The CLARION Cognitive Architecture: A Tutorial

Sébastien Hélie (helies@rpi.edu)
Cognitive Science Department, Rensselaer Polytechnic Institute
110 Eighth Street, Troy, NY 12180, USA

Nick Wilson (wilson3@rpi.edu)
Cognitive Science Department, Rensselaer Polytechnic Institute
110 Eighth Street, Troy, NY 12180, USA

Ron Sun (rsun@rpi.edu)
Cognitive Science Department, Rensselaer Polytechnic Institute
110 Eighth Street, Troy, NY 12180, USA

Abstract

This full-day tutorial introduces participants to CLARION, a dual-process/dual-representation cognitive architecture that focuses on the distinction between explicit and implicit cognitive processes. CLARION is also integrative, involving cognition, motivation, metacognition, and so on. This tutorial presents a detailed description, along with many simulations, advanced topics, and formal results. Although some prior exposure to cognitive architectures and artificial neural networks can be helpful, prior understanding of these areas is not required, as the full-day format allows a detailed presentation of basic, as well as advanced, topics related to cognitive modeling using CLARION. This tutorial will enable participants to apply the basic concepts, theories, and computational models of CLARION to their own work.

Overview

CLARION is a cognitive architecture composed of four main subsystems: the Action-Centered Subsystem (ACS), the Non-Action-Centered Subsystem (NACS), the Meta-Cognitive Subsystem (MCS), and the Motivational Subsystem (MS). The ACS is used mainly for action decision-making. The NACS is usually a slave system to the ACS and is used to store declarative and episodic knowledge. This subsystem is also responsible for reasoning in CLARION. The MS is responsible for determining motivational drive levels (which in turn lead to the setting of goals). The MCS is responsible for cognitive monitoring and parameter setting in both the ACS and NACS, and makes the goal setting determinations based on drive levels reported from the MS.

In addition to the aforementioned subsystem structure, CLARION is based on two other basic assumptions: representational differences and learning differences of two different types of knowledge: implicit versus explicit (Sun, Merrill, & Peterson, 2001; Sun, Slusarz, & Terry, 2005). The main difference between these two types of knowledge is accessibility. In each subsystem, the top level contains explicit knowledge (easily accessible) whereas the bottom level contains implicit knowledge (harder to access).

The second assumption in CLARION concerns the different learning processes in the top and the bottom level of each subsystem (Sun et al., 2001, 2005). In the bottom level, implicit associations are learned through gradual trial-and-error learning. In contrast, learning of explicit knowledge is often one-shot and represents the abrupt availability of explicit knowledge (following "explicitation" or through newly acquired linguistic information in the top level). The emphasis on bottom-up learning (i.e., the transformation of implicit knowledge into explicit knowledge) is, in part, what distinguishes CLARION from other cognitive architectures. Nevertheless, top-down learning is also included in CLARION.

The Action-Centered Subsystem

In the Action-Centered Subsystem, the top level contains simple "State → Action" rules, while the bottom level uses multi-layer perceptrons to associate states and actions. Learning in the bottom level is captured by a reinforcement learning algorithm (with backpropagation), while rule learning in the top level is mostly "one-shot" and can be performed bottom-up or independently.

The ACS has been used to model navigation in mine fields (Sun et al., 2001). In addition, because CLARION focuses on the dichotomy between explicit and implicit knowledge, benchmark psychological tasks used to show implicit learning were also successfully captured and explained (Sun et al., 2005).

The Non-Action-Centered Subsystem

In the Non-Action-Centered Subsystem, the top level contains simple logical rules while the bottom level uses a nonlinear neural network. Learning in the bottom level is captured by associative (e.g., contrastive Hebbian) learning. Rule learning in the top level is mostly "one-shot" (similar to the ACS).

The NACS in CLARION has been used mainly to simulate reasoning. In particular, CLARION was able to capture data showing the mixed effect of rule-based reasoning and similarity-based reasoning when judging the likelihood/strength of simple deductive forms. Other reasoning phenomena can also be naturally explained using CLARION (e.g., inheritance-based reasoning, reasoning from incomplete information, etc).

The Meta-Cognitive Subsystem and the Motivational Subsystem

The Motivational Subsystem contains both low- and high-level primary drives that take into account environmental and internal factors in determining drive strengths. The drive states determined by the MS are reported to the Meta-Cognitive Subsystem, which regulates not only goal structures but also cognitive processes to facilitate the achievement of the goals.

Previous simulations using these subsystems have shown how anxiety-inducing drives within the MS can affect the parameters within the ACS in terms of explicit versus implicit response weighting (and therefore performance). Other simulations have detailed the combination of various drives in the MS toward the setting of goals by the MCS.

References

Naveh, I. & Sun, R. (2006). A cognitively based simulation of academic science. *Computational and Mathematical Organization Theory*, *12*, 313-337.

Sun, R. (2000). Symbol grounding: A new look at old ideas. *Philosophical Psychology*, *13*, 149-172.

Sun, R. (2002). *Duality of the Mind: A Bottom-up Approach Toward Cognition*. Mahwah, NJ: Lawrence Erlbaum Associates.

Sun, R. (2003). *A Tutorial on CLARION 5.0*. Technical Report, Cognitive Science Department, Rensselaer Polytechnic Institute.

Sun, R. (2004). Desiderata for cognitive architectures. *Philosophical Psychology*, *17*, 341-373.

Sun, R. (Ed.). (2006). *Cognition and Multi-Agent Interaction: From Cognitive Modeling to Social Simulation*. Cambridge, UK: Cambridge University Press.

Sun, R., Coward, L.A., & Zenzen, M.J. (2005). On levels of cognitive modeling. *Philosophical Psychology*, *18*, 613-637.

Sun, R., Merrill, E., & Peterson, T. (2001). From implicit skills to explicit knowledge: A bottom-up model of skill learning. *Cognitive Science, 25*, 203-244.

Sun, R. & Naveh, I. (2007). Social institution, cognition, and survival: A cognitive-social simulation. *Mind and Society*, *6*, 115-142.

Sun, R. & Peterson, T. (1998). Autonomous learning of sequential tasks: Experiments and analyses. *IEEE Transactions on Neural Networks*, *9*, 1217-1234.

Sun, R. & Peterson, T. (1998). Some experiments with a hybrid model for learning sequential decision making. *Information Sciences*, *111*, 83-107.

Sun, R., Slusarz, P., & Terry, C. (2005). The interaction of the explicit and the implicit in skill learning: A dual-process approach. *Psychological Review, 112*, 159-192.

Sun, R. & Zhang, X. (2004). Top-down versus bottom-up learning in cognitive skill acquisition. *Cognitive Systems Research*, *5*, 63-89.

Sun, R. & Zhang, X. (2006). Accounting for a variety of reasoning data within a cognitive architecture. *Journal of Experimental and Theoretical Artificial Intelligence*, *18*, 169-191.

Sun, R., Zhang, X., & Mathews, R. (2006). Modeling meta-cognition in a cognitive architecture. *Cognitive Systems Research*, *7*, 327-338.