Editors' Introduction

Stewart, Terrence C.; de Jong, Joost

Published in:
Topics in Cognitive Science

DOI:
10.1111/tops.12625

TOPICS
TOPICS IN COGNITIVE SCIENCE

Topics in Cognitive Science 14 (2022) 825–827

ISSN: 1756-8765 online
DOI: 10.1111/tops.12625

This article is part of the topic "Best of Papers from the 19th International Conference on Cognitive Modeling", Terrance C. Stewart and Joost de Jong (Topic Editors).

Editors' Introduction: Best Papers from the 19th International Conference on Cognitive Modeling

Terrence C. Stewart,[a] Joost de Jong[b]

[a]*National Research Council Canada*
[b]*Department of Experimental Psychology, University of Groningen*

Received 1 September 2022; received in revised form 1 September 2022; accepted 2 September 2022

Abstract

The International Conference on Cognitive Modeling brings together researchers from around the world whose main goal is to build computational systems that reflect the internal processes of the mind. In this issue, we present the five best representative papers on this work from our 19th meeting, ICCM 2021, which was held virtually from July 3 to July 9, 2021. Three of these papers provide new techniques for refining computational models, giving better methods for taking empirical data and producing accurate computational models of the cognitive systems that produce them. The other two papers focus on explanation: using models to elucidate the underlying processes affecting cognition in such diverse domains as logical reasoning and the effects of caffeine.

Keywords: Cognitive modeling; ICCM; Best papers

Cognitive modeling is the practice of building computational simulations of cognitive processes; that is, building computer programs that replicate the internal steps that occur inside the mind. Different parts of the mind work together in complex ways, combining memory, perception, learning, logic, movement, localization, and myriad other components. Moreover, these cognitive processes can be understood at varying levels of description, from neurobiology to social coordination. Given the complexities of these interactions, cognitive modelers instantiate their theories as computer programs and then run those programs to determine

Correspondence should be sent to Terrence C. Stewart, William M. Tatham Centre, 200 University Ave W, Waterloo, ON N2L 3G1, Canada. E-mail: terrence.stewart@nrc-cnrc.gc.ca

the quantitative predictions their theories make. At the same time, the complexity of these cognitive models themselves creates the challenge of connecting them to empirical data. This special issue collects the latest results from this field, presenting the top-reviewed papers from the 2021 edition of the International Conference on Cognitive Modeling (ICCM).

Since 2017, ICCM has been held jointly with the annual meeting of the Society for Mathematical Psychology. This merging of events has been mutually beneficial, broadening the scope of models and researchers in attendance. However, as with ICCM 2020, the ongoing pandemic meant that the conference was held virtually. While this limited some forms of researcher interaction, the reduced costs for attending meant that the talks and online question periods were accessible to a wider audience.

The five papers presented here give a representative sense of the breadth of the cognitive modeling field. Three of the papers focus on new techniques to make cognitive models more realistic and accurate at describing people's behavior. This process allows us to take a generic model and customize it, making it fit more closely to a particular person or situation. The other two papers focus on using models to explain behavior, showing how understanding the internal steps going on inside a mind (or brain or body) can make it clear why people behave in particular ways. Indeed, one can view these papers as two sides of the same coin: the complexity of cognition, and the complexity of cognitive models. Our selected papers either (1) model the complexity and multi-scale nature of cognition, from physiological effects of caffeine on vigilance (Halverson et al.) to modeling brain-wide dynamics across a variety of task domains (Hake et al.), or (2) handle the complexity of cognitive models to keep them tethered to real-world data, from formalizing connections between cognitive- and mathematical models of memory and decision-making (van der Velde et al.) to finding a common format to describe the behavior of humans and models to align them (Hiatt et al.), or using existing models to aid with hypothesis generation and testing (Brand et al.).

Halverson, Myers, Gearhart, Linakis, and Gunzelmann start by noting that while most cognitive modelers would acknowledge the potent role of physiology in explaining high-level cognitive phenomena, this low level of description is typically avoided. This is not surprising given the intricate neurochemical mechanisms that shape cognition. Halverson et al. set out to integrate the physiological effects of a familiar substance, caffeine, on vigilance in sleep-deprived individuals. The model takes into account how caffeine is processed by the body and links its uptake to formal cognitive mechanisms underlying performance in a vigilance task. The authors systematically test several hypotheses, all informed by the neurophysiological effects of caffeine on specific brain structures.

Hake, Sibert, and Stocco demonstrate the true breadth of our field by examining how the architecture of the mind is instantiated in the brain. In recent years, a consensus has been proposed on the core structure of the mind: the Common Model of Cognition (CMC). The CMC makes very specific predictions about the causal connectivity between brain regions. Indeed, studies confirm that such a wiring diagram fits the neural data quite well, but it is not clear whether the CMC would emerge as a plausible candidate from a more data-driven approach. Hake et al. use Granger-causality to show that an updated version of the CMC, which includes connections between perception, action, and long-term memory, should be considered. These

neural connections may have important theoretical implications for cognitive architectures themselves in turn.

Van der Velde, Sense, Borst, and van Rijn are concerned that cognitive models, in their attempt to model complex cognitive processes, inadvertently inherit some of that unwieldy complexity. Fitting cognitive models to empirical data is typically done by simulating the model iteratively, which can take much time and provides little guarantees. Van der Velde et al. prove that one component of such a large-scale model, the declarative memory component of ACT-R, neatly maps onto a well-known model of decision-making, the linear ballistic accumulator (LBA). Notably, the LBA has closed-form solutions and can be fitted with relative ease. The authors demonstrate that memory parameters can be recovered through the LBA and successfully apply their methods to an empirical dataset.

Hiatt, Brooks, and Trafton address a major challenge of complex cognitive models, that many processes work together to produce observable behavior which can be matched to the empirical data. However, a good fit to the empirical data does not identify which processes do the explanatory work. Similarly, a poor fit does not suggest which parts of the model should be fixed. Hiatt et al. develop a method for describing human- and model behavior as a hidden Markov model, revealing whether they share a common strategy for performing the task. Their method identified crucial dissimilarities between the model and human behavior, and they showed that some simple but informed adjustments significantly improved the model fit. Crucially, the hidden Markov models also identified an "embodied" strategy that would be difficult to uncover based on conventional measures, such as accuracy and reaction time.

Brand, Riesterer, and Ragni focus on another central goal of cognitive modeling: developing theories that predict more than just the empirical data on which they were founded. Cognitive models should be able to guide theoretical development by connecting with the data in novel ways. Brand et al. show exactly how this can be done in the field of syllogistic reasoning (e.g., all A are B, some B are C, what conclusion follows?). The authors are interested in the effect of feedback on a specific kind of response in syllogistic reasoning problems: no valid conclusion (i.e., nothing follows from the premises). The authors fit several models to participants that do and do not receive feedback. They were able to identify specific parameters in the model that changed as a result of feedback and derived several clever predictions that were subsequently tested. Crucially, they were able to conclude that some models were better able to account for feedback effects than others.

These papers demonstrate the variety of methodologies and the ongoing progress in discovering how the mind itself works, and we are proud to present these five papers as representatives of our field.