Research Article

Simplifying Academic Knowledge: Why and How

Michael Wood[1]

1. University of Portsmouth, United Kingdom

Academic knowledge is often difficult, or time-consuming, to understand. AI and other computer technologies have an important role in helping people use academic knowledge: for example, they facilitate just-in-time learning and enable computer-intensive approaches like simulation. But if the knowledge itself could be simplified, or made more user-friendly, so that it is easier to learn, understand, and use, without sacrificing its power and usefulness, this would be of enormous help to many stakeholders. Experts and researchers could reach the frontiers of their discipline quicker and have more time to advance the frontiers of knowledge. Polymaths could draw on a wider and deeper range of expertise. Students would need less time to study or could take their studies further. And society might be richer and wiser. Sometimes simplification may not be possible, but often it is, although in most corners of academia, searching for simpler versions of established ideas is right off the agenda. I distinguish three approaches to simplifying knowledge: conceptual re-engineering, changing jargon and symbolism, and the judicious use of "black boxes" to hide some aspects of the knowledge. User-friendliness is rarely taken seriously as a criterion for judging academic knowledge: I argue that it should be.

Corresponding author: Michael Wood, michael.wood@port.ac.uk

1. Introduction

It is a well-worn platitude that life is getting more complicated. In the academic world, this is reflected in the increasing amount and complexity of the knowledge that academics discover or create, and pass on by teaching, books, articles, and other media. This places obvious constraints on what we can achieve, both in academic work and in day-to-day life. The access of lay people to knowledge on, for example, medicine, is limited by the time and background expertise necessary to understand the latest ideas.

 doi.org/10.32388/RHTT8D.3

Experts only have a limited amount of time to master their discipline, which in practice may mean that they only have time to master one narrow specialism, but probably not aspects of other fields of study relevant to their work. And polymaths, like Leonardo da Vinci, are no longer really possible if each sphere of expertise takes decades to acquire.

There are several obvious approaches to this problem: improving learning and educational methods, using technology to enhance the effectiveness of human thought processes via computer technology (including AI, which I discuss below) or smart drugs, increasing the time devoted to education, and, in the long term, more extreme possibilities like genetic engineering, to make us, or our successors, more capable of understanding and making use of increasingly complicated domains of knowledge.

In this article, I want to explore the possibility of tackling the problem from the other end by simplifying knowledge itself.

The word possibility is important. I am not arguing that simplification is always possible, but just that it is sometimes, perhaps often, possible, and it has large potential benefits. Throughout my university teaching and research career, I often felt that it ought to be possible to create a simpler and better version of knowledge that I was teaching and using – there are references to some of these ideas in Section 6 below.

I had difficulty formulating an appropriate title for this article. The word "simple" provides a convenient slogan, but the idea is not a simple one. People typically interact with academic knowledge by learning about it; they may have a deep, or a shallow, or a mistaken, understanding of it; and then they may make use of it, or simply enjoy it, in a variety of ways across a narrow or wide domain. The word "simple" is relevant to all these aspects. It may or may not be simple to learn and understand and use; misunderstandings may or may not be likely. It is important that the simplicity of a piece of knowledge should be judged against the background of its usefulness, the domain in which it can be applied, and the background knowledge of the users in question.

In many ways, the phrase "user friendliness" gives a more accurate picture of what I have in mind because this implicitly takes account of the "user". Matrix algebra may be "friendly" from the perspective of a mathematician, but not from the perspective of most other people. But the phrase "user-friendly" is usually used in relation to software and users with a relatively low level of expertise, whereas the term "simple" is a word that makes sense in relation to beginners, and it is widely espoused as a goal in science: even Einstein is said to have recommended keeping things as simple as possible (but not simpler). Earlier phrases I wondered about were "empower the ignorant" and "empower the masses".

doi.org/10.32388/RHTT8D.3

These are both consistent with what I have in mind but suggest that the market for the idea is limited to the ignorant, the lazy and the stupid, which is not at all what I intend. Geniuses should also be able to expand their reach further. I will stick with the word "simple", but please bear in mind that my interpretation of this word is not simple.

There are many books and articles giving simplified versions of scientific ideas for non-experts. Popular science is a thriving genre. However, in general, these are not equivalent to the original science in terms of the ability to make predictions and understand the rationale behind the science. What I am interested in here are simplifications which have at least the same power as the original. A popular science account of quantum mechanics will give the reader a rough idea, but will be far short of the ability to make detailed predictions.

Despite searching on Google and Google Scholar and asking ChatGPT, I found very little on the general idea of simplifying academic knowledge. There were articles on, for example, simplifying knowledge bases for computer systems, and simplifying text to make it easier to understand, but nothing on the general problem of simplifying academic knowledge. This did not seem to be on anyone's agenda. I think it should be.

In an earlier paper [1] I focused on the idea of simplifying knowledge from the educational perspective, and the barriers to the idea that are likely to be imposed by educational systems. In the present article, I want to extend this argument and take a more general perspective.

2. Knowledge and its propagation

What do I mean by knowledge? To some philosophers, knowledge is "justified true belief", but this is too narrow for my purposes here. Knowledge may concern, for example, how to do something, in which case the criterion of truth may not apply. And I will include hypotheses, theories and models which might not be considered "truths". I am concerned with *academic* knowledge, which I will define as knowledge of the kind that is learned, taught, discovered, or invented in the academy (colleges and universities and similar institutions). In general, this knowledge is, in some sense, difficult: otherwise, we would not need special institutions to deal with it. The context in which it is actually learned, taught, discovered or invented is irrelevant. Such knowledge may be communicated by teaching, textbooks, research papers, practical examples, YouTube videos, etc. The recipient may be a student, a fellow researcher or any other interested party, whether in an academic institution or not. The only restriction is that the recipient should be human: communicating with monkeys or computers is a different ball game which is not my concern

doi.org/10.32388/RHTT8D.3

here. Knowledge is not the act of communication, or what's in the knower's head, but the content that is communicated, or, more precisely, that is intended to be communicated: as we all know, sometimes people misunderstand some academic knowledge, and sometimes they forget essential points. So, the content of textbooks, academic papers etc. is the knowledge. Tacit knowledge – ideas which are not made explicit but may be essential to a full understanding – could be included if this is part of the intention behind, for example, videos and practical examples.

For the purpose of this article, I am excluding knowledge held in, or implicit in, computer systems. Statistical computer packages, and large language models (LLMs) like ChatGPT, obviously incorporate a lot of knowledge in some sense, but if there is no intention to communicate this directly to humans, it does not count as knowledge in the sense of this article. Knowledge in books and articles, of course, does count because these are designed to be read by humans. (There is, of course, a strong argument that the knowledge in LLMs should be made simpler for humans to understand, but this is not my concern in this article.)

There are various words connected with knowledge whose appropriateness depends on the context and type of knowledge we are considering. By what criteria should it be evaluated: truth, correctness, beauty, usefulness, resistance to misinterpretation? Does it have an audience or users? There are obviously many types of knowledge, and the terminology appropriate to one type may not be appropriate for other types.

It is helpful to divide—in rough terms—the development and propagation of knowledge into three stages. The first stage is the initial invention, or discovery, of new ideas—which I will call the leading edge. In due course, these new ideas are passed on to other workers in the discipline and taught to students of the discipline. This is the stage at which the standard ideas of the field are absorbed from textbooks, teaching or by some other means. I will use the phrase textbook stage as a convenient label, although textbooks may not be involved in practice. A few people at the textbook stage will go on, after a suitable apprenticeship, to make new innovations at the leading edge. Finally, aspects of the expertise may be picked up, possibly in a distorted or popularised form, by the general public: I will call this third stage the *common sense stage*. What is the relevance of simplicity to these three stages?

It seems likely that thinkers at the leading edge of their field will strive for simplicity. If the problem is difficult, finding a simple way to look at it may be the only way forward. Some examples of this are discussed below. There is also an assumption, often implicit, among some pioneers in disciplines such as physics that simple laws are more likely to be true than complicated ones. For example, the Nobel prize winner Roger Penrose, in his Complete guide to the laws of the universe [2] observes that "Maxwell's theory had gained in strength" not only because of empirical support but also because it is "subsumed into a mathematical scheme of remarkable elegance and essential simplicity".

However, there may be exceptions to this striving for simplicity. If the problem is not difficult, making ideas simple may run the risk of making the pioneers appear rather ordinary. Making ideas difficult may be a way of keeping outsiders out, keeping the club exclusive and ensuring the necessity of teachers and teaching institutions [3]. It is tempting to formulate a law of simplicity at the leading edge of a discipline:

> If the problem is hard, it may be helpful to find a perspective which makes it easier, but if the problem is easy there may be an incentive to make it look hard.

My main concern in this article is with the textbook stage. Becoming an expert means becoming familiar with the jargon, notation, conventions and key ideas of the discipline. But there are, I will argue below, often unrecognised opportunities to simplify knowledge at this stage.

Finally, some of this expertise may filter through to the common sense level, where it may be absorbed without formal education. This is obviously more likely if the knowledge is simple, but there is a danger that some knowledge may be absorbed in a distorted form—I will return to this problem in Section 8 below.

In practice, these three stages may be more confused than this summary might imply. There are often several leading edges if the pioneers disagree about the best way forward. And at the textbook stage, the trainee experts may have different backgrounds, motives and technology from the original pioneers and from other trainee experts, so they may learn different versions of the knowledge.

It is also important to note that simpler versions may answer a slightly different, possibly more relevant, question. There is an example of this in Section 6.1 on statistics below. On a more radical level, changes to the core concepts of a discipline—Thomas Kuhn's "scientific revolutions" [4] – often result in a simpler "paradigm". There are some examples of this at the beginning of the next section.

2.1. Some examples of how knowledge has been simplified in the past

One of the clearest historical examples of simplification is the adoption of the modern system of numerals in place of earlier systems such as the Roman one: e.g., 2025 instead of MMXXV. The modern system obviously makes arithmetic far easier and caters for arbitrarily large numbers (with the Roman system, you need to invent more and more symbols as the numbers get larger). As well as being simpler, the modern notation is also far more powerful in terms of what you can do with it.

Similarly, Copernicus's idea that the planets revolve around the sun was far simpler and made it far easier to understand the motions of the planets than systems like the Ptolemaic model [5], which necessitated an intricate system of wheels within wheels. In both cases, the newer framework has reached the common sense level, so it is easy for modern readers to appreciate how much more complicated the older frameworks were.

This is not the case with many other areas of science. Take Newton's law of motion: F=ma. To those without the appropriate expertise to understand what the symbols stand for, this may not seem remotely simple. However, to those with the necessary expertise who appreciate the power and scope of this equation, its simplicity is staggering. Together with a few other laws from the same stable, it can be used to predict how stones move if thrown, how the planets move around the sun, how much energy you need to ride a bike, and so on. Before Newton, there was no general framework for making predictions like these; it would have been necessary to use different rules of thumb in each scenario. It is in this sense that this equation, and others like it, are simple. However, many people do not have the necessary background to appreciate the simplicity of this equation, which raises the question: could this expertise be made even simpler? I think the scope here is limited, but it might be helpful to write the equation in Modified Excel format as suggested in Section 6.2 below.

Much of the point of mathematics, of course, is to produce simple models of complex real-world phenomena, but this is sometimes at the expense of leaving out some aspects of the real world—such as air resistance when predicting the flight path of a projectile—so the model may only be an approximation. In addition, this simplicity is only useful if the models can be understood by potential users.

In the late 1940s and 1950s, so-called Feynman diagrams were introduced

> “as a bookkeeping device for simplifying lengthy calculations in one area of physics—quantum electrodynamics, or QED, the quantum-mechanical description of electromagnetic forces.... With the diagrams’ aid, entire new calculational vistas opened for physicists. Theorists learned to calculate things that many had barely dreamed possible before World War II ... By using the diagrams to organize the calculational problem, Feynman had thus solved a long-standing puzzle that had stymied the world’s best theoretical physicists for years.” [6]

doi.org/10.32388/RHTT8D.3

This is an example where I, and I suspect most readers of this article, do not have the necessary background knowledge to appreciate either the problem or its solution. But it is an example of the value of simplicity at the leading edge of research. Kaiser goes on to say that Schwinger, who invented an alternative to Feynman diagrams, "sniffed that Feynman diagrams had 'brought computation to the masses.'" The diagrams, he insisted, were "pedagogy, not physics". Which, of course, fails to take account of the fact that physics is of little use if nobody can understand it. Bringing computation to the masses sounds like a good thing to me.

Computer software development is another interesting area where simplification is very much part of the goal. This has progressed from machine code, which involves telling the computer exactly what to do in strings of 0s and 1s, to tools like *App Inventor* [7] which has simplified the process of writing apps (programmes) for Android phones to such an extent that their claim that "anyone can build apps with global impact" is almost reasonable (although "anyone" is perhaps too strong).

These are a few examples of how knowledge has been simplified in the past. The important question, of course, is how present-day academic knowledge might be simplified. This sort of expertise often seems set in stone, unchangeable, but this attitude deserves to be challenged. I will discuss some possibilities below, but first I will discuss the general rationale for simplifying knowledge, the approaches that might be taken, and consider the obvious objection that AI removes the need for simplifying knowledge: if something is too complicated, can't we just ask an AI for help?

3. Why simplify academic knowledge?

There must be a limit to the amount of knowledge that any individual can cope with, or at least a point beyond which it becomes increasingly difficult. This may be because of the number of neurons in our brains or, more likely, the time we have to absorb new information or the effectiveness of the filing system for retrieving stored ideas and memories. As the amount and complexity of academic knowledge increase, this limit will inevitably impose restrictions on what we can achieve. So simplifying knowledge so that it takes less bandwidth means that, in principle, we can progress further.

In science, as the examples in the previous section illustrate, simplicity is a key criterion for evaluating, and so creating and choosing, theories. Theories that are too complicated are less useful. As an extreme example of this problem, Khamsi [8] quotes Keith Devlin: "I think that we're now inescapably in an age where the large statements of mathematics are so complex that we may never know for sure whether they're true or false." Obviously, it would help if these statements could be made simpler.

Simplicity is also an important criterion in the design of technological artefacts, and academic knowledge can be regarded as such an artefact. In his TED talk, Whitesides [9] makes the point that there is almost no drive for simplicity in the academic world, whereas in "the real world of people who make things... there is an intellectual merit to asking: How do we make things as simple as we can, as cheap as we can, as functional as we can and as freely interconnectable as we can?" He also uses the word "stackable" - electronic components are simple in the sense that they are sufficiently reliable and predictable to be assembled into devices like mobile phones, and blocks of stone can be stacked to build a cathedral. If we think of academic concepts and theories as "things", I would say there is enormous merit in asking just the same questions of academic creations.

If we take an evolutionary perspective on knowledge in general, the main criterion that new ideas have to satisfy is that they should be useful, either in the biological sense of enhancing the capacity of the organism to survive and breed or in the cultural sense of their usefulness to individuals and groups - and knowledge is likely to be more useful if it is simple (other things being equal). Unfortunately, incremental evolution may increase complexity [10], which suggests the idea that intelligent design for simplicity might be beneficial. And, of course, simplification is a natural and necessary part of the way human beings make sense of the world. Concepts like "animal" and "rock" enable us to manage our environment without plunging into all the overwhelming complexity of the different types of animals and rocks - unless, of course, circumstances demand more precise categories.

In a sense, this is a continuation of a trend that has been going on for at least the last 3000 years. In this period, human brain size has been decreasing which, according to DeSilva et al [11], may be the result of "the externalization of knowledge and advantages of group-level decision-making due in part to the advent of social systems of distributed cognition and the storage and sharing of information." According to this hypothesis, now that we have computers, books and large communities of other people to help us, we no longer need to think as hard and can make do with smaller brains.

Or, of course, we can do more with the brains we have. Just what this might lead to in the future is, of course, an open question. Stephen Wolfram [12], in an article entitled "What If We Had Bigger Brains? Imagining Minds beyond Ours", concludes in a rather feeble final sentence, "And it'll take progress in our whole human intellectual edifice to be able to fully appreciate what it is that minds beyond ours can do."

4. Don’t AI and other computer technologies solve the problem?

There has recently been a lot of publicity following the release of various “large language models” (LLMs), which are the latest result of the long-running search for artificial general intelligence (AGI). These models can interact with the user in natural language and provide help with, or undertake, a wide range of problems and tasks. If the user does not understand something, or wants some help writing something, they can ask the “chatbot” to explain or help with the task, just like a patient teacher. The present generation of chatbots does sometimes get things wrong (these errors are dubbed “hallucinations”), but in time they are likely to get more reliable.

Doesn’t this solve the complicated knowledge problem?

To some extent, yes. Digital technologies, from calculators onwards, are designed to do tasks which would otherwise require some human input, and so lessen the burden of dealing with our increasingly complicated web of knowledge. Statistical computer packages perform statistical calculations and relieve users of the burden of working through detailed algorithms. Word processors format documents and offer tips on grammar and spelling. Google Search will find information about many things far more easily than was possible a few years ago. The present AI tools have taken this process further. Technology must always have had an impact on what is worth knowing and how knowledge can be simplified. Calculators and computers have reduced the need for human beings to understand the detail of arithmetical and statistical algorithms, and going back a few years, the invention of writing must have influenced the nature of communities' knowledge, as must the introduction of printing presses.

But none of these tools simplifies the underlying knowledge. The calculator or the statistical computer package will do the sums, but the human being in charge still needs to understand something about the process and what the answers mean. The AI may take the user through a complicated argument, but the human user still needs to understand the answer and follow the argument in some sense to establish its credibility and relate it to other things. Clearly, the simpler the knowledge is, the easier these processes are likely to be.

But... there are a few qualifications to the above paragraph. First, it may be possible to take the requirement of human understanding out of the process or part of it – some of these possibilities are explored in Sections 4.3 and 5.3 below. And second, an AI may be able to come up with genuinely creative ideas which do simplify the knowledge, as opposed to explaining it in simple terms. In principle, it seems

doi.org/10.32388/RHTT8D.3

unlikely that the current crop of LLMs would be able to do this because they are based on the analysis of vast quantities of text which, by definition, encode existing ideas, not innovative new ones. But LLMs are notorious for defying expectations.

The next three subsections outline ways in which computer technologies may avoid the need for simplification. Then I will turn to approaches to simplifying knowledge.

4.1. Just-in-time learning

I asked an LLM (ChatGPT), "Can AI be used to make knowledge simpler?" and the response was:

AI can **simplify complex knowledge** by:

- **Summarising** dense information (like research papers) into key points.
- **Explaining** difficult ideas in plain language, like how a good teacher would.
- **Using analogies and examples** tailored to who's asking, making ideas easier to grasp.
- **Creating visual aids** like diagrams or simple charts that explain complicated systems.
- **Answering questions interactively**, so people can learn step-by-step at their own pace.

Kind of like having a personal tutor who can explain quantum physics with pizza slices if you want.

This is not really simplifying knowledge, but rather making it easier to learn things when you want them. The fact that the LLM can speed up the process of learning just about anything means that it may not be necessary to learn, and probably forget, lots of things *just-in-case* (JIC) they are needed because it is practicable to learn them if and when they are needed. This is *just-in-time* (JIT) learning, which is similar in principle to just-in-time manufacturing, the system whereby components arrive as they are needed, thus avoiding the need to carry extensive stocks.

Defibrillators, or, strictly, automated external defibrillators (AEDs), are another example of this principle. They are for treating cardiac arrests, and they are designed to be used by people without training: the device speaks to the person operating it and tells them what to do. This person is thus told what they need to know when they need to know it.

The trade-off between learning well in advance *just-in-case* the knowledge is needed, and learning *just-in-time* when needed, always was an important consideration. Just-in-time learning avoids the problems of forgetting, of learning lots of things that are never needed and perhaps failing to learn things that do turn out to be necessary. On the other hand, the just-in-time approach may lead to a shallower understanding and may simply not be possible. However, with the expanding amount of human

doi.org/10.32388/RHTT8D.3

knowledge and smarter tools to implement it, the balance seems likely to swing increasingly in favour of the just-in-time approach.

4.2. Simulation and trial and error

What proportion of three-child families comprises three girls? For readers familiar with probability theory, the answer is obviously one in eight (1/8 or 12.5%). But if you are not familiar with probability theory, you could *simulate* the situation by tossing three coins lots of times and checking how many times you get three heads (letting a head represent a girl): the answer will be about one in eight.

Now imagine you know how to multiply but not divide and you want to know what you need to multiply 6 by to get 42. Not knowing about division, you might start by guessing the answer is 5 and work out 5 times 6 and get 30. Obviously too small, so try, say, 8. Too big. With luck, you will eventually home in on 7.

These are elementary examples of tricks mathematicians and statisticians use when the problem is too difficult to come up with a neat formula – which does actually happen a lot. From the perspective of someone without the necessary mathematical background, these methods have two big advantages. First, they get the answer without using any extra technical concepts. Second, they are generally more transparent because you can see how they work.

I have called methods like these *crunchy methods* because you crunch through problems without using clever mathematical trickery [13]. In practice, computers are a must for implementing methods like these. Simulation, for example, is widely used in weather forecasting, in statistics [14][15], and in many other domains.

4.3. Complete automation

Some problems, which would previously have required human input, can now be dealt with entirely by AI and other computer systems. These are the “holes” in human knowledge which are discussed in Section 5.3 below.

5. How to simplify knowledge

When I asked ChatGPT, “How can knowledge be simplified?” the response started, “Knowledge can be simplified by transforming complex information into clearer, more accessible forms without losing its essential meaning. This often involves the following strategies”, the first one being the “Use of Analogies and Metaphors”. These points are largely concerned with pedagogy, rather than simplifying the knowledge itself. But the final statement from ChatGPT was, “the goal of simplification isn't to "dumb down" knowledge, but to make it more **usable and transferable** across contexts”, which is certainly consistent with my argument here.

Simple should not be assumed to mean inferior. The alternative framework suggested for the exponential function in Section 6.3 below can easily be converted to the standard functions and vice versa. In the history of science, new simple methods are often much more powerful—for example, the decimal system for numerals and Copernicus's and Newton's innovations discussed in Section 2.1 above.

I have identified three broad approaches to simplifying knowledge, which are outlined in the three subsections below, starting with the most radical.

5.1. Conceptual re-engineering

There is a tendency for the way a subject developed historically to become entrenched as the one truth, as the only viable possibility. The theory of the exponential function (Section 6.2 below) was developed over 250 years ago, and the modern approach, which is mirrored in textbooks and other teaching materials, largely follows the historical development. The widespread use of significance tests and p-values is probably largely due to the influence of Ronald Fisher in the 1920s, but textbooks and courses still follow his lead despite the problems discussed in Section 6.1 below.

Normally the training of experts—whether formally by courses in schools, colleges, and universities, or informally by picking up the basics of a discipline by reading textbooks or research papers—follows the path taken by the innovators on the leading edge. The hierarchy of concepts used, the jargon, and the methods of research and argument are likely to mirror the historical development of the discipline. When they reach the leading edge, the typical expert understands thoroughly all the steps taken to reach the pinnacle, so this may well seem like the only possible route up.

However, this may not be the only route up. Having got to the top, the view may reveal easier routes up, or even better mountains to climb. The followers may also be able to avoid some of the problems of the pioneers by using the ropes left by them: the followers may be able to jump over a few hurdles without worrying about what lies in the chasm below. In short, there might be alternative, easier routes which the followers could take. However, this may not be obvious to those who have reached the leading edge, for whom the route they took may seem the only way up. This is likely to apply to senior academics whose work provides the basis of academic curricula: they are unlikely to be receptive to the idea of simplifying academic knowledge. And this attitude is likely to be reflected in textbooks, which are likely to follow the pioneers' route on the left of Fig. 1 rather than the two easier routes.

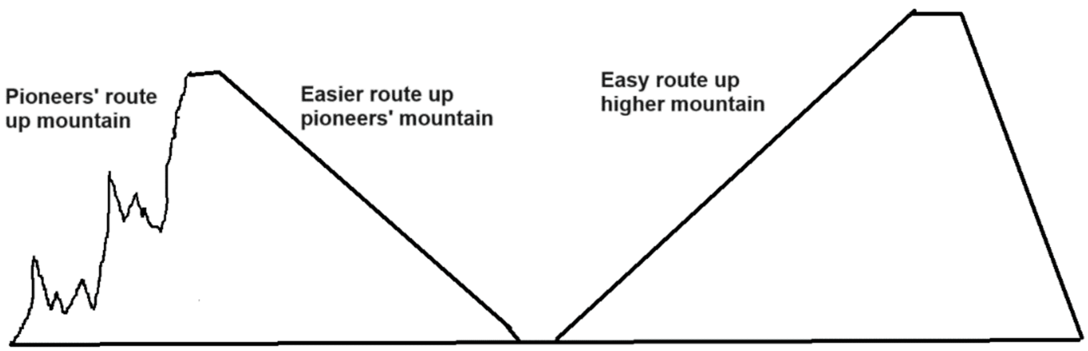

Figure 1. Three routes up two mountains

But... you may object that trainee experts should familiarise themselves with the "proper" version of the expertise. Anything else is giving in to the temptation to cut corners. To which the answer is: what's wrong with cutting corners?

I will refer to this idea of changing the conceptual basis of a discipline as *conceptual re-engineering* by analogy with business process re-engineering. When this process involves a whole discipline, it is often referred to as a *scientific revolution* or a *paradigm shift*. For example, according to Roger Penrose, in Einstein's theory of relativity, "Gravitation is not to be regarded as a force ... Instead, gravitation manifests itself in the form of spacetime curvature" [16]. This is a fairly drastic conceptual change. There are some examples of this on a more limited scale in Sections 6.1 and 6.3 below.

One possible aim of conceptual re-engineering may be to reduce the amount of prerequisite understanding as much as possible. When I have difficulty understanding something, the problem is often that to make progress I need to understand something else, and when I try to understand the something else I may come across another thing I don't follow, and so on. There is thus a hierarchy of things to be learned. Obviously, the shallower this hierarchy is, the better.

Figure 2 below shows two different structures for a domain of knowledge: the circles represent bits of knowledge, and the arrows represent the fact that the circles at the start of the arrow must be grasped before the ones at the end. Obviously, Structure 2 has the advantage that people can just choose the bits they are interested in, whereas Structure 1 requires knowledge of all the circles to get to the top.

doi.org/10.32388/RHTT8D.3

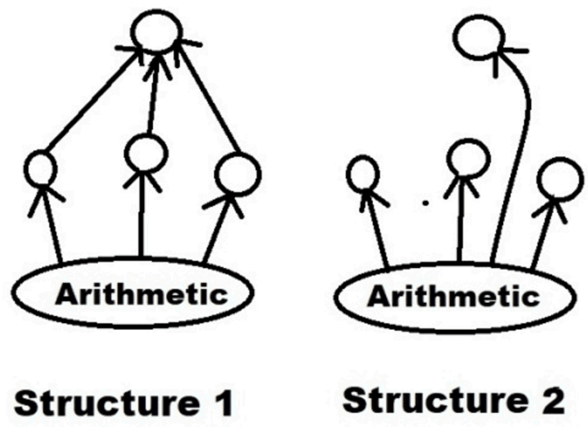

Figure 2. Different prerequisite structures

I discuss two examples of conceptual re-engineering in Sections 6.1 and 6.3 below.

5.2. Changing jargon and notation

Researchers at the leading edge of a discipline often need to invent names for concepts and notation systems to facilitate communication. For workers at the leading edge of the field, the precise nature of this jargon is probably not a big issue because they will absorb it by repeated exposure. For newcomers, on the other hand, jargon is often a problem. Sometimes it is overly complicated, sometimes it has no relation to the audience's frame of reference, and sometimes jargon may be likely to mislead.

Consider the conclusion that "orthoptists in the GSC [German-speaking countries] preferred using spectacles plus occlusion as their first-choice treatment, significantly more than their UK counterparts who preferred spectacles only as their first choice ($p<0.001$)" [17]. Interpreted as ordinary English, the word "significantly" implies that the difference between the GSC and the UK is a large one. Statistically, however, this is not the meaning at all: the word significantly means that the results obtained in the study were unlikely to have arisen if there were no systematic differences between the GSC and the UK—a convoluted concept that makes the misinterpretation of the word "significantly" almost inevitable. It implies nothing whatsoever about the size or importance of the difference. This problem is discussed in more detail in Section 6.1 below.

The design of transparent jargon to avoid such problems should be a flourishing area of research—which, to the best of my knowledge, it isn't. Names invented by leading-edge researchers have a tendency to

doi.org/10.32388/RHTT8D.3

stick when more user-friendly alternatives might be helpful. Often concepts are named after their originator or some key person in the history of the field. Bayesian statistics, for example, is named after Thomas Bayes, an eighteenth-century clergyman who first came up with the theorem on which this approach to statistics is based (although it was not published until after his death). A name like Updating Probability Methods would give a better impression of the nature of the Bayesian approach, which involves updating probabilities as you acquire more data.

Similar issues apply to the symbols used in a discipline—see, for example, Section 6.2 below.

5.3. Black boxes or holes in understanding

A person's understanding of almost anything typically has holes in it. Nobody knows everything about how to make a pencil or how a computer works. Ideas can be simplified by leaving out inessential details – the holes in the knowledge that the human understands. Knowledge is holey, and the location and nature of the holes deserve careful consideration. And the bigger the holes, the simpler the resulting web of knowledge becomes.

This is an essential approach to simplifying knowledge. The discipline of statistics is a good illustration of how planning holes can be a vital tool for reducing the burden of human understanding. The t-test in statistics serves as a good illustration of what is possible. The original pioneers would have invented the mathematics behind the technique, and the early users would (probably) have been familiar with the mathematics. But then the results of the mathematics were summarised in tables so that users just needed to understand what the answers from the tables meant and the circumstances in which they could be meaningfully used. They then do not need to be familiar with the mathematics, which is then treated as a "black box" whose inside is hidden from view, or a hole in their understanding of the process. Computer packages such as SPSS take this process further – the human partner then does not need to know how to use the tables, or even whether the t-test is appropriate, because the computer package will tell them. The more holes there are, and the bigger they are, the simpler the knowledge becomes – but the simplification is only useful to the extent to which the interface between the human and the hidden technique allows the technique to be meaningfully used. Planning these holes in human understanding, and the interface between the knowledge hidden in the black boxes and what the human understands, is obviously vital.

Statistics is one of the examples discussed below (Section 6.1) because it provides a good illustration of all three categories of approach to simplifying knowledge.

6. Some examples of how current knowledge might be simplified

One comment on an earlier version of this article posed the question: "How can I simplify quantum chromodynamics? I don't know." Which, of course, is the point. I don't know either, but somebody, someday, may come up with the answer – which must be a good thing! If it were easy, it would have been done already because, as I acknowledged in my law of simplicity at the leading edge of a discipline (Section 2 above), when even the experts acknowledge that something is difficult, they are likely to look for ways to make it easier.

The next three subsections outline some ideas for simplifying a few areas of knowledge which are widely used across a variety of academic disciplines. These are intended to illustrate the principle that simplification is possible and may be useful, not to establish how widespread this possibility is. I think there will be many similar examples in other areas, so the combined effect of simplifications across the whole web of knowledge should be substantial.

As well as the suggestions in the next three subsections, many of my publications [18] suggest simplifications in several areas, including quality management, statistics and decision analysis.

6.1. Statistics: the strength of evidence for a hypothesis

Statistical concepts like correlation coefficients, standard deviations, regression analyses, significance tests and so on, are widely used but often with little understanding of their background or rationale. Mistakes, misunderstandings and general bafflement are common. It is an area crying out for appropriate simplifications. One particularly problematic area is significance testing (p-values), which is the subject of this subsection. It illustrates all three of the approaches to simplifying knowledge outlined above.

The p-value, or significance level, is a very widely used way of deciding if the evidence for a hypothesis stacks up. Low p-values indicate that the chance explanation, based on a "null hypothesis", is unlikely, so it is assumed that the hypothesis of interest must be right. In most contexts, the mathematics behind the calculation is complicated, but this is usually done by a computer package, so it is not an issue for the researcher. The knowledge has been simplified by treating the mathematical algorithms as black boxes (see Section 5.3 above).

However, p-values may be, and very often are, misinterpreted. This problem is very widely acknowledged (see, for example, [19]), but just as widely ignored. In many domains of study, p-values (otherwise known as significance levels) are still the gold standard for assessing statistical hypotheses. In other areas, the problems are acknowledged, and journals will not accept articles citing p-values, but there is no generally accepted alternative.

The first, obvious, remedy would be to use more transparent jargon, or at least to avoid misleading jargon, as suggested in Section 5.2 above. The word "significant" in ordinary English means large or important, whereas the statistical meaning is (roughly) "unlikely to have arisen by chance". There is a strong case for avoiding the term "significant". I [20] suggested that the p-value could be described as the *plausibility* of the null (chance) hypothesis, which has the advantage of giving a rough idea of the meaning: low p-values suggest that the chance hypothesis is not plausible.

However, a more serious problem with p-values is that they do not tell you what you probably want to know – which is how likely the hypothesis of interest is, as opposed to how plausible the null (chance) hypothesis is. This requires some conceptual re-engineering (Section 5.1 above).

One suggestion is to cite confidence intervals instead of p-values [21]. I have suggested [22] building on this concept to calculate confidence levels for hypotheses which could be called "tentative probabilities". Then, instead of qualifying the conclusion that "patients treated by female surgeons were slightly less likely to die within 30 days" with the statement "p = 0.04" [23], we could qualify it by writing "confidence level, or tentative probability = 98%". Unlike the p-value, this gives the reader a direct assessment of how likely the hypothesis of interest is to be true. "Confidence" is a standard statistical term with a meaning similar, but not identical, to probability. The advantage of the term "tentative probability" is that it makes it clear that we should not have too much confidence in the idea because it depends on assumptions that may not be fully satisfied. I published this proposal in a research methods journal. The reaction of a reviewer for a statistical journal was withering – the problem being that confidence is considered a completely different concept from probability. My suggestion is more of a conceptual change, or paradigm shift, than it might initially appear.

6.2. Modified Excel notation for mathematical formulae

The formula below is an example of standard mathematical notation. (This is the formula for the normal probability density for which Excel has a built-in function, but this is irrelevant here because I am just using it as an example of mathematical notation.)

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

To a mathematician, this is beautifully concise. However, people without a mathematical background are likely to have a few issues. What is e and how does it relate to the symbols above and to the right of it? What do the symbols mean? And how can we type it into a computer so that we can work out what it comes to in specific situations? And if you are not familiar with the Greek alphabet, the Greek letters pose an additional challenge.

My suggested simplification to help with problems like these is a *modified Excel notation.* The only modification in this particular example is the use of three different types of brackets, which help to clarify how the brackets match up. The equivalent formula is (npd is the normal probability density, sd is standard deviation, and pi is the ratio of the circumference of a circle to its diameter, which is approximately 3.142):

$$\text{npd} = \{1/[\text{sd*SQRT}(2\text{*pi})]\}\text{*EXP}\{\text{-0.5*}[(\text{x-mean})/\text{sd}]\hat{\ }2\}$$

The key points are:

1. The formula is a sequence of symbols that can easily be typed on an ordinary keyboard, which means that it can easily be made compatible with computer software like Excel, and it is possible to search for the meanings of function names like EXP and operations like ^ and * with a search engine.
2. The variables (for which I've used lower-case letters) and function names (upper case) are designed to be recognisable words or abbreviations. Greek letters, and symbols from other scripts, are avoided because users may not be familiar with them, which may make them difficult to remember and incorporate into their thought processes.
3. In conventional notation, the expression "sd" would be interpreted as "s" multiplied by "d". To avoid this sort of misinterpretation, we always use * to denote multiplication.

This is an example of changing the notation as suggested in Section 5.2. The concepts are unchanged; all that is changed is the notation used to describe the function. This idea could be extended to cater for a wider range of mathematical concepts – integrals, vectors and so on.

6.3. Exponential or compound growth and decline

I used to teach reliability theory to M.Sc. students. One of the key formulae is the reliability function for the exponential distribution:

$$R(t) = e^{-\lambda t}$$

or in Excel format (λ is the failure rate, which I'll call fr, and t is the length of a time interval):

$$R(t) = \text{EXP}(-fr * t)$$

This formula involves the *exponential function*, e^x: it was easy to explain to the students how to work it out with a calculator or the spreadsheet Excel. Calculators typically have a button for e^x, and Excel has a built-in function EXP. What was not so easy was to explain what the function meant and where it came from. Historically (according to Wikipedia), the concept of e was introduced by Jacob Bernoulli in 1683, and the symbol e was first used by Leonhard Euler in 1727 or 1728. It has mathematically interesting and powerful connections to logarithms, calculus, infinite series, imaginary numbers, and the normal distribution in statistics (see Section 6.2 above), as well as its role in modelling exponential growth.

Most of my students, however, had either never met all this mathematics or had long since forgotten it and had no wish to revisit it. So, I was forced to present the calculator or computer as a black box: you put some numbers in and you get the answer out, but you really do not know what is inside the box.

Does treating the exponential function as a black box matter? No, in the sense that my students were happy with my explanation of what this reliability function meant: they could put numbers for the variables into the black box and get an answer out that they understood reasonably well.

But it is possible to re-engineer the reliability function so that its origin and meaning are clearer, and so that it would not involve the exponential function. The exponential function, e^x, is helpful for analysing growth or decline—such as compound interest, or the growth of populations of people or bacteria, or the decline in the numbers of components that are still operational. It crops up in many mathematical formulae. My suggestion is that if this mathematics were to be reformulated with the *Compound Growth Multiplier* (CGM) as its core concept instead of e^x, its meaning and rationale would be far clearer to people like my MSc students, and it could be completely disentangled from theories of calculus, logarithms, infinite series and so on.

To see how this would work, let's take a simple example. If you invest some money at an interest rate of 2% per year, over a period of 40 years it will generate interest and at the end of 40 years the total amount of money will have grown by a factor of 80% (40 x 2%). This is *simple* interest, so we can call 80% the *Simple Growth Multiplier* (SGM). However, if the interest is added to the investment throughout the 40 years so that you get interest on the interest – known as compound interest – the *Compound Growth*

doi.org/10.32388/RHTT8D.3

Multiplier would be 122.6%, which is considerably more than the 80% you would get from simple interest because you are getting interest on the interest as it is earned. How we can work out CGM from SGM is straightforward and is explained in the Appendix: logarithms, infinite series, calculus and so on do not appear in this story. The answer can be looked up in a table like Table 1, which could easily be built into Excel, or other software, as a standard function. The calculation of compound growth depends on whether interest is added on every year, or month or day: CGM represents the limiting case as the time intervals get smaller and smaller, as explained in the Appendix.

SGM	CGM	SGM	CGM	SGM	CGM	SGM	CGM
-1	-0.632	0	0.000	1	1.718	2	6.389
-0.8	-0.551	0.2	0.221	1.2	2.320	2.2	8.025
-0.6	-0.451	0.4	0.492	1.4	3.055	2.4	10.023
-0.4	-0.330	0.6	0.822	1.6	3.953	2.6	12.464
-0.2	-0.181	0.8	1.226	1.8	5.050	2.8	15.445

Table 1. Compound Growth Multipliers (CGM) from Simple Growth Multipliers (SGM)

These figures refer to the growth, not the total at the end of the time period. And, obviously, to convert to percentages they should be multiplied by 100: e.g. the bottom row in the second column means that an SGM of 80% corresponds to a CGM of 122.6%.

To see how this applies to reliability, imagine we have 1000 components with a failure rate of 1% per hour and we want to know what percentage will still be working after 40 hours. This is the reliability at 40 hours. The assumption behind the exponential distribution is that the failure rate is constant throughout the time period: the component does not wear out and become less reliable. At first sight, the obvious answer is that 40 × 1% or 40% will have failed, so 60% will still be working. However, this ignores the fact that as time progresses there will be fewer working components because some have failed, so the number failing will also decline. This is like compound interest, except that there is a decline, not growth.

From Table 1, if SGM is -40% (-0.4, the negative sign indicating decline), then CGM = -0.33. So the proportion remaining is 1 – 0.33 = 0.67 = 67%, which is the reliability after 40 hours.

In general terms, the reliability formula would be:

$$R(t) = 1 + \mathrm{CGM}(-fr * t)$$

The advantage of this formulation over the traditional exponential function is that it would be easy to explain to beginners how the figures in Table 1 are calculated – see the Appendix for more details. And it is in no sense an approximation: CGM and SGM are related to the traditional concepts by these relationships (LN is the Excel function for the natural logarithm):

$$\mathrm{CGM(SGM)} = \mathrm{EXP(SGM)} - 1, \mathrm{SGM(CGM)} = \mathrm{LN(CGM} + 1)$$

$$\mathrm{EXP(X)} = \mathrm{CGM(X)} + 1, \mathrm{LN(X)} = \mathrm{SGM(X} - 1)$$

The relationship between SGM and CGM can be used whenever the growth of something is proportional to its size: this is what is meant by exponential growth. To take another example, according to Wikipedia, the world population is increasing by about 1.1% each year, which means that over 800 years SGM will be 800 × 1.1% = 880% or 8.8. From Figure 3 in the Appendix, CGM will be over 6000 (6633 to be more precise, using the figures the graph is based on). This means that the population will be over 6000 times its present level of 7.8 billion. If, of course, the population keeps growing at 1.1% per year.

The words “compound” and “simple” are derived from financial terms relating to interest. There may well be better labels that are more natural in many contexts. As discussed in Section 5.2, jargon deserves to be designed with care.

7. Some further issues about simplifying knowledge

7.1. The inertia of established knowledge

Any change to the established order may meet with resistance just because that is what people are familiar with, courses are set up to teach it, and so on. Any changes will just feel wrong. If it works, don't change it, is often excellent advice, but it ignores the fact that occasionally change might help. So-called "normal science" is often a good idea, but sometimes a "paradigm shift" may be beneficial.

My first article on the general topic of simplifying knowledge was inspired by the title of a *Telegraph* leader column: "Maths should be hard" [24]. My point is exactly the opposite: Maths should be as easy as

doi.org/10.32388/RHTT8D.3

possible. However, this is often seen in the educational world as letting "standards" slip, or "dumbing down". The business model of colleges, universities and many experts implicitly depends on keeping knowledge hard so that the need for their services is maintained. If knowledge were too easy, university courses and expensive experts might no longer be necessary. Or they would need to adapt their game to work at a level which is genuinely hard.

The peer review system could have been invented to discourage change. Almost by definition, the peer reviewers used by journals to vet articles are steeped in conventional ways of looking at their subject and so may not be receptive to alternatives. There is a strong case for supplementing peer reviews with reviewers from outside the discipline [25].

7.2. Changes in technology may change the best approach

This is entirely obvious. Computers and calculators mean that the simplest way of doing arithmetic no longer needs long multiplication, log tables or slide rules. Artificial intelligence and Internet search engines may have made some human knowledge redundant, but the interface between these technologies and human knowledge is worth very careful consideration.

It is important to remember that there are many different means of communicating knowledge: words, symbols, icons, graphs, videos, etc. Within each type of medium, such as words on a page or screen, there may be different genres: philosophical arguments, stories, and so on. Some things we take for granted now, like time-series line graphs, are comparatively recent inventions and would have bewildered audiences a couple of hundred years ago. Kramer [26] discusses the use of icons (e.g. the concept of "future" might be "the icon of a clock surrounded by a clockwise arrow") and points out that "on smartphones and computers, writing icons can now be faster than writing alphabetic words" [27].

In the future, new possibilities are likely to surface and become accepted as technology progresses and habits change, and the need to make knowledge more accessible becomes more urgent.

7.3. Keep it short

I have three books on my desk as I write this. Richard Dawkins's *The God Delusion* is 400 pages long. I've dipped into it, and it looks interesting, and I'm sure God is a delusion, but I am not prepared to read 400 pages on the topic. It's far too long. On the other hand, Bertrand Russell's *History of Western Philosophy*, and the third book on my desk—a maths textbook—are OK because these are collections of relatively brief expositions of particular topics.

doi.org/10.32388/RHTT8D.3

Many books are too long. In the days when most people read things on physical pages, the book was a convenient size to sell and read. Now, of course, the advance of technology means that we can be more flexible over the length of documents. A similar argument applies to many (by no means all) academic articles, which would benefit from more focus on the main argument and less on reviewing the field: interested readers can easily be given links to suitable review articles. But habits often last well past the point at which they cease to make sense, and authors who want to make their mark feel the need to expand their efforts to fill a decent-sized book or article.

Suppose Richard Dawkins had reduced *The God Delusion* to 50 pages. Then I would have the time to read it and eight similar works in the time it would have taken me to read the 400-page tome. This principle is the basis of the app and website Blinkist.com, which provides summaries of books with the slogan "More knowledge in less time." Wikipedia is also an important source of summaries of ideas for people who do not have the time or inclination to consult the original. But, of course, there are dangers in taking this principle too far.

7.4. Don't forget the aesthetic dimension

In the science of physics, beauty is sometimes seen as a guide to truth. If it's beautiful, it's more likely to be true according to some physicists, although others will say that the universe is messy, so a good physical theory should reflect this. But regardless of one's view about this, it does seem to me undeniable that beautiful theories are likely to have the advantage of being more pleasurable to develop and use. Ideas that are fun and inspiring will almost inevitably be absorbed more efficiently and used more productively than those that are seen as dull and boring. If the discipline of statistics is seen as boring and ugly, people will make little effort to master it. If, on the other hand, it could be made fascinating and elegant, everyone would be better off.

8. The problem of over-simplification

Obviously, the simpler knowledge is, the better, provided the simple version is at least as good as the complicated version. However, it is possible that sometimes the simple version may be a lot worse: it may be a very rough approximation, misleading, useless, or simply wrong.

Simple statements like "The Swiss are much happier than Nigerians", or "Exposing yourself to strong sunlight is a bad idea" or "There are two types of social research - quantitative and qualitative", or "Britain could derive a huge amount of energy from renewable sources" are—for many purposes—

oversimplified and potentially very misleading. Some Swiss are doubtless much more miserable than some Nigerians: the generalisation just refers to averages. People who don't expose themselves to any sunlight run the risk of vitamin D deficiency. If you think there are only two types of social research, you will probably identify the analysis of subjective feelings with the qualitative pole, ignoring the fact that there is a whole industry based on assessing subjective feelings on 1–5 scales analysed with quantitative statistics. And it is not enough to know that the potential of renewables is "huge"; we also "need to know how it compares with another 'huge,' namely our huge consumption" [28]. The use of adjectives like "huge" oversimplifies the problem: "to make such comparisons, we need numbers, not adjectives."

Politicians need neat soundbites like "we must balance the budget" because "the economy is like a household", which of course it isn't. This is an oversimplification, but any more nuanced view would be unlikely to have as much impact on the electorate. Which is a problem.

In 2008, the world economy plunged into a crisis triggered, according to Nate Silver [29], largely by over-simplified, and horribly inaccurate, measures of risk. Banks and other financial institutions buy and sell securities like mortgages, and they obviously need an estimate of the risk of losing their money on these transactions. In practice, estimating these levels of risk is a complicated task, so they simplified the problem by using the assessments of rating agencies—these organisations categorise risk into bands. AAA, for example, is intended to mean a probability of default of 0.12%, but during the crisis, 28% of these securities defaulted. This led to losses far greater than expected, and to the necessity to bail the banks out and all the other consequences of the crisis.

Even organisations whose job was to manage financial risk felt the need to use simplified measures provided by a third party. And the reason that these risk assessments were wrong was that the rating agencies over-simplified the task of making these assessments. They made an assumption—that the component risks were independent of each other—which was a long way from the truth, leading to a massive underestimation of the risk of default. This was an elementary mistake, but without it, the task of assessing risk becomes difficult and the answers become vaguer, so the temptation to make the simplifying assumption was probably overwhelming. Perhaps with a more thorough understanding of how probability theory works, these mistakes would have been less likely.

There are many ways in which we can oversimplify things, but it is worth mentioning one that seems to appeal to the academic mindset: over-extending appealing concepts. One such example is the idea of statistical significance (Section 6.1 above). And, as should be apparent from what I have said above, the concept of simplicity itself is far more multifaceted and problematic than my use of it as a slogan might make it appear. Many subdivisions into two or three categories (simple/complex, qualitative/quantitative, left-wing/right-wing, heavy drinker/light drinker/teetotaller) run a serious, and often unacknowledged, risk of over-simplification.

Over-simplification is certainly a problem. But the cause is often that a more appropriate understanding is too complicated to make sense of, so we may have little option but to go for the crude and unhelpful over-simplification. Complicated knowledge may push us into dumbing down. The remedy is dumbing up: sensible and thoughtful simplification.

Finally, there is the concept of simplicity itself. A realistic assessment of how simple a piece of knowledge is needs to take many factors into account: the audience and what they know already, what the knowledge will be used for, what technology will be available to assist in the learning and use of the knowledge, whether the knowledge facilitates a deep understanding of its meaning, rationale and limitations, how broad the domain of application is, and so on. Oversimplifying the concept of simplicity runs the risk of ignoring some of these dimensions.

9. Conclusions

If we don't start to simplify our increasingly complicated web of knowledge, human progress will slow down or cease as our minds become clogged with unnecessary technicalities, and inevitable over-simplifications take control of our thoughts and actions. We need to see the design of elegant, fit-for-purpose perspectives which help us to make wise judgements as an important task for academia. Then perhaps 10-year-olds will be able to understand quantum mechanics, and the leading edge of science will be beyond anything we can imagine now.

AI and other computer technologies can, of course, help. The ability to explain ideas as and when they are needed is likely to facilitate a *just-in-time* approach to learning, which may be bad news for universities whose core business is teaching stuff to students *just-in-case* they need it. But this does not mean that simplification is not beneficial and, perhaps in the long term, essential.

Conventionally, academic knowledge is viewed as a given: it should not be fiddled with to suit the requirements of users and the context of use. I think this is a mistake: it should be designed, or redesigned, to make it as simple as possible for the context of use. We have looked at a few examples where knowledge might usefully be simplified. These are just a few areas I know something about: there are likely to be many similar opportunities across the whole spectrum of human knowledge. It is in areas

doi.org/10.32388/RHTT8D.3

which seem trivial to experts, but difficult for novices, that the biggest benefits of simplification are likely to lie. The difficulty is that, in most areas of academic knowledge, there is no tradition of trying to design simpler versions of well-known concepts, techniques or theories.

The benefits brought by such simplifications are potentially enormous. Let's imagine that some difficult knowledge can be simplified by a factor of about a quarter. (I think in many cases this could be nearer 50% or even more.) This might mean that people spend 25% less time learning about it, or using it, or that the simplification means that they can master 25% more than they would otherwise have been able to, or that they make 25% fewer mistakes, or that 25% more people are able to master it. Over the whole spectrum of difficult knowledge, this has the potential to make an enormous difference. Imagine that students around the world could spend 25% less time on their studies. The rest of the time could be spent taking their studies further or doing something completely different. And researchers would arrive at the frontiers of their discipline sooner, or with a better understanding of other relevant areas, both of which should lead to faster progress.

Why isn't this happening already? The main reason is probably that nobody seems to have pursued the idea as a general principle, perhaps because of the assumption that academic knowledge expresses the truth, and the truth is fixed and not adjustable to suit the circumstances. Or because the only people in a position to produce a useful simplification are the experts in the domain who are unlikely to see the need —for them the expertise is trivial and an essential part of the discipline. Like all paradigm shifts, the most likely champions are outsiders, but outsiders may not have a sufficiently deep understanding to create a viable alternative.

But whatever the reason, the idea of simplifying knowledge does not seem to be on anybody's agenda. This lack of interest is reinforced by the complete absence of academic journals on the theme of simplification. To get published, an academic needs to produce something complicated; a simple version of an existing idea is rarely viewed favourably by the gatekeepers of academia. There is also the conservative influence of the education system, and the attitude of teachers at all levels that "standards" should be maintained, that knowledge should not be "dumbed down", and that, in the words of the *Daily Telegraph* leader column, "Maths should be hard". But surely maths should be as easy as possible, and "dumbing up" is always a worthy goal.

I would like to see simplification on the agenda. Two projects, for example, appeal to me. The version of statistics taught in the academic curriculum is a major source of confusion and incomprehension in urgent need of reform. And I would love to understand quantum mechanics at a deeper level than I do, but I think I need to wait for a version more in tune with my aptitudes and the time I have available. Such a version is probably right outside the possibilities envisaged by current physicists but, eventually, I suspect there will be a version of quantum mechanics which is appropriate for schoolchildren.

Appendix: Re-engineering the exponential function

What I want to propose here is a way of reformulating the exponential function so that it is more appropriate for people like my M.Sc. students who want to understand it thoroughly but don't want to get bogged down in calculus and logarithms. To do this I'll use a slightly easier example and come back to reliability later.

Let's imagine that a population (of human beings, bacteria, rabbits or whatever) grows at 2% per year. How big will the population be after 40 years?

At first sight, the answer is that the population will have grown by 80% (2% times 40 years, which is 80% or 0.8) so at the end of 40 years it will be 180% (1+0.8 or 1.8) of its size at the start. This, however, ignores the fact that each year the population will be a bit bigger, so 2% of the population will get bigger and bigger, so the population will grow faster.

This is like the difference between simple interest and compound interest. If you invest some money with 2% per year simple interest for 40 years, at the end of the 40 years your interest will be 80% of what you invested, so you will end up with 180% of, or 1.8 times, your initial investment. Compound interest is a little trickier to work out. After one year your investment will have grown by 2% to 1.02 times your initial investment. After the second year, it will have grown to 1.02 times what it was at the end of the first year, so it will be 1.02*1.02 (1.02x1.02) or 1.0404 times your initial investment. This is a little more than the 4% growth you'd have got with simple interest because you're getting interest on the interest. If you repeat this argument for each of the 40 years you will find that the final investment is 1.02^40 (or 1.02^{40} in conventional notation) times the initial investment, which comes to 220.804% of (or 2.20804 times) the initial investment. This, for obvious reasons, is a bit more than the 1.8 (180%) multiplier you get from simple interest.

The population growth question is obviously like compound interest except for one thing. After, say, six months the population will have grown by 1%, so we could apply the compound interest method with 80 intervals in which the growth is 1%. This suggests the final population is multiplied by a factor of 1.01^80 or 2.216715. This is a little bit more than you should expect. But why use six-month intervals? If we used a

doi.org/10.32388/RHTT8D.3

tenth of a year and a growth rate of 0.2%, the final answer would be 1.002^400 or 2.223764. Again, a little more but not much. You'll find if you take smaller and smaller intervals that the answer settles down to about 2.226 and never gets bigger than this. (This is known as a limit in mathematical terminology.)

And this, of course, is the answer you get from the exponential function: $e^{0.8}$ or EXP(0.8) = 2.226. The function e^{x} gives us an easy way of working out compound growth problems like this so that we don't need to go through this rigmarole each time we need to work out something about compound growth.

However, from the perspective of my students, there are four problems with e^{x} from the user-friendliness perspective:

- The symbol e^{x} and the name exponential function. The link between these and the idea of compound growth is rather hazy.
- The name of the reverse function for going back from the compound to the simple case is loge (LN in Excel): again, this would seem arbitrary and meaningless to someone without a mathematical background.
- How the two functions—(1) and (2) above—are explained. An explanation which does not involve logarithms and calculus would help our beginners.
- The fact that you start with a number representing growth (0.8) but you finish with a number representing the total of what you started with plus the growth (2.226).

I'll start with the last point. The difficulty is that as well as the difference in terms of simple or compound growth, 0.8 and 2.226 also differ in that the first represents the increase or growth whereas 2.226 represents the total including what you started with. This can only be a distraction. For my proposed reformulation, we need to decide whether we are going to go for the increase or the total. I'll go for the increase or growth because I think this makes things a little easier. The growth in the simple case is 0.8, and in the compound case is 1.226 (2.226-1). They are both, of course, multipliers: you need to know what population (or investment) you start with, and then you multiply by 0.8 for the simple case and 1.226 for the compound case. I'll refer to 0.8 as a Simple Growth Multiplier (SGM) and 1.226 as a Compound Growth Multiplier (CGM).

I've explained how we can start with an SGM of 0.8 and calculate the corresponding CGM (1.226). We could obviously do this for other SGMs and then make a table like Table 1 above.

Making the reverse table where we start off with a value of CGM and then work out the corresponding value of SGM is a little harder because it involves trial and error. Imagine we start with CGM=1. Looking at

doi.org/10.32388/RHTT8D.3

the table, SGM obviously has to be between 0.6 and 0.8. So, we might try 0.7, look at the resulting CGM, and possibly then try again until we have got it close enough. Hard work without a computer, but trivial with one.

We can also represent the relationship between SGM and CGM by a graph. People tend not to realise just how large the compound multiplier can be—the graph below illustrates this nicely.

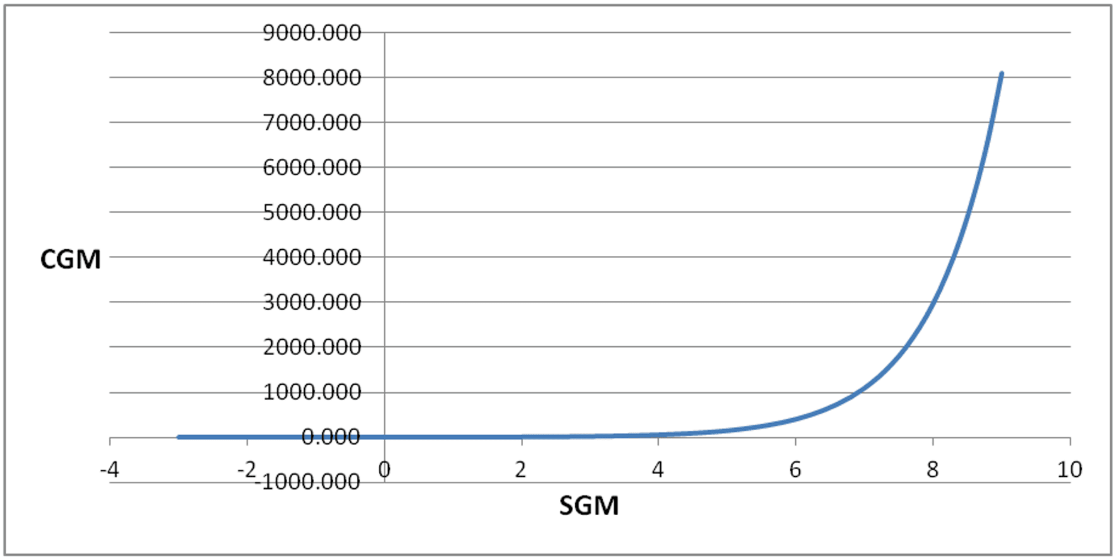

Figure 3. Relationship between SGM and CGM

We could build these two functions into a spreadsheet, calculator or other software. So, for example:

$$\mathrm{CGM}(0.8) = 1.226$$

$$\mathrm{SGM}(1.226) = 0.8$$

These names now refer directly and obviously to what the functions represent. The procedure for going from SGM to CGM is long-winded but the rationale is relatively straightforward and does not involve any extraneous higher mathematics.

If the growth is compound, any mention of simple growth, and so SGM, is hypothetical. In the original example, SGM was 0.8: this is what would happen *if the growth were simple.* But it is not; if it were, we would not be interested in CGM. The only way we could get around this problem of having to think in terms of hypothetical quantities is by bringing in the time period (40) and the growth rate (0.02), which

 doi.org/10.32388/RHTT8D.3

would make it a function with three variables, which immediately makes everything more complicated. Tables and graphs then would not work. I will stick with the hypothetical SGM.

Notes

Earlier versions of this article, with different titles, were posted on SSRN and Qeios. I am grateful for the feedback from readers of the post on Qeios.

References

1. ^ *Wood M (2002). "Maths Should Not Be Hard: The Case for Making Academic Knowledge More Palatable." Higher Education Review.* ***34****(3):3–19.* *http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1545187.*
2. ^ *Penrose R (2004). The Road to Reality. London: Jonathan Cape. p. 401.*
3. ^ *http://scepticalacademic.blogspot.com/2012/11/peer-regard-for-pot-noodles-critique-of.html*
4. ^ *Kuhn T (1962). The Structure of Scientific Revolutions. 1st ed. University of Chicago Press.*
5. ^ *https://en.wikipedia.org/wiki/Geocentric_model*
6. ^ *Kaiser D (2005). "Physics and Feynman's Diagrams: In the Hands of a Postwar Generation, a Tool Intended to Lead Quantum Electrodynamics Out of a Decades-Long Morass Helped Transform Physics." Am Sci.* ***93*** *(2). https://www.jstor.org/stable/27858550.*
7. ^ *http://appinventor.mit.edu/*
8. ^ *Khamsi R (2006). "Mathematical Proofs Getting Harder to Verify." New Sci. https://www.newscientist.com/article/dn8743-mathematical-proofs-getting-harder-to-verify/.*
9. ^ *Whitesides G (2010). "Toward a Science of Simplicity." TED. https://www.ted.com/talks/george_whitesides_toward_a_science_of_simplicity/transcript?language=en.*
10. ^ *Cohen J, Stewart I (1995). The Collapse of Chaos: Discovering Simplicity in a Complex World. New York: Penguin. pp. 135–8.*
11. ^ *DeSilva JM, Traniello JFA, Claxton AG, Fannin LD (2021). "When and Why Did Human Brains Decrease in Size? A New Change-Point Analysis and Insights From Brain Evolution in Ants." Front Ecol Evol.* ***9****:742639. doi:10.3389/fevo.2021.742639.*
12. ^ *Wolfram S (2025). "What If We Had Bigger Brains? Imagining Minds Beyond Ours." https://writings.stephenwolfram.com/2025/05/what-if-we-had-bigger-brains-imagining-minds-beyond-ours.*

13. ^Wood M (2001). "The Case for Crunchy Methods in Practical Mathematics." Philosophy of Mathematics Education Journal. **14**. http://socialsciences.exeter.ac.uk/education/research/centres/stem/publications/pmej/pome14/wood.htm.
14. ^Simon JL (1992). Resampling: The New Statistics. Arlington, VA: Resampling Stats Inc.
15. ^Wood M (2005). "The Role of Simulation Approaches in Statistics." J Stat Educ. **13**(3). doi:10.1080/10691898.2005.11910562.
16. ^Penrose R (2004). The Road to Reality. London: Jonathan Cape. p. 459.
17. ^Tan JYH, Thompson JR, Gottlob I (2003). "Differences in the Management of Amblyopia Between European Countries." Br J Ophthalmol. **87**:291–296. doi:10.1136/bjo.87.3.291.
18. ^https://soths.wordpress.com/michael-woods-publications-etc/
19. ^Wasserstein RL, Lazar NA (2016). "The ASA's Statement on P-Values: Context, Process, and Purpose." Am Stat. **70**:129–133.
20. ^Wood M (1984). "Making the Idea of Significance Easier to Understand." Teach Stat. **6**(2):57–59.
21. ^Gardner M, Altman DG (1986). "Confidence Intervals Rather Than P Values: Estimation Rather Than Hypothesis Testing." BMJ. **292**:746–750.
22. ^Wood M (2019). "Simple Methods for Estimating Confidence Levels, or Tentative Probabilities, for Hypotheses Instead of P Values." Methodol Innov. January-April 2019:1–9. https://journals.sagepub.com/doi/full/10.1177/2059799119826518.
23. ^Wallis CJD, Ravi B, Coburn N, et al. (2017). "Comparison of Postoperative Outcomes Among Patients Treated by Male and Female Surgeons: A Population Based Matched Cohort Study." BMJ. **359**. doi:10.1136/bmj.j4366.
24. ^The Telegraph (2001). The Telegraph, 20 December, 2001.
25. ^Wood M (2024). "Beyond Journals and Peer Review: Towards a More Flexible Ecosystem for Scholarly Communication." https://arxiv.org/abs/1311.4566v2.
26. ^Kramer P (2022). "Iconic Mathematics: Math Designed to Suit the Mind." Front Psychol. **13**:890362. doi:10.3389/fpsyg.2022.890362.
27. ^Kramer P (2023). "Icono: A Universal Language That Shows What It Says." Front Psychol. **14**:1149381. p. 1. doi:10.3389/fpsyg.2023.1149381.
28. ^MacKay DJC (2008). "Sustainable Energy – Without the Hot Air: A 10 Page Synopsis." http://www.withouthotair.com/.

29. ^ *Silver N (2013). The Signal and the Noise: The Art and Science of Prediction. London: Penguin.*

Declarations

Funding: No specific funding was received for this work.

Potential competing interests: No potential competing interests to declare.