Designing an Automated Negotiator: Learning What to Bid and When to Stop

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ABSTRACT

In this paper, the ongoing research of the author on designing an automated negotiator is described. One of the key challenges of designing a successful negotiation agent is that usually only limited information is available about the other party. Therefore, we need to combine various learning techniques to decide what offers to make, and when to accept. Our goal is to investigate techniques for developing a versatile automated negotiator that can effectively conduct negotiations in an incomplete information setting.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*intelligent agents, multi-agent systems*

General Terms

Algorithms, Experimentation, Performance, Theory

Keywords

Negotiation; Artificial Intelligence; Machine Learning

1. INTRODUCTION

Negotiation is an important activity in human society, and is studied by various disciplines, ranging from economics and game theory [15], to electronic commerce [9], social psychology, and artificial intelligence [10, 12].

Traditionally, negotiation is a necessary, but also time-consuming and expensive activity. Therefore, in the last decades there has been a large interest in the *automation* of negotiation [7, 9, 10], for example in the setting of e-commerce [14]. This interest is fueled by the promise of automated agents eventually being able to negotiate on behalf of human negotiators.

One of the key challenges for a successful negotiation is that usually only limited information is available about the other party. Despite the fact that sharing private information can result in mutual gains, negotiators are often unwilling to share this information to avoid exploitation. This problem can be partially overcome by *learning* from the offers that are exchanged during the negotiation. This can be done in many ways, ranging from strategy prediction (*"what will the opponent do?"*) to preference estimation (*"what does the opponent want?"*).

What is learnt about the opponent can then be used to improve the decision of what offers to make, and what offers to accept. For example, in order to send out bids that are beneficial to the opponent (thereby increasing the chances of reaching a deal), it is necessary to estimate the opponent's preferences. Conversely, when the agent is presented with an offer by the opponent, strategy prediction may help in deciding what to do next. The agent has to make a choice between accepting the offer that is currently on the table, or rejecting it and continuing the negotiation; both options involve an inherent risk, and predicting the opponent's future offers is essential for making the right decision.

2. APPROACH

Every year, automated negotiation agents are improving in various ways, and there is now a large body of negotiation strategies available, all with their unique strengths and weaknesses (for an exposition, see [1, 7]). For example, some agents are able to predict the opponent's preferences very well, while others focus more on having a sophisticated bidding strategy. Naturally, we would like to learn from previous approaches, and improve upon them, in order to create a versatile and generic negotiating agent.

However, most agents are designed to function in very different environments, so there is no straightforward way to compare different approaches, let alone combine them. Therefore, our approach has been as follows: first of all, we created a generic negotiation environment called Genius [13], which can fully support a diversity of different negotiation protocols, scenarios, and agents. Second, we amended the Genius repository with various existing agents [8], scenarios [11], and protocols [15] from literature. Additionally, we organized a yearly international negotiation competition (ANAC) [1, 6] to harvest even more strategies and scenarios, and to learn new, improved approaches to effective agent design.

With this in place, we were able to pinpoint additional structure in most agent designs. We identified three main components of a general negotiation strategy; namely a *bidding strategy*, possibly an *opponent model*, and an *acceptance strategy* (BOA) [4]. These BOA components enable us to do two things: first, they allow us to study the behavior and performance of individual components; and second, they make it possible to systematically explore the space

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of possible negotiation strategies by recombining different components.

We started with the first part: seeking out the best of each BOA component. We mainly focused on the logical starting points, namely the opponent modeling and acceptance mechanism components.

For opponent modeling, there was no recent overview of the field available, so we conducted a survey of currently existing opponent modeling techniques (to appear, see Section 3). In tandem with surveying the state of the art, we studied the performance of a variety of different opponent models, and we concluded that simple heuristics usually outperform more sophisticated methods such as Bayesian learning [2]. We believe this is due to the fact that usually, the simple methods assume less about the opponent, which makes them more robust in everyday negotiation settings.

For the acceptance mechanisms, we studied and classified current approaches in [5]. We found that designing a good acceptance mechanism amounts to solving the acceptance dilemma: accepting bad to mediocre offers yields more agreements of relatively low utility, while accepting only the best offers produces less agreements, but of higher utility. Most of the current acceptance mechanisms are on either side of the extreme, and this insight led us to believe that more consideration has to be given to exactly what is the right time to accept. Consequently, we have adopted a more principled approach in [3], where we calculate the optimal time to accept when estimates of the opponent's future behavior is available.

3. FUTURE WORK

The next steps in our research revolve around a number of themes. First, we believe there is still room for improvement in both opponent preference estimation and strategy prediction methods, and we think online genetic algorithms can be promising in this regard. Also, learning across multiple negotiation sessions (against different opponents, and across different scenarios) has not yet received much attention, but ANAC 2013 will incorporate such learning mechanisms, which we hope will stimulate research in this area.

Second, we believe there is still a lot of research to be conducted in terms of the bidding strategy. Research in automated negotiation has mostly focused on learning techniques, but it is still rather unclear what to do with the information once it is learned.

Lastly, after analyzing all components separately, we have begun working on putting the pieces back together again. We are basically interested in three questions:

- Does combining the best of each component in the end create the best strategy?
- Which component is the most important with respect to the agent's performance?
- What aspects of the opponent should we learn, and what measures can we use to predict a good outcome?

We hope in the end, this will shed some light on where researchers should direct their effort and time when designing a negotiating agent.

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