Jonny Black: A Mediating Approach to Multilateral Negotiations

Osman Yucel, Jon Hoffman and Sandip Sen

Abstract We describe the strategy of our negotiating agent, "Jonny Black", which received the 3rd place in ANAC 2015 competition in the "Nash Product" category. The agent tries to act as a mediator to find the best outcome for all the agents, including itself, in the negotiation scenario. The agent models other agents in the negotiation, and attempts to find the set of outcomes which are likely to be accepted by the other agents, and then picks the best offer from its own viewpoint. We give an overview of how to implement such a strategy and discuss its merits in the context of closed multilateral negotiation.

1 Introduction

This paper presents our agent called "Jonny Black" and its strategy, which we developed and entered into the Fifth Automated Negotiating Agent Competition[1] (ANAC2015). ANAC is a tournament between a set of negotiating agents which perform closed multilateral negotiation using the alternating offers protocol. The negotiation environment consists of multi-issue scenarios and includes uncertainty about the opponents preferences.

Bazerman et al. showed that introducing a mediator agent significantly reduces the probability of an impasse [2]. Based on this observation, we chose to design

[1] http://mmi.tudelft.nl/anac.

O. Yucel (✉) · J. Hoffman · S. Sen
The University of Tulsa, Tulsa, OK, USA
e-mail: osman-yucel@utulsa.edu

J. Hoffman
e-mail: hoffman.jon.m@gmail.com

S. Sen
e-mail: sandip-sen@utulsa.edu

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our agent to act as a mediator between the other agents.[2] In the process, it attempts to offer the best outcome for itself from the set of solutions in the intersection of acceptable set of outcomes for both opponents.

We treat the negotiation process as a search process where we try to find an existing outcome within the acceptable region for both opponents. In order to be able to do that we need to know what offers are acceptable for the opponents, which requires a model of the opponent of the form studied in the literature [1, 3, 4].

2 Strategy

We present an outline of our agent's strategy in four steps. First we explain the parameters we used for our strategies. Then we explain how we model the opponent. In the following subsection we explain how our agent decides to accept an offer or not. Finally we explain the strategy out agent uses for choosing the bid to offer to it's opponents.

2.1 Parameters

The agent uses 5 parameters to make decisions: *Minimum Offer Threshold (MoT), Agreement Value (AV), Care (C), Number Of Bids to Consider From Opponent's Best Bids (N), and Reluctance (R)*. We will now explain what these parameters are used for and how they are calculated.

2.1.1 Minimum Offer Threshold

Minimum Offer Threshold (MOT) is a constant value used to eliminate the bids from consideration which give our agent less than a desirable outcome. We have empirically set this value to 0.6. With this setting our agent will never offer a bid which gives itself a utility which is less than 0.6.

2.1.2 Agreement Value

Agreement Value (AV) is a parameter that is recalculated with each offer, which determines if our agent should accept an offer or not. The calculation of this variable will be explained in Sect. 2.4.

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[2]Every round of negotiation takes place between 3 agents.

2.1.3 Care

Care (C) is a parameter that represents how much we care about our opponent's happiness. Our agent assumes that the opponent will accept a bid which gives the opponent a utility greater than the care value. Care value starts with the value 0.4 and increased by 0.4% every 10 turns. Both of these values are experimentally determined. Even though the negotiations in the competition were multilateral, we only consider one of the opponents at a time. We will explain how the multilateral negotiation aspect is addressed in Sect. 2.5.

2.1.4 Number of Bids to Consider from Opponent's Best Bids

Number Of Bids to Consider From Opponent's Best Bids (N) is a parameter we use for the calculation of the Agreement Value. This parameter determines how many of the best bids we created will be considered for each opponent. As mentioned in Sect. 1, we are trying to offer within the acceptable range of the opponents and this parameter allows us to predict the range that we believe the opponent will accept. Initially we keep this range wide, and narrow it down over time. We start this value from 100 and decrease it by 5 every 10 turns until it gets down to 10, after which it is held steady at 10. The use of this parameter will be explained in Sect. 2.4.

2.1.5 Reluctance

Reluctance (R) is the parameter we use for tracking time. It makes our agent less willing to accept the bids offered during the early periods of the negotiation while becoming more willing with the passage of time. We use this parameter while calculating the Agreement Value. The value of Reluctance starts at 1.1 and is decreased by 0.5% every 10 turns.

2.2 *Initialization*

During the initialization of the agent, we calculate every possible bid which gives us a greater utility than MOT. We refer to this set of bids as $Bids_{Feasible}$.

2.3 *Opponent Modeling*

In this section, we will explain the working of our opponent modeling algorithm. Our modeling approach tries to find the opponent's weights on the issues and their relative preferences of the options for every issue. We have two main assumptions in the opponent modeling process:

- The more preferred option for the opponent appears more frequently in the bids offered or accepted by that opponent.
- The opponent will be less likely to change from its best option for more important issues.

2.3.1 Order of Options

To find the preference order and the value of options for an opponent, we calculate the frequency of the options' appearance in the bids accepted and proposed by the opponent. When we order the options for an issue by their frequencies, we do so using V_o, the value predicted for option o. It is calculated using n_o, the rank of the option o, and k, the number of possible options for the issue:

$$V_o = \frac{k - n_o + 1}{k} \tag{1}$$

This calculation values the most frequent option as 1 and least frequent option as $\frac{1}{k}$.

2.3.2 Weights of Issues

As mentioned above, we are assuming that the opponents will be less willing to change the option for more important issues. We use *Gini Index* [5] as the impurity measure, and the issues which have higher Gini-Impurity scores are weighted more by the opponent. $\hat{w_i}$ is the unnormalized weight of issue i, f_o is the frequency of option o, and t is the total number of prior bids as follows

$$\hat{w_i} = \sum_{o \in O_i} \frac{{f_o}^2}{t^2}, \text{where } O_i \text{ is the set of options for issue } i \tag{2}$$

Using $\hat{w_i}$, we calculate w_i, the normalized weight of issue i as:

$$w_i = \frac{\hat{w_i}}{\sum_{j \in I} \hat{w_j}}, \text{ where I is the set of issues} \tag{3}$$

2.3.3 Example Model

We now provide an example scenario to illustrate our modeling approach. The frequencies of offered or accepted options in the issues by the opponents for our example is presented in Table 1.

Table 1 The frequencies of options for issues for one opponent

	Option 1	Option 2	Option 3
Issue 1	9	1	0
Issue 2	3	5	2

Table 2 The calculated values for every option

	Option 1	Option 2	Option 3
Issue 1	1	0.66	0.33
Issue 2	0.66	1	0.33

The order of the option preferences are the same as the order of the frequencies of the options. So the relative order in the issues are $I_1(O_1 > O_2 > O_3)$ and $I_2(O_2 > O_1 > O_3)$. From the formula given in Sect. 2.3.1 we calculate the values for the options as $V(I_1, O_1) = \frac{3-1+1}{3} = 1$. We calculate the values for all the issue-option pairs using the same approach. The results of the calculations are listed in Table 2.

We then calculate the weight for the issues using the formula given in Sect. 2.3.2

$$\begin{aligned} \hat{w_1} &= \frac{9}{10}^2 + \frac{1}{10}^2 &&= \frac{82}{100} \\ \hat{w_2} &= \frac{3}{10}^2 + \frac{5}{10}^2 + \frac{2}{10}^2 &&= \frac{38}{100} \end{aligned} \tag{4}$$

We proceed by normalizing the values we calculated

$$\begin{aligned} w_1 &= \frac{\frac{82}{100}}{\frac{82}{100} + \frac{38}{100}} &&= \frac{82}{120} \\ w_2 &= \frac{\frac{38}{100}}{\frac{82}{100} + \frac{38}{100}} &&= \frac{38}{120} \end{aligned} \tag{5}$$

For an offer which has the option O_1 for I_1 and the option O_3 for I_2 we predict the valuation for the modeled user to be

$$V(O_1, O_3) = \frac{82}{120} \times 1 + \frac{38}{120} \times 0.33 \approx 0.789 \tag{6}$$

2.4 Accepting Strategy

Every time the agent receives an offer, it checks if the utility of the offer is greater than our parameter AV. The agent accepts only if that condition is met.

Every 10 turns, the following steps are taken to recalculate AV:

- Evaluate every bid in $Bids_{Feasible}$ using the model of each user.
- Find Set_u: the set which contains the N best bids for opponent u.
- Find $Set_{common} = \bigcap_{u \in Opp} Set_u$, where Opp is the set of opponents.
- Find $Bid_{Best} = \underset{b \in Set_{common}}{\text{argmax}}\ Utility(b)$.
- Finally $AV = Utility(Bid_{Best}) * R$.

This approach estimates AV is the best utility we can get by staying in the acceptable region of both ourselves and our opponents. Multiplying it with R prevents the agent from accepting too early in the negotiations or waiting too long.

2.5 Bidding Strategy

In this part we explain how out algorithm chooses which bid to make. During the initialization of the agent we sort the bids in $Bid_{Feasible}$ by their utility for our agent, and set the variable $lastBid$ to 1.

Beginning at the previous bid, search $Bid_{Feasible}$ for the next bid that both our agent and the agent we favor will likely accept. If we find that bid, offer it, set $lastBid$ to that bid's index, and switch the agent we favor. If we do not find an acceptable bid in the set between lastBid and the end of $Bid_{Feasible}$, we simply bid the best bid for us, set $lastBid$ to 1 and switch the agent we favor.

Algorithm 8 pseudocode for selection of a bid

for $i = lastBid + 1$ to $BidSet.size()$ **do**
    if $Util(BidSet[i]) \geq AgreeVal$ **and**
$Pred.Util(BidSet[i], agentToFavor) \geq Care$ **then**
        $Offer(BidSet[i])$;
        $lastBid = i$; $agentToFavor = otheragent$
        return;
$Offer(BidSet[1])$;
$lastBid = 1$;
$agentToFavor = otheragent$

This algorithm goes down the list of bids until a suitable bid cannot be found and then returns to the top of the list. Figure 1 shows the utility of the offers on the table for the participating agents. In this figure, Party 1 represents our agent while Party 2 and Party 3 are instances of Boulware and Conceder agents respectively, which were

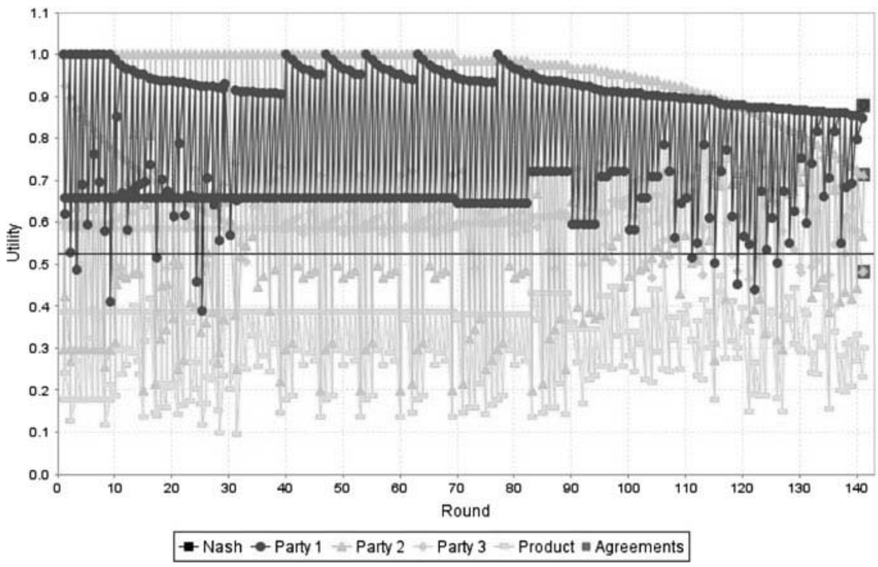

Fig. 1 Utility of the bids for 3 agents in the negotiation

provided by the organizers. The method we mentioned, going down the list as long as the bids are suitable and then returning to top, can be seen from the offers made by Party 1.

3 Conclusion and Future Work

In this paper, we have provided an overview of the strategy of the agent named "Jonny Black", which received the 3rd place in the ANAC 2015 competition in the "Nash Product" category. We have designed our agent to act as a mediator between all participating agents, including and favoring itself. We described the methods used for modeling the opponents and the strategies for accepting and making offers.

The results of the tournament shows that our approach was successful at increasing the social welfare, which was our initial intent while deciding the strategy. However the results also revealed that our agent may concede too much from its own payoff while it is trying to increase the social welfare. For further improvements on this agent, the method of conceding on its own utility for achieving higher social utility should be revised to restrict the agent from conceding too much.

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References

1. T. Baarslag, M. Hendrikx, K. Hindriks, C. Jonker, Measuring the performance of online opponent models in automated bilateral negotiation, in *AI 2012: Advances in Artificial Intelligence* (Springer, 2012), pp. 1–14
2. M.H. Bazerman, M.A. Neale, K.L. Valley, E.J. Zajac, Y.M. Kim, The effect of agents and mediators on negotiation outcomes. Organ. Behav. Hum. Decis. Process. **53**(1), 55–73 (1992)
3. R.M. Coehoorn, N.R. Jennings, Learning on opponent's preferences to make effective multi-issue negotiation trade-offs, in *Proceedings of the 6th International Conference on Electronic Commerce* (ACM, 2004), pp. 59–68
4. K. Hindriks, D. Tykhonov, Opponent modelling in automated multi-issue negotiation using bayesian learning, in *Proceedings of the 7th International Joint Conference on Autonomous Agents and Multiagent Systems-Volume 1* (International Foundation for Autonomous Agents and Multiagent Systems, 2008), pp. 331–338
5. M. Mohri, A. Rostamizadeh, A. Talwalkar, *Foundations of machine learning* (MIT press, 2012)