Automating the Mentor in a Serious Game: A Discourse Analysis Using Finite State Machines

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1 Introduction

Serious games are increasingly becoming a popular, effective supplement to standard classroom instruction [1]. Similar to recreational games, multi-party chat is a standard method of communication in serious games. As players collaborate in a serious game, mentoring is often needed to facilitate progress and learning [2, 3, 4]. This role is almost exclusively provided by a human at the present time. However, the cost incurred with training a human mentor represents a critical barrier for widespread use of a collaborative epistemic game. Although great strides have been made in automating one-on-one tutorial dialogues [5, 6], multi-party chat presents a significant challenge for natural language processing. The goal of this research, then, is to provide a preliminary understanding of player-mentor conversations in the context of an epistemic game, Land Science [7].

1.1 Land Science

Land Science is an extension of the epistemic game Urban Science, created by education researchers at the University of Wisconsin-Madison [7], designed to simulate an urban planning practicum experience. Young people role-play as professional urban planners in an ecologically-rich neighborhood to develop new ways of observing and acting in the world they inhabit. Players are assigned to one of three planning teams, each of which represents a stakeholder group (e.g., People for Greenspace). Players conduct a virtual site visit to learn about the issues their Non-Player Character (NPC) stakeholders care about. The players ultimately submit and defend a new plan for the city that aims to meet the needs of the community. During the game, players communicate with other members of their planning team, as well as with an adult mentor role-playing as a professional planning consultant.

These conversations between the mentor and players were analyzed with respect to meaning, syntax, and discourse function by classifying contributions into individual speech acts. The categorized speech acts were then analyzed to identify speech act sequences in the conversations, represented as Finite State Machines (FSM).

C. Stephanidis (Ed.): Posters, Part II, HCII 2013, CCIS 374, pp. 591–595, 2013.

1.2 Speech Act Classification and Finite State Machines

We selected a system for classifying speech acts [8]. Analyses of a variety of corpora, including chat and multiparty games, have converged on a set of speech act categories that are both theoretically justified and that also can be reliably coded by trained judges [9]. Our classification scheme has 8 broad categories:

- **Statements** are verbal reports on scientific facts, the status of the game activities, or other information about the Land Science domain (e.g., "Each of the stakeholders needs to give you feedback on your preference survey").
- **Requests** include asking other participants in the conversation to provide information or to take some action (e.g., "Please check your inbox").
- **Questions** are queries for information from the addressee (e.g., "Tina, have you finished your intake interview?").
- **Reactions** are short verbal responses to requests or questions (e.g., "Yes, Frank").
- **Expressive Evaluations** consist of feedback regarding the players' performance or feedback from the players on the program or activity (e.g., “That’s a great idea”).
- **MetaStatements** are statements about the communication process or the metacognition of participants (e.g., “Oops. Sorry for the double chat”, “I’m lost.”).
- **Greetings** are expressions regarding any party’s entrance to or exit from the conversation (e.g., "Hi Janet and William!”, “So long, folks”).
- **Other** represents speech acts which did not fit into the above categories (e.g. nonsensical contributions).

Our assumption is that there are patterns in multi-party conversation that can be captured in sequences of speech acts, and that FSMs provide a first step to discover these patterns. For example, FSMs can identify particular nodes (i.e., speech acts) which are frequently connected to other nodes in the chat room. Sequences of speech act categories can be quite enlightening even when the content of the speech acts is not analyzed. Our goal is to identify the conversational patterns in multi-party conversations in a serious game (such as Land Science) with the ultimate objective of automating the mentor’s role.

2 Methods

2.1 Participants

Players participated in the epistemic game, Land Science, which enabled them to complete an urban planning internship for a fictitious urban planning firm. During the game, participants worked in different teams and interacted with mentors who were trained in the urban planning profession, the game’s activities, and preferred mentoring strategies. The primary task of the players was to redesign the Northside neighborhood in Madison, WI.

2.2 Procedure

Players participated in the epistemic game, Land Science, which enabled them to complete an urban planning internship for a fictitious urban planning firm. During the game, participants worked in different teams and interacted with mentors who were trained in the urban planning profession, the game's activities, and preferred mentoring strategies. The primary task of the players was to redesign the Northside neighborhood in Madison, WI.

Players completed three phases of Land Science: Introduction, Stakeholder, and Final Plan. The three phases were subdivided into 19 stages, with each stage requiring different tasks, skills, and goals. Across all three phases, players conversed with their planning team and a human mentor via a chat window.

2.3 Automated Speech Act Classification and STN Creation

Player and Mentor contributions were automatically categorized into speech acts using the Naive Bayes classification algorithm on word features. The classification compares favorably to trained human coders with a kappa of 0.677, compared to a kappa of 0.797 between two humans [10].

STNs were created by calculating the conditional probability of each transition between speech acts as well as the overall frequency of each speech act in the corpus. For example, a mentor statement might be followed by a player reaction 28% of the time, and a player reaction might constitute 0.8% of the entire corpus. For each transition, a minimum conditional probability threshold of 15% was used for inclusion in the network, as well as an overall frequency of 0.3%. Additionally, although there are only two roles in the game (player and mentor), one crucial piece of information that the STNs can provide is the identity of the speaker. Specifically, in the case of adjacent player contributions, it is critical to distinguish whether the response is a follow-up from the same player ("P → P") or whether it is a reply by some Other Player ("P → OP"). This distinction helps in identifying player collaborations.

3 Results and Discussion

An overall FSM for Land Science is shown in Figure 1. One important pattern to note is a "Question → Response → Feedback" sequence (Mentor Question, followed by a Player Statement or Reaction, followed by a Mentor Statement). This didactic pattern is common and aligned with previous research [11]. Overall, two distinct epistemic networks emerged: scaffolding and collaboration. Scaffolding occurs when mentor responses to player contributions help guide players to the next step. This is necessary to facilitate goal completion throughout the game. Conversely, collaboration represents meaningful interactions between players. These player-player interactions are essential for collaborative problem-solving as members of a team.

M = Mentor; P→P = follow-up by same player; P→OP = reply by some Other Player

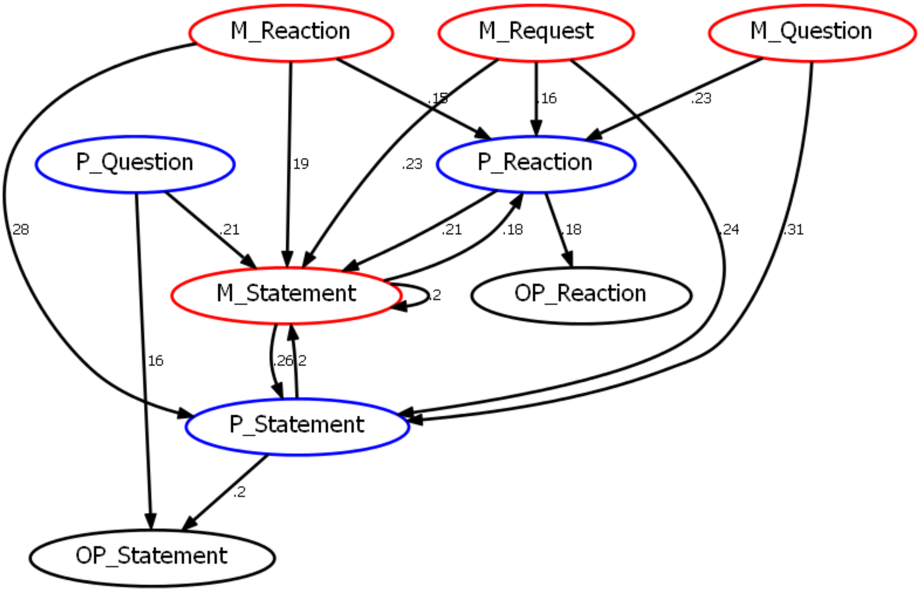

Fig. 1. Finite State Machine for Land Science

These data are applicable to a number of current and future investigations. First, we are currently analyzing additional chat room interactions between players and mentors in order to replicate these findings and allow for additional data mining. This includes predicting points in the conversation where a mentor should provide a contribution, as well as the appropriate speech act at a given point. Recurrence connectionist models can be used to predict the generation of speech act category N+1 on the basis of category sequences 1 through N. Additionally, the chat room conversations can be analyzed by human coders to link each contribution to its intended recipient. If sequential mismatches or breakdowns end up being more frequent than expected, additional context is needed to improve our understanding of chat room dynamics.

In analyzing these transitions between speech acts, the goal is to ease the burden of training human mentors and the accompanying logistical constraints. Even a semi-proficient automated mentor would represent significant progress, as fewer human mentors would be needed for each instance of gameplay. Hence, the current findings, combined with other analyses will help guide the implementation of an AutoSuggestor. The AutoSuggestor program will aid human mentors by providing recommendations for mentor contributions at various points in the conversation. In addition to making the human mentor's role easier, the human mentors can rate the quality of AutoSuggestor's recommendations. These ratings can then be analyzed to improve the quality of AutoSuggestor's contributions, and progress towards fully automating the role of the mentor in an epistemic game.

Acknowledgments. This work was funded in part by the Macarthur Foundation, National Science Foundation (REC-0347000, DUE-091934, DRL-0918409, DRL-0946372, BCS 0904909, DRK-12-0918409), the Gates Foundation, and U.S. Department of Homeland Security (Z934002/UTAA08-063). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of these funding agencies, cooperating institutions, or other individuals.

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