Fuzzy counter-offers in agent-mediated negotiations

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Abstract. Negotiation plays a fundamental role in systems composed of multiple autonomous agents. Some negotiations may require a more elaborated dialogue where agents would explain offer rejections in a general and vague way. We propose that agents would represent their disappointment about an offer through fuzzy logic. Fuzzyness can also be very useful in order to make human-like negotiations, consequently, user profiles may become more difficult to acquire in detail. Specifically we study two alternatives: a piece-wise fuzzy set or a linguistic label applied to each attribute of the offer. These alternatives are evaluated comparing the performance of both types of counter-offers with a classical approach based on linear programming. Therefore, the average of negotiation length, benefits and percentage of agreements allow us to conclude the accuracy of the alternatives proposed.

1. Introduction

In recent years, there has been an increasing interest in the economic uses of Internet. The number of possible merchants available is one of the advantages of Internet, but they also avoid human supervision of commercial interactions [19]. Therefore, automation is desirable to exploit the possibilities of spanning geographical, cultural and political boundaries. It can be achieved through the use of autonomous programs often called ‘agents’ [26].

But the success of agents in electronic commerce did not come up to expectations [21]. Among the reasons could be the fear of human users to possible misunderstandings leading to negative consequences such as wasting money and revealing their shopping profile. If the behaviour of these agents exhibited a comprehensive intelligence in the six steps of any shopping process: identification of necessity, profiling the desired product, selection of merchant, automatic negotiation, electronic payment and evaluation [24].

From them, this research is interested just in automated (bargaining) negotiations from the point of view of buyers, since the final intention of this research is to make potential buyers feel more sure delegating in computational agents. So we adopt a one-sided approach along all the paper that limits the generality of this research since it do not address interesting issues related to the two-sided bargaining studies [8] that could be a possible direction of future research.

Bargaining negotiations take place by the exchange of messages that look forward an agreement satisfactory to both parts. This type of negotiations have been largely studied by Game Theory [25]. The major issues in whatever negotiation are protocols and strategies. Protocols rule the communication acts allowed in each moment of a negotiation. They should be public and accepted previously by both parts. Strategies rule the particular behaviour of each part in a negotiation. They should be private because they should reflect the personal preferences of the corresponding part.

Classic Strategic Bargaining Theory presupposes that the negotiating parts have common knowledge and a rational preference ordering that entails completeness and transitivity. The former means even more than knowing the preferences and beliefs of all participants (complete knowledge), the latter means the ability of reproducing the computations of any other participant. However these assumptions are often under discussion and artificial intelligence techniques could...
possibly cooperate with Strategic Bargaining Theory to jointly overcome them.

In open environments of agents with possibly opportunistic behaviour, we can count on a shared ontology of universally accepted terms of the dominion, a protocol publicly known and private strategies that are not optimal but computed in real time [3]. Therefore, complete knowledge can not be presupposed [17]. The standard Game Theoretic approach to deal with this problem of incomplete knowledge is based on Bayes Theorem. Nevertheless, the bayesian approach has also some disturbing consequences on negotiations [20,10] that suggest mapping states with sets of consequences instead of mapping states with singletons of consequences. So using fuzzy logic rather than bayesian solutions seems to be justified from the previous works in that direction [13–15] although the applications of fuzzy logic on bargaining settings are still scarce [1].

The possibility of reversing the preference-based reasoning of the other side has been discussed by psychologists since they consider that there is no common mechanism between valuation and choice. Additionally, related work on agent-mediated auctions showed that focusing negotiations in just only one issue (price) is a too restrictive approach [18]. In other way, if artificial intelligence intends to reflect the real behavior of society [26], then more criteria than price should be involved. Therefore preferences become more complex and imprecise and transitivity becomes affected [12].

With the same intention of emulating human-like negotiations, in daily market bargains both parts avoids revealing too much detailed information about their preferences using some ambiguity in the dialogue. Reflecting such typically human behaviour in agent-mediated bargaining negotiations is one of the aims of this contribution, other final intentions are: reaching more agreements without wasting computational resources in cyclic or nonsense negotiations.

In other words, the cooperation of Artificial Intelligence with Strategic Bargaining Theory is intended to support buyers interests in the negotiation leading their offers towards their particular preferences and to protect the private information called shopping profile through the use of fuzzy logic.

The next section contains a description of the generic negotiation scheme and protocol proposed. The following section details an example of intelligent behaviour from buyers and merchants. Section 5 describes the experimental results of the proposal. And finally, conclusions point out the relevance of the contribution presented.

2. Proposed scheme of negotiation

We intend agents to hide preferences of the buyer while persuading merchants of improving their offer. Due to this pretension, we propose to use fuzzy sets to express counter-offers in a protocol extremely simple: a sequence of offers and fuzzy counter-offers. The protocol follows the next execution cycle:

- The buyer agent asks for a product/service
- The merchant agent makes an offer
- The buyer agent rejects the offer, sending a fuzzy counter-offer as response.
- Both agents exchange offers and fuzzy counter-offers sequentially.
- Negotiation ends when the buyer agent accepts the offer, or when any of them withdraws the negotiation (possibly when certain number of messages was exchanged).

Since we intend that agents reason about their beliefs and intentions in a human-like way, agents architecture follow a sample structure of beliefs, plans and intentions, much alike the BDI paradigm [16]. They were implemented in java and includes the use of fril [2] to compute fuzzy operations with mass assignment theory. Each communication message between agents is KQML [9] typed and therefore, it has an performative associated, these are: request, offer, accept, reject, withdraw. In the next figure we outline the sequence of messages described above, with a state diagram, whose transitions are messages of the protocol.

The details of both, offers and counter-proposals, are usually represented by a list of (attribute, value) pairs. However in our protocol, the type of the values, related to the same attribute, are different in offers and counter-offers. In other words, the merchant agent would fill the attributes with concrete values detailing the agreement proposed. But the buyer agent would explain his rejection through in a general and vague way. This ambiguity reflects the way humans act in popular markets. Buyers give an approach of how much he expects an attribute of the offer to be improved. Commerce should reason with the fuzzy preferences of the user about the desired terms of the agreement. Human reasoning with ambiguity, and vague concepts as tall and young is tackled in Artificial Intelligence with Fuzzy Logic. We propose that only buyer agents would represent their disappointment about an offer through fuzzy values applied to the attributes of the offer. Fuzzyness can be very useful in order to hide the decision thresholds of the user, and also to increment the expressiveness of his offer.
rejections. Using a fuzzy set, buyer agents may implicitly transmit a graduation of preferences, together with a measure of their flexibility. We can express these nuances of meaning mathematically with the four squares of a trapezium. The quantity of doubts/ambiguity about what should be considered an acceptable value, could be interpreted from the gradient of the trapezium sides. For instance, fuzzyness let agents represent that price is far away from the expected value, since the fuzzy set is not centered. And price is also an important attribute, since the high sensitivity reflected in the scarce width of the fuzzy sets. On the other hand, the proposed delivery time is acceptable since it is completely centered, and this issue is not so much important since certain modification of this value on both senses would be still acceptable (the corresponding fuzzy set is wider). We can graphically observe two examples of these fuzzy values in the Fig. 2.

We then conclude that a rejection message express the expected offer with a fuzzy valuation. The list of (attribute, value) pairs in rejections might not be exhaustive. The buyer agent could forgive them because they are already acceptable, or because they are going to be negotiated later. Nevertheless, the offers are composed of an exhaustive list of attributes, and the agent of the merchant is committed to them.

3. Intelligent behaviour of agents

In order to test the role played by fuzzyness in counter-offers of buyers, the negotiation scheme proposed implemented with both linguistic and numerically defined fuzzy sets is compared with corresponding negotiations where buyers reject the offer of merchants in a concrete way. First we present the space of negotiation including the preferences function and strategy of buyers and merchants. Next we explain how buyers generate crisp counter-offers, afterwards how buyers generate piece-wise fuzzy sets of counter-offers, and finally how linguistic labels are generated by buyers and interpreted by merchants.

3.1. Negotiation setup

So the protocol used have to be complemented with the bargaining behaviour of merchants, crisp buyers and fuzzy buyers defined by some preferences function and strategy.

The preferences function of each part consists of a boundary value and a weight for each negotiation attribute. For instance, a buyer may have a positive weight and a minimum threshold value for the attribute 'quality' and a negative weight together with a maximum threshold value for the attribute 'price'. Obviously, the weights of merchants should have opposite sign. Additionally weights should have a value different from zero since we assume that every attribute have certain influence (positive/negative) over the desired agreement.

Therefore an agreement is reached when the offer satisfies the next requirements:

\begin{equation}
\forall i \in \text{Attributes} : \text{benefit} > \sum_i \text{weight}_i \cdot \text{offer}_i \tag{1}
\end{equation}

\begin{equation}
\forall j \in \text{Attributes}, \text{weight}_j > 0 : \text{offer}_j > \text{threshold}_j \tag{2}
\end{equation}

\begin{equation}
\forall k \in \text{Attributes}, \text{weight}_k < 0 : \text{offer}_k < \text{threshold}_k \tag{3}
\end{equation}

The weights and thresholds of each part are chosen with certain randomness but in a way that agreements are possible, satisfying the next condition:

\begin{equation}
\forall j \in \text{Attributes}, \text{weight}_j > 0, \forall k \in \text{Attributes}, \text{weight}_k < 0 : |\text{weight}_k| \cdot \text{threshold}_j > |\text{weight}_j| \cdot \text{threshold}_k \tag{4}
\end{equation}
Finally, the initial offer from the merchant is computed from the next equation (where dim stands for the dimension of the negotiation -number of attributes-):

$$\forall i \in \text{Attributes} :$$

$$\text{offer}_i = \text{threshold}_i + \text{benefit} \frac{1}{(\text{weight}_i \cdot \text{dim})}$$

(5)

### 3.2. Generation of crisp counter-offers

Buyers intend two different aims: maximize benefits and minimize the distance with the offer of merchants. Such distance is denoted as $x$ and is then used as argument of the goal function $z$ to maximize. Applying parameter $\lambda$ to simplex method in problems of linear programming with several goals, was initially proposed by Zadeh in 1963 [27]. Therefore the definition of goal function $z$ results:

$$\max z = \lambda \cdot \left( \sum_i \text{weight}_i \cdot x_i \right) + (1 - \lambda) \cdot \left( \sum_i -x_i \right)$$

(6)

The restrictions posed over such goal function are obtained from expected benefit from the weighted offer, and from the thresholds of each attribute:

$$\sum_i \text{weight}_i \cdot x_i \geq \text{benefit} - \sum_i \text{weight}_i \cdot \text{offer}_i$$

(7)

$$\forall j \in \text{Attributes, weight}_j > 0 :$$

$$x_j \geq \max(0, \text{threshold}_j - \text{offer}_j)$$

(8)

$$x_j \leq \text{offer}_j \cdot (\lambda + \frac{|\text{weight}_j|}{\sum_i |\text{weight}_i|})$$

(9)

Using parameter $0 < \lambda < 1$ with small values ($\lambda = 0.1$), benefits are rather less important than the distance with the offer received. It avoids counter-offers going very far away from the offer (overreaction). If the problem defined with such $\lambda$ was infeasible, then $\lambda$ would be increased until the problem becomes feasible.

### 3.3. Generation of piece-wise fuzzy counter-offers

This kind of counter-offers consists of four values for each attribute, representing a piece-wise definition of a trapezium over a dominion of fictitious values. Therefore, merchants could not translate straightforward these values to real values of the dominion corresponding to the given attribute.

However, the shape and relative position of the trapezium should reflect in an indirect way the preferences of the buyer over such attribute. So buyers assign their own scale to the dominion of fictitious values using a value called $m$. The corresponding dominion results then from $\text{offer}_i - m$ to $\text{offer}_i + m$. The value $m$ is computed from:

$$m = \max(|\text{offer}_i - \text{threshold}_i|, |\text{benefit} \div \text{weight}_i - \text{offer}_i|)$$

(10)

Therefore the four points that define the fuzzy set are the next ones:
3.4. Generation and evaluation of linguistic labels as fuzzy counter-offers

In this kind of counter-offer, buyers send two linguistic labels per each attribute. One of them represents one of five possible fuzzy sets: smaller, small, medium, great, greater. The other label represents a linguistic modifier: more or less, somewhat, none, very and extremely. Modifiers only change the gradient of the sides of the trapezium.

In order to generate this pair of labels from an offer of the merchant, two values are computed: distance and gradient with the next equations:

\[
\forall j \in \text{Attributes, weight}_j > 0 : \\
\begin{align*}
\text{distance} &= \text{offer}_j \cdot \text{weight}_j \cdot \text{dim} \div \text{benefit} \\
\text{gradient} &= (\text{offer}_j - \text{threshold}_j) \cdot (\text{weight}_j \cdot \text{dim}) \div \text{benefit} - \text{threshold}_j
\end{align*}
\]

As these variables are valued in [0,1], each of the five possible labels corresponds to one of these subsets: [0, 0.2), [0.2, 0.4), [0.4, 0.6), [0.6, 0.8), [0.8, 1]. Distances determine the first linguistic label, while gradients determine the linguistic modifier. When the merchant receives such linguistic labels, a graphical interpretation of the linguistic label is drawn over the domination scaled with the preferences of the merchant. The crossover of the fuzzy set built up the preferences of the merchant and the fuzzy set corresponding to the interpretation of the linguistic labels, is then re-scaled to obtain a crisp offer answering to the previous fuzzy counter-offer based on linguistic labels.

4. Experimental results

We have test an illustrative example with only two attributes to negotiate: price and quality. One of them (quality) has a positive weight in the preferences function of buyers, and the other (price) has a negative influence over the possibility of accepting an offer.

For evaluation purposes, we have considered 100 negotiations between a merchant and each type of buyers. In each of these 100 negotiations, buyers and merchants use different preferences functions computed randomly (essentially weights and thresholds of the negotiation attributes). Since conditions defined over weights and thresholds in equations 1.2 and 3 lead to very few agreements, we added extra conditions correlating both negotiation attributes:

\[
\forall j, k \in \text{Attributes, weight}_j, \text{weight}_k < 0 : \\
\begin{align*}
\text{distance} &= 1 + \text{offer}_k \cdot \text{weight}_k \cdot \text{dim} \div \text{benefit} \\
\text{gradient} &= (\text{threshold}_k - \text{offer}_k) \cdot (\text{weight}_k \cdot \text{dim}) \div \text{benefit}
\end{align*}
\]

It is also stated that negotiations fail after a sequence of 10 pairs of offers and counter-offers. So negotiations may never last more than 20 messages. With all these conditions we obtained the following results: As we can see in Table 1, for the negotiations involving fuzzy
sets, a higher percentage of success is reached using less computational resources, although the benefit obtained is lower than the other two alternatives. So it seems that fuzzy sets are specially useful to face fast negotiations and to avoid failed negotiations. Furthermore, the velocity of convergence of this alternative does not mean an easier acquisition of buyers’ shopping profile as it is shown in [4].

On the other hand, negotiations involving fuzzy labels last much more than the others, and obtain a percentage of success similar to negotiations involving crisp counter-offers. Nevertheless the final agreement obtained satisfies better the preferences of buyers. So this type of counter-offer obtains better agreements lasting more time.

5. Conclusions

The main contribution entails with the application of fuzzy logic to agent-mediated negotiations. Our proposal first intends to make negotiation dialog more human, and second, it also intends to make negotiations more profitable for buyers, and finally that negotiations do not waste computational resources in no-way-out negotiations. All these intentions are tackled by fuzziness in the counter-proposals generated by users. This idea was previously proposed in [5,6] combined with the anonymous use of arguments in persuasive negotiations.

In this paper, that extends a preliminary publication [7], a realistic scenario was defined with three different kinds of buyer. One of them uses fuzzy sets to suggest improvements in the offer of the merchant. Other type of buyer uses linguistic labels to express ambiguity in offer rejections, and finally, the last type of buyer uses concrete values to reply with a crisp counter-offer. An illustrative example of a possible behaviour of all of them, and of merchants, is mathematically described in this document. They were implemented and tested to evaluate the comparative performance of them. From the experimental results we can conclude that negotiations with fuzzy labels are more exhaustive and the process followed is more similar to human negotiations, and probably they will receive a broad acceptance although they last more than the other alternatives while the results are more or less equal to crisp negotiations. On the other hand negotiations based on the transmission of fuzzy sets achieve relevant improvements such as less time involved and a greater level of agreements although the quality of those agreements become slightly sacrificed.

The inclusion of more attributes does not change the nature of the experiments hold, although it involves more time to execute them, since it has less possibilities to obtain feasible solutions unless we would define much more complex conditions correlating negotiation attributes than those showed in Eq. (15). So for simplicity, we restricted the experiments to an illustrative example with just two attributes.

As a final conclusion, this paper proposed two alternatives based on the fuzzy nature of human dialogs in bargaining. These alternatives showed different behavior than the classical (crisp) negotiations in efficiency terms. Both of them improve a particular point of view (number of messages, percentage of agreements reached, quality of agreements). These reasons make our approach become a valid alternative to implement automatic negotiations between autonomous agents.

The research may be applied in the future to any multi-criteria bargaining negotiations, specifically to those that require a high human acceptance from one-side. Two-sided incomplete bargaining could contribute even more to make electronic commerce a bit more successful and it is a natural way of continuing this work. We are also using this negotiation scheme in the problem of coordinating several cameras monitoring the movement of many targets while surveilling a given physical location [11]. That application of this research is supported by national (CICYT TIC2002-04491-C02-02) and local (CAM 07T/0034/2003 1) projects.

References


