Introduction: Modern Approaches to the Study of Human Cognition

Bourama Toni

Abstract This introductory chapter presents some background and context for some of the techniques and approaches to cognitive modeling and simulations. It includes the summarizing ideas drawn for the contributed chapters to reveal the topical link between them while presenting hints as to the direction of future research. Indeed cognitive science has been endeavoring to harness the rigor and efficiency of mathematical modeling, in particular, in times of machine learning, artificial intelligence, and quantum computing and information science.

Keywords Human cognition · Qualitative modeling-agent-based modeling · Nyayasutra inference · Pheromone trail algorithm · Social Laser · Probabilistic learning · Physicalistic perspective · Conjunction fallacy · Quantum modeling · Compositional vector semantics · Optimality · Color perception

1 Background

Human cognition broadly includes perception, attention, memory, learning, reasoning, decision-making, critical thinking, and problem-solving. Its modeling and simulation, that is, the so-called *cognitive modeling and simulation*, necessitates powerful tools including the design and development of mathematical and computational models to decipher the underlying cognitive mechanisms allowing human thinking, behavior, and performance in all aspects of human life. Ultimately cognitive modeling and simulation aim at enhancing our understanding of how the brain processes data to retrieve information leading to human decision-making and related behavior.

Cognitive modeling and simulation are therefore major undertaking in psychology, neuroscience, computer science, artificial intelligence, education, and

B. Toni (✉)
Department of Mathematics, Howard University, Washington, DC, USA
e-mail: bourama.toni@howard.edu

T. Veloz et al. (eds.), *Trends and Challenges in Cognitive Modeling*, STEAM-H: Science, Technology, Engineering, Agriculture, Mathematics & Health,
https://doi.org/10.1007/978-3-031-41862-4_1

human-computer interaction. In these various fields, hypotheses and theories are formulated through mathematical or computational models and then tested and evaluated through simulations to replicate cognitive processes in the form of computer programs or virtual environments. Algorithms are developed and implemented on systems to perform human-like reasoning and decision-making. One of these well-known simulation techniques is the so-called agent-based modeling (ABM), an offshoot of game theory, to assess individual agents and interactions (strategic or otherwise) within a system (simple or complex). As in the broader game theory, ABM has served in the study of the spread of infectious diseases, the emergence of social norms and cooperation, financial markets dynamics, and evolutionary dynamics of biological systems. Social norms are self-enforcing patterns of behaviors, often sustained by multiple mechanisms, to include the desire to coordinate and follow the lead of others, the fear of being sanctioned, etc. Stochastic evolutionary game theory has proven to be the best cognitive model and simulator to study the resulting dynamics of social norms.

2 Current Approaches

Cognitive modeling and simulation are indeed very powerful tools, and sometimes they are the only tools to understand and predict human data and information processing and decision-making in interacting with complex systems. As a modern scientific endeavor, the theory of *cognitive modeling and simulation* has its challenges; one of these challenges is how to effectively harness the rigor and efficiency of mathematics to achieve the same results as the physical sciences. That is, the lack of an efficient analytical framework. For instance, psychology has been trying to be an exact science, but so far to no avail.

Note that precise measurement and predictions in the physical sciences occur after centuries of experimentation, leading, among other outcomes, to the creation of differential equations in mathematics.

Oftentimes in social and behavioral sciences, modelers resort to off-the-shelves mathematical methods, e.g., using real analysis instead of p-adic analysis, for lack of adequate training in advanced mathematics. Much like a drunk looking around the street lamppost for keys, he lost elsewhere only because "the light is better here." Work by Khrennikov (Khrennikov 1998, 2000) on the dynamics of mental spaces is a good reference of the complexity of cognitive modeling and simulations. The author discusses the adequate mathematical model of mental space.

Cognitive modeling and simulation found an application in artificial intelligence (AI), which is basically the decoupling of intelligence from consciousness. And nonconscious intelligence is developing at a tremendous speed. We are witnessing the emergence of surprisingly powerful AI tools, such as ChatGPT, raising serious questions about the so-called *Mathematical Creativity*. Mathematics has been and is still a human construct. But for how long? AI may soon produce a very different sort of mathematics. A long-held belief has been that human cognition, i.e., human mind and intelligence, has unique creativity capabilities unknown to animals and machines including computers. Von Neuman (1958) in his remarkable book *The Computer and the Brain* discussed the idea that computer/AI thinking, when this occurs, must be of a very different nature than human's thinking. This was also considered by Alan Turing in *Computing machinery and intelligence* (Turing 1950).

Computers and their capabilities have been assisting mathematical creativity for some time, performing, e.g., heavy logical and numerical tasks oftentimes beyond human capabilities: for example, the proof of the *four-color theorem* by Appel and Haken (1989). The Gosper's algorithm implemented on a symbolic manipulation program and using the *Wilf-Zeilberger pairs (WZ)* has produced new identities involving hypergeometric functions. A well-established trend is the so-called *computer-verified formal proof*. Human is known to have limited memory and to be prone to errors. The famous mathematicians Hadamard and Poincaré have seen doing mathematics as a combinatorial task leading to an elegant theorem by gluing pieces together. If so, then we will soon witness an *artificial mathematical creativity* by computer/AI.

The acquisition of language in the evolution of human cognition seems to have led to the ability to do mathematics, evolution favoring the ability to speak, the ability to count from 1 to 10 but possibly not the ability to master Galois Theory in higher mathematics. More on mathematical creativity and post-human mathematics could be found in Ruelle's book *The Mathematician's brain* (Ruelle 2007) which also inspired some of the above ideas. Ruelle has also coined the term *Artificial Mathematical Creativity*.

Human cognition went through revolutions transforming an insignificant African ape into the ruler of the world (creation of gods, corporation, cities, empires, writing and money, splitting of atom, reaching to the moon, genetic engineering, nanotechnology, brain-computer interfaces, etc.). Cognitive modeling aims at designing mathematical and computational models of the cognitive mechanisms underlying human behavior and then running these models to simulate human performance on numerous tasks. Many of these mechanisms have been perfected by the biological evolution of the human brain.

However, most of the research today involving cognitive modeling and simulation, i.e., about human mind and brain, is happening in the so-called WEIRD societies (western, educated, industrialized, rich, and demographic); that is to say it is fundamentally biased and flawed. The premise of this research endeavor is that, since Darwin's "On the origin of Species" organisms are seen as just biochemical algorithms similar to the electronic/silicone algorithms, sophisticated since Alan Turing. Indeed, exactly the same mathematical laws and principles apply to both, with the potential that the electronic algorithm will somehow outperform the biochemical one. Human cognitive activity amounts to processing data into information, information into knowledge, and knowledge into decision-making (wise or otherwise). In other words, human beings are reduced to data processing systems that need to be modeled and simulated for a deeper understanding. Cognitive science has been morphing into computational algorithmic science.

It should be emphasized here that cognitive modeling must be of a *qualitative* nature, i.e.., not quantitative as for the physical sciences. As claimed by Levins (1974), scientific modeling can maximize at most two of the three virtues: *generality*, *realism*, and *precision*.

Sacrifice generality for precise quantitative predictions about specific systems and maximize realism by representing as many system details as possible.

Sacrifice realism to make unrealistic assumptions so systems can be described with general mathematically tractable equations producing precise quantitative predictions.

Sacrifice precision to abandon quantitative accuracy for qualitative relations between variables for maximum generality and realism.

Indeed in cognitive systems, the relevant information is of qualitative nature. It is usually impossible, infeasible, or impractical to determine the quantitative value or the precise functional form of many of the interactions between system parts, whereas it is often possible to determine the qualitative properties of these interactions. For example, in complex systems, what can be only ascertained is that there is or there is not interaction between the variables, which could be represented by yes or no, 0 or 1 (Boolean models). For instance, in psychology, an accurate mathematical function is not available to represent exactly human behavior, e.g., in imprecise belief states or social preferences.

In most complex systems including cognitive systems, relevant information resides in the rules of construct of the system, and not in the absolute quantitative values; what is being analyzed/investigated (data, phenomena, behavior, etc.) is essentially qualitative. Several qualitative modeling methods are available in the literature; we have proposed one based on the so-called Dynamical Roles of Jacobian Feedback Loops, in Toni (2014). See also Justus (2006) and Puccia and Richard (1985). In other words, qualitative analysis should be the main tool to understand complexity, key in the evolution of systems, versus the usual quantitative idealization of most mathematical models.

3 Conclusion

The volume features a variety of approaches and applications in the science of cognitive modeling and simulation. Drawing from the respective chapters' abstract, we highlight the outcomes of the study undertaken in each one of the chapters.

Enrique Canessa, Sergio Chaigneau, and Nicolas Marchant address in Chapter "Use of Agent-Based Modeling (ABM) in Psychological Research", stressing, in particular, the infrequent use in psychology of a tool the authors deem the main research tool in social sciences. The authors present some general drawbacks and some specific to psychology; they include the benefits/advantages of using such a tool to outweigh its shortcoming.

The chapter titled Miguel Lopez-Astorga discusses "Nyāyasūtra Proof Pattern: An Interpretation of Similarity as the Fact of Sharing Two Properties". The author proposes a relation to first-order calculus and explores the link between the Nyayasutra, an inference by Schayer to first-order predicate logic, to Carnap's reduction sentences, showing that, despite their differences, the Indian inference and Carnap's reduction sentences have a similar potential for the analysis of scientific definitions.

The Chapter "Using Pheromone Trail Algorithm to Model Analog Memory" by Trung Pham, Ramon Castillo, Xiaojing Yan, and Heidi Kloos proposes such a use to model how the human mind registers data into memory in the brain. They also extend the model with algorithms to register and recall data embedded in an overlaid manner to represent the analog memory of a theoretical quantum computer. Numerical simulations are provided to illustrate the concept and to demonstrate the workability of the algorithms.

Andrei Khrennikov presents, in Chapter "Review on Social Laser Theory and Its Applications", an overview completed with new developments and applications, to include the detailed study of the dynamic interactions of the so-called *infons* with social atoms and the processes of absorption and emission.

The Chapter "Challenges from Probabilistic Learning for Models of Brain and Behavior" contains the contribution by Nicolas Marchant, Enrique Canessa, and Sergio Chaigneau. The authors discuss the historical background of probabilistic learning, its theoretical foundations, and its applications in various fields such as psychology, neuroscience, and artificial intelligence. They also review key findings from experimental studies on probabilistic learning, to include the role of feedback, attention, memory, and decision-making processes.

Karl Svozil discusses in Chapter "The Emergence of Cognition and Computation: A Physicalistic Perspective" to support the idea that cognition is an emergent property driven by dissipation. Cognitive agents are better equipped to acquire physical resources and means, giving them an advantage in survival and reproduction.

In Chapter "Analysing the Conjunction Fallacy as a Fact", Tomas Veloz and Olha Sobetska analyze *conjunction fallacy* (Tverky and Kahneman) range of factual possibilities. Reviewing samples of experiments between 1983 and 2016, the authors show that the majority of the related research has focused on a narrow part of the a priori factual possibilities, implying that explanations of the *conjunction fallacy* are fundamentally biased by the short scope of possibilities explored.

"Yes Ghosts, No Unicorns: Quantum Modeling and Causality in Physics and Beyond" is the imaginative title of the chapter by Kathryn Schaffer and Gabriela Barreto Lemos. Drawing from examples in physics, the authors urge caution in cross-disciplinary modeling comparisons and illustrate the kind of explanatory causal reasoning underlying Bell tests. They also argue that Bell inequalities are not portable: their bounds need to be re-derived and interpreted appropriately for each use.

In Chapter "Compositional Vector Semantics in Spiking Neural Networks", Martha Lewis proposes a way for compositional distributional semantics to be implemented within a spiking neural network architecture, with the potential to address problems in concept binding, and gives a small implementation. The author also describes a means of training word representation using labeled images.

Igor Douven and Galina Paramei report in Chapter "Optimality, Prototypes and Bilingualism" a study comparing Italian monolingual, English monolingual, and Italian-English bilingual speakers with regard to focal color choices in the BLUE region of color space suggesting that cultural and linguistic factors play a role in the categorical structuring of color space.

In Chapter "The Dimensionality of Color Perception", Javier Fdez, Oneris Rico, and Olaf Witkowski study the trade-off between finding an embedding for color perception with the minimal number of dimensions while maximizing the discriminations between colors. They experiment with 13 subjects reporting the similarity between 20 colors randomly generated using the Munsell color system: their result is that the optimum number of dimensions is 3 when using a cosine similarity measure, indicating a resemblance to the way the perception of colors is cognitively encoded from mere physical properties of color maps.

Acknowledgments We express our sincere gratitude to all the contributors for their state-of-art research on such an important topic and to all the anonymous referees for their professionalism.

References

K. Appel and W. Haken. *Every Planar Map is four-Colorable*. AMS Providence, 1989

J. Justus, *Loop Analysis and Qualitative Modeling: limitations and merits*. Biology and Philosophy, 21, 647–666, (2006)

A. Khrennikov, *Human subconscious as the p-adic dynamical systems*. J. of Theor. Biology 193, 179–196, 1998

A, Khrennikov, *p-adic discrete dynamical systems and collective behaviour of information states in cognitive models*. Discrete Dynamics in Nature and Society 5, 59–69, 2000

R. Levins, *The qualitative analysis of partially specified systems*. Annals of the New York Academy of Sciences, 231, 123–138 (1974)

J. von Neuman. *The Computer and the Brain*. Yale U.P., New Haven, 1958.

C. Puccia and L. Richard. *Qualitative Modeling of complex systems*. Cambridge, MA: Harvard University Press. (1985).

B. Toni, *Dynamical Roles of Jacobian Feedback Loops and Qualitative Modeling*. New Frontiers of Multidisciplinary Research in STEAM-H. Spring PROMS 90, 205–240 (2014)

A. Turing. *Computing Machinery and Intelligence*. Mind 59, 433–460 (1950)

D. Ruelle, *The Mathematician's Brain*. Princeton U.P., Princeton, 2007