Intelligent Agents

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Abstract. In this paper we analyze the design and implementation of a negotiation agent built on the *GENIUS* framework [1].

1 Design

In this section we explain the design choices we made in constructing our agent. As per this year ANAC competition [2], the agent has to be designed to work with uncertainty and discrete values. In the following subsections we explain the different aspects of our design.

1.1 Uncertainty

When an agent works with uncertainty it means that does not have full knowledge of its utility space. Instead, the agent has a list of bids sorted from the worst to the best one. It is fundamental to know our utility space in order to be able to bid on the preferred items and obtain a successful negotiation result. To solve this issue, we designed our agent to model its utility space by analyzing the order of the preferred bids.

1.2 Concession strategy

A concession strategy is needed in order to reach an agreement with the opponent. The idea is that if both agents start bidding their best options there is a high chance that an agreement is never found if they do not renounce to maximizing their utility. A concession strategy is all about renouncing to maximize our utility and, hence, offer bids that are not at the top of our agent's list. We opted for a time dependent concession strategy. This means that our agent starts conceding more as time passes. We can see the mathematical notation of what we have just described at 1.

$$utility = 1 - time^{1/\beta} \tag{1}$$

Figure 1 represents the different concession strategy based on different β value. We designed our agent to play a Boulware concession strategy with $\beta = 0.3$. As we can observe from figure 1 we can see that this strategy provides the flexibility of utility slow descent until reaching a low enough utility to find an agreement.

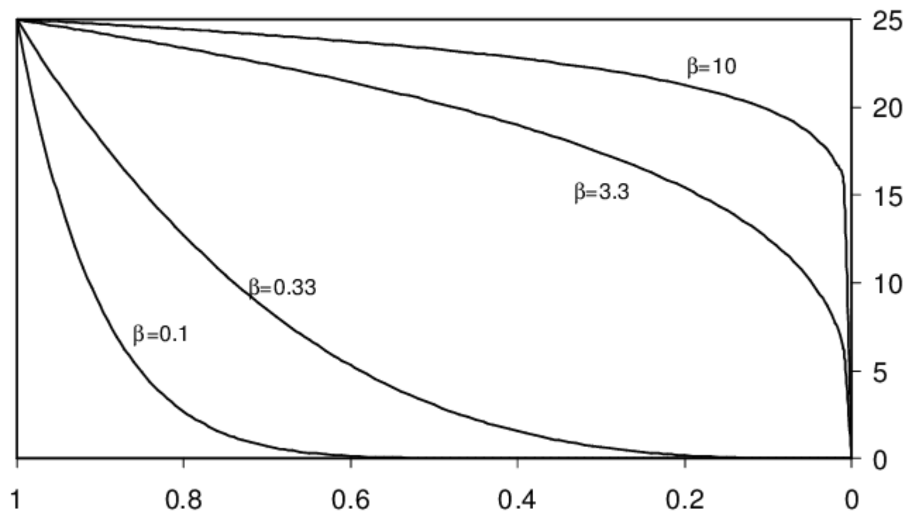

Fig. 1. Different β values for the concession strategy. Utility at x-axis and time at y-axis.

1.3 Opponent modelling

Another important feature of our strategy is opponent modelling. The breakthrough of this idea is that if our agent knows what the opponent wants we can find a bidding that maximizes both agents utility and, hence, have an higher probability to be closer to both the Pareto frontier and the Nash point. We apply this technique by exploiting the Johnny Black strategy [3]. The main idea is that the options the opponent bids the most are also a good measure of the opponent's preferences. In order to model these preferences we construct a frequency table where we store the opponent's bidding history. Every time our agent receives an offer, the frequency table is updated. When the agent gathers enough information about the opponent, it updates its model by first ordering the options of the issues following equation 2. k is the number of possible options for the given issue and n_o the rank of the current option o.

$$V_0 = \frac{k - n_0 + 1}{k} \tag{2}$$

The weights of the issues are then given by equation 3. f_o and t represent respectively the frequency of option o and the total number of opponent's previous bids.

$$\hat{w}_i = \sum_{o \in O_i} \frac{f_o^2}{t^2} \tag{3}$$

The issues weights are then normalized following equation 4.

$$w_i = \frac{\hat{w}_i}{\sum_{j \in I} \hat{w}_j} \tag{4}$$

1.4 Offer strategy

Our agent's offer strategy is based on the opponent modelling and on the concession strategy. The utility space is searched in order to find all the bids within a utility range. The upper bound is 1, the maximum possible utility, while the lower bound is given by the result of the concession strategy equation 1. The estimation of the opponent utility is described in 1.3. From all the obtained bids we offer to the opponent the one that has the best joint utility for our agent and for the opponent as well, see equation 5.

$$joint_{utility} = agent_{utility} * opponent_{utility} \tag{5}$$

This strategy allows our agent to offer bids that are close to the Pareto frontier and to the Nash point.

1.5 Acceptance strategy

Our agent's acceptance strategy is consistent with the offer one. We accept the opponent's offer if it meets one of the following requirements:

- The joint utility is bigger than our agent's last offer joint utility.
- Our agent utility is bigger than our agent's last offer utility.

This strategy allows to end the negotiation with a reasonable agreement, avoiding the utility descent caused by the concession strategy.

2 Results

In this section we analyze the results of our Agent. The results have been gathered during the agents competition organized by the course *Intelligent Agents (COMP6203)* of *University of Southampton*. In this competition all the implemented agents for the course have been tested against each other on three different domain sizes: small, medium and large. The metrics of evaluation were the agent's utility, distance to Nash point and agreement rate. We can see the results summarized in tables 1, 2 and 3, showing our agent, *Agent 9*, and all other agents outcome.

Table 1. The agreement rate results.

Agents	**Small Domain**	**Medium Domain**	**Large Domain**
Agent 9	96.39%	59.36%	71.98%
All agents	95.49%	72.25%	82.07%

Table 2. The average utility results.

Agents	**Small Domain**	**Medium Domain**	**Large Domain**
Agent 9	0.946	0.661	0.791
All agents	0.685	0.648	0.654

Table 3. The average distance to Nash point results.

Agents	**Small Domain**	**Medium Domain**	**Large Domain**
Agent 9	0.070	0.510	0.334
All agents	0.147	0.763	0.552

We can observe that, regarding the agreement rate (see table 1), our agent performs well for the small domains but below average in the medium and and large domains. This is probably because our agent's Boulware strategy is too strong. Having a strong time dependent concession strategy, as described in subsection 1.2, causes a slow utility descent. In medium and large domains the increased number of possible bids requires a less strong concession strategy that facilitates utility descent and, hence, the possibility to find an agreement with the opponent.

The average utility data, see table 2, suggest that our agent's strong ability is indeed finding an agreement with an high utility. In all the three domains our agent performs better than the average of the other agents. We can also observe that it performs extremely well for the small domains and that the average utility is always bigger than 0.5.

Our agent, with respect to the distance to Nash point (see table 3), performs better than the average of the other agents. The results, though, are not entirely satisfactory for the medium and large size domains. An average Nash point of 0.510 and 0.334 means that the possible offer bids have not been adequately searched and that the last proposed offer, or the accepted one, was mistakenly recognized as acceptable.

We can see, throughout all the data, a general pattern in our agent's behaviour. It performs incredibly well on small domains and, in contrast, more poorly on medium and large domains. This is not only dependent on the concession strategy but on the opponent modelling as well. In medium and large domains, in fact, the utility space is much bigger and the Johnny Black opponent modelling, see section 1.3, fails in producing an accurate model. A weak knowledge of opponents preferences causes the agent to bid or accept offers that are interpreted with wrong joint probability results (see 5).

3 Conclusion

In this paper we have addressed the design of an intelligent agent based on the *GENIUS* framework [1]. We have analyzed our agent's behaviour regarding the agreement rate, average utility and average distance to Nash point metrics (section 2). We have also observed, given the results data, some limitations of our design. In order to improve our agent, future work should consider implementing an adaptive concession strategy based on the domain size and a better opponent modelling for medium and large domains.

References

1. Ii.tudelft.nl. (2019). Genius. [online] Available at: http://ii.tudelft.nl/genius/ [Accessed 2 Jan. 2019].
2. Mmi.tudelft.nl. (2019). Automated Negotiating Agents Competition (ANAC) - Negotiation. [online] Available at: http://mmi.tudelft.nl/negotiation/index.php/Automated_Negotiating_Agents_Competition_(ANAC) [Accessed 2 Jan. 2019].
3. Yucel, O., Hoffman, J. and Sen, S., 2017. Jonny Black: A Mediating Approach to Multilateral Negotiations. In Modern Approaches to Agent-based Complex Automated Negotiation (pp. 231-238). Springer, Cham.