

Shortening Automated Negotiation Threads via Neural Nets

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INTRODUCTION

In the artificial intelligence domain, an emerging research field that rapidly gains momentum is *Automated Negotiations* (Fatima, Wooldridge, & Jennings, 2007) (Buttner, 2006). In this framework, building intelligent agents (Silva, Romão, Deugo, & da Silva, 2001) adequate for participating in negotiations and acting autonomously on behalf of their owners is a very challenging research topic (Saha, 2006) (Jennings, Faratin, Lomuscio, Parsons, Sierra, & Wooldridge, 2001). In automated negotiations, three main items need to be specified (Faratin, Sierra, & Jennings, 1998) (Rosen-schein, & Zlotkin, 1994): (i) the negotiation protocol & model, (ii) the negotiation issues, and (iii) the negotiation strategies that the agents will employ.

According to (Walton, & Krabbe, 1995), “*Negotiation is a form of interaction in which a group of agents, with conflicting interests and a desire to cooperate try to come to a mutually acceptable agreement on the division of scarce resources*”. These resources do not only refer to money, but also include other parameters, over which the agents’ owners are willing to negotiate, such as product quality features, delivery conditions, guarantee, etc. (Maes, Guttman, & Moukas, 1999) (Sierra, 2004). In this framework, agents operate following predefined rules and procedures specified by the employed negotiation protocol (Rosen-schein, & Zlotkin, 1994), aiming to address the requirements of their human or corporate owners as much as possible. Furthermore, the negotiating agents use a reasoning model based on which their responses to their opponent’s offers are formulated (Muller, 1996). This policy is widely known as the negotiation strategy of the agent (Li, Su, & Lam, 2006).

This paper elaborates on the design of negotiation strategies for autonomous agents. The proposed strategies are applicable in cases where the agents have strict deadlines and they negotiate with a single party over the value of a single parameter (*single-issue bilateral negotiations*). Learning techniques based on MLP and GR Neural Networks (NNs) are employed by the client agents, in order to predict their opponents’ behaviour and achieve a timely detection of unsuccessful negotiations. The proposed NN-assisted strategies have been evaluated and turn out to be highly effective with regards to the duration reduction of the negotiation threads that cannot lead to agreements.

The rest of the paper is structured as follows. In the second section, the basic principles of the designed negotiation framework are presented, while the formal problem statement is provided. The third section elaborates on the NN-assisted strategies designed and provides the configuration details of the NNs employed. The fourth section presents the experiments conducted, while the fifth section summarizes and evaluates the results of these experiments. Finally, in the last section, conclusions are drawn and future research plans are exposed.

THE AUTOMATED NEGOTIATION FRAMEWORK BASICS

This paper studies a single issue, bilateral automated negotiation framework. Thus, there are two negotiating parties (Client and Provider) that are represented by mobile intelligent agents. The agents negotiate over a single issue based on an alternating offers protocol

(Kraus, 2001) aiming to maximize the utilities of the parties they represent.

We hereafter consider the case where the negotiation process is initiated by the Client Agent (CA) that sends to the Provider Agent (PA) an initial Request for Proposal (RFP) specifying the features of the service/product its owner is interested to obtain. Without loss of generality, it is assumed that the issue under negotiation is the price of the product or service. Thus, the PA negotiates aiming to agree on the maximum possible price, while the CA aims to reduce the agreement price as much as possible. Once the PA receives the RFP of the CA, it either accepts to be engaged in the specific negotiation thread and formulates an initial price offer, or rejects the RFP and terminates the negotiation without a proposal. At each round, the PA sends to the CA a price offer, which is subsequently evaluated by the CA against its constraints and reservation values. Then, the CA generates a counter-offer and sends it to the PA that evaluates it and sends another counter-offer to the CA. This process continues until a mutually acceptable offer is proposed by one of the negotiators, or one of the agents withdraws from the negotiation (e.g. in case its time deadline is reached without an agreement being in place). Thus, at each negotiation round, the agents may: (i) accept the previous offer, if their constraints are addressed, (ii) generate a counter-offer, or (iii) withdraw from the negotiation.

Quantity p_l^a denotes the price offer proposed by negotiating agent a during negotiation round l . A price proposal p_l^b is always rejected by agent a if $p_l^b \notin [p_m^a, p_M^a]$, where $[p_m^a, p_M^a]$ denotes agent- a 's acceptable price interval. In case an agreement is reached, we call the negotiation successful, while in case one of the negotiating parties quits, it is called unsuccessful. In any other case, we say that the negotiation thread is active. The objective of our problem is to predict the PA's behaviour in the future negotiation rounds until the CA's deadline expires. More specifically, the negotiation problem studied can formally be stated as follows:

Given: (i) two negotiating parties: a Provider that offers a specific good and a Client that is interested in this good's acquisition, (ii) the acceptable price interval $[p_m^C, p_M^C]$ for the Client, (iii) a deadline T_C up to which the Client must have completed the negotiation with the Provider, (iv) the final negotiation round index L_C for the Client, (v) a round threshold L_C^d until which the Client must decide whether to continue be-

ing engaged in the negotiation thread or not, and (vi) the vector $P_l^P = \{p_l^P\}$, where $l = 2k - 1$ and $k = 1, \dots, \lfloor \frac{L_C^d}{2} \rfloor$, of the prices that were proposed by the Provider during the initial $L_C^d - 1$ negotiation rounds, *find* (i) the vector $P_{l'}^P = \{p_{l'}^P\}$, where $l' = 2k' - 1$ and $k' = \lfloor \frac{L_C^d}{2} \rfloor + 1, \dots, L_C$, of the prices that will be proposed by the Provider during the last $L_C - L_C^d$ rounds, and (ii) decide on whether the Client should continue being engaged in the specific negotiation thread or not.

A NEGOTIATION STRATEGY BASED ON NEURAL NETWORKS

The policy employed by negotiating agents in order to generate a new offer is called *negotiation strategy*. In principle, three main families of automated negotiation strategies can be distinguished: time-dependent, resource-dependent and behaviour-dependent strategies (Faratin, Sierra, & Jennings, 1998). These strategies are well defined functions that may use various input parameters in order to produce the value of the issue under negotiation to be proposed at the current negotiation round. The proposed mechanism enhances any of the legacy strategies with learning techniques based on Neural Networks (NNs). In the studied framework, the NN-assisted strategies are used by the CA in order to estimate the future behaviour of the PA. This section presents the proposed NN-assisted strategy and describes the specifics of the NNs employed.

Enabling PA Behaviour Prediction

As already mentioned, the research presented in this paper aims to estimate the parameters governing the PA's strategy enabling the CA to predict the PA's future price offers. The objective is to decide at an early round whether to aim for an agreement with the specific PA, or withdraw from the negotiation thread as early as possible, if no agreement is achievable. For this purpose, two different Neural Networks (NNs) have been employed. These NNs are trained off-line with proper training sets and are then used during the on-line negotiation procedure whenever the CA requires so. The procedure starts normally, and as long as there are enough proposals made by the PA, the CA uses the NNs to make a reliable prediction of its opponent's strategy. This requires only a few negotiation rounds (compared to the CA's deadline expiration round) and

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