

Chapter 17

Cognitive Learning Methodologies for Brain– Inspired Cognitive Robotics

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ABSTRACT

Cognitive robots are brain-inspired robots that are capable of inference, perception, and learning mimicking the cognitive mechanisms of the brain. Cognitive learning theories and methodologies for knowledge and behavior acquisition are centric in cognitive robotics. This paper explores the cognitive foundations and denotational mathematical means of cognitive learning engines (CLE) and cognitive knowledge bases (CKB) for cognitive robots. The architectures and functions of CLE are formally presented. A content-addressed knowledge base access methodology for CKB is rigorously elaborated. The CLE and CKB methodologies are not only designed to explain the mechanisms of human knowledge acquisition and learning, but also applied in the development of cognitive robots, cognitive computers, and knowledge-based systems.

1. INTRODUCTION

A cognitive robot is a brain-inspired robot system that is capable of inference, perception, and learning mimicking the cognitive mechanisms of humans. The fundamental theories and methodologies underpinning cognitive robotics are the cognitive learning engines (CLE) and cognitive knowledge bases (CKB) supported by a collection of contemporary mathematics known as *denotational mathematics* (Wang, 2003, 2007a,b, 2008c, 2009c, 2010a, 2012a,b,c, 2014a,b, 2015a,d,e; Wang & Berwick, 2012, 2013).

A Cognitive Knowledge Base (CKB) represents and manipulates knowledge as a dynamic concept network mimicking human knowledge processing. CKB is demanded in machine learning, knowledge-based systems, cognitive computers, and cognitive robots in general, as well as in the development of the Cognitive Learning Engine (CLE) for cognitive robots in particular. CKB is a central component for machine learning via autonomous knowledge acquisition and manipulation, because the general

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form of learning is a knowledge acquisition and manipulation process according to the latest studies in cognitive science, brain science, and neuroinformatics (Debenham, 1989; Chang et al., 2006; Brewster et al., 2004; Wang, 2003, 2009a, 2010a, 2011a; Wang & Fariello, 2012).

Conventional knowledge bases are studied in three categories known as the *linguistic knowledge bases* (Crystal, 1987; Brewster et al., 2004; Fellbaum, 1998; Liddy, 2001; Pullman, 1997; Wang, 2014a, 2015c; Wang & Berwick, 2012, 2013), *expert knowledge bases* (Bender, 1996; Wang, 2007a; Wilson & Keil, 2001), and *ontology* (Gruber, 1993; Brewster et al., 2004; Leone et al., 2006; Tiberino, et al. 2005; Wang et al., 2011). Typical linguistic knowledge bases are generic lexical databases such as WordNet and ConceptNet (Fellbaum, 1998; Liu & Singh, 2004). Linguistic knowledge bases only provide general materials or dictionaries for applied knowledge bases of individuals and systems. Expert knowledge bases are elicitations of various domain knowledge represented by logical and fuzzy logical rules (Bender, 1996; Surmann, 2000; Zadeh, 1956, 2004; Wang, 2014c; Wang & Berwick, 2012, 2013). However, human knowledge representation and retrieval are more complicated and semantics-centric beyond logical rules. Ontology deals with small-scale knowledge in a certain domain as a hierarchical network of a set of natural words and their semantic relations (Brewster et al., 2004; Cocchiarella, 1996; Gruber, 1993; Sanchez, 2010; Tiberino, et al. 2005; Wang et al., 2011). Ontology represents small-scale acquired knowledge by a static and application-specific model, which cannot be applied as a general knowledge base for machine learning and real-time knowledge manipulations.

According to studies in cognitive science and neurophysiology (Leone et al., 2006; Pojman, 2003; Wang, 2009b, 2012b, 2013a; Wang & Wang, 2006; Wang et al., 2006), the foundations of human knowledge and long-term memory can be represented by an Object-Attribute-Relation (OAR) model based on the synaptic structure of human memory. The OAR model represents the hierarchical and dynamic neural clusters of knowledge retained in memory, which leads to the development of the logical model of cognitive knowledge bases.

Definition 1: The *OAR model of knowledge* as retained in long-term memory (LTM) is a triple, i.e.:

$$OAR A (O, A, R) \quad (1)$$

where O is a finite set of objects identified by unique symbolic names, A is a finite set of attributes for characterizing each object, and R is a set of relations between objects and attributes.

The OAR model can be illustrated as shown in Figure 1 for formally modelling the structure of human knowledge and its representation in LTM and CKB.

This paper presents a novel cognitive learning engine (CLE) for cognitive robots powered by the cognitive knowledge base (CKB). The structure model of CKB is described in Section 2, which encompasses the formal concept model for itemized knowledge representation and the dynamic concept network model for the entire knowledge base composition. Knowledge manipulations in CKB are embodied by a set of knowledge acquisition and retrieval operations on the structural models of CKB. On the basis of CKB, the CLE architecture and methodologies are formally described in Section 4 for implementing autonomous learning of cognitive robots.

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