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Understanding and Improving the Human Condition: A Vision of the Future for Social-Behavioral Modeling

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Technology is transforming the human condition at an ever-increasing pace. New technologies emerge and dramatically change our daily lives in months rather than years. Yet, key aspects of the human condition – our consciousness, personalities and emotions, beliefs and attitudes, perceptions, decisions and behaviors, and social relationships – have long resisted description in terms of scientific, falsifiable *laws* like those found in the natural sciences. Past advances in our knowledge of the human condition have had valuable impacts,[1] but much more is possible. New technologies are providing extraordinary opportunity for gaining deeper understanding and, significantly, for using that understanding to help realize the immense positive potential of the humankind.

In the information age our understanding of the human condition is deepening with new ways to observe, experiment, and understand behavior. These range from, say, identifying financial and spatiotemporal data that correlate with individual well-being to drawing on the narratives of social media and other communications to infer population-wide beliefs, norms, and biases. An unprecedented volume of data is available, an astonishing proportion of which describes human activity and can help us explore the factors that drive behavior. Statistical correlations from such data are

1 Examples include epidemiological modeling and an understanding of collective behavior that has helped make it possible to blunt, contain, and then defeat epidemic outbreaks; the destigmatizing of mental health problems; the use of game theory in developing nuclear deterrence theory; and applications of *nudge theory* in behavioral economics, as in instituting *opt-in-as-a-default* policies resulting in more workers availing themselves of economic benefits in pension plans.

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already helping to inform our understanding of human behavior. New experimentation platforms have the potential to support both theory-informed and data-driven analysis to discover and test the mechanisms that underlie human behavior. For example, millions of users of a social website or millions of players of online games can be exposed to different carefully controlled situations – within seconds – across regional and cultural boundaries. Such technologies enable heretofore impossible forms and scales of experimentation. At the same time, these new capabilities raise important issues of how to perform such experimentation, how to correctly interpret the results, and, critically, how to ensure the highest ethical standards.

Such advances mean that theory development and testing in the social-behavioral sciences are poised for revolutionary changes. Behavioral theories, whether based on observation, in situ experiments, or laboratory experiments can now be revisited with new technology-enabled instruments. Applying these new instruments requires confronting issues of reproducibility, generalizability, and falsifiability. Doing so will help catalyze new standards for scientific meaning in the social-behavioral sciences. The massive scale of some such studies will require complex experimental designs, but these could also enable substantially automated methods that can address many problems of reproducibility and generalizability.

Similarly, representation of knowledge about the human condition is poised for revolution. Using mathematics and computation to formally describe human behavior is not new (Luce et al. 1963), but new and large-scale data collection methods require us to reconsider how to best represent, verify, and validate knowledge in the social and behavioral sciences. New approaches are needed to capture the complex, multiresolution, and multifaceted nature of the human condition as studied with different observational and experimental instruments. Capturing this knowledge will require new thinking about mathematical and computational formalisms and methods, as well as attention to such engineering hurdles as achieving computational tractability.

Advances in knowledge representation will also motivate advances in social and behavioral science. The need for accuracy and precision in describing the current understanding of the human condition will require models with structured descriptions of data sources, data interpretations, and related assumptions. These will support calibration, testing, and integration and, critically, identifying gaps in current theory and instruments. Mathematical, computational, and structured qualitative can models provide a comprehensive epistemology for the social and behavioral sciences – describing not only what is known but also the certainty and generalizability of that knowledge. This will allow comparing different and even conflicting sources of knowledge and resulting theories, as well as identifying future research needs.

The combination of computational models with new technology-enabled instruments for studying human behavior should result in a tightly coupled and partly automated ecosystem that spans data collection, data analysis, theory development, experimentation, model instantiation, and model validation. Such an ecosystem, if constructed to maximize the soundness of the science, would radically transform how we pursue our understanding of the human condition.

Revolutions in the scientific process of creating and encoding knowledge about human behavior will allow applications that aid human decision-making. Computational models provide the means to readily apply (and democratize nonexpert access to) knowledge of human behavior. However, access to an ever-expanding body of knowledge about the human condition must be appropriately managed, especially as techniques for reflecting and combining the inherent uncertainties in the growing knowledge base are developed. Also, we must understand how to use these increasingly accurate models and how to quantify and share information transparently, including information about uncertainty, so as actually to assist human decisionmaking rather than increase confusion. Accurately representing the growing bounds of our knowledge about the human condition is essential for ensuring ethical application of the knowledge and maximizing its benefit for society (Muller 2018).

Challenges

We are at the beginning of an era in which sound computational models of human behavior and its causes can be constructed. Such models have vast potential to positively affect the human condition. Yet, despite this heady promise, a great deal of creativity and innovation will be needed to surmount the considerable challenges. Even describing these challenges remains a subject for scholarly debate; therefore, the list of challenges below should be considered representative rather than comprehensive (see also Chapter 2, Davis and O'Mahony 2018).

Challenge One: The Complexity of Human Issues

First and foremost, it is for good reasons that the social and behavioral sciences have not progressed in the same way as the natural sciences. The human condition is inherently complex with overlapping multiresolution features across multiple dimensions (e.g. from short to long time frames, from individual behavior to group activities and governance, and from individual neuronal physiology to brain-region activation, psychophysical action,

cognitive task performance, and intelligence and consciousness). Further, the factors driving behavior change at different rates as a function of the physical world, technology, and social interactions, resulting in emergent, population-wide change. Such complexities contribute to what have been called *wicked problems* (Churchman 1967; Rittel and Noble 1989). Recognizing the implications of these complexities in studying the human condition is a critical first step.

Challenge Two: Fragmentation

The social and behavioral sciences are fragmented within and across such constituent disciplines as psychology, sociology, political science, and economics. Each discipline has made many contributions to our knowledge and methods, but few attempts have been made to integrate that knowledge. Fragmentation occurs as the result of (i) studying separately different aspects of the human condition (e.g. trust in information, mental health, community formation), (ii) studying at different levels of detail (e.g. psychomotor systems, individual cognition, economic systems, political systems), (iii) using diverse methods (e.g. qualitative observation, structured interviewing, surveys, controlled laboratory experiments, in situ experiments, analysis of existing data sets, natural experiments, computational simulation), and (iv) applying differing concepts of and standards for meaningful *scientific rigor* as evidenced by variations of acceptance criteria across peer-reviewed publications (e.g. acceptance criteria for studies on just-noticeable differences in psychomotor responses necessarily differ from those for studies on delayed gratification in infants). Some prominent researchers have argued for standards within their disciplines (King et al. 1994) but different standards are clearly needed for different conceptual and empirical approaches (Brady and Collier 2010).

A fifth important manifestation of fragmentation is the awkward and overly narrow relationship between theoretical and empirical inquiry (Davis et al. 2018) (see also Chapter 2). In the domain of social-behavioral work, the theory and models are overly narrow – focusing on some particular variables and ignoring others. They are also not adequately related to empirical data, in part because such data has been hard to come by. Most data analysis is insufficiently informed by suitable theory: empirical comparisons are often made to particular very narrow theories, but not to theories that *put the pieces together*. Relationships among theory, empirical, and computational work are not yet well drawn. Let us comment briefly on some of these matters.

Empirical Observation

Observational approaches view behavior in naturalistic and uncontrolled settings (i.e. with no managed interventions). They include traditional

trained-observer approaches (e.g. manual coding of behaviors according to some schema, ethnographic observation) as well as newer approaches applying statistical and other methods to the masses of data on human activity now available. These approaches identify factors meriting additional experimental study and confounding factors to be managed in such experiments. One complicating issue is that analytic results can vary significantly not just across disciplines but also from study to study as uncontrolled factors influence results. Technology continues to change the realm of the possible in such work, but the few attempts to create standard practices have quickly fallen behind the state of the technologically possible.

Another issue is that observational data are necessarily interpreted by the researcher. That is, the meaning of the observed behavior is inferred, often without standards on how such meaning is derived (e.g. the notion of *economic health* could be based on the price of electricity, the number of transactions at restaurants, or stock market fluctuations). Another issue is that the opportunity to study a phenomenon may be transient and impossible to re-create because of the real-world circumstances that led to the phenomenon or because of limitations in access to reliable data (e.g. regulatory limits on access to financial data). We must recognize, then, that the ability to derive and substantiate causal factors from observation alone is likely to be highly limited, although more recent work on finding *natural experiments* (also called quasi-experiments) is sometimes quite valuable. Observational approaches rely on the space of what has happened or is happening and do not permit creating new situations. Analytic results from such approaches are ripe for misinterpretation by nonexperts (and, sometimes, experts) who generalize outcomes without understanding the limits of the observations and the quality of inferences made from those observations. Unfortunately, the social and behavioral sciences also lack consistent standards for quantifying the certainty around such analytic results (e.g. while data scientists may report standard deviations, they may fail to report the span of the underlying data and/or noise-correction methods used).

Empirical Experiments

Experimental approaches hold conditions constant except for those variables that are systematically varied (sometimes referred to as *managing an intervention*). Such experimentation is a pillar of traditional science. Experimental approaches lie along a spectrum of controlled to semi-controlled – that is, the degree to which potentially confounding factors can be controlled, independent variables manipulated, and dependent variables measured. For example, a typical laboratory experiment will differ in these dimensions from a randomized controlled trial conducted in situ. Experiments necessarily introduce some artificiality (e.g. participants in a study may change their behaviors simply because they are aware of being in a study). Managing this artificiality is difficult and relies on the researcher's expertise and his or her discipline's accepted practices.

Artificiality in terms of the participant population is a related problem. The social and behavioral science community has recognized, for example, a broad bias toward Western, educated populations from industrialized, rich, developed countries (Henrich et al. 2010). A further difficulty in experimental approaches is that even a carefully designed experiment may fail to accommodate some unknown confounding variable. Worse, should such a confounding factor be found after the original experiment was conducted, it is unlikely that that additional data on that factor was collected in the original experiment, meaning that the overall validity of that experiment may be dramatically reduced. The discovery of new variables therefore has the ability to undermine the value of past empirical work. This leads to the problem of reproducibility, such as the degree to which empirical studies adequately document all aspects of an experiment so that they may be independently tested and potentially unknown confounding factors can be exposed. These problems have been well documented in a number of recent studies (Nosek and Open Science Forum 2015). As with observational approaches, experimental data is also subject to a degree of interpretation, although standards for statistical analysis are generally clear and accepted. Regardless, the potential for unknown confounds means that while statistical confidence intervals describe one form of uncertainty, other forms are difficult to quantify.

Generative Simulation

As discussed above and in Chapter 2, we see computational social science as one of the three pillars of modern science (along with theory and empiricism). One crucial aspect of computational social science is its generative ability. Generative simulation supports study of (i) heretofore unencountered and/or hard-to-anticipate situations, (ii) situations that are hard to study or measure because of access restrictions, and (iii) situations for which real-world experiments could be considered overly artificial (e.g. a population's response to a deadly pandemic or disaster) (Waldrop 2018). Significantly, the data from such generative models can be studied by both observation and experimentation. That is, the output of simulated data can be observed in an uncontrolled way or after systematic changes to some variables.

Such simulations range in complexity. The most complex simulations generate masses of data and require advanced analytic capabilities to explain the emergent behavior of the simulated system. Simpler simulations (e.g. some game theory-based simulations) also have the potential to inform understanding of individual and social behavior. In both simple and complex simulations, describing the propagation of uncertainty remains a significant issue. These approaches (even if rough) supplement empirical observational and experimental methods.

Unification

A major challenge, then, is how to unify across theoretical, observational, experimental and generative approaches (and variant sub approaches within each). Any such unification requires understanding the qualities of each approach. This is akin to challenges in the natural sciences where conclusions draw on theory (and sometimes competing theories), experimental data obtained with different instruments and methods, and computations based on the best physical models available. Although no single set of standards is in the offing for such unification, there is need for a common understanding of sound ways to unify knowledge.

Challenge Three: Representations

Creating mathematical or computational representations of complex human behavior is itself a challenge. While applied mathematicians and computer scientists offer many representational formalisms (e.g. differential equations, hidden Markov models, Bayesian networks, theorem approaches, system dynamics), deciding which to use in describing a particular social-behavioral phenomenon requires careful consideration. For example, when and where do behavior processes follow different probability distributions? A core issue is coping with the multiple types of uncertainty across different data sources and the under-specification of social-behavioral theories. That is, not only is the selection of particular computational or mathematical formalisms deserving of scrutiny but also their ability to represent the phenomena of interest and, critically, the many associated uncertainties and assumptions. For example, what computational representations can best integrate laboratory – experiment data on a specific population with the statistical analysis of correlations across populations? Selecting and integrating multiple formalisms, to include dealing with the propagation of uncertainty, and developing mappings across them, will be an active area for future research.

Challenge Four: Applications of Social-Behavioral Modeling

The final and most consequential challenge is translating knowledge of the human condition into the decisions and actions of individual citizens, of corporate or government leadership, or, increasingly, automated systems. Communicating current knowledge of the human condition and its uncertainties is critical. Society does some of this today, as when engineers use knowledge of human behavior to design roads and place warning signs appropriately. However, modern social-behavioral knowledge is also being applied in domains that raise profound ethical and moral considerations

that have not been adequately explored. At the root of such concerns is yet another type of problem – the need to ask how the consumer of knowledge about human behavior can realistically use that knowledge. Fortunately, some aspects of this challenge are already active areas of research, such as work on communicating uncertainty, on creating explanations of complex analytic methods (e.g. explaining machine learning techniques), and on how to help decision-makers to assess the trustworthiness of data and analyses of data. So also, research is underway on how to allow humans to better understand privacy issues and how to protect themselves (see Chapter 3, Balebako et al. 2018). In any case, given that improved and accessible understanding of the human condition can be used for both good and bad purposes, more research is needed to understand the issues and develop protections.

About This Book

Interest in social-behavioral modeling for complex systems has waxed and waned, but is now very much ascending. This book came about because we recognized that a large community was very interested and deeply involved, as illustrated by a large number of studies and conferences, many of them related to data and data analytics and others being broader in scope.[2] Identifying and articulating common questions, challenges, and opportunities across all of these activities has become a priority.

With that in mind, we began the book project and solicited chapters from prominent and diverse researchers to represent a broad perspective on recent developments and the future of research on modeling of the human condition. Their chapters offer a great deal of wisdom and numerous suggestions based on their experience and visions. Many of the chapters posit pathways for future work in specific areas, each of which could revolutionize our understanding of the human condition. Although even this sizable volume is addressing only a sampling of the myriad efforts underway, it draws on work in at least the following areas: anthropology, cognitive psychology, complex adaptive systems, computer science, data science, economics, electrical engineering, health research, law, medicine, modeling and simulation, neuroscience, physics, policy analysis, political science, social psychology, and sociology. Interestingly, many of the

2 A few of many examples include the ongoing "Decadal Survey of the Social and Behavioral Sciences and Applications to National Security" by the National Academy of Sciences, DARPA-sponsored RAND workshops on privacy and ethics (Balebako et al. 2017), and priority challenges for social and behavioral modeling (Davis et al. 2018) and various professional conferences by, e.g. the Society for Computational Social Sciences and Social Computing, Behavioral-Cultural Modeling & Prediction and Behavior Representation in Modeling (SBP-BRIMS). Chapter 2 of this volume also cites numerous foundational documents from earlier work, including an important National Academy study from a decade ago (Zacharias et al. 2008).

contributors no longer identify exclusively with a single academic discipline but rather engage problems that cross disciplines. Many are also concerned with application to real-world problems.

With all humility, then, we hope the book will be an inspirational crosscutting milestone volume that helps set the agenda for the next decade of research and development. We hope that it will prove stimulating to a number of audiences: (i) scientists and modelers; (ii) organizations that support basic and applied research; (iii) practitioners who apply social-behavioral science and computational modeling; and (iv) decision-makers responsible for addressing individual and societal-level problems. All of the chapters reflect the ultimate goal of this book: to reflect on the opportunities for technology to help transform the social and behavioral sciences while – at the same time – honoring our duty to create scientifically sound knowledge and assure that it is responsibly used to benefit mankind. We (the editors) see researchers as having heavy and nontrivial responsibilities for creating models with a solid basis in reality and for ensuring that the models and related analytic tools are used responsibly to benefit humanity.

Roadmap for the Book

The book is divided into distinct parts (see Table 1.1). Part I sets the stage. Chapter 2 is an overview of social-behavioral modeling for complex systems. It structures the subject area in terms of three pillars: theory, empirical observation and experimentation, and computational observation and experimentation. These exist in an ecology that includes infrastructure, governance, and technology. Chapter 2 also establishes goals of *usefulness* of social-behavioral modeling and identifies priorities. Chapter 3 recognizes the fundamental importance of seeing opportunities and challenges in a framework that recognizes ethical and privacy issues from the very start. Since modeling is an attempt to represent and exploit knowledge, it needs foundations in science. Part II, Social-Behavioral Science Foundations, is a set of nine chapters about frontier aspects of social-behavioral science and its implications for modeling. Part III is a set of nine chapters discussing how social-behavioral modeling can and should be informed by underlying theory and modern ubiquitous data, not only traditional data from social science research, but new forms reflecting social media, recreational games, and laboratory experiments. One of the themes is the need to better relate theory and data: theory should be informed by data, and both data collection and data analysis should be informed by theory; but neither should be unduly constrained by the other, and competition of inquiry should be encouraged. Part IV is about modeling itself, describing innovations and challenges in doing so. Some of the 12 chapters describe new methods; some address frontiers in crossing the boundaries of model types and formalisms and of spatial,

Table 1.1 A view of the book's composition.

Part	Chapter	Authors	Title (abbreviated)	Overview	Theory and its modeling	Social science data	Theory-data linkages	Validation	Modeling theory and technology	Models for decision aiding	Model-based decision aiding
I	1	Pfautz et al.	Understanding and Improving the Human Condition								
	2	Davis and O'Mahony	Improving Social-Behavioral Modeling								
	3	Balebako et al.	Ethical and Privacy Issues in Social-Behavioral Research								
II	4	Nyblade and O'Mahony	Building on Social Science								
	5	Brashears	How Big and How Certain? Defining Levels of Analysis								
	6	Corman et al.	Generative Narrative Models of Conflict and Its Resolution								
	7	Read and Miller	A Neural Network Model of Everyday Decision-Making in Social Behavior								
	8	Matthews	Dealing with Culture as Inherited Information								
	9	Cowherd and Lende	Social Media, Global Connections, and Information Environments								
	10	Thompson et al.	Using Neuroimaging to Predict Behavior								
	11	Pavlic	Social Models from Nonhuman System								
	12	Sieck et al. (panel)	Moving Social-Behavioral Modeling Forward: Insights from Social Scientists								
III	13	Gabbay	Integrating Computational Modeling and Experiments								
	14	Sliva et al.	Combining Data-Driven and Theory-Driven Models for Causality Analysis								
	15	Rand	Theory-Interpretable, Data-Driven Agent-Based Modeling								
	16	Miller et al.	Bringing the *Real World* into the Lab: Transformative Designs								
	17	Lakkaraju et al.	Online Games for Studying Human Behavior								
	18	Guarino et al.	Using Sociocultural Data from Online Gaming and Game Communities								
	19	Osoba and Davis	An Artificial Intelligence/Machine Learning Perspective on Social Simulation								
	20	Giridhar and Abdelzaher	Social Media Signal Processing								
	21	Grace et al.	Evaluation and Validation Approaches for Simulation of Social Behavior								
IV	22	Garibay et al.	The Agent-Based Model Canvas: A Modeling Lingua Franca								
	23	Tolk and Glazner	Representing Socio-behavioral Understanding with Models								
	24	Yilmaz	Toward Self-Aware Models as Cognitive Adaptive Instruments								
	25	Osoba and Kosko	Beyond DAGs: Causal Modeling with Feedback Using Fuzzy Cognitive Maps								
	26	Swarup et al.	Simulation Analytics for Social and Behavioral Modeling								
	27	Sukthankar and Beheshti	Using Agent-Based Models to Understand Health-Related Social Norms								
	28	Hadzikadic and Whitmeyer	Lessons from a Project on Agent-Based Modeling								
	29	Scaumann and Kapadia	Modeling Social and Spatial Behavior in Built Environments								
	30	Orr	Multi-scale Resolution of Human Social Systems								
	31	Gribaudo et al.	Multi-formalism Modeling of Complex Social-Behavioral Systems								
	32	Carley	Social-Behavioral Simulation: Key Challenges								
	33	O'Mahony et al.	Panel Discussion: Moving Social-Behavioral Modeling Forward								
V	34	Rouse	Human-Centered Design of Model-Based Decision Support								
	35	Thompson et al.	Understanding Policy and Management Interventions in Health Care								
	36	Lofdahl	Modeling Information and Gray Zone Operations								
	37	Paul	Modeling Narrative in Human Understanding								
	38	Sieck	Aligning Behavior with Desired Outcomes: Lessons from the Marketing World								
	39	Myers	Future Social Science That Matters for Statecraft								
	40	Davis	Lessons on Decision Aiding for Social-Behavioral Modeling								

temporal, and other scales of description. Part V addresses how models and modeling can and should relate to decision-making and those who must make those decisions. It is more applied in character, drawing on examples from international security, health research, and marketing, among others.

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