A Hybrid Negotiation Strategy Mechanism in an Automated Negotiation System *

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ABSTRACT

This paper describes a hybrid negotiation strategy mechanism using a *strategy pool framework* that allows negotiation agents more flexibility and robustness in an automated negotiation system. The strategy pool framework supports: a) dynamically assigning an appropriate negotiation strategy to a negotiation agent according to the current negotiation environment and b) creating new negotiation rules by learning from past negotiations. Learning forms we use here for the framework are Feed Forward Back Propagation (FFBP) neural networks and multidimensional inter-transaction association rules mining.

Categories and Subject Descriptors

I.2.1 [**Artificial Intelligence**]: Applications and Expert Systems; K.4.4 [**Computers and Society**]: Electronic Commerce

General Terms

Management, Economics, Design

Keywords

Automated Negotiation, Data Mining, Neural Network

1. INTRODUCTION

It has been widely accepted that two important tasks in automated negotiation are formalizing the negotiation process and incorporating necessary negotiation knowledge and intelligence. The first task is often associated with a negotiation ontology approach and is not dealt with here. The second task concerns negotiation strategies.

A variety of research work exists on negotiation strategies in the areas of social science, game theory, negotiation support systems, agent technologies, and machine learning. Unfortunately, automated negotiation agents based on any of these techniques usually face two problems. First, agents are not as flexible and adaptive to different *negotiation environments* as desired. Negotiation environment is a set of pre-defined negotiation features which are not negotiable in negotiations. This means an agent may work well under one set of negotiation features, but perform worse in others. Second, a fixed strategy or a static group of strategies may become known by competing agents as a result of negotiation processes, after which those agents can potentially exploit this knowledge in future negotiations.

We introduce a hybrid negotiation strategy mechanism based on SCENS [3], the Secure/Semantic Content Exchange System. This mechanism can: 1) dynamically assign the appropriate strategy to a negotiation agent according to that negotiation environment and 2) create new negotiation rules and negotiation strategies by learning from past negotiations. By incorporating this mechanism, we show how a negotiation agent can solve the two problems above.

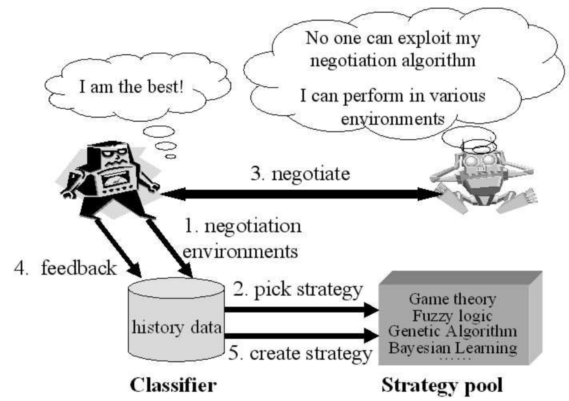

Figure 1: Work flow of Strategy Pool Framework

2. STRATEGY POOL FRAMEWORK

The *Strategy pool* is a repository for multiple negotiation strategies. By using the strategy pool, negotiation agents have a variety of choices for their strategies instead of always depending on a single strategy. To support strategy selection and the generation of new strategies, a classifier is adopted to learn from history data. Figure 1 shows the Strategy Pool framework we are implementing in SCENS, a three layer Web Services-based negotiation system that enables automated negotiation for scientific data sharing. In each negotiation process, the negotiation agent enters the current negotiation environment features into a classifier; the classifier then selects a negotiation strategy from the

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strategy pool according to past experiences and feedback. The agent then uses this negotiation strategy to negotiate with the party. After the negotiation process ends, the agent and its user can provide a negotiation history and feedback on the result to the classifier. Over time, based on the negotiation results from past negotiation processes, the system can thus make use of machine learning to find the preferred strategy for each different negotiation environment. Moreover, the system may create new negotiation strategies by formalizing new negotiation rules and incorporating them into existing strategies. Each such new strategy will then be added to the strategy pool for later use.

By using the strategy pool framework, we argue that the negotiation agent is made more adaptive and robust in different negotiation environments. This is because the negotiation strategy picked for the agent for a particular negotiation process is generally one that performed well on similar negotiation cases in the past (if such cases are known) or that is at least predicted to perform well based on experience. Since in each negotiation process the strategy is potentially different and is always subject to revision, it is difficult for the other agents to infer the strategy the agent uses. Therefore, there is no theoretical vulnerability inherent in the agent's negotiation strategy, as is the case with a fixed strategy.

3. TWO LEARNING FORMS

There are two learning forms in this framework. In the first form, the classifier uses Feed Forward Back Propagation (FFBP) neural networks to help negotiation agents benefit from their experience. We divide negotiation features in a negotiation environment into five categories [1]: *who, what, when, where,* and *how*. To a certain negotiation, those negotiation features which can be quantified (*e.g.*, party reputation) are the input nodes of the neural network. Those negotiation features which can not be quantified (*e.g.*, product or service category) are the filters that are used to select the training data set from the past negotiation history. The output nodes of the neural network represent the negotiation result (*i.e.*, expected negotiation attributes values or the user satisfactory ratio) of each possibly adopted negotiation strategy in the strategy pool. Figure 2 shows an example of the FFBP neural network structure for negotiation strategy selection.

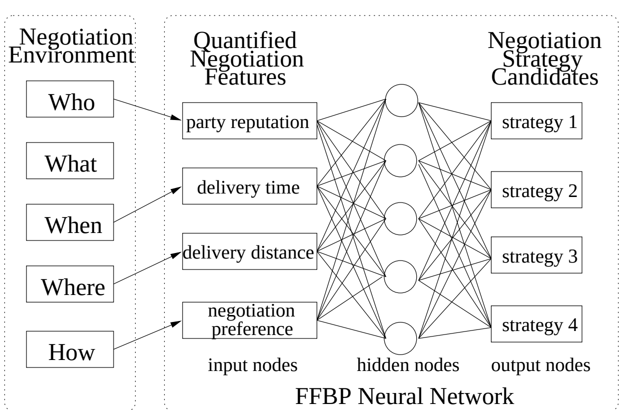

Figure 2: The Feed Forward Back Propagation neural network used for strategy selection

The second learning form generates the negotiation rules automatically by mining history data. These negotiation rules are event trigger rules such as: *"if the seller party proposes a 15 dollars concession on price and requires 2 days more in the delivery time, the buyer party should counteroffer 10 dollars more on price and allow only 1 day extension on delivery"*. As there are multiple negotiation attributes (*e.g.*, time, amount, price, warranty) in the negotiation offer, this kind of learning is actually mining *multidimensional inter-transaction association rules* [2] if we think each offer or counteroffer as a transaction and each negotiation attribute as a dimension.

Let $T = \{t_0, t_1, \ldots, t_n\}$ denote a series of offers and counteroffers in a negotiation process for a certain item. Let $D = \{d_1, d_2, \ldots, d_m\}$ denote the attributes (dimensions) for any negotiation offer about this item. Thus each transaction can be considered as a point in an m-dimension space. Furthermore, the relation of two transactions can be measured by calculating the relative difference of their corresponding points in the space. Define $\Delta(j,k) = t_j - t_k (j > k)$ as the relative difference of t_j and t_k. Moreover, if we are interested in a subset of attributes in the relative difference, we can project the difference onto those dimensions, so we have:

$$\Delta_{c_1,\ldots,c_k}(j,k) = \{t_j - t_k \text{ on } d_{c_1}, \ldots, t_j - t_k \text{ on } d_{c_k}\}\ .$$

Here, each of $c_1, \ldots, c_k$ is the index of a certain dimension in D. In our previous example, if we assume the price (dollars) and time (days) are the first two attributes in the negotiation offer, the rule can therefore be represented as:

$$\forall k \geq 0, \Delta_{0,1}(k+2,k) = \{-15, 2\} \Rightarrow \Delta_{0,1}(k+3,k+1) = \{10, 1\}\ .$$

Here t_k, t_{k+2} are two consecutive offers from the seller and t_{k+1}, t_{k+3} are the buyer's counteroffers.

Given a negotiation history with the same set of negotiation attributes, we calculate all $\Delta(j,k)$ and their projections. Since the Δ operation maintains the monotonic property of the support of item sets, we can still adopt traditional methods to compute the support and confidence for the multidimensional inter-transaction association rules. The history data used for mining can be either all negotiation history which have similar negotiation environments in the system, or those satisfied negotiation processes reaching a required user satisfaction ratio. The latter is more preferable because qualified negotiation processes are more popular with users and have more values in generating rules in which users might be interested. Generated rules are incorporated into existing strategies where appropriate, or combined to form new strategies. The updated or newly generated strategies are then added to the strategy pool.

4. REFERENCES

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