

Bargaining strategy formulation with CRM for an e-commerce agent

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Abstract

The growth of electronic commerce has created the need of automated bargaining agents for improving the efficiency of online transactions. From the perspective of customer relationship marketing (CRM), establishing and maintaining the best possible relationship with valuable customers is a good way to survive in the competitive global market. In order to retain valuable customers, high share customers ought to be treated differently from the low share customers in the bargaining process. In our research, we formulate strategies for a bargaining agent based on the CRM principle. Bargaining tactics are expressed as fuzzy rules that mimic a human bargainer's knowledge and judgment in making decisions. Actions of the bargaining agent are determined by using approximate reasoning from the set of fuzzy rules. Our bargaining agent and three other bargaining agents found in the literature are employed in an experimental online store. Experimental results indicate that our bargaining agent is more efficient and creates greater customer satisfaction and customer loyalty than do the bargaining agents from the literature.

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1. Introduction

The fast growing Internet and World Wide Web have provided a new channel for marketing and selling. As estimated by Nordan [1], retail revenue online contributed to half a percent of total retail sales worldwide. However, the underlying problem seems to be that many retailers have been unable to convert these revenues into profits [2]. For this reason, retailer managers are now facing the problem of how to ensure online revenues generates higher profits for each transaction.

The low transaction profitability of online shops has arisen from the following combination: reduced barriers to product information, easier access to a great number of potential suppliers, and increased threat of substitutes [2]. Furthermore, the Internet has reduced the differentia-

tion among products and services and hence has switched the focus of customers to price discounting [3]. Consequently, buyers generally surf through many shops and compare their list prices of the target product to look for the best offer on the Internet. Therefore, unless visitors of the online shop can be converted into buyers and be kept by creating value for them, online transactions will not be profitable [2].

From the above discussions we find that there are two related factors to enhance the profitability of online stores: providing dynamic pricing to keep customers staying at the store, and appropriate bargaining strategies to increase the chance of closing a deal. A dynamic pricing mechanism can encourage the customer's staying at the shop to negotiate an acceptable price instead of searching for a lower price somewhere else. By a well-designed bargaining strategy, it is expected to increase the chance of converting a visitor to a buyer and hence create profits for the store. The present study aims to establish the dynamic pricing mechanism in an online shop by a price bargaining function and

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applies the concept of customer relationship marketing (CRM) in the negotiation process to increase visitors' purchasing inclination.

In real life, a buyer and a seller usually bargain over the price of a product to maximize their own interests. People bargaining on the Internet may face a lot of barriers, such as anxiety from competition, communication difficulties over the Internet, and lack of bargaining experience [4]. In order to remove these bargaining impediments, there is a need to implement an automated bargaining mechanism in online stores.

In the literature, there are two famous e-marketplace platforms that provided automated bargaining by allowing users to create autonomous agents to buy and sell goods on their behalf: Kasbah [5] and AuctionBot [6]. At Kasbah, users give agents instructions on how to change the desired price over a time frame. Strategies of these agents are rather simplistic and inflexible, because the functions used to specify the changing rate of desired price are fixed and the opponent's actions are not considered during negotiations. AuctionBot is an online auction server that allows software agents to place bids, create auctions, or request auction information. In addition to the above approaches, Liang and Doong [7] proposed three bargaining agents with different bargaining strategies for an experimental online store. The bargaining strategies of these agents are similar to those used at Kasbah (i.e. they use fixed concession functions without considering the opponent's actions). The common problem of the above approaches is that they did not appropriately take the customer's responses into account in the bargaining process.

The main theme of this paper is to develop an autonomous agent that represents the owner of an online store to bargain with customers. We consider that customers' behaviors are different, and the store should identify a customer's characteristics and apply different tactics to make profits on customers. For blow-in customers, the store will attempt to obtain as much profit as possible from them; on the other hand, for those customers who are very likely to buy and may come back again in the future, the store is willing to sacrifice part of its profit to retain these customers. The above concept complies with the principle of customer relationship marketing, which suggests differentiating customers and applying different marketing strategies to them. Customer relationship marketing enables companies to provide real-time service to customers by developing a relationship with each customer through the effective use of individual account information [8].

In this study, the concept of CRM is implemented on our online store and the intelligent agents will assist customers in finding their favorite products and allowing them to bargain over the prices of products with different concession degree based on the differentiation of customers on their potentiality. Customer potential value is generally defined in the literature, e.g. [9–11], as the expected profits from a customer if this customer purchases additional products or services from the store. The present study mod-

ifies the definition of customer potentiality as the loyalty and purchasing probability of a customer, which is considered to be more related to customer's purchasing decision (i.e. buy or not buy). In our approach, the computation of customer potentiality will involve the total monetary value the customer has spent at the store and the statistics of ad views and ad clicks by the customer. Our strategy is first to differentiate customers by computing such an index, and then to apply different bargaining tactics to customers with different index values. Those customers with a greater index are considered as prospective buyers, and they will be granted a wider concession margin in the bargaining process in order to reinforce their purchasing inclination. Our strategy is achieved through a set of bargaining tactics in the format of fuzzy rules. These fuzzy rules enable the bargaining agent to mimic a human bargainer in making decisions.

Recent studies have argued that the relationship between customer loyalty and profitability is weak. For example, Reinartz and Kumar [12] discovered little or no evidence suggesting that customers who purchase steadily from a company over time were necessarily cheaper to serve, less price sensitive, or particularly effective at bringing in new business. Nevertheless, the present study still considers loyal customers are important to the store because our purpose is to convert visitors to buyers as discussed earlier. Moreover, the cost to serve a loyal customer is neither more significant nor different from serving a disloyal customer owing to the automated service process by agent technology.

In the next section, we will present the architecture of our online store. Our approach of customer identification and differentiation as well as the formulation of bargaining tactics are discussed in Section 3. Experiments are described in Section 4 to illustrate the performance of our approach by comparing it with the approach of Liang and Doong [7].

2. CRM and the architecture of the online store

Using the concept of customer relationship marketing, we focus on recruiting and retaining customers by incorporating the four steps of one-to-one marketing [13] in our online store. The architecture of our online store is depicted in Fig. 1.

Customers log on to the store through WWW browsers. In our online store, three agents – the ID (Identification) agent, the bargaining agent, and the TM (Tactic Management) agent – work together to carry out one-to-one marketing. When a customer logs on to the store, the ID agent computes the customer's potentiality index according to the customer's profile data retrieved from the profile database. For the case of a new customer, the lowest index value found in the profile database is assigned to this customer. The customer's behavior during shopping is also written to the profile database to update the customer's record. When a customer visits the store, the ID agent

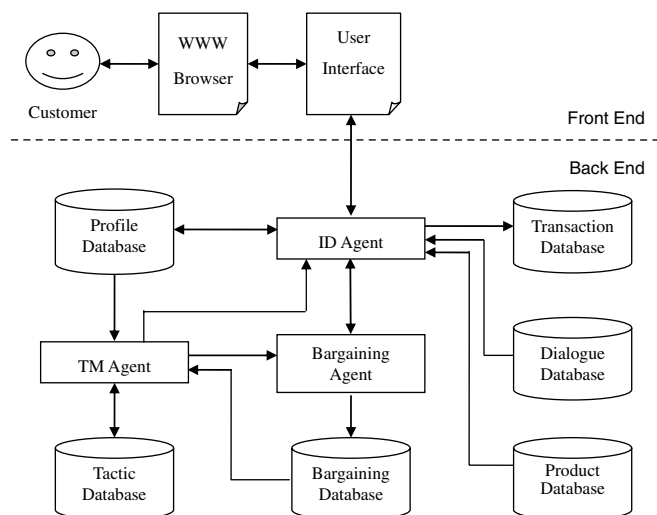


Fig. 1. Architecture of the proposed online shopping mall.

mimics human conversation with the customer by employing the dialogue database and provides the customer with product information from the product database at appropriate times. The computation of the customer's potentiality index is based on an evaluation function. Parameters of this evaluation function are provided by the TM agent, which regularly adjusts these parameters according to the pattern of customer characteristics found in the profile database. Such parameters are saved in the tactic database.

The information of customer potentiality together with the accumulated concessions made so far is passed to the bargaining agent. The bargaining agent will incorporate this information in determining the action to the customer's request of price bargaining by employing a set of fuzzy rules with adaptive parameters. These parameters are also stored in the tactic database and updated by the TM agent according to the bargaining patterns found in the bargaining database. Bargaining rules and parameters of evaluation functions are stored in the tactic database. When a deal is closed, it is written to the transaction database for future analysis.

In summary, our experimental store aims to enhance the efficiency of online shopping from three perspectives: (1) providing a price bargaining function to encourage customers staying at the store, (2) customizing the price bargaining process based on CRM concept, and (3) utilizing fuzzy logic to mimic the decision making of a human bargainer.

3. Customer potentiality evaluation and bargaining tactics

The bargaining agent's strategy is to retain customers with greater potentiality by conceding with wider margins, while gaining as much profit as possible immediately from blow-in customers. By this strategy, the store can maintain its overall expected profit at a certain level. In other words, though the store gains less profit from high potential customers, the probability of closing deals with them is

greater; on the other hand, the probability of closing deals with low potential customers is less, but the store can obtain greater profits from them. The strategy is achieved through a set of tactics, which are expressed as fuzzy rules to specify appropriate actions for different conditions. Activation conditions of these rules include the customer's potentiality and the concessions that have been granted to the customer so far.

A customer's potentiality is calculated from his/her characteristics referred to as the profile which is described by a set of attributes. The adoption of these attributes, as seen in Table 1, is modified from those used by Yuan and Chang [14]. The first three attributes in Table 1 are the behavior of a customer for the current visit, and they are the factors related to the customer's purchasing probability. In particular, we consider that when a customer views more advertising banners than others, he/she is more likely to buy something. Such measure is referred to as ad clicks [15] and is commonly used as a basis for charging advertising fees by portals. Attributes 4–7 are cumulative records of a customer, and they are used to evaluate customer loyalty. That is, if a customer buys more, visits the store more often, or stays longer with the store that customer is considered to be more loyal to the store. These attributes relate to the RFM (recency, frequency, and monetary value) variables widely used in CRM practice, e.g. [16–18]. Shaw et al. [17] used customer profiling for knowledge-based marketing, based on which the marketer decided on the right strategies and tactics to meet the needs of customers. Shaw et al. adopted customer transaction characteristics, including frequency of purchases and size of purchases, to construct customer profiles. The frequency of purchases means how often the customer buys the product or visits the shop, which is the sixth attribute in our model, while the size of purchases means how much the customer has spend, which is equivalently measured by the forth and the fifth attributes in Table 1.

A correlation analysis is also conducted to justify the relation between the aforementioned attributes and the purchasing decision (i.e. buy or no buy). Forty-eight testing buyers are invited to do purchasing at the shop before the formal experiments. The correlation between these attributes and the testing buyers' latest purchasing decision are computed. The resultant correlation coefficients of the attributes in Table 1 are 0.530, 0.496, 0.497, 0.555, 0.555,

Table 1
Attributes of customer profile

Attribute	Description
A_1	Total product categories clicked for the current visit
A_2	Total product items clicked for the current visit
A_3	Total product items sent to shopping cart for the current visit
A_4	Total number of products purchased
A_5	Total monetary amount of products purchased
A_6	Total number of visits
A_7	Time with the store (the time between the customer's first visit and now)

0.497, and 0.460, respectively. This result suggests that the use of these attributes is reasonable in predicting the customer's purchasing probability.

3.1. Customer potentiality function

The present study assumes that the attributes in Table 1 are related to the potentiality of a customer. A greater potentiality indicates the customer is more loyal and has a greater purchasing probability. The customer potentiality is estimated by the following function, which is defined as an aggregation of the measures on individual attributes:

$$V = \sum_{i=1}^7 w_i \cdot f(A_i), \quad (1)$$

where $0 \leq V \leq 1$ is the index of customer potentiality, A_i is the i th attribute of the customer profile as presented in Table 1, $f(\cdot)$ is a function for determining the contribution of an attribute toward the potentiality of a customer, and w_i is the weight of this attribute in this evaluation and $\sum_{i=1}^7 w_i = 1$. A customer with a higher V is considered more likely to purchase at the online store. The function $f(\cdot)$ is used to rate a customer's previous contribution or purchasing probability to the store by comparing it with the average value from the statistics of historical data that are stored in the profile database. The cumulative density function of a normal distribution function is chosen for $f(\cdot)$; that is

$$f(A_i) = \int_{-\infty}^{A_i} \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left(-\frac{(x - \mu_i)^2}{2\sigma_i^2}\right) dx, \quad (2)$$

where μ_i is the mean of the i th attribute, and σ_i is its deviation. The function $f(A_i)$ is within the interval $[0, 1]$ and strictly increases. An example of the function $f(A_i)$ with a mean of 3.5 and a deviation of 1.9 is depicted in Fig. 2. The mean μ_i and deviation σ_i in Eq. (2) are regularly updated by the TM agent to keep up with the changes in the customer profile database. It is assumed in this study that the number of available customer records in the data-

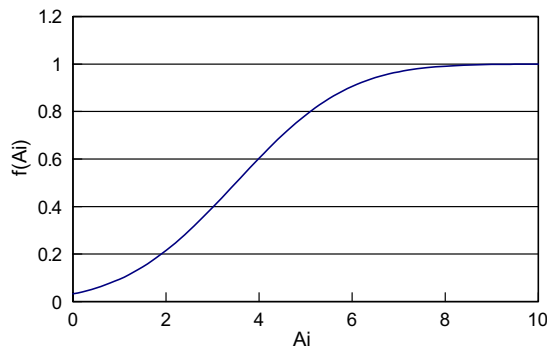


Fig. 2. Graphical illustration of $f(A_i)$ with mean = 3.5 and deviation = 1.9.

base is at least greater than 30 to support a reasonable computation of μ_i and σ_i . Thus, the purchasing data of the 48 testing buyers mentioned earlier are used to calculate μ_i and σ_i before the formal experiments. It is also noted that there are other choices of distribution function for the function $f(A_i)$ as long as they can appropriately describe the distribution of the data.

3.2. Bargaining tactics

The principle of “not all customers are created equally” has been established by Hallberg [19]. Thus, a customer with greater potentiality will be granted a wider concession margin in price bargaining in order to reinforce this customer's purchasing inclination and attract him/her to come back to the store. Moreover, bargaining is a dynamic process and the concession already made to the customer would affect the agent's subsequent actions. When the concession margin is already large, the agent would become conservative. The formulation of our bargaining tactics is based on these thoughts.

The action of the bargaining agent is to determine how much to concede. Let p_{t-1} be the previous offer and Δp_t be the concession will be determined at time t , then the new price (p_t) offered to the customer is

$$p_t = p_{t-1} - \Delta p_t, \quad (3)$$

and p_t is set to the seller's reserved price P_R , if $p_t \leq P_R$. In addition,

$$\Delta p_t = M \cdot D_t, \quad (4)$$

where M is the maximum margin of concession (the difference between the list price and the seller's reservation price of a product), and $0 \leq D_t \leq 1$ is the concession degree at time t . The concession degree D_t is determined through a set of tactics that will be presented later in this section. The concession Δp_t is always greater than or equal to 0. When Δp_t is 0, it means that the agent refuses to concede. The following example illustrates the calculation of p_t .

Example 1. Let the list price and the seller's reservation price of a product be \$1000 and \$800, respectively (i.e., $M = \$200$). In the beginning ($t = 0$), the customer rejects the list price and asks for a bargain. The seller decides to make a 10% concession ($D_1 = 10\%$); therefore,

$$\Delta p_1 = 200 \times 10\% = 20, \quad \text{and}$$

$$p_1 = p_0 - 20 = 980.$$

The customer is still not satisfied with p_1 and asks for a lower price, so the seller gives another 5% concession ($D_2 = 5\%$). The new price becomes

$$p_2 = p_1 - \Delta p_2 = 980 - 200 \times 5\% = 970.$$

The bargaining tactic that determines D_t under the conditions of a customer's potentiality and the total granted concession is expressed as a fuzzy rule in the following format.

If V is L_1 and C_t is L_2 , then D_t is T ,

where L_1 and L_2 are linguistic terms, such as *high*, *low*, *large* or *small*, and C_t is the total concession made so far. The statement after “if” and before “then” is called antecedent, and the statement after “then” is called consequence. In our tactics, the consequence T is either a random number drawn from a pre-defined range or an auxiliary offer. The total concession made so far (C_t) is presented as a ratio of the total concession over the maximum concession margin; that is,

$$C_t = \frac{P_L - p_t}{M}, \quad (5)$$

where P_L denotes the list price of a product. Since $p_t \geq P_L$, C_t is in the range of $[0, 1]$.

The linguistic terms for the customer potentiality include *very low*, *low*, *moderate*, *high*, and *very high*; the linguistic terms for total concessions are *very small*, *small*, *medium*, *large*, and *very large*. These linguistic terms are qualitative descriptions and are treated as fuzzy sets for computational purposes. Fuzzy set theory [20] directly addresses the limitation of the sharp boundaries found in classical set theory and hence fuzzy sets are well suited to quantify linguistic terms. A fuzzy set is defined by a membership function which maps objects in a domain of concern to their membership value in the set. The degree of membership in a set is expressed as a smooth and gradual transition from 0 to 1. Such a transition yields fuzzy set flexibility in modeling linguistic expressions. Membership functions defined for the above linguistic terms are depicted in Figs. 3 and 4.

The membership functions in Figs. 3 and 4 are parameterized by left points, middle points, and right points, as indicated in Fig. 3 for the linguistic term “moderate”.

The parameters of a membership function can be subjectively defined by the user or obtained by clustering techniques. Based on the profile database and the bargaining database in our online store, we define the parameters of linguistic terms as shown in Tables 2 and 3. The TF agent

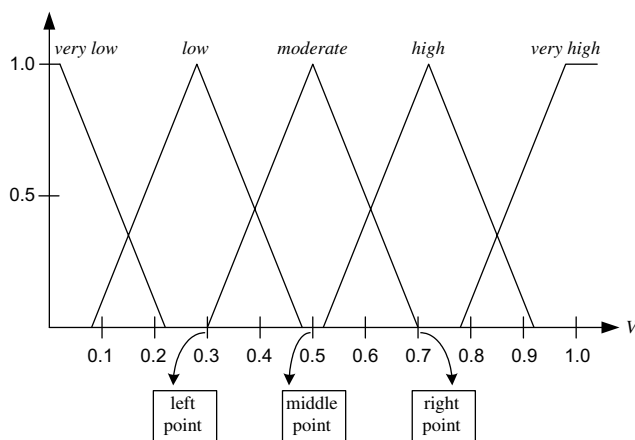


Fig. 3. Membership functions for linguistic terms of V .

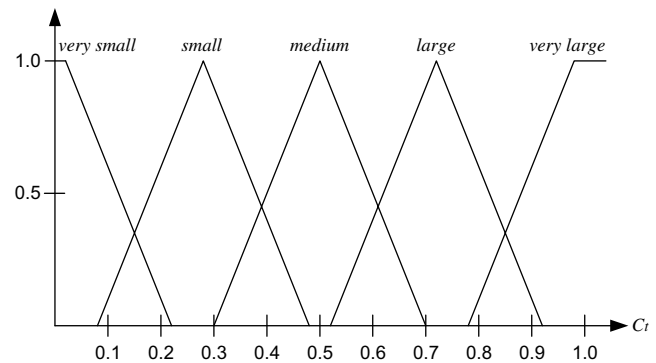


Fig. 4. Membership functions for linguistic terms of C_t .

Table 2

Parameters of linguistic terms of V

Linguistic term	Left point	Middle point	Right point
Very low	–	0.02	0.22
Low	0.08	0.28	0.48
Moderate	0.30	0.50	0.70
High	0.52	0.72	0.92
Very high	0.78	0.98	–

Table 3

Parameters of linguistic terms of C_t

Linguistic term	Left point	Middle point	Right point
Very small	–	0.02	0.22
Small	0.08	0.28	0.48
Medium	0.30	0.50	0.70
Large	0.52	0.72	0.92
Very large	0.78	0.98	–

regularly updates these parameters according to the changes in the bargaining database.

All the bargaining tactics are presented in Table 4. These tactics vary the concession degree (D_t) according to a customer's potentiality and how many concessions have already been made to this customer. In the bargaining process, the agent usually makes a higher discount on the initial offer, and then reduces the concession tolerance gradually. This strategy is similar to the utility-decreasing strategy of Liang and Doong [7], and they have shown by experiments that such a strategy is more effective for attracting customers. Our first tactic is at the upper-left corner in Table 4, and it is read as

Rule 1: If V is *very low* and C_t is *very small*, then D_t is $r\{0, r(1\%, 5\%)\}$.

In the consequence of the above rule, the notation $r\{a, b\}$ means randomly choosing a or b with equal chance, and $r(a, b)$ means randomly picking a value from the real interval $[a, b]$. The use of the real interval is to mimic human behaviors in decision-making where people usually have a range of options in mind instead of a fixed number. Rule 1 states that under the conditions as stated in the antecedent the bargaining agent would

Table 4
Bargaining tactics

C_t	V				
	Very low	Low	Moderate	High	Very high
T					
Very small	1: $r\{0, r(1\%, 5\%)\}$	6: $r\{0, r(1\%, 10\%)\}$	11: $r(1\%, 15\%)$	16: $r(5\%, 20\%)$	21: $r(10\%, 20\%)$
Small	2: $r\{0, r(1\%, 3\%)\}$	7: $r\{0, r(1\%, 6\%)\}$	12: $r\{0, r(1\%, 15\%)\}$	17: $r(5\%, 15\%)$	22: $r(10\%, 15\%)$
Medium	3: 0	8: $r\{0, r(1\%, 3\%)\}$	13: $r\{0, r(1\%, 10\%)\}$	18: $r(5\%, 10\%)$	23: 10%
Large	4: 0	9: 0	14: $r\{0, r(1\%, 5\%)\}$	19: 5%	24: $r(5\%, 10\%)$
Very large	5: 0	10: 0	15: 0	20: 0 & a.f.	25: 0 & a.f.

a.f. : auxiliary offer.

insist on the current price or concede to a degree between 1% and 5%. Similarly, the other rules are read as

Rule 2: If V is very low and C_t is small, then D_t is $r\{0, r(1\%, 3\%)\}$.

Rule 3: If V is very low and C_t is medium, then D_t is 0.
⋮

Rule 25: If V is very high and C_t is very large, then D_t is 0 and the bargaining agent proposes an auxiliary offer.

The auxiliary offers proposed in Rules 20 and 25 are to avoid the failure of a bargaining that may result in losing a potential customer; such offers could be a gift from the store or a coupon to be used at a later date for further shopping. The auxiliary offer also extends the originally single issue (i.e., price) bargaining to a multi-issue negotiation, and this transforms the fully competitive price bargaining to a cooperative atmosphere.

3.3. Inference mechanism of bargaining agent

The bargaining agent determines its actions to the customer's request price by using a fuzzy inference system that contains the rules in Table 4. In this fuzzy inference system, rules are activated with different degrees of strength depended on the satisfaction levels of each rule. The activation degree is a real number from 0 to 1, in which a degree of 1 means full activation, 0 means inactive, and a degree between 0 and 1 indicates a partial activation. The determination of the activation degree of a rule is discussed as follows.

Recall the rule format “if V is L_1 and C_t is L_2 , then D_t is T ”. The activation degree of this rule is determined by the conformance of V to L_1 and the conformance of C_t to L_2 . Let $\mu_{L_1}(\cdot)$ and $\mu_{L_2}(\cdot)$ be the membership functions defined for the linguistic terms L_1 and L_2 , respectively. The simultaneous conformance of V to L_1 and C_t to L_2 are defined as $\{\mu_{L_1}(V)$ and $\mu_{L_2}(C_t)\}$. This simultaneous conformance is used to calculate the activation degree of the rule, i.e. the activation degree s is defined as

$$s = \mu_{L_1}(V) \otimes \mu_{L_2}(C_t), \quad (6)$$

where “ \otimes ” is an operator of “fuzzy and”, or referred to as a t -norm operator [21]. In this study, the operation of a

t -norm is defined as a minimum operator. For instance, the activation degree of the first rule in Table 4 is

$$s = \min\{\mu_{\text{very low}}(V), \mu_{\text{very small}}(C_t)\}.$$

The following example illustrates the calculation of activation degrees of rules.

Example 2. Let us recall Example 1. Suppose the customer's potentiality $V=0.9$ and the latest price (p_{t-1}) offered to the customer is \$830. The customer is still not satisfied with this price and asks for a lower one. Suppose the total concession made so far is $C_t=0.85$. Based on the current values of V and C_t , and the membership functions in Figs. 3 and 4, the bargaining agent finds

$$\mu_{\text{very low}}(V) = \mu_{\text{low}}(V) = \mu_{\text{moderate}}(V) = 0,$$

$$\mu_{\text{high}}(V) = 0.1, \mu_{\text{very high}}(V) = 0.6,$$

$$\mu_{\text{very small}}(C_t) = \mu_{\text{small}}(C_t) = \mu_{\text{medium}}(C_t) = 0,$$

$$\mu_{\text{large}}(C_t) = \mu_{\text{very large}}(C_t) = 0.35.$$

By Eq. (6), the bargaining agent computes the activation degrees of all rules. Let s_j denotes the activation degree of the j th rule. For instance, the activation degree of the 19th rule is

$$s_{19} = \min\{\mu_{\text{high}}(V), \mu_{\text{large}}(C_t)\} = \min\{0.1, 0.35\} = 0.1.$$

Similarly, $s_{20} = 0.1$, $s_{24} = 0.35$, $s_{25} = 0.35$, and the activation strengths of the remaining rules are 0.

The overall conclusion of a fuzzy inference system is an aggregation of the consequences of individual rules. Such an aggregation is called approximation reasoning. In this study, the approximate reasoning technique of Takagi and Sugeno [22] is used. Let s_j and T_j be the activation degree and the consequence of the j th rule, respectively. The approximation reasoning of Takagi and Sugeno obtains a conclusion (Φ) from n rules by

$$\Phi = \frac{\sum_{j=1}^n s_j T_j}{\sum_{j=1}^n s_j}. \quad (7)$$

It must be noted that Eq. (7) is only applicable to rules with numerical consequences. However, the consequences of the rules in Table 4 are not always numerical values; in particular, the consequences of Rules 20 and 25 contain auxiliary

offers which are not numerical. Therefore, the result of (7) is tailored to our fuzzy inference system as

$$D_t = \begin{cases} \frac{\sum_{j=1, j \neq 20, 25}^{25} s_j T_j}{\sum_{j=1, j \neq 20, 25}^{25} s_j}, & \text{if } s_{20} + s_{25} \leq 0.5, \\ 0 \text{ and an auxiliary offer,} & \text{otherwise.} \end{cases} \quad (8)$$

Eq. (8) means that when the summed activation of rules 20 and 25 is minor, then Eq. (7) is used to compute the overall conclusion of the fuzzy inference system; otherwise, the consequence of rules 20 or 25 is directly used as the overall conclusion.

The inference procedure discussed above is demonstrated by the following example.

Example 3. Let us continue onto Example 2. With the activation degrees obtained in Example 2 and by Eq. (8), $D_t = (0.1 \times T_{19} + 0.35 \times T_{24}) / (0.1 + 0.35)$. From Table 4 we find $T_{19} = 5\%$ and $T_{24} = r$ (5%, 10%). Suppose the realization of T_{24} is 9%, then $D_t = 8\%$ and hence the new price $p_t = 814$. If the customer is still not satisfied, the procedure in Example 2 is repeated to find $C_t = 0.93$, and $s_{20} = 0.1$ and $s_{25} = 0.75$. Again, by Eq. (8), the overall conclusion is determined as $D_t = 0$ and an auxiliary offer.

4. Experiments and findings

To compare the performances of our CRM-based bargaining agent with other reported bargaining strategies, many experiments were carried out. The bargaining agent proposed in the previous section as well as three other agents from Liang and Doong [7] were employed in our experimental online store. The three agents of Liang and Doong are each based on a different strategy and are described below.

- (1) Utility-decreasing strategy (UDC): The agent makes a higher discount on the initial offer, followed by smaller and smaller concessions.
- (2) Utility-increasing strategy (UIC): The agent makes a smaller discount on the initial offer, followed by larger and larger concessions.
- (3) Utility-neutral strategy (UNC): The agent makes an intermediate discount on the initial offer, followed by fixed concessions.

4.1. Implementation and experiments

Our experimental online store is built by using PHP programming language and MySQL database on a Linux system. When a customer logs onto the shopping mall, the ID agent will check the customer's profile from the profile database and also record the customer's behavior to update the profile database.

The purpose of our experiments is to test whether the effects of different bargaining strategies vary. The effect of bargaining strategies is evaluated in terms of economic outcomes and perceptual outcomes. Economic outcomes

include the number and length of time of the bargaining rounds, and the bargaining gain of the customer. The bargaining gain of a customer is defined as

$$\text{Bargaining gain} = \frac{P_L - P_a}{P_L} \times 100\%,$$

where P_L is the list price and P_a is the final agreed price.

Perceptual outcomes of bargaining include customer satisfaction and customer loyalty. To obtain the measurement of customer satisfaction and customer loyalty, customers were asked to fill out a questionnaire when they finished shopping. The questionnaire includes four items for measuring customer satisfaction, and three items for measuring customer loyalty (see Table 5). Each item is graded with a five-point Likert scale: 1 = strongly disagree, 2 = disagree, 3 = uncertain, 4 = agree, and 5 = strongly agree.

A total of 213 subjects participated in the experiments. Participants were students (average age 28) taking extended education courses at the undergraduate level, and they all had online shopping experiences. Participants were randomly divided into four groups. Each group was assigned to a different bargaining agent, as shown in Table 6, in which our bargaining agent is named CRM. Due to the stochastic nature of our bargaining tactics, the fourth group (i.e. the group with CRM) contained more subjects than the others in order to obtain reliable outcomes. The concession margins of the three agents from Liang and Doong [7] during bargaining are set as in Table 7.

Before the subjects formally participated in the experiments, they were asked to practice at the online store. This practice is especially important for the fourth group because the activities of participants will be written into the customer profile database and further used in the formal experiment for the bargaining agent to determine its actions.

Table 5
Questionnaire for measuring perceptual outcomes

Customer satisfaction	
1	This shopping mall provides personalized service
2	This shopping mall provides convenient shopping
3	This shopping mall helps me make better shopping decisions
4	I am satisfied with the bargaining process
Customer loyalty	
5	I believe the deal I got at this shopping mall is the best offer I could find
6	This shopping mall can stimulate my shopping desire
7	I would like to come back to this shopping mall for future shopping

Table 6
Experimental groups and corresponding bargaining agents

Group	Number of subjects	Bargaining agent
1	31	UDC
2	31	UIC
3	31	UNC
4	120	CRM ^a

^a CRM denotes the proposed bargaining agent of this study.

Table 7
Concession margins of the UDC, UIC, and UNC agents

Agent	Concession margin (in percentage) at each concession
UDC	20%, 18%, 16%, 14%, 10%, 7%, 6%, 4%, 3%, 2%
UIC	2%, 3%, 4%, 6%, 7%, 10%, 14%, 16%, 18%, 20%
UNC	10%, 10%, 10%, 10%, 10%, 10%, 10%, 10%, 10%, 10%

The concerns with the performance of different bargaining strategies are formulated as the following hypotheses.

Hypothesis 1. The CRM-based bargaining strategy reaches an agreed price faster than the UDC, UIC, and UNC strategies.

Hypothesis 2. The CRM-based bargaining strategy yields greater customer satisfaction than the UDC, UIC, and UNC strategies.

Hypothesis 3. The CRM-based bargaining strategy yields greater customer loyalty than the UDC, UIC, and UNC strategies.

4.2. Analysis of the experimental results

From the log file we obtained statistics of the number of bargaining rounds, length of bargaining time, and customer's bargaining gain for bargaining agents with different strategies, as shown in Table 8.

From Table 8 we found that the number of bargaining rounds and the length of bargaining time were significantly different between different agents at the 5% level. Further analyses by *t*-tests revealed that our bargaining agent

reached agreements faster than the UDC agent, the UIC agent, and the UNC agent in terms of the number of bargaining rounds ($p = 0.000 < 0.05$) and length of bargaining time ($p = 0.000 < 0.05$). These results supported Hypothesis 1.

Except for the UIC agent, the other three agents were not significantly different with respect to customer's bargaining gains ($F = 0.593 < F_{0.05,2,179}$). This result implies that our bargaining agent performed no worse than the agents of Liang and Doong [7] in striving for the store's profits (the customer's gain is the store's loss). On the basis of about equal bargaining gains, we argue that our CRM-based bargaining agent can create greater customer satisfaction and customer loyalty. To support this argument, the questionnaire results are analyzed and described below.

These questionnaire results are considered to be reliable because their Cronbach coefficient α values are all greater than 0.75. According to the questionnaire results, average scores for the measurements of customer satisfaction and customer loyalty are given in Table 9.

From Table 9 we found that customer satisfaction and customer loyalty were significantly different between different agents. Further analyses by *t*-tests indicated that our bargaining agent outperformed the other three agents in both customer satisfaction and customer loyalty. The rank of customer satisfaction is CRM > UDC ($p = 0.000 < 0.05$) > UNC ($p = 0.000 < 0.05$) > UIC ($p = 0.000 < 0.05$), and the rank of customer loyalty is CRM > UDC ($p = 0.000 < 0.05$) = UNC ($p = 0.21 > 0.05$) > UIC ($p = 0.000 < 0.05$). These results supported Hypothesis 2 and Hypothesis 3.

Table 8
Economic outcomes of bargaining agents with different strategies

Outcome		Agent				Statistics
		UDC	UIC	UNC	CRM	
Number of bargaining rounds	Mean	31.4	25.4	28.7	8.2	$F = 86.8$
	Deviation	8.7	12.0	7.9	4.0	$p = 0.000^a$
Length of bargaining time (s)	Mean	112.6	105.5	108.4	57.1	$F = 28.5$
	Deviation	35.5	29.6	39.2	42.7	$p = 0.000^a$
Customer's bargaining gain	Mean	17.3%	9.7%	15.5%	16.2%	$F = 13.2$
	Deviation	2.2%	6.3%	10.6%	6.1%	$p = 0.000^a$

^a Significant at 0.05 level.

Table 9
Perceptual outcomes of bargaining agents with different strategies

Outcome		Agent				Statistics
		UDC	UIC	UNC	CRM	
Customer satisfaction	Mean	3.92	3.48	3.56	4.43	$F = 14.49$
	Deviation	0.11	0.01	0.11	0.09	$p = 0.000^a$
Customer loyalty	Mean	3.81	3.43	3.75	4.31	$F = 12.94$
	Deviation	0.30	0.30	0.28	0.12	$p = 0.000^a$

^a Significant at 0.05 level.

5. Conclusions

This study has proposed a dynamic pricing mechanism by agents with strategies based on CRM concepts to keep visitors staying at the store and to reinforce their purchasing inclination. Our approach identifies individual customer's potentiality and applies customized bargaining strategies to this customer according to his/her potentiality. Bargaining strategies are implemented through a set of tactics explicitly expressed by fuzzy rules that mimic a human bargainer's knowledge and judgment.

Our CRM-based bargaining agent and three other bargaining agents of Liang and Doong [7] were employed in an experimental online store. Test subjects consisting of 213 undergraduate students were invited to purchase goods at the store. Bargaining behaviors of these subjects were recorded and a questionnaire survey was conducted after the subjects finished their shopping. We found two major results in this study: (1) our bargaining agent reached the final agreed price faster than the other three agents, and (2) our bargaining agent created greater customer satisfaction and customer loyalty to the shopping mall. It must be noted that the research results presented in this study are subject to the use of student subjects who may have limited the findings' generalization. Though the present study has showed the bargaining agent's superiority in increasing customer satisfaction and loyalty, recent studies, e.g. Reinartz and Kumar [12], have argued that the relationship between customer loyalty and profitability is weak because customers who purchase steadily were not necessarily cheaper to serve. However, we still consider customer loyalty and satisfaction are important to the store because our purpose is to convert visitors to buyers and the cost to serve a loyal customer is neither more significant nor different from serving a disloyal customer owing to the automated service process by agent technology.

The measurement of customer potentiality is an important element in the proposed approach to determine the bargaining agent's actions. This study employs a function based on the statistics of customer weblog data to calculate an index for customer potentiality. Due to the limited information content of weblog data, such an index may not provide an accurate estimate of a customer's potentiality and hence limit the use of the proposed approach. It is therefore important to formulate a better procedure for determining the customer potentiality in future research. Moreover, the proposed approach did not take the customer's preferences into account in the bargaining process. Knowing the customer's preferences (e.g. reservation price) can enhance the efficiency of the bargaining process. Our future research will also attempt to introduce learning tech-

niques such as Bayesian learning in the bargaining process to predict the customer's preference.

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