Automated Negotiation Based on Sparse Pseudo-Input Gaussian Processes[1]

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Abstract

This paper deals with a prominent type of complex negotiations. We propose a novel negotiation strategy called **Dragon** which employs sparse pseudo-input Gaussian processes (SPGPs) to model efficiently the behavior of the negotiating opponents. The experimental results provided in this paper show that **Dragon** outperforms the state-of-the-art negotiation agents from the 2012 and 2011 Automated Negotiating Agents Competition (ANAC) in a variety of scenarios.

1 Introduction

This work studies complex negotiation scenarios that show the following features: (i) the agents have no prior information about their opponents – neither about their preferences nor about their negotiation strategies –, (ii) negotiation is executed with discount and under real-time constraints, and (iii) each agent has a private reservation value below which an offered contract is not accepted. Although several negotiation methods have been proposed for such complex scenarios, they typically suffer either from simplifying assumptions they make about the opponent's model or from the computational complexity of the approximation techniques they use. The approach described here aims at tackling these shortcomings and makes two main contributions. First, an efficient negotiation strategy called **Dragon** is proposed that makes use of sparse pseudo-input Gaussian processes (SPGPs) to (1) relax the modeling assumptions of other approaches by employing a non-parametric functional prior and (2) reduce the computation complexity of learning in such a non-parametric setting. Second, a new adaptive decision-making strategy is described that (1) allows an agent to appropriately adapt its own concession rate and (2) avoids the risk of "irrational concession".

2 Proposed Method

Dragon consists of three functional components. First, the opponent-modeling component, which adopts a non-parametric and computationally efficient regression technique in order to approximate the opponent's model. This allows a negotiating agent to calculate more accurate estimates that are used to predict the future behavior of its opponent. Second, after having learned the opponent's model, the concession-making component determines the optimal concession behavior using a novel adaptive decision-making strategy that automatically avoids the problem of "irrational concession" as discussed in [2]. Finally, the responding component enables an agent to determine the time at which it should better terminate rather than continue the negotiation session.

The opponent-modeling component of **Dragon** adopts SPGPs in order to accurately and efficiently learn the opponent's model. After having learnt a suitable (sufficiently approximated) model, SPGPs forecast the

[1]This is a shortened version of our paper previously published in [1].

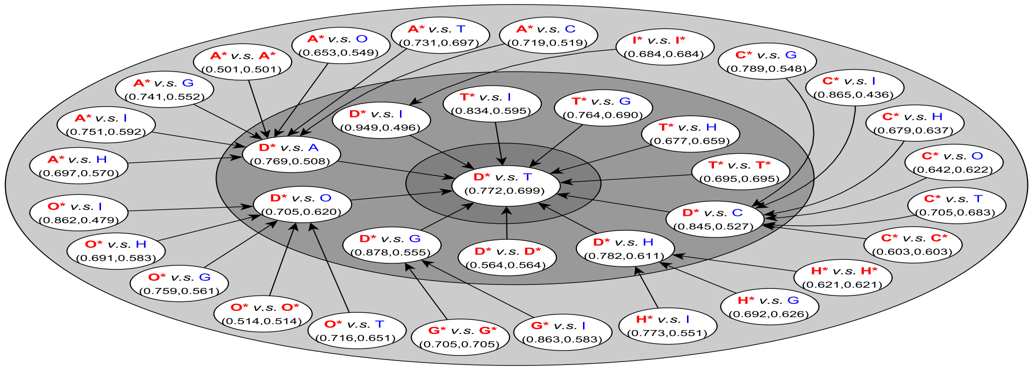

Figure 1: Deviation analysis for the two-player negotiation setting. Each node shows a strategy profile and the scores of two involved strategies (the higher scoring agent resp. strategy is marked by a star). Each letter represents a specific strategy, where the strategies are taken from ANAC 2011-2012. "D" stands for **Dragon**. The arrow indicates statistically significant deviations between strategy profiles.

future behavior of the opponent. Using the approximated model, the concession-making component aims are setting the optimal concession rate. To avoid "irrational concession", this component employs a dynamic conservative expectation function $R(t)$, which carefully suggests target utilities. The R-function primarily considers two factors. The first one is called the compromise point (ρ) that adaptively specifies the time at which **Dragon** should stop exploiting the opponent and instead start to compromise. The second one is the lowest expectation (E_{low}) that aims at approximating the most possible lowest outcome of a negotiation session. In addition, $R(t)$ is inversely proportional to the discounting factor δ because smaller values of δ motivate rational agents to try to reach agreements earlier. After the expected utility u' has been determined, the responding component decides responses to counter-offers and when to withdraw from a negotiation.

3 Empirical Evaluations

Dragon turned out to be the best strategy in a number of extensive experiments. With an average normalized score of 0.806, its performance was 23.5% abover the mean score of its opponents across all domains. Moreover, **Dragon** led by 17.5% over the mean score of the group consisting of the best agents from the 2012 ANAC. This margin was even larger for the best agent group of the 2011 ANAC (namely, over 30%). Moreover, in order to address strategy robustness appropriately, we applied empirical game theory (EGT) analysis to the competition results. More precisely, we applied the EGT technique to the scenarios where two players are involved and each agent can freely choose one of the available strategies. The results are depicted in Figure 1. Under this EGT analysis, there exists only one pure Nash equilibrium, namely, the strategy profile ($\mathbf{D}^{\star}$ v.s. **T**), i.e., **D**ragon versus **T**heNegotiator Reloaded. For any non-Nash equilibrium strategy profile there exist a path of statistically significant deviations (strategy changes) that lead to this equilibrium. This observation is of great interest, as it indicates that this strategy profile is the most stable profile among all possible profiles. Moreover, the equilibrium profile constitutes a solution with the highest social welfare. This is desirable because, as a measure of the negotiation benefit for all participants rather than the benefit for an individual agent, higher social welfare results in a better overall value of a negotiation. To summarize, **Dragon** significantly outperforms state-of-the-art automated negotiators in a variety of application scenarios.

References

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