Spoken Language Tutorial Dialogue

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Abstract

An existing natural language speech dialogue system will be integrated with an existing mathematics tutor to provide adaptive instruction for grade school children. The resulting dialogue tutor will use general linguistic knowledge, including a fairly complex model of English and task-oriented dialogues, to speak to the student when he or she has trouble solving a problem. The tutor will initiate an interaction to *diagnose* missing knowledge and provide a customized explanation, select appropriate *hints* for a particular diagnosed problem based on student gender, cognitive development and student history, and provide a *summary* to ensure that students have the correct information. This work explores issues such as representation, lexical meaning, dealing with ambiguity, making use of information about context, mixed-initiative planning, and development of a formal model of plans based on explicit objects.

Goals of the Research

Spoken language interfaces are an essential part of future tutoring systems. We will build a conversationally proficient teaching assistant and demonstrate spoken language systems, providing a research platform for issues in natural language understanding, mixed-initiative teaching, representation and reasoning. The system will understand what a student says and emulate human responses.

An existing natural language speech (input and output) dialogue system will be integrated with an existing intelligent tutoring system. The existing mixed-initiative language and planning system, TRAINS-96, enables humans and computers to work together in a tightly coupled way to solve problems that neither alone could manage, within the context of command and control (Ferguson and Allen 1998; Allen et al. 1995). It helps a manager solve routing problems in a simple transportation domain.

Tutorial discourse is different from other types of discourse, including problem solving and advisory discourse, in that it should facilitate student understanding rather than help formulate a plan of action. In a cooperative problem-solving situation both machine and human try to solve the same problem using their respective knowledge and abilities. The system we will build should understand domain knowledge and reason about the state of the student's presumed knowledge. Questions in the tutorial dialogue will be used to diagnose student understanding and then provoke knowledge construction. Another prominent characteristic is that the student may not be familiar with the concepts being discussed or possibly even the vocabulary being used.

Existing intelligent tutors can analyze student behavior and customize their responses (e.g., generate a specific learning opportunity or produce an appropriate hint) based on inferences about student knowledge and prior actions (Eliot and Woolf 1995, 1996; Beck et al. 1997; Beal et al. 1998). In several cases these intelligent tutors are used in higher education or grade schools with thousands of students.

Comparison to Existing Dialogue Tutors

TheTRAIN-Tutor system will differ from other dialogue systems in that it will accept and generate spoken language input and output. Therefore it will be particularly useful for tutoring dialogue and helpful for younger students. Additionally, it will be knowledge-based, having full natural language parsing, understanding, planning and generation systems. It differs from Auto-Tutor, based on Lexical Semantic Analysis (LSA), primarily in that it keeps track of the history of the student and does not require large numbers of training. For each new domain, LSA requires numerous essays or dialogues to be encoded and compared with input students. For example to encode 3 topics, 175 pages of student protocols or 1,000 items per topic might be encoded. LSA does not handle dialogue, does not track focus of attention and does not resolve anaphoras. Circsim-Tutor, another dialogue tutor, only handled small input sentences and relied on shallow processing (e.g., classifying the input sentences by recognizing key words). It was effective only for evaluating content based on inclusion of relevant vocabulary. Atlas-Andes has full pedagogical knowledge and possibly deeper natural language knowledge than Circsim, but it does not yet handle complex dialogues.

Our goal is to support a deeper level of analysis and to identify complex relationships between concepts in longer student answers. We intend to support collaborative dialogue between the student and tutor, to understand sub dialogues and to recognize when new beliefs are adopted by the student. We plan to use discourse coherence principles, that is, to structure and take advantage of the focus of attention as it shifts through the conversation. Tracking the focus of attention is necessary for generating coherent student tutor dialogue and for pronoun or anaphora interpretation and generation.

Dialogue Tutoring for Arithmetic Problems

The TRAINS Dialogue system will be integrated with AnimalWatch, which provides adaptive and effective mathematics instruction for grade school children (Arroya et al. 1997; Beck et al. 2000). The dialogue system will speak to the student when he or she has trouble solving a problem. Currently the tutor initiates an interaction and provides customized hints to help the student work through a problem. The student model maintains an accurate assessment of the student's strengths and weaknesses, has a record of his or her cognitive development and helps 1) generate appropriately difficult problems and 2) respond to the student's errors with feedback tailored to her or his needs. Machine learning techniques are used to select the problem and help, based on the experience of hundreds of previous users, (Beck et al. 2000). Multimedia is used judiciously to engage the student by animating key concepts and providing interactive manipulables based on those used by classroom teachers. Math problems are not "canned" or pre-stored. Rather, hundreds of problem templates are used to generate novel problems "on the fly."

Evaluation studies showed that students responded differently to help and feedback. For example, highly adaptive feedback is especially important to girls (Arroya et al. 1999). Also, both boys and girls of lower cognitive development need more hints to solve problems (Arroya et al. 1999). However, there was a strong relation between a girl's cognitive development and her view of how helpful different hints were: hints that were highly interactive (i.e., structured) were rated as significantly more helpful than less interactive hints, and were more effective (i.e., were followed by fewer errors in subsequent problems). No such relation was found for boys. Overall, results indicate that not only is adaptive feedback especially important for girls, certain specific types of feedback are preferred by girls, whereas boys do not appear to show such consistent preferences. Several evaluation studies showed significant improvements in attitudes towards math (confidence, value, liking) after students worked with AnimalWatch (Beck et al. 1999).

The TRAINS-Tutor will produce three dialogue types:

Diagnosis Dialogue. If the student provides a wrong answer, the Tutor may choose to change the direction of the dialogue, to identify missing knowledge and provide an explanation. This dialogue will be tailored to the problem on which the student is working.

Tutor: Do you know how to add fractions?

Student: I think so. You add the tops and then you add the bottoms.

Tutor: Let's look at this more closely. The first step is to check that you have equivalent denominators. Do you have equivalent denominators?

Student: Why do I need equivalent denominators?

Tutor: The denominators must be equal to ensure that you are adding similar quantities.

Hint Dialogue. The tutor will select from a large supply of hints, those most appropriate for a particular diagnosed problem. The hint will be chosen based on student gender, cognitive development, response to earlier hints, problem history, etc**.**

Tutor: Did you find the Least Common Multiple?

Student: Do you mean when the denominators are equal?

Tutor: Let me explain Least Common Multiple with an animation.

Summary Dialogue. After the tutor has given the student several hints, it will provide a summary. This is to ensure that student has correct information even if he or she provided the correct answer by simply following hints without understanding the procedures.

Student answers might be correct, wrong, near-miss or unrelated. The NLP data base can already handle affirmative, negative answers as well as partial misunderstanding, thanks to its representation of natural language. All idiomatic expressions, such as "I haven't got a clue" must be added to the lexicon.

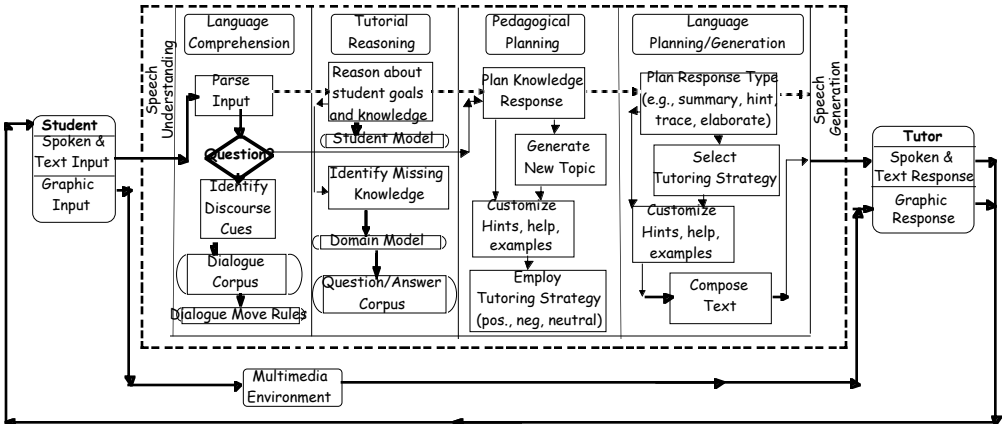
TRAINS can handle anaphora and can generally interpret the user's input within context. Thus it can recognize what part of the problem a student is referring to but from the expert point of view.

Architecture

Figure 1 provides an overview of the reasoning and representation required by the Tutor. The TRAINS-Tutor will comprehend spoken and graphical actions. During such an interaction, the **tutor** might:

- Reason about the users' knowledge or utterances, knowledge of the domain and history of interaction;
- Break down the problem to present prerequisite topics;
- Generate new topics, presenting text, graphics and spoken responses;
- Adapt its tutoring strategy, to provide more examples or graphics based on the user model;
- Supply answers requested by the user.

Figure 1: Spoken Language Tutorial Dialogue System



The **student** might:

- Respond to questions in a multimedia environment;
- Ask the tutor to illustrate a concept with a customized example;
- Comment about the teaching process or topic;
- Ask questions about problems solved;
- Question why the tutor presented the answer it did.

Natural Language Approach

The TRAINS-96 natural language dialogue system has general linguistic knowledge, including a fairly complex model of English, and already covers task-oriented dialogues. Generally, moving to a new domain does not require an author to do much work to prepare TRAINS-96. The system manages discourse history, deals with tracking focus of attention, and handles pronouns. It responds to "Why?"/"How?" questions using strategies which should work well in every domain. The difficult part, for the TRAINS-Tutor will not be in linguistics reasoning, but rather in understanding the context of the question, e.g., to which topic is the student referring.

To adopt TRAINS-96 to tutor-student dialogues we will add information about tutoring dialogues on top of existing models and dialogues and expect the process to converge quickly. The added protocols will incrementally expand the existing model. This process will not require as many encoded protocols as say LSA or the Atlas-Andies system since the basic linguistic knowledge of TRAINS-96 already covers many contingencies. It already represents procedures and fairly complex quantifiers. We will add several new strategies for answering "Why"/ "How" questions in a tutoring dialogue.

Methodology

This research will focus on issues of collaborative natural language processing (NLP) and intelligent tutoring systems. NLP dialogue research will support speech, text, graphic display, menus and pointing with a mouse (Ferguson and Allen 1998; Allen et al. 1995). The existing TRAINS-96 system uses natural language input and graphical displays to understand dialogue. By maintaining an explicit representation of its own actions (including interactions with information retrieval agents and with the human-computer interface), the NLP system can discuss information about the user's confusion or knowledge. The existing tutors have proven successful with hundreds of students, and one system (Chemistry Problem Solver) has been used with over 1400 students (Eliot and Woolf 1995;1996; Woolf et al. 2000; Arroya et al. 1997, 2000). The proposed dialogue tutor will reason about communication, ensuring that each response:

- Is properly situated (i.e., relevant to the current location of the student);
- Contains appropriate dialogue moves (i.e., fitting to the conversation context) and is sensitive to the learner's abilities;
- Is interesting (i.e., based upon clues about the student's attitude);
- Is comprehensible (i.e., within the zone of proximal development).

By viewing the learner as an essential part of the planning process, we will dramatically change the problems that are important for the ultimate successful application of planning and teaching. Towards this end, we will research and develop the following infrastructure and tools.

Representational Issues. The tutor will represent lexical meaning, deal with the problem of ambiguity, make use of information about context and find a connection between the content of the current utterance and the plan being jointly developed by system and user (Poesio et al. 1994). A wide-ranging knowledge representation formalism will be designed expressively to support many different forms of reasoning about tutoring plans. Language will support reasoning about action and presumed knowledge. The tutor will represent domain knowledge as well as both correct and incorrect teaching plans and reason about why plans might or might not fail. New representations of actions and plans will be developed that increase the expressiveness of

plan representations, especially in dealing with tutorial events and interacting overlapping actions. Particular attention will be paid to the interactions between language understanding and plan reasoning components. These two tasks will constrain and inform each other, as in problem-solving NL systems (Traum et al. 1994).

Theories of Discourse. Previous research on human tutoring has analyzed video tapes of untrained tutors in naturalistic tutoring sessions and shown that even untrained tutors with minimal common ground with their learners are extremely effective, enhance learning by .4 to 2.3 standard deviation units compared to classroom controls (Cohen, Kulik and Kulik 1982; Bloom 1984). Existing dialogue corpora of hundreds of hours of dialogue between people interacting will be evaluated to show how a mixed-initiative agenda is coordinated among participants (Grosz and Sidner 1986; Graesser, Person, and Magliano 1995; Person, Kreuz, Zwaan and Graesser 1995; Grosz 1997; Grosz and Hirshberg 1992). We will investigate why human tutors and learners have frequent breakdowns in communication, how tutors formulate pedagogical goals, and how students are corrected by tutors.

Theory of Mixed-Initiative Dialogue. A theory of tutorial discourse structure and processes will be formulated. Research shows that tutors typically set most of the agenda, introduce 95% of new topics and ask 80% of the questions (Graesser and Person 1994; Graesser et al. 1995). The dialogue theory will include the role of collaboration in dialogue processing and provide a formalization of collaboration that may be used as the basis for collaborative human-computer communication systems (Gross et al. 1983, 1987, 1989). The structure and context of human dialogue in terms of computational linguistics and dialogue systems will be identified (Grosz 1994, 1996; Gross and Sidner 1986, 1985, 1990, Gross and Hirshberg 1992; Lochbaum et al. 1990; Grosz 1994, 1996).

Natural Language Dialogue System. Speech recognition language understanding technologies will be studied along with a dialogue tutoring system based on existing technology used for expert planning (Allen et al. 1995a, 1995b, 1995c, 1996a, 1996b; 1996c). TRIPS, developed by Allen at Rochester, maintains a domain-independent dialogue-based model of the interaction which mediates between the user and diverse information agents (Ferguson and Allen 1998). The dialogue agent will interact with the user to produce effective multimedia presentations of information. Experience building natural language dialogue systems and research in computational linguistics and cognitive systems will be leveraged (Traum and Allen 1996; Allen 1994, 1993; Allen and Litman 1987; 1990).

Domain and User Models. Existing tutors use graphic user interfaces to support a student's progress through problems and scenarios and dynamically track knowledge about the domain and the student (Beck et al. 1997; Eliot and Woolf 1995). They support complex reasoning about both domain and student knowledge. The proposed NLP tutors will use language as well as the environment to reason about student knowledge, goals and errors, see Figure 1. The graphical plan representation will be independent but connected to the underlying representation of the spoken language dialogue. The type of plan recognition needed will be identified. Tutors will modify the curriculum dynamically by reasoning about the appropriate machine response, including type of example, text, animation, or explanation to provide (Beck et al. 1997; Beck and Woolf 1998; Suthers et al. 1992). We have years of experience building intelligent tutoring systems and have developed interactive plan recognizers, student models and machine learning to infer the user's information needs and mediate information gathering and reporting (Woolf and Hall 1995; Beck and Woolf 1998; Woolf 1991).

Mixed-initiative Planning. A model of mixed initiative planning for tutoring will be developed (Allen et al. 1995). Plan communication is the ability to suggest aspects of a plan, accept such suggestions from other agents, criticize plans, revise them, etc., in addition to building plans (Allen et al. 1996). A formal model of plans will be developed based on explicit objects that can be used to provide a semantic basis for statements about learning. The system will encode sophisticated plan reasoning capabilities and represent plans for mixed-initiative planning, where several participants cooperate to develop plans (Ferguson and Allen 1994; 1996). The human is considered an essential part of the planning process. Techniques will be utilized to provide additional information to a natural-language parser beyond recognition output so that it can effectively handle problems in spontaneous dialogue (Allen et al. 1996), i.e., the ability to identify and realize speech utterances (Heeman et al. 1996). Given speech input, the spoken language understanding system reconstructs the user's intended utterance: both segmenting the speaker's turn into utterances units and determining user intent. The parser will also have to correct speech recognition errors. Spontaneous speech is significantly harder to recognize than read or controlled speech. A language and channel model will be developed to correct errors committed by a continuous speech recognizer. It will also handle utterance segmentation (i.e., identifying utterance units). Work in traditional speech recognition techniques, simple models of prosodic feature detection, language models and traditional parsing techniques will be used (Allen et al. 1996). Stochastic techniques will be used to predict likely recognition errors, speech repairs, and prosodic features. This informantion will be passed on to the parser which determines the best interpretation.

Authoring Tools. Using a high degree of modularity and keeping system knowledge distinct from system implementation will improve the usability and replicability of our dialogue methodology. Authoring tools will be developed to produce additional spoken dialogue tutors in a variety of domains and to replicate the development process. Necessary resources and tools will be identified to

allow developers to create a suite of dialogue tutors using our modules and processes. In support of this goal and to provide valuable feedback on the methodology, we will reveal problems, technologies and portions of the process that must be improved.

Discussion

Fundamental scientific contributions will be made in computational linguistics, artificial intelligence and education. In computational linguistics, behavioral and linguistic analysis of dialogue will be explored to discover key structural characteristics and identify factors to predict teaching effectiveness; discourse processing will be studied to emulate language behavior of human tutors; and speech recognition/generation and language understanding will be integrated using deep knowledge about a student and discourse. Efficiency issues in natural language dialogue will be addressed by developing a set of reasoning algorithms for handling very large-scale knowledge bases. We will extend our ability to represent and reason about discourse, domain and student knowledge. We will need to improve the naturalness of generated tutorial speech and enhance our knowledge about authoring modules to facilitate development of components for intelligent dialgoue tutors in a variety of domains. New representations of knowledge and plans will be developed to increase the expressiveness of plan representations, especially in dealing with presumed student knowledge and interacting overlapping actions. And finally, we will address the problem of developing plans in the real world by defining a model of mixed-initiative planning using an interactive dialogue-based model of plan management. Spoken language tutoring has tremendous potential to improve education and training. Teaching requirements have increased in a technological society while available training decreased (Regian 1998). Citizens require more complex intellectual and technological knowledge while traditional teaching opportunities continue to be ineffective (Fletcher 1996). More robust training solutions are needed. Dialogue-based tutors will enable trainees to more realistically explore concepts and procedures within simulation environments. Interwoven dialogue and graphic manipulables will provide realistic practice, procedural guidance, navigational directions and supplemental information.

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