# TheNegotiator: A Dynamic Strategy for Bilateral Negotiations with Time-Based Discounts

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**Abstract.** Recently developed automated negotiation agents are starting to outperform humans in multiple types of negotiation. There has been a large body of research focusing on the design of negotiation strategies. However, only few authors have addressed the challenge of time-based discounts. In the ANAC2011, negotiation agents had to compete on various domains both with and without time-based discounts. This work presents the strategy of one of the finalists: *TheNegotiator*. Our contribution to the field of bilateral negotiation is threefold; First, we present the negotiation strategy of *TheNegotiator*; Second, we analyze the strategy using various quality measures; Finally, we discuss how the agent could be improved.

## 1 Introduction

Past decade, virtual negotiation agents were developed which outperformed humans on some negotiation domains [3]. There is an increasing interest in using automated negotiation in e-commerce settings [5]. This interest is fueled by the promise of computer agents outperforming human negotiators [5], reducing the time and negotiation costs [2], and the ability to improve the negotiation skills of humans [4].

Despite the potential of automated negotiations within the e-commerce domain, there has been limited development in applying the theory to practice [5]. In addition, while many negotiation strategies have been developed, only few take the realistic setting of time-based discounts into account.

Towards stimulating the development of negotiation strategies for environments with time-based discounts, this work discusses *TheNegotiator*. Our contribution to

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the field of bilateral negotiation is threefold; First, Section 2 discusses the negotiation strategy; Second, Section 3 uses a toolkit of quality measures implemented in Genius to analyze the negotiation strategy using various quality measures; Finally, Section 3 provides directions for future research.

## 2 Negotiation Strategy

*TheNegotiator* uses a time-based, domain-dependent strategy. Section 2.1 specifies the concession curve. Section 2.2 discusses the acceptance strategy. Section 2.3 describes the bidding strategy.

### *2.1 Derivation of the Concession Curve*

The concession curve of *TheNegotiator* depends on the mode – discount or no discount (a number between 0 and 1) – and the different phases. Initially, the negotiation starts in no discount mode. A transition to discount mode occurs after the negotiation time surpasses the discount factor. For a negotiation with no discount factor, this entails that a transition does not occur as the discount is 1. Each of the two modes has the same three phases. In each phase a different bidding and acceptance strategy is used to increase the acceptation chance. The time of phase transition is determined differently for both modes.

In the no discount mode, *TheNegotiator* creates three phases based on the duration of the negotiation: the length of the first phase is $\frac{28}{36}$, second phase $\frac{7}{36}$, and the final phase $\frac{1}{36}$ of the time. The next step is to divide the utility range into three ranges [0 - $\frac{5}{8}$], [$\frac{5}{8}$ - $\frac{7}{8}$], and [$\frac{7}{8}$ - 1]. In each phase a linear concession curve determines the target utility. The target utility of the first phase starts at the maximum utility and decays linearly to $\frac{7}{8}$ of the full utility range. Given the length of the phase, this entails that *TheNegotiator* concedes very slowly during most part of the negotiation. Next, the second phase starts with a utility of $\frac{7}{8}$ and decays to $\frac{5}{8}$. Finally, the last phase considers the remaining range.

In the discount mode, which starts when discount time has passed, the remaining time and utility range is determined. To concede more quickly, each phase is set to visit $\frac{1}{3}$ of the remaining utility range. The duration of each phase is determined by dividing the number of bids in the range by the total amount of bids and multiplying by the remaining time. In contrast to the no discount mode, an equal amount of time is spend on each bid. Given the utility range and time per phase, the target utility can be found by using linear interpolation identical to the no discount mode.

### 2.2 Acceptance Strategy

*TheNegotiator* uses the concession curve to determine if a bid should be accepted. In all phases, a bid is accepted when the utility of the bid is higher or equal to the target utility. In the third phase there is the extra condition that a bid is accepted without further consideration if *TheNegotiator* estimates that there are less than 15 player moves remaining, where a move is defined as an action by both agents. The amount of rounds left is determined by using Equation 1, where $\mu_{15}$ average time between the last 15 bids and $(T-t)$ is the remaining time.

$$RoundsLeft = \frac{(T-t)}{\mu_{15}} \tag{1}$$

### 2.3 Bidding Strategy

*TheNegotiator* uses the concession curve to offer bids. A random bid with a utility within the target utility window $[l,u]$, which is calculated by using the concession curve, is chosen to offer. The lowerbound $l$ of the window corresponds to the target utility calculated by using the concession curve. The upperbound $u$ is determined by using Equation 2.

$$u = l + 0.2 \cdot (1-l)] \tag{2}$$

In the first phase, 70% of the time a random bid is chosen with a utility within this range. In the other cases, the upperbound $u$ is ignored. In the second and third phase, *TheNegotiator* uses opponent bids which are above the lowerbound $l$ A random bid is chosen from these bids as a counteroffer. If there is not a single bid which falls in the target utility window, then the same strategy as the first phase is applied.

## 3 Empirical Evaluation

This Section evaluates the negotiation strategy of *TheNegotiator*. Section 3.1 discusses the setup of the tournament used to evaluate the quality of the negotiation strategy. Section 3.2 discusses which quality measures are used to evaluate the negotiation strategy. Section 3.3 evaluates the results.

### 3.1 Tournament Setup

From the eight domains of the ANAC2011, five domains were chosen based on size and opposition (Adg, Camera, Grocery, IS_BT_Acquisition, and Laptop). Large domains and discounts were not used, as most ANAC2010 agents do not handle these well.

The top three agents of the ANAC2010 (Agent K, Yushu, Nozomi), ANAC2011 (HardHeaded, Gahboninho, IAMhaggler2011), and *TheNegotiator* competed on these five domains in order to establish the quality of the negotiation strategy of *TheNegotiator*. The tournament results were averaged over three runs to increase the reliability of the results and four computers were used in combination with a distributed version of Genius which divided the 1680 sessions.

## 3.2 Quality Measures

Three types of quality measures were implemented in Genius to evaluate the quality of the negotiation strategy: tournament measures (average time of agreement, percentage of agreement, and average utility), outcome quality measures (average Pareto distance, average Nash Distance) and trajectory analysis (percentage of unfortunate moves) [1]. The results are calculated after a negotiation session to ensure that the calculation does not influence the session.

## 3.3 Evaluation of Results

The results of the tournament are shown in Table 1. The average time of agreement was high, this is in line with the winners of the ANAC2010 (Agent_K) and ANAC2011 (HardHeaded). Despite not having an opponent model, *TheNegotiator* scores above average on unfortunate moves. In many of the cases (averaged final utility, averaged Pareto distance, averaged Nash distance and percentage of agreement) the results from the *TheNegotiator* differed only slightly from the other agents.

The avg. time of agreement gives us reason to believe that the acceptance criteria could be improved to increase the avg. utility. We believe that the avg. utility could

**Table 1** Overview of the tournament results. The best value is bold; the worst underlined.

| **Agent** | **Avg. time of agreement** | **Percentage agreement** | **Avg. utility** | **Avg. Pareto distance** | **Avg. Nash distance** | **Percentage unfortunate** |
|---|---|---|---|---|---|---|
| Agent_K (2010) | 0.651 | 99.167 | 0.881 | 0.012 | 0.106 | 0.108 |
| Gahboninho (2011) | 0.563 | 99.167 | 0.821 | 0.012 | 0.116 | <u>0.158</u> |
| HardHeaded (2011) | 0.673 | <u>98.056</u> | 0.891 | <u>0.024</u> | <u>0.148</u> | **0.034** |
| IAMhaggler 2011 (2011) | **0.325** | 98.333 | <u>0.794</u> | 0.022 | 0.126 | 0.142 |
| Nozomi (2010) | 0.583 | **99.722** | 0.887 | **0.007** | **0.085** | 0.042 |
| TheNegotiator (2011) | 0.626 | 99.167 | 0.873 | 0.013 | 0.107 | 0.064 |
| Yushu (2010) | <u>0.681</u> | 99.167 | **0.928** | 0.012 | 0.110 | 0.071 |

be even further improved by adding a frequency model similar to HardHeaded to decrease the percentage of unfortunate moves.

It should be noted that the results are not in line with the ANAC competition results. This can partly attributed to the selection of domains – there is no large domain in the set of domains as ANAC2010 agents do not scale well – and the usage of only domains without discounts.

## 4 Conclusion and Future Work

In this paper, we presented an negotiation strategy which allows an agent to negotiate efficiently in domains with time-based discounts. We provided an overview of the strategy of *TheNegotiator* (see Section 2) which is domain dependent. The strategy of *TheNegotiator* was empirically evaluated against the best ANAC2010 and ANAC2011 agents (see Section 3) using different types of quality measures. For future work, we plan to adapt the negotiation strategy such that it takes the opponent's behavior into account by employing a Bayesian or Frequency model.

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