UNREAL MODELS OF REAL BEHAVIOR: THE AGENT-BASED MODELING EXPERIENCE

By Lee D. Hoffer

Introduction

Like many applied anthropologists who have worked for 20 or so years in public health and drug addiction research, I have sat in more than my fair share of overly quantitative presentations on the "behaviors" of drug users that dominate conferences in the field. Like my peers in these circumstances, I am often frustrated not because the models, tables, graphs, figures, correlations, *p*-values, or odds ratios presented are difficult to understand or because I have an aversion to basic science, epidemiology, or survey research. Rather, it is because the numbers rarely reflect the histories, concepts, relationships, interactions, and other nuances that have shaped my fieldwork experience. The highly personal narratives of participants framed by equally complex social environments are not visible in the numbers. To epidemiologists and other like-minded health researchers, the numbers *are* the narrative and all that is required for informing and evaluating theories, models, interventions, treatment programs, or policy.

Here, I offer an alternative proposition: wouldn't a better approach be to develop concepts in the field then observe how they *generate* quantified outcomes? More than just another survey informed by ethnography or mixed method concession, what if anthropologists could actually experiment with how we understand participants to behave and/or believe? Could this bridge the gap between field experience and numbers? Could it ground our policy recommendations in something more than "anecdotes?" Could it provide more detailed, accurate, or authoritative explanations and theories? One important distinction before continuing: constructing agent-based models (ABMs) using ethnographic data does not mean transforming ethnography into epidemiology; in fact, it does not necessitate making any change in *how* we collect data or derive findings (Agar 2005). It does not minimize the importance of ethnography. On the contrary, it presents a qualitatively different and unique approach for conceptualizing the importance of our discoveries.

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Since 2005, these promises have sustained three research projects I have conducted on combining ethnography and ABM. Because ABMs remain rare in anthropology, this paper gives the reader a sense of this work and insight on some hard lessons I have learned in putting it to use. In the process, I hope to inspire more anthropologists to take up this challenge.

Why Agent-Based Modeling?

Agent-based modeling (a.k.a., multi-agent modeling, social simulation, generative social science, and computational social science) is a form of computational simulation that uses agents to represent (i.e., model) something about real people (Gilbert 2008). Agents are robots that rely on computational functions to operate. They can be programmed to do many things people can, such as communicate, search, move, interact, exchange, consume, allocate, make decisions, remember, learn, act randomly, adapt, change, disappear, transform, and execute rules/strategies. But agents are NOT people; they are only very rudimentary likenesses of them in some simplistic ways. Also, although agents are programmed, ABMs generate unpredictable outcomes.

ABMs are tools for studying Complex Systems. Complex Systems are non-linear and generate outcomes that cannot be reduced to the simple sum, or aggregation, of individual behaviors. Rather, they are a decentralized and self-organized creation of groups of individuals: (1) interacting with other groups and (2) constructing, shaping,

and being shaped by their environment. Outcomes in such systems are unpredictable because they incorporate heterogeneity and complicated feedback systems. Consistent macro-patterns (i.e., organization) occur in such systems that are not possible to perceive at the behavioral micro-level. In short, Complex Systems are *emergent* (Holland 1998). Although called the "new science," complex systems are *not new* to anthropologists with their understanding of culture as "webs of significance" and social life as the interaction between agency and structure. Cultural anthropology has been writing about emergence since its inception (Agar 1999; Lansing 2003).

If emergence is not new, why bother with ABM? In short, it is because *under controlled conditions ABMs can generate emergent outcomes by mimicking the targeted likeness of people* (Axelrod 1997). This means by using "what if" experiments we can test how agents behave in ways designed specifically to measure the non-linear product of our reasoning. Put in more stark terms, we can test what cannot be tested in real life. This is a unique tool for facilitating discovery in anthropology but also in presenting its significance to others, namely policymakers, community groups, and other key stakeholders (Agar 2001). What follows is a simple demonstration.

The Real Price of Heroin

Guided by Adam Smith's invisible hand, we know if the supply of a product in a market is diminished, its price will increase. It is precisely this thinking that justifies some 60 percent, or $15 billion (FY2013), in annual United States drug policy spending. Supply-reduction (a.k.a., the War on Drugs) works by decreasing drug supplies to increase retail prices. But we also know increases in price do not always equate to reduced consumption. Price can be inelastic to demand. Setting aside the numerous problems in collecting accurate illegal drug price data, heroin prices are notoriously inelastic to demand compared to some studies of marijuana and cocaine prices. Why? A simple, one-time popular, and wrong explanation is heroin users are willing to pay more compared to other drug users because heroin is more addictive, but increased prices lower nicotine consumption, a drug more addictive than heroin. Other explanations suggest the ineffectiveness of law enforcement in diminishing supply. The assumption is if only supply reduction interventions could be improved, reductions in consumption would follow, and all that is required is more money and resources. Our ethnographically informed ABM suggests the true culprit might be an emergent feature of heroin markets.

Through generous grant support from the National Science Foundation, Cultural Anthropology, over the last three years the Social Dynamics Research Group has conducted ethnographic research on the heroin market in Cleveland, Ohio, with the purpose of developing ABMs and integrating this tool with ethnography. One consistent finding we have documented, also noted in many previous ethnographies, is that most heroin users do NOT purchase heroin from dealers. Instead, users usually buy the drug with the assistance of a broker, a fellow user. Heroin users call this "copping" drugs for others. Although not a remarkable discovery, this suggests some interesting things about how heroin markets function and is a non-linearity not previously modeled using ABM.

First, copping insulates dealers from a certain amount of risk, as no one in this exchange circuit is a stranger, and police intrusion is rare. Also, it allows customers to discover better deals, because indirect sales also diffuse information about deals through the marketplace. For example, heroin buyers can buy from a dealer but also seek deals (and connection to other dealers) through the people that cop for them. Nothing is free, however, since a buyer is required to *pay* a broker for making the sale. This "tax" can be significant, sometimes resulting in the two users (broker and buyer) equally sharing the drug purchased. Therefore, there is no doubt that copping changes users' costs in consuming heroin. But how can we measure or evaluate this feature of the marketplace? Real world experimentation is impossible; it is hard to even envision what that might look like. We can, however, design agents that behave like the participants and set them loose in an *unreal* world invented for this purpose.

A Heroin Market *In Silico*

Our ABM heroin market is highly idealized. Heroin customer agents have been programmed with unlimited funds, to purchase one gram of heroin at a time for $120, and immediately consume the drug they purchase. In the model, customers buy grams directly from a dealer or indirectly using a broker. In the latter, purchases cost buyers an additional $20, which is credited to the broker. After between three and six indirect sales, customers can cut out the middleman and switch to a direct sales relationship with the dealer. We then provide customer agents with networks of dealers and brokers and give them a probability of "sharing" deals, set in this example at .25. Customer agents evaluate deals and are rational. Because better deals allow customers more time between purchases, saving them money, they always choose the best available deal. They also only share their better deals with peers to promote repeat copping opportunities.

In our ABM, dealer agents sell grams of different values, but value is not varied by price or purity, indicators preferred by policymakers. We intend to model these indicators in the future. Instead, our agents use a third technique employed by real world dealers: altering the actual size (weight) of grams. Altering weight of drug units (e.g., grams, bags) is a simple, common, and convenient way real world dealer's reward and punish customers (Hoffer 2006). Our dealer agents decide to change the value of their product based on the sales they make. They increase value (i.e., sell bigger grams) to attract more customers, and when they have more customers, they decrease value to

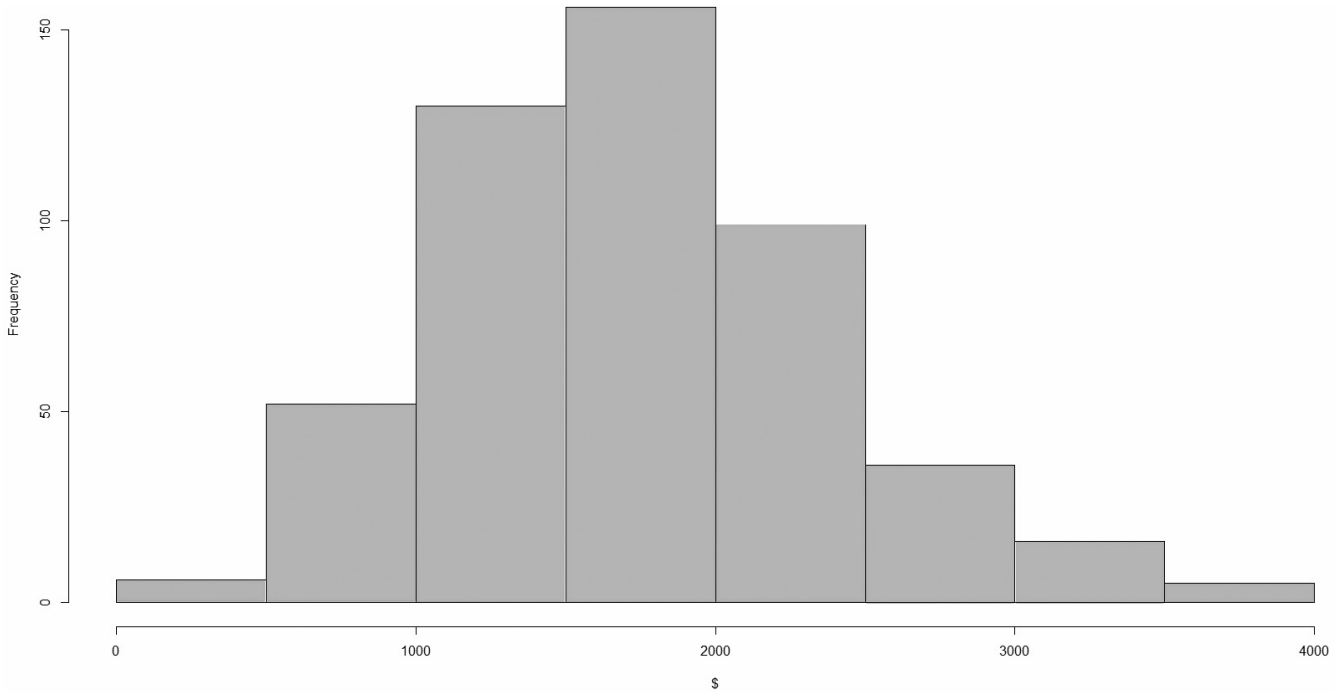

Figure 1. Distribution of Total Taxes Collected from Brokering (N-500 Customers, 350 Days)

increase profits. Companies in the legal economy employ this same devious strategy to raise prices without making it obvious to customers, calling it "downsizing." Also, if a dealer gets too busy, they generate a new dealer, allocating this neophyte to some of their customers. Finally, dealers are removed from the simulation ("arrested") based on a random probability that increases proportionally to the size of a dealer's network (i.e., more customers = more risk).

This fairly simplistic ABM is an unabashed blend of the real and unreal. Agents' behavior, interactions, motives, and rudimentary cognition are based on the ethnography with real heroin users and dealers, but circumstances are purposefully unreal to test what the former produces. What does this "what if" experiment show? With retail price fixed at $120 per gram, over 350 days, the baseline for heroin purchases should roughly cost customer agents $42,000, assuming a use rate of one gram per day. After considering copping and changes to gram sizes, the net (adjusted) average spent by agents (*N*=500) in our model is $44,436. Agents also earn considerable money from the heroin "tax" associated with brokering, and profits are distributed (see Figure 1). But how does this connect to why heroin price is inelastic?

Although we are still in the process of testing and thinking about our model, the short answer appears to be: the "tax" and improved deal values from brokering buffer the effects of price changes by efficiently and rapidly distributing cost. In economic terms, the *actual* cost of heroin in real heroin markets is greater than its retail price suggests, implying price increases have much less of an effect on consumption because most people are already paying higher prices through taxes and downsizing; they just don't know it. We are now testing how the parameters in our model, such as arrest rate, sharing probability, sales before cutting out the middleman, and money made from brokering, all influence this outcome. Furthermore, although we cannot test it yet, we can imagine increasing dealer arrests will increase deal sharing and improve deals. Under these circumstances and apart from any coordinated effort, the market might adapt by lowering prices. This possibility is intriguing because it may connect with why some studies find increased police pressure actually *reduces* retail heroin prices. In summary, our ABM provides new data to interpret.

Lessons in Using ABM

Designing ABMs to understand discoveries made in fieldwork has been extremely gratifying. At times, it has also been exasperating. In an effort to encourage more anthropologists to take up this challenge, the following are lessons I have learned, some at great cost in expense, effort, time, and sanity. I only concentrate on major issues I believe are the most helpful for those interested in getting started using ABM. Many comments overlap, and after the first, which I consider the most essential, they are not presented in any particular order.

The "type" of ABM matters. If the reader takes only one thing away from this reflection, it should be: *determine the type of ABM you want to program BEFORE you do anything else, and do not change your mind*. When I first

started this work, because no one had figured it out yet, I did not fully appreciate that ABMs come in three subtle but distinct varieties: abstract, middle range, and facsimile models (Gilbert 2008). Using the same toolkit, these ABMs differ in orientation, data requirements, and objectives. In social complexity research, abstract models are the most popular. At the other end of this continuum of scope, facsimile ABMs represent a specific case, history, geography, or human-environment interaction and typically incorporate very precise data. Taking this approach, ABMs in archeology, linguistics, resource management, and social epidemiology run time-forward, observing outcomes associated with adaptation, change, evolution, extinction, or other time-dependent events (Lansing 2003). The example provided in this paper represents a middle range model. In these models, *concepts* that are neither completely generalizable nor case specific are simulated. In middle range models, the ethnographic analysis is complete, and the intent is to understand what its implications mean. For me, this represents the best balance because it connects well with other issues, the first of which relates to numbers.

Representation by numbers is different than numerical data. ABMs are mathematical but do not require using or collecting numerical *data* to program. In middle range models, it is best to avoid using quantitative data in programming and instead allow a programmer to intuitively devise and create parameters. Quantitative data here can confuse things. For instance, in a previous model (Hoffer, Bobashev, and Morris 2009), we designed agents with an "addiction level" that changed based on agent's actions. The algorithm generating this parameter (number) incorporated information about tolerance and withdrawal but was not real; addiction is far too complicated for this (Hoffer, Bobashev, and Morris 2012). Many parameters in ABMs are theoretical in this way; there are times one can "plug" real numbers into ABMs, but the allure of this can discretely transform abstract or middle range models into facsimile models. I have made this frustrating mistake, and it is something to avoid because it conflates the unique characteristics of the model being programmed. My recommendation is to accept that ABM parameters and survey data are different. The more you can bring them together the better, but take care not to change the type of ABM you are programming in the process.

Empirical validation of ABMs is still a work in progress. So what about the validity of ABMs; can this be tested? A lot has been written about validating ABMs, but because most do not actually use data, discussions typically center on if the program is operating properly. Comparing ABM outcomes and "real" data, whatever that might be, is another story. ABMs are primarily descriptive and not predictive models. From my perspective, ABMs informed by anthropology are valid if the data informing agents' behavior is valid. This linkage is tricky, however, if ABMs simulate concepts rather than "first-hand" data. Without a definitive solution, it is important to beware that trying to devise ABMs to link with survey or administrative data for validation presents challenges. In the example provided, surveying a heroin market to capture the necessary data to validate our model is likely impossible.

Collaborating to program ABMs has important benefits. While it is possible for an anthropologist to program his or her own ABM, to code, debug, modify, evaluate, and extract and analyze data from them often involves considerable nuance. Professionals can do a better job, and I have collaborated with a diverse group of programmers, statisticians, mathematicians, and complexity researchers over the years for this purpose. This, of course, adds the requisite challenge of cross-disciplinary collaboration. However, if you are consistent about the type of ABM you want to design and write clear specifications, professional programmers can offer many different solutions to program your ABM. Clarity, transparency, and good communication are absolutely essential; a good programmer should be able to show you exactly what each line of code does in the simulation.

Keeping your ABM simple is essential. Considering the above, "freeze" your model as soon as possible. This means to try at all costs to keep your model simple enough to represent the minimum of what you want to demonstrate; each degree of freedom beyond that will complicate analysis. ABMs work because they are simple. In fact, the simpler the better. One major problem I have experienced on more than one occasion, and still struggle with, is including too much in an ABM. Because ABMs are programmed in such an intuitive way and because anthropologists always want to add important context to our stories, this is a frighteningly easy trap in which to fall. The best way to resist this urge is to remember three things about ABMs, or any model for that matter. First, ABMs are abstractions to focus inquiry. Second, it is *impossible* for ABMs to tell the full story, nor is this their purpose. And finally, agents exhibit only limited behaviors.

Feedback + outcome = content for ABMs. Finally, locating the content for an ABM in ethnography is not difficult. Anthropologists have extensive opportunity because we collect data on precisely the two things ABMs are particularly suited to program: (1) interactive processes occurring between people and (2) interactive processes occurring between people and the environment. The key here is to identify what *feedback* occurs between these processes and how it connects to research goals. As noted in the example presented, developing a contrast to current policy or conventional thinking helps isolate and frame potential experiments to conduct with your thinking (see also Agar et al. 2004). Once again, the idea is to keep the ABM simple, which means only addressing the minimal dynamics and parameters. Ethnography is best understood as a dialectical process. We go into the field, collect data, make sense of it, and return to the field with questions that emerge. In this process, concepts take shape beyond the data, moving from data to what data tell us. It is "what the data tell us" that provides the most productive content areas for ABMs. Search the diagrams, flowcharts,

or memos you use to organize statements you make with your data, and chances are you will find content for an ABM.

Although copping heroin for others is not new, forcing very targeted and precise thinking about how these activities scale-up using agents, our ABM generates lots of new ways to think about how this micro-behavior affects overall market patterns. Conducting experiments on what we understand about participants is the first way ABMs can improve ethnography. ABMs are also a new form of representation that can correct less nuanced or conventional thinking and contrast the linear models commonly encountered at the bedrock of policy. Here, our ABM on heroin price does not imply Adam Smith is wrong but shows that assuming retail price reflects consumption in heroin markets is incorrect. To those primarily interested in numeric storytelling, the ABM numbers now tell a very different story. This is important. Having presented ABMs to the National Institute of Health, I can attest that policymakers are receptive to this intuitive breed of modeling. But perhaps best of all, to program and present ABMs, anthropologists can remain genuinely close to what originates the model—our ethnographic experience. Finally, although Complexity Theory may not be new to anthropologists, ABMs offer a truly unique approach for discovering (and measuring) unanticipated patterns in complex systems, extending both the boundaries and capabilities of ethnography. Considering culture a socially emergent phenomena, ABMs provide new evidence and perspective on why culture matters.

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