A COMPREHENSIVE HUMAN-AGENT NEGOTIATION FRAMEWORK: PREFERENCES, EMOTION & INTERACTION

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A COMPREHENSIVE HUMAN-AGENT NEGOTIATION FRAMEWORK: PREFERENCES, EMOTION & INTERACTION

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In the words of Isaac Newton,

“If I have seen further, it is by standing on the shoulders of giants.”

To my family, you are those giants.

ABSTRACT

In today's increasingly interconnected world, human-agent negotiation plays a pivotal role in reaching socially beneficial agreements when stakeholders need to make joint decisions. Developing intelligent agents capable of understanding not only human negotiators' preferences but also attitudes is a significant prerequisite for effective human-agent interactions. Awareness of a human's emotional state and ability to express an agent's mood to influence the human negotiator might significantly affect the negotiation outcome.

This thesis presents a comprehensive framework that revolutionizes the field of human-agent negotiation, integrating two critical elements: Emotionally aware negotiation strategy and Conflict-Based Opponent Modeling (CBOM). By combining these novel approaches, the framework enhances negotiation outcomes and fosters cooperation between agents and human negotiators, ultimately leading to mutually advantageous agreements.

The thesis establishes the research context and motivation, underscoring the escalating importance of human-agent negotiation in a world where collaborative decision-making is essential for addressing complex challenges. It highlights the need for advanced agents to accurately interpret human preferences and behaviors, enabling admissible settlements that serve joint interests. Shedding light on the limitations of conventional approaches that heavily rely on opponent offers and remaining time. Additionally, it explores the critical role of emotional awareness and opponent modeling strategies in human-agent negotiation. The synthesis of existing research lays the groundwork for developing the proposed comprehensive framework.

Emotional awareness takes center stage in the proposed negotiation strategy. Solver Agent: Emotional Extension of the Hybrid Agent bidding strategy is introduced. The Solver Agent considers the opponent's emotional state during negotiation, leading to higher

social welfare scores and faster agreement times. The experimental study emphasized the profound impact of emotional awareness on negotiation outcomes, particularly in human-agent settings. CBOM efficiently extracts maximum information from limited interaction rounds in human-agent negotiation settings, surpassing traditional approaches in prediction performance. Experimental analyses confirmed the superiority of CBOM in human-agent and automated negotiation scenarios, even when the exploration of the outcome space is limited. The experimental findings establish CBOM as a powerful tool for modeling human behavior and preferences in negotiation.

In conclusion, the comprehensive human-agent negotiation framework presented in this thesis represents a significant advancement in the field. By seamlessly combining Conflict-Based Opponent Modeling and Emotional Awareness, the framework empowers intelligent agents to discern human preferences and behaviors more accurately, facilitating cooperative interactions and achieving mutually beneficial agreements. The framework's effectiveness in human-agent and automated negotiation settings highlights its potential for designing negotiation agents that interact adeptly with human negotiators, fostering understanding and optimizing negotiation outcomes. The future of human-agent negotiation lies in forging a new era of cooperation, where intelligent agents serve as capable partners, promoting social welfare and driving positive change through admissible settlements that incorporate joint interests. This thesis contributes valuable insights towards realizing this vision, marking a significant step forward in the field of human-agent interaction.

ÖZETÇE

Günümüzün giderek daha birbirine bağlı dünyasında, insan-etmen müzakereleri, paydaşların ortak kararlar alması gerektiğinde sosyal olarak faydalı anlaşmalara ulaşmada önemli bir rol oynamaktadır. Hem insan müzakerecilerin tercihlerini hem de tutumlarını anlama yeteneğine sahip akıllı etmenlerin geliştirilmesi, etkili insan-etmen etkileşimleri için önemli bir önkoşuldur. Bir insanın duygusal durumunu anlama ve bir etmenin duygusal durumunu ifade etme yeteneği, müzakere sonucunu önemli ölçüde etkileyebilir.

Bu tez, insan-etmen müzakeresi alanını devrim niteliğinde değiştiren iki önemli unsur olan Duygusal Farkındalıklı Müzakere Stratejisi ve Çatışma Temelli Rakip Modelleme (ÇTRM) öğelerini entegre eden kapsamlı bir çerçeve sunar. Bu yeni yaklaşımları birleştiren çerçeve müzakere başarısını artırır ve etmenler ile insan müzakereciler arasındaki işbirliğini teşvik eder, nihayetinde karşılıklı fayda içeren anlaşmalara yol açar.

Tez, araştırma bağlamını ve motivasyonunu oluşturarak, işbirliğine dayalı karar vermenin karmaşık zorlukları ele almak için kaçınılmaz olduğu bir dünyada, insan-etmen müzakeresinin artan önemini vurgular. İnsan tercihlerini ve davranışlarını doğru bir şekilde yorumlamak için gelişmiş etmenlere olan ihtiyacı belirtir ve ortak çıkarlara hizmet eden kabul edilebilir çözümleri mümkün kılar. Geleneksel yaklaşımların rakip tekliflerine ve kalan süreye yüksek ölçüde bağlı olduğunu gösterir. Ayrıca, insan-etmen müzakeresinde duygusal farkındalık ve rakip modelleme stratejilerinin kritik rolünü keşfeder. Mevcut araştırmanın sentezi, önerilen kapsamlı çerçevenin geliştirilmesi için temel oluşturur.

Duygusal farkındalık, önerilen müzakere stratejisinde merkezi bir rol oynar. Çözümleyici Etmen (Solver Agent), Hibrit Etmen Teklif Stratejisi'nin duygusal farkındalığa sahip olarak geliştirilmiş bir versiyonudur. Çözümleyici Etmen, müzakere

sırasında rakibin duygusal durumunu dikkate alır, bu da daha yüksek sosyal fayda puanlarına ve daha kısa anlaşma sürelerine yol açar. Duygusal farkındalığın, özellikle insan-etmen ortamlarında müzakere sonuçları üzerindeki derin etkisini vurgulayan deneysel bir çalışma yapılmıştır. ÇTRM, sınırlı etkileşim deneyimi içerisinden maksimum bilgiye verimli bir şekilde ulaşır ve özellikle insan-etmen ve otomatik müzakere senaryolarında geleneksel yaklaşımlardan daha başarılı bir tahmin performansı gösterir. Deneysel analizler, ÇTRM'nin müzakerede insan davranışı ve tercihlerini modelleme konusunda üstün olduğunu doğrulamıştır.

Sonuç olarak, bu tezde sunulan kapsamlı insan-etmen müzakere çerçevesi, alandaki önemli bir ilerlemeyi temsil etmektedir. Çatışma Temelli Rakip Modelleme ile duygusal farkındalığı sorunsuz bir şekilde birleştiren çerçeve akıllı etmenlerin insan tercihlerini ve davranışlarını daha doğru bir şekilde anlamalarına yardımcı olur, işbirliği yapmalarını kolaylaştırır ve karşılıklı faydayı önceleyen anlaşmalara ulaşır. Bu çerçevenin insan-etmen ve otomatik müzakere ortamlarında etkili olması, müzakere etmenlerinin insan müzakerecilerle yetkin bir şekilde etkileşimde bulunabilme, anlayışı teşvik etme ve müzakere sonuçlarını optimize etme konusundaki potansiyelini vurgular. İnsan-etmen müzakerelerinin geleceği, akıllı etmenlerin, ortak çıkarları içeren kabul edilebilir çözümler aracılığıyla sosyal faydayı teşvik eden ve pozitif değişikliği destekleyen yetenekli ortaklar olarak hizmet etmesinde yatar. Bu tez, bu vizyonu gerçekleştirmeye yönelik değerli görüşler sunar ve insan-etmen etkileşimi alanında önemli bir adım olarak kayda geçer.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

Negotiation is a common process in which parties with different interests try to find common ground. Such interactions are frequently seen, from personal activities like planning holidays to complex societal matters like deciding on effective energy distribution. Due to the complexity and time demands of the decisions, there has been increasing interest in using Artificial Intelligence (AI) to streamline negotiations [3, 4, 5, 6]. A recent focus in this area is human-agent negotiations, where AI-driven agents negotiate directly with humans [7, 8, 9]. For these AI-powered agents to truly influence society, they need to understand human decision-making deeply, such as why certain offers are made [10]. This highlights the crucial role of opponent modeling in negotiations and which factors influence their decisions (e.g., effective use of nonverbal communication).

Human-agent negotiations require considering human factors such as emotional state of the opponent, the idea of returning favors, and a sense of fairness [11], and negotiating parties can exchange varying information such as emotional state or mood as well as offers. While AI agents can quickly make many offers, humans usually make fewer [11, 12, 13, 14]. AI agents need to be sensitive to human emotions during negotiations. Previous research has shown how crucial emotions are to human negotiations [15, 16, 17]. To improve negotiations, AI agents should recognize and respond to human emotions. Therefore, this thesis proposes a novel negotiation strategy considering the human negotiator's emotional feedback. Human-robot negotiation experiments were conducted to investigate the performance of the proposed emotion-aware negotiation strategy. According to the experimental results, the emotion-aware agent gained higher individual utility scores, and both sides reached a mutual agreement in less time. The experimental results revealed that incorporating emotional awareness significantly impacts negotiation outcomes. Specifically, the proposed approach led to higher social welfare scores and decreased agreement time, indicating that emotional awareness plays a crucial role in successful negotiation. This study highlights the potential of incorporating emotional awareness into negotiation strategies, particularly for human-agent negotiations. The proposed approach can be a valuable framework for designing negotiation agents that interact more effectively with human negotiators and improve negotiation outcomes.

Furthermore, the current research on opponent modeling in AI negotiations offers a wide range of methods [18]. Many of these methods analyze past offers to gain insights but often make assumptions about the other party's behavior and preferences. Some more straightforward methods, like the frequentist approach, have been effective in negotiations [19, 20]. However, applying these methods to human-agent negotiations, which often have fewer offers, can be challenging [21, 22]. Accordingly, we propose a new way to understand human negotiation preferences in this thesis. We aim to analyze the reasons behind human offers to identify patterns. Accordingly, we introduce a method focusing on conflicts to better understand each party's priorities. Our evaluations and experiments with human participants showed that the proposed approach provides more accurate predictions than traditional methods in learning human opponents' preferences over time [19, 20]. According to the results of human-agent studies, the proposed model outperforms them despite the diversity of participants' negotiation behaviors. Besides, the conflict-based opponent model estimates the entire bid space much more successfully than its competitors in automated negotiation sessions when exploring a small portion of the outcome space. This study may contribute to developing agents that can perceive their human counterparts' preferences and behaviors more accurately, acting cooperatively, and reaching an admissible settlement for joint interests.

Given this, it is clear that AI-driven negotiations offer both exciting opportunities and complex challenges. In negotiations, the relationship between humans and AI requires a deep understanding of existing methods, human behaviors, and new technologies.

This thesis is organized as follows. First, Chapter 2 presents the literature survey on human-agent negotiation and opponent model strategies. Chapter 3 explains the necessary background about automated negotiation dynamics and protocols—furthermore, the Human-Agent Negotiation Framework and proposed negotiation strategies are explained in Chapter 4. Chapter 5 evaluates the performance of the emotion-aware human agent negotiation strategy, while Chapter 6 examines the performance of the conflict-based negotiation approaches in three different studies. Finally, Chapter 7 summarizes the conclusion of the thesis.

CHAPTER II

RELATED WORK

Automated negotiation, a topic of extensive study spanning several decades, has evolved through various frameworks and methodologies [4, 23]. Most of these works focus on automated negotiation where two or more software agents negotiate with each other on behalf of their users. Recently, the need for AI systems interacting with humans arises in the research on human-agent negotiation systems [10]. Those interactions requires considering different dynamics such as bounded rationality, interaction medium, emotions [24], and gestures [11]. While human factors such as facial expressions, emotions, or gestures do not take place in automated negotiation in which smart software agents negotiate with each other, these factors play a key role in human-human and human-agent negotiations. There are various approaches to design negotiation frameworks for human-agent negotiations considering those factors [7, 8, 25, 26, 27]. While some of those works focus on the effect of emotion in human-agent negotiation (e.g., adopting angry facial expression versus happy facial expression during the negotiation) [28, 29, 30], others investigate negotiating strategies resulting in efficient outcomes while establishing a good relationship with human counterparts [31, 32]. In the following part, we first mention the existing human-agent frameworks (Section 2.1) and then discuss the state-of-the-art opponent modeling approaches in agent-based negotiations (Section 2.2).

2.1 Human-Agent Negotiation

Shifting the focus to human-agent negotiations, studies have either adapted existing automated negotiation strategies or introduced novel dimensions, such as emotional expression and arguments [33, 31, 34, 35, 32]. Although some works consider their opponent's behavior to some extent [31], they do not consider their opponent's awareness of the changes in their behavior. We argue for the importance of recognizing the opponent's awareness of strategy shifts, underscoring the necessity of gauging the opponent's sensitivity to these changes.

Regarding negotiation strategies for human-agent negotiations, Vahidov *et al.* introduce a variant of a time-based concession function for human-agent negotiation [36]. Based on their model, Aydoğan *et al.* propose a stochastic time-based concession strategy in which the agent determines its lower and upper boundaries according to the Boulware and Conceder tactics [37] and picks a random offer within the given utility range. Jonker *et al.* introduce *Deniz Agent*, which takes into consideration its opponent's moves and accordingly determines its moves (e.g., concession, selfish, silent) [31]. The concession amount is determined by the optimal bidding strategy [38]. Lin *et al.* introduce the 'QOAgent' capable of negotiating with boundedly rational agents under conditions of incomplete information [39]. The study shows that QOAgent performs better than humans in negotiations. Briefly, they assume a finite set of possible preference profiles for the opponent. The agent tries to predict the opponent's profile and accordingly makes a bid acceptable to its opponent. Agent designer extends their agent (KBAgent) by exploiting past negotiation history with others to model their current human opponent [40]. While QOAgent repeats the offers that annoy the human participant, KBAgent avoids making such an offer. Therefore, KBAgent has achieved more successful results than the negotiations between QOAgent and humans. Although the studies mentioned above present sophisticated techniques, they dismiss the opponent's emotional state and the awareness of the opponent against the change in the agent's offers. However, this thesis aims to improve the negotiation by considering those elements.

Moreover, the ANAC organizers introduced a human-agent negotiation league to facilitate research in human-agent negotiation. When we investigate the agents developed for the Human-Agent Negotiation League [14], we observe that LyingAgent is inclined to mislead their opponents about their preferences so that they can gain more. Elphaba aims to find the best offer for both sides, while Murphy makes some jokes to establish a friendly relationship. Some agents make offers using a utility threshold (e.g., Agent Cena, Boulware). Pinocchio waits for an idea about all the issues until it gives suitable offers for both parties. None of those agents considers their opponent's emotions and awareness to adapt their behavior. In addition, some agents use emotional expressions such as anger to make their opponents concede more.

Emotion plays a pivotal role in negotiations, with various studies elucidating its impact [15, 16]. For instance, research has demonstrated that human negotiators are more cooperative when confronted with a virtual agent expressing anger instead of joy [17, 41]. Similarly, the study of [42] shows that dominant movements and emotional expressions are variables that provide higher scores during human-agent negotiations. Another study shows that people are more willing to renegotiate with warm agents, although there is no significant difference found in negotiation outcome in their experiments [43]. While these studies shed light on the agent's emotional expression's effect on human behavior, our approach pivots towards tailoring negotiation strategies based on the human opponent's emotional state.

Several frameworks have emerged to facilitate human-agent negotiations. For example, IAGO provides an emoji-enhanced chat-based interaction [7], while NegoChat employs Natural Language Processing for text-based dialogues [8]. Divekar *et al.* have pioneered a speech-based interaction with a virtual agent [44]. Instead of a virtual agent, a humanoid robot negotiates with a human counterpart through the speech in this thesis. A few works have studied human-robot negotiation, and those works mostly focus on only the interaction, not the negotiation strategy. For example, Takayama *et al.* investigate the effect of a robot's disagreement attitude and its source of voice on the negotiation process with a human counterpart [45]. A Nao humanoid robot that commanded remotely was used to examine whether the handshaking with feedback affected the negotiation outcome [46]. The results show that negotiations reached a more cooperative outcome if partners shake hands before starting to negotiate than if they do not. Aydoğan *et al.* study the effect of gestures [9] in human-robot negotiations. Complementary to these works, this thesis studies the effect of considering the perceived emotional state of the human opponent on negotiation outcome and process. In the dynamic landscape of negotiations, the interplay between humans and AI presents unparalleled opportunities and intricate challenges. This research aims to navigate this space, innovating strategies that meld AI features with human sensibilities, ensuring not just a successful negotiation but a harmonious one.

2.2 Opponent Modeling Strategies

The main opponent strategy focuses on identifying opponents' preferences by analyzing offer exchanges between parties. Afterward, the agent examines the opponent's negotiation offers with estimated opponent preferences to understand its strategy/attitude. As Hindriks, Jonker, and Tykhonov point out that agents can benefit from learning about their opponent during negotiation [47], a variety of opponent modeling approaches have been proposed in the negotiation community, such as opponent's preferences (e.g., [19, 20, 22, 39, 47, 48]), the acceptability of an offer (e.g., [10, 32, 49]) and negotiation strategy/attitude (e.g., [50, 51, 24]). Various modeling techniques have been used in these strategies, such as kernel density, Bayesian learning, and frequentist models. While building up their model, those opponent modeling approaches rely on some assumptions such as having a predetermined deadline, capturing their preferences in the form of an additive utility function, and following a turn-taking negotiation protocols such as (Stacked) Alternating Offers Protocol [23] and conceding over time (e.g., time-based concession strategies). A more detailed explanation about opponent modeling can be found in the survey [18].

Coehoorn and Nicholas propose an opponent model using kernel density estimation (KDE) to estimate the opponent's issue weight vectors [52]. Their approach analyzes differences between two consecutive offers made by the opponent. Considering the entire offer history, a more holistic view can yield profound insights into opponent preferences.

Another common preference model technique in the literature is based on Bayesian learning [47, 48]. Hindriks *et al.* use Bayesian learning to predict the shape of the opponent's utility function, the corresponding rank of issue values, and issue weights [47]. As an extension of Hindrik's work, Yu *et al.* incorporate regression analysis into Bayesian learning by comparing the predicted future bids and actual incoming bids. Accordingly, they update the Bayesian belief model by considering both current and expected coming bids.

Recent studies' most common preference modeling strategies are variations of the frequentist models. The winner of the Second Automated Negotiating Agents Competition [53] called Hardheaded agent [19] uses a simple counting mechanism for each issue value and analyzes the contents of the opponent's consequent offers. The main heuristic is that the opponent would concede less on the essential issues while using the preferred values in its offers. Therefore, while analyzing the opponent's current and previous offer, if the value of an issue is changed, that issue's weight is decreased by a certain amount. While such a simple approach is initially intuitive, information loss seems inevitable. Due to the nature of the negotiation, the opponent may need to concede even on important issues. Those moves may mislead the model. In addition, the concession amount may vary during the negotiation, which the frequentist approach needs to capture.

Moreover, suppose the opponent repeats the same bid multiple times. In that case, the model may overvalue those repeated issue values while underestimating the unobserved values (e.g., converging a zero utility since it is not seen). Tunalı, Aydoğan, and Sanchez [20] aim to resolve those problems by comparing the windows of offers instead of consecutive pairs of offers and offering a more robust estimation of the opponent's behavior. It adopts a decayed weight update to avoid incorrect updates when opponents concede on the most critical issues. Furthermore, it smoothly increases the importance of issue values to avoid unbalanced issue value distributions when the opponent offers the same offer repeatedly. Although their approach outperforms the classical frequency approach, it still suffers from only counting the issue value appearance because it ignores the varying utility patterns of the opponent's offers.

Apart from the opponent modeling in automated negotiation, we review the opponent modeling approaches designed for human-agent negotiations. Lin *et al.* introduce the QOAgent using kernel density estimation (KDE) for modeling opponent's preferences [39]. According to their results, the QOAgent can reach more agreements. In most cases, it achieves better agreements than the human counterpart playing the same role in individual utility. As an extension of QOAgent, Oshrat *et al.* present an agent unlike most other negotiating agents in the automated negotiation, the KBAgent attempts to utilize previous negotiations with other human opponents having the same preferences to learn the current human opponent [10]. This approach requires an essential assumption that human participants will behave similarly to each other. Thus, KBAgent builds a broad knowledge base from its previous opponents and accordingly offers based on a probabilistic model constructed from the knowledge base utilizing kernel density estimation. In their experimental comparison, the KBAgent outperformed the QOAgent. In these studies, the authors focus on the overall negotiation performance rather than the performance of the proposed opponent modeling approach. However, we examine the accuracy of the opponent modeling and the performance of the whole negotiation strategy.

Furthermore, Nazari, Lucas, and Gratch follow a similar intuition with frequentist models for human-agent negotiation [22]. However, they only consider the negotiation issues' preference ranking instead of estimating each outcome's overall utility. For issue values, they consider a predefined ordering. However, those assumptions may not hold in negotiations where a human participant may evaluate issue values differently. In their negotiation, their agent considers the importance of the issues and the expected ordering of the issue values while generating their offers. A similar heuristic with the frequentist approach holds here. That is, an issue is more important if the opponent consistently asks for more on that issue. It leads to the same intrinsic problem of the frequentist approach.

Instead of learning an explicit preference model, some studies focus on understanding what offers would be acceptable for their opponent. Sanchez *et al.* use Bayesian classifiers to learn the acceptability of partial offers for each team member in a negotiation team [49]. They present a model for negotiation teams that guarantees unanimous decisions consisting of predictable, compatible, and unforeseen issues. The model maximizes the probability of being accepted by both sides. While their model relies on predictable issues such as price, our model is designed to handle unpredictable discrete issues. Lastly, it is good to mention the reinforcement learning approach proposed for human-agent negotiation [32]. Lewis *et al.* collect a large dataset consisting of offers represented in natural language from 5808 sessions on Amazon's Mechanical Turk. They present a reinforcement learning model to maximize the agent's reward against human opponents. Accordingly, they aim to estimate the negotiation states acceptable for their human counterparts.

More recently, researchers have been trying to incorporate deep learning models in opponent modeling. For instance, Sengupta *et al.* has implemented a reinforcement learning-based agent that can adapt to unknown agents per experiences with other agents. In order to model the opponent, they have applied the Recurrent Neural Networks model, specifically LSTM, since they use time series data from the negotiation steps. However, due to data limitations, they switched their implementation to a 1D-CNN classifier. They observe an opponent agent's bidding strategy according to the agent's self-utility and try to cast it into a class of known behaviors. According to this classification, the agent swaps negotiation strategy within the runtime [54].

Meanwhile, Hosokowa and Fujita expand upon the classical frequentist approach through the addition of the ratio of offers within specified slices of the negotiation timeline, and they implement a weighting function to stabilize the ratios as time passes to capture the change of an opponent's concession toward the end of negotiation [55].

CHAPTER III

BACKGROUND

In the rapidly advancing domain of human-robot interactions, the negotiation process becomes a cornerstone for effective collaboration. This chapter formalizes the negotiation problem and mentions the main components of the negotiating agent present how to make offers by considering remaining time and the opponent's offer pattern. Then, it explains the most widely used negotiation protocol governing agents' interaction and hybrid negotiation strategy, which combines fundamental negotiation strategies namely time-based and behavior-based strategies.

In the automated negotiation, agents engage in negotiations concerning a finite set of n issues, denoted as $\mathcal{I} = 1, 2, \ldots, n$. Each issue i within this set possesses a range, denoted as $\mathcal{D}_i$, which encompasses all the possible outcomes or values it can take. An outcome represented as $o \in \Omega$ constitutes a comprehensive assignment to this set of issues. Here, Ω is defined as the Cartesian Product of the ranges of possible instantiations for each issue. To express this formally, the collection of all conceivable outcomes can be written as Ω = $\mathcal{D}_1$ X $\mathcal{D}_2$ X... X $\mathcal{D}_n$. Each offer or outcome is evaluated using a utility function that maps each negotiation result to a real number within the range of [0, 1]. This real number signifies the desirability of that particular outcome. The utility function serves as a mathematical representation of the agent's preferences. Additive utility functions are typically employed for this purpose, as described in [56]. Equation 8 illustrates this function, where w_i denotes the significance of the negotiation issue I_i (referred to as issue weight), o_i signifies the value of issue i in the offer o, and V_i represents the valuation function for issue i," which determines the desirability of the issue's value. It is worth noting that, without any loss of generality, we assume that $\sum_{i \in n} w_i = 1$, and the domain of V_i spans from (0 to 1) for any given i. In this context, an issue value is deemed preferable when its valuation value, V_i, is higher. When navigating the negotiation process, an agent relies on its utility function to decide what to offer and when to accept an offer.

3.1 Negotiation Protocol

The negotiation protocol serves as a structured guideline for agents to interact during the negotiation process. Historically, many human-agent negotiation frameworks have predominantly employed text-based communication. Nevertheless, mediums like speech and vision are intrinsic to human communication [57]. It is common knowledge that humans often gravitate towards verbal interaction in negotiations and use gestures to reinforce their points or convey emotions [58]. In this thesis, agents and human participants negotiate with each other by following the Alternating Offers Protocol [23]. Figure 1 shows a visual representation of this protocol.

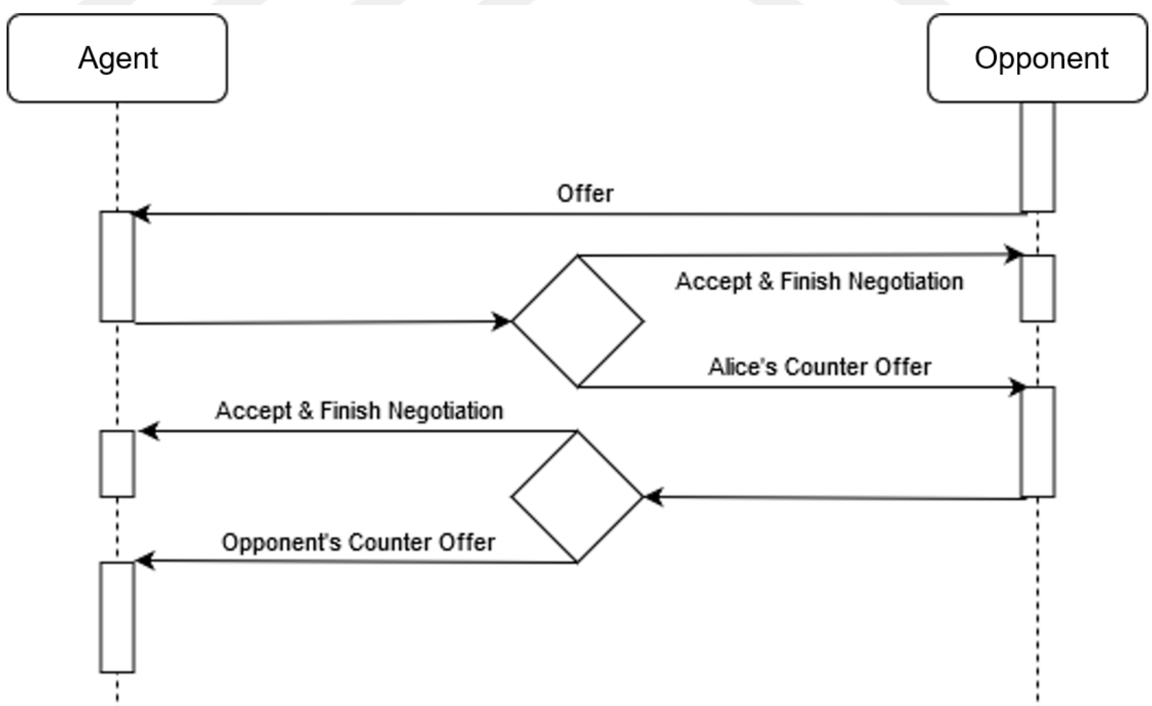


Figure 1: FIPA Representation of Speech-based Protocol [1]

Following this protocol, one of the parties, human negotiator in our cases, initiates the negotiation with an offer. Then, the agent can take the following actions:

- **Processing speech acts**: Agent processes the verbal proposal upon the human's signal. Instead of confining users to specific phrases, our approach champions flexibility. Agent employs dictation methods, converting spoken sentences into structured offers.

- **Acceptance**: Agent evaluates the offer according to their acceptance criteria. If it aligns, it accepts, concluding the negotiation.

- **Counter-offer**: If the given offer is not acceptable, then the agent makes a counteroffer.

Similarly, human subsequently assesses the given offers and the process iterates in a turn-taking fashion until a mutual agreement or a set deadline. A challenge during these interactions was potential misinterpretations due to speech recognition inaccuracies. To mitigate this, detected words with a negotiation lexicon could be compared by using the Levenshtein distance [59] to measure word similarities.

3.2 Hybrid Negotiation Strategy

Since agents must deal in a limited time, the remaining time should be considered during the negotiation. However, only considering the time and adopting a time-based concession strategy would not be sufficient. Therefore, it is crucial to consider the opponent's attitude during the negotiation and act accordingly. Faratin *et al.* propose behavior-dependent bidding tactics, mimicking to some extent opponent's behavior [37]. Similar to [60], we suggest adopting a hybrid strategy [24] that uses both time and behavior-based strategy as a baseline strategy. That strategy calculates a target utility, as shown in Equation 1. The principal intuition is that when time is not crucial (e.g., at the beginning of the negotiation), the agent pays more attention to its opponent's behavior while deciding its next bid's target utility. As the deadline approaches, it tends to find an agreement urgently; therefore, it cares more about the remaining time.

$$TU_{Hybrid} = (t^2) \times TU_{Times} + (1 - t^2) \times TU_{Behavior} \tag{1}$$

$$TU_{Times} = (1 - t)^2 \times P_0 + [2 \times (1 - t) \times t \times P_1] + t^2 \times P_2 \tag{2}$$

$$TU_{Behavior} = U(O_j^{t-1}) - \mu \times \Delta U \tag{3}$$

$$\Delta U = \sum_{i=1}^{4} [W_i \times (U(O_h^{t-i}) - U(O_h^{t-i-1}))] \tag{4}$$

$$\mu = P_3 + t \times P_3 \tag{5}$$

To estimate target utility (TU_{Times}), the tactic uses a time-dependent concession function proposed by Vahidov [36]. Equation 2 represents the adopted concession function where t denotes the scaled time $t \in [0, 1]$ and P_0, P_1, P_2[1] are the maximum value, the curvature, and minimum value of the curve respectively.

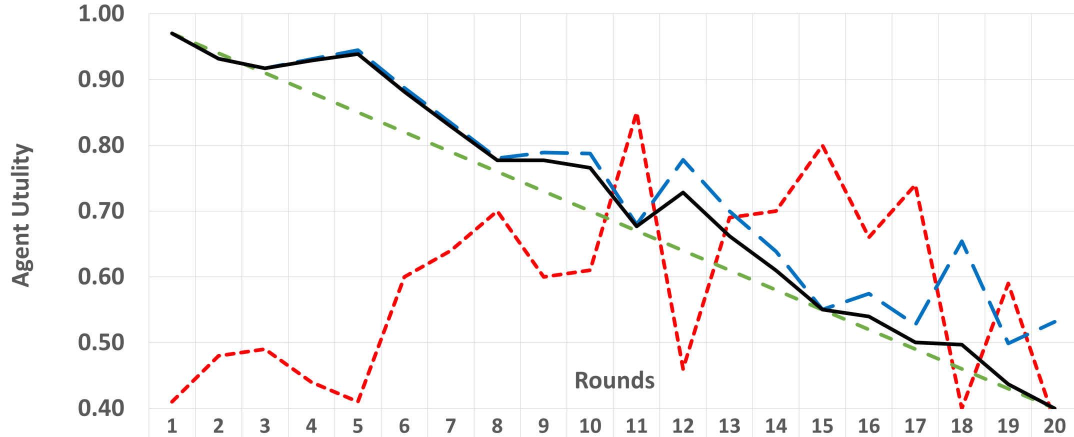
An extension of Tit-For-Tat Strategy [37], which mimics the opponent's moves to some extent, is adopted for the behavior-based target utility. One of the main differences is that this tactic adapts the mimicking ratio dynamically rather than using a fixed ratio. Moreover, [37] considers only the opponent's last two offers and ignores the opponent's other offers. Therefore, it is inclined to miss the opponent's general bidding pattern. In contrast, the extended tactic considers a window of the opponent's bids to deal with this issue. It estimates the utility changes of the opponent's bids within this window by giving more priority to the changes on the most recent ones. In this thesis, the agent considers the opponent's last five offers and estimates the weighted utility difference since human-agent negotiation sessions are at most 20 rounds on average.

To mimic the opponent's behavior, the agent scales the overall utility change by a time-dependent parameter, μ, to estimate a target utility as seen in Equation 3 where $U(O_j^{t-1})$

[1] P_0, P_1, P_2 are 0.9, 0.7, 0.4 respectively in our experiment.

denotes the utility of agent's previous offer. The positive changes mean the opponent concedes; hence, the agent should also concede. Equation 4 shows how the overall utility changes are calculated by considering the opponent's last five consecutive bids where W denotes the weight vector of each utility difference (e.g., W_1 is the weight for the utility difference of the opponent's last two bids). The entire opponent's history is not considered because human strategies fluctuate dynamically. As seen in Equation 5, the empathy coefficient μ is determined by the current time and P_3. Since acting more dominant at the beginning of the negotiation is more efficient for the agent score according to [42], the agent tends to decrease/increase the target utility less than its opponent does at the beginning after the degree of mimic increases over time. The Hybrid agent utilizes the AC_{Next} acceptance strategy, which compares the current target utility with the received utility from the opponent's current offer. If the utility of the opponent's offer is higher or equal to the current target utility, the agent accepts the opponent's offer.

To illustrate how the hybrid bidding strategy works, an example negotiation session of 20 rounds is given in Figure 2 where the red line denotes the Hybrid agent's received utility by the opponent's offer, and the green line, blue dashed line, and bold black line show the target utility estimated by time-based strategy (Equation 2), by behavior-based strategy (Equation 3), and by hybrid strategy (Equation 1) respectively. While the hybrid strategy acts like the more behavior-based strategy at the beginning (See rounds 1-11), its behavior approximates the time-based strategy over time, especially while approaching the deadline (See rounds 15-20). Note that to explore the target utility changes elaborately, the acceptance strategy of the agents is dismissed in this example.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Opponent's Offer	0.41	0.48	0.49	0.44	0.41	0.60	0.64	0.70	0.60	0.61	0.85	0.46	0.69	0.70	0.80	0.66	0.74	0.40	0.59	0.38
Time Based	0.97	0.94	0.91	0.88	0.85	0.82	0.79	0.76	0.73	0.70	0.67	0.64	0.61	0.58	0.55	0.52	0.49	0.46	0.43	0.40
Behavior Based		0.93	0.92	0.93	0.94	0.89	0.83	0.78	0.79	0.79	0.68	0.78	0.70	0.64	0.55	0.57	0.53	0.65	0.50	0.53
Hybrid Strategy	0.97	0.93	0.92	0.93	0.94	0.88	0.83	0.78	0.78	0.77	0.68	0.73	0.66	0.61	0.55	0.54	0.50	0.50	0.44	0.40

Figure 2: Hybrid Agent with Its Components (Time & Behavior-Based)

CHAPTER IV

HUMAN-AGENT NEGOTIATION FRAMEWORK

To research the development of intelligent negotiating agents, we first introduce a framework to distinguish the main negotiation components of agents and necessary utilities. Those components, including the developed interaction mechanism, are explained elaborately in Section 4.1. As our main focus is to design an emotion-aware negotiating agent taking the opponent's emotional state into account, we present an extension of the hybrid negotiation strategy incorporating the human opponent's emotional state into target utility estimation in Section 4.2. Furthermore, we propose a constraint-based opponent modeling and aligned offering strategy for human-agent negotiations in Section 4.3.

4.1 General System Architecture & Components

The nature of human-agent negotiation requires considering different dynamics such as bounded rationality, reciprocity, fairness, and emotional awareness [11]. Different from automated negotiating agents, it is not feasible for humans to make hundreds of offers. On average, the number of offers typically does not exceed 20 offers in human-agent negotiation [11, 12, 13]. In the first annual human-agent negotiation competition, most negotiations end in less than 20 rounds [14]. Apart from exchanging offers, human negotiators exchange arguments and emotional states during their negotiation [28]. While designing a negotiating agent for such a setting, it is necessary to consider how that additional information should be used to utilize the negotiation process. In addition, it is also important the way of communication may influence the interaction. Instead of text-based communication, human negotiators may prefer to communicate via speech. Therefore, such a framework should enable agents to process the speech acts and express offers and arguments via speech.

Moreover, emotions can be crucial in how we think and act. Therefore, it is essential to consider the emotional factor while designing agents negotiating with their human counterparts. There are a number of studies investigating the effect of emotions in negotiation [15, 16, 17]. For instance, de Melo, Carnevale, and Gratch found that human negotiators tend to concede more to a person showing anger than a person mostly expressing their happiness [41]. Similarly, in the study of [42], it was shown that dominant movements and emotional expressions are variables that provide higher scores during human-agent negotiations. However, those studies focus on only the agent's emotional expression. For better interaction, negotiating agents should be not only able to express their emotions in line with the underlying situation but also be able to *perceive their human partner's emotional state and adapt their strategy and interaction accordingly*. Though exchanging emotional state through emoji is supported by the IAGO framework [7], the emotional state of the opponents has yet to be elaborately addressed in Human-Agent Negotiation Competition so far [14].

Accordingly, we present a human-agent negotiation framework including components for the aforementioned requirements as illustrated in Figure 3. In the proposed framework, an agent interacts with its human counterpart via speech, where the human speech is transformed to offer vectors that agents can reason on as well as arguments. The Alternating Offers Protocol, as explained in Chapter III, governs their interaction.

The proposed framework can analyze human negotiator's facial expressions and extract emotional feedback in terms of an emotion vector so that the agent can directly use them in its offering strategy. To generate this vector, the pre-trained emotion recognition model presented by Li [2], which utilizes a CNN with a Deep Locality-Preserving method, is used. This model provides 75% average accuracy with the categorical facial expression feedback of the RAF-DB, one of the most robust in the wild facial recognition databases. It presents a wide range of training instances in terms of gender and race, but before the training, using the balanced version of the dataset is recommended for diversity concerns. This pre-trained

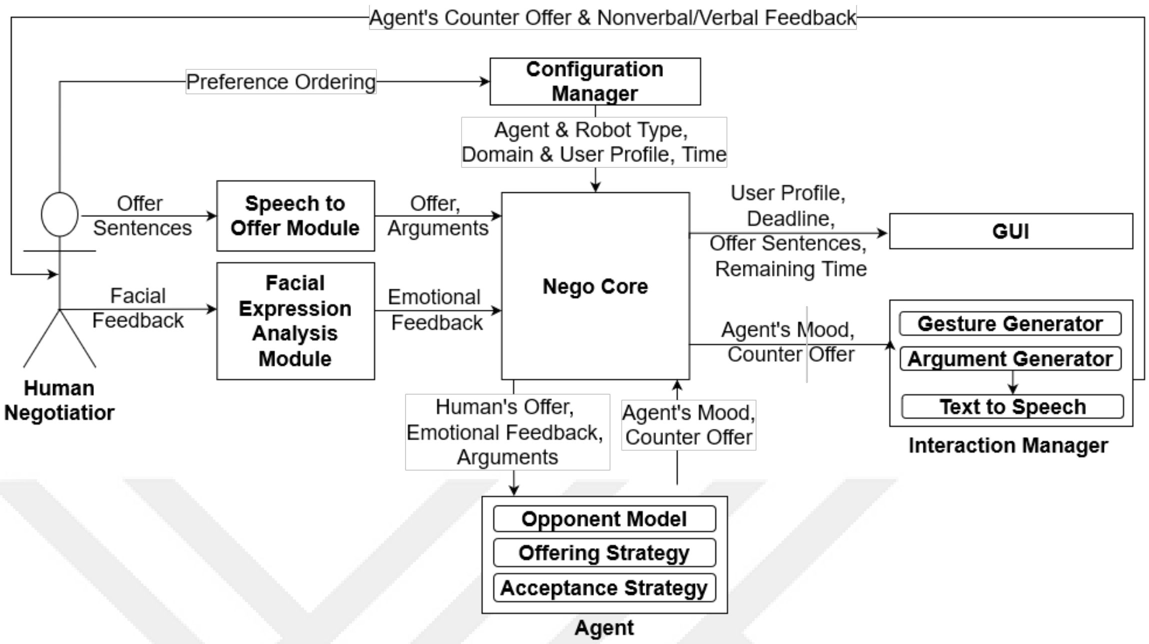


Figure 3: General System Architecture & Components

facial expression analysis model recognizes seven emotions: surprised, fearful, disgusted, happy, sad, angry, and neutral, from the given human facial expressions. Since disgust and fearful categories do not play a role in negotiation, those categories are discarded in this work. Figure 4 shows that the agent collects instant images of human negotiators during the negotiation via a 1080p 60 fps camera. Those images feed the mentioned facial expression analysis model earlier.

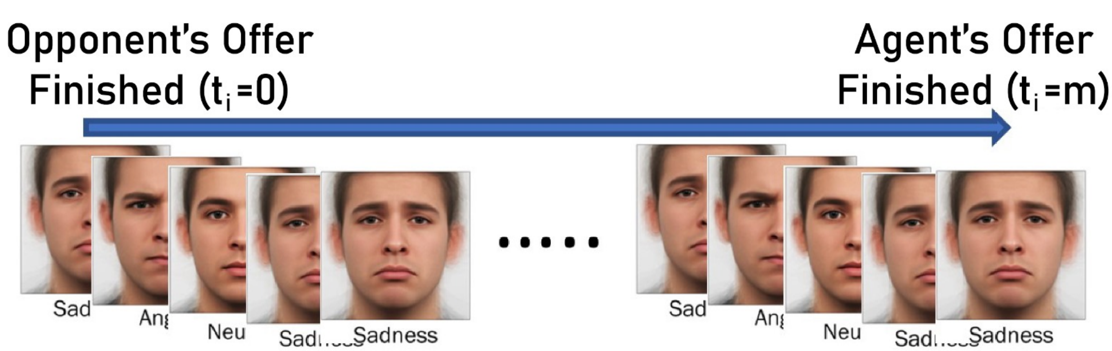


Figure 4: Example Facial Expression Feedback Vector [2]

In addition to utilizing the emotional feedback given by the human negotiators, agents can also express their emotional state or underlying mood to influence the human negotiator's decision. Their attitude can vary depending on their opponent's behavior and remaining time. In our framework, we define eight moods for the agent as follows:

- **Happy:** The agent becomes happy when it finds the opponent's offer satisfactory and accepts it.
- **Pleased:** If the opponent concedes significantly but the opponent's offer is still below the agent's acceptance threshold, it enters a state of pleasure. This mood is triggered only when the opponent's offer utility falls short of the acceptance threshold, indicating the agent's intention to reject the offer.
- **Hopeful:** The agent adopts a hopeful behaviour if the opponent concedes slightly, even if there is no substantial change in its utility. Like the pleased mood, this state is activated when the opponent's offer utility is below the acceptance threshold.
- **Neutral:** The agent feels neutral when the opponent does not modify their offer or its utility remains unchanged.
- **Dissatisfied:** If the opponent makes a self-serving move that marginally decreases the agent's utility but increases their own utility, it becomes dissatisfied.
- **Annoyed:** The agent's mood transitions into an annoyed state when the opponent's self-serving move causing a significant decrease in the agent's utility or when the opponent presents the same offer repeatedly.
- **Frustrated:** The agent experiences frustration under three conditions: (1) when the utility of the opponent's offer falls below the reservation utility, (2) when the current negotiation time surpasses a time threshold, and the opponent's offer utility for the agent remains below its aspiration level or (3) when the opponent presents the same offer three or more times.

- **Worried:** As the negotiation deadline approaches, the agent urges its opponent to expedite the process.

Body language, particularly gestures, is indispensable in human negotiations [61]. Incorporating gestures into the negotiation can naturalize communication, potentially altering the negotiation's dynamics. Agents can signal its underlying mood by means of gestures and arguments. Inspired by real-life negotiations, several gestures are developed for our framework as shown in Figure 5.

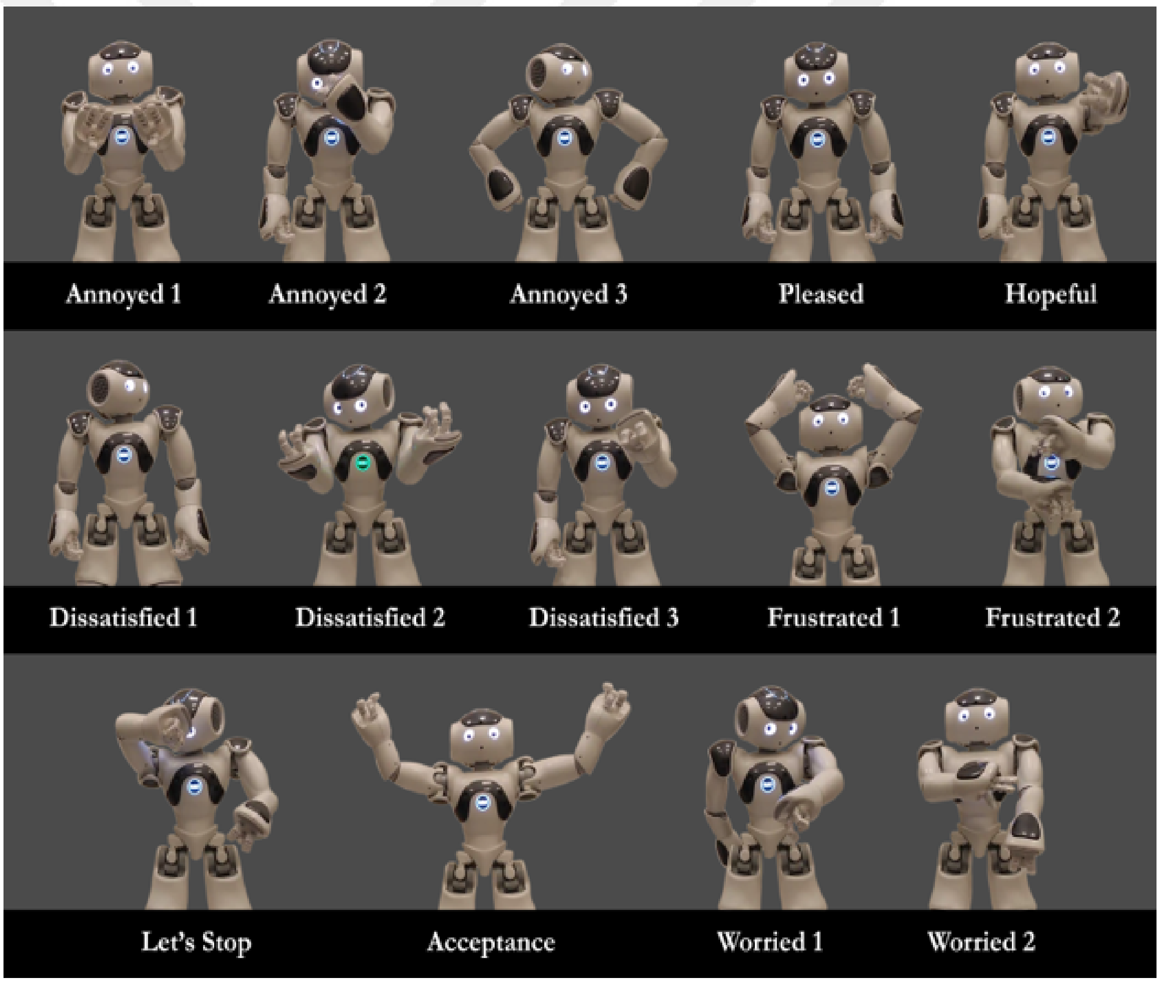


Figure 5: Gestures Aligned with Agent's Mood

Furthermore, agents can express their moods by exchanging some arguments. For the moods above, a set of candidate arguments is defined in the framework. Agents choose the most convenient one according to their mood and strategy. Table 1 shows the alternative arguments for each mood.

Table 1: Predefined Arguments for Each Agent Mood

Mood	Arguments
Happy	Great! I accept your offer!
Pleased	It is getting better but not enough. That sounds good but you can give me a bit more.
Hopeful	Let me think about it. It is getting better, but not enough. I appreciate your offer. It would be great if you concede a bit more. Sounds good; we are almost there.
Neutral	Let's talk about other options.
Dissatisfied	No, I can't accept that, unfortunately. Sorry, I can't accept that. That is not going to work for me! I'm sorry, but I could not agree to your offer. I really can't agree with your offer.
Annoyed	No, It is not acceptable! I wish you did not make this offer. How am I supposed to accept this offer? I don't like your offer. You should revise it. I hope we can find a deal today!
Frustrated	Do you really think that is a fair offer? It is not acceptable at all. I am very disappointed with your offer. It is not acceptable at all. Your offer is not acceptable. Please put yourself in my shoes. We cannot reach an agreement. Let's try to be more collaborative.
Worried	The deadline is approaching. Let's find a deal soon. We are running out of time. Let's be more cooperative to find a deal. Hurry up! We need to find an agreement soon.

4.2 Emotion-Aware Negotiation Strategy

Negotiation is an essential process for resolving conflicts between parties, and in recent years, automated negotiation has attracted significant attention. However, existing negotiation approaches primarily rely on opponent offers and remaining time and overlook the critical role of perceiving the opponent's emotional change during negotiation. Emotional awareness may significantly impact finding mutual agreement in human-agent negotiations. To fill the gap, this thesis presents a promising bidding strategy for negotiating agents, considering the opponent's emotional state and analyzing its effectiveness through human-robot negotiation experiments. The approach aims to establish better interactions between the agent and human negotiators, leading to more admissible settlements.

To achieve it, we extend the hybrid negotiation strategy [24] by incorporating the opponent's emotional state and awareness of our bidding behavior. This negotiation strategy is called "Solver Agent" where two new parameters are introduced in the aforementioned behavior-based target utility calculation, as shown in Equation 6. Here, P_A and P_E denote the awareness and the emotion coefficient, respectively.

$$TU_{BB} = U(O_j^{t-1}) + ({P_A}^2 \times P_E) - [(1 - {P_A}^2) \times (\mu \times \Delta U)] \tag{6}$$

One of the challenges here is estimating the emotion coefficient capturing the opponent's facial expression feedback during the negotiation. Instead of classifying the opponent's primary facial feedback (e.g., Sad and Happy) and adopting a rule-based behavior in line with the perceived categorical emotion, we aim to use the perceived emotions as a complementary or diminishing effect for the decision vector. This approach is considered more dynamic for interactions, instantly changing expressions such as negotiation. Thus, the proposed agent creates and updates a vector of the opponent's facial expressions. Note that Scherer and Ekman utilized categorical facial expression datasets for analyzing participants' facial feedback, which is a well-known and easy-to-use approach while capturing the facial expressions in real-time under daylight in an experimental environment [62, 63]. It is worth noting that we use a vector of categorical emotions (e.g., [sadness: x, happiness: y, ...] where x and y are the percentages of the perceived emotional state) rather than a single perceived emotion. Besides, the dimensional circumplex models [64, 65] that contain valence and arousal could be utilized in the same manner, but this work does not focus on the dimensional model since the accuracy of the 2D prediction can be a new challenge for our research scope.

Recall that emotion analysis model outputs the certainty of the prediction per each emotion (e.g., sad: 0.7, happy: 0.1). Let m be the number of frames collected from the starting time of agent's offer until the time of the opponent's response. Equation 7 shows how P_E – emotion vector, is calculated where F_i^k denotes the certainty value of i^{th} emotion in k^{th} frame and V_i indicate the weights of the i^{th} emotion as seen in Figure 6. Here, V_i is associated with negative weights if the facial expression is labeled with a negative category, such as sadness and anger. Otherwise, they are associated with a positive value. That is, P_E is the weighted average of certain values of each emotion. It is worth noting that the framework can also output the underlying emotional state such as happy or sad depending on the agent's strategy.

$$P_E = \sum_{i=1}^{5} V_i \times (\sum_{k=1}^{m} F_i^k)/m \tag{7}$$

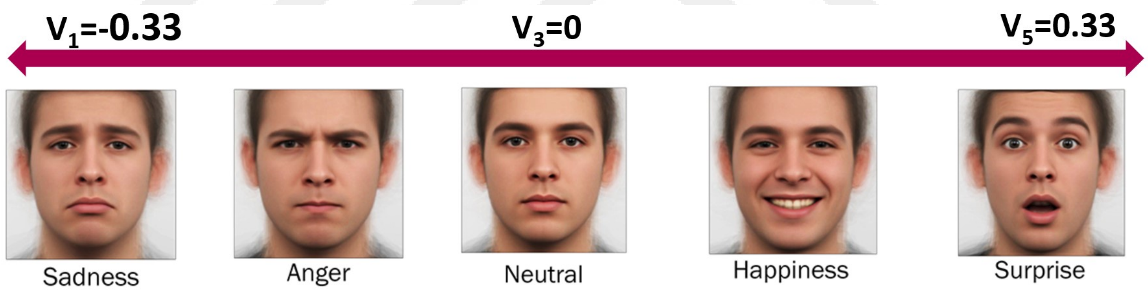


Figure 6: Weights of Categorical Facial Expressions

Considering the situation, such as misclassification of the facial expression, and deception of the opponents (e.g., Showing a sad expression while being pleased with the current offer), the agent should consider to what extent the opponent's behavior is in line with the changes in agent's offer pattern. To estimate opponent awareness coefficient P_A – the degree of the opponent's response to the agent's behavior changes, both agents' subsequent moves [66] (e.g., silent, nice, concession, unfortunate, fortunate, selfish) are analyzed. First, the agent calculates the number of times the opponent changes its behavior from one type to another when the agent changes its behavior type. It corresponds to the degree of the opponent's response to the agent's behavior changes. This number is normalized (i.e., is divided by the total number of the agent's behavior changes). This percentage equals P_A and acts as a seat belt for understanding the correlation between emotional changes received with the camera and the opponent's offer. In this way, the emotion-aware bidding strategy can deal with human manipulation and camera errors. The accurate calculation of P_A depends on how well the agent estimates its opponent's utility function. Since there is a relatively lower number of offers exchanged during human-agent negotiation compared to automated negotiation, conflict-based preference modeling is adopted in this thesis, which is explained elaborately in the following section.

Finally, the Solver Agent adjusts related concession parameters in Equation 1 after a certain number of rounds – the average number of rounds to complete human-agent negotiation. The agent's move plays a crucial role in the received utility at the end of the negotiation when it approaches the deadline. Therefore, the agent acts more carefully and adjusts its concession parameters strategically. To achieve this, we classify the human negotiators' behavior in terms of the percentage of each move type they made in another human-agent negotiation dataset comprising 116 negotiations [1]. A clustering algorithm, K-means [67], categorizes the human players according to their move percentages. This categorization is named as negotiation moves S_T defined in [66]. As a result, five clusters are obtained, where we name them as *fortunate*, *standard*, *silent*, *selfish*, and *concession* according to the most dominant move type. The Solver Agent calculates the move types of its opponent after reaching a certain number of rounds n by checking which cluster the opponent fits and accordingly updates the parameters of its strategy as specified in Table 2. The main intuition is that the agent's mimicking level increases against a selfish opponent while declining the mimicking level against a silent opponent. When our agent notices that its opponent tends to concede, it decreases its concession rate to gain higher utility.

Algorithm 1 shows how Solver Agent makes its offers during the negotiation. The first round offers according to the time-based strategy (Lines 10-11). In the following rounds,

Table 2: Dominant Move Type and Actions

Dominant Move Type	Action
Fortunate	Increase Concession Rate (i.e., declining P_1)
Silent	Decrease the Empathy Score (μ)
Selfish	Increase the Empathy Score (μ)
Concession	Decrease Concession Rate (i.e., inclining P_1) Decrease Time-Based Target Utility (i.e., inclining P_2)

it first evaluates the emotion coefficient (Line 13), as explained above. Note that P_A is initially set to 0.5, and its value will be updated after a certain number of rounds, n (Line 19). If the number of rounds is less than n (Line 14), the agent generates offers after calculating the emotion coefficient (Line 15). Otherwise, it uses its opponent model to calculate the awareness coefficient (Line 18) and sensitivity coefficient (Line 19) and updates the parameters of the offer tactics accordingly (Line 20). A heuristic-based conflict search method estimates the opponent's preference model. This method works effectively for small-sized negotiation domains. After n rounds, the agent can approximate the opponent's preferences well. In our setup, n is set to 8. After generating offers with those parameters (Line 21) and calculating the Nash offer (Line 22), it checks whether the utility of the Nash offer is higher than the generated offer. If so, it offers the Nash offer (Line 23); otherwise, the generated offer is offered.

4.3 Conflict-Based Opponent Modelling and Negotiation Strategy

Day by day, human-agent negotiation becomes more and more vital to reach a socially beneficial agreement when stakeholders need to make a joint decision together. Developing agents who understand not only human preferences but also attitudes, is a significant prerequisite for this kind of interaction. Studies on opponent modeling are predominantly based on automated negotiation and may yield good predictions after exchanging hundreds of offers. However, this is not the case in human-agent negotiation in which the total number of rounds does not usually exceed tens. For this reason, an opponent model technique is needed to extract the maximum information gained with limited interaction. This

Algorithm 1 Solver Agent's Offer Strategy

t_{cur}: current time, $O_j^{t_{cur}}$: Alice's counter offer
$O_h^{t_{cur}}$: human opponent's current offer
$nash_{offer}$: generated Nash offer
$U(nash_{offer})$: the utility of the Nash offer for Alice
$U(O_h^t)$: the utility of the human opponent's offer for Alice
H_o: human opponent's bid history, A_o: Alice's bid history
$EstOpp_{pref}$: estimated opponent's preference profile
$tactic_{time}$: Alice's time based bidding tactic
$tactic_{solver}$: Alice's time and behavior based bidding tactic
if $|H_o| < 2$ **then**
    $O_j^{t_{cur}} \leftarrow$ generateOffer($tactic_{time}$);
else
    $P_E \leftarrow$ updateEmotionEffect($opponent_{emotions}$);
    if $|H_o| < n$ **then**
        $O_j^{t_{cur}} \leftarrow$ generateOffer($tactic_{solver}$);
    else
        $EstOpp_{pref} \leftarrow$ updateOpponentProfile(H_o);
        $P_A \leftarrow$ updateAwareness(A_o, H_o, $EstOpp_{pref}$);
        $S_T \leftarrow$ updateSensitivityClass(H_o, $EstOpp_{pref}$);
        $tactic_{solver} \leftarrow$ updateTacticParams(S_T,P_A,P_E);
        $O_j^{t_{cur}} \leftarrow$ generateOffer($tactic_{solver}$);
        $nash_{offer} \leftarrow$ generateNashOffer($EstOpp_{pref}$)
        if $U(nash_{offer}) > O_j^{t_{cur}}$ **then**
            $O_j^{t_{cur}} \leftarrow nash_{offer}$
        end if
    end if
end if

thesis presents a conflict-based opponent modeling technique and compares its prediction performance with the well-known approaches in human-agent and automated negotiation experimental settings.

4.3.1 Proposed Conflict-Based Opponent Modelling

Our opponent modeling called *Conflict-Based Opponent Modeling* (CBOM) aims to estimate the opponent's preferences represented utilizing an additive utility function shown in Equation 8 where w_i represents the importance of the negotiation issue I_i (i.e., issue weight), o_i represents the value for issue i in offer o, and V_i is the valuation function for issue i, which returns the desirability of the issue value. Without losing generality, it is assumed that $\sum_{i \in n} w_i = 1$ and the domain of V_i is (0,1) for any i. The higher the V_i is, the more preferred an issue value is.

$$\mathcal{U}(o) = \sum_{i=1}^{n} w_i \times V_i(o_i) \tag{8}$$

Regarding the issue valuation/weight functions (i.e., preferences on issue values), targeting to learn these functions directly from the opponent's offer history may not be a reliable approach since the opponent's negotiation strategy may mislead us. Although the contents of the opponent's offers give insight into which values are more preferred over others, depending on the employed strategy, we may end up with a different model estimation. For instance, the frequency of the issue value appearance might be a good indicator for understanding the ranking of issue values. However, it is not sufficient to deduce to what extent each issue value is preferred. Fluctuations in the opponent's offers or repeating the exact offers often mislead the agent into accurately estimating the additive utility function. Therefore, we aim first to detect the preference ordering pattern rather than quantifying an evaluation function directly and then interpolate it.

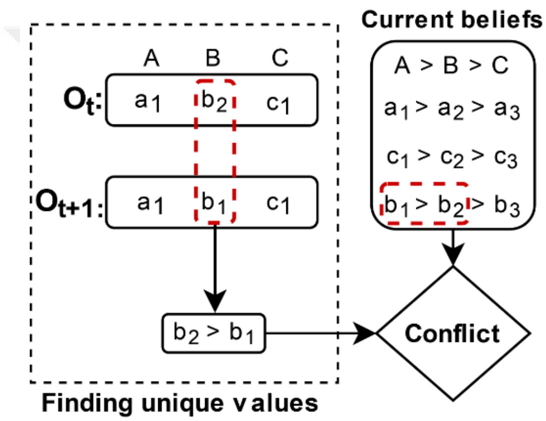
As most of the existing opponent models in the literature do, our model assumes the opponent concedes over time. Initially, the agent does not know anything about its opponent's preferences; therefore, it creates a template estimation model according to the given domain configuration. In other words, the agent starts with an initial belief in ranking the issue values (V_i) and issues (W_i). The agent may assume that the opponent's value function is the opposite of its value function. For instance, If the agent prefers $V_1 >$ to V_2, it may consider that its opponent prefers V_2 to V_1. Alternatively, it may consider an arbitrary ordering for the opponent. Consider that we have n issues and for each issue i there are possible issue values denoted by $D_i = \{v_1^i, \ldots, v_m^i\}$. Assuming an arbitrary preference ordering for the opponent, Equation 9 and Equation 10 shows how the initial valuation values and issue weight are initiated. The agent keeps the issues and issue values in order in line with the estimated opponent preferences. Meaning that v_k^i is preferred over v_j^i by the opponent where where $k > j$. Accordingly, Equation 9 assigns compatible evaluation values via max normalization. Similarly, the issue weights are initialized by sum normalization, where each issue weight is in the $[0, 1]$ range, and their sum is equal to 1. Equation 10 ensures that their sum equals one.

$$v_j^i = \frac{j}{|D_i|} \tag{9}$$

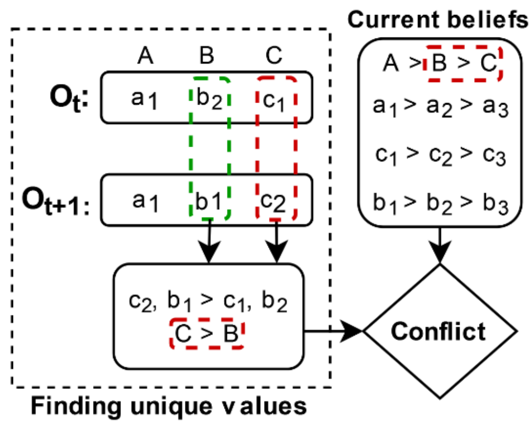
$$W_i = \begin{cases} W_{i-1} + \frac{W_{i-1}}{n} & i > \frac{n}{2} \\ W_{i+1} - \frac{W_{i+1}}{n} & i < \frac{n}{2} \\ \frac{1}{n} & i = \lceil \frac{n}{2} \rceil \end{cases} \tag{10}$$

As the agent receives the opponent's offers during the negotiation, it updates its belief incrementally based on the inconsistency between the current model and the opponent's offers. To achieve this, it stores all bids made by the opponent so far, and when a new offer arrives, the current offer is compared with the previous bids with respect to any conflicting ordering. In particular, common and different values in the offer contents are detected. For different values, the system checks whether there is any conflicting situation with the current model. Recall that the current offer is expected to have the less preferred values since the model assumes that the opponent concedes over time. However, according to the learned model, the ordering may not match the expectation. In such a case, the model is updated.

Two types of conflict in the estimated model could be detected: *issue value conflict* and *issue conflict*. To illustrate those conflicts, let us examine some examples where agents negotiate over three issues (i.e., A, B, and C) in Figure 7. As current belief indicates $b_1 \succ b_2 \succ b_3$ where b_i denotes a possible issue value for the issue B, b_1 is preferred b_2. In the given negotiation dialogue in Figure 7, it can be seen that the opponent's previous offer and current offers are O_t $=< a_1, b_2, c_1 >$ and O_{t+1} $=< a_1, b_1, c_1 >$, respectively. Agents can examine the contents of the offers and find unique value changes to make some inferences on the preferences. For our case, the only difference in the offers is the value of the issue B. Relying on the assumption that the human negotiator leans towards concession over time, the agent could infer $b_2 \succ b_1$. Recall that the most preferred values would appear early. As seen clearly, this preference ordering conflicts with that of the agent's belief. We call this type of conflict "issue value conflict" in our study.



(a) Issue value conflict



(b) Issue conflict

Figure 7: Preference Conflict Extraction Example

The latter conflict type is about the importance of the issues. In the given an example in Figure 7, the consecutive offers involve more than one issue value difference, particularly on issues B and C. Then, the agent can deduce $(c_1, b_2) > (c_2, b_1)$ by relying on the concession assumption mentioned above. Individually, ordering in issue C is consistent with the belief (i.e., $c_1 \succ c_2$); however, the ordering on issue B is conflicting (i.e., $b_2 > b_1$). Therefore, in order to have $(c_1, b_2) \succ (c_2, b_1)$, the importance of the issue C should be higher than that of B (i.e., $C \succ B$). This inference conflicts with the current belief of the agent, which says B is more important than C.

Algorithm 2 shows how the ranking of the issue values is extracted. When the opponent makes an offer (O_c), the agent compares the content of the current offer with that of each offer in the opponent's offer history to find the unique values and consequently extract some preferential comparisons (Lines 1–4). Afterward, the agent keeps all those comparisons in a dictionary called CM (Line 3). By reasoning on each comparison in this set by considering the current belief set, each conflict is extracted and stored in AC (Line 5-7). It is worth noting that the method can find issue value conflicts consisting of multiple issues. After keeping track of all possible conflicts, the agent must determine how to update its beliefs. Counting the number of conflicts on each issue value pair, it considers the issue value orderings having the least conflicts and updates its belief accordingly (Lines 8-16). The agent detects issue value pairs in the conflict set for each issue and compares their occurrences to determine which one to stick on. For instance, if the agent observes conflicting information, the more frequent ordering becomes more dominant, and the agent adapts its beliefs accordingly. After updating the beliefs about issue value orderings, it does the same kind of updates for the issue ordering (Lines 18-25). After finalizing the updates on the rankings, it estimates the utility space of the opponent by utilizing the update operations in Equation 9 & 10.

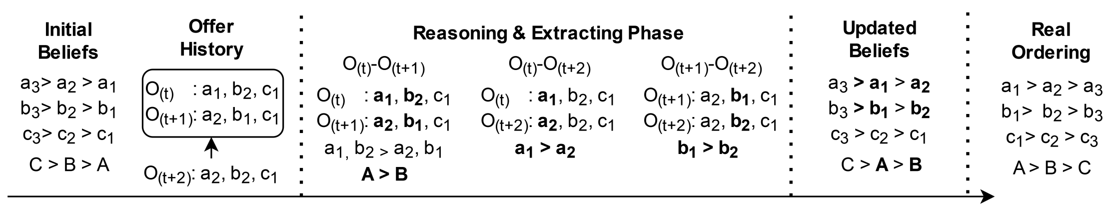


Figure 8: Example Process of the Conflict-based Opponent Model (CBOM)

To illustrate this, we trace the negotiation in Figure 8, where we can observe how this opponent model works. Following the same domain, we first arbitrarily set our initial beliefs about preference ordering (e.g., $a_3 \succ a_2 \succ a_1$ for the values of issue A).The agent keeps track of offers made by the opponent so far. In our example, you can see the offer history at time $t + 2$. Following, the agent compares all previous offers with each other (i.e., pairwise comparison) and tries to extract an ordering relation. Here, O_t and O_{t+1} denote the first and second offer made by the opponent. Since the agent believes that the opponent's earlier offers are more preferred over the later offers, it extract that a_1, $b_2 \succ$

a_2, b_1. This knowledge does not give any novel insight to update our beliefs, but we store this ordering for future analysis in the following rounds. When the opponent makes the offer O_{t+2}, the model compares it with all the previous offers pairwisely as well as the previously extracted information (e.g., the a_1, $b_2 \succ a_2$, b_1 relation). Starting from the first offer in the offer history (O_t-O_{t+2}), the model acquires the information of $a_1 \succ a_2$, since there is only one issue with a different value. When it compares O_{t+1} with O_{t+2}, it extracts ($b_1 \succ b_2$) and updates its beliefs accordingly. Similarly, the extracted information could be utilized to reason about the ordering of the negotiation issues (e.g., $A \succ B$) based on the contradiction between (a_1, $b_2 \succ a_2, b_1$) and ($b_1 \succ b_2$). Consequently, the agent deduces that the importance of issue A is more than issue B considering the assumption that one-issue comparisons are more reliable than multi-issue comparisons, which conflicts with the current belief and updates its belief accordingly.

4.3.2 Proposed Conflict-Based Negotiation Strategy

This section presents our negotiation strategy employing the opponent model mentioned above. This strategy incorporates the estimated opponent modeling into the Hybrid strategy [24], which estimates the target utility of the current offer based on time and behavior-based concession strategies.

Algorithm 3 elaborates how the agent makes its decisions during the negotiation. In each round, it calculates a target utility by employing the hybrid bidding strategy. Consequently, it generates candidate offers that were not offered by the agent (i.e., CBOM Agent). Its utility is in the range of lower and upper target utility (i.e., TU_{cbom} - ϵ and TU_{cbom} + ϵ) (Lines 1–9). If there is no such an offer, the boundary is enlarged with a dynamically generated small number according to the domain size (Line 8). We define a round count n where we believe the agent has enough offers from its opponent to estimate their preferences. The value of n may vary depending on whether the agent negotiates with a human or agent negotiator. If the number of received offers from the opponent is less than the n, the agent picks the offer maximizing its utility among potential offers (Lines 10–12). Shortly, the system does not engage the opponent model until there are enough offers accumulated in the history of opponent offers. Otherwise, the agent selects the offer whose estimated utility product is the maximum (Line 14). If the opponent made an offer with a utility higher than our lowest utility bid and the utility of the current candidate's offer (Line 16), the agent accepted its opponent's offer instead of making the offer. This acceptance condition is slightly more cooperative than the AC_{next} acceptance strategy. Otherwise, it makes the chosen offer (Line 19).

Equation 1 outlines how the agent computes the target utility for its upcoming offer, according to [24]. The concession function (TU_{Times}), represented by Equation 2, incorporates t, the scaled time ($t \in [0, 1]$), and P_0, P_1, P_2, which correspond to the curve's maximum value, curvature, and minimum value, respectively. Note that the values of P_0, P_1, and P_2 in our experiment are 0.9, 0.7, and 0.4, respectively. The behavioral aspect of the "Hybrid" strategy involves scaling the overall utility change by a time-varying parameter, μ, to estimate the target utility, as demonstrated in Equation 1. $U(O_a^{t-1})$ signifies the agent's utility for its preceding offer. Positive changes imply that the opponent has made concessions; hence, the agent should also make concessions. In Equation 3, $U(O_a^{t-1})$ again represents the agent's utility for its prior offer. Positive changes indicate that the opponent has conceded, prompting the agent to make concessions. Considering the opponent's previous n bids, where W_i represents the weights of each utility difference, the behavior-based approach determines overall utility changes, as demonstrated in Equation 4. Equation 5 reveals that the value of the coefficient μ is determined by the current time and P_3, which controls the degree of mimicry. Initially, the agent decreases or increases the target utility less than its opponent; subsequently, the degree of mimicry rises over time. Therefore, the "HybridAgent" strategy can smoothly conform with domains of varying sizes and harmonize with distinctive opponents utilizing behavior-based components of the HybridAgent. As an extension of the bidding strategy, CBOM agent also generates a target utility value by combining different p-values for various domain sizes. It cares about the social welfare score for both parties, choosing the most agreeable offer from the list of offers that the opponent model creates. Thus, it is expected that CBOM agent can achieve higher utility while maximizing social welfare and finding quicker mutual agreement.

In accordance, Figure 9 illustrates an example of the selected offer of the CBOM Agent according to its boundaries. The figure is structured with the y-axis representing the agent's utility and the x-axis representing the opponent's utility for the potential outcomes in the domain. Each outcome is depicted by blue dots on the graph. The red dot represents the target utility offer at a given time, indicating the preferred outcome for the agent. The red circle is drawn by adding the target utility to an epsilon value. Within this boundary, the agent selects the offer closest to the Nash offer (d_N), depicted in green.

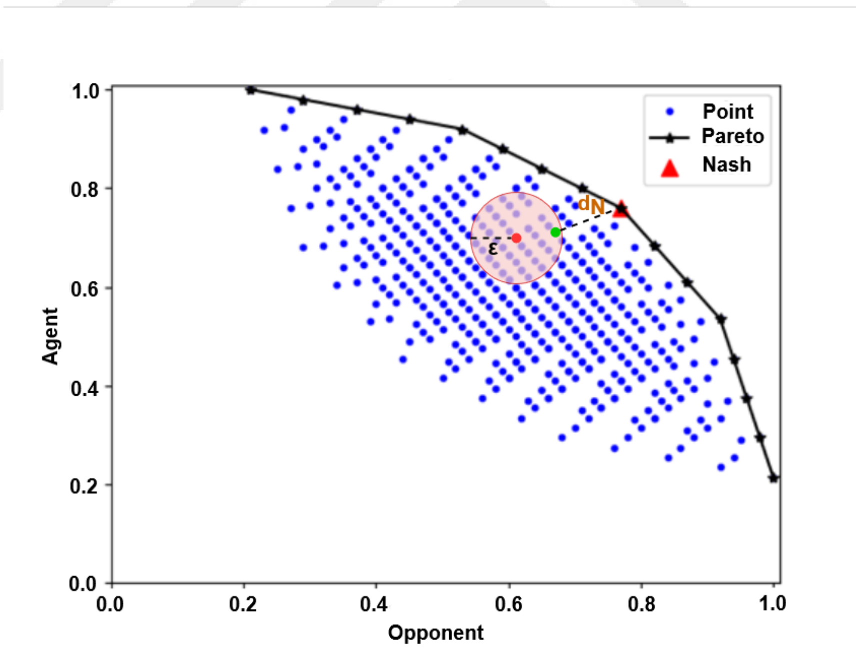


Figure 9: Offer Selection Example of the CBOM Agent According to ϵ Boundary

Algorithm 2 Conflict-based Opponent Model (CBOM)

Require:

O: Offer history, O_c: Current Offer, B_c: Current Belief, I: Issues, V_i: Values

UV: A list of unique values for a given offer pair

CM: Comparison map of unique values per each offer pair

AC: All conflicts extracted from comparison map

VC: A list of conflicted value pairs for an issue

IC: A list of conflicted issue pairs

U_{opp}: The estimated opponent utility space

```
for each O_i ∈ O do
    UV ← findUniqueValues(O_i, O_c)
    CM.append(UV)
end for
for each c ∈ CM do
    AC.append(extractConflictsFrom(c, B_c))
end for
for each i ∈ I do
    VC ← getValueConflictbyIssue(AC, i)
    for each (p, r) ∈ VC do
        if ‖VC(r, p)‖ > ‖VC(p, r)‖ then
            B_c(i) ← r ≻ p
        else
            B_c(i) ← p ≻ r
        end if
    end for
end for
IC ← getIssueConflict(AC)
for each (A, B) ∈ IC do
    if ‖IC(A, B)‖ > ‖IC(B, A)‖ then
        B_c(I) ← A ≻ B
    else
        B_c(I) ← B ≻ A
    end if
end for
U_opp ← estimateOppUtilitySpace(B_c)
```

Algorithm 3 Conflict-based Negotiation Strategy

O_{space}: Offer space, n: Minimum number of round required for CBOM
O_{opp}, O_{cbom}: Opponent's & CBOM agent's offer history, respectively
$U_{cbom}(o)$: The utility of an offer o for the CBOM agent
U_{opp}: The estimated utility space of the opponent
ϵ: Parameter controlling the bid utility window
TU_{Hybrid}: Calculated target utility with Hybrid Bidding Strategy
$O_{potential} \leftarrow \{\}$
while $\|O_{potential}\| \succ 0$ **do**
  for each $o \in O_{space}$ **do**
    if $(U_{cbom}(o) \in [TU_{Hybrid} - \epsilon, TU_{Hybrid} + \epsilon])$ & $(o \notin O_{cbom})$ **then**
      $O_{potential} \leftarrow O_{potential} + o$
    end if
  end for
  $\epsilon \leftarrow \epsilon + 0.01$
end while
if $\|O_{opp}\| < n$ **then**
  $O^t_{cbom} \leftarrow \arg\max_o U_{cbom}(O_{potential})$
else
  $U_{opp} \leftarrow CBOM(O_{opp})$
  $O^t_{cbom} \leftarrow \arg\max_o U_{cbom}(O_{potential}) * U_{opp}(O_{potential})$
end if
if $(min(U(O_{cbom} \cup O^t_{cbom})) \leq U(O^t_{opp}))$ **then**
  Accept O^t_{opp}
else
  Return O^t_{cbom}
end if

CHAPTER V

EVALUATION OF EMOTION-AWARE STRATEGY

To evaluate the performance of proposed negotiation agents, we designed a user experiment where our humanoid robot called “Alice” negotiates with participants on resource allocation. Each participant is asked to negotiate with Alice two times (one session with a hybrid strategy and one session with the Solver Agent). In our experiments, both agents employ the AC-Next acceptance strategy where the agent accepts an offer if the utility of the given offer is higher than or equal to the utility of its following offer [56]. We use the randomization technique to minimize the learning effect on negotiation results (i.e., counterbalancing). For half of the participants, Alice employs a Solver Agent in the first negotiation session, while she employs a Hybrid Agent in the second. Alice employs those strategies in reverse order for the rest of the participants.

We have recruited 28 participants (i.e., 23 male and 5 female university students; median age: 23.7) for our human-robot experiments. We also asked participants to rate their English level on a scale of 1-5 (1 for beginner, 5 for advanced); the average is 4.4. For the experiment, we first asked participants to fill out the pre-negotiation form and to rank the following items concerning their priorities; decreasing the opponent’s utility, decreasing agreement time, increasing their utility, and getting the best deal for both sides where the highest and lowest priority is denoted by 4 and 1 points, respectively. Figure 10 shows that we have diversified types of negotiators whose priorities vary since the score distributions for each item are close to each other.

According to our scenario, the participants and Alice are lucky customers in a supermarket who will receive free fruits as a gift. All they need is to find an agreement on how they will share fruits between them. There are four types of fruits, and we have four for

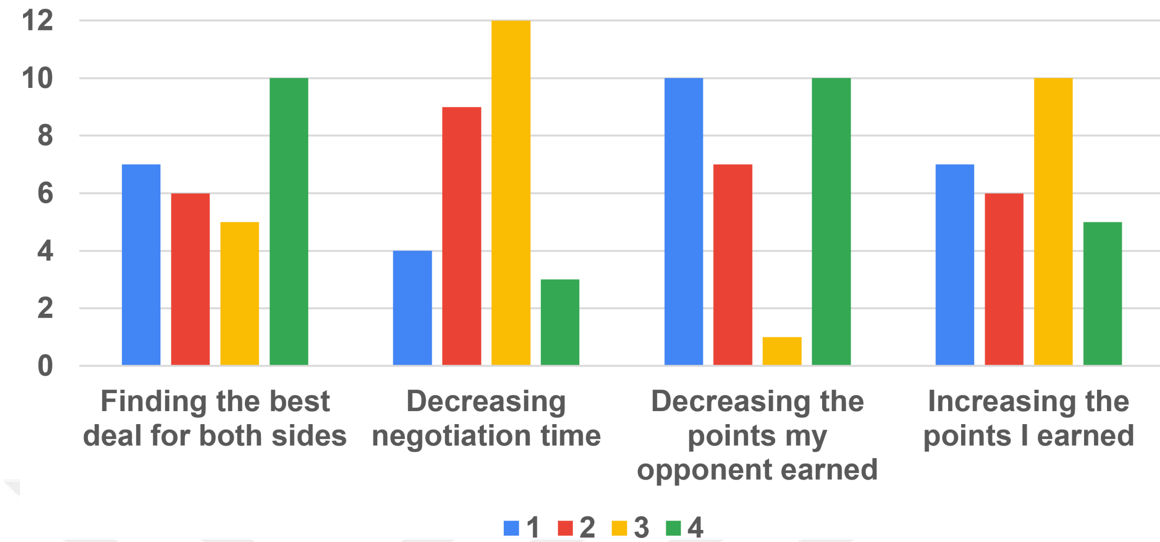


Figure 10: Ranking of Participants Priorities

each of them. For a successful allocation, each participant should collect at least 40 points; otherwise, they will receive zero points. There is also a time limitation for this game. They need to come up with an agreement in 10 minutes. Table 3 shows Alice and the participant's preference profiles for both sessions. It is worth noting that the participants know only their scores and are informed that Alice does not know their scores either. Before their negotiation, the interaction protocol is explained to the participants before their negotiation via a demo video. Besides, they have a training session where they negotiate a more straightforward problem for 10 minutes.

Table 3: Preference Profiles for Negotiation Sessions

	First Negotiation		Second Negotiation	
Items	**Alice's Preferences**	**Participant's Preferences**	**Alice's Preferences**	**Participant's Preferences**
Watermelon	4	12	12	4
Banana	1	8	8	1
Orange	12	4	4	12
Apple	8	1	1	8

After the training session, participants receive their preference profile for their negotiation session. After studying the given profile, they are asked to negotiate with Alice accordingly. After completing their negotiation, participants fill out a questionnaire form regarding their first negotiation. After a 10-minute break, they start their second negotiation with a new preference profile. They are told that their preferences are utterly different to prevent the learning effect. However, only the order of the scores is changed, and the value distribution of the scores remains the same for a fair evaluation. During their negotiation, participants can see their preference profile, offer information, remaining time, and whose turn is on display, as shown in Figure 11.

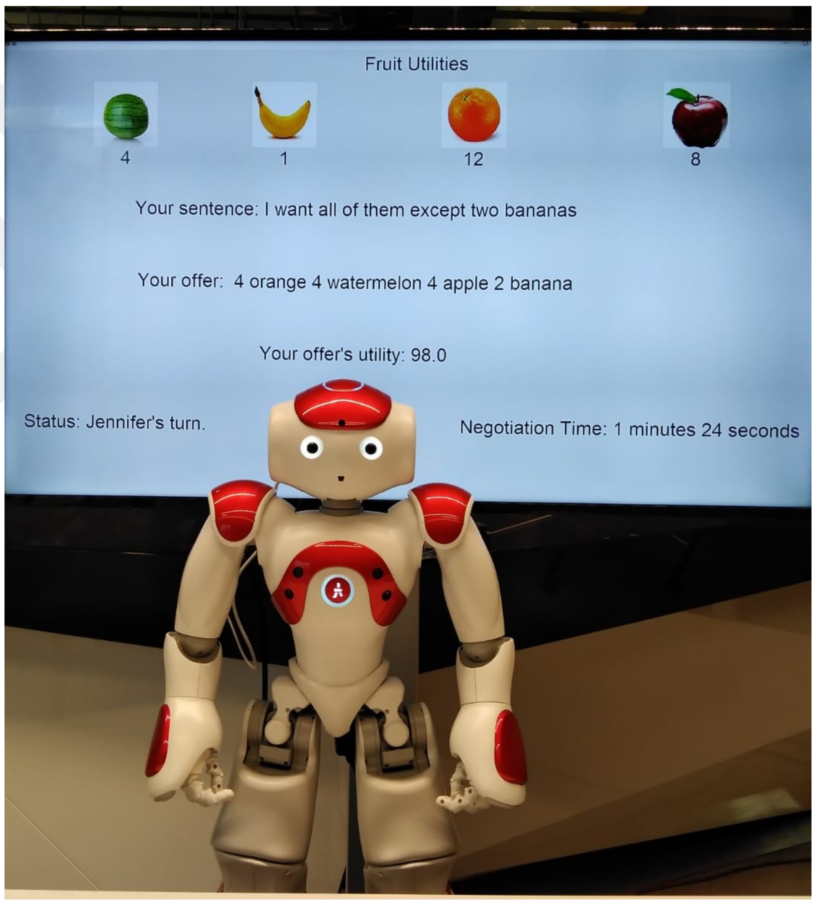


Figure 11: Experimental Setup

Figure 12 shows the average scores gained by both parties separately and the average normalized products of scores. As far as the individual agent score is concerned, it is seen that Alice received higher scores on average when it employed Solver Agent (0.727 versus 0.677). The results are statistically significantly different on agent scores under the two-tailed paired sample T-test with a 95% confidence interval where T=-2.134 and p =0.042. When the average score gained by the human participants is investigated, we observed that their averages are close to each other (0.770 vs. 0.787). Since these scores are not normally distributed according to the Kolmogorov-Smirnov test, we applied a non-parametric statistics test, namely the Wilcoxon-Signed Rank Test. We have observed no statistically significant effect of using different negotiation agents on the user score [Z=-1.1, p = 0.272]. It supports that considering the emotions and awareness of the opponent does not decrease the score of the human negotiator while it increases the agent's score on average. Normalized score product is calculated by dividing the product of scores by the Nash Product. In our scenario, the Nash Product is equal to 0.64. As seen in Figure 12, the average of the products of the scores received by Alice and her human opponent is higher when Alice employs Solver Agent (0.871 vs. 0.821). Wilcoxon-Signed Rank Test shows their means are statistically significantly different with a 90% confidence interval where Z=-1.843, p = 0.066. That means the agreements are better for both parties when Alice adopts Solver Agent.

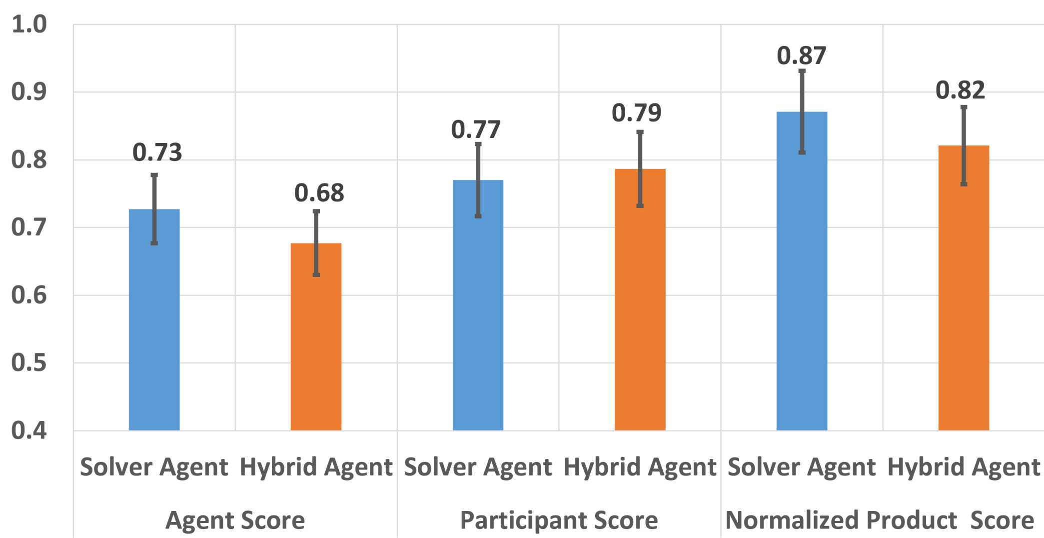


Figure 12: Average of Individual and Normalized Product Scores

Figure 13 demonstrates the average agreement time and round, respectively. Regarding the normalized agreement time, the parties reached agreements faster when Alice employed Solver Agent (on average agreement time for Solver: 0.405 versus for Hybrid: 0.509). We have applied the two-tailed paired sample T-test to see if there is a statistically significant difference in the negotiation agreement time when Alice uses different negotiation strategies. We have observed a statistically significant effect of using other negotiation agents on agreement time [T=1.795, p = 0.083] with a 90% confidence interval. We compare the total number of bids in both settings. The average of total bids is 14.96 when Alice employs the Solver Agent, while it equals 19.39 when it uses Hybrid Agent. According to the two-tailed paired sample T-test with a 95% confidence interval, the mean values are statistically significantly different [T=2.062, p = 0.048].

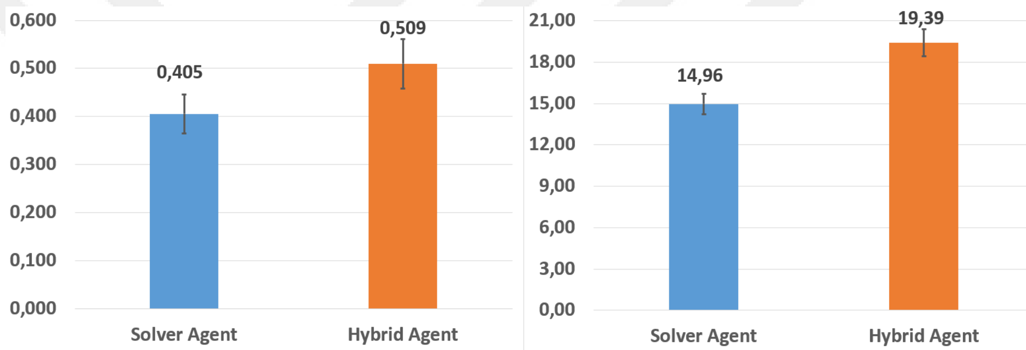


Figure 13: Average Negotiation Time and Rounds

Furthermore, we evaluate the human participants' responses to the 9-point scaled questions listed in Table 4 where 1 denotes that participants "strongly disagree" and 9 denotes that participants "strongly agree" the given arguments. Figure 14 shows the average ratings given by the participants. Regarding fairness, human participants found that Solver Agent's bidding is fairer than Hybrid Agent's bidding (7.4 versus 6.8 for Q1; 7.3 versus 6.5 and 3.9 versus 4.4 for Q8). Regarding human-likeness, they all agree that the developed strategies are human-like (on average ratings: 7.2 and 7.4 for Q2). We ran a 2-tailed t-test, and the p-value for Q5 is 0.052. There is a statistical difference with a 90% confidence interval. Participants perceived that the robot with the Hybrid strategy cares about their preferences more than that with the Hybrid one. There is no statistically significant difference for other questions, but it does not change the fact that, on average, our strategies are evaluated positively.

Table 4: Question Descriptions

Question	Description
Q-1	Alice negotiated in a fair way.
Q-2	Jennifer negotiated with me human likely.
Q-3	Alice took into account my emotional states and adapted her next offer.
Q-4	Alice tried to find the best deal for both of us.
Q-5	I observed that Alice cared about my preferences
Q-6	I observed that Alice consider my behavior.
Q-7	I am satisfied with my negotiation performance.
Q-8	Alice often made very unfair offers.

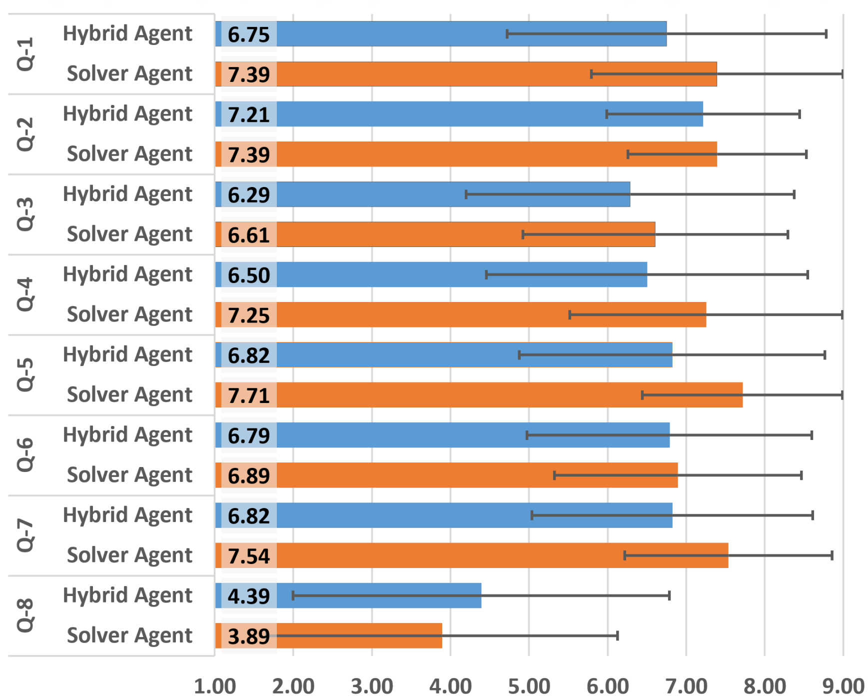


Figure 14: Questionnaire Results

CHAPTER VI

EVALUATION OF CONFLICT-BASED APPROACHES

We first examine the performance of the proposed Conflict-based Opponent Model (CBOM) by conducting two different human experiments (Section 6.1 & 6.2) and extend this evaluation by considering the performance of the proposed strategy using this opponent model through agent-based negotiation simulations (Section 6.3). To show how well the proposed opponent modeling approach predicts the human opponent's preferences, we conducted experiments where participants negotiated with our agent on a given scenario to find a consensus within limited rounds by following the Alternating Offers Protocol (see Chapter III).

We consider the performance metrics to assess the quality of the predictions: Spearman's correlation and root-mean-square error (RMSE). The former metric indicates the accuracy of the predicted order of the outcomes according to the learned utility function, whereas the latter measures how accurate estimated utilities are. For correlation estimation, possible outcomes are sorted concerning the learned opponent model, and this ranking is compared with the actual ordering. Consequently, the Spearman correlation is calculated between the actual outcome ranking and the estimated one. The correlation would be high when both orderings are similar to each other. The correlation coefficient **r** ranges between -1 and 1, where the sign of the coefficient shows the direction, and the magnitude is the strength of the relationship. For RMSE, the utility of each outcome is estimated according to the learned model, and the error in the prediction is calculated (See Equation 11). When the estimated utility values are close to the actual utility values, the RSME values would be low. In summary, low RSME and high correlation values are desired in our case.

$$RMSE = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}\Big(U(o_i) - \hat{U}(o_i)\Big)^2} \tag{11}$$

Baarslag *et al.* compare the performance of the existing opponent models in automated negotiation [68]. Their results show that frequentist-based opponent modeling approaches are the most effective among the existing ones despite the approach's simplicity. Therefore, we use a benchmark involving two different state-of-the-art frequentist opponent modeling approaches widely used in automated negotiation employed in HardHeaded [19] and Scientist [20] agents to evaluate the performance of the proposed opponent model. Frequentist opponent modeling techniques mostly rely on heuristics, assuming that the opponent would concede less on the essential issues and the preferred values appear more often than less preferred ones. Consequently, they check the frequency of each issue value's appearance in the offers. Furthermore, they compare the content of the consecutive offers and find out the issues with changed values. In other words, if the value of an issue is changed in the opponent's consecutive offers, the weights of those issues are decreased by a certain amount (i.e., becoming less critical). In the Scientist Agent, Tunalı *et al.* aims to resolve some update problems and enhance the model by comparing a group of offer exchanges instead of only consecutive pairs of offers and adopting a decayed weight update mechanism. Each opponent model is fed and updated in each round by simulating the negotiation data obtained from human-agent negotiation experiments. At the end of each negotiation, the estimated models are evaluated according to the RMSE and Spearman correlation metrics explained above.

6.1 Study 1: Human-Agent Negotiation in Deserted Island Scenario

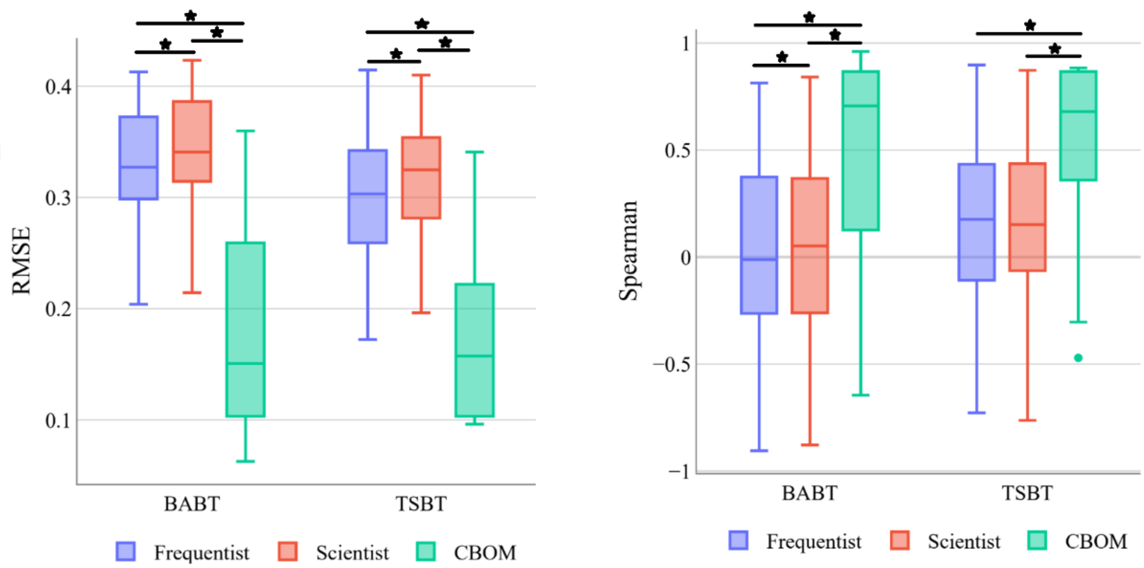
We analyzed and utilized the negotiation log data collected during the human-agent negotiation experiments in [1], where the participants negotiated on a particular scenario called "Deserted Island". They negotiated resource allocation based on the division of eight survival products by two partners who fell on the deserted island. Each participant attended two negotiation sessions where the utility distributions of the issues were the same, but the orderings differed. Table 5 shows the preference profiles for both sessions. During the experiments, participants only know their preferences, and so does the agent. In this study, 42 participants (21 men, 21 women, median age: 23) were included and asked to negotiate with our agent on a face-to-face basis, and the agent made counteroffers. Offer exchanges in both sessions were recorded separately for each session. At the end of this data collection process, 46 sessions using the time-based stochastic bidding tactic (TSBT) and 38 sessions using the behavior-based adaptive bidding tactic (BABT) were obtained. The average negotiation rounds to reach an agreement was 14.84, with a standard deviation of 5.2.

Table 5: Agent's and Participants' Preference Profiles in Deserted Island Scenario

	First Negotiation		**Second Negotiation**	
Items	Agent	Participant	Agent	Participant
Compass	13	5	6	13
Container	22	20	13	5
Food	17	7	20	22
Hammer	6	13	5	10
Knife	5	10	10	17
Match	20	22	7	6
Medicine	7	6	17	7
Rope	10	17	22	20

Figure 15 shows box plots for each opponent modeling technique's RMSE and Spearman correlation values. As far as the correlation values are concerned, it can be said that *CBOM*'s ranking predictions are better than Scientist and Frequentist (See Figure 15). To apply the appropriate statistical significance test, we first check the normality of the data distribution via the Kolmogorov-Smirnov normality test and then the homogeneity of variance via Levene's Test. We applied the dependent sample t-test or the Wilcoxon Signed Rank test, depending on the results. If the data distribution passes these tests, the paired t-test is applied; otherwise, a non-parametric statistics test, namely the Wilcoxon-Signed Rank test. All statistical test results are given at the 99% confidence interval (i.e., $\alpha = 0.01$).

When we apply the statistical tests, it is seen that *CBOM*'s ranking performance is statistically significantly better than others ($p < 0.01$). Similarly, the errors on the estimated utilities via *CBOM* are lower than the errors via other approaches (see Figure 15). Furthermore, it is seen that *Scientist* statistically significantly performed better than *Frequentist* for both metrics except when the agent employs the TSBT strategy.



(a) RMSE

(b) Spearman Correlation

Figure 15: RMSE & Spearman Correlations for the Experiment in Island Scenario ($\star$ represents $p < 0.001$)

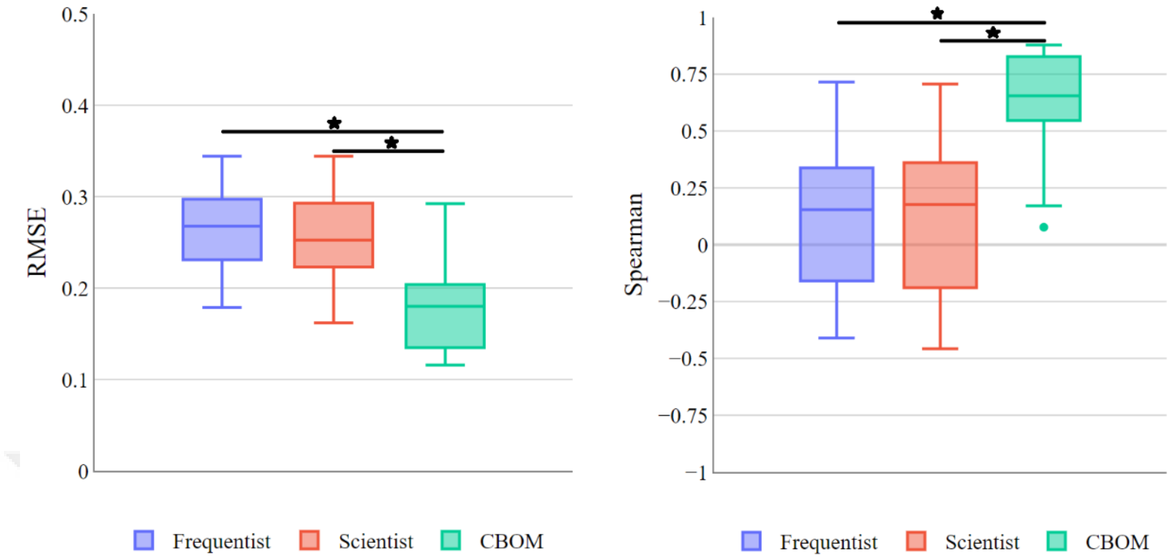
6.2 *Study 2: Human-Agent Negotiation in Grocery Scenario*

In this part, we analyzed and utilized the negotiation log data collected during another human-agent negotiation experiment in [24] where the participants negotiated on a particular scenario called "Grocery". Different from the first study, the negotiation domain does not consist of binary resource items (i.e., *allocate* or *not allocate*). Instead, the negotiation parties negotiate on the number of items to be allocated (i.e., how many items will be allocated). In this scenario, there are four types of fruits, where each participant can have up to four of each, and the opponent gets the rest. The participants aim to find an adequate division of the fruits. Table 6 shows the agent and participant's preference profiles for both sessions. It is worth noting that each party only knows its scores. In this experiment, the participants negotiated against an agent employing the hybrid strategy where TSBT and BABT strategies are used together for bidding. 28 participants attended two negotiation sessions where all negotiation sessions ended with an agreement, thus, totaling up to 56 negotiation sessions against the agent. The average negotiation rounds to reach an agreement was 19.39, with a standard deviation of 11.82.

Similar to the previous study, we update each opponent modeling by using the offer exchanges by the human participants and calculate the error and correlation values with the final model at the end of each negotiation. Figure 16 shows box plots for RMSE and Spearman correlation values per each opponent modeling technique in this scenario. We can conclude that *CBOM* statistically significantly outperformed others, whereas *Frequentist* performs better than *Scientist* when we analyze the statistical test results. Those results are in line with the first study and strongly show the success of the proposed opponent modeling in human-agent negotiations. It is worth noting that the prediction error in the grocery scenario is lower than in the island scenario. Although the number of possible outcomes in these scenarios is the same (256), the number of issues in grocery scenarios is lower than in the island scenario. Therefore, one can intuitively think it is easier to predict the evaluation values in the grocery scenario compared to island scenarios. In addition, this study's average number of rounds is higher (19.39 versus 14.84). When we receive more offers, the model's accuracy may increase depending on the model.

Table 6: Preference Profiles for Grocery Negotiation Sessions

	First Negotiation		**Second Negotiation**	
Items	Agent	Participant	Agent	Participant
Watermelon	4	12	12	4
Banana	1	8	8	1
Orange	12	4	4	12
Apple	8	1	1	8



(a) RMSE (b) Spearman Correlation

Figure 16: RMSE & Spearman Correlations for the Experiment in Grocery Scenario ($\star$ represents $p < 0.001$)

6.3 Study 3: Automated Negotiation Experiments

In this section, we evaluate the performance of our agent employing the proposed *CBOM* opponent modeling by comparing its performance with that of the state-of-the-art negotiating agents available in automated negotiation literature. We built a rich benchmark of 15 successful negotiating agents who competed in the International Automated Negotiating Agents Competition ANAC [53] between 2011 and 2017. We ran negotiation tournaments in GENIUS [6], where each agent bilaterally negotiated on various negotiation scenarios. Six negotiation scenarios were used during the tournament, and the details of those scenarios are given in Table 7. As can be seen, the size and opposition degree of preference profiles in the given scenario is different. The size of the scenarios determines the search space. The larger the search space is, the more difficult it might be to estimate an accurate model based on the opponent's offers exchanges. Next, the opposition is valuable information regarding understanding the domain's capacity to satisfy both parties [68]. That is, it indicates how difficult it is to find a consensus. Taking the opposition of the preference profiles into account while analyzing the negotiation results may help us get an insight into how well the proposed negotiation strategy is in terms of social welfare with varying difficulties in finding an agreement.

Table 7: Negotiation Scenarios in Automated Negotiation Settings

Domain (ANAC Year)	# of values for each I	Total Bids	Opposition
Car (2015)	3, 4, 4, 5	240	0.209
Smart Energy Grid (2016)	5, 5, 5, 5	625	0.362
Grocery (2011)	4, 4, 4, 5, 5	1,600	0.354
Party (2012)	3, 4, 4, 4, 4, 4	3,072	0.191
Politics (2015)	2, 3, 3, 4, 4, 4, 4, 5	23,040	0.221
Supermarket (2012)	4, 6, 6, 7, 7, 7	49,392	0.155

We formed a pool of agents involving our Conflict-based agent and the ANAC finalists in different categories. We ran a tournament in Genius [6] where each agent bilaterally negotiated with each other on scenarios described in Table 7. The ANAC agents used in this evaluation are listed as follows:

- **Boulware** and **Conceder** are baseline agents available in Genius framework.
- **Hardheaded** [19] was the winner of individual utility category in ANAC 2011.
- **NiceTitForTat** [69] was the finalist of individual utility category in ANAC 2011.
- **CUHKAgent** [70] was the winner of individual utility category in ANAC 2012.
- **IAmHaggler2012** [71] was the winner of the Nash category in ANAC 2012.
- **Atlas3** [72] was the winner of individual utility category in ANAC2015, .
- **ParsAgent2** [73] was the winner of the Nash category in ANAC 2015.
- **AgentX** [74] was fourth of the Nash category in ANAC 2015.
- **Caudeceus** [75] was the winner of individual utility category in ANAC 2016.
- **YXAgent** [76] was the second of individual utility category in ANAC 2016.

- **PonPoko Agent** [76] was winner of individual utility category in ANAC 2017.

- **AgentKN** [76] was the second of the Nash category in ANAC 2017.

In order to study how well our opponent model performs when it negotiates with automated negotiating agents, we compare the performance of opponent models used in Conflict-based (CBOM), Scientist, and HardHeaded by integrating those opponent models into our negotiation strategy. We calculated the Spearman correlation between the actual and estimated ranks of the outcomes per each scenario and reported their averages. Note that the higher correlation is, the better the prediction is. Table 8 shows those Spearman correlations and RMSE in the utility calculations where the best scores are boldfaced. It is seen that CBOM is more successful than others in terms of Spearman correlation, except for the results obtained in the grocery and politics domains. Furthermore, RMSE results show that the CBOM is more successful in all domains.

Table 8: Average Spearman and RMSE Results for Six Domains

Domains	**SPEARMAN**			**RMSE**		
	CBOM	**Scientist**	**Hardheaded**	**CBOM**	**Scientist**	**Hardheaded**
Car	**0.73 ± 0.1**	0.29 ± 0.0	0.33 ± 0.0	**0.15 ± 0.0**	0.31 ± 0.0	0.27 ± 0.0
Energy Grid	**0.68 ± 0.1**	0.25 ± 0.0	0.25 ± 0.0	**0.16 ± 0.0**	0.22 ± 0.0	0.30 ± 0.0
Grocery	0.81 ± 0.0	**0.85 ± 0.0**	0.82 ± 0.0	**0.12 ± 0.0**	0.17 ± 0.0	0.20 ± 0.0
Party	**0.90 ± 0.0**	0.82 ± 0.0	0.50 ± 0.0	**0.10 ± 0.0**	0.13 ± 0.1	0.26 ± 0.0
Politics	0.82 ± 0.0	**0.86 ± 0.0**	0.79 ± 0.0	**0.20 ± 0.0**	0.22 ± 0.0	0.16 ± 0.0
Supermarket	**0.66 ± 0.0**	0.58 ± 0.0	0.56 ± 0.0	**0.21 ± 0.0**	0.18 ± 0.0	0.30 ± 0.0

Next, we analyze the performance of the proposed negotiation strategy relying on the CBOM opponent modeling against the ANAC finalists. The most widely used performance metric in negotiation is the final received utility, which is intuitive and in line with Kiruthika's approach to Multi-Agent Negotiation systems [77]. There are other metrics, such as nearness to Pareto optimal solutions/Kalai point/the Nash point, the sum of both agents' agreement utility (i.e., social welfare), and the product of those agreement utilities. Accordingly, we evaluate the performances regarding average individual received utility, Nash distance, and social welfare.

First, we analyze the average individual utilities received by each agent. Table 9 shows those utilities per each agent in each negotiation scenario where the highest scores are boldfaced. The last column shows the average scores of each agent in all domains. Our agent took in the first top three agents. We noticed that the worst performance of our agent was in the supermarket domain, where the outcome space is too large to search. Moreover, our agent performed well in the smart energy grid and grocery scenarios, whose opposition levels are high.

Table 9: Average Agent Individual Utility

Agent Name	Car	Energy Grid	Grocery	Party	Politics	Supermarket	Average ± Std
CBOMAgent	0.833	**0.777**	**0.846**	0.838	0.594	0.868	0.793 ± 0.09
Atlas3	0.875	0.758	0.828	0.809	0.578	0.848	0.783 ± 0.10
AgentKN	0.832	0.728	0.793	0.820	**0.609**	0.756	0.756 ± 0.07
NiceTitForTat	0.804	0.680	0.767	**0.848**	0.569	0.853	0.753 ± 0.10
HardHeaded	**0.882**	0.670	0.795	0.832	0.533	0.741	0.742 ± 0.12
ParsCat	0.800	0.726	0.792	0.833	0.501	0.767	0.736 ± 0.11
CUHKAgent	0.750	0.684	0.763	0.800	0.543	0.765	0.717 ± 0.09
IAMcrazyHaggler	0.836	0.546	0.819	0.771	0.416	**0.872**	0.710 ± 0.17
IAMhaggler2012	0.782	0.496	0.796	0.841	0.491	0.792	0.700 ± 0.15
PonPokoAgent	0.773	0.606	0.785	0.783	0.427	0.802	0.696 ± 0.14
Caduceus	0.731	0.546	0.801	0.703	0.489	0.711	0.663 ± 0.11
ParsAgent2	0.779	0.540	0.713	0.698	0.424	0.805	0.660 ± 0.14
Boulware	0.712	0.611	0.671	0.752	0.460	0.642	0.641 ± 0.09
AgentX	0.672	0.582	0.655	0.801	0.347	0.642	0.616 ± 0.14
YXAgent	0.770	0.553	0.721	0.625	0.397	0.553	0.603 ± 0.12
Conceder	0.598	0.505	0.391	0.649	0.306	0.335	0.464 ± 0.13

Table 10 shows the average Nash distance for each agent in all scenarios separately, and the final column indicates the average of all scenarios. Here, the lower the Nash distance is, the fairer the agent's outcomes are. Our conflict-based agent outperformed the ANAC finalist agents except for Nice TitForTat, which is known for maximizing social welfare in the Politics scenario. Similar results were obtained when we analyzed the social welfare in terms of summation of both agents' agreement utilities (See Appendix). Overall results support the success of our agent, and the reason may stem from the fact that our agent aims to learn its opponent's preferences over time and aims to find win-win solutions for both sides.

When we investigate the overall agreement rate, it can be seen that most of the agents

Table 10: Average Nash Distances

Agent Name	Car	Energy Grid	Grocery	Party	Politics	Supermarket	Average ± Std
CBOMAgent	**0.077**	**0.104**	**0.068**	**0.120**	0.311	**0.058**	**0.123 ± 0.09**
Atlas3	0.183	0.216	0.105	0.230	0.253	0.198	0.197 ± 0.05
AgentKN	0.139	0.194	0.166	0.213	0.250	0.229	0.198 ± 0.04
ParsCat	0.133	0.173	0.130	0.156	0.438	0.178	0.201 ± 0.11
NiceTitForTat	0.154	0.209	0.178	0.230	**0.187**	0.250	0.201 ± 0.03
IAMhaggler2012	0.115	0.500	0.095	0.152	0.363	0.145	0.228 ± 0.15
HardHeaded	0.142	0.357	0.183	0.198	0.487	0.279	0.274 ± 0.12
AgentX	0.210	0.273	0.230	0.267	0.418	0.262	0.277 ± 0.07
Boulware	0.217	0.271	0.254	0.278	0.326	0.334	0.280 ± 0.04
IAMcrazyHaggler	0.156	0.495	0.176	0.156	0.686	0.064	0.289 ± 0.22
Caduceus	0.190	0.462	0.178	0.238	0.431	0.254	0.292 ± 0.11
PonPokoAgent	0.201	0.392	0.177	0.205	0.640	0.154	0.295 ± 0.17
CUHKAgent	0.361	0.428	0.280	0.205	0.457	0.261	0.332 ± 0.09
ParsAgent2	0.197	0.474	0.274	0.306	0.576	0.210	0.340 ± 0.14
YXAgent	0.268	0.526	0.350	0.376	0.718	0.450	0.448 ± 0.15
Conceder	0.321	0.360	0.534	0.459	0.458	0.652	0.464 ± 0.11

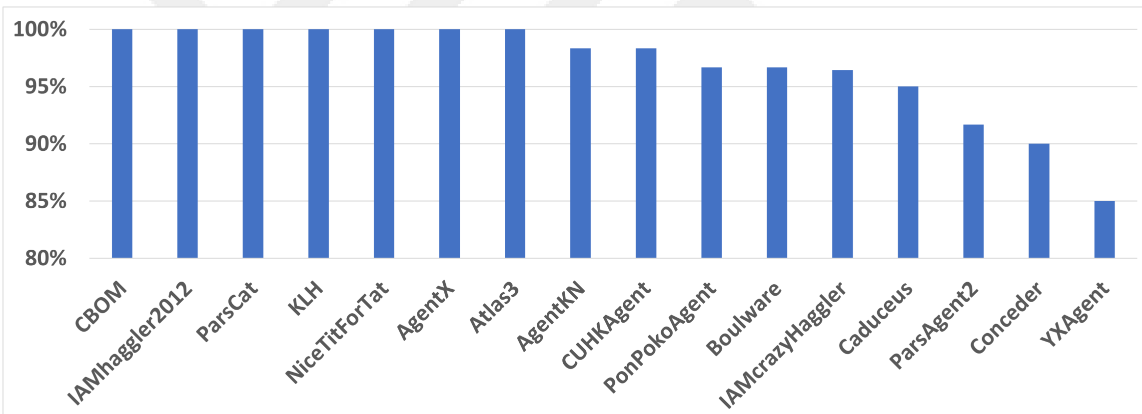


Figure 17: Agreement Rates of Agents

have a high acceptance rate, and the leading ones, like ours and Atlas3, found agreements in all negotiations, as seen in Figure 17. The final metric that we investigated is the average rounds to reach an agreement. In our experiments, the deadline is set to 5000 rounds per negotiation scenario. Table 11 shows the average rounds that the agent reached their agreement. It can be observed that the size of the outcome space and the opposition level may influence the agreement round. In large and competitive scenarios, agents needed more rounds to reach an agreement. Among all agents, Agent X tended to reach a consensus sooner than all other agents. Furthermore, IAMHaggler2012 and ParsCat agents tend to explore the offered space as much as they can in the given time. Therefore, these are the agents least affected by the size of the outcome space and its competitiveness. Our conflict-based agent could reach an agreement sooner than more than half of the agents, but it is worth noting that it took more time in terms of seconds due to its computational complexity, similar to AgentKN.

Table 11: Average Agreement Rounds

Agent Name	Car	Energy Grid	Grocery	Party	Politics	Supermarket	Average ± Std
AgentX	**205**	**816**	**440**	**477**	**1,868**	**162**	**661 ± 580**
Conceder	1,222	1,826	2,626	2,017	2,559	3,095	2,224 ± 611
IAMhaggler2012	2,765	4,393	2,096	2,829	4,146	2,378	3,101 ± 864
ParsCat	2,899	3,988	2,741	3,034	4,254	2,567	3,247 ± 639
CBOMAgent	3,506	3,859	2,978	3,452	4,407	2,403	3,434 ± 633
IAMcrazyHaggler	3,526	4,202	2,984	3,104	4,489	2,553	3,476 ± 682
PonPokoAgent	3,673	4,321	3,330	3,564	4,489	3,202	3,763 ± 481
Boulware	3,604	4,005	3,650	3,705	4,317	3,560	3,807 ± 270
NiceTitForTat	3,367	4,002	4,061	3,654	4,142	4,053	3,880 ± 277
AgentKN	3,612	4,054	3,809	3,898	4,362	3,712	3,908 ± 246
Atlas3	4,252	4,473	2,298	4,355	4,369	3,973	3,953 ± 756
YXAgent	3,907	4,171	3,597	4,053	4,565	3,754	4,008 ± 312
ParsAgent2	3,658	4,249	3,870	4,024	4,527	3,736	4,011 ± 301
Caduceus	4,070	4,501	3,628	4,148	4,473	4,012	4,139 ± 296
HardHeaded	4,099	4,399	3,968	4,196	4,646	4,243	4,258 ± 217
CUHKAgent	4,301	4,458	4,512	4,272	4,659	4,236	4,406 ± 150

As a result of all the automated negotiations, we determined the six most successful agents in both the individual and fairness category. Figure 18 shows clearly that our agent gains the highest individual gain while having a fairer win-win solution (i.e., minimum distance to Nash solution). It is worth noting that while having high utility, our agent lets its opponent gains relatively high utility in contrast to other top agents.

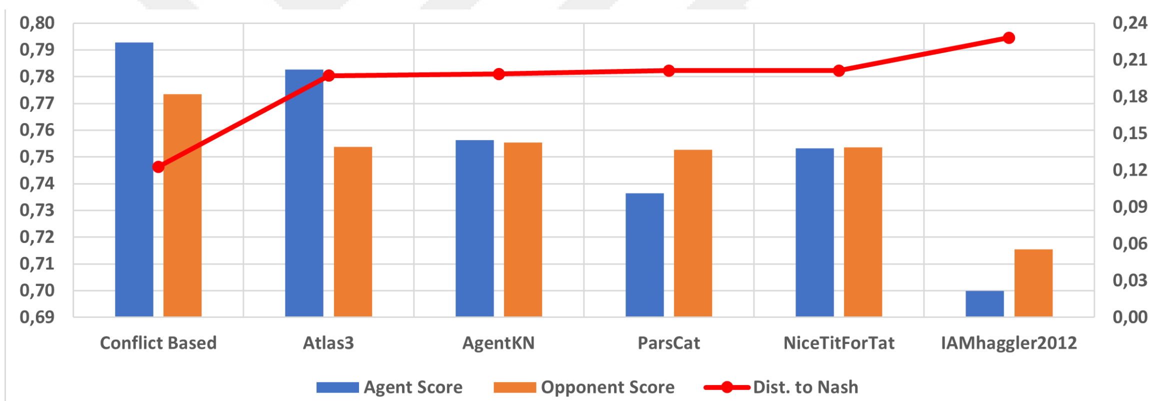


Figure 18: Best Six Agents in All Automated Negotiation Results

CHAPTER VII

CONCLUSIONS

This thesis introduces a novel offering strategy, Solver Agent, which incorporates the opponent's awareness of the agent's changing behavior and emotional state as well considering the opponent's bidding behavior and remaining time. We experimentally evaluate and compare the proposed emotion-aware strategy's performance with a hybrid strategy combining time-based and behavioral-based concession tactics. The empirical results showed that the Solver Agent gained higher individual scores while not diminishing the score of the human participants and reached agreements sooner than the hybrid agent. According to the user surveys, participants were more satisfied with their performance negotiation when they negotiated with the robot employing the Solver strategy. They perceived that the robot with the Solver strategy cared more about their preferences and tried to find the best deal for both of them than the Hybrid agent.

Furthermore, this thesis also presents a conflict-based opponent modeling approach and a bidding strategy employing this model for bilateral negotiations. Apart from evaluating the performance of the proposed opponent model in two different human-negotiation experiment settings, the proposed strategy was also tested against the finalist of the ANAC agents, considering various performance metrics such as individual utility and distance to the Nash solution. The results show that the proposed approach outperformed the state of the negotiating agents, and the proposed opponent model performed better than other frequency-based models. The contribution of this part is twofold: (1) introducing a novel opponent modeling approach to learn human negotiators' preferences from limited bid exchanges and (2) presenting a suitable bidding strategy relying on the proposed opponent model for both collaborative and competitive negotiation settings.

Due to the algorithm's complexity, the agent's performance decreases when the outcome space becomes more extensive, or the number of generated offers made by the opponent increases in automated negotiation. We are planning to reduce the computational complexity of the opponent modeling by adopting dynamic programming properties and local search. The upcoming study will focus on opponent model strategies that decrease the human-agent negotiation duration with the optimal number of rounds. It would be interesting to create stereotype profiles by mining the previous negotiation history and matching the current opponent's profile based on their recent offer exchanges.

Moreover, understanding and discovering the opponent's preferences over negotiation may play a key role in adopting strategic bidding strategies to find mutually beneficial agreements. However, as stated before, creating a mental model for the opponent's preferences is challenging based on a few bid exchanges. In contrast to automated negotiation, the number of exchanged bids is limited in human-agent negotiation. That requires a bidding strategy smartly exploring the potential bids and building upon an opponent model, capturing the critical components of the opponent's preferences. While creating such modeling is not trivial with limited bid exchanges, the agent can exploit its previous negotiation experiences and take advantage of repeated patterns.

As future work, we also plan to utilize dimensional circumplex models and appraisal theory to consider emotional states while negotiating with a human. Furthermore, it would be interesting to analyze the impact of argumentation on human-agent negotiation since human arguments contain domain-specific preference and sentiment information, which can be utilized in multimodal interaction studies. Besides, it would be interesting to create different mental models from previous negotiation experiences by applying the proposed model and trying to detect which mental model fits better for the current human negotiators. Furthermore, the agent can exploit different types of inputs, such as the opponent's arguments and facial expressions, to enhance opponent modeling.

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VITA

Mehmet Onur Keskin obtained his B.S. degree in Computer Science from Özyegin University, Istanbul, and is progressing toward an M.Sc. degree in Artificial Intelligence from the same institution. As a research assistant at the OZU Interactive Intelligence Systems Laboratory since 2017, Keskin has focused on advancing autonomous agent frameworks. His academic journey was enriched with research internships at well-known institutions such as Technische Universiteit Delft, University of Cambridge, Brown University, and Oregon State University Collaborative Robotics Institute, where he delved into human-robot negotiations, supply chain management, and 3D printing path optimization respectively.

Keskin's academic prowess is further exemplified by his achievements in competitions like the Automated Negotiating Agents Competition (ANAC), where his team secured a victory in 2020 and clinched second place in two categories at the Supply Chain Management League the subsequent year. His research contributions span a wide array of topics, from decentralized multi-agent pathfinding to human-agent negotiations, leading to his recognition with awards like the Richard E. Merwin Student Scholarship by the IEEE Computer Society and the Best Research Assistant Award at Özyeğin University's Graduate School of Engineering and Science in 2022.

The list of his publication is given below:

1. **O. Keskin**, F. Canturk, C. Eran & R. Aydoğan, 2023, **"Decentralized Multi-Agent Path Finding Framework and Strategies Based on Automated Negotiation"**, Autonomous Agents and Multi-Agent Systems, **[Under Review]**.

2. A. Doğru, **O. Keskin** & R. Aydoğan, 2023, **"Taking into Account Opponent's Arguments in Human-Agent Negotiations"**, ACM Transaction on Interactive Intelligent Systems, **[Under Review]**.

3. **O. Keskin**, B. Buzcu & R. Aydoğan, 2023, **"Conflict Based Negotiation Strategy for Human-Agent Negotiation"**, Applied Intelligence, Springer.

4. U. Çakan, **O. Keskin** & R. Aydoğan, 2023, **"Effects of Agent's Embodiment in Human-Agent Negotiations"**, 23^{rd} ACM International Conference on Intelligent Virtual Agents.

5. G. Yesevi, **O. Keskin**, A. Dogru & R. Aydoğan, 2022, **"Time Series Predictive Models for Opponent Behavior Modeling in Bilateral Negotiations"**, PRIMA 2022: Principles and Practice of Multi-Agent Systems.

6. R. Aydoğan, **O. Keskin** & U. Çakan, 2022, **"Would You Imagine Yourself Negotiating With a Robot, Jennifer? Why Not?"**, in IEEE Transactions on Human-Machine Systems, vol. 52, no. 1, pp. 41-51.

7. C. Eran, **O. Keskin**, F. Canturk, & R. Aydoğan, 2021, **[Second Best Paper]**, **"A Decentralized Token-Based Negotiation Approach for Multi-Agent Path Finding"**, 18^{th} European Conference on Multi-Agent Systems (EUMAS 2021), Springer, pp. 264–280.

8. **O. Keskin**, U. Çakan, & R. Aydoğan, 2021, **"Solver Agent: Towards Emotional and Opponent-Aware Agent for Human-Robot Negotiation"**, Proceedings of the 20^{th} International Conference on Autonomous Agents and Multi-Agent Systems (AAMAS 2021), pp. 1557–1559.

9. R. Aydoğan, **O. Keskin**, & U. Çakan, 2020, **"Let's negotiate with Jennifer! Towards a Speech-Based Human-Robot Negotiation"**, Advances in Automated Negotiations, Springer, pp. 3–16.