Negotiation-Driven Learning

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Abstract. Negotiation mechanisms used in the current implementations of Open Learner Models are mostly position-based and provide minimal support for learners to understand why their beliefs contradict with that of the system. In this paper, we propose the paradigm of Negotiation-Driven Learning with the aim to enhance the role of negotiations in open learner models with special emphasis on affect, behavior and metacognitive abilities of the learners.

Keywords: Intelligent tutoring systems · Open learner models · Negotiation · Metacognition · Affect · Learner behavior · Interest-Based negotiation

1 Introduction

The paradigm of Open Learner Models (OLM) was introduced in Intelligent Tutoring Systems in order to involve the learner in the overall learning experience [1,11]. OLMs provide learners with the opportunity to view and edit their Learner Models (LM). This is done in order to provide transparency and increase learner's trust in the system. Allowing the learner to edit their LM resulted in scenarios where the learner's belief about their own knowledge is different from that of the system. Such events trigger an interrupt where the system tries to negotiate the changes made by the learner in an effort to remove the difference of beliefs. The aim of this negotiation is to increase the accuracy of the system's LM [2,12].

The underlying principle of negotiation in current OLMs is to *"test"* whether the learner can justify the change they made to their LM. The system deploys a direct questioning strategy to test the learner's knowledge and the results are used to update the LM accordingly. Although this strategy of OLMs has shown to produce significant learning gains, the negotiations in OLM follow a very Position-Based Negotiation (PBN) [3] approach, since the dialogues primarily focus on the *"positions"* held by the learner. This strategy of negotiation is often challenging because as the negotiations advance, the negotiating parties become more and more committed to their positions and without any information about why a certain position is held by the learner, any agreement that is reached produces unsatisfactory results.

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In OLM implementations, the affective and behavioral states of a learner are mostly ignored. A vast body of research shows that expert human-tutors are successful as they try to engage students according to these states, which provides a sense of empathy and encourages learner involvement [5]. The negotiations in OLM are confined into the scope of *"testing"* with little cues about the learner's states, which results in a disengaging partial negotiation.

Although improving the metacognitive abilities of the learner has always been a key role of OLMs [13], the current OLMs rarely scaffold the metacognitive processes. Since the system is actively involved in testing the learner about their knowledge, how they are reflecting or evaluating themselves is mostly left on the part of the learner. The system does not explicitly involve the learner into a discussion that can motivate them to practice these skills more actively.

A conflict may occur because the learner may be confused about their knowledge, or simply have a misconception which leads them to change their LM. The system challenges the change made by the learner and requires them to justify himself. This creates an interesting prospect to involve the learner into a discussion about their belief and what led them to believe so. Humans become stronger advocates of their beliefs once they are challenged and are intrinsically motivated to defend their beliefs [10]. This provides an excellent opportunity to involve an intrinsically motivated learner in a deep learning dialogue which not only tests their knowledge but also encourages them to reflect upon their own thinking. In order to capture this opportunity and make use of the context, we propose a paradigm of Negotiation-Driven Learning (NDL).

Learning is maximized by proactive participation of learners; we believe that such a context is ideal to engage a learner in a dialogue that explicitly targets the metacognitive skills of the learner and provides them the scaffolding to utilize and enhance these skills. Research on the effects of using learner's affective and behavioral states to shape negotiations has shown a positive impact on the overall learning gains [6]. However this has been missing in the context of OLMs. In contrast to the current implementations of OLMs which undermine the negotiation by using it as a testing tool, in NDL we aim to exploit the utility created by the occurrence of a conflict by engaging a learner according to their affective and behavioral states. The rest of the paper is organized as the follows; Section 2 introduces the paradigm of Negotiation-Driven Learning. Section 3 discusses the design of dialogues in NDL. Section 4 illustrates the approach with a case study and Section 5 concludes the paper.

2 Negotiation-Driven Learning

This paper proposes a learning paradigm of Negotiation-Driven Learning which aims at *"enhancing"* the role of negotiations in OLMs to facilitate constructive learning. When a learner is involved in a learning exercise, they are not only learning something new, but they are also implicitly involved in learning how to learn. More often than not they are more inclined towards executing well-practiced strategies rather than monitoring themselves. NDL aims at encouraging learners to use these metacognitive skills more actively and effectively.

NDL acts as a component of the ITS which is triggered when a conflict between the beliefs of the system and the learner occur. During its interaction with the learner the system tries to understand why the learner holds a certain belief (cause of the conflict) and tries to help them understand why it might not be true. The system uses the information about the learner's affective and behavioral states to engage them more actively. An NDL dialogue session is concluded when the learner is able to defend their claim, or shows an understanding of their incorrect belief by accepting the system's justification/proposal. The system's LM is updated with the outcome of the dialogue and the ITS resumes the normal course of tutoring.

2.1 Generating Dialogues in NDL

Unlike most OLM implementations, NDL allows learners to interact with the system in an open environment. In order to accomplish this, the system follows the negotiation protocol proposed in [7] to allow the learner to provide justification of their change. The justification provided by the learner is challenged by the system if it contains an incorrect idea. The system then initiates a reasoning process which is used to understand the motivation behind the change made by the learner. The system and the learner have equal rights to accept or reject a justification provided by the other party; therefore the system needs to be capable of deploying an alternative strategy in case a learner rejects its proposal/justification.

2.2 Facilitating Metacognitive Skills

Facilitating metacognitive skills has been the core of recent research on ITSs and OLMs. It has been shown that learners who are good at using their metacognitive skills perform better than those who are unable to use such skills actively. NDL emphasizes the importance of actively using and enhancing these skills during an interaction between the learner and the system. Fig. 1 shows the dialogue session after a few dialogue moves encompassing domain-specific reasoning. Once the learner is able to answer the domain specific questions to an acceptable standard, the system requires them to summarize their answers and reflect upon how they were able to improve them.

The dialogue session in Fig. 1 highlights how NDL is different from the current implementations of OLMs. At the end of a dialogue session, the system explicitly encourages the learners for self-assessment. This is the time when the learner feels confident about their knowledge and is able to use this understanding to cognize where he was wrong. Engaging the learner to reflect upon the task and evaluate their final answers with respect to their initial answers encourages self-reflection.

2.3 Identifying Learner's States

All ITSs aim to engage learners to maximize learning; however a learner's engagement highly depends upon the affective and behavioral state they are in [4].

T: Great! Now can you summarize your answers in one paragraph?

S: A Stack is a Data Structure that uses the First In Last Out scheme. It allows us to put an element on the top of the stack by using the Push function. We can only remove the Top element of the stack by using the Pop function. When an element is popped it reduces the size of the stack, so it has one less element.

T: Good job! Do you see the difference between the flow of logic in your initial answer and the last answer?

S: Yes! My first answer was not complete. I think I missed out some important details. The last answer looks much more complete and I think it covers the important points about a stack. I think it is a proper definition of a stack.

T: Why do you think you were not able to come up with a complete answer the first time?

S: I thought that was a complete answer. But now I realize that it wasn't. I think I was not sure about the requirements of your question. But as you asked me further questions, I realized that I had only given a partial answer. I knew what stacks are, but I was not able to synchronize the details. When you asked me to summarize my answer, I realized that I had known all the details about a stack, but I was not able to combine them into a complete answer.

Fig. 1. Envisioned NDL dialogue

If a learner is in some sub-optimal state, the system needs to diagnose such states in order to help a learner move into an optimal state that is more conducive to learning. When a learner is in an optimal state of learning, they are more focused and learn better. Hence the system needs to ensure that such a state is maintained. There is an abundance of literature on modeling affect, metacognition and behaviors with varied conflicting views. However it is agreed that an exact estimation of such states is not required in practice as the main focus of an ITS is to improve the cognitive state of a learner, and the knowledge about these states support the system in its reasoning process [6]. The outcome of an interaction between a learner and the system highly depends upon the affective & behavioral state a learner is in. It is to say that the process of learning requires the learner to be interested, motivated and confident to engage in a productive discussion with the system. Table 1 shows a list of Affective & Behavioral states that are used in NDL in order to model the affective state of the learner. These states have been selected from previous research on the subject [4,6]. These are not the only states that affect the learner and the selection of these states may be argued but as pointed out earlier, these states have been shown to provide a good approximation of the learner [4]. The precision of modeling these states is not of principal importance, but an approximation of these states can allow the system to engage the learner more actively.

2.4 System Architecture

As discussed earlier, the use of a PBN like approach in OLMs confines the scope of negotiations. As an alternative to PBN, we propose the use of Interest-Based Negotiations (IBN) [3] in NDL. IBN aims at exploring underlying interests of the parties rather than their negotiating positions and considers negotiating

Table 1. Affective & Behavioral States of learner in NDL

Affective States

Confusion	Poor comprehension of material, attempts to resolve erroneous belief
Frustration	Difficulty with the material and an inability to fully grasp the material
Engagement	Emotional involvement or commitment

Behavioral States

POSITIVE STATES	NEGATIVE STATES
Confident	Unconfident
Motivated	Demotivated
Interested	Uninterested

parties as allies working together for mutual gain. Since in NDL, we are not only concerned with testing a learner but also helping them understand how they learn. For this the system needs to be able to understand the underlying goals/beliefs of the learner. Therefore IBN is more suited in such a scenario. In order to realize the envisioned interactions in NDL we extend the computational model proposed in [8] on the automation of IBN. Our system consists of the following functional components:

- *State Engine*: handles all the state related tasks. It generates the State Model (SM) for the learner by translating learner inputs to the corresponding affective, behavioral and metacognitive states. The SE updates all these state in real-time with each transaction. It also stores previously held states of the learner to understand learner progression.
- *Reasoning Engine*: uses the information from the SM in conjunction with the LM in order to select the next system move with the maximum utility. It consists of a *Context_Analyzer* submodule which uses the information from the SE and the DE in order to articulate the current context.
- *Dialogue Engine*: this is the core module for providing a Natural Language interface to the learner. NDL does not require a complete NLP understanding as we are interested in the concept-level cognition of the learner's input. To accomplish this, the DE consists of submodules which include; i) *Concept_Classifier*: uses a minimum-distance matcher to return a list of concept identifiers that most closely match the learner input. ii) *Normalizer*: manages stemming and spell checking for the learner input. iii) *History_Manager*: stores information about the concepts used by the system and the concepts expressed by the learner. This information is passed to the RE, which uses it to classify the current context. iv) *Sentence_Generator*: uses the concepts identified along with the current context to generate a list of possible utterances of the system. These possibilities are matched with the library of template phrases and the best matching phrase is selected to generate sentences automatically.

– *Plan Base*: holds the different negotiation moves available to the system according to the current context. The information regarding the consequences of using a move in a specific context and state are used to update a move's adequacy to that context in the PB.

3 Designing Dialogues for NDL

Realizing an interaction such as the one shown in the Fig. 1 requires that the system not only understands the learner's characteristics but is also able to comprehend their answers to provide a proper response. In order to understand the typical learner response to system stimuli and their relationship to the current context, a Wizard-of-Oz (WoZ) experiment was conducted. The WoZ approach has been shown to be valuable for collecting data in scenarios which require complex interactions between the users and the systems [9]. Since in the WoZ experiments, users are under the impression that they are interacting with a system, many application-specific characteristics of a textual dialogue can be elicited.

3.1 Experimental Setup

The study was conducted with the students of Bahria University, Islamabad, Pakistan. A total of 45 students from semester of the Software Engineering course participated in the experiment. All participants had completed the compulsory courses of computer programming (C++, OOP, and Data Structures) as a course requirement. The participants were given a short introduction to ITSs and an initial survey was conducted to understand their expectations from such a system. The participants were provided with a web interface to interact with the system. All interactions between the system and the participants were logged and the interaction transcripts were stored for future analysis. Once the participants had completed their sessions with the system, another survey was conducted to get their feedback about the system and the interaction possibilities it provided.

3.2 Results

The interaction logs and the conversation transcripts form the WoZ experiment were transcribed and analyzed in order to understand the kind of dialogues the participants engaged in with the system. In the 45 conversations between the student's and the wizard there were a total of 195 negotiation fragments. The number of user initiated conversations was 80. The mean interaction time was 27.4 minutes. Off-topic discussions or small talk constituted 13.4% of all conversations. 45.6% of the conversations were related to domain-specific discussions while the remaining 41% conversations constituted the inputs used to approximate learner characteristics. These inputs were analyzed to generate a list of possible markers in the input that identified the learner's current state.

To ensure transparency in selecting the specified states, learners were also requested to mark their inputs from a list of given states periodically. Analysis of these choices showed that the states identified in NDL were used majority of the time by the learner to define their current situation.

Inputs Related to Affective. The inputs provided by the learners were transcribed to corresponding possible affective and behavioral state. Learner responses were translated to correspond to specific category of affective state. Table 2 shows a list of learner inputs and their corresponding affective state.

Table 2. User inputs and corresponding affective states

User Input	Affective State classified
I don't understand	Confusion
No, I still don't understand	Confusion, Frustration
I don't know	Confusion, Frustration
I don't need your help	Frustration
What is this?	Confusion
How?	Confusion
I can't do this	Frustration
Wow, I did it!	Engagement
Yes, I think I got it	Engagement
I know it	Engagement

Inputs Related to Behavioral States. User inputs were also used to identify the approximate behavioral state of the learner. As with the affective states, an approximation of the behavioral states were considered to be sufficient for the purpose of this study. Table 3 shows a list of learner inputs and corresponding behavioral states.

Table 3. User inputs and corresponding behavioral states

User Input	Behavioral State
Yes I know	Confident
Ok, Yes, Yeah sure, sure, Yeah (context dependent)	Motivated, Confident
I want to discuss this	Motivated, Interested
No (context dependent)	Uninterested
I'm not sure	Unconfident
I don't think so..	Unconfident
I don't want to…	Uninterested
I can't do this	Demotivated
I want to solve this	Motivated
Can you help me?	Interested
Let's talk about something else	Uninterested
Not now	Uninterested

4 Case Study

The data collected in the WoZ experiment helped us in indentifying the different state-transitions that are likely to occur during a dialogue session in NDL. Using the states identified in our experiment and their relations with learner inputs we envision the following generalized dialogue in NDL. The example describes how the system classifies a learner utterance and uses this information to generate a corresponding feedback. Consider an arbitrary time t where the system has the following parameters, State Model (SM){Affective State (AS), Behavioral State (BS) and Metacognitive State (MS)} in the working memory (WM):

$$WM(ASprevious\{..\}, BSprevious\{..\}, MSprevious\{..\}) \tag{1}$$

The system identifies a conflict and interrupts the current interaction with the following question:

`T: You just updated your belief in your knowledge about Stacks to "high". I am afraid I do not agree with your assessment. What made you change your belief?`

The learner responds with the following:

`S: I just completed the section on Stacks. I know what stacks are now!`

This statement is interpreted by the system as follows:

– The learner has confidence in their belief about their knowledge. (**Confident**)

The SE updates the WM as:

$$WM(ASprevious\{..\}, BScurrent\{Confident\}, MSprevious\{..\}) \tag{2}$$

The RE infers that the learner is confident; hence provides them with an overview of their performance in order for them to understand why their claim might be wrong.

`T: That's good! But you did not perform well in your test on Stacks! You answered 05 questions and got 02 answers correct.`

A confident learner would take this opportunity to justify why they could not do well. The learner responds:

`S: Yes I know that! I don't understand why I couldn't get more correct answers. I completed the whole topic!`

This statement provides the following information:

1. The student is aware of his performance in the past test. This shows they have **evaluated** how they have performed the task. (**Evaluation**)
2. The student doesn't **understand why** they couldn't perform better.(**Confusion**)
3. The student showed effort to complete the whole topic. (**Motivation**)

The WM is updated as follows:

$$WM(AScurrent\{Confusion\}, BScurrent\{Confident + Motivated\},\\ MScurrent\{Evaluation\}) \tag{3}$$

The system infers that this is a *positive* situation since the student is motivated and has shown his ability to deploy metacognitive skill.As this is a positive situation where the student is confused, the next move t+1 by the system provide feedback that encourages the student to go over the topic again in order to clarify any misunderstandings. Hence the move t+1 is:

`T: Maybe you need to revise what you have just learned. Do you want to discuss the topic with me? We can try to improve your understanding of the topic.`

`S: Yeah, I would like to do that.`

When the learner accepts the systems advice to revise the topic shows that they are interested in discussing the topic. Hence the WM would be as follows:

$$WM(AScurrent\{Confusion\}, BScurrent\{Confident + Motivated + Interested\},\\ MScurrent\{Evaluation\}) \tag{4}$$

This creates an "ideal" situation where the learner attributes are all positive while their affective state is that of confusion. The RE selects the "comprehension gauging questions" to help the learner understand their knowledge gaps. The system provides the necessary scaffolding to the learner to help them remove any misconception of incorrect knowledge.

Once the learner is able to answer the system's questions, the system engages them in explicit metacognitive tasks. The learner is asked to summarize their discussion with the system and reflect upon how they were able to improve their answers. This is done entirely to promote self-reflection in learners and to encourage them to evaluate themselves at the end of each interaction.

5 Conclusion

OLMs have deployed different strategies of negotiation to improve the accuracy of the learners LM. Most of these implementations follow a PBN approach that restricts the role of negotiation as a means of testing the learners knowledge. In this paper we proposed a paradigm of Negotiation-Driven Learning which follows the notion that learning is maximized by learner participation by exploiting good opportunities provided by negotiation in OLM contexts. While OLMs confine the scope of negotiation, NDL builds on this by approximating the different affective & behavioral states of a learner, to generate engaging dialogues that explicitly target the learners metacognitive skills.

We specified the system architecture and provided an overview of the modules responsible for handling different aspects of the interactions. Providing a NL interface to learners can ease the communication process but adds to the overall complexity. NDL does not require a complete NL understanding therefore to keep this complexity to a minimum; we used the minimum-distance classifier which has been widely used for pattern recognition because it is simple and fast as compared to other complex classifiers. Automatic sentence generation was made possible by merging the template phrases with the concepts and context of the current interaction. We conducted a case study to illustrate the feasibility of how the NDL system will be able to generate the envisioned dialogue. We are currently acquiring rules for handling the envisioned dialogues by analyzing the logs generated by WoZ experiment.

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