Chapter 26

SOCIALLY INTELLIGENT AGENTS IN EDUCATIONAL GAMES

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Abstract We describe preliminary research on devising intelligent agents that can improve the educational effectiveness of collaborative, educational computer games. We illustrate how these agents can overcome some of the shortcomings of educational games by explicitly monitoring how students interact with the games, by modeling both the students' cognitive and emotional states, and by generating calibrated interventions to trigger constructive reasoning and reflection when needed.

1. Introduction

In this paper, we explore the potential of enriching educational computer games with socially intelligent agents that can help students learn effectively from the games while maintaining the high level of engagement and motivation that constitutes the strong appeal of electronic games in non-educational settings.

Several authors have suggested the potential of video and computer games as educational tools (e.g., [18], [17]). However, empirical studies have shown that, although educational games are usually highly engaging, they often do not trigger the constructive reasoning necessary for learning [4] [13]. For instance, studies performed by the EGEMS (Electronic Games for Education in Math and Science) project at the University of British Columbia have shown that the tested educational games were effective only when coupled with supporting classroom activities, such as related pencil and paper worksheets and discussions with teachers. Without these supporting activities, despite enthusiastic game playing, the learning that these games generated was usually rather limited [13].

An explanation of these findings is that it is often possible to learn how to play an educational game effectively without necessarily reasoning about the target domain knowledge [4]. Insightful learning requires meta-cognitive skills that foster conscious reflection upon one's actions [6] [7], but reflective cognition is hard work. Possibly, for many students the high level of engagement triggered by the game acts as a distraction from reflective cognition, especially when the game is not integrated with external activities that help ground the game experience into the learning one. Also, educational games are usually highly exploratory in nature, and empirical studies on exploratory learning environments [19] have shown that they tend to be effective only for those students that already possess the meta-cognitive skills necessary to learn from autonomous exploration (such as self-monitoring, self-questioning and self-explanation [6]).

In this chapter, we discuss how to improve the effectiveness of educational games by relying on socially intelligent agents (SIAs). These agents are active game characters that can generate tailored interventions to stimulate students' learning and engagement, by taking into account the student's cognitive states (e.g., as knowledge, goals and preferences), as well as the student's meta-cognitive skills (e.g., learning capabilities) and emotional reactions.

2. SIAs as mediators in educational games

We argue that the effectiveness of educational games can be increased by providing them with the capability to (i) explicitly monitor how students interact with and learn from the games; (ii) generate calibrated interventions to trigger constructive reasoning and reflection when needed.

However, this must be done without interfering with the factors that make games fun and enjoyable, such as a feeling of control, curiosity, triggering of both intrinsic and extrinsic fantasies, and challenge [13]. Thus, it is not sufficient to provide educational games with the knowledge that makes more traditional Intelligent Tutoring Systems effective for learning: an explicit representation of the target cognitive skills, of pedagogical knowledge and of the student's cognitive state. It is fundamental that the educational interventions be delivered within the spirit of the game, by characters that (i) are an integral part of the game plot; (ii) are capable of detecting students' lack of engagement, in addition to lack of learning; (iii) know how to effectively intervene to correct these negative emotional and cognitive states.

Basically, these characters must play, in the context of the game, the mediating role that teachers and external instructional activities have played during the most successful evaluations of the EGEMS prototypes. The requirement that these agents be socially intelligent is further enforced by the fact that we are currently interested in investigating the educational potential of multi-player computer games to support collaborative learning. In the last few years there has been increasing research on animated pedagogical agents and there is already empirical evidence of their effectiveness in fostering learning and motivation [20]. Our work extends existing research toward making pedagogical agents more socially apt, by enabling them to take into account users' affective behaviour when adapting their interventions and to engage in effective collaborative interactions.

2.1 SIAs to Support Game-Based Collaborative Learning

Effective collaborative interaction with peers has proven a successful and uniquely powerful learning method [15]. Students learning effectively in groups encourage each other to ask questions, justify their opinions, and reflect upon their knowledge. However, effective group interaction does not just magically happen. It depends upon a number of factors, including the group composition, the task at hand, and the roles that the group members play during the interaction [15]. Some of these factors (such as the composition of the group), need to be taken into account when creating the groups. Others can be enforced during the interaction by a human or artificial agent that oversees the collaboration process and detects when the conditions for effective collaboration are not met. We are working on creating artificial agents that can provide this mediating role within multi-player, multi-activity educational games designed to foster learning through collaboration. As a test-bed for our research we are using Avalanche, one of the EGEMS prototype games, in which four players work together through a set of activities to deal with the problems caused by a series of avalanches in a mountain ski town. Each of the Avalanche activities is designed to foster understanding of a specific set of mathematical and geometrical skills, including number factorisation as well as measurement and estimate of area/volume.

Preliminary pilot studies have shown that the collaborative nature of the game triggers a tremendous level of engagement in the students. However, they also uncovered several problems. First, students seldom read the available on line help and the canned instructions provided within each activity. Thus, students often lose track of the game goals and of the means available to achieve them. Second, often students succeed in the game by learning heuristics that do not necessarily help them learn the target instructional knowledge. Third, the game at times fails to trigger effective collaboration. For instance, students that are not familiar with the other group members tend to be isolated during the interaction, while highly competitive students sometime turn an activity designed to foster collaboration into a competition.

3. A comprehensive computational model of effective collaborative learning

The above examples show that Avalanche can greatly benefit from the addition of SIAs that help students find their way through the game, trigger constructive learning and reflection, and help mediate and structure the collaborative interaction. To succeed in these tasks the agents need to have:

- explicit models of the game activities they are associated with, of the emotional states that can influence learning from these activities and of effective collaborative interaction.
- the capability of modeling, from the interaction with the game, the players' cognitive and meta-cognitive skills, along with their emotional states and the status of the collaborative interaction;
- the capability of making intelligent decisions as to when and how to intervene to improve effective collaboration and learning, without compromising the level of motivation and engagement fueled by the game.

3.1 Architecture

Figure 1 sketches our proposed general architecture underlying the functioning of socially intelligent characters for a multi-player, multi-activity educational game. As students engage in the different activities available within the game, their behavior is monitored by the agents currently involved in the interaction, through their Behavior Interpreters. Each Behavior Interpreter specializes in interpreting actions related to a specific player's behavior (e.g., behavior related to game performance, meta-cognitive skills, collaboration and emotional reaction) and updates the corresponding elements in the student model for that player.

A Game Actions Interpreter, for instance, processes all the student's game actions within a specific activity, to infer information on the student's cognitive and meta-cognitive skills. A Meta-Cognitive Behavior Interpreter tracks all the additional student's actions that can indicate meta-cognitive activity, (e.g., utterances and eye or mouse movements) and passes them to the student model as further evidence on the student's meta-cognitive skills. The agent's action generator then uses the student model and the expertise encoded in the agent's knowledge base (which depend on the agent's pedagogical role) to generate actions that help the student learn better from the current activity.

The agents in the architecture include a Game Manager, the Collaboration Manager and agents related to specific game activities (like Help Agent for activity A and Peer Agent for activity K in Figure 1). The Game Manager knows about the structure of the game and guides the students through its

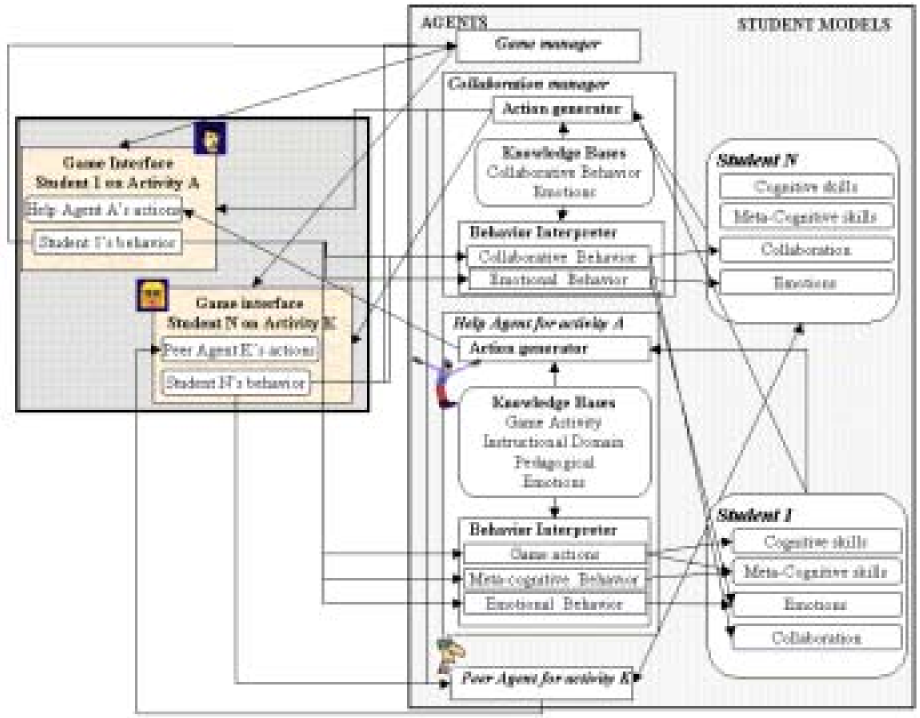

Figure 26.1. Architecture for SIAs in a multi-player, multi-activity educational game

activities. The Collaboration Manager is in charge of orchestrating effective collaborative behavior. As shown in Figure 1, its Behavior Interpreter captures and decodes all those students' actions that can indicate collaboration or lack thereof, along with the related emotional reactions. The actions that pertain to the Collaboration Manager include selecting an adequate collaboration role and partners for a student within a particular activity. The pool of partners from which the Collaboration Manager can select includes both the other players or the artificial agents (e.g., the Peer Agent selected for Student N in activity K in Figure 1), to deal with situations in which no other player can currently be an adequate partner for a student, because of incompatible cognitive or emotional states.

The artificial agents related to each game activity have expertise that allow them to play specific roles within that activity. So, for instance, a Help Agent (like Help Agent for activity A in Figure 1) has expert knowledge on a given activity, on the emotional states that can influence the benefits of providing help and on how to provide this help effectively. Peer agents, on the other hand, will have game and domain knowledge that is incomplete in different ways, so that they can be selected by the Collaboration Manager to play specific collaborative roles in the activity (e.g., that of a more or less skilled learning companion).

3.2 Student Models

The student models in our architecture are based on the probabilistic reasoning framework of Bayesian networks [11] that allows performing reasoning under uncertainty by relying on the sound foundations of probability theory. One of the main objections to the use of Bayesian networks is the difficulty of assigning accurate network parameters (i.e. prior and conditional probabilities). However, even when the parameters cannot be reliably specified by experts or learned from data, providing estimates for them allows the designer to clearly define the assumptions the model must rely upon and to revise the assumptions by trial and error on the model performance. Thus, we believe that Bayesian networks provide an appropriate formalism to model and integrate in a principled way the multiple sources of uncertainty involved in monitoring a student's cognitive and emotional states, and the unfolding of a collaborative interaction.

Modeling cognitive and meta-cognitive skills. Bayesian networks have been extensively used to build user models representing user's knowledge and goals [12]. In [3], we have described how to automatically specify the structure and conditional probabilities of a Bayesian network that models the relations between a user's problem solving behavior and her domain knowledge. In [8], we have extended this work to model learning of instructional material through the meta-cognitive skill known as self-explanation. We plan to adapt this approach to formalize the probabilistic relationships between player's behavior, meta-cognitive skills and learning in the student models for SIAs in educational games.

Modeling collaboration. A preliminary Bayesian model of effective collaborative interaction has been proposed in [14]. The model attempts to trace the progress of group members through different collaborative roles (e.g., leader, observer, critic) by monitoring the actions that they perform on an interface especially designed to reify these roles. We also adopt a role-based approach to model effective collaboration, but we cannot structure and constrain the game interface as in [14], because this kind of highly constrained interaction could compromise the level of fun and engagement that students experience with Avalanche. Hence, we need to devise alternative ways to capture the collaborative roles that students adopt during the interaction. We plan to start by making the adoption of different collaborative roles one of the mandatory game activities, orchestrated by the Collaboration Manager. This will reduce the collaboration-monitoring problem to the problem of verifying that students effectively perform the role they have been assigned. However, as the research proceeds, we hope to also achieve a better understanding of how to monitor and support less constrained collaboration.

Modeling emotions. Since emotional engagement is the element that makes educational games attractive to learners, it is fundamental that this variable be accurately monitored and taken into account by SIAs for these games. Starting from existing research on the structure of emotions [1], we are working on a general Bayesian student model to represent relevant emotional states (such as frustration, boredom and excitement) and their dynamics, as they are influenced by the interaction with an educational game, by the SIAs interventions and by the player's personality [2]. The formalization includes a theory of how the players' emotions can be detected, based on current research on how to measure emotional reactions through bodily expressions such as facial expressions, vocal intonation, galvanic skin response and heart rate [16].

3.3 Action Generators

The action generator for each SIA in the game relies on a decision-theoretic model of decision-making predicting that agents act so as to maximize the expected utility of their actions [10]. Other researchers have started adopting a decision theoretic approach to regulate the behavior of interactive desktop assistants [9] and of an intelligent tutor to support coached problem solving [5].

In our architecture, the function representing an agent's preferences in terms of utility values depends on the role of the agent in the game. So, for instance, the Collaboration Manager will act so as to maximize students' learning as well as their collaborative behavior. A Help Agent will act to maximize the student's understanding of a specific activity, while an agent in charge of eliciting a specific meta-cognitive skill will select actions that maximize this specific outcome. All the agents will also include in their utility functions the goal of maintaining the student's level of fun and engagement above a given threshold, although the threshold may vary with the agent's role. The action generators' decision-theoretic models can be represented as influence diagrams [10], an extension of Bayesian networks devised to model rational decision making under uncertainty. By using influence diagrams, we can compactly specify how each SIA's action influences the relevant elements in the Bayesian student model, such as the player's cognitive and emotional states. We can also encode the agent's utility function in terms of these states, thus providing each agent with a normative theory of how to intervene in the students' game playing to achieve the best trade-off between engagement and learning.

4. Conclusions

We have presented a preliminary architecture to improve the effectiveness of collaborative educational games. The architecture relies on the usage of socially intelligent agents that calibrate their interventions by taking into account not only the students' cognitive states, but also their emotional states and the unfolding of collaborative interactions within the game. We propose to rely on Bayesian networks and influence diagrams to provide our agents with a principled framework for making informed decisions on the most effective interventions under the multiple sources of uncertainty involved in modelling interaction and learning in multi-player, multi-activity educational game.

References

[1] A. Orthony and G.L. Clore and A. Collins. *The cognitive structure of emotions*. Cambridge University Press, Cambridge, England, 1988.

[2] C. Conati. Probabilistic Assessment of User's Emotions During the Interaction with Educational Games.

[3] C. Conati and A. Gertner and K. VanLehn and M. Druzdzel. On-line student modeling for coached problem solving using Bayesian networks. In A. Jameson and C. Paris and C. Tasso, editor, *User Modeling: Proceedings of the Sixth Int. Conf., UM97*. Spring Wien, New York, 1997.

[4] C. Conati and J. Fain Lehman. EFH-Soar: Modeling education in highly interactive microworlds. In *Lecture Notes in Artificial Intelligence*. Springer-Verlag, New York, 1993.

[5] C. Murray and K. VanLehn. DT Tutor: A decision-theoretic dynamic approach for optimal selection of tutorial actions. In *ITS 2000, Montreal, Canada*, 2000.

[6] M.T.H. Chi. Self-Explaining: The dual process of generating inferences and repairing mental models.

[7] C. Conati and K. VanLehn. Toward Computer-Based Support of Meta-Cognitive Skills: a Computational Framework to Coach Self-Explanation. *Int. Jour. of Artificial Intelligence in Education*, 11, 2000.

[8] C. Conati and K. VanLehn. Providing adaptive support to the understanding of instructional material. In *IUI 2001, International Conference on Intelligent User Interfaces, Santa Fe, New Mexico, USA*, 2001.

[9] E. Horvitz. Principles of mixed initiative interaction. In *CHI '99, ACM SIGCHI Conf. on Human Factors in Computing Systems., Pittsburgh, Pennsylvania*, 1999.

[10] M. Henrion, J. Breeze, and E. Horvitz. Decision Analysis and Expert Systems. *AI Magazine*, 1991.

[11] J. Pearl. *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. Morgan Kaufmann, San Mateo, California, 1988.

[12] A. Jameson. Numerical uncertainty management in user and student modeling: An overview of systems and issues. *User Modeling and User-Adapted Interaction*, 5, 1995.

[13] M. Klawe. When Does The Use Of Computer Games And Other Interactive Multimedia Software Help Students Learn Mathematics? In *NCTM Standards 2000 Technology Conference, Arlington, VA*, 1998.

[14] M. Singley and P. Fairwater. Team Tutoring Systems: Reifying Roles in Problem Solving. In *CSCL '99, Stanford, California*, 1999.

[15] P. Dillenbourg and M. Baker and A. Blaye and C. O' Malley. The evolution of research on collaborative learning. In E. Spada and P. Reiman, editors, *Learning in Humans and Machine: Towards an interdisciplinary learning science*, pages 189–211. 1996.

[16] R. Picard. *Affective Computing*. M.I.T. Press, Cambridge, Massachusetts, 1997.

[17] S. B. Silvern. Classroom Use of Videogames. *Educational Research Quarterly*, pages 10–16, 1986.

[18] T. W. Malone and M.R. Lepper. Making learning fun: A taxonomy of intrinsic motivations for learning. In R. E. Snow and M. J. Farr, editor, *Aptitude, learning and instruction: Volume III Conative and affective process analyses*. Lawrence Erlbaum: Hillsdale, NJ, 1987.

[19] V. J. Shute. A comparison of learning environments: All that glitters... In S.P.L. and S.J. Derry, editor, *Computers as Cognitive Tools*, pages 47–73. Lawrence Erlbaum Associates, Hillsdale, New Jersey, 1993.

[20] W. L. Johnson and J.W. Rickel and J.C. Lester. Animated Pedagogical Agents: Face-to-Face Interaction in Interactive Learning Environments. *International Journal of Artificial Intelligence in Education*, 11:47–78, 2000.