Multiagent Coordination for Planning and Enacting an Assessment Game

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Abstract. Research shows that the inclusion of games in educational curricula is beneficial to the learning process. Social games are sometimes more preferable than single player games. However, their capability has yet to be developed in social games although much thought has been put into optimizing the playability (fun) and educational value (challenge) of such games. To overcome the above limitations, based on the new concept of social assessment games for online education, this paper proposes a multiagent framework including agent coordination mechanisms and planning models for social assessment games. We explore the benefits and liabilities of agent negotiation in the scheduling and assignment of work across the intelligent agents that form the foundation of the platform for developing social assessment games. More specifically, we show how the Contract Net Protocol in multiagent systems can be adapted to model the interaction between the gaming host agent and the player agents.

Keywords. Multiagent System; Multiplayer Games; Assessment Game.

1 Introduction

The use of games for education has proven to be an effective means to motivate learners and enhance learning for a very long time, with simulation games in educational settings dating all the way back to the 1960's (Bookcok, 1968). Multiplayer games (social games) are more preferable than single player games for the following main reasons: (1) there are great entertainment and social successes like World of Warcraft and Second Life which industry gurus love extolling; and (2) multiplayer experiences feel real, are rich in interface and are dynamic. There are many opportunities for social games to improve learning in ways that go beyond what a single-player game can achieve because the presence of others can be used to not only increase playability (fun) but also help teach team-working and social skills. However, there are some limitations of social games. In most current educational games, multiplayer games share many characteristics of a classroom role-play such as: (1) The logistics of setting them up is expensive and brittle; (2) People can go through them once or twice, but then the players get bored. Recent research confirms the intrinsic value of educational games not only as a complementary learning tool, but also as a non-intrusive method for assessing learner/player skills (Evans et al., 2011; Shute, 2011; Wang, 2008). Leveraging the assessment information to improve learning is a critical success factor for game-based learning because assessment procedure serves as the basis for adaptive interventions, for instance, by providing the learner with guidance or feedback (Augustin et al., 2011). However, this capability has yet to be developed in social games although much thought has been put into optimizing the playability (fun) and educational value (challenge) of such games. The potential of these games as a tool to accurately assess a learner's progress and learning achievements remains largely unrealized. To overcome the above limitations, based on the new concept of social assessment games for online education, this paper proposes a new methodology, a framework, and agent coordination mechanisms and planning models for social assessment games.

2 Literature Review

Over the last decade, a number of research efforts have investigated a new class of game-based assessment systems, as the existing game engines generally lack the overall infrastructure for assessment. A key challenge has been to develop methods for making valid inferences about what the student knows using actions and events observed during gameplay as the basis for the assessment. For games to be effective as a learning tool, a delicate balance must be maintained between playability (fun) and challenge (educational value) (Van Eck, 2008; Augustin et al., 2011; Shute, 2011). For example, Mislevy et al. （2003) proposed evidence-centered-design (ECD) that allows designers to link competency, evidence and tasks (actions) together into a single coherent model. Another important concept proposed by Shute (2011) that has been emerging in the last few years is that of "stealth assessment" (Shute, 2011) to describe situations where assessment functions are so interwoven into the fabric of the game that the learners are unaware that they are being tested. Most of the new concepts are targeting the ever-changing learning environment and learner needs, as today’s education is moving towards a digital, social, and fun fashion. As in the case for all competitive games, an equal match between contestants/players is essential to self-esteem and for maintaining a high degree of interest in the game, hence the need for an algorithm that can accurately predict student performance in the game. The ability to accurately model learner skills and knowledge is a critical aspect of assessment, and this is area that has been intensively researched in recent years. A trend in that area is the use of interaction data to paint a more accurate picture of learner characteristics. McCalla (2004) suggests, for example, that snapshots of student models be attached to the learning objects they interact with, opening the door for point-in-time data mining（McCalla, 2004). Using McCalla’s ecological approach as a general philosophy for designing intelligent systems, Champaign and Cohen created an algorithm and a system to solve the problem of content sequencing, explored through a framework of simulated students (Champaign & Cohen, 2010). Belief-Desire-Intention (BDI) agents have been used to implement consistent long-term intelligent behaviour in games (Oijen & Dignum, 2011), multiagent collaborative team-based game (Patel & Hexmoor, 2009), and adaptive and believable non-player character (NPCs) agents simulating virtual students (Lim et al., 2012). This trend shows two aspects. The first is that game-based learning activities should be carefully orchestrated to be *social* and *fun* and the second is that the game planning and coordination should be highly *adaptive* and *challenging*. However, a suitable game planning and coordination system particularly for game-based learning, especially targeting at social assessment games for online education, has not been implemented yet.

3 Methodology

Game planning and coordination in social assessment games for online education is a challenging problem. A complete system is very difficult to implement, because it requires not only a seamless integration of game planning, scheduling, and coordination, but also a transparent open architecture of knowledge modeling and learner modeling. The methodology proposed is based on group decision-making in coordination, stealth assessment in user modeling, and an ecological approach in system design.

Individual learners have particular models and preferences that result in conflictive learning goals. In addition, environmental influences worsen the problem of simply resolving different interests. The proposed system will be operating in a highly dynamic environment generating the need to adapt very fast and be highly flexible to environmental variables and their changes. In addition to learner agents, three key types of intelligent agents are being developed. They are: (a) the game planning agent (an instance of GM), who uses this information to form a team and develop a game plan adapted to the team's knowledge level and assign a game host agent; (b) The game host agent, who receives the game plan and executes the game sequence with the learners. The game host agent is responsible for capturing player performance information; (c) The assessment agent, who receives and interprets game events, updating the student model as necessary.

Contract Net Protocol (CNP) (Smith, 1980) is used by the game-planning agent to form a team through mutual selection, exchange information in a structured way to converge on assignments. In the proposed methodology, we use CNP as a coordination mechanism for planning and enacting the team formation collective decision-making task. Each involved learner can delegate the negotiation process to its agent. These agents strive to find a compromise schedule obeying hard learning constraints while simultaneously resolving individual conflicts of interest. In this research, Stealth Assessment is being seamlessly woven directly into the fabric of the instructional environment to support learning of important content and key competencies. This represents a quiet, yet powerful process by which the learner continuously gathers performance data during the course of playing/learning and inferences are made about the level of relevant competencies (Shute et al. 2009). Inference on competency states is stored in a dynamic model of the learner. An Evidence-Centered-Design (ECD) approach (Mislevy & Haertel, 2006) has been used to drive the interactions between the game planning agent, the game host agent, and the assessment agent. ECD has been shown to be a viable means of planning for game actions as a function of the evidence to be captured, and also for capturing and processing evidence and linking these to actions in game based environments (Shute, 2011).

4 Experimental Framework Design

To verify the proposed methodology and architecture and to gain first hand experience for further improvement, we are using open source MAS toolkit Jason (http://jason.sourceforge.net/wp/). Our main hypotheses for this research were that: A BDI based approach in which goals and plans are declaratively coded would be superior to programmatic MAS architectures for coordinating the activities surrounding competitive quiz games. More specifically, given that beliefs and plans are defined outside of compiled code, we theorized that beliefs and plans could be manipulated at runtime without having to recompile the code. Within the BDI model, CNP would be a viable and flexible mechanism for coordinating game planning activities, taking into account user preferences, and achieving load balancing across a large number of hosts. To test our hypotheses, we designed and developed a test bed, based on a Quiz game model QuizMASter (Dutchuk et al., 2009), for our experiments. Jason is used since it is a popular implementation of the BDI agent paradigm, with AgentSpeak as the underlying programming language.

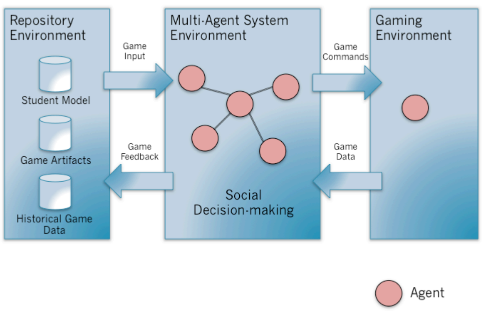

Fig.1: The proposed architecture.

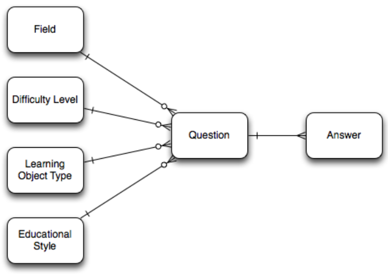

Fig. 2: Ontology Data Model.

4.1 Architecture

The key elements of the architecture proposed include: (1) A repository, which stores the student's model, the game artifacts and historical data on game performance; (2) The Multi-Agent System Environment itself, which uses the repository as main input for the decision making process and for establishing actions in the gaming environment; (3) The gaming environment, a web based framework that enacts the gaming scenarios, accepts student input and feeds student performance data to the MAS core system. Figure 1 shows the architecture proposed and Figure 3 shows the high-level design of the multiagent system.

Creating ontology for quiz game questions was identified as a critical building block of the overall architecture early in initial discussions. In the context of our research, the content to be presented and standardized is basically the set of questions to be asked in each session of the QuizMASter competition; where each question is one learning object (LO). The purpose of LOs ontology is for the game agent to find proper and relevant questions for each game. We have adopted IEEE Standard for

Learning Object Metadata (http://ltsc.ieee.org/wg12/par1484-12-1.html), which specifies a conceptual data schema that defines the structure of a metadata instance for a learning object. Metadata structure Learning Objects in QuizMASter is: (a) General category group that describe the learning object as a whole. For the purpose of our project in this group we limit our general category to “LO type” with only one possible value of “Question”; (b). Educational category group that describe the educational and pedagogical characteristics of the learning object. For the purpose of our project in this group we limit the educational category to “Edu Style” which identifies the educational method, with only one possible value of “Quiz Game”; (c) Relation category group that define the relationship between the learning object and other related learning objects. In this category we have one item, “level of difficulty”. In each field, questions can possibly have either of three values in the level of difficulty category, “Easy”, “Intermediate” and “Difficult”; (4) Classification category that describes learning objects in relation to a particular classification system. In our case we have one category of “Field” and two possible values of “Geography” and “Culture”. The data model we developed to support the ontology is shown in Figure 2.

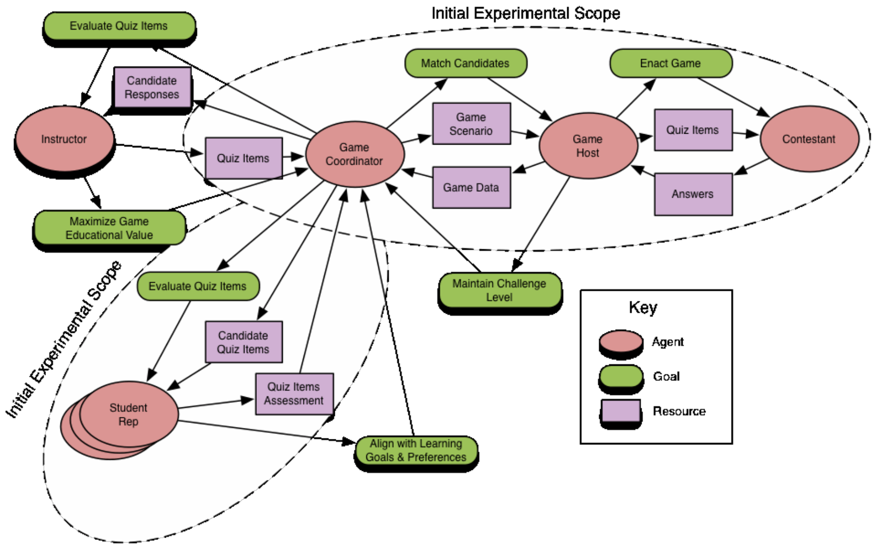

Fig. 3: High Level MAS Design Diagram (TROPOS Notation).

Our agent architecture is based on previous design efforts by Weng et al. (2011) and Shabani et al. (2012), and the focus of our initial experimentation has been on matching candidates based on their perceived strengths in different subject areas, selecting a suitable game host based on availability and enacting the game, as shown in Figure 3. We have designed a coordination protocol based on CNP. CNP has been applied to the following interaction sequences: the selection of a host for the game, based on host availability; user selection and assignment of contestants to the game, a process during which user agents are required to vote ("make an offer" in the case of the CNP) on a proposed game plan (question set).

5 Experiment

To test our first hypothesis (dynamic belief base and behavior), we designed an experiment aimed at determining how beliefs and behavior could be manipulated at run time without re-compiling the application. To test our second hypothesis (viability of CNP as a means to coordinate the game planning process and allocate games to hosts based on their availability), we designed a set of two experiments aimed at confirming how different utility algorithms could be inserted into the CNP-based coordination model to achieve more optimal allocations to users and hosts based on preferences and availability, respectively. For all experiments, we simulated the performance of contestants with automated agents that mimicked average performances from team members. The main findings are described below.

BDI agent dynamic behavior test results. Our experimentation with dynamic manipulation of beliefs and behavior was overall successful. Not only were we able to drive the belief system from the database (questions and ontology), but we also determined that AgentSpeak's programmatic interface allows the dynamic insertion of behavioral specifications (plans). The mechanisms we used to test the dynamic capabilities are summarized in Table 1.

Table 1 - BDI Dynamic Capabilities.

Functional Area	Enabling API Component(s)	Code sample
Beliefs	Beliefbase	Beliefbase bb = ag.getBB(); Literal l1 = Literal.parseLiteral("game_difficulty(Easy)"); bb.add(l1)
Plans	PlanLibrary Plan	PlanLibrary pl = ag.getPL(); pl.add(Plan.parse(" +host_completed_contract(CNPId)[source(A)]:true <- - +plays(host,A); !finduser."));

The above capabilities show some of BDI's advantages over standard object oriented programming, particularly when it comes to plan manipulation. Plans are to agents what methods are to objects. They define behavior. The enabling API components we tested allow agents to dynamically reconfigure their behavior at runtime, something that would not be possible in standard object oriented programming, under which a re-compilation and re-deployment would be necessary.

CNP-based Game-User coordination test results. The base coordination between the Game agent and User agents was implemented using CNP. We limited the scenario to having a single game agent with a variable number of users. The key distinguishing characteristic of the Game-User agent coordination model we designed is that a call for proposals (CFP) is issued for a particular game plan, which is comprised of a pre-selected set of questions defined by an ontology we identified for that purpose. Then, offers are made by user agents based on preferences. Due to time constraints, we had to settle for pre-determined set of questions (i.e. not selected as a function of knowledge gaps) and a random generator in user agents to evaluate the proposed set of questions. Our observations of agent behavior have confirmed that contestants having the highest preference for a given set of questions are selected as contestants for a given game. However, the one-time introductions of users to the game agent and the lack of availability control flags currently result in CFPs being sent to engaged users. Ultimately this could be adjusted to make the network traffic more efficient. In spite of these limitations, the flexibility afforded by our coordination model would allow for more advanced valuation functions and item pre-selection algorithms.

CNP-based Game-Host coordination test results. As was the case for Game-User interactions, we used CNP to orchestrate the interactions between the Game agent and the Host agents. In this case, however, offers made by hosts are based on availability as opposed to preference. In our test case, we implemented a very simple sequence in which a game plan proposal is refused when the host is busy, and an offer is made when the host is availability. We ran our scenario using a variable number of hosts and in each case our analysis of the interaction logs suggest that this approach enables scalability and enforces load balancing across multiple hosts.

While this scenario was quite limited in terms of sophistication, advanced scheduling optimization algorithms could be used in this context. Also, we didn't end up making use of the Jason's Jade infrastructure mode. This would have allowed inter JVM/Physical Machine communication as is part of the overall design and as such we were unable to our hypothesis in a distributed physical environment.

6 Conclusions and Future Work

Our initial experiments with MAS for the purpose of orchestrating and enacting social assessment games under simulated conditions were revealing. We have created several key building blocks for a scalable MAS infrastructure, and the beliefs/desires/intentions paradigm has shown its worth as a programming model, and our main discovery has been the realization of how dynamic BDI programming can be. However, while the declarative approach and logic based programming language shows the promise of yielding more elegant and compact code, our experience with it was limited and we found the learning curve very steep. This resulted in a tendency for procedural approaches to sneak in to the overall approach. As our results demonstrate, the multi agent coordination model we developed is functional and can be extended in several ways. We have shown that CNP is a viable option for orchestrating activities around game planning and resource allocation. This approach allows for the introduction of more advanced algorithms for game plan evaluation and host allocations. However, we feel that the protocol has its limitations in terms of scalability. The repeating cycles of call for proposals/offers/contract award can easily lead to less than optimal performance. We feel that other methods, such a combinatorial auctions (Vazirani et al., 2007), may be better suited to achieve higher performing orchestrations in large-scale environments. A wealth of recently developed game analytics techniques, as explored by El-Nasr et al. (2013), would be of extreme value to the MAS approach. These are areas worth exploring in future iterations of the project.

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