Prologue

The Card Catalogue

Did he appear a sensible young man; a young man of information?

Jane Austen's Emma

In the fall of 1981, I enrolled as a freshman, major: undecided, at the University of Michigan. I remember walking into the graduate library, one of the largest in the world, and being awestruck by the card catalogue room – rows and rows of wooden cabinets with small file drawers containing cards listing author, subject, and title to literally millions of volumes, journal articles, pamphlets and portfolios. Over the next four years, I spent hours shuffling through those manilla cards seeking information. I spent many more wandering the stacks, roaming from book to book, subject to subject.

At the time, I assumed that those years in Ann Arbor would be my sole opportunity to have access to so much information. I anticipated that like most people, I'd settle into a life where any question whose answer wasn't bound inside thirty Word Book Encyclopedia volumes would go unanswered.

How wrong I proved to be. We're now awash in information. Most of what's in that library plus a whole lot more now belongs to the world. Content once bound up in hard copy we now store diffusely in silica. With a simple query, it flows in tiny packets through the very air that we breathe into mobile devices. So, too, information about the here and now, about stock prices sports scores, political events and cultural happenings. What once arrived in black and white on the doorstep now sits at our fingertips, accessible on whim or demand.

The same technological advances that nearly drown us in information have also contributed to increasing complexity by speeding adaptation and increasing connectedness..[1] Companies that used to wait for monthly statements now track sales in real time and respond accordingly. I've heard it said that when you put a gallon of milk in your push cart that Wal-Mart phones the cow. Inflation, once estimated only quarterly, can now be tracked instantaneously on the Internet.[2] Moreover, using global positioning satellites (GPS) a great deal of information can now be encoded by geographic location allowing for fast, targeted responses and strategic maneuvers by governments, businesses, and social movements alike.

As for connectedness, little needs to be said. We're now connected to one another, to our work, and to our interests at levels that would have boggled the mind just a few decades ago. The complexity wrought by the increases in information, adaptability, and interconnectedness implies a lack of predictability about what's next. Almost none of the thousands of experts who analyze the Middle East predicted the Arab spring of 2011. And while some predicted the mortgage crises in advance, one can argue that at any given moment someone's always predicting a downturn. To borrow Duncan Watt's elegant turn of phrase "everything is obvious: once you know the answer."

How then do we cope with this complexity? How do we plan? See around the bend in the curve? What actions do we take? How do we cope with the plethora of problems and opportunities sitting on our collective placte: improving education, reducing poverty, cre-

[1] See Mitchell 2009 and Page 2010.
[2] MIT instantaneous inflation.

ating sustainable growth, and designing robust financial, economic, and political systems.[3]. These problems span traditional disciplines, so we cannot just hand them to subject area experts. More problematic, most of these challenges don't sit still. They change as the world changes.

The answer doesn't lie in the Internet. We're not going to solve these problems with data and information alone. [4] We need two things that are even more precious. We need knowledge. And we need wisdom.[5]

By knowledge, I mean an understanding of relationships and connections between pieces of information. Knowledge of basic physics enables me to know that that energy is neither lost nor gained –so that when I'm coasting downhill on my bike, I know I'm not getting a free ride. Knowledge of chemistry explains how metallic bonds are stronger than hydrogen bonds, which explains why I can dive into a lake and rely on the hydrogen bonds giving way, but why if I attempt to dive through a steel floor, I encounter significantly more resistance.

By wisdom, I mean an understanding of which knowledge to apply. Almost by definition, complex situations will have multiple forces at play. Wisdom requires the capacity to identify those components and forces that are most relevant at any given moment in time. One can have complete knowledge of the functioning of the human body, but it takes wisdom to know how to cure the sick.

How though do we acquire general wisdom? Advocates of liberal arts education argue for broad exposure to great works of literature and to the basic ideas from multiple disciplines. I agree in principle, but I believe the great books approach to be incomplete. The great

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[3]See Acemoglu and Robinson (2012) on growth, Bednar (2008) on robust political systems

[4]Information theorists find it useful to distinguish between data and information. *Data* refers to raw bits or experiences: videos, political speeches, and laundry soap advertisements. Data may be necessary, but on it's own it's of little value. It's like a book written in secret code. To be of scientific use, data must be organized. Then it becomes *information*. Rain falling on your head is data. A chart showing the total rainfall for the month is information.

[5]See Adler, Mortimer Jerome (1970). The Time of Our Lives: The Ethics of Common Sense. Holt, Reinhart and Winston.

books tell us next to nothing about how to leverage massive amounts of information to make better choices They say little about how to distinguish a trend from a sequence of fortunate or unfortunate events. We can pour through their pages and find little about the conditions required for a system to reach an equilibrium. They say nothing about the causes of economic growth, the effects on network connectedness and rates of social learning. They may identify collective action problems and common pool resource problems, but they do not tell us how to solve them. Meanwhile, the information pours out of the fire hose producing ever more complexity. How do we cope? What tools do we need?

We need models. Models provide formal frameworks within which to embed all of this data and information. Within those frameworks we can logically deduce the implications of our assumptions and test their veracity. With models, we can better see around the bend in the curve – we can anticipate whether a linear trend will likely continue, amplify, or tail off.

In this book, I provide a starter set of models, not unlike that Crayola box of twenty-four crayons that children take to elementary school. These models provide a means for transforming data and information into knowledge. They impose logic to our thinking and provide conditions under which intuitions hold and don't hold. They also ease communication by providing common languages. Learning these models and developing an inclination to refine and combine them will make you a better thinker.

Now of course, models are necessarily simplifications. They leave stuff out. And, as a result, modelers often say "all models are wrong, but some are useful." That's true. But it takes experience to distinguish the models that will be of use. One prerequisite though is having multiple models and developing the ability to speak across them. If you only have one model, you'll often be wrong. We'll even have a model that shows that!

As a society, we'd collectively be a lot better off if we had what I like to call "a crowd of models" to bring to bear whenever we have an important decision to make. The more models at our disposal, the more ways to organize that information into knowledge, and the more likely we make a sound decision. Also, the more models that we have, the more possibilities we have for recombining their parts and producing ever better models, all of which we may need given the growing complexity of our world.

Introduction: Why Models?

If I had a hammer, I'd hammer in the morning.

I'd hammer in the evening, all over this land.

Lee Hays and Pete Seeger

In this book, I present a starter set for the model thinker. Think of it as a Crayola box of thirty-two. Learning how these models work and their implications won't give you the keys to answer all the problems the world throws at you, but it will help. Each of these models provides a lens through which you can interpret parts of your world. Reading this book will also endow you with the ability and confidence to acquire other models, and to communicate with other people who also understand these models. And, as most new models come about from people thinking about existing models, working through this book will, I hope, encourage you to construct your own models.

Almost by accident, models have become a big part of my life. For over a decade, I've taught a class on models to undergraduates at the University of Michigan. The course has the catchy title "An introduction to Modeling." I might instead have called it "Thirty-Two Models That Will Turn You Into a Genius" but the academy prizes humility (and the course already fills up with eager students). Not that I think the "turn you into a genius" framing a huge exaggeration. Model thinkers have several legs up. They acquire a deeper, more coherent understanding of the world about them. They improve their abilities to solve problems, make predictions, identify inconsistencies, and design things.[6] And they learn how to create a dialogue between ideas and data.

The great investor Charlie Munger once said that to have worldly wisdom, "You've got to have models in your head. And you've got to array your experience—both vicarious and direct—on this latticework of models" (Munger 1994). I agree. The most effective thinkers blend knowledge of models with a foundation in facts. Allow me an example, on October 9, 2009, Iceland's currency, the króna collapsed. Some people working in the financial services industry panicked. Would the collapse spread? What should be done to hedge? A wise investor whom I know responded by invoking two models. The first was a model of network failure. Banks are connected he thought. If one fails, others may follow. This chain of reasoning led him to wonder which assets in his portfolio were near to Iceland, not geographically near, but financially connected. The second model related to supply and demand. For prices to change in world markets, demand or supply has to shift substantially. This second model reminded him to keep an eye on the magnitude of the event. He then pulled from memory an important piece of information regarding the size of Iceland: it's small. He then announced to his team "Relax. Iceland's the size of Fresno. Get back to work." Two models plus one fact put the matter in the proper perspective.[7]

Munger was right. Using models makes you a clearer thinker, produces better choices, and leads to deeper, more coherent understandings of the world. The use of models also produces humility and skepticism. These pedagogical claims in support of models have been made elsewhere.[8]. Here, I'm less interested in pedagogy than in learning the models themselves. That said, some framing and housecleaning must still be done. I am compelled

[6] To give just one example, Tetlock (2005) shows that the best experts are foxes – people whose heads contain lots of competing and contradictory models – and the worst are hedgehogs – people who have a single vision for how the world works. In other words, those talking heads you see on TV are terrible at predicting. Chimps with darts do better.

[7] For the record, Fresno's about 30% larger than Iceland.

[8] Cites from class here.

to explain some of the hows and whys of models and describe how modeling fits with other efforts to teach ways of thinking. I must also clear up some common misunderstandings such as the equating of models with lots of math, and the idea that each problem should be contemplated using a single model. I limit pedagogical concerns to the remainder of this chapter. Then I get on to the fun part, the models themselves.

The Many Model Thinker

Models provide formal frameworks with which we can make sense of the world. However, as is often noted, all models are wrong (some more so than others in any given case). The inaccuracy of models obliges two responses. First, we must constantly refine and improve them. We must open dialogues between models and reality. By identifying when a model fails, we learn more about the conditions necessary for it to work. By the way, were models not wrong, we would not live in such interesting times. We'd just pick the appropriate formula and solve every problem that came our way.

Second, owing to the fact that no model is perfect, we must accumulate collections of models. Models don't have flaws so much as they have limited scope. Models are simplifications. Each focuses on only a part of the whole. By possessing a collection of models, an individual or a collection of people can see the limitations of each singular approach and gain a more comprehensive understanding.

Modelers who know a single model have no alternative but to apply it too broadly. They have a hammer, and they set out to find nails. When they run out of nails, they start pounding in screws. When they run out of screws, they start chopping down trees. They do all of this with that same hammer. It's an ugly mess. Yet, as the song goes, because they know only one way to make sense of the world, they hammer all evening all over this land.

In some situations, a single model explains the phenomenon of interest. This is often true in the physical sciences. If we want to calculate force, we apply $F = MA$. If we want to know the relationship between the volume and pressure of a gas, we use Boyle's law. Mathematical models have proven eerily effective at explaining the physical world. Quantum theory can predict phenomena to nine decimal points. Even models that we know are incorrect, such as Newtonian physics, are unreasonably effective.

Wigner (1960) considers this unreasonable effectiveness of physical models a mystery. I think that their accuracy can be explained. Three attributes of physical systems (1) simple parts (2) interacting in large numbers (3) that follow fixed rules render physical models amenable to mathematics. Any two atoms or water molecules put in the identical situations follow the same fixed rules, and those rules are pretty simple. When heated, the molecules in a pan of water all respond in the same way. Further, molecules, atoms, quarks, muons, and so on exist in such large numbers that even if they do wobble a bit, averaging cancels out any randomness. [9]

Systems that include people as actors– and these include ecological systems – lack the three attributes that produce regularity. The parts of these systems aren't simple: People are sophisticated, multi-dimensional, and capable of a range of behaviors. We march to our own drummers. Further, though billions of people exist, we interact in small to moderate sized groups. Finally, we don't follow the same fixed rules. Unlike carbon atoms, we learn. We adapt. We do crazy things. Hence, attempts to model social processes such as economies, political systems, or violent behavior can explain only modest amounts of the variation that exists in the world and can identify few factors whose effects have large magnitudes (Ziliak and McCloskey 2008).

[9] It is also true that simple parts following fixed rules can produce complexity (Wolfram 2001). And, complexity, by definition, isn't easy to explain or predict (Page 2010). However, models can explain why some systems are complex and others are not. So even though no simple model can predict the patterns of water on the windows of your car as you drive through a rainstorm, a simple model can explain why we cannot predict them.

The lack of single causal explanations for complex systems provides second reason for possessing multiple models. To make sense of complex processes, we need many lenses. Permit me another example. Suppose I want to understand income inequality. I might construct a model of firms that pay wages based on the skills. My model might show that wages increase linearly in education level. I might then test this model to discover whether income correlates positively with education level. I will find that it does, but that I can only explain a modest amount of income variation. A model that Income = α IQ won't be unreasonably effective.

My model will be of limited explanatory power because income depends on many other factors – inherited wealth, geographic location, social networks, and IQ (Bowles and Gintis 2002). Furthermore, no two people are the same. This diversity implies that the mechanisms through which these various causes influence income may differ as well. Heterogenous parts and diverse responses combine to form a messy reality in which even writing income as a function of social networks, IQ, education, inherited wealth, and location won't be unreasonably effective. It'll be mediocre. To understand variation in income, we therefore need multiple models. Each one highlighting some of the causal relationships between income and some set of relevant attributes. By having this crowd of models, we can see the strengths and limitations of each explanation. We can also delve into their differences and similarities.

These models must highlight distinct causal relationships with each shedding light from a different angle. We can sometimes combine two or three models to learn about interactions between variables, but we cannot construct a grand model containing every possible causal factor. If we did, and that's assuming we had enough data to disentangle all of the interaction terms, we would wind up with something as difficult to comprehend as the real world,

Owing to the importance of this point, it bears restating. As I mentioned above, many physical problems can be solved with a single model. Engineering leverages this fact to build bridges, electrical generators, and silicon chips. Once those problems have been solved, the solutions stick. No need to go back and check if the atomic weight of argon has changed over the past decade.

In complex social systems, single models don't work. To make sense of our world, a person needs a crowd of models to create an internal dialogue between logic and the world. A person needs to follow what Anatol Rappaport calls a "reality model feedback loop." That dialogue leads to understanding. Societies need an even larger crowd of models if they hope to respond to the challenges they face.

Great Models, Books, and Ideas

The model thinker aims to possess a collection of deep, diverse understandings of processes relevant to the world. That's not a new goal. It also underpins the Great Books movement, which recommended texts that every educated person should read. The parallels between the two visions are worth unpacking. The Great Books curriculum, as put forth by Robert Hutchins and Mortimer Adler, had the following desiderata: works had to be contemporarily and historically relevant and to be written with sufficient style to be worth rereading. If I were to list a criterion for a Great Model, it would be that the model should produce useful knowledge with broad application.

This is not to say that the difference between Great Books and Great Models is merely a matter of style or form. To the contrary, the differences are quite stark. Models are formal. They rely on defined parts and interactions and implications depend on assumptions. The person who thinks with models is tethered to logic. That's not necessarily true of the ideas in the Great Books. They can be incomplete, and their assumptions may not be clear. The value of this book largely rests on the distinction between models and ideas. Models do more than capture ideas. They make ideas formal and they reveal flaws in those ideas.

Indulge me a moment's description of the Great Books. Hutchins and Adler, include four hundred and thirty one texts by seventy-three authors, an entire bookshelf.[10] Even if someone did read that entire bookshelf, the more troublesome problem would be making sense of them all – separating transcendent ideas from plot. What are we to take from the Odyssey: That you should put wax in your ears? That you should remain faithful to your spouse? Or perhaps, that you should build an unusually large bed?

This dastardly duo: the time commitment and the problem of separating anecdote from deep analogy led Adler and Hutchins to produce the Syntopicon: a glossary of sorts to the Great Ideas inside the Great Books.[11] The Syntopicon debuted in 1952. Inside, it listed one hundred and two Great Ideas including as *imagination*, *physics*, *liberty* and *death*. Connecting all of these ideas back to the texts required prodigious outlays of time and effort, and, one can only imagine, produced long discussions over interpretations. Why or how they decided to stop at one hundred and two is mystifying to me. Had they thought of just two more, they could have released them as a bridge set of playing cards. As for the wax ears of Odysseus's crew, the faithful Penelope, and the enormous bed, these would seem to fall into the categories *desire*, *prudence*, and *symbol*, so all should make the list.

I mention the Syntopicon because the Great Models align more closely with the Great Ideas than with the Great Books. Models formalize many of the Great Ideas, though not all (*dialectic* and *prophecy* would be difficult to model). Hutchins and Adler did not devote much attention to models. In fairness, the tools we use to make sense of have changed since the Syntopicon was created. When they began selecting the Great Books, the library from which they chose contained few books from outside the natural sciences that contained models. Darwin didn't use models. Neither did Adam Smith. Not because Darwin and Smith's ideas

[10]Four hundred and thirty-one should sound familiar. The star Polaris, the beacon used by escaped slaves to find their way to the North, sits exactly four hundred and thirty one light years away from the earth: one light year for each book. For many, that's how long it might seem to take to work through those weighty tomes. In point of fact, a steady diet of a book a week would occupy a mere eight years. That's assuming of course that you get through *War and Peace* in a week.

[11]Cynics claim that the Syntopicon was written to boost sales. I do not doubt that better sales were a byproduct, but the effort put into the book reveals a deep belief in the cause.

couldn't have been improved with models (they have been!), but because the relevant models had yet to be developed. Today if you take a course on evolution or economics, you learn models. That's also true if you take courses in psychology, anthropology, or archeology.

At first blush, models and narrative ideas are quite similar. We can map the parts of a model into the building blocks of sentences nouns, adjectives, verbs, adverbs and so on. Later in this book, I describe a model of disease spread. People and the disease are nouns. The attributes of the people: susceptible, infected, and recovered play the role of adjectives. And the verbs describe how the adjectives get assigned. If models just capture common intuitions, why then go to the trouble of constructing a model of disease, why not just give a verbal description?

Here's why: *to get the logic correct.* We have lots of intuitions. Some are correct (heavier objects produce more force), some are incorrect (the sun does not revolve around the earth), and some contradict. Thus, we say "nothing ventured, nothing gained" as well as "better safe than sorry." To sift through these opposite proverbs, we need logic. That's true of ideas we think up on the fly. It's also true of ideas found in the Syncopticon.

To demonstrate how our intuition can be incorrect, here's an example. Draw a small number of points on a graph. Think about how you might draw edges between the points until the graph is *connected*, i.e. until you can get from any one point to any other. Try to draw that set of connecting edges so that it is of minimal total length. This exercise won't be difficult unless you drew a lot of points.

Here's the question. Suppose you add another point. Will the minimal total length of connecting edges increase? Will more points imply more edges, and therefore imply greater minimal total length? The obvious answer? Of course, it will. The correct answer: no! Let's build a simple graphical model. The picture on the left shows four points as corners of a square. If we assume the length of a side the square equals one, to connect those four points

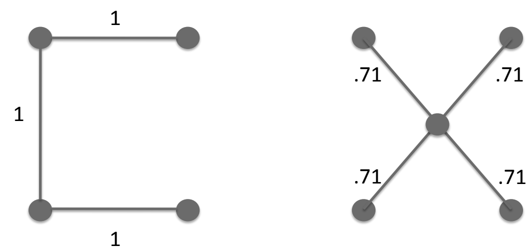

Figure 1: Increasing the number of nodes decreases the minimal connecting path

requires three edges equal to the length of a side of that square. The picture on the right includes a fifth point in the center. Connecting all five points requires four edges: one from each corner to the center. These edges have a total length equal to $4 \cdot 0.71$, which is less than 3. Our intuition fails us here. More (edges) turns out to require less (distance).

This may seem like a parlor trick, but it reveals a useful insight. The total length of electric lines, pipelines, ethernet lines, and roads can sometimes be reduced by adding more points.

By modeling the network explicitly, we reveal flaws in our logic and implicit assumption. In a model, the parts and their interactions must be defined, and the outcomes must follow logical from the assumptions. In writing a narrative or drawing an analogy, we can be looser. We leave vague some of the particulars. Sure, we can omit details in a model too, but we have to say what we're putting in and what we're leaving out.

Let me return to the example of a disease. In a model of disease spread, we must define the probability that people interact and the probability that the disease spreads from one person to another. Once all of these parts are put together our model tells us something that we wouldn't necessarily expect or anticipate: *diseases exhibit threshold phenomena.* If the virulence of the disease times the likelihood that people meet exceeds a threshold, then the disease will spread. If that same produce lies below that threshold, the disease won't spread. A narrative account would not reveal that if threshold exists, nor would it characterize the functional relationship that determines whether a disease spread.

To experience the distinction between a model and a narrative first hand, try the following exercise. First, explain to a friend why a particular book or movie was or was not popular. Then sit down and write a model that formalizes your account. You might find yourself staring at an incoherent collection of boxes and arrows. Making models isn't easy.

New Uses for an Old Idea

The idea that we should teach modeling has been around for more than half century. Early motivations for modeling were less expansive. They also tended to take a single model approach – to borrow from the natural sciences the idea that each situation could be addressed with a single model. For example, in their excellent modeling textbook, Jean Lave and James March give three reasons for constructing models. I should add they were considering only social science models, but these reasons carry over to the physical and natural sciences as well. These reasons were:

- To explain and predict phenomena
- To predict other (and new) phenomena
- To build and design systems

In their view, a primary reason to construct models is to explain phenomena. I disagree slightly. I believe it's to become a better thinker. In taking their position, Lave and March follow a long line of people who believe that the essence of good science is to build a model and then subject the model to empirical testing. Take even the most mundane phenomenon like the fact that most objects fall to the earth (helium balloons being a notable counterexample). Rather than just be puzzled by this phenomenon, I could try to construct a model. In fact, I might construct two. One could be a model based on attraction. Another could be a model based on suction. Both work. Both also tell us something we already know – that we have our feet firmly on the ground. We can compare these models by how well they perform. In this case, both might work quite well.

When we build a model to predict or explain one thing, we often generate other predictions as well. We don't demand that all of these other explanations make sense, but we'd like some of them to be. Otherwise, we cannot place much faith in the model's explanation of the phenomenon that interested us. So, while one good test of a model is not only whether it can generate the thing that it set out to explain, another is whether it can explain or predict other related phenomena.

Return to my suction model. This model explains why things fall but little else. It cannot explain why heavy objects fall at the same rate as light objects. If my model was correct, lighter objects should get sucked in faster. Balloons should drop right to the floor while bricks gently fall. Clearly, then, this model isn't right, and we should place our faith in the gravity model.

The Newtonian model of gravity, by the way, the one that most of us carry around in our heads also approximates reality. It's not factually correct. Though, it is a better model than the suction model, it's wrong nonetheless. Yet, as models go, it's pretty darn good. No one calculating how far a canon will shoot abandons Newton for Einstein's curved space time model based on general relativity because that model's too complicated. The added accuracy exists at a level of precision beyond what is needed. Astrophysicists, though, do leave Newton behind, at least sometimes.

Lave and March also highlight the value of models in design. This benefit should be evident. If given the opportunity to design a bridge, I could do so without any knowledge of physics. However, if I wanted to be sure that the bridge would not collapse under its own weight, then I'd do better with models. Suppose that I am building a pergola. I need to decide whether I should use two by sixes or two by eights as supporting beams and how to space the beams. If I just guess at which boards to use, I could get lucky and wind up with a sturdy, cost effective pergola. But, I could also overbuild the pergola spending too much money and get a clunky outcome, or I could build a pergola that collapses.

By using a model and then calibrating that model with the known strengths of the materials I'm using, I improve my chances of getting a good outcome. A similar logic applies to the crafting of social policies. Most social policy has a basis or at least a rationalization in some model or set of models. Government leaders rely on a collection of models to guide their decisions. The models don't give definitive answers. They guide decisions.

I want to emphasize that models have many more uses than those highlighted by Lave and March. Models can help predict the future, fill in data from the past, and even tell us what data to collect (Epstein 2006). Models help us to identify necessary and sufficient conditions for a phenomenon to occur. For example, in my research on the effects of diversity (Page 2008), I've used models to disentangle another set of opposite proverbs: the one that says two heads are better than one and, and the one that says too many cooks spoil the broth. Models helped me sketch out the line separating when each chain of logic applies. Models also help us to consider counterfactuals and to explore the effects of changing parameters. And models help us to design better experiments as well as policies. Further, models can help explain general properties of a system, whether it will go to an equilibrium, cycle, produce complexity, or result in chaotic dynamics.

Misconceptions about Models

Now that I've driven home, why you should want to model, I can get to the models themselves. First though, I feel compelled to clarify three common misconceptions about the use of models. The first causes some people to place too much faith in models. The second leads some people to discredit models for political reasons. The third conflates models with what they're made of, it's sort of like confusing a tree with wood.

The first misconception, what I call the *single model fallacy*, is the idea that we only need a single best model. I've already mentioned this, but it's sufficiently important to reiterate. In confronting complex situations, no single model can capture everything. Thus, we need to bring several of models to bear, not just one. Policy decisions and strategic choices would be so much easier if we had single, perfect models of complex phenomena, but we don't. Nor will we ever.

The next misconception conflates models in social science with models that include an assumption that human actors make *rational choices*. Most, though far from all, economics models make this assumption, but they need not. And increasingly, with the rise of behavioral and neuro economics, fewer of them do.

Logically speaking, rational choice models are to models what heated seats are to cars: an option, a matter of choice. This misconception arises because rational choice models occupy a central place in economics and in political science, the two social sciences that rely the most on modeling.

Rational choice is a common assumption for good reasons. It serves as a benchmark because it represents an ideal state (who wouldn't optimize if she could?). And, as odd as this may sound, finding optimal actions (in a model anyway) is often easiest. If you know calculus you can optimize. Also, there's often only one way to optimize. So that makes the models cleaner and easier to interpret. Realistic models of human behavior would be messy, just like real people. Further, an assumption of rationality produces results that don't become obsolete the instant they're stated. By that I mean, if a model assumes that people do not optimize and then that model purports to produces some predictable pattern, then that pattern can often be exploited by someone who does optimize. Or at a minimum, by someone who as read the model. For this reason, many economists believe that any model that does not assume rationality lacks coherence.

Further, in many cases rational choice passes empirical muster. Decades of experiments on decision making and strategic play show that in repeated, high stakes interactions of low complexity, people act darn close to rationally. However, in idiosyncratic, interactions of high complexity, it's probably a not so good assumption. One of the theses that drives this book is that we're living in a complex world. As a result, I'm not going to blindly assume rationality blindly. For balance, I'll include some models that assume rational actors and some that don't. According to hardcore rational choice theorists, this makes me rational in some cases and not so rational in others. When I do abandon rationality, I'll assume that actors are purposeful, that they either have explicit goals and ambitions or that their actions implicitly align with recognizable ends.

Finally, models are often equated with mathematics. In fact, models take many forms. They can be mathematical, such as the model that force equals mass times acceleration. They can also be computational (Miller and Page 2008). They can even be constructed of physical parts, such as the Phillips' hydraulic model of the British economy.

In this book, I'm only going to show you mathematical and computational models. That said, I must admit that upon seeing a reproduction of the Phillip's model in the London Science Museum, I had pangs of physical model envy. I strongly encourage anyone to build physical versions of the models in this book. If you do, send me pictures!

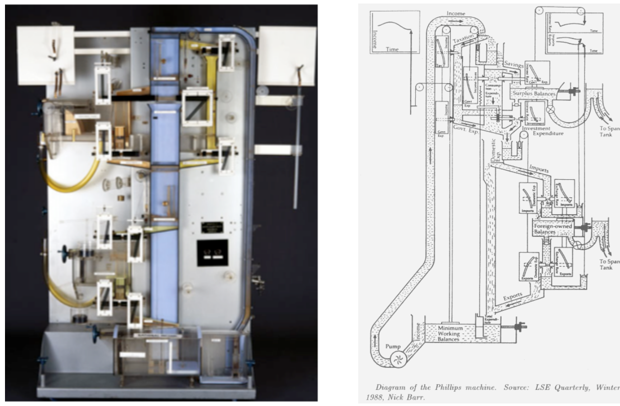

Figure 2: The Phillips Hydraulic Model of the British Economy

Your Own Private Syntopiconian Toolbelt

A diverse set of motivations led me to write this book. As an educator, I wanted to create better thinkers. Getting around in the modern, complex, information rich world requires that you think clearly and diversely. Models help you do both. Each model enforces logical consistency. Thinking with multiple models exposes the limitations of each model and leads toward wisdom. Yet, many people are frightened of models. Models conjure up notions of complicated equations with integrals signs and the C+ in physics that forced you to drop ambitions to attend medical school.

I also wanted to produce a volume that exhibited the myriad uses of models to a wider audience. When applied to physical phenomena, a model might be used to explain and predict outcomes. It might do so with high accuracy. In the social world, the goal may be more modest. We might hope that the model identifies causal or generative mechanisms of the phenomenon of interest.[12] Models can also help us figure out what data or information we need. They can help us figure out what must have happened or must not have happened

[12]See Daniel Little's Blog *Understanding Society* for more on the ontology of social science.

in the past. And they can tell us whether a process will be stable, cyclic, random, or complex.

I hoped that by putting models from different disciplines together in one place, I could highlight the fact that similar ideas and concerns exist in disparate academic fields. Though each of the models in this book originated in one discipline, I take effort to show how most of them can be applied in other disciplines as well. Physical models can generate insights that are relevant to the social world, and models from social science will provide insights about ecological and biological processes. In my opinion, a good economist should know some ecology and a good ecologist should know some economics.

In an analysis of thousands of forecasts by quote-unquote experts, Phil Tetlock (2008) found that single model thinkers – what he called hedgehogs – were worse than random at foretelling the future. In other words, having a single model, be it “markets work,” “history repeats itself,” or ”long run averages hold” may be worse than having none at all. He also finds that people who invoke multiple models are better than random. That shouldn’t be a big surprise. What is a surprise is that we tend to pay undue attention to single model thinkers. We shouldn’t. We should heed the advice of those who think more subtlety. Better still, we should learn many models ourselves.

Becoming a model thinker will make you better at you career, enhance your ability to make informed votes, and improve the advice you give others and yourself. As impressive as they may be, these substantial material benefits pale in comparison to the cognitive benefits from thinking with models. The modern complex world offers up so many interesting things to contemplate. Models enable us to make sense of that complexity. Moreover, each model has the versatility of a Ginzu knife. It will slice, dice, and chop a wide range of phenomena. Throughout the book, I will make a point to emphasize how each model apply across myriad contexts, a version of the Great Models idea. The more models at our disposal, the more likely that we’ll know two or three that provide useful insights about the world. The wiser and the larger we will be.

Part I

The Power of Simple Models

Chapter 1

Supertankers and Exploding Elephants

The human brain can be awe inspiring. That an elaborate web sending chemical and electrical signals can produce conscious thought, conjugate firms, and recall all fifty state capitals – under duress even – remains somewhat of a mystery. I say somewhat because with the use of models, cognitive neuroscientists have begun to make sense of how neurons retain memories and make computations.

As impressive as our brains may be, they're not perfect. They make mistakes, such as deciding to tape conversations in the White House or to dally with an intern. The list of documented human cognitive biases exceeds a hundred. Among the most pronounced are recall biases: systematic errors in how we recall information. Here are two: first, people find it much easier to generate words that begin with the letter "r" than words that have "r" as their third letter even though the latter are more frequent. This bias occurs because of how we store words in memory. Second, we interpret stimuli based on importance not on frequency. If walking in the dark, we will often categorize a curved linear object as a snake and not as a stick even though snakes are much rarer than sticks. To give another example, recently, I stepped on a cold, wet piece of cooked asparagus that had fallen off its plate enroute to the dining room table. My brain, perhaps channeling some deep fear of snakes, responded by informing me to jump, and to jump quickly.

Experts debate the cause of these biases. Some, including Gert Gigerenzer (CITE), believe that over time we accumulate heuristics that enable us to make accurate choices quickly. There's a catch though. No simple hueristic can always be right. And in fact, almost any simple heuristic will be systematically wrong. Thus biases occur as a consequence of the fact that we use simple rules of thumb. An alternative theory relies on evolution. This theory states that our brains evolved over time and that the structure of our brain builds in certain cognitive biases. A long time ago, those individuals who reflexively jumped when they stepped on a snake, probably lived longer. As a result, their cognitive architectures got passed on with greater frequency. Now, we're stuck with an asparagus fearing cognitive apparatus. Both theories have empirical support. And both agree that as impressive as we are, we still make mistakes, and do so often. And that's a big reason why we need models. They help us avoid mistakes. They're especially good at helping us think through sequence of logic.

In this chapter, I take two simple models from elementary school geometry and show how they can explain the existence of supertankers and why elephants have lower metabolism than mice. I choose these diverse applications – shipbuilding and zoology – on purpose to highlight the range of applications of models. Models are not just something used by engineers to design bridges and macro economists to make policy. They can be used by anyone anywhere. They can also be mixed and matched across contexts.

Two Simple Geometric Models

The first models that most of us learn are based on geometry. We learn these models early in elementary school, Armed with pencils, rulers, and a large erasers, we work through formulae for perimeter, area, and volume. We learn that the area of a rectangle equals the product of the length of the two sides and that the volume of a three dimensional box equals the product of the length of all three sides.

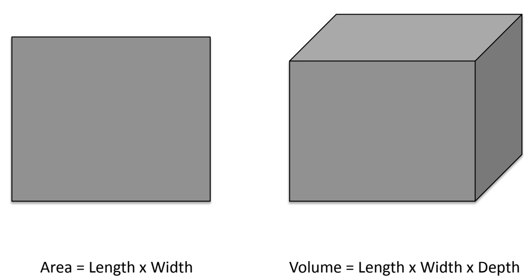

Figure 1.1: Two Geometric Formulae

These simple models have a variety of uses. We can employ them to make estimations for material use: how much material do I need to make curtains?or how much wood do I need to side a house? They can also help us answered novel or even ridiculous questions such as how many bloodhounds can you fit in the Empire State building or how many golf balls can you fit in a school bus. (Google, by the way, at one point would ask the latter question to job candidates.)

One of the core themes of this book will be that knowing models adds richness to your life. Knowing and applying a diverse set of models deepens your understanding of the world around you and helps you make better decisions. You can also apply insights from models to make great breakthroughs. That statement holds true for any model. It's even true of those simple models that you learn in elementary school. By that I mean, you can use the model for the volume of a box to think outside the box.

Allow me to explain, I once was giving a presentation on the benefits of diverse thinking to a small group of CEOs and senior executives from a variety of industries. During the post presentation discussion, one of the CEOs expressed interest in this idea of having diverse models. He then asked the million dollar question (literally): "can someone turn one of these models into ten million bucks?" To which I responded, yes, any model can make you ten million bucks. You just have to know when and how to apply it.

A Rectangular Supertanker

You can even make ten million bucks (or more) from the two simple geometric models that we just covered. Stavros Niarchos, the Greek Shipping Magnate, did just that when he built the first supertankers. Niarchos knew geometry. He knew that surface area of a ship scales differently than its volume. And that therefore, the bigger the ship, the greater his return on his investment. Hence, supertankers.

Let's work through his logic using the geometric models. Keep in mind, models are approximations. So, we're going to model a ship as a rectangular box (formally, a cuboid) of height S, width S and length $8S$. I assume a length to width ratio of eight to approximate the ratio of most ships. We can assume that the cost of building a ship is approximately proportional to the amount of steel needed in construction, hence, it's proportional to the ship's surface area. There are reasons that this wouldn't be true. Larger ships require thicker steel and stronger welds, so making larger ships costs relatively more. However, navigational equipment does not depend on the ship size, making the larger ships relatively cheaper. On balance, surface area seems a reasonable proxy for cost.

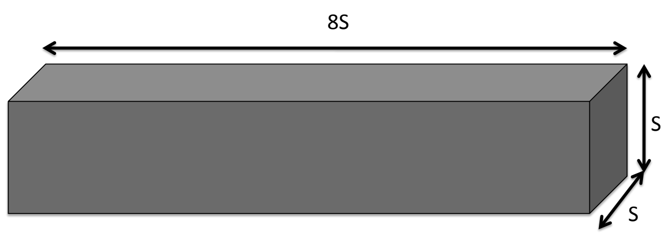

Figure 1.2: A Model of a Supertanker

To compute how much steel would be required to make a ship, we need to calculate the surface of the top and bottom, sides, and front and back. The front and back have surface areas equal to S^2, while the sides and the top and bottom have surface areas equal to $8S$ times S or $8S^2$. Therefore, the total surface area of our model ship equals two times S^2 plus four times $8S^2$, which equals $34S^2$. The volume of our ship equals S times S times $8S$ or $8S^3$. Thus, the surface area goes up with the square of S, but the volume increases with its cube. This is what Niarchos remembered from geometry.

Using this elementary school model, the enormous gains from supertankers becomes evident with just a few calculations. Let's compare the surface area and volume for a ship thirty feet wide and two hundred and forty feet long to a supertanker five times as large: that means one hundred and fifty feet wide and twelve hundred feet long. In our model, for the ship, $S = 30$, while for the supertanker, $S = 150$. Using the formulae for surface area and volume that we all learned in elementary school, the ship has a total surface area of 30,600 square feet and a volume of 216 thousand cubic feet. The supertanker has a surface area

765,000 square feet (twenty-five times that of the ship) and a volume of 27 million cubic feet *one hundred and twenty five times the volume of the ship*. In other words,, the supertanker carries one hundred and twenty five times as much oil, but only requires twenty-five times the steel. It's a bargain. By the way, the first supertankers paid for themselves after just a few payloads.

The story of supertankers provides a brilliant example of how simple models can be employed. It's also of pedagogical value for showing the limits of models. Absent any knowledge about ships and the shipping industry, one might logically conclude that ships should become enormous. That's not true. The longest supertankers stretch only a little more than a quarter mile and are just sixty meters wide. The reason they're this size isn't due to any limitations on the ambitions of shippers but because of the Suez Canal. It is only sixty meters wide at its narrowest point. Any ship wider than that could not take the short cut into the Mediterranean. So, as powerful as models may be, they're only guides to thinking. We have to maintain contact with reality.

Exploding Elephants

Good models are fertile. They apply across multiple domains, often in unexpected ways. Our geometric models teach us that size and volume scale differently. Volume goes up much faster than surface area. We just saw how that made larger ships more cost effective. It also means that larger animals must be more efficient. To see why, we need just a little chemistry and physics.

First, some chemistry: every living entity has a metabolism, a repeated sequence of chemical reactions that breaks down organic matter, transforms it into energy and then puts that energy to use in cellular reproduction. The *metabolic rate* for an organism equals the amount of energy required to keep an entity alive. Metabolic rates are measured in calories, units of energy. When you eat, you take in calories, which we use to power our bodies. People with high metabolisms burn more calories than people with low metabolisms.

Next, we need our geometric models. In our previous model, we created a rectangular supertanker. Here, we'll create a rectangular mouse and elephant. Let's model a mouse as a rectangular box three inches long, an inch high and and inch wide and an elephant as ten feet long, ten feet high, and five feet wide. Finally, we need a little physics. We want to think of our mouse and our elephant as composed of one inch cubic cells. Each cell has a metabolism that produces energy that releases heat as a byproduct. That heat dissipates through the surface of the animal. Our mouse has a surface area of fourteen square inches and a volume of three cubic inches. That means it has four and two thirds square inches of surface area for each cell. Or, to put this another way, each of the three one inch cubic cells has six sides, for a total of eighteen. Only four of those eighteen sides – two sides of the middle box and the inner sides of the two end boxes – cannot dissipate heat. Thus, it's as if, each little heat producing one inch square has four and two thirds sides through which it can dissipate heat.

Let's compare this to our elephant. It has two sides of ten feet by ten feet and four sides of five feet by ten feet, for a total surface area of 400 square feet. Each square foot has 144 square inches, so that's 57,600 sides of one inch boxes that are exposed and can dissipate heat. Our elephant has a volume of 500 square feet, which equal 864,000 one inch boxes. Dividing the number of boxes by the number of exposed sides shows that the elephant has one exposed side for each fifteen boxes. The elephant cannot possibly dissipate heat as well as the mouse. In fact, we might wonder why don't elephants just explode from all that heat. The answer is that if their metabolism matched that of mice, they could, but fortunately it doesn't. It's more than twenty times slower. So, they don't blow up, and they also don't eat as much. An elephant that had the metabolism of a mouse would eat approximately fifteen thousand pounds of food per day.

In sum, simple geometric models can be quite powerful. They can help us build ships and explain why, relatively speaking, elephants eat so little. But they're just a start. By creating, richer models we can learn even more.