Taking into Account Opponent's Arguments in Human-Agent Negotiations

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Autonomous negotiating agents, which can interact with other agents, aim to solve decision-making problems involving participants with conflicting interests. Designing agents capable of negotiating with human partners requires considering some factors, such as emotional states and arguments. For this purpose, we introduce an extended taxonomy of argument types capturing human speech acts during the negotiation. We propose an argument-based automated negotiating agent that can extract human arguments from a chat-based environment using a hierarchical classifier. Consequently, the proposed agent can understand the received arguments and adapt its strategy accordingly while negotiating with its human counterparts. We initially conducted human-agent negotiation experiments to construct a negotiation corpus to train our classifier. According to the experimental results, it is seen that the proposed hierarchical classifier successfully extracted the arguments from the given text. Moreover, we conducted a second experiment where we tested the performance of the designed negotiation strategy considering the human opponent's arguments and emotions. Our results showed that the proposed agent beats the human negotiator and gains higher utility than the baseline agent.

CCS Concepts: • **Computing methodologies** → **Artificial intelligence**; *Intelligent agents*; • **Human-centered computing** → *Empirical studies in HCI*;

Additional Key Words and Phrases: Human-Agent Negotiation, Argumentation, Opponent Modeling

ACM Reference format:
Anil Doğru, Mehmet Onur Keskin, and Reyhan Aydoğan. 2025. Taking into Account Opponent's Arguments in Human-Agent Negotiations. *ACM Trans. Interact. Intell. Syst.* 15, 1, Article 2 (January 2025), 35 pages.
https://doi.org/10.1145/3691643

1 Introduction

Negotiation is one of the most widely-used resolution processes for decision-making problems involving participants with conflicting interests in multi-agent systems [38]. Participants can negotiate over any joint decision (e.g., holiday plan, resource/task allocation, and scheduling problems).

This work has been partially supported by the Chist-Era grant CHIST-ERA-19-XAI-005, and by the Scientific and Research Council of Turkey (TÜBİTAK, G.A. 120N680). Besides, we thank Duru Balpinarli for her valuable contributions and feedback.
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ACM 2160-6463/2025/1-ART2
https://doi.org/10.1145/3691643

This process can be automatically performed via the use of intelligent agents. During the negotiation, the behavior of an autonomous agent depends on various factors such as time pressure, opponent's behavior, negotiation domain, and so on [20, 38]. Besides, designing sophisticated strategies that can negotiate with their human counterpart requires taking into account additional factors such as human arguments and emotions for a better understanding of their preferences and behaviors so that well-targeted offers could be generated [6, 36]. Consequently, agents can act wisely to achieve better negotiation outcomes.

Depending on the context, autonomous negotiating agents aim to maximize their utility or increase social welfare under some extent of uncertainty about their opponent. The main components of such an agent involve bidding strategy, opponent modeling, and acceptance strategy [7]. The bidding strategy decides what to the offer. For this decision, agents mostly calculate a **target utility (TU)** considering the remaining time and/or opponent's behavior and make an offer whose utility is closest to the calculated TU [3, 19, 29, 32, 44]. The acceptance strategy decides when to accept the opponent's offer. In the literature, some strategies only consider the received utility, whereas others consider remaining time as well [8]. Lastly, agents negotiate without revealing their preferences fully. Therefore, one of the main challenges is to estimate the opponent's preferences [45, 48] and, eventually, their strategy based on the offer exchanges [53, 55] during the underlying negotiation. Accordingly, an agent can adapt its behavior and bidding strategy. To achieve this, the opponent's bid history must be analyzed to estimate an accurate opponent model. It is worth noting that opponent modeling is not mandatory in automated negotiation, where the agents mainly focus on maximizing utility. However, it could be useful if the agents want to maximize social welfare. On the other hand, when an agent negotiates with its human counterpart, it needs to consider its preferences. Building a rapport with the partner is essential, and human negotiators should feel that the agent considers their preferences and feedback during the negotiation. For this purpose, agents may also utilize other inputs, such as arguments exchanged by their opponents to increase the accuracy of their models. Negotiating agents concerning the human opponents' expectations would perform better against their human counterparts. For instance, the Solver Agent analyzing the facial expressions of the human negotiators and adapting its behavior depending on the opponent's emotional state achieves better negotiation outcomes [32]. Moreover, acting like a human negotiator (e.g., robot gestures, facial expressions with avatars) improves the human-agent negotiation process [6, 26, 49]. Therefore, a multi-modal agent design utilizing these factors as much as possible plays a key role in better negotiation outcomes and an effective interaction in human-agent negotiations.

During the negotiation, human negotiators can share partial preferences, make arguments, express their emotional states, and specify their hard constraints in a chosen natural language [10, 14, 24, 35]. Therefore, understanding and generating arguments in a natural language is one of the essential research questions in Artificial Intelligence [22, 42]. Understanding human arguments and incorporating the knowledge embedded in natural language may significantly improve negotiation ability and, consequently, negotiation outcome. Accordingly, this article addresses how agents can recognize human arguments and utilize them to improve their gain while negotiating with a human negotiator. Enabling users to use natural language to express their interests and emotional states has attracted attention in recent decades. Researchers develop several frameworks such as NegoChat [43] and IAGO [39] supporting natural language.

In contrast, others aim to collect some datasets from human-human negotiation sessions to enable agents to generate offers/arguments in a chosen natural language [24, 35]. The CaSiNo dataset contains some labeled argument types [14], but it cannot recognize issue-value constraints directly. Some datasets involve emoji exchanges to express emotional states but need to capture free-format sentences to get insights about their opponent's emotional states [12, 39]. Therefore, we aim to construct a dataset involving various arguments that could be useful during the negotiation.

Güngör et al. categorize three main argument types (i.e., rewarding, explanatory consisting of three sub-categories such as "self," "other" and "both," and threatening), which can be exchanged in human-agent negotiations [21] based on the taxonomy introduced in [33]. However, those argument types are not detailed enough for a sophisticated agent design. This study extends those argument types by defining new sub-categories. The proposed hierarchical argument-type structure is an opportunity for designing an agent concerning human arguments. Thus, this study proposes a novel agent design that considers human arguments in enhancing opponent modeling and in well-targeted offer generation mechanism. To meet the aforementioned needs, we collected a dataset of human arguments with corresponding labels. We also share the corpus on the Internet[1] to lead future studies. A hierarchical machine learning approach is applied while training models to extract argument types from a text. In agent-based negotiation systems, the preferences of the other party is private, and negotiator parties are reluctant to share their preferences directly. However, the proposed human-agent negotiation protocol allow negotiating parties can share their preferences indirectly through arguments (i.e., preference statements), especially when they believe it may persuade the other party or lead to concessions. In the most of the cases, in competitive settings, direct preference sharing is not favored. On the other hand, in collaborative settings, sharing partial preferences through preference statements helps agent narrow down the search space by eliminating the unacceptable offers so that the agents can wisely explore their coming offers. Consequently, we present a negotiation strategy utilizing those arguments and feeding the opponent modeling with exchanged preference statements. Following, a human-agent negotiation experiment is designed and conducted to evaluate the performance of the underlying negotiation strategy.

Reasoning on the given preferences to create well-targeted offers is essential in agent-based negotiation. It highly depends on how the preferences are represented: qualitatively (i.e., ordinal) or quantitatively (i.e., cardinal). From the point of the agent's view, reasoning on cardinal preferences is straightforward (e.g., agents can quickly determine which offer is more preferred by comparing their overall utilities). On the other hand, human negotiators primarily represent their preferences qualitatively (e.g., x is preferred over y. The most crucial issue is Z). It is intuitive for them to rank the outcomes or possible issue values rather than associating an actual number (i.e., utility) with them. Therefore, while designing our experimental setting, we ask participants to rank the importance of the issues as well as the possible values of the issues according to their preferences (ordinal preferences). Those ordinal preferences are mapped onto a predefined utility function in our system to evaluate to what extent the offers are good for them under the designed negotiation scenario. Besides, participants can make ordinal preference statements/arguments during their negotiation, where our learning algorithms try to recognize such statements and extract the relevant preference information to update our opponent model. We empirically compare the performance of the Solver strategy [32], designed particularly for human-agent negotiation, with a variant of that strategy enhanced with argumentation (NLPSolver). In addition, the prediction performances of the windowed frequency-based opponent modeling [45] and its extension with the arguments are assessed. Our experimental results showed that incorporating arguments into negotiation strategy and opponent modeling yielded better results regarding the prediction accuracy of the learned preferences and individual utility of the agreements.

[1]Corpus is available on GitHub: https://github.com/aniltrue/Taking-into-Account-Opponent-s-Arguments-in-Human-Agent-Negotiations.

The following sections in this work are as follows: Section 2 provides the information on the review literature and comparison of studies. Section 3 also provides the necessary background about agent design. Section 4 introduces the novel argument type taxonomy. The developed human-agent negotiation framework and collected corpus are explained in Section 5, while the proposed hierarchical classifier to extract corresponding argument types is described in Section 6. Section 7 explains the proposed agent design. Also, the evaluation of the proposed agent design is reported in Section 8. Finally, Section 9 concludes this work with future work.

2 Related Work

One of the challenges in human-agent negotiation is preprocessing statements in a given natural language, such as English, and adapting behavior accordingly. Recent studies in this field focus on how to deal with negotiating in natural language. This section provides an overview of these studies.

Mell et al. present a human-agent negotiation framework where a human negotiator can interact with an automated negotiating agent via a chat-based interface [39]. In their framework, human negotiators can make offers and send predefined arguments during their negotiation. Moreover, they can express their emotional states by exchanging emojis. It is worth noting that the framework is also used for human-agent negotiation competition [30] to motivate researchers to design effective negotiating strategies. However, this framework does not support free-speech exchanges between an agent and a human negotiator. The human negotiator can choose sentences from available predefined templates. It would be necessary to emphasize that this work does not mainly focus on dealing with the difficulties of using natural languages in negotiations.

Unlike template-based sentences, processing free-speech texts requires more sophisticated methods, such as machine learning. It is proven that deep learning techniques provide effective solutions to handle this kind of **natural language processing (NLP)** task [17, 41, 52]. For instance, Bakker et al. propose a deep learning approach that can generate a consensus opinion based on the participants' statements about a debate [10]. Firstly, the model collects the opinion of each participant on a debatable question. For this purpose, they trained a language model called "*chinchilla*" by using a large-scale corpus [27]. On top of this model, a few-shot learning technique is adopted to learn how to build consensus statements from the given opinions. To enhance the model, the participants' feedback on the generated statements (i.e., Likert-scale score) is collected to increase the social welfare (i.e., the total score of participants). Apart from this, they developed another "*chinchilla*" language model called the "*Reward Model*" to estimate the total score of the participants. Hence, the "*Reward Model*" enables the selection of the consensus text among the generated candidate texts with the highest estimated score. In contrast to their approach in which the agent plays like a mediator to find a consensus among human participants, our work utilizes human arguments to generate convincing offers in a bilateral negotiation. Likewise, Cicero agent which is able to play *Diplomacy* game employs large language models and **reinforcement learning (RL)** techniques [18]. It can also negotiate with the other players via free-speech. However, it is game-oriented rather than bilateral negotiation.

Furthermore, Lewis et al. introduce an end-to-end approach called DealOrNoDeal [35] where the agent receives input sentences in English from human negotiators and produces a text as a response during the negotiation. They first built a corpus involving text message exchanges in human-human negotiations, which is available on the Internet.[2] Afterward, they apply a deep RL approach to train an end-to-end model producing the text to be sent to the human negotiation as

[2]The human-human negotiation corpus can be found in the following github repository: https://github.com/facebookresearch/end-to-end-negotiator

a response. The reward mechanism is based on the received utility of the outcome and whether or not an agreement is reached. In contrast to that work, our aim is not to generate offers in text based on a black box machine learning approach; instead, our ultimate aim is to design opponent modeling and bidding strategies benefiting from analysis of the human arguments.

Besides, the RL model may generate poor, short, and insufficient sentences compared to human arguments. He et al. propose a novel approach splitting the end-to-end structure into two models [24]. The first model takes the opponent's text and negotiation history as input and determines an action to take among a set of predefined actions (e.g., greeting, asking a question, offering, accepting) by utilizing an RL approach. The second model takes the chosen action by the first model and selects the most appropriate template sentence from its corpus (CragList), which can fit the best with the chosen action. This sentence template is adapted to the current action. Note that the corpus with the corresponding action labels is available on the Internet.[3] Consequently, their approach can generate more complex sentences during the negotiation.

Furthermore, Yang et al. revise the Craiglist model by taking the personal behavior of the opponent into account [54]. They analyze the negotiation behavior of each participant and incorporate this analysis into their decision model, determining the action to be taken by the agent. They improve the reward function as well. Moreover, Zhou et al. present a decision support system utilizing the same corpus [56]. To sum up, the designers must have complete control over the negotiation strategy developed in the RL-based NLP studies. On the other hand, we focus on manually designing strategies benefiting from argument exchanges in human-agent negotiations instead of relying on a black box strategy.

Chawla et al. point out the significance of understanding human arguments during negotiation [14]. They built a new negotiation corpus called CaSiNo from human-human negotiations and defined relevant argument types. In that work, the exchanged text can be associated with multiple labels. It is worth noting that the negotiation addressed in that work is a resource allocation problem. Similarly, they introduce a classifier to extract corresponding argument types from the given text. They adopted BERT-based models [17], whereas we rely on classical machine learning techniques with relatively low computational requirements. Note that the text in the CaSiNo dataset also involves emojis. They analyzed the CaSiNo dataset by considering the personal information, negotiation behavior, and emojis that appeared in the sentences received from each participant to extract their emotional state [12]. Accordingly, they propose an opponent model to predict the human negotiator's emotional state [13]. Note that the CaSiNo dataset is not fully available on the Internet. Following that study, Hoegen et al. build a novel negotiation corpus called *DyNego-WOZ*, which also contains the facial expression of the human participants [26]. They aim to recognize the emotional state along with the underlying reason, not only from the types of arguments extracted from the text but also from the participant's facial expression. It is worth noting that they utilize the argument types defined in the CaSiNo corpus. Additionally, RL-based negotiating agents are also designed by utilizing CaSiNo corpus [16].

By utilizing exchanged arguments, the preferences of an opponent can be estimated during a negotiation. For this purpose, Nazari et al. introduce an argument-based opponent model to estimate the weight of an issue in cardinal (i.e., utility-based) preferences [40]. With a sentiment analysis (i.e., identifying whether a given statement is positive or negative), they predict how much that issue is preferable for the opponent. They combine classical frequentist [51] and sentiment analysis approach to derive an argument-based opponent model. In addition to this, Johnson et al. develop a similar method by utilizing the sentiment analysis approach in the IAGO framework [28].

[3]The human-human negotiation corpus can be found on the following website: https://huggingface.co/datasets/craigslist_bargains.

Table 1. Comparison Matrix for Text-Based Human-Agent Negotiation Studies

	Data Labeling	Value Based Labeling	Strategy	Emotional Statement
Güngör [21]	No	No	No	Yes
NegoChat [43]	No	Yes	Partial Offering	No
DealOrNoDeal [35]	No	No	End-to-End	No
CraigList [24, 54, 56]	Action Types	Only Offer	Action-based	No
CaSiNo [13, 14]	Argument Types	No	Opponent Model	Emojis
DyNego-WOZ [26]	Argument Types	No	Opponent Model	Facial Expressions
Our Approach	Argument Types	Yes	Opponent Model and Bidding Strategy	Emojis with rates

The difference is that they extend the Bayesian opponent model [25] instead of the frequentist one. For the sentiment analysis, they utilize the predefined arguments about preferences in the IAGO framework. Although both works study cardinal preferences, they also indicate the potential research to develop an argument-based opponent model for more complicated preference settings (e.g., ordinal preferences). Whereas those studies update the weight of the issues (i.e., the importance of the issues) based on the given arguments during the negotiation, our approach focuses on updating the entire model, including both issue weights and issue value weights (i.e., individual utilities for each possible value). Consequently, we enhance a state-of-art frequentist opponent model [48] by considering exchanged arguments during negotiation.

Like our work, Rosenfeld et al. support NLP and allow researchers to design agent strategies for human-agent negotiation [43]. Their dialog manager consists of three components: **natural language understanding (NLU)**, autonomous negotiating agent, and **natural language generating (NLG)**. The NLU component extracts the structured offer content from the received text. The autonomous negotiating agent applies its strategy by considering the given content by the NLU component to determine its next offer. This offer is converted to a corresponding text by the NLG component. Their main focus was dealing with partial offers instead of analyzing human arguments expressing their constraints, preferences, and feedback.

As we mentioned, we want to analyze arguments exchanged between human negotiators. Güngör et al. have already presented a hierarchy of arguments (e.g., rewarding, threat, and explanations) [21] based on existing literature [2, 33, 47]. We enriched this hierarchy by introducing fine-grained categories. Although that framework enables human negotiators to express freely their emotions and arguments, it does not analyze the arguments as we did in this work. We labeled our corpus with the enriched set of categories, and some of those arguments are used to strengthen the opponent modeling and bidding.

To summarize, we listed the comparison of text-based human negotiation studies in Table 1. In the given table, the first column denotes whether the corpus includes arguments and the second column indicates whether the content of the offers is labeled in the corpus. Similarly, the last column presents whether emotional statement labeling is performed in their corpus. The third column is about the strategy proposed in the corresponding work. As seen in Table 1, only a few studies aim to apply a data-driven approach to process arguments in human-agent negotiations. Moreover, issue-value labeling is rarely done (e.g., offer content as well as explanation using issue values). While some of the studies, such as [13, 14, 26] use their corpus to model the opponent during the negotiation (e.g., predicting their emotional state from a given sentence). Some studies, like [35], focus on learning how to generate offer texts from given counter-offers. In contrast, we use arguments in both opponent modeling and manually-designed bidding strategy benefiting from the analysis of some arguments.

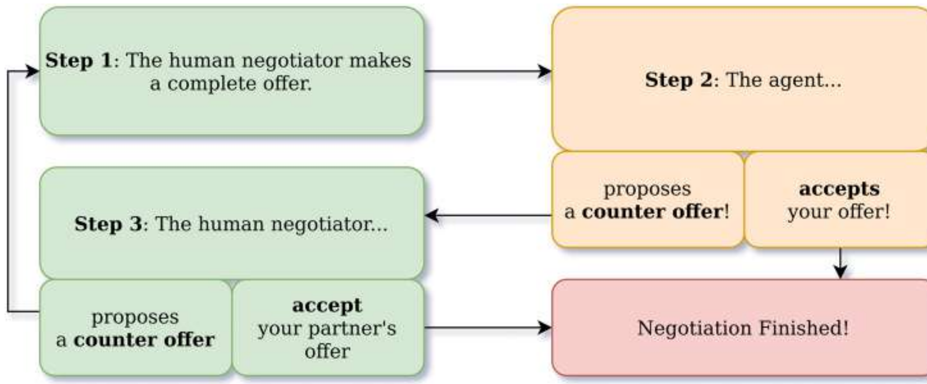


Fig. 1. The alternative offer protocol in the human-agent negotiations.

To sum up, many studies introduce their own corpus and agents [15]. However, their primary focus lies within the realm of NLP, whereas there is a distinct need for an argument-based agent equipped with a comprehensive argument-type taxonomy, especially in the context of human-agent negotiations. Besides, the agents must exploit a corpus involving issue-value and emotional state labeling. Accordingly, this study aims to meet the needs mentioned above as explained in Section 7.

3 Background

This section explains the necessary background information to understand the proposed approaches in human-agent negotiations. The automated negotiation enables the two parties to reach an agreement without fully revealing their preferences. Various protocols governing the interaction among the agents are available for humans and automated agents to negotiate and reach an agreement [4, 5]. The most common of these protocols is the *stacked alternative offers protocol* [4]. According to this protocol, one of the parties initiates the negotiation by making the first offer. The opponent can accept the offer or make a counter-offer. This process continues in a turn-taking fashion until reaching an agreement or the deadline. Figure 1 shows an example of the alternative offer protocol in human-agent negotiations. Both sides get zero or the reservation utility when the deadline is up. Otherwise, agents received the utility of the outcome concerning their private utility functions. In our work, the agents exchange offers and their emotional states via emojis and arguments via chat.

The preferences of each party are represented mainly by utilizing an additive utility function. Equation (1) shows the calculation of the utility of an offer, o. The negotiators can infer to what extent an offer is preferred; consequently, they can compare the offers while determining their offers during the negotiation. In Equation (1), W_i represents the importance of an issue i, while V_i denotes the value evaluation for the ith issue value. The summation of W_i always equals one, and V_i is between 0 and 1. An autonomous negotiating agent is usually designed based on the utility score of the given offers. It is worth noting that each agent only knows their preferences

$$U(o) = \sum_i W_i \times V_i(o). \tag{1}$$

Designing a sophisticated negotiating agent is a crucial research question of multi-agent negotiation systems. This process requires an advanced framework and design patterns. The main

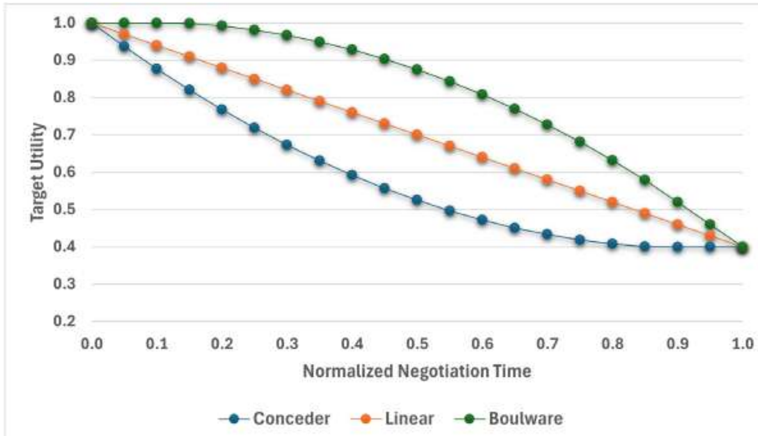


Fig. 2. The TU over time of the time-based behaviors.

components of an automated agent are the bidding strategy, the acceptance strategy, and the opponent model [7]. The bidding strategy decides what offer will be made (Section 3.1), the acceptance strategy decides when to accept the opponent's offer (Section 3.2), and the opponent model predicts the opponent's preferences and strategy (Section 3.3). However, many factors affect reaching an agreement in human-agent negotiations. The human negotiator can express the emotional state via facial express [32], make some arguments via text [14, 35, 43], express their feelings via body gestures [6], and so on. Therefore, an autonomous agent requires more components for human-agent negotiations.

3.1 Bidding Strategy

A negotiator mainly aims to maximize the received utility of the agreement at the end of the negotiation. Accordingly, it adopts a bidding strategy that determines the TU at the current round. Various bidding strategies have been proposed so far [3, 9, 19, 29, 32, 44, 45]. This section presents the fundamental bidding strategies adopted in negotiation and the Solver agent strategy we extend in this study.

3.1.1 Time-Dependent Bidding Strategy. The fact that underlying negotiations have deadlines causes time pressure on the negotiators. This pressure makes the negotiators tend to concede more as time passes to reach an agreement. Therefore, they start with the maximum desired TU (1.0) and go down to the minimum desired TU ($\geq RU$), where RU is the reservation utility—a minimum utility that can be acceptable for the agent. The speed of the concession may vary concerning the remaining time. Faratin et al. propose three time-dependent bidding behaviors: Boulware, Linear, and Conceder [19] where Figure 2 shows the TU calculation function of those behaviors separately. In this example, it is worth noting that the reservation value is set to 0.4, and all time-dependent bidding behaviors go down to this reservation utility value by the end of the negotiation.

Moreover, Vahidov et al. present a concession strategy for human-agent negotiation that adopts the aforementioned time-based concession idea [50]. Equation (2) shows the calculation of The TU where P_0 is the maximum TU at the beginning of the negotiation, P_2 is the minimum TU at the end of the negotiation. Here, P_1 determines the concession speed

$$TU = (1-t)^2 \times P_0 + (1-t) \times t \times P_1 + t^2 \times P_2 \tag{2}$$

$$\text{Behaviour} = \begin{cases} \text{Boulware}, & \text{if } P_1 > \frac{P_0+P_2}{2} \\ \text{Linear}, & \text{if } P_1 = \frac{P_0+P_2}{2} \\ \text{Conceder}, & \text{if } P_1 < \frac{P_0+P_2}{2} \end{cases}. \tag{3}$$

3.1.2 Behavior-Dependent Bidding Strategy. An autonomous negotiating agent can adapt its behavior concerning the opponent's behavior [9, 32]. It requires knowing the opponent's preferences; however, the agents only know them. Here, the agents can rely on their opponent modeling via analysis of the offer exchanges during the negotiation. Mimicking the opponent's behavior is the most common strategy used in behavior-based autonomous agent design [9, 32]. We adopted our behavior-based strategy presented in [6]. Initially, a high TU is set, and the agent updates the TU based on its opponent's moves (i.e., concession, selfish moves). The agent determines the current TU ($TU_{current}$ by considering its utility change in its opponent's consecutive offers (ΔU). Hence, the agent concedes if the opponent concedes regarding the received utility. The mimicking amount is also adjusted depending on the current time and a parameter (P_3) regulating the magnitude of the TU update. Equation (4) shows the TU calculation. It is worth noting that the magnitude of the updates is smaller at the beginning of the negotiation but increases toward the deadline

$$\begin{aligned} TU_{current} &= U(O_j^{t-1}) - \mu \times \Delta U \\ \mu &= P_3 + P_3 \times t. \end{aligned} \tag{4}$$

However, comparing the last two subsequent offers may not capture the real intention or behavior of the opponent. The opponent may manipulate the utility changes and use them in her/his favor. Therefore, Keskin et al. introduce a window mechanism for TU calculation [32]. They calculate the agent utility change in a window involving a certain number of subsequent offers as shown in Equation (5). Here, the utility changes are multiplied by their weights (W_i)—the more recent pairs have higher weights

$$\Delta U = \sum_{i=1}^{4} [W_i \times (U(O_h^{t-i}) - U(O_h^{t-i-1}))]. \tag{5}$$

3.1.3 Hybrid Agent. The hybrid strategy determines the TU by combining time and behavior-based strategies [32]. Hybrid agent calculates a time-based TU (TU_{time}) and a windowed behavior-based TU ($TU_{behavior}$) as mentioned above and combines them as shown in Equation (6). At the beginning of the negotiation, $TU_{behavior}$ has a higher weight, whereas the weight of the time-based TU calculation increases when the deadline is approached

$$TU_{hybrid} = t^2 \times TU_{time} + (1 - t^2) \times TU_{behaviour}. \tag{6}$$

3.1.4 Solver Agent. Keskin et al. extend the hybrid negotiation strategy by incorporating the opponent's emotional feedback into bidding behavior as shown in Equation (7) where P_E and P_A denote the emotion coefficient, and awareness constant respectively[4]

$$TU_{Behavior} = (1 - P_A) \times [U(O_j^{t-1}) - (\mu \times \Delta U)] + (P_A \times P_E). \tag{7}$$

One of the challenges is estimating the emotion coefficient capturing the opponent's emotional feedback during the negotiation. Instead of assigning primary emotional feedback (e.g., sad, happy), a vector of different emotions is considered. Our work considers a percentage per each relevant

[4]Opponent awareness could be estimated during the negotiation. Since it requires some minimum number of interactions, we take a constant value for this parameter in this work.

Table 2. The Normalized Valence Values of Five Basic Emojis in Negotiation

Emoji	**Angry**	**Sad**	**Neutral**	**Happy**	**Excited**
Emotion Effect	−1.00	−0.17	0.02	0.44	1.0

emotion in negotiation. P_E is calculated as the weighted sum of each emotion value in Table 2. These values are the normalized valence values of emojis presented in [34].

3.2 Acceptance Strategy

A negotiation lasts until reaching an agreement or the deadline. When there is no agreement, both sides get a zero utility score or the reservation value if available when the deadline is up. In the literature, several acceptance strategies have been developed [8]. The most common and successful strategy is the next utility acceptance strategy (AC_{next}). According to this strategy, the agent accepts its opponent's offer when the received utility of the opponent's current offer is equal to or greater than the agent's TU estimated for the current round.

3.3 Opponent Model

The opponent modeling in this work mainly aims to estimate the opponent's utility function by analyzing the bid exchanges during the negotiation. In the literature, it is mostly assumed that agents concede over time and have additive utility functions to capture their preferences. By comparing the values in subsequent offers made by the opponent, the models try to guess which issues are more critical and which values are preferred.

The most widely used opponent modeling approaches are the frequency-based opponent models [45, 48, 51]. In the basic frequency-based methods [51], agents have two heuristics: (i) the opponent concedes less on essential issues, and (ii) the preferred values appear more often in the opponent's offers (i.e., a negotiator tends to offer the most desired values). If a given value for an issue appears more frequently, the evaluation value of that value increases. As shown in Equation (8), the evaluation value for issue values is increased by one when they appear in the opponent's subsequent offer again. We scaled those updated values by dividing the maximum evaluation value so that the range will stay between zero and one, as shown in Equation (9). They are assumed to be equally essential and preferred at the beginning

$$V_i^j = V_i^j + 1 \tag{8}$$

$$V_i^j = \frac{V_i^j}{\max(V_i)}. \tag{9}$$

If the value of an issue remains the same in the subsequent offer, its importance value (W_i) is increased by a coefficient (n) as shown in Equation (10). A negotiator tends to concede the least significant issues. However, due to the time pressure, the agent may need to concede even on the most important issues. Hence, the remaining time is taken into consideration in the basic frequency-based approach.[5] Moreover, the summation of the issue weights always has to equal 1.

[5]The coefficient of the issue update depends on negotiation time ($n = 1 - t$) [51].

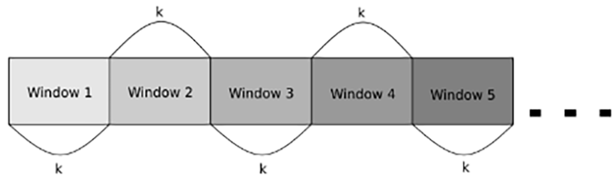


Fig. 3. The demonstration of the consecutive windows.

Therefore, the issue weights should also be normalized. The issue score (W_i) updates are shown in Equation (11)

$$W_i = W_i + n \tag{10}$$

$$W_i = \frac{W_i}{\sum_i W_i}. \tag{11}$$

Tunali et al. extended the frequency-based approach by introducing the window approach [48]. Instead of comparing two subsequent offers, they compare the fixed number of following offers (i.e., window). They test whether there is a statistical difference between the distribution of issue values in a current window to determine whether the issue weights should be updated. For updating issue weights, α and β parameters are used to adjust the amount of update, as shown in Equation (12). The issue update approach works well if the opponent makes a concession. However, opponents can make other moves, such as silent and selfish moves. Therefore, Tunali et al. apply the issue update if there is a concession between the windows. Note that these windows are consecutive and disjoint windows of the negotiation history of the opponent. Figure 3 demonstrates the consecutive windows, and every window has k offers received from the opponent. The normalization of the value weight is similar to the basic frequency-based approach, but this approach uses a smoothing factor (γ) to make value utility estimation more stable. Equation (13) shows the value weight normalization

$$W_i = W_i + \alpha \times (1 - t)^{\beta} \tag{12}$$

$$V_i^j = \left(\frac{V_i^j}{\max(V_i)}\right)^{\gamma} \tag{13}$$

4 Proposed Argument Taxonomy

In human-agent negotiation, different types of arguments could be exchanged to convince the opponent or give feedback so that the opponent can generate better offers that benefit both sides. Some argument taxonomies [2, 21, 33, 47] have already been introduced in the literature. By exploiting our expertise in the field of agent-based negotiation, we extend those taxonomies to capture more fine-grained argument types as depicted in Figure 4 by introducing new subcategories. While main categories are borrowed from the existing hierarchies, the subcategories are determined based on our elaborate analysis of existing negotiation corpora (CaSiNo [14], Craiglist [24], and DealOrNoDeal [35]). Our ultimate goal is to design a negotiating agent that can process human partner's arguments and take a strategic action accordingly. As human negotiators, the designed agents should be able to adopt different behaviors concerning the given argument types. For instance, if the argument is recognized as a "Hard Constraint," the agent should process the arguments to extract the "Hard Constraint" and maintain its knowledge base accordingly to avoid making such offers violating those constraints. Processing the arguments (i.e., deducing the formal representation from the given text in natural language) may highly depend on their argument types.

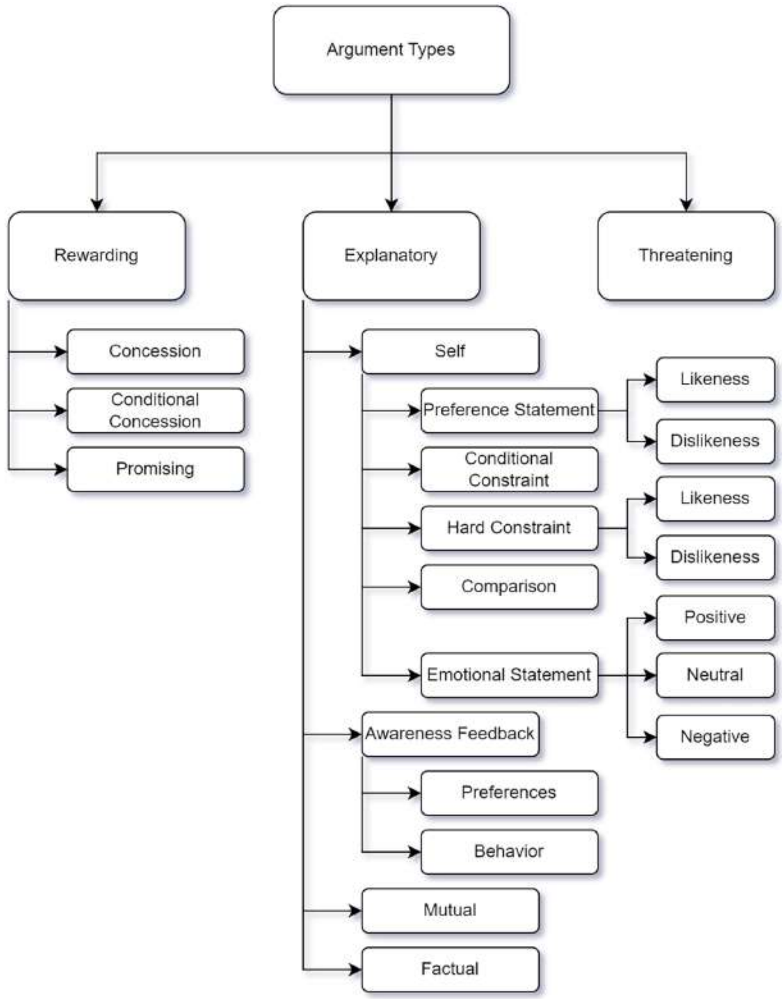


Fig. 4. The proposed argument type taxonomy.

Therefore, we introduce a fine-grained taxonomy taking into account this processing procedure. Accordingly, agents can first employ a classification model identifying the argument type and then adopt the most convenient processing methods for the underlying argument types.

As seen in Figure 4, some argument types contain sub-argument types. These sub-argument types and some example sentences are listed below:

— *Rewarding*
  – *Concession Statement*: Expressing the negotiator making a concession.
    "Let's go to Barcelona as you wish."
  – *Conditional Concession Statement*: Asking for something in exchange for concessions on another issue.
    "If we go to Barcelona as you wish, I want to stay in a tent in summer."
    "If we go to Barcelona, you can choose the accommodation option."

  - *Promise Statement*: Promising something for future negotiations.
    "If you accept my offer, I promise our next vacation will be as you wish."
- *Explanatory*
  - *Self*: Explaining about itself.
    - *Preference Statement (i.e., soft constraints)*: Stating preferences (e.g., likeness or dislikeness).
      "I do not want to go to London."
      "London is the best option for me."
      "Location is not important for me."
    - *Conditional Statement (i.e., conditional constraints)*: Stating preferences/constraints depend on two or more issues.
      "If we go to Barcelona, I prefer summer."
      "Staying in a tent in winter would be cold, I cannot accept."
    - *Hard Constraint*: Indicating something desired or undesired.
      "Destination is the most important issue for me. It should be London."
      "I have no free time in winter. Winter is unacceptable for me."
    - *Comparison*: Comparing two items according to preferences.
      "I prefer Tokyo rather than Milan."
      "Location is more important than transportation for me."
    - *Emotional Statement*: Expressing emotional state (i.e., positive or negative)
      "I feel happier."
      "I am tired of negotiating with you."
  - *Awareness Feedback*: Expressing awareness of the opponent's preferences or behavior.
    - *Preferences*: Awareness of the opponent's preferences.
      "You do not want to go to Istanbul."
      "You prefer Istanbul rather than London."
    - *Behavior*: Being aware of the opponent's behavior.
      "You are insisting on Istanbul."
      "Why are you so selfish?"
      "Thank you for your concession."
  - *Mutual*: Stating some explanation indicating that the offer benefits both sides.
    "Going to Istanbul makes us happier."
    "Taking a taxi will be expensive for us."
    "We both love Barcelona."
  - *Factual*: Other than personal opinion (i.e., preferences), opponent can express factual statements relying on a reasoning or statistical information.
    "Staying in a tent is not a safe accommodation option."
    "Taking a taxi is the most expensive option for the transportation."
    "Riding a bike is dangerous in Istanbul."
- *Threatening*: Threatening or warning the opponent.
  "We cannot agree like that."
  "It is your last chance."
  "Time is almost up!"

The example sentences above are chosen from the collected data through our human-agent framework introduced in Section 5. The collected data were labeled according to these argument types. It is worth noting that the experimental data has not been used to create our taxonomy. The taxonomy is the output of a deep analysis of the existing studies in argumentation-based negotiation.

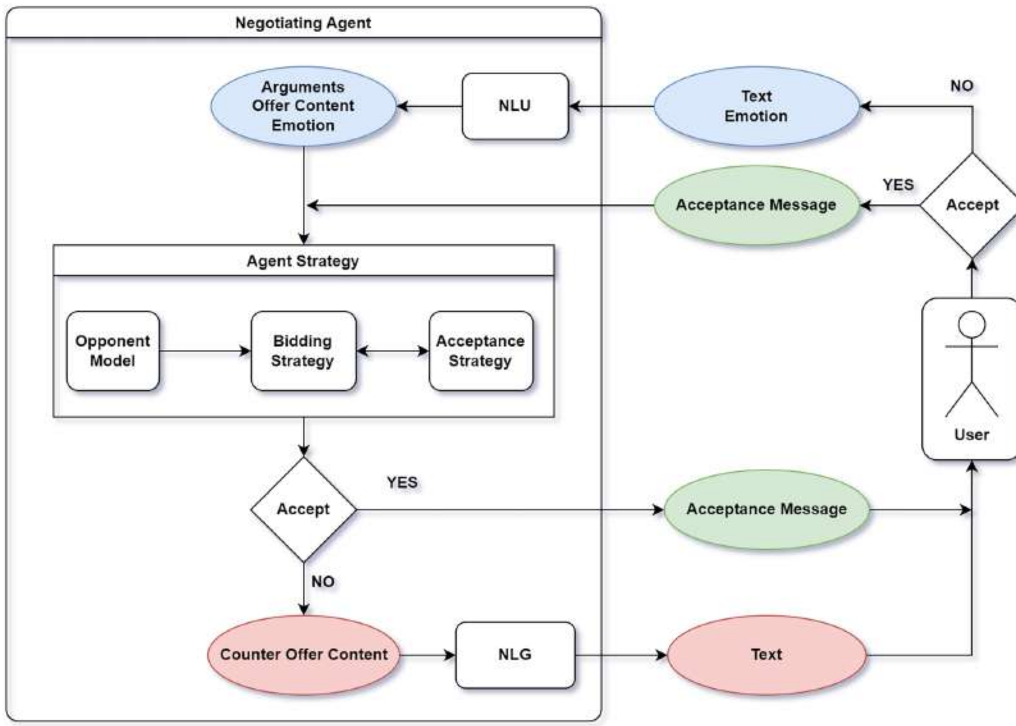


Fig. 5. The agent components and protocol for argument-based bilateral negotiation.

5 Human-Agent Negotiation Framework and Negotiation Corpus

In this section, the argument-based human-agent negotiation protocol is introduced in Section 5.1. For the negotiation experiments, a human-agent negotiation framework is developed. The framework is also introduced in Section 5.2. Lastly, the process of the collection of the corpus is described in Section 5.3.

5.1 Argument-Based Negotiation Protocol and Agent Components

For the bilateral human-agent negotiations, stacked alternative offer protocol [4] can be adapted, and an autonomous negotiating agent can be designed based on BOA components [7]. However, human negotiators can negotiate by not only exchanging offers but also expressing their emotional state and arguments. Thus, the negotiation protocol must be specialized, and some additional components are necessary. Figure 5 displays the extension version of the components and protocol in NegoChat [43]. In this novel protocol and agent design, negotiators can indicate their emotional state via emoji bars and exchange text, including their offers and arguments. The agent has two additional components such as NLU and NLG. NLU component extracts the corresponding arguments and offer content from given text sent by the human negotiator. NLG component generates a human-readable text from agent's structured offer. Briefly, human negotiator and agent exchange text involving offers and arguments in a bilateral fashion. This process continues until an agreement or the deadline is reached, as in the stacked alternative offer protocol. It is worth noting that the acceptance strategy is AC_{Next} [8], which is widely-used in agent-based negotiation systems.

In our study, how to extract the offer content and the corresponding arguments (i.e., NLU component) is described in Section 6. Our novel argument-based opponent model and bidding

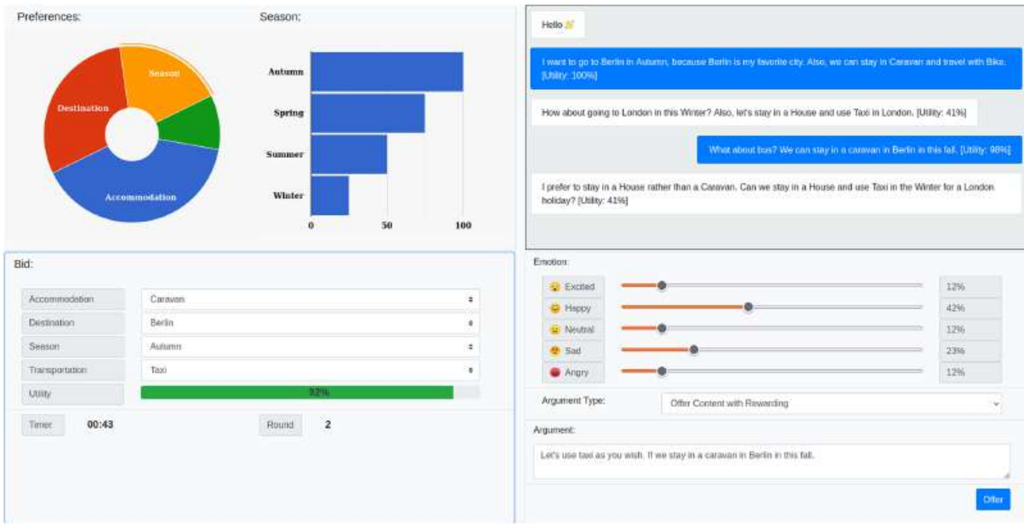


Fig. 6. The data collection experiment interface.

strategy are introduced in Sections 7.1 and 7.2, respectively. Lastly, the NLG component is a simple rule-based mechanism, which can be enhanced later since it is out of the scope of this study.

5.2 Negotiation Framework

Since the currently available negotiation corpora primarily focus on resource allocation problems and do not cover all argument types introduced in our taxonomy. Therefore, we developed a human-agent negotiation framework to build up our corpus in line with the taxonomy described above based on the proposed human-agent protocol. This framework enables human negotiators to make their offer in English and specify it through more structured drop-down boxes. They can express their emotional feedback on relevant emotions such as anger, sadness, neutral, happiness, and excitement elaborately (e.g., specifying their percentages where the summation of these percentages always equals 100%). They can also write arguments to convince the agent.

As seen in Figure 6, the participants can see their preference profiles in the upper left-hand corner. The participants can see the chat history with their utility scores in the upper right-hand corner. They can make an offer in the lower left-hand corner by choosing the values of each issue from the given drop-down lists. It is worth noting that the issues and corresponding values are sorted according to the participants' preference profiles to decrease their cognitive load. Here, they can also see the current time, round, and utility of the offer they constructed. Note that to minimize the time pressure on participants so they can provide an enriched set of arguments, we avoid displaying the remaining time; thus, we only show the current time. On the lower right-hand side, the participants can type an offer content and the corresponding arguments as text in English. Besides, the participants express their emotional state as a combination of five emojis. This enables participants to express their complex emotional states during negotiation. For instance, someone can feel sad but surprised at the same time. Therefore, forcing them to map their feelings to one category sounds unnatural.

On the other hand, it is required to represent the emotional states as a vector to employ the baseline strategy (i.e., SolverAgent [32]), which analyzes the emotional state of an opponent to decide what to offer. In literature, some researchers use "affect buttons" to capture a vector of emotional states [11]; however, those components may create additional cognitive load and uncertainty on some participants while scrutinizing 40 available expressions and determining which one expresses the participant's most dominant emotional state. Some participants may be indecisive between several options. When participants are on the fence about which expression to pick, it causes a cognitive load and pressure on them. Consequently, we decided to utilize slider bars to indicate to what extent that emotion is dominant. Finally, to accept the opponent's offer, the participant should select the argument type Acceptance, write an agreement sentence and express the emotional state.

While entering the arguments, the participants need to choose one of the following actions: (i) *"Only Offer Content,"* (ii) *"Offer Content with Explanatory,"* (iii) *"Offer Content with Rewarding,"* (iv) *"Offer Content with Threatening,"* and (v) *"Acceptance"* and enter the corresponding text. This categorization simplified the labeling process and derived from the baseline taxonomy [21, 33]. Besides, other dialogue types that human negotiators might propose, such as "Greeting" and "Question-Answering," are not considered as they are beyond the scope of our study. After the data collection experiment, the human annotators who took place in the design of the overall taxonomy labeled each text entered by the participants according to the subcategories in our taxonomy to train required classifiers. It is worth noting that some texts have multiple class labels. For instance, some sentences involve both comparisons and rewarding arguments.

5.3 Data Collection Experiment

To collect the data, we conducted human experiments where the participants were asked to negotiate twice on the holiday domain, with our negotiating agent employing a different strategy in each session. In each negotiation session, participants have 30 minutes to complete their negotiation. It is worth noting that participants know only their scores and are informed that agents do not know their scores either. At the beginning of the experiment, the interaction protocol and the framework were explained to the participants via a demo video. Besides, have a training session where they negotiate a more straightforward problem for 5 minutes to get familiar with the negotiation process and the framework. Moreover, the supervisor waits in a Zoom meeting to answer any questions and to provide guidance. Before starting the experiments, participants signed the consent form.[6]

During their negotiation, the participants communicate with the agent via text, combo boxes, and buttons on the web page. They negotiated on the holiday domain in both sessions, but there were slight differences, such as different destination locations in each setting. In total, 64 participants attended our experiments, resulting in 3,013 text exchanges. Afterward, those texts are manually labeled according to the categories in our taxonomy. The corpus is available on the Internet,[7] offering a valuable resource for researchers to leverage in future studies.

6 Classification of Human Opponent's Arguments

This section introduces how to extract the arguments from a given text via machine learning algorithms in Section 6.1. Besides, the training process and the evaluation of the classifiers are indicated in Section 6.2.

6.1 Hierarchical Classification

In order to process and utilize the meaning of the sentences given in a text, the agent first needs to detect what type of arguments they are. With this purpose, we aim to build a classifier to predict which argument types in the taxonomy correspond to the given text. Recall that human annotators

[6]The experiment protocol in this study was approved by the Ethics Committee of Özyeğin University on 21 December 2021.
[7]Access link of the corpus: https://github.com/aniltrue/Taking-into-Account-Opponent-s-Arguments-in-Human-Agent-Negotiations.

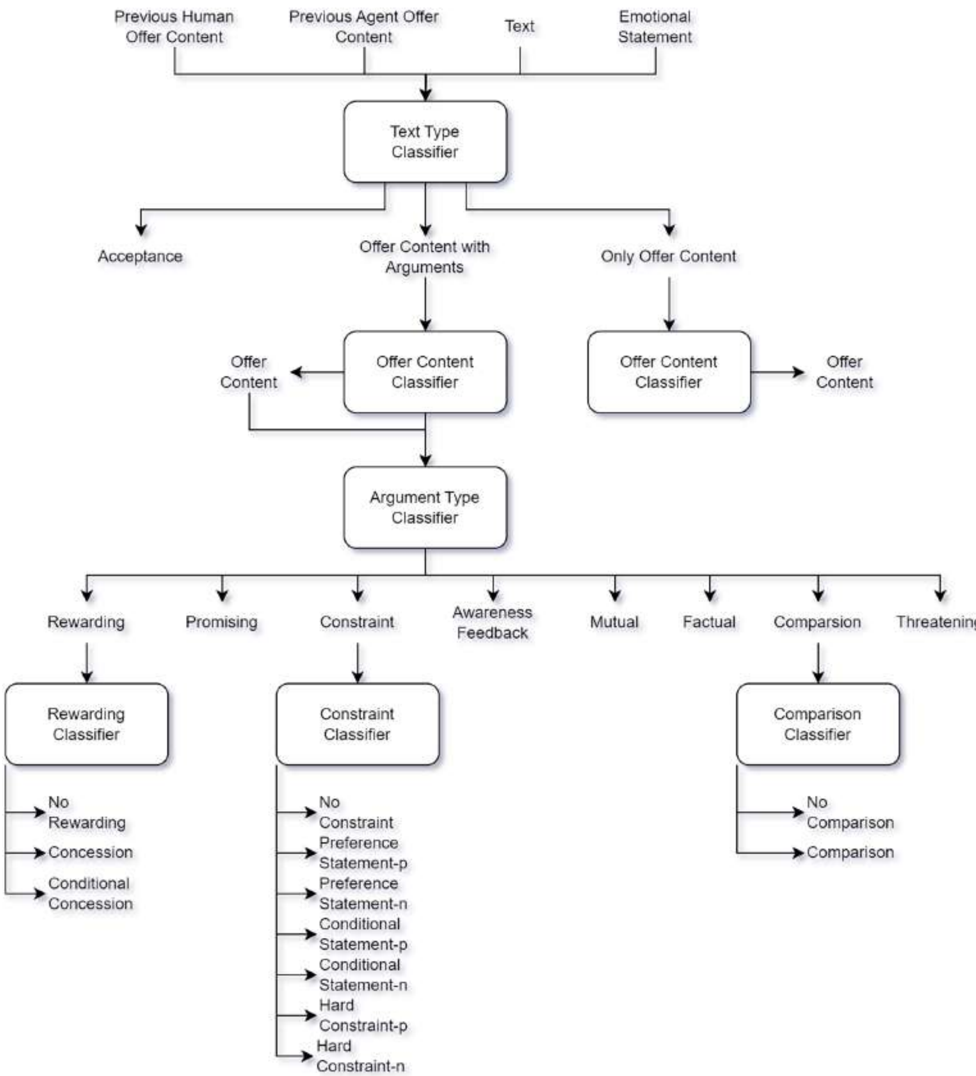


Fig. 7. The proposed hierarchy of the classifiers.

labeled the dataset we collected during human-agent negotiations. According to the proposed taxonomy and dataset, this classification problem can be defined as a multi-label classification task and hierarchical classification task, as illustrated in Figure 7.

The proposed approach relies on having multiple classifiers where each classifier aims to learn a particular task. The text-type classifier detects whether the given sentence is an acceptance statement, offers content with arguments, or only involves the offer content. This classifier utilizes the available inputs, such as the underlying text to be classified, the agent's and human opponent's previous offer contents, and the emotional statement expressed by emojis and a scroll bar for their percentages. If the text involves the content of the offer, an offer content classifier is used to detect the issue values per each issue. For example, the classifier predicts the value of the destination from the given text, where the outputs could be London, Tokyo, and other possible destinations

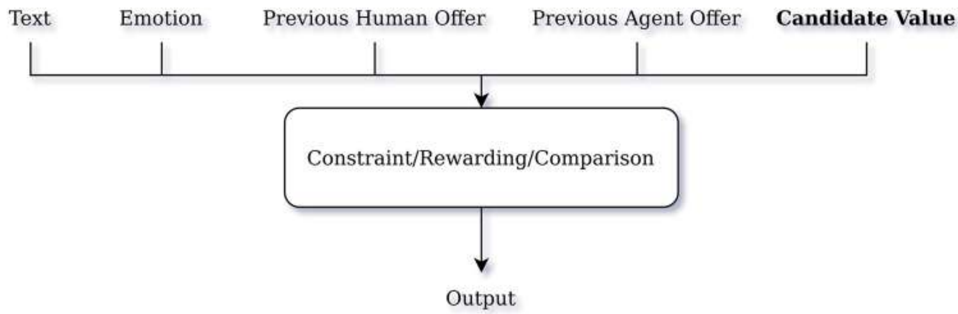


Fig. 8. The inputs of constraint/rewarding/comparison classifiers.

defined in the negotiation domain. If the text involves arguments, a classifier predicts whether the given argument is rewarding, promising, constraint, awareness feedback, mutual explanation, comparison, or threatening argument. As seen from the classifier hierarchy, there are more fine-grained classifiers if the arguments fit their category. For example, if the argument type is detected as constraint, a constraint classifier aims to detect what type of constraint the argument involves (e.g., preference statement or hard constraints).

Besides predicting predefined categories, rewarding, constraint, and comparison classifiers should also extract the corresponding value. Therefore, these classifiers also take the candidate value as an input and classify it depending on the given inputs and the candidate parameters. In other words, they iterate on each candidate value to extract the proper argument type with the corresponding value. The inputs of these classifiers are shown in Figure 8. For instance, the same data instance may contain a positive preference statement on the "Istanbul" value. Therefore, the constraint classifier should extract this value-argument pair from the given data instance. While iterating over the whole values in that domain (e.g., "Tokyo," "Milan," and "Istanbul"), the classifier should predict "Preference Statement-p" when "Istanbul" is the candidate value. The other values in that domain (e.g., "Milan" and "Tokyo") should output as "No Constraint."

To illustrate the complexity of this classification task, an example text data from the dataset is examined in Figure 9. In this example, the given text involves both the content of the offer and the arguments. From the given text, we need to extract the content of the offers in a structured way (i.e., extracting the offer in terms of issue-value pairs). We also need to pull out all specific arguments from the text, such as comparison and threat arguments. In our case, the size of the collected data might be insufficient to train such complex models. Furthermore, our dataset was unbalanced. Two kinds of data augmentation techniques are applied before training the models to increase the classification prediction performance. The first one is augmentation from predefined template-based sentences. This approach uses all combinations of the values in the domain to generate new sentences from the template sentences. Secondly, new sentences from the existing ones are generated by changing the values in the sentence. Note that we ensure that the augmented sentences have no inconsistency or negating variations to avoid a negative impact on classifiers. As a result, nearly 51k data instances were obtained.

6.2 Training and Evaluation

We adopted classical machine learning approaches for training models such as Naive Bayes, K-nearest Neighbor Classifier, Logistic Regression, **Multilayer Perceptron (MLP)**, decision trees, and Random Forests on the collected dataset. For representation of text, Bag-Of-Words approach is applied with NGram method ($n \in [1 - 3]$) [23]. Five-Fold cross-validation approach is applied to

- **Text:** *"I have no free time in Winter. I want to go to London in the Summer and stay in a Hotel. Also, I prefer to use the Subway more than Taxi. This is your last chance!"*
- **Text Type:** Offer Content with arguments.
- **Offer Content:**
    - **Accommodation:** Hotel
    - **Destination:** London
    - **Transportation:** Subway
    - **Season:** Summer
- **Arguments:**
    1. **Label**: Threatening **Value**: None
    2. **Label**: Hard Constraint Negative **Value**: Winter
    3. **Label**: Comparison **Value**: Subway > Taxi
- **Emotional Statement:**
    - **Excited:** 0%
    - **Happy:** 0%
    - **Neutral:** 0%
    - **Sad:** 15%
    - **Angry:** 85%

Fig. 9. An example text data in our corpus.

Table 3. Performance Results for Each Classification Task

Classification Task	Best Performing Model	F_1 on Training Set	F_1 on Test Set	$F_{0.5}$ on Training Set	$F_{0.5}$ on Test Set
Text Type	Mix. Average	1.00	0.69	1.00	0.92
Rewarding	MLP	1.00	0.79	0.97	0.91
Constraint	Mix. Weighted	0.86	0.80	0.94	0.84
Offer	Mix. Average	0.92	0.88	0.93	0.89
Argument Type	MLP	1.00	0.93	1.00	0.94
Comparison	Mix. Average	1.00	0.93	0.94	0.84

split training and test sets [1]. The primary goal of the hierarchical classifier is to achieve accurate predictions of arguments. For this reason, F_β score (Equation (14)) that combines precision and recall is employed for the evaluation metric. It is worth noting that F_β is commonly preferred when the data is unbalanced.

Among those models, we observed that the performance of the MLP and Random Forests is higher than that of the rest of the classifiers. To see whether the performance increases when we combine those algorithms. Consequently, the mixture of MLP and Random Forests is also used where we refer to Mix Average and Mix Weighted in our evaluation. Note that the weights are calculated depending on the performance of the models. Furthermore, *F-Score* metric is utilized to performance analysis, which is denoted F_β—a harmonic average of precision and recall. Here, β is a parameter controlling to what extent recall is as crucial as the precision, as shown in Equation (14). When β equals one, the calculation equally considers the precision and recall. For each classification task, the models are trained, and their F_1 scores on both training and test sets are analyzed. Note that the higher the F_1 score is, the better the predictions are. In addition, precision is more crucial than recall because a false positive (i.e., classified as positive, but it is not) is more harmful to the proposed strategies. Thus, we also reported the $F_{0.5}$ values which weight the precision more than the recall. Table 3 shows the best-performing models with the corresponding F_1 and $F_{0.5}$ scores.

Therefore, our negotiating agent uses those classifiers during the negotiation

$$F_\beta = \frac{(1+\beta^2) \times precision \times recall}{(\beta^2 \times precision) + recall}. \quad (14)$$

In order to enhance the precision of the argument extraction methodology, a rule-based approach is employed to eliminate invalid/inconsistent predictions. For example, the participant stated, "I cannot go to Istanbul. I want to go to London." Suppose our classifier predicts a "Negative Hard-Constraint" for "London," meaning that "London" is unacceptable for the human negotiator. If "London" is part of the offer, our rule-based approach detects this inconsistency, ignores previous predictions, and acts as if it is not detected. Similarly, the classifier cannot detect the "rewarding" (i.e., concession) argument type for issue value if it is not detected as a part of the offer. This argument-elimination approach significantly improves the precision of the argument extraction process. However, it is important to note that this approach is relevant to domain-specific considerations. Note that the classifiers used in this methodology should also be re-trained with a domain-specific corpus. Besides, it is worth noting that the corpus does not contain any "Factual" argument type. Therefore, factual statements are ignored in the evaluation of the classifiers.

7 Proposed Negotiation Strategy

A human negotiator can make arguments to achieve an agreement sooner and achieve a better negotiation outcome. This means that understanding human arguments is crucial for a sophisticated agent. This section explicates the argument-based opponent modeling (Section 7.1) and the argument-based bidding strategy (Section 7.2). The proposed opponent modeling enriches the windowed frequency opponent model [45, 48], while the proposed bidding strategy is an extended version of Solver Agent [32].

7.1 Opponent Modeling

Frequency-based opponent models take the value observation frequency and the issue value change rate into consideration [45, 48, 51]. Tunali et al. presented a state-of-art approach called a windowed frequency-based opponent model [45, 48]. In this study, the windowed frequency-based opponent model is extended with arguments. For this purpose, some issue and value update rules for some argument types (rewarding, preference statement, hard constraint, and comparison) are set on the windowed frequency-based opponent model. The updated rules when the classifier detects the corresponding argument type are described below.

7.1.1 Preference Statement. Preference statements express the likeness or dislikeness of a value for an issue. If the statement is positive, the corresponding evaluation value of the corresponding value should be increased. Otherwise, it should be decreased. Therefore, the value score will be increased when a positive preference statement is received (Lines 5–7 in Algorithm 1). When a negative preference statement is detected, the value scores of the other values for the underlying issue are increased to avoid negative scores (Lines 8–10 in Algorithm 1). Regarding the importance of the issues, the human negotiator tends to make preference statements on important issues. Therefore, we update the importance of the issue positively considering the current negotiation time when a preference statement argument type is made. Equation (15) shows the issue importance update

Algorithm 1: Value Estimation Update

1: **procedure** VALUE ESTIMATION UPDATE($\hat{V}$,$Pref$,$Offer$,$concession$,γ)
2: **for each** $i \in I$ **do**
3: **for each** $j \in J_i$ **do**
4: update_greater $\leftarrow False$
5: **if** $(j \in Pref_{positive})$ **or** $(j \in Offer$ **and** $j \notin concession)$ **then**
6: $\hat{V}^i_j \leftarrow \hat{V}^i_j + 1$
7: update_greater $\leftarrow True$
8: **else if** $j \in Pref_{negative}$ **then**
9: $\hat{V}^i_k \leftarrow \hat{V}^i_k + 1 \; \forall \; k \neq j$
10: update_greater $\leftarrow True$
11: **end if**
12: **for each** $\hat{V}^i_{greater} \in$ Greater$(\hat{V}^i_j)$ **do**
13: **if** update_greater $= True$ **then**
14: $\hat{V}^i_{greater} \leftarrow \hat{V}^i_{greater} + 1$
15: **end if**
16: **end for**
17: **end for**
18: **end for**
19: **for each** $i \in I$ **do**
20: **for each** $j \in J_i$ **do**
21: $\hat{V}^i_j \leftarrow \left(\frac{\hat{V}^i_j}{max_j(\hat{V}^i)}\right)^{\gamma}$
22: **end for**
23: **end for**
24: **end procedure**

$$
\text{issue weight update: } \begin{cases} W_i = W_i + \alpha_{pref} \times (1-t)^{\beta_{pref}}, & \text{if } i \text{ has any preference statement} \\ W_{others} = W_{others} + \alpha_{rew} \times (1-t)^{\beta_{rew}}, & \text{if } i \text{ has any rewarding} \\ W_i = W_i + \alpha_{comp} \times (1-t)^{\beta_{comp}}, & \text{if } i \text{ has any comparison} \\ W_i = W_i + \alpha_{hard} \times (1-t)^{\beta_{hard}}, & \text{if } i \text{ has any hard constraint} \end{cases} . \tag{15}
$$

7.1.2 Rewarding. Under time pressure, negotiators tend to make concessions [19]. Frequentist opponent models update their estimation by relying on this assumption [45, 51]. Apart from concession moves, a human negotiator can make rewarding argument types to indicate a concession. Note that we assume that the negotiators do not lie. Leveraging rewarding argument types can provide a more reliable indication of concession, making them valuable for integration into opponent models. In this case, it is assumed that negotiators reward by conceding on their most minor preferred issues and values more than the most preferred ones. Hence, the value/weight scores of the other issues/values are increased. The weight score update is indicated in Equation (15) while the value score update is shown in Algorithm 1 (Lines 5–7). Note that the issue values appeared in the offer, but the human negotiator does not concede as a reward is updated.

7.1.3 Comparison. A human negotiator can state preferences via comparison argument type. In comparison argument type, there are more preferred and less preferred values for an issue. This

Table 4. The Optimized Parameter Values by Genetic Algorithm

Parameter	α	β	α_{pref}	β_{pref}	α_{hard}	β_{hard}	α_{comp}	β_{comp}	α_{rew}	β_{rew}	k	γ
Value	10	5	2	5	2	5	1	3	1	1	2	0.15

relationship should be established as a rule in the value score update process. The estimated value of more preferred values should be enforced to have higher than that of the less preferred ones, as seen in Algorithm 1 (Lines 12–15). Assuming that the negotiator states comparisons on essential issues; thus, the agent increases the weights of those issues that appeared in the comparison statements. The weight update of an issue is denoted in Equation (15) when a comparison is detected.

7.1.4 Hard Constraint. Human negotiators can set some hard constraints to denote an issue's most desired or undesired values. If the constraint is positive, the corresponding value should always be greater than the other values for the underlying issue. As in comparison argument type, corresponding relationship rules should be established and applied in Algorithm 1 (Lines 12–15). As we increase the importance of the issues that appeared in the comparison or preference statements, we increase the weight of the issues mentioned in the hard constraints, as shown in Equation (15). Additionally, the relationship rules established by comparison and hard constraint argument types may cause inconsistency. A cycle detection method is applied to find the inconsistent relationship rules to avoid it. If a cycle is detected, the oldest relationship rule in that cycle should be removed to maintain consistency.

A Genetic Algorithm approach is implemented to optimize the hyperparameters of the proposed opponent model. The main objective of an opponent model is estimating the opponent's preferences accurately. For this purpose, some evaluation metrics (e.g., Spearmann, RMSE, Kendall's Tau, etc.) can be employed. For the fitness function of Genetic Algorithm, the previous human-agent negotiation data is used to maximize Kendall's Tau metric (i.e., the higher the value, the more desired it is). Note that Kendall's Tau is one of the most reliable evaluation metrics for the performance analysis of an opponent model, since it can measure how accurate the estimated order of bids is. The parameter values optimized by the Genetic Algorithm are given in Table 4. It is worth mentioning that the collected corpus is used for the parameter tuning of the opponent model.

The issue weight estimation is almost the same with the distribution-based frequentist opponent model [45, 48]. The difference is that the issue scores are updated with proper parameters when the corresponding argument type is detected, as shown in Equation (15).

7.2 Bidding Strategy

While making an offer, one challenge is generating well-targeted offers against the human negotiator. It requires considering the opponent's bid history, emotional state, and arguments. Keskin et al. introduced an emotional and opponent-aware agent (called Solver Agent) for human-agent negotiations [32]. On the other hand, this strategy does not utilize human arguments. In this work, we extend Solver Agent to pre-process the human opponent's arguments and revise its opponent model accordingly. Although the TU estimation is the same as the original algorithm, we apply a window-based bid search approach instead of searching for an offer with a utility closest to the TU. As it is common, the agent employs the AC_{next} strategy to decide when to accept the opponent's offer.

Algorithm 2 demonstrates the windowed offer search with a constraint satisfaction approach. The windowed offer search approach chooses an offer around the TU instead of the closest one. This window is defined by some thresholds (δ). This means that this approach generates an offer

Algorithm 2: Windowed Offer Search with The Constraint Satisfaction

1: **procedure** WINDOWED_OFFER_SEARCH(δ, α_{lower}, C)
2: $\quad TU \leftarrow$ Solver Agent
3: $\quad offers \leftarrow$ The offers in range $[TU - \delta_{lower}, TU + \delta_{upper}]$
4: $\quad offers \leftarrow$ Eliminate$(offers, C)$
5: $\quad$ **while** $(offers = \emptyset)$ **and** $(\delta_{lower} < \alpha_{lower}$ **or** $\delta_{upper} \leq 1 - TU)$ **do**
6: $\quad\quad \delta_{upper} = \delta_{upper} + 0.01$
7: $\quad\quad$ **if** $\delta_{lower} < \alpha_{lower}$ **then**
8: $\quad\quad\quad \delta_{lower} = \delta_{lower} + 0.01$
9: $\quad\quad$ **end if**
10: $\quad\quad offers \leftarrow$ The offers in range $[TU - \delta_{lower}, TU + \delta_{upper}]$
11: $\quad\quad offers \leftarrow$ Eliminate$(offers, C)$
12: $\quad$ **end while**
13: $\quad$ **if** $offers = \emptyset$ **then**
14: $\quad\quad offers \leftarrow$ The offers in range $[TU - \delta_{lower}, TU + \delta_{upper}]$
15: $\quad$ **end if**
16: $\quad offer \leftarrow$ The offer with the maximum estimated product utility in $offers$
17: $\quad$ **return** $offer$
18: **end procedure**

pool with utility values between $TU - \delta_{lower}$ and $TU + \delta_{upper}$ in the provided bid space (Line 3). Note that δ_{lower} and δ_{upper} are not equal. Afterward, the bid having the highest estimated product utility will be offered. The estimated product utility is calculated by multiplying the utility of the bid for the agent (i.e., U_{Agent}) and the estimated utility of the bid for the opponent via the opponent model (i.e., U^{Est}_{Opp}) as shown in Equation (16)

$$Product\_Utility^{Est} = U^{Est}_{Opp} \times U_{Agent}. \tag{16}$$

A human negotiator can specify some constraints during the negotiation. Finding offers that align with the opponent's constraints is essential for beneficial agreements. Thus, the offers conflicting with the hard and conditional constraints should be eliminated from the candidate offer list (Line 4). Our strategy chooses the offer with the highest estimated utility product (Line 16). However, if no candidate offer satisfies the given constraints, the windowed offer search thresholds (δ) increase until at least one candidate offer is found (Lines 5–12). If the lower bound drops significantly, the agent may make undesired offers; therefore, we limit the decrease in this threshold with an α_{lower} parameter (Lines 7–9). If the candidate offers have still been empty where $\delta_{lower} = \alpha_{lower}$ and $\delta_{upper} = 1 - TU$, *offers* will be generated without constraint satisfaction (Lines 13–15). Furthermore, the defined α_{lower} and the initial values of the thresholds can vary domain by domain.[8] They should be carefully determined by considering the domain specifications. Besides, human negotiators may concede over time; therefore, their hard constraints might turn into soft constraints. The hard constraint rule is removed from the constraint set in such a case.

8 Evaluation of Agent Design

This section reports the performance evaluation of the proposed argument-based agent design. We explain the details of the experimental setting (Section 8.1) and report the performance of the proposed opponent model (Section 8.3) and NLPSolver Agent (Section 8.4).

[8] In our domain, we take $\alpha_{lower} = 0.1$, $\delta_{lower} = 0.03$ and $\delta_{upper} = 0.03$.

Table 5. The Weights of Issues and Values of Holiday Domain

Domain: Holiday

Issues	**Accommodation** (0.4)	**Destination** (0.3)	**Transportation** (0.2)	**Season** (0.1)
Values	Caravan (1.0) Hotel (0.8) House (0.6) Hostel (0.4) Tent (0.2)	London/Amsterdam (1.0) Berlin/Barcelona (0.8) Tokyo/Boston (0.6) Paris/Milan (0.4) Istanbul/Seoul (0.2)	Subway (1.0) Bus (0.8) Taxi(0.6) Car (0.4) Bike (0.2)	Winter (1.0) Summer (0.75) Spring (0.5) Autumn (0.25)

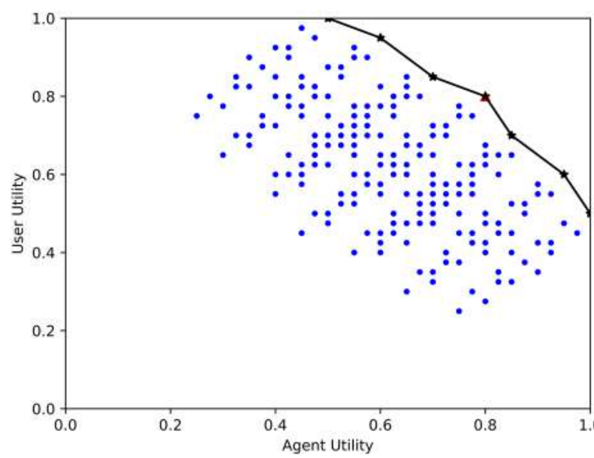


Fig. 10. The utility space for all possible outcomes on the holiday scenario.

8.1 Experiment Setup

In order to evaluate the performance of the proposed approach, we created a Holiday domain consisting of four issues. According to the designed scenario, the participants earned a vacation gift from a draw. However, another person they have never known also earned this vacation and must go on vacation together. Therefore, they should negotiate where to go (Destination), where to stay (Accommodation), when to go (Season), and how to travel in the city (Transportation). In agent-based negotiation, it is assumed that both parties know the negotiation issues and their possible values. Therefore, the issues with corresponding values were defined before the negotiation started and known by all stakeholders. Agents and participants can make only valid offers and additional arguments by following the alternative offers protocol. Consequently, the predictors ignore all invalid values that appear in the offer or arguments.

It is a role-playing game; however, it works better when the participants embrace their preferences instinctively. Therefore, before each session, participants are asked to order the issues regarding their importance and possible values per each issue in line with their preferences. These orderings are mapped onto a predefined utility function. Accordingly, a conflicting preference profile is generated for the agent. It is worth noting that each party knows its preferences during the negotiation. Table 5 displays the negotiation issues and possible values, with an example order and utilities. To reduce the learning effect between consecutive sessions, we slightly changed the destination for their second negotiation. Accordingly, the utility space for all possible outcomes on the Holiday scenario is displayed in Figure 10. Note that the Nash solution denotes the fairest solution for both sides where both parties can take 0.80 utility. If the participants do not reach an agreement with the agent, both sides receive a zero utility.

Table 6. Parameters of Agents

	P_0	P_1	P_2	P_3	P_A	δ_{lower}	δ_{upper}	α
Solver Agent	0.9	0.8	0.5	0.5	0.5	-	-	-
NLPSolver Agent	0.9	0.8	0.5	0.5	0.5	0.03	0.03	0.1

We recruited 40 participants for our negotiation experiments where participants are either university students or recently graduated from the university with varying majors from engineering to social sciences in Turkiye. The participants are nearly evenly split between males and females, with 22 male and 18 female participants. Participants gave their consent voluntarily to participate in this experiment. It is worth noting that participants who did well received a supermarket gift for their effort.

In our setting, participants negotiate separately with two agents, Solver Agent, and NLPSolver Agent. We use the same values for both agents as seen in Table 6. Each negotiation session has a deadline of 30 minutes. If the participants do not reach an agreement in 30 minutes, the negotiation fails. To minimize the learning effect, we counterbalance the negotiation session order. Half of the participants negotiate with Solver Agent and then negotiate with NLPSolver Agent, while the other half negotiate in reverse order. Note that there is a 5-minute break between two negotiation sessions.

At the beginning of the experiment, the interaction protocol and the framework were explained to the participants via a demo video, as in the data collection experiment. Additionally, they have a training session with 5 minutes deadline to get familiar with the negotiation process and the framework. After completing both sessions, participants are asked to fill out a questionnaire regarding their negotiation experiences for each session separately. Consequently, we analyze negotiation logs and survey responses to evaluate the proposed approach in the following sessions.

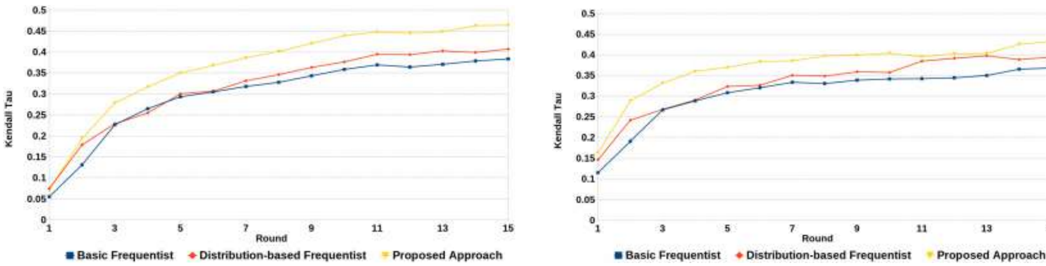
8.2 Evaluation Objectives and Metrics

Regarding the evaluation objectives and metrics on agent design [37], we can list two main evaluation objectives: (i) assessing the accuracy of the estimated opponent modeling and comparing it with the baseline model and (ii) showing the superiority of the proposed negotiation strategy against the baseline agent. Apart from these objectives, we also analyze how participants perceive the designed agent's behavior through survey questionnaires.

Kendall's Tau correlation metric is utilized for the first evaluation objection (i.e., opponent model performance). All potential offers are sorted according to the actual utility functions (i.e., ground truth) and estimated opponent models, respectively. Kendall's Tau measures the difference between the real and estimated offer orders [31]. The calculation of τ_b is indicated in Equation (17). In that calculation, n_c is the number of the concordant pairs while n_d is the number of the discordant pairs. Additionally, n_r is the number of ties (i.e., equally preferred offers) in the real offer ordering, while n_e is the number of ties in the estimated offer ordering

$$\tau_b = \frac{n_c - n_d}{\sqrt{(n_c + n_d + n_r) * (n_c + n_d + n_e)}}. \tag{17}$$

To calculate the number of concordant pairs (n_c) and the number of the discordant pairs (n_d), two pair instances which are $(o_i, \hat{o}_i)$ and $(o_j, \hat{o}_j)$ are compared. If $o_i < o_j$ and $\hat{o}_i < \hat{o}_j$, or vice versa, these pairs are concordant pairs. Otherwise, these pairs are discordant pairs. Note that i is always less than j.



(a) Corpus Dataset

(b) Experimental Dataset

Fig. 11. Kendall Tau results of the opponent models.

For the second objective, we employ the widely used metrics in agent-based negotiation: *average agreement utility for agent and human negotiators*, *average normalized product utilityaverage normalized time and round to reach an agreement*. The individual utility of an offer denotes how desired that offer is. The higher the utility is, the better performance the individual has. The average normalized product utility indicates the product of utilities of the agreement for the agent and human opponent, as seen in Equation (18)

$$\text{Normalized Product Utility} = \frac{U_A \times U_O}{NashU_A \times NashU_O}. \tag{18}$$

8.3 Evaluation of Proposed Opponent Model

The proposed opponent model is compared with the basic frequency-based [51] and distribution-based frequentist [48] opponent models. Kendall's Tau, measuring the ranking correlation, is used for the evaluation metric [31]. The actual offer rankings and estimated bid rankings are compared with respect to this metric round by round. Remark that a higher Kendall's Tau value is desired.

Recall that we have two types of data: *corpus data* and *experimental data*—human annotators label argument types in the corpus data, whereas hierarchical classifiers extract them. Figure 11(a) and Figure 11(b) shows the average Kendall's Tau values on *corpus* and *experimental* data, respectively. It is worth mentioning that the average negotiation round in the data collection experiment is 15, whereas the average round of the evaluation experiment is 10. Therefore, the opponent model evaluation considers only the first fifteen rounds.

According to the evaluation results of the proposed argumentation-based opponent model, our approach outperforms the state-of-art frequentist opponent models in both datasets. It can be seen that the performance of the model in the corpus is higher than that in the experimental data. This may stem from the misclassification of some arguments by the classifiers. That is, the performance of the opponent model slightly depends on how accurate the classifiers' predictions are. The take-home message is that we can improve the performance of the opponent modeling by utilizing the arguments exchanged during the negotiations.

8.4 Evaluation of the Negotiation Strategy

We analyze the received individual utilities for both users and agents to study whether our extension improves the performance of the negotiating agent. Figure 12 denotes a box-whisker plot on the received utilities for both sides. We applied Kolmogorov–Smirnov normality and homogeneity test to see whether we could directly apply the dependent t-test (paired samples t-test) for a significant difference in the results. Consequently, we applied the dependent t-test. We observed a statistically significant difference in the received utility between Solver Agent (0.77 ± 0.13) and

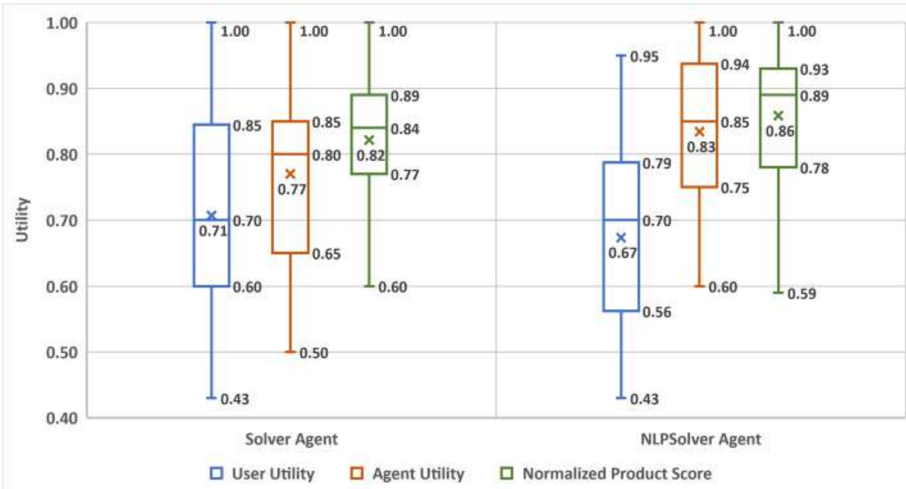


Fig. 12. Average agreement utility for both agents and human negotiators.

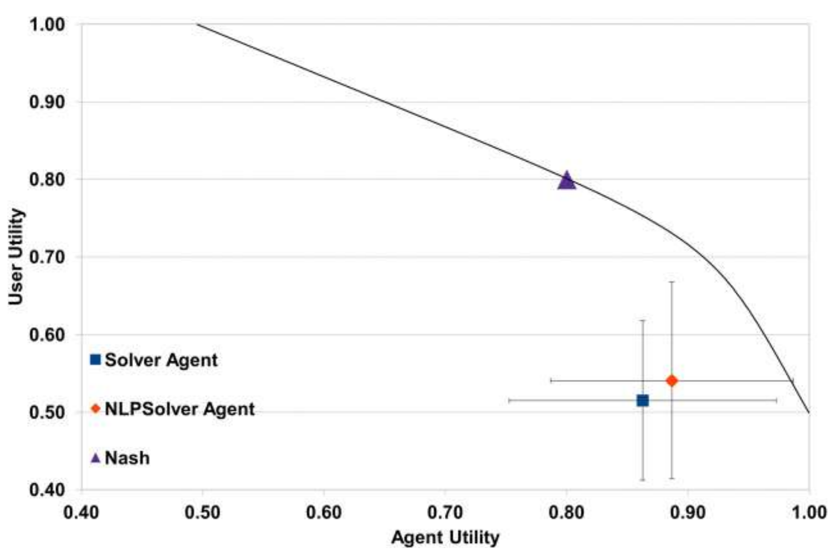
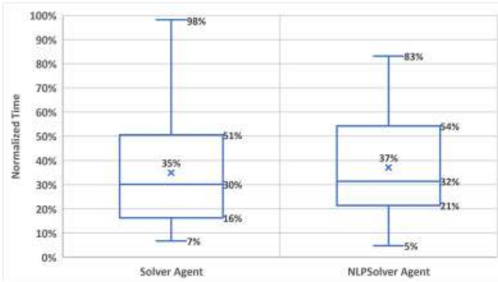


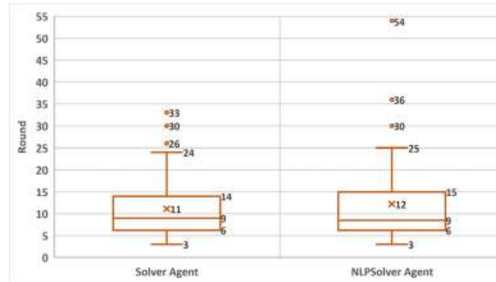
Fig. 13. Bidding distribution of agents.

NLPSolver Agent (0.83 ± 0.11) with a 95 confidence interval ($p = .00256 < 0.05$), with the statistical power of $0.86 > 0.8$. However, there is no significant difference in the human participants' utilities ($p = .13019$) between Solver Agent (0.71 ± 0.15) and NLPSolver Agent (0.67 ± 0.13). That shows that without worsening the human negotiator's gain, our agent can improve its received utility thanks to incorporating the arguments into opponent modeling and bidding strategy.

Moreover, Figure 13 displays the bidding distribution of the strategies during negotiation. As shown from the figure, on average, NLPSolver Agent made offers closer to Pareto-frontier by increasing both the agent and user utilities compared to the Solver agent. We can say that it is still a competitive agent, but the offers proposed by the NLPSolver Agent dominate the Solver Agent's offers in general.



(a) Normalized Times



(b) Rounds

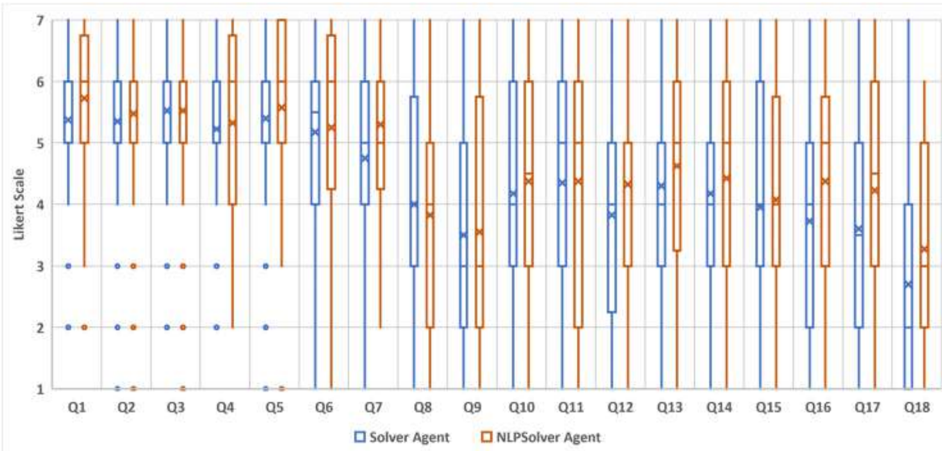
Fig. 14. Average agreement times and rounds for agreement.

We also analyze the agreement times. Figure 14 shows each agent's average agreement round and time to complete their negotiation with a box-whisker plot. It seems that the Solver Agent (35% ± 22% for normalized time and 11.15 ± 7.33 for round) slightly reached agreements sooner than NLPSolver Agent (37% ± 20% for normalized time and 12.23 ± 9.84 for round). However, when we apply the statistical significance tests, there is no statistical difference in the negotiation round and time to reach an agreement ($p = .4725$ and $p = .44401$ for time and round, respectively).

Apart from analyzing the negotiation logs, we analyze the feedback given by the participants during the post-experiment surveys. Figure 15 shows the average ratings of seven-scaled Likert questionnaire responses after each negotiation session. We applied Kolmogorov–Smirnov normality test and homogeneity test. The response data satisfied the precondition for dependent t-test (paired samples t-test). The results of this test show that there is a statistically significant difference in Question 7 ($p = .03074$), Question 16 ($p = .04333$), and Question 17 ($p = .0375$) for the Solver and NLPSolver agent settings. Figure 16 shows the box-whisker plot on the responses for these questions. Recall that four correspond to neutral; thus, the above four indicate agreement. The participants agree that they observed their opponent consider their preferences (3.73 ± 1.76 versus 4.38 ± 1.80) out of 7 after negotiating Solver and NLPSolver, respectively) and arguments (3.60 ± 1.75 versus 4.23 ± 1.87 out of 7 after negotiating Solver and NLPSolver, respectively) while making its offer more when they negotiated with the NLPSolver. That shows they knew the agent's attitude changed concerning arguments and preferences.

As seen in Figure 15, the participants agree that they made arguments (e.g., explanatory, rewarding) in general in both settings (around 5.51 ± 1.26). Similarly, they agree that they express their preferences via arguments and use some arguments to convince their opponents. Figure 17 shows the total number of arguments given by 40 participants. The majority tended to share rewarding and preference statements and some conditional constraints. Note that the classifier ignores "Factual" statements as the corpus does not include any instances of this type. Although the NLPSolver Agent is more collaborative than the Solver Agent, it is still a competitive agent, as seen in bidding analysis in Figure 13. Responses to our questions, such as Q8 and Q9, show that the participants disagreed that the agents found the best deal for both (i.e., fairness). Regarding whether our agent negotiated as a human negotiator, the average rate of the participants is around 4–5 and slightly higher in the case of NLPSolver Agent (4.37 ± 1.87 versus 4.13 ± 1.49). The average rating for Q11 is approximately 4.29 ± 1.95, so the participants noticed that the agents adapted their behavior concerning their emotional feedback. However, there is still room for improvement.

Furthermore, while the participants still disagree with the statement that agents did not offer options after they expressed they did not want them, this agreement rating is higher for the NLPSolver Agent (3.24 ± 1.70 versus 2.74 ± 1.70 for NLPSolver Agent and Solver Agent, respectively).



Q-1 I made arguments (e.g., explanatory, rewarding) during the negotiation.
Q-2 I tried to convince my opponent via some arguments.
Q-3 I shared some of my preferences with my opponent via arguments.
Q-4 I expressed how I felt during the negotiation utilizing some arguments.
Q-5 I expressed my emotional state during the negotiation.
Q-6 My emotional state influenced my bidding behavior.
Q-7 **My opponent's attitudes were important for my offer during negotiation.**
Q-8 My opponent negotiated in a fair way.
Q-9 My opponent tried to find the best deal for both of us.
Q-10 My opponent negotiated with me like a human negotiator.
Q-11 My opponent adapted her strategy with respect to my current emotional state.
Q-12 My opponent modified her bidding behavior in line with my offers during the negotiation.
Q-13 I believed that my arguments influenced my opponent"s bidding behavior.
Q-14 While my opponent was making her offers, I observed that s/he considered my negotiation behavior.
Q-15 While my opponent was making her offers, I observed that s/he considered the remaining time.
Q-16 **While my opponent was making her offers, I observed that s/he considered my preferences.**
Q-17 **While my opponent was making her offers, I observed that s/he considered my arguments.**
Q-18 I observed that my opponent did not offer the options after I expressed that I did not want them.

Fig. 15. Average ratings of questionnaire responses.

It may stem from our agent considering the soft and hard constraints while offering. That supports our agent's success; however, the human participants are only partially convinced. Therefore, this part could be revised in the following studies.

In a final analysis, we also investigate the usage of emoji values across consecutive rounds, calculating the percentage of emoji changes as the total number of changes divided by the total number of rounds for each session. Figure 18(a) illustrates the distribution of emoji changes across the 40 participants. It is observed that participants have a tendency to exhibit changes in their emotional states, with a rate of 64% ± 28%. Additionally, Figure 18(b) presents the correlation between emoji change rates and utility gain (correlation coefficient: −0.02). The results suggest that the utility gain and the change rates of emojis are independent. Apart from the frequency of emoji changes, how the participants change their emotional state may have an strategically impact to lead promising negotiation outcomes. Furthermore, no significant difference is observed between agents, as their emotion-based negotiation strategy is the same.

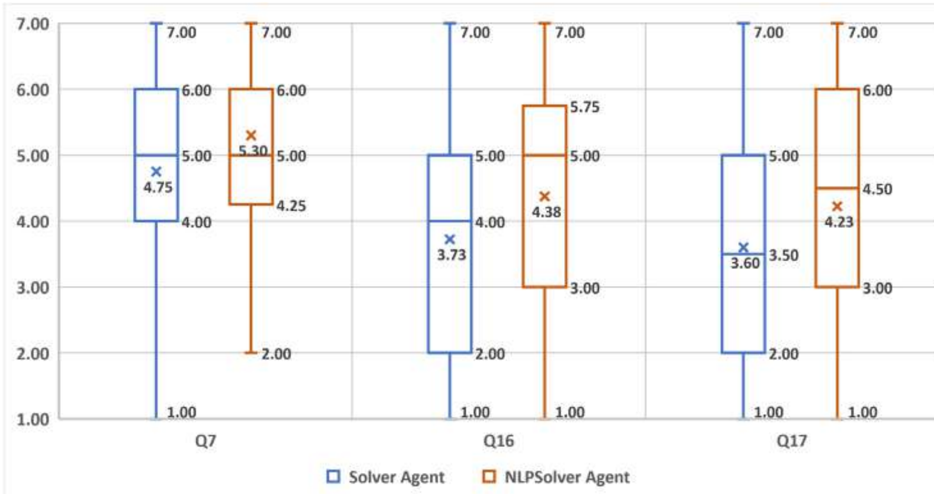


Fig. 16. Box plot of questions with significant differences.

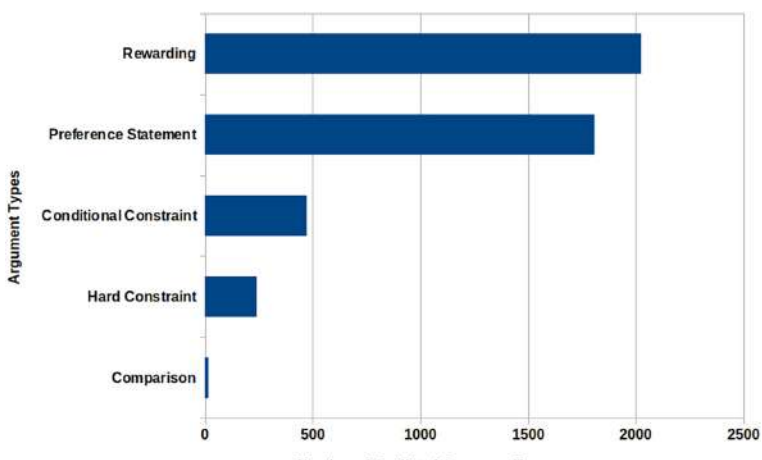
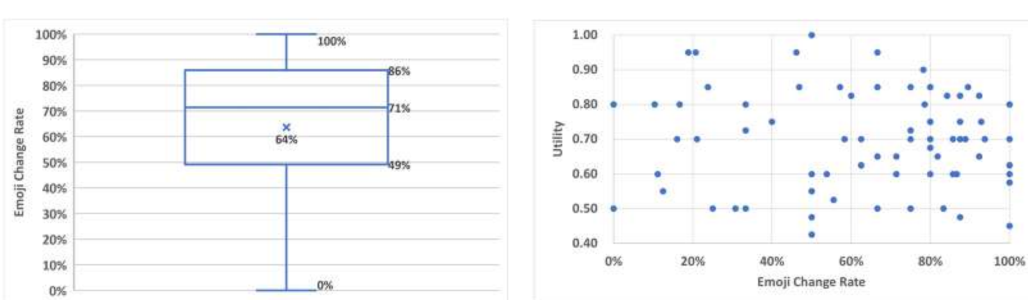


Fig. 17. Number of argument types predicted by the classifiers.



(a) Emoji Usage Rate (b) Correlation to Utility Gain

Fig. 18. Average emoji change rates and their correlation to utility gain.

9 Conclusion

The challenge of understanding and responding appropriately to human negotiators' arguments in human-agent negotiation systems is addressed in this article. We have introduced a taxonomy of argument types for negotiation and a hierarchical classifier approach that preprocesses and extracts meaningful information from the presented arguments. Crucially, the extracted preferential information is used in opponent modeling and implicitly within bidding strategies. We assessed the effectiveness of our approach through human-agent negotiation experiments. The experimental evaluation confirms that our argument-based frequency opponent modeling approach outperforms existing frequentist models. Additionally, the NLPSolver bidding strategy consistently surpasses human negotiators, yielding higher utility on average than the Solver Agent. The primary insights gleaned from this study are as follows:

- Integrating human negotiators' arguments into the negotiation process enhances the accuracy of preference estimation.
- By taking into account human negotiators' arguments, an agent's overall negotiation performance, specifically in terms of received individual utility, can be improved.
- Building opponent estimation models that utilize preference-related arguments enhances the perception of human negotiators about the agent's awareness of preferences and arguments.

Instead of sharing the whole preferences, negotiators can implicitly share the partial preferences when they consider it necessary and beneficial for reaching an agreement. This type of preference statement is not just theoretical but finds practical applications in real-world scenarios, including e-commerce, debating [10], and so on. For example, a seller or buyer can share a portion of preferences during a negotiation to lead a concession. Instead of explicitly expressing the desired price, a buyer can state "it is expensive" (i.e., preference statement) or "If you discount on this phone, I will also purchase headphones" (i.e., conditional concession). These instances from the real-world applications underscore the significance and relevance of the insights provided by this study.

Furthermore, our proposed argument-based negotiation strategy and taxonomy of argument types are designed for broad application. The strategy can be easily customized for diverse human-agent negotiation tasks. However, the argument-extraction module is domain-specific and must be trained using a relevant corpus to the desired domain. The rule-based mechanism for eliminating invalid argument types must also be adapted. More complex domains, such as nuclear deals, peace treaties, trade agreements, and aerospace contracting, where predefined issues and possible values are not easily available, present unique challenges. Here, the structure of the offer content and possible values can change dynamically during the negotiation, posing intricate research questions for multi-agent negotiation systems. While some attempts have been made to address these challenges (e.g., the mediator agent for debate questions [10]), a fully satisfying bidding strategy has not yet been formulated. Given the need for detailed preference elicitation in these complex negotiation domains, our study has focused on the simpler, well-known "Holiday Domain." We anticipate that future research will extend our foundational work to more diverse negotiation domains and further underscore the importance of understanding an opponent's arguments to enhance human-agent negotiation strategies. Moreover, human negotiators often utilize their prior knowledge of their partners and can propose partial offers in real-life scenarios. In the experimental settings, we reported that our agent could beat the human participants. Human negotiators can learn their opponent's behavior if they repeatedly negotiate. Following this, human participants could beat the proposed agent in their further negotiations. However, it is worth noting that our agent behavior is also adaptive to its opponent's behavior. Therefore, there is no guarantee that human negotiators can beat our agent in their next negotiations. We would like to emphasize that our aim is not to develop a negotiating agent that can beat all human opponents. Instead, our primary focus is utilizing argumentation in human-agent negotiation systems.

Based on our experimental results, arguments significantly impact the preference elicitation phase. Our opponent model, which incorporates the human negotiator's arguments into its update mechanism, outperforms the variant that disregards these arguments. This study primarily centers around using arguments in opponent modeling and preference elicitation during negotiation, a process that implicitly influences the bidding process. Our strategy predominantly focuses on arguments related to hard and soft constraints (i.e., preferences). Greater emphasis on arguments used for convincing partners would improve our current strategy. Studying how humans reach agreements in realistic linguistic negotiation settings would be beneficial without relying exclusively on utility maximization. Such a scenario might require more sophisticated knowledge, enabling robust reasoning and linguistic skills. Therefore, investigating the types of arguments that effectively convince opponents presents an exciting future research direction.

Our main limitation is that a sentence must contain either an offer content with supportive arguments or an acceptance statement. In other words, this work does not consider other statements (e.g., "greeting," "question-answering," and so on). It would be interesting to cover such statements in the future. Another limitation is dealing with using synonyms of the offer content unless the training data contains them. For example, instead of "autumn" if the participant uses "fall," and the training data does not involve such an example, the classifier cannot recognize it as a "season." Therefore, we extended our training data with their synonyms. Another challenge is identifying the offer content if the human negotiator specifies only a part based on the previous offer. For example, the participant proposes a complete offer in the last turn and now asks for a different location in the current turn. The system must know the content of the previous conversation to recognize the entire offer content. Therefore, we added the content of the last offer as input for the classifiers. We pursue improving the performance of the classifiers to handle such cases.

As future work, we intend to enhance our bidding strategy by fully capturing human negotiators' preferences, enabling agents to generate automatic arguments that show consideration of human negotiators' concerns. This adjustment would give the impression that agents respect their opponents' arguments. Additionally, since the accuracy of argument prediction influences both the opponent model and bidding strategy, we plan to boost predictor performance by applying advanced deep learning techniques, such as GloVe or BERT-based models [17, 41, 46].

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Received 26 November 2022; revised 16 April 2024; accepted 12 August 2024