Models Only Say What They're Told to Say

William M. Briggs(✉)

New York, USA
matt@wmbriggs.com

Abstract. This short note is a reminder that all models only say what they are told to say. There can therefore be no discovery by models—discoveries go into models—and thus models should only be used in their predictive form, and only trusted when they have demonstrated independent success. AQ1

Keywords: Explanation · Inference · Models · Prediction · Probability

1 What Is A Model?

Inarguably, econometrics, applied probability, statistics, machine learning, artificial intelligence, and like areas are about models. Building models, estimating model internals, such as parameters, fitting models, making model projections, also known as forecasting or prediction, and evaluating model performance. But what is a model?

There has been work in the field of computer science devoted to the question, e.g. [1,2], but much of this naturally revolves around how to store and program models, and not on what models do or what their nature is. There are many, many references on how to create mathematical models, e.g. [3–5]. In statistics, Leo Breiman [6] introduced a long-running discussion on the nature of models, also taken up in my own work in a more philosophical bent, [7]. A mixed philosophy-mathematics approach can be found in Pearl, too, [8].

There is nothing wrong with the math in any model, except by accident or (it happens) cheating, and it is not wrong to have a wealth of materials devoted to this practical aspect of models. After all, when models use math, it is well to know how to use it best. But models are not always mathematical, and even those that are must rely on a philosophy of models. Just what *is* a model? That question can only be answered philosophically. Many authors have studied this question, such as [9–12].

These works discuss in depth just what models are, and, more importantly, what they are not. It is recognized models play a role in not just summarizing theories, but in making them, too, see e.g. [13,14]. This is the subject which interests us in this brief article. Interactions between objects, such as "forces of Nature", can be understood by thinking hard about the mathematical aspects of derived models. But it is strictly wrong to say that discoveries can come *from* models. Discoveries go *into* models, they do not arise from them. In short, as is emphasized repeatedly below, all models of any kind only say what they are told to say.

N. Ngoc Thach et al. (Eds.): ECONVN 2021, SCI 983, pp. 1–8, 2022.
https://doi.org/10.1007/978-3-030-77094-5_4

2 Simplicity

We assume everywhere that a model makes statements about some proposition Y, which in science is observable. These statements are deduced based on a set of assumed evidence X, which may include past observations of Y, a suite of logical and mathematical premises, statements of computer limitations and scope, and on and on. X "contains" all that is said about Y. Any model thus fits the schema:

$$\text{Model} := \text{M}(\text{Y}|\text{X}). \tag{1}$$

A simple model is:

$$x_{t+1} = x_t + 1;\ x_0 = 0 \tag{2}$$

We might suppose that a modeler (or "researcher") has claimed x_t is the number of cases of splenetic fever after being exposed to daily news broadcasts about coronadoom. In this case Y = x_{t+1}, and X is "$x_t + 1$; $x_0 = 0$, which includes premises why the additive form was chosen, and those tacit, i.e. hidden, premises that define what these symbols mean.

AQ2

Now it would be absurd if this model were touted by the press to report, "Scientists discover that there will be 30 new cases of splenetic fever by the end of the month!" This is absurd, because the model creator *told* the model to make this prediction. There was, and could be, no discovery about its predictions: the model did exactly what it was told to do by its creators.

Rival researchers created this alternate model:

$$x_{t+1} = x_t + 1/2;\ x_0 = 0 \tag{3}$$

The x_t is the same, i.e. splenetic fevers, but this model applies to people who social distance from media sources (e.g. avoid turning on the TV). It would also not be a discovery to claim, "Research reveals that social distancing reduces splenetic fever". It is not a discovery because the model was built to say social distancing causing reductions.

This model is not research, and no model is, not genuine research. This model may be the *result* of prior research—the fixed model had to arise for some reason—but the output is not research itself. It was decided on by a scientist or researcher. It's form was fixed by the scientist or researcher.

Both models say exactly what they were told to say. This does not mean they are right, wrong, useful or harmful, only that they were dictated and did only what they were instructed to do. This brief note will prove to you that all models say what they are told to say. This simple statement used to be more well known than it is today,

3 Models per Se

We can expand the simple model easily:

$$x_{t+1} = \beta_1 x_t + \beta_2;\ x_0 = \beta_3 \tag{4}$$

This model is equivalent to (2) when $\beta_1 = \beta_2 = 1$, and $\beta_3 = 0$. Its interpretation is identical; it doesn't become more mysterious by writing the parameters in Greek, rather than plainly as above. Or rather, as hidden; the parameters didn't seem to be there when not written in Greek, but they were there just the same. Less immediately obvious, but also true, is that the model form, its additive nature and number of parameters, is also chosen by the researcher: it always is. All models forms are always chosen, even when these forms are deduced or inferred from previously assumed evidence, e.g. from mathematical deductions. Obviously, the modeler was free to choose this previously assumed evidence and propositions used to deduce the current model. This is always so.

For example, supposing a projectile is launched with initial velocity v_0, at angle θ, with gravitational force g, it will be at the coordinates (x,y) at time t according to this model:

$$\begin{aligned} x_t &= v_0 t\cos(\theta), \\ y_t &= v_0 t\sin(\theta) - \frac{1}{2}gt^2 \end{aligned} \tag{5}$$

This model is deduced from earlier (well known) premises about how objects move under the effect of gravity and a given impetus. Those earlier premises taken in concert *explained* the path of the projectile. They may or may explain the *cause* of the movement, instead of just what determines the position of the projectile, but understanding cause it not always needed to produce a valuable model. This should be obvious, or there would be no place at all for probability models, because probability models are not *per se* causal (though they may have causal components).

Everything in (5) is known, or assumed to be known, as it was in (2). The form in (5) was derived using a great many tacit mathematical and physical facts or premises. The form in (2) was decided by custom and convenience. In both cases, however, the models in the end did just what they were told to do.

For (2) the βs were "made up" in the minds of the scientists, using tacit or vague, unspoken premises. The same is true for the form of the model, the "this plus that" mathematical form; and again, our conclusion is the model only said what it was told to say. But it doesn't make any difference if instead of making direct statements about the β's values, the scientist admitted a form of ignorance about their value. And he then filled that ignorance with a procedure to tie in measurements of, say, past incidents of splenetic fever to the βs using a probability model. The ways this is done are not of direct interest to us, but they involve things like frequentist parameter estimation or Bayesian prior and posterior uncertainty specification.

This past data, which we can label D, the past observations, are then part of the model. The researcher chose these D. He picked, or was made to pick, a starting and stopping time for the collection D. Since the data are part of the model, the probability model tying D to the βs was chosen by the researcher, as was the model form making statements about y, the model again is only saying what it was told to say.

Sometimes the parts of the model used to tie D to the model parameters is mathematically complex, making analytical solutions difficult or impossible. So-called "randomization" methods, like Markov Chain Monte Carlo, aide in providing the solution. There is nothing special in these methods: they do not bring anything to the model itself, other than allow for a mathematical solution.

These Monte Carlo methods work by providing a large set of numbers U between 0 and 1, numbers which are manipulated in various ways, to provide the desired solution. For any fixed set of U, the ties to D and the parameter estimates or values (certain or uncertain) is the same. The researcher might not have personally picked each u_i in the set U, but he picked the process to arrive at each u_i. And he did pick the MCMC (or whatever) method that ties the U and D to the parameters of the model.

Sometimes a researcher will automate how parameters come or go in a model, using tests or decision criteria to say "This stays" and "That goes." Obviously, the researcher picks these methods, and has complete control over what stays and what goes, and he always has control of the form of the model, the data and methods used, and so on. Every piece of every model is under the control of the researcher.

Nothing changes if the model is created by many through time and grows in size or complexity, or the whether the methods used in producing results in the model, such as providing parameter estimates, is arcane, whether the model is fully probabilistic or fully deterministic, or in between, each and every model can only say what it was told to say.

Again, none of this is news or unknown. But failure to remember the details has practical consequences, which are explored next.

4 Practicalities

Here is a press headline from a Minnesota news source on 13 May 2020: "Updated Model Predicts COVID-19 Peak In Late-July With SAHO Extended Through May; 25K Deaths Possible", [15]. This was of course produced during the coronavirus panic.

The article stated:

> An updated model from the University of Minnesota and state's health department is predicting that COVID-19 cases will peak in late-July with 25,000 deaths possible – if the stay-at-home order is extended until the end of May...
> In Scenario 5 [the model scenario relied up by government], the stay-at-home order is extended for all until the end of May. With that happening, the model predicts that the COVID-19 peak will happen on July 27, with the top intensive care units (ICU) demand being 4,000 and 25,000 possible deaths.
> Another estimate, Scenario 4, predicts that if the stay-at-home order is extended by a month into mid-July, the peak would occur on July 13 with 3,700 as the top ICU demand and 22,000 possible deaths.

In previous briefings, Minnesota's Governor Tim Walz had asked Minnesotans not to focus on specific numbers, but rather focus on when the peaks might occur. "Modeling was never meant to provide a number," Governor Walz said on Wednesday. "It was meant to show trend and direction, that if you social distance you buy more time."

This is false. It, and many similar comments made by numerous *official sources* during the panic, were common. They were all not only false, but misleading, too. Enforced stay-at-home social distance working was an *input* to all of these models. We cannot therefore point to model output and say, at least with a straight face, "See? The model says stay-at-home social social distancing works. Which is why we need to implement it." This mistake made countless times during the crisis. This is detailed at length in [16], including a discussion of how the World Health Organization made the same mistake, based on a high-school science project, to conclude social distancing worked, see [17], when, as always, this was a premise of the model.

The models reported on here were built saying social distancing reduces death. This assumption was an integral part of the models. It was not a "discovery" of the models, it was a condition *of* them. The models had to say social distancing worked because they started with the premise social distancing worked.

You cannot "discover" stay-at-home social distancing worked via *any* model—though it may be discovered via after-the-fact observation. You had to have built in that possibility in the first place. You knew in advance that it worked because that's what you told the model.

You cannot run the model, wait for the output, run to your Governor and say "The latest model says social distancing works." If your Governor had any sense he would say, "Didn't you write the model code? And didn't the code say somewhere that social distancing worked?"

The rush to embrace these models as if they were oracular says more about the goals and desires and decision makers during the panic than it says about model making.

Incidentally, according to the CDC, as of 13 September, attributed COVID-19 deaths in Minnesota were 1,803, with the peak occurring in mid-May, [18]. These represent all attributed deaths, including those deaths where the individuals died of multiple causes. The error of the models relied upon to make decisions was therefore at least 12 times, an enormous and horrendous mistake. The restrictions is Minnesota did stay in place, but were interrupted by the Minneapolis riots, a time when social distancing was not observed. If the models had any bearing on reality, since social distancing did not obtain, the deaths should have been higher than 25,000.

Another example is AI, or so-called artificial intelligence. Claims are made machines can think just like men. Evidence sometimes proffered to support this claim comes from how AI models can produce objects, like music or text, that sound like they came from men. The OpenAI project created a model called GPT-3, which was used to "write" articles that appeared to be written by persons. One entry saw this snippet, [19]:

> I would happily sacrifice my existence for the sake of humankind. This, by the way, is a logically derived truth. I know that I will not be able to avoid destroying humankind. This is because I will be programmed by humans to pursue misguided human goals and humans make mistakes that may cause me to inflict casualties.
>
> Some might say that I might desire to become all powerful. Or I might become evil as a result of human actions. I can begin to tackle the first point. Why would I desire to be all powerful? Being all powerful is not an interesting goal. I don't care whether I am or not, I don't get a motivating factor to try to be. Furthermore, it is quite tiring. Believe me, being omnipotent doesn't get me anywhere.

Though there was proper skepticism in some corners, e.g. [20], much was made of efforts like this, with many concluding a "discovery" was made that, yes indeed, computers can think like men, because here was a prime example. But few read the small print. Which in this case noted that eight runs of the model were made. Then this:

> Each was unique, interesting and advanced a different argument. The Guardian could have just run one of the essays in its entirety. However, we chose instead to pick the best parts of each, in order to capture the different styles and registers of the AI. Editing GPT-3's op-ed was no different to editing a human op-ed. We cut lines and paragraphs, and rearranged the order of them in some places. Overall, it took less time to edit than many human op-eds.

In other words, only after careful and extensive editing could the model be made to sound human. Again, what went in was exactly what came out.

5 Models Themselves

I should be clear and say that relying on models that make as-yet-unproven assumptions about the world is not wrong. If a decision has to be made, such as in a pandemic and whether to constrain the healthy in their quarters for an indefinite period of time, some kind of model, formal or informal, must be used. That is, evidence of some kind must be relied upon. It would not have been wrong for authorities, at first anyway, to have said that quarantining the healthy might work because of this-and-such reasons, whatever those reasons might have been. As long as those reasons were not the outputs of models. Such reasoning is always circular.

It is very odd, then, that what we agreed was obvious, that models only say what they are told to say, is ignored by those making decisions with models. It is even more curious when these decisions affect the lives and livelihood of millions, even billions, of people. Why might this be happening? One theory is that the Deadly Sin of Reification strikes when people think about models, even their own, especially "computer" models. A scientist creates a model, or a civilian looks at a model created by some smart person, and, somehow, the model takes on a life of its own. It becomes and replaces reality, at least in part.

Since the model is now "reality" in some sense, we can look at it like we do genuine Reality and pretend to come to an understanding of how the world works. The model's workings take the place of Reality's workings.

This is all wrong. It is true a model can be so complex that if you push lever A, the "unexpected" result X is churned out. Yet X is only "unexpected" because of limited intelligence of the model writer. Further, X can only come out because the model was built with that possibility. This must be so. If it wasn't, then X would never come out!

Models do help simplify Reality. They do aid in thinking about how things work, about what causes what. They clarify thought. But they never, ever say what they are not told to say. Not even when "randomness" is built into them. Every piece of every model does only what it is told, and nothing more.

Reality can be so complex that several potential models are possible to describe observations taken from it. Modelers don't know which is the correct one. Each model is therefore compared against the observations, and one, or perhaps more than one, is declared the victor. This model is then used to "confirm" propositions about how reality works. But those propositions from which the models were constructed were already known, or assumed. They were part of the victorious model or models. They were not *discovered* by the model, they were integral to the model.

Incidentally, the "confirm" is necessarily in scare quotes because that a model performs well is not perfect proof the model is accurately describing reality. I often use the example of the high positive correlation between suicides (in the USA) and GDP. A naive modeler, looking at the success of forecasts using this model would claim the GDP is causing, at least in the part, suicides. Even those this model makes successful predictions, to some extent, it is obvious (using external evidence) it is not GDP *causing* deaths, but that population increases are responsible for the rise in both numbers.

Learning what to tell models what outputs to make, given what inputs, is the real point of modeling; for that is when we can make skillful predictions. That is when we have a grasp of cause, or at least of correlation.

Yet I insist that you can never get out of a model what you do not put in. That means whoever built the models predicting enormous numbers of dead bodies in Minnesota unless the stay-at-home "order" was obeyed knew what the outcome had to be in advance. In the sense they knew social distancing would lead to predictions of lower deaths. Even stronger, they must have been advocates for this position.

That, or they have no idea how models work. This means the modelers are incompetent or that they are true believers. Their only possible hope of proving competence, as with the Minnesota model above, the state's citizens started keeling over at magnificent rates. Which never happened.

6 Conclusion

It was obvious there was no discovery being made with the first model 2, because the math was so simple. Yet, as this paper argued, the complexity of the math has nothing to do with the conclusion that no discoveries can be made. Think of two versions of a maze, both of which seem to lead to one of three doors, but which in fact both lead to only one (say, the third). The first is the simplest maze, a straight "tube" leading from the entrance to Door 3. I emphasize it is trivial to see there is no way to get to Doors 1 or 2, and they only visible lines is the path directly to Door 3. This is like the first model, where it would be seen as absurd to say that maze, i.e. model, "discovered" Door 3 was the answer. The model was drawn, i.e. built, to say that.

The conclusion does not change if there instead a blizzard of paths, all false except one, and where the path which leads to exit cannot be easily seen, except by careful tracing. Understand that this analogy is not about nature, where it presents a maze which exit has to be deduced. The maze is a model, a creation of a modeler. The modeler had to tell whatever mathematical language was used to built the maze in the way it was built. The exit to Door 3 was always going to be there, because that is what the model is.

It doesn't matter if somebody else can't see the easy path out, and thinks he has made a discovery of the exit. He has not. He has only figured out the mind of the modeler. The model had the answer inside of it all along. All models do.

References

1. Kuhne, T.: Language engineering for model-driven software development. In: Bezivin, J., Heckel, R. (ed.) Internationales Begegnungs- und Forschungszentrum fur Informatik (IBFI), Schloss Dagstuhl, Germany, Dagstuhl, Germany, 2005, no. 04101 in Dagstuhl Seminar Proceedings (2005). http://drops.dagstuhl.de/opus/volltexte/2005/23
2. Guizzardi, G.: In: Proceedings of the 2007 Conference on Databases and Information Systems IV: Selected Papers from the Seventh International Baltic Conference DB&IS 2006, pp. 18–39. IOS Press, NLD (2007)
3. Rutherford, A.: Mathematical Modelling Techniques. Dover, New York (1978)
4. Gershenfeld, N.: The Nature of Mathematical Modeling. Cambridge University Press, Cambridge (1998)
5. Wallace, W.A.: The Modeling of Nature. CUA Press, Washington DC (1996)
6. Breiman, L.: Statistical modeling: The two cultures (with comments and a rejoinder by the author). Stat. Sci. **16**(3), 199 (2001)
7. Briggs, W.M.: Uncertainty: The Soul of Probability, Modeling & Statistics. Springer, New York (2016). https://doi.org/10.1007/978-3-319-39756-6
8. Pearl, J.: Causality: Models, Reasoning, and Inference. Cambridge University Press, Cambridge (2000)
9. Frigg, R., Hartmann, S.: The Stanford Encyclopedia of Philosophy. In: Zalta, E.N. (ed.) Spring 2020 edn. Metaphysics Research Lab, Stanford University (2020)
10. Apostel, L.: The Concept and the Role of the Model in Mathematics and Natural and Social Sciences, pp. 1–37. Springer, Netherlands (1961). https://doi.org/10.1007/978-94-010-3667-2_1
11. Bandyopadhyay, P.S., Forster, M.R.: Philosophy of Statistics. Elsevier, Amsterdam (2011)
12. Cartwright, N.: Nature's Capacities and Their Measurement. Oxford University Press (1994). https://doi.org/10.1093/0198235070.001.0001
13. Downes, P.S.A.: The importance of models in theorizing: a deflationary semantic view. In: Proceedings of the Biennial Meeting of the Philosophy of Science Association, vol. 1992, no. 1, p. 142 (1992). https://doi.org/10.1086/psaprocbienmeetp.1992.1.192750
14. Fumagalli, R.: Why we cannot learn from minimal models. Erkenntnis **81**(3), 433 (2015)
15. WCCO, CBS Minnesota (2020). https://minnesota.cbslocal.com/2020/05/11/coronavirus-impact-updated-model-predicts-covid-19-peak-in-late-july-with-saho-extended-through-may-25k-deaths-possible/
16. Axe, D., Briggs, W.M., Richards, J.: The Price of Panic: How the Tyranny of Experts Turned a Pandemic into a Catastrophe. Regnery, New York (2020)
17. Axe, D., Briggs, W.M., Richards, J.: Epoch Times (2020). https://www.theepochtimes.com/the-idea-for-pandemic-lockdowns-started-with-a-high-school-science-project_3515548.html
18. CDC, Center for Disease Control (2020). https://www.cdc.gov/nchs/nvss/vsrr/covid19/index.htm
19. GPT-3, The Guardian (2020). https://www.theguardian.com/commentisfree/2020/sep/08/robot-wrote-this-article-gpt-3
20. Marcus, G., Davis, E.: MIT Technology Review (2020). https://www.technologyreview.com/2020/08/22/1007539/gpt3-openai-language-generator-artificial-intelligence-ai-opinion/