Enabling Computer to Negotiate with Human in E-Commerce: A Strategy Model

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Abstract

Human-computer negotiation plays an important role in dynamic trading online, especially in B2C e-commerce. Further scientific investigations about designing the software agent that can deal with the human’s random and inconsistent offer is in need, which is crucially useful for the online merchants to achieve better trading outcomes and save vast trading cost. The lack of such studies has decelerated the process of applying automated negotiation to real world applications. To address the critical issue, this paper develops a strategy model. To demonstrate the effectiveness of this model, we develop a prototype and conduct human-computer negotiation experiments over 121 participants. The experimental result shows that the agent with our newly designed strategy model can significantly increase the agreement rate and joint outcome of the both sides, and even can outperform human negotiators.

1. Introduction

The dynamic trade online, represented by e-commerce oriented negotiation, is increasingly assuming a pivotal role in organizations [1, 2]. A lot of prominent negotiation models have been developed over the past decades [3-5]. While the e-commerce and AI literatures mirror that most of the extant studies primarily focus on the computer-computer negotiation, which use intelligent software agent to surrogate both the buyer and seller, leaving the human-computer negotiation comparatively unexplored [6]. Owing to the randomness of the human’s behavior, the e-commerce human-computer negotiation context is assumedly more complicated. The human-computer negotiation system accordingly needs much smarter software agents to process the human’s random and non-deterministic negotiation behavior effectively. Thus, for example, the agent should be able to try different strategies to obtain a better negotiation outcome. The ability to quickly and autonomously combine appropriate strategies among the candidates to cope with the negotiation situation is a very important aspect for evaluating the designed agent’s intelligence level. So the main objective of this study is to construct and validate a generic and robust concession model in an effort to support various strategies combination during the human-computer negotiation in e-commerce.

In order to develop a negotiating agent that has the ability to negotiate with human, it is of vital importance to elucidate how to design a negotiation strategy model to guide the agent’s concession in the process of negotiation. A negotiation strategy is a decision-making model used by the participants to persuade the opponent towards the outcome they desire. There are two major approaches to design the strategy [7-9]: the heuristic-based approach and the machine learning approach. However, several important dimensions have received limited attention in existing research of negotiation strategies. Firstly, past studies primarily focus on computer-computer automated negotiation, while relatively few studies have been carried out in assessing the potential of human-computer negotiations [6]. None can ignore the fact that the computer simulating negotiation environment is quite different with the negotiation that has human participating in, but systematic design and evaluation of agent strategies that incorporate a human counterpart’s perspective is lacking [9]. Secondly, most of the previous studies are to design a single strategy, based on heuristic or machine learning, and then study its effectiveness in a negotiation. Few studies have been focused on the overall effect generated from the combination of multiple strategies. The obvious flaw of a single strategy, especially for heuristic-based approach, is lacking variety, and thus easy to be detected its future offer trend. Thirdly, a negotiation strategy is essentially a concession model that defines the utility decreasing sequence of offers. Most of the previous strategy researches mainly abide by a preset monotonic [10] or segmented [11] concession function to implement the concession model, few investigations make efforts to realize a concession model that can properly respond to the opponent’s
ever-changing offers dynamically. This could be a big problem in human-computer negotiation because a preset lacking-variety concession model ignores the opponent’s reaction, thus very likely to enrage the human negotiator when no obvious concession is made to respond to the human’s offer, even if the human makes huge concession [12].

In conclusion, from our perspective, human-computer negotiation is essentially a behavioral game process [13], in which single strategy can hardly process all the possible complicated situation generated by the human’s random and dynamic negotiation behavior. Our aim of this paper is designing a negotiation strategy that combines various strategies, which enables the agent to deal with as much complex negotiation context as possible to satisfy the practical application environment of e-commerce.

2. The Agent Strategies

Our strategy model includes five strategies: time-dependent (including competitive and collaborative), behavior-dependent, selection and punishment, where the first two strategy model are from the classic work [14], while the selection and punishment strategy are derived from the former two classic strategy model. The agent switches among these different strategies to deal with human’s inconsistent negotiation behavior. So, these strategies together are called combined strategy.

In real life negotiation, human negotiators usually do not fix on one strategy, but try different strategies from time to time during the process of negotiation [5]. As we can see from [10], the time dependent strategy model is actually a family of monotonic functions, which can be depicted as a bunch of offer curves in the solution space of the negotiation. The task of our selection strategy is to select among all of these offer curves dynamically to deal with the ever-changing opponent’s offers, rather than fixing on one function curve from the beginning to the end of the negotiation as the previous studies did. To do so, the agent needs to keep learning its counterpart’s negotiation behaviors, and accordingly adjusts its current strategy to a proper one to respond properly the opponent’s possible price changes.

When it is necessary to change a strategy, the agent needs a criterion, which defines when and to what extent will the strategy be changed. When a negotiator suddenly increases or decreases concession drastically, that usually means the negotiator is changing strategy. On the contrary, if a negotiator keeps a steady concession (i.e., makes same or similar concession in a period), that means the negotiator intends to keep the current strategy unchanged in the coming rounds. The increase and decrease of concession can be described by the concession rate, which is the ratio between the two neighboring concessions. The detailed model can be found in our previous works[14, 15].

The typical situations of the selection model are shown in Figure 1, from which we can see there would not have been an agreement point between the two initial strategies of the buyer and seller, but due to the seller’s strategy selection ability, after several rounds of offer exchanges, the seller adjusted its strategy according to the buyer’s concession change, finally find a deal point between them.

Normally, unlike a regular strategy function, which is usually monotonously increase or decrease, human often negotiates in a non-monotonic way. Especially, when they negotiate with a computer, due to the superiority feeling against the computer, human would probe the computer through a lot of irregular offers. This has been verified by our massive human-computer experiments (see section 3 for details). The selection strategy does not consider an exception that the human probably stalls the time deliberately in order to snipe the agent near its deadline, such that the agent could be a potential target of exploitation [9]. According to the time dependent strategy, when the time approaches the system deadline, the agent will make an apparent big concession, which can be obviously perceived by the human. Therefore, the human might wait for this signal and try to snipe near the agent’s reservation price (as shown in Figure 2), thereupon causing enormous loss to the computer side. Aiming at this situation, we design the punishment strategy to treat the human’s abnormal or cheating behaviors.

The human’s cheating behaviors that cause time stalling can be classified into three categories: (1) keeping a same offer unchanged in several continuous round of negotiation (e.g., type I in Figure 2); (2) retrogressing from the last offer to a inferior one (e.g., type II in Figure 2); (3) inputting illegal characters except for numbers, which equals to stalling for time. These cheating behaviors do not help the negotiation process proceeding to a deal, but wasting time. If the agent cannot process such situations properly, the wasting time will cause the agent leak its private deadline information, the more close to deadline the more dangerous. A typical situation is shown in Figure 2.
Figure 1: Computer-computer negotiation experiment for selection strategy

Figure 2: An instance of human play tricks with the agent for getting extra profits
In order to avoid the human’s cheating behavior harming the negotiation’s fairness and the benefits of the agent owner, we design the punishment strategy that the main idea is increasing the agent’s reservation price in case that the human negotiator takes the above three cheating behaviors, so that even if the time is delayed by human to the system deadline, the agent would at most be sniped at a new reservation price much better than its initial reservation price. The main process logic of the punishment strategy is: the agent first calculates its punishment increment for the current round of negotiation, and then makes an offer same to its last offer, finally through adding the punishment increment and the last reservation price to create a new reservation price, which cannot exceed a preset threshold, otherwise the final reservation price should be the threshold.

Figure 3 gives an illustration for the implementation of the punishment strategy, which comes from a true negotiation case in our human-computer experiments. From the figure we can see that the human negotiator started playing tricks by offering lower price than the initial offer of 20 till the offer point of A, which was higher than 20. During this period, the agent activated the punishment strategy, kept the offer unchanged and increased the reservation price to a level that is near to the preset threshold, and then the agent will not offer price lower than this level and accordingly protected its own benefits. The human cannot take advantage from the agent, and finally make a deal at a point near to the win-win point of 60. Through a lot of similar experiments, the punishment strategy has been proved to be effective.

3. Experiment Evaluation

This section will conduct lots of experiments to evaluate the effectiveness of our combined strategy, which will practically benefit real human-computer negotiation system development.

3.1 Experimental Design
To empirically validate our combined strategy, we conducted a between-subject experiment. The negotiation is conducted via a human-computer interaction interface, through which the human participant can input their offer, see the computer’s offer, accept or reject the computer’s offer. 121 human participants, who were recruited from classes (including MBA, postgraduate and undergraduate) in 2014, played the role of buyers negotiating purchases with the same number of agent sellers, and were randomly assigned to negotiate with 3 kinds of seller agent differentiated by the strategy type that the agent employs. The randomly assigned result is depicted in Table 1.

Table 1: The experiment design

<table>
<thead>
<tr>
<th>Experiment Groups</th>
<th>Single Fixed Strategy</th>
<th>Combined Strategy</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Competitive</td>
<td>Collaborative</td>
</tr>
<tr>
<td>Participant Number</td>
<td>40</td>
<td>42</td>
</tr>
</tbody>
</table>

Referred to [6], competitive strategy and collaborative strategy were used by the agents to negotiate with the human participants. The Competitive and Collaborative are two most representative strategies, and have been discussed in many other previous studies [10, 12, 16-20] in different names: competitive and collaborative, or boulware and conceder, or aggressive and conciliatory. Additionally, our research target is to compare the effect between the traditional single fixed strategy (all the five strategies belong to this category) and our combined strategy. Therefore, in our experiment, we select Competitive and Collaborative to compare with our Combined Strategy.

3.2 Experimental procedure

The experiment followed a three-stage procedure: pre-negotiation stage, negotiation stage and post-negotiation stage.

In the pre-negotiation stage, participants first read general instructions and were briefed on the procedure. They were then given a task sheet that the main content has been introduced in Section 3.1. Their goal was to maximize their own utility scores for purchasing the portable power via the negotiation system. Participants were asked to take a quiz to make sure that they understood the task. They were also asked to record their psychological price, at which they would be at least satisfied to buy the product in the real-life transaction. After this, the computer interface and the negotiation rules were introduced.

In negotiation stage, in order to facilitate comparing our model with the other previous strategy studies, the participants were randomly divided into three groups. In the first group, the participants negotiated with an agent using fixed Competitive negotiation strategy. In the second group, the participants negotiated with an agent using fixed Collaborative negotiation strategy. In the third group, the participants negotiated with an agent using our Combined strategy. In this stage, participants negotiated with the agent till they reached an agreement, or till no agreements are reached when one party rejected the other party’s final offer. The participants were not informed the exact time limit for the negotiation, though the seller agent actually has a limit that is equal to the system’s deadline. The negotiation will terminate when the deadline is hit regardless of whether the two parties make a deal or not.

In the third, post-negotiation stage, upon completing the task, participants were asked to record their agreement, and then to complete a post-negotiation questionnaire with which their demographic information was collected for control checks. In order to avoid leaking the key information of the strategy that the agent is implementing, the participants were told to keep their experimental experiences confidential with each other before receiving their participation rewards. Performance rewards were announced after the completion of each experiment session.

4. Data Analysis, Results And Discussion

This section experimentally compares the effects of combined strategy and the classical fixed strategy in the human-computer negotiation. Table 2 and Table 3 summarize our experiment results for agreement rate, and agent winning ratio.
According to the data in Table 2, overall, among the 121 agent-human negotiations, 96 ones reached agreement and 25 ended up with no agreement. Among the 96 agreed ones, there are 32 ones where agents accept humans’ offer, and 64 ones where humans accept agents’ offers. By the “final offer” rule enforced in the experiment, non-agreement cases only occurred when participants reject the agent’s final offer, or a counteroffer fell into the agent’s rejection region.

Agreement rate depends on different strategies that the agents employ. Among the 40 competitive seller agents, only 40% made deals with the human buyer. Towards the 42 collaborative seller agents, almost all can reach agreements with human buyer (100%). The reason for so high agreement rate is due to the feature of the collaborative strategy, which represents the kind of negotiator who eagers to make a deal as soon as possible. Synthesizing the result of competitive and collaborative, the agents that use single fixed strategy could make 70.7% deals, which is lower than the ratio when the seller agent uses our combined strategy (97.4%). As to the overall effect for employing agent to negotiated with human, nearly 79.3% negotiation succeeded, which implies the feasibility for using negotiating agent in e-commerce negotiation.

5. Contributions and Conclusion

The significant contribution of this study is exploring a innovative way for agent’s negotiation strategy design, which can deal with the human’ random and dynamic negotiation behavior in a human-computer negotiation context, and proved that the traditional fixed strategy developed and widely used in computer-computer automated negotiation cannot adapt to the human-computer negotiation environment. Specifically, the contributions lie in the following three aspects:

The first contribution is our combined strategy complementing the research of negotiation strategy from a novel perspective. The previous heuristic and learning-based strategies were the product of computer-computer automated negotiation. The heuristic strategy makes offer according to a well pre-designed function, ignoring the opponent’s response [10]; while the machine learning strategy use intelligent algorithm to predict the opponent’s behavior [19, 21], hoping to get benefits at a future predictable point. In human-computer negotiation, however, as we can see from our experiments, the single fixed heuristic strategy completely cannot satisfy the dynamic and complicated negotiation situations with human beings. On the other side, it is highly unlikely for a software agent to predict the human’s negotiation behavior in advance as the most learning-based strategies do. Although there have been some studies trying to set negotiation strategy through capturing the human’s trade-off behaviors beforehand [22], human’s behavior is nondeterministic and ever-changing during the course of a negotiation as we can see from our massive human-computer negotiation experiments. Different from all the previous studies, our newly designed strategy neither abides by a fixed offer function, nor predicts the opponent’s future behavior, but autonomously responds to the counterpart’s offer in a
human way. During this process, we need to combine various strategies to deal with all possible situations, rather than only using one single strategy to play all possible role in a complex negotiation, so as to initiating new ideas for development of the negotiation strategy research. From the perspective of agent theory, our design is more accordance with the core idea of agent: tell it what to do but not how to do. The experimental results show our strategy design provides agent larger flexibility and robustness. Comparing with the previous studies [6, 10, 12, 20], our model leads to a higher negotiation agreement rate and a better performance than human.

Secondly, different from the most negotiation strategy studies that mainly abide by a preset monotonic concession function [10, 23] or segmented concession function [11], our work actually builds up a novel concession model, i.e., the agent’s concession is made dynamically by different strategies together, thereby increasing the flexibility and robustness of the negotiation agent when facing the human’s random and non-deterministic negotiation behavior. For instance, how to deal with the human’s tricking behavior (e.g., stalling time and detection) is a difficult problem in the process of designing the agent’s strategy. Some previous studies bypassed strategy design but tried to employ protocol rules to regulate the human’s behavior, such as “non-concession detector” and “maximum sessions” policy, from the managerial perspective [9]. However, such regulations probably cause uncomfortable to human customers, and cannot embody agent’s intelligence. The better method is to enable the agent with the ability to recognize human’s intention and process it just like human does. Our punishment and anti-detection strategy can do this. As such, our mechanism provides a new thought for the study of concession model in automated negotiation.

Thirdly, the most previous strategy studies aim at agent-agent automated negotiation, and can hardly obtain the actual negotiation situation under such pure computer-computer circumstance. Our study, on the more practical side, through massive human-computer negotiation experiments, have obtained valuable empirical knowledge (including agent’s initial settings for negotiation strategy, reservation price and deadline) for building and using the human-computer negotiation system, hence representing a step close to more realistic practical e-commerce agent-based negotiations. Our study proves that the ability to dynamically change and adjust the negotiation strategy according to the opponent’s offer is a required component for a negotiating agent. That can significantly help the practical design and implementation of the construction and application of a human-computer negotiation system.

REFERENCES


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