RESEARCH ON THE BAYESIAN LEARNING MODEL FOR SELECTING ARGUMENTS ON ARGUMENTATION-BASED NEGOTIATION OF AGENT

Guorui Jiang, Xiaoyu Hu and Xiuzhen Feng

School of Economics and Management, Beijing University of Technology
No. 100 Pingleyuan, Chaoyang District, Beijing, P.R. China

Keywords: Argumentation-based negotiation, Agent, Selecting arguments, Bayesian learning.

Abstract: In the Argumentation-based negotiation of agent, it is important to enhance the agent's ability according to the environment, which would improve the argumentation efficiency significantly. Introducing Bayesian learning model to select arguments in Argumentation-based negotiation, the agent is able to learn and adjust itself according to a dynamic environment. This helps in making more rational and scientific choice for advancing efficiency of argumentation, when it is facing a variety of options for sending arguments. Finally, an example was presented for showing the rationality and validity of the model.

1 INTRODUCTION

As a widespread and important phenomenon in the society, negotiation not only brings opposition to all parties as they hold differences, but also makes them dependent on each other as they all commit themselves to consistency. With the rapid development of economic globalization and market networking, the traditional business negotiation has been replaced by e-business negotiation because of the shortcomings on the efficiency and effectiveness. In order to improve the decision-making of participants more scientifically and reasonably during the negotiation, the theory and technology of agent in Artificial Intelligence have been introduced; such as Game-theoretic approaches, Heuristic-based approaches and Argumentation-based approaches (Rahwan *et al.*, 2003). However, in most game-theoretic and heuristic models, agents are not allowed to exchange any additional information other than what is expressed in the proposal (i.e. potential agreements or potential deals) itself; another limitation of the two approaches is they both assume that agents' utilities or preferences have been fixed, which means that one agent cannot directly influence another agent's preference model, or any of its internal mental attitudes (e.g., beliefs, desires, goals, etc.) when it is generating its own preference model. Therefore, more and more

researchers are contributing their study on Argumentation-based negotiation of agent in the field of e-business negotiation.

The selection of argument is one of the hot topics on studying Argumentation-based negotiation of agent. Kraus studied this topic much earlier with all argument types from the weakest one to the most aggressive one. The mechanism of selection is that the agent will first try to use the weakest argument. If it does not succeed, it will go further with the following stronger arguments (Kraus *et al.*, 1998); in this case, we could see that the agent has to face varied negotiation environments when it was ready to send an argument. Obviously, the rules proposed by Kraus can not be universally applied. Recently, many researches have been focusing on evaluating the strength of various arguments and making the final choice with the comparison among all evaluation results. The representative one is the evaluation model contributed by Amgoud (Amgoud *et al.*, 2004; Amgoud *et al.*, 2005). An extended model in order to select sending argument is present, which makes the evaluation of strength as a core of the selection, chooses the certainty level (or priority level) of the knowledge and goal related to the argument as the main influencing factors of the strength; and for the vague and qualitative characteristics of evaluation of above factors, introduces some methods of representation and measurement in fuzzy mathematics; finally, makes the comprehensive evaluation as the scientific basis

for the selection of the argument's type and content (Guorui Jiang *et al*., 2009). However, the values of the main influencing factors of the arguments' strength in the whole argumentation interaction are fixed, and they do not fully take into account the dynamic of the actual negotiating environment, as well as how the agent can adapt to its dynamic environment.

To solve the problem mentioned above, a representative study is the models of opponent agents proposed by Carabelea (Carabelea, 2002); agents can adjust their strategy for argumentation through building and modifying models of opponents during and after the negotiation process. But how to build and modify the opponent's model was not specifically explained in the paper. In addition, we can find in Agent-based negotiation, through giving agents certain ability to learn, to have access to more information of opponents' preferences and the negotiating environment during the negotiation interaction, you can effectively improve their self-regulating capacity to the dynamic environment, so as to achieve the purpose of improving the efficiency of the negotiations. Bayesian learning method is common in traditional e-business negotiation (Zeng *et al*., 1998), it mainly focus on learning to the feedback of negotiating opponent, but the research on its use in Argumentation-based e-business negotiation is unusual now. Saha first proposed a Bayesian network approach to build opponents belief model to help agent to select a more effective argument. Unfortunately, the paper only demonstrated the possibility of the method, but it did not give an opponent model which can be updated in the true sense (Saha *et al*., 2004; Saha *et al*., 2005).Vreeswijk and Nielsen also introduced Bayesian network to generation or comparison of arguments(Vreeswijk, 2005; Nielsen *et al*., 2007).But we can find, these research mostly focused on traditional social Argumentation-based negotiation, not the Multi-issue e-business Argumentation-based negotiation; and the agent's belief model (including information about opponent's goals and the negotiation environment) can not be specifically formalized, thus can not effectively influence the strategy for argumentation like selection of arguments in negotiation.

Based on the background upwards, in this paper, we will introduce Bayesian learning to Argumentation-based negotiation. The agent is empowered the ability of learning and adjusting itself according to a dynamic environment, which helps in making more rational and scientific choice when it is facing a variety of options for an argument. In this way, the efficiency of the argumentation will be improved. At the same time, in order to be easy understood, we verify the rationality and validity of the model with calculation and analysis of an example at the end of the paper.

2 CLASSIFICATION OF THE ARGUMENTS

2.1 Threat

During a negotiation an agent A can force another agent B to do α by threatening to do an action β, to achieve the goal himself. A threat is then made up of three parts: the knowledge relative to this threat (the threat itself), the goal that A wants to achieve, and finally the goal of the threatened agent B (Amgoud *et al*., 2004; Amgoud *et al*., 2005).

Example 1 During an e-business negotiation, the buyer agent A wants the seller agent B to lower the price (LowPri) in a proposal, but it was refused. In this status, A may put forward that it will choose another seller (ChosAnoSel) as the threat to make B modify his beliefs and accept the proposal as soon as possible. And this threat can formally be expressed as follows:

$$A_t =< \{\neg LowPri \rightarrow ChosAnoSel\}, LowPri, \neg ChosAnoSel >$$

2.2 Reward

During a negotiation an agent A can entice another agent B to do α by offering to do an action β as a reward, to achieve the goal himself. A reward is then made up of three parts: the knowledge relative to this reward (the reward itself), the goal that A wants to achieve, and finally the goal of the rewarded agent B (Amgoud *et al*., 2004; Amgoud *et al*., 2005).

Example 2 During an e-business negotiation, the buyer agent A wants the seller agent B to lower the price (LowPri) in a proposal, but it was refused. In this status, A may put forward that it will buy some other related products (BuyOthPro) from B as the reward to make B modify his beliefs and accept the proposal as soon as possible. And this reward can formally be expressed as follows:

$$A_r =< \{LowPri \rightarrow BuyOthPro\}, LowPri, BuyOthPro >$$

2.3 Appeal

During a negotiation, an agent A may refer to some positive or negative facts as examples to persuade another agent B to do the business with it as an

appeal, to achieve the goal himself and the biggest profit of both of them (Amgoud *et al.*, 2005; Jinghua Wu *et al.*, 2006). Besides, we found that the appeals also concern the goals of the receiving agent like threats and rewards. So, in this paper we extend the definition of Appeal proposed by Amgoud. An appeal is made up of three parts: the knowledge relative to this appeal (the appeal itself), the goal that agent A wants to achieve, and finally the goal of the appealed agent B.

Example 3 In the same negotiation stalemate mentioned above in Examples 1 and 2, the buyer agent A may refer to some interests (SelfValue) that the seller agent B doesn't know but these behaviors may bring to such as many other agents will come to buy this product after seeing it through the use of A to persuade B to accomplish the business, and that will also achieve the goal of high buying quantity (HigBuy) of B. This appeal can formally be expressed as follows:

$$A_{a3} = < \{SelfValue \rightarrow LowPri\}, LowPri, Higbuy >$$

3 FORMAL MODEL OF EVALUATION ON THE ARGUMENTS' STRENGTH AND SELECTING ARGUMENTS

During the course of evaluation, we can conclude three main factors influencing the argumentation strength: the certainty level of the knowledge related to the argument, the priority of the goal that the agent sending argument wants to achieve, and the priority of the goal that the agent receiving argument wants to achieve. However, evaluation on these factors can be hardly found with accurate value in practice, it could be "very high" or "high", "Medium" and other vague concepts. Problems related to those vague concepts can not be solved by the traditional mathematics and statistics. Accordingly, we would introduce the methods in fuzzy mathematics to quantify the qualitative factors, and make the comprehensive evaluation finally. The details of the model mentioned above can be found in the previous study (Guorui Jiang *et al.*, 2009).

4 BAYESIAN LEARNING MODEL FOR SELECTING ARGUMENTS ON ARGUMENTATION-BASED NEGOTIATION

4.1 Bayesian Learning Model

The essence of the Bayesian learning model consists of using the Bayesian formula to processing the received information to amend the prior knowledge of learning objects. The Bayesian formula can be expressed as follows:
There is a set of events A_1, A_2... A_n concern with event H set:

1）$P(A_i) > 0$；2）$A_i \cap A_j = \varphi$，$i \neq j$；3）$\cup (A_i) = \Omega$,

Where $P(A_i)$ is priori probability; Ω is the union of events A_1, A_2...A_n.
The Bayesian formula is defined as follows:

$$P(A_i/H) = P(H/A_i)P(A_i)/\sum_{i=1}^{n} P(H/A_i)P(A_i) \quad (1)$$

Where $P(H/A_i)$ is conditional probability, which means that the probability of occurrence of event H on the condition of the occurrence of event A_i; $P(A_i/H)$ is posterior probability, which means the understanding of learning objects after revising.

4.2 The Basic Contents of Bayesian Learning Model on Argumentation-based Negotiation

In Argumentation-based negotiation, the basic framework of Bayesian learning model can be summarized as follows:

- Learners: participating agents; in this paper, we stand on the buyer agent's point of view as the learner.
- Learning objects: the information of opponent's preferences and negotiating environment. In this paper, they are referred to the main factors of the assessment of argument's strength, namely, "the certainty level of knowledge in argumentation" and "the priority level of related goals of negotiating partner in argumentation".
- Priori knowledge: the sample space and distribution of probability of the two main factors mentioned above.
- Information: the interactive information of learning object received during the course of negotiations. In this paper, the information is

319

the responded message as accepting or rejecting from seller agent after receiving an argument.

- Bayesian beliefs: in this paper, it refers to the estimate of the seller's responded policy of after receiving an argument; it is the basis to obtain the conditional probability. For example, in the buyer's opinion, the higher the priority level of seller's related goals in the argument is, the higher the probability of the argument's acceptance by the seller will be; On the contrary, the lower priority level is, the lower probability of acceptance will be.

- Posterior knowledge: after obtaining the conditional probability, combined with a priori probability, the posterior probability is calculated by Bayesian formula, which is the updated knowledge of learning objects after the buyer agent's Bayesian learning.

4.3 The Process of Bayesian Learning for Selecting Arguments

In e-commerce negotiations, the buyer sends an argument to the seller firstly, the seller would make a decision to accept or reject after the assessment of the intensity of the argument. The buyer receives a response message and analyzes it, updating information of negotiating partner's preferences or the information of negotiating environment by Bayesian learning Model. This paper updates the certainty of relevant knowledge that concerns with the argument and the priority of relevant objectives of seller. The buyer will make assessment of arguments with different types or contents according to the updated value of intensity factors, and then sends a new argument.

For example, let $R = \{Ri | i = 1, 2, ..., n\}$ be the assuming set relating to the priority of the seller-related goals of the buyer agent. Based on their prior knowledge, each hypothesis has a probability estimate, constitutes a probability set $P(R) = \{P(Ri) | i = 1, 2, ..., n\}$, which satisfy with $\sum_{i=1}^{n} P(Ri) = 1$. Subsequently, the buyer will receive the feedback signal e from the seller (this shall be accepted or rejected), according to the current observed domain knowledge, the buyer assumes a priori for each conditional probability $P(e | Ri)$. At this point, the buyer generates hypothetical posterior probability based on the Bayesian learning model as:

$$P_t(R_i | e) = \frac{P_{t-1}(R_i)P(e|R_i)}{\sum_{k=1}^{n} P_{t-1}(R_k)P(e|R_k)} \quad (2)$$

where $P_t(R_i | e)$ indicates the probability of R_i in the interaction of *t-th* round of argumentation, after the buyer agent receives the seller's feedback *e*. Therefore, in the *t-th* round, the buyer will re-predict priority of target related of the seller as:

$$\Pr_{gi} = \sum_{i=1}^{n} P_{t-1}(R_i | e) \times Ri \quad (3)$$

The updated value of the corresponding intensity factors will also be applied to evaluate the strength of the optional arguments, and thus choose to send a new round of argumentation. The details on the evaluation and selection can be found in (Guorui Jiang *et al.*, 2009).

5 ANALYSIS OF AN EXAMPLE

5.1 Negotiation Parameters and Basic Assumptions

This paper discusses mainly the buyer's selection on sending in Argumentation-based e-commerce bilateral negotiations. The main negotiation terms are price, quality and delivery time.

The buyer agent will first estimate the certainty level of knowledge and the priority level of the seller agent's goals related to the optional arguments(initial beliefs).Here, we will explain this by an example, suppose the buyer sends the first argument as "a reward , if the price is cut by seller, the buyer will buy more such products from him"; Table 1 shows the buyer's priori probability estimation of the priority level of the seller agent's goals related to the argument; Table 2 shows the priori conditional probability when the seller accepts or rejects the argument based on table 1.These priori knowledge are all gained by the past online transactions between the buyer and the seller. For example, in the buyer's common cognizance, the higher the priority of seller's related goals in the argument is, the higher the probability of the argument's acceptance by the seller will be; On the contrary, the lower priority level is, the lower probability of acceptance will be.

Table 1: The buyer's priori probability estimation of the priority level of the seller agent's goals related to the argument.

The priority level of the seller agent's goals related	R1: very low	R2: low	R3: lower	R4: medium	R5: higher	R6: high	R7: very high
Probability $P_0(Ri)$	0	0	0	0.1	0.3	0.4	0.2

Table 2: The priori conditional probability when the seller accepts or rejects the argument.

The priority level of the seller agent's goals related	The seller's response to the argument	
	Acceptance	Rejection
Very low	0.125	0.875
Low	0.25	0.75
Lower	0.375	0.625
Medium	0.5	0.5
Higher	0.625	0.375
High	0.75	0.25
Very high	0.875	0.125

5.2 The Process of Bayesian Learning for Selecting Arguments

During e-business negotiation, the proposal given by the buyer agent A is quite different from the expectation of the seller agent B, for its profit, B may reject, which may bring the negotiation into a stalemate. In this situation, to guarantee the profit of both of them and the negotiation to be continued successfully, A will send argument to B to persuade it make some concession, suppose there are three optional arguments including: (1) price cut, A will purchase more such products from B if the price cuts, (2) improve the quality, A will purchase more such products from B if the quality improves, (3) shorten the delivery time, B has promised A to shorten delivery time in the past; the above optional arguments can formally be expressed as follows:

$A_1 =< \{LowPri \rightarrow BuyMorePro\}, LowPri, BuyMorePro >$

$A_2 =< \{HigQua \rightarrow BuyMorePro\}, HigQua, BuyMorePro >$

$A_3 =< \{PastPromise \rightarrow ShortDelivery\}, ShortDelivery, HigRep >$

A send the first argument A_1, then receive the acceptance by B to A_1. Based on the feedback by B and the priori knowledge of B(for example as Table 1 and Table 2), A use Bayesian learning model to update the belief on the certainty level of the knowledge and the priority level of the seller agent's goals related to A_1. Here, we explain this by showing updating of the priority level of the seller agent's goals related to A_1 as follows: according to formula (2) and data from Table 1 and Table 2, we can achieve the results after calculation, for example,

$$P_1(R_4|e) = \frac{P_0(R_4)P(e|R_4)}{\sum_{i=1}^{7} P_0(R_i)P(e|R_i)}$$

$$= \frac{0.1 \times 0.5}{0.1 \times 0.5 + 0.3 \times 0.625 + 0.4 \times 0.75 + 0.2 \times 0.875}$$

$$\approx 0.07$$

in it, $P_1(R_4|e)$ indicates the buyer A's posterior probability to R_4 after it received the acceptance of A_1 from B. Similarly, there are $P_1(R_5|e) \approx 0.263, P_1(R_6|e) \approx 0.421, P_1(R_7|e) \approx 0.246$ and $P_0(R_1) = P_0(R_2) = P_0(R_3) = 0$ because of $P_0(R_1) = P_0(R_2) = P_0(R_3) = 0$.

Before A receives the feedback from B to A_1, its belief about the priority level of the seller agent's goal (as buy more such products) can be calculated by formula (3) as follows:

$$\Pr_{g1} = \sum_{i=1}^{7} P_0(Ri) \times Ri$$

$$= 0.1 \times (0.4, 0.45, 0.55, 0.6) + 0.3 \times (0.55, 0.6, 0.7, 0.75)$$

$$+ 0.4 \times (0.7, 0.75, 0.85, 0.9) + 0.2 \times (0.85, 1, 1, 1)$$

$$= (0.655, 0.725, 0.805, 0.845)$$

During this, we have used knowledge in fuzzy mathematics, the detail can be found in (Guorui Jiang *et al.*, 2009). Similarly, after A receives the feedback, its belief about the priority level of the seller agent's goal will be updated as follows:

$$\Pr'_{g1} = \sum_{i=1}^{7} P_1(Ri) \times Ri$$

$$= 0.07 \times (0.4, 0.45, 0.55, 0.6) + 0.263 \times (0.55, 0.6, 0.7, 0.75)$$

$$+ 0.421 \times (0.7, 0.75, 0.85, 0.9) + 0.246 \times (0.85, 1, 1, 1)$$

$$= (0.67645, 0.75105, 0.82645, 0.86415)$$

And, the probability distribution of the priority level of the B-related goal "buy more products (BuyMorePro)" will be updated as Table 3:

Table 3: The updated probability distribution of the priority level of B's related goal.

The priority level of the seller agent's goals related	R1: very low	R2: low	R3: lower	R4: medium	R5: higher	R6: high	R7: very high
Probability $P_1(Ri)$	0	0	0	0.07	0.263	0.421	0.246

After the buyer agent respectively updated the certainty level of the knowledge and the priority level of the seller agent's goal related to A_1, it will evaluate the strength of the rest optional arguments according to the updated values of the main influencing factors, and thus choose to send a new argument. The details can be found in (Guorui Jiang et al., 2009). In the example, as an agent can not allowed to send two same arguments continuously, so A_2 and A_3 are the new optional arguments, we finally select to send A_2 in a new round after the evaluation. We can find that it is precisely because the priority level of the B-related goal "buy more products" has been updated after the first round, while this goal is also B's related to A_2, allowing A_2 be the better choice; also the choice is more effective and scientific because of update of agent's belief on the dynamic negotiation environment.

6 CONCLUSIONS

In this paper, a Bayesian learning model has been introduced along with Argumentation-based negotiation, and the process of Bayesian learning for argument selection has been analyzed with an example. This could make more scientific and rational choice of different types and contents of arguments and increase the possibility of acceptance of arguments. It gives an agent a certain ability to learn by Bayesian learning model. So that it can be continuously adjusted according to dynamic environment, self-awareness, and effectively improve the efficiency of argumentation. It overcomes shortcomings of argument selection followed a static environment in the previous study, and appears to be more practical and effective.

But, in the model, more complete prior knowledge is needed and the reasonableness and accuracy of prior distribution also need to be further improved. At the same time, more information from the opponent and the negotiation environment should be considered into the learning object of the agent, to help it to greatly improve its self-adaptive ability to the dynamic negotiation environment.

ACKNOWLEDGEMENTS

REFERENCES

Amgoud, L., Cayrol, C., 2004. Generation and Evaluation of Different Types of Arguments in Negotiation. In *Proceedings of International Workshop on Non-Monotonic Reasoning (NMR'04)*, pp. 10-15.

Amgoud, L., Prade, H., 2005. Formal Handling of Threats and Rewards in a Negotiation Dialogue. In *Proceedings of the 4th International joint Conference on Autonomous Agents and Multi-Agent Systems, AAMAS'2005*, pp. 529-536.

Carabelea, C., 2002. Adaptive Agents in Argumentation-based Negotiation. *Multi-Agent Systems and Applications*. 2322, 87-122.

Guorui Jiang, Xiaoyu Hu, 2009. Research on the Evaluation Model for Selection of the Argument's Type and Content in Argumentation-based Negotiation of Agent. In *Proceedings of the 11th International Conference on Informatics and Semiotics in Organisations*, pp. 173-180.

Jinghua Wu, Guorui Jiang and Tiyun Huang, 2006. Using Two Main Arguments in Agent Negotiation. *Agent Computing and Multi-Agent Systems*. 4088, 578-583.

Kraus, S., Sycara, K., McBurney, P., and Evenchik, A., 1998. Reaching Agreements through Argumentation. *Artificial Intelligence*. 104(1-2), 1-69.

Nielsen, S. H., Parsons, S., 2007. An Application of Formal Argumentation: Fusing Bayesian networks in multi-agent systems. *Artificial Intelligence*. 171(10-15), 754-775.

Rahwan, I., Ramchurn, S. D., McBurney, P., Parsons, S., and Sonenberg, L., 2003. Argumentation-based Negotiation. *The Knowledge Engineering Review*. 18(4), 343-375.

Saha, S., Sen, S., 2004. A Bayes Net Approach to Argumentation. In *Proceedings of the 3rd International Joint Conference on Autonomous Agents and Multiagent Systems*, pp. 1436-1437.

Saha, S. and Sen, S., 2005. A Bayes Net Approach to Argumentation Based Negotiation. *Artificial Intelligence*. 3366, 208-222.

Vreeswijk, G. A. W., 2005. Argumentation in Bayesian belief networks. *Artificial Intelligence*. 3366, 111-129.

Zeng, D., Sycara, K., 1998. Bayesian learning in negotiation. *Human-Computer Studies*. 48(1), 125-141.