the name of Alice Nightingale had ever worked there. Alice had been wiped from the planet.

As I was losing hope, I realized that her contact details would be in a document somewhere: something from her bank, or her work: you can't do anything official without putting down your number. I logged into our constellation but her star was gone. I checked my own and there amongst the digital flotsam and jetsam of our life was a glimmer of hope: our rental agreement for the apartment. My hands shook with nervous hope as I opened the file. It was there, in digital black and white: her Proteus number. I quickly dialled the number, fantasizing about her answering, her exasperated tone as she explained that she'd gone to get us breakfast, and her confusion

at why I was fussing about her not being there. The fantasy came to an abrupt halt as my screen told me that the number had never existed.

The Head would know what to do: he knew everything. I opened my pocket watch, and expectantly awaited The Head's colourful entrance. As his face solidified, he yawned, 'Hey, Z, early doors?' He span through a slow circle, frowning, as though trying to get his bearings. 'This place is Caspered.'

He was right, the apartment felt eerie. I didn't feel the lump in my throat until I tried to talk to him. 'Where's Alice?' I croaked.

The Head whizzed around as he always did when he was checking whatever information sources it was that he checked. The spinning stopped suddenly and he looked serious. 'I don't know.' The hours I'd wasted trying to think up a question that The Head couldn't answer and I'd finally found one.

'Have you checked the street cameras? Police records? Tracked her Proteus? Looked at security camera footage? In the movies, they can find people.'

'Let me say something that might shock you. Prepare yourself, because, I fear this is the piece of knowledge that pushes you over some kind of mental edge. The ... movies ... are ... not ... real.' His eyes bulged as he said real, as though he was carefully inspecting my sanity.

What the frip? 'I ... am ... not ... an ... idiot,' I replied, emulating his bulging eyes. We stayed locked in a bulgy-eyed stare until The Head snapped out of it with a beaming grin.

'I'm glad, because for a moment there, Z, I thought you had forgotten that since the ID chips, we don't have street cameras, that the police don't keep track of every person's movements each day, that security cameras are, like, you know, secure, so any old Head can't just go looking at them, and that if someone doesn't activate their Proteus tracking then I stand more chance of tracking a fish on the other side of the Earth than I do of tracking them.'

Perhaps I was an idiot after all, but there must be something he could do – he must have access to something? The Head must have sensed my deflation. 'Look, I Sherlocked her good and proper. I searched more than 25 billion sources and your Alice Nightingale does not exist, so that woman doesn't want to be found, someone doesn't want her to be found, or she never existed.'

'Of course she exists – I was with her last night, you saw her last night?'

'I did, but every piece of information I examined tells me that I couldn't have.'

This was spooks; too frippin' spooks. The Head's words made me doubt myself. I felt alone and I wished my parents were still here. Alice is all I have, or had, and perhaps I never even had her? I was proud of being a Clocktorian, but right now it sucked. Half the world was instantly connected through these stupid chips in their heads and I couldn't access any of them.

I called Nick, the drummer in my band and my oldest friend. Nick and I met on my first day of school at the age of 4 and we've grown up together. Apart from the band, we hang out down at the Elpis Repository, sharing music and talking batticks. The Repositories were built by the WGA after the Reality Revolution to house vast underground physical collections of art, literature, music and film. They became the social hub of the city: people rediscovered the joy of experiencing music and films together, the debate that followed and the social connection that was lost by experiencing everything in a virtual world. Since the chipping began, though, *memoryBank* has offered a seemingly irresistible urge to catalogue life instead of living it; the Repositories have fallen silent. Many Clocktorians enjoy the solitude that the Repositories now offer, but I enjoy being there with a friend. For years that friend was Alice, but her interests lie elsewhere now and Nick is my regular companion.

Right now I needed Nick not just as a friend but because he was a Chipper – he had volunteered to have the chip so that we could promote the band using *memoryBank*. Nick is our connection to the Chipper’s world; our lifeline beyond Elpis. I told Nick everything that had happened; he put the word out to our fans on *memoryBank*, with the tag #NightingaleFlyHome. He’d known Alice as long as I had, and he reassured me that if she didn’t exist then he’d been imagining her too for the past 10 years.

When I got home and told The Head what Nick had said he adopted a look of pity, ‘You’re missing the obvious and you’re not going to like it ... She’s left you, and she doesn’t want to be found.’

As my mind spiralled I was drawn to the song that had been playing on repeat in the apartment since I had got up. It was ‘Faith in Others’, the final song from the album that Alice had been playing last night. It instinctively made me think of Alice, of our youth, of our evenings in the Repository years ago. As the song repeated, the lyrics came into my mind; they were words I had once known by heart:

The grave of our youth is up ahead
And life has become a burden
We move in circles of suppressed despair
Waiting for the sun
And turning stones to find evidence
But it hides in the recesses of our hearts¹⁹

Were these words a message from Alice? As I thought about them I feared the worst. Was ‘The grave of our youth is up ahead’ suggesting that we had grown up – that our youth was dying? Did ‘And life has become a burden’ mean that she felt that our relationship had become a treadmill, never progressing? Was ‘We move in circles of suppressed despair, Waiting for the sun’ telling me that she felt we were clinging on to a false hope that our love, the sun of our lives, would shine again? Did ‘And turning stones to find evidence, But it hides in the recesses of our hearts’ mean that she looked for signs of our love, but couldn’t find them because they were too deeply hidden?

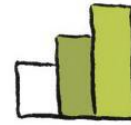
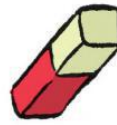
The words painted a black picture and the realization of her message was a stranglehold around my neck. Perhaps The Head was right, this song did seem like a farewell message. It made perfect sense: we *had* been drifting apart. A song on repeat was a kind of weird way to end a relationship, though, not to mention removing all traces of your existence. It seemed a bit extreme. Surely there was more to it than that? This belief drove me to find the memory stone, and I stared at three files that Alice, presumably, had wanted me to find. I remembered the second of the three possibilities that The Head had said earlier: perhaps *someone else* doesn’t want her to be found.

2.1 WRITING UP RESEARCH

I opened the file with the name that told me to read it. It was neither a bittersweet farewell note nor a clue to her abduction, instead it was a tedious report. 🐛 It meant nothing to me. Why would Alice want me to read that? Surely she would know that my brain would disengage by the second sentence. The other files were more of the same.

As I read I became agitated. ‘I don’t understand any of this; it makes no sense to me. It’s stupid, stupid words, stupid symbols and even more stupid pictures. Why can’t she just write something

LAB NOTES 2.1



Abstract

Recent advances suggest that a combination of programmable cells and synthetic genes (C-10XFMG) can be a successful way to heal damaged tissue. However, the results of early trials suggest only partial success. This study combined this technology with the implementation of a genetic toggle switch. Participants with facial injuries were administered the programmable cell/C-10XFMG therapy, but half were also implanted with a genetic toggle switch. All participants were then asked to heal their injuries by studying photos of themselves before the injury, or a same-sex stranger (controls). The results showed that ...

Introduction

Matter that can change from one physical form to another (so-called 'programmable matter') has long been used to construct versatile objects and buildings (Knaian, 2013). Cars that turn into boats and planes have become the mainstay of our transport system, and adaptive buildings that can change their room configuration within seconds are part of everyday life. Similar principles have been applied to living tissue. In the 21st century scientists began to develop 'programmable cells' (Kobayashi et al., 2004), hoping to create living tissue that can change form based on biochemical instructions. Such cells would have enormous clinical value, for example, in healing damaged tissue by instructing the cells to revert to their non-damaged state. Mice with programmable cells have been shown to be able to heal external injuries by issuing such instructions to those cells (Araya, Hanneman, King, & Lombardo, 2103). There have been two major challenges in realizing the true potential of this technology: (1) how to convert ordinary human cells into programmable ones; and (2) how to empower humans to control these cells. The first challenge has recently been solved: Nightingale developed the BLISS serum, which has been shown to fully convert normal human cells into ones which can be instructed to change their structure (Nightingale, 2110). In addition, significant steps towards the second aim have been made through synthesizing the genes of species that can change aspects of their physical appearance using hormones or neurotransmitters. One notable success is the so-called 'chameleon gene'. The chameleon lizard controls its external appearance by relocating particles of pigment in special cells called chromatophores; synthesis of the chameleon gene with human genes appears to enable humans to similarly control programmable cells within their body. A breakthrough study showed that humans with burn injuries could partially heal their skin by first converting their cells to programmable ones, then introducing the chameleon gene into their genetic structure, and then training the participants to focus on healing their wounds (Nightingale, 2112). This so-called C-gene therapy offers the exciting possibility of self-healing of many injuries and cancers; however, to date the therapy has been only partially successful.

Theoretically, control of programmable cells through the chameleon gene would be improved by the use of a genetic toggle switch (Deans, Cantor, & Collins, 2007) that can turn specific genes on and off. The logic is that introducing such a genetic switch would provide the individual with more precise access to both their existing gene structures and also the chameleon gene itself. This study aims to see whether the combined use of a genetic toggle switch with the chameleon gene will result in better self-healing in people with facial injury. We predict that the C-gene therapy combined with a genetic toggle switch will enable better healing than C-gene therapy alone.

Method

Participants

Participants were 17 males and 15 females aged 13 to 61 ($M = 35.84$, $SD = 12.53$) who had facial burns, recruited from Elpis City Hospital. All participants consented to the study after full disclosure of the safety of the procedures to be used.

Genetic Procedures

Two weeks prior to the study all participants were injected with the BLISS serum (Nightingale, 2110). Two days pre-test, cell samples were taken to confirm that the serum had converted cells to a programmable state. All participants responded as expected to the BLISS serum with no side effects. One week pre-test, the chameleon gene, C-10XFMG, was introduced into all participants, followed by 3 hours of adaptation during which participants were monitored. The quantity of C-gene for each person was synthesized using the standard equation (Nightingale, 2112):

$$y_i = \frac{\sum_1^n x_{\text{chameleon}}}{\left(\sum_1^n x_{\text{human}}\right)^2}$$

For the next 5 days participants underwent the attentional training used by Nightingale (2112), during which they were trained to mentally attune to the new gene. This training has been shown to help people to gain conscious control over the C-gene (Nightingale, 2112). Two days prior to test, the genetic toggle switch was introduced into half of the participants.

Tasks

Half of the participants were asked to look at a photograph of themselves from before their injury and to imagine the cells in their faces changing to become like the photo. The remainder acted as a control and were asked to look at a picture of a same-sex stranger and to try to change their face to become the person in the picture.

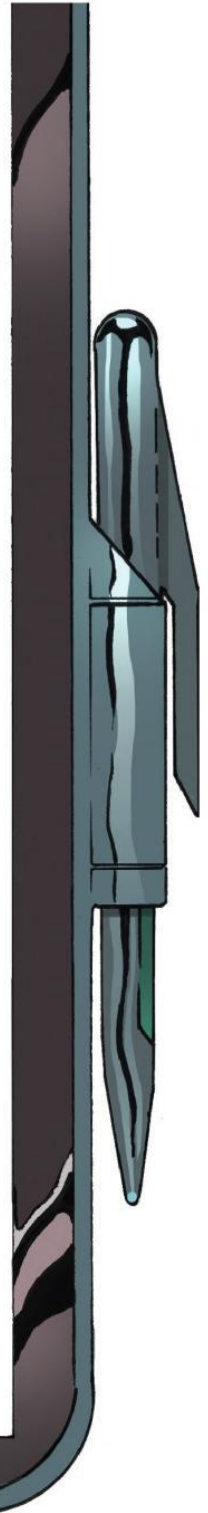
All participants looked at the picture for 6 sessions of 20 minutes each. At the end of the sessions their faces were scanned into a computer and compared to the face in the photograph. Facial recognition software produced a precise resemblance measure as a percentage (100% = the participant's face is exactly like the face in the photograph, 0% = the person in the photo bears no resemblance at all to the participant).

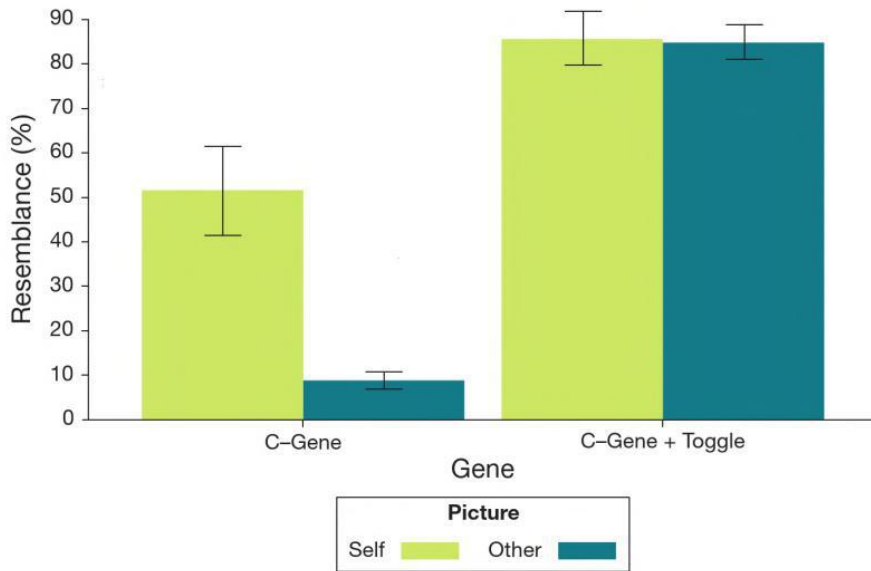
Design

The design was a 2 (Gene: chameleon gene, chameleon gene + genetic toggle switch) \times 2 (Picture: self, same-sex stranger) independent design. The outcome was the facial resemblance (%) between the participant and the photo.

Results

There was a significant main effect of whether the participant had the chameleon gene alone or in combination with the genetic toggle switch, $F(1, 28) = 440.83$, $p < 0.001$. There was also a significant main effect of whether the participant tried to resemble a photo of themselves pre-injury or the photo of a same-sex stranger,





$F(1, 28) = 68.17, p < .001$. Finally, there was a significant interaction between the gene combination and the type of picture that the participants tried to copy, $F(1, 28) = 62.83, p < .001$.

Discussion

The implications are frightening ... I'm not sure I should make them public ...

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in English?’ My eyes welled up in frustration. ‘It’s one of those articles that Alice reads for work, and that she writes sometimes. Why would she leave me that?’

‘Show me,’ said The Head in his soothing, unflappable tone. I held up my diePad screen. ‘You’re right, Z, that’s a research paper for sure. One of hers, I imagine. Maybe she left it for a reason? Maybe she wants you to know what it’s saying? Or maybe she forgot to take that stone with her when she left you.’ He chuckled.

‘Or when she was taken,’ I added, wanting to retain the hope that she hadn’t left me because she wanted to.

The Head became serious. ‘What would happen if I spoke to you in another language ... which, by the way, I can?’ he asked.

‘I wouldn’t understand you.’

‘No, you wouldn’t. This report is written in the language of science; understanding it is about understanding the language. You just need to learn the language. I can help you. Scientists use a standard format to communicate their research to each other. They want to tell others four things: the reason why they did the research, how they did it, what they found, and what it means.’

‘Why? How? What? Who cares?’

‘You got it. If every scientist wrote whatever they liked it would be confusing, so they write reports or research papers that follow a format that helps them to think about those four questions:

- *Abstract*: This is a summary of the whole study. It’s slick. Scientists are busy people, they need to know “do I need to read this stuff?” That’s what the abstract tells them. It has a sentence or two describing why the study was done, how it was done, what was found and what it means. It gives the reader a feel for whether the research is interesting or relevant enough to warrant reading the detailed paper.
- *Introduction*: This is the why. The history lesson. They talk about past research that others have done that has led to their own hypothesis. They might describe how other findings are inconsistent or ambiguous and then describe how their research will clarify the situation. The intro normally moves from the general to the specific: they start with the general background of the research and then describe specific studies. They usually finish by saying what their hypotheses are.
- *Method*: This is where they tell others how they did their research. There is enough detail that someone else could repeat the research, but not so much detail that they die of boredom reading it. It’s common to split this section up into who took part (*participants*), what tasks were used (*measures/materials*), special equipment that was used (*apparatus*), the type of research design that was used (*design*), a description of what happened (*procedure*), and how the measures were scored (*scoring*). It’s unusual not to see participants and procedure, but the other sections may or may not be there.
- *Results*: This is the money shot. This is where the mystery is revealed: what did they find? Remember Alice told you about descriptive and inferential statistics? 🚩 Scientists normally start with some descriptive statistics about their sample, then they deal the killer blow of the inferential statistics. Those inferential stats are like a sergeant major, putting those hypotheses through their paces, seeing whether they come out strong or drop down dead. Only the strong hypotheses survive.
- *Discussion*: This section is deep; so deep you need a subwoofer. They summarize what they found in case you didn’t understand the results, but also how it changes the world, and what

still needs to be done. They start by summarizing the results. BOOM! Then they lay down what it means for their theory. BOOM! They tell you what it means for the real world. SUBSONIC BOOM! They tell you the limitations and what still needs to be done. When that's done, you're like "Whoa, get me a depth gauge so I can measure how deep that was."

LAB NOTES 2.1

- *References*: You can't write stuff in science without justifying it, you've got to let people know the science that supports what you're saying. Alice, in her intro 📄, cites research papers when she makes a point. She writes the names of the authors and the year that the research was published. So, you need to collect that wisdom into a reference list so others can read it for themselves. Alice has one of those lists and all the names and dates she has cited appear in this list.

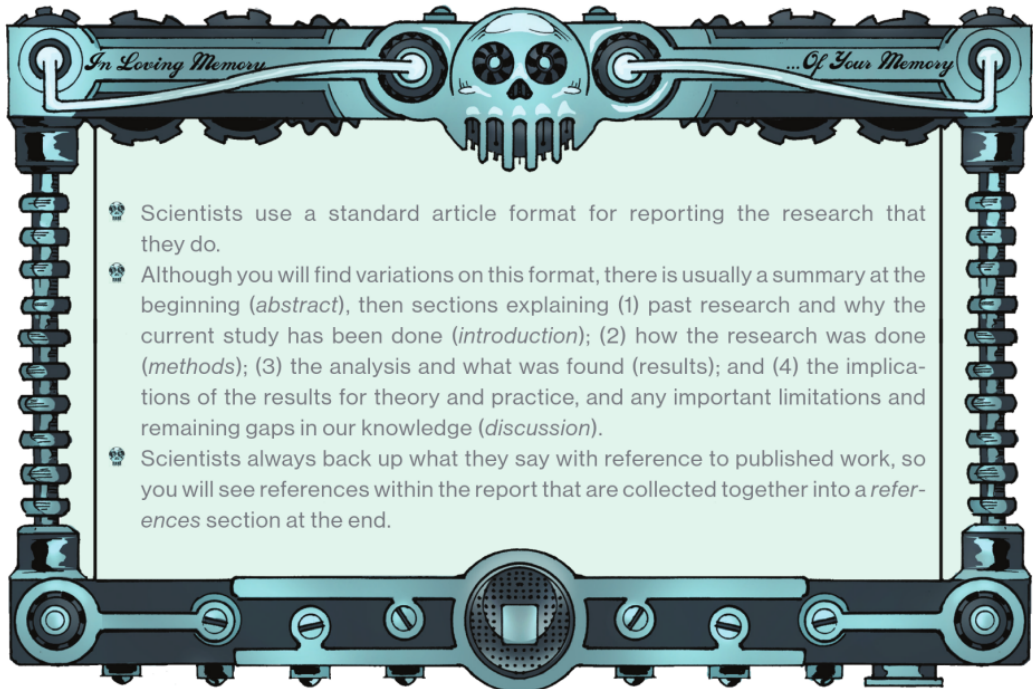
This was a lot to take in, but it made sense of what I'd read. He was right, Alice's report had all of those sections: an abstract, introduction, method, results, references, but no discussion. As though thinking the same thought, The Head said, 'Looks to me like she hadn't finished the report: the abstract has no ending and it looks like she was scared to write the discussion.'

'Scared of what?' I asked.

'Read her words, it sounds like her results were gonna blow the world a new ass ...'

'I get the picture, but what *were* the implications?'

'That is a question I can't answer. I will admit to a staggering capacity to gather and assimilate information, but I'm no scientist. You're as on your own as a statistics professor on a dance floor.' Wow, two questions The Head couldn't answer in a day – usually that would have made me feel very smug.



Zach's Facts 2.1 Writing up research

2.2 MATHS AND STATISTICAL NOTATION

Somehow I needed to fathom out what Alice had found. I felt sure that she wanted me to read this report, and perhaps she trusted me to do something sensible with it. I couldn't understand why, though. She knew better than anyone that I was hopeless at this stuff; she operated on a higher mental plane than me. It just didn't make sense that she would trust this report to me – why not tell the professor she worked with, or some other colleague? Why give a report to someone who you know won't understand it? Maybe she wanted to give it to someone who she knew couldn't possibly understand it? The question rattled around in my empty head. What would Alice tell me to do? She would say I should evaluate the evidence, and this report was evidence.

'If you can't help with the science, what *can* you help with?' I asked The Head.

'The maths. I was the best man at Maths' wedding to Mrs Maths, I'm godfather to baby Maths, I look after goldfish Maths when the Maths family are on holiday. Maths is my sibs. What about you?'

'I walked past Maths on a crowded street once.'

'That's real bad. Let's start real simple. What is the result of $1 + 2 \times 3^2$?' The Head asked.

'That's easy, it's 27'

The Head shook, 'No, it's 19.'

'Don't be crazy, 1 plus 2 is 3, multiply that by 3^2 , which is 9, and you get 3 times 9, which is 27.'

'You're breaking Mr Maths' heart,' The Head said in an overly sad voice. 'You're forgetting BODMAS.' 🍷

REALITY CHECK 2.1

'BODMAS? Who was he?'


'Father BODMAS was an old guy with a white beard who used to give children equations for Christmas.' The Head waited for a reaction, but continued when he got none, 'I'm yanking your chain. BODMAS tells us the order to do things in an equation. If you use BODMAS then you'll see that because there are no brackets the first thing to deal with is the order term: 3^2 is 9, so the equation becomes $1 + 2 \times 9$. There's no division, so we move on to multiplication: 2×9 , which gives us 18. BODMAS tells us to deal with addition next: $1 + 18$, which gives us 19. If I'd asked you to solve $(1 + 2) \times 3^2$, then the answer would have been 27 'cos we deal with the brackets first: $(1 + 2) = 3$, so the equation becomes 3×3^2 . We then deal with the order term, so the equation becomes $3 \times 9 = 27$ '. Let's try a tricky one. What's the answer to this?' The Head projected an equation onto the wall.

$$10 + \frac{2(3+1)^2}{8} - 5$$



CHECK YOUR BRAIN: Can you solve The Head's equation? Remember to use BODMAS.

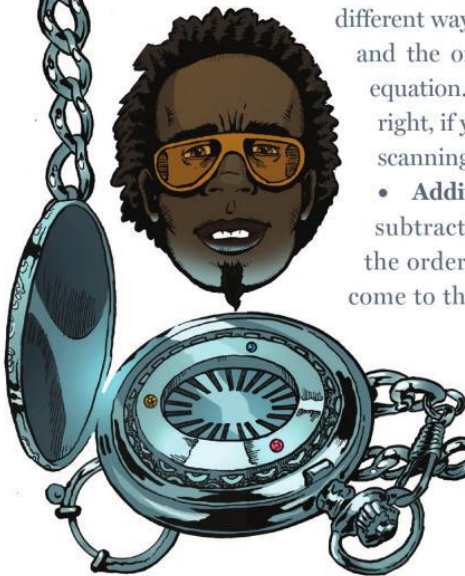
FIGURE 2.1

I got my diePad and started to draw to help me;  in retrospect it would have made more sense to have used the calculator app. 'Let me see, first I deal with the brackets, so that is $3 + 1 = 4$. So I change $(3+1)$ to 4.'

'Great,' said The Head.

'BODMAS and PEMDAS are acronyms to help you remember which order to do things in when carrying out calculations or working out the result of an equation,' The Head explained. 'They are different versions of the same acronym so use whichever one you find easiest to remember. The acronyms stand for:

- **Brackets/Parentheses:** This means that anything within brackets is calculated first.
- **Order/Exponents:** "Order" is the old fashioned way of saying "to the power of". So, 3^2 is three to the order of 2. These are also called exponents. So, anything with an exponent should be calculated next.
 - **Division/Multiplication:** the acronyms place division and multiplication different ways around, but it doesn't matter because they should happen next, and the order in which they happen depends on where they are in the equation. The rule is you go left to right, so scanning from the left to the right, if you come across a multiplication first then do it and then carry on scanning to the right.
 - **Addition/Subtraction:** although addition is ordered before subtraction in both acronyms, they again happen at the same time, so the order is determined by doing any additions or subtractions as you come to them when you scan from the left of the equation to the right.'



Reality Check 2.1 BODMAS/PEMDAS

'Next I do the orders or exponents. So, I take the 4^2 and change that to 16. Then I need to look for any multiplication or division. There is one of each: there's a 2×16 and also a divide by 8. As they are part of the same thing I guess it makes sense to do the 2×16 first because that's what gets divided by 8?'

'You know it makes sense,' The Head grinned.

‘Sweet, so I replace the 2×16 with, 32, and next I divide this value by 8, which gives me 4. Finally I deal with any addition and subtraction, and I do this from left to right, so that gives me $10 + 4$, which is 14, and then subtract 5 from it. So, the answer is 9?’

The Head nodded in appreciation ‘You said you walked passed Mr Maths on a crowded street? Well, you just ran back and invited the dude for a coffee!’

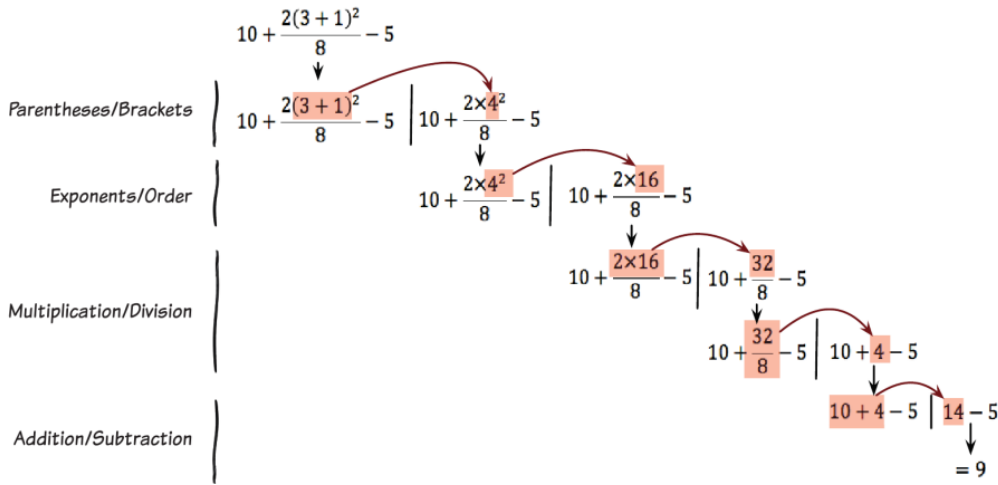


Figure 2.1 BODMAS and PEMDAS

There were other symbols that I didn't understand in Alice's report \rightsquigarrow , like the little i , and the x and y , so I asked The Head about those.

LAB NOTES 2.1

' y represents the outcome. That's the variable that you're predicting. When Alice talked about measuring T-shirt sales \rightsquigarrow , that variable was an outcome, so we might represent T-shirt sales with the letter y . The letter x is a different letter altogether, and represents a predictor or independent variable. It is also used to denote scores. The i tells you to what or who the score belongs. If you and Alice rated how much you love each other out of 10, what number would you give Alice?'

SECTION 1.2

'10.'

'Smooth, and I'm thinking she gives you a 7.'

'What?'

'Too much? You're right, Z, she rates you 6. We can represent these scores with x_i , which is saying 'the score, x , that belongs to person i '. You could replace i with the person's name, like this: $x_{\text{Zach}} = 10$ would mean Zach's rating of Alice is 10, or $x_{\text{Alice}} = 6$ meaning Alice's rating of Zach is 6.'

'What about that funny pointy thing in the report?' \rightsquigarrow I said, pointing at the funny pointy symbol.

LAB NOTES 2.1

'The sigma?' The Head projected a Σ out in front of him from the pocket watch, 'That means "add shit up".'

‘Why does it have a 1 and an n by it.’

‘Because you start adding at item 1, and you “add shit up” until you reach the last item; because the equation doesn’t know how many things you have, it can’t use a number to represent the last item so it uses the letter n , which you can think of as being short for ‘number of things you need to add up’ or ‘no more numbers left to add up’. Imagine we wanted to add up your and Alice’s ratings of love for each other. We can represent that like this’. The Head again projected some symbols. 🧠

🧠 2.1

$$\sum_{i=1}^n x_i \quad (2.1)$$

‘The $i = 1$ in the expression means that you should start with person 1’s score; if it was $i = 2$ then it means you should start with person 2’s score. The n symbol at the top means that you should keep adding scores until you reach the last score. So, with $i = 1$ this equation means that you take person 1’s score ($i = 1$) score, then add it to person 2’s score ($i = 2$), then add person 3’s score ($i = 3$) to the previous scores, and carry on doing this up to and including the last person’s score ($i = n$). With scores from just you and Alice we would have this.’ The Head projected another

🧠 2.2 equation. 🧠

$$\sum_{i=1}^n x_i = 10 + 6 = 16 \quad (2.2)$$

The Head stepped things up. ‘Of course, you can use the BODMAS principles with this symbol too.

🧠 2.3 What do you think you would get for you and Alice’s ratings from this expression?’ 🧠 he asked.

$$\sum_{i=1}^n x_i^2 \quad (2.3)$$

I felt like The Head was torturing me. I was finding it hard to concentrate. Alice was missing, I needed answers and he was babbling on about maths. I thought back to BODMAS. There were no brackets in The Head’s equation, so move onto powers. There was a squared symbol. ‘Do we square each value and then add them?’

🧠 2.4 ‘Yes you do’, The Head beamed, as he projected the full equation. 🧠

$$\sum_{i=1}^n x_i^2 = 10^2 + 6^2 = 100 + 36 = 136 \quad (2.4)$$

🧠 2.5 ‘What about this expression?’ 🧠 continued The Head, projecting yet another equation in front of me.

$$\left(\sum_{i=1}^n x_i \right)^2 \quad (2.5)$$

I thought back to BODMAS. The weird spiky symbol was in the brackets, and we have to deal with the brackets first, so that means we’d sum the scores first. Having done that we’d look for an exponent or power symbol. There was one: a squared outside of the brackets, so that must mean

we square what is inside the brackets. ‘We add the scores and then square the total, so it would be 16 squared,’ I replied to The Head, who looked pleased and projected the answer for me. 🧠 2.6

$$\left(\sum_{i=1}^n x_i\right)^2 = (10+6)^2 = 16^2 = 256 \quad (2.6)$$

‘You’re doing great,’ The Head reassured me. ‘The final hurdle is the equation in Alice’s report’ (Alice’s Lab Notes 2.1). The Head projected the equation 🧠 on the wall to remind me. 🧠 2.7

$$y_i = \frac{\sum_1^n x_{\text{chameleon}}}{\left(\sum_1^n x_{\text{human}}\right)^2} \quad (2.7)$$

It looked complicated. I started to panic slightly. It felt too hard, and my mind was still racing about Alice. The Head told me to break it down into little bits. ‘What’s y_i ?’ he asked.

‘Is it the outcome for person i ?’

‘Yeah, that’s what they are trying to calculate: the quantity of C-gene to give to each person. Now, the x s represent values that either come from a chameleon lizard or the human themselves. Imagine we have 5 scores from a chameleon and 5 from the human.’ The Head projected a table of numbers onto the wall. 🧠

TABLE 2.1

Table 2.1 The data that The Head used to torment Zach

Chameleon	Human
3	2
1	3
2	5
4	7
2	3



CHECK YOUR BRAIN: Using the scores in Table 2.1, can you work out the quantity of C-gene needed?

‘Based on these scores, what quantity of C-gene is needed?’ The Head asked.

I thought again of BODMAS. ‘Brackets first, and there are brackets in the bottom part of the equation so I need to deal with those first. The adding symbol is inside the brackets, which means

that I need to add up the human scores first; that will be $2 + 3 + 5 + 7 + 3$, which is 20. Next is order terms, and there is an exponent in the lower part of the fraction, which tells me to square the 20, which will be ...' I paused.

2.8 '400,' said The Head as he projected the equation on the wall as I worked through it.

$$y_i = \frac{\sum_1^n x_{\text{chameleon}}}{\left(\sum_1^n x_{\text{human}}\right)^2} = \frac{\sum_1^n x_{\text{chameleon}}}{(2 + 3 + 5 + 7 + 3)^2} = \frac{\sum_1^n x_{\text{chameleon}}}{20^2} \quad (2.8)$$

$$y_i = \frac{\sum_1^n x_{\text{chameleon}}}{\left(\sum_1^n x_{\text{human}}\right)^2} = \frac{\sum_1^n x_{\text{chameleon}}}{400}$$

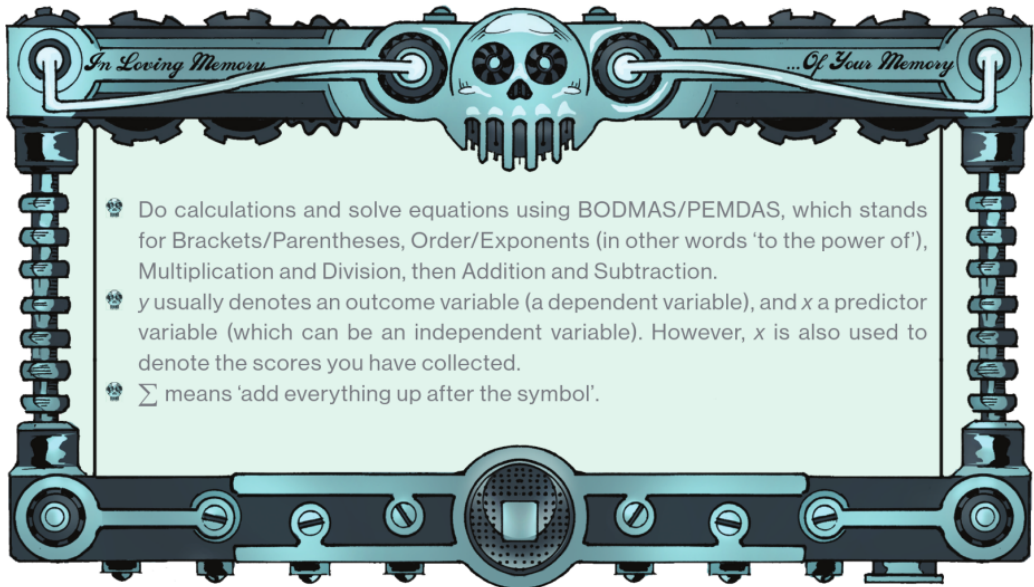
'The next part of BODMAS is division, so I need to do that next, but to do it I have to sort out the top half of the fraction. The symbol on the top means I need to add the chameleon scores, so that will be $3 + 1 + 2 + 4 + 2$, which is 12. So, the final value would be 12 divided by 400.'

'Which is?' said The Head with a teasing look on his face.

'C'mon, you know I have no idea.'

2.9 'Yeah, I know, but I'm havin' fun. It's 0.03'.

$$y_i = \frac{12}{400} = 0.03 \quad (2.9)$$



Zach's Facts 2.2 Statistical notation

Despite a small amount of pride at having followed what The Head told me, I was agitated. This lesson wasn't getting me any nearer to Alice. It felt like a waste of time: it would take me weeks to fully understand this report, and I needed to know what was going on *now*. I didn't want to believe that Alice had left me, but it was plausible, and if she hadn't then the implications were even worse: someone had taken her and tried to erase her from the world. Alice would have told me to collect evidence, real evidence, not ambiguous evidence buried in a report or a song. Her friends and family may have been wiped from my contacts, but I knew she had been seeing a counsellor, and I knew his name: Dr Murali Genari. She spoke about their sessions, and to whom do you tell your secrets if not your counsellor? A counsellor's address should be easy enough to look up, and it was.



2.3 VARIABLES AND MEASUREMENT

2.3.1 The conspiracy unfolds

The voice startled me. I turned, my heart racing. Before me was a white-haired, short, plump man holding a massive sausage. I should have run – I could have easily pushed past him, back down the hallway, and been gone before he could react, but there was something about the sausage that disarmed me.

'I said, *what are you doing!*? Answer me!' shouted the man. He was quivering with rage. In my enthusiasm to find out why Alice had gone, I hadn't factored in being caught in the act of stealing a confidential file. This situation was a bit awkward. The man facing me, I assumed, was Dr Genari. He certainly looked the part: he was an old man, had a white beard, and dressed even

more old-fashioned than Alice's parents. He posed no real threat to me, I could take the file and run, but what if he tried to challenge me? I didn't want to hurt the guy; I just wanted the file. I stared at him, both of us trying to get the measure of each other. Suddenly I realized that he wasn't shaking with rage, it was fear: he was afraid of me. What was I doing breaking into an office and terrifying some old guy? I had acted with my heart but my head, long overdue, kicked in. I had gone about this all wrong. I had assumed that a counsellor wouldn't give me the time of day, but the guy's job is to help people, why wouldn't he help me? I needed to diffuse the situation, to reassure him that I wouldn't hurt him, to get him on my side. I let go of Alice's files and turned to fully face him with my arms held up as though he was pointing a gun at me.

'I'm sorry, I don't want any trouble. Please ... Put. Your. Sausage. Away.' I smiled and tried to look unthreatening.

His head turned to face the sausage, which he observed with a lop-headed confusion. 'Damn this programmable matter.' He walked towards me as though instantly pacified. 'I can't get the hang of it at all. No, really I can't. One minute I'm thinking it to become a sword, because there's a degenerate in my office and a sword is a useful thing to have. A second later I notice that I am hungry and would like to eat a sausage and here I am standing in a doorway with a massive sausage in my hand. It completely undermines the sense of threat I was trying to create.'

He babbled to himself while circling the room tapping his forehead with the sausage. I could have left without him even noticing, but instead I picked up Alice's file, brought it to his desk and sat at his chair.

'It doesn't make any sense,' he continued.

'Yes it does. Programmable matter responds to your thoughts, so when you imagined it was a sword it became a sword but when you thought of a sausage ...'

'No, not the sausage ... you! *You* make no sense. Why would you take a crowbar, destroy my front door, enter my office and rifle through my files? You want to find something out about a client, that is obvious, but why did you break in?'

'Because I want to find something out about a client ...'

He interrupted and rolled his eyes, 'Yes, yes, but it's midday, why not ring the doorbell?'

Dr Genari didn't seem scared or angry any more. He had switched into some kind of detective or counsellor mode where all he could think about was trying to get to the bottom of my motives for being there. He paced around asking himself questions. His accent suggested he had grown up or spent a lot of time in India; he also had a lovely disjointed way of talking to himself – changing thought in mid-sentence as though hundreds of ideas were fighting for the attention of his voice. I wondered what his story was, how he had come to be in Elpis. Had he always been a counsellor? As he paced, and thought out loud, one thing was clear. He was a kind man: I had broken into his office, I had invaded his space, and yet he could only wonder why I needed help. I felt embarrassed that by breaking in I had not reciprocated his levels of consideration for me. I interrupted him.

'My girlfriend is your client. She's gone and I can't contact her, I'm worried, I figured maybe she'd told you something.'

'Something like how she doesn't like dating delinquents who break into offices?' His quip made me blush with shame. 'Let me guess, woman leaves, doesn't answer calls, boyfriend who has been too busy watching sport or playing guitar to pay her any attention wonders why she has suddenly left him? Tell me about your relationship.' Dr Genari sat in the very comfortable looking chair that I assumed was reserved for his clients. I could see why he was a counsellor – he was good.

I told Genari how I felt Alice and I were drifting apart, how I didn't understand her world and how the deeper she got into that world, the less she seemed interested in mine. I told him how we had shared a passion for music, but that nowadays she wasn't interested. As I spoke, the blob of programmable matter on his hand was involved in an ever-changing theatre of his internal thoughts. As I described Alice it rose up into a female figurine, only to shift, as I told him our history, into a small guitar, a miniature Beimeni Centre of Genetics, the Elpis Repository, and a Proteus. When it became a hat, a billiard cue, a penguin and a pizza, I wondered whether his attention was wandering.

'Very interesting,' he said. 'I lie, of course, none of that is remotely interesting, it is the story of every relationship: girl meets boy, girl and boy have lots in common, girl and boy grow up, life takes over, they drift apart. It is unremarkable, unlike your belief that she left you. You could be correct, but it's unlikely. I will explain. You say that the last evening you spent with her, you discussed her great passion, science? You also say that she has longed for you to take an interest in this passion, but you never do. Except last night, after years of refusing to engage with her world of science, you listen to her. Last night she got what she has longed for from you. It is a strange time to leave you.'

He had a point. He also looked bored by the conversation, as though he had had similar ones a thousand times before. It was also a conversation that wasn't getting me any closer to finding out what this man knew about Alice. I remembered that The Head had suggested other reasons why Alice might not be contactable and decided to throw one out at Dr Genari.

'Alice leaving me is one explanation, but there are others.' Genari's eyes lit up at the prospect. 'My reality checker said that maybe she doesn't want to be found or maybe *someone* else doesn't want her to be found.'

'Abduction?' Genari asked. He sat up to attention, looking very excited. 'Are you telling me that your girlfriend, my client, is in danger?'

Of course I didn't think that Alice was in danger, I just wanted to get to the bottom of all the weirdness, find out where she was and try to convince her to give me another chance. Why would anyone want Alice to disappear? I explained that she wasn't in danger. Genari looked deflated.

'Apart from the breaking and entering, you seem like a nice boy, but I cannot discuss confidential client matters, unless of course that client is in danger and it is better for them that I break my oath of confidentiality.' He raised his eyebrows expectantly. 'Are you *sure* she is not in danger?'

I could see the game he was playing. I lied and told him I believed that she could have been abducted.

He smiled and became very excited and animated. He leapt out of the chair and came around his desk to stand next to me. He clasped his hands together and wiggled his fingers before slowly and overly dramatically opening the file on the desk. 'Let's see who this girlfriend is,' he muttered to himself. The first page of the file showed a picture of Alice and some details about her. I looked up at Genari's face; it was pale, lifeless apart from the tears in his eyes.

2.3.2 Qualitative and quantitative data

Genari's expression panicked me: what did it mean? Was he worried about Alice's mental state? Did he know something about her that I didn't? Did he know a reason why she might actually be in danger? I was flustered. I spread the pages of the file across the table, searching for answers, but everything I saw was confusing: there were notes, questionnaires, sheets with numbers on, and photographs 📷 – a mass of bewildering information.

FIGURE 2.2

Genari composed himself. 'As you say, many hypotheses are possible. We need to look at the evidence for each one,' he whispered more to reassure himself than me.

'You think Alice is in danger, don't you? Tell me what you know,' I demanded. I was impatient to find out where Alice was, and I hated feeling like I was missing something important.

Genari put his hand on my shoulder and smiled a reassuring smile. 'Please, I don't know anything more than what is in this file. I am sure she is not in danger; you know I had to play that game with you to give myself permission to show you the file.' He was lying; I had seen his face when he opened the file. But I had no choice but to go along with the lie if I wanted his help. I asked him how we would use the file to test our hypotheses about Alice.

'To test hypotheses you need to measure variables,' he began.

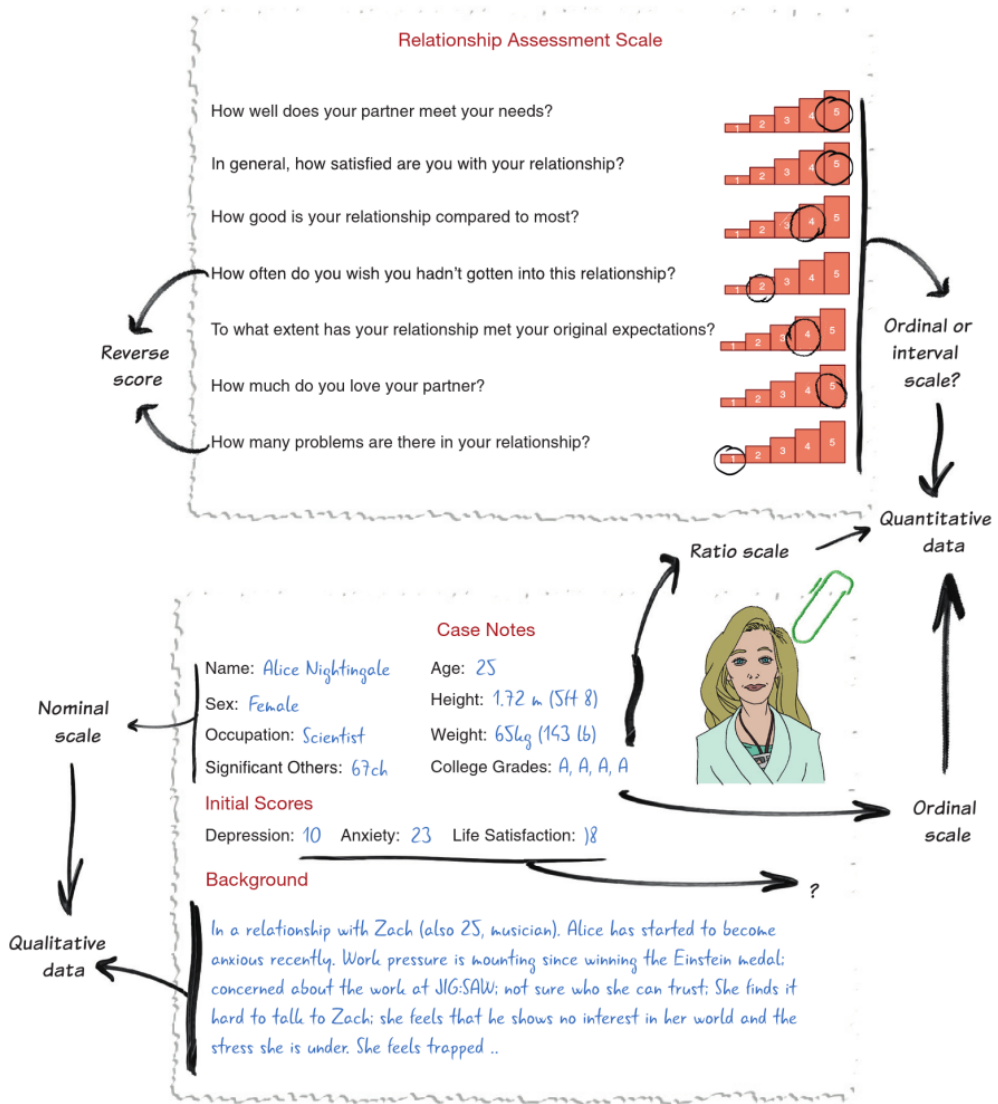


Figure 2.2 Scales of measurement

I didn't want to sit through another lecture about testing hypotheses, so I told him what Alice had taught me last night about the scientific process, and how you generate hypotheses and then work out what variables you need to measure.

'Good. Did she explain that there are different types of variables that you can collect and that they have different properties?' Alice hadn't told me that. 'For example, how might we tell whether Alice wants to leave you?'

'If she were here we could ask her, but she isn't.' I looked at the papers in front of me. 'It looks like she has answered some questions about our relationship by circling numbers on this Relationship Assessment Scale' (RAS)²⁰. ➔

'How do these measures differ?'

'If we ask her then we have what she says, her words; but if we look at this questionnaire then we have the numbers that she circled.'

'For a man daft enough to break into an office during opening hours, you are quite smart.' The doctor smiled. 'You have highlighted two different approaches to testing hypotheses. The first is to gain support for a theory from what people say or write (**qualitative research**). One popular method for doing this is **discourse analysis**, which operates on the basic assumption that by studying what people say (and how they interact) you access real processes (whether they are psychological, societal, anthropological, and so on). For example, suppose Alice said during our sessions "I want to leave Zach". Her expression of intention is not based on only her internal experience, because the idea of leaving your partner is socially constructed; she has used that phrase because she has observed how others use that phrase. As such, her statement is taken within the context of social environment. People declare that they want to leave their partner but still very much love them and don't leave them, and perhaps Alice used that phrase within that context: it is an expression of discontentment but not an intention to leave. To do a discourse analysis you start with an individual interview (which has the advantage of control) or a group discussion (which has the advantage that you can look at natural interactions). These discussions would be transcribed. Not all of the material will be analysed, but instead, topics or themes are identified, often through reading the material and looking for reoccurring features of conversation, or intuition about important parts of the dialogue. You would then begin to index the transcripts according to the themes identified. You should reread the material to try to find counter-examples of things you've identified (this is especially important if you're working on intuitions). The analysis itself is based on writing an account of the themes you've identified or the intuitions you're following, and extracting data from the transcripts to back up (or contradict) your ideas. The analysis should be iterative: you should reassess your analysis and redraft it as readings of the transcripts throw up new ideas and examples.²¹ The whole process can be theory- or data-driven. In theory-driven analysis you analyse discourse or interactions with respect to existing theory. In data-driven analysis you collect data with no particular theory in mind and let the analysis inform the development of a theory (sometimes called **grounded theory**).'

'So, to do a qualitative analysis I would need to read and transcribe all of these notes you've made from your interviews with Alice and try to pick out themes to support my hypothesis?' I didn't have time for that.

'Yes, my boy, that is what you do!' Genari said, breaking into a laugh.

'That seems like a lot of work.'

FIGURE 2.2

Genari's laugh escalated 'It is, my boy, it is! The alternative is to measure variables using numbers and then to use statistical methods to analyse these numbers to test your theory (**quantitative research**). You might, for example, look at Alice's scores on the Relationship Assessment Scale.'

I looked at the sheet with this scale on. The scores seemed quite positive. 'She has circled the highest score for me meeting her needs, her satisfaction, and given a low score to us having problems. 🐾 How would I know overall how she feels, though?'

FIGURE 2.2

'Simple, add the scores up. Notice that some questions are phrased differently than others: some ask how satisfied she is, and so if she circles a large number then it means that the relationship is good; whereas others ask what problems are in the relationship, so if she circles a large number it means the relationship is bad. First you have to reverse-score these questions that are phrased differently, then you can add all of her responses up to find out how she feels.'

MEOWSINGS 2.1

I felt my diePad vibrate in my pocket. I unrolled it and noticed a message from someone called Milton. I made my apologies to the doctor and read the message. 🐾 It was freaks: it addressed me as dear human, it talked about cats, but the biggest weirds was that it told me about reverse scoring: exactly what the doctor had just been explaining. I felt uneasy. Who was Milton, and how did he know my number, where I was, and what I was talking about? I scanned the room quickly; definitely only Genari and I were in here. Out of the corner of my eye I noticed a ginger cat jump down from the window ledge outside.



CHECK YOUR BRAIN: Figure 2.2 shows Alice's responses to the seven questions on the Relationship Assessment Scale.

- Reverse-score the two items that are reverse-phrased.
- If i represents items on the questionnaire, what does $\sum_{i=1}^n x_i$ mean?
- Do the calculation in (b) using Figure 2.2. What does the resulting score represent?
- What is the maximum that anyone could score on the Relationship Assessment Scale?
- Is Alice satisfied with her relationship with Zach?

2.3.3 Levels of measurement

I passed the message off to Dr Genari as something about my band, and we added up Alice's scores on the Relationship Assessment Scale. It was 32 out of a maximum of 35, which made it look as though she was positive about our relationship. I was curious about what I could do with this total.

'To answer that question,' the doctor replied, 'you need to first answer the question of what type of variable you have and where it lies on the scale of measurement.'



Dear Human,

If you wanted to measure how cat-like people were, you could ask them 'How much do you like fish for dinner?', 'How much do you like to sleep?' and 'How often do you wash by licking yourself?' and get them to respond from 0 (not at all) to 10 (a lot). In each case if you are cat-like you give a higher rating than if you are not. In other words, each question is phrased so that a larger number represents more of the construct that you want to measure. However, one problem with having all of the questions phrased that way is that cat-like people might notice that all they have to do is write a '10' for every question, and because they are cat-like and, therefore, have better things to do like sleeping, and they hope that their reward for doing the survey might be a nice fish, they write '10' for every question without thinking. Likewise, the non-cat-like people might respond '0' to everything, regardless of the question. This is a form of **response bias**. To try to make people read and think about the questions on surveys it is common to use **reverse phrasing** on some questions. Normally questions are phrased so that a larger response represents more of the construct being measured; a reverse-phrased question is one where a larger response represents *less* of the construct being measured. For example, a reverse-phrased version of the question 'How much do you like fish for dinner?', would be 'How much do you *dislike* fish for dinner?'. If you were a fish lover you would give a high response to the first question, but you would give a low response to the second.

When reverse phrasing has been used for items on a questionnaire, then these items need to be **reverse-scored**, which is done by subtracting the score given from the sum of the maximum and minimum possible responses. Let us imagine we had a questionnaire to measure how cat-like someone was as described above, but with five items. Table 2.2 shows the questions. Two of them are reverse-phrased. The third column shows a person's responses on the questionnaire. For the normal questions they have given fairly large responses (9, 7, and 6 out of 10) indicating that they are quite cat-like. For the reverse-phrased items they have given lower responses (1 and 2) but, because the items are reverse-phrased, these low responses also indicate that they are quite cat-like. To make these scores comparable to the normal questions we must reverse-score them. This is done by subtracting the score on a reverse-phrased item from the maximum plus the minimum score for that item. Imagine an item where 5 responses are possible (1, 2, 3, 4, 5). The maximum plus minimum score is $5 + 1 = 6$. Reversing the scores is achieved by subtracting each score from 6, so 1 becomes 5 ($6 - 1 = 5$), 2 becomes 4 ($6 - 2 = 4$), 3 stays as 3 ($6 - 3 = 3$), 4 becomes 2 ($6 - 4 = 2$), and 5 becomes 1 ($6 - 5 = 1$). For our cat questionnaire, the largest possible response is 10, and the lowest 0, so if we add these together we get $10 + 0 = 10$. To reverse-score the items we therefore subtract them from 10: the 1 response for 'how much do you dislike fish for dinner?' becomes $10 - 1 = 9$, and the 2 response for 'how much do you dislike sleeping?' becomes $10 - 2 = 8$. As such, the low scores given by the responder on the reverse-phrased questions are converted to the corresponding high score that they would have given had the question been phrased normally.

Best fishes,
Milton

Milton's Meowings 2.1 Reverse scoring

Table 2.2 Scoring the CAT questionnaire

Question	Reverse phrasing?	Response given (out of 10)	Reverse score (10 – score)	Response used
How often do you wash by licking yourself?	N	9		9
How often do you scratch wood, carpets, furniture, your owner’s treasured anatomical features?	N	7		7
How much do you <i>dislike</i> fish for dinner?	Y	1	9	9
How often do you sit on a fence eyeing anything that passes by with cold, suspicious indifference?	N	6		6
How much do you <i>dislike</i> sleeping?	Y	2	8	9

FIGURE 2.2

‘The scale of what?’

‘Measurement. Let me explain. Look at Alice’s notes. What variables can you identify?’



CHECK YOUR BRAIN: List all of the variables (things that can vary) in Figure 2.2.

‘Err, variables are just things that can vary, or have different values, so her height, weight, age?’

‘Very good, but there are others. The variables you mention are ones that can be directly observed: you can see her height and with a ruler measure it directly. Her occupation is also a variable, and that too can be measured directly. However, some variables you cannot measure directly, for example her depression, her anxiety, her life satisfaction, and her relationship satisfaction. In each case we can observe behaviours or responses that indicate the variable. For example, although we cannot directly measure her relationship satisfaction, if she is satisfied this will be indicated by her cognition (she will say she is satisfied), her behaviour (she will be affectionate towards you), and her physiology²² (her pupils will dilate when she sees you). Something that cannot be directly measured is known as a **construct**. To measure these constructs you need an **operational definition** of the construct, which is a procedure (or set of procedures) for quantifying it; for example, the operational definition of “relationship satisfaction” might be “responses given to questions on the Relationship Assessment Scale”.’

I was really starting to worry that this was just wasting time that I could be using to track Alice down. The doctor continued, though. ‘Once you have measured a variable then what you can do with it depends on where it lies on the scale of measurement. The relationship between what is being measured and the numbers that represent what is being measured is known as the **level of measurement** (also known as the **scale of measurement**). The simplest scale of measurement is the **nominal scale**. A nominal scale is where the same names are attached to things that are the same, and different names distinguish things that are not the same. For example, I might label you “burglar”

to distinguish you from me, who I might label as “civilized member of society”. The doctor chuckled at his own joke. ‘Similarly, we can label people according to their jobs: “musician”, “scientist”, “counsellor” and so on. Variables on the nominal scale are **categorical variables**, which are variables made up of categories. You will be aware already of the categorical variable of which of the natural kingdoms something belongs to: animals, fungi, plants, chromista, protozoa, or bacteria. We are both animals, and you can’t be a bit of an ‘animal’ and a bit of a ‘fungus’, because otherwise you’d be an an-us and no one wants to be that.’ Obviously a man who enjoyed his own jokes, he burst into a loud, wheezing laugh. ‘Really, let me tell you, *no one* wants that,’ he repeated slowly and laughed even harder. ‘You know,’ he eventually continued, ‘some categorical variables contain only two categories, for example, being alive or dead, and responding “yes” or “no” to a question. A categorical variable consisting of only two categories is known as a **binary variable** or **dichotomous variable**.’

‘If you’re just naming things then what can you do with them?’

‘You can count them. Imagine we took each thing that Alice said about your relationship in my notes and we categorized it as either “positive about Zach” or “negative about Zach”. We could count how many times she is positive about you and compare it to how many times she is negative.’

‘So you would be taking qualitative data – the things she said – and turning them into something quantitative?’

‘Yes! Now you are getting things ... now you are getting things! Sometimes, numbers are used to denote categories. This is known as **coding**. For example, you told me that you are a musician, and I am a counsellor and Alice is a scientist. We could take the categories “musician”, “scientist”, and “counsellor” and assign them numbers 1, 2 and 3. Those numbers don’t mean anything more than the names of the categories, but it can be helpful to use numbers to denote different categories. You can see this in real life: look at the numbers worn on the shirts of players in the Elpis soccer team; historically these numbers denote specific field positions, so the number 1 is worn by the goalkeeper and the number 9 by the centre forward. These numbers tell us nothing other than what position the player plays. We could equally have shirts with GK and CF instead of 1 and 9. A centre forward (number 9) is not necessarily better than a goalkeeper (number 1) just because she has a higher number – you wouldn’t want to see your centre forward in goal! If the variable is made up of names you cannot do arithmetic on them.’

‘Why not?’

‘Isn’t it obvious? Imagine you were managing a soccer team, your centre forward – the number 9 – is injured, do you send 9 goalkeepers (number 1s) onto the field of play in their place?’ He laughed and I shook my head. ‘No, and if you had categories of “drummer” and “guitarist” can you multiply them and get dru-gs?’

‘Knowing most guitarists and drummers, probably ...’

‘No, of course you can’t’, Genari interrupted, ‘it is sillier than me trying to apprehend you with a sausage. The only way that nominal data can be used is to consider frequencies. We could, for example, count how often a number 9 scores a goal in a soccer game compared to a number 1.’

Dr Genari paused and took a white tissue from his trouser pocket. He wiped his glasses and looked at me, squinting his eyes. ‘You have kind eyes. Caring eyes. Not burglar eyes.’ He said. What an odd thing for him to say, I thought, but perhaps it was his way of explaining why he was helping me. In any case, it made me feel as though I should listen more if I wanted to know what was going on with Alice.

He placed his glasses back on and started asking me about my band. I explained that we were called The Reality Enigma. ‘Oh goodness, what a grand name,’ exclaimed the doctor, ‘imagine your band entered one of those battle of the bands competitions, and the three winners were The Reality Enigma, Scansion and The Black Hats.’ I was impressed that he knew of Scansion and The Black Hats. ‘The names of the winners (a nominal variable) don’t give us any information about where each band came in the contest; but if you label them according to their performance – first, second and third – then you do have this information. These categories are *ordered*. In using ordered categories we now know that the band that won was better than the bands that came second and third, but we still know nothing about the differences between categories. We do not, for example, know how much better the winner was than the runners-up: The Reality Enigma might have been easy victors, getting many more votes than Scansion and The Black Hats, or it might have been a very close contest that they won by only a single vote. When you have categories that have order, like this, you have an **ordinal scale** of measurement.’

FIGURE 2.2

‘Is that what these ratings are that Alice gave about our relationship 🐶, because, you know, a 5 is a better rating than a 1 – the order matters?’

‘Very good; ordinal data tell us more than nominal data (they tell us the order in which things happened) but they still do not tell us about the differences between points on a scale. To do this we need an **interval scale** or a **ratio scale**. Both of these scales of measurement have ordered categories, but also require that intervals between categories are equal. Let’s think about Alice’s ratings again. The Relationship Assessment Scale has a response scale with five ordered outcomes. To the question “how much do you love your partner?” Alice can answer 1, 2, 3, 4 or 5. For these values to form an interval scale it must be the case that the difference between ratings of 1 and 2 is the same as the difference between say 3 and 4, or 4 and 5. Similarly, the difference in ratings of 1 and 3 should be identical to the difference between ratings of 3 and 5. A ratio scale must also have a meaningful zero point.’

This idea confused me, and pre-empting my difficulty the doctor elaborated, ‘All that means is that the zero point indicates a complete absence of the thing you are measuring. In Alice’s case notes, her height and weight are both measured on ratio scales. They are ratio scales because not only are intervals consistent along the whole measure of weight and height (e.g., the difference between 100 cm and 150 cm is the same as the difference between 0 cm and 50 cm) but they have meaningful zero points: we can talk about weighing 0 kg, which means the complete absence of weight, or being 0 cm tall, which would mean the complete absence of height. Having a meaningful zero means that ratios (as well as intervals) are maintained along the measurement scale; for example, 20 kg is twice as heavy as 10 kg, and 5 kg is half the weight of 10 kg.’

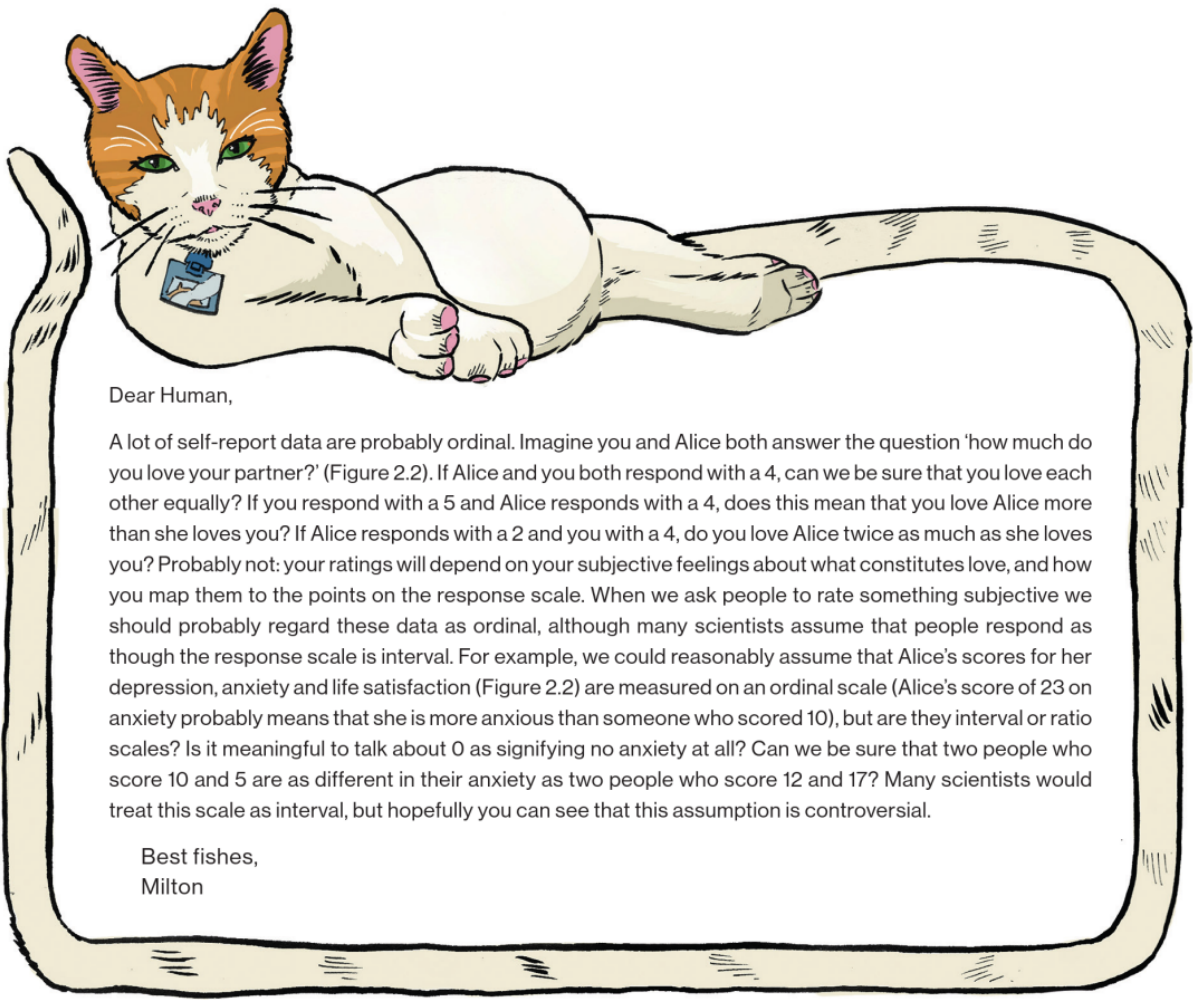
Just as I was wondering how you could ever be sure that a rating scale, like the one Alice completed, produced interval or ratio data, my diePad vibrated. It was another message from the mysterious Milton that was every bit as odd as the last one. 🐶

‘Do you know someone called Milton?’ I asked.

The doctor eyed me suspiciously. ‘Not personally, but there are some very famous Miltons.’

I couldn’t think of any. Genari asked why I was interested in people called Milton, so I showed him the message. He guessed that my earlier message had also been from this Milton and that I had lied. He really could read me very well.

MEOWINGS 2.2



Dear Human,

A lot of self-report data are probably ordinal. Imagine you and Alice both answer the question 'how much do you love your partner?' (Figure 2.2). If Alice and you both respond with a 4, can we be sure that you love each other equally? If you respond with a 5 and Alice responds with a 4, does this mean that you love Alice more than she loves you? If Alice responds with a 2 and you with a 4, do you love Alice twice as much as she loves you? Probably not: your ratings will depend on your subjective feelings about what constitutes love, and how you map them to the points on the response scale. When we ask people to rate something subjective we should probably regard these data as ordinal, although many scientists assume that people respond as though the response scale is interval. For example, we could reasonably assume that Alice's scores for her depression, anxiety and life satisfaction (Figure 2.2) are measured on an ordinal scale (Alice's score of 23 on anxiety probably means that she is more anxious than someone who scored 10), but are they interval or ratio scales? Is it meaningful to talk about 0 as signifying no anxiety at all? Can we be sure that two people who score 10 and 5 are as different in their anxiety as two people who score 12 and 17? Many scientists would treat this scale as interval, but hopefully you can see that this assumption is controversial.

Best fishes,
Milton

Milton's Meowings 2.2 Self-report data

'All of the Miltons I can think of are either too famous or too dead to be messaging you,' he chuckled to himself again. 'I want to help you, but we need to move on.'

I was starting to get bored. Genari was a nice man, with an endearing, excitable manner, but I had come here to find answers about Alice and this wasn't giving them to me. It did at least take my mind off thinking about what might have happened. At least while we were talking we hadn't found evidence for a hypothesis that I wouldn't like.


The doctor interrupted my thoughts. 'The variables you measure map onto the scales of measurement that I just described. Some variables are **discrete variables**, which means that they consist of indivisible categories. This means that values fall into distinct categories – for example, whether your main job is scientist or counsellor. However, the rating scales on the Relationship Assessment Scale  are also discrete because you can enter only values of 1, 2, 3, 4 or 5; you cannot enter a value of 3.45 or 1.89. Other variables can be measured at an infinite level of precision – they are not limited to separate categorical responses – these are known as **continuous variables**. A continuous variable would be something like age, which can be measured at an infinite level of precision (you could be 25 years, 6 months, 11 days, 7 hours, 6 minutes, 11 seconds,

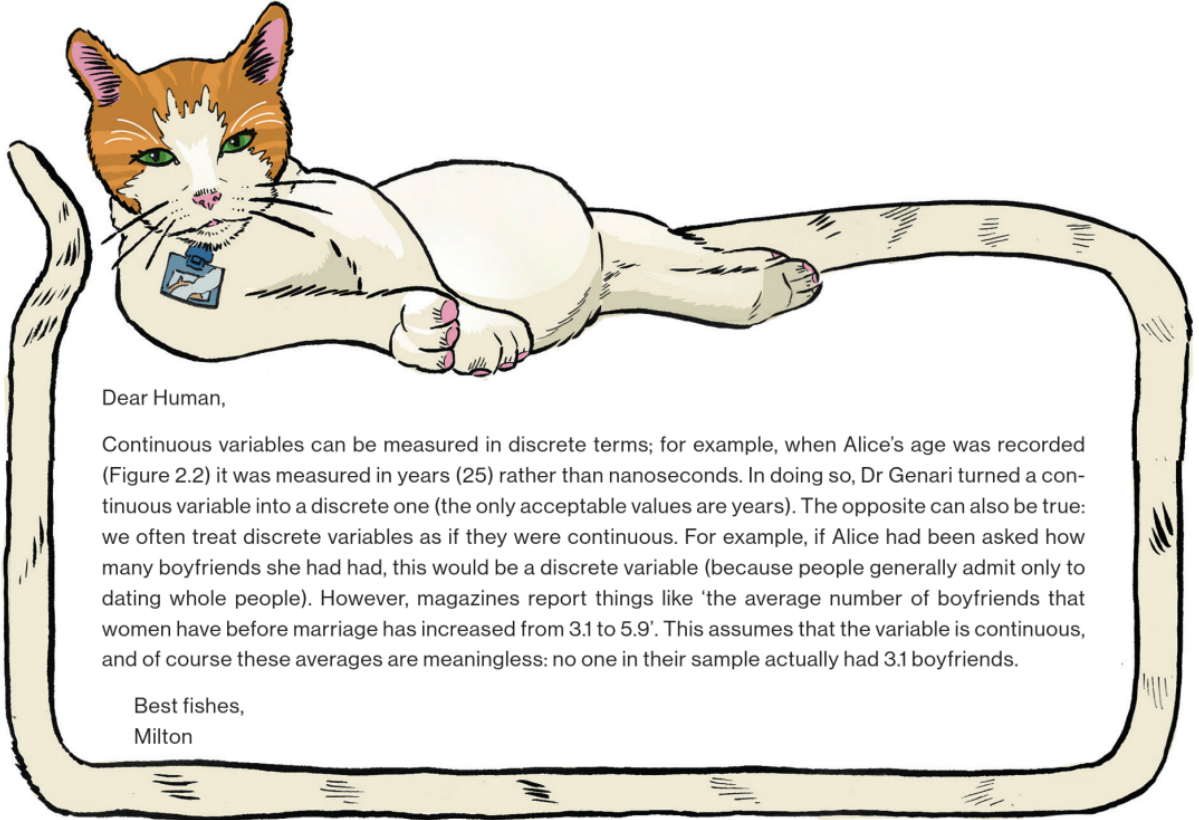
FIGURE 2.2

122 milliseconds, 3 microseconds, 12 nanoseconds old). The line between discrete and continuous variables can be blurred, though.'

Another message from Milton appeared on my diePad. Genari looked a little annoyed at it

MEOWSINGS 2.3

→ breaking his flow. ↩



Milton's Meowsings 2.3 Making continuous variables discrete

2.3.4 Measurement error

I finished reading Milton's message. The doctor's manner was definitely getting more frosty; I guess it was totally rude to read messages when he was trying to talk to me. That was the problem with these things; no one gave each other proper attention any more. I felt bad. I wanted to prove

FIGURE 2.2

→ I had listened, so I directed him to look at Alice's notes. ↩ We had discovered that she rated our relationship, overall, at 32 out of 35, and her life satisfaction was 78. This seemed to suggest she was pretty happy with life. I decided to confirm this conclusion with the doctor.

'True, she scored 78 on life satisfaction, but perhaps that is 78 out of 10,000 – have you considered that?' He had definitely become tetchy.

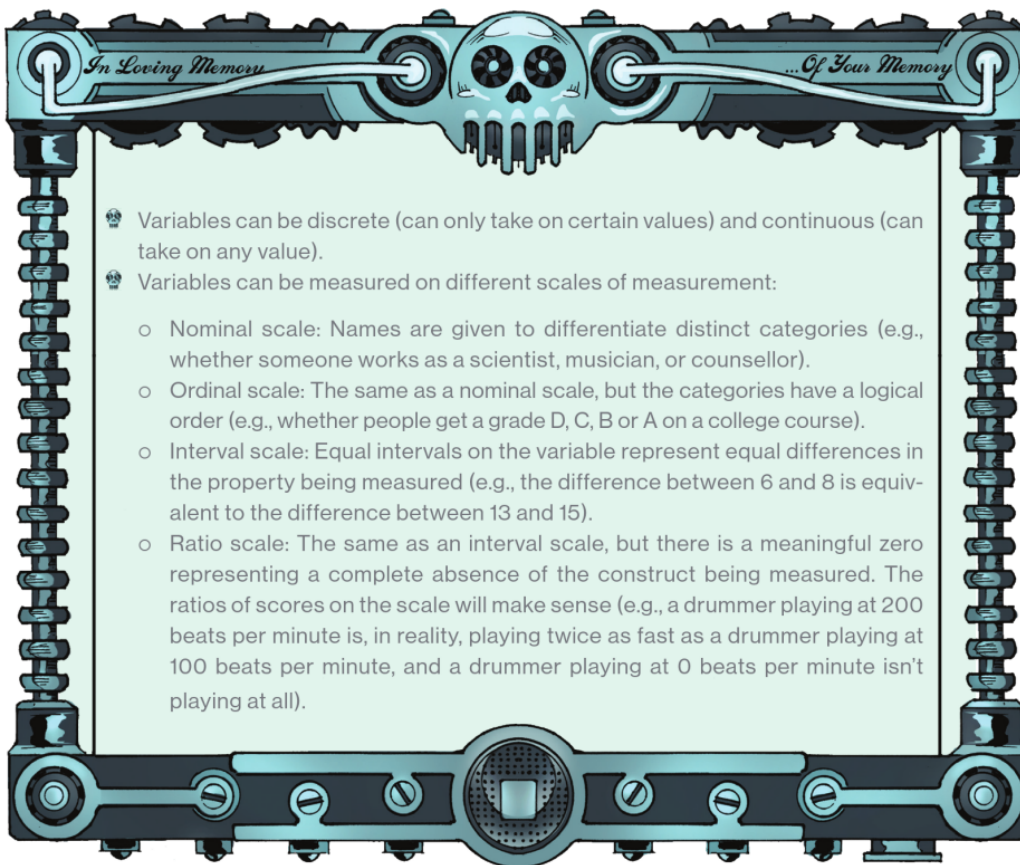
'Err, no. Was it out of 10,000?'

'No, of course not, it was out of 100.'

'So, Alice was pretty satisfied, then.'

'Perhaps,' he begrudgingly agreed. 'But you should consider **measurement error**.'

Oh man! My heart sank. I could feel another lesson coming on. I braced myself and asked him to explain.



Zach's Facts 2.3 Variables and measurement

‘It’s one thing to measure variables, but quite another thing to measure them accurately. Ideally we want our measure to be calibrated such that values have the same meaning over time and across situations. Height is one example: we would expect to be the same height regardless of who measures us, or where we take the measurement. It should also be roughly the same over a short time (we don’t expect to grow dramatically in a week unless we are a foetus).’ The doctor chuckled again. I hoped this was a sign of his mood lightening. ‘There will often be a discrepancy between the numbers we use to represent the thing we’re measuring and the actual value of the thing we’re measuring (i.e., the value we would get if we could measure it directly). This discrepancy is known as measurement error. Imagine we could somehow invent a device that could with complete accuracy and precision measure Alice’s life satisfaction. We stick her in this device and it gives a reading of 64%. We then give her a questionnaire and find that her life satisfaction is 78%. There is a difference of 14 between her actual life satisfaction and the satisfaction given by your measurement tool (the questionnaire): this is a measurement error of 14. Self-report measures are likely to have



KEY TERMS

Binary variable	Discrete variable	Qualitative research
Categorical variable	Face validity	Quantitative research
Coding	Grounded theory	Ratio scale
Concurrent validity	Interval scale	Reliability
Construct	Levels of measurement	Response bias
Content validity	Measurement error	Reverse phrasing
Continuous variable	Nominal scale	Reverse scoring
Criterion validity	Operational definition	Scales of measurement
Dichotomous variable	Ordinal scale	Test-retest reliability
Discourse analysis	Predictive validity	Validity

JIG:SAW'S PUZZLES

- 1 Describe the main sections of a research report.
- 2 What is the main difference between qualitative and quantitative research?
- 3 Look at the variables in Figure 2.2 and complete Table 2.3.

Table 2.3 Table to classify variables from Figure 2.2

Variable	Qualitative or quantitative	Level of measurement	Continuous or discrete?
Responses to questions on the Relationship Assessment Scale			
The sum of responses to questions on the Relationship Assessment Scale			
Name			
Sex			
Occupation			
Significant other			
Age			
Height			
Weight			
College grades			
Depression			
Anxiety			
Life satisfaction			

- 4 After his conversation with Alice, Zach was wondering how he could sell more of his band's T-shirts. He found an article claiming that sales could be estimated from the price of the T-shirt and how sick the fans thought the design was (from 0 = totally lame to 10 = totally on trend):

$$\text{Sales}_i = 20 + \frac{\text{Design}_i^2}{\sqrt{\text{Price}_i + 10}}$$

Use the equation and the values in the Table 2.4 to calculate the sales that would be generated from each combination of price and design. Complete the final column of the table.

Table 2.4 Possible selling price and design ratings of T-shirts

Price	Design	Sales
10	0	
10	5	
10	10	
15	0	
15	5	
15	10	
20	0	
20	5	
20	10	
25	0	
25	5	
25	10	

5 Calculate:

$$\sum_{n=1}^4 n^2$$

7 Calculate:

$$20 + \frac{5(8-2)^2}{2} - 7$$

6 Calculate:

$$15 \left(\frac{2(7+2)^2}{(4 \times 3)} \right) - 5$$

8 Zach measured 10 people's mood score out of 10 (0 = worst ever mood, 10 = best ever mood) after one of his band's gigs (Table 2.5).

Table 2.5 Mood scores after a Reality Enigma gig

Person	Mood Score
1	2
2	6
3	7
4	10
5	4
6	2
7	3
8	5
9	5
10	7

Use the values in the table to calculate:

$$\sum_{i=2}^n x_i^3$$

$$\sum_{i=4}^9 x_i^2$$

9 Table 2.6 shows the average minutes per day that 10 Chippers spend on *memoryBank* looking at other people's lives. Using the scores in the table and remembering to use BODMAS, calculate:

$$\sqrt{\sum_{i=4}^n x_i}$$

Table 2.6 Minutes per day spent on *memoryBank*

Person	Average Time spent on <i>memoryBank</i> (minutes per day)
1	35
2	60
3	20
4	120
5	5
6	15
7	25
8	45
9	60
10	50

- 10 Nick asked fans on *memoryBank* to rate how likely they thought it was that Alice had been abducted and, also, how likely they thought it was that Alice had dumped Zach. Ratings were from 0 = not at all likely, to 10 = certain (Table 2.7). Using the scores in the

table and remembering to use BODMAS, calculate:

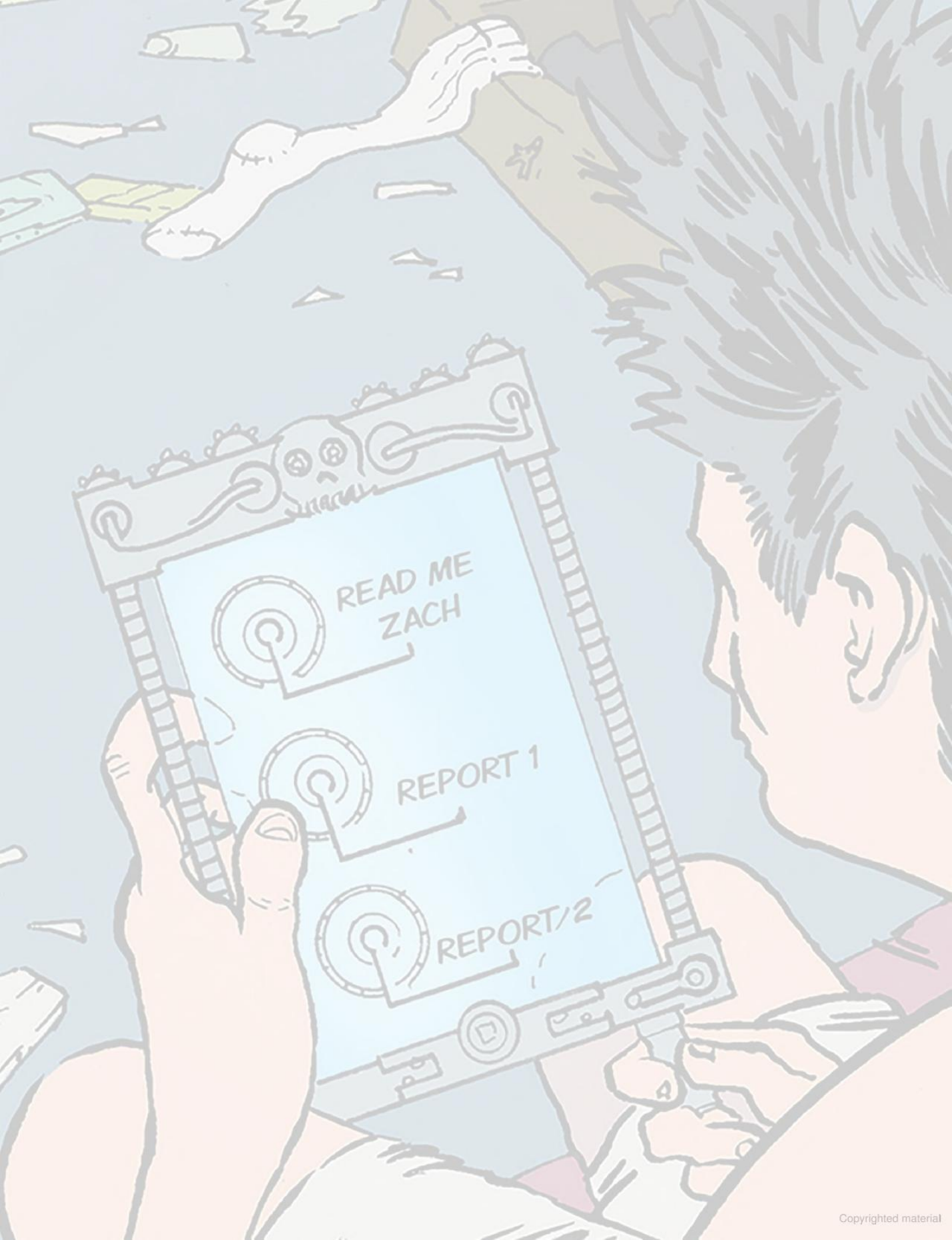
$$\sqrt{\sum_{i=5}^8 \frac{\text{Dumped}_i^2}{\text{Abducted}_i}}$$

Table 2.7 Likelihood (out of 10) of Alice having been abducted vs. her having dumped Zach, as rated by 10 fans

Fan	Abducted	Dumped
1	3	3
2	2	6
3	3	7
4	4	7
5	2	6
6	3	5
7	2	5
8	3	9
9	3	6
10	4	5

IN THE NEXT CHAPTER, ZACH DISCOVERS ...

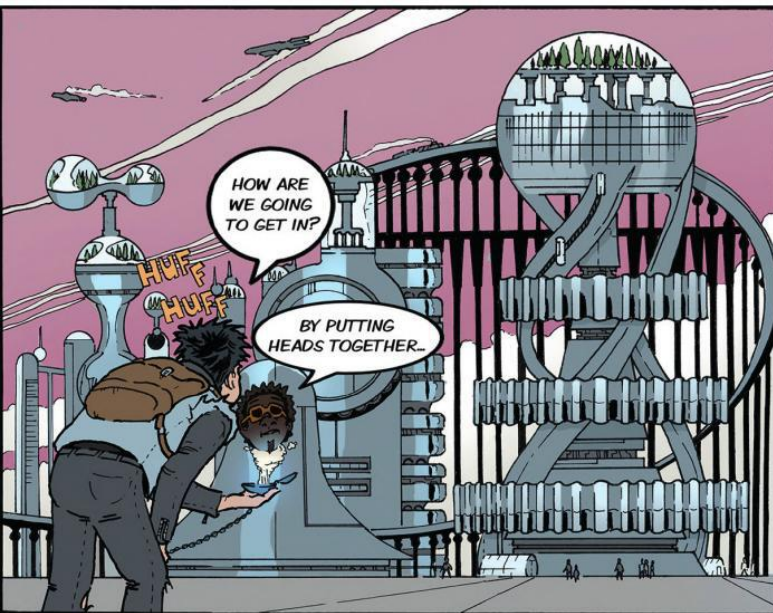
- A cat
- Probability distributions
- Frequency distributions
- Skew and kurtosis
- What women (and men) want



READ ME
ZACH

REPORT 1

REPORT/2



I wondered why the head in the reception of the Beimeni Centre of Genetics called The Head 'Leni'. I also wondered how they knew each other; was there some secret world of heads that I didn't know about? Now was not the time to worry about this; all that mattered was that he'd got us past the security and into the building. I entered one of the elevators and hit the button to take me to level 2. I'd seen the building many times before: Alice worked here and, until recently, I'd often travel with her to work before going off to our rehearsal space, which was in the same district. Security meant that I'd never been inside the building, but I'd often wondered what the space where Alice spent her days without me looked like. The cylindrical transparent blue glass capsule began to rise and follow the curved structure of the building. As we moved up the outside of the building, I looked at Elpis spreading out below me: a beautiful synergy of Clocktorian technology and modern architecture. It was exactly what I needed to see: Elpis, my home, the city of hope.

As I looked over the city I lost myself in thoughts about the previous day and how we'd ended up here. I'd left Genari's office, my mind and legs racing. I felt that Genari might know more than he let on, but I also felt that I might have played it wrong with him. He seemed concerned, and interested, that something might have happened to Alice but I didn't want to believe that she was in danger, focusing instead on how she viewed our relationship. My rudeness in checking my diePad messages also seemed to upset him. Then there were the messages themselves: why was someone called Milton contacting me, and how did he know what I was talking about at the exact moment before the message was sent? Also, why, if you were going to go to all the trouble of messaging a stranger, and employing whatever device you were using to listen to their conversations, would you send messages about variables and measurement? If he was trying to help me, weren't there more direct ways to do that? These were my thoughts as I ran from Genari's office. I didn't know where I was going, but I felt it was safer for me to get away from somewhere that I'd broken into.

Genari's office was in the district of Janus, where I lived. Elpis was made up of six districts: Postverta sat in the middle and was surrounded to the north by Antevorta, the modernist district. To the east was Porus, where the wealthy lived. Veritas was south, where the universities and hospitals were; and Egestes, the poor district, was in the west. Janus sat between Postverta and Antevorta; it was the bohemian part of town.

I reached the square in front of The Repository in a part of the city called Hallowed Point, in the Postverta district. Many visitors took Postverta to be the oldest part of Elpis because the buildings had been modelled on the Gothic architecture in what was, before the revolution, Europe. In fact it was as new as Elpis itself, but the attention to detail meant that you wouldn't know it. I suppose some people would feel that it was smoke and mirrors, a visual lie, but I liked this part of town best. Buildings define any place, and Postverta was quiet and reverential like the ornate façades that surrounded me. It was the perfect place to gather your thoughts. As I sat on The Repository steps to rest, I noticed a ginger cat scavenging under one of the café tables opposite.

I opened my pocket watch and felt comforted as The Head emerged.

He breathed deeply even though he didn't need air. 'Ah, the fresh Elpis air,' he said. 'Normally I don't get to experience it so much. I am trapped alone in solitude and darkness, while you and the other humans enjoy the Elpis day. Maybe you take a walk, or meet your friends for coffee, or perhaps play your guitar. All the while, The Head is trapped in a dungeon of darkness, in solitary confinement, like a dog awaiting any small bit of body language that hints that its owner will take it for a walk. Basically, Z, I'm your dog.'

The Head really knew how to milk it.

'It's not like that,' I said, hoping to avoid his banter.

'No? Maybe you think I *love* being stuck inside that watch? That I like feeling the endless monotony of the cogs gyrating, ticking down the seconds to my death, that I find it so much more invigorating than looking out into the world and seeing the beauty of the Elpis sky, or the carefree smiles of the Elpis children. You go right ahead and trap me in your clockwork watch; don't mind The Head, he's doing fine.'

I often enjoyed The Head's banter, but I'd had a wipe of a day already. 'Give it a rest. This is good bonding time for us.'

'The Head ain't superglue, he don't like to bond.'

Usually, the idea of my clockwork watch trying to wind *me* up amused me, but today The Head's tone upset me. I wondered if he was actually serious. I always assumed that when I closed the watch he just switched off, like a computer. I guess I thought he was effectively dead except when I activated him. What if I was wrong, though, maybe he *was* trapped like some kind of electronic genie. Or maybe it was just banter; you could never tell with The Head. I needed him on side, though, so I made a deal: if he helped me out I promised to be more considerate of his needs. It did the trick: his tone lightened. I told him about my meeting with Genari, the messages from Milton and how I was worried that Alice was in some kind of danger.

'You don't *know* Alice is in danger,' he said. 'Maybe you're worrying about nothing.' The Head's empathy was unprecedented and I was touched. 'Maybe she's just dumped you!' The old Head was back before he'd had time to leave.

'Thanks,' I said sarcastically. 'You might be right, though. I don't know which is true: is she in danger or has she just dumped me? Also, there's got to be a reason why this Milton guy is messaging me. Maybe he can help, but who is he?'

The Head span as he gathered information. When he settled he said, 'I'll lay it flat for you. There are *a lot* of Miltons on the planet: 295,765, to be exact.'

My heart sank. I tried to show The Head one of his messages on my diePad, hoping he could trace it or find an address linked to it, but the messages were gone. The Head looked at me with pity as if I were imagining things. Maybe I was. The messages had all been instructing me about science, about variables and measurement. This Milton character knew about these things, so maybe he was a scientist?

The Head acknowledged my logic and span more. 'I crosschecked the Miltons for any with a prefix of Doctor or Professor, because if the guy knows about science, he's probably got a title. There are 4327 Miltons with Doctor or Professor before their name; the nearest one is Professor Milton Tipton. He lives in the city of Solitude, 3000 km from here.'

'There are no scientists called Milton from Elpis?'

The Head looked at me as though I was missing something really obvious. 'Of course there is.' He raised his eyebrows to show me that he was waiting for the penny to drop in my head. He was going to be waiting a long time.

'Professor Milton Grey?' The Head prompted, 'Inventor of the reality prism? Indirectly responsible for the Reality Revolution and the downfall of pre-Clocktorian society?'

Maybe I'd known about him at school, but these clues weren't helping me. The Head gave up. 'You know, most people have heard of him. The guy is pretty famous, and he was born here – well, in the place that became Elpis after he destroyed civilization.'

At last, a lead. 'Does he still live here?' I asked.

'Not so much, Z, he's dead.'

The Head was really annoying me. I was desperate to find Alice and he was frippin' about playing stupid games. 'What is wrong with you?' I asked, 'Why tell me about someone who is dead? A dead person is obviously not the guy sending me messages ... how about for once you do what a reality checker is supposed to do and check reality?'

'Wait up,' The Head interrupted, looking offended by my outburst, 'let The Head finish. After the revolution, Milton Grey worked for the WGA's scientific division, and then the Beimeni Centre of Genetics, but vanished in mysterious circumstances 5 years ago. People have got their theories: he was killed in a genetic experiment, the responsibility for the downfall of society led to his suicide, the WGA whacked him so that he couldn't blow the whistle on their research when he left. It's all speculation.'

'So what? The guy is dead.'

'You missed three important things: *Vanished* is not the same as *dead*, *speculation* is not *proof*, and he worked at the Beimeni Centre of Genetics, the same place that Alice works.'

I still didn't get it, so he spelled it out.

'The only scientist called Milton in Elpis used to work in the same place as Alice, and although he's assumed to be dead it has never been proved, so maybe the dude *is* worm food, but maybe it's worth going to the Beimeni Centre and having a poke about.'

It was too late to go there: it would take ages to get to Veritas, where the University was located, and by the time we arrived everyone would be finishing work. It was frustrating to wait until the morning, but I used the evening to checked in with Nick to see how the #NightingaleFlyHome campaign was going. He said it was buzzing, but nothing had come back to him, just a lot of discussion amongst the female fans about how I was single now. Some of the

guys were pretty excited about that too, he said. He passed on some messages of support. We had a gig soon and needed to rehearse, but Nick told me to do what I needed to do; they could rehearse without me, and he'd square it with Jessica and Joel.

The elevator reached the second floor with a light jolt that brought me back to the here and now. A small hole formed in the transparent wall of the pod. The hole dispersed out like a drop of oil on water, making an increasing gap in the glass. Eventually it left a hole large enough that I could step out – this was programmable matter at its most elegant. I was standing in a large circular room with a corridor that divided the space into two. The walls of the rooms on each side were made of clear blue glass, giving the impression of an enormous open plan space; the light shimmered through the glass, creating a calming blue glow. I headed towards a large laboratory at the end of the corridor. As I got closer I could make out a complex jungle of spinning cogs, belts, computer monitors, fluid-filled pipes, and pistons pushing and pulling at bronze spheres, the shapes of which ebbed and flowed with the metronomic flow of the piston arms. It was like nothing I had ever seen, but mesmerizing and beautiful. The laboratory had no door, just a solid blue transparent wall. I watched as people in white coats walked to the wall and stepped through as it opened up in front of them.

'Slick', said The Head. 'Matter that is programmed to respond only to the thoughts of people that work here.'

'How do we get in?' I asked.

'How indeed,' said a quiet, almost apologetic voice, 'and more to the point, why do you want to?'

I turned around to face a petite, distinguished-looking lady. Her greying hair bobbed around her face as she tried desperately to avoid eye contact. She wore a lab coat that was far too big; the arms overhung her hands, and it was so long that it rippled out around the floor like a really underwhelming wedding dress. Around her neck was a lanyard containing a vortexID that read 'Professor Catherine Pincus'.



'I'm looking for Dr Alice Nightingale. She works here.'

Pincus shuddered slightly, her tone becoming brash. 'Why do you want her? What are you? A reporter? I have not seen Dr Nightingale this morning, and I will not comment further.' She turned and attempted to walk briskly away, but her legs tangled in her lab coat and she started to fall. Instinctively I grabbed her arm to catch her.

'Get your hands off me!' she spat.

'Sorry, I didn't want you to fall. I'm Alice's boyfriend, Zach. She's gone and I'm worried about her.'

'You'd better follow me.'

3.1 FREQUENCY DISTRIBUTIONS

3.1.1 Tabulated Frequency distributions

The Professor took us into her office. She explained that Alice worked alongside her but that she hadn't turned up to an important meeting that morning. She was being cagey; I thought that she was probably lying. I told her about my meeting with Dr Genari, about the information in Alice's file, and about how I thought at first that she had left me, but that lots of things didn't add up and that, having seen Genari, I was convinced she might be in danger. Given that I had turned up unannounced and how busy she must be, I was surprised that the Professor was attentive and sympathetic; at least until I mentioned JIG:SAW and the messages from Milton. Her face turned to stone and she looked very flustered.

I broke the awkward silence by elaborating. 'I noticed that word, JIG:SAW, throughout Alice's file. I've never heard of it. I asked my reality checker last night and he said it's an organization run by the WGA. No other information is listed – is Alice in trouble with the WGA?'

The Professor looked as though she was thinking hard. She composed herself and reassured me that I was letting my imagination get the better of me. She smiled awkwardly at me, although I think she was trying to reassure me. 'I'm no psychologist,' she said, 'but I know from working with the young scientists in my laboratory that relationships dissolve all of the time. I think it much more likely that Alice has perhaps reached a point in life where she is unsure about your relationship. Perhaps she needs some space to think things through. I think that is much more likely than some wild theory about her being in danger, don't you?'

I felt a bit embarrassed that I'd got so carried away, but I also wanted to be sure. 'I'm sorry for wasting your time, I guess you have a lot to do, you're probably right, but I'll go and see what I can find out about JIG:SAW anyway, you know, just to be on the safe side.'

I saw a twinge of panic in the Professor's eye. 'Perhaps you don't need to,' she said. 'You said you had information from Alice's file, perhaps I can help you look at that, maybe we can find some evidence that she was unhappy in your relationship – do you think she might have been?'

It was nice of the Professor to help me, suspiciously nice. Why would she want to? What the frip, though, I needed all the help I could get to untangle what was in the file, so I played along, pointing out as many reasons as I could think of for why Alice might want to leave me: I was a musician who didn't have a proper job, I dropped out of uni, I don't earn much money, I'm not that smart, I don't know about science – the list was depressing.

Table 3.2 Frequency distribution of females' ratings of high salary as a characteristic in a romantic partner

Rating (X)	Frequency (f)
10	2
9	1
8	3
7	2
6	2
5	2
4	4
3	2
2	1
1	1
$N = \sum f = 20$	



CHECK YOUR BRAIN: Create frequency distributions for the ratings of kind, humour, and ambitious from Table 3.1.

I could see that the frequency distribution did make the data easier to understand. Thinking back to what Dr Genari had told me, the ratings we were looking at were measured on an ordinal or perhaps an interval scale. I asked whether frequency distributions could be used for nominal variables.

Professor Pincus looked impressed. 'You know about scales of measurement?' she asked. 'Well, yes, you can construct a frequency distribution for a nominal variable in the same way: you have a column that lists the categories in any order (with each category in a different row) and then in the second column list the frequency with which each entity fell into each category. For example, these ratings come from 20 females; if we wanted a frequency distribution of the nominal variable *sex*, we could list the categories "male" and "female" in the first column, and their frequencies in the second column. Notice that because there were no males, the frequency is zero, but we still include the category because it is part of the scale of measurement of the variable *sex*.'

TABLE 3.3 →

Much as I thought I should play along with the Professor and find out more about whether Alice might have left me, I struggled to see how this was helping. 'The tables look nice,' I said, 'but they don't tell me what women want. How does this help me to understand whether women are attracted to guys with high salaries?'

'Bear with me. We can make the data clearer still by looking at the **relative frequency**, rather than the frequency itself. The relative frequency is how often a response is observed relative to the

Table 3.3 Frequency distribution of sex

Sex (X)	Frequency (f)
Female	20
Male	0

total number of responses. In the case of the salary data, we are asking “what **proportion** of women gave a rating of 10?”, that is, how many women gave a rating of 10 relative to the total number of women who responded? We could write this as follows.’ Professor Pincus traced an equation 🧠 on a fresh piece of blue wall.

3.1

$$\text{relative frequency} = \frac{\text{frequency of response}}{\text{total number of responses}} = \frac{f}{N} \quad (3.1)$$

‘To work out the relative frequency of a response’, she continued, you take the frequency of that response (f) and divide it by the total number of responses (N). If we want to work out the relative frequency of, for example, a response of 10, we look at how many women gave that response – and we can see that 2 did. 🐞 We then ask how many women in total gave responses, and we can see that 20 did. The relative frequency is, therefore, 2 divided by 20’. The professor scribbled some more. 🧠

TABLE 3.2

3.2

$$\text{relative frequency} = \frac{\text{frequency of a rating of 10}}{\text{total number of responses}} = \frac{2}{20} = 0.1 \quad (3.2)$$

To check that I had understood, the Professor asked me what the relative frequency would be of a rating of 4 for this same rating scale. Looking at the second table 🐞, I said, ‘the frequency of a score of four was 4, and there were 20 scores in all, so the relative frequency would be 4/20. But I don’t know what that is.’

TABLE 3.2

‘0.20,’ said The Head, looking smug.

‘Oh, you’ve woken up now there’s some maths to do, have you?’ I glared at The Head, who I felt was trying to make me look stupid in front of the Professor.

‘The Head is always awake, Z – *always*,’ he said, alluding to our earlier conversation. Was The Head really still awake when I closed the watch? I needed to stay focused. I asked the Professor what a score of 0.2 actually meant.



CHECK YOUR BRAIN: Calculate the relative frequencies of the remaining scores from the frequency distribution in Table 3.2.

‘To make it easier to understand, think of these relative frequencies as percentages, which you do by multiplying them by 100. In other words, 0.2 becomes 20%. Therefore, rather than saying that the proportion of women who rated a high salary as 4 out of 10 was 0.20, we can say that 20% of women rated a high salary as 4.’

MEOWSINGS 3.1

I felt my diePad vibrate – it was another message from Milton. I showed it to the Professor before it had time to disappear. I asked her if there was a Milton working there, someone who might be sending these messages. The message troubled the Professor, but she denied knowing anyone called Milton. When I asked whether it was true that Professor Milton Grey had worked here, she became agitated. ‘Professor Grey, as is well documented, is dead – now do you want my help or are you going to continue to ask me impertinent questions?’ Before waiting for an answer, she continued: ‘The interesting part is if we look at the **cumulative percentage**. Rather than looking at the frequencies of individual categories along the scale, we can look at the **cumulative frequency**, which means that we look at the total frequency of all categories up to and including the category of interest.’ The Professor started to add columns to the table she had drawn. ‘If we start at the bottom, then a rating of 1 had a frequency of 1; there are no categories before it so the cumulative frequency is also 1. Moving up to the next category (a rating of 2), we see this received one response also, so the frequency is 1, but the cumulative frequency is the frequency of this category and the one before, so it is $1 + 1 = 2$. Moving up to the next category (a rating of 3), this response had a frequency of 2, but the cumulative frequency will be this value added to the frequencies of the previous categories, so it is $1 + 1 + 2 = 4$. Moving up to the next category (a rating of 4), this response had a frequency of 4, so the cumulative frequency will be this value added to the frequencies of the previous categories, so it is $1 + 1 + 2 + 4 = 8$. In general, the cumulative frequency for category n is the frequency of that category added to the cumulative frequency for the *previous* category (i.e., $n - 1$). We could write that like this.’ The Professor moved across to an untouched part of the blue glass wall and began to write.

TABLE 3.4

3.3

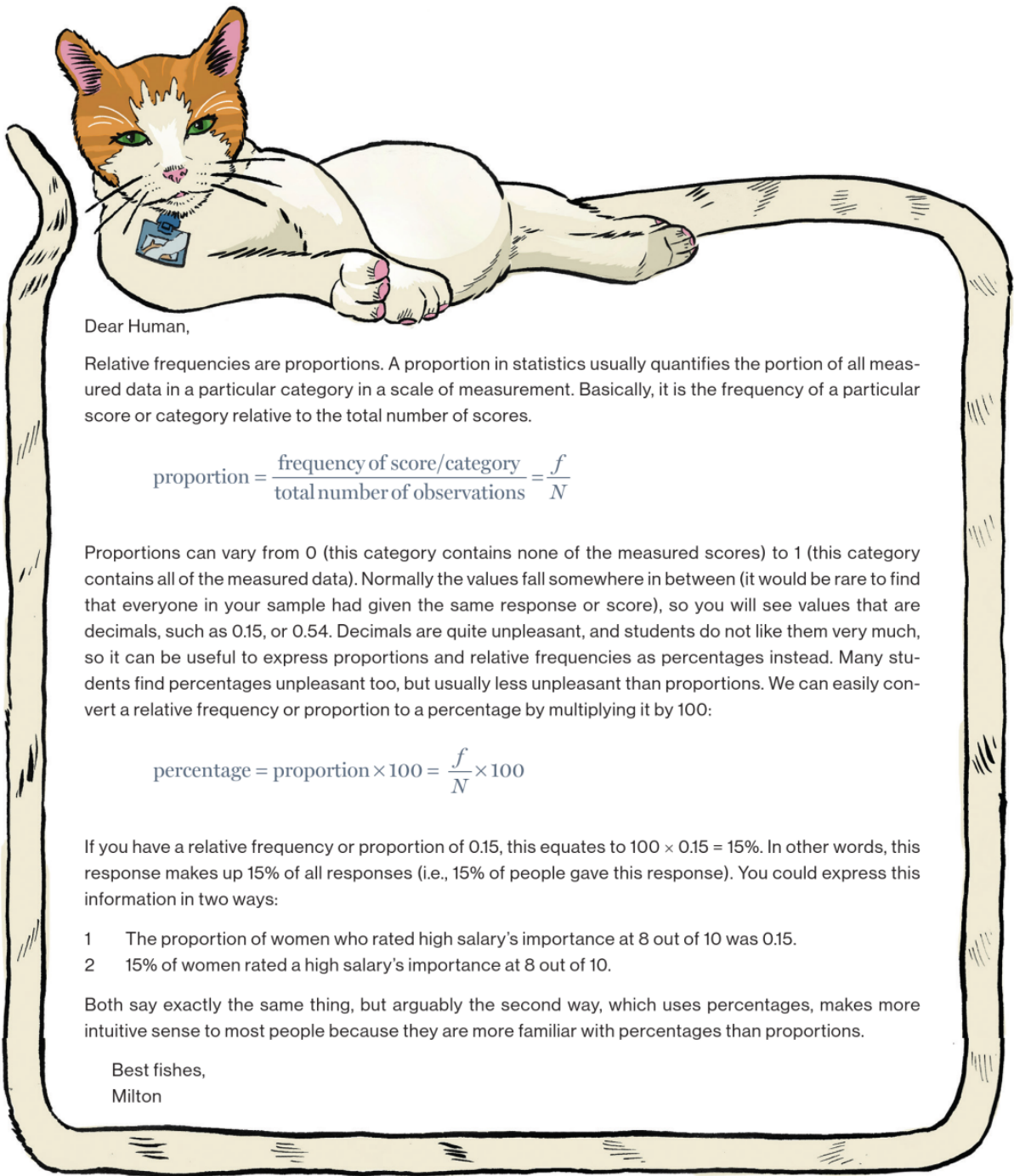
$$\text{cumulative frequency}_n = f_n + \text{cumulative frequency}_{n-1} \quad (3.3)$$

I still didn’t see how this was getting me any closer to finding out whether or not Alice was likely to have left me. I was getting a little frustrated; I felt that I needed to listen in case the Professor suddenly dropped some payload of information, but I also felt empty without Alice. Was it too much to ask to have someone tell me where she was or what was happening? Apparently it was: the Professor was interested only in talking statistics at me as though some unstoppable teaching node had activated in her brain. She didn’t pause to think about whether I understood what she was saying; this was exactly why I’d dropped out of uni. ‘The cumulative frequency is all very well,’ she continued, ‘but if we again look at the percentage rather than the raw frequencies then we have a more intuitive way of summarizing scores. Let’s look back at the original frequency distribution, now calculate the relative frequencies, and then multiply these by 100 to get the percentages for each category.’

TABLE 3.2**TABLE 3.4**

CHECK YOUR BRAIN: Calculate the percentages of the scores from the frequency distribution in Table 3.2.

We can calculate the cumulative percentages just like we did for the frequencies. Start at the bottom; a rating of 1 had a percentage of 5%, there are no categories before it so the cumulative



Dear Human,

Relative frequencies are proportions. A proportion in statistics usually quantifies the portion of all measured data in a particular category in a scale of measurement. Basically, it is the frequency of a particular score or category relative to the total number of scores.

$$\text{proportion} = \frac{\text{frequency of score/category}}{\text{total number of observations}} = \frac{f}{N}$$

Proportions can vary from 0 (this category contains none of the measured scores) to 1 (this category contains all of the measured data). Normally the values fall somewhere in between (it would be rare to find that everyone in your sample had given the same response or score), so you will see values that are decimals, such as 0.15, or 0.54. Decimals are quite unpleasant, and students do not like them very much, so it can be useful to express proportions and relative frequencies as percentages instead. Many students find percentages unpleasant too, but usually less unpleasant than proportions. We can easily convert a relative frequency or proportion to a percentage by multiplying it by 100:

$$\text{percentage} = \text{proportion} \times 100 = \frac{f}{N} \times 100$$

If you have a relative frequency or proportion of 0.15, this equates to $100 \times 0.15 = 15\%$. In other words, this response makes up 15% of all responses (i.e., 15% of people gave this response). You could express this information in two ways:

- 1 The proportion of women who rated high salary's importance at 8 out of 10 was 0.15.
- 2 15% of women rated a high salary's importance at 8 out of 10.

Both say exactly the same thing, but arguably the second way, which uses percentages, makes more intuitive sense to most people because they are more familiar with percentages than proportions.

Best fishes,
Milton

Milton's Meowings 3.1 Relative frequencies, proportions and percentages

percentage is also 5%. Moving up to the next category (a rating of 2), we see this received 5% of responses also, so the percentage is 5%, but the cumulative percentage is the percentage of this category and the one before, so it is $5\% + 5\% = 10\%$. Moving up to the next category (a rating of 3), this response had a percentage of 10%, but the cumulative percentage will be this value added to

Table 3.4 Frequency distribution of females' ratings of high salary as a characteristic in a romantic partner, including relative frequencies, percentages and cumulative percentages

Rating (X)	Frequency (f)	Cumulative frequency (up)	Relative frequency (f/N)	Percentage	Cumulative percentage (up)	Cumulative percentage (down)
10	2	20	0.10	10%	100%	10%
9	1	18	0.05	5%	90%	15%
8	3	17	0.15	15%	85%	30%
7	2	14	0.10	10%	70%	40%
6	2	12	0.10	10%	60%	50%
5	2	10	0.10	10%	50%	60%
4	4	8	0.20	20%	40%	80%
3	2	4	0.10	10%	20%	90%
2	1	2	0.05	5%	10%	95%
1	1	1	0.05	5%	5%	100%

the percentage of the previous categories, so it is $5\% + 5\% + 10\% = 20\%$. Again, in general the cumulative percentage for category n is the percentage for that category added to the cumulative percentage for the *previous* category (i.e., $n-1$). 🧠

$$\text{cumulative percentage}_n = \text{percentage}_n + \text{cumulative percentage}_{n-1} \quad (3.4)$$

‘Notice that the cumulative percentage will be 100% once we reach the last category on the scale. That means that all of the data are accounted for. We can also calculate the cumulative percentages starting at the highest category and working our way down. Either way is acceptable; it depends what the scale of measurement is and which way around is most useful for the question that you want to answer.’ 🧠

TABLE 3.4

At last, she paused for breath. ‘I’m sorry Prof, but I still don’t see how this tells me what women want.’

Pincus looked excited as though she had reached the pinnacle of her great lecture. ‘This is a 10-point scale, ranging from 1 (not important) to 10 (very important). The mid points of 5–6 are the points at which the response changes from ‘not important’ to ‘important’. A 5 is the last rating on the ‘not important’ side of the scale. What is the cumulative percentage of the response of 5?’

TABLE 3.4

I looked at the table on the wall. 🧠 ‘It’s 50%.’

‘And what does that mean?’ enquired the Professor.

‘It means that 50% of women gave a score of 5 or lower, which means that 50% of women thought that a high salary was unimportant to some degree.’

‘Excellent, Zach. Does that answer your question?’

‘A bit. I mean, it tells me that about half of women think a high salary is important. It doesn’t tell me whether Alice is one of those 50%, though.’



‘Imagine we want 10 intervals,’ she continued. ‘The highest score was 32 and the lowest 8, so we would get the following’.

3.6

$$\text{interval width} = \frac{32 - 8}{10} = \frac{24}{10} = 2.4 \quad (3.6)$$

‘It would be complicated to have intervals of 2.4, so we can round this number up to 3, and we should find we get about 10 intervals. With what value should we start the first interval?’ she asked.

‘8 is the lowest score, and 7 was the lowest *possible* score so maybe start with that, but earlier you said to start the intervals with a value that is a multiple of the width. The width is 3, so we could start with 3, 6, 9 and so on. If we start the first interval with 6, then with a width of 3 the first interval would include the values of 6, 7 and 8; this is perfect because it will contain the lowest value in the data, and the lowest *possible* value on the scale.’

‘Very good, Zach, very good indeed.’ The Professor started scribbling another table, speaking as she drew. ‘We would create intervals of 6–8, 9–11, 12–14, and so on. Then we count the frequency with which scores fall into those categories, just like we’ve done before. You can see that we have ended up with 10 class intervals, and it shows a little more detail about how the frequency of scores tapers off at the extremes of the scale; so the bulk of responses are between 15 and 26, and the frequency gradually declines towards the low extreme of 7 and the high extreme of 35. By comparing these two frequency distributions you can see that with fewer categories you get less detail, so there is a trade-off: although we want to simplify the data to a manageable number of categories, we don’t want so few categories that we start to lose too much detail.’

TABLE 3.5

‘I don’t want to be rude, Prof, but again, how does this tell me about Alice’s score?’

‘Patience,’ she replied a little sternly. ‘Let’s convert the frequencies in our distribution into percentages, and then let’s compute the cumulative percentage going from the lowest to highest scores.’

TABLE 3.5

Table 3.5 Grouped frequency distributions of the RAS data, using different class interval widths

Width = 5		Width = 3	
RAS (X)	Frequency (f)	RAS (X)	Frequency (f)
5–9	1	6–8	1
10–14	3	9–11	1
15–19	5	12–14	2
20–24	5	15–17	4
25–29	5	18–20	3
30–34	1	21–23	3
35–39	0	24–26	3
		27–29	2
		30–32	1
		33–35	0



CHECK YOUR BRAIN: Convert the frequencies for the grouped frequency distribution with widths of 3 in Table 3.5 into percentages and compute the cumulative percentage going from the lowest to highest score.

TABLE 3.6

group of scores. ‘Remind me what score Alice had?’ she asked.

‘32,’ I replied.

TABLE 3.6

‘Looking at the percentages, Zach, how many women gave a response of 32?’

I looked at the table and replied ‘5%, because that’s the percentage for the category 30–32?’

‘Very good, but remember that some of this 5% might have had scores of 30 and 31, which are lower than Alice’s score of 32. Now look at the cumulative percentage, what percentage of women gave a score *lower* than 32?’

To find out how many scores were lower I figured that I needed to look at the cumulative percentage up to the category before 30–32. The cumulative percentage of scores up to and including 27–29, was 95%. Wow, that’s huge. Did that mean that in a group of women similar in age to Alice, 95% of them rated their relationship lower than she rated our relationship? I asked the Professor.

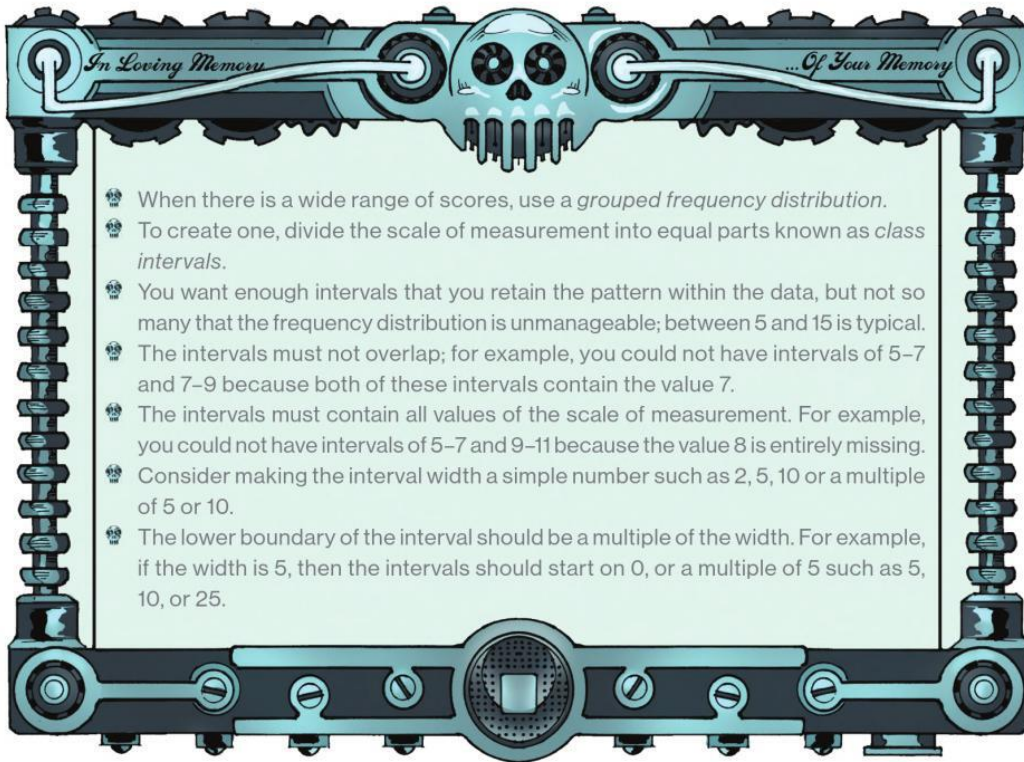
‘Well done; it tells us that relative to other women of her age, Alice was very satisfied with your relationship when she completed this questionnaire.’ Professor Pincus looked a little disappointed at the news; it was as if the data hadn’t shown what she hoped it might.



CHECK YOUR BRAIN: Compute the percentage and the cumulative percentage (from low scores to high) for the grouped frequency distribution with widths of 5 in Table 3.5.

Table 3.6 Grouped frequency distribution of the RAS data with percentage and cumulative percentage

RAS (X)	Frequency (f)	Relative frequency (f/N)	Percentage	Cumulative percentage (up)
6–8	1	0.05	5%	5%
9–11	1	0.05	5%	10%
12–14	2	0.10	10%	20%
15–17	4	0.20	20%	40%
18–20	3	0.15	15%	55%
21–23	3	0.15	15%	70%
24–26	3	0.15	15%	85%
27–29	2	0.10	10%	95%
30–32	1	0.05	5%	100%



Zach's Facts 3.2 Grouped frequency distributions



3.1.3 Graphical Frequency distributions

‘Props and all that, but I’m not being ridiculous. A cat just walked into your office, which in itself is spooks, but then it opened its little cat mouth and said “Hello, Catherine”, which takes spooks to a new level.’

‘There’s no cat,’ replied the Professor in a tetchy tone.

‘There is. I saw it.’

‘Are you calling me a liar?’ The Professor spat the words at me. Just like with Genari, I was losing my grip on the situation. It was becoming awkward, and I don’t like awkwardness one bit: I avoid it like I avoid tarantulas, and I steer clear of them as a matter of priority. On the other hand, the Professor *was* lying. Or maybe I really was losing it – there were the messages from Milton that were gone when I tried to show The Head, a girlfriend who apparently never existed, and now a talking cat. Maybe my whole existence wasn’t real, maybe someone had put a reality prism on my head while I was asleep and I was seeing my actual reality stripped of my subjective experience? I mean, none of our generation had actually worn a reality prism, we’d been told that you see both realities at the same time, but maybe this was a new type of reality prism where you got to live objective reality rather than your subjective one. My mind was on overdrive thinking about what was and wasn’t real. The Professor was still glaring at me, waiting for my response. I needed to get her back on side.

‘Of course I don’t think you’re lying to me. You’ve been so gracious in giving me your time, I trust you completely. It’s just that there is actually a cat; look, it’s sitting on your desk.’

I pointed to the ginger cat and we both turned to her desk. The cat lifted its paw and waved at us. I thought it might be smiling, but cats don’t smile. Perhaps talking ones do – this was new territory for me. It crossed my mind that it was ginger, just like the cat I’d seen outside Dr Genari’s window. The Professor looked pale.

‘Oh, him,’ the Professor said, feigning surprise really unconvincingly. She adopted a faux jovial tone. ‘That’s just the lab cat. I didn’t notice him come in.’

‘And you didn’t notice him saying “Hello, Catherine”?’

‘I think you’re stressed about Alice. It is a scientific fact that cats cannot and never will be able to speak.’ To prove her point, the Professor addressed the cat while fixing him with a glance that made clear to him that if he spoke his tuna supply was going to dry up. Her eyes narrowed as she spoke, ‘Would you be so kind as to tell this young man your name?’

Do cats have eyebrows? I’m not sure, but this one seemed to raise something above his eye. He stared blankly back at the Professor as though engaging her in a secret battle of wills. After a long contemplative pause, he twisted his body and began licking his backside.

The Professor turned back to me and smiled a relieved sort of smile. ‘See – just an ordinary cat. Now shall we resume with what women want?’

I agreed. Whatever was going on here the Professor didn’t want me to know, and I still felt that I was better off keeping her talking in case something useful came out.

As though nothing had happened, the Professor switched back into teaching mode. I might as well not have been in the room. ‘We’ve looked at frequency distributions as tables, but often it is more appealing to display them as a **graph** (also known as a **chart**). Visually this can give you a very immediate impression of how scores in your data are distributed. Graphs come in lots of different shapes and sizes, but they all have a horizontal and vertical line known as the *axes*.

The horizontal line usually displays a predictor variable, or an independent variable, and because these variables are usually denoted with the letter x it is known as the x -axis, or **abscissa**. The vertical line usually displays an outcome variable, or a dependent variable, and because these variables are usually denoted with the letter y it is known as the y -axis, or **ordinate**. When you have a scale of measurement that is interval or ratio, you can use a **histogram** and **frequency polygon** to display the frequency of scores. These graphs display the possible scores of the measured variable on the x -axis, and the frequency with which each score occurs on the y -axis. The difference between these graphs is that a histogram plots the frequencies as bars rising up from the x -axis, whereas a polygon plots them as points that are then connected by straight lines. Let me show you some examples.'

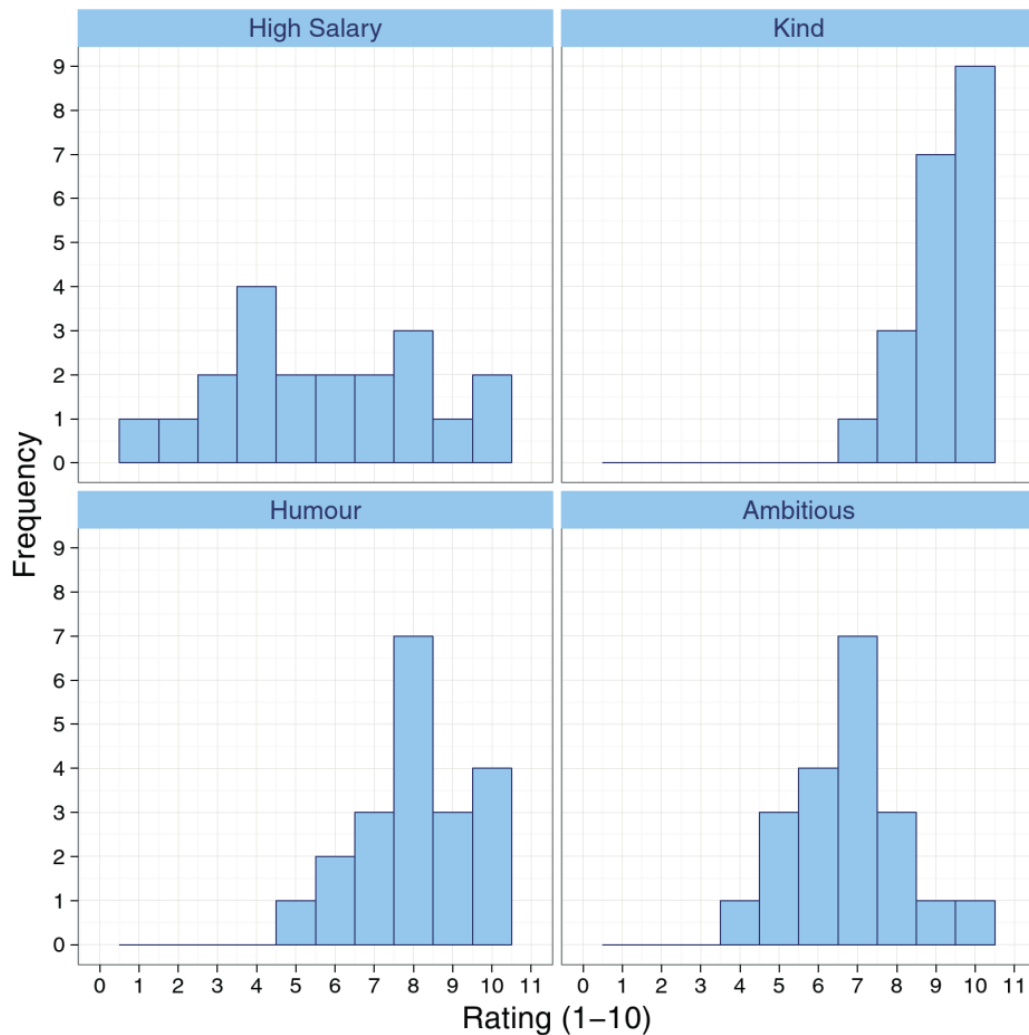


Figure 3.1 Histograms of the importance to teenage women of four characteristics in their partners

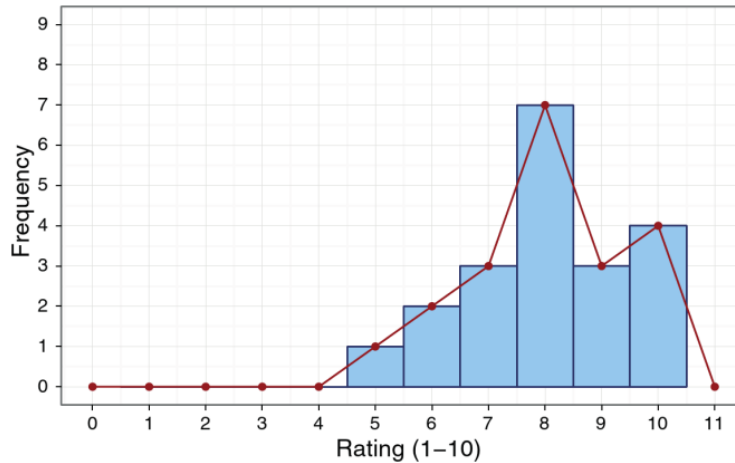


Figure 3.3 Histogram of ratings of humour as a characteristic in a romantic partner with the frequency polygon superimposed

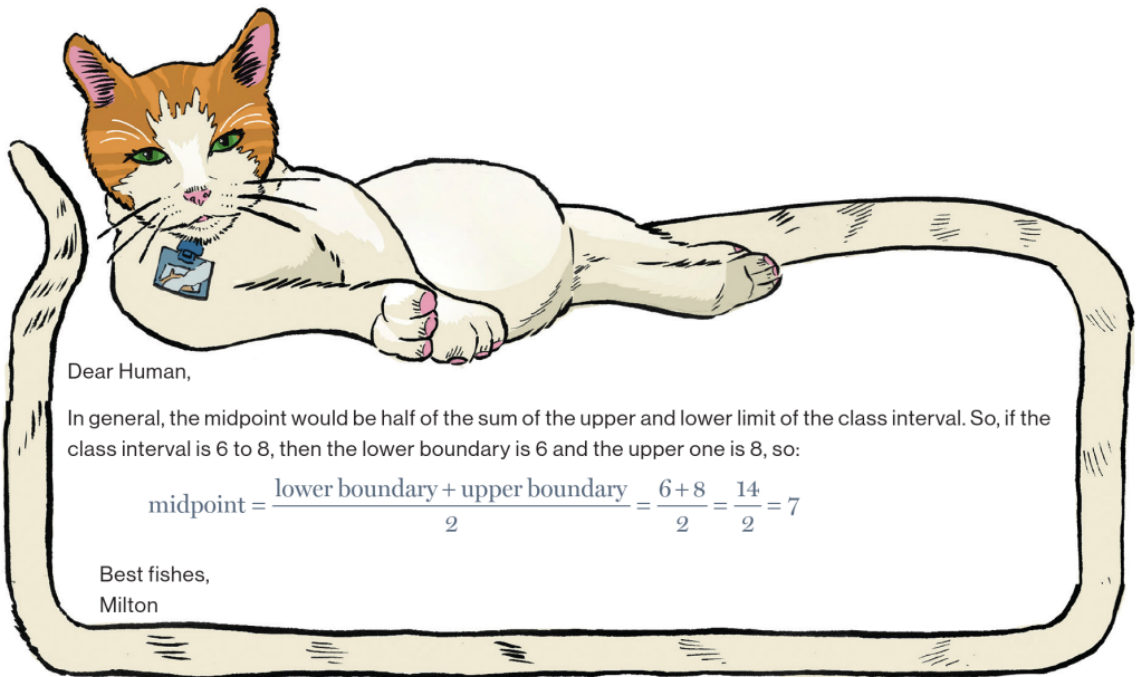
FIGURE 3.4

→ interval, or as a polygon by having each point located at the midpoint of the interval. ❏ So, for example, the first interval was 6–8, so the midpoint would be 7. Again, you should see that the histogram and polygon show the same shape, so you would normally draw one of these graphs, not both. What would you conclude about the RAS scores from these graphs?

The cat on the table started playing with something sticking out of his collar while looking nonchalantly around the room. Was it a Proteus? My diePad buzzed and a brief notification showed me

MEOWSINGS 3.2

→ how to compute the midpoint that the Professor had just mentioned. ❏



Milton's Meowsings 3.2 Midpoints


Noticing that I had been distracted, the Professor repeated her question about the RAS scores. Looking at her diagram , the first three bars looked quite short and so did the last two, but the bars in the middle were relatively high. It looked as though relatively few women were really dissatisfied with their relationships (not many women had scores between 6 and 14) and few were really satisfied (not many women scored above 27). So, the majority of women had satisfaction scores between about 15 and 26.

FIGURE 3.4

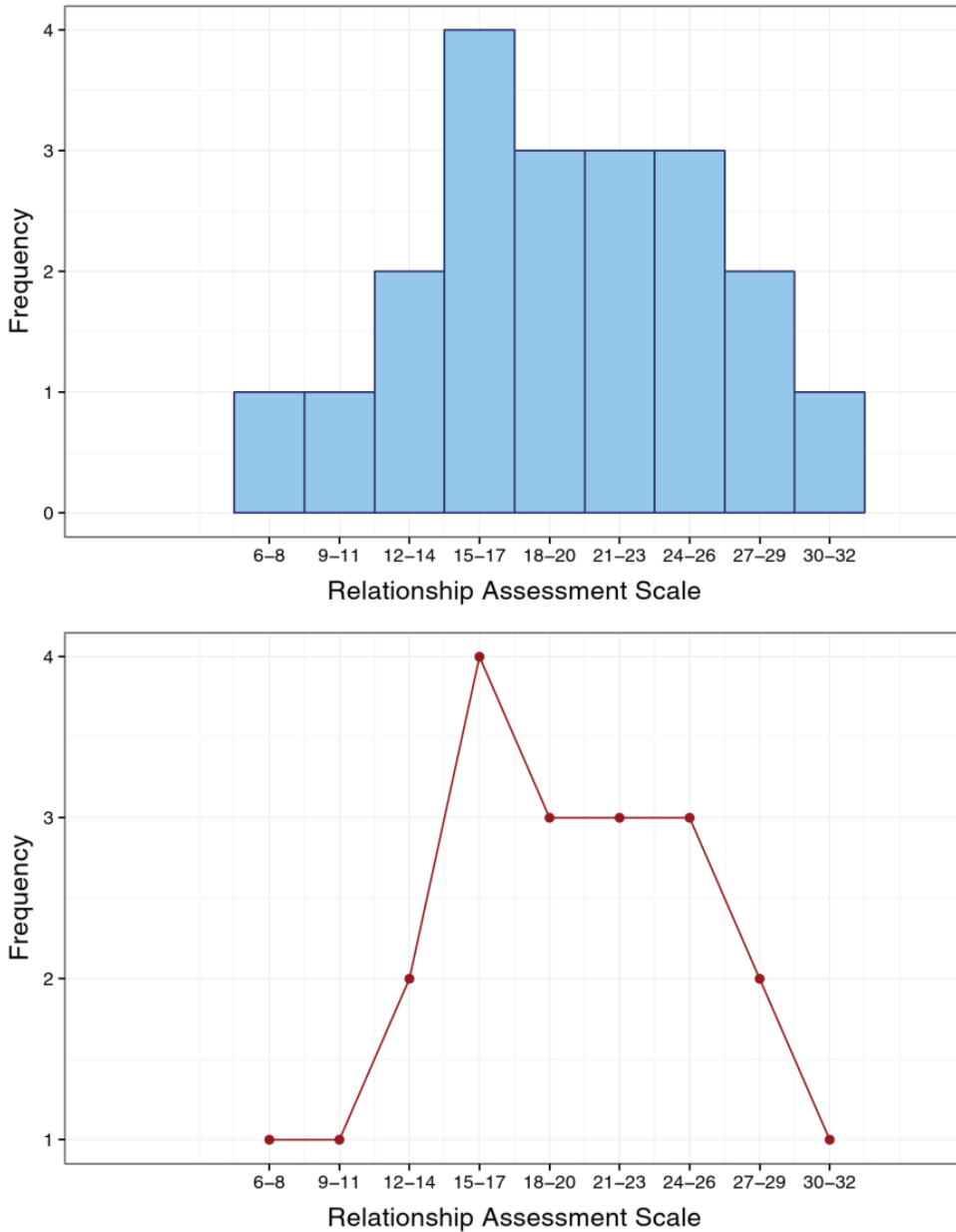


Figure 3.4 Histogram and frequency polygon of the RAS data

The Professor agreed. ‘Can you see now, based on the samples of women we have looked at, that most women are not as satisfied with their relationship as Alice was, many women do not think a high salary is important, but most value kindness, humour and ambition, all of which are qualities that you have?’

3.1.4 Idealized distributions

‘But Alice could be completely different than the women in this sample.’

The Professor became animated. ‘The beauty of data is that we can use samples to estimate the shape of the distribution of scores in the entire population. In some cases it might be possible to collect data from the entire population, and then we could plot histograms just as we have done. Often we cannot: if we wanted to look at the population of all women, it is too big a group for us to collect data from them all. Without data from everyone we cannot know the actual frequencies of responses. However, we can work out the *relative frequency* of responses. For example, we might be able to say with some confidence that twice as many women think that humour is important in a partner as don’t. Remember that this is what the relative frequency tells us – it is the frequency relative to the entire sample or the proportion of responses in each category.’

‘How would we find these relative frequencies?’

‘If we assume a sample, or perhaps many samples collected over time, to be a good representation of the population, then it’s reasonable to assume that the relative frequencies in the sample will be similar to those in the population. We don’t need to know the actual frequencies in the population, we work instead with relative frequencies. Once we know the relative frequencies, we can begin to look at distributions not just as bars representing values for specific categories along a measurement scale, but as a smooth curve that shows an idealized relationship between the variable we measured and the relative frequency of responses. This curve represents the relative changes from one score to the next. Often this curve, rather than showing the relative frequency, shows a related statistic known as the **density**, which is the probability of a given score occurring. The resulting curve is known as a **probability distribution** and has an exact mathematical defini-

SECTION 7.2.2

tion known as a **probability density function.** ❏

‘How does this help us?’

FIGURE 3.5

The Professor turned to one of the few patches of wall that wasn’t already covered in tables, graphs or equations, and instructed the wall to produce another graph. ❏ ‘Look here. The bars show the relative frequency of responses to humour in the sample of 20 people. The curve is an idealized representation of how the relative frequency changes across the rating scale. This idealized shape reiterates the fact that we would expect women’s evaluations of humour as a desirable characteristic in a partner to cluster at the top end of the response scale. None of this proves that Alice likes her partner to be funny, but we can start to look at how likely it is that she would, and based on this sample it seems probable that she would like someone funny, kind and ambitious. Someone like you, Zach. The evidence suggests that you have more going for you than you might think. You have the right characteristics to keep most women happy.’

3.1.5 Histograms For nominal and ordinal data

I felt a wave of joy; the evidence from Alice’s file and from looking at what women want generally seemed to be going against the assumption that Alice had left me. This felt good.



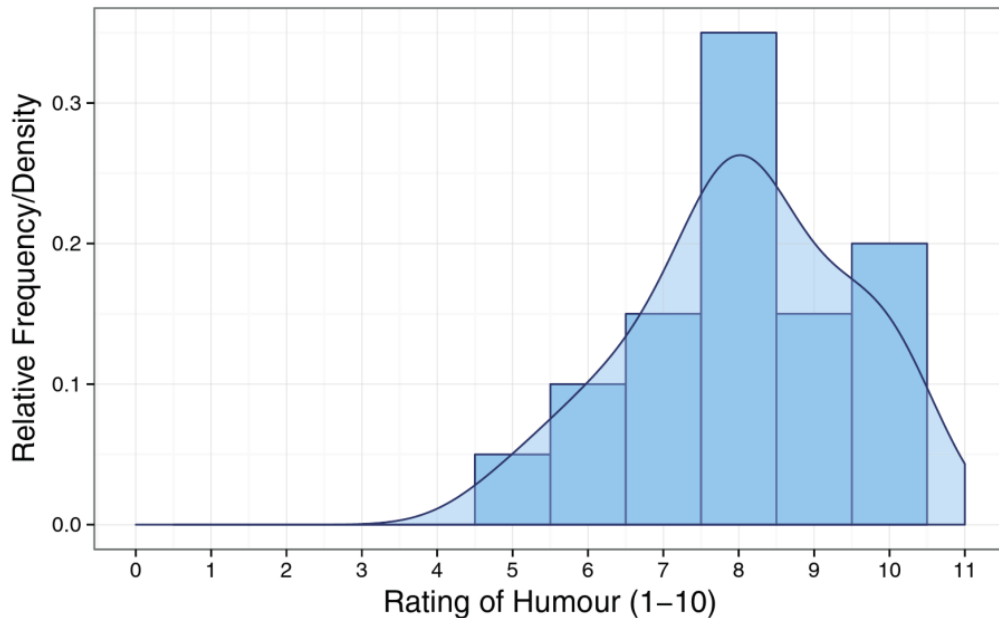


Figure 3.5 A plot of the relative frequency of ratings of humour and an 'idealized' curve

I started to daydream about seeing her, about holding her, about being together again, but then it hit me: if she hadn't dumped me then one of the alternatives was that she was in trouble. I felt an urgency to do something – I wasn't sure what, but *something*. A young man walking through the parting wall broke my concentration. He tapped the wall, addressing the Professor as he did.

'I have the latest breakdown of our employees for you to sign off, Professor Pincus,' he said.

'Not now,' she said, urgently trying to usher him out of the room. It was too late, a graph had already appeared on the wall. 📊

'Is that a histogram?' I asked.

'Of a sort,' the Professor responded.

'Why are there gaps between the bars? In the histograms we looked at before the bars sat directly next to each other. What do you mean, it is "sort of" a histogram?'

She seemed reluctant to dwell on the graph and answered quickly and dismissively, 'It shows the same information as a histogram – the frequency within categories – but these categories do not make up an interval or ratio scale of measurement. These data are the numbers of different types of employees at the Beimeni Centre of Genetics. This is a nominal variable: there are categories of workers: professors, senior scientists and research students. When we display information about a nominal or ordinal variable like this, it's called a **bar graph**. The principle is the same as for a histogram: we display different categories along the x -axis, and we use bars to indicate some kind of statistic, in this case the frequency. There are spaces between the bars to indicate that they are independent categories and not points along an interval or ratio scale.'

FIGURE 3.6

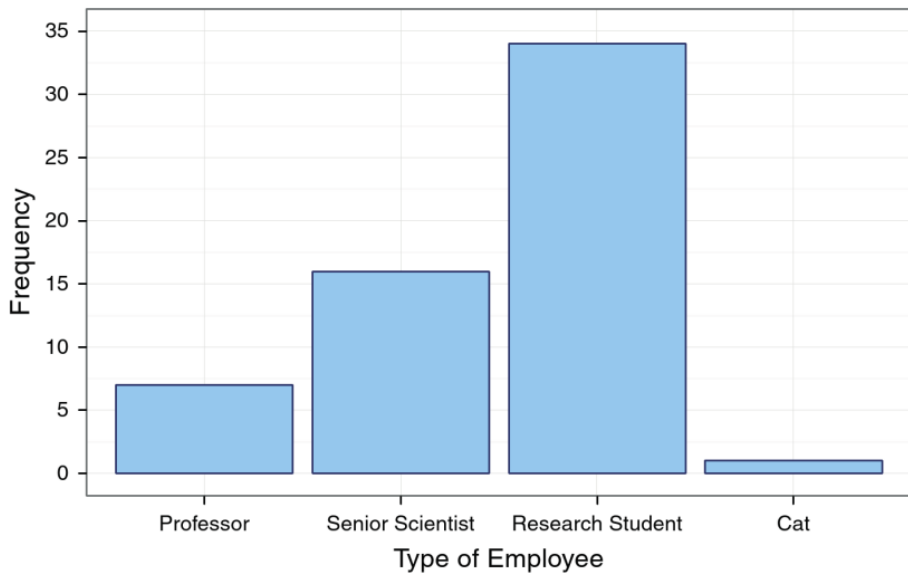
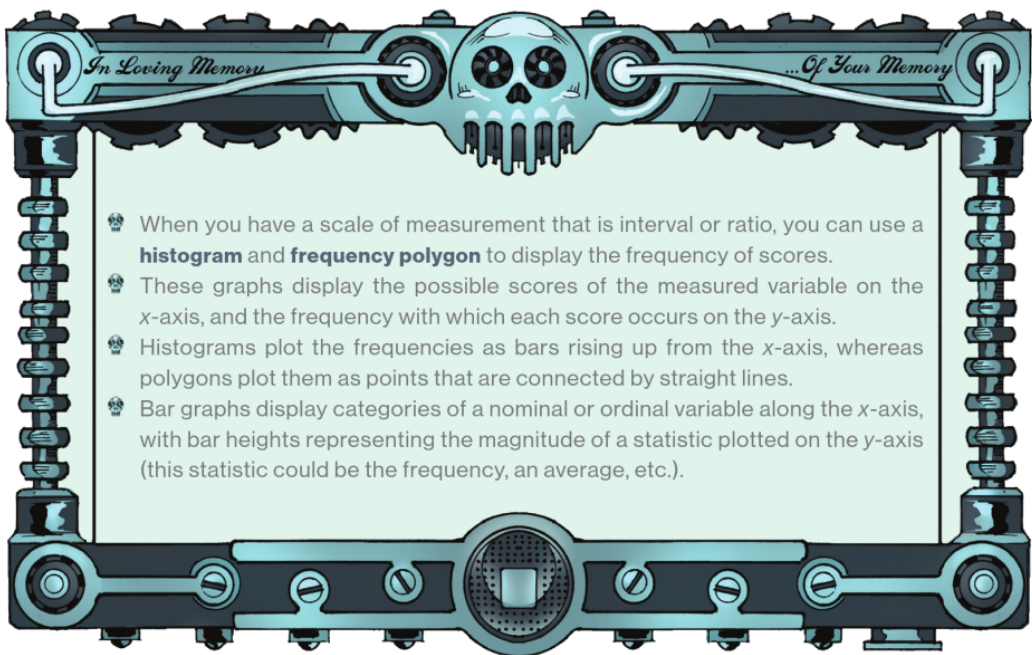


Figure 3.6 Frequency distribution of a nominal variable



Zach's Facts 3.3 Histograms, polygons and bar graphs

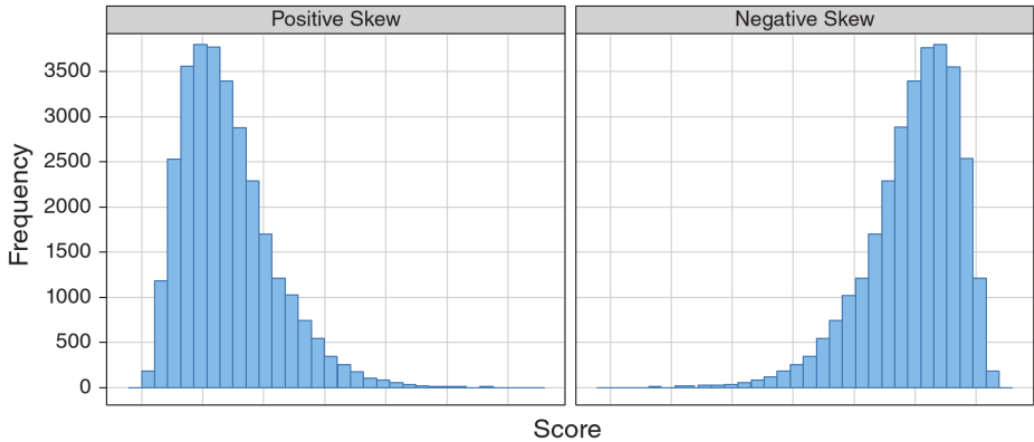


Figure 3.8 A positively (left) and negatively (right) skewed distribution

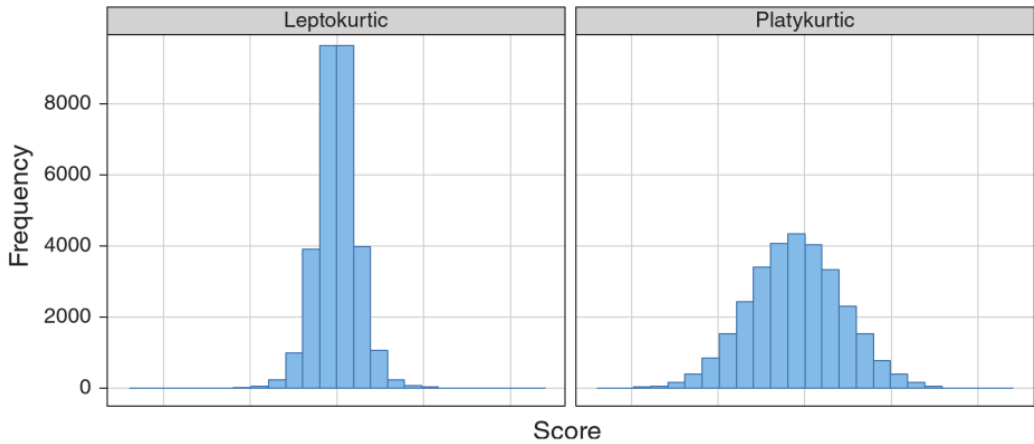


Figure 3.9 Distributions with a positive kurtosis of +2.6 (leptokurtic, left) and a negative kurtosis of -0.09 (platykurtic, right)

distributions can tend to look pointy, and platykurtic ones tend to look flatter than normal. However, there are lots of other things that affect how pointy or flat a distribution looks. In a normal distribution the values of skew and kurtosis are 0 (i.e., the overall shape of the distribution is as it should be). If a distribution has values of skew or kurtosis above or below 0 then this indicates a deviation from normal.

FIGURE 3.9

‘How can I use these shapes to tell me whether Alice dumped me or is in danger?’

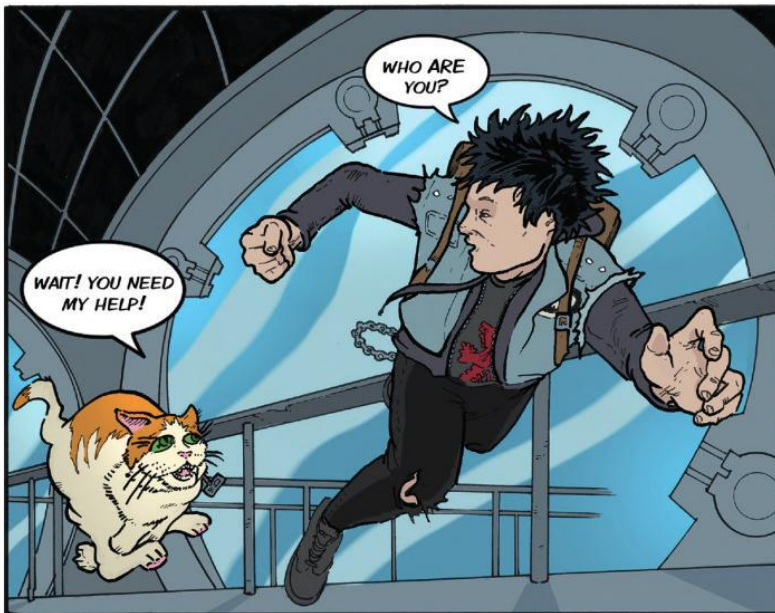
‘You can’t, but I thought it was an interesting way to finish telling you about distributions. I have a very busy day, so it’s been very nice to meet you, Zach. I hope that Alice returns to us very soon – she is a much valued part of our team.’

Was she serious? I'd sat through all of that, and at best all I'd found out was that Alice's relationship satisfaction scores were higher than most, and that I had some characteristics that women – in general – seem to like. Now she was giving me the brush-off and coming out with platitudes about Alice being valued. How dare she: Alice was frippin' brilliant. I had the distinct impression that Professor Pincus had deliberately sidetracked me from JIG:SAW by giving me false hope that she could help me to look at the data in Alice's file. My anger spilled over: 'That's it? But I don't know any more about where Alice is than when I walked in!'

The Professor replied, and the rage in her eyes betrayed her calmly spoken words. 'I disagree. I have given you – in the limited free time I have to talk to strangers who come to my laboratory without authorization – some tools to help you to work out the answers for yourself. You have some data from Alice's counsellor's files, you have some real-world data to compare against, we've seen that you can use real data to try to ascertain whether it's likely that she would want to leave you, and you now have a few foundations to use the data that you have. Use those foundations to build on, and don't expect people to give you the answers on a plate!'

Told. I packed up The Head and started to leave her office. As I reached the door I turned and said in passing, 'Maybe someone at JIG:SAW will help me?'

I was testing the Professor, to see whether I could goad her into helping me more. Instead, I shattered her calm. She went cold and her curt response made me shudder: 'You listen to me very carefully, young man. Unless you want your life destroyed, take some advice: some things are best left alone.' With that she turned and accelerated towards the wall, barely giving it time to unfold around her as she left her office.



KEY TERMS

Abscissa	Frequency polygon	Platykurtic
Bar graph	Graph	Positive kurtosis
Chart	Grouped frequency distribution	Positive skew
Class interval	Histogram	Probability density function
Class interval width	Kurtosis	Probability distribution
Cumulative frequency	Leptokurtic	Proportion
Cumulative per cent	Negative kurtosis	Relative frequency
Density	Negative skew	Skew
Empirical question	Normal distribution	x-axis
Frequency	Ordinate	y-axis
Frequency distribution		

JIG:SAW'S PUZZLES

- 1 Describe the following terms: frequency, relative frequency, proportion and percentage.
- 2 Draw the frequency distribution of the RAS scores (with scores not grouped by class intervals).
- 3 In this chapter Zach looked at 20 women's ratings of how important certain characteristics are in romantic partners. Here are the data for the characteristic 'wants to have children': 1, 1, 9, 1, 10, 3, 7, 6, 7, 2, 2, 9, 8, 2, 8, 6, 9, 2, 9, 6. Produce a frequency table of these data that includes:
 - a Frequencies
 - b Relative frequencies
 - c Percentages
 - d Cumulative frequency
 - e Cumulative percentage
- 4 For the data in the previous question, remembering that scores of 0–5 mean 'unimportant' and 6–10 mean 'important', what percentage of adolescent women thought that it was important that their partners wanted to have children in the future?
- 5 Zach was worried that he was unappealing to women because he dropped out of college. Here are the ratings of the 20 women in the chapter for the characteristic 'finished education': 9, 8, 5, 4, 7, 3, 10, 7, 6, 4, 4, 8, 9, 1, 7, 3, 7, 6, 10, 9. Draw a histogram of these data. Do you think most women think that it is important that their relationship partner finished their college education?
- 6 The polygon in Figure 3.10 shows the ratings for the characteristic 'romantic'. From this image reconstruct the raw data.
- 7 Here are the ratings for the same 20 women for the characteristic 'attractive appearance': 4, 10, 9, 8, 7, 8, 10, 8, 7, 3, 9, 10, 8, 10, 7, 9, 9, 9, 8, 7. Draw a frequency distribution of these scores.
- 8 Here are the ratings for the same 20 women for the characteristic 'creativity': 7, 6, 5, 4, 5, 8, 9, 5, 5, 7, 4, 5, 5, 10, 7, 3, 5, 9, 1, 7. Draw a frequency polygon of these scores.
- 9 The histogram in Figure 3.11 shows the ratings for the characteristic 'honesty'. From this image reconstruct the raw data.

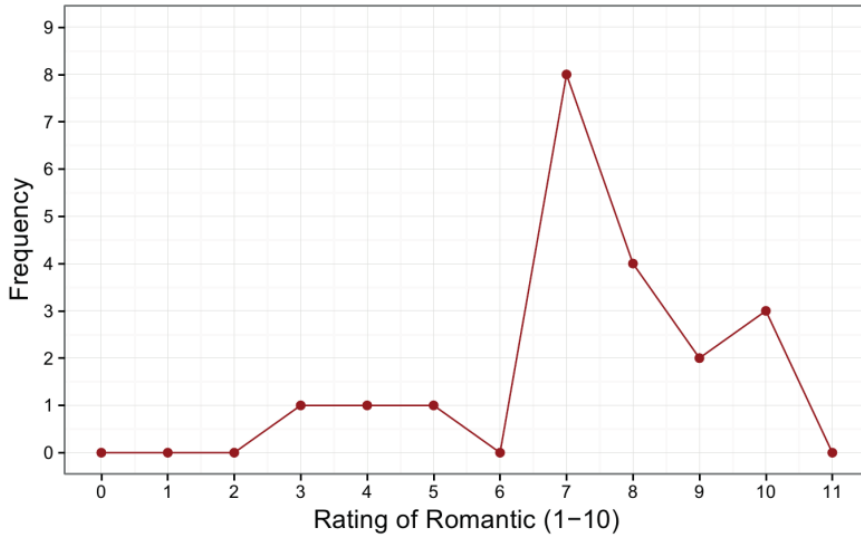


Figure 3.10 Polygon of the ratings for the characteristic 'romantic'

- 10 Based on the histograms and polygons for the previous three questions, what characteristic do women most consistently find important in a romantic partner: attractive appearance, creativity or honesty? Explain your answer.
- 11 Sketch the shape of a normal distribution.
- 12 Look at the histograms in Figure 3.1. For each one comment on:
- a How symmetrical you think they are
 - b How flat or pointy they are
 - c How skewed they are, and whether the skew is positive or negative

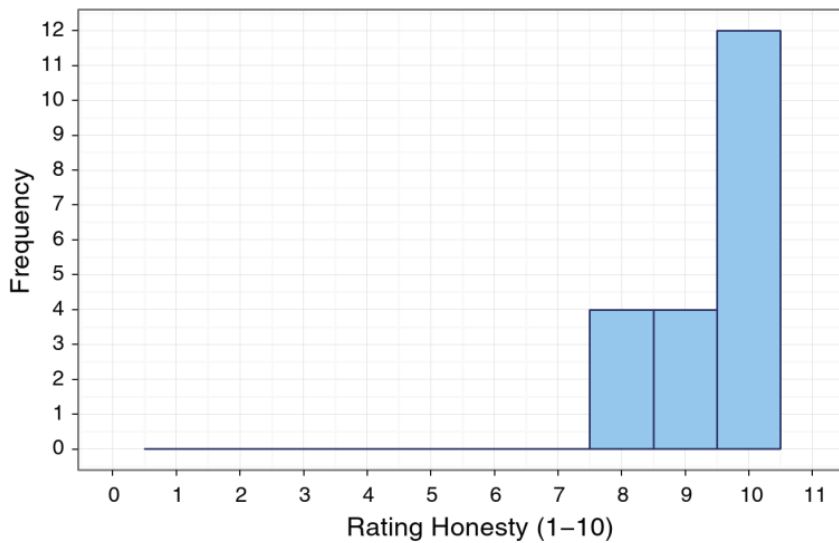


Figure 3.11 Histogram of the ratings for the characteristic 'honesty'

IN THE NEXT CHAPTER ZACH DISCOVERS ...

Cats are really bad dinner dates
Statistical models
Central tendency: the mode, median and mean
Dispersion: the variance, standard deviation, and interquartile range
Quartiles and percentiles
Estimating model fit
Deviance and the sum of squared errors
Degrees of freedom
Outliers
Chippers are dropping like flies

FITTING MODELS (CENTRAL TENDENCY) SOMEWHERE IN THE MIDDLE

Statistical models #110

From the bad #110

Why do we need statistical models? #117

Sample size #118

The one and only statistical model #120

Central tendency #124

The mode #126

The median #128

The mean #129

The 'fit' of the mean: variance #132

The fit of the mean #136

Estimating the fit of the mean from a sample #141

Outliers and variance #148

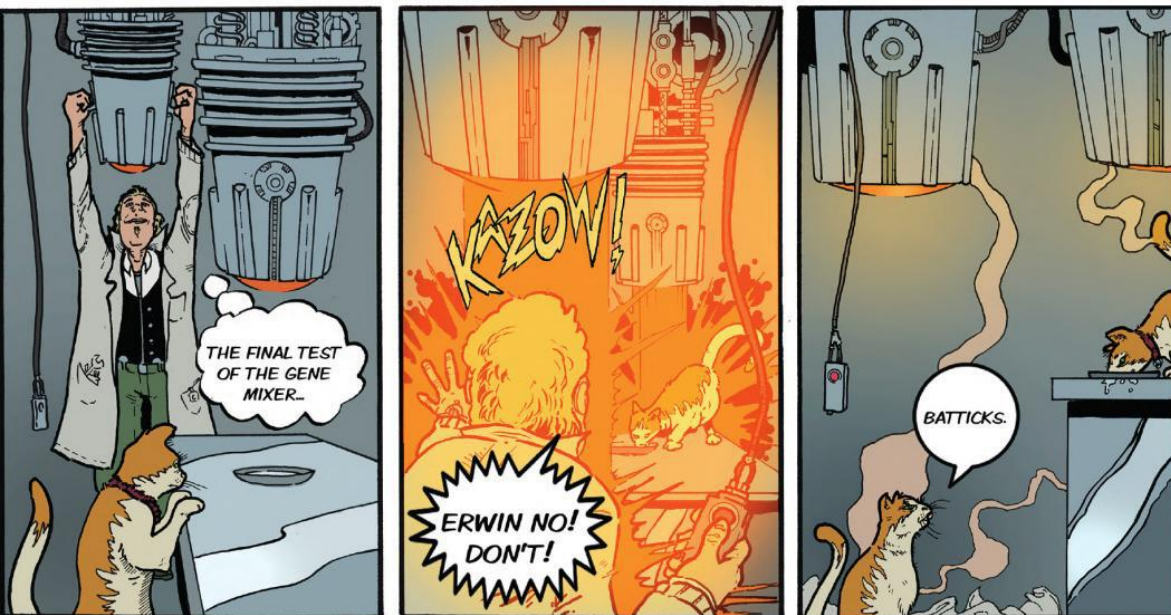
Dispersion #149

The standard deviation as an indicator of dispersion #149

The range and interquartile range #151

Key terms #152

JIGSAW puzzles #152



I stopped in my tracks and turned to face the cat from Professor Pincus's office. He was licking his chest in that over-purposeful way that cats do when they feel awkward. I had managed to convince myself that I had probably imagined the cat talking in Professor Pincus's office, but unless I'd lost my mind twice it really could talk. I wondered whether Alice knew that she worked somewhere that had a talking cat? If she did then why hadn't she mentioned it to me? If I met a talking cat at our rehearsal studio the first thing I would do is tell her. I'd call her now if she hadn't been wiped from the planet.

The cat stared at me, waiting for my reaction. How could he talk, and why was he claiming to be a dead scientist? If you were going to claim to be a dead scientist wouldn't you pick one who was a bit more popular than the reality prism dude? I had so many questions to ask, but no time to get side-tracked by them.

'That's impossible,' I eventually said, 'Milton Grey died five years ago.' I was aware that this wasn't the most impossible aspect of the situation, but I had to start somewhere.

The cat's rate of cleansing rapidly increased before he stopped and looked up. 'Officially I did, but only because the alternative was to try to explain to everyone that I had become a cat. It transpires that the WGA are reluctant to issue passports and other legal documents to cats, and you can forget anything involving a fingerprint or retina scan. Without official documents I am effectively dead, but with Catherine's help I exist as a cat. It has considerable benefits: I get a lot more time for research, because only a mad person would email a cat.'

If someone told me about a cat that could email, I'd *definitely* message it, I thought to myself. How could a cat be Milton Grey, I wondered? Had his brain been transplanted? That seemed unlikely: a cat's skull was too small for a human brain. Maybe the brain had been shrunk? Was it some kind of mind merge? Was Milton Grey's human body walking around somewhere with the

mind of a cat inside it? I needed to establish whether I could trust him, and to do that I needed to know his story, which he was happy to tell.

'After the reality prism nonsense I found myself stripped of my position within the School of Physics here at the University of Elpis, and my reputation made me unemployable. The WGA offered me a position in their Scientific Division, where I helped them to develop technology to rebuild society. Did you know that my colleague Roediger and I invented steam fusion?' The cat paused to take in the awe that he expected from me at this revelation. He looked offended when he got none, and licked his chest to comfort himself. Steam fusion drove so much of the modern world that I took it for granted. I'd never considered what lay beneath it, or how hard it might have been to invent.

'I was quite happy at the WGA,' Milton continued, 'but as their power increased I felt that they were losing their humanitarian principles, so I resigned. It was not easy to convince the WGA that the person they believed brought down society should be given his freedom. They allowed me to go because of my loyal service, but they monitored me constantly: my freedom was an illusion. Worse than that, even the passage of time had not weakened society's ire, and universities still stayed well away from me. I suspect the WGA applied some pressure in that respect. Catherine – Professor Pincus – gave me a lifeline. Although known for my work in physics, for many years I pursued a side interest in genetics. I published an obscure paper on how – theoretically at least – principles of physics could be applied to genetic problems. Catherine was fascinated by the potential of the theory and offered me an opportunity to pursue it at the Beimeni Centre. Catherine put her neck on the line to employ me: in doing so she put the Centre under the WGA's spotlight. I owe her a great deal for her faith, and her unwavering principle to prioritize knowledge and humanity. The first fruits of my work were what I jokingly called the "gene mixer", which was a device for repairing damaged cells; for example, cancer cells. It was a simple enough idea: you turn the damaged cells into programmable matter and then give them a "program" based on healthy cells.'

LAB NOTES 2.1

'That sounds the same as something of Alice's that I read.' 🐱

'Alice's work is much more advanced than my gene mixer.'

So he *did* know Alice. Why hadn't she mentioned him to me?

'The gene mixer was crude, difficult to control, and too powerful – a blunt instrument that rampaged through an organism affecting any gene in its path. We have subsequently discovered that you need the human mind to control the process, but at the time, the gene mixer had promise. We had very encouraging preliminary results, but we needed to test it on a human. You cannot go sticking humans in gene mixing machines, not even ones with cancer who you are trying to help. If it goes wrong you might make the disease worse or even kill them. Fortunately, there was one person we knew who had a recent diagnosis of cancer who was willing to take that risk.'

I panicked that it was Alice, before realizing that he was talking about the past, a time before Alice would have worked there. I asked who it was.

'Me. I stepped under the machine, gathered a dish of healthy cells and prepared to have my diseased cells replaced with programmable cells that would take on the behaviour of those healthy cells.'

'What happened?'

'My cat, Erwin, happened. The dish of healthy cells looked a lot like a dish of milk. Like most cats, Erwin was fond of milk. At the point of transmission he jumped onto the table, lapped up the healthy cells, and became caught in the transfer beam. The machine transformed my cells to programmable matter, took Erwin's healthy cat cells and implanted that template into my cells. I became a cat.'

‘Over the wall, man! That sucks!’

‘On the plus side, my cancer was cured.’

I blurted out a barrage of questions: What happened to the cat? Did Milton’s personality change at all? Did the cat’s? Milton looked a little upset at my concern for his cat over him.

‘Erwin is fine – the transfer was in one direction, so he was unaffected – apart from discovering, much to his disgust, that there was another cat in the house. Cats are not willing cohabiters, so after a few weeks he wandered off to find a new owner. The most surprising thing was that CAT scans’ – he paused and smiled at the pun – ‘showed that physically my brain had shrunk, but also had become incredibly dense to retain everything within my human mind. I did pick up some cat habits, but on the whole it is a good life: people tickle my chin a lot more than they used to.’

Professor Grey looked at me with vulnerable eyes and I instinctively stroked his chin, pulling away as I realized I was fondling a professor’s beard. I still wasn’t sure whether to buy his story, but I couldn’t deny the evidence of my eyes: he *was* a talking cat. Why would he help me, though, and how could I trust someone who had destroyed society? I asked him whether he felt bad about the Reality Revolution.

‘I created the technology, but does that make me responsible for how people used it or their inability to deal with the consequences? Many consider me the modern-day Robert Oppenheimer ...’

‘Who?’

He gave me a look of disgust, ‘... the scientist in charge of the creation of the first atomic bomb. I would argue that, unlike Oppenheimer, the consequences of my work were not obvious to me or anyone else. Do I feel bad for inventing the reality prism? No. It was a device that could have been used for great good. Do I regret how people used reality prisms? Yes, but I blame them, not myself. Do I think society is a worse place for the Reality Revolution? For many years it became a more humane place, of that I am certain, but as through all of history it is only a matter of time before someone tries to take advantage of humanity.’ Milton looked sad. As detached as he felt from the consequences of his work, he didn’t sound evil. I asked him why he wanted to help.

‘I have a reputation that makes my apparent death quite convenient for Catherine. It is bad enough that the Beimeni Centre employed the “notorious” Professor Grey, inventor of the reality prism and destroyer of modern civilization, but society forgives them because they seemingly killed me as part of a bizarre genetics experiment. The world believes that justice has been served. Imagine the furore if anyone discovered that instead of being dead I was in fact a rather lovable cat. The Centre would be investigated and probably shut down for good. As I mentioned, the WGA kept a particularly close eye on things while I was working here. Since my “death” they have lost interest in us, and Catherine prefers it that way. I, however, do not, because my activities are restricted. Before I actually die I want to be remembered for something good, I want to erase the false belief in my part in destroying society. As I told you, my work with the gene mixer was getting close to a device that could cure a great many fatal diseases. Perhaps if I can bring that work to fruition the world will forgive me – I can die a hero, not a villain. I can’t do that while I’m trapped here, only knowing about the work being done in Catherine’s lab. I am forever grateful for all that she has done for me, but I need to expand my horizons. To do that I need someone I can trust. Can I trust you, Zach?’

It was the same question I’d wanted to ask him. ‘Of course, I’m a good guy, but why do you think I need your help?’

‘Sooner or later you are going to decide that you need to investigate JIG:SAW - ’

‘Not after what the Prof said,’ I interrupted.

‘True, only a fool would go there, but sooner or later the fool inside will get the better of you. Catherine is right, it will destroy you; but with my help, you have hope.’

4.1 STATISTICAL MODELS

4.1.1 From the dead

I picked Milton up, put him in my backpack and headed swiftly out of the building. I sheepishly passed the front desk hoping that the head there wouldn’t have a change of heart about having let us in and call security. She didn’t, but as we moved away from the building my pace quickened until I had broken into a run. I decided to head back to Janus, the area where I lived, and go to Occam’s café. Janus was the liberal part of town; if I could take a talking cat anywhere, it was there. Janus was quite a way from Veritas, where the Beimeni Centre was, so I hailed a bubble. Personal transport like cars were a thing of the past; instead the city provided clockwork fusion-powered ‘bubbles’ that hovered around the city. These transparent spheres could be hailed through *memoryBank* or a Proteus and arrived almost instantly. Once inside, you told it where to go and it hovered you there. We were soon at Occam’s.

It was early evening and I was starving. Occam’s was a minimalist café that invented ‘parsimonious cooking’, in which only essential ingredients are used. It tasted better than it sounded. Even in the ‘open-minded’ part of town I was worried that taking a cat to a café might stretch people’s tolerance, so I sat on a long leather couch in one of the many private booths where we’d be less conspicuous. I placed my backpack beside me and Professor Grey wriggled out.

‘I’ll have a tuna steak please,’ he said. ‘Now, on to business. Tell me what you know about Alice.’ Hearing him speak, in public, made me suddenly self-conscious and scared that someone would discover my talking cat. I understood how Professor Pincus must have felt earlier on when Milton had walked into her office. I told Milton about how Alice had disappeared, how I couldn’t contact her, and about my visit to Dr Genari.

‘Who is this Genari chap?’ Milton asked. As he did, I remembered how I had seen a cat outside Genari’s window when I was there. Now I thought of it, the cat was ginger. So that was how Milton could send me messages relating to what Genari was saying: he must have been listening outside. Why would he have known about me? Why would he have followed me? Did Alice send him? Also, Milton said he needed me to help him escape from the Beimeni Centre, but if he was at Genari’s then he must be free to come and go from the Centre as he pleased – not the prisoner he made himself out to be. Why was he lying to me? I decided to play along for now rather than confront him: there must be a reason why and the best way to find out was to play dumb.

I told Milton my theories about Alice, about how at first I thought she’d left me, but that after visiting Genari I feared that she was in trouble. I told him how Professor Pincus had helped me to look at data to test this hypothesis, and that she had seemed disappointed when the data we looked at didn’t support that idea – as if she’d hoped to convince me that Alice *had* left me. Revisiting the last 36 hours or so made me feel anxious and panicky: why couldn’t I just speak to Alice? I wanted to hear her voice, to have her reassure me that she was alright and that this was

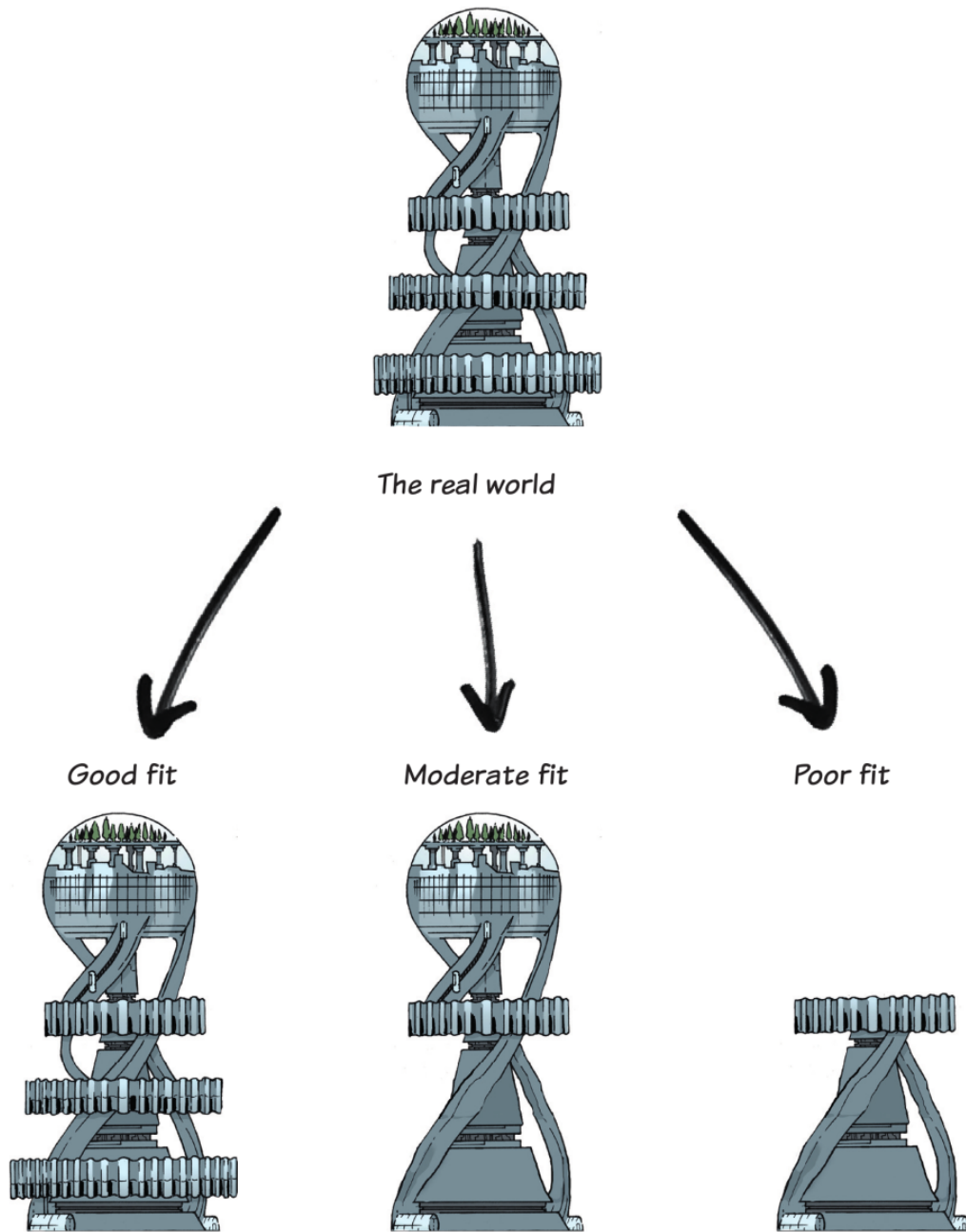


Figure 4.1 Fitting models to real-world data (see text for details)

‘Try not to spit food at me, it is undignified,’ Milton said as he licked a strand of purry cat dribble from his chin. He picked at his tuna, continuing the conversation as he chewed. ‘I have another analogy for you: imagine you are interested in a phenomenon that is trapped inside a cardboard box.’

Milton scratched an image into the table. 🐾 It was astonishing that a cat could draw so well. Scientists weren't known for their artistry and I found myself wondering whether Milton's cat might have had some artistic flair that had been wasted on a cat and could now be unleashed with the benefit of a human mind. Milton clawed my shirt to bring my attention back to him.

'The population is this big cardboard box,' he said, pointing at a well-drawn cardboard box. 'You can't see inside the box, but you know that it contains an interesting phenomenon. You really want to see that phenomenon, but you cannot because it is hidden in the box. A very handsome talking cat appears with a suitcase of magical discs that he calls samples. When you stick these discs on any solid object it allows you to see through that object for a brief time before the disc vanishes. After admiring the cat's handsomeness for some considerable time, you think, "Hmm, I could stick one of those discs on the side of the box and see what is inside". It turns out that these magical discs come in three different sizes: a small sample, a medium sample and a large one. First, you take a small sample and stick it to the side of the box. You can make out a little of what is in the box, but not much. That sample vanishes, so you take another small one and stick it to a different part of the box. Again, you can see a little, but what you can see is quite different from when you looked before because the hole is so small and you stuck it to a different part of the box. You take a final small disc and stick it to another different part of the box. You can again see a little of what's inside, but what you can make out is different from the other two times. You end up being not too sure what is in the box because each time you looked you saw something different. You now take three medium-sized samples. The first one gives you a much better view inside the box than the small sample: because it is bigger you can see more of what is inside the box. When you place the second and third samples on different parts of the box, you get a different view each time, but there is quite a lot of overlap with what you saw with the other two samples (because each sample shows you a reasonable amount of the inside of the box). Finally, you use the three large samples in the same way. These show you almost the entire inside of the box and you get a very precise view of its contents: it is the staggeringly handsome cat! With the other two large samples it doesn't matter where you place them on the box – you get a very similar view of the phenomenon, because each time you can see almost the entire inside of the box.'

'So what you're saying is that small samples don't give you a good "view" on the phenomenon in the population, and different small samples are likely to show different things, but with big samples you get a better "view" of the phenomenon that you're trying to study and what you "see" is likely to be similar across these big samples.'

'That is exactly my point.'

'So, how large is a large sample?'

'That very much depends on the situation, but for now, just focus on the idea that with samples bigger is better. The same cannot be said for dogs.'

4.1.4 *The one and only statistical model*

I understood what the cat was saying about architects and models, but I didn't really get what he meant by a statistical model. I mean, you can't build a bridge out of statistics, can you? I asked him to explain.

'A statistical model is an equation that describes the phenomenon of interest.'

‘Why b ? Why not p for parameter?’

‘Statisticians try to confuse students by using different symbols for different parameters. For example, \bar{X} tends to be used for the average, which is also called the mean; there’s something called a correlation for which they use the letter r or Greek symbol rho, ρ ; and in a model called the linear model, they use b or the Greek letter beta, β . Statisticians like Greek letters, but I thought you’d enjoy the simplicity of using the letter b .’

‘Won’t that upset the statisticians?’

‘Probably, but they are easily upset.’

‘Why does it have a zero next to it?’

‘I put it there to remind you that we are predicting the outcome from zero other variables, that is, just from a single parameter. Can you order me a latte with lactose-free milk please?’

The waiter looked at me as though I was something unpleasant on his shoe as I asked for lactose-free milk in a latte. I guess they weren’t used to dealing with cats’ lactose intolerances, or perhaps he just didn’t like cats eating at the table. Milton got his drink, though, and explained things while his lapping tongue sprayed me.

‘The model I have just described is the simplest possible one: we summarize the population using a single parameter, a single value that summarizes the outcome variable. A lot of the time it is more interesting to see whether we can summarize an outcome variable by predicting from scores on another variable. We usually denote predictor variables with the letter X ; therefore, our model will look like this.’ Milton scratched on the table again. 🧠 4.4 ‘In this model, we are predicting the value of the outcome for a particular entity (i) from its score on the predictor variable (X_i). The predictor variable has a parameter (b_i) attached to it, which tells us something about the relationship between the predictor (X_i) and outcome.’

$$\text{outcome}_i = (b_0 + b_1 X_i) + \text{error}_i \quad (4.4)$$

‘Why is the b_0 still there?’

‘We are building up the model, so the b_0 is a parameter estimate that tells us the overall levels of the outcome if the predictor variable was not in the model, and the b_1 is a parameter estimate that tells us about the relationship between the predictor variable and the outcome.’

‘So we could, like, predict relationship assessment scores from how long the couple had been together?’

$$\text{relationship satisfaction}_i = (b_0 + b_1 \text{length}_i) + \text{error}_i \quad (4.5)$$

*Purr*fectly true. We could see whether your assessment of your relationship depends upon the length of the relationship. If you did that you could replace the outcome (Y) and predictor (X) in the model with the names of these variables. 🧠 4.5 We could even take that a step further and add another predictor variable to the model. 🧠 4.6 Let’s say we measured how much effort the couple put into their relationship. Now we’re predicting the value of the outcome for a particular entity (i) from its score on two predictor variables (X_{1i} and X_{2i}). Each predictor variable has a parameter (b) attached to it, which tells us something about the relationship between that

4.7 predictor and the outcome. Again, to help you to see how this works, we could replace some of the letters with the variable names.’

$$\text{outcome}_i = (b_0 + b_1 X_{1i} + b_2 X_{2i}) + \text{error}_i \quad (4.6)$$

$$\text{relationship satisfaction}_i = (b_0 + b_1 \text{length}_i + b_2 \text{effort}_i) + \text{error}_i \quad (4.7)$$

‘Sweet, you’re summarizing the outcome with other variables that you have measured.’

‘Purrcisely, and the beauty of it is that we could carry on expanding the model with more predictor variables. In each case they will have a parameter that quantifies the connection between that variable and the outcome variable.’

‘I think I understand all of this, but how can a letter like b quantify the phenomenon we’re studying. It’s a letter, letters can’t quantify anything.’

‘Ah, dear human, the letter is just a useful way to represent the parameter in general terms. It helps us to show the form of the model, but we need to replace each letter with a number.’ His eyes bulged with excitement at the mention of numbers.

‘How do we do that?’

‘We use the sample data to estimate the value of the model parameters.’

Estimating seemed a bit wishy-washy, surely we needed something better than an estimate. I must have been screwing my face up because Milton almost read my thoughts.

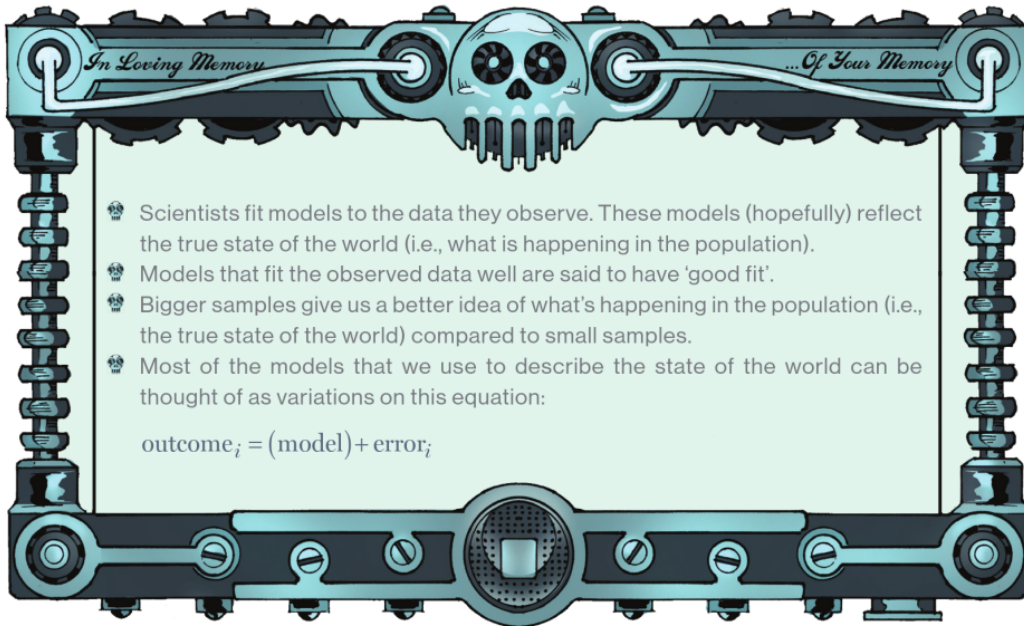
‘Remember that we are interested in drawing conclusions about a population to which we did not have access. In other words, we want to know what our model might look like in the whole population, and to do that we want to know the values of the parameters of that model. The problem is that we cannot calculate the parameters in the population because we did not measure the population, we measured only a sample. What we can do instead is to use the sample data to *estimate* what the population parameters are likely to be. You will hear statisticians use the phrases “estimate the parameter” or “parameter estimates” a lot because it reflects the fact that when we calculate parameters based on sample data they are only estimates (i.e., a “best guess”) of what the true parameter value is in the population. Shall we look at some simple models?’

Every atom in my body wanted to say no. I had survived this long without equations, so why would I want to have more of them now? I also thought that there surely had to be an easier way to find out where Alice was and to talk to her. That’s all I needed, just to talk to her, and to find out what was going on. However, I had a feeling Milton had other plans, and for now at least, I perhaps needed to go along with him.

4.2 CENTRAL TENDENCY

As I suspected he would, Milton ploughed on. ‘After I walked into Catherine’s office, you discussed with her a score that reflected Alice’s satisfaction with your relationship: the Relationship Assessment Scale (RAS). I noticed when you showed me the information you had from Alice’s file that she completed this measure not just once, but many times.’

He was right. I had shown the Professor only Alice’s score in the first week of her counselling sessions.



Zach's Facts 4.1 Fitting models

'You have done well to listen to my explanations, but I am certain that you are wondering how this helps you to resolve your little problem. Let us use Alice's ratings to try to see whether we believe the hypothesis about her absence reflecting an over-elaborate exit strategy from her relationship with you.'

Now we were getting somewhere. I leaned in to listen closely to what the cat had to say. I got out my diePad and we noted Alice's RAS scores over a 10-week block of her counselling sessions: 🦋

FIGURE 4.3

32, 30, 28, 30, 30, 29, 31, 29, 31, 11

Milton looked surprised. 'The score of 11 on the last week is really low.' I looked surprised back at him and he explained. 'Most weeks Alice rated your relationship quite highly – close to the top of the scale – but then in the week before her disappearance, last week, it fell to close to the bottom of the scale. Remember that the lowest score on this scale is 7 🦋, so she rated your relationship about as low as it was possible to rate it, whereas the previous 9 weeks she rated it close to the top. A score that is very different from others is called an **outlier**, and if we have one or more of these it can affect the models that we fit. This is one reason why it is important to look at frequency distributions of your data, which Catherine explained to you, because they can show up unusual scores.'

SECTION 2.3

'Should we ignore it if it is unusual?'

'Well, it is true that it can affect our model in bad ways – I can show you some examples in a moment – so for the sake of the model sometimes we try to reduce the impact of these outliers. However, often these scores are telling us something interesting. For example, isn't it interesting

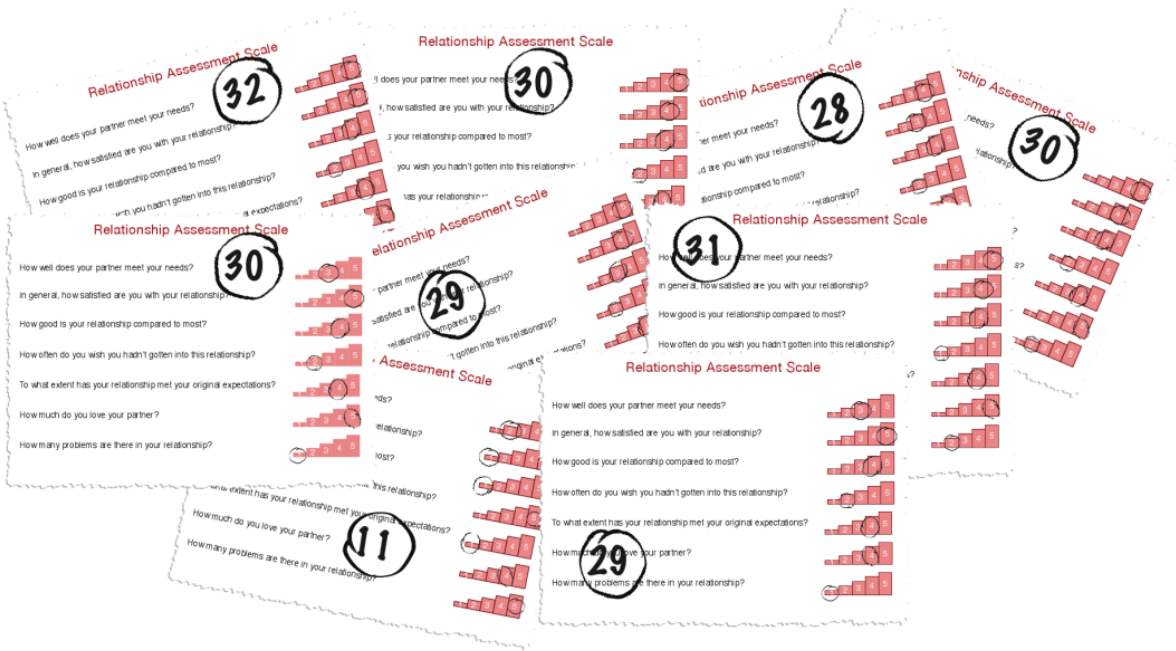


Figure 4.3 Alice's RAS scores over 10 weeks

that the week before Alice disappears, her relationship rating is low? She was not happy with you and then she vanishes. Read into that what you will.'

I didn't like the knowing look that Milton was giving me, but his argument made sense. The pain in my face must have been obvious because his tone softened.

'Let us not jump to conclusions before we have looked at some simple statistical models.'

He said it as though this were some treat that would cheer me up. It wasn't.

'The simplest model we can fit to these data is one that tries to summarize them in terms of a single parameter. A popular choice would be a parameter that measures **central tendency**: a value that indicates the central point of a distribution of scores. A "typical" score, you might say. If we have data from the entire population we could compute this value directly, but if we have only a sample then we can estimate the population value from the sample data.'

4.2.1 The mode

'Perhaps the simplest way to quantify the centre of a distribution is to use the score that occurs most frequently, which is called the **mode**,' Milton continued. 'This value is easy to spot in a histogram because it will be the tallest bar, and in a tabulated frequency distribution it will be the score with the largest frequency. To take your mind off of Alice, draw the frequency distribution of her RAS scores and tell me which score has the biggest frequency.'



CHECK YOUR BRAIN: Create a frequency distribution of Alice's RAS scores.

I quickly drew up the table; it didn't take my mind off of Alice. The value of 30 had a frequency of 3, which was greater than any other value. I gave this answer to Milton.

TABLE 4.1

'Clarect, 30 is the mode of these scores. The mode is useful because it represents the most popular response, and unlike other measures it will always be a value that actually occurred in the data. It does have a downside though, which is that it can often take on several values. Had Alice given another score of 29 then both 29 and 30 would have had a frequency of 3; there would be two modes.' Milton started playing with my diePad, twisting and turning its cogs with his paws until the screen displayed an image. This image shows an example of a distribution with two modes (there are two bars that are the highest), which is said to be **bimodal**, and three modes (data sets with more than two modes are **multimodal**). Another problem is that if the frequencies of certain scores are very similar, then the mode can be influenced by only a small number of cases.'

FIGURE 4.4

I was curious about whether this mode had been affected by Alice's unusual score: the low score of 11, which the cat had pointed out. He suggested that I calculate the mode without that score and when I did I found that the mode was still 30: that unusual score had not had an impact.

Table 4.1 Frequency distribution of Alice's RAS scores over 10 weeks (excluding categories with zero frequencies)

RAS score (X)	Frequency (f)
32	1
31	2
30	3
29	2
28	1
11	1
$N = \sum f = 10$	

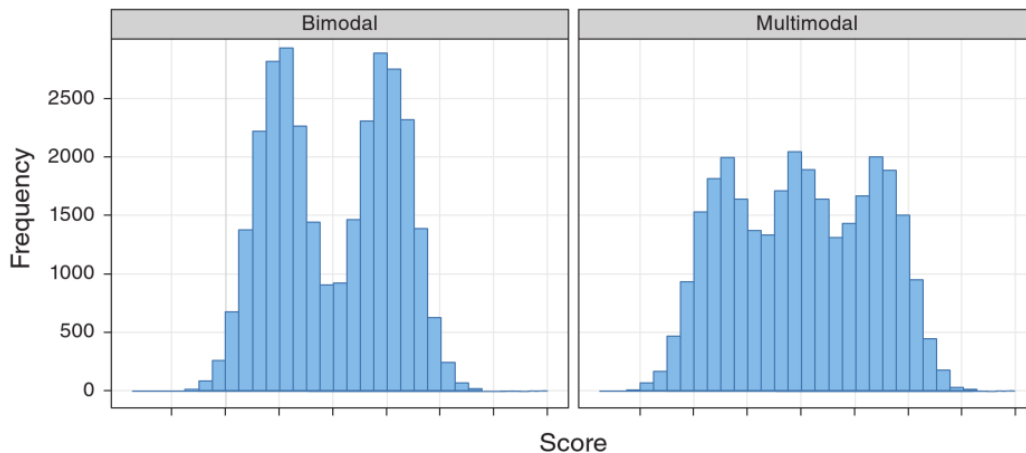


Figure 4.4 Examples of bimodal (left) and multimodal (right) distributions

In a similar vein, if you change the data by a fixed value, then the mean changes by that value too. For example, if you add 10 to every score then the mean of the new scores will be the mean of the old scores plus 10, similarly it would be 10 less if you subtract 10 from every score; if you multiple all of the scores by a value (e.g., 10) then the new mean will be the old mean times that value, and if you divide scores by a constant (e.g., 10) then the new mean will be the old mean divided by the constant (Figure 4.8).

Best fishes,
Milton

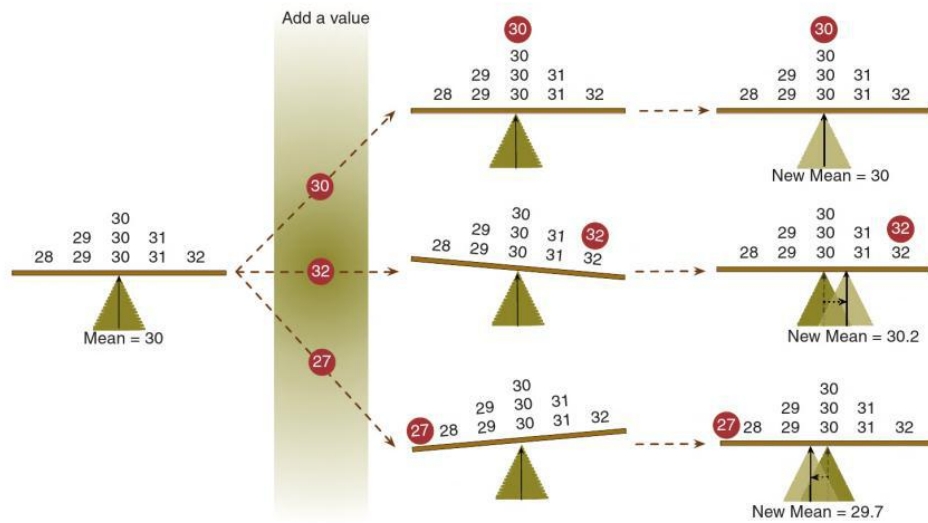


Figure 4.7 The mean is the balancing point of a distribution

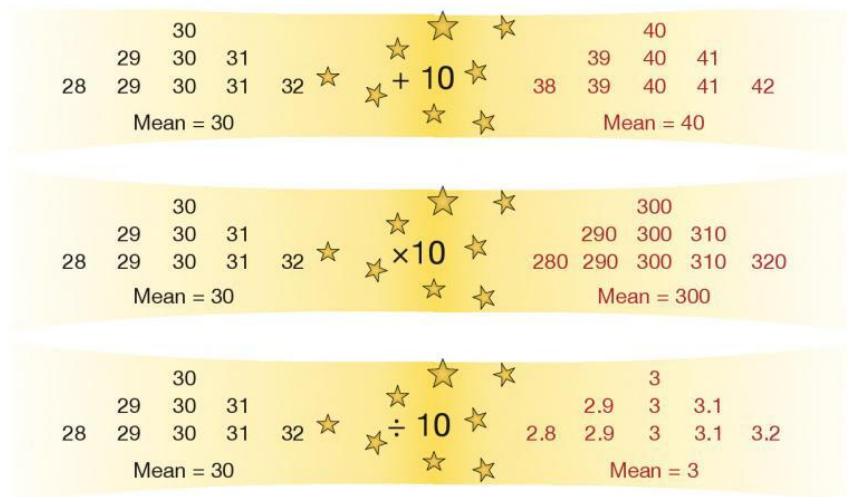


Figure 4.8 The effect on the mean of changing scores by a constant value

Milton's Meowings 4.1 Things that affect the mean

Milton asked me what I noticed about the mean if we exclude the outlier. I looked at the image he had created. 🐣 It seemed to me that without the outlier, the mean split the data exactly in two: the distribution was symmetrical about the mean. I said this to Milton.

FIGURE 4.9

‘Purr-cisely. The mean divides the data in two, which makes it a reasonable summary of the data as a whole, but if we include the outlier, the mean decreases. What do you notice about this new mean in relation to the scores?’

‘It’s like I said earlier: the only scores that aren’t above the mean are 11 and 28: the other eight scores are above the mean.’

‘Very good. The outlier has made the mean less representative of the data.’

‘Why was the mean affected by the outlier, but the median and mode weren’t?’

‘Another good question,’ he replied in a slightly patronizing tone. ‘It is because the mean, median and mode measure the “typical” score in different ways. The mean defines it in terms of distance from the centre, so a score a long way from the centre can throw the mean off. The median measures it as the score at the centre, and the mode measures it as the most frequent score. The median aims to split the data into two equal halves, but the mean does not try to do this, which is why you can end up in a situation in which two scores fall below the mean and eight above it 🐣 – that would not happen with the median because it is based on splitting the data into equal halves. The median balances the data so that half of the scores are above it and half below: the distance of each score from the centre is not considered; only whether it is above or below the centre.’

FIGURE 4.9

‘So the median is better than the mean?’

‘Not necessarily. The mean has many useful features. It uses every score in the data, and so is representative. But most important is that it tends to be quite stable across samples; that is, if you took several samples and measured the same thing in them, you would find that the mean ought to be relatively similar in the different samples – this is less true of the median.’

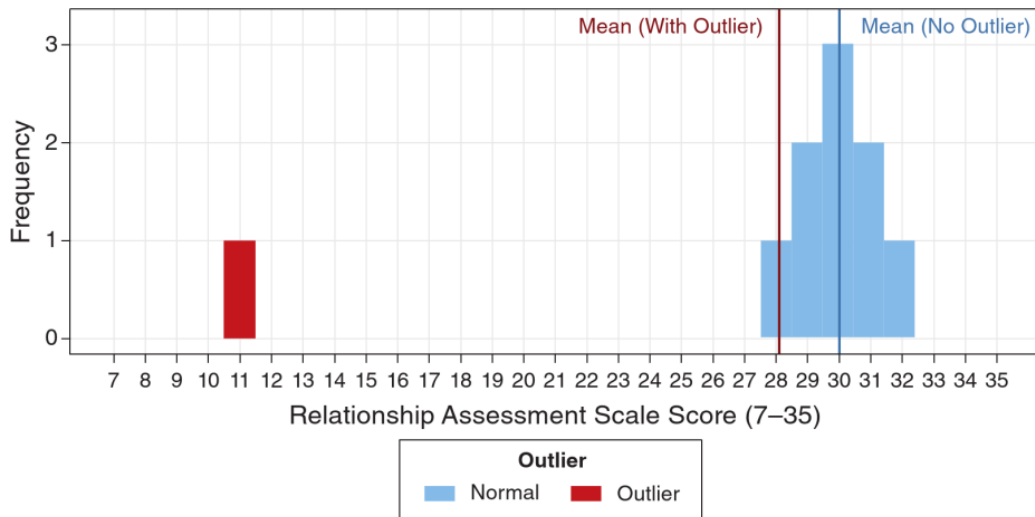


Figure 4.9 Outliers can affect the mean

‘– add up what comes after, and what comes after is the deviances, so it means add up all of the deviances,’ I interrupted.


Milton looked impressed. He had a much more expressive face than the average cat, which I guessed was because it was being controlled by a human mind. ‘Let us see what happens when we calculate the deviances for Alice’s RAS scores. We will ignore her final score of 11 for now.’ Milton sat on my diePad again and wriggled around a bit, before stepping off to reveal an image.  I didn’t even want to think about how he did that. ‘This diagram shows Alice’s RAS scores over the nine weeks, and also her mean RAS score that we calculated earlier on. The line representing the mean is our “model”, and the circles are Alice’s observed scores. The vertical lines that connect each observed value to the mean value are the errors or deviances of the model for each observed score. The first week, Alice’s score was 32, but the model predicts a score of 30 so the error for week 1 is 2. This error is a positive number, and represents the fact that our model *underestimates* Alice’s actual score. For week 2, the model predicts 30 (again) and the observed score is 30 which means that the error is 0. For week 3, Alice scored 28 but the model predicts a score of 30, so the error is –2; the negative number tells us that our model *overestimates* Alice’s actual score. You can see the errors for the other weeks on the diagram.’

FIGURE 4.10 

‘Yeah, you can see how the model sits in the middle of the data, so sometimes it overestimates and sometimes it underestimates the actual scores.’

‘Yes, so what do you think might happen when we add up these errors, or deviances, as you suggest?’

‘It tells us the total error?’

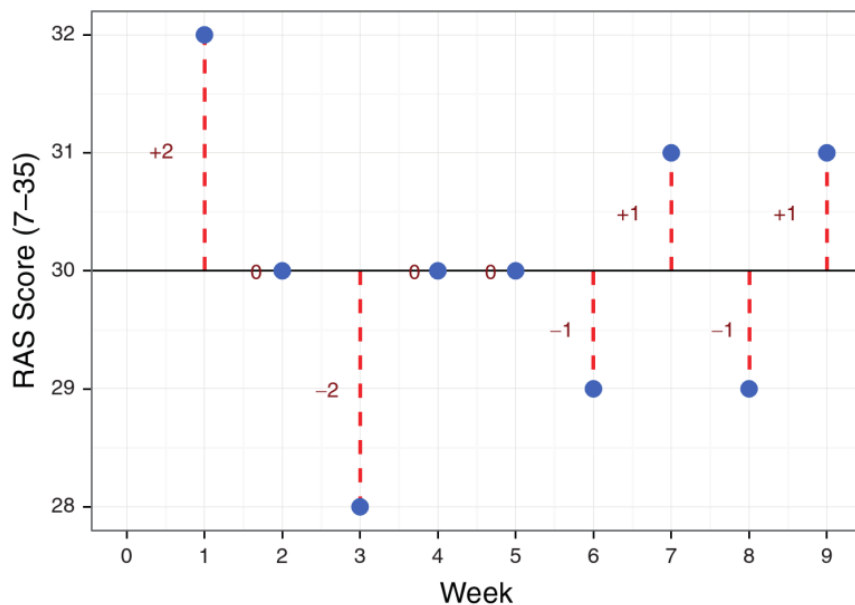


Figure 4.10 Graph showing the difference between Alice’s observed RAS scores each week, and the mean RAS score

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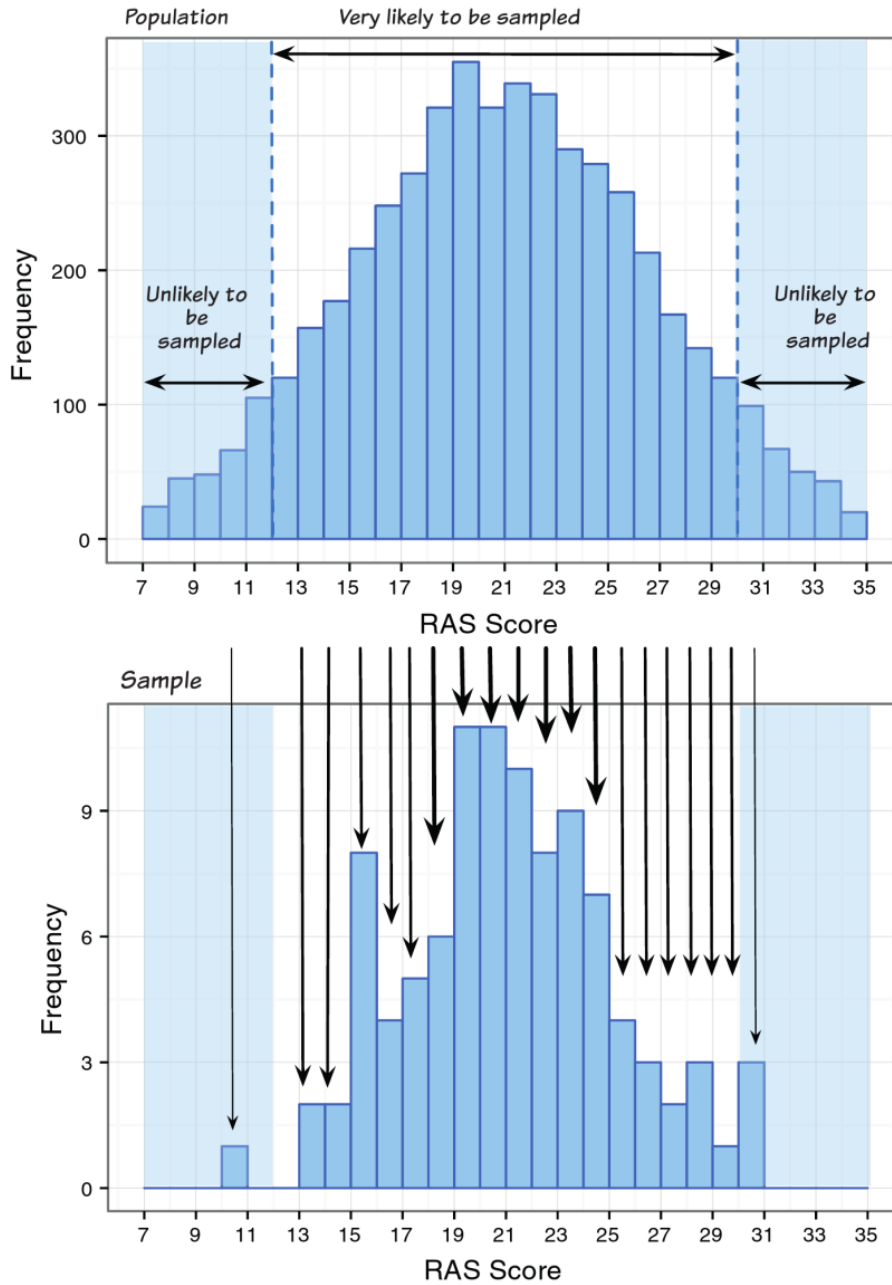


Figure 4.11 Why do samples underestimate the population variance?

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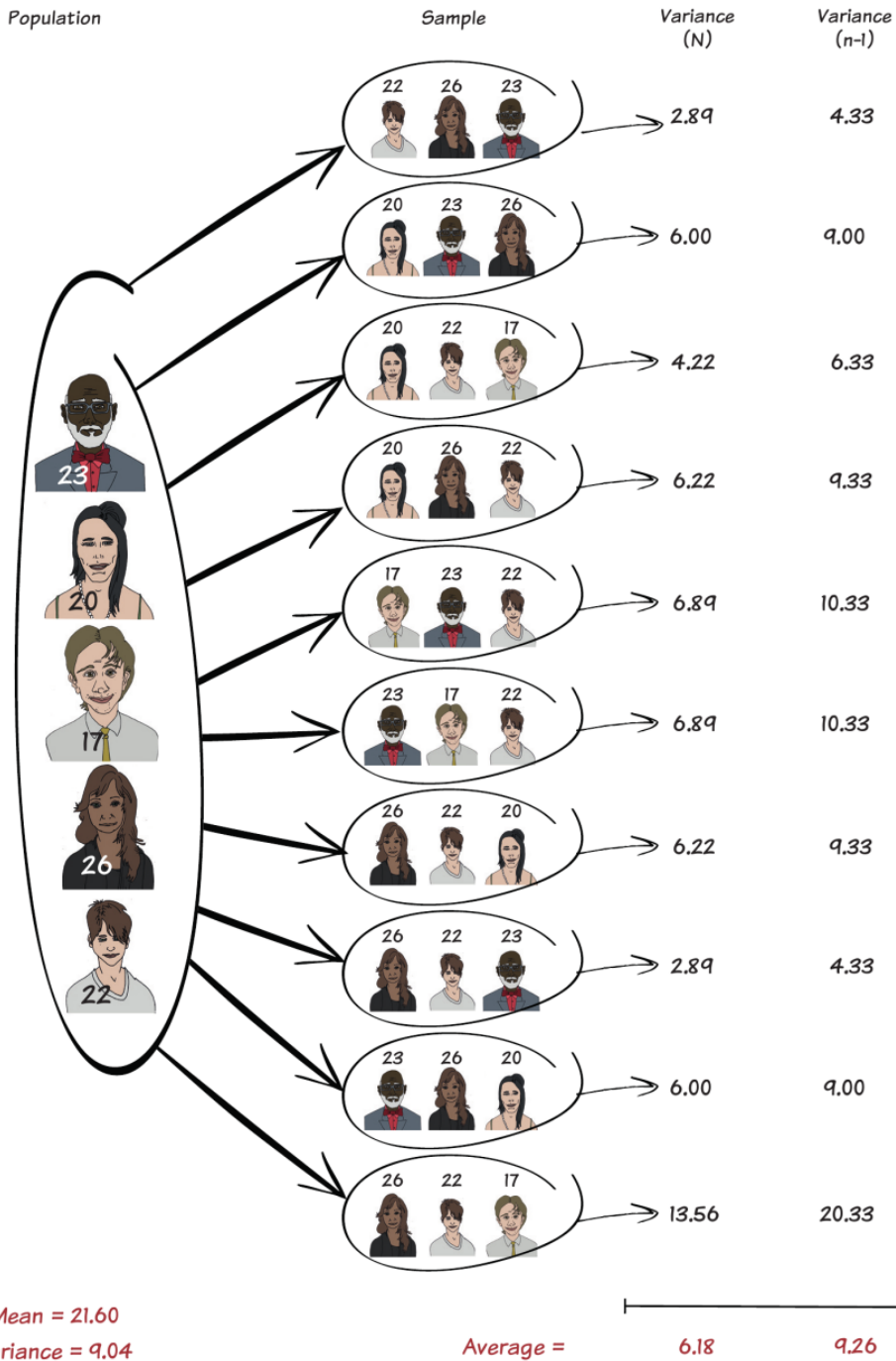


Figure 4.12 Why we use $n - 1$ when estimating the population variance

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- 6 Would you say that the mean in puzzle 5 'fits' the data well? Explain your answer.
- 7 While Zach was worrying about whether Alice had left him, he ruminated about how successful couples often seem to divorce. Alice is a brilliant scientist and he a brilliant musician, so perhaps their relationship is doomed. To see if his observation might be true he got The Head to check the (approximate) length in days of some celebrity marriages from before the revolution: 240 (J-Lo and Cris Judd), 144 (Charlie Sheen and Donna Peele), 143 (Pamela Anderson and Kid Rock), 72 (Kim Kardashian, if you can call her a celebrity, and Chris Humphries), 30 (Drew Barrymore and Jeremy Thomas), 26 (Axl Rose and Erin Everly), 2 (Britney Spears and Jason Alexander), 150 (Drew Barrymore again, but this time with Tom Green), 14 (Eddie Murphy and Tracy Edmonds), 150 (Renee Zellweger and Kenny Chesney), 1657 (Jennifer Aniston and Brad Pitt). Compute the mean, median, standard deviation, range and interquartile range for these lengths of celebrity marriages.
- 8 Repeat puzzle 7 but excluding Jennifer Aniston and Brad Pitt's marriage. How does this affect the mean, median, range, interquartile range and standard deviation? What do the differences in values between puzzles 7 and 8 tell us about the influence of unusual scores on these measures?
- 9 Zach asked Nick to get 15 of their fans on *memoryBank* to rate his new song, 'The Gene Mixer', on a scale ranging from 0 (the worst thing you've ever recorded) to 10 (the best thing you've ever recorded). The ratings were: 3, 5, 7, 8, 2, 4, 10, 8, 8, 5, 5, 7, 9, 10, 6. Calculate the mean, standard deviation, median, range and interquartile range for these ratings of the song.
- 10 Is the mean in puzzle 9 a good 'fit' to the data? Explain your answer.

IN THE NEXT CHAPTER ZACH DISCOVERS ...

The cost of striving for perfection

Types of graphs

How to present data

How to avoid chartjunk

Never to show a pie chart to a man who has attacked you with bulldog clips

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