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Question-Asking vs. Model-Tracing Tutors in Dialog-Based Educational Systems

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Abstract: - In this paper, we study the advantages and disadvantages between question-asking and model-tracing tutors. Our analysis is based on parameters acquired from some of these systems, the most important ones, such as natural language understanding mechanism, interaction - dialog managing - , and responses - natural language generation. We use tables and schemes to classify and compare these systems. The analysis results show that (a) a significant factor for the configuration of the interactions between students and tutors is the fact that the usage of dialog is much more effective than the presentation of hints, (b) most important of the two types – deep and shallow analysis - of natural language understanding is proved to be the hybrid method and (c) asking from the students to write down explanations for the steps in their proofs has a significant impact on the development of an effective learning strategy.

Key-Words: Natural Language Understanding, Dialog Manager, Natural Language Generation, Self-explanation, Dialog-Based Education

1. Introduction

E-learning environments provide facilities mainly for helping course generation and management and refer to both the tutors and the students. Adding facilities (intelligent or not) for tutors in WBIESs make them a kind of intelligent e-learning systems (IELSs) [1]. Additionally understanding natural language student responses has been a major challenge for ITS's. Approaches have ranged from encouraging one-word answers to full syntactic and semantic analysis of the responses [2].In this work we attempt to classify and compare Intelligent Tutoring Systems as it concerns the effectiveness of their learning strategy, separating these systems in two main categories (a) Question-Asking Tutors (b) Model-Tracing tutors and a third one that is conducted from the previous two (c) Model-Tracing Tutors with Dialog that appears to be some kind of combining the advantages of the two main categories replacing the presentation of hints with a tutorial dialog – breaking down problems into smaller steps - managing the misconceptions of the students.

Our aim in this study is to examine and categorize the ITS that already exist in order to build our ITS (Fig. 1) that will concentrate to the most effective strategies of these systems. So, we analyze mainly three parameters (a) the Natural Language Understanding, (b) Dialog Manager and (c) Natural Language Generating components.

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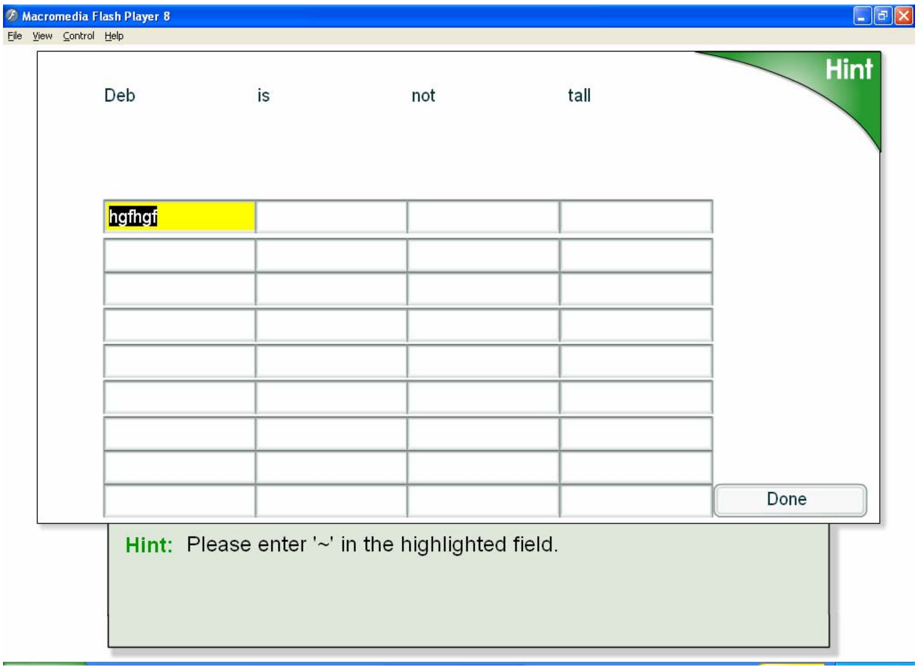

Fig. 1: Converting Natural Language to FOL.

The systems that we analyze belong in a lot of domains like Mathematics (PACT Geometry Tutor, [Aleven, et al., 1999] E-Tutor [www.wpi.edu/~leenar/E-tutor]), Electronics (BE&E, [Tutor Rose, Di Eugenio, & Moore, 1999]), Computer Literacy (AutoTutor, [Graesser et al.], RMT – an Autotutor child –), Programming Languages (JITS [Sykes and F. Franek]), Medical Diagnosis (CIRSIM, [Woo et al., 1991; Zhou et al. 1999]), Physics (ATLAS [Freedman, 1999])-Andes Tutor, [Conati, Gertner, VanLehn, & Druzdzel, 1997; Gertner, Conati, & VanLehn, 1998;VanLehn, 1996] and e-commerce (Happy Assistant [Joyce Chai, et al.]).

2. Natural language Understanding

2.1 Question-Asking Tutors

In our study we examined AutoTutor (Fig. 2), a question-asking Tutor that presents all domain knowledge as vectors and it doesn’t try to understand the student’s utterances completely but instead of that it uses the shallow statistical approach – LSA -, a method based on similarity between the student’s utterances and ideal answers that pre-exist in a large corpus of text. The two most common relatedness are the cosine math and the dot product. The advantages of this method are (a) Lexicon is built automatically and (b) Aspects – ideal answers – are just natural language that a trained – non programmer – domain expert can enter. As a disadvantage we can refer the fact that “X causes Y” is the same as “Y causes X”.

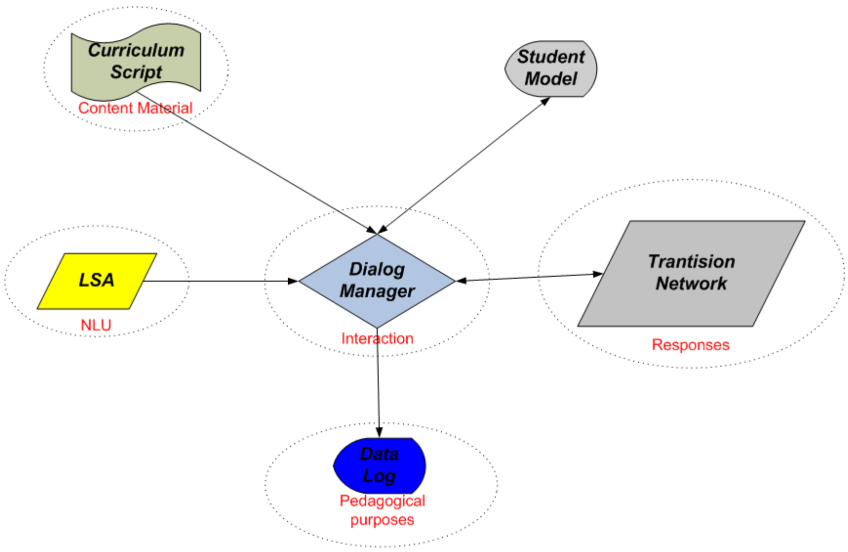

Fig. 2: Autotutor Architecture

On the other hand another question-asking tutor CIRSIM uses deep – based on compositional semantics (syntactic parse tree, semantic structure) - and shallow analysis based on statistical techniques of student's utterances but it allows only short answers in order to use keyword lookup. The system tries first compositional approaches and if it fails to analyze the student's explanations then light parsing is tried. Compositional NLU is implemented by two modules a parser and a semantic interpreter which also handles discourse integration.

The light parsing that Autotutor uses allows to the system to be fast enough to be web-based using an impressive interface constituted from a Talking Head (a Microsoft Agent that incorporates some important properties of a pedagogical agent). Pedagogical agents have the added burden of facilitating the learning process. The parameters of the facial expressions and intonation are generated by fuzzy production rules.

2.2 Model-Tracing Tutors

There are two main categories in the Model-Tracing Tutors (a) the standard cognitive tutors (Fig. 3) where tutors provide context-sensitive hints on students' request and (b) model-Tracing Tutors with Dialog (Fig. 4) where instead of presenting hints, tutors begin a dialog based on student's errors.

A more sophisticated model-tracing tutor in the domain of Geometry is PACT Geometry Tutor where students write down explanations for the steps in their proofs (self-explanation is an effective learning strategy). Tutor provides context-sensitive hints on students' request and decides also when to advance a student to the next curriculum section. Tutor uses the hybrid approach (Tutor relies primarily on a Knowledge-based approach and when it fails uses a statistical text classifier).

Another Tutor in the area of Mathematics is E-Tutor. It's a production rule system that uses techniques like working memory, rule memory and "match-conflict resolution-act" cycle. There are two versions of E-Tutor with and without hints.

In the area of Electronics BE&E Tutor uses compositional semantics as Natural language understanding mechanism and provides feedback and hints.

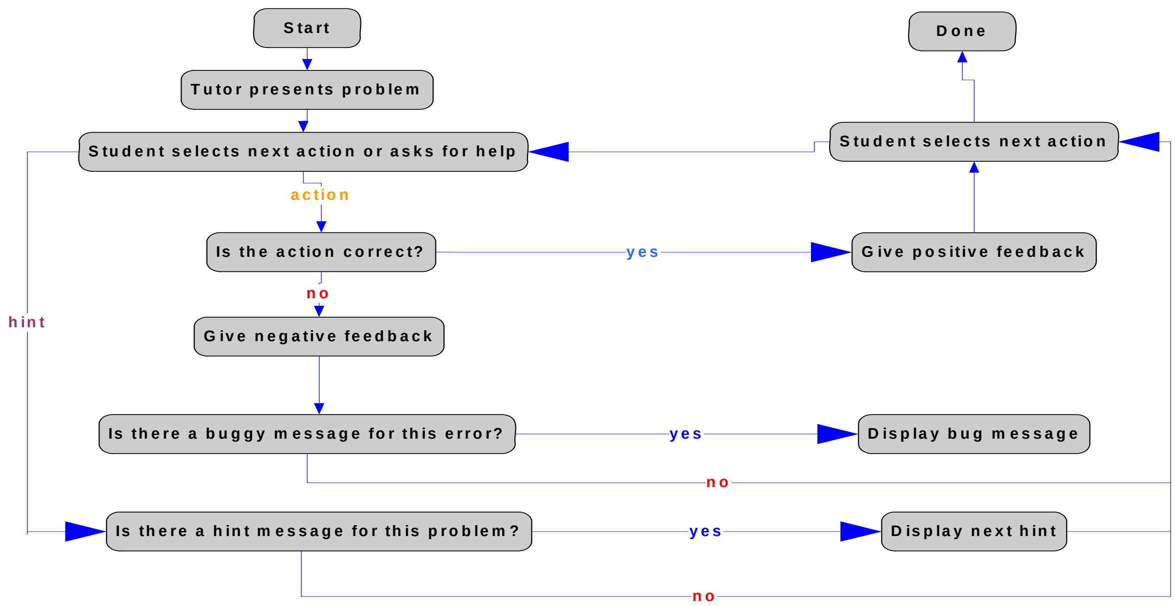

Fig. 3: Model-Tracing Tutor

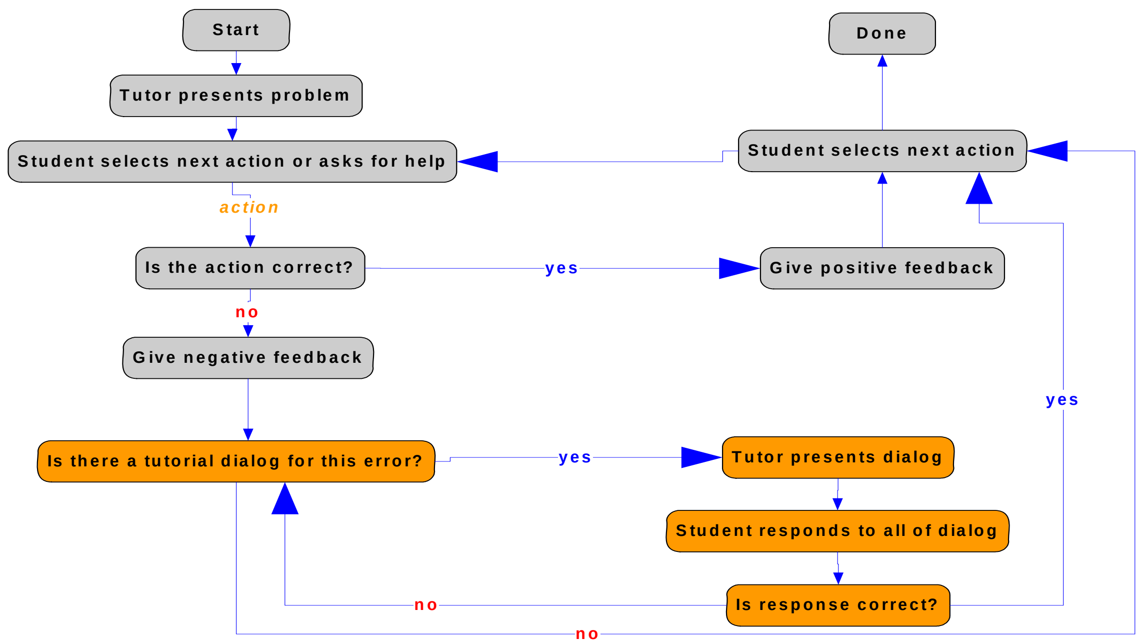

Fig. 4: Model-Tracing Tutor with Dialog

3. Dialog Manager (Interaction)

3.1 Finite-state Dialog Managers

Finite-state dialog managers keep track of either history or future goals of a dialog and use transition network (Fig. 5) parsers to analyze student's utterances. A transition network parser is defined using two mutually recursive functions, ***parse*** and ***transition***. Parse takes a grammar symbol as argument and if it is a terminal – i.e. a word in a sentence -, parse checks it against the next word in the input stream. If it is not a terminal – i.e. a sentence, noun-phrase, verb-phrase etc. -, parse retrieves the transition network associated with the symbol and calls transition to find a path through the network. Transition takes a state in a transition network as an argument and tries to find a path trough that network in a depth-first fashion.

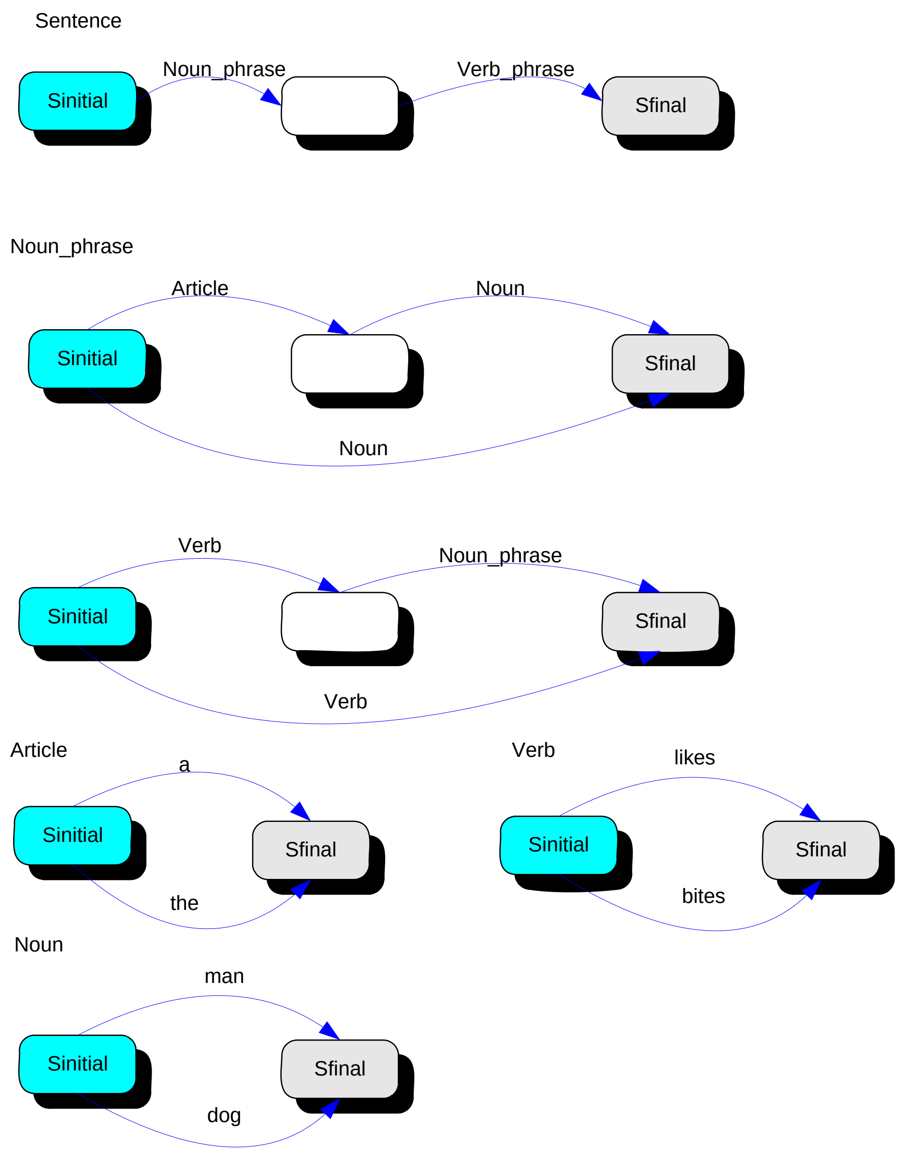

Fig. 5: Transition Network

BE&E Tutor uses a finite-state dialog manager (not usual for compositional semantics NLU) to replace the usual hint sequences with a natural dialog.

Autotutor uses also a finite-state dialog manager with mixed-initiative techniques (as impression) in order to keep prompting and guiding the student for more and more explanations.

CIRSIM and Atlas-Andes Tutors use similar finite-state dialog managers to replace the usual hint sequences with a natural dialog. Dialog-generation techniques handle nested dialogs, drop one sub-dialog and replace it with another, add or delete topics from the agenda and generate dialog to fix errors.

3.2 Dialog planning managers

Dialog planning managers produce a single plan that is not changed during execution. When these planners are reactive keep track of unsatisfied goals and can revise their goals after student's turn.

Pact Geometry Tutor and E-Tutor use planning dialog managers in order to present a tutorial dialog in student's errors, breaking down problems into smaller steps and providing them with canned explanations while they don't have hint buttons at all. These explanations are providing (a) through menus (b) through Natural Language engaging Dialog and (c) through natural language engaging Dialog with Feedback to help students generate better explanations.

Another special category there is e-commerce sites that use Natural Language Dialogs. We studied HappyAssistant (Fig. 6) a hybrid forward and backward chaining rule based system for matching.

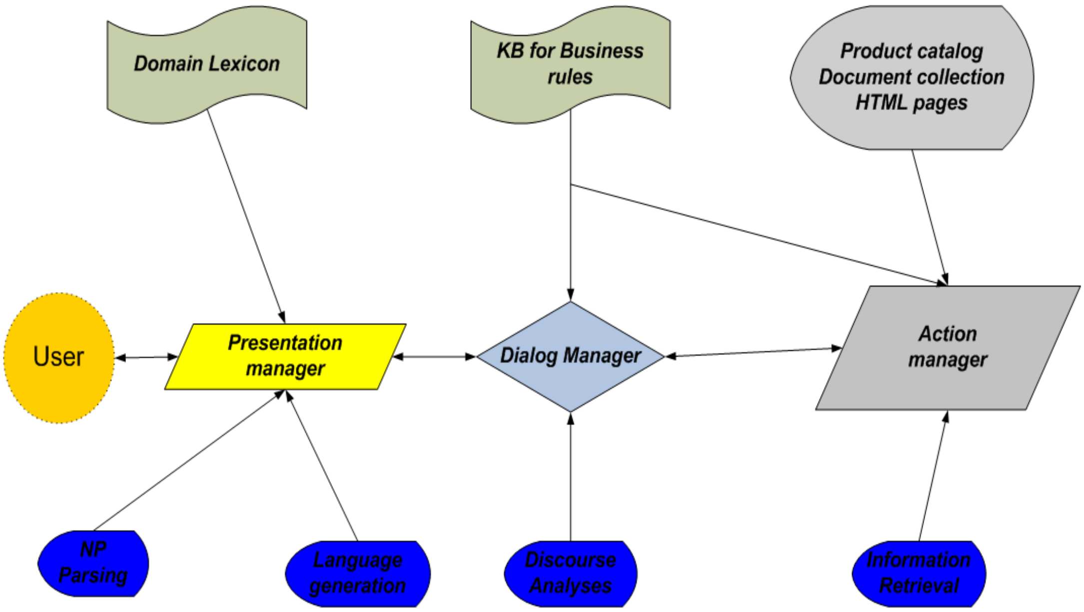

Fig. 6: HappyAssistant Architecture

Dialog manager uses limited language analyses, only for noun phrase parsing and simple language generation while apply business specific policies via business rules knowledge base to translate user's requests to action plans sent to action manager. The interface of this system is multimodal supporting textual input for testing, speech over a phone, speech over a microphone, mouse input and data glove.

4. Natural Language Generation

The NLG module is responsible for the responses that the Tutor gives to the student's questions. It applies techniques like content planning (an overall plan for the dialogue), turn planning (organizing a single tutorial turn) and surface generation (outputs text, adds syntactic and semantic structures to the discourse history, getting plurals and tenses right).

AutoTutor use Transition Network method to represent its explanations while BE&E's NLG component (BEETLEGEN) synthesizes English text from logical forms using hybrid generator combining a template-based approach with grammar-based processing.

5. Conclusions

The results from our study that we try to embed to our prototype system are (a) a significant factor for the configuration of the interactions between students and tutors is the fact that the usage of dialog is much more effective than the presentation of hints , (b) most important of the two types – deep and shallow analysis - of natural language understanding is proved to be the hybrid method and (c) asking from the students to write down explanations for the steps in their proofs has a significant impact on the development of an effective learning strategy.

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