Incorporating Autonomous Bargaining Capabilities into E-Commerce Systems

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ABSTRACT

Bundling is a technique e-commerce companies have adopted from traditional retail stores to increase the average order size. It has been observed that bargaining helps increase customer satisfaction while increasing the average order revenue for retailers. We propose a mathematical framework to incorporate bargaining capabilities with the product bundles provided by e-commerce websites. Our method creates a virtual agent that uses the modular Bidding-Opponent-Acceptance model for its bargaining strategy and the Thomas-Kilmann conflict mode instrument to model buyer behavior. We incorporate bargaining capabilities with bundles in an e-commerce system by using a negotiation agent that uses business logic for better strategy. It uses real-time data generated during a negotiation session, since the buyer behavior during a negotiation is crucial. No requirement exists for data from past negotiation sessions of the buyer, which removes bias as well as allowing for rapid changes to buyer behavior. The agent behavior can be altered by various hyperparameters. Our model provides utility metrics to measure buyer and agent satisfaction. Our results show that the agent successfully negotiates with humans from diverse backgrounds.

CCS CONCEPTS

• **Computing methodologies → Cognitive science**; *Probabilistic reasoning*; *Vagueness and fuzzy logic*; *Temporal reasoning*.

KEYWORDS

negotiation agent, bargaining, product bundling, e-commerce, Thomas-Kilmann conflict mode instrument, BOA model, human-agent model

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1 INTRODUCTION

E-commerce has seen huge success around the world in recent times. With its share in the retail industry ever increasing, it has shown promising potential for the future. Better internet facilities for people in the developing world has ensured that they experience the luxury of choosing from a wide variety of products from the comfort of their own home. E-commerce companies have used various techniques that have been highly successful in more traditional retail stores such as bundling products that are frequently bought together and providing an additional discount for buying bundles rather than individual products. Numerous studies [11, 16, 28] have pointed out the benefits of bundling products. It increases the average order revenue for retail shops while also providing a sense of satisfaction for buyers. Johnson and Bauer [17] have concluded that bundles can subconsciously affect buyer decisions making it easier for users to select the products for purchase.

While e-commerce websites have used the method of product bundling to increase their sales, they presently miss a crucial aspect of bundling as seen traditional retail sales—bargaining. Bargaining is a method used by buyers to lower the selling price of products. Traditionally bargaining has often been used and studied along with bundling [12, 22]. Buyers negotiate a lower price in return for buying a bundle of products from the seller. In addition to the benefits that bundling provides for sellers, bargaining provides higher customer satisfaction leading to an increase in future visits to the shop thus resulting in better business in the long run. Product bundles currently provided by e-commerce websites are rigid and adding bargaining capabilities can offer flexibility in two ways. Firstly, bargaining provides the buyer with an option to ask the e-commerce site to lower the price of the current offer. This shows the buyer's interest in the product bundle, which could then be used as feedback to make better offers to increase sales. Feedback is unavailable with a fixed discount structure and often results in customers ignoring the offer. Secondly, it provides flexibility to the buyer to change the products in a bundle—bundle customization. Our agent incorporates both these ways of increasing flexibility. While Cao et al. [8] and Cao [7] have incorporated bargaining in e-commerce for a single product, none of them have taken the bundling strategy adopted by e-commerce sites into account.

Negotiations have been a human-human interaction for a large part of our civilization. Negotiation and bargaining have been recognized and studied for many years in psychology and related disciplines [4], and strategies for negotiation are likewise of interest in business and marketing [26]. An early effort at an automated approach for automated negotiation was by Sycara [27], who used case-based reasoning and multi-criteria decision making. More recent works on automated negotiations [10, 21] have tried to mimic human behaviors. Agent-agent automated negotiations have been studied extensively in multi-agent systems [1–3, 6, 14, 15]. The rise of deep-learning methods has led to a huge increase in performance related to pattern-matching tasks like image classification. Due to their limitation in modeling reasoning-based tasks, deep-learning approaches have time and again failed to accurately model multiple aspects of human behavior such as emotions and ethics. Beheshti and Mozayani [5], Dong [13], Oprea [23] have used neural networks for negotiation based tasks but the inexplicable nature of deep-neural models gives rise to extreme uncertainty which can be catastrophic for e-commerce websites. Cheng et al. [9] have used adversarial methods to increase the robustness of a negotiating model, and Lewis et al. [20] have used reinforcement learning techniques to provide a higher reward for better negotiations during training. But the main focus of those papers is to make the conversations better, but they do not manifest the strategic skills required for the task. Therefore, we propose an approach that does not require the use of deep-learning.

While agent-agent negotiation models are useful for simulating and understanding human behavior, human-agent negotiations have a higher scope in practice. Park et al. [24] have studied an integrative bargaining model with an argumentation-based negotiation strategy. However, their work does not use business logic to model the agent, making it less likely to be effective in real-world scenarios. It also does not use utility to measure the efficacy of the negotiation outcome for the agent and the buyer. Fujita [15] used past negotiation session data to learn the opponent negotiation style by characterizing buyers using a conflict handling model called the Thomas-Kilmann conflict mode instrument (TKI) [18]. As shown by Koley and Rao [19], Fujita's work can be adapted to use real-time data instead of negotiation history. Koley and Rao provide a general framework for negotiation in a human-agent setting using heuristics like "most changed least preferred" (MCLP) and "most offered most preferred" (MOMP) to estimate buyer preference. However, these heuristics are generic in nature and do not consider business logic of sales, thus resulting in unrealistic negotiations. Moreover, their algorithm does not incorporate any prior knowledge to provide realistic initial offers. Using such prior information is especially important since data of past negotiation sessions are not used to provide an initial offer. Neither do the existing works provide options to customize agent behavior nor do they guarantee a minimum profit to sellers.

Human-agent negotiation modeling has been studied relatively less compared to agent-agent negotiation modeling. While prior information might provide some information about user preferences, it is often seen that the interest of the human during a negotiation decides the outcome. Since the agent deals with a human who might change their strategy frequently, this paper is focused on modeling human behavior in real-time to better assess the scenario and provide offers that have higher chances of being accepted.

We use a recommendation system to provide the likelihood value for each product being bought together with the product the buyer wishes to purchase. These likelihood values enable the agent to provide an initial bundle as an offer since we do not yet have a model of the buyer. Our algorithm then calculates the agent and the buyer utilities using the selling price, the cost price, and the offered price. We use simple assumptions to provide a unique mathematical framework for calculating the utilities.

We use the bidding-opponent-acceptance (BOA) model [2] to create a realistic agent that is capable of understanding the current negotiation situation by dividing the task into three parts. The bidding model decides the bids (offers) that are reasonable to be considered by the agent in the next round and the opponent model models the opponent (buyer) behavior. We use a modified version of the Thomas-Kilmann conflict mode instrument (TKI) to model buyer behavior. The acceptance model decides whether to accept the current offer by the buyer or to provide a counteroffer using the inputs from the bidding and the opponent models.

We introduce three hyper-parameters—the minimum profit margin rate η, the maximum initial discount rate φ and the bidding distance μ to provide flexibility to our agent. Agent behavior can be altered by modifying one or more of these parameters.

We provide a mathematical foundation for negotiations involving the purchase of bundles. Our model incorporates the following ideas to make realistic bargains:

(1) Using retail business logic to calculate buyer and agent utilities which are used later in the BOA model [2].
(2) Using trivial assumptions such as "the first offer from a buyer is the best offer for them" and "the buyer will not offer a price greater than the initial selling price of products" to calculate utilities.
(3) Modeling buyer behavior using a modified TKI algorithm and real-time negotiation data.
(4) Providing hyperparameters that can be used to alter agent behavior.
(5) Using prior information from a recommendation system to create an initial offer.

Our model provides offers that are reasonable and flexible. It results in a win-win outcome for both the parties involved in most negotiation sessions, which is the ultimate goal of any bargaining process. To demonstrate this, trials were performed on 50 volunteers from various age groups using an application that was built for the same purpose. 94% of the negotiations resulted in a successful agreement with an average of 4.55 rounds showing a relatively fewer number of iterations in a larger sample base compared to Koley and Rao [19]. 76% of the negotiations resulted in both the buyer and the agent utilities higher than 0.6 which shows that a majority of the trials reached a near-optimal outcome using our model. Our success rate also shows the ability of the model to change strategies based on buyer behavior without compromising seller constraints.

The remainder of the paper proceeds as follows—Sections 2 and 3 describe the functioning of our model. We discuss the results and analysis in Section 4 and present the conclusion in Section 5.

2 AUTOMATED NEGOTIATION AGENT

Our agent uses the BOA model and the Thomas-Kilmann conflict mode instrument to model buyer behavior, and a recommendation system that relies on customer purchase history to create bundles. This section describes the design of the agent along with the core mechanisms it uses.

2.1 Negotiation Environment

Our model consists of the components shown in Figure 1. The flow of the negotiation and the environment is as follows:

(1) The buyer adds a product to their cart. This is the selected product denoted by s.
(2) The recommendation system provides the agent with a bundle of products that are frequently bought together with the selected product s.
(3) The bundle is provided at a discounted price by an algorithm that uses the likelihood of the bundle being bought, which is also provided by the recommendation system. This bundle is offered at the discounted price to the buyer and is called the initial bid β_{A_1}.
(4) The buyer is provided an option to either accept the offer or to bargain by providing a counteroffer. The offer contains a list of products and an offer price. "Offer" and "bid" are used interchangeably here and it is denoted by β_t at iteration t.
(5) The opponent model of our BOA framework then calculates the buyer utility $U_B(\beta_t)$ of the current bid. It also provides a target utility U_T based on buyer behavior and the history of the current negotiation. The target utility is the minimum agent utility required by a bid in order to accept the bid.
(6) The agent then creates a list of all reasonable bids which have utilities higher than the target utility. This is called the bid space B.
(7) Once the bid space has been created, the acceptance model calculates the agent utility $U_A(\beta_t)$ of the bid made by the buyer and accepts the bid if $U_A(\beta_t)$ is higher than the target utility U_T provided by the opponent model. Otherwise, the agent selects the most appropriate bid from the bid space provided by the Bidding model and proposes it as a counteroffer.
(8) Steps 4 to 7 are repeated until a compromise is reached (the buyer buys the bundle) or the negotiation exceeds the maximum allowed number of iterations N, when the agent terminates the session.

2.2 The BOA Model

The Bidding-Opponent-Acceptance (BOA) model gives a general framework for negotiations. The model has three main components:

(1) Bidding Model—It consults the opponent model to determine the counter offer using a set of valid bids (offers).
(2) Opponent Model—It is responsible for modeling opponent behavior and providing the opponent utility for a given bid.
(3) Acceptance Model—It decides whether to accept the opponent's offer or to give a counter offer determined by the Bidding Model.

Each of the three models is flexible and can adapt to the business logic. Baarslag [2] gives a detailed description of the BOA model.

2.3 Thomas-Kilmann Conflict Mode Instrument

The Thomas-Kilmann Conflict Mode Instrument (TKI) is a conflict-handling method [18]. An individual is presented with multiple pairs of statements and is expected to choose between the two statements in each pair. A score is assigned to measure assertiveness—the extent to which the individual attempts to fulfill their interest and cooperativeness—the extent to which the individual attempts to fulfill the opponent's interest [19]. Five modes of conflict are defined along these two dimensions as shown in Figure 5 of Fujita [15].

Fujita [15] proposes an efficient automated method to model opponent behavior using the TKI and historical negotiation data in agent-agent interactions. Table 1 summarises the conditions that are used to model buyer behavior. U_B is the buyer utility, β_t is the buyer bid at time t, μ_B is the mean buyer utility for the past negotiation sessions, $\sigma^2(t)$ is the variance of the bid at time t, and σ_B^2 is the variance of the past negotiation sessions.

Koley and Rao [19] propose heuristics that use only the data from the ongoing negotiation session with the TKI to determine buyer strategy. We adapt the TKI to determine buyer behavior and model buyer strategy using the data from only the ongoing negotiation. Further, our agent uses concrete calculations based on business logic rather than heuristics to model buyer strategy. The independence of each negotiating session allows the agent to accurately model the opponent's current behavior and grants it the flexibility to adapt to many kinds of scenarios that it might confront.

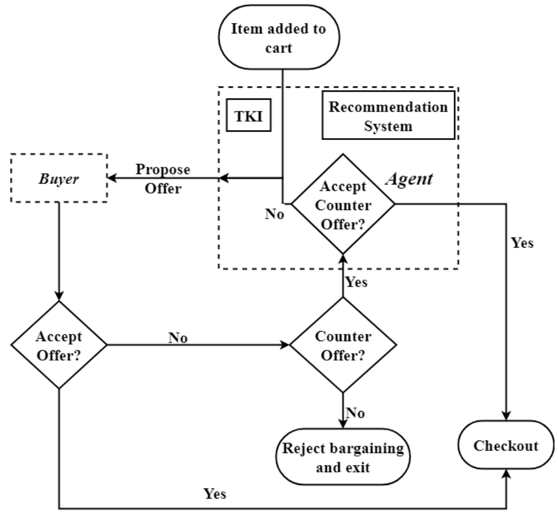

Figure 1: Flow of the Automated Negotiation

Table 1: Estimation of Cooperativeness and Assertiveness. Source : Fujita [15]

Condition	Cooperativeness	Condition	Assertiveness
$U_B(\beta_t) > \mu_B$	Uncooperative	$\sigma^2(t) > \sigma_B^2$	Passive
$U_B(\beta_t) = \mu_B$	Neutral	$\sigma^2(t) = \sigma_B^2$	Neutral
$U_B(\beta_t) < \mu_B$	Cooperative	$\sigma^2(t) < \sigma_B^2$	Assertive

2.4 Recommendation System

A Recommendation System is a type of machine learning model that seeks to predict the rating a user would give to an item [25]. Recommendation Systems thus find a natural use in the domain of e-commerce where they are used to provide recommendations to customers to increase sales. They are also used to create personalized bundles to a user based on their purchase history.

Recommendation Systems, specifically those based on collaborative filtering assume that people who agreed in the past will agree in the future and that they will like items similar to those that they liked in the past. The agent proposed in this paper requires a recommendation system to create bundles, typically based on the most frequently bought-together items. It uses a simple apriori recommendation system, which can be supplanted by a more powerful, sophisticated system due to the modular architecture.

3 NEGOTIATION LOGIC

The agent design incorporates business logic. The various components that drive negotiations are described in detail.

3.1 Initial Bid

This is the bid offered by the agent initially to the user denoted by β_{A_1}. It includes a list of products at a discounted price. The list contains 2 products that are most frequently bought together along with the product that the user wants to buy s. These products are obtained from our recommendation system.

We first calculate the product prior utility U_P as the mean of the likelihood values of the products in the bundle given the selected product $p(b|s)$ obtained from the recommendation system in (1).

$$U_P = \frac{\sum_{b \in \beta_{A_1} \setminus \{s\}} p(b|s)}{|\beta_{A_1} \setminus \{s\}|} \tag{1}$$

We then calculate the discount amount d which captures the fact that a product with higher utility is more likely to be bought with a lesser discount offered. This also takes into account that discounts should not be more than the profit margin of the product calculated using the cost price Γ and the selling price Υ of the products. (2) also provides a cap based on the maximum initial discount rate (φ) that can control the behavior of the agent by preventing high discounts for products with a low likelihood value.

$$d = \left\{ \sum_{b \in \beta_{A_1} \setminus \{s\}} \Big(\Upsilon(b) - \Gamma(b) \Big) \right\} \times \min(1 - U_P, \varphi) \tag{2}$$

Finally, we calculate the initial discounted selling price ξ by (3). This ensures that the total price of the bid is not lower than the original price of the selected product.

$$\xi = \left\{ \sum_{b \in \beta_{A_1} \setminus \{s\}} \Gamma(b) \right\} - d + \Upsilon(s) \tag{3}$$

3.2 Bidding Strategy

The bidding model provides a list of all reasonable bids that can be offered based on the target agent utility function provided by the opponent model. Algorithm 1 describes the strategy to create a reasonable bid space. The procedure in Algorithm 1 requires a bundle x as input.

Algorithm 1: Strategy to create a reasonable bid space B

Function `get_bid_space`(x):
    $k \leftarrow \max(0, 2 \times \Phi(\beta_t) - \Phi_A(\beta_{t-1}))$ ▷lower bound
    $B \leftarrow \emptyset$ ▷Initialize an empty bid space
    for $p \leftarrow k$ ***to*** $\Phi_A(\beta_{t-1})$ ***by*** 1 ▷Iterate search range
    do
        $\beta \leftarrow (x, p)$ ▷Create bid with x at price p
        if $|U_A(\beta) - U_T(\beta_t)| \leq \mu$ **then**
            $B \leftarrow B \cup \{\beta\}$ ▷Add bid β to bid space B
        end
    end
    return B

The bidding distance μ is the threshold that decides the maximum possible difference between a bid's agent utility $U_A(\beta_t)$ and the target agent utility $U_T(\beta_t)$. Our experiments revealed that a value of 0.05 for μ works well. We start from a price p equal to $\Phi(\beta_t) - \Phi_A(\beta_{t-1})$ where $\Phi(\beta_t)$ is the price offered by the buyer for the current bid and $\Phi_A(\beta_{t-1})$ is the price offered by the agent in the previous round. Our search range is then restricted to $[\Phi(\beta_t) - \{\Phi_A(\beta_{t-1}) - \Phi(\beta_t)\}, \Phi(\beta_t) + \{\Phi_A(\beta_{t-1}) - \Phi(\beta_t)\}]$.

3.3 Opponent Strategy

The opponent model uses the Thomas–Kilmann Conflict Mode Instrument to analyze buyer behavior. We use the instrument in a way very similar to that mentioned by Koley and Rao [19]. We modify the TKI to incorporate business logic in calculating the minimum target utility $\gamma_{\min}$. Unlike Koley and Rao [19] who used $\gamma_{\min}$ as a hyperparameter, we derive it through (7), (8), and (9). $\gamma_{\min}$ influences the target utility U_T.

To calculate the target utility U_T, we first find the utility search space Δ. The utility search space is the difference between the maximum target utility $\gamma_{\max}$ and the minimum target utility $\gamma_{\min}$ as given in (4).

$$\Delta = \gamma_{\max} - \gamma_{\min} \tag{4}$$

Then, we calculate the absolute target utility τ, which depends on the current iteration of the negotiation t, the maximum number of rounds N (which is a hyper-parameter that prevents infinitely long negotiations), the buyer utility U_B of current bid, and the concession rate α to ensure that the target utility U_T is realistic by (5). c is a constant that is set to 1.3 in our experiments.

$$\tau = 1 - \left\{ c \times U_B(\beta_t) \times \min\left(\frac{N+t}{10}, 1 \right)^{\frac{1}{\alpha}} \right\} \tag{5}$$

We then restrict τ to the utility search space Δ to get the target utility U_T as in (6).

$$U_T(\beta_t) = \gamma_{\min} + (\Delta \times \tau) \tag{6}$$

The algorithm to calculate the concession rate α based on the cooperativeness and assertiveness of the buyer as shown in Table 1 has been given by Koley and Rao in [19]. We modify their algorithm to Algorithm 2. c is a placeholder for the `cooperativeness` of the buyer that can take on a value of `uncooperative`, `neutral`, or `cooperative`. Similarly, a is a placeholder for the `assertiveness` of the buyer and can take on a value of `passive`, `neutral`, or `assertive`. c_1, c_2, and c_3 are constants whose values were set to 0.15, −0.05, and −0.25 in our experiments.

Algorithm 2: Updating concession rate α using our TKI

Function `tki`$(U_B(\beta_t))$:
  $\mu_B \leftarrow \frac{\sum_{i=1}^{t} U_B(\beta_i)}{t}$ ▷ μ_B is mean of U_Bs
  $\sigma_B^2 \leftarrow \frac{\sum_{i=1}^{t} \left(U_B(\beta_i) - \mu_B\right)^2}{t}$ ▷ σ_B^2 is variance of U_Bs
  $v \leftarrow \left(U_B(\beta_t) - \mu_B\right)^2$ ▷ v is variance of current U_B
  if $U_B(\beta_t) > \mu_B$ **then**
    $c \leftarrow$ `uncooperative` ▷ c is the cooperativeness
  else if $U_B(\beta_t) = \mu_B$ **then**
    $c \leftarrow$ `neutral`
  else
    $c \leftarrow$ `cooperative`
  end
  if $v > \sigma_B^2$ **then**
    $a \leftarrow$ `passive` ▷ a is the assertiveness
  else if $v = \sigma_B^2$ **then**
    $a \leftarrow$ `neutral`
  else
    $a \leftarrow$ `assertive`
  end
  if $c =$ `cooperative` ***and*** $a =$ `assertive` **then**
    if $\alpha < 1$ **then**
      $\alpha \leftarrow \alpha + c_1$
    end
  else if $c =$ `neutral` ***and*** $a =$ `neutral` **then**
    $\alpha \leftarrow \alpha + c_2$
  else
    if $\alpha > 0.3$ **then**
      $\alpha \leftarrow \alpha + c_3$
    end
  end

We use $\gamma_{\max} = 1$ in our experiments. To calculate the minimum target utility $\gamma_{\min}$, we first calculate the original profit χ from the selected product s as in (7).

$$\chi = \Upsilon(s) - \Gamma(s) \tag{7}$$

We also calculate the maximum profit (m) that can be obtained from all the products in the bid at time t (β_t) as in (8).

$$m = \sum_{b \in \beta_t} \Big(\Upsilon(b) - \Gamma(b) \Big) \tag{8}$$

$\gamma_{\min}$ ensures that the profit is at least the original profit by performing an interpolation between χ and m using a hyperparameter called the minimum profit margin η which controls the greediness of the agent. To ensure $\gamma_{\min} \in [0, 1]$ we divide the profit obtained with m as given by (9).

$$\gamma_{\min} = \frac{\{(1-\eta) \times \chi\} + \{\eta \times m\}}{m} \tag{9}$$

Hence we see that the purpose of γ_{min} is to ensure that the profit that the agent receives from a bundle is always more than the profit earned if the buyer buys only the product they selected. While the maximum initial discount rate φ determines the initial offer, η determines the offers beyond the first negotiation.

3.4 Acceptance Strategy

Given the agent and buyer utility, the acceptance model decides whether to accept or reject the offer by the buyer. The offer is accepted if one of the following conditions is met:

(1) The current offer received is better than the previous offer by the agent.
$$U_A(\beta_t) > U_A(\beta_{A_{t-1}})$$
(2) The agent utility of the current bid is greater than the mean agent utility of all bids in the previous rounds.
$$U_A(\beta_t) > \frac{\sum_{i=1}^{t} U_A(\beta_i)}{t}$$

If rejected, the model has to propose a new bid from the bid space provided by the bidding model whose agent utility is closest to the target agent utility calculated by the opponent model using the TKI.

3.5 Agent Utility

The agent utility is higher if the offered price Φ is closer to the selling price Υ of the bundle. It should be 0 if there is no profit and 1 if the selling price equals the offered price. Thus, a ratio of the profit obtained with a bid β_t to the profit obtained without any discount satisfies all the requirements of U_A as seen in (10).

$$U_A(\beta_t) = \frac{\Phi(\beta_t) - \sum_{b \in \beta_t} \Gamma(b)}{\sum_{b \in \beta_t} \Big(\Upsilon(b) - \Gamma(b) \Big)} \tag{10}$$

We require that $0 \leq U_A \leq 1$, and this is achieved by (11).

$$U_A(\beta_t) = \min\big(\max(U_A(\beta_t), 0), 1\big) \tag{11}$$

3.6 Buyer Utility

The assumption used to constrain the buyer utility U_B between 0 and 1 is that the first offer made by the buyer is the best offer to them. The value of a bid at time t, denoted by $\nu(\beta_t)$, is the ratio of the amount saved by the buyer to the total selling price for the bid at time t as shown in (12). This ensures that $0 \leq \nu(\beta_t) \leq 1$.

$$\nu(\beta_t) = \frac{\left\{\sum_{b \in \beta_t} \Upsilon(b)\right\} - \Phi(\beta_t)}{\sum_{b \in \beta_t} \Upsilon(b)} \tag{12}$$

In (13), we calculate the buyer utility of the current bid $U_B(\beta_t)$ by using our hypothesis that the first bid offered by the buyer in negotiation is the best bid for them.

$$U_B(\beta_t) = \frac{\nu(\beta_t)}{\nu(\beta_1)} \tag{13}$$

We also use the prior product utility $U_P(\beta_t)$ from (1) to introduce the prior knowledge that we have about the importance of a product to buyers given by the recommendation system. Finally we calculate the Buyer Utility (U_B) for the current bid by interpolating between $U_B(\beta_t)$ and $U_P(\beta_t)$ using the decay factor δ. The decay factor decreases exponentially with time as shown in Figure 2.

$$U_B(\beta_t) = \left\{(1-\delta) \times U_B(\beta_t)\right\} + \left\{\delta \times U_P(\beta_t)\right\} \tag{14}$$

Similar to the agent utility, we require $0 \le U_B \le 1$.

$$U_B(\beta_t) = \min\big(\max(0, U_B(\beta_t)), 1\big) \tag{15}$$

Since the agent starts with no knowledge of the current negotiation, it relies heavily on the prior utility values given by the recommendation system. We require the agent to utilize the opponent model as soon as the negotiation begins. Thus, the decay factor has to fall exponentially, such that not much weight is given to the prior utility values as we proceed with the negotiation. Empirically, the function $t^{-2.2}$ where t is the number of iterations serves this purpose as shown in Figure 2.

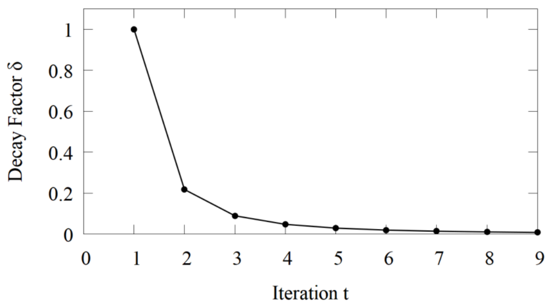

Figure 2: Decay Factor varying with iterations

4 RESULTS

We first address the issue of experimenting with human volunteers in Section 4.1. Since we propose a solution for human-agent negotiations, we look at human responses to the algorithm and analyze the real-time performance of our agent. We provide a comparison of the agent and the buyer utilities in Section 4.2. We determine the importance of the concession rate α in the Thomas-Kilmann Instrument algorithm and analyze the difference in the average value of the concession rate between successful and unsuccessful negotiations in Section 4.3. We then analyze the total number of rounds taken during the negotiations and the average number of rounds taken by successful and unsuccessful negotiations in Section 4.4. Finally, we analyze the role played by the maximum initial discount rate φ in Section 4.5 and by the minimum profit margin η in Section 4.6.

4.1 Experimental Setup

To test the model against a fairly wide range of users, an application was created. It featured a simple user interface that allowed the buyer to choose a product from the 10 displayed. Then the agent provided a bundle to the buyer with a discounted price and let the buyer negotiate by either changing the items in the bundle or by citing a different price for the offered bundle. In this negotiating phase, the offer history was displayed alongside the current offer for user convenience.

We created an artificial dataset for the experiment which contained 10 products. We provided the selling price and cost price of the products based on their average market values. To create realistic data that could capture the dependency of different products with each other, we generated a dataset by giving likelihoods of products being bought together. With this synthetic dataset, we trained a simple *a priori* recommendation system.

50 volunteers of various ages used the software. Most volunteers were students who use e-commerce websites often, and were not aware of the internal working of our model. The volunteers were allowed to withdraw from the bargaining process at any point of time but were asked to get the best deal possible. The results showed that the agent was always able to achieve a reasonable profit-margin and a win-win situation for both the agent and the buyer.

94% of the negotiations resulted in the buyer accepting a deal from the agent or providing a deal that the agent accepted. This shows that the agent was able to model human behavior in real-time and was able to generate realistic offers which resulted in a high acceptance rate.

4.2 Comparing agent and buyer utilities

We observe a pattern of high values for both the agent and the buyer utilities as shown in Figure 3. This indicates a successful negotiation. A high agent utility indicates that the agent managed to drive a bargain that was highly beneficial to itself, while also being acceptable to the buyer which is an ideal situation. High buyer utility values indicate that the negotiations resulted with the buyer nearly obtaining their ideal bargain.

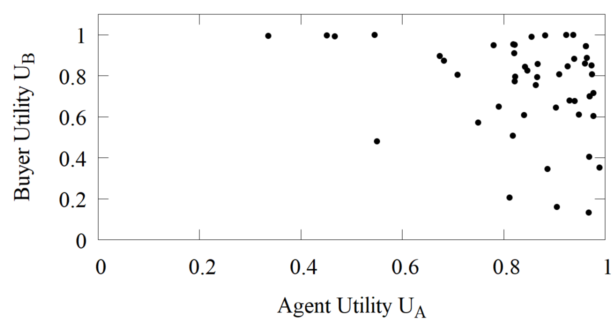

Figure 3: Agent Utility U_A vs Buyer Utility U_B

We observe slightly lower values in some of the negotiations which indicate a compromise by one (or both) of the parties. 76% of the negotiations resulted in both the agent and the buyer utilities having values more than 0.6. 92% of the negotiations ended with agent utility higher than 0.6 while 82% of the negotiations resulted in buyer utility grater than 0.6. This shows that the model does not compromise to the extent where it is detrimental to itself although this behavior could be achieved by changing our hyperparameters such as maximum initial discount rate φ and minimum profit margin η. We also infer that the buyers viewed the negotiations as satisfactory.

4.3 Role of Concession Rate α

A low value of α suggests that the buyer has been uncooperative and assertive. This helps us model the current buyer behavior and

Table 2: Comparison of average concession rate (α) values with the outcome of the negotiations in the experiment.

Outcome	Average α value
Successful	0.63
Unsuccessful	0.22

Table 3: Average number of iterations taken by successful and unsuccessful negotiations

Outcome	Average number of iterations
Successful	4.55
Unsuccessful	10

hence plays a crucial role in determining the next offer for the buyer in our algorithm. From Table 2, we see that if α is a small value, then the negotiation will most likely fail, while if α is high it is likely to succeed. This provides empirical evidence that the agent was able to model the current buyer behavior and was able to provide offers accordingly, which resulted in a high acceptance rate.

4.4 Impact of Number of Rounds

Figure 4 shows the histogram of the number of rounds taken during every negotiation for the agent to conclude. 47 negotiations were successful while 3 were rejected by the buyer. We can see that most of the negotiations ended in less than 6 rounds which matches the behavior of a buyer who wants to bargain for a product. We averaged of 4.55 rounds for successful negotiations showing a relatively fewer number of iterations in a larger sample base compared to Koley and Rao [19]. We infer that the model can determine buyer behavior and provide an offer that is acceptable to the buyer within a few rounds. It also justifies our decision to use a decay factor that reduces drastically by the 3rd round as shown in Figure 2.

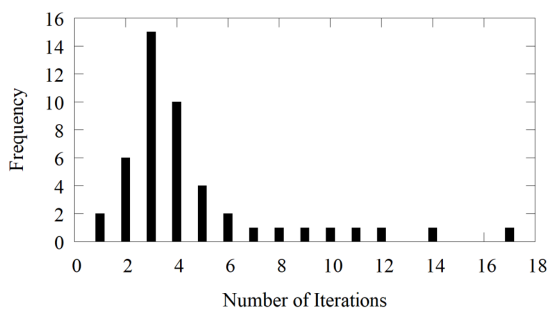

Figure 4: Histogram of number of iterations over all negotiations

As seen in Table 3, the average number of rounds of unsuccessful attempts is much higher than in the successful attempts. This shows that the model did not surrender to offers resulting from the unrealistic expectations of buyers causing a long negotiation session. This analysis points to the primary function of the agent to search for a balanced offer to satisfy both the parties involved.

4.5 Impact of Maximum Initial Discount Rate φ

Figure 5 shows the impact of the maximum discount rate φ on the agent utility of the initial offer by the agent. We choose 4 products arbitrarily (products A, C, E, F were chosen) and calculate the agent utility for different φ values keeping all other factors constant. As expected, a higher φ value results in the agent being more open to higher discounts which in turn reduces the initial agent utility. As seen in (2) the discount depends on the prior utility U_P resulting in different initial agent utility for different products.

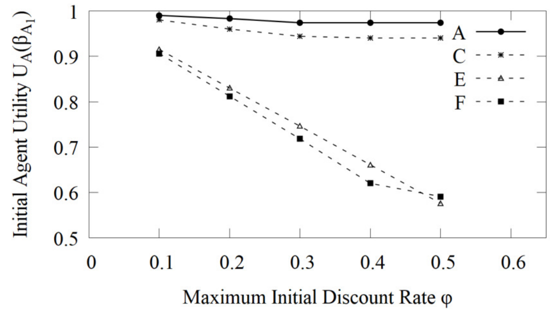

Figure 5: The impact of maximum initial discount rate φ on the agent utility of the initial offer by the agent $U_A(\beta_{A_1})$ for 4 products used in our experiments.

4.6 Impact of Minimum Profit Margin η

To find the extent to which the minimum profit margin η influences the target utility U_T, we see how the average target utility across the rounds in a negotiation varies for different η values as seen in Figure 6. For this, we provide the same offers (acting as buyer substitutes) for corresponding rounds in a negotiation and calculate the average target utility of the offers made by the agent across all rounds of the negotiation.

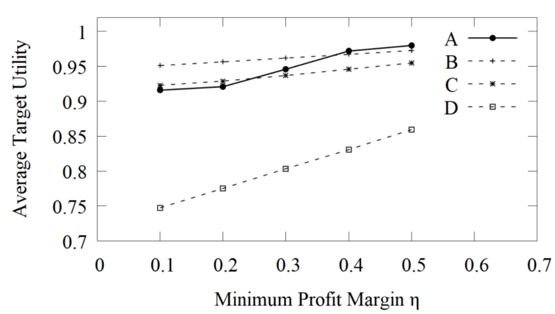

Figure 6: The impact of minimum profit margin η on the average target utility of the offers made by the agent to the buyer for 4 products. All other factors are constants.

Our experiment shows that the minimum profit margin η can directly impact the offer made by the agent as the target utility U_T

is directly proportional to it. A lower value of η makes the agent cooperative, while a high η makes it assertive. A lower value will mean a lower target utility that the agent aims for, leading to a better bargain from the buyer's perspective. Similarly, a higher value of the minimum profit margin η would mean that the model is assertive in nature and wants to make a higher profit from the deal. For products with very low profit margins, our model ensures that there is no loss to the seller, but cannot guarantee a high profit. Hence our model is sufficiently flexible to bargain with different strategies.

5 CONCLUSION

This paper focuses on modeling buyer behavior using real-time data generated during a negotiation session in an e-commerce environment to provide bargaining capabilities with product bundles offered. It uses prior knowledge of the likelihood of products being bought together and incorporates e-commerce business logic into the negotiation strategy to create a realistic model. The approach is modular, which gives flexibility to use different models for different components, including neural-network based recommendation engines.

From our experiments, we have been able to show that the agent can accurately model human purchasing behavior and provide a reasonable bargaining strategy for the e-commerce domain. 94% of our volunteers were ready to accept an offer that was made to them by the agent after a negotiation. At the same time, most of the offers still resulted in good profit margins for the agent, which showed a win-win situation for both the parties involved. The buyer was able to get a good discount because of the bundled offer, while the agent was able to make more profit than it would have if it had sold the single product. We also showed that the model is flexible and can behave differently based on the hyperparameters provided to it.

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