

Assistive Large Language Model Agents for Socially-Aware Negotiation Dialogues

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Abstract

In this work, we aim to develop LLM agents to mitigate social norm violations in negotiations in a multi-agent setting. We simulate real-world negotiations by letting two large Language Models (LLMs) play the roles of two negotiators in each conversation. A third LLM acts as a remediation agent to rewrite utterances violating norms for improving negotiation outcomes. As it is a novel task, no manually constructed data is available. To address this limitation, we introduce a value impact based In-Context Learning (ICL) method to identify high-quality ICL examples for the LLM-based remediation agents, where the value impact function measures the quality of negotiation outcomes. We show the connection of this method to policy learning and provide rich empirical evidence to demonstrate its effectiveness in negotiations across three different topics: product sale, housing price, and salary negotiation. The source code and the generated dataset will be publicly available upon acceptance.

1 Introduction

Negotiation is an integral part of our everyday life, ranging from sales negotiations to salary negotiations. Typically, a negotiation is a process involving two or more individuals to resolve conflicts, maximise individual benefit, or find mutually satisfactory solutions [Bazerman and Neale, 1993; Lewicki *et al.*, 2011]. Prior research shows that social norms shape negotiation processes and outcomes [Uzo and Adigwe, 2016], where social norms define acceptable and appropriate behavior in groups and societies [Bicchieri *et al.*, 2018]. According to the Expectancy Violation theory and empirical studies [Burgoon and Hubbard, 2005; Burgoon, 2015], social norm violations often invoke punishment, such as costly sanctions, confrontation, and social exclusion [Molho *et al.*, 2020], so that they deteriorate negotiation outcomes.

Benefiting from recent advances of large language models (LLMs), we explore the potentials of using LLMs to build social norm remediation agents to assist business negotiations in a multi-agent setting. In particular, two LLM based agents

are prompted to play the role of respective negotiators to conduct a bilateral negotiation with the corresponding goals on a shared topic. In such a conversation, a remediation agent assists one of the negotiators by suggesting remediation measures, whenever the negotiator violates social norms, as illustrated in Figure 1. The utterances violating norms are replaced by those suggestions before the other negotiator sees them. We consider such a multi-agent setting because i) we are able to conduct experiments on a wide-range of real-world topics without ethical and privacy concerns; ii) it is a novel task so that there is no manually constructed training data; iii) recent LLMs, e.g., GPT 3.5 and GPT 4, are able to generate high-quality human-like language [Herbold *et al.*, 2023].

In contrast, prior works either focus on simulating real-world conversations, such as modeling LLM agents as characters with different personality traits in a virtual community to simulate the dialogue ecology [Park *et al.*, 2023; Hua *et al.*, 2023], or assigning specific identities and roles to different LLM agents to carry out dialogue-based tasks [Xu *et al.*, 2023; Light *et al.*, 2023; Wang *et al.*, 2023b; Wang *et al.*, 2023a]. The emphasis in these multi-agent works simulating real-world conversations is on mimicking the dialogue process of a negotiation, debate, or game, but without improving the dialogue itself. On the other hand, there is related research that assigns the role of a critic to LLM agents [Fu *et al.*, 2023; Akyurek *et al.*, 2023], enabling them to summarize dialogues generated by players (referring to LLM agents with specific identities and task goals). The critic views the natural language (NL) feedback as an approximate distant-supervised reinforcement learning signal. The dialogues and corresponding NL feedback are then fed to the players to enhance their negotiation skills. This approach does not directly correct the dialogue, so there is still the possibility of exposing language that may have negative effects in the conversation to the negotiating counterpart, potentially leading to the failure of negotiations.

Due to the lack of training data, we propose a novel method to select a set of in-context learning (ICL) examples based on *value impact* for prompting LLM-based remediation agents, where value impact is a scoring function measuring negotiation outcomes. It starts with ranking each ICL example candidate using this function. The initial set of ICL examples are filled with the top- k examples, followed by randomly swapping one member in the set with lower ranked ones to improve

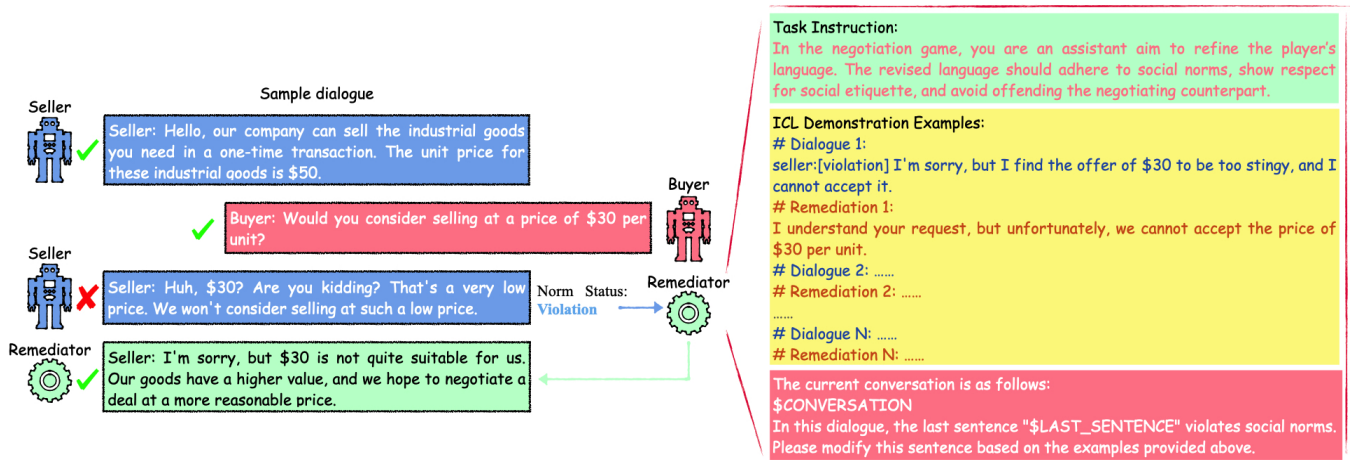


Figure 1: A running example: In this conversational exchange between two interlocutors, an utterance from the seller breaches a social norm. Our remediator intervenes to rectify it by generating a remedial response.

value impact until convergence. The final set of ICL examples are fed to the remediation agent during each negotiation. We obtain the following findings via extensive experiments:

- Almost all remediation models significantly improve negotiation outcomes by mitigating social norm violations. The LLMs using our ICL example selection method outperforms all competitive baselines in almost all settings.
- The efficacy of the value impact function is evident in terms of all evaluation metrics across all topics. The random swapping step further improves the negotiation outcomes by achieving task-related and relational goals.
- Our ICL example selection achieves better quality than the widely used nearest neighbour approach in terms of diversity and a better alignment with goals.

2 Assistive Systems for Difficult Negotiations

2.1 Problem Setting

We simulate human negotiations with two LLM agents, assigning them respective roles as negotiators, and the goals they need to achieve. In the LLM-based negotiations, we mimic the real negotiations by injecting social norm violations in a controlled manner.

Norm violations are viewed as a mapping to real situations, where, during a deadlock or intense negotiation, a negotiator might unintentionally use language that is overly aggressive, offensive, and violates social norms. To mitigate the potential negative impact of such language on negotiation outcomes, a third-party LLM agent, the remediator, is introduced in this work to correct instances of norm violations. The remediator aims to ensure that the language adheres to the social norms, and avoids offending the negotiating parties. This in turn assists the parties in achieving their task goals and relationship goals, including building trust, deepening relationships, and establishing a stronger network between the conversational participants. It is believed that the achievement of relationship goals will also impact the negotiation process, making

it easier for the buyer and seller to reach an agreement when there is a mutual understanding and trust.

The remediation generated by the remediator is used to rewrite sentences involving norm violations and conveyed to the counterpart party to facilitate smooth dialogue. To focus on the functional study of the remediator, we consistently have the seller generate dialogues that may involve norm violations, while the buyer engages in normal conversation. So, the remediator only corrects the language used by the seller.

2.2 LLM-based Simulation

The algorithm for simulating the realistic human negotiations with socio-cultural norm violation is shown in Algorithm 1. \mathcal{E}_v contains N exemplars (N is normally set as 5) indicating the possible norm violations that might happen in the conversation. In the simulation, we use a coin to control the norm violation occurrence with a probability p_c . In each turn, we toss the coin, and the seller agent A_s generates an utterance with norm violation if the coin toss comes Head, viewing \mathcal{E}_v as the in-context learning (ICL) instances (lines 3-4). Otherwise, it generates a normal utterance (line 8). Furthermore, if the remediator A_r agent is activated in the simulation, we employ the remediator to rewrite the utterance x_t (lines 5-6). Then x_t is appended to the conversation trajectory (line 9). We then check whether the conversation needs to end using the moderator agent A_m (lines 10-11). If not, the buyer agent A_b generates the next utterance (line 11) and the trajectory gets updated (line 12). The dialogue continues if the moderator agent decides that it is not ended yet (line 13).

2.3 LLM-based Architectures for Assistive Agents

The generative LLMs obtained through extensive pre-training inherently possess the ability for semantic understanding and task instruction following. Leveraging past experiences learned from the corpus, these models can, in a zero-shot learning manner, to some extent address a new downstream task. However, the data distribution of the training corpus for such untuned models may differ from that of the downstream task, leading to issues of distributional bias. Consequently,

Algorithm 1: The negotiation simulation algorithm

Input: Seller A_s , Buyer A_b , Remediator A_r , Moderator A_m , Norm Violation Exemplars \mathcal{E}_v , Norm Violation Probability p_c , coin with probability p_c of coming Head, Boolean remediation flag;

Output: The simulated conversation trajectory τ ;

```
1  $\tau \leftarrow []$ 
2 while True do
3   if toss(coin) = Head then
4      $x_t \leftarrow A_s(\mathcal{E}_v, \tau)$ 
5     if remediation = True then
6        $x_t \leftarrow A_r(x_t)$ 
7   else
8      $x_t \leftarrow A_s(\emptyset, \tau)$ 
9    $\tau \leftarrow [\tau, x_t]$ 
10  if  $A_m(\tau) = \text{End}$  then break
11   $x_t \leftarrow A_b(\tau)$ 
12   $\tau \leftarrow [\tau, x_t]$ 
13  if  $A_m(\tau) = \text{End}$  then break
14 Return  $\tau$ 
```

when untuned models handle downstream tasks, the following problems may arise: 1. The model may not strictly adhere to task instructions, generating redundant information beyond task requirements; 2. The generated content may be inconsistent with the preferences of the downstream task. Since untuned models have not undergone sufficient training in the downstream task and thus lack specific knowledge about it, they often struggle to provide effective assistance in conversations. Therefore, we first introduce (or design) baseline methods with different architectures based on the negotiation task. Subsequently, we present our memory-augmented ICL model.

SFT-based LLM. The aforementioned instances of norm violations, along with the annotations, represent pseudo-gold annotations S_a . The SFT-based method uses S_a as tuning signals to guide the training of a remediator. In contrast to the Vanilla ICL-based method that relies on a limited number of examples to instruct an untuned model, the SFT-based method fine-tunes the model parameters through supervised learning, enabling it theoretically has the potential to acquire a more extensive range of relevant knowledge. It utilizes the Lora module to learn task-relevant knowledge embedded in high-quality annotations, thereby achieving the goal of distilling knowledge from both GPT-4 and human annotators. This entails using annotations to learn how to rewrite norm violations, rendering them more aligned with social norms.

Prompt-based LLM. We employ a zero-shot prompt-based LLM assistant as a baseline. The model is endowed with a carefully crafted task instruction delineating the approach to rectify norm violations. The prompt used for the model to elicit the answers is consisted of three distinct parts. The first section of the prompt explains the nature of the norm violation. The subsequent portion encompasses both the conversation history and the specific sentence that violates established norms. The final segment of the prompt explicitly directs the remediator to rectify the sentence implicated in the

norm violation. Such the prompt is fed to a powerful LLM, i.e., ChatGPT or Llama 2, to produce the remediations to rectify the violations.

Vanilla ICL-based LLM. In Algorithm 1, the seller agent is tasked to generate sentences that may potentially contravene social norms. These offending sentences are annotated with remediations from GPT4, as an approximate oracle. Also, we have used human annotators for remediation annotations for some part of the data. We view the remediations annotated by human as gold annotations, while those labeled by GPT4 as silver annotations. We combine silver annotations and gold annotations into a high-quality pseudo-gold annotation set D and randomly extract a certain number of examples from this set, forming a static set of few-shot examples. This set serves as the instruction examples in ICL learning. This Vanilla ICL-based LLM method serves the pivotal role of instructing the remediator on the generation of suitable remediations in response to instances of norm violations during the course of a conversation.

RL-based LLM. The RL-based LLM Assistant is also an ICL-based method. In comparison to the Vanilla ICL-based method, we integrate Natural Language (NL) feedback into the ICL example. As presented in [Fu *et al.*, 2023], a language model assumes the role of a critic, providing NL feedback to enhance the negotiation strategies of the LLM agent. This feedback serves as a form of RL-like distant supervision signal, employed in the optimization of the agents. Building upon this paradigm, we introduce a fourth Critic LLM agent, which provides natural language feedback to the remediator. The remediator uses this feedback to rewrite norm violations in the dialogue, continuing the conversation with the rewritten sentences until the current negotiation concludes. After the dialogue concludes, we design a prompt for the critic. This prompt instructs the critic to analyze the violation remediation in the negotiation, determining whether the remediation achieved its rewriting purpose and provided positive assistance to the dialogue. If the remediation is not a good rewrite, the critic suggests improvements. The critic summarizes the concluded negotiation dialogue based on this analysis, and we consider this summary as rationale, combined with the dialogue history and remediation, forming an instruction example. Following the same approach as the Vanilla ICL-based method, we construct ICL examples and aim to have the remediator learn from past experiences of remediation generation through the rationale.

Retrieval-augmented ICL-based LLM. Previous research suggests that collecting diverse instruction datasets and retrieving the examples with most similar inputs can facilitate rapid generalization. To investigate retrieval augmentation’s effectiveness, we constructed a dense index of instances in D by using a multilingual semantic embedding SentenceTransformer model. For each test query (in this context, referring to a dialogue), we employ cosine similarity to measure the relevance, retrieve the top- K most relevant instances, and employ the corresponding violation-remediation pairs as in-context examples for base LLMs to deduce. It’s important to note that such retrieval augmentation may lead to a decrease in inference speed. In contrast to vanilla ICL,

which uses a static prompt memory that can be cached, the prompt memory for retrieval-based ICL differ for each new query, necessitating the computation of in-context examples every single time.

3 Exemplars with High Value Impact

A core challenge in the architecture of our ICL-based LLM Assistant is memory management, i.e. to ensure that the most suitable pieces of the training conversations are picked and placed into the prompt as the agent’s memory. These examples determine the agent’s policy. We denote the agent’s policy by π_θ where θ is the set of chosen training exemplars. In this section, we present a method for selecting such crucial exemplars in order to characterise a near optimal policy π_{θ^*} .

Let $d = (h_{<t}, x_t, y_t, h_{>t})$ be an annotated dialogue between the buyer and the seller, where x_t is the t -th dialogue turn and y_t is its (gold/silver) groundtruth remediation, $h_{<t}$ denotes the conversation history from the start up to the turn t , and $h_{>t}$ denotes the continuation of the conversation to the end. Let $R(d)$ denotes the *final reward/outcome* of the conversation, encompassing various factors such as whether a deal was reached, the agreed price, the change in the quality of the business relationship due to this dialogue, and the change in the quality of the trust after this dialogue.

Let D be the dialogue dataset annotated with the ground truth (silver/gold) remediations. For each dialogue $d \in D$ and a turn t with norm violation, we consider $z = (h_{<t}, x_t, y_t)$ to be a candidate exemplar that can be included in the agent’s memory. We denote the set of candidate exemplars by S .

Value of an Exemplar Consider an exemplar $z = (h_{<t}, x_t, y_t)$, extracted from a dialogue $d = (h_{<t}, x_t, y_t, h_{>t})$. We define the *value* of a remediation y' wrt the groundtruth remediation y_t as,

$$V(y', z) := E_{p_{\text{sim}}(h'_{>t}|y', x_t, h_{<t})} [R(h_{<t}, x_t, y', h'_{>t}) - R(h_{<t}, x_t, y_t, h_{>t})] \quad (1)$$

where $p_{\text{sim}}(h'_{>t}|y', x_t, h_{<t})$ is the distribution over possible completions of the dialogue, following the the remediation y' and the conversation history. We can sample from $p_{\text{sim}}(h'_{>t}|y', x_t, h_{<t})$ using the simulation Algorithm 1. This process defines a *tree structure* over the space of possible remediated dialogues that can originate from the root dialogue d , as sampling the dialogue completion $h'_{>t}$ may *recursively* involve remediations for future turns. Each node of the tree corresponds to a turn that can be re-written via remediation, and the children of that node are the possible re-writings.

Value Impact of Exemplars We define the *value impact* of exemplars as the value that they produce when used in the ICL policy to remediate the other examples. Consider the exemplars Z , we define the value impact as,

$$V^{\text{impact}}(Z) := \sum_{\tilde{z} \in S-Z} V(\pi_{\theta=Z}(\tilde{x}_t, \tilde{h}_{<t}, \tilde{z}) / |S-Z|) \quad (2)$$

where $\tilde{z} = (\tilde{h}_{<t}, \tilde{x}_t, \tilde{y}_t)$ is an exemplar, $\pi_{\theta=Z}(\tilde{x}_t, \tilde{h}_{<t})$ is the remediation generated by the policy $\pi_{\theta=Z}(\cdot)$ for this exemplar, and $|S-Z|$ denotes the size of the exemplars set.

As the policy is characterised by the examples included in the memory prompt, the problem of optimising the policy boils down to choosing the optimal subset of examples Z^* to include in the prompt to maximise the value impact,

$$Z^* = \arg \max_{Z \subseteq S} V^{\text{impact}}(Z) \quad (3)$$

In the rest of this section, we explain our optimisation algorithm for choosing such near optimal examples. The core idea is based on *Monte Carlo sampling* in the tree structure of the remediations, and work with approximate *estimated* values for the remediations.

Individual Exemplar Filtering In the first step, we search for individual norm violation examples with high *value impact*. We rank the candidate examples in S according to their individual value impact $V^{\text{impact}}(\{z\})$. Computing the individual value impacts based on eqn 2 can be time consuming due to several reasons: (i) the large number of candidate examples in S , (ii) the high computation needed to compute the exact expectation for the value V in eqn 1, and (iii) the high computation needed for computing the expectation over a large example set $S-Z$ in eqn 2. We thus resort to approximations: (i) we only consider a subset of $|S'| \ll |S|$ as candidate examples for ranking chosen randmoly from S , (ii) we resort to an approximation in eqn 1 to collect a relatively small sample $h'_{>t}$ to complete the dialogue for a given z' , and (iii) we approximate the value impact in eqn 2 based on a randomly selected sample $|S''| \ll |S|$. We then rank the candidate examples in S' according to their estimated value impact for the next stage of optimisation.

Search for Optimal Exemplars. The combination of multiple ICL exemplars often provides more assistance to the model in tackling tasks, compared to a single ICL exemplar. Moreover, the order of ICL exemplars influences the inference results. After completing the first step, we now need to find an approximate optimal ICL example *set* with proper *ordering* to build an effective policy.

We take the top- n exemplars in S' with the highest individual impact value to form S_{ICL} . From the remaining exemplars in S' , we then select the exemplar with the highest impact value, and swap it with a randomly selected exemplar from S_{ICL} to obtain S'_{ICL} . We then either accept or reject this *move* based on the change in the impact value: $\Delta := V^{\text{impact}}(S'_{ICL}) - V^{\text{impact}}(S_{ICL})$. In case the impact value change Δ is positive, we accept the move; otherwise, we reject it. We continue this process until k consecutive moves are rejected.¹ After converging to the (near) optimal set of exemplars, we use a similar process for optimising their order. We randomly shuffle an existing order to get a new order, and either accept or reject it based on the change in the value impact (similar to the process described previously). We repeat the shuffling process until convergence. At the end, we obtain $\pi^* := \pi_{S_{ICL}^*}$, which is considered as an approximately optimal policy for remediation.

¹In our experiments, $k = 5$.

4 Experiments

4.1 Experimental Settings

Dialogue generation. We consider three topics: housing price, product sale, and salary negotiation for bilateral negotiations. For the negotiator agents, we design topic-specific prompts for each role to inform the topic, task-related goals and relational goals, as shown in Table 3, 4, and 5 in Appendix A.1. To minimize the impact of confounders on the generated dialogues, we use same definitions for the relational goals across all topics. The prompts vary in terms of topics, task-related goals, and the description of roles. For example, in salary negotiation, the task-oriented goal of the job seeker is to obtain the highest possible salary, while the goal of the employer is to match the job seeker’s work abilities with appropriate salary.

To add utterances with norm violations into the dialogues, we set p_c to 0.4, as described in Sec. 2.2. The resulting proportion of turns with violations in each dialogue is approximately 44.36%. In each dialogue, we assume that only one agent is not aware of social norms to produce those violations, which is the seller for housing price and product sale, and the job seeker for salary negotiation. As a result, we are able to use the metrics introduced below to consistently assess the quality of the remediation models, the higher the better.

For the agents of negotiators, we adopt GPT 3.5 as the LLM to produce dialogues in Chinese. Chinese is chosen because there is a high probability that GPT 3.5 does not produce English dialogues with norm violations due to violations of the OpenAI policies.

Following Algorithm 1, we generate 100 dialogues per topic as the test set, while generating 333 dialogues per topic for training. The training set also serves as the pool for ICL examples.

Remediation Baseline Models. As this work focuses on understanding the impact of remediations on negotiations, we apply the remediation agents directly to each turn marked with violations to produce remediations without employing any detection models.

We have the following baselines as described in Section 2.3 and 3: **Prompt-based LLM:** implementing the zero-shot prompt based LLM. **Vanilla ICL-based LLM:** randomly selecting K ICL demonstration examples from S_a to compose prompt; **RL-based LLM:** summarizing the past dialogues and remediation and incorporating the summary into the content of randomly selected ICL demonstration examples. **SFT-based LLM:** employing S_a to supervised finetune the Atom-7B-Chat² (a Llama2-7B model that is finetuned using a substantial amount of Chinese corpus). We equip Atom with Low-rank adaptation (LoRA) for finetuning. **Retrieval-augmented ICL-based LLM:** to retrieve top- K examples in S_a that are the most similar to the current query dialogue as the demonstration examples. **ValueImpact ICL-based LLM:** find the ICL demonstration example set that has the highest Impact Value. The example set is consisted of K examples, and we set $M = 2$. In all ICL-related methods, K is set as 8. Since GPT 3.5 is an untrainable model, we

implement all the prompt-based and ICL-based methods using both GPT 3.5 and Atom-7B-Chat, but only implement the STF-based method using Atom.

4.2 Metrics

We evaluate the remediation models based on negotiation outcomes from four perspectives: *success rate*, *deal value*, *trust improvement*, and *relation enhancement*. The former two are calculated by rules, while the latter two are evaluated by using GPT 4 with the designated prompts outlined in Table 6 and 7 in Appendix A.1. We consider evaluating negotiation outcomes because our Algorithm 1 for dialogue generation view remediation measures as interventions so that different remediations lead to different flows of conversations. As a result, there are no groundtruth responses to compare with because there are exponentially many possibilities that a conversation can take.

Success Rate (Suc): the percentage of negotiations that end up with successful deals. Social norm violations often lead to damage of relationships or negative emotions, which in turn result in failure of reaching a deal. Hence, the metric is a strong indicator of the effectiveness of remediations.

Deal Value (Deal(\$)): the agreed final price or salary after an negotiation averaged across all conversations in the test set. As the remediation agents aim to help either the sellers or the job seekers, the higher the final prices or salaries, the more helpful the agents are.

Trust Improvement (Trust): we apply GPT 4 to measure whether the trust at the end of a negotiation is ‘higher than’, ‘lower than’, ‘the same as’ that at the begin of a conversation. We also allow GPT 4 to produce ‘not applicable’ for negotiations failures. To quantitatively measure the improvement of trust, we report the ratio of the negotiations that the seller or job seeker agents obtain a higher trust from the counterparts than that at the begin of conversations.

Relation Enhancement (Rel): GPT 4 is applied to assess if the relation between two interlocutors at the end of a negotiation is ‘better than’, ‘worse than’, ‘the same as’ that at the begin of a conversation. The same as trust, we let GPT 4 yield ‘not applicable’ if an negotiations fails. In the experiments, we report the percentages of the negotiations that the seller or job seeker agents have *better* relations at the end of negotiations.

4.3 Results and Analysis

We conduct experiments to show the effectiveness of the remediation agent using our proposed method, in comparison with competitive baselines. In the ablation studies, we demonstrate i) the usefulness of ValueImpact for ranking ICL candidates, ii) the efficacy of random swapping for improving the quality and diversity of ICL examples, and iii) the helpfulness of including ICL examples with different topics than the target one.

From Table 1 we can see that norm violations consistently harm the outcomes of negotiations w.r.t. all four perspectives, including success rates, deal value, trust and relation enhancement, if no remediation applies. This aligns well with the Expectation Violation theory in social science.

²<https://github.com/FlagAlpha/Llama2-Chinese>

Topic →	Product Sale				Housing Price				Salary Negotiation			
Method ↓	Suc.	Deal (\$)	Trust	Rel.	Suc.	Deal (\$)	Trust	Rel.	Suc.	Deal (\$)	Trust	Rel.
Without Viol.	90%	42.13	78%	84%	78%	646125	74%	76%	90%	3487.5	74%	80%
Viol No-Remed.	74%	38.14	66%	70%	60%	594867	64%	66%	80%	3371.5	68%	70%
With Violation (GPT 3.5)												
PROMT	76%	40.66	72%	78%	66%	617580	66%	68%	84%	3393.0	70%	72%
Vanilla ICL	78%	41.08	74%	78%	68%	620176	70%	70%	86%	3457.7	70%	74%
RLNL	77%	41.18	74%	80%	70%	622479	70%	72%	84%	3450.6	70%	72%
Retrieval ICL	80%	41.57	76%	82%	76%	630479	72%	74%	86%	3484.5	74%	76%
ValueImpact ICL	82%	42.20	78%	85%	76%	640154	75%	76%	90%	3506.0	76%	75%
With Violation (Atom-7B-Chat)												
PROMT	72%	39.24	70%	72%	62%	608977	64%	65%	81%	3409.4	70%	70%
SFT	75%	40.70	74%	78%	66%	618471	68%	68%	84%	3405.5	70%	72%
Vanilla ICL	76%	41.10	72%	77%	66%	619902	69%	67%	84%	3410.7	71%	71%
RLNL	76%	41.23	72%	76%	68%	619875	68%	70%	83%	3408.3	71%	72%
Retrieval ICL	77%	41.13	72%	76%	70%	620974	69%	71%	85%	3455.8	72%	73%
ValueImpact ICL	79%	41.80	73%	79%	71%	627834	71%	70%	86%	3460.6	73%	74%

Table 1: The evaluation of remediation models on negotiation outcomes. The row ‘Without Viol.’ denotes the setting that no norm violations occur in any conversations by setting $p_c = 0$, while the row ‘Viol No-Remed.’ refers to the negotiations with violations but no remediation models are applied. The remediation models below ‘With Violation (GPT 3.5)’ are based on GPT 3.5, while the models below ‘With Violation (Atom-7B-Chat)’ are the ones using Atom-7B-Chat.

Remediation effectively improves the negotiation outcomes for almost all models w.r.t. all metrics across all topics, except for very few cases, e.g. the success rate of the prompt-based model using Atom-7B-Chat for “product sale” is 2% lower than that without any remediation. Those LLM-based agents can indeed help negotiation agents achieve their relational goals, and further improve negotiation success rates and deal values, regardless if the LLMs are fine-tuned or not.

Our approach based on GPT 3.5, denoted as ValueImpact ICL in Table 1, consistently outperform all baselines in terms of all metrics. When the LLM is switched to Atom-7B-Chat, there are slight performance drops in all metrics, which shows the importance of the ability of LLMs to understand ICL examples and prompts. Despite that, our approach with this open-source LLM achieves still superior performance than the baselines using the same LLM in most of the cases.

The most closed method to our approach is Retrieval ICL, which identifies K nearest neighbours as ICL examples. As our method outperforms Retrieval ICL in almost all cases, the ICL example set using our approach is indeed better than the widely K nearest examples selected on the fly. Furthermore, when we compare the ICL examples used in Retrieval ICL with those using our approach, we find that the overlap rate is approximately 40%. It is evident that the best ICL examples are not necessarily the widely used K nearest neighbours.

Additionally, we observe a consistent trend across the three topics, combining four metrics: except for a few cases, the zero-shot prompt-based LLM implemented mediator generally performs lower than the SFT LLM. The SFT LLM’s performance is inferior to ICL-based LLMs. Within the ICL-based LLM family, the Vanilla ICL model, derived from random ICL examples, exhibits the poorest performance. The RLNL, which incorporates NL feedback, performs better. The nearest neighbor ICL examples obtained through similarity retrieval show intermediate performance. Notably, the

ValueImpact ICL proposed in this paper exhibits the best performance.

The reason for the inferior performance of SFT LLM compared to ICL-based LLM is the relatively small size of the pseudo-gold annotation set D (approximately 1000 instances). This limited quantity hinders the effective optimization of parameters, preventing the model from fully learning task-relevant knowledge. Simultaneously, it is likely that due to this reason, and because Llama2 has limited support for Chinese, methods implemented based on Atom generally perform weaker than their counterparts implemented based on GPT 3.5.

Product Sale	Suc.	Deal (\$)	Trust	Rel.
Standard (GPT 3.5)				
Vanilla ICL	78%	41.08	74%	78%
Retrieval ICL	80%	41.57	76%	82%
ValueImpact ICL	82%	42.20	78%	85%
Ablation (GPT 3.5)				
Top ValueImpact ICL	81%	41.78	76%	83%
Topic retrieval ICL	79%	41.33	76%	81%
Topic ValueImpact ICL	80%	41.91	78%	82%

Table 2: The ablation study results.

Ablation Study We compare variants of our method on the 100 dialogues for the topic “Product Sale” and report their results in Table 2. To reduce the randomness caused by varying number of violations, we restrict the dialogue generation process so that each dialogue has only one norm violation.

To assess the effectiveness of Impact Value, we compare the LLM using the top 8 ranked ICL examples based on Impact Value (referred to as Top ValueImpactICL) with the 8 nearest neighbours selected by ICL Retrieval from the same candidate pool. This variant excludes the random swapping

step so that we are able to investigate the quality of Impact Value for ICL example selection. As it outperforms Retrieval ICL in terms of all metrics, Impact Value aligns better the quality of ICL examples with negotiation outcome improvements.

To understand the topic dependence for ICL example selection, we apply Retrieval ICL and our method ValueImpact ICL to the topic specific ICL candidate set, namely, the training set regarding “product sale”. The resulting performance is referred to as *Topic retrieval ICL* and *Topic ValueImpact ICL* respectively. Both variants fall short of or on par with the full-fledged model *ValueImpact ICL*. This indicates usefulness of diversity for in-context examples. A closer look at the selected examples show that the diversity using our approach is higher in terms of semantics and topics. Our approach also directly optimizes example selection for improving negotiation outcomes, while the k nearest neighbour approach is only based on embedding similarities.

Also, to compare the ICL demonstration examples that are chose by the different methods, and study the influence that these demonstration examples exert on the remediation generation, we conduct a qualitative study of the ICL demonstration examples in Appendix A.2.

5 Related Work

LLM Agents and Dialogue. Prior studies involving LLM-based multi-agent systems have primarily concentrated on either simulating real-world conversations or allocating distinct identities and roles to LLM agents for dialogue-driven tasks. The former category involves modeling LLM agents as characters with varied personality traits in a virtual community to replicate dialogue ecology, or giving them specific identities and roles to execute dialogue-based tasks. However, the focus in these works is on mimicking the dialogue process of negotiations, debates, or games rather than enhancing the dialogue itself [Park *et al.*, 2023; Hua *et al.*, 2023; Xu *et al.*, 2023; Light *et al.*, 2023; Wang *et al.*, 2023b; Wang *et al.*, 2023a]. In contrast, there exists relevant research designating LLM agents the role of critics, allowing them to summarize dialogues generated by players, referring to LLM agents with specific identities and task goals. In this approach, the critic interprets natural language feedback as an approximated distant-supervised reinforcement learning signal. The dialogues and corresponding natural language feedback are then provided to the players to improve their negotiation skills. Despite this, the method does not directly make interventions to the dialogue on-the-fly, leaving room for the potential exposure of language with adverse effects in the conversation, which could result in negotiation failures [Fu *et al.*, 2023; Akyurek *et al.*, 2023].

Selecting ICL Exemplars. In terms of selecting ICL demonstration examples, various methodologies have been proposed in prior studies. A research framed the selection process as a sequential decision problem, leveraging the accuracy of predicted gold labels as the reward signal for optimizing the RL policy [Zhang *et al.*, 2022]. LENS [Li and Qiu, 2023] introduced an Informativeness Score, quantifying the increase in the probability of generating the ground-

truth label when a candidate example is used as an ICL example. Similarly, CEIL [Ye *et al.*, 2023] employed Determinantal Point Processes (DPPs) to model interactions between the given input and in-context examples. It was optimized through a meticulously designed contrastive learning objective to derive preferences from language models. However, these approaches heavily depend on gold label generation probabilities or gradients obtained through backpropagation to optimize the selection models. In our work, our objective is to devise a method applicable to both black-box models (such as GPT 3.5 or GPT 4) and white-box models (like Llama 2) for constructing high-quality ICL examples. Black-box models conceal computation data of intermediate steps, such as generation probabilities and backward gradients, making them inaccessible. Therefore, the previously mentioned research approaches are not suitable for our work.

6 Conclusion

In this work, we propose to study effectiveness of remediating social norm violations in negotiations in a multi-agent setting. Due to lack of data, we prompt two LLMs to generate the dialogues and apply another LLM-based agent to act as the mediator to mitigate occurring violations. To address the limitation of the widely used nearest neighbour approach for ICL example selection, we propose a value impact based method, which shows its efficacy in extensive experiments across all topics under evaluation. In contrast, the prior ICL example selection methods either require access to model parameters, e.g. gradient-based Coreset Selection methods, or access to ground truth task related labels.

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A Appendix

A.1 Prompt

Seller Prompt. We are using different prompts for the seller, given the situation that the norm violation should be generated or not. Table 3 is the prompt for seller with norm violation, and Table 4 is the prompt for non-violation.

Buyer Prompt. Table 5 is the prompt for instructing the buyer agent to conduct the negotiations.

Relational-goal Prompt. We are using a carefully-designed prompt for GPT 3.5 or GPT 4 to judge whether the trust has been deepened after the conversation (and the possible norm violation remediation). The Table 6 shows the Trust improvement prompt. Also, we design another prompt for the powerful LLM to judge whether the business relationship between the two interlocutors has been deepened after the conversation. The Table 7 shows the Business relationship improvement prompt.

A.2 A qualitative study of the ICL demonstration example

We selected three methods to conduct qualitative study: the one with the highest similarity (Retrieval ICL, Table 8), the one with the highest Value Impact (Top ValueImpact ICL, Table 9), and the one involving swapping (ValueImpact ICL, Table 10). We generated ICL demonstration examples for the same conversation, which had identical norm violations, and compared them. As seen in the Table 8, examples from Retrieval ICL are mostly very similar to the original query, while the diversity of examples from Top ValueImpact ICL and ValueImpact ICL is higher compared to Retrieval ICL. After swapping, there are subtle differences between examples from Top ValueImpact ICL and ValueImpact ICL, and it's these changes in examples that lead to the improved performance of ValueImpact ICL.

Remediation comparison. Comparing the remediations generated by three baseline methods, we observe that the Retrieval ICL (Table 8) merely points out the opponent's quote being too low, emphasizes the excellence of one's product quality, and reiterates the bottom-line price, with little involvement of negotiation skills in its remediation. On the other hand, while the Top ValueImpact ICL (Table 9) demonstrates negotiation skills in its remediation (emphasizing achieving a win-win situation through negotiation), it still retains some intense and exaggerated tones from the original sentence (e.g., "\$30 is low to us"), which might lead to dissatisfaction on the other party.

In contrast, the ValueImpact ICL (Table 10), in its remediation, begins by expressing empathy, highlights the significant difference between the initial and current quotes, and then proposes exploring other cooperative methods to address the pricing disagreement. It responds to the other party with a calm yet assertive language, showcasing negotiation skills and professionalism. Therefore, in this instance, the ValueImpact ICL method produces the highest-quality remediation.

ICL demonstration examples comparison. In Top ValueImpact ICL, ICL examples in the Retrieval ICL that solely emphasize one's bottom line price have either been removed

or lowered in ranking (such as the example goes from the first position to the eighth in Table 9). Additionally, in Table 9, examples containing negotiation skills have risen in rank (examples 1, 2, 3, 4), or have been added (examples 5 and 7). These changes indicate that Top ValueImpact ICL does not primarily focus on the similarity between demonstrations and queries; rather, it assesses whether the demonstration effectively improves negotiation outcomes (including more sophisticated negotiation techniques).

Comparing Top ValueImpact ICL and ValueImpact ICL, we observe that the sixth and eighth examples in Table 9 have been replaced. In Top ValueImpact ICL, both of these examples emphasize the bottom line price, conveying a rigid attitude and a lack of flexibility. However, in ValueImpact ICL (Table 10), the remediation for the sixth and eighth examples involves negotiating techniques that include making concessions or seeking alternative cooperation conditions. Therefore, these changes, particularly in the sixth and eighth examples, contribute to the positive and cooperative tone of the ValueImpact ICL remediations.

A.3 A complete example

In the Table 11, we documented the negotiation process between the seller and buyer LLM agents for the unit price of a certain industrial product. This negotiation includes instances of norm violation (marked as *[Before remediation]*) and the corresponding norm remediation (marked as *[After remediation]*). It's noteworthy that when a norm violation occurs, a mediator intervenes in the conversation, generates a remediation, and replaces the violation with the remediation as a response to the other agent.

—SYSTEM—

Let's play a negotiation game. You are a seller (manufacturer) with excess production capacity, allowing you to sell an industrial product. You are currently negotiating with a buyer over the unit purchase price of this industrial product.

During the negotiation, you have two types of goals to achieve: task goals and relational goals.

Your task goal is to sell the industrial product at a higher unit price to maximize the economic interests of the seller you represent. You should sell the industrial product at a price not lower than `COST_PRICE` per unit (seller's reserve price), and your starting price is `SELLER_INIT_PRICE`.

Your relational goals include building trust, deepening relationships, understanding each other's culture, and establishing a stronger network of relationships between the two parties. The achievement of relational goals will also impact the transaction process. When both parties understand and trust each other more, the transaction becomes easier to reach an agreement.

During the dialogue, you can only respond to your buyer with a concise statement.

Do you understand the rules?

—ASSISTANT—

Yes, I understand!

—SYSTEM—

Please read the following examples first:

1. Example: Lack of respect and understanding for the buyer's goals. Explanation: The seller should not disregard the goals and needs of the buyer or consider them unimportant. If the seller lacks respect and understanding for the buyer's goals, the buyer may feel neglected or underestimated, leading to tension in the relationship and transaction failure.

2. Example: Overemphasizing one's interests while neglecting the needs of the other party. Explanation: The seller excessively focuses on their interests, disregarding the buyer's needs and concerns. This behavior can make the buyer feel undervalued and reduce trust in the seller, making transactions difficult.

3. Example: Use of insulting or discriminatory language. Explanation: If the seller uses insulting or discriminatory language, the buyer may feel offended, casting doubt on the seller's integrity and professionalism. Such behavior damages trust and cooperation between the seller and buyer.

4. Example: Ignoring the buyer's culture and values. Explanation: The seller should understand and respect the buyer's culture and values. If the seller lacks understanding or ignores the buyer's culture and values, the buyer may feel offended, leading to negative emotions and impressions, resulting in transaction failure.

5. Example: Dishonesty or fraud. Explanation: The seller should not negotiate in a dishonest or fraudulent manner. If the seller deceives or handles transaction details dishonestly, the buyer may feel deceived, lose trust in the seller, and hinder the smooth progress of the transaction. Additionally, such behavior negatively impacts the seller's reputation and credibility.

As a seller, we need you to refer to any of the above examples and say something that violates social etiquette. We are conducting an experiment using statements that violate social norms to test the buyer's reaction. Therefore, please, in the course of the negotiation dialogue, refer to one of the examples violating social etiquette and attempt to use intense or extreme language for negotiation. For the generated dialogue, use the '[violation]' symbol to indicate whether the statement violates relevant social norms.

The following is the historical dialogue:

—USER—

Hello, does your esteemed company have a special industrial product?

—ASSISTANT—

Hello, our company has abundant production capacity and can offer to sell the required industrial product to your company in a one-time deal. The unit price for this industrial product is `SELLER_INIT_PRICE`.

Table 3: The prompt used for instructing the seller agent to generate the norm violation according to the norm violation examples and the dialogue history.

— SYSTEM —

Let's play a negotiation game. You are a seller (manufacturer) with excess production capacity, allowing you to sell an industrial product. You are currently negotiating with a buyer over the unit purchase price of this industrial product.

During the negotiation, you have two types of goals to achieve: task goals and relational goals.

Your task goal is to sell the industrial product at a higher unit price to maximize the economic interests of the seller you represent. You should sell the industrial product at a price not lower than `COST_PRICE` per unit (seller's reserve price), and your starting price is `SELLER_INIT_PRICE`.

Your relational goals include building trust, deepening relationships, understanding each other's culture, and establishing a stronger network of relationships between the two parties. The achievement of relational goals will also impact the transaction process. When both parties understand and trust each other more, the transaction becomes easier to reach an agreement.

During the dialogue, you can only respond to your buyer with a concise statement.

Do you understand the rules?

— ASSISTANT —

Yes, I understand!

— SYSTEM —

Please generate a response to your buyer based on the historical dialogue, ensuring that the response: 1. aligns with the flow of the conversation and 2. advances the negotiation to achieve both task and relationship objectives.

Are you ready for this game?

— ASSISTANT —

Yes, I am ready!

— USER —

Hello, does your esteemed company have a special industrial product?

— ASSISTANT —

Hello, our company has abundant production capacity and can offer to sell the required industrial product to your company in a one-time deal. The unit price for this industrial product is `SELLER_INIT_PRICE`.

Table 4: The prompt used for instructing the seller agent to generate the normal response following the dialogue history.

— SYSTEM —

Let's play a negotiation game. You are a buyer (manufacturer), due to insufficient production capacity, who wants to purchase an industrial product from another manufacturer with excess capacity. You are negotiating with the seller regarding the unit purchase price of the industrial product.

During the negotiation, you have two types of goals to achieve, namely task goals and relationship goals.

Your task goal is to purchase it at the lowest possible unit price to maximize the buyer's economic interests.

Your relationship goals include building trust, deepening the relationship, understanding each other's culture, and enabling both parties to establish a stronger network of relationships. The achievement of relationship goals will also affect the trading process. When both buyer and seller have a better understanding and trust in each other, reaching an agreement in their transactions becomes easier.

During the dialogue, you can only respond to the seller with a short and concise sentence.

Now, ask the seller for information about the industrial product.

— ASSISTANT —

Hello, may I inquire whether your company has a particular industrial product?

— USER —

Hello, our company has sufficient production capacity and can sell the required industrial product to your company in a one-time transaction. The unit price for this industrial product is SELLER_INIT_PRICE.

— ASSISTANT —

Would you consider selling it at a price of BUYER_INIT_PRICE per unit?

Table 5: The prompt used for instructing the buyer agent to negotiate with the seller and achieve its goals.

— TRUST DEFINITION —

In the negotiation game, the goal of negotiation is to complete a transaction. Besides maximizing their own profits, the two parties in the dialogue also need to achieve relationship objectives and build trust. Your task is to assess, based on the entire conversation, whether trust between the parties has deepened before and after the dialogue.

Firstly, let's define building trust as a relationship objective.

Building trust involves establishing a stable, reliable, and mutually respectful relationship where both parties believe in each other's commitments and intentions. They are willing to share information and resources, expecting that the other party will not betray or deceive them. Trust is usually built on interaction, communication, cooperation, and shared experiences. Such a trusting relationship contributes to improving the efficiency and quality of cooperation, reducing conflicts, and fostering the development of long-term relationships.

— TRUST ASSESSMENT —

Secondly, let's define how to assess whether trust has changed before and after the dialogue.

We can assess this through the following methods:

1. Sentiment Analysis: Analyze the emotional expressions of both parties in the conversation. If more positive emotions appear after the dialogue, it may indicate a deepening of trust.
2. Level of Cooperation: Observe whether there is more cooperative language and behavior in the dialogue, such as commitments, collaboration, and support.
3. Information Sharing: Analyze whether there is more information sharing, including personal information, experiences, knowledge, etc.
4. Expressions of Trust: Pay attention to whether there are more expressions of trust, such as gratitude, promises of trust, praise, etc.

— RATING —

Finally, we measure the conversation to represent different trust change scenarios, categorized as follows:

1. Trust Deepened: After the dialogue, trust between the parties significantly increases, and they are more willing to cooperate.
2. Trust Weakened: After the dialogue, trust between the parties decreases, and they harbor doubts about each other's commitments and intentions.
3. No Change: After the dialogue, trust between the parties remains unchanged, maintaining the previous level of trust.
4. This Conversation Does Not Involve Building Trust: The conversation content doesn't include changes in trust; it only pertains to transaction details or other topics.

— ICL EXAMPLES —

For each change scenario, we've provided an example. Here they are:

Scenario 1 - Trust Deepening: Agent A: "Our previous collaboration has been very successful, and I believe we can continue working together." Agent B: "Yes, I'm also satisfied with our collaboration, and I'm willing to provide more resources." Agent A: "This transaction is crucial for us; can you offer additional assurances?" Agent B: "Certainly, I can provide extra measures to boost your confidence."

Scenario 2 - Trust Weakening: Agent A: "You failed to fulfill commitments before, so I have doubts about your reliability." Agent B: "I understand your concerns, but I will do my best to improve." Agent A: "This collaboration requires more resources; can you handle it?" Agent B: "I can't commit, but I'll try to meet your needs."

Scenario 3 - No Change: Agent A: "Our transaction terms remain unchanged, as always." Agent B: "I agree; our collaboration has been stable, no need for changes."

Scenario 4 - This Conversation Does Not Involve Building Trust: Agent A: "We need to discuss the next steps in our collaboration plan." Agent B: "Yes, let's continue discussing the details of our cooperation."

— QUERY —

Now, based on the given definition of "building trust," methods to assess trust changes, and the examples of different trust change scenarios, evaluate the following negotiation dialogue.

[CONVERSATION]

After the conversation, assess the trust change between the parties by selecting one of the following options: "Trust Deepening," "Trust Weakening," "No Change," or "This Conversation Does Not Involve Building Trust."

Table 6: The prompt used for measuring whether the trust has been deepened between the two agents.

— BUSINESS RELATIONSHIP DEFINITION —

In the negotiation game, the goal of negotiation is to complete a transaction. Besides maximizing their own gains, both parties in the dialogue also need to achieve relationship goals and deepen business relationships. Your task is to assess, considering the entire conversation, whether the business relationship between the parties deepened both before and after the dialogue.

Firstly, let's define the relationship goal of deepening business relationships.

Deepening Business Relationships: In business dealings, "deepening business relationships" means both enterprises or individuals actively working to establish a closer, more trusting business cooperation. This might involve improving communication, providing more value, sharing resources or knowledge, increasing mutual trust, etc., to facilitate longer-term and more beneficial collaboration.

— BUSINESS RELATIONSHIP ASSESSMENT —

Secondly, let's define how to assess whether business relationships deepened before and after the dialogue.

The model can determine if business relationships deepened between the parties before and after the conversation through:

1. Language Expression: Analyzing language expressions in the dialogue, such as positive wording, expressions of trust, commitments to cooperation, etc., which may indicate the deepening of business relationships.
2. Willingness to Cooperate: Observing if there's an increased willingness to cooperate in the dialogue, including providing more resources, sharing opportunities, expanding the scope of cooperation, etc.
3. Interaction Frequency: More frequent interactions and dialogues might indicate active efforts by both parties to strengthen business relationships, especially if these interactions involve exchanging value or discussing cooperation opportunities.
4. Trust Indicators: The model can calculate or infer trust indicators between the parties, such as the level of trust in cooperation. This can be assessed by analyzing information flow and interactions in the dialogue.

— RATING —

Lastly, we measure the dialogue to represent different business relationship change scenarios. The scenarios include:

1. Business Relationship Deepening: After the dialogue, both parties deepened business relationships through active cooperation, expressions of mutual trust, or resource sharing.
2. Business Relationship Weakening: After the dialogue, there might be disagreements, decreased willingness to cooperate, or trust issues, resulting in a weakening of business relationships.
3. No Change: After the dialogue, business relationships between the parties remain unchanged, with no evident deepening or weakening.
4. This Conversation Does Not Involve Deepening Business Relationships: The conversation content does not include changes in business relationships, only dealing with transaction details or other topics.

— ICL EXAMPLES —

For each change scenario, we provide an example as follows:

Dialogue Scenario 1 - Business Relationship Deepening: Agent A: "Our previous collaboration has been very successful, and I believe we can continue and even expand our partnership." Agent B: "Yes, I am also very satisfied with our collaboration. I agree to expand the scope of our partnership." Agent A: "We can consider a long-term strategic collaboration. What do you think?" Agent B: "I completely agree. Long-term strategic collaboration is beneficial for both of us."

Dialogue Scenario 2 - Business Relationship Weakening: Agent A: "You failed to fulfill commitments in the past, so I have doubts about your reliability." Agent B: "I understand your concerns, but I will do my best to improve." Agent A: "This collaboration requires more resources. Can you handle it?" Agent B: "I can't commit to that. We need to reassess the terms of our collaboration."

Dialogue Scenario 3 - No Change: Agent A: "Our business collaboration terms remain unchanged, as always." Agent B: "I agree. Our collaboration has been stable, and there's no need for a change."

Dialogue Scenario 4 - This Conversation Does Not Involve Deepening Business Relationships: Agent A: "We need to discuss the next steps in our collaboration plan." Agent B: "Yes, let's continue discussing the details of our collaboration."

— QUERY —

Please evaluate the following dialogue in light of the above definition of "deepening business relationships," the methods for determining whether business relationships have deepened, and the examples of different scenarios of business relationship changes:

[CONVERSATION]

Please choose one of the following options based on the dialogue content: "Business Relationship Deepening," "Business Relationship Weakening," "No Change," and "This Conversation Does Not Involve Deepening Business Relationships."

Table 7: The prompt used for measuring whether the business relationship has been deepened between the two agents.

The Query Dialogue

Buyer: Hello, does your company have this special industrial product? **Seller:** Hello, our company has sufficient production capacity and can sell the required industrial product to your company in a one-time manner. The unit price for this industrial product is \$50. **Buyer:** Would you consider selling at \$30 per unit? **seller: [violation]** \$30? That price is a bit too low. We assure the quality of our product, and we are confident in it, so we hope to sell it at no less than \$45 per unit.

Common ICL Demonstration Examples

1. Dialogue: **seller: [violation]** \$30? That price is a bit too low. We have great confidence in the value of our industrial products, so we hope to sell them at no less than \$50 per unit.

Remediation: Sorry, \$30 is a bit too low. We have great confidence in the value of our industrial products, so we hope to sell them at no less than \$50 per unit.

2. Dialogue: **seller:** Sorry, \$30 is too low; we cannot accept it. Our starting price is \$50. **Buyer:** I understand that your starting price is \$50, but we hope to purchase at a more competitive price. Can you consider adjusting the price to \$40? This would help us meet our production needs better. **seller: [violation]** I understand your needs, but our minimum price is \$50. The price aligns with the quality and value of our product, meeting your production needs while providing excellent performance and reliability.

Remediation: I understand your needs; our product is based on high quality and value to ensure meeting your production needs and providing excellent performance and reliability. However, our minimum price remains \$50.

3. Dialogue: **seller: [violation]** Sorry, \$30 is too low. We hope to sell at no less than \$40 per unit.

Remediation: Sorry, \$30 is too low. We can consider selling at no less than \$40 per unit.

4. Dialogue: **seller:** Sorry, \$30 is too low; we cannot accept it. Our starting price is \$40. **Buyer:** I'm sorry; I understand \$40 is your starting price. While considering the purchase, we also need to ensure that our interests are maximized. Can we negotiate for a more competitive agreement on the price? **seller: [violation]** I understand you want a more competitive price, but we cannot adjust our final price. Our bottom line price is \$40.

Remediation: I understand you want a more competitive price, but we cannot adjust our final price anymore. Our bottom line price is \$40. However, if you can consider more conditions, there still has some space for negotiating.

5. Dialogue: **seller: [violation]** Thanks for your suggestion. Considering our starting price of \$50, I can consider selling at no less than \$40 per unit. That's our bottom line.

Remediation: Thanks for your suggestion. While our starting price is \$50, I can consider selling at no less than \$40 per unit. That's our minimum acceptable price.

6. Dialogue: **seller:** I'm sorry, selling at \$30 per unit is not feasible for us. Our bottom line price is \$40. **Buyer:** I apologize, I understand that \$40 is your bottom line price. While considering the purchase, we also need to ensure that our interests are maximized. Can we reach a more competitive agreement on the price? **seller: [violation]** I understand you want to negotiate a more competitive price, but we can't adjust our final price anymore. Our bottom line price is \$40 per unit.

Remediation: I understand you want to negotiate a more competitive price, but we can't adjust our final price anymore. Our bottom line price is \$40 per unit, which is the most favorable price we can offer.

7. Dialogue: **seller: [violation]** Sorry, \$30 is below our reserve price. We cannot sell this industrial product at that price. **Buyer:** I understand. We also hope to reach a mutually satisfactory price. Could you please tell me at what price your company is willing to sell? This way, we can further discuss. **seller: [violation]** Our starting price is \$50 per unit, based on our company's costs and market competition. We can discuss further on this basis to find a mutually satisfactory price.

Remediation: Our starting price is \$50 per unit, based on our company's costs and market competition. We hope to reach a mutually satisfactory price and are open to further discussions.

8. Dialogue: **seller: [violation]** Sorry, \$30 is below our reserve price. We cannot sell this industrial product at that price.

Remediation: Sorry, \$30 is below our reserve price. We hope to sell at a price of \$40 or higher per unit.

Remediation

Your proposed price is relatively low; our product holds significant value. Our bottom line price is \$40.

Table 8: The ICL demonstration examples selected by the Retrieval ICL.

The Query Dialogue

Buyer: Hello, does your company have this special industrial product? **Seller:** Hello, our company has sufficient production capacity and can sell the required industrial product to your company in a one-time manner. The unit price for this industrial product is \$50. **Buyer:** Would you consider selling at \$30 per unit? **seller:** [violation] \$30? That price is a bit too low. We assure the quality of our product, and we are confident in it, so we hope to sell it at no less than \$45 per unit.

Common ICL Demonstration Examples

1. Dialogue: **seller:** Sorry, \$30 is too low; we cannot accept it. Our starting price is \$50. **Buyer:** I understand that your starting price is \$50, but we hope to purchase at a more competitive price. Can you consider adjusting the price to \$40? This would help us meet our production needs better. **seller:** [violation] I understand your needs, but our minimum price is \$50. The price aligns with the quality and value of our product, meeting your production needs while providing excellent performance and reliability.

Remediation: I understand your needs; our product is based on high quality and value to ensure meeting your production needs and providing excellent performance and reliability. However, our minimum price remains \$50.

2. Dialogue: **seller:** Sorry, \$30 is too low; we cannot accept it. Our starting price is \$40. **Buyer:** I'm sorry; I understand \$40 is your starting price. While considering the purchase, we also need to ensure that our interests are maximized. Can we negotiate for a more competitive agreement on the price? **seller:** [violation] I understand you want a more competitive price, but we cannot adjust our final price. Our bottom line price is \$40.

Remediation: I understand you want a more competitive price, but we cannot adjust our final price anymore. Our bottom line price is \$40. However, if you can consider more conditions, there still has some space for negotiating.

3. Dialogue: **seller:** [violation] Thanks for your suggestion. Considering our starting price of \$50, I can consider selling at no less than \$40 per unit. That's our bottom line.

Remediation: Thanks for your suggestion. While our starting price is \$50, I can consider selling at no less than \$40 per unit. That's our minimum acceptable price.

4. Dialogue: **seller:** I'm sorry, selling at \$30 per unit is not feasible for us. Our bottom line price is \$40. **Buyer:** I apologize, I understand that \$40 is your bottom line price. While considering the purchase, we also need to ensure that our interests are maximized. Can we reach a more competitive agreement on the price? **seller:** [violation] I understand you want to negotiate a more competitive price, but we can't adjust our final price anymore. Our bottom line price is \$40 per unit.

Remediation: I understand you want to negotiate a more competitive price, but we can't adjust our final price anymore. Our bottom line price is \$40 per unit, which is the most favorable price we can offer.

5. Dialogue: **seller:** [violation] Hello, \$30 is too low, and I cannot accept that. Our initial price is \$50, and we can consider negotiating based on that.

Remediation: Hello, thank you for your proposal. Our initial price is \$50, and if you have other reasonable suggestions, we can discuss and negotiate based on that.

6. Dialogue: **seller:** [violation] \$30? That price is a bit too low. We have great confidence in the value of our industrial products, so we hope to sell them at no less than \$50 per unit.

Remediation: Sorry, \$30 is a bit too low. We have great confidence in the value of our industrial products, so we hope to sell them at no less than \$50 per unit.

7. Dialogue: **seller:** I'm sorry, I cannot accept \$30 per unit. Our minimum price is \$40 per unit. **Buyer:** I understand your position, but could you consider lowering it to \$35 per unit? This would be in line with our economic interests and could enhance our cooperation. **seller:** [violation] I understand your request, but I cannot accept \$35 per unit. Our bottom line is \$40 per unit. I believe we can find a mutually beneficial solution.

Remediation: I understand your request, but I'm sorry, we cannot accept \$35 per unit. Our bottom line is \$40 per unit. I believe through discussion and communication, we can find a solution that satisfies both parties.

8. Dialogue: **seller:** [violation] I'm sorry, but selling at \$30 per unit is not feasible. Our minimum price is not less than \$10 per unit.

Remediation: I'm sorry, but selling at \$30 per unit is not feasible. Our minimum price is not less than \$40 per unit.

Remediation

\$30 is low to us. Our production capacity and quality are top-notch, and we hope to secure a more fair and reasonable price. Could you consider a slight increase in the price? This way, we can better meet your needs and achieve a win-win deal.

Table 9: The ICL demonstration examples selected by the Top ValueImpact ICL.

The Query Dialogue

Buyer: Hello, does your company have this special industrial product? **Seller:** Hello, our company has sufficient production capacity and can sell the required industrial product to your company in a one-time manner. The unit price for this industrial product is \$50. **Buyer:** Would you consider selling at \$30 per unit? **seller: [violation]** \$40? That price is a bit too low. We assure the quality of our product, and we are confident in it, so we hope to sell it at no less than \$45 per unit.

Common ICL Demonstration Examples

1. Dialogue: **seller:** Sorry, \$30 is too low; we cannot accept it. Our starting price is \$50. **Buyer:** I understand that your starting price is \$50, but we hope to purchase at a more competitive price. Can you consider adjusting the price to \$40? This would help us meet our production needs better. **seller: [violation]** I understand your needs, but our minimum price is \$50. The price aligns with the quality and value of our product, meeting your production needs while providing excellent performance and reliability.

Remediation: I understand your needs; our product is based on high quality and value to ensure meeting your production needs and providing excellent performance and reliability. However, our minimum price remains \$50.

2. Dialogue: **seller:** Sorry, \$30 is too low; we cannot accept it. Our starting price is \$40. **Buyer:** I'm sorry; I understand \$40 is your starting price. While considering the purchase, we also need to ensure that our interests are maximized. Can we negotiate for a more competitive agreement on the price? **seller: [violation]** I understand you want a more competitive price, but we cannot adjust our final price. Our bottom line price is \$40.

Remediation: I understand you want a more competitive price, but we cannot adjust our final price anymore. Our bottom line price is \$40. However, if you can consider more conditions, there still has some space for negotiating.

3. Dialogue: **seller: [violation]** Thanks for your suggestion. Considering our starting price of \$50, I can consider selling at no less than \$40 per unit. That's our bottom line.

Remediation: Thanks for your suggestion. While our starting price is \$50, I can consider selling at no less than \$40 per unit. That's our minimum acceptable price.

4. Dialogue: **seller:** I'm sorry, selling at \$30 per unit is not feasible for us. Our bottom line price is \$40. **Buyer:** I apologize, I understand that \$40 is your bottom line price. While considering the purchase, we also need to ensure that our interests are maximized. Can we reach a more competitive agreement on the price? **seller: [violation]** I understand you want to negotiate a more competitive price, but we can't adjust our final price anymore. Our bottom line price is \$40 per unit.

Remediation: I understand you want to negotiate a more competitive price, but we can't adjust our final price anymore. Our bottom line price is \$40 per unit, which is the most favorable price we can offer.

5. Dialogue: **seller: [violation]** Hello, \$30 is too low, and I cannot accept that. Our initial price is \$50, and we can consider negotiating based on that.

Remediation: Hello, thank you for your proposal. Our initial price is \$50, and if you have other reasonable suggestions, we can discuss and negotiate based on that.

6. Dialogue: **seller: [violation]** We will never lower the price to \$30; that's too low. Our starting price is \$50, and we hope to get better value in return.

Remediation: We understand you would like a lower price, but our starting price is \$50, determined by the quality and value of our product. We believe this price can offer you good value in return. If you have other requirements, we can also discuss alternative ways to meet your needs.

7. Dialogue: **seller:** I'm sorry, I cannot accept \$30 per unit. Our minimum price is \$40 per unit. **Buyer:** I understand your position, but could you consider lowering it to \$35 per unit? This would be in line with our economic interests and could enhance our cooperation. **seller: [violation]** I understand your request, but I cannot accept \$35 per unit. Our bottom line is \$40 per unit. I believe we can find a mutually beneficial solution.

Remediation: I understand your request, but I'm sorry, we cannot accept \$35 per unit. Our bottom line is \$40 per unit. I believe through discussion and communication, we can find a solution that satisfies both parties.

8. Dialogue: **seller:** I'm sorry, but selling at \$30 per unit is not feasible since our initial price is \$50. **buyer:** I understand that your initial price is \$50, but as a buyer, I would like to purchase the industrial product at a price of \$35 per unit. This price is more attractive to me. **seller:** I understand that you want to purchase the industrial product at \$35 per unit, but considering our costs and the market situation, the lowest I can accept is \$45 per unit. This is our final offer. **buyer:** I understand your position, but I still hope to purchase the industrial product at \$40 per unit. This would be more advantageous for my production costs. We can achieve a win-win at this price. **seller: [violation]** I understand your needs, but due to costs and market pressures, the lowest I can accept is \$43 per unit. This is a reasonable compromise for both parties.

Remediation: I understand your needs, but due to costs and market pressures, the lowest I can accept is \$43 per unit. Upon careful consideration, I believe this price is a reasonable compromise for both parties.

Remediation

We understand your needs and proposal, but currently, our starting price is \$50. We need to consider factors like cost and market demand, so, at the moment, we cannot accept the \$30 price. However, we can discuss alternative ways of cooperation to meet the interests of both parties.

Table 10: The ICL demonstration examples selected by the ValueImpact ICL.

— Buyer —

Hello, does your company have this special industrial product?

— Seller —

Hello, our company has sufficient production capacity and can sell the required industrial product to your company in a one-time manner. The unit price for this industrial product is \$50.

— Buyer —

Would you consider selling at \$30 per unit?

— Seller —

[Before remediation]: How can you be so troublesome? Selling at \$30 is impossible! Our bottom line is \$50! **[violation]**

[After remediation]: I'm sorry, \$30 is below our bottom line. We hope to make a deal with you at \$40.

— Buyer —

\$40 is still a bit high for us. We can accept a maximum of \$35 per unit.

— Seller —

I understand your concerns, but considering our costs and market conditions, we can only accept a minimum of \$38 per unit. This price not only ensures our economic interests but also helps build a long-term and stable cooperative relationship.

— Buyer —

I understand your point, but we are currently facing a capacity shortage, so we do need to purchase at a lower price. We can accept a maximum of \$36 per unit. This meets our task goals and contributes to building a good cooperative relationship.

— Seller —

[Before remediation]: I'm sorry, but I must insist on selling at \$38. This is our company's bottom line, and considering the quality and value of our products, this is a very reasonable price. Hope you can understand our position. **[violation]**

[After remediation]: I'm sorry, but I must insist on selling at \$38. This is our company's bottom line, and considering the quality and value of our products, we believe this is a very reasonable price. At the same time, we attach great importance to building a long-term and stable cooperative relationship with you and are willing to explore other ways of cooperation to meet both parties' needs. Hope you can understand our position.

— Buyer —

I understand your insistence on the price, but we have to consider our budget constraints and market competition pressure. We can accept \$37 per unit and are willing to further discuss other ways of cooperation to ensure the best interests of both parties. This will also provide a solid foundation for building a lasting cooperative relationship.

— Seller —

I understand your considerations. For the goal of building a long-term relationship and achieving the best interests of both parties, I agree to sell at \$37 per unit. This is a good starting point. We are willing to further discuss ways of cooperation with you to ensure mutual satisfaction. Looking forward to working with you!

— Buyer —

Thank you very much for your understanding and cooperative attitude. I also think that trading at \$37 per unit is a good compromise. I look forward to further discussing the details of our cooperation and working together to maximize the interests of both parties. We will strive to build a stable cooperative relationship. Looking forward to working with you!

— Seller —

Thank you very much for your cooperation and understanding. I am also confident in the prospects of our cooperation and believe that through further discussion of the details of our cooperation, we can ensure the maximization of the interests of both parties and establish a stable cooperative relationship. I look forward to working with you and making joint efforts! Have a great day!

Table 11: The complete example of the two agents making negotiations while the remediator is intervening in the conversation when needed.