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Cognitive Modeling at ICCM: State of the Art and Future Directions

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Abstract

The goal of cognitive modeling is to build faithful simulations of human cognition. One of the challenges is that multiple models can often explain the same phenomena. Another challenge is that models are often very hard to understand, explore, and reuse by others. We discuss some of the solutions that were discussed during the 2015 International Conference on Cognitive Modeling.

Keywords: Cognitive modeling; Cognitive architecture

The premise of cognitive modeling is that human intelligent behavior involves computation. This idea has been around since the beginning of computers with pioneers such as Newell and Simon (1963), and it is also reflected in formalizations such as grammars for natural language. Since its beginning, the original Artificial Intelligence/Cognitive Science research has branched off in many directions. It includes basic and applied research across a wide variety of domains, from low-level perception and action to higher level speech processing and metacognition. To simulate all these different systems, the spectrum of cognitive modeling approaches is wide, including ideas such as connectionism, symbolic modeling, dynamical systems, Bayesian modeling, and cognitive architectures.

Despite the diversity of the field, cognitive modelers are still united by the original goal of understanding the human mind through computer simulation. A major forum for sharing, discussing, and integrating ideas is the International Conference of Cognitive Modeling (ICCM), which meets twice every 3 years to discuss the latest developments in the field. The best five papers of the 2015 conference—reflecting the breadth of the current state of the art—have been selected for this special section. While the best papers

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show the advances in the field, several challenges that were touched upon during the conference remain for the field of modeling cognition.

One of the main challenges of cognitive modeling is that it is always possible to fit some model to the data, but that this does not mean that the model is correct, because there are many possible other models that could also fit the data. Mathematical and statistical models of cognition have remedied this by building models that are as simple as possible, and metrics have been developed to compare different models. An example of this is Horeau, Lemaire, Portrat, and Plancher (2016), who elegantly show what model parameters of different working memory models are impacted by aging. A problem with such simple models, however, is that they typically only implement a single strategy toward solving a task, whereas in reality people may use a mixture of strategies. A promising development in this regard is demonstrated by Maanen (2016), who showed that with some clever mathematical tricks it is possible to determine whether participants use multiple strategies or a single strategy in simple decision-making tasks. A different issue with mathematical models is that it is not always clear what the correspondence is to psychological and neurological processes.

A complementary solution to the problem of model constraints is to build models within a cognitive architecture (Anderson, 1983; Newell, 1990). The claim here is that cognitive architectures offer constraint to the possible space of cognitive models, thereby ensuring that models within such an architecture, and especially the architecture itself, generalize over a wide set of tasks. Although cognitive architectures certainly have been successful, they have not been able to solve the problem all together, because most architectures do not incorporate mechanisms that make it easy to use knowledge gained in one model in another model. Therefore, many models remain isolated theories with a common ground. This plays out both at the level of theory: most models only use what is provided in the architecture and no other knowledge, and at a practical level: few cognitive modelers ever use, or even look at, models built by other modelers.

Several new developments that were discussed at the conference address the issue from different directions. A first development is the increasing realization that the human cognitive system gradually builds up experience and skills over the course of life, and it is also able to use knowledge gained in one task for other tasks. Most cognitive modelers, or cognitive scientists for that matter, focus their research on particular tasks and try to generalize from that task. This approach is problematic, as new tasks lead to the design of new models, resulting in a multitude of highly task-specific models that often fail to generalize to new tasks (Cassimatis, Bello, & Langley, 2010). A whole different approach is to build general systems that have the capability to be given new tasks just by instruction or example, and that have to rely on prior knowledge, trial and error, and requests for further instruction to figure out how to do them (Forbus & Hinrichs, 2006; Kirk & Laird, 2014; Taatgen, 2013). This is an exciting new development, because it can add quite some constraint to cognitive models. Cognitive architectures are typically limited to innate mechanisms of the brain, but mechanisms for lifelong learning can offer a huge boost in theoretical power. In addition, if architectures can use their prior knowledge to discover for themselves how to do new tasks, this adds additional credibility to the plausibility of these architectures.

A second development consists of rooting model activities in brain activity. Work by Anderson and others had already linked symbolic model activity to fMRI data, but new studies establish connections with EEG data (Anderson, Zhang, Borst, & Walsh, unpublished data; van Vugt, 2014). The link to neuroimaging is critical in establishing that the hypothesized processing steps in cognitive models have plausibility in reality (Forstmann & Wagenmakers, 2015). In addition to the model-based analysis of neuroimaging data, a new branch of investigation is to infer the knowledge and processing states in the model from the neuroimaging data (Anderson & Fincham, 2014; Borst & Anderson, 2015). This means that instead of being constructed by modelers, models can be directly inferred from the data. One example presented at ICCM is the work of van Gerven and colleagues, whose models are informed by statistical analyses that elucidate how perceived and remembered stimuli are represented across different levels in the cortical hierarchy (e.g., van Gerven et al., 2013). Both of these developments promise cognitive models that are not directly constructed by modelers, but models where the system either generates a new model based on instructions, experience, and prior knowledge, or where it infers that model from the data.

Another very different challenge of cognitive modeling that received attention at the conference is that models are often difficult to communicate. They tend to be hard to understand when explained in text, and even a well-described model can leave the reader with many "what-if" questions. The possible impact of models can be enhanced substantially if they are made publicly available by the authors in a manner that does not require specific software or lengthy installation procedures (Addyman & French, 2012). Ideally, a public model should be easy to run and get insight in, and options should be offered to adjust parameters of the model, or supply it with different input. It could take the form of an application that runs in a web browser, or a stand-alone application that has little or no additional hardware and software requirements. Publicly available models can also help reviewers evaluate the quality of the work and ensure that the model can in fact produce the claimed result. Fortunately, there are many modern tools that can support this type of dissemination. Examples of such tools are Sweave (Leisch, 2002) and Markdown for writing papers in which the code for generating graphs and tables are embedded, and iPython notebooks (Pérez & Granger, 2007) for integrating code with results and publishing those as web pages. A major hurdle toward sharing models is the lack of immediate credit such an effort gives, even though the payoff in the long term (citations, extra exposure, ease in reproducing your own results for paper revisions and follow-up studies) may be well worth it.

Even if a promising model has been developed, it is often hard to use such cognitive models in practical applications. A step in this direction is made by the speech analyzer developed by Kieras, Wakefield, Thompson, Iyer, and Simpson (2016), which can separate the auditory streams associated with different speakers. Sense, Behrens, Meijer, and Van Rijn (2016) show how low-level mechanisms from cognitive models of memory can be used to help learners memorize materials, improving results markedly over standard learning methods.

A final challenge of cognitive modeling is to expand into domains that were until now thought to be too difficult for modeling. The example highlighted in this issue, by

Stevens, Taatgen, and Cnossen (2016), shows how modeling can be used to understand the process of negotiation. While traditionally such a topic was considered to be too difficult to deal with or irrelevant for cognition, the paper proves that cognitive modeling has ventured into these domains.

Taken together, the future of cognitive modeling will hopefully see the fruition of several new developments with great promises toward uncovering the mysteries of the human mind.

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