Declarative-Procedural Memory Interaction in Learning Agents

(Extended Abstract)

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ABSTRACT

It has been well recognized that human makes use of both declarative memory and procedural memory for decision making and problem solving. In this paper, we propose a computational model with the overall architecture and individual processes for realizing the interaction between the declarative and procedural memory based on self-organizing neural networks. We formalize two major types of memory interactions and show how each of them can be embedded into autonomous reinforcement learning agents. Our experiments based on the Toad and Frog puzzle and a strategic game known as Starcraft Broodwar have shown that the cooperative interaction between declarative knowledge and procedural skills can lead to significant improvement in task performance.

Categories and Subject Descriptors

I.2.6 [**Learning**]: Knowledge acquisition

Keywords

declarative memory, semantic memory, memory interaction

1. INTRODUCTION

Human brains have been well recognized as multi-memory systems consisting of notably declarative memory and procedural memory. Declarative memory is an explicit record of what we encounter and what we learn. Procedural memory, on the other hand, refers to the implicit memory of skills and reflex responses, wherein the knowledge is usually difficult to articulate or explain. In view that memory interaction is an integral element of human cognition, this paper reports our investigation into the interaction between declarative and procedural memory. To this end, we present a cognitive model with an explicit procedural memory module and the declarative memory module. Each of the memory modules in our system is built based on self-organizing neural network models known as fusion ART [1]. As a generalization of Adaptive Resoannce Theory (ART), the multi-channel network provides a set of universal computational processes for encoding, recognition, and reproduction of patterns. Previous works [3] have used fusion ART as a building block for semantic memory and procedural memory. In this work, we identify and formalize two major types of memory interaction and knowledge transfer processes between the two types of memory memory. Furthermore, this research also aims to embed these memory modules into autonomous agents so as to improve their decision making and problem solving capability through the collaborative memory interactions.

We have conducted the experiments on two problem domains: (1) the Toad and Frog puzzle and (2) a strategic game known as Starcraft Broodwar. Our experimental results show that the interaction between declarative knowledge and procedural skills can lead to a significant improvement in both learning efficiency and performance.

Appears in: *Alessio Lomuscio, Paul Scerri, Ana Bazzan, and Michael Huhns (eds.), Proceedings of the 13th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2014), May 5-9, 2014, Paris, France.*

2. THE OVERALL ARCHITECTURE

In this paper, we present a neural network-based cognitive model with an explicit modeling of both procedural and declarative memory. The proposed architecture contains the minimal structure just sufficient to illustrate the encoding of and interactions between the two types of memory. This dual memory system may in turn form an integral part of a cognitive agent. As shown in Figure 1, the proposed model contains four main components: (1) an intentional module to maintain a set of goals in hand; (2) a working memory module to keep all the necessary information and knowledge online for use in performing the current task; (3) a procedural memory module to maintain a collection of action rules to perform the familiar routines and other well-rehearsed tasks; (4) a semantic memory module to store meanings, concepts, rules, and general facts about the world.

In this proposed architecture, each of long-term memory modules is capable of performing its own basic operations, including encoding, learning, consolidation and retrieval, in-

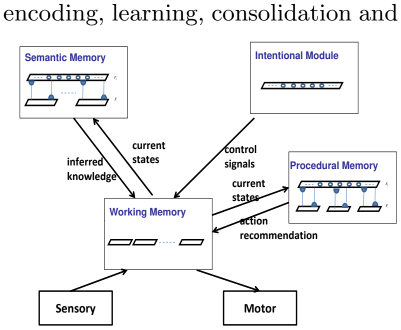

Figure 1: Architecture of the multi-memory model.

dependently from the other components. However, the overall decision process is a result of the complex interactions. In contrast to most cognitive models, the proposed architecture involves no centralized executive control to direct and manage the various components and the learning process. Instead, the interactions among different modules are fully based on the neural connections and the activity propagation mechanism.

3. MEMORY INTERACTION

We first present a mathematical formulation for long-term memory, as follows.

Semantic Memory, denoted by $S = \{S_1, S_2, ...\}$, can be viewed as a set of semantic fragment or rules, where each semantic rule S_i, can be one of the two basic types described as follows: (1) an association rule indicates the co-occurrence of two memory states and is represented as $S_i = (s, s')$, where s and s' indicate the two associated concepts; (2) a causal relation rule states the causality between two memory states and is written as $S_i : s \rightarrow s'$, wherein s refers to the cause and s' represents the effect.

Procedural Memory, denoted by $P = \{P_1, P_2, ...\}$, is a set of action rules which performs familiar tasks and routines. Each action rule P_k suggests a possible action a with a certain level of expected reward r (payoff), based on a given situation s. Therefore, each action rule can be represented as $P_k : s \rightarrow (a, r)$.

Together, the two memory systems constitute the knowledge bases of the cognitive architecture, which guide the behaviors of the agent through their interactions.

3.1 Semantic to Procedural Interaction

Semantic memory is used to provide the contextual information in order to activate the relevant action rules in the procedural memory. More formally, the interaction involves the flow of information from semantic memory to procedural memory, as defined below.

Definition 1 (SP Interaction). *Given the current state s, a threshold τ, and the following knowledge fragments from semantic memory and procedural memory:*

$$\begin{cases} S_i : s \rightarrow s' \quad \text{or} \quad S_i = (s, s') \\ P_k : s' \rightarrow (a, r) \\ r \geq \tau \end{cases}$$

the semantic memory infers s' and triggers the procedural rule P_k to perform action a.

Upon SP interaction, if the procedural rule indeed leads to a favorable outcome, the procedural memory may learn to directly associate the memory state of s with action a, which can be expressed as: $P_{new} : s \rightarrow (a, r)$.

3.2 Procedural to Semantic Interaction

For making a decision, procedural memory may explicitly prime the semantic memory for the unknown information and knowledge for firing a specific action rule. More formally, the interaction involving the flow of directive signals from procedural to semantic memory is defined as follows.

Definition 2 (PS Interaction). *Given the current state s and a procedural rule*

$$P_k : s' \rightarrow (a, r),$$

the semantic memory is primed to search for semantic knowledge of the form:

$$S_i : s \rightarrow s' \quad \text{or} \quad S_i = (s, s')$$

which will lead the current state from s to s'. If S_i is found, the procedural rule P_k is fired.

Upon PS interaction, if the selected procedural rule leads to a favorable outcome, the procedural memory may learn to directly associate the memory state of s with the action a as $P_{new} : s \rightarrow (a, r)$.

4. EXPERIMENTS AND DISCUSSION

We illustrate how the proposed declarative-procedural memory systems can cooperate in decision making process through the Toads and Frogs puzzle. At the beginning of each game trial, three toads are placed on the three leftmost squares of a seven-square board while three frogs are placed on the three rightmost squares. The central square is initially empty. The goal of the game is to swap the animal positions between the different animal types. We proposed a semantic memory module to implement various playing strategies which are developed by expert players to improve the process of problem solving. On the other hand, the procedural memory learns and performs the move selection based on the current contents of the puzzle through the reinforcement learning algorithm (i.e. TD-FALCON) [2]. The experiments show that the cooperative interactions between the semantic and procedural memory lead to a higher success rate of resolving the puzzle, compared to pure procedural learning on the game play.

We also investigate the overall performance of the dual-memory systems embedded into autonomous learning agents playing the strategy game known as Starcraft Broodwar. During the game play, while the proposed procedural memory module acquires the procedural knowledge and skills to accomplish various tasks (e.g. construct buildings and produce units) through interacting with the game environment via reinforcement learning, the semantic memory module stores the general knowledge on the necessary conditions to perform certain tasks. The results show that the cooperative interaction between the two memory modules can lead to a significant improvement in both learning efficiency and performance of the learning agents, in terms of average decision-making time and the attained game scores at the game end.

5. ACKNOWLEDGMENTS

This work was supported in part by the DSO National Laboratories under Grant No. DSOCL11258.

6. REFERENCES

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