Extracts about Modeling

Extracted from: Page, S.E. The Model Thinker: What you need to know to make data work for you. Hachette Group Book, 2018. Chapters 1 & 2.

The many-model thinker

This is a book about models. It describes dozens of models in straightforward language and explains how to apply them. Models are formal structures represented in mathematics and diagrams that help us to understand the world. Mastery of models improves your ability to reason, explain, design, communicate, act, predict, and explore.

This book promotes a many-model thinking approach: the application of ensembles of models to make sense of complex phenomena. The core idea is that many - model thinking produces wisdom through a diverse ensemble of logical frames. The various models accentuate different causal forces. Their insights and implications overlap and interweave. By engaging many models as frames, we develop nuanced, deep understandings. The book includes formal arguments to make the case for multiple models along with myriad real - world examples.

The book has a pragmatic focus. Many-model thinking has tremendous practical value. Practice it, and you will better understand complex phenomena. You will reason better. You exhibit fewer gaps in your reasoning and make more robust decisions in your career, community activities, and personal life. You may even become wise.

Twenty - five years ago, a book of models would have been intended for professors and graduate students studying business, policy, and the social sciences along with financial analysts, actuaries, and members of the intelligence community. These were the people who applied models and, not coincidentally, they were also the people most engaged with large data sets. Today, a book of models has a much larger audience: the vast universe of knowledge workers, who, owing to the rise of big data, now find working with models a part of their daily lives.

Organizing and interpreting data with models has become a core competency for business strategists, urban planners, economists, medical professionals, engineers, actuaries, and environmental scientists among others. Anyone who analyzes data, formulates business strategies, allocates resources, designs products and protocols, or makes hiring decisions encounters models. It follows that mastering the material in this book — particularly the models covering innovation, forecasting, data binning, learning, and market entry timing — will be of practical value to many.

Thinking with models will do more than improve your performance at work. It will make you a better citizen and a more thoughtful contributor to civic life. It will make you more adept at evaluating economic and political events. You will be able to identify flaws in your logic and in that of others. You will learn to identify when you are allowing ideology to supplant reason and have richer, more layered insights into the implications of policy initiatives, whether they be proposed greenbelts or mandatory drug tests.

These benefits will accrue from an engagement with a variety of models — not hundreds, but a few dozen. The models in this book offer a good starting collection. They come from multiple disciplines and include the Prisoners' Dilemma, the Race to the Bottom, and the SIR model of disease transmission. All of these models share a common form: they assume a set of entities — often people or organizations — and describe how they interact.

The models we cover fall into three classes: simplifications of the world, mathematical analogies, and exploratory, artificial constructs. In whatever form, a model must be tractable. It must be simple enough that within it we can apply logic. For example, we cover a model of communicable diseases that consists of infected, susceptible, and recovered people that assumes a rate of contagion. Using the model, we can derive a contagion threshold, a tipping point, above which the disease spreads. We can also determine the proportion of people we must vaccinate to stop the disease from spreading.

As powerful as single models can be, a collection of models accomplishes even more. With many models, we avoid the narrowness inherent in each individual model. A many - models approach illuminates each component model's blind spots. Policy choices made based on single models may ignore important features of the world such as income disparity, identity diversity, and interdependencies with other systems. 1 With many models, we build logical understandings of multiple processes. We see how causal processes overlap and interact. We create the possibility of making sense of the complexity that characterizes our economic, political, and social worlds. And, we do so without abandoning rigor — model thinking ensures logical coherence. That logic can be then be grounded in evidence by taking models to data to test, refine, and improve them. In sum, when our thinking is informed by diverse logically consistent, empirically validated frames, we are more likely to make wise choices.

Models in the Age of Data

The appearance of a book on models may seem out of place in the era of big data. Today, data exists in unprecedented dimensionality and granularity. Customer purchase data, which used to arrive in monthly aggregates on printed paper, now streams instantaneously with geospatial, temporal, and consumer tags. Student academic performance data now includes scores on every homework, paper, quiz, and exam, as opposed to semester - end summary grades. In the past, a farmer might mention dry ground at a monthly Grange meeting. Now, tractors transmit instantaneous data on soil conditions and moisture levels in square - foot increments. Investment firms track dozens of ratios and trends for thousands of stocks and use natural - language processing tools to parse documents. Doctors can pull up page upon page of individual patient records that can include relevant genetic markers.

A mere twenty - five years ago, most of us had access to little more than a few bookshelves' worth of knowledge. Perhaps your place of work had a small reference library, or at home you had a collection of encyclopedias and a few dozen reference books. Academics and government and private - sector researchers had access to large library collections, but even they had to physically visit the material. As late as the turn of the millennium, academics could be found shuttling back and forth between card catalog rooms, microfiche collections, library stacks, and special collections in search of information.

That has all changed. Content that had been paper - bound for centuries now flows in tiny packets through the air. So too does the information about the here and now. News that arrived

on our doorsteps on newsprint once a day now flows in a continuous digital stream into our personal devices. Stock prices, sports scores, and news of political events and cultural happenings can all be accessed with a swipe or query.

 As impressive as the data may be, it is no panacea. We now know what has happened and is happening, but, owing to the complexity of the modern world, we may be less capable of understanding why it happened. Empirical findings may be misleading. Data on piece - rate work often shows that the more people are paid per unit of output, the less they produce. A model in which pay depends on work conditions can explain those data. If conditions are poor so that producing output is difficult, per unit pay may be high. If conditions are good, per unit pay may be low. Thus, higher pay does not lead to less productivity. Instead, more difficult work conditions require higher per unit pay. 2

 In addition, most of our social data — that is, data about our economic, social, and political phenomena — documents only moments or intervals in time. It rarely tells us universal truths. Our economic, social, and political worlds are not stationary. Boys may outscore girls on standardized tests in one decade and girls may outscore boys the next. The reasons people vote today may differ from the reasons they vote in coming decades.

 We need models to make sense of the fire - hose - like streams of data that cross our computer screens. Thus, it is because we have so much data that this might also be called the age of many models. Look across the academy, government, the business world, and the nonprofit sector, and you struggle to find a domain of inquiry or decision not informed by models. Consulting giants McKinsey and Deloitte build models to formulate business strategies. Financial firms such as BlackRock and JPMorgan Chase apply models to select investments. Actuaries at State Farm and Allstate use models to calibrate risk when pricing insurance policies. The people team at Google builds predictive analytic models to evaluate its more than three million job applicants. College and university admissions officers construct predictive models to select from among tens of thousands of applicants.

 The Office of Management and Budget constructs economic models to predict the effects of tax policies. Warner Brothers applies data analytics to create models of audience responses. Amazon develops machine learning models to make product recommendations. Researchers funded by the National Institutes of Health build mathematical models of human genomics to search for and evaluate potential cures for cancer. The Gates Foundation uses epidemiological models to design vaccination strategies. Even sports teams use models to evaluate draft prospects and trade opportunities and to formulate within - game strategies. By relying on models to select players and strategies, the Chicago Cubs won a World Series championship after more than a century of failures.

 To people who use models, the rise of model thinking has an even simpler explanation: models make us smarter . Without models, people suffer from a laundry list of cognitive shortcomings: we overweight recent events, we assign probabilities based on reasonableness, and we ignore base rates. Without models, we have limited capacity to include data. With models, we clarify assumptions and think logically. And, we can leverage big data to fit, calibrate, and test causal and correlative claims. With models, we think better. In head - to - head competitions between models and people, models win.

Why We Need Many Models

In this book we advocate using not just one model in a given situation but many models. The logic behind the many - model approach builds on the age - old idea that we achieve wisdom through a multiplicity of lenses. This idea traces back to Aristotle, who wrote of the value of combining the excellences of many. A diversity of perspectives was also a motivation for the great - books movement, which collected 102 important transferable ideas in *The Great Ideas: A Syntopicon of Great Books of the Western World*. The approach finds a modern voice in the work of Maxine Hong Kingston, who wrote in The Woman Warrior , "I learned to make my mind large, as the universe is large, so that there is room for paradoxes." It is also the basis for pragmatic actions in the world of business and policy. Recent books argue that if we want to understand of international relations, we should not model the world exclusively as a group of self - interested nations with well - defined objectives, or only as an evolving nexus of multinational corporations and intergovernmental organizations. We should do both.

As commonsensical as the many - model approach may seem, keep in mind that it runs counter to how we teach models and the practice of modeling. The traditional approach — the one taught in high school — relies on a one - to - one logic: one problem requires one model. For example: now we apply Newton's first law; now we apply the second; now the third. Or: here we use the replicator equation to show the size of the rabbit population in the next period. In this traditional approach, the objective is to (a) identify the one proper model and (b) apply it correctly. Many - model thinking challenges that approach. It advocates trying many models. Had you used many - model thinking in ninth grade, you might have been held back. Use it now, and you will move forward.

Academic papers, for the most part, follow the one - to - one approach as well, even though they use those single models to explain complex phenomena: Trump voters in the 2016 election were those who had been left behind economically. Or: the quality of a child's second - grade teacher determines how economically successful that child will be as an adult. 5 A stream of best - selling nonfiction titles present cures for our ills based on single - model thinking: Educational success depends on grit. Inequality results from concentrations of capital. Our nation's poor health is due to sugar consumption. Each of these models may be true, but none is comprehensive. To confront the complexity of these challenges, to create a world of broader educational achievement, will require lattices of models.

By learning the models in this book, you can begin to build your own lattice. The models originate from a broad spectrum of disciplines, addressing phenomena as varied as the causes of income inequality, the distribution of power, the spread of diseases and fads, the conditions that precede social uprisings, the evolution of cooperation, the emergence of order in cities, and the structure of the internet. The models vary in their assumptions and their structure. Some describe small numbers of rational, self - interested actors. Others describe large populations of rule - following altruists. Some describe equilibrium processes. Others produce path dependence and complexity. The models also differ in their uses. Some help predict and explain. Others guide actions, inform designs, or facilitate communication. Still others create artificial worlds for our minds to explore.

The models share three common characteristics: First, they simplify, stripping away unnecessary details, abstracting from reality, or creating anew from whole cloth. Second, they

formalize, making precise definitions. Models use mathematics, not words. A model might represent beliefs as probability distributions over states of the world or preferences as rankings of alternatives. By simplifying and making precise, they create tractable spaces within which we can work through logic, generate hypotheses, design solutions, and fit data. Models create structures within which we can think logically. As Wittgenstein wrote in his Tractatus Logico - Philosophicus , "Logic takes care of itself; all we have to do is to look and see how it does it." The logic will help to explain, predict, communicate, and design. But the logic comes at a cost, which leads to their third characteristic: all models are wrong , as George Box noted. 6 That is true of all models; even the sublime creations of Newton that we refer to as laws hold only at certain scales. Models are wrong because they simplify. They omit details. By considering many models, we can overcome the narrowing of rigor by crisscrossing the landscape of the possible.

To rely on a single model is hubris. It invites disaster. To believe that a single equation can explain or predict complex real - world phenomena is to fall prey to the charisma of clean, spare mathematical forms. We should not expect any one model to produce exact numerical predictions of sea levels in 10,000 years or of unemployment rates in 10 months. We need many models to make sense of complex systems. Complex systems like politics, the economy, international relations, or the brain exhibit ever - changing emergent structures and patterns that lie between ordered and random. By definition, complex phenomena are difficult to explain, evolve, or predict.

Thus, we confront a disconnect. On the one hand, we need models to think coherently. On the other hand, any single model with a few moving parts cannot make sense of high - dimensional, complex phenomena such as patterns in international trade policy, trends in the consumer products industry, or adaptive responses within the brain. No Newton can write a three - variable equation that explains monthly employment, election outcomes, or reductions in crime. If we hope to understand the spread of diseases, variation in educational performance, the variety of flora and fauna, the effect of artificial intelligence on job markets, the impact of humans on the earth's climate, or the likelihood of social uprisings, we must come at them with machine learning models, systems dynamics models, game theory models, and agent - based models.

The Wisdom Hierarchy

To sketch the argument for many - model thinking, we begin with a query from poet and dramatist T. S. Eliot: "Where is the wisdom we have lost in knowledge? Where is the knowledge we have lost in information?" To that we might add, where is the information we have lost in all this data?

Eliot's questioning can be formalized as the wisdom hierarchy . At the bottom of the hierarchy lie data: raw, uncoded events, experiences, and phenomena. Births, deaths, market transactions, votes, music downloads, rainfall, soccer matches, and speciation events. Data can be long strings of zeros and ones, time stamps, and linkages between pages. Data lack meaning, organization, or structure.

Information names and partitions data into categories. Examples clarify the distinction between data and information. Rain falling on your head is data. Total rainfall for the month of July in Burlington, Vermont, and Lake Ontario's water level are information. The bright red

peppers and yellow corn on farmers' stands surrounding the capitol in Madison, Wisconsin, on market Saturdays are data. The farmers' total sales are information.
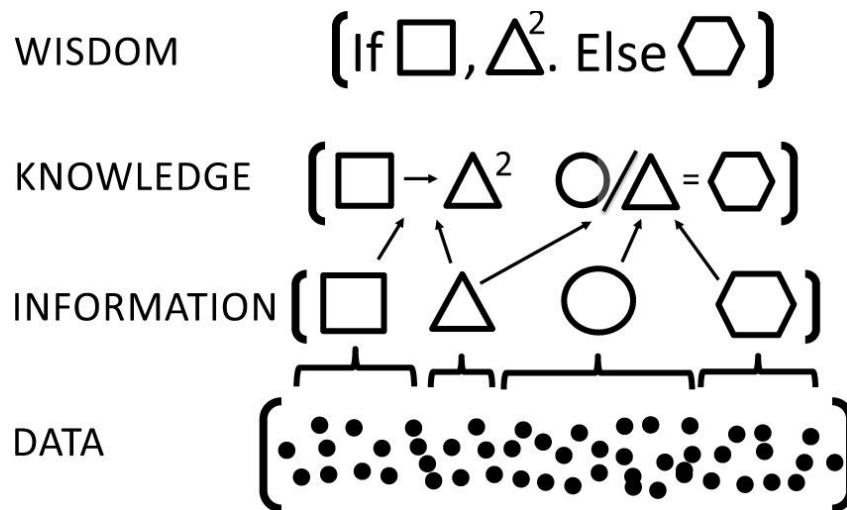

Figure 1.1: How models transform data into wisdom

We live in an age of abundant information. A century and a half ago, knowing information brought great economic and social status. Jane Austen's Emma asks if Frank Churchill is "a young man of information." Today she would not care. Churchill, like everyone else, would have a smartphone. The question is whether he could put that information to use. As Fyodor Dostoyevsky writes in Crime and Punishment , "We've got facts, they say. But facts aren't everything; at least half the battle consists in how one makes use of them!"

 Plato defined knowledge as justified true belief. More modern definitions refer to it as understandings of correlative, causal, and logical relationships. Knowledge organizes information. Knowledge often takes model form. Economic models of market competition, sociological models of networks, geological models of earthquakes, ecological models of niche formation, and psychological models of learning all embed knowledge. Those models explain and predict. Models of chemical bonds explain why metallic bonds prevent us from putting our hands through steel doors while hydrogen bonds yield to our weight when we dive into a lake.

 Atop the hierarchy lies wisdom , the ability to identify and apply relevant knowledge. Wisdom requires many - model thinking. Sometimes, wisdom consists of selecting the best model, as if drawing from a quiver of arrows. Other times, wisdom can be achieved by averaging models; this is common when making predictions. (We discuss the value of model averaging in the next section.) When taking actions, wise people apply multiple models like a doctor's set of diagnostic tests. They use models to rule out some actions and privilege others. Wise people and teams construct a dialogue across models, exploring their overlaps and differences.

 Wisdom can consist of selecting the correct knowledge or model; consider the following physics problem: A small stuffed cheetah falls from an airplane's hold at 20,000 feet. How much damage will it do upon landing? A student might know a gravity model and a terminal velocity

model. The two models give different insights. The gravity model predicts that the stuffed animal would tear through a car's roof. The terminal velocity model predicts that the toy cheetah's speed tops out at around 10 mph. 9 Wisdom consists of knowing to apply the terminal velocity model. A person could stand on the ground and catch the soft cheetah in her hands. To quote the evolutionary biologist J. B. S. Haldane, "You can drop a mouse down a thousand - yard mine shaft; and, on arriving at the bottom, it gets a slight shock and walks away, provided that the ground is fairly soft. A rat is killed, a man is broken, a horse splashes."

In the stuffed - cheetah problem, arriving at the correct solution requires information (the weight of the toy), knowledge (the terminal velocity model), and wisdom (selecting the correct model). Business and policy leaders also rely on information and knowledge to make wise choices. On October 9, 2008, the value of Iceland's currency, the króna, began a free fall. Eric Ball, then treasurer of software giant Oracle, was faced with a decision. A few weeks prior he had dealt with the domestic repercussions of the home mortgage crisis. Iceland's situations posed an international concern. Oracle held billions of dollars in overseas assets. Ball considered network contagion models of financial collapse. He also thought of economic models of supply and demand in which the magnitude of a price change correlates with the size of the market shock. In 2008, Iceland had a GDP of $12 billion, or less than six months' revenues for McDonald's Corporation. Ball recollected thinking, "Iceland is smaller than Fresno. Go back to work." 10 The key to understanding this event, and many - model thinking generally, lies in recognizing that Ball did not search among many models to find one that supported an action that he had already decided to take. He did not use many models to find one that justified his action. Instead, he evaluated two models as possibly useful and then chose the better one. Ball had the right information (Iceland is small), chose the right model (supply and demand), and made a wise choice.

We next show how to create a dialogue among multiple models by reconsidering two historical events: the 2008 global financial market collapse, which reduced total wealth (or what had been thought to be wealth) by trillions of dollars, resulting in a four - year global recession, and the 1961 Cuban missile crisis, which nearly resulted in nuclear war.

The 2008 financial collapse has multiple explanations: too much foreign investment, over - leveraged investment banks, lack of oversight in the mortgage approval process, blissful optimism among home - flipping consumers, the complexity of financial instruments, a misunderstanding of risk, and greedy bankers who knew the bubble existed and expected a bailout. Superficial evidence aligns with each of these accounts: money flowed in from China, loan originators wrote toxic mortgages, investment banks had high leverage ratios, financial instruments were too complex for most to understand, and some banks expected a bailout. With models we can adjudicate between these accounts and check the internal consistency of these accounts: Do they make logical sense? We can also calibrate the models and test the magnitude of the effects.

The economist Andrew Lo, exercising many - model thinking, evaluates twenty - one accounts of the crisis. He finds each to be lacking. It does not make sense that investors would contribute to a bubble that they knew would lead to a global crisis. Hence, the extent of the bubble must have been a surprise to many. Financial firms may well have assumed the other firms had done due diligence when in fact they had not. Second, what were, in retrospect, clearly toxic (low - quality) bundles of mortgages found buyers. Had global collapse been a foregone conclusion,

the buyers would not have existed. And while leverage ratios had increased since 2002, they were not much higher than they had been in 1998. And as for the notion that the government would bail out the banks, Lehman Brothers collapsed on September 15, 2008; with over $600 billion in holdings, it was the largest bankruptcy in US history. The government did not intervene.

Lo finds that each account contains a logical gap. The data, such as it is, privileges no single explanation. As Lo summarizes: "We should strive at the outset to entertain as many interpretations of the same set of objective facts as we can, and hope that a more nuanced and internally consistent understanding of the crisis emerges in the fullness of time." He goes on to say, "Only by collecting a diverse and often mutually contradictory set of narratives can we eventually develop a more complete understanding of the crisis." No single model suffices. 11

In Essence of Decision , Graham Allison undertakes a many - model approach to explain the Cuban missile crisis. On April 17, 1961, a CIA - trained paramilitary group landed on the shores of Cuba in a failed attempt to overthrow Fidel Castro's communist regime, increasing tensions between the United States and the Soviet Union, Cuba's ally. In response, Soviet premier Nikita Khrushchev moved short - range nuclear missiles to Cuba. President John F. Kennedy responded by blockading Cuba. The Soviet Union backed down, and the crisis ended.

Allison interprets events with three models. He applies a rational - actor model to show that Kennedy had three possible actions: start a nuclear war, invade Cuba, or impose a blockade. He chose the blockade. The rational - actor model assumes that Kennedy draws a game tree with each action followed by the possible responses by the Soviets. Kennedy then thinks through the Soviets' optimal response. If, for example, Kennedy launched a nuclear attack, the Soviets would strike back, resulting in millions dead. If Kennedy imposed a blockade, he would starve the Cubans. The Soviet Union could either back down or launch missiles. Given that choice, the Soviet Union should back down. The model reveals the central strategic logic at play and provides a rationale for Kennedy's bold choice to blockade Cuba.

Like all models, though, it is wrong. It ignores relevant details, allowing it to initially appear a better explanation than it really is. The model neglects to add a stage in which the Soviets put the missiles in Cuba. If the Soviets had been rational, they should have drawn the same tree as Kennedy and realized that they would have to remove the missiles. The rational - actor model also fails to explain why the Soviets did not hide the missiles.

Allison applies an organizational process model to explain these inconsistencies. A lack of organizational capacity explains the Soviets' failure to hide the missiles. The same model can explain Kennedy's choice to blockade. At the time, the United States Air Force lacked the capacity to wipe out the missiles in a single strike. If even a single missile remained, it could kill millions of Americans. Allison deftly combines the two models. An insight from the organizational model changes the payoffs in the rational - choice model.

Allison adds a governmental process model. The other two models reduce countries to their leaders: Kennedy acts for the United States and Khrushchev for the Soviet Union. The government process model recognizes that Kennedy had to contend with Congress and that Khrushchev needed to maintain a political base of support. Thus, Khrushchev's placing of the missiles in Cuba signaled strength.

Allison's book shows the power of models alone and in dialogue. Each model clarifies our thinking. The rational - actor model identifies possible actions once the missiles have arrived and allows us to see the implications of those actions. The organizational model draws our attention to the fact that organizations, not individuals, carry out those actions. The governmental process model highlights the political cost of invasion. By evaluating events through all three lenses, we gain a broader and deeper understanding. All models are wrong; many are useful.

In both examples, the different models explicate distinct causal forces. Multiple models can also focus on different scales. In an oft - repeated tale, a child claims that the Earth rests on the back of a giant elephant. A scientist asks the child what the elephant stands on, to which the child replies, "A giant turtle." Anticipating what's about to come next, the child quickly adds, "Don't even ask. It's turtles all the way down." 12 If the world were turtles all the way — if the world were self - similar — then a model of the top level would apply at every level. But the economy, the political world, and society are not turtles all the way down, nor is the brain. At the sub - micron level, the brain is made up of molecules that form synapses, which in turn form neurons. The neurons combine in networks. The networks overlap in elaborate ways that can be studied with brain imaging. These neuronal networks exist on a scale below that of functional systems such as the cerebellum. Given that the brain differs at each level, we need multiple models, and those models differ. The models that characterize the robustness of neuronal networks bear little resemblance to the molecular biology models used to explain brain cell function, which in turn differ from the psychological models used to explain cognitive biases.

The success of many - model thinking depends on a degree of separability. In analyzing the 2008 financial crisis, we rely on separate models of foreign purchases of assets, of the bundling of assets, and of increased leverage ratios. Allison drew implications from the game theoretic model without considering the organizational model. In studying the human body, doctors separate the skeletal, muscular, limbic, and nervous systems. That said, many - model thinking does not require that these distinct models divide the system into independent parts. Confronted with a complex system, we cannot, to paraphrase Plato, carve the world at its joints. We can partially isolate the major causal threads and then explore how they are interwoven. In doing so, we will find that the data produced by our economic, political, and social systems exhibits coherence. Social data is more than sequences of incomprehensible hairballs that might have been spit up by the family cat.

Summary and Outline of the Book

To summarize, we live in a time awash in information and data. The same technological advances generating those data shrink time and distance. They make economic, political, and social actors more agile, capable of responding to economic and political events in an instant. They also increase connectedness, and therefore complexity. We face a technologically induced paradox: we know more about the world, but that world is more complex. In light of that complexity, any single model will be more likely to fail. We should not though abandon models. To the contrary, we should privilege logical coherence over intuition and double, triple, and even quadruple down on models and become many - model thinkers.

Becoming a many-model thinker requires learning multiple models of which we gain a working knowledge; we need to understand the formal descriptions of the models and know how to

apply them. We need not be experts. Hence, this book balances accessibility and depth. It can function both as a resource and as a guide. The formal descriptions are isolated in stand - alone boxes. It avoids line after line of equations, which overwhelm even the most dedicated readers. The formalism that remains should be engaged and absorbed. Modeling is a craft, mastered through engagement; it is not a spectator sport. It requires deliberate practice. In modeling, mathematics and logic play the role of an expert coach. They correct our flaws.

The remainder of the book is organized as follows: Chapters 2 and 3 motivate the many - model approach. Chapter 4 discusses the challenges of modeling people. The next twenty or so chapters cover individual models or classes of models. By considering one type of model at a time, we can better wrap our heads around its assumptions, implications, and applications. This structure also means that we can pull the book from our bookshelves or open it in our browsers and find self-contained analyses of linear models, prediction models, network models, contagion models, and models of long - tailed distributions, learning, spatial competition, consumer preferences, path dependence, innovation, and economic growth. Interspersed throughout the chapters are applications of many - model thinking to a variety of problems and issues. The book concludes with two deeper dives into the opioid epidemic and income inequality.

Why to model?

> Knowing reality means constructing systems of transformations that correspond, more or less adequately, to reality.
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> — Jean Piaget

Models are often described as simplifications of the world. They can be, but models can also take the form of analogies or be fictional worlds mined for ideas and insights. We also describe the uses of models. In school, we apply models to explain data. In practice, we can also use models to predict, design, and take actions. We can use models to explore ideas and possibilities. And we can use models to communicate ideas and understandings.

The value of models also resides in their ability to reveal conditions under which results hold. Most of what we know holds only in some cases: the square of the longest side of a triangle equals the sum of the squares of the other sides only if the longest side is opposite a right angle. Models reveal similar conditions for our intuitions. With models we can parse out when diseases spread, when markets work, when voting leads to good outcomes, and when crowds make accurate predictions. None of those is a sure thing.

This chapter consists of two parts. In the first, we describe the three types of models. In the second, we cover the uses of models: to reason, explain, design, communicate, act, predict, and explore. These form the acronym REDCAPE, a not so-subtle reminder that many-model thinking endows us with superpowers.

Types of Models

When constructing a model, we take one of three approaches. We can aim for realism and follow an embodiment approach . Such models include the important parts and either strip away unnecessary dimensions and attributes or lump them together. Models of ecological glades, legislatures, and traffic systems take this approach, as do climate models and models of the brain. Or we can take an analogy approach and abstract from reality. We can model crime spreading like a disease and the taking of political positions as choices on a left - right continuum. The spherical cow is a favorite classroom example of the analogy approach: to make an estimate of the amount of leather in a cowhide, we assume a spherical cow. We do so because the integral tables in the back of calculus textbooks include tan(x) and cos(x) but not cow(x). 2

While the embodiment approach stresses realism, the analogy approach tries to capture the essence of a process, system, or phenomenon. When a physicist assumes away friction but otherwise makes realistic assumptions, she takes the embodiment approach. When an economist represents competing firms as different species and defines product niches, she makes an analogy. She does so using a model developed to embody a different system. No bright line differentiates the embodiment approach from the analogy approach. Psychological models of learning that assign weights to alternatives lump together dopamine responses and other factors; they also invoke the analogy of a scale on which we balance alternatives.

A third approach, the alternative reality approach, purposely does not represent or capture reality. These models function as analytic and computational playgrounds in which we can explore possibilities. This approach allows us to discover general insights that apply outside our physical and social world. They help us to understand the implications of real - world constraints: What if energy could be sent safely and efficiently through the air? And they allow us to run impossible experiments: What if we tried to evolve a brain? This book contains a few such models, notably the Game of Life, which consists of a checkerboard whose squares are classified as either alive (black) or dead (white) that switch between alive and dead according to fixed rules. Though unrealistic, the model produces insights into self - organization, complexity, and, some argue, even life itself.

Whether embodying a more complex reality, creating an analogy, or building a made - up world for exploring ideas, a model must be communicable and tractable . We should be able to write the model in a formal language such as mathematics or computer code. When describing a model, we cannot toss out terms like beliefs or preferences without providing a formal description. Beliefs can be represented as a probability distribution over a set of events or priors. Preferences can be represented in several ways such as a ranking over a set of alternatives or as a mathematical function.

How tractable something is means how amenable it is to analysis. In the past, analysis relied on mathematical or logical reasoning. A modeler had to be able to prove each step in an argument. This constraint led to an aesthetic that valued stark models. English friar and theologian William of Ockham (1287 – 1347) wrote, "Plurality must never be posited without

necessity." Einstein summed up this principle, known as Ockham's Razor, as follows: everything should be made as simple as possible, but not simpler. Today, when we run up against the constraint of analytic tractability, we can turn to computation. We can build elaborate models with many moving parts without concern for analytic tractability. Scientists take this approach when constructing models of the global climate, the brain, forest fires, and traffic. They still pay heed to Ockham's advice, but recognize that "as simple as possible" might require a lot of moving parts.

The Seven Uses of Models

The academic literature describes dozens of uses of models. Here, we focus on seven categories of uses: to reason, explain, design, communicate, act, predict, and explore.

The Uses of Models (REDCAPE)

- Reason: To identify conditions and deduce logical implications.
- Explain: To provide (testable) explanations for empirical phenomena.
- Design: To choose features of institutions, policies, and rules.
- Communicate: To relate knowledge and understandings.
- Act: To guide policy choices and strategic actions.
- Predict: To make numerical and categorical predictions of future and unknown phenomena.
- Explore: To investigate possibilities and hypotheticals.

R EDCAPE: Reason

When constructing a model, we identify the most important actors and entities along with relevant characteristics. We then describe how those parts interact and aggregate, enabling us to derive what follows from what, and why. In doing so, we improve our reasoning. While what we can derive depends upon what we assume, we uncover more than tautologies. Rarely can we infer the full range of implications of our assumptions from inspection alone. We need formal logic. Logic also reveals impossibilities and possibilities. With it, we can derive precise and sometimes unexpected relationships. We can discover the conditionality of our intuitions.

Arrow's theorem provides an example of how logic reveals impossibilities. The model addresses the question of whether individual preferences aggregate to form a collective preference. This model represents preferences as ordinal rankings over alternatives. If applied to five Italian restaurants, denoted by the letters A through E, the model allows any of the 120 orderings. Arrow required that the collective ordering be monotonic (if everyone ranks A above B, then so does the collective), independent of irrelevant alternatives (if no person's relative rankings of A and B are unchanged but rankings of other alternatives change, then the order of A and B in the collective ranking does not change), and nondictatorial (no single person should decide the collective ordering). Arrow then proved that if any preferences are allowed, then no collective ordering necessarily exists. 3

Logic can also reveal paradoxes. Using models, we can show the possibility of each subpopulation containing a larger percentage of women than men but the total population containing a larger percentage of men, a phenomenon (Simpson's paradox). This actually

happened: 1973, the University of California, Berkeley, accepted a larger percentage of women in most departments. Overall, it accepted men at a higher rate. Models also show that it is possible for two losing bets, when played alternately, to produce a positive expected return (Parrondo's paradox). With models, we can show that it is possible to add a node to a network and reduce the total length of the edges needed to connect all the nodes. 4

We should not dismiss these examples as mathematical novelties. Each has practical applications: efforts to increase the population of women could backfire, combinations of losing investments could win, and the total length of a network of electric lines, pipelines, ethernet lines, or roads could be be reduced by adding more nodes.

Logic also uncovers mathematical relationships. Given Euclid's axioms, a triangle can be uniquely determined by any two angles and a side, or by any two sides and an angle. With standard assumptions about consumer and firm behaviors, in markets with a large number of competing firms, price equals marginal cost. Some results are unexpected: among them the friendship paradox , which states that in any friendship network, on average, people's friends have more friends than they do.

The paradox arises because highly popular people have more friends. Figure 2.1 shows Zachary's Karate Network. The person represented by the dark circle has six friends, denoted by gray circles. His friends have nine friends on average. These people are represented by white circles. Over the entire network, twenty - nine of the thirty - four people have friends who are more popular than they are. 5 Later we show that if we make a few more assumptions, most people's friends will also be, on average, better - looking, kinder, richer, and smarter than they are.
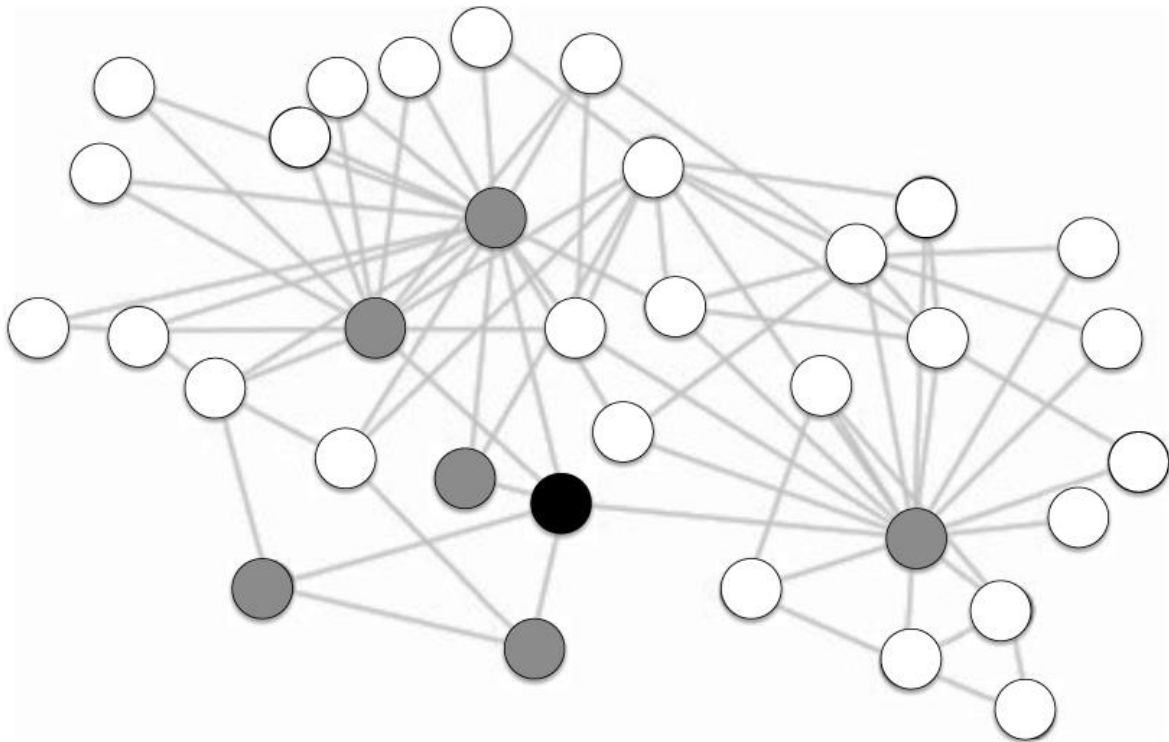

Figure 2.1: The Friendship Paradox: A Person's Friends Have More Friends

Last, and most important of all, logic reveals the conditionality of truths. A politician may claim that lowering income taxes increases government revenue by spurring economic growth. A rudimentary model in which revenue equals the tax rate times the income level proves that revenue increases only if the percentage growth in income exceeds the percentage cut in taxes. 6 Thus, a 10% cut in income taxes increases revenue only if it causes income to grow by more than 10%. The politician's logic only holds given certain conditions. Models identify those conditions.

The power of conditionality becomes evident when we contrast claims derived from models with narrative claims, even when the latter have empirical support. Consider the management proverb first things first : the idea that when facing multiple tasks, you should do the most important task first. This rule is also known as big rocks first , because when filling a bucket with rocks of various sizes, you should put the big rocks in first — if you put the little rocks in first, the big rocks will not fit.

The rule big rocks first, inferred from expert observation, may be a good rule most of the time, but it is unconditional. A model - based approach would make specific assumptions about the task and then derive an optimal rule. In the bin packing problem, a set of objects of various sizes (or weights) must be allocated into bins of finite capacity. The objective is to use as few bins as possible. Imagine, for example, you are packing up your apartment and putting everything into 2 - foot - by - 2 - foot boxes. Ordering your possessions by size and putting each object in the first box with sufficient space (known as the first fit algorithm) turns out to be quite effective. Big rocks first works well. However, suppose that we consider a more complex task: allocating space on the International Space Station for research projects. Each project has a payload weight, a size, and power requirements along with demands on the astronauts' time and cognitive abilities. Each also makes a potential scientific contribution. Even if we came up with some measure of bigness as a weighted average of these attributes, big rocks first would prove a poor rule given the dimensionality of interdependencies. More sophisticated algorithms and possibly market mechanisms would perform much better. 7 Thus, under some conditions, big rocks first is a good rule. Under other conditions, it is not. With models, we can trace the boundaries of when we should place the big rocks first and when we should not.

Critics of formalism claim that models repackage what we already know, that they pour old wine into shiny mathematical bottles, that we do not need a model to know that two heads are better than one or that he who hesitates is lost. We can learn the value of commitment from reading of Odysseus tying himself to the mast. That criticism fails to recognize that inferences drawn from models take conditional forms: if condition A holds, then result B follows (e.g., if you are packing bins and size is the only constraint, pack the biggest objects first). Lessons drawn from literature or proverbial advice from great thinkers often provide no conditions. If we try to lead our lives or manage others by unconditional rules, we find ourselves lost in a sea of opposite proverbs . Are two heads better than one? Or, do too many cooks spoil the broth?

- Proverb : Two heads are better than one
- Opposite : Too many cooks spoil the broth
- Proverb : He who hesitates is lost
- Opposite : A stitch in time saves
- Proverb : Tie yourself to the mast
- Opposite : Keep your options open

- Proverb : The perfect is the enemy of the good
- Opposite : Do it well or not at all
- Proverb : Actions speak louder than words
- Opposite : The pen is mightier than the sword

While opposite proverbs abound, opposite theorems cannot. Within models, we make assumptions and prove theorems. Two theorems that disagree on the optimal action, make different predictions, or offer distinct explanations must make different assumptions.

R E DCAPE: Explain

Models provide clear logical explanations for empirical phenomena. Economic models explain price movements and market shares. Physics models explain the rate of falling objects and the shape of trajectories. Biological models explain the distributions of species. Epidemiological models explain the speed and patterns of disease spread. Geophysical models explain the size distribution of earthquakes.

Models can explain point values and changes in their values. A model can explain the current price of pork belly futures and why prices rose over the past six months. A model can explain why a president appoints a moderate Supreme Court justice and why a candidate moves to the left or right. Models also explain shape: models of the diffusion of ideas, technologies, and diseases produce an S - shaped curve of adoption (or contagion).

The models we learn in physics, such as Boyle's Law (a model stating that the pressure of oxygen times the volume equals a constant ($PV = k$)), explain phenomena unreasonably well. 8 If we know the volume, we can estimate the constant k , and then explain or predict pressure P as a function of V and k . The model owes its accuracy to the fact that gases consist of simple parts that exist in large numbers and follow fixed rules: any two oxygen molecules placed in the identical situation follow the same physical laws. They exist in such large numbers that statistical averaging cancels out any randomness. Most social phenomena share none of these three attributes: social actors are heterogeneous, interact in small groups, and do not follow fixed rules. People also think. Even more problematic, people respond to social influences, meaning that behavioral variations may not cancel out. As a result, social phenomena are much less predictable than physical phenomena.

The most effective models explain both straightforward outcomes and puzzling ones. Textbook models of markets can explain why an unanticipated increase in the demand for a normal good like shoes or potato chips increases the price in the short run, an intuitive result. These same models explain why in the long run, demand increases have less of an effect on price than the marginal cost of producing the good. Increases in demand can even produce reductions in price that result from increased returns to scale in production, a more surprising result. The same models can explain paradoxes such as why diamonds, which have little practical value, have high prices, but water, a necessity for survival, costs little.

As for the claim that models can explain anything: it is true, they can. However, a model - based explanation includes formal assumptions and explicit causal chains. Those assumptions and causal chains can be taken to data. A model that claims that high levels of criminal behavior can be explained by low probabilities of being caught can be tested.

RE D CAPE: Design

Models aid in design by providing frameworks within which we can contemplate the implications of choices. Engineers use models to design supply chains. Computer scientists use models to design web protocols. Social scientists used models to design institutions.

In July 1993, a group of economists met at Caltech in Pasadena, California, to design an auction to allocate the electronic spectrum for cellular phones. In the past, the government had allocated spectrum rights to large companies for modest fees. A provision within the Omnibus Budget Reconciliation Act of 1993 allowed for auctioning the spectrum to raise money.

The radio signal from a tower covers a geographic range. Therefore, the government sought to sell licenses for specific regions: Western Oklahoma, Northern California, Massachusetts, Eastern Texas, and so on. This created a design challenge. The value of any given license for a company depended on the other licenses that company won. The license for Southern California would be worth more to a company that also owned the license for Northern California, for example. Economists refer to these interdependent valuations as externalities. The externalities had two main sources: construction and advertising. Holding neighboring licenses meant lower construction costs and the potential to exploit overlapping media markets.

The externalities created a problem with holding simultaneous auctions. A company trying to win a bundle of licenses might lose one license to another bidder and therefore lose the externalities. That company might then want to back out of its bids on other licenses. Sequential auctions had a different shortcoming. Bidders would underbid in early auctions to hedge against losing subsequent licenses.

A successful auction design had to be immune to strategic manipulation, generate efficient outcomes, and be comprehensible to participants. The economists used game theory models to analyze whether features could be exploited by strategic bidders, computer simulation models to compare the efficiency of various designs, and statistical models to choose parameters for experiments with real people. The final design, a multiple - round auction that allowed participants to back out of bids and prohibited sitting out early periods to mask intentions, proved successful. Over the past thirty years, the FCC has raised nearly $60 billion using this type of auction.

RED C APE: Communicate

By creating a common representation, models improve communication. Models require formal definitions of the relevant features and their relationships that we can then communicate with precision. The model F = MA relates three measurable quantities, force, mass, and acceleration, and does so in equation form. Each term is expressed in measurable units that can be communicated without fear of mis - interpretation. By comparison, the claim that "bigger, faster things generate more power" offers far less precision. Much can get lost in translation. Does bigger mean weight or size? Does faster mean velocity or acceleration? Does power mean energy or force? And how do bigger and faster combine to produce power? Attempts to formalize the claim could result in any of several forms: power could be written incorrectly as weight plus velocity (P = W + V), weight times velocity (P = WV), or weight plus acceleration (P = W + A).

When we formally define an abstract concept like political ideology using a reproducible methodology, those concepts take on some of the same features as physical qualities such as

mass and acceleration. We can use a model to say that one politician is more liberal than another based on their voting records. We can then communicate that claim with precision. Liberalness is well defined and measurable. Someone can use the same method to compare other politicians. Of course, voting records may not be the only measure of liberalness. We might construct a second model that assigns ideologies based on textual analysis of speeches. With that model as well, we can communicate with clarity what we mean by more liberal.

Many underappreciate the impact of communication on progress. An idea that cannot be communicated is like a tree falling in a forest with no one around to notice it. The remarkable economic growth in the Age of Enlightenment was due in no small part to the transferability of knowledge, often in model form. In fact, the evidence suggests that the transferability of ideas may have contributed more to economic growth during that time than did levels of education: city - level growth in eighteenth - century France correlates more strongly with the number of subscriptions to Diderot's Encyclopédie than with literacy rates.

REDC A PE: Act

Francis Bacon wrote, "The great end of life is not knowledge but action." Good actions require good models. Governments, corporations, and nonprofits all use models to guide actions. Whether it be raising or lowering prices, opening a new location, acquiring a company, offering universal health care, or funding an after - school program, decision - makers rely on models. On the most important actions, decision - makers use sophisticated models. Models are linked to data.

In 2008, as part of the Troubled Asset Relief Program (TARP), the Federal Reserve gave $182 billion in financial assistance to bail out the multinational insurance company American International Group (AIG). According to the US Department of the Treasury, the government chose to stabilize AIG "because its failure during the financial crisis would have had a devastating impact on our financial system and the economy." 12 The purpose of the bailout was not to save AIG but to prop up the entire financial system. Businesses fail every day, and the government does not intervene.

The particular choices made within TARP were based on models. Figure 2.2 shows a version of a network model produced by the International Monetary Fund. The nodes (circles) represent financial institutions. The edges (the lines between the circles) represent correlations between the values of the holdings of those institutions. The color and width of an edge corresponds to the strength of the correlation between the institutions, with darker and thicker lines implying greater correlation.

AIG occupies a central position in the network because it sold insurance to other firms. AIG held promises to pay other firms if those firms' assets lost value. If prices fell, then AIG owed those firms money. By implication, if AIG failed, so too would the firms connected to AIG. A cascade of failures might ensue. By stabilizing AIG's position, the government could prop up the market values of other firms in the network.
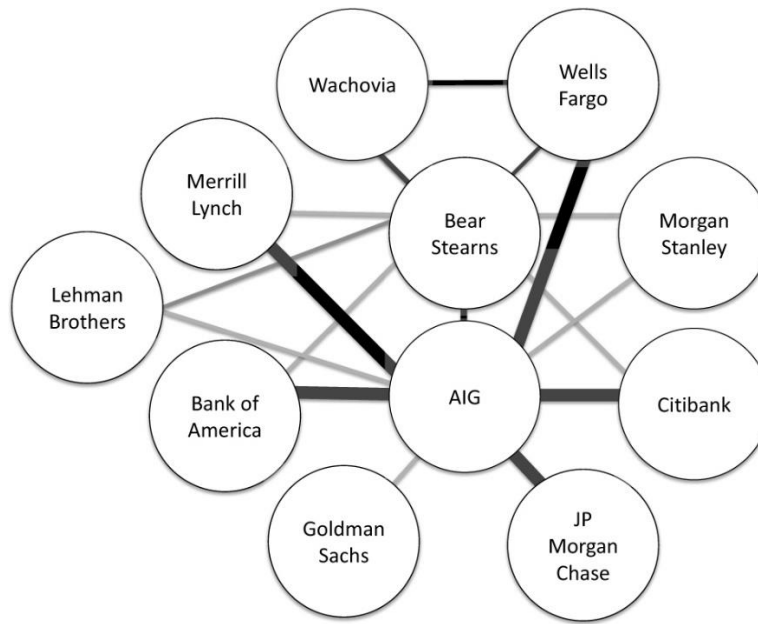
Figure 2.2: Correlation Graph Between Financial Institutions

Figure 2.2 also helps to explain why the government let Lehman Brothers fail. Lehman did not occupy a central position in the network. We cannot rerun history, so we cannot know if the Federal Reserve took the correct action. We do know that the financial industry did not collapse as a result of Lehman's failure. We also know that the government earned a $23 billion profit on its loan to AIG. So, we can infer that the policy choices — based on many - model thinking — were not a failure.

Models that guide action, such as policy models, often rely on data, but not all do. Most policy models also use mathematics, though that was not always true. In the past, policymakers built physical models as well. Phillips's hydraulic model of the British economy was used to think through policy choices in the mid - twentieth century, and a physical model of San Francisco Bay was instrumental in the decision not to dam the bay for fresh water. 16 The Mississippi River Basin Model Waterways Experiment Station, which covers nearly 200 acres near Clinton, Mississippi, is a miniature replica of the river's basin built on a horizontal scale of 1:100. The model can test the upstream and downstream effects of building new dams and reservoirs. The released water follows the laws of physics within the physical structure. In these physical models, the entities themselves are analogs of the real world. The models are logical because they follow the laws of physics.

Our examples so far have considered organizations using models to act. People can do the same. When taking important actions in our personal lives, we should also use models. In deciding to purchase a home, take a new job, return to graduate school, or buy or lease a car, we can use models to guide our thinking. Those models may be qualitative rather than tied to data. Even in those cases, the models will oblige us to ask relevant questions.

REDCA P E: Predict

Models have long been used to predict. Weather forecasters, consultants, sports handicappers, and central bankers all predict using models. Police agencies and the intelligence community

use models to predict criminal behavior. Epidemiologists use models to predict which strain of flu will be most widespread in the upcoming flu season. As data has become more available and granular, this use of models has grown. Twitter feeds and internet searches are used to predict consumer trends and social uprisings.

Models can predict individual events as well as general trends. On June 1, 2009, Air France flight AF 477, en route from Rio de Janeiro to Paris, crashed over the Atlantic. In the days following, rescuers found floating debris but could not locate the fuselage. By July, the batteries in the plane's acoustic beacons were depleted, halting search efforts. A year later, a second search led by the Woods Hole Oceanographic Institution using US Navy side - scan sonar vessels and autonomous underwater vehicles also proved unsuccessful. The French Bureau d'Enquêtes et d'Analyses eventually turned to models. They applied probabilistic models to ocean currents and identified a small rectangular region as being most likely to contain the fuselage. Using the model's prediction, searchers found the wreckage within a week. 17

In the past, explanation and prediction tended to go hand in hand. Electrical engineering models that explain voltage patterns can also predict voltages. Spatial models that explain politicians' past votes can also predict future votes. In perhaps the most famous example of applying an explanatory model to predict, the French mathematician Urbain Le Verrier applied the Newtonian laws created to explain planetary movements to evaluate the discrepancies in the orbit of Uranus. He discovered the orbits to be consistent with the presence of a large planet in the outer region of the solar system. On September 18, 1846, he sent his prediction to the Berlin Observatory. Five days later, astronomers located the planet Neptune exactly where Le Verrier had predicted it would be.

That said, prediction differs from explanation. A model can predict without explaining. Deep - learning algorithms can predict product sales, tomorrow's weather, price trends, and some health outcomes, but they offer little in the way of explanation. Such models resemble bomb - sniffing dogs. Even though a dog's olfactory system can determine whether a package contains explosives, we should not look to the dog for an explanation of why the bomb is there, how it works, or how to disarm it.

Note also that other models can explain but have little value as predictors. Plate tectonics models explain how earthquakes arise but do not predict when they occur. Dynamical systems models can explain hurricanes, but they cannot predict with much success when hurricanes will form or what paths they will take. And while ecology models can explain patterns of speciation, predict new types of species.

REDCAP E : Explore

Last, we use models to explore intuitions and possibilities. These explorations can be policy - related: What if we make all city buses free? What if we let students choose which assignments determine their course grades? What if we put signs on people's lawns showing their energy consumption? Each of these hypotheticals can be explored with models. We can also use models to explore unrealistic environments. What if Lamarck had been correct and acquired traits could be passed on to our offspring, so the children of parents with orthodontically corrected teeth would not need braces? What happens in such a world? Asking that question and exploring its implications can help to reveal the limits of evolutionary processes. Abandoning

the constraints of reality can spur creativity. For this reason, advocates of the critical design movement engage in speculative fictions to generate new ideas.

Exploration sometimes consists of comparing common assumptions across domains. To understand network effects, a modeler might begin a collection of stylized network structures and then ask whether and how network structure affects cooperation, disease spread, or social uprisings. Or a modeler might apply a collection of learning models to decisions, two - person games, and multiperson games. The purpose of these exercises is not to explain, predict, act, or design. It is to explore and learn.

When we apply a model in practice, we may use it in any of several ways. The same model may explain, predict, and guide action. As an example, on August 14, 2003, sagging trees leaning on power lines near Toledo, Ohio, created a localized power outage that spread when a software failure prevented an alarm from alerting technicians to redistribute power. Within a day, more than 50 million people in the northeastern United States and Canada had lost power. That same year, a storm knocked out a power line between Italy and Switzerland, leaving 60 million Europeans without power. Engineers and scientists turned to models that represent the power grid as a network. The models helped to explain how the failures occurred, offered predictions of regions where future failures might be likely, and also guided actions by identifying locations where new lines, transformers, and power supplies would enhance the robustness of the network. Putting one model to many uses will be a recurrent theme in this book. As we see next, one - to - many is a necessary complement to our central theme of applying many models to make sense of complex phenomena.