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Prediction Strategy for E-Commerce Price Negotiation

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ABSTRACT

Automated negotiation plays an important role in dynamic trading online, especially in B2C e-commerce, as it is crucially useful for the online merchants to achieve better trading outcomes and save vast trading cost. To address the critical issue, this paper develops a prediction strategy that using linear regression to predict the opponent's future offer trend, the theoretical model and the algorithm are proposed. To demonstrate the effectiveness of this model, we develop a prototype and conduct computer-computer automated negotiation to make comparison with the previous negotiation strategy model. 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.

Keywords: B2C electronic commerce, automated negotiation, negotiating agent, linear regression.

INTRODUCTION

Negotiation is a process in which parties interact to settle a mutual concern to improve their own status quo. As negotiation is a core activity in human society, it is studied by various disciplines, including economics, artificial intelligence, game theory, and social psychology. The economics and social psychology researchers usually focuse on human to human negotiation, while the researchers using artificial intelligence and game theory pay more attention to computer to computer negotiation. Due to the the unavoidable space-time limitation of the negotiation, human-human negotiation is a necessary but time-consuming and expensive activity. Therefore, in the last two decades, there has been a growing interest in the automated negotiation systems, which has a promissing prospective in future e-commerce. In automated negotiation, the software agents are designed to negotiate on behalf of human negotiators partially (i.e., human-computer negotiation) or totally (i.e., computer-computer negotiation) and to find better outcomes than human negotiators. The potential benefits of automation include reduced time and negotiation costs, a potential increase in negotiation usage when the user can avoid social confrontation, the ability to improve the negotiation skills of the user, and the possibility of finding more interesting deals by exploring more promising portions of the outcome space, which is normally hard to solve by human as there would be implying much calculation that is unaffordable to human.

BACKGROUD AND MOTIVATION

The core problem of the automated negotiation research is the negotiating agent design. In order to obtain a better outcome in negotiation, an agent needs to find out some private information of the opponent (e.g., strategy, tactics, reservation price, deadline, etc) so that the agent can choose an appropriate strategy among all the candidates to deal with the negotiation situation for getting a better deal. However, in competitive bilateral negotiation, a negotiator has little information about their opponent. In fact, the only available information in most cases is the previous offers from the opponent. So the agent needs to predict the opponent's key private information or possible future offer trend based on the previous offers [1]. Most existing prediction approaches are based on machine learning mechanisms, which can be divided into two categories, off-line learning and online learning.

The off-line learning focuses on learning from previous encounters of the negotiation, such as Bayesian learning [2, 3], reinforcement learning [4], neural networks [5], and evolutionary computation [6]. Normally, this approach comprises two steps. In the first step, an estimation function needs to be well trained by training data, which are from the previous encounters. Therefore, the performance of the estimation function is somehow decided by the training result. In the second step, the trained estimation function is employed to predict opponents' behaviours. Since the unavailability of historical interaction data of the past encounter, which benefits the off-line learning, makes it is difficult to obtain private information of opponents, on-line learning methods are proposed to make prediction through the historical offers of current encounter and adapt to the negotiation opponent behaviour. This approach can be summarized to statistical approaches, e.g., linear regression, non-linear regression, and difference based mathematical models. [7] classified agents' negotiation strategies and tactics into time-dependent, resource-dependent and behavior-dependent ones and defined them formally. Based on Faratin's definition, [8] gave a nonlinear regression to predict opponent's tactic family, tactic parameter and next offer. He also gave a heuristic method to estimate opponent's reservation price and deadline. Similarly, [9] proposed a method to adapt the factor of negotiation tactics according to the prediction results of opponent's next offers. [10, 11] gave a difference-based offers prediction method. These prediction-based one-issue bargaining strategies predict private information (tactics, reservation price, deadline, etc.) of opponent before making appropriated counter-proposal based on two assumptions. One is that the opponents offer according to the strategies and tactics models defined by [7], the other is the opponents make consecutively concessions. These assumptions limit the coverage of opponents as it is impossible to enumerate all the offering patterns (model) of the opponent, and there are lots of opponents who do not offer according to any concession patterns, or even take some strategies to prevent their private information to be learned.

According to the analysis of above literatures, in price negotiation environment, it is needed to propose a new self-adaptive strategy that does not depend on any knowledge base about opponents and no need to model the opponents, enabling the agent to accurately and autonomously predict the opponent's future offer trend, and then adapts its concession according to the observation of the opponent's recent offer and its own recent offer. The remainder of this paper is organized as follows. Section 2 discusses the resear background and why we do this study. Section 3 elaborates the linear regression model for our prediction strategy. Section 4 presents computer-computer negotiation experiment, introduce the experimental design and evaluation measures for the model, and discusses the experimental results and their insights revealed. Finally, Section 5 summarizes the findings, discusses the contributions, and draws the picture of the future work.

BILATERAL NEGOTIATION

This paper focuses on one-issue-price negotiation over product or service between negotiating partners, either agent vs. agent or agent vs. human. The automated negotiation environment is characterized as follows: 1) Only one seller and one buyer are involved in a negotiation process. 2)The negotiation involves one issue (i.e., price). 3) Reserve price, deadline, and offer function of negotiators are private information that cannot be explored by the opponent. That is because the more information known by opponents, the larger probability to be exploited by opponents. Therefore, each negotiator can only observe opponent's past offers. 4) The aim of the buyer (seller) is to buy (sell) the item or service at a price as low (high) as possible. 5) Any offer given by agents cannot be canceled or withdrawn. All of the assumptions are rational and derived from real negotiaon situations. Based on these environmental constraints, a bargaining is formally defined as follows.

Definition 1: A bilateral negotiation BN is a 15-tuple:

$$BN = (Seller, Buyer, Protocol, Strategy, Time, A_x^t, \overline{p_s}, \underline{p_s}, \overline{p_b}, \underline{p_b}, p_{s\to b}^t, p_{b\to s}^t, \overline{t_s}, \overline{t_b}, D), \quad (1)$$

where

- $Seller$ and $Buyer$ are denoted by s and b respectively.
- $Protocol$ specifies the rules that govern the bargaining process. The alternating offer protocol is adopted in this paper, which will be illustrated later in this section.
- $Strategy$ is a set of bargaining strategies that can be used by agents. Each strategy is an offering function of the negotiator.
- $Time$ is denoted by t denoting the number of negotiation round.
- $A_x^t = \{accept, reject, offer, quit\}$ is a set of actions that can be chosen by negotiator x $(x \in (s, b))$ in round t of the negotiation. The system is designed for facilitaing both human-agent negotiation and agent-agent negotiaiton. The agent is binded with the negotiation system, the agent can quit the negotiation as the time deadline has reached, but cannot reject the opponent's offer, as rejection is a more emotional behavior that could be used by human, therefore, human can reject the agent's offer but cannot quit the system. As a result, the human's action is defined as $A_{human}^t = \{accept, reject, offer\}$, while agent's action is defined as $A_{agent}^t = \{accept, offer, quit\}$.
- $\overline{p_s}$ is the initial price or the highest price that the seller s can offer.
- $\underline{p_s}$ is the reserve price or lowest acceptable price of seller s.
- $\underline{p_b}$ is the initial price or the lowest price that the buyer b can offer.
- $\overline{p_b}$ is the reserve price or highest acceptable price of buyer b.
- $p_{s\to b}^t$ (or $p_{b\to s}^t$) is the offer from seller s (or buyer b) to buyer b (or seller s) in round t, which is delimited by the acceptance range of buyer and seller.
- $\overline{t_s}$ or $\overline{t_b}$ represent the maximal number of rounds that seller or buyer is willing to negotiate. $\overline{t_s}$ and $\overline{t_b}$ are generally independent with each other.
- D is the deadline of the system or the negotiation process, which can be regarded as the minimal one of $\overline{t_s}$ and $\overline{t_b}$, i.e., $D = min\{\overline{t_s}, \overline{t_b}\}$.

Negotiation Strategy

A negotiation strategy is a decision-making model used by the participants to persuade the opponent towards the outcome they desire. Heuristic-based approach is always used to design the negotiation strategy function to implement the concession process. The well-known early work was the work of [7, 12], which mathematically formalized strategies into function families, such as: time-dependent strategy, resource-dependent strategy and behavior-dependent strategy. For these classic negotiation strategies, concession is the main method to eliminate conflict and obtain mutual benefit for both sides in negotiation. An agent concede according to its own offering pattern as well as considering opponent's concession.

Taking the classic time-dependent strategy [7, 12] as an example, it indicates that an agent is likely to concede more rapidly if it needs to reach an agreement by a deadline. The offer price proposed by seller s to buyer b at time t is:

$$p_x^t = \underline{p_x} + (1 - \alpha_x(t))(\overline{p_x} - \underline{p_x}) \quad (2)$$

where $\alpha_x(t)$ is a family of the offer curves that can be defined as:

$$\alpha_x\ (t) = exp^{(1-\frac{min(t,\overline{t_x})}{t_x})^{\beta} lnK_x}, \tag{3}$$

where K_x is a constant that determines the value to be offered in the first proposal by agent x. There is actually a family of concession curves, which can be defined simply by varying the value of parameter β determining the convexity degree of the curve. The shape of each concession curve represents a human's possible negotiation offer track. As there are infinite offer curves (corresponding to infinite values of β, one for each curve) in the solution space, theoretically speaking, the model covers the entire possible offer curves the human might choose during the process of negotiation.

The Prediction Strategy

Supposing the offer points of buyer and seller distribute in a rectangular coordinate system, in which the x-coordinate denotes round number (t), while y-coordinate denotes the offer price (p). Each offer point can be expressed as a tuple $(t, p_{b\to s})$ for buyer or $(t, p_{s\to b})$ for seller. The linear regression is conducted by seller to model the buyer's offer trend according to the buyer's previous offer points. The regression line is typically stated in the form of

$$p = \alpha + \beta t + \varepsilon, \tag{4}$$

where p is the dependent variable, α is the p intercept, β is the slope of the linear regression line, t is the independent variable, and ε is the random error. Assuming that we observe n pairs of data $(t_1, p_1), (t_2, p_2), \cdots, (t_n, p_n)$ from a negotiation experiment, and model in terms of the n pairs of the data can be written as

$$p_i = \alpha + \beta t_i + \varepsilon_i, for\ i = 1,2,\cdots,n, \tag{5}$$

after model is specified and data are collected, the next step is to find "good" estimates of α and β for the linear regression model that can best describe the data. Suppose a and b are the estimates of the α and β respectively, while the estimate of p is $\hat{p}$. We use the least square method to find parameter estimates by choosing the regression line that is the closest to all data points. So, we are going to find the estimates a and b such that the sum of the squared distance from actual response p_i and predicted response $\hat{p}_i = a + bt_i$ reaches the minimum among all possible choices of regression coefficients a and b, i.e., to minimize the sum of squares

$$\sum_{i=1}^{n} (p_i - \hat{p})^2 = \sum_{i=1}^{n} \varepsilon^2 = \sum_{i=1}^{n} (p_i - a - bt_i)^2 \tag{6}$$

Mathematically, the least squares estimates of the simple linear regression are given by solving the following system:

$$\frac{\partial}{\partial a}\sum_{i=1}^{n}(p_i - a - bt_i)^2 = -2\sum_{i=1}^{n}(p_i - a - bt_i) = 0 \tag{7}$$

$$\sum_{i=1}^{n}(p_i - a - bt_i)^2 = -2\sum_{i=1}^{n} t_i(p_i - a - bt_i) = 0 \tag{8}$$

Denote a and b be the solution of the above system, we can describe the relationship between t and p by the regression line $\hat{p} = a + bt$, which is called the fitted regression line by convention. Now it is easy to calculate

$$b = \frac{\sum_{i=1}^{n}(p_i - \bar{p})(t_i - \bar{t})}{\sum_{i=1}^{n}(t_i - \bar{t})^2} \tag{9}$$

$$a = \bar{p} - b\bar{t} \tag{10}$$

where $\bar{t} = \frac{1}{n}\sum_{i=1}^{n} t_i$, and $\bar{p} = \frac{1}{n}\sum_{i=1}^{n} p_i$.

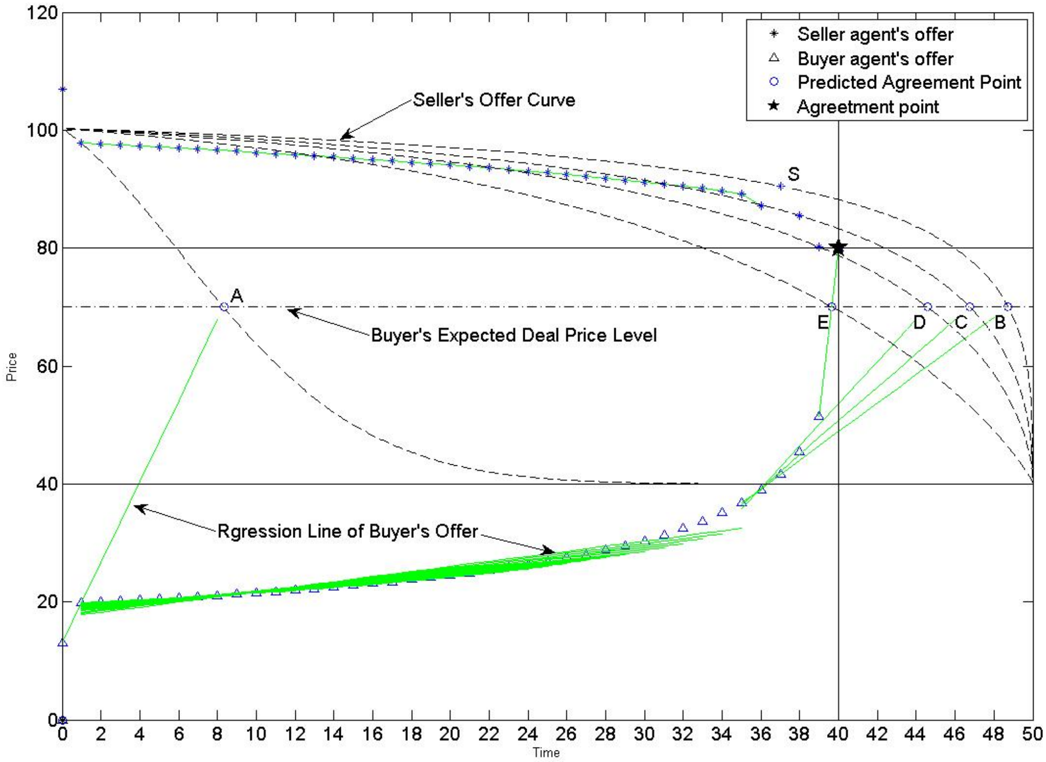

Figure 1: the agent using prediction strategy that embodies a linear regression concession model

Now, we have a regression line $p = a + bt$ indicating the buyer's future offer trend, but how can the agent seller use this regression line to make offer decision? This problem was not solved well by the previous studies[7-9, 11] [13]. As we all know, negotiators usually have a deal price expectation that the negotiator expect to make agreement with the opponent [14, 15], then the agreement would probably be near the intersection between the deal price expectation and the offer trend prediction line. As shown in figure 1, the expected price level is indicated by the doted line $\tilde{p}$, and the green lines are the regression line of the buyer's offers. Since this is a segmented linear regression model, the regression lines distribute in different sections of the buyer's offers. The segmented criteria will be introduced in latter section. Some of the regression lines have intersection points (indicated by A, B, C, D, E in the sequence of appearence) with the expected deal price level. Each point is indicated as a tuple $(\tilde{t}_i, \tilde{p})$, where $i = 1,2,3,4$. The abscissa of each point is the expected agreement time $\tilde{t}$ as long as the buyer comply with the current offer trend. So, we have

$$\tilde{t} = \frac{\tilde{p} - a}{b} \tag{11}$$

There are two situations for the expected agreement time $\tilde{t}$, legal and illegal. For the illegal situation, which means the expected agreement time is less that the current time ($\tilde{t} \leq t$), or is larger than the seller's deadline ($\tilde{t} \geq \overline{t_s}$), the seller agent will imitate the slope of the buyer's regression line, and can easily calculate the next offer at time t as

$$p_{s\to b}^{t} = p_{s\to b}^{t-1} - b \tag{12}$$

For the legal situation, which means the expected agreement time is within the time limit, i.e., $t \leq \tilde{t} \leq \overline{t_s}$, since we already know the future possible agreement point, the seller's current strategy should be a time-dependent tactic curve that pass through the predicted agreement point, as the doted curve indicates in figure 1, but how to generate these curves? The time-dependent strategy model actually defines a family of monotonic functions, which can be depicted as a bunch of offer curves in the negotiation space. The initial intention for using the time-dependent strategy is letting the agent to choose one offer curve at the beginning, and keep on it to the end of the negotiation. However, in our strategy model, the agent need to select one tactic curve that can lead the agent to the predicted agreement point, but not just fix on one tactic curve from the beginning to the end of the negotiation as the previous studies did.

The derivation process for generating the new tactic curve from the known possible agreement point is as follows. As designed in the time dependent tactic model, parameter β solely determines the curve's shape of the negotiation strategy. Since different negotiation strategies correspond to different values of β, the process is actually to select an appropriate value for β. Then we discuss how to get a value for β from a known point $(\tilde{t}, \tilde{p})$. According to [7], the offer price proposed by seller s to buyer b at time t is:

$$p_{s\to b}^{t} = \underline{p_s} + (1-\alpha_s(t))(\overline{p_s} - \underline{p_s}) \tag{13}$$

Since the agent's offer price $p_{s\to b}^{t}$ is known as $\tilde{p}$, then we can calculate $\alpha_s(t)$ as:

$$\alpha_s(\tilde{t}) = (\overline{p_s} - \tilde{p})/(\overline{p_s} - \underline{p_s}) \tag{14}$$

According to Equation (3), we can calculate seller agent's new value of β as:

$$\beta = \ln(\frac{ln(\alpha_s(\tilde{t}))}{lnK_s})/\ln(1-\frac{\min(\tilde{t},\overline{t_s})}{\overline{t_s}}) \tag{15}$$

where the $\alpha_s(t)$ has been calculated by Equiation (16). Then, we can obtain the agent seller's new negotiation strategy function as:

$$p_{s\to b}(t) = \underline{p_s} + (1-exp^{(1-\frac{\min(t,\overline{t_s})}{\overline{t_s}})^{\beta} lnK_s})(\overline{p_s} - \underline{p_s}) \tag{16}$$

where t is independent time variable and $p_{s\to b}$ is the dependent offer price variable.

COMPUTER TO COMPUTER NEGOTIATION EXPERIMENT

An negotiation environment is characterized by the number of agents in negotiation, the issues to be discussed, the deadline for reaching an agreement, and the expectations of the agents. Formally, the experimental environment can be uniquely defined by: $[\beta^b, \beta^s, t_{max}^b, t_{max}^s, k^b, k^s, min_{price}^b, max_{price}^b, min_{price}^s, max_{price}^s]$, i.e., time available to make an agreement (t_{max}^b, t_{max}^s), the initial offer (k^b, k^s), and price the intervals of the buyer and seller. Since it is impossible to discuss infinitely possible environments, we consider a representative in which we can assess an agent's negotiation performance to test our prediction strategy. To this end, the experiments are bilateral negotiations between a buyer and a seller over the single issue of price. Thus, we have $[k^b, k^s, min_{price}^b, max_{price}^b, min_{price}^s, max_{price}^s]$=$[0.1, 0.1, 20, 80, 40, 107]$, in which we refer from [7] to set $k^b = k^s = 0.1$ for both agents. Then several groups of experiments will be conducted according to different ranges of β, t_{max}^b and t_{max}^s. More specifically, there are 3 different relationships between t_{max}^b and t_{max}^s, i.e., $t_{max}^b > t_{max}^s$, $t_{max}^b < t_{max}^s$ and $t_{max}^b = t_{max}^s$. In our computer-computer negotiation experiment, the seller agent acting as the online vendor employs our prediction strategy, while the buyer agent negotiates according to a pre-set time-dependent strategy. For analytical tractability, we follow the setting of [7] to set the buyer's β in the interval $0 < \beta < 50$, in which $0 < \beta < 1$ defines competitive tactics, and $1 < \beta < 50$ defines collaborative tactics. At the very beginning, the buyer agent chooses the value of β randomly to set its strategy curve, and then fixes its strategy at this value of β until the end of the negotiation. Meanwhile, the seller implements our prediction strategy to respond to the buyer's offers.

The experiment compares the performance of our prediction strategy and the selection strategy, which has been recently proposed by [16]. The selection strategy is a heuristic-based model derived from the classic time-dependent and behavior-dependent strategy. The selection strategy can dynamically select appropriate tactic among all the candidate time-dependent tactics, hence possesses good flexibility and robustness in treating with the dynamic and inconsistent negotiation behavior of the opponent. The reason why we choose selection strategy as the reference substance is that the selection strategy is innovatively proposed recently and has been proved to be superior to the classic time-dependent strategy.

The experiment is divided into two parts. In the first part, the seller agent employs the selection strategy, while the prediction strategy is used in the second part. The comparison is conducted between the two parts. In each part, the buyer employs time-dependent strategy, but the value of β is generated randomly in two intervals: $(0, 1)$ for competitive tactics, and $(1, 50)$ for collaborative tactics, by which almost all the buyer's possible offer tactics are included. In each interval, the deadline of the buyer and seller are divided into three cases: $t_{max}^b > t_{max}^s$, $t_{max}^b < t_{max}^s$ and $t_{max}^b = t_{max}^s$, in which the exact values of the maximum trading time are also randomly generated in the integer interval [10, 70]. Thus, we need to conduct 12 experiments. In each experiment, we run negotiation 200 times. Therefore there are 2400 computer-computer negotiation simulation will be implemented as Table 1 shows.

Table 1: The experiment design

Seller's Strategy	Selection						Prediction					
Buyer's Strategy	Boulware (*0<β<1*)			Conceder (*1<β≤50)*			Boulware (*0<β<1*)			Conceder (*1<β≤50)*		
Time Relation	$\bar{t_s} > \bar{t_b}$	$\bar{t_s} < \bar{t_b}$	$\bar{t_s} = \bar{t_b}$	$\bar{t_s} > \bar{t_b}$	$\bar{t_s} < \bar{t_b}$	$\bar{t_s} = \bar{t_b}$	$\bar{t_s} > \bar{t_b}$	$\bar{t_s} < \bar{t_b}$	$\bar{t_s} = \bar{t_b}$	$\bar{t_s} > \bar{t_b}$	$\bar{t_s} < \bar{t_b}$	$\bar{t_s} = \bar{t_b}$
Number of Times	*200*	*200*	*200*	*200*	*200*	*200*	*200*	*200*	*200*	*200*	*200*	*200*

The experimental data shows that, as compared to the selection strategy, the adoption of prediction strategy can truly improve the settlement ratio of the negotiation (61.5% vs. 94%) when buyer's strategy is competitive and the seller's deadline is later than the buyer's, but when the seller's deadline is earlier than the buyer's, very low settlement ratio occurs (10.5% and 2.5%). As consistent with the previous study Cao (2015), a short deadline setting cannot be accepted for the agent who adopts the intelligent strategy like selection and prediction. Finally, when the buyer employs collabrative strategy, there is no significant difference on settlement ratio between selection strategy and prediction strategy.

In order to investigate the effects of the two strategy variables (selection and prediction) on negotiation outcome measures, i.e., finish time (FT), buyer utility (BU), seller utility (SU), utility product (UP) and utility difference (UD), a one-way ANOVA is conducted with the result shows the difference degree over all the five measurement indexes (BU, SU, UD, UP and FT), comparing between the selection strategy and prediction strategy that the seller employs. The result shows, when the buyer employs competitive strategy, the prediction strategy can lead better individual utility for both sides (insignificant when the seller's deadline is later than buyer's) but worse joint outcome (i.e., utility difference and utility product), while no significant effect on the end time of negotiation. When the buyer employs collaborative strategy, the prediction strategy performs significantly worse in individual utility but better in joint outcome and end time of negotiation than the selection strategy. The implication is meaningful for the actual system application. When the negotiation situation is competitive, the prediction strategy can protect the individual benifit though difficult to satisfy the both sides, while when the negotiation situation is collaborative, the prediction strategy can guarantee the both sides to obtain a win-win result without sacrificing more on one side's profit, meanwhile can help the parties to reach agreement quickly.

CONCLUSIONS AND FUTURE WORK

We extend the current technique in automated negotiating agent and propose a linear regression concession model, which can predict the opponents' futuer offer trend and then dynamically adjust its negotiation strategy in response to the opponent's offer. We developed a prototype of an automated negotiating agent and conducted computer-computer negotiation experiments to validate the performance of the proposed system. The preliminary results are encouraging, when the negotiating software agent employs the linear regression concession model, it can achieve higher settlement ratio, seller utility, and joint outcome than other state strategy. The results demonstrate the potential of our negotiating agent techniques in enhancing the efficiency and effectiveness of the merchants' online transactions and increasing turnover rate as well as decreasing transaction cost.

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