Int. J. Appl. Math. Comput. Sci., 2015, Vol. 25, No. 3, 455–470
DOI: 10.1515/amcs-2015-0034

A BELIEF REVISION APPROACH FOR ARGUMENTATION–BASED NEGOTIATION AGENTS

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Negotiation is an interaction that happens in multi-agent systems when agents have conflicting objectives and must look for an acceptable agreement. A typical negotiating situation involves two agents that cannot reach their goals by themselves because they do not have some resources they need or they do not know how to use them to reach their goals. Therefore, they must start a negotiation dialogue, taking also into account that they might have incomplete or wrong beliefs about the other agent's goals and resources. This article presents a negotiating agent model based on argumentation, which is used by the agents to reason on how to exchange resources and knowledge in order to achieve their goals. Agents that negotiate have incomplete beliefs about the others, so that the exchange of arguments gives them information that makes it possible to update their beliefs. In order to formalize their proposals in a negotiation setting, the agents must be able to generate, select and evaluate arguments associated with such offers, updating their mental state accordingly. In our approach, we will focus on an argumentation-based negotiation model between two cooperative agents. The arguments generation and interpretation process is based on belief change operations (expansions, contractions and revisions), and the selection process is a based on a strategy. This approach is presented through a high-level algorithm implemented in logic programming. We show various theoretical properties associated with this approach, which have been formalized and proved using Coq, a formal proof management system. We also illustrate, through a case study, the applicability of our approach in order to solve a slightly modified version of the well-known *home improvement agents* problem. Moreover, we present various simulations that allow assessing the impact of belief revision on the negotiation process.

Keywords: argumentation-based negotiation, collaborative agents, belief revision, multi-agent system.

1. Introduction

Negotiation is a form of interaction in which two or more agents with different goals find some acceptable agreement. A typical scenario for negotiation involves two agents which have the need to collaborate for mutual benefit. Even though there is no agreed approach to characterizing all negotiation frameworks, it has been argued (Jennings *et al.*, 2001) that automated negotiation research can be considered to deal with three broad topics: *negotiation protocols* (the set of rules that govern the interaction), *negotiation objects* (the range of issues over which agreement must be reached) and *agents' decision making model* (which accounts for the decision making apparatus the participants employ to act in line with the negotiation protocol in order to achieve their objectives).

Moreover, various approaches can be used to model negotiation in a multiagent setting (MAS). Rahwan *et al.* (2003) distinguish three different kinds of such approaches: those which are *game-theoretic*, those which are *heuristic-based*, and finally those based on *argumentation* (*argumentation-based negotiation*, or ABN for short). Game-theoretic approaches are built on studying

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and developing strategic negotiation models based on game-theory precedents (Rosenschein and Zlotkin, 1994). The interaction in the negotiation process is considered a game in which each agent tries to maximize its utility. Given a protocol, most researchers in this line of work attempt to analyze the optimal strategy. While this approach is very powerful in terms of analyzing the obtained results, it suffers from some drawbacks due to the assumptions upon which it is built. The most important ones are that agents are only allowed to exchange offers without any other information. On the other hand, heuristic-based approaches come to cope with some limitations of the game-theoretic approach. Some strong assumptions made in the latter are relaxed using heuristics. Most of these assumptions concern the notion of rationality of agents as well as their resources. The support for particular heuristics is usually based on empirical testing and evaluation. In general, these methods offer approximations to the decisions made according to game-theoretic studies. Unfortunately, most of those approaches assume that agents have unbounded computational resources and that the space of outcomes is completely known. In most realistic environments, however, these assumptions fail.

Finally, argumentation-based negotiation has been proposed as an alternative to the two previous approaches (Parsons *et al.*, 1998; Rahwan *et al.*, 2003; 2007; Amgoud and Vesic, 2011). This approach allows the negotiating agents not only to exchange offers but also reasons that support these offers in order to mutually influence their preference relation on the set of offers, and consequently the outcome of the dialogue. Moreover, as the agents that negotiate usually have incomplete beliefs about the others, the exchange of arguments gives them information that makes it possible to update their beliefs. Rahwan *et al.* (2003) depict an ABN framework in terms of the interaction between the negotiating agents and the environment. They outline those central elements in the design of an ABN framework, classifying them into *external* and *internal* (wrt the agent). External elements are those that define the environment in which ABN agents operate and interact: *communication language* (the language that facilitates the negotiation, normally including basic locutions such as `propose`, `accept` and `reject`), *domain language* (the language for referring to concepts of the environments, agents, resources, etc.); the *negotiation protocol* (the conventions that govern the interaction among participants), and *information stores* (stores that keep track of relevant information for the negotiation externally, such as past utterances, reputations of the participants, etc.). On the other hand, internal elements are the main components needed by an agent in order to be capable of engaging in a negotiation.

Figure 1 shows the sketch of a generic ABN agent, identifying the components discussed before, as well as their interrelationship. The *locution interpretation* component parses incoming messages. These locutions usually contain a proposal, or an acceptance or rejection message of a previous proposal. The *proposal database* component stores proposals for future reference. The *proposal evaluation and generation* component makes a decision about whether to accept, reject or generate a counterproposal, or even terminate the negotiation. The *locution generation* component sends the response to the relevant party. The *argument interpretation* component updates the agents' mental state accordingly. Finally, the *argument generation* mechanism is responsible for deciding what response to actually send to the counterpart and what (if any) arguments should accompany the response.

In order to formalize their offers in a negotiation setting, ABN agents must be able to generate, select and evaluate arguments associated with such offers, updating their mental state accordingly. In this paper, we focus on providing a novel characterization for these elements, proposing an argumentation-based negotiation model between two cooperative agents. For our analysis we will assume that each agent is *benevolent* (it will always try to do what is asked for if it is able to do so) and *truthful* (i.e., it will not knowingly communicate false information). Besides, we will assume that neither of the agents can reach their respective goals by themselves, so that they have to ask for help from one another. The agents can thus exchange different resources, including the knowledge associated with possible plans to reach their goals.

The resulting negotiation dialog is composed of an exchange of proposals, where every proposal adopts the form of an argument whose claim is a possible exchange (which are the resources the agent is asking for and what it is willing to offer in return). As the agents initially may have incomplete or wrong beliefs about the other agent's goals and resources, during the negotiation process they update their beliefs and, consequently, their mental state, according the arguments exchanged. Thus, in the context of the ABN framework previously described, we will use

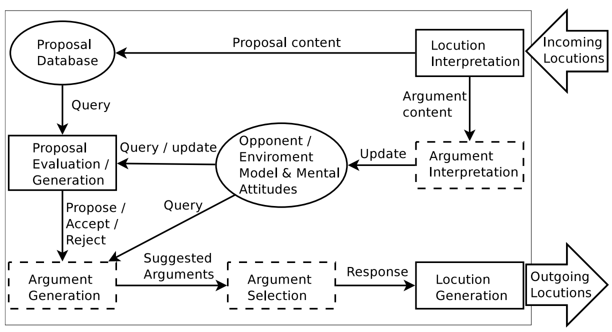


Fig. 1. Elements of an ABN agent (Rahwan *et al.*, 2003).

a belief revision approach for both *argument interpretation* and *argument generation*. The proposed approach is presented through a high-level algorithm implemented in logic programming. We will show different theoretical properties associated with this negotiation model, which have been formalized and proved using Coq[1], a formal proof management system. We will also illustrate through a case study the applicability of our approach in order to solve a motivational example.

In order to carry out an empirical assessment of our proposal, simulations of different types of agents were run, considering 100 possible negotiating scenarios. For these simulations, three agent types are defined: (a) NBR agents, which do not make use of belief revision, (b) PBR agents, which make partial use of belief revision, and (c) BR agents, which apply belief revision on all the information contained in the received messages. Our experiments allowed us to identify relevant features and potential advantages of those negotiating agents that make full use of belief revision by considering all the information received from their counterpart in the negotiation process.

Motivational example. For the rest of this article, we will work on a slightly modified version of the well-known *home improvement agents* (HIA) problem as a motivational example (Parsons *et al.*, 1998). We will assume two benevolent agents Ag_1 and Ag_2. Agent Ag_1 has as the goal of hanging a picture, and it has a screw and a hammer. Also, it knows how a hammer and a nail can be used to hang a picture and how a screw and a screwdriver can be used to hang mirrors. Ag_1 believes that Ag_2 has a nail and a screwdriver (a correct, but incomplete belief), and it believes that Ag_2's goal is to have a screw (wrong belief). On the other hand, Agent Ag_2 has as a goal to hang a mirror, and it has a nail, a screwdriver and the knowledge of how to hang a mirror using a hammer and a nail. Neither Ag_1 nor Ag_2 can reach their goals on the basis of their knowledge and resources. Consequently, they need to perform some exchanges in order to do so. Our proposal aims at modelling how such exchanges can be determined by combining belief revision and argumentation.

The remainder of this paper is structured as follows. In Sections 2 and 3 we define the agent architecture and the negotiation protocol, formalizing the notions of proposal, dialogue and deal. Then in Section 4 we show how to integrate belief revision operators in a high-level algorithm for solving negotiation problems between two argumentative agents. We also discuss some theoretical properties of our approach. In Section 5 we show how the HIA problem can be solved in the context of our proposal. Then, in Section 6, we present simulations of three types of agents in diverse negotiation scenarios where different advantages and salient features of agents using belief revision can be assessed. Section 7 discusses related work, and finally in Section 8 we discuss the main conclusions obtained and outline some future research topics.

[1]Coq (`http://coq.inria.fr/`) is an interactive theorem prover. It provides a formal language to write mathematical definitions, executable algorithms and theorems, together with an environment for semi-interactive development of machine-checked proofs.

2. Agent architecture

For our negotiation scenario, each agent will have, in its mental state, *resources*, *goals* and *plans*, as well as *beliefs* on the other agent's resources and goals. From the information available in such a mental state, an agent will decide which proposals it can offer to the other agent in order to reach an agreement. In order to characterize the agent architecture, we will consider a propositional language $\mathcal{L}$, in which the following subsets are distinguished:

- $Objects_{\mathcal{L}}$: a set of atoms representing objects which are the resources an agent may have (e.g., $nail$, $hammer$);
- $G_{\mathcal{L}}$: a set of atoms representing goals (e.g., $hangMir$ represents the goal of hanging a mirror);
- $Plans_{\mathcal{L}}$: a set of propositional formulae encoding plans, which may involve objects for achieving a goal (e.g., $nail \land hammer \to hangPict$).

In several areas of computer science (e.g., operating systems), the term *resources* is generally considered in a broadest sense and can represent memory, programs, commodities, services, time, money, etc. In short, *anything* that is needed to achieve something. In this work the set of resources, noted by $R_{\mathcal{L}}$, will also include plans for achieving goals, i.e., $R_{\mathcal{L}} = Objects_{\mathcal{L}} \cup Plans_{\mathcal{L}}$.

The plans represent the agent's knowledge of how to use objects to reach a particular goal. Consequently, a plan will be considered a special kind of resource that the agent can share with others without consuming it. We assume that an agent can have infinite copies of each plan it knows. Given a set $X \subset R_{\mathcal{L}}$, we will write $X^{\downarrow o}$ and $X^{\downarrow p}$ to distinguish the subset of objects and the subset of plans in X, respectively. Formally, $X^{\downarrow o} =_{def} X \cap Objects_{\mathcal{L}}$ and $X^{\downarrow p} =_{def} X \cap Plans_{\mathcal{L}}$.

Definition 1. (*Agent mental state*) Let two agents Ag_i, Ag_j be involved in a negotiation. The *mental state (MS)* of Agent Ag_i is the quintuple $MS_i = \langle R_i, G_i, B_iR_j, B_iG_j, H_i\rangle$, where $R_i, B_iR_j \subset R_{\mathcal{L}}$; $G_i, B_iG_j \subset G_{\mathcal{L}}$ and H_i is the history of the negotiation [2].

[2]In what follows, we will refer to Ag_i as a generic agent, Ag_j being the counterpart agent.

Thus, the mental state of Ag_i includes a set of available *resources* (R_i) the agent is willing to negotiate, a set of *goals* to achieve (G_i), as well as belief sets about which resources are available for the opponent Agent Ag_j (B_iR_j), and which goals it believes Agent Ag_j has (B_iG_j). Its mental state includes as well the history of the dialogue (see Definition 6) with Ag_j.

Example 1. Consider the HIA problem given in Section 1. In the beginning of the negotiation process, Ag_1's mental state can be represented as $MS_1 = \langle R_1, G_1, B_1R_2, B_1G_2, H_1\rangle$, where

$$\begin{aligned} R_1 =& \{screw, hammer,\\ & screw \wedge screwDriver \rightarrow hangMir,\\ & hammer \wedge nail \rightarrow hangPict\},\\ G_1 =& \{hangPict\},\\ B_1R_2 =& \{nail, screwDriver\},\\ B_1G_2 =& \{screw\},\\ H_1 =& [\,], \end{aligned}$$

and similarly, Ag_2's mental state can be represented as $MS_2 = \langle R_2, G_2, B_2R_1, B_2G_1, H_2\rangle$, where

$$\begin{aligned} R_2 =& \{hammer \wedge nail \rightarrow hangMir,\\ & nail, screwDriver\},\\ G_2 =& \{hangMir\},\\ B_2R_1 =& \{nail\},\\ B_2G_1 =& \{\},\\ H_2 =& [\,]. \end{aligned}$$

♦

From a global viewpoint we want to characterize the sets that account for the agents' correct, wrong and missing beliefs with respect to its counterparts resources. Formally, we have the following.

Definition 2. (*Missing, correct and wrong beliefs*) Let Ag_i, Ag_j be two agents. We shall write M_i to denote the set of resources that Ag_i does not know that Ag_j has, T_i to denote the set of resources that Ag_i believes that Ag_j has and this is actually the case, i.e., such beliefs are correct, and F_i to denote the set of resources that Ag_i believes that Ag_j has and this is actually not the case, i.e., such beliefs are wrong. Formally $M_i = \overline{B_iR_j} \cap R_j$, $T_i = B_iR_j \cap R_j$, and $F_i = B_iR_j \cap \overline{R_j}$.

Thus, in Example 1 Agent Ag_1 believes that Ag_2 has $nail$ and $screwDriver$, and this is correct, so that $T_1 = \{nail, screwDriver\}$ but it does not know that Ag_2 also has the plan $hammer \wedge nail \rightarrow hangMir$, so that $M_1 = \{hammer \wedge nail \rightarrow hangMir\}$. As Ag_1 does not have wrong beliefs, in this particular case $F_1 = \emptyset$, as shown in Fig. 2. Similarly, we can determine these sets for Ag_2 as $M_2 = \{screw, hammer, screw \wedge screwDriver \rightarrow hangMir, hammer \wedge nail \rightarrow hangPict\}$, $T_2 = \{\}$ and $F_2 = \{nail\}$.

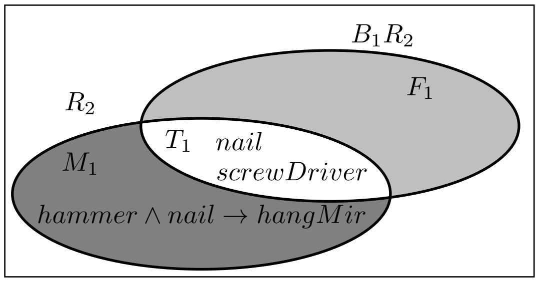


Fig. 2. M_1: missing beliefs (dark gray), T_1: correct beliefs (white), and F_1: wrong beliefs (gray).

The decision making apparatus the agents employ to act in order to achieve their objectives depends on their mental states (see Definition 1). This apparatus will be in charge of computing those proposals the agent will make to the other agent. We will write $Proposal$ to denote the set of all possible proposals (the formal definition of a proposal is given in Definition 5). As the first dialogue move associated with the initial proposal is a particular one, we will single it out by using an initialization function $Init$. Further proposals and counter-proposals are computed by another function $Answer$. Formally, we have the following.

Definition 3. (*Decision making apparatus*) The decision making apparatus of Agent Ag_i is a tuple $DM_i = \langle Init_i, Answer_i\rangle$, where

$$\begin{aligned} Init_i :& MS_i \rightarrow MS_i \times Proposal,\\ Answer_i :& MS_i \times Proposal \rightarrow MS_i \times Proposal. \end{aligned}$$

We will purposely leave unspecified the actual definitions of $Init_i$ and $Answer_i$ at this stage. Later on, in Section 4, we will provide their specification through high-level algorithms. Thus, in our approach, an ABN agent model will be composed of its mental state and its decision making apparatus. Formally, we have the following.

Definition 4. (*Agent model*) Agent Ag_i is the pair $\langle MS_i, DM_i\rangle$, where MS_i is its mental state and DM_i its decision making apparatus.

3. Generating proposals as arguments to reach deals

Based on their mental states, the agents using their decision apparatus will generate proposals towards reaching their goals. In our formalization, a proposal is a statement that includes what the agent wants to obtain and what the agent is willing to give in return, together with an *explanation* justifying why an agent needs what it is asking for. Thus, proposals will have the following intended meaning:

I propose that you provide me with Y in exchange of X, because if I use O, then I can achieve G,

where Y, O, and X stand for resources, and G is a set of goals.

Note that an agent's proposal can be thought of as an *argument*[3] whose claim is associated with what the agent needs to achieve its goals (namely, Y) and the resources that the agent offers in exchange (X), together with its support, i.e., the reasons given for requesting that resource from the other agent. The following definition formalizes this concept.

Definition 5. (*Proposal*) Let X, Y, O be subsets of $R_{\mathcal{L}}$, and let G be a subset of $G_{\mathcal{L}}$. *A proposal* performed by Ag_i is the pair $\langle \mathcal{A}, [\![X, Y]\!]_i \rangle$, where $[\![X, Y]\!]_i$ corresponds to the claim of the argument, and $\mathcal{A} = (O, G)$ provides the support associated with the claim, and the following conditions hold:

$$Y \cup O \vdash G, \tag{1}$$

$$O \nvdash G, \tag{2}$$

$$X \cap (Y \cup O) = \emptyset. \tag{3}$$

A proposal $\langle \mathcal{A}, [\![X, Y]\!]_i \rangle$ will be *minimal* iff there is no other proposal $\langle \mathcal{A}, [\![X, Y']\!]_i \rangle$, such that $Y' \subset Y$.

Notice that (1) states that both the sets of resources O and Y are needed for the agent to reach the goal G, (2) means the agent cannot reach the goal using only O and (3) states that no element of X is needed by the agent to reach G as it suffices to use $Y \cup O$ to reach G, as stated in the condition (1).[4]

Example 2. (*Continuation of Example 1*) Suppose that in this scenario Ag_2 begins the negotiation process by offering Ag_1 the following proposal:

I propose that you provide me with a hammer in exchange for nothing, because if I use a nail and the knowledge about how to hang a mirror using a nail and a hammer, then I can hang a mirror.

Then this proposal is denoted by $\langle \mathcal{A}, [\![\{\}, \{hammer\}]\!]_2 \rangle$ where the support associated with the claim is $\mathcal{A} = (\{nail, nail \wedge hammer \rightarrow hangMir\}, \{hangMir\})$. ♦

A dialogue between two agents will be defined as a finite sequence of proposals (which account for arguments in favor of some particular exchange), performed alternatively by each of the agents involved in the dialogue, ending with $accept$ (there is a deal) or $withdraw$ (no deal is possible).

Definition 6. (*Negotiation dialogue*) A *dialogue* between Agents Ag_i and Ag_j is a finite sequence of utterances $[u_1, \ldots, u_{n-1}, u_n]$ where, for $r < n$, u_r is a proposal and $u_n \in \{accept, withdraw\}$, such that (i) there are no repeated utterances, i.e., $u_s \neq u_t$, with $t, s < n$; (ii) utterance u_k with $k > 1$ is performed by Agent Ag_i only if utterance u_{k-1} is performed by Agent Ag_j (i.e., agents alternate moves). A dialogue will be *initiated* by Ag_i iff u_1 is performed by Ag_i.

Note that dialogues can be warranted to be finite, as there is a finite set of possible combinations of proposals and utterance repetition is not allowed. From Definitions 3 and 6, we can see that the dialogue between Agents Ag_i and Ag_j will be started by one of the agents with a proposal computed by $Init$, followed by a counter-proposal by the other agent computed by $Answer$, a counter-counter-proposal by the first agent, and so on. With no loss of generality we assume Agent Ag_i is the one who starts the negotiation dialogue. Figure 3 represents the negotiation dialogue flow initiated by Ag_i as a finite-state machine.

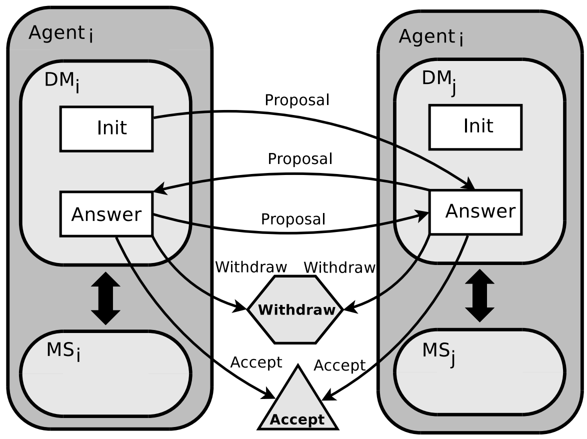


Fig. 3. Dialogue flow initiated by Ag_i.

Proposal evaluation. As previously mentioned, we assume Agents Ag_i and Ag_j cannot reach their goals on their own, and, therefore the problem each agent faces is to find a suitable exchange of resources in the space of

[3]A full account of argumentation theory as well as its applications in multiagent systems and belief revision is outside the scope of this article. For further references and insights, the reader is referred to Dix *et al*. (2013) and Falappa *et al*. (2011).

[4]We write $X \vdash G$ whenever $G \subseteq Cn(X)$, where Cn is a logical consequence operator.

possible exchanges ($\mathcal{P}(R_i) \times \mathcal{P}(R_j)$) in order to reach its own goal. In this setting, a proposal can be thought of as an argument $\langle (O, G), [\![X, Y]\!]_i \rangle$ supporting an exchange of resources. By definition, the pair of resources $[\![X, Y]\!]_i$ provides a solution to reach Ag_i's goal.

We define the function $\odot$ that assigns to each proposal $\langle (O, G), [\![X, Y]\!]_i \rangle$ its *associated solution*.[5]

Following Rahwan *et al.* (2003), we assume that in our approach agents have an *objective consideration* when they evaluate proposals (i.e., they consider a proposal a tentative proof to reach their goals, and they verify it by examining the validity of its underlying assumptions, such as resource availability). Since each agent is aware of its own resources and goals, it can determine first, in a selfish way, which are the exchanges that provide a solution for its problem. This is formalized in the following definition.

Definition 7. Let Ag_i be an agent involved in a negotiation, where its mental state is $MS_i = \langle R_i, G_i, B_iR_j, B_iG_j, H_i \rangle$. A *solution for* Ag_i is any pair $[\![X, Y]\!]_i$, $X, Y \subseteq R_{\mathcal{L}}$ such that

(i) $X \subseteq R_i$;

(ii) $(R_i - X^{\downarrow o}) \cup Y \vdash G_i$.

We will denote by $\mathcal{S}_i$ the set of all possible solutions for Ag_i.

Note that X stands for those resources that Ag_i is willing to give to Ag_j, whereas Y is the set of resources that are given to Ag_i to achieve its goal. In a similar way $\mathcal{S}_j$ is defined. A *deal* for Ag_i and Ag_j will be a solution which is applicable for both of them, being formally defined as follows.

Definition 8. We will say that $[\![X, Y]\!]_i$ where $X, Y \subseteq R_{\mathcal{L}}$, is a *deal* for Ag_i and Ag_j iff $[\![X, Y]\!]_i \in \mathcal{S}_i \wedge [\![Y, X]\!]_j \in \mathcal{S}_j$. We will denote by $\mathcal{D}$ the set of all deals between Ag_i and Ag_j.

From the definitions presented before, the agents' evaluation process can be defined in a simple way as follows: If $prop = \langle (O, G), [\![X, Y]\!]_i \rangle$ is an Ag_i proposal, then $prop$ will be accepted by Ag_j if $[\![Y, X]\!]_j \in \mathcal{S}_j$. Notice that a proposal $prop$ will be accepted only if it is a deal.

4. Integrating belief revision in ABN agents

In this section we will show how belief revision can be used in an ABN agent to improve two important issues in a negotiation: (i) proposal interpretation and (ii) proposal generation. We assume that the information contained in a proposal can be used by an agent to revise the beliefs it has about the other agent and then, by having more accurate beliefs, the first agent can make proposals that are more likely to be accepted. In order to make our analysis self-contained, we will summarize some notions of belief change theory that will be applied in our approach.

4.1. Belief revision operators.

Classic belief change operations introduced in the AGM model (Alchourrón *et al.*, 1985) are known as *expansions*, *contractions* and *revisions*. An expansion incorporates a new belief without warranting the consistency of the resulting epistemic state. A contraction eliminates a belief α from the epistemic state as well as all those beliefs that make the inference of α possible. Finally, a revision incorporates a new belief α to the epistemic state warranting a consistent result, assuming that α itself is consistent.

As discussed before, in our setting we assume that the agents have their own beliefs about the other agent's resources and goals. It must be noted that the sets of resources and objectives do not change during the negotiation. Only if a deal succeeds at the end of the negotiation process will the actual exchange of resources take place, and consequently the sets X and Y will be changed. In order to model such a negotiation process in terms of belief revision, we will use the notion of the *choice kernel set* and *multiple choice contraction* proposed by Hansson (1994) and followed by Fermé *et al.* (2003). These notions will be useful for providing a practical approach to belief revision in our context.

We provide below a brief review of the formal definitions involved.

Definition 9. (*Choice kernel set*) (Fermé *et al.*, 2003) Let $\mathcal{L}$ be a logical language, Cn a consequence operator, $R \subseteq \mathcal{L}$ and $G \in \mathcal{L}$. Then $R \perp\!\!\!\perp G$ is the set of all $X \subseteq R$ such that

(i) $G \subseteq Cn(X)$;

(ii) If $Y \subset X$, then $G \not\subseteq Cn(Y)$.

The set $R \perp\!\!\!\perp G$ is called the *choice kernel set*, and its elements are called *G-kernels of R*.

Informally, a choice kernel set is a minimal belief subset of the epistemic state from which G can be deduced. An element in R contributes to make R imply G if and only if it is an element of some G-kernels of R. Therefore, removing at least one element of each G-kernels of R, it is no longer possible to derive G. The function that selects sentences to be removed will be called an *incision function* since it makes an incision into every G-kernel.

Definition 10. (*Incision function*) (Fermé *et al.*, 2003) A function σ is an incision function for R, iff it satisfies, for all G,

(i) $\sigma(R \perp\!\!\!\perp G) \subseteq \bigcup(R \perp\!\!\!\perp G)$;

(ii) If $\emptyset \neq X \in R \perp\!\!\!\perp G$, then $X \cap \sigma(R \perp\!\!\!\perp G) \neq \emptyset$.

[5]The function $\odot$ corresponds to the second component projection.

The multiple choice contraction operator allows to remove the elements selected by an incision function. Formally:

Definition 11. (*Multiple choice contraction*) (Fermé *et al.*, 2003) Let σ be an incision function for R and $G \in \mathcal{L}$. The *multiple choice contraction* $\approx$ for R is defined as

$$R \approx G = R - \sigma(R \perp\!\!\perp G).$$

Next, a revision operator is expressed using two sub-operations: first a contraction and then an expansion (i.e., adding G to the resulting set).

Definition 12. (*Revision operator*) (Hansson, 1999) Let $\approx$ be a global kernel contraction. Given a set of sentences R, we define for any set G the revision operator $*$: $R*G = (R \approx \neg G) \cup G$

Contracting by the finite set $\neg G$ is equivalent to contracting by a single formula, namely, the disjunction of all negations of elements in G.

4.2. Argument generation. In a negotiation dialogue, the beliefs a particular agent has about the other agent's resources and goals are significant for proposal generation, as they can help reaching a deal. From this information, an agent can infer which proposals it believes are more suitable for the other and, consequently, more likely to be accepted. To formalize this notion, we define the following concepts.

Definition 13. Let Ag_i and Ag_j be two agents and $X, Y \subseteq R_{\mathcal{L}}$. We will say that Ag_i *believes* $[\![X, Y]\!]_i$ is a *solution* for Ag_j whenever

(i) $Y \subseteq B_i R_j$;

(ii) $(B_i R_j - Y^{\downarrow o}) \cup X \vdash B_i G_j$.

Define

$$\mathcal{B}_i\mathcal{S}_j = \{[\![X, Y]\!]_i \mid Ag_i \textit{ believes} [\![X, Y]\!]_i \textit{ is a solution for } Ag_j\}.$$

Definition 14. Let Ag_i and Ag_j be two agents. We will say that Ag_i *believes* $[\![X, Y]\!]_i$ is a *deal* iff

(i) $X \subseteq R_i$;

(ii) $(R_i - X^{\downarrow o}) \cup Y \vdash G_i$;

(iii) $Y \subseteq B_i R_j$;

(iv) $(B_i R_j - Y^{\downarrow o}) \cup X \vdash B_i G_j$.

Define

$$\mathcal{B}_i\mathcal{D} = \{[\![X, Y]\!] \mid Ag_i \textit{ believes} [\![X, Y]\!]_i \textit{ is a deal}\}.$$

From Definitions 13 and 14, the following results hold:[6]

Proposition 1. *$[\![X, Y]\!]_i \in \mathcal{S}_i$ and $[\![X, Y]\!]_i \in \mathcal{B}_i\mathcal{S}_j \Leftrightarrow [\![X, Y]\!]_i \in \mathcal{B}_i\mathcal{D}$.*

Proposition 2. *$[\![X, Y]\!]_i \in \mathcal{B}_i\mathcal{D}$ and $[\![Y, X]\!]_j \in \mathcal{S}_j \Rightarrow [\![X, Y]\!]_i \in \mathcal{D}$.*

Proposition 3. *$[\![X, Y]\!]_i \in \mathcal{B}_i\mathcal{D}$ and $[\![Y, X]\!]_j \in \mathcal{B}_j\mathcal{D} \Rightarrow [\![X, Y]\!]_i \in \mathcal{D}$.*

Proposition 1 states that if a pair $[\![X, Y]\!]_i$ is a solution for Ag_i and it believes that it is also a solution for Ag_j, then Ag_i believes that $[\![X, Y]\!]_i$ is a deal, and the reciprocal is also held. Similarly, Proposition 2 asserts that if Agent Ag_i believes that $[\![X, Y]\!]_i$ is a deal and $[\![Y, X]\!]_j$ is also a solution for Ag_j, then $[\![X, Y]\!]_i$ is a deal. Finally, Proposition 3 states that if Ag_i believes that $[\![X, Y]\!]_i$ is a deal and Ag_j believes that $[\![Y, X]\!]_j$ is a deal, then it holds that $[\![X, Y]\!]_i$ is a deal.

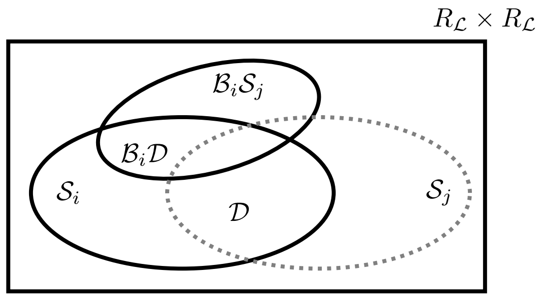


Fig. 4. Solutions' space from the Ag_i viewpoint.

Figure 4 shows the set of solutions from the viewpoint of Ag_i. The dotted line represents that the agent does not know $\mathcal{S}_j$. Because of this, Ag_i cannot be sure of making a proposal *prop* such that $\odot(\textit{prop}) \in \mathcal{D}$. So, in order to entice Agent Ag_j to accept some proposed agreement, Ag_i must choose a proposal *prop* such that it believes its *associated solution* is a deal, i.e., $\odot(\textit{prop}) \in \mathcal{B}_i\mathcal{D}$.

The function Gen is defined to compute the proposals that are a solution to Ag_i (i.e., $\odot(\textit{prop}) \in \mathcal{S}_i$) and to compute proposals that are potential solutions (i.e., $\odot(\textit{prop}) \in \mathcal{B}_i\mathcal{S}_j$). The Gen function is specified using belief revision operations, and some properties that follow from its specification are given.

Definition 15. Let $R, R' \subset R_{\mathcal{L}}$ and $G \subset G_{\mathcal{L}}$. We define a function Gen as

[6] All the propositions and their proofs were formalized in Coq and are available at `http://web.cifasis-conicet.gov.ar/~pilotti/Automated_Agent_Negotiation.v`.

$$\begin{aligned}\mathsf{Gen}(R, R', G, i) &\\ \stackrel{\text{def}}{=} \{\langle(O, G), [\![X, Y]\!]_i\rangle &: Y \cap R = \emptyset,\ O \subseteq R,\\ (O \cup Y) &\in (R \cup R' \cup Y) \perp\!\!\!\perp G,\\ X &\subseteq R - O\}.\end{aligned}$$

In Definition 15 the Gen function receives two sets of resources (R and R') and a set of goals (G). As an outcome it generates a set of proposals $prop = \langle(O, G), [\![X, Y]\!]_i\rangle$, where Y and the first set of resources (R) are disjoint sets, but O is a subset of it. The union of Y and O is a minimal set from which G can be deduced. The set X corresponds to the unused resources of R to achieve G.

Proposition 4. *Given Agent Ag_i, where its mental state is $MS_i = \langle R_i, G_i, B_iR_j, B_iG_j, H_i\rangle$, the following holds:*

(i) If $prop \in \mathsf{Gen}(R_i, B_iR_j, G_i, i)$, then $prop \in Proposal$ and $\odot(prop) \in \mathcal{S}_i$;

(ii) If $prop \in \mathsf{Gen}(B_iR_j, R_i, B_iG_j, j)$, then $prop \in Proposal$ and $\odot(prop) \in \mathcal{B}_i\mathcal{S}_j$.

The condition (i) in Proposition 4 establishes that the Gen function computes all the minimal proposals that are solutions for Ag_i from *its point of view*, namely, using as parameters its resources (R_i), its belief about the other agent's resources (B_iR_j) and its goal (G_i). On the other hand, in (ii) the Gen function computes the proposals that Ag_i *thinks that are solutions for* Ag_j, i.e., using as parameters its beliefs about the other, agent's resources (B_iR_j), its own resources (R_i) and its belief about the other agent's goal (B_iG_j). In summary, Proposition 4 shows that the possible proposals that can be generated via an implementation of Gen are potential solutions for the negotiation problem between the agents involved.

4.3. Argument selection. An important point related to the argument generation mechanism is argument selection. This mechanism should provide an answer to the following question: Given a set of proposals that an agent may send to its counterpart, which is the more appropriate from the point of view of the speaker?

Rahwan *et al.* (2003) present an overview of some relevant selection mechanisms—we summarize some of them. In the work of Kraus *et al.* (1998), arguments are selected according to strength order, from "appeal to prevailing practice" to "a threat". The intuition is that a negotiator would progress from weak arguments up to the strongest. In the framework by Ramchurn *et al.* (2003), agents use a fuzzy rules based system that combines trust and utility in order to decide which candidate argument to send with a request. Agents in the framework presented by Parsons *et al.* (1998) provide the strongest argument possible based on the acceptability classes (e.g., a tautological argument if possible). For Amgoud *et al.* (2000), agents compare arguments based on preferential ordering over their constituent propositions in a manner similar to that in argument evaluation (i.e., based on the argumentation system of Dung (1995)). In the work of Sadri *et al.* (2001), agents can compare the costs of different alternative plans to present to the counterpart.

Sierra and Debenham (2007) consider five dimensions relevant to negotiations: legitimacy, options, goals, independence, and commitment. They introduce a negotiation model built upon an information-based measure (to represent the information gain) and a utility-based function (to represent the utility gain) defined for each one of these dimensions. The negotiation strategies rely on two primitive concepts: intimacy (degree of closeness) and balance (degree of fairness). Arguments are selected in order to obtain a successful deal and to reach a target intimacy level.

In our approach, inspired by Sierra and Debenham (2007) and considering only the dimension *options* (i.e., "the possible agreement the agent can accept"), the agent selection mechanism is based on an information function $I : H \times Proposal \to \mathbb{R}$ (where H stands for the history of the negotiation, see Definition 1) and a utility function $U : Proposal \to \mathbb{R}$. Various selection mechanisms can be defined combining these functions to represent different agent behaviors. According to the agent personality and the relation it has with its counterpart agent (the intimacy relation), the function combining I and U may be defined in a suitable way (e.g., using a weighted sum).

4.4. Argument interpretation. When an agent receives a proposal, an argument interpretation mechanism must be invoked in order to update the agent's mental state accordingly. In our framework, the proposal interpretation is based on the following intuition: Since agents are truthful, benevolent and aware of their own resources, when Agent Ag_j receives a proposal $prop = \langle(O, G), [\![X, Y]\!]_i\rangle$ from Ag_i, then Ag_j can infer the following information:

(i) If Ag_i asks for Y, then Ag_j believes Ag_i does not have Y as resource;

(ii) If Ag_i uses O, then Ag_j believes Ag_i has O as a resource;

(iii) If Ag_i offers X, then Ag_j believes Ag_i has X as resource;

(iv) If Ag_i wants to reach G, then Ag_j believes Ag_i has G as Goal.

Thus, Ag_j can change its beliefs accordingly, contracting its belief set as in 1 or revising it as in (ii)–(iv). In this way the computation of the belief set $\mathcal{B}_i\mathcal{S}_j$ may be closer to $\mathcal{S}_j$ and, consequently, the resulting set of possible deals $\mathcal{B}_i\mathcal{D}$ may be closer to $\mathcal{D}$ as well (as illustrated in Fig. 4).

The agents will change their beliefs according to the intuitions presented before, using belief revision operations. Let $contract$ and $revise$ be implementations of the operators $\approx$ and $*$, respectively (see Definitions 11 and 12), and $prop = \langle (O, G), [\![X, Y]\!]_i \rangle$ an Ag_i proposal received by Ag_j. The following steps, which can be seen as variable assignments, implement the agent's interpretation process:

(i) $B_jR_i \leftarrow contract(B_jR_i, Y)$,

(ii) $B_jR_i \leftarrow revise(B_jR_i, O)$,

(iii) $B_jR_i \leftarrow revise(B_jR_i, X)$,

(iv) $B_jG_i \leftarrow revise(B_jG_i, G)$.

4.5. Decision model: High-level algorithms. The agent's decision making apparatus has been defined in Section 2 and implemented using two algorithms $Init$ and $Answer$. The algorithm $Init$ is in charge of starting the negotiation. In a first place, it selects a proposal that Agent Ag_i believes is a deal ($\mathcal{B}_i\mathcal{D}$) that has not been proposed before. If such a proposal does not exist, it tries to send a proposal associated with its own solutions ($\mathcal{S}_i$). If this fails, the agent sends a withdraw message. On its turn, $Answer$ receives the proposal generated from $Init$ and checks if it is an associated solution to the agents problem, and in that case the proposal is accepted. If that is not the case, the agent's beliefs are revised and $Init$ is invoked to generate a new proposal. High-level algorithms for $Init_i$ and $Answer_i$ are given next.

Algorithm 1. Init function.

Require: MS_i
Ensure: $Proposal$
1: $p\mathcal{S}_i \leftarrow \mathsf{Gen}(R_i, B_iR_j, G_i, i)$
2: $p\mathcal{B}_i\mathcal{S}_j \leftarrow \mathsf{Gen}(B_iR_j, R_i, B_iG_j, j)$
3: $p\mathcal{B}_i\mathcal{D} \leftarrow p\mathcal{S}_i \oplus p\mathcal{B}_i\mathcal{S}_j$
4: $propSet \leftarrow p\mathcal{B}_i\mathcal{D} - sent_i(H)$
5: **if** $propSet \neq \emptyset$ **then**
6: $\quad prop \leftarrow select(propSet, H)$
7: $\quad add(H, prop)$
8: $\quad$ **return** $prop$
9: **else**
10: $\quad propSet \leftarrow p\mathcal{S}_i - sent_i(H)$
11: $\quad$ **if** $propSet \neq \emptyset$ **then**
12: $\quad\quad prop \leftarrow select(propSet, H)$
13: $\quad\quad add(H, prop)$
14: $\quad\quad$ **return** $prop$
15: $\quad$ **else**
16: $\quad\quad$ **return** $withdraw$
17: $\quad$ **end if**
18: **end if**

Algorithm 2. Answer function.

Require: $MS_i, Proposal$
Ensure: $MS_i, Proposal$
1: $add(H, prop)$
2: $p\mathcal{S}_i \leftarrow \mathsf{Gen}(R_i, B_iR_j, G_i, i)$
3: **if** $\odot(prop) \in \bigodot(p\mathcal{S}_i)$ **then**
4: $\quad$ **return** $accept$
5: **else**
6: $\quad B_iR_j \leftarrow contract(B_iR_j, Y)$
7: $\quad B_iR_j \leftarrow revise(B_iR_j, O)$
8: $\quad B_iR_j \leftarrow revise(B_iR_j, X)$
9: $\quad B_iG_j \leftarrow revise(B_iG_j, G)$
10: $\quad prop \leftarrow Init_i(MS_i)$
11: $\quad$ **return** $prop$
12: **end if**

Algorithm 1: In Line 1, the function Gen (i.e., a suitable implementation of the Gen function specified in Definition 15) is used to compute the set of proposals $p\mathcal{S}_i$ such that their associated solutions belong to $\mathcal{S}_i$ (see Proposition 4). Similarly, in Line 2, Gen is used to compute the set of proposals $p\mathcal{B}_i\mathcal{S}_j$ that the agent believes their associated solutions belong to $\mathcal{B}_i\mathcal{S}_j$ (see Proposition 4). In Line 3, the set $p\mathcal{B}_i\mathcal{D}$ is computed as those proposals in $p\mathcal{S}_i$ such that their associated solutions are potential deals (see Proposition 1). In Line 4, those proposals that have been offered before are discarded. The $select$ function chooses one proposal out of the set $propSet$ of possible candidate proposals.[7] Finally, the selected $prop$ is added to H.

Algorithm 2: In Lines 1 and 2, the history H is updated, and the set $p\mathcal{S}_i$ is computed. In Line 3, we check if the solution associated with the received proposal is a solution for Ag_i. For this purpose, we use $\odot$ to denote the associated solution with a given proposal and $\bigodot$ to denote the set of associated solutions for a set of proposals. Then, in Lines 6 to 9, the agent updates its mental state following the steps presented in Section 4. For generating a counter-proposal the same lines of the code as the ones in $Init$ are to be executed (as $Init$ generates proposals). Therefore, for the sake of simplicity and in order to avoid repeating code, a call to $Init$ is used in Line 10.

The proposed argumentation-based negotiation framework for two agents has been implemented using logic programming following the algorithms presented above. Based on such algorithms, concrete negotiating agents can be specified by instantiating their mental state and setting the selection function in charge to choose the proposal to negotiate.

[7] In Section 5, for the *home improvement agents* problem, we give an example of how this selection function may be defined.

5. HIA problem revisited

As already mentioned in Section 1, we consider a slightly modified version of the *home improvement agents* example (Parsons *et al.*, 1998) as a case study of our approach. We will assume two benevolent agents Ag_1 and Ag_2. Agent Ag_1 has as goal hanging a picture, and it has a screw and a hammer. Also, it knows how a hammer and a nail can be used to hang a picture and how a screw and a screwdriver can be used to hang mirrors. Ag_1 believes that Ag_2 has a nail and a screwdriver (correct, but incomplete belief) and it believes that Ag_2's goal is to have a screw (wrong belief). On the other hand, Agent Ag_2 has as goal to hang a mirror, and it has a nail, a screwdriver and the knowledge of how to hang a mirror using a hammer and a nail. Therefore, Ag_1 has the following initial mental state:

$$\begin{aligned} R_1 &= \{\ screw, hammer,\\ &\quad\ screw \wedge screwDriver \rightarrow hangMir,\\ &\quad\ hammer \wedge nail \rightarrow hangPict\ \},\\ G_1 &= \{hangPict\},\\ B_1R_2 &= \{nail, screwDriver\},\\ B_1G_2 &= \{screw\},\\ H_1 &= [\,], \end{aligned}$$

and Ag_2 has as its initial mental state

$$\begin{aligned} R_2 &= \{\ hammer \wedge nail \rightarrow hangMir,\\ &\quad\ nail, screwDriver\ \},\\ G_2 &= \{hangMir\},\\ B_2R_1 &= \{nail\},\\ B_2G_1 &= \{\},\\ H_2 &= [\,]. \end{aligned}$$

In this example, we assume that the agents select the proposal $prop \in Proposal$ that maximizes a weighted sum $\lambda_U U(prop) + \lambda_I I(prop)$. For simplicity, both agents use the same utility and information functions, but each agent considers different weights, which stand for different kinds of agents. For Ag_1, the weights are $\lambda_U = 0.25$, $\lambda_I = 2$, prioritizing the proposals that are more informative, and for Ag_2: $\lambda_U = 2$, $\lambda_I = 0.25$, preferring those proposals that have a higher utility function. Also, we assume that the different resources they negotiate have the same costs for them. The agents' Utility function is defined as the difference of the cost of the resources offered to be exchanged, and it is expressed as follows:

$$U_i(prop) = \sum_{r\in Y} Cost(r) - \sum_{r\in X} Cost(r),$$

where $prop = \langle (O,G), [\![X,Y]\!]_i\rangle$ and

$$\begin{aligned} Cost\ = \{&(hangMir, 10), (hangPict, 10),\\ &(hammer, 4), (screwDriver, 4), (screw, 2),\\ &(nail, 2), (hammer \wedge nail \rightarrow hangPict, 8),\\ &(screw \wedge screwDriver \rightarrow hangMir, 8)\}, \end{aligned}$$

and the agents' information function is defined as

$$\begin{aligned} I_i(H, prop) = &\sum_{r\in Y} \mathbf{1}_{get}(H,r) + \sum_{r\in X} \mathbf{1}_{give}(H,r)\\ &+ \sum_{r\in O} \mathbf{1}_{own}(H,r) + \sum_{r\in G} \mathbf{1}_{goal}(H,r), \end{aligned}$$

where $\mathbf{1}_{get}(H,r)$ returns 1 if, for all $\langle (O,G), [\![X,Y]\!]_i\rangle \in H$, $r \notin Y$. In a similar way, $\mathbf{1}_{give}, \mathbf{1}_{own}$ and $\mathbf{1}_{goal}$ are defined. The intuition is that given a dialogue H a proposal $prop$ is more informative if its elements were not stated in previous locutions.

Suppose that Ag_1 is the agent that starts the negotiation. For the sake of example, we summarize next the main steps in the first two moves in the negotiation process:

Move 1: Ag_1 uses the algorithm $Init_1$ to compute the first proposal. The functions $\mathsf{Gen}(R_1, \{nail\}, \{hangPict\}, 1)$ and $\mathsf{Gen}(\{nail\}, R_1, \{screw\}, 2)$ are computed, obtaining as a result

$$\begin{aligned} p\mathcal{S}_1 = \{&\langle(\emptyset, \{hangPict\}), [\![\{hangPict\}, R_1]\!]_1\rangle,\\ &\langle(\{nail \wedge hammer \rightarrow hangpicture,\\ &hammer\}, \{hangPict\}), [\![\{nail\}, \emptyset]\!]_1\rangle, \dots\},\\ p\mathcal{B}_1\mathcal{S}_2 = \{&\langle(\{screw\}, \emptyset), [\![\emptyset, \{screw\}]\!]_1\rangle\}. \end{aligned}$$

Now Ag_1 can compute the potential deals from the set of its proposals (i.e., $prop \in p\mathcal{S}_1$) considering those it believes are solutions for Ag_2 (i.e., $\odot(prop) \in \bigodot(p\mathcal{B}_1\mathcal{S}_2)$):

$$\begin{aligned} p\mathcal{B}_1\mathcal{D} = \{&\langle(\emptyset, \{hangPict\}), [\![\{hangPict\}, \{screw\}]\!]_1\rangle\\ &\langle(\{hammer, nail \wedge hammer \rightarrow hangPict\},\\ &\{hangPict\}), [\![\{nail\}, \{screw\}]\!]_1\rangle\}\\ = \{&prop1, prop2\}. \end{aligned}$$

Since this is the first move, H_1 is empty and thus $propSet = p\mathcal{B}_i\mathcal{D}$. Then the *select* function, which maximizes a weight sum, must choose between $prop1$ and $prop2$. Note that the first proposal is less informative and the resources allocation is less balanced than the second proposal, computing $U(prop1) = 8$, $U(prop2) = 0$, $I(prop1) = 3$, $U(prop2) = 5$, therefore $\lambda_U U(prop1) + \lambda_I I(prop1) = 8$, and $\lambda_U U(prop2) + \lambda_I I(prop2) = 10$. Therefore the *select* function chooses the second proposal, adding it to H_1 and Ag_1 is ready to start the negotiation with the following proposal:

I propose that you provide me with nail, because if I use hammer and $nail \wedge hammer \rightarrow hangPict$, then I can achieve $hangPict$ in exchange for $screw$.

Move 2: Ag_2 receives Ag_1's proposal, and invokes the $Answer_2$ algorithm. Ag_2 adds the proposal to H_2 and then uses the Gen function to compute $p\mathcal{S}_2$:

$$\begin{aligned} p\mathcal{S}_2 &= \mathsf{Gen}(R_2, \emptyset, \{hangMir\}, 2) \\ &= \{\langle(\{hammer\}, \emptyset), [\![R_2, \{hangMir\}]\!]_2\rangle\}. \end{aligned}$$

Since $\odot(prop) \notin \bigodot(p\mathcal{S}_2)$ (that is to say, $[\![\{screw\}, \{nail\}]\!]_2 \notin \{[\![\{hammer\}, \emptyset]\!]_2\}$), Ag_2 does not accept, using the proposal information to update its beliefs, and its $Init_2$ function to generate a proposal to answer Ag_1. The current mental state of Ag_2 is now as follows:

$$\begin{aligned} R_2 &= \{nail, screwDriver, hammer \wedge nail \rightarrow hangMir\}, \\ G_2 &= \{hangMir\}, \\ B_2R_1 &= \{screw, hammer, nail \wedge hammer \rightarrow hangPict\}, \\ B_2G_1 &= \{hangPict\}, \\ H_2 &= [\langle(\{hammer, nail \wedge hammer \rightarrow hangPict\}, \{hangPict\}, \{screw\}), \{nail\}\rangle]. \end{aligned}$$

Notice that Ag_2 through its interpretation process has revised its previous beliefs about Ag_1's goal, and now it believes that its goal is $hangPict$.

The whole dialogue obtained in the negotiation program for this scenario is the following:

1 Says: *I propose that you provide me with* $[nail]$, *because if I use* $[hammer, nail\&hammer => hangPicture]$, *then I can achieve* $[hangPicture]$ *in exchange for* $[screw]$.

2 Says: *I propose that you provide me with* $[hangMirror]$, *because if I use* [], *then I can achieve* $[hangMirror]$ *in exchange for* $[nail]$.

1 Says: *I propose that you provide me with* $[nail]$, *because if I use* $[hammer, nail\&hammer => hangPicture]$, *then I can achieve* $[hangPicture]$ *in exchange for* $[screw, screwDriver\&screw => hangMirror]$.

2 Says: *accept. I give you* $[nail]$ *and you give me* $[screw, screwDriver\&screw => hangMirror]$.

6. Simulations

In order to assess the benefits of using belief revision in the context of our proposal for argument-based negotiation, simulations of bilateral negotiation were carried out, considering different scenarios. In each case, agents had to cope with missing and wrong beliefs about their counterpart.

Generating the scenarios. The assessment of our proposal was based on 100 randomly generated negotiation scenarios. The process for generating a scenario is based on randomly selecting the goals for each agent $G_1, G_2 \in G_\mathcal{L}$, generating then three disjoint sets of resources $F, S, T \in R_\mathcal{L}$ such that $F \vdash G_1$, $S \vdash G_2$ and $T \vdash G_1 \wedge G_2$. Then the mental state for Ag_1 and Ag_2 was defined as $MS_1 = \langle R_1, G_1, B_1R_2, B_1G_2, H_1\rangle$ and $MS_2 = \langle R_2, G_2, B_2R_1, B_2G_1, H_2\rangle$ such that

(i) $R_1 = F_1 \cup S_1 \cup T_1$, $R_2 = F_2 \cup S_2 \cup T_2$, where F_1, F_2 (resp., S_1, S_2, and T_1, T_2) are partitions of F (resp., S and T);

(ii) $B_1R_2 \subset R_2 \cup R_1$, $B_2R_1 \subset R_1 \cup R_2$;

(iii) $B_1G_2 = G_1$, $B_2G_1 = G_2$;

(iv) $H_1 = H_2 = \langle\rangle$.

We can see that $F = F_1 \cup F_2$ is a solution for Ag_1, $S = S_1 \cup S_2$ is a solution for Ag_2, and $T = T_1 \cup T_2$ can be a solution for both agents. With this allocation of resources and the agent's beliefs, we ensure that initially each agent cannot achieve its own goal by itself and both agents have incomplete and wrong beliefs about their counterpart.

After creating these negotiation scenarios, three different types of agents were distinguished, based on the characterization of their decision making apparatus. In each case, a particular definition of the $Answer$ function was considered, characterizing

1. *NBR agents*: these agents do not use belief revision techniques for argument generation and interpretation;

2. *PBR agents:* these agents implement belief revision using only the information contained in the argument claim (proposal);

3. *BR agents:* these agents take advantage of belief revision using all the information contained in the argument (i.e., proposal and support). This corresponds to the full-fledged version of our proposal.

It must be noted that these different types of agents (NBR, PBR, BR) share the same underlying structure and the only difference among them is associated with the role of the belief revision process during the negotiation (i.e., no belief revision for NBR agents, applying belief revision using only the proposal for PBR agents, and applying belief revision considering both proposal and support for BR agents). In order to implement these different characterizations, we will modify part of the code of Algorithm 2, as discussed below.

We ran simulations using two negotiating agents of the same type (i.e., NBR, PBR and BR) in the different negotiating scenarios which were randomly generated (100 cases). In all the simulations, both agents used the selection function described previously, i.e., the agents select the proposal $prop \in Proposal$ that maximizes a weighted sum $\lambda_U U(prop) + \lambda_I I(prop)$, using a balanced approach that weights equally the informativeness of the proposal and its associated utility, i.e., $\lambda_U = \lambda_I = 0.5$. Besides, in all the negotiation scenarios it was assumed that Ag_1 starts the negotiation dialogue.

In each simulation we analyzed (i) whether there was an agreement in the negotiation (i.e., it finished with $accept$ or $withdraw$) and (ii) the length of the negotiation process (i.e., the number of iterations). Besides, we were interested in assessing the evolution of the agent's beliefs with respect to its initial mental state. In order to do this, we analyzed two ratios: on the one hand, for each scenario we evaluated the decrease in the agent's missing and wrong beliefs (see Definition2). We computed the ratio of these two kinds of beliefs an agent has at the end of negotiation with respect to the initial ones it had as follows:

$$\frac{|M^{end}| + |F^{end}|}{|M^{init}| + |F^{init}|}.$$

On the other hand, for each case we compute how the correct beliefs increase during the negotiation process. This is computed as

$$\frac{|T^{end}|}{|T^{init}|}.$$

Simulations of NBR agents. We modeled the decision making apparatus of the agents Ag_1 and Ag_2 using the proposed algorithms (i.e., $Init$ and $Answer$) but without considering the belief revision process. To proceed accordingly, Algorithm 2 (Section 4.4) was modified, eliminating Lines 6 to 9. The outcomes of the 100 negotiations with agents modeled as NBR agents are shown in Fig. 5. We can observe that there is an agreement in only 15% of the negotiation cases, with an average of negotiation length of 35 (i.e., the number of messages exchanged). On the other hand, 85% of the negotiations finished without an agreement (i.e., ending with a $withdraw$). Since the agents do not implement a belief revision process during the negotiation, their beliefs about their opponent remain unchanged (i.e., their missing and wrong beliefs wrt their counterpart's resources are not modified during the negotiation process).

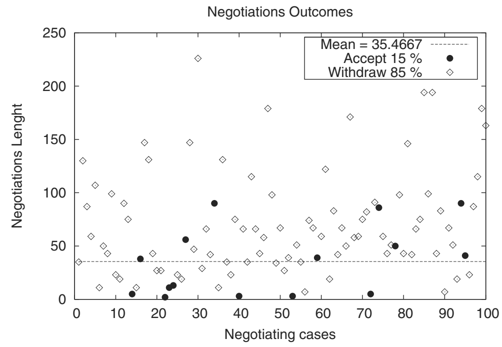


Fig. 5. Output of negotiations with NBR agents.

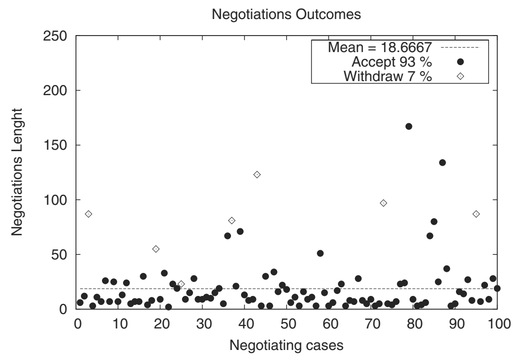
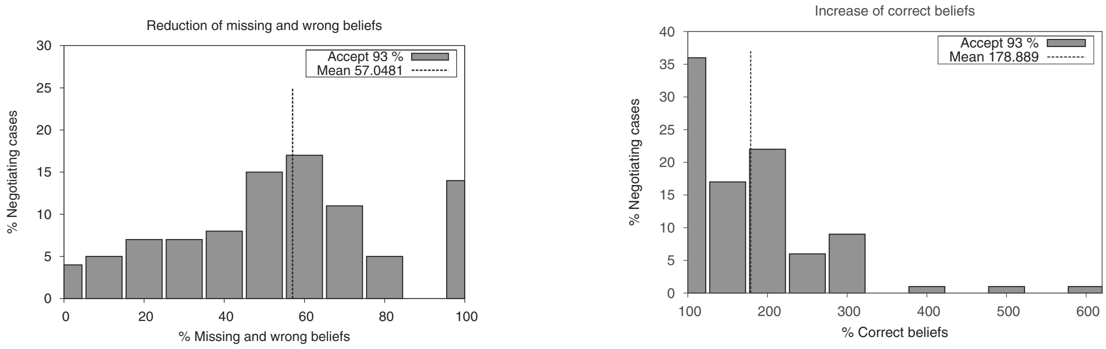


Fig. 6. Output of negotiations with PBR agents.

Simulations using PBR agents. For these simulations we modeled the agent's decision making apparatus by restricting the belief revision process only on the arguments claim (without considering it for proposal justification). To achieve this, we modified Algorithm 2 eliminating Lines 7 to 9. In Fig. 6 we show the output of negotiations using PBR agents. We can observe that the agents reached an agreement in 93% of the negotiations, whereas only in 7% they did not. Moreover, in Fig. 7(a) we can see the percentage of reduction of missing and wrong beliefs for Ag_1 about its counterpart, and in Fig. 7(b) the increase in correct beliefs for Ag_1 about its opponent. We can see that a PBR agent reduces to an average of 57% its missing and wrong beliefs about its counterpart. On the other hand, its correct beliefs about its opponent resources increase an average of 178% until the agent reaches an agreement.

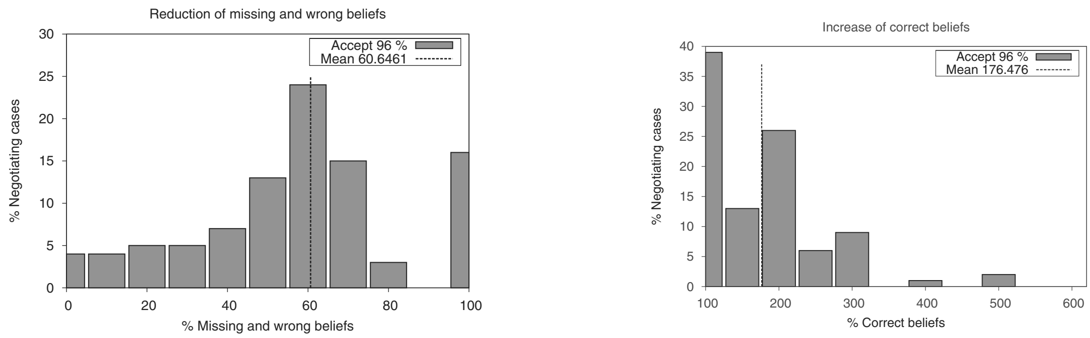
Simulations of BR agents. Finally, we will analyze the simulations using the full-fledged proposed agent negotiation model (BR agents). The output is shown in Fig. 8, where an agreement was reached in 96% of the cases, whereas only 4% ended with a withdraw.

Figure 9(a) shows the reduction in missing and wrong beliefs for Ag_1, and Fig. 9(b) illustrates the percentage of the increase in its correct beliefs (knowledge acquisition) wrt its counterpart's resources. It can be observed that in reaching an agreement the BR agent reduced on average 60% of its missing and wrong beliefs with respect to Ag_2 and increased on average 176% of



(a) (b)

Fig. 7. PBR agents: reduction in missing and wrong beliefs (a), acquired knowledge (b).



(a) (b)

Fig. 9. BR agents: reduction in missing and wrong beliefs (a), acquired knowledge (b).

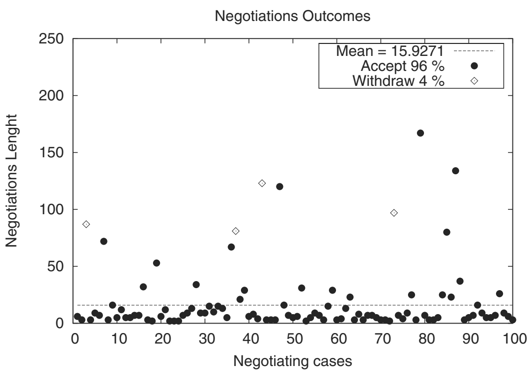


Fig. 8. Output of negotiations with BR agents.

its correct beliefs on its counterpart resources when the negotiation finished.

These simulations allow assessing the impact of belief revision on the negotiation process. On the one hand, agents that implemented belief revision (PBR and BR agents) reached agreements in many more cases (93% and 96%) than NBR agents, which do not use revision (15%). On the other hand, the negotiation length tends to be shorter in those agents that take advantage of belief revision (as the average number of iterations decreased from 35.47 in NBR agents to 18.67 in PBR agents, and the smallest average of 15.93 was obtained for BR agents). Concerning the reduction of missing and wrong beliefs, PBR agents had an average of 57.05%, a slightly lower value than the one for BR agents (60.65%). Besides, the average of increase for correct beliefs is 178.89% for PBR agents and 176.48% for BR agents (i.e., percentages which are very similar). BR agents they have achieved agreements in more negotiation cases and faster than PBR agents. However, they end the negotiation having on average slightly more missing and wrong beliefs and less correct beliefs than PBR agents. Intuitively, BR Agents are able to reach an agreement under more incomplete or wrong beliefs. Finally, we can observe that there is a considerable difference in the negotiation results (i.e., the number of agreements and length) between agents that incorporate belief revision as part of their decision making machinery and those which do not.

7. Related work

In contrast with the original argumentative framework to solve the HIA problem (Parsons *et al*., 1998), our negotiation model allows the agents to gain and revise their beliefs as the dialogue takes place. Consequently, in our approach an agent does not need to have initial (or correct) beliefs about the other agent involved in the negotiation. In the works of Rahwan *et al*. (2007) and Pasquier *et al*. (2011), a similar scenario is analyzed, but agents are aware of all the agents' resources, and the agents' plans (or their knowledge about plans) are not consider negotiable. We think that our proposal is more flexible in this respect, as plans are also negotiation objects in our formalization.

There have been previous approaches integrating belief revision and negotiation. In the work of Zhang *et al*. (2004) a formal characterization of negotiation from a belief revision perspective is given, but no implementation issues are considered. Additionally, it must be noted that in our proposal we assume that agents are benevolent. This approach can also be found in several frameworks (e.g., Parsons *et al*., 1998; Amgoud *et al*., 2000). In addition, in our work, agents are assumed to be truthful. Recent research has led to considering other situations such as negotiation among *dishonest* agents (Sakama, 2011), which is an interesting scenario for future work. Another relevant approach to argumentation-based negotiation can be seen in the work of Amgoud *et al*. (2007), where the proposed framework makes it possible to study the outcomes of the negotiation process. In contrast to this approach, our proposal relies on the characterization of belief revision operations to model agents' arguments generation, which their claims are the resources to be exchanged.

Formal models of belief change can be very helpful in providing suitable frameworks for rational agents (Bonanno *et al*., 2009), in which the information from inter-agent dialogues can be better exploited. Part of our recent research work (Pilotti *et al*., 2014) includes adding a justification when a proposal is rejected. However, no empirical analysis of this model has been carried out yet.

Inspired in human negotiation procedures, Sierra and Debenham (2007) consider five dimensions relevant to successful negotiation: legitimacy, options, goals, independence, and commitment. They introduce a negotiation model based on these dimensions and two primitive concepts: intimacy (degree of closeness) and balance (degree of fairness). As the agents representing their human principals may not be just utility maximizers, in some cases they aim at building long lasting relationships with progressing levels of intimacy that determine what balance in information and resource sharing is acceptable to them. These two concepts, intimacy and balance, are key to understanding competitive and co-operative game theory as two particular theories of agent relationships (i.e., at different intimacy levels).

8. Conclusions

In this paper we presented a novel approach to automated negotiation between two argumentative agents. An intentional architecture was given to each agent as to represent not only its own resources and goals but also its beliefs about the other agent's resources and goals. In our approach, the interpretation and generation of arguments are based on belief revision operators. In order to achieve their goals, agents engage in a benevolent dialogue, exchanging information that supports which resources they are willing to exchange. During the negotiation, the agents continuously update their mental states to generate proposals more likely to be accepted. All the propositions presented in our approach were formalized in Coq. A revised version of HIA was solved, showing how the agents can negotiate to solve this kind of cooperative problem, starting with incomplete and wrong beliefs about the other agent's resources, plans and goals. As discussed in Section 6, we carried out an empirical analysis of our proposal, assessing the impact of considering belief revision during the negotiation process.

Part of our future work is focused on studying complexity issues related to our proposal, as done by Zhang (2010) in the context of belief-revision based bargaining and negotiation. Furthermore, we want to identify different kinds of negotiation problems for which either BR or PBR agents are to be preferred, considering the trade-off between negotiation results and computational complexity. We are also investigating the logical properties of our approach, as well as the impact of different cost assignments in our model. In this setting, we contend that extending the integration of argumentation and belief revision in the context of agent negotiation dialogues is a very promising area for future research.

Acknowledgment

This research work was partially supported by the research projects PICT-ANPCyT 2009-0015, PID-UNR ING 466, PIP-Conicet 112-200801-02798 and the LACCIR project R1211LAC004.

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Received: 7 July 2014
Revised: 15 November 2014