Foreword

A CURE FOR THE DISMAL SCIENCE

I earn a living solving real economic and strategic problems for real businesses. After a number of years of this regimen, I have lost my taste for big theories of human behavior—especially economic theories. My version of game theory consists of playing the game and forgetting about the theory. That's because my incentive system is based not on the aesthetics of theorem proving, but rather on my ability to ease the pain of suffering managers. I no longer derive any satisfaction from irrelevant elegance. The foundations of economics have for so many years ignored the realities of human behavior and decision making that it has become a joke for business practitioners, managers, and consultants. I believe that the mutual distaste of practitioners and theorists is coming to an end as a new breed of economists is emerging. These new economists embrace the complexities and subtleties of human behavior; they acknowledge the dynamic, evolving nature of the economy; they design economic experiments that involve, God forbid real people; while they do not reject mathematics as a tool, they do not view it as a purpose; they believe that computational experiments can take them beyond confined, provable situations. The handbook that Jean-Philippe Rennard has assembled is a wonderfully diverse collection of points of view from this new breed of economists and social scientists, a vibrant cross-section of the field of economics as I hope it will evolve in the near future.

The main thread throughout this collection of essays is human behavior, individual or collective, and how it can be understood, modeled, approximated, or even enhanced using a range of techniques and approaches from "complexity science." Evolutionary algorithms, co-evolution, swarm intelligence, social networks, multi-objective decision making, and agent-based modeling are some of the techniques employed. That there is a need for such approaches is crystal clear from the viewpoint of practical applications. Let me use some examples from consumer behavior and marketing to illustrate why in particular agent-based modeling (ABM) is the keystone of the new computational edifice.

When a customer makes a purchase or switch decision, it is often the result of a history. Impulse decisions, while they do happen, are the exception rather than the rule. That does not mean that most decisions are rational, simply that they cannot be explained by just looking at the time they happen. When a wireless phone customer decides to switch carriers, such a decision is the result of all the interactions and experiences this customer had with his carrier as well as with other sources of information. Failing to recognize the temporal dimension of decision making can lead to dramatic prediction errors. ABM, and only ABM, can explicitly deal with all aspects of time: learning, waiting, simmering, habituation, forgetting, and so forth. For example, in the casino industry, common wisdom holds that customers have a fixed budget and stop playing when their budget is exhausted. An ABM fed with real slot data from a loyalty card program showed that in reality customers stop playing when their total experience over time (TEOT—a combination of the dynamics of their wins and losses weighted by demographic attributes and day of the week, and, yes, budget) reaches a threshold. TEOT is a much better predictor than budget or any combination of demographic attributes which enables a major casino owner and operator to implement effective real-time marketing and promotional offers. Of course the dirty little secret is data and how to use it effectively to estimate complex time-dependent models of decision making. When the data exists, in the absence of a coherent theoretical framework, not to mention theorems, one has to perform rigorous computational experiments based on statistical machine learning techniques.

Another example is health insurance, where a customer's demographic attributes are not sufficient to predict which plan he or she will select. Instead, the characteristics of each plan are viewed through a looking glass that puts more weight on certain characteristics as a function of the customer's experience with his current plan, which is a combination of his and his family's health in the past year and satisfaction or dissatisfaction with the health care afforded by the plan. Furthermore, if specific adverse health events have happened in the recent past, they strongly affect the way the possibility of catastrophic losses is perceived. By using an ABM that explicitly deals with the effects of experience and recency, prediction error could be reduced by an order of magnitude at Humana, a leading U.S. health insurer. No amount of traditional econometric modeling with demographic attributes as explanatory variables would have been able to achieve this level of accuracy.

In retail, the layout of a supermarket is known to be a key sales driver, yet shopper behavior is an emergent property with a strong spatio-temporal component that is never taken into account in traditional econometric modeling: while the trajectory of a shopper in a supermarket is influenced by the shopper's shopping list, the trajectory in turn influences what the shopper buys beyond the shopping list. Through the use of a spatial behavioral model of shoppers in a supermarket, Pepsi was able to predict hot spots in any supermarket as a function of the supermarket's layout and the demographic attributes of its shopper population. With the knowledge of hot spot locations, Pepsi could determine the best location not only for its products, but also for promotional signs. Here again, the dirty little secret is data and how to use it. Not only did we have to develop special estimation techniques to infer trajectories and reconcile them with scanner data, data collection itself was a challenge: shoppers were given "smart carts" equipped with tags for path tracking.

Customers experience, learn, adapt, adjust. Their decisions are *path dependent*: in other words, decisions are dependent upon a contingent history. Existing statistical or econometric techniques do not deal satisfactorily with path dependence. When done properly (and that's a big IF) ABM combines the statistical rigor of existing techniques with the ability to accurately model the temporal components of decision making. As a result, not only does predictability go through the roof, the outputs of what-if scenarios also become more reliable because behavioral models are fundamentally causal rather than correlational. Knowing that two variables are correlated is good enough to predict the past, but robustly predicting the future requires understanding the underlying causal mechanisms of decision making.

At the risk of repeating myself, taking data seriously is the dirty little secret of success. We must not lose sight of data in the excitement of playing with our synthetic little worlds. It is ok for the theory to be ahead of the data, but not by light-years. A case in point is the over-theorization of social networks in the last few years. In my experience good social network data (whatever that means) is a rarity. The data is often inadequate, ranges from incomplete to sparse, is noisy, sensitive to minute details, and lacks such important characteristics as frequency, quality, and nature of the interactions. In other words it is unusable in practice for predictive purposes. For example, in 1954 pharmaceutical giant Pfizer was interested in determining how physicians decide to adopt a new drug so that it could more effectively market its products through detailing and traditional media. By knowing how physicians acquire reliable information and who they trust, Pfizer could market its new drugs more effectively, optimizing the allocation of marketing resources among detailing, media advertisement, continuing medical education, and so forth. They funded a landmark social network study aimed at showing the effect of interpersonal influences on behavior change in relation to the adoption of Tetracycline, a powerful and useful antibiotic just introduced in the mid-1950s. Pfizer hoped tetracycline would diffuse rapidly because it was a tremendous improvement over existing antibiotics. The Pfizer-funded study contained two major advances over previous studies in that it relied on a behavioral measure of time of adoption by looking at prescription records and used network analysis to identify opinion leaders. However, numerous subsequent studies of this work revealed a number of weaknesses in the collection and analysis of the data, and the consensus among social network scientists today is that the study is inconclusive: the uptake in tetracycline adoption cannot be assigned with confidence to social network effects. Over the last fifty years, in a movement that accelerated over the last ten, social network researchers have been developing more and more complex models of network diffusion, but there is very little data to back them up; there is a lot of "anecdotal" evidence, a euphemism for poor statistical work on ambiguous data.

One of the issues facing those who want to study the influence of social networks on the diffusion and adoption of innovations to design marketing interventions is the lack of reliable data. There are situations, however, where the community of adopters is sufficiently small that it can be mapped accurately. My team and I studied the adoption of a new drug used exclusively in intensive care units (ICUs), where the number of individuals (doctors, nurses, pharmacologists) involved in the decision to prescribe the drug is between 10 and 20 in a given hospital. The study revealed that the temporal structure of the social network is the key to prescription behavior. While a snapshot of the social network is unhelpful (we found no correlation between such snapshots and probabilities of adoption), its dynamics over time are a great predictor of the speed with which the drug is adopted: this can be explained by the fact that in many hospital ICUs, physicians work only a few months per year and teach or work in other departments for the rest of the year, so that the only opportunities physicians have to interact is when their assignments overlap for a few days. We discovered that the degree of overlap correlates positively with the speed of adoption, suggesting that ICUs that are organized to provide more overlap between physicians are more favorable marketing targets. Promoting the drug to these ICUs first accelerates adoption. ICUs that are more difficult to penetrate can be targeted in a second marketing wave, as it is easier to market a product when you can tell your customers that their competitors or peers are already using it.

So, where does that leave us? Clearly, from the perspective of a practitioner, there is a need for the various approaches advocated in this book's chapters. The authors are leading the way in defining a cure for the dismal science. I am convinced that it is only by combining these new approaches with a relentless focus on data and reality that the cure will gain credibility.

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