

Toward Efficient Agreements in Real-time Multilateral Agent-based Negotiations

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Abstract—Negotiations among autonomous agents have gained a mass of attention from a variety of communities in the past decade. This paper deals with a prominent type of automated negotiations, namely, multilateral multi-issue negotiation that runs under real-time constraints and in which the negotiating agents have no prior knowledge about their opponents’ preferences over the space of negotiation outcomes. We propose a novel negotiation approach which enables an agent to reach an efficient agreement with multiple opponents. The proposed approach achieves that goal by, 1) employing sparse pseudo-input Gaussian processes to model the behavior of opponents, 2) learning fuzzy opponent preferences to increase the satisfaction of other parties, and 3) adopting an adaptive decision-making mechanism to handle uncertainty in negotiation. The experimental results show, both from the standard mean-score perspective and the perspective of empirical game theory, that the agent applying the proposed approach outperforms the state-of-the-art negotiation agents from the recent Automated Negotiating Agents Competition (ANAC) in a variety of negotiation domains.

Keywords—Distributed Artificial Intelligence; Multi-agent systems; Automated Negotiation; Empirical game theory

I. INTRODUCTION

Negotiation is ubiquitous in our daily life and serves as an important approach to facilitate conflict-resolving and reaching agreements between different parties. Development of automated negotiation techniques enables software agents to perform negotiations on behalf of human negotiators. This can not only significantly alleviate the efforts of human negotiators, but also aid human in reaching better negotiation outcomes by compensating for the limited computational abilities of humans when they deal with complex negotiations.

During negotiations, a negotiating agent usually keeps its negotiation strategy and its preference as its private information to avoid being exploited. Thus one major research challenge is to effectively estimate the negotiation partner’s preference profile [1], [2] and predicate its decision function [3]. On one hand, through getting a better understanding

of the negotiation partners’ preferences, it would increase the chances of reaching mutually beneficial negotiation outcomes. On the other hand, effective strategy prediction techniques enable the negotiating agents to maximally exploit their negotiating partners and thus receive as much benefit as possible from negotiation.

Until now, a lot of research efforts have been devoted to developing automated negotiation strategies and mechanisms in different negotiation scenarios [1], [3], [4], [5], [6], [7]. Especially recent years have witnessed the emergence of a number of advanced negotiation strategies participated in the last few years’ *automated negotiating agents competition* (ANAC) [8]. The ANAC competition provides a general and uniform negotiation platform which enables different negotiation agents to be evaluated against a wide range of opponents within various realistic negotiation environments. However, most research efforts have been devoted to bilateral negotiation scenarios, which only models the strategic negotiation among two parties. However, in real life the more common and general way of negotiations usually involve multiple parties. It is in common agreement from the automated negotiation research community that more attention should be given to multilateral negotiations and investigate effective negotiation techniques for multilateral negotiation scenarios.

In this paper, we propose a novel negotiation approach for automated agents to negotiate in multilateral multi-issue real-time negotiation environments. During negotiation, the agents’ negotiation strategies and preference profiles are their private information, and the available information about the negotiating partner is its past negotiation moves. Due to the huge strategy space that a negotiating partner can consider, it is usually very difficult (or impossible) to predict which specific strategy the negotiating partner is using based on this limited amount of information. To this end, instead of predicting the exact negotiation strategies

of the opponents, we adaptively adjust the non-exploitation point λ to determine the perfect timing that we should stop further exploits the opponents, and then determine the aspiration level (or the target utility) for proposing offers to opponents before and after the non-exploitation point following different rules. The value of λ is determined as the timing when the estimated expected future utility we can obtain over all opponents is maximized. The future utility that each opponent offers can be efficiently predicted using the Sparse Pseudo-inputs Gaussian Process (SPGP) technique by dividing the negotiation history into a number of atomic intervals.

Given the aspiration level for offering proposals, another important question is how should we select an optimal proposal to reach efficient agreements with other parties, which can also improve the possibility of accepting this offer by the negotiating partners. In this work, we measure the efficient degree of an outcome from a practical perspective – the social welfare of participants. We propose modeling the preferences of each opponent using the least square error regression technique based on the negotiation history. After that, the offer with the highest social welfare is selected as the offer to be proposed with certain exploration. We evaluate the performance of our strategy from two different perspectives: *efficiency* in terms of the average payoff obtained under a particular negotiation tournament and *robustness* in terms of how likely the agents have the incentive to adopt our strategy rather than other strategies. First, simulation results show that our strategy is more efficient against a variety of state-of-the-art negotiation strategies in both discounting and non-discounting domains with various domain sizes. Second, we evaluate the robustness of our strategy using empirical game-theoretic analysis. Experimental results show that our strategy is the most robust one compared with the existing state-of-the-art strategies. Moreover, a light-weight implementation of the proposed negotiation approach finished second in the category of Nash product in the ANAC 2015.

The remainder of the paper is organized as follows. Section II introduces the multilateral negotiation model we adopt. In Section III, our negotiation approach is introduced in details. Section IV shows the detailed evaluation of the proposed agent compared with the state-of-the-art negotiating agents under different negotiation contexts in terms of the negotiation efficiency and robustness. Lastly conclusion and future work are given in Section V.

II. MULTILATERAL NEGOTIATION MODEL

To govern the complex process of a multilateral negotiation, we adopt an extension of a basic bilateral negotiation protocol [9] which is widely used in the agents field [5], [6], [8], [10], [11]. The participating agents try to establish a contract for a product (service) or reach consensus on certain matter on behalf of their parties. Precisely, let $A = \{a_1, a_2, \dots, a_i, \dots, a_m\}$ be the set of negotiating agents,

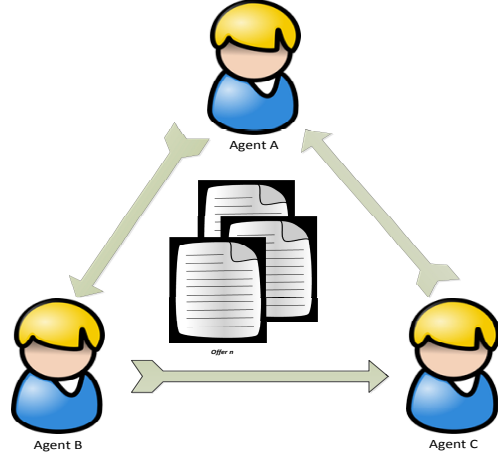


Figure 1: Multilateral negotiation protocol.

J be the set of issues under negotiation with j a particular issue ($j \in \{1, \dots, n\}$ where n is the number of issues). Following the alternating bargaining model of [9], each agent, in turn, has a chance to express its opinion about the ongoing negotiation. The opinion can be communicated in a form of a contract proposal (e.g., a new offer), or an acceptance of the latest offer on the table (note that previous offers would not be accepted once there exists a new proposal), or terminating the negotiation according to its interpretation of the current negotiation situation. A simple illustration of the multilateral negotiation process is shown in Figure 1. Due to space constraints we refer the interested reader to the website of ANAC for more details about the protocol.

An offer is a vector of values, with one value for each issue. The utility of an offer for agent i is calculated by the utility function defined as follows:

$$U^i(O) = \sum_{j=1}^n (w_j^i \cdot V_j^i(O_{j,k})) \quad (1)$$

where w_j^i and O are as defined above and V_j^i is the evaluation function of agent i for issue j , mapping every possible value of issue j (i.e., $O_{j,k}$) to a real number. The weight vector \mathbf{w} denotes the weighting preference of an agent, in which w_j^i represents its preference for issue j . The issue weights of an agent are normalized (i.e., $\sum_{j=1}^n w_j^i = 1$ for each agent i). In addition an agent has a lowest expectation for the outcome of a negotiation – the reservation value ϑ .

In this work we consider negotiation being conducted in a real-time way instead of being restricted by a fixed number of exchanged offers; specifically, each negotiator has a hard deadline by when it must have completed or withdraw the negotiation. The negotiation deadline of agents is denoted by t_{\max} . In negotiations under real-time constraints, the number of remaining rounds are not fixed and the outcome of a negotiation depends crucially on the time sensitivity of the

Algorithm 1 The overview of the proposed negotiation approach. Let t_c be the current time point, δ the time discounting factor, and t_{max} the deadline of negotiation. O_{opp} is the latest opponent offer, Ω_i the previous offers of opponent i and O_{own} a new offer to be proposed by our agent. χ is the time series including the average utilities over intervals. E denotes the expected utility of incoming counter-offers. λ is the non-exploitation time point and u' the target utility. \mathbf{W} denotes the set of learnt opponent weight vectors.

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1: Require:  $\vartheta, \delta, t_{max}$ 
2: while  $t_c \leq t_{max}$  do
3:    $O_{opp} \leftarrow receiveMessage$ ;
4:    $\Omega_i \leftarrow recordOfferSet(t_c, O_{opp}, i)$ ;
5:   if  $myTurn(t_c)$  then
6:     if  $updateModel(t_c)$  then
7:        $\chi \leftarrow preprocessData(t_c)$ 
8:        $E \leftarrow Predict(\chi, \Omega)$ ;
9:        $(\lambda, U_{min}) \leftarrow updateParas(t_c)$ ;
10:       $\mathbf{W} = updatePrefrenceModels()$ ;
11:     end if
12:   end if
13:    $u' = getTargetUtility(t_c, E, \lambda)$ ;
14:    $O_{own} \leftarrow constructOffer(u', \mathbf{W})$ ;
15:   if  $isAcceptable(u'_c, O_{opp}, t_c, \delta)$  then
16:      $accept(O_{opp})$ ;
17:   else
18:      $checkTermination()$ ;
19:      $proposeNewBid(O_{own})$ ;
20:   end if
21: end while

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agents' negotiation strategies. For domains where the value of agreements is discounted over time, the discounting factor δ ($\delta \in [0, 1]$) is defined to calculate the discounted utility as follows:

$$D(U, t) = U \cdot \delta^t \quad (2)$$

where U is the (original) utility and t is the standardized time. As an effect, the longer it takes for agents to come to an agreement the lower is the utility they can obtain.

III. NEGOTIATION APPROACH

Our proposed approach consists of three core components: deciding aspiration level, generating new offers and responding mechanism, all of which are described in detail in this section. We first give an overview of our approach shown in *Algorithm 1*. Following that, the individual steps of *Algorithm 1* are explained in details.

A. Deciding Aspiration Level

Aspiration level indicates the target utility of an agent in the negotiation process. In order to respond to uncertainty in a negotiation where opponents' private information is unknown, the aspiration level is updated due to the environment (e.g., available negotiation time and discounting effect) and opponent behaviors. The agent can therefore predict

opponent future moves to assist its decision by analyzing past moves of the opponent. The prediction technique we use here is a computationally efficient variant of standard Gaussian Processes (GPs) – Sparse Pseudo-inputs Gaussian Processes (SPGPs), which proves effective in negotiation context [11]. Another advantage of SPGPs over other type of regression techniques is that it not only provides accurate prediction but also the measure of confidence in the prediction.

Following the notation of GPs in [12], given a data set $\mathcal{D} = \{\mathbf{x}^{(i)}, y^{(i)}\}_{i=1}^m$ where $\mathbf{x} \in \mathbb{R}^d$ is the input vector, $y \in \mathbb{R}$ the output vector and m is the number of available data points when a function is sampled according to a GP, we write, $f(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}'))$, where $m(\mathbf{x})$ is the mean function and $k(\mathbf{x}, \mathbf{x}')$ the covariance function, fully specifying a GP. Learning in a GP setting involves maximizing the marginal likelihood of Equation 3.

$$\log p(\mathbf{y}|\mathbf{X}) = -\frac{1}{2}\mathbf{y}^T (\mathbf{K} + \sigma_n^2 \mathbf{I})^{-1} \mathbf{y} - \frac{1}{2} \log |\mathbf{K} + \sigma_n^2 \mathbf{I}| - \frac{n}{2} \log 2\pi, \quad (3)$$

where $\mathbf{y} \in \mathbb{R}^{m \times 1}$ is the vector of all collected outputs, $\mathbf{X} \in \mathbb{R}^{m \times d}$ is the matrix of the data set inputs, and $\mathbf{K} \in \mathbb{R}^{m \times m}$ is the covariance matrix with $|\cdot|$ representing the determinant.

To fit the hyperparameters that best suit the available data set we need to maximize the marginal likelihood function of Equation 3 with respect to Θ , the vector of all hyperparameters. The problem with GPs is that maximizing Equation 3 is computationally expensive due to the inversion of the covariance matrix $\mathbf{K} \in \mathbb{R}^{n \times n}$ where n is the number of data points. We for this specific reason employ a fast and more efficient learning technique – SPGPs. The most interesting feature of SPGPs is that these approximators are capable of attaining very close accuracy in both learning and prediction to normal GPs with only a fraction of the computation cost. This property makes them extremely suitable to the multilateral negotiation domain where a complex and low cost function approximation framework is highly demanded.

Using only a small amount of pseudo-inputs, SPGPs are capable of attaining very similar fitting and prediction results to normal GPs. To clarify, the idea is to parametrize the model by $M \ll n$ pseudo-input points, while still preserving the full Bayesian framework. This leads to the parametrization of the covariance function by the location of $M \ll n$ pseudo-inputs. These are then fitted in addition to the hyperparameters in order to maximize the following new marginal likelihood:

$$p(\mathbf{y}|\mathbf{X}, \bar{\mathbf{X}}, \Theta) = \int p(\mathbf{y}|\mathbf{X}, \bar{\mathbf{X}}, \bar{\mathbf{f}}) p(\bar{\mathbf{f}}|\bar{\mathbf{X}}) d\bar{\mathbf{f}} \\ = \mathcal{N}(\mathbf{y}|\mathbf{0}, \mathbf{K}_{NM} \mathbf{K}_M^{-1} \mathbf{K}_{MN} + \mathbf{\Lambda} + \sigma^2 \mathbf{I}), \quad (4)$$

where $\bar{\mathbf{X}}$ is the matrix formed by the pseudo-inputs with $\bar{\mathbf{X}} = \{\bar{\mathbf{x}}\}_{m=1}^M$. \mathbf{K}_{NM} is the covariance matrix formed by the pseudo and the real inputs as $\mathbf{K}_{MN} = k(\bar{\mathbf{x}}_m, \mathbf{x}_n)$ with

$k(\cdot, \cdot)$ being the covariance kernel. \mathbf{K}_M^{-1} is the inverse of the covariance matrix formed among the pseudo inputs with $\mathbf{K}_M = k(\bar{\mathbf{x}}_m, \bar{\mathbf{x}}_m)$. $\mathbf{\Lambda}$ is a diagonal matrix having the diagonal entries of $\lambda_n = k_{nn} - \mathbf{k}_n^T \mathbf{K}_M^{-1} \mathbf{k}_n$. The noise variance and the identity matrix are represented by σ and \mathbf{I} , respectively.

When a counter-proposal from agent i arrives at time t_c , our agent records the time stamp t_c and the utility $U(O^i)$ that is evaluated in our agent's utility space. To reduce misinterpretation of the opponent's behavior as much as possible that is caused by the setting of multi-issue negotiations, the whole negotiation is divided into a fixed number (denoted as ζ) of equal intervals. The average utilities at each interval with the corresponding time stamps, are then provided as inputs to the SPGPs. Results in [13] show a complexity reduction in the training cost (i.e., the cost of finding the parameters of the covariance matrix) to $\mathcal{O}(M^2N)$ and in the prediction cost (i.e., prediction on a new set of inputs) to $\mathcal{O}(M^2)$. The results further demonstrate that SPGPs can fully match normal GPs with small M (i.e., few pseudo-inputs), successfully producing very sparse solutions.

After learning a suitable model, SPGPs makes forecast about the future concession of the opponent as shown in line 7 of Algorithm 1. Our agent keeps track of the expected discounted utility based on the predictive distribution at a new input t_* , which is given by:

$$p(u_*|t_*, \mathcal{D}, \bar{\mathbf{X}}) = \int p(u_*|t_*, \bar{\mathbf{X}}, \bar{\mathbf{f}}) p(\bar{\mathbf{f}}|\mathcal{D}, \bar{\mathbf{X}}) d\bar{\mathbf{f}} = \mathcal{N}(u_*|\mu_*, \sigma_*^2), \quad (5)$$

where

$$\begin{aligned} \mu_* &= \mathbf{k}_*^T \mathbf{Q}_M^{-1} (\mathbf{\Lambda} + \sigma^2 \mathbf{I})^{-1} \mathbf{u} \\ \sigma_*^2 &= \mathbf{K}_{**} - \mathbf{k}_*^T (\mathbf{K}_M^{-1} - \mathbf{Q}_M^{-1}) \mathbf{k}_* + \sigma^2 \\ \mathbf{Q}_M &= \mathbf{K}_M + \mathbf{K}_{MN} (\mathbf{\Lambda} + \sigma^2 \mathbf{I})^{-1} \mathbf{K}_{NM} \end{aligned}$$

With the given probability distribution over future received utilities and the effect of the discounting factor, the expected utility E_{t_*} is then formulated by

$$E_t = \frac{1}{C} \int_0^1 D(u \cdot p(u; \mu_t, \sigma_t), t) du \quad (6)$$

where μ_* and σ_* are the mean and standard deviation at time t_* , and the normalizing constant C is introduced to preserve a valid probability distribution.

Our agent employs the target utility function as given in Equation 7 to determine the aspiration level over time. The function adopts a tough manner (i.e., slowly conceding) before the non-exploitation time point (λ) for seeking higher expected profits, then it quickly goes to the expected minimal utility such that negotiation failure/disagreement could be avoided in the end. The non-exploitation time point is adjusted according to the behavior of other negotiation participants. More precisely, the higher the average opponent

concession (measured in the our own utility space), the later our agent begins to compromise.

$$u' = \begin{cases} U_{\max} - \Delta (\frac{t_c}{\lambda})^{1+\delta} & \text{when } t_c \leq \lambda, \\ (U_{\max} - \Delta) (1 - \frac{t_c - \lambda}{t_{\max} - \lambda})^{1+\delta} & \text{otherwise} \end{cases} \quad (7)$$

where U_{\max} is the maximal utility, U_{\min} is the minimal utility ($U_{\min} = \max(\vartheta, \gamma)$) and γ the received lowest opponent concession), constant Δ is the maximal concession amount (i.e., $U_{\max} - U_{\min}$), with

$$\lambda = \operatorname{argmax}_{t \in T} \frac{1}{|A| - 1} \sum_{i \in A \setminus o} \frac{1}{C_i} \int_0^1 D_\delta(u \cdot p(u; \mu_t, \sigma_t), t) du \quad (8)$$

with o representing our agent and $T \in [t_c, t_{\max}]$.

B. Generating Offers

Given an aspiration utility level to achieve, our agent next needs to consider what offer to send such that the likelihood of an offer being accepted could be maximized. Performing this task would require certain knowledge about opponents' preferences. However, negotiation opponents unfortunately have no motivation to reveal their true likings over proposals (or their utility functions) to avoid exploitation. In order to address this problem, we model the opponent concession tactics as time-dependent tactics (originated in [10]) shown in Equation 9, which are classic tactic in the current literature.

$$\tilde{u} = U_{\max} - (U_{\max} - \vartheta)(t_c/t_{\max})^\alpha \quad (9)$$

where α is the concession factor controlling the style of concessive behavior (e.g., bouldware ($\alpha < 1$), conceder ($\alpha > 1$) or linear ($\alpha = 1$)). Time-dependent tactics are widely used in automated negotiation community to decide concession toward opponents since a negotiator needs to make more or less compromise over time so as to resolve conflicts of the parties. In more detail, bouldware tactic maintains the target utility level until the late stage of a negotiation process, whereupon it concedes to the reservation utility. By contrast, conceder tactic makes quick compromise to other parties once a negotiation session starts. For linear tactic, it simply reduces the target utility from the maximal utility to the reservation utility in a linear way.

Learning opponent preferences, while useful, is indeed challenging because information about opponent preferences over different issues (e.g., the weight vector \mathbf{w}) is severely lacking. To tackle this issue, researchers typically assume that opponent concession tactic is fully known or preferences follow a certain distribution. In many real-world applications, it is however difficult or costly to acquire the exact information about opponent concession.¹ Therefore we make a mild assumption that we could enquire of

¹Note that the opponent concession is the amount of concession measured in the utility space of the opponent instead of ours.

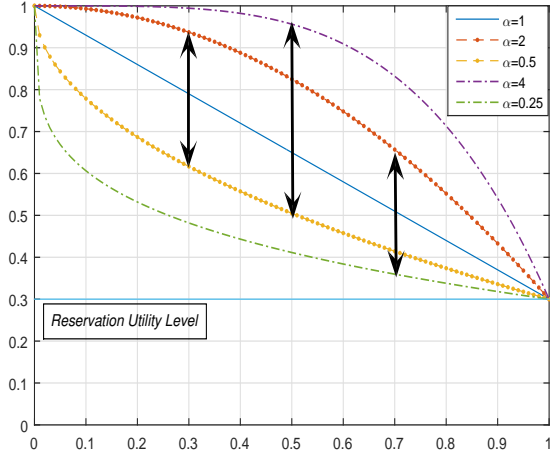


Figure 2: A toy example of opponent concession ranges given by the pairs of concession factors (0.5,2) at time 0.3, (0.5,4) at 0.5 and (2,0.25) 0.7, respectively.

domain experts about the approximate concession range of an opponent. This fuzzy knowledge is provided in form of a pair of concession factors that indicate the upper and lower concession an opponent makes at each time point. This idea is illustrated in Figure 2. Thus, the agent can estimate opponent preferences with the aid of the fuzzy information about opponent concession. Specifically, the preferences are learnt through minimizing the loss function L , which gives the expected loss associated with estimating opponent concession based on a weight vector. The loss function is constructed as in Equation 11. The loss is calculated by the difference between the mean of concession and the utility of an offer based on a weight vector \mathbf{w} ; moreover an additional penalty is imposed by φ when an expected utility for \mathbf{w} exceeds the upper and lower bounds of opponent concession. When calculating the utility of an offer for opponent i , yet the valuation of each issue choice is needed. We here simply assume that the importance order of issue choices is known, and approximate the valuation like [1] as follow,

$$V_{j,k}^i(O_{j,k}) = \frac{2r_{j,k}^i}{K(K+1)} \quad (10)$$

where K is the number of possible choices for issue j , while $r_{j,k}^i$ denotes the ranking of the issue choice $O_{j,k}$.

Let the opponent utility of an offer for a weight vector \mathbf{w} be $\hat{u}_{\mathbf{w}}$. With the opponent concession tactic given in Equation 9 and the two concession factors (which denote the approximate concession range suggested by experts), our agent can estimate the weight vector of opponent i by means of linear least squares. This can be achieved by minimizing the following loss function,

$$L^i(\mathbf{w}) = \begin{cases} \left| \frac{(u_{upper}^i + u_{lower}^i)}{2} - \hat{u}_{\mathbf{w}} \right| + \varphi(u_{lower}^i, \hat{u}_{\mathbf{w}}), & \hat{u}_{\mathbf{w}} \leq u_{lower}^i \\ \left| \frac{(u_{upper}^i + u_{lower}^i)}{2} - \hat{u}_{\mathbf{w}} \right| + \varphi(\hat{u}_{\mathbf{w}}, u_{upper}^i), & u_{upper}^i \leq \hat{u}_{\mathbf{w}} \\ \left| \frac{(u_{upper}^i + u_{lower}^i)}{2} - \hat{u}_{\mathbf{w}} \right|, & \text{otherwise} \end{cases} \quad (11)$$

with u_{upper}^i and u_{lower}^i being the upper and lower bound of concession made by opponent i at time t , and φ the penalty function as below,

$$\varphi(x, y) = \beta |x - y|^{\frac{1}{2}} \quad (12)$$

where β denotes the confidence of the expert, and the lower the value, the more confidence the expert has about the perdition (to limit further complexness, we let β be 1).

After the estimation of weight vectors of other parties has been done, our agent chooses an offer being capable of maximizing the social welfare (e.g., the sum of the utility of all participants in the negotiation) given a aspiration level, shown as below:

$$\operatorname{argmax}_O \frac{1}{|A| - 1} \sum_{i \in A \setminus o} (\hat{u}_{\mathbf{w}}^i(O) - \vartheta)^2 \quad (13)$$

subject to

$$U^o(O) \geq u'$$

Although opponent preferences could be learnt on the basis of the provided concession tactics, it sometimes may be ineffective due to the fuzzy nature of the information; therefore our agent needs an alternative approach to choosing new offers. Fortunately, a real-time negotiation typically allows agents to exchange a large number of offers, thereby giving them many opportunities to explore the outcome space. Therefore, the proposed approach generates a new offer for next round following an ϵ -greedy strategy. The strategy selects either a greedy action (i.e., exploit) with $1-\epsilon$ probability ($\epsilon \in [0, 1]$) or a random action with a probability of ϵ . It is worth noting that random action means choosing one offer from the set whose utility is above the given aspiration level by chance. The greedy action aims at choosing an offer that are expected to satisfy other sides' preferences most in order to improve their utilities over the negotiation outcome and the chance of the offer being accepted through fuzzy preference learning. With a probability $1 - \epsilon$, the approach randomly picks one of those offer whose utility is equal or larger than the given aspiration level. In the latter case, the agent constructs a new offer which has an utility within some range around u' . The reason is twofold: 1) it is possible, in multi-issue negotiations, to generate a number of offers whose utilities are the same or very similar to the offering agent, with granting the opposing negotiators different utilities, and moreover 2) it is sometimes not possible to make an offer whose utility is exactly equivalent to u' . Thus it is reasonable that an agent

selects an offer whose utility is in the narrow range $[(1-0.005)u', (1+0.005)u']$. If no such solution can be found, our agent repeats the latest bid again in the next round.

C. Responding mechanism

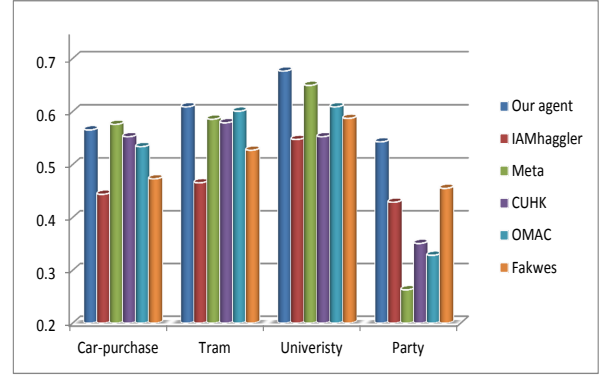
This responding mechanism of the proposed approach corresponds to lines 15–20 of Algorithm 1. After receiving a counter-proposal, the agent should decide whether to accept the proposal by checking two conditions. First the agent has to validate whether the utility of the latest counter-offer is better than u' , while in the second the agent has to determine whether it had already proposed this offer (i.e., the opponent’s counter-offer) earlier in the negotiation process. If either one of these two conditions is satisfied, the agent then accepts the offer as shown in line 16 and the negotiation will be completed if the proposal is also supported by the remaining agents.

Moreover, when the negotiation situation becomes hard and might offer our agent a utility even lower than the reservation utility, the agent should consider whether to terminate/leave the negotiation to receive the corresponding reservation utility or not. Here we treat the reservation value as an alternative offer from a negotiating partner with a constant utility. Thus the agent needs to check if the aspiration utility is smaller than the reservation utility. If positive, our agent is going to leave the negotiation table in the next round. If our agent decides neither to accept the latest counter-proposal nor to leave the negotiation, it proposes a new offer following the steps of lines 19 of Algorithm 1.

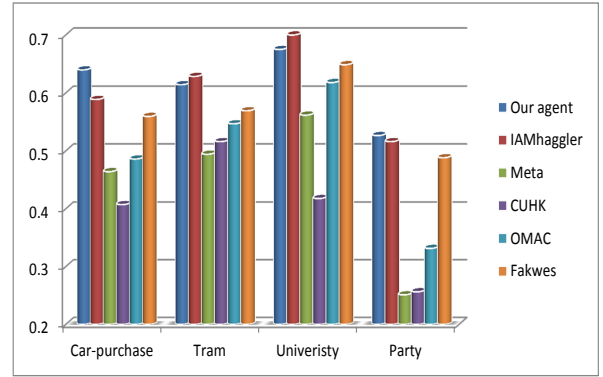
IV. EMPIRICAL EVALUATION

The performance evaluation of the proposed approach is done with GENIUS [14] – the well-known negotiation simulation environment. GENIUS implements an open architecture for negotiating agents (representing different negotiation strategies), allowing to compare agents across application domains with varying environmental settings. This simulation environment is also used by Automated Negotiating Agent Competition (ANAC) as the official competition platform, thereby providing a library of state-of-the-art negotiation strategies. We compare the performance of our agent from the traditional scoring perspective as well as from the empirical game theoretic one. The first part of evaluation is detailed in Section IV-A. The other part is used to study the robustness of the proposed approach as the opponents vary. The details of game-theoretic analysis are described as needed in Section IV-B.

In order to test the negotiating ability, we introduce several top agents of recent ANAC editions as benchmarks – Fawkes, MetaAgent, CUHKAgent, OMACAgent and I-AMhaggler2012 – to cover a range of classes of negotiation strategies. Furthermore, the negotiation simulation is carried out on four domains for multi-party negotiation provided



(a) Average individual utilities of all agents in each domain



(b) Average opponent utilities of all agents in each domain

Figure 3: Performance of all agents in the test domains. The vertical axis represents utility and horizontal axis represents domain. Agent order in each domain corresponds to the ordering on the right side.

by GENIUS – *Car-purchase*, *Tram*, *University* and *Party*, which are chosen to be the respective representative of small, medium, large outcome space domains.

A. Simulation results

We show the experimental results in Figure 3, where 3(a) and 3(b) give the average individual (own) utility and opponent utility (scores of opponents playing against an agent) of each agent, respectively. As depicted in the figures above, our agent demonstrates excellent performance against a variety of existing approaches over a number of scenarios, which is on average the best performing approach from the perspective of the own utility. In more detail, our agent takes the first place in three domains and only finishes second in *Car-purchase* domain; the average performance of the five opponents reaches 85% of ours, while our agent surprisingly advances others also by a margin of 22% in terms of average opponent utility. We speculate this leading performance both in individual and opponent utility is due to the effective opponent behavior and preference learning mechanism.

Further, for convenience to compare agents’ performance

Table I: Overall Performance over domains.

Agent	Normalized Score		
	Own Util.	Std. Dev.	Social welfare
Our agent	0.821	0.005	0.838
MetaAgent	0.637	0.010	0.551
OMACagent	0.636	0.006	0.609
Fakwes	0.619	0.008	0.683
CUHKAagent	0.615	0.006	0.489
IAMhaggler2012	0.529	0.012	0.687

across domains, we normalize each agent’s utility, and normalization is done in the standard way using the maximum and minimum score obtained by all agents as in [15]. According to the overall performance shown in Table I, the proposed approach retains the top place with an average normalized score of 0.82; it has an advantage of more than 35% over the mean score of other agents across all domains. More notably, our agent also leads to an impressive social welfare (e.g., the sum of normalized utility of agents of a negotiation), which is the highest among the candidates, or precisely there is a margin of 39% above the average level in social welfare achieved by other agents. This is desired, because, as a measure of the benefit of a negotiation to all participants, rather than the profit of an individual, higher social welfare results in better overall value of a negotiation and also a more efficient outcome. In addition, our agent experiences the smallest standard deviation among all agents considered in the experiments. In contrast, MetaAgent, being the second place among all participants, only obtains an utility of approximate 80% of ours. The difference becomes even larger for IAMhaggler2012; this agent merely achieves 50% of ours and is the worst performing one observed in the our simulation. To summarize, these results show that our agent is effective (i.e., in terms of individual profit) and efficient (i.e., in terms of social welfare), and it significantly outperforms the state-of-the-art automated negotiators in a variety of application scenarios.

An interesting observation of the experimental results is the performance difference between our agent and IAMhaggler2012 is the largest (e.g., this agent on average achieves less than half the performance of ours) though both agents employ similar regression techniques as a tool to model opponent. The reason behind it is that our agent advances IAMhaggler2012 in three ways, 1) our agent employs a more powerful method – SPGPs, which in the setting of agent-based negotiation prove more successful and effective than GPs, 2) IAMhaggler2012 sets its aspiration level fully on the basis of the whole preceding negotiation process and tends to magnify opponent concession, which seems to be vulnerable to “irrational concession making” induced by pessimistic predictions [11], while our agent adopts its aspiration level in a more adaptive manner, and lastly 3) IAMhaggler2012 does not consider the use of preference learning to aid its offer generating.

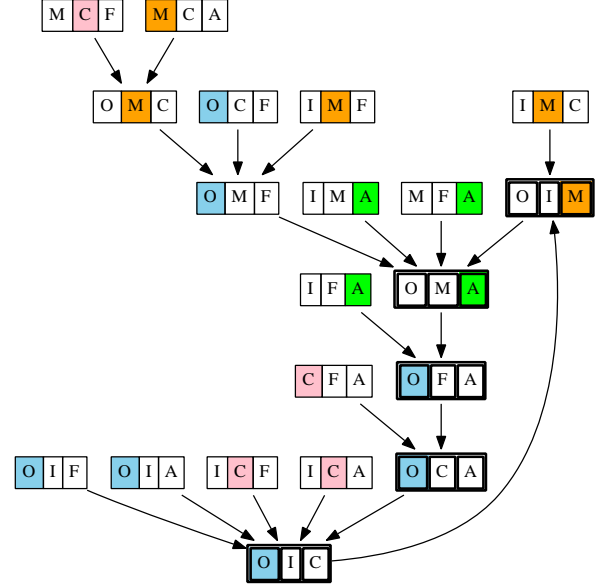


Figure 4: Deviation analysis for three-player negotiation. Each node shows a strategy profile. The arrow indicates unilateral strategy change, and thus the statistically significant deviation between strategy profiles. Nodes with bold border denote empirical equilibria.

B. Empirical game theoretical analysis

In the previous subsection, the strategy is evaluated in terms of efficiency from the mean-score perspective. However, this analysis is limited as it cannot reveal information about the robustness of these strategies, or to put it differently – would any of the agents in those competition, for pursuing better outcome, have an incentive to deviate from one strategy to a different one if allowed. To address robustness issue appropriately, empirical game theory (EGT) analysis [16], which was initially developed to analyze the Trading Agent Competition, is applied to the simulation results. In the analysis we consider the best single-agent deviations as in [11], in which there is an incentive for one agent to unilaterally change the strategy in order to statistically improve its own benefit. The goal of using EGT is to search for pure Nash equilibria where no agent has an incentive to deviate, or to find a best cycle. Such a cycle consists of a set of profiles (e.g., the combination of strategies chosen by players) for which a path of statistically significant single-agent deviations (whose definition is given next) exists that connect them, with no deviation leading to a profile outside of the set [15]. These two types are both referred to as empirical equilibria in this work.

In the analysis we apply the EGT technique to the three-player scenarios based on *Tram* domain² where each

²Please note that the similar results can be observed also in other domains, which are omitted due to space limitation.

player has freedom to use one from the strategy set \mathcal{S} that includes the six strategies considered in our experiments shown in Section IV-A. For brevity, let the initial letter of each strategy be the identifier (e.g., O means our agent), except A represents OMAC to avoid repetition; and $\mathcal{S} = \{O, M, A, F, C, I\}$. The score achieved by a strategy in a profile is averaged by all encounters of any three strategies in a domain.

The results are depicted in Figure 4, where each node represents a single strategy profile being a mix of three different strategies from \mathcal{S} . The strategy that achieves the highest score among others in a profile is highlighted with a specific color background. Under this EGT analysis, there exists a best cycle of statistically significant single-agent deviations, including five strategy profiles given by OIM, OMA, OFA, OCA and OIC. This observation shows that for any non-Nash equilibrium strategy profile there exist a path of statistically significant deviations which leads to one of the profiles involved in the best cycle. When compared with the other strategies in the cycle, our agent (O) is included in all empirical equilibria, which in other words attracts a player to deviate for 100% of state transitions in this particular figure. Thus it indicates that our proposed strategy is the most robust one among all strategies.

V. CONCLUSION

This work introduced a novel approach for multilateral agent-based negotiation in complex environments (multi-issue, time-constrained, and unknown opponents). Our proposed strategy, based on the adaptive decision-making scheme and the effective preference learning method, outperformed the top agents of the recent International Automated Negotiation Agents Competitions. Experiments show that our agent not only generates a higher mean individual utility but also leads to better social welfare compared to the state-of-the-art negotiation agents. Further game-theoretic analysis clearly manifests the robustness of the proposed approach. We think the exceptional results justify to invest further research efforts into this approach. In the future work, we plan on comparing the opponent modeling scheme with the other available approachers and further, extend this framework to other negotiation settings like concurrent negotiation negotiation.

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