Refining the Common Model of Cognition Through Large Neuroscience Data

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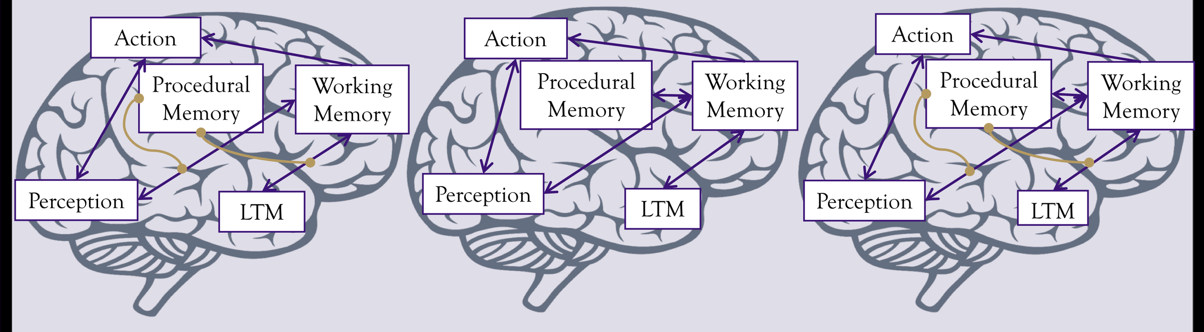
Introduction

The Common Model of Cognition (CMC) outlines common key insights into the structure, function and connectivity of minds across all fields concerned with the study of the mind [1]. Although the CMC has strong support from a theoretical point of view, there has been little investigation into its empirical validity. Previous empirical evidence found that the CMC provided a better architecture to account for human fMRI data on four different tasks than alternative models, but had approximately 25 participants per task. Therefore, a large scale investigation of the CMC is needed to further validate the model, and the Human Connectome Project (HCP) provides an ideal data repository for this.

The goal of this project is to investigate how the CMC can be refined and how the CMC can inform brain architecture, using Dynamic Casual Modeling on a subset of Human Connectome data.

Models

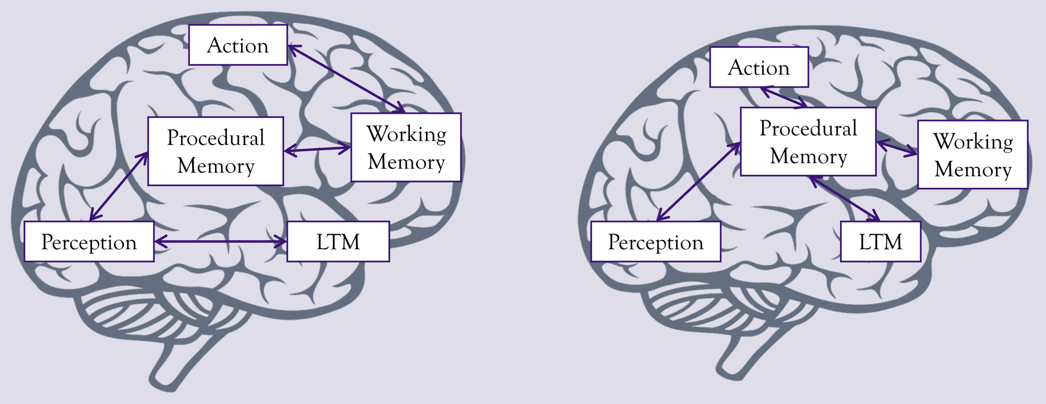
Common Model of Cognition Family



Common Model of Cognition | Direct Common Model of Cognition | Mixed Common Model of Cognition

To refine and improve the current CMC (see center model), we created a family of CMC models (see models above). We also created a set of alternative models (see models below), to test and validate the revised version of the CMC. Each model has five different modules to provide a system with primitives to gather information, store it, update it, and act upon it. Arrows indicate direction of connections. Curvy lines indicate modulatory connections.

Alternative Models



Hierarchy Model | Star Procedural Model

Methods

Datasets and Tasks:

Participants - 172 participants, aged 22-35, from the "S1200" (July 21, 2017) release of the HCP Young Adult dataset.

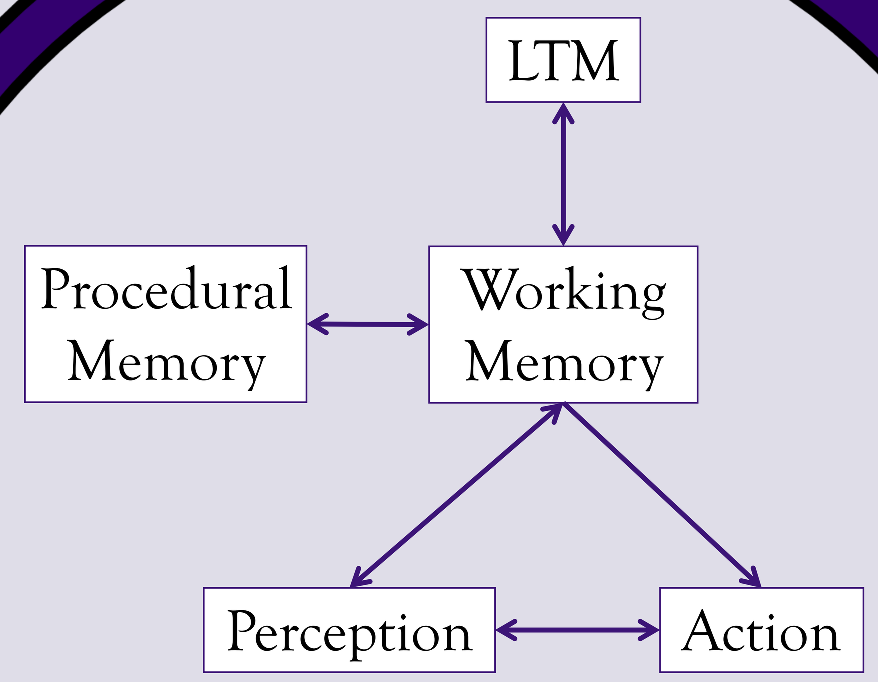
Imaging Parameters - fMRI images were acquired from Siemens 3T scanners with a multiband factor of 8x with TR = 720ms, TE = 33.1ms, and FA = 52°, and an echo spacing of 0.58ms. Each functional image consisted of 72 2-mm thick oblique slices with had an in-plane resolution of 104×90 voxels and a field of view of 208×180mm, with 2×2×2mm isomorphic voxels.

Relational Task - Participants viewed two pairs of objects, and had to first determine how the top pair differed, and then determine if the bottom pair differed in the same way. The possible range of objects included six different shapes and six different possible textures, thus participants had to determine if a pair of objects differed by its shape or texture. In the control condition, participants were shown two objects at the top, one at the bottom and a word in the middle (either "shape" or "texture"). Participants had to determine if the object on the bottom matched one of the top two objects in the dimension indicated by the word in the middle. [3]

Working Memory Task - An *N*-back task using faces, places, tools and body parts as the four categories of objects. The 2-back task asked participants to respond when the current object shown was the same as the one shown two objects back. The 0-back task presented a target object at the beginning and asked participants to respond when the current object shown was the same as the target object. [3]

DCM Procedures:

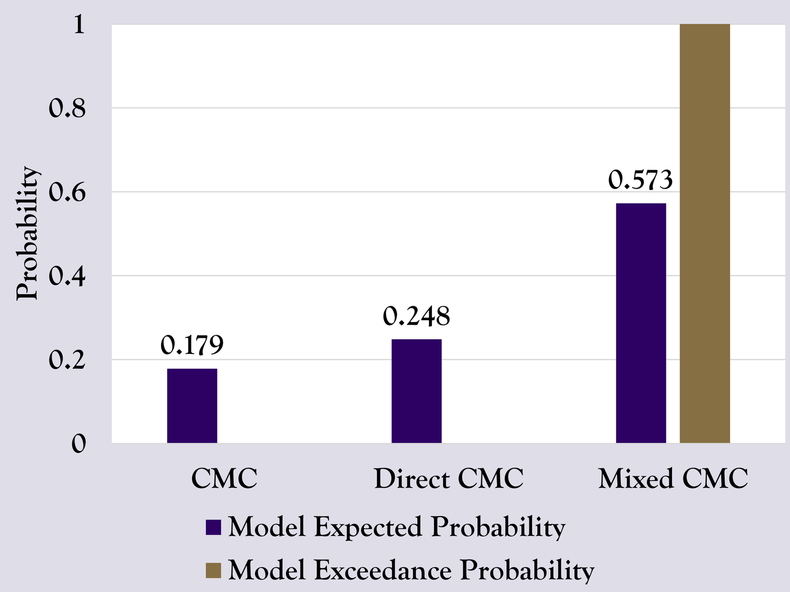
Each of the five components of the CMC was identified with a single Volume of Interest (VOI). The location of each VOI was established by identifying the highest peak of functional activity during the task. The location of each VOI was allowed to vary from task to task within each participant. Each VOI included only active voxels within an 8-mm sphere. We chose Random-Effects analysis for Bayesian model comparison, because we suspected that the two tasks stress different parts of the CMC architecture. We first compared the models within the CMC model family using Bayesian prediction. We then compared the model that performed the best of all CMC family models to the alternative models.



The Common Model of Cognition, as introduced in [1]

Results

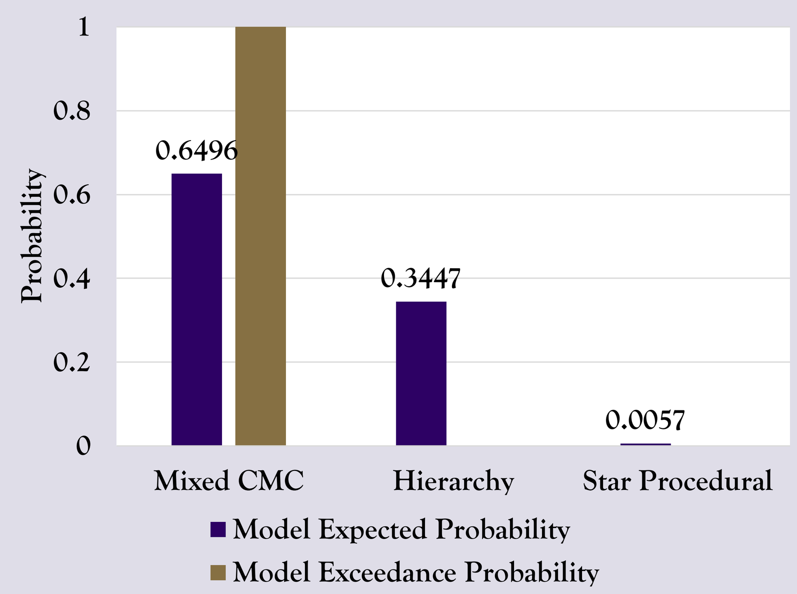
Results of Bayesian Model Selection within the CMC family



To compare the CMC family models across the two tasks, we used a group-level Bayesian model selection algorithm. The graph above shows the results from this model comparison. Across both tasks the Mixed variant of the CMC best explained the human neuroimaging data, with an expected probability of 57% (compared to 25% and 18% for the Direct and Modulatory models). These results suggest that the CMC's Procedural module should include both direct and modulatory connections to Working Memory.

Given that the Mixed CMC performed the best of the CMC family, we compared the Mixed CMC to the alternative models. The graph below shows the results from this model comparison, which is based on the exceedance probability of the model matching the data. Again, the Mixed CMC model outperformed the other two, with an expected probability of 65%. Therefore, overall the Mixed CMC performed the best of all the models we analyzed.

Results of Bayesian Model Selection between the best CMC model and two alternative models



Discussion

One version of the CMC, what we call the Mixed CMC, is a reasonable model for a large spread of human cognitive data. This model likely performed well because it included the two possible connections between Procedural Memory and Working Memory. By including more connections, there are more ways for these two important high level modules to exchange and modify information. These results further validate the CMC as a common model to explain minds, with the understanding that the human mind must be at least one example of an intelligent mind.

The results also indirectly suggest how the CMC can implement attention. The capacity of the modulatory variant to fit human data from attention-based tasks [2] suggests that modulatory connections from the Procedural module could provide the necessary computational mechanisms to account for attention in the human data.

The results also provide a better understanding of how information is shared in the brain. **The brain likely does not use a strictly bottom up approach to information exchange, nor a central director, but rather a more distributed approach.**

Future work should look to test the CMC with more tasks, especially resting state data, as it may provide a better understanding of the "pure" or native architecture of the human mind.

References

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