Using Intelligent Multi-Agent Systems to Model and Foster Self-Regulated Learning: A Theoretically-Based Approach Using Markov Decision Process

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Introduction

We provide a new theoretical model of MetaTutor, a multi-agent hypermedia learning environment, using Markov Decision Processes (MDPs). Specifically, we propose how this intelligent, multi-agent learning environment for science could be defined using MDPs (Carlin & Zilberstein, 2011; White, 1993) to convert Pedagogical Agents (PAs) to sequential decision makers that effectively interact with learners and help them better self-regulate their cognitive, metacognitive, affective and motivational (CAMM; Azevedo et al., 2010, 2012) processes over time.

Purpose

The proposed architecture is based on current theoretical models of self-regulated learning (SRL; Winne & Hadwin, 1998, 2008), assumptions regarding SRL as an event (Azevedo et al., 2010; Biswas et al., 2010; Veenman, in press; Winne, 2011), and emerging empirical evidence regarding the complex nature of CAMM processes deployed during learning with intelligent, multi-agent learning environments.

We use MDPs to enhance the quality of agents' decision making and provide a dynamic and adaptive agent-learner interacting environment.

Methods

In MetaTutor, PAs are effective in helping students plan and monitor their learning, and use effective learning strategies. However, they do not have control regarding learners' overall progress through the content of the learning environment. In this regard, MDPs are extremely useful in optimizing such complex systems via the use of reinforcement learning techniques. In the proposed MDP, we expose details regarding how the interactions of participants with MetaTutor can be broken down into different states (e.g., selecting a relevant page) and how these states are correlated (via information exchange) while a student navigates through them. Figure 1 provides a preliminary state diagram that consists of two separate parts associated with the Sub Goal (SG) setting phase and the learning phase. After learning about a SG, the learner takes the generated quiz to conclude the SG and moves on to the next one.

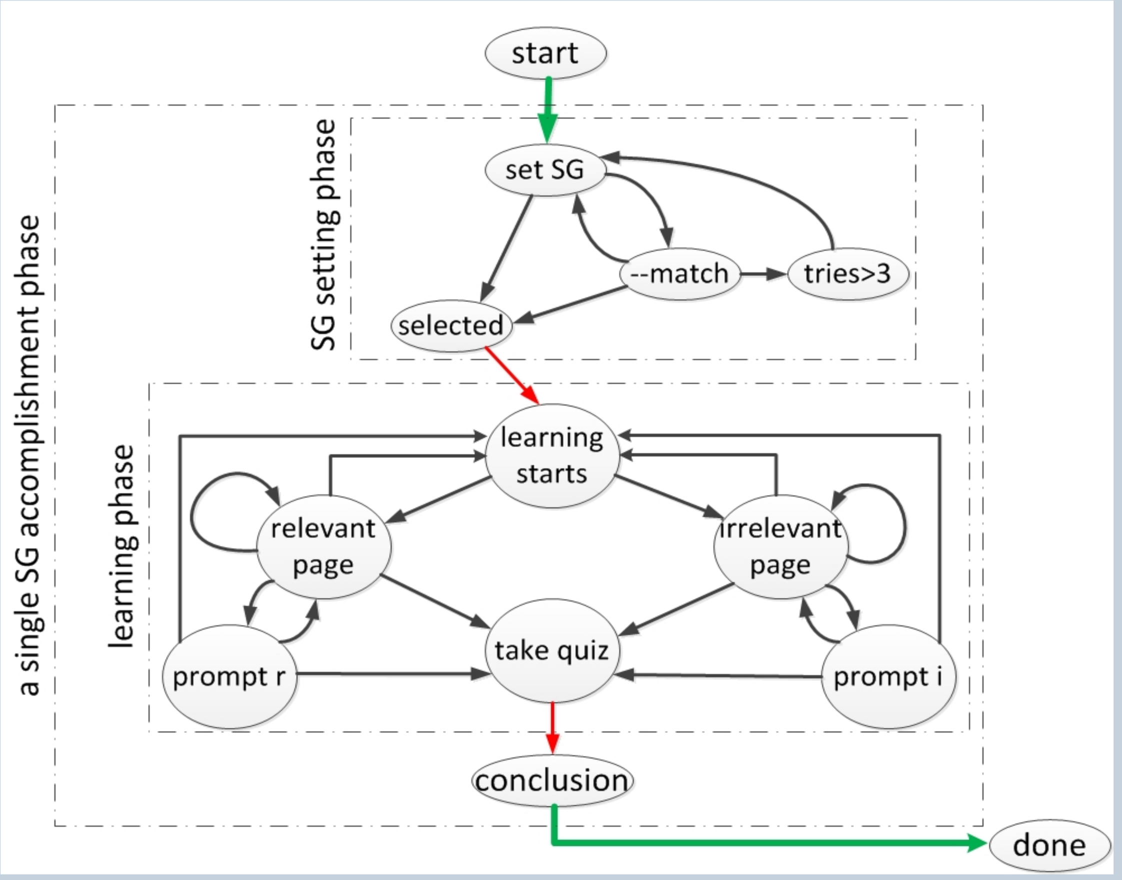

Figure. 1. MetaTutor's designed state diagram in accomplishment of a sub-goal (SG).

Data Analyses

Analyses of the log-file data provide rich detail about individual learners' interactions with MetaTutor. We map this file (Figure 2) to the proposed state diagram and highlight the state transitions. We use the log-file data as a resource for the reinforcement learning technique that PAs are equipped with. We anticipate that results will demonstrate how effective MDP would be in enhancing the quality of learning in multi-agent environments.

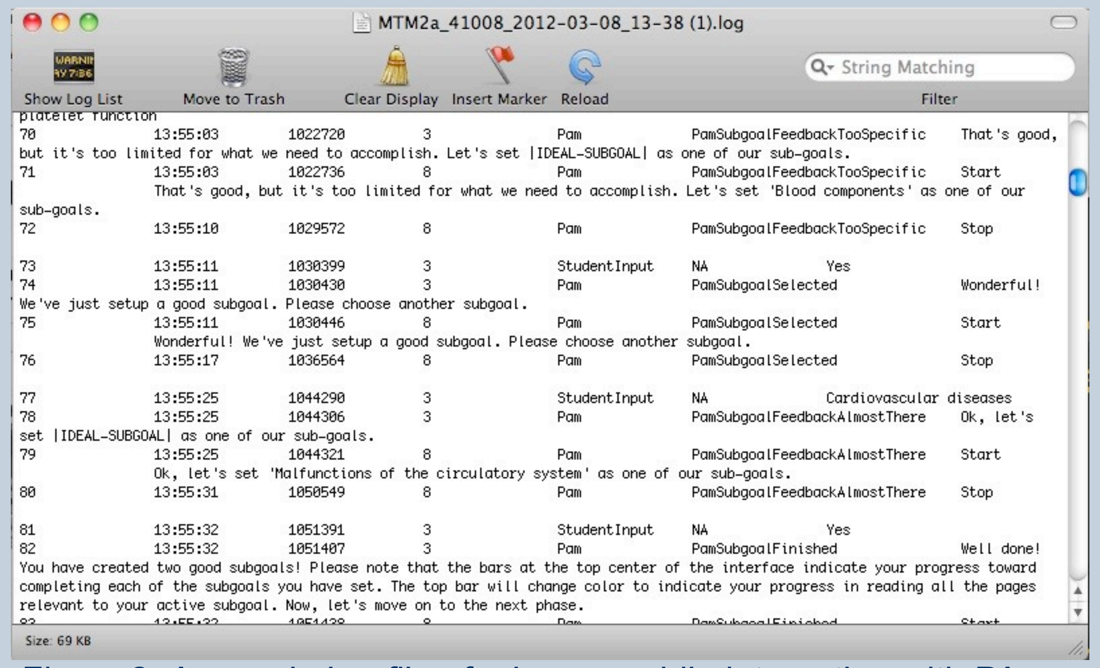

Figure 2. A sample log-file of a learner while interacting with PAs. In this part, a SG is ideally selected.

The results and ensuing proposed architecture demonstrate the advantage of using intelligent, multi-agent computerized learning environments to advance our understanding of what, how, when, and why students' know and feel during complex learning sessions. The data sources provides evidence that has the potential to advance current conceptual, theoretical, methodological, and analytical frameworks related to SRL processes.

Discussion and Conclusion

The aforementioned advances in turn allow researchers to design more effective multi-agent learning environments that are sensitive and responsive to students' cognitive, metacognitive, affective, and motivational needs during learning. In addition, the proposed architecture has the potential to advance current systems by emphasizing a coordinated effort in understanding and sharing CAMM processes across agents: coordinating efforts in sharing data about individual students as key in fostering the right amounts and types of scaffolding, feedback, and adaptivity (for each CAMM process and across CAMM processes); facilitating the development of a more accurate student model (Woolf, 2009), and may lead to more correct inferences about students' understanding of the content and ability to regulate certain aspects of their learning.

References

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