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Introduction to the Issue on Computational Models of Memory: Selected Papers from the International Conference on Cognitive Modeling

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This topic presents work on computational models of memory as it is used in the context of different tasks. The five papers we include were all presented at the *2016 International Conference on Cognitive Modeling*, held at Penn State in University Park, Pennsylvania. They represent a selection of the best work on memory presented there.

The work we selected demonstrates how empirical data and modeling methodologies at different levels of representation—from neural architectures through cognitive architectures to mathematical models—can facilitate the study of cognitive processes. The breadth of methods is remarkable, but it is juxtaposed with an aim to remain within the context of cognitive architectures that allow us to converge on a unified theory of the mind that can explain the constraints affecting any experimental task. Three of the papers present contribute to modeling in the ACT-R cognitive architecture and in related ones; the model in one paper is situated within a neural architecture; all of the studies have implications for models for memory.

(a) Parker and Lantz in their contribution model grammatical acceptability in language comprehension. Their model is a cognitive, not a linguistic one. The authors program a new way of encoding linguistic knowledge in memory, and they integrate it with ACT-R. This way, they can reuse an existing ACT-R model of language comprehension and test it.

There are many rewarding aspects of this work: it reuses rather than reinvents the prior model, it relates its mechanisms to a cognitive architecture, and perhaps most importantly, it is an integrated account of linguistic performance and general cognitive resources. Their memory account is interesting for another reason: holographic memory systems (e.g., Jones & Mewhort, 2007) provide distributed semantic representations related to Landauer's Latent Semantic Analysis (Landauer, Foltz, & Laham, 1998), and they relate their model to the representation of word embeddings, which map words to a high-dimensional vectors, and which have been remarkably successful in the world of computational linguistics in recent years.

(b) Thomson and colleagues solve an open problem in ACT-R's model of learning the cues in cue-based memory retrieval: associations between memory items can be learned, but prior learning accounts have failed to balance long-term and short-term learning and forgetting effects. Their model accounts for a standard result concerning spreading activation: the fan effect.

(c) Veksler and colleagues contrast slot-based and decay-based models of visual working memory in an eye-tracking experiment that leads to a modeling analysis (as opposed to hypothesis testing). Their continuous resource model adopts frequency and recency effects from declarative memory in ACT-R, and it turns out to provide, by far, the best model fit to data on a visual working memory task.

(d) Li and Kohanyi examine how to incorporate large-scale knowledge-bases such as WordNet and DBPedia into a cognitive model of the Deese-Roediger-McDermott false memory task. Their verdict is not all-around positive, but very useful to cognitive modelers nonetheless: the assumptions made by the designers of these ontologies do not necessarily correspond to behaviorally evident relatedness between concepts. The authors are able to provide some theoretical and practical guidance.

(e) Duggins et al. use a spiking neural network model of working memory to predict the reaction to two drugs known to affect working memory (guanfacine and phenylephrine). The model can provide explanations at the biophysical and behavioral level, and it can be used to computationally simulate a hypothesis about the mechanism of action of these drugs, that is, that they change the firing rate of neurons in the prefrontal cortex. The results compare well to empirical data from monkeys on a memory task.

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