ABSTRACT

Within cognitive science and cognitive informatics, computational modeling based on cognitive architectures has been an important approach to addressing questions of human cognition and learning. This paper reports on a multi-agent computational model based on the principles of the Unified Learning Model (ULM). Derived from a synthesis of neuroscience, cognitive science, psychology, and education, the ULM merges a statistical learning mechanism with a general learning architecture. Description of the single agent model and the multi-agent environment which translate the principles of the ULM into an integrated computational model is provided. Validation results from simulations with respect to human learning are presented. Simulation suitability for cognitive learning investigations is discussed. Multi-agent system performance results are presented. Findings support the ULM theory by documenting a viable computational simulation of the core ULM components of long-term memory, motivation, and working memory and the processes taking place among them. Implications for research into human learning, cognitive informatics, intelligent agent, and cognitive computing are presented.

Keywords: Cognitive Modeling, Computational Simulation, Human Learning, Multi-Agent, Unified Learning Model (ULM)

1. INTRODUCTION

Human learning in the sense of knowledge storage, exchange, and retrieval is an increasingly important topic in many areas of science. Fields such as neuroscience, cognitive science, psychology and education are engaged in the study of how humans acquire knowledge and develop skill and expertise. Modeling and understanding human learning is especially salient in the emerging fields of cognitive informatics (Wang, 2007; Wang et al., 2010; Wang, Widrow, et al., 2011) and cognitive computing (Wang, 2009a; Wang, 2011; Wang et al., 2010). Cognitive informatics is a transdisciplinary inquiry bringing together computer science, information sciences, cognitive science, and intelligence science to investigate and understand the in-
ternal information processing mechanisms and processes of the brain and natural intelligence (Wang, 2007). Learning is clearly central to this effort as most human thought and behavior that could be described as intelligent emerges from knowledge and behavior that was learned either directly or through experience (Wang, Kinsner, & Zhang, 2009). This learning is realized in the brain through neural plasticity which produces the micro-architecture of neuron connectivity (Kandel, Schwartz, & Jessell, 2000); Shell et al., 2010). A goal of cognitive informatics is to inform cognitive computing; the emerging paradigm of intelligent computing methodologies and systems based on cognitive informatics that attempts to implement computational intelligence by mimicking the mechanisms of the brain in cognitive computers (Wang, 2009a; Wang, 2011). Clearly, cognitive computers would benefit from being able to learn in ways similar to those which underlie neural plasticity.

Recently, an interdisciplinary team of researchers in psychology, education, and teaching published a comprehensive learning theory derived from a synthesis of research in cognitive neuroscience, cognitive science, and psychology: the Unified Learning Model or ULM (Shell et al., 2010). The ULM has begun to influence thinking and practice in fields such as scholarship of teaching and learning (Wilson-Doenges & Gurung, 2013), situated cognition (Durning & Artino, 2011), pedagogy (Nebesniak, 2012), and cognitive function (Wasserman, 2012).

Learning in ULM results from the interaction of three cognitive components: long-term memory, working memory, and motivation. Long-term memory (or LTM) is the relatively permanent store of knowledge possessed by a person. In the ULM, knowledge refers to the totality of what a person knows. This includes factual and conceptual knowledge sometimes referred to as declarative knowledge, cognitive and behavioral skills sometimes referred to as procedural knowledge, episodic knowledge of personal experience, and sensory or perceptual knowledge. Long-term memory for declarative and procedural knowledge resides in the cortex with procedural knowledge involving primarily the sensory-motor cortical regions and cerebellum. Sensory/perceptual, linguistic, and number knowledge generally resides in specialized modular processing areas (Kandel et al., 2000).

Working memory (or WM) is the term for the currently active part of cognition. Brain areas such as the forebrain and hippocampus have been implicated in working memory functioning (Kandel, Schwartz, & Jessell, 2000), however, working memory is better thought of as a process than an anatomical location. Two aspects of working memory affect learning. The first is capacity limitation, which is thought to be somewhere around 4-7 elements (Saults & Cowan, 2007). Elements, however, can be chunks, that increase functional working memory capacity. The second aspect is attention (Knudsen, 2007). Central to the ULM is the proposition that attention is a necessary precondition to learning. Only attended knowledge in working memory can add to or change knowledge in long-term memory.

The final ULM component is motivation. Motivation derives both from biological components like drives (e.g., hunger) and emotions and from cognitive components such as goals and beliefs (Schunk & Zimmeman, 2008; Shell et al., 2010). The ULM holds that these motivators are intimately connected to working memory and direct attention such that knowledge in working memory is attended only when there is motivation to attend to it.

Within long-term memory, connections between neurons are strengthened and weakened through neural plasticity that follows a Hebbian learning process (Kandel et al., 2000; Caporale & Dan, 2009). The basic ULM learning mechanism merges Hebbian neural plasticity with statistical learning. In the ULM, knowledge in long-term memory is built when distinct pieces of knowledge, either from sensory input or retrieved from long-term memory, that are held simultaneously in working memory are attended, connected, and stored as chunks in long-term memory. The connections in these chunks continue to strengthen or decay depending on repetition due to knowledge retrieval.
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