An opponent-driven strategy to increase fairness in automated multi-issue negotiations

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Abstract. In an automated negotiation, software agents try to gain the best possible utility on behalf of their owners. In general, agents, like human negotiators, do not share information about their preferences to avoid undue pressure from the other side, resulting in what is known as an incomplete information environment. This issue can be resolved through opponent modelling, but modelling can be time-consuming and computationally intensive. We need to negotiate swiftly in fields like supply-chain management, the sale of perishable items, and the fashion sector, making modelling difficult. By modelling the preference profile of the opponent during the negotiation session, this strategy sets its concession factor proportional to the model to concede more adaptively to the opponents, thereby achieving improved utility, social welfare, and fairness for the agent. This is coupled with time-based (considering the time elapsed) and history-based (considering a short history of opponents' offers) bidding strategies to negotiate in a competitive yet fair manner. Experimental results show that 'TwistedFate,' an agent built on this multi-policy strategy, fares well while negotiating with state-of-the-art agents.

Keywords: Multi Agent System · Automatic Multi-Issue Negotiation · Negotiation Strategy · Bidding Strategy · Opponent Modelling · Social Welfare Maximisation · Individual-Social Trade-off

1 Introduction

In bilateral negotiation, two parties aim to reach a joint agreement. They accomplish this by exchanging numerous offers or bids via a protocol such as an alternating offers protocol. In achieving such an agreement, both parties typically seek to satisfy their interests as best they can. However, they must also consider their opponent's preferences to reach an agreement. This is complicated by the fact that, in order to avoid exploitation, negotiation parties are often unwilling to share their preferences. As a result, both sides have insufficient knowledge, making it challenging to settle on a solid negotiation strategy and reach an optimal agreement.

The performance of a negotiating agent can be judged by its utility and the social welfare resulting from the negotiations in which it participated. An agent's utility represents how desirable the final agreement is to the agent. It is determined solely by the agent's utility function. Social welfare measures how beneficial the agreement is to all parties concerned. It is estimated using the utility functions of the entire population. To date, most automatic negotiation tactics proposed over the years have aimed at maximising the agent's utility rather than social welfare, which makes sense given that in most negotiation scenarios, the negotiator negotiates in his or her self-interest.

The lack of data makes it impossible for most game theory methods to be applied in negotiations. Besides, with this limitation, negotiators, especially in multi-issue domains, may reach an agreement when a better bid exists for both parties. Agents use different techniques to overcome this problem, such as learning from previous bids or sessions.

People's inclination for long-lasting agreements also explains why social-welfare maximising agreements are appealing. An agreement that is good for one party but bad for the other will not last. For example, a worker who agrees to dire working circumstances will quickly look for a better position. This research presents and evaluates an autonomous bargaining agent strategy to maximise a tradeoff between society and individual welfare. We concentrate on linear trade-offs between the two (i.e., a weighted sum), ranging from caring exclusively for one's utility to an entirely social objective function.

The bidding strategy or negotiation tactic is the most complex part of a negotiator agent. There are two categories of bidding strategies:

1. Behaviour-based tactics: these try to choose the next bid following the opponent's behaviour history. So a behaviour-based strategy is tightly coupled with the opponent modelling component.
2. Time-based tactics: the next bid is proposed based on the time passed from the beginning of the negotiation. The bidding strategy uses a decision function that maps the current negotiation state into a target utility value. Then a bid (or a set of bids) that has a closer utility to the target utility is selected.

Time-based techniques are more robust and less likely to be exploited by hypocritical opponents than behaviour-based strategies. TwistedFate's time-based tactic leverages opponent modelling techniques to outperform behaviour-based ones. The approach in these agents generally generates a pool of essentially identical bids, and their opponent model component selects the one that appears most appealing to the opponent.

The modelling of negotiators' utility from a given agreement is a fundamental difficulty in constructing such an agent. This is because there is no way to distinguish which agent maximises individual utility and which agent is also interested in societal welfare (and to what extent), as exposing one's genuine preferences gives the other negotiators power. First, based on the correlation between the two, we show in our technique that an accurate assessment of an opponent's bid acceptance probability may be utilised as a good measure of its usefulness from the bid. Second, we show that maximising individual utility and social welfare independently and then averaging the two leads to an optimal hybrid strategy for any tradeoff between individual utility and social welfare.

2 The BOA Framework

The BOA framework divides the negotiator agents into three distinct components, bidding strategy, opponent model, and acceptance condition (or acceptance strategy). The components can be described as follows:

1. Bidding Strategy: produces the successive offered bids in each round (The most complex component).
2. Opponent Model: tries to learn the opponent's behaviour or preferences and chooses the most appealing bid (for the opponent) from a set of bids using the built model.
3. Acceptance Strategy: a component that chooses whether to accept the current opponent's bid or offer the selected proposal.

The main goal of this communication is to present a mutually acceptable bid to increase the chance of an agreement.

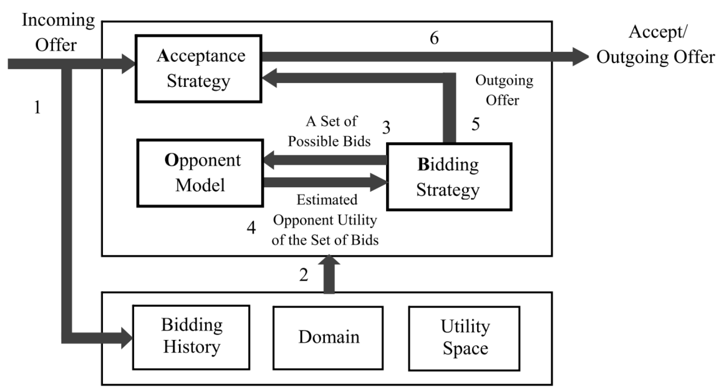

Fig. 1: The BOA Framework

In this study, an agent is presented who does not always give up on their preferences based on the passage of time. Instead, it attempts to simulate opponents in the early stages and builds a neighbourhood around its goal benefit. By gradually expanding the neighbourhood, the agent strives to increase the number of bids analysed and selects the bid with the highest utility for its opponent. In other words, by building a new communication channel between the bidding strategy and opponent model, this agent enables the formation of a new agent that decreases its expectations during a session based on the preferences of its opponent.

3 The TwistedFate Strategy

A negotiation strategy works as follows, according to the BOA framework. Whenever the agent receives a new offer2 from the opponent, the bidding history and the opponent model are promptly updated. This procedure ensures that the agent has the most up-to-date information on its opponent. The bidding strategy module then generates multiple candidate bids for the agent with similar utilities and sends them to the opponent model. In response, the opponent model calculates the estimated utilities of the received offers and returns them to the bidding strategy component. The bidding strategy component selects one of the candidate bids based on an opponent model strategy (for example, the best bid). It transmits this bid to the acceptance strategy module. Finally, the acceptance strategy determines whether to accept the newly received bid from the opponent or to send the recently obtained bid from the bidding strategy component.

TwistedFate incorporates the BOA architecture into its core framework by utilising the robust pipelines between the Bidding Strategy and the Opponent Modelling to generate a neighbourhood of ”acceptable” bids for every round.

3.1 Bidding Strategy

The Bidding Strategy can be divided into 3 parts depending on two factors:

1. current time
2. opponent model availability

The early stage During the initial rounds of the negotiation, TwistedFate only offers the most favourable bid to the opponents. The initial stages are used to gather data from our opponents (in the form of bids) and analyse them as the rounds proceed. Since a reliable opponent model isn't ready for use in the early stage, TwistedFate acts stubbornly. This stubbornness also helps TwistedFate fare well against opponents who try to model our behaviour as we would appear as a hardliner agent who isn't ready to negotiate other than the best.

The middle stage Our opponent model becomes more accurate with time. When the opponent model is assumed to be ready, each round creates a neighbourhood around the goal utility, and all bids in this neighbourhood are evaluated in terms of their utility for the opponent, with the best bid chosen. The challenging part in this step is to choose the neighbourhood's radius as it has the most impact on the resulting bid. It expands during the bargaining session to give a space for concession. However, the growth rate must be carefully chosen. If it increases too quickly, it may result in an unsuitable agreement for the agent. If a modest growth rate is set, the likelihood of a no-deal scenario increases. To solve this, TwistedFate increases the growth rate near the end of the middle stage.

The final stage As the deadline approaches, TwistedFate begins to make offers with the highest social welfare since they have a better chance of being accepted.

3.2 Opponent Modelling

The advantages of using an opponent model include identifying mutually beneficial offers and avoiding non-agreement offers and earlier agreements. Despite the diversity of opponent modelling strategies, most contemporary models rely on a restricted set of conventional learning techniques. This is thought to be related to the constraining nature of the negotiation problem.

Opponent Models can be roughly categorised into the following:

The Bayesian models estimate the opponent's preference profile by producing a collection of candidate profiles (hypotheses) and then updating the probabilities of each hypothesis using Bayesian learning. The models in this section make some assumptions about the opponent's bidding strategy.

The Frequency models determine issue weights and assessment values by considering the changing frequency of each issue's value between successive bids and the frequency at which each issue value is given, respectively.

Unlike Bayesian models, which make strong assumptions about the opponent's bidding strategy, the Frequency models work on the following assumptions:

1. The opponent's first bid has the highest utility in the opponent's utility space. At the start of the bargaining session, the opponent sends its preferred bid. The first proposal represents the best possible values for each negotiable topic. Given that all rational agents strive to maximise their utility, it is unsurprising that this assumption holds for the vast majority of rational beings.
2. The importance of an issue and the number of times its value changes during the negotiation session have an inverse relationship. In other words, agents rarely modify the value of significant concerns; the more important the topic, the less likely the agents are to change its value.
3. The significance of an issue value is proportional to the number of times it is offered. In this case, the agents try to offer a higher issue value (a higher assessment value) in each successive offer they make during a negotiating session.

TwistedFate uses a **multi-variate Frequency model** that builds upon the existing opponent models by accounting for the priority of issues using the issue-values dispersion.

TwistedFate also keeps track of the following two kinds of bids:

1. Running Bid: The average of the last N (a small window) bids proposed by the opponent.
2. Opponent's Best Bid: The bid proposed to us with the highest utility (to us).

While finding an optimal bid at any given point, TwistedFate weighs the above-mentioned bids and the best bid from the neighbourhood to find a good bid that the opponent is likely to accept. Note that, the opponent model is only accurate after a considerable amount of time has passed. This could vary by the number of issues that are part of the domain.

TwistedFate also attempts to model the similarity of the Bids by creating a mutual issues list, which can be used as an extra step if we intend to bid closer to the Pareto Frontier.

3.3 Acceptance Strategy

TwistedFate's acceptance strategy varies based on time limits. In the early stages of the negotiation, a suggestion is rigorously accepted if its value for IQSon is greater than or equal to a high threshold (0.85 in our case). Later on, the core idea behind the acceptance policy is that it accepts any offered bid whose utility is higher than TwistedFate's current optimal bid. Finally, to avoid conflict at the end of the negotiation, TwistedFate will accept any agreement that is better than its reservation value. It signifies that the agent will accept the bid if the reservation value is less than the utility of the current bid.

4 Conclusion

A time-based bidding strategy geared to opponents during concession negotiations for agents was discussed in this paper.

5 References

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