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Cognitive Computational Neuroscience: A New Conference for an Emerging Discipline

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Abstract

Understanding the computational principles that underlie complex behavior is a central goal in cognitive science, artificial intelligence, and neuroscience. In an attempt to unify these disconnected communities, we created a new conference called Cognitive Computational Neuroscience (CCN). The inaugural meeting revealed considerable enthusiasm but significant obstacles remain.

What is CCN?

A common goal of cognitive science, artificial intelligence, and neuroscience is to identify the computational principles that underlie perception, action, and cognition. Despite this shared goal, the three disciplines largely work independently of one another and have developed strikingly different languages, concepts, and tools. To bridge these disparate approaches, we convened a new conference called CCN. In September 2017 more than 600 research leaders and trainees from the different disciplines came together for three days of

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talks, posters, and debates. The inaugural meeting of CCN revealed divergent perspectives on the essential computational principles underlying intelligence, thought, and behavior, how these are instantiated in the brain, and what an appropriate benchmark of success would be. Nonetheless, the conference was met with much enthusiasm, demonstrating the research community's commitment to overcoming the barriers between the disciplines.

CCN connects three highly successful research communities. The field of cognitive science identifies information-processing operations that give rise to behavior. The field of artificial intelligence develops algorithms and techniques that solve complex computational problems. The field of neuroscience studies the biological basis of how the brain implements thought and behavior. A common thread that connects these disciplines is the goal of understanding how complex behavior is produced, in either biological or artificial systems. We started CCN to deepen interactions between the communities and to discover ways that the communities can benefit one another and leverage each other's successes. Interest in integration has been building since the early 2000s (Figure 1) and so we believe the time is ripe for CCN. Here we highlight major themes that emerged from the first CCN meeting.

Building Bridges between the Disciplines

A thread that appeared many times at the conference was David Marr's classic thesis that the task of understanding intelligent systems can be addressed separately at the computational, algorithmic, and implementation levels [1]. At the computational level, a theory characterizes the problem to be solved in terms of available inputs and desired outputs. The algorithmic level proposes representations and operations that solve the computational problem. Finally, the implementation level reveals how the components of a physical system (biological or otherwise) instantiate these representations and operations. Some researchers at CCN related the three disciplines of cognitive science, artificial intelligence, and neuroscience to Marr's levels of analysis (Tenenbaum talk[i], 0:54; Griffiths talk[ii], 7:20). For example, it could be argued that cognitive science starts at the computational level and attempts to move toward finer levels of analysis (Tenenbaum talk[i], 0:54). Although Marr's levels of analysis provide a useful conceptual framework, a key tenet of CCN is that this framework should not justify isolationism: researchers should strive to transcend traditional divides between communities and seek an integrated understanding across Marr's levels.

A major impediment to cross pollination across disciplines is their distinct approaches to selecting cognitive tasks for study. Some speakers expressed concern that the tasks studied in neuroscience and cognitive science are too simple, in the sense that they could be solved by trivial algorithms that clearly lack the computational power of the brain (Closing Panel Discussion[iii], 4:02). Meanwhile, tasks studied by artificial intelligence elicited frustration because these tasks are narrowly defined, admitting solutions that do not resemble flexible intelligence (Tenenbaum talk[i], 3:07; LeCun talk[iv], 2:30) or solutions that are difficult to interpret (Opening Panel Discussion[v], 28:14). An implicit suspicion was that systems currently being designed in artificial intelligence are fundamentally limited to doing only

[i–ix] Specific video time codes are provided in the text. A full list of videos from CCN 2017 is available at http://ccneuro.org/2017videos/.

one thing well and that such systems, however impressive, are unlikely to reveal general principles of intelligence. One task that was discussed as a potentially useful target for future interactions between communities is learning to play a video game (Closing Panel Discussion[iii], 7:10). Playing a video game involves many sensory, motor, and cognitive skills that might generalize to other domains. Although this task has been studied extensively in artificial intelligence, it has yet to receive the same amount of attention from the other disciplines.

There were some positive examples of bridge building across disciplines. Several talks (Fyshe talk[vi], 9:16; LeCun talk[iv], 6:26) reviewed the history of convolutional neural networks. In this case, research in neuroscience inspired a machine-learning architecture that led to radical improvements in artificial intelligence. In turn, the building of large-scale neural network systems using modern-day computational power has provided neuroscientists with new tools for probing and predicting brain activity in the visual system. Thus, convolutional neural networks constitute a case where exchange of an idea across disciplines has led to mutual progress. Future efforts could explore whether this common computational architecture can be further improved with respect to engineering benchmarks and biological realism [e.g., the use of more realistic models of neurons and circuits (Opening Panel Discussion[v], 10:38)].

The Need for Intuitive Models of the World

There was much discussion of the ingredient critical for intelligence, variously described as the ability to explain, problem solve, infer, predict, fill in the blanks, or interact successfully in the real world (Tenenbaum talk[i], 6:08; LeCun talk[iv], 21:40; Shadlen talk[vii], 36:20; Bengio talk[viii], 49:15). For example, it is easy for biological organisms to understand the basic physics of the world, such as whether a stack of blocks will fall (Tenenbaum talk[i], 23:20), and to infer the emotional states of others (Saxe talk[ix], 1:00). An idea receiving apparent consensus across disciplines is that an intuitive model of the world – which includes not only the physical environment but also the minds of other agents – might be the key ingredient necessary for intelligence. World models can be run forward to predict the next state of the world or the probable consequence of a certain action or can be run backward to infer the state of the world that caused the currently observed sensory information.

How might such models of the world be achieved? Researchers at CCN presented recent advances in cognitive and neural network models that provide generative models of processes in the world. Cognitive science has made progress on probabilistic programming languages (Tenenbaum talk[i], 11:01), which can learn generative models and use them to perform flexible inferences. Other researchers demonstrated how deep learning methods can be used to construct neural networks capable of generating samples of real-world images, sounds, or sentences (LeCun talk[iv], 40:13; Fyshe talk[vi], 37:31). This generative capacity might constitute a step toward building world models. We eagerly await more research on this challenging problem.

The Dilemma of Biological Detail

A fundamental issue faced by neuroscientists is the level of detail at which to characterize neural computation. Many presentations at CCN championed deep neural networks and probabilistic models. Although these systems are biologically plausible at a superficial level (e.g., a probabilistic model can account for behavioral data, neural network models use simple operations that can be implemented by biological neurons), the components of these systems do not yet have clear biological substrates. There are basic questions about scale; for example, does one layer in a deep neural network correspond to the nonlinear processing of a single dendrite, an entire cortical area, or something in between? There are also questions about implementability; for example, several speakers noted the vast difference in energy usage between the human brain and artificial intelligence systems (Opening Panel Discussion[v], 37:30). However, it is unclear whether more biological detail is always better: detailed models of biological hardware have rarely yielded genuine advances in computational capabilities (Closing Panel Discussion[iii], 27:50).

Future Outlook

CCN is motivated by the belief that cognitive science, artificial intelligence, and neuroscience should come together. The inaugural CCN conference revealed enthusiasm for this idea but also highlighted the challenge of integration. Cognitive scientists find cognition amazing, neuroscientists are excited about neural measurements, and computer scientists champion the fact that their algorithms solve hard problems. Simply discussing the progress of each field in isolation does not teach us which neuroscience experiments could fundamentally advance cognitive science, which algorithms best describe brains, or which insights from cognitive science would be useful to incorporate into artificial systems. We hope that members of each community will put effort, both in talks and in papers, into elucidating how their work might inform answers to burning questions in the other communities.

Bringing disciplines together is a daunting challenge that will take time and patience. In the short term, we expect that simple exposure to the language and frameworks developed by each community will increase the likelihood that researchers will correctly understand and also value one another’s contributions. For example, one discussant pointed out that the term ‘attention’ has very distinct meanings and almost parallel literatures in psychology and neuroscience (Closing Panel Discussion[iii], 19:03). Furthermore, since quantitative tools can be easily generalized to different types of data, linking the disciplines in a single conference will promote sharing of tools and code across disciplines.

In the long term, the prospects of an integrated cognitive computational neuroscience depend on sustaining structured interactions across communities, the formation of deep collaborations, and training young researchers with tools and techniques from all three disciplines. We are optimistic that integration is possible: cases in point include the mainstreaming of machine-learning techniques for neural and behavioral data analysis that has occurred over the past 15–20 years and the emergence of neural network models in neuroscience. If and when integration occurs, CCN may become not merely a conference, but, as promised by the moniker, a unified field of its own. We invite readers to decide for themselves by reviewing the debates and discussions from the inaugural CCN conference at http://ccneuro.org.

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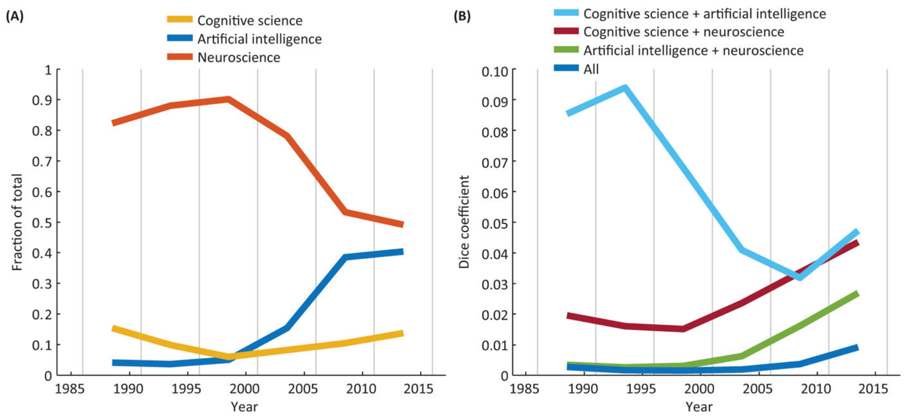

Figure 1. Emergence of Cross-Disciplinary Interest

We used Google Scholar to track the historical progression of the three fields of cognitive science, artificial intelligence, and neuroscience. In 5-year blocks (1986–1990, 1991–1995, etc.), we counted the number of papers associated with each term as well as combinations of the terms (we used the popular term ‘machine learning’ for the field of artificial intelligence). We acknowledge that number of papers is not necessarily a robust indicator of knowledge gained, but it is a quantifiable and therefore useful metric. (A) General trends in field sizes. For each 5-year bin, we express the number of papers belonging to a given field as a fraction relative to the total number of papers across all three fields. The results show that neuroscience produced relatively more papers in the 1990s, but artificial intelligence has recently undergone massive growth. (B) Tracking the intersections of fields. For each combination of fields, we quantified the level of overlap by calculating the Dice coefficient (i.e., the number of papers belonging to the intersection of the fields divided by the average of the number of papers in each field). Although levels of interaction between fields have been relatively low, in the past 10–15 years we have observed increased integration between the fields, demonstrating the need for a conference like CCN.