

Nonlinearity and Ambiguity in our Program Theories and Models

Jonny Morell
jamorell@jamorell.com

In recent years much evaluation conversation has bemoaned the fact that we have been basing our work on linear models, which is to say that we hypothesize linear relationships among program outcomes. We argue that we need to move away from linearity. What I believe is that almost none of our models have ever been linear. We have been tilting at windmills. As you follow my argument, it is helpful to appreciate a few beliefs that guide my work.

Logic models are models: I prefer “model” to “logic model” because the use and nature of models have been treated extensively across many disciplines. Evaluation should set itself within that knowledge domain.

Bare bones examples: I like to illustrate model behavior by abstracting the fewest elements from an elaborate model that I need to make my point.

Assumptions about connectors: In the absence of an indicator I assume the simplest explanation for a model. For instance, are two inputs equally important or is one just nice to have? If the model does not say, I assume the inputs are equally important.

Program theory and model: My focus is on nonlinearity in models. But models reflect program theories. Any time we construct a model, our underlying question is about the program.

Our Traditional Models are Seldom Mathematically Linear

What does “linear” mean? In graphical terms, “linear” means that if an equation is graphed, the result is a straight line. In algebraic terms, there are two characteristics of linearity. Additivity is a condition in which if inputs are added, the output is the sum of the inputs [$2+2 = 4$]. Scaling is a condition such that if an input is multiplied, the output is multiplied by the same number [$3(2+2)=3(4)=12$]. But do we really believe our models are linear? If we were to specify the relationships, would all of them be of the form $A+B$, and not some other form such as AxB or A^2 that would make the model nonlinear?

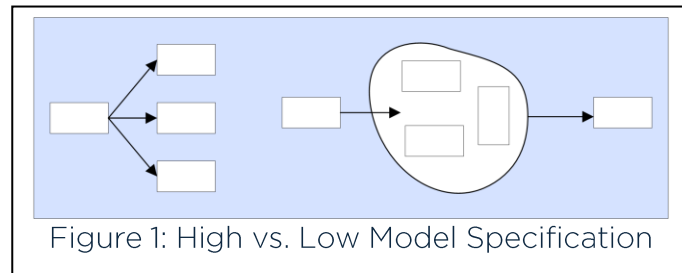
As an example, imagine a technical support effort to improve agricultural productivity. Do the designers of that program believe that small changes in productivity will always lead to only small changes in living standards? Or do they believe that there is an inflection point at which a small improvement in agricultural productivity would lead to a disproportionate improvement in living standards?

I believe that even though we never specify one way or the other, our models are rife with these kinds of nonlinear relationships. In that sense we do need to move away from linear program theories and the models that reflect those theories. But it is not a very long move. We can keep our traditional model architectures, but we need to put

in some work to step away from assuming linear relationships for all relationships depicted. (For what it's worth, I am as guilty as anyone when it comes to not making such specifications.)

When we say Nonlinear we Sometimes Mean Ambiguous

One way we use the terms linear and nonlinear is as I described them above – in mathematical terms. But I think that sometimes when we talk about linearity we are really worried about ambiguity. We construct models that convey a foggy understanding about causal relationships. The two models in Figure One illustrate the problem. They capture the essence of two fundamentally different logics. The logic embedded in the model on the left is that we know precisely what is connected to what. The model on the right acknowledges that we know the relevant model elements but that we have only some idea of how they are connected. We see both forms in evaluation, but it is all too common to see over-specification, In both of the models I omitted the possibility that we don't even know what all the elements are, (an ignorance that goes a long way toward explaining unintended consequences). Addressing this topic would lead to a long and interesting discussion, but it would not be essential to the argument I am making here.



Depicting Nonlinearity and Minimizing Ambiguity

We could ameliorate many of these difficulties if we put some work into applying relevant literature and expert judgement to our models. Figure Two shows some examples. The first two deal with mathematical nonlinearity. The third and forth with reducing ambiguity.

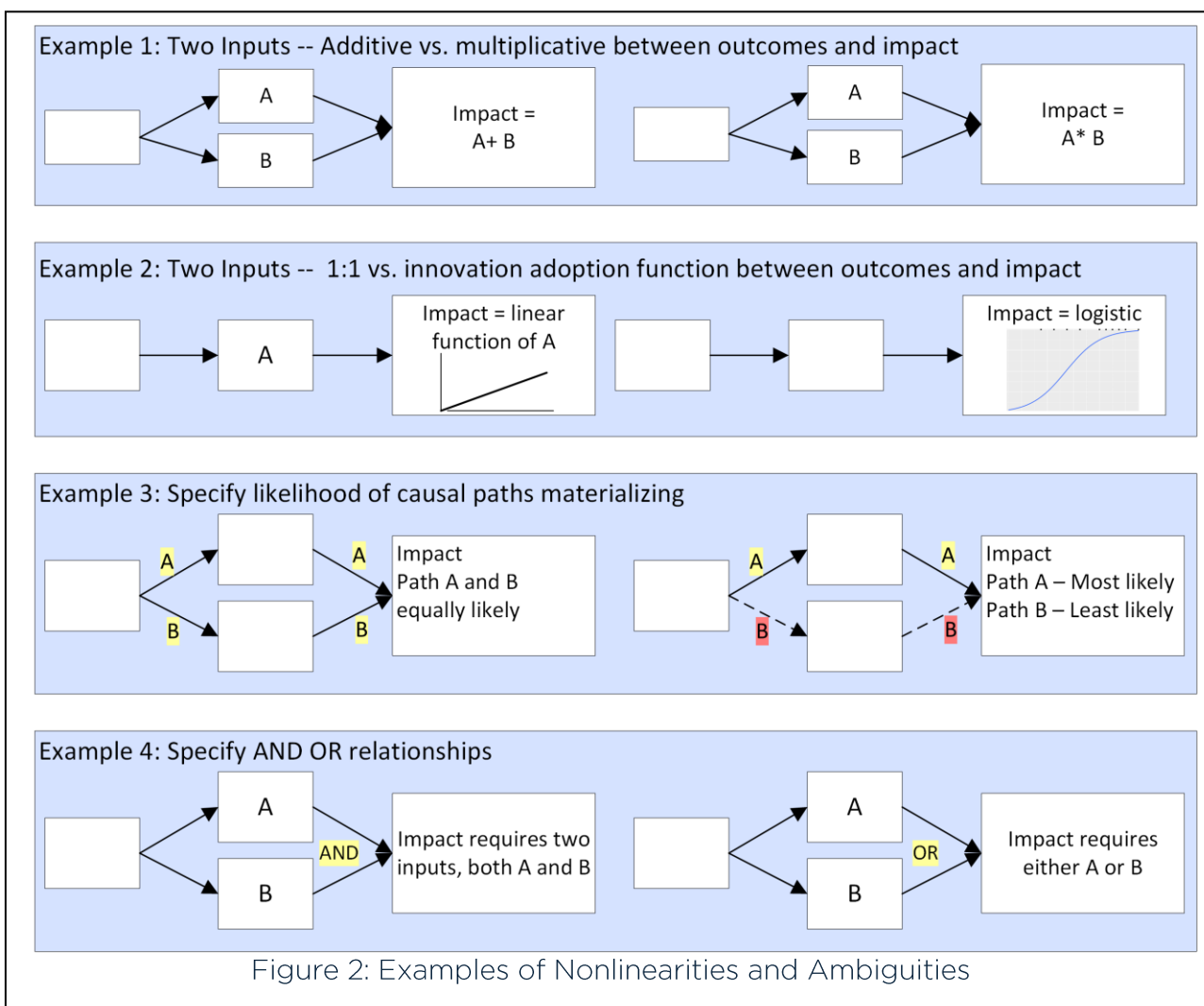


Table 1: Explanation of Examples in Figure Two

Example 1: left

The outcome is the sum of both of its inputs, a linear relationship. In the absence of specification to the contrary, it seems reasonable to assume an additive fixed relationship between connected model elements. If A causes 1 unit of change and B 0.5, then the total change is 1.5. As with the model, so too with the program theory.

Example 1: right

The outcome is nonlinearly related to the inputs because one input variable is multiplied by the other.

Table 1: Explanation of Examples in Figure Two	
<u>Example 2: left</u> “A” represents a traditional linear relationship.	<u>Example 2: right</u> We are specifying the classic innovation adoption curve. That is a logistic equation which is decidedly not linear.
<u>Example 3: left</u> Because the visual form of all the relationships is the same, it is reasonable to assume that the program theory and model builders have equal confidence in all the relationships depicted in the model. No ambiguity. We know that two different causal paths have equal potential to lead to the outcome.	<u>Example3L right</u> The use of solid and dotted lines indicate that the developers of the program theory and the model believe that two different causal paths are possible, but that one is more likely than the other,
<u>Example 4: left</u> Impact requires two inputs, both A and B.	<u>Example 4: right</u> Impact requires only one of the two inputs.

For the purposes of explanation I drew a distinction between mathematical linearity and ambiguity. In practice though, there can be quite a bit of overlap. The scenarios on the right in examples One and Two in Figure Two show mathematical nonlinearity. But one could just as easily label the examples as ambiguity because we have drawn the causal connections without specifying the function that connects one end of the relationship to the other. Now take the OR example in Example Four. If either A or B alone can cause the impact, then the situation is akin to Example 2, but with an interesting added complication. A might have a linear relationship with the impact, and B might have a nonlinear relationship.

Note that in each of the four cases the architecture of the model on the left and the model on the right is exactly the same. Thus the evaluation methodology and the data needed to test the model are the same. What’s different is the analysis and the data interpretation.

I have no illusion that program and model designers have the knowledge needed to specify relationship types for all relationships in an elaborate model, But I do think they should be aware of the importance of doing so and have a willingness to take a stab at it for the most consequential aspects of a model.

Complexity

I am leaving complex system behavior out of this discussion because treating it would take us on an entirely different path from the one I have been pursuing. The theories would be different, and the constructs would be different. My blog contains a great deal of information [on this topic](#), as does my article on [applying complexity to evaluating transformation](#). But folding that information into this post would divert attention from the main point that I want to make, i.e., that our traditional models are very seldom linear. We don’t need to move away from linear thinking, but we do need

to put some work into recognizing nonlinearities in the models that we construct. But no matter how much nonlinear thinking we add to our traditional models, something will always be missing. The models may depict nonlinearity, but they won't explain why the nonlinearity is occurring or why it is functioning as it is. For that we do need to delve into complexity science.