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Cognitive Systems Research 6 (2005) 320–332

Cognitive Systems RESEARCH

www.elsevier.com/locate/cogsys

An artificial intelligent counter

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Received 3 May 2004; accepted 20 December 2004
Available online 29 January 2005

Abstract

This article, using a counter as an example, explores a novel approach in constructing a cognitive system. The system is a paired memory system of "left and right brain" consisting of a number of memory units. The "left brain" is dedicated to the cognitive process of symbols, and the "right brain" to the representation of the symbols. The left and right subsystems are connected by bundles of internal communication signals. The paired memory system can learn facts and generalize concepts. Its cognitive capability is realized through the communication among these memory units at different cognitive levels within the system. The key claims in this paper are supported by empirical findings and theoretical principles. An AI counter is built and demonstrated in terms of concept learning and responding.

Keywords: Counting; Concept learning; Split brain; Symbol; Representation; Memory

1. Introduction

The ability to learn concepts from examples is one of the core capacities of human cognition. Concept learning refers to the development of the ability to respond to common features in categories of objects or events. In learning a concept, one must focus on the relevant features and ignore those that are irrelevant (Bourne, Dominowski, Loftus, & Healy, 1986). We learn natural concepts in everyday life through examples rather than abstracted rules (Rosch, 1978). And, human concept learning is remarkable for the fact that very successful generalizations are often produced after experience with only a small number of positive examples of a concept (Feldman, 1997).

There are two fundamentally different paradigms in modeling human cognitive capabilities: one is symbolic and the other is numerical. In order to realize concept learning, symbolic AI always has to face the issue of symbol grounding in terms of its necessity, definition and implementation (e.g., Davis, Shrobe, & Szolovits, 1993; Harnad, 1990; Minsky, 1982; Newell & Simon, 1976; Searle,

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1389-0417/$ - see front matter
doi:10.1016/j.cogsys.2004.12.002

1980a, 1980b). For numerical approach, the issue is about its limitation in high-level cognition (e.g., Franklin, 1995). It is widely reported that these two paradigms have complementary strengths and weaknesses. Ultimately, an approach in the form of networking, which can combine the advantages of both paradigms, would be a better reflection of how brain works. The question is how to integrate the advantages so that a system can focus on common features and learn concepts through examples.

The concept of counting holds a unique position in modeling the cognitive capability of concept learning. First of all, an AI counter is relatively simple to build and there are only three concepts to be learned and categorized before it can count. Secondly, human counting is the most well established concept, best defined by the five principles of Gelman and Gallistel (1978). So, the success of an AI counter can be tested by these principles. Finally, the cognitive process of counting has been intensively studied in terms of cognitive psychology and neuro-psychology. Then, an AI counter can be judged by the empirical studies. It has been asserted that humans are born with an innate, abstract competence for numbers (Butterworth, 1999; Chomsky, 1988; Dehaene, 1997). This assertion is supported by a great number of experiments with animals, young infants, brain-lesioned patients (Dehaene & Cohen, 1994; Dehaene, 1997; Geary & Hoard, 2001). Counting capability is also known as one of the essential capacities human gained in the very early age of humanity (Pepper, 1967; Rappenglueck, 2001).

This paper presents an AI counter, for the first time, to explore a novel approach in constructing a cognitive system. The counter's framework is laid out from memory unit, memory group, to an overall system. The system will be demonstrated in terms of concept learning and responding and will be tested by a number of empirical finds. Before the framework is laid out, some necessary background about symbolic AI, neural networks and symbol grounding is introduced.

2. Background

The two paradigms – symbolic AI and neural network (also named connectionism, parallel distributed processing or numerical processing) – are fundamentally different. Neural network is based on artificial neuron that is simplified from the biological neuron model. The central idea of neural network is that cognition can be modeled as the simultaneous interaction of many highly interconnected neuron-like units (McClelland & Rumelhart, 1986; Rumelhart & McClelland, 1986). A neural network has two or more layers (e.g., input layer, hidden layer, and output layer). Each layer has a number of artificial neurons. Each neuron in the upper layer (e.g., hidden layer) receives inputs from every neuron in the lower layer (e.g., input layer) after multiplied by its weight. The weight is like the synapse of a biological neuron. The output of the neuron depends on the sum of all inputs received. Learning in neural networks takes place via changing of weight. Therefore, learning can be viewed as a search problem in weight space. Neural network is strong in pattern recognition, real world data processing and noise tolerance. Its criticism is centered on its difficulties at high-level cognition since neural network is not structure-sensitive (Fodor & Pylyshyn, 1988; Fodor & McLanghlin, 1991); and, some have argued that neural network is not yet cognitive system (Rosenberg, 1997; Franklin, 1995).

In the symbolic paradigm, mental structures (goals, knowledge, actions, etc.) of mind can be formalized by language and rules of thought (Smolenshy, 1997). A symbol system is made up by a set of arbitrary "physical tokens" (i.e., symbols) that can be manipulated on the basis of explicit rules (i.e., syntax). It solves problem by searching its problem space for a goal state. The symbolic paradigm is strong in formal aspects of high-level mental structures like goals, beliefs, concepts, schemata, knowledge and inference. Its criticism is centered on whether a symbolic AI program understands the problems it deals with. Searle (1980a) asserts such a program understands nothing of what it talks about even as it answers questions correctly. Many believe the answer to the problem is symbol grounding (e.g., Harnad, 1990; Smolenshy, 1997). Some models of direct grounding have been tested successfully (Cangelosi, Greco, & Harnad, 2002; Plunkett, Sinha,