Adaptive Multi-Agent Architecture to Track Students' Self-Regulated Learning

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Abstract. Intelligent Tutoring Systems (ITS) can be designed to improve learning and performance through Pedagogical Agents (PAs) that are designed to foster self-regulated learning through interactions and exchange of information with human learners. PAs are intelligent and follow rational behaviors, but to adaptively track students' progress, they need to be systematically and specifically designed. However, in order to follow a common goal, different self-regulatory systems have been designed that use PAs, but fail to provide an adaptive multi-agent architecture which provides such feature that agents adaptively track students' scaffolding. In this paper, we introduce a multi-agent framework designed for an agent-based ITS. We also define the agent architecture, multi-agent framework and communication mechanism.
Keyword. Pedagogical Agents, Self-Regulated Learning, Multi-Agent Systems, Agent Communication Mechanism.

1 Introduction

Increasing adaptivity is being devoted to frameworks involving intelligent components that receive (or search for) data and dynamically update their internal engine to efficiently acquire and integrate information. This adaptivity is becoming a crucial feature in ITSs that provide scaffolding for students to effectively self-regulate their learning. There are various ITSs [1–4, 6], which are used to conduct educational research. But in this paper, we only concentrate on agent-based ITSs [1, 3, 4, 6] where PAs continuously interact with students and objectively provide guidance to facilitate the process of learning and use of effective SRL processes. We concentrate on this category of ITSs because agents are intelligent components that could be equipped with adaptive applications and dynamically track student behaviour, based on the scaffolding they are receiving.

Current ITSs are not entirely adaptive to students' knowledge acquisition during learning in real-time. This may be because in most agent-based ITSs [1, 4, 6], agents are developed to interact with students to facilitate their navigation through parts of the system and provide adaptive scaffolds and feedback to facilitate their learning. This is done using rule-based (predefined) decision maker modules that pick a specific action, which can be either feedback to the students or some sort of communication with the system. The action selection mechanism has been thoroughly defined and enables agents to effectively react to students' progress based on predefined scenarios. In such ITSs, agents generally have a narrower focus on specific performance features/outcomes that illustrate acquisition of knowledge in the target domain.

To address the aforementioned adaptivity problem, PAs need to maintain decision making procedures [5] that continuously interact with the student (in the form of direct interaction and recording the data about that interaction) and dynamically analyze the collected data to update the scaffolding model that the agent builds as it assesses students' progress. By analyzing collected data, agents are able to better interact with students since they are aware of students' detailed work and progress in learning. In this paper, we focus on a multi-agent framework designed for an agent-based ITS that is being designed to analyze a much wider array of student behavior, activities, responses to agents, and performance in order to better understand many aspects of both students' understanding of domain knowledge and underlying self-regulatory abilities.

2 Multi-Agent Architecture

The proposed multi-agent architecture is a simulation environment designed to model and scaffold learners' SRL processes as they learn a biology topic. This environment is focused on further understanding of students' deployment of SRL processes by providing a computer-based learning environment with Pedagogical Agents (PAs) that model and track students' progress while learning complex science topics. In the proposed muti-agent architecture, there are three PAs that directly interact with students:

Peer agent, that interacts the most with the student and obtains basic information (like his/her knowledge level) from the student. In fact, the peer agent is the one that builds the student model and dynamically updates the model with respect to students' activities and deployment of SRL processes;

SRL agent, that tracks students' progress towards using effective SRL processes. This agent is in charge of guiding the student in accomplishing the learning goal and effectively finalizing the process of learning about the complex topic. The SRL agent also provides relative data (computed knowledge level) that influence the peer agent's further interaction with the student.

Science agent, that is in charge of helping and scaffolding the student to understand the science content. This agent informs the other two agents when the student is having difficulties with the content, choosing relevant page sequences, reading the content at an optimal time, and evaluating his/her goals.

The three introduced agents directly interact with students and are known by students as their interactive partners. These agents also interact with each

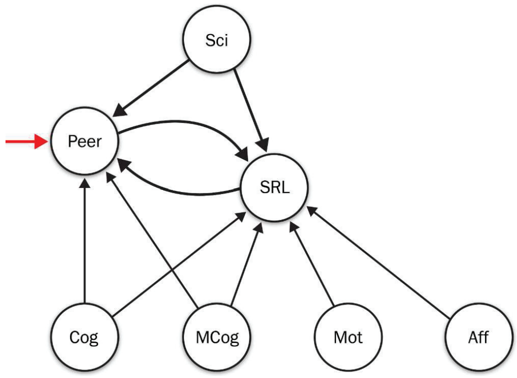

Fig. 1. Multi-agent framework.

other to better guide the student to accomplish the goal of learning about the complex science topic. To adaptively track and model students' scaffolds, there are various data types regarding students' use of SRL processes that need to be collected and analyzed in order to maintain adaptive scaffolding and provide effective guidance to the student. In the proposed framework, we assign four hidden agents, each of which are associated to a category that captures related data, analyses the data and provides relative reports in the form of messages to other involving agents. These massive data is categorized into four groups:
Cognitive agent, that provides details regarding students' learning-related parameters, including their content reading process, highlighting, note taking, and all other cognitive processes;
Metacognitive agent, that provides details regarding students' performance-related parameters, such as scores on various quizzes, accuracy of judgment of learning, and all other metacognitive processes;
Motivational agent, that provides details regarding students' task difficulty, attributions, self-efficacy;
Affective agent, that provides details regarding students' motivations while interacting with the system.

The whole architecture enhances the performance of data collection, and analyzes agents' decision making. Moreover, the multi-agent architecture provides modular functionalities that makes it simpler to test, analyze, and integrate in the system. Figure 1 illustrates the multi-agent architecture together with the involved agents. Hidden agents are rational intelligent components that are capable of analyzing data related to a specific architecture and a pre-defined logic. PAs are rational and are developed with goals related to educational purposes, such as, to optimize learning for students. The core of an agent architecture is its data processing engine that analyses the data that is collected from the surrounding environment and provides an action that best fits its goal-directed purpose. In the proposed architecture, PAs also run data analyses and react to the environment via a selected action by the student. We focus here on the obtained data that help (whether one of the three PAs or the four hidden agents) to analyze and better understand environmental changes, specifically students' decisions and actions.

In the proposed architecture, hidden agents continuously communicate to capture students' activities while interacting with the system and therefore provide accurate information, evidence, and reasoning to the three interactive agents who can then adaptively provide feedback and scaffolds to the students. In the proposed architecture, the main role of these four agents is to collect data regarding cognitive, metacognitive, motivational, and affective SRL processes. These massive data are continuously collected, analyzed and updated to adaptively track their learning progress and adaptations based on the scaffolding they are being provided with.

3 Conclusion

This paper introduces an adaptive multi-agent framework designed for intelligent tutoring systems. This framework could be used in agent-based learning environments where pedagogical agents coordinate with one another to facilitate SRL processes in learners [3]. The main objective is to enable PAs to effectively track students' progress while interacting with the system throughout the learning session. In future research, we intend to propose different mechanisms to develop adaptive multi-agent communication and decision making to represent an optimally efficient learning environment to facilitate the acquisition, internationalization, application, and transfer of self-regulatory processes.

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