Towards the Application of Argumentation-based Dialogues for Education.

Elizabeth Sklar
Department of Computer Science
Columbia University
New York, NY 10027 USA
sklar@cs.columbia.edu

Simon Parsons
Department of Computer and
Information Science
Brooklyn College
City University of New York
Brooklyn, NY 11210 USA
parsons@sci.brooklyn.cuny.edu

Abstract

This paper describes our work constructing a generalized framework for modeling multi agent interactions in education-related applications. Historically, interactive learning systems are highly engineered to the particular knowledge domain to which they are applied, often using scripts to guide interactions between agent tutors and human learners. We are motivated to explore a more general methodology for interactions, moving beyond a traditional scripted model and following the general trend in human education towards more open, learner-centered, constructivist environments. In order to accomplish this, we need a framework in which to define general types of interactions that can occur between a learner and a tutor, as well as interactions between these agents and their sets of beliefs — not only about the knowledge domain that is the subject of the learning system, but also about each other. In this paper, we describe early work in this direction, which involves using argumentation and extending existing dialogue protocols to allow for various types of tutor-learner interactions.

1. Introduction

We are interested in constructing a generalized framework for modeling multi agent interactions in education-related applications. Currently, we are working on two such projects. One is traditional in the sense that it concerns building agents to interact with human learners in a web-based interactive learning environment [23]. The other involves modeling the education system as a multi agent simulation in order to be able to demonstrate and explore the types of interactions and interplays that occur between teachers and students in classrooms, principals and teachers in schools, superintendents and teachers in school districts, and so on [24]. Although fundamentally different in terms of who will use and directly benefit from each system, there is an underlying commonality in both projects — the inherent need to understand and be able to simulate the way that learners interact in educational environments.

Historically, interactive learning systems (ILS), in general, and intelligent tutoring systems (ITS), more specifically, are highly engineered to the particular knowledge domain to which they are applied [4, 5]. As well, interactions in these systems are highly tailored to the designers' notions of who the users (students who use the system) are, their needs and background in the system's knowledge domain . More recent work has involved the use of *pedagogical agents* as a means of providing more flexible interactions between human learners and the computer tutoring system [1]. Some of these agents are modular in that they have been injected into different learning environments and only require re-scripting in order to be effective in a new domain [9]. However, these agents still follow scripts and these scripts restrict behavior patterns on the part of the agents as well as the learners, in addition to being highly domain dependent.

We are motivated to explore a more general methodology for interactions, beyond a traditional scripted model. Following the direction of education over the last 30 years, there is a general trend towards learner-centered learning, where the learner takes the initiative and the teacher (or tutoring system, for that matter) offers support but not the same kind of teacher-centered instruction that had been used previously [8, 20, 17, 13, 7]. In a learner-centered environment, the learner actively takes the initiative in structuring his/her own learning; whereas in a teacher-centered environment, the learner is a passive recipient of instruction emanating from the teacher . With this learner-centered trend in mind, we are working towards building on-line learning environments that cannot be scripted because, by definition, the direction of the learning comes from the student and cannot be engineered *a priori*.

In order to accomplish this, we need a framework in which to define general types of interactions that can occur between a learner and a tutor, as well as interactions between these agents and their sets of beliefs — not only about the knowledge domain that is the subject of the learning system, but also about each other. In this paper, we describe early work in this direction. We begin with an explanation of the interaction models we are using, describe the pre and post conditions of each type, which entails detailing the changes in the belief sets of both types of agents.

We have chosen *argumentation* as our interaction model, for the following reasons. In related work, Sklar and colleagues [21, 25] describe the *meta-game of learning (MGL)*, an interaction game between two agents in the style of the Iterated Prisonner Dilemma (IPD) [2, 3]: a $Teacher$ and a $Student$[1] interact in an environment where the goal is for the student to learn. Each agent is able to make one of two moves, which effectively represent *cooperation* and *defection* in the IPD. However, when we begin to model complex environments, agents naturally need to be able to say more things than just $cooperate(C)$ or $defect(D)$.

Hence, we are motivated to explore richer interaction models, which drives us to the area of *mechanism design*. *Auctions* [12, 22] allow for more complex locutions than simply C and D. The locution uttered by an agent engaged in an auction is called a *bid* or an *ask*, depending on whether the agent is a *buyer* or a *seller*. The content of the locution is usually not a binary value (like C or D), but rather a vector indicating price and number of goods. If an agent issues the locution, it has to be prepared to follow by paying the price associated with that bid. There is no scope within auction mechanisms for agents to gather information from each other and/or discuss their positions, for example, before placing bids.

Negotiation [11] allows agents to make a series of *proposals* (i.e., locutions), with the hope that they will eventually reach agreement, as defined by the environment in which they are interacting. But traditional negotiation does not allow agents to explain their positions or to gather information from or with each other without making statements that imply some type of commitment on the part of the agent issuing the locution.

Argumentation-based dialogues allow agents to engage in "conversation" for a variety of purposes and enable systems to reach beyond resource allocation tasks [14], which are what auctions and negotiation were designed to address. As described in the next section, it will be seen that argumentation is a rich mechanism for agents interacting, sharing knowledge, learning from each other — which makes argumentation perfect for pedagogical agents.

1 In this paper, we use the more general terms $Tutor$ and $Learner$ in place of $Teacher$ and $Student$, as described below.

2. Background

The idea of the meta-game of learning leads naturally to the idea of handling locutions in scenarios like the MGL as a form of dialogue game. That is a dialogue structured in terms of *moves* made by two players. An influential model devised by Walton and Krabbe [29] defines six primary types of argumentation:

- *Information-Seeking Dialogues* (where one participant seeks the answer to some question(s) from another participant, who is believed by the first to know the answer(s));
- *Inquiry Dialogues* (where the participants collaborate to answer some question or questions whose answers are not known to any one participant);
- *Persuasion Dialogues* (where one party seeks to persuade another party to adopt a belief or point-of-view he or she does not currently hold);
- *Negotiation Dialogues* (where the participants bargain over the division of some scarce resource in a way acceptable to all, with each individual party aiming to maximize his or her share);
- *Deliberation Dialogues* (where participants collaborate to decide what course of action to take in some situation. Participants share a responsibility to decide the course of action, and either share a common set of intentions or a willingness to discuss rationally whether they have shared intentions); and
- *Eristic Dialogues* (where articipants quarrel verbally as a substitute for physical fighting, with each aiming to win the exchange).

Others have introduced additional types of dialogues. Girle [10] discusses a *command dialogue* in which one agent tells another what to do. McBurney [15] presents *chance discovery dialogue* where two agents arrive at an idea that neither one had prior to the exchange; instead, the idea arises from or is realized by the agents' discussion. For example, the chance discovery would be acknowledged by a phrase such as "Oh, I never thought of that!"[2]

In this paper, we develop a dialogue game for education, building on the previous work in the dialogue field and demonstrating how existing dialogue protocols must be modified and expanded in order to work in the education environment. Dialogues for education take place between two agents, each having specific roles. In a traditional classroom, these could be considered a teacher and a student. Here, we refer to these agents more generally as $Tutor$ and $Learner$. This allows us the ability to apply the dialogic

2 This example, of course, is only if the exchanges were taking place as natural language.

framework (described herein) to situations where two students learn from (or with) each other, also known as *peer tutoring*. It also permits situations where the teacher learns from the student.

3. Education dialogues

In an education-based relationship between a Learner and a Tutor, there are three relevant interactions[3]:

- $Tutor \rightarrow Learner$
- $Learner \rightarrow Tutor$
- $Learner \rightarrow Learner$

These denote dialogues initiated by the agent on the left side of the arrow and carried out with the agent on the right side of the arrow. For example, if a Learner (L) does not understand his homework assignment, he would ask his Tutor (T) a question about it by initiating an *information-seeking* (IS) dialog and this would be represented as: $IS^{L \rightarrow T}$, following the notation from [18].

Despite this example, many dialogues in the context of education do not sit comfortably in the framework discussed in the previous section. They seem to require new protocols, and new locutions within those protocols. We will refer to the new category of dialogues as *education dialogues (ED)* and describe them in detail in the remainder of this paper. Some of these education dialogues will appear similar to information-seeking dialogues, but there is a key difference. When one agent asks another agent a question, in an information-seeking dialogue, the "asking" agent does not know the answer and assumes that the "receiving" agent does. But in an education dialogue, if the asking agent is a Tutor, then she actually does know the answer to the question she is posing — she is *quizzing* the Learner. The Tutor may be coaxing the Learner to progress, by asking a question that the Learner has not previously answered, but one that the Tutor believes the Learner has the ability to answer — and in doing so may *learn* the answer. The Tutor may also be trying to refine her perception of the Learner's knowledge. Here, the Tutor is seeking information that is not the direct answer to the question, but rather seeking *meta-level knowledge* about the Learner — to see if the Learner knows the answer, rather than what the answer is. We represent this type of dialogue as: $ED^{T \rightarrow L}$.

We define: $ED^{L \rightarrow L}$ as *peer learning*, where either of the following dialogue games could be occurring: $ED^{T \rightarrow L}$, $IS^{L \rightarrow T}$ or $I^{L \rightarrow L}$. In the first case, imitating $ED^{T \rightarrow L}$, the initiating Learner knows the answer and he is testing his peer to see if his peer knows the answer. In the second case, imitating $IS^{L \rightarrow T}$, the initiating Learner does not know the answer and he is asking his peer for help. But in this case, the peer being asked, the one assuming the Tutor role, may not know the answer. In this case the dialogue game transforms to an inquiry dialogue $I^{L \rightarrow L}$, in which neither student knows the answer and they thus seek out the right answer together.

We will further detail the syntax and semantics of the education dialogue in the next sections, explaining the notion of *meta-knowledge*, describing a typical sequence of locutions between tutor and learner and introducing a methodology for updating the agents' belief sets to represent *learning*. But first, we review some notational conventions from prior work in the field of argumentation which will be used throughout the rest of this paper.

4. Conventions

Building on Parsons' earlier work (for example [19]) education dialogues are constructed around the following notions. Since we don't require the full formal apparatus of [19] here, we introduce the important elements informally:

- Σ_i represents the *knowledge base*, or beliefs of each agent i. If the dialogue takes place between two agents T (the Tutor) and L (the Learner), then their corresponding knowledge bases are referred to as Σ_T and Σ_L, respectively. This term loosely refers to all the beliefs of the agent.
- An argument (S, p) is a pair. p is the conclusion p and S is the support. p is a logical consequence of S, and S is a minimal set of Σ_i from which it can be inferred.
- $\mathcal{A}(\Sigma)$ is the set of all arguments which can be made from Σ.
- $\underline{S}(\Sigma)$ is the set of all acceptable arguments in Σ. Arguments that are acceptable are those that an agent has no reason to doubt. There are either no arguments that *undercut* them, or all the arguments that undercut them are themselves undercut.
- We can partition an agent's belief set by identifying relevant portions of it. The agent's *commitment store* (CS) refers to statements that have been made in the dialogue and which the agents are prepared to defend. CS_T refers to the Tutor's commitment store, and CS_L refers to that of the Learner. We think of Σ as the agent's private knowledge base – all of the agent's beliefs – whereas CS is the agent's public knowledge base – all the beliefs that the agent has discussed in public (i.e., with other agents).

[19] shows how these simple elements can be used to construct information-seeking, inquiry, and persuasion dialogues.

3 Note that we will not consider $Tutor \rightarrow Tutor$ since the focus of our model is, by definition, on the Learner.

assert

LOCUTION:

- $M \rightarrow U : assert(p)$

PRE-CONDITIONS:

1. $p \in \Sigma_M$
2. $(S, p) \in \underline{S}(\Sigma_M)$
3. $(S, p) \in \underline{S}(\Sigma_M \cup CS_U)$

POST-CONDITIONS:

1. $CS_{M,i} = CS_{M,i-1} \cup \{p\}$ (update)
2. $CS_{U,i} = CS_{U,i-1}$ (no change)
3. `if (pre-condition-1) or (pre-condition-2)`
   $\Sigma_{M,i} = \Sigma_{M,i-1}$ (no change)
   `else`
   $\Sigma_{M,i} = \Sigma_{M,i-1} \cup \{p\}$ (update)
4. $\Sigma_{U,i} = \Sigma_{U,i-1}$ (no change)

Table 1. Operational semantics for $assert$

accept

LOCUTION:

- $M \rightarrow U : accept(p)$

PRE-CONDITIONS:

1. $p \in \Sigma_U$
2. $(S, p) \in \underline{S}(\Sigma_U)$
3. $(S, p) \in \underline{S}(\Sigma_U \cup CS_M)$

POST-CONDITIONS:

1. $CS_{M,i} = CS_{M,i-1} \cup \{p\}$ (update)
2. $CS_{U,i} = CS_{U,i-1}$ (no change)
3. $\Sigma_{M,i} = \Sigma_{M,i-1} \cup \{p\}$ (update)
4. $\Sigma_{U,i} = \Sigma_{U,i-1}$ (no change)

Table 2. Operational semantics for $accept$

5. Meta-knowledge

We introduce a new type of knowledge, which we call *meta-knowledge*. This is knowledge about the other agent(s) engaged in the dialogue, as perceived by each agent. While this could conceivably be included in Σ, it will be seen that like the commitment store, it is convenient to distinguish it as a separate set of formulas from Σ. For example, there maybe instances in which, after an exchange, an agent has gained some information about another agent but not some general knowledge about the world; or there are cases where an agent bases its decision about its next action according to its belief about the other agent(s) with which it is interacting. Although applicable in other domains as well, this notion is particularly relevant in the education domain where the Tutor has a model of the Learner and uses that model to determine what lessons are appropriate to present to the learner. There is a vast literature on the specifics of this type of modelling, formally called *student modelling* (or *user modelling* in the more general sense) [28, 16]. Here we are not concerned with the precise details of individual student models, but rather use the concept abstractly in order to refer to a tutor's general meta-knowledge about a learner — the tutor's beliefs about what the learner knows, or what is in the learner's knowledge base (i.e., Σ_L).

We represent this meta-knowledge as $\Gamma_i(j)$, where i refers to the agent who holds this meta-knowledge and j refers to the agent whom the meta-knowledge describes. For example, $\Gamma_T(L)$ refers to the tutor's beliefs about what the learner knows. This convention will become convenient in later work (see section 10) as we begin to model entire classrooms and need a method of storing a teacher's beliefs about what each of her individual students knows. The convention also allows us to use $\Gamma_L(T)$ to refer to the learner's knowledge about the tutor. This is useful, for example, for considering the learner's attitude towards learning and his emotional state, both of which must be considered in building agents that represent human learners. See section 8 for a discussion of these aspects.

Now that we have defined notational conventions and introduced the notion of meta-knowledge, we will demonstrate how to put these components to work in the dialogue game. This involves more than simply spouting locutions, since the goal here is for the learner to learn, which means that Σ_L needs to be updated. Additionally, the tutor's beliefs about what the learner knows also need to be updated, i.e., the meta-knowledge $\Gamma_T(L)$. The rules for updating both Σ and Γ are deferred to section 7, which describes in detail the pre and post conditions not only for the new locutions introduced in the next section (6) but also for locutions discussed in previous work — since this aspect has not been explored previously.

6. A typical exchange

Below, we imagine a typical exchange between tutor T and learner L, in order to demonstrate and enumerate the new locutions contained in our education dialogue protocol. These are: *quiz* and *answer*. The remaining locutions used (*accept*, *assert*, *question* and *challenge*) have the same meaning as in previous work.

challenge

LOCUTION:

- $M \rightarrow U : challenge(p)$

PRE-CONDITIONS:

(a) M does not $accept$ p when it is $assert$ed by U.

POST-CONDITIONS:

(a) $CS_{M,i} = CS_{M,i-1}$ (no change)

(b) $CS_{U,i} = CS_{U,i-1}$ (no change)

(c) $\Sigma_{M,i} = \Sigma_{M,i-1}$ (no change)

(d) $\Sigma_{U,i} = \Sigma_{U,i-1}$ (no change)

Table 3. Operational semantics for $challenge$

1. T quizzes L. Note that T knows the answer to the quiz, but does not know whether L knows the answer or not. The goal of this dialogue is for T to determine if L does know the answer. The syntax for this initial locution is:

$$T \rightarrow L : quiz(p)$$

Note that this is semantically different from $question(p)$ in an information seeking dialogue because T already knows the answer to the quiz and so the purpose of the locution is to determine if L knows the answer. Although the format is similar to $question(p)$, the pre and post conditions are sufficiently different that we have defined this new locution, $quiz(p)$. See section 7 for a detailed comparison.

2. L gives an answer to T's question:

$$L \rightarrow T : answer(p)$$

3. This step depends on the correctness of the answer (above). Note that while $answer(p)$ is similar to $assert(p)$ in an information-seeking dialogue, its pre and post conditions are different (again, see the next section).

   - If T agrees with L (i.e., L got the "right" answer), then:

   $$T \rightarrow L : accept(p)$$

   This is the same *accept* as in an information-seeking dialogue.

   - If T disagrees with L (i.e., L got the answer "wrong"), then:

   $$T \rightarrow L : assert(\neg p)$$

   This is the same *assert* as in an information-seeking dialogue.

question

LOCUTION:

- $M \rightarrow U : question(p)$

PRE-CONDITIONS:

1. $(S, p) \notin \underline{S}(\Sigma_U \cup CS_M)$, $(S, \neg p) \notin \underline{S}(\Sigma_U \cup CS_M)$

POST-CONDITIONS:

1. $CS_{M,i} = CS_{M,i-1}$ (no change)
2. $CS_{U,i} = CS_{U,i-1}$ (no change)
3. $\Sigma_{M,i} = \Sigma_{M,i-1}$ (no change)
4. $\Sigma_{U,i} = \Sigma_{U,i-1}$ (no change)

Table 4. Operational semantics for $question$

   - If T does not know the answer (i.e., L provides an answer which may or may not be right, but T does not know which it is), or is not prepared to accept it without support, then:

   $$T \rightarrow L : challenge(p)$$

   and This is the same *challenge* as in an information-seeking dialogue.

7. Operational semantics

Recall our longterm goal, stated in the opening paragraph of this paper: to apply the education dialogues to two developing projects. In moving from an abstract theoretical framework to specific applications, we need an operational semantics for all the locutions mentioned, in order to be able to say under precisely what conditions agents may use certain locutions.

We present these semantics for the general case of two agents interacting, not specifically a tutor and learner in an education dialogue. Note that some of these updates were introduced in earlier work [19] while others have not been specified before. Then we repeat the same exercise for the new education dialogue locutions. The belief sets affected are: Σ, Γ and CS.

To describe the general case, we will make use of two agents M (me) and U (you). The pre-conditions indicate what must be true before M is allowed to utter the locution being described. These are specified in two ways. The first way, e.g., $p \in \Sigma_M$, means that M has to have knowledge of p. The second way, e.g., $(S, p) \in \underline{S}(\Sigma_M)$, means that M has to have knowledge of a set of arguments that support p in its own belief set (e.g.). The post-conditions indicate what happens after M utters the locution being described, at time i. The pre and post conditions of four gen-

quiz

LOCUTION:

- $T \rightarrow L : quiz(p)$

PRE-CONDITIONS:

1. $p \in \Sigma_T$
2. $(S, p) \in \underline{S}(\Sigma_T)$
3. $(S, p) \in \underline{S}(\Sigma_T \cup CS_L)$
4. $p \in \Gamma_T(L)^*$
5. $(S, p) \in \underline{S}(\Gamma_T(L))^*$

*The last two conditions will be discussed in detail in the following section. For now, suffice it to say that in either or both conditions, the operator $\in$ may be changed to $\notin$, depending on the attitude of agent T.

:

(what happens after T utters locution $quiz(p)$ at time i)

1. $CS_{T,i} = CS_{T,i-1} \cup \{p\}$ (update)
2. $CS_{L,i} = CS_{L,i-1}$ (no change)
3. $\Sigma_{T,i} = \Sigma_{T,i-1}$ (no change)
4. $\Sigma_{L,i} = \Sigma_{L,i-1}$ (no change)

Table 6. Operational semantics for $quiz$

answer

LOCUTION:

- $L \rightarrow T : answer(p)$

PRE-CONDITIONS:

1. $p \in \Sigma_L$
2. $(S, p) \in \underline{S}(\Sigma_L)$
3. $(S, p) \in \underline{S}(\Sigma_L \cup CS_T)$

POST-CONDITIONS:

1. $CS_{T,i} = CS_{T,i-1}$ (no change)
2. $CS_{L,i} = CS_{L,i-1} \cup \{p\}$ (update)
3. $\Sigma_{T,i} = \Sigma_{T,i-1}$ (no change)
4. $\Sigma_{L,i} = \Sigma_{L,i-1}$ (no change)

Table 7. Operational semantics for $answer$

eral locutions are contained in: *assert* (table 1), *accept* (table 2), *challenge* (table 3) and *question* (table 4). Note that the pre-conditions for each locution need not be mutually exclusive. Indeed, they often overlap. The idea is that we consider the most specific (the earlier in the list) to be the one that applies. This formulation of the pre-conditions is necessary, for example, to distinguish whether a proposition is $assert$ed because (1) the speaker knows it, (2) the speaker can figure it out from what it does know (2), or can figure it out using something the other agent said (3).

Following the general case, we define the specifics of the two new types of locutions created for this education dialogue. For these specific locutions, we revert to the use of T and L, to indicate the tutor and learner agents (as opposed to the more general M and U). The pre and post conditions of two education dialogue locutions are contained in: *quiz* (table 6) and *answer* (table 7).

8. Attitude

Now that we have defined the rules governing who can say what, the next implementation issue is this: when there is a choice, what should an agent say? The answer is that this can be specified in terms of the *attitude* of the agent (a similar idea to the assertion and acceptance attitudes of [19]). We define the personality of an agent using ideas from the MGL (mentioned in section 1).

The simple form of the MGL is shown in figure 1. In the MGL, the tutor can present to the learner either a HARD or an EASY quiz; and the learner responds with either a RIGHT or a WRONG answer. These terms correspond loosely to $Cooperate$ and $Defect$, as mentioned earlier. In the MGL, when hard quizzes are answered correctly, the learner is *learning*, i.e., the result of mutual cooperation on the part of both agents.

$Learner$:	RIGHT (cooperate)	WRONG (defect)
$Tutor$: HARD (cooperate)	*learning*	*frustration*
EASY (defect)	*verification*	*boredom*

Figure 1. The Meta-Game of Learning (MGL).

In related work, we have been examining the *attitude* of the agents, as represented by a combination of factors: primarily *emotion* and *motivation* [6]. Detailed discussion of these features and their derivation is beyond the scope of this paper. What is relevant here is the *attitude* of the tutor in deciding whether to ask the learner an easy or a hard quiz, and the *attitude* of the learner in deciding, if she knows the right answer, whether she will respond with the right or wrong answer (if she does not know the right answer, then we can assume she has no choice but to provide the wrong answer). We can use the definitions in section 7 to precisely specify what the tutor believes to be an easy quiz as:

$$(p \in \Gamma_T(L)) \vee ((S, p) \in \underline{S}(\Gamma_T(L)))$$

In other words, a quiz is easy if the tutor believes the student knows the answer, or can figure it out from what the tutor believes she knows. Similarly, we can define a hard quiz as:

$$(p \notin \Gamma_T(L)) \vee ((S, p) \in \underline{S}(\Gamma_T(L)))$$

Note that we assume that the teacher believes the student can figure out the answer, because the obvious alternative:

$$(p \notin \Gamma_T(L)) \vee ((S, p) \notin \underline{S}(\Gamma_T(L)))$$

would seem to be an *impossible* quiz rather than just a hard one.

In current work, we are looking at different attitudes that lie somewhere between *easy* and *hard*, constructing these as different logical combinations of what the tutor and student know. (For example, an *achievable* quiz might be one where the student knows some of the material necessary to infer the answer and the tutor knows the rest, so the student can get the answer by working with the tutor.)

It is important to realise that T's precise belief about whether a quiz is easy or hard is a direct function of T's perception of L. The above statements hold true when there is perfect information between the two agents, but that is not a real-world situation. The next section discusses the notion of *misconceptions*, i.e., what happens when one (or both) agents perceive the world incorrectly. Note that this relates not only to the difference between what T believes is in Σ_L (i.e., $\Sigma_L - \Gamma_T(L)$) but also about the difference between what the tutor knows and what the learner knows (i.e., $\Sigma_T - \Sigma_L$). If we assume that the tutor knows all the right answers and the learner does not, we can consider this to represent a general misconception on the part of the learner about the domain she is studying.

9. Representing misconceptions

The identification and representation of misconceptions in a learner's knowledge is often a large portion of an intelligent tutoring system [27, 26]. As alluded to above, within our framework, there are two types of misconceptions we are interested in representing. The first type is that typically discussed in the ITS literature, namely a learner's misconception about the knowledge base she is trying to acquire (i.e., learn); for example, if a student thought that $2+2=5$, then she would have a misconception about adding 2 and 2. The second type is when the tutor misunderstands what the learner actually knows; if such a misunderstanding occurs, then the learner's belief set (Σ_L) will not align with the tutor's set of beliefs about the learner ($\Gamma_T(L)$).

We represent the first kind of misconception (about knowledge) as follows. If

$$\begin{aligned}&(((p \in \Sigma_T) \vee ((S, p) \in \underline{S}(\Sigma_T)))\wedge\\ &\quad((\neg p \in \Sigma_L) \vee (\neg(S, p) \in \underline{S}(\Sigma_L)))\end{aligned}$$

then we can say that L has a misconception about p. This also holds for when

$$\begin{aligned}&((\neg p \in \Sigma_t) \vee (\neg(S, p) \in \underline{S}(\Sigma_T)))\wedge\\ &\quad((p \in \Sigma_L) \vee ((S, p) \in \underline{S}(\Sigma_T)))\end{aligned}$$

The second type of misconception (about meta knowledge) is represented as:

$$\begin{aligned}&((p \in \Sigma_L) \vee ((S, p) \in \underline{S}(\Sigma_L)))\wedge\\ &\quad(((\neg p \in \Gamma_T(L)) \vee (\neg(S, p) \in \underline{S}(\Gamma_T(L)))) \vee\\ &(((\neg p \in \Sigma_L) \vee (\neg(S, p) \in \underline{S}(\Sigma_L))))\wedge\\ &\quad((p \in \Gamma_T(L)) \vee ((S, p) \in \underline{S}(\Gamma_T(L)))) \vee\\ &\qquad((\neg p \in \Gamma_T(L)) \vee (\neg(S, p) \in \underline{S}(\Gamma_T(L))))\end{aligned}$$

This means, for example, that the learner knows the answer, but the tutor thinks the learner does not know the answer (or does not know whether the learner knows the answer or not). This type of situation might arise because either (a) the tutor has not asked the learner a question about p or (b) the learner has decided not to reveal that fact that s/he knows about p.

We can also represent a learner's misconceptions about the tutor, but leave that as an exercise for the reader.

10. Summary

This paper has presented some initial work on the subject of argumentation-based dialogue games for tutor-learner interactions. This work is novel — we are the first, as far as we know, to formalise this dialogic framework — and, in doing so, we have introduced some new kinds of dialogue and locution. We see this work as the first step in a broad exploration of education dialogues, an exploration that, unlike the theory of [19], is slanted towards implementation.

From our investigation, it appears that dialogue game representations of educational agent interactions have something to offer both work on dialogue games and educational agents. For the former, they are a source of new kinds of dialogue, to push the existing theoretical models and demonstrate their power through real-world application. For the latter, they provide a precise characterisation of the features of the interactions, resulting in a strictly modelled yet flexible basis for a wide range of implementations.

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