Opportunities and Challenges in Applying Generative Methods to Exploring and Validating the Common Model of Cognition

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Abstract

Dynamic Causal Modeling (DCM), a generative method for fitting large scale functional connectivity data, has provided a method of validating the architectural network structure proposed by the Common Model of Cognition (CMC). As the CMC expands, however, different methods will be required to handle the increased model complexity. While other generative methods exist that can deal with networks containing larger numbers of modules and connections, and even investigate the plausibility of different connections, a method for comparing these alternative structures will still be needed to make strong conclusions about the connection of the CMC and its variants to the true structure underlying human cognition.

Introduction

Many fields of research, including cognitive neuroscience and computational modeling, share a goal of exploring and understanding the structures and mechanisms of cognition. However, these goals are often pursued in isolation, with each community approaching the problem using their own tools and methods. Computational cognitive modeling often takes a more top-down approach, building large scale architectural models that capture the functions and dynamics of cognition and comparing them to the behavior of human subjects in a variety of tasks. Cognitive neuroscience, by contrast, often favors a bottom-up approach that examines patterns of brain activity and functional connectivity. Both communities have benefited from the insights of the other, but significant crossover between them is rarer. One commonly-cited reason for this is the difficulty of validating any given model structure. Cognitive modeling has produced various models at different levels of complexity that are capable of capturing human behavior, but while many share common elements or underlying assumptions, the sheer number and variety of options makes it difficult to identify a single, unified theory. In addition, the top-down approach of computational modeling can be difficult to connect to the physical biological mechanisms that drive cognition in the brain.

The Common Model of Cognition

The Common Model of Cognition (CMC) aims to address at least one of these issues, by framing itself as a consensus model that incorporates the common elements and dynamics of several of the most widely applied cognitive architectures like ACT-R, Soar, and SPAUN (Laird, Lebiere, and Rosenbloom 2017). Additional research has explored the direct connection of this model to functional brain activity, using the structure of modules and connections proposed by the CMC as a framework for Dynamic Causal Modeling (DCM), a commonly used generative modeling technique that extracts the functional connectivity within a network of Regions of Interests (ROIs) by uncovering their time-dependent hidden states (Friston, Harrison, and Penny 2003). By equating model components to ROIs and connecting them according to the structure proposed by the CMC, the DCM analysis was able to produce better quality predictions than several plausible alternative structures, both during task activity and at rest (Stocco et al. 2021; Sibert, Hake, and Stocco 2022). While this result provides compelling evidence for the validity of the CMC theory, the current structure consists of only five basic modules, and many suggestions for additional modules or separating current modules into more specific components and subnetworks have yet to be explored.

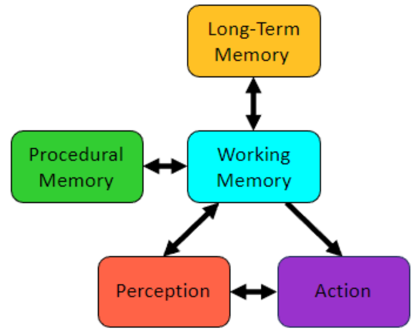
The Challenges of Expansion

However, while using DCM to compare these new and alternate CMC configurations seems like a reasonable continuation of this line of research, as the models grow more complex, so too do the challenges involved in fitting and comparing them. Fitting increasingly complex networks quickly becomes computationally expensive, and generally intractable with networks of ten or more modules. Though the current CMC only has five modules, the potential for expansion will quickly outpace the capacity of the current approach. Figure 1 illustrates an example of a simple extension to the current framework, splitting the current "Perception" module into separate modules for visual and auditory perception. The figure illustrates only two possible ways to incorporate this change, but clearly demonstrates how a seemingly basic addition can increase the size of the model from five to six or seven modules, and further expansions would result in an even greater increase in complexity. Luckily, several other generative approaches have been suggested for highly complex functional connectivity analyses (Li and Yap 2022).

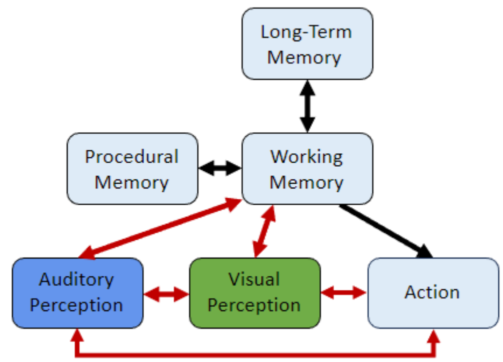
One possible alternative is the recently introduced regression Dynamic Causal Modeling (rDCM), a more computationally efficient variation of the original DCM method (Frässle et al. 2017). This method shifts the modeling framework from time dependency (used by DCM) to frequencies using a Bayesian linear regression model, allowing for model structures of more than 100 regions and 100,000 connections. This increased model complexity can result in a weaker connection to the actual biological structure, so other generative methods, like Biophysical Network Modeling (BNM), that uses spiking neural mass models to make similar predictions about network dynamics (Woolrich and Stephan 2013), could be used in place of or in conjunction with the more traditional DCM approach. These are only two of the generative approaches that provide methods for fitting models of increasing complexity that could support the expansion of the CMC, but two problems remain. First, determining the exact structure of the networks to be fitted, and second, comparing the quality of fit provided by the different model structures.

So far, the CMC-based network structures that have been tested using DCM have contained connections proposed by the CMC theory. Support for these proposed connections is provided by a relatively better fit when compared to networks containing alternate, but still plausible sets of connections. A bottom-up approach using Granger Causality to investigate the likelihood of connections between any of the CMC modules suggested a network structure very close to the current CMC, with a few critical additions (Hake, Sibert, and Stocco 2022). This suggests, then, that the underlying structure of cognition may contain more connections than currently proposed by the CMC theory, and that as the proposed networks grow in complexity, it will be necessary to more closely examine the plausibility of connections between larger collections of nodes. Sparse rDCM (srDCM), which takes complex network structures and prunes the connections to only those that are deemed most relevant (Frässle et al. 2018), is a potential tool that could help to identify potential network structures before fitting parameters that best fit the brain activity. This approach could also be useful in exploring more hierarchical structures for the CMC, with individual modules at the highest level containing specialized sub-networks of smaller modules.

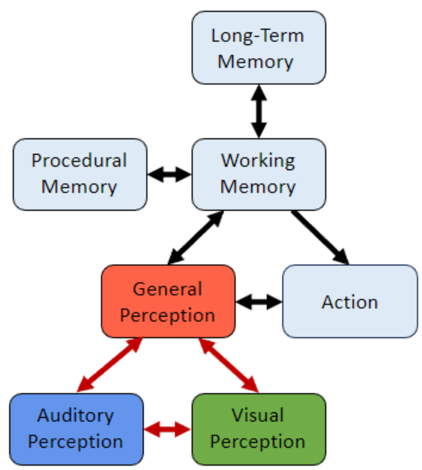
However, while the aforementioned methods display great potential for increasing the complexity of the CMC and testing the plausibility of its connections, they do not solve the second issue of reliably evaluating the quality of the proposed models. DCM and similar methods provide a measure of how well its predicted pattern of brain activity fits the actual observed pattern of brain data. However, brain data is very noisy, and even the best current models are capable of capturing only a small portion of the observed activity. As an isolated metric of similarity, then, an individual fit is not very informative about the overall quality of a given model, and models are better evaluated in comparison with alternatives. Previous work has used Bayesian Model Selection (BMS) to determine the likelihood that a particular model (in



(a) Base Common Model of Cognition, with five total modules



(b) CMC with separate modules for visual and auditory perception that run as parallel processes, six total modules



(c) CMC with separate modules for auditory and visual perception that connect to a general, higher level perceptual module that connects to the rest of the network

Figure 1: Three configurations of perception in the Common Model of Cognition: (a) a single perceptual module, (b) separate auditory and visual modules, (c) separate sensory modules that connect to a general perceptual module. Each configuration contains different numbers of modules, making direct comparison difficult.

this case the CMC) would provide a better prediction than six alternative model structures (Stocco et al. 2021). These models all contained the same modules with slightly different sets of connections. BMS is able to account for some variation in model complexity and compare model structures with slightly different numbers of connections, so the result that the CMC consistently outperformed its competitors provides strong evidence for the CMC reflecting elements of an actual underlying structure. However, most of the proposed extensions to the CMC would require the addition of one or more module, and the corresponding increase in model complexity means that BMS would no longer be a reliable means of comparing model fit. So far, it seems there is no agreed upon method for comparing model structures with different numbers of modules, and it remains an open question if it will be possible to continue the current approach to validating the CMC or if new methods will need to be adopted.

Conclusion

Overall, generative methods for the analysis of functional connectivity provide a promising opportunity to bridge the gap between theoretical architectural models and brain activity signals, both by making predictions on the basis of increasingly complex networks, and by evaluating the plausibility of possible connections between large groups of modules. However, the current methods for determining overall model quality rely on comparing models of equal complexity, and in order to explore the next generation of CMC-based model structures, a robust method for model comparison at different levels of complexity will be required. Strengthening the connection between CMC-based structures and the biological reality of the brain will lead to a firmer foundation on which to build functional implementations of the CMC that can be used for building human-like cognitive models.

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