The Model Thinker

What’s in it for me? Discover how models can help us make sense of the world.

Thanks to modern technology, facts and figures about your spending habits, diets, favorite music, and even romantic preferences are collected and transmitted at an unprecedented rate. But what’s the use of all of this raw data? How do we make something valuable out of it? The short answer is: by using models. Models come in many forms, from mathematical formulas to charts. What they all have in common is that they allow us to make sense of data. With models, you can explain perplexing phenomena; design products, events, and institutions; and even predict the behavior of systems as diverse as the stock market and the spread of diseases. These blinks lay out how models can guide us in our understanding of complex, and sometimes counterintuitive, phenomena, helping us navigate the world and make better decisions. In these blinks, you’ll learn

how modeling helped to recover a missing plane; what exactly a linear regression is; and why our enjoyment of pizza is a concave function.

Models help us to explain, design, and predict.

In June 2009 Air France flight AF 477 crashed in the Atlantic ocean. After searching in vain for weeks, and after a second failed search attempt a year later, the French authorities eventually turned to using complex data models to locate the plane. Using data on ocean currents and sophisticated modeling, they pinpointed a small region where they predicted the fuselage might lie. Within a week, they’d found it! The key message here is: Models help us to explain, design, and predict. The success in locating Air France flight AF 477 shows the power of using models. By simplifying the world into straightforward variables, models reduce the confusing background noise and identify the truly significant factors that determine real-world outcomes. Sound a little abstract? Then picture real-world models like, for instance, those in physics which explain missile trajectories, or ecological models that explain the distribution of species in an ecosystem. Each of these draws on observable facts to create accounts of why things happen the way they do. But that’s not all. As useful as models are for analyzing and visualizing data that already exists in the world, they're equally helpful in imagining what things might look like. Using models to visualize all sorts of designs – for example, social policies, innovative products, or marketing campaigns – allows us to project and envision outcomes without actually committing to them. With models, then, we can consider the implications of our choices and redesign things in response to our discoveries. From imagining the form a design could take, it's a short step to thinking about what will happen. Models help us predict the future. They don’t always do this perfectly, of course – as anyone who’s ever been misled by a weather forecast knows. But, as you’ll learn in the following blinks, models can make it much easier to predict the outcomes of uncertain events.

Multiple models increase accuracy.

In politics, polls are a fact of life. Polls help people visualize the state of a race, and in the past, they were usually taken to be more or less reliable predictors of who'd win. In recent elections, though, this hasn't always been the case – presidential candidates have been favored to win states by a landslide, only to lose or squeak by with a narrow win when the day comes. There are a lot of theories about why this is, but one reason surely has to be the creators of the polls: human beings. Humans are fallible. We make mistakes. So the same holds true for our models. Although they may rely on logic and math, models are ultimately things that we've created – meaning they can be wrong, just like us. So how do we improve the explanations, predictions, and designs that models provide? What can we do to make them more accurate and more penetrating? The key message here is: Multiple models increase accuracy. Imagine that you're facing a big decision. If you're like most people, you probably confide in a few close friends. By hearing a diversity of opinions, you hope to make a better, more rational decision about the important decision. A similar approach works with models. Just as you're better off talking to some friends and seeing your dilemma from various angles, it's usually a good idea to consult a number of models rather than relying on any single approach. There's actually a theorem, called Condorcet's jury theorem, that confirms this idea. Think of it in terms of a courtroom jury. Let's say that each juror is correct more often than not. Mathematically, it then follows that a group of jurors are more likely to make the right decision than any individual one. As you add up each juror's odds of being right, the chances of the majority verdict being wrong dwindles. This works for modeling, too. If each model is correct more often than not, then adding more models increases overall accuracy. The problem is that using lots of diverse models is easier said than done. For example, if we're trying to predict the way a state will vote in a presidential election, we might construct one model that categorizes citizens based on their income levels and another that categorizes them based on their level of education. The catch here is that these apparently distinct categories often overlap – meaning that our "variety" of models can end up being less diverse than we'd like.

Normal distributions underlie many basic models.

Most teachers would probably say that C students are pretty common. Intuitively, that seems to make sense – a C is, by definition, pretty average. But why is that? What makes us think of a C as the average grade? The answer's simple: Grades tend to follow a normal distribution. Now, a distribution assigns probabilities to events or values. A normal distribution is a spread of values that cluster in a symmetrical pattern around one central mean. It's also known as "the bell curve," because the cluster of values forms the shape of a bell, gently rising, then peaking and falling again. The point at the top of the bell is the mean result – in the case of grades, it's a C. As the grades taper off on either side of that mean, you start to see those less-common results. Then, at the extremes on each side, you find the rare A+ and F- students. If this sounds pretty intuitive, that's not surprising – as we'll see, normal distribution crops up all over the place. The key message here is: Normal distributions underlie many basic models. Not all systems follow a normal distribution. Take individuals' wealth, for example. A handful of very wealthy people possess as much as millions of poorer people do – meaning that the distribution of wealth is skewed towards relatively few rich outliers.

When a system follows a bell curve, its relationship to outliers is much different: every deviation from the mean is as likely as a proportionate deviation in the opposite direction. Think of it this way: If the average man's height is 5' 9" and height follows a bell curve, then we should see as many men who are 5' 6" as we do men who are 6' – given that each is three inches from the mean. Despite these equivalent deviations, normal distributions chart a data set in which the outliers are rare, with most values gravitating towards a frequently-occurring mean. The further you travel from that mean, the less common the result in question. Knowing whether a given system produces a normal distribution is of great importance. Height, for example, follows a bell curve – meaning that airlines don't build planes that cater to nine-foot passengers.

Many important systems can be modeled as power laws.

Normal distribution isn't the only important type of distribution. Some data sets conform to what's called a long-tailed distribution. Remember how normal distribution is shaped like a symmetrical bell? Well, long-tailed distribution looks like the tail of a creature standing just outside the graph, its "long tail" running along the horizontal axis when the distribution is graphed. One common type of long-tailed distribution is what's known as a power-law distribution, or "power law." A power law usually describes a system in which something is amplified or exaggerated. The key message here is: Many important systems can be modeled as power laws. To visualize the kind of amplification that a power-law distribution describes, think about wealth. If you were to graph the way wealth generates more wealth when it's invested, you'd be looking at a pretty good example of a power law. The same goes for book sales, the spread of infectious disease, or the popularity of viral videos. To explain how some of these things get amplified over time in a power-law system, there's the preferential attachment model. It describes how certain things "grow at rates relative to their proportions." In other words, more leads to more. When you graph that kind of growth, it tends to end up looking like a power-law distribution. Let's break that down. Imagine students arriving on a college campus. The first student to arrive starts the college's first club. Now, when the second student arrives, she has a choice: either join the existing club or start a second one. Odds are, she'll join the existing group. By the time the first ten students arrive, they've created three clubs – meaning that when the eleventh student arrives, he faces three options. Join the original group, which now contains seven members; join the second club, which contains two; or join the third club, which has only a single member. According to the preferential attachment model, these clubs will, on average, be attractive in proportion to their size. The eleventh student will join the group of seven 70 percent of the time, the group of two 20 percent of the time, and the solitary student just 10 percent of the time. Put simple, in a power law, growth makes growing easier.

Linear regression can help us discover whether variables are correlated.

Although linear models are some of the simplest of all models, they can help to explain quite a few of the systems in operation in our world – like the effects of education on income, or of exercise on gains in life expectancy. So how do we know if a phenomenon can be explained using a linear model? Well, when you graph a linear function you get a straight line. This fact is important: it means that if you plot a set of values on a graph and can then draw a line straight through them, the relationship between the variables can be described using a linear model. In other words, you can prove that the variables in question are associated. This process is called linear regression. The key message here is: Linear regression can help us discover whether variables are correlated. Plotting values on X and Y axes and checking whether the values form a straight line is called linear regression, a technique that allows us to model the relationship between various straightforward systems. Let's imagine that you suspect there's a linear association between the amount of tea people drink and their risk of experiencing depression. After plotting the relevant variables on a graph, you might find that your values are all over the place and that there's no hope of drawing a straight line through them. In that case, your hypothesis would have to be abandoned. If, on the other hand, you find that you can draw a straight line between the values on the graph, then you've established a correlation between drinking tea and rates of depression. In that case, the sign of the association is said to be negative. That just means that an increase in one variable is associated with a decrease in the other. If an increase in one variable was associated with an increase in the other, the sign would be positive. But there's an important caveat. Identifying an association just shows that the variables correlate: it doesn't prove causality. It may be the case that tea drinkers just happen to experience less depression. In order to prove causality, you'd need to actually conduct a full-blown experiment, not just a linear regression. But a linear regression can point you in the right direction by suggesting the avenues worth exploring with more precise experiments and analyses.

Concave and convex functions can help us model some very diverse systems.

Imagine that you've been on a long hike and you haven't eaten in hours. You're hungry, to say the least – and so, to reward yourself, you order a large pizza as soon as you get home. The first slice is divine. The second is delicious too. But by the time you're nearing the end of your meal, you're not even paying attention to how it tastes. Your attention has simply drifted. A graph of your enjoyment probably wouldn't end up being linear. It would peak at the very start, and then smoothly curve and drop off as your hunger abated and your interest waned. In other words, we'd graph a concave function. The key message here is: Concave and convex functions can help us model some very diverse systems. Enjoyment can often be modeled using a concave function, which forms a decreasing curve. In an entirely different domain, a company's per-unit costs of production can also be modeled this way. In other words, as a company produces more and more of a thing, the costs of producing them go down, thanks to economies of scale. The downward-sloping line of those costs is concave. Profit per unit, on the other hand, is probably curving upwards at the same time, making a convex function. A convex function is a concave one turned upside down – instead of curving downwards, it rises. Concave and convex functions can help us to predict change. When we consider the future, we often go wrong by expecting change to be linear. If China's economic growth is 10 percent this year, and there's no reason to expect a downturn, we intuitively assume that it'll probably grow 10 percent next year too. In fact, lots of the systems around us need to be modeled in a nonlinear way. From 1960 to 1970, Japan's economy also grew by 10 percent year on year – but as its per capita GDP neared that of western countries, its growth leveled off in a concave curve. And that's exactly what's happened in China too, where economic growth has averaged between 6 and 7 percent annually since 2013. In short, nonlinear models are useful because a huge number of systems of interest and significance operate in a nonlinear way.

Modeling humans is a thorny endeavor.

People can be troublesome: if that’s true when it comes to real life, then it’s doubly true when it comes to modeling. Unlike bowling balls or weather cycles, humans have agency. We have minds of our own and we use them to make decisions. We experience social pressure, we have different preferences, and we often make mistakes. Sometimes, we might even learn from those mistakes. That’s what makes us fascinating – but from the point of view of modeling, it also makes us frustrating. So does that mean it’s hopeless to try to model human behavior? The key message here is: Modeling humans is a thorny endeavor. Whenever we try to model human behavior, there are some choices and assumptions that we can’t avoid. The first decision we have to make is between two different ways of picturing it – as rule-based or as rational. Rule-based behavior can be broken down into two main types: fixed and adaptive. Fixed rules don’t evolve as time passes and circumstances change. If we were to formulate a fixed rule in words, we might come up with something like “If the conversation lulls for longer than 20 seconds, change the topic.” An adaptive rule, on the other hand, changes and evolves in response to new circumstances and novel information. An adaptive rule might allow silences to go on for longer than 20 seconds if it became apparent that these conversational lulls ultimately led to better discussions. By contrast, the rational-actor model of human behavior assumes that people make rational decisions in order to achieve optimal outcomes. Instead of following set rules, they calculate what the best action is in any given situation and act on that information. Think of someone buying a house and calmly weighing up their options: the number of bedrooms each house has, the view out the kitchen windows, even the schools in each neighborhood. Neither rule-based nor rational-actor models work for every situation. When choices are simple or made by sophisticated decision-makers, they're likely to be rational ones. But when a choice is fairly low-stakes, like what color coat to buy, it’s likely that people will apply fixed rules. In others, like deciding who to trust in a delicate negotiation, people might apply adaptive rules. When it comes to modeling humans, we can rarely hope for complete accuracy. But choosing the right models can make our predictions, designs, and explanations far more accurate.

Final summary

The key message in these blinks: In an increasingly complex world, we need models to make sense of the perplexing systems around us. They can help us to explain the world, to create new designs, and to predict what’s coming next – but only if we’re careful to apply the right ones. In fact, to optimize our results, we should try to tackle a problem using as many diverse and relevant models as we can. Got feedback? We’d love to hear what you think about our content! Just drop an email to with The Model Thinker as the subject line and share your thoughts!