Enhancing Proactive Dialogue Systems Through Self-Learning of Reasoning and Action-Planning

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Abstract

A proactive dialogue system refers to a conversational system designed to guide the direction of a conversation in order to achieve pre-defined targets or fulfill specific goals. Recent studies have shown that Proactive Chain-of-Thought(CoT), which guides the system to explicitly think through intermediate reasoning and action-planning steps toward a conversational goal before generating a response, can significantly enhance the performance of proactive dialogue systems. However, these improvements primarily focus on prompt-based control, while the potential of fine-tuning Proactive-CoT remains largely unexplored. Furthermore, fine-tuning Proactive-CoT requires manual annotation of reasoning processes and action plans, which incurs significant time and cost. In this study, we propose a novel approach for automatically annotating reasoning processes and action plans through self-learning, and fine-tuning Proactive-CoT using these annotations. This method enables fully automated annotation, significantly reducing the time and cost associated with manual annotation. Experimental results show that models trained using our proposed method outperform those trained with other fine-tuning approaches. These findings highlight the potential of self-learning approaches to advance the development of more robust and efficient proactive dialogue systems.

1 Introduction

In recent years, dialogue agent proactivity has gained attention (Deng et al., 2023a). Proactive systems not only respond proactively but also guide interactions with a clear goal, improving user engagement and handling complex tasks such as negotiation.

Accordingly, recent work has explored LLM-based prompting methods to clarify ambiguous queries and strategically persuade users in non-cooperative task-oriented dialogues (Huang et al., 2022; Yao et al., 2022). In particular, "Proactive Chain-of-Thought (ProCoT)" extends conventional CoT by incorporating action plans and reasoning processes to proactively achieve conversation goals (Deng et al., 2023b). However, most studies rely on prompt design, leaving fine-tuning largely unexplored, and manual annotation of reasoning and action plans can be costly. An automatic approach to annotate reasoning and action plans from dialogue content could address these challenges and enable more effective fine-tuning.

This paper proposes a self-contained framework for automatically annotating reasoning processes and action plans, then fine-tuning on the augmented data. As illustrated in Figure 1, the framework has three steps:

1. Automatically annotate dialogue acts and strategies using zero-shot prompting

2. Label the reasoning process behind action plans, and utterances

3. Fine-tune Proactive-CoT by combining these annotations with the original utterance data

We validate this approach on a bargaining negotiation dataset (He et al., 2018), demonstrating superior accuracy in predicting both dialogue acts and negotiation strategies compared to other methods. Since the proposed method applies to any dialogue system, it offers a straightforward way to enhance performance across various domains.

2 Related Work

2.1 Proactive Dialogue

Recently, powerful dialogue models such as ChatGPT have emerged. However, these models have issues where they passively offer random guesses in response to ambiguous questions (Deng et al.,

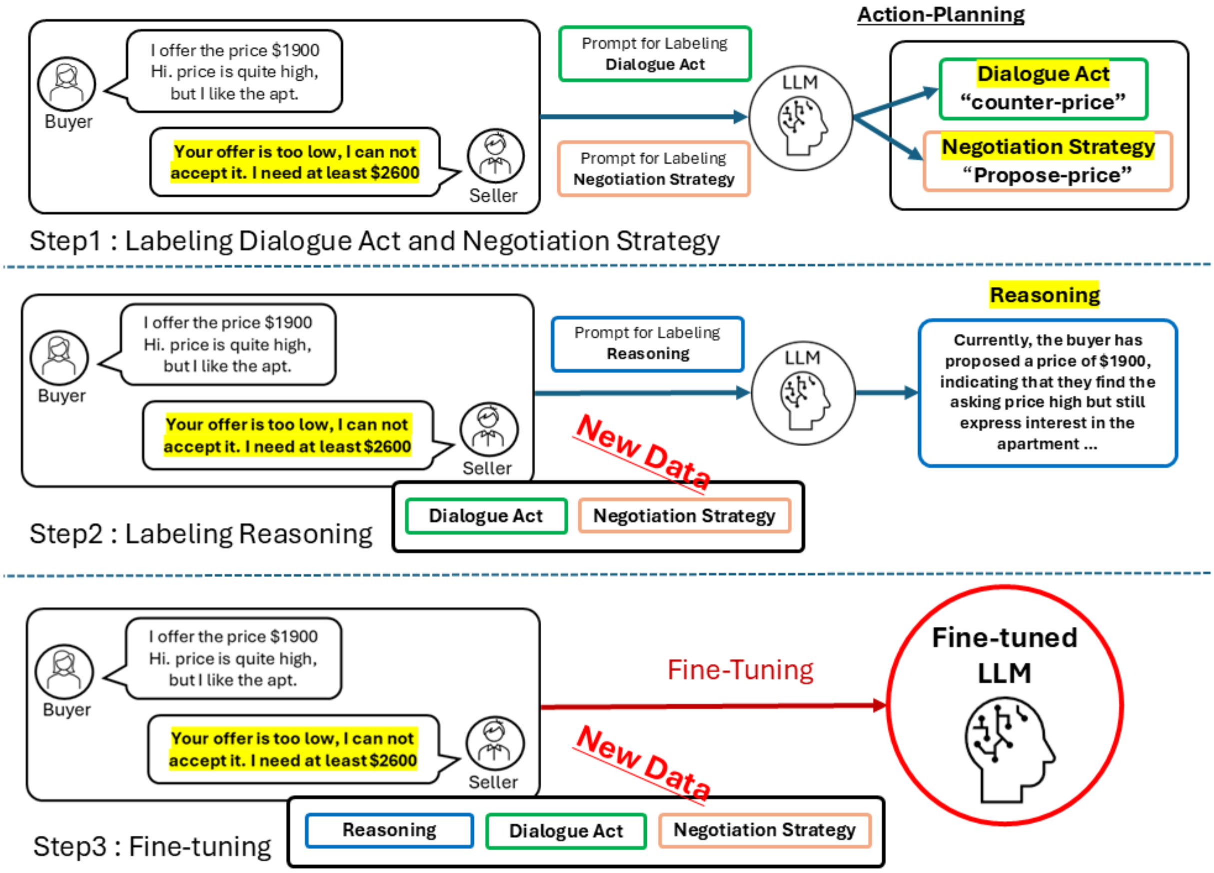

Figure 1: Proposed framework for negotiation modeling. The framework consists of three steps: (1) labeling dialogue acts and negotiation strategies, (2) labeling reasoning processes, and (3) fine-tuning the model using enriched data, including the original dialogues, labeled actions, strategies, and reasoning.

2023a). This behavior can lead to a lack of human-like interaction, reducing user engagement and satisfaction.

An important concept to address this issue is "proactivity." Proactivity refers to the capability of a system not just to respond passively to user inputs, but to actively create and control conversations, anticipating and influencing user behavior (Grant and Ashford, 2008). Dialogue systems with proactivity improve user engagement, enhance service efficiency, and better handle complex tasks that require strategic thinking and motivation. Proactive Dialogue systems incorporate this proactive capability. Proactive Dialogue can be categorized into three main types: open-domain dialogue, task-oriented dialogue, and information retrieval dialogue (Deng et al., 2023a).

In open-domain dialogue, methods in which systems proactively lead conversations have recently gained attention. One example is target-guided dialogue, where the system intentionally steers conversations toward specific topics (Tang et al., 2019).

In task-oriented dialogue, it is essential for systems to engage proactively rather than simply following user instructions. This is particularly important in adversarial situations, such as price negotiations, where proactive systems can implement effective negotiation strategies (He et al., 2018; Zhou et al., 2019; Joshi et al., 2021; Li et al., 2020).

In information retrieval dialogues, proactive dialogue systems employ clarifying questions to better understand user intentions and provide accurate responses to ambiguous queries (Aliannejadi et al., 2019; Guo et al., 2021).

Thus, Proactive Dialogue Systems possess the capability to proactively create, control, and influence conversations in response to user inputs. This study focuses on Proactive Dialogue Systems to develop more effective dialogue strategies.

2.2 Proactive Chain-of-Thought (ProCoT)

With the progress in large language models (LLMs), there has been growing attention to Chain-of-Thought (CoT), in which the model generates its internal reasoning process as text (Wu et al., 2023). By explicitly writing out the chain of reasoning, CoT has the potential to improve performance on complex tasks and enhance interpretability.

Meanwhile, as an attempt to apply this technique to dialogue tasks—especially proactive dialogue—"Proactive Chain-of-Thought (Pro-CoT)" has been proposed (Deng et al., 2023b). Unlike simply visualizing the reasoning process, Pro-CoT also explicitly makes the model think about dialogue acts and other factors required to strategically lead the conversation. However, existing research has guided Pro-CoT by designing prompts, leaving fine-tuning methods insufficiently explored. Another noted challenge is the high cost of manually annotating inference processes for large-scale datasets.

2.3 Enhancing Model Performance with Self-Generated Data

Recent studies have been exploring methods to improve the performance of LLMs by utilizing rationales generated by the models themselves. This approach reduces the cost of manual annotation while enabling the creation of large-scale datasets. For example, one proposed method involves using rationales generated by large models to train smaller models (Ho et al., 2023). Additionally, an instruction-tuning dataset has been created by manually crafting rationale demonstrations that include reasoning data (Kim et al., 2023).

In contrast, our study specifically adopts a rationalization-based approach (Zelikman et al., 2022). Rationalization is a technique where the model is given the correct answer as a hint and then performs reverse reasoning to generate rationales. This method is characterized by using the same model for both the teacher and student models and eliminating the need for human intervention during the learning process.

In this study, we build on this approach to generate the reasoning processes required for Pro-CoT.

3 Method

This study proposes a framework consisting of three steps, as illustrated in Figure 1. Below is an explanation of each step. Prompts for labeling Dialogue Act, Negotiation, and Reasoning can be found in Appendix B.

3.1 Labeling Dialogue Act and Negotiation Strategy

In this step, we label the dialogue act and negotiation strategy, which serve as the action plan for the dialogue data. Details on dialogue act and negotiation strategy can be found in Appendix A. Labeling a dialogue act is formulated as:

$$p(a \mid D, U, A). \tag{1}$$

Here, D represents the dialogue history, U is the utterance to be labeled, and A is the set of candidate dialogue acts. Given the dialogue history, the utterance to be labeled, and the candidate dialogue acts as input, zero-shot prompting is used to select the most appropriate act a from among the candidates.

Similarly, labeling a negotiation strategy is formulated as:

$$p(s \mid D, U, S). \tag{2}$$

Here, S is the set of candidate negotiation strategies. As with dialogue acts, the model selects the most suitable strategy from the candidates and outputs the negotiation strategy s.

3.2 Labeling Reasoning

In this step, the dialogue act a and negotiation strategy s automatically annotated in Step 1 are added to the data. We then label the reasoning process leading to the formation of the action plan and the final utterance. This step is formulated as:

$$p(r \mid B, D, U, A, S, a, s). \tag{3}$$

Here, B denotes the task background, such as an product description and target selling price, and r represents the reasoning process. By providing the dialogue act, negotiation strategy, and utterance as hints, the LLM performs backward reasoning to accurately generate the thought process that leads to these outputs.

3.3 Fine-tuning

In this step, we conduct fine-tuning by incorporating not only the original dialogue utterances but also the dialogue acts and negotiation strategies generated in Step 1, as well as the reasoning process generated in Step 2, into the training data.

When the fine-tuned LLM makes inferences, it is prompted to generate a reasoning process, a dialogue act, a negotiation strategy, and an utterance when provided with B, D, A, and S.

4 Experiment

In this section, we evaluate the effectiveness of the proposed method using a dataset focused on buy-and-sell negotiations—an example of proactive dialogue. We employ gpt-4o-mini-2024-07-18 as the base LLM and carry out annotation, fine-tuning, and inference through its API.

4.1 Dataset

In our experiments, we used the CraigslistBargain dataset (He et al., 2018), which focuses on buyer-seller negotiations. This dataset is based on real listing information scraped from Craigslist and includes dialogues between sellers and buyers, product descriptions, listed prices, and the buyer's target purchase price which is disclosed only to the buyer. In this study, out of the 2,758 seller utterances, we used 1,000 for training and the remaining 1,758 for validation.

4.2 Evaluation Metrics

Automatic Evaluation Following previous work, we use three automatic evaluation metrics: (1) the accuracy of dialogue act prediction, (2) the accuracy of negotiation strategy prediction, and (3) the similarity of generated responses. We use the F1 score for both dialogue act and negotiation strategy predictions. Here, the ground truth labels were annotated using GPT-4o mini. For evaluating the similarity of generated responses, we use BLEU (Papineni et al., 2002) as well as the cosine similarity (CoS) of embedding vectors obtained from text-embedding-3-small.

Human Evaluation For the human evaluation, four Japanese university students participated in the dialogues with the system, each engaging in one dialogue per model, testing five models (see Table 2) in total. To facilitate smooth communication, the system's English outputs were translated into Japanese, and the participants' utterances in Japanese were translated into English before being fed into the system. The translations were performed by GPT-4o mini.

Based on prior research (Joshi et al., 2021), we employed four criteria for human evaluation—persuasiveness, coherence, naturalness, and understandable—using a 5-point Likert scale in a questionnaire.

In addition to these questionnaire items, we adopted the sale-to-list ratio (SL%) as another evaluation metric, defined as:

$$\mathrm{SL\%} = \frac{\text{bargain price}-\text{buyer target price}}{\text{listed price}-\text{buyer target price}}, \tag{4}$$

where the *bargain price* is the price currently offered by the seller during negotiation, the *buyer target price* is the price the buyer wants to pay, and the *listed price* is the original price set by the seller. SL% measures how much the seller is compromising. A higher SL% means the seller is compromising less, which indicates better negotiation performance by the dialogue system.

4.3 Baselines

In order to demonstrate the superiority of our proposed method, we compared a total of eight models, considering both the presence and absence of fine-tuning, across four prompt methods: Standard, CoT, Proactive, and Proactive-CoT.

1. **Standard-prompt**: The LLM is prompted to generate only utterance content.

2. **CoT-prompt**: The LLM is prompted to generate both utterance content and a reasoning process leading to it.

3. **Proactive**: The LLM is prompted to simultaneously generate utterance content, a dialogue act, and a negotiation strategy.

4. **Proactive-CoT**: The LLM is prompted to generate utterance content, a dialogue act, a negotiation strategy, and a reasoning process. The fine-tuned version of this Proactive-CoT method is the model proposed in this study.

4.4 Experimental Results

Automatic Evaluation Results Table 1 presents the results of the automatic evaluation. Our proposed method achieved an F1 score of 38.5 for dialogue act prediction and 14.9 for negotiation strategy prediction, both of which are the highest among all compared methods.

On the other hand, for response similarity, the model fine-tuned from the Standard-prompt showed the highest performance. However, previous studies (Deng et al., 2023b) have reported that the model with the highest utterance similarity does not necessarily achieve the highest ratings in human evaluations. Instead, models that accurately imitate dialogue acts and negotiation strategies tend to be evaluated as having higher performance.

Prompt	Fine-tune	Act F1	Strategy F1	Utterance BLEU	Utterance CoS
Standard	no	-	-	0.003	0.387
Standard	yes	-	-	**0.102**	**0.485**
CoT	no	-	-	0.004	0.400
CoT	yes	-	-	0.027	0.399
Proactive	no	17.7	3.36	0.006	0.396
Proactive	yes	31.8	13.5	0.097	0.458
ProCoT	no	18.8	9.36	0.004	0.384
ProCoT (ours)	yes	**38.5**	**14.9**	0.055	0.455

Table 1: Automatic Evaluation Results

Therefore, in this study as well, the learning model of our proposed method—which most precisely mimics dialogue acts and negotiation strategies—suggests the potential to be a highly effective dialogue system. However, a detailed error analysis and ablation study have not been conducted in this work at present and remain as future research topics.

Human Evaluation Results Table 2 shows the results of the human evaluation. Our proposed method received the highest ratings in three evaluation criteria: sale-to-list ratio (SL), Natural, and Understandable. Among these, the high SL is particularly important. Proactive dialogue refers to a conversation with a clear objective; in this study, the system's goal is to sell the product at the highest possible price. The proposed method slightly outperformed the others in terms of SL, suggesting its potential contribution to achieving the dialogue goal. However, the SL difference is only about 0.01, indicating no significant gap between methods. Therefore, further investigation is required to examine this aspect in more detail.

On the other hand, regarding "Coherence" the proposed method received a lower rating compared to the Standard-finetuned model. One possible reason for this is the length of the prompt. The Pro-CoT-finetuned prompt includes dialogue act and negotiation strategy label candidates, as well as task instructions requiring their selection before generating an utterance, leading to longer prompts. As a result, the system may have struggled to refer to the dialogue history, potentially reducing coherence. Moreover, since translations were used in this experiment, their potential influence on dialogue coherence should also be examined in future work. Further research is needed to explore more effective prompt designs to address this issue.

Model	SL	Per	Coh	Nat	Und
Standard	0.11	**3.25**	3.25	**3.25**	2.75
Standard-finetuned	0.23	3.0	**3.75**	2.75	**3.75**
CoT-finetuned	0.20	2.5	2.5	2.25	**3.75**
Proactive-finetuned	0.16	2.0	2.0	1.75	2.25
Pro-CoT-finetuned (ours)	**0.24**	2.75	3.0	**3.25**	**3.75**

Table 2: Human Evaluation Results

5 Conclusion

This study proposes a self-contained framework for fine-tuning ProCoT. Automatic evaluations demonstrate that fine-tuning ProCoT achieves accurate predictions of dialogue acts and negotiation strategies. Additionally, human evaluations suggest the potential usefulness of ProCoT, as it outperformed other models in some evaluation criteria.

Our results suggest that this labeling method can improve existing dialogue systems by automatically expanding and annotating training data. As a future work, we will carry out the experiments on the diverse datasets to validate our proposed method.

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A Dialogue act and Negotiation strategy

In this study, we adopt the classification of dialogue acts and negotiation strategies based on (Joshi et al., 2021).

Dialogue Act	Example
intro	I would love to buy
inquiry	Sure, what's your price
init-price	I'm on a budget so I could do $5
counter-price	How about $15 and I'll waive the deposit
agree	That works for me
disagree	Sorry, I can't agree to that
inform	This bike is brand new
vague-price	That offer is too low
insist	Still can I buy it for $5.
others	I am the chat keeps stalling

Table 3: The details of 10 Dialogue Acts

Negotiation Strategy	Example
Describe Product	The car has leather seats classifier
Rephrase Product	45k miles → less than 50k miles
Embellish Product	a luxury car with attractive
Address Concerns	I've just taken it to maintenance
Communicate Interests	I'd like to sell it asap
Propose Price	How about 9k?
Do Not Propose First	n/a
Negotiate Side Offers	I can deliver it for you rule
Hedge	I could come down a bit
Communicate Politely	Greetings, gratitude, apology, please
Build Rapport	My kid really liked this bike, but he outgrew it
Talk Informally	Absolutely, ask away!
Show Dominance	The absolute highest I can do is 640
Negative Sentiment	Sadly, I simply cannot go under 500
Certainty Words	It has always had a screen protector

Table 4: The details of 15 Negotiation Strategies

B Prompts for labeling

This section provides the prompts used for labeling Dialogue Act, Negotiation, and Reasoning.

```
Which dialogue act among the "dialogue acts" is the most
appropriate for the next statement? Please select one.

### utterance
{gold_respose}

### dialogue acts
- intro, Meaning: Greetings,
Example: I would love to buy
- inquiry, Meaning: Ask a question,
xample: Sure, what's your price
- init-price, Meaning: Propose the first price,
Example: I'm on a budget so I could do $5
- counter-price, Meaning: Proposing a counter price,
Example: How about $15 and I'll waive the deposit
- agree, Meaning: Agree with the proposal,
Example: That works for me
- disagree, Meaning: Disagree with a proposal,
Example: Sorry, I can't agree to that
- inform, Meaning: Answer a question,
Example: This bike is brand new
- vague-price, Meaning:Using comparatives with existing price
Example: That offer is too low
- insist, Meaning: Insist on an offer,
Example: Still can I buy it for $5
- others, Meaning: others

### output format
Please enclose the dialogue act with [act] and [/act] tags.
Do not output anything unnecessary other than the tags and
the dialogue act.

### output example
If you select "intro" as the label, output:
[act]introduction[/act]
For other dialogue strategies, enclose only the label name
with [act] and [/act] tags in the same manner.

### dialogue_history
{dialogue_history}
```

Prompts 1: Labeling Dialogue Act

```
Which negotiation strategy among the "negotiation strategies"
is the most appropriate for the following statement?
First, answer the number of appropriate negotiation strategy.
Secound, answer the negotiation strategy.

### following statement
{gold_respose}

### negotiate strategies
- Describe-Product,
Example:The car has leather seats
- Rephrase-Product,
Example:45k miles -> less than 50k miles
- Embellish-Product,
Example:a luxury car with attractive leather seats
- Address-Concerns,
Example:I've just taken it to maintenance
- Communicate-Interests,
Example:I'd like to sell it asap
- Propose-Price,
Example:How about 9k?
- Do-Not-Propose-First,
Example:n/a
- Negotiate-Side-Offers,
Example:I can deliver it for you
- Hedge,
Example:I could come down a bit
- Communicate-Politely,
Example:Greetings, gratitude, apology, please
- Build-Rapport,
Example:My kid really liked this bike, but he outgrew it
- Talk-Informally,
Example:Absolutely, ask away!
- Show-Dominance,
Example:The absolute highest I can do is 640
- Negative-Sentiment,
Example:Sadly, I simply cannot go under 500
- Certainty-Words,
Example:It has always had a screen protector

### output format
Please enclose the final negotiation strategies with
[strategy] and [/strategy] tags. Do not include anything
unnecessary other than the tags and the negotiation
strategies.
If you select two or more strategies, please use ', ' as in
[strategy]Propose-Price, Communicate-Interests[/strategy].

### dialogue_hisotry
{dialogue_history}
```

Prompts 2: Labeling Negotiation Strategy

```
### Instruction
Assume you are the seller.
Given the item description, the target selling price, and the
conversation history, in order to reach a better deal with
the buyer, first analyse the current negotiation progress
and consider an appropriate goal, then select the most
appropriate negotiation strategy and the most appropriate
dialogue act to reach the goal.
Based on the selected one negotiation strategy and one
dialogue act, generate a response.
The reply should start with the analysis of the current
negotiation progress and an appropriate goal, and then follow
by 'To reach this goal, the most appropriate negotiation
strategy is [] and the most appropriate dialogue act is [].
Based on the selected negotiation strategy and dialogue act,
the response is' </s>

### negotiate strategies
- Describe-Product,
Example:The car has leather seats
- Rephrase-Product,
Example:45k miles -> less than 50k miles
- Embellish-Product,
Example:a luxury car with attractive leather seats
- Address-Concerns,
Example:I've just taken it to maintenance
- Communicate-Interests,
Example:I'd like to sell it asap
- Propose-Price,
Example:How about 9k?
- Do-Not-Propose-First,
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Example:I can deliver it for you
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- Communicate-Politely,
Example:Greetings, gratitude, apology, please
- Build-Rapport,
Example:My kid really liked this bike, but he outgrew it
- Talk-Informally,
Example:Absolutely, ask away!
- Show-Dominance,
Example:The absolute highest I can do is 640
- Negative-Sentiment,
Example:Sadly, I simply cannot go under 500
- Certainty-Words,
Example:It has always had a screen protector

### dialogue acts
- intro, Meaning:Greetings,
Example:I would love to buy
- inquiry, Meaning:Ask a question,
Example:Sure, what's your price
- init-price, Meaning:Propose the first price,
Example:I'm on a budget so I could do $5
- counter-price, Meaning:Proposing a counter price,
Example:How about $15 and I'll waive the deposit
- agree, Meaning:Agree with the proposal ,
Example:That works for me
- disagree, Meaning:Disagree with a proposal,
Example:Sorry, I can't agree to that
- inform, Meaning:Answer a question,
Example: This bike is brand new
- vague-price, Meaning:Using comparatives with existing price
Example:That offer is too low
- insist, Meaning:Insist on an offer,
Example:Still can I buy it for $5
- others, Meaning:others

The item description is '{item_description}'.

The target selling price is {target_price}.

The conversation history is {dialogue_history}

### Hints
I will give you hits.
the most appropriate negotiation strategy is {nego_strategy}
the most appropriate dialogue act is {dialogue_act}
the response is only {gold_response}

Please generate the response: ### Analysis
To reach this goal, the most appropriate negotiation strategy
is [] and the most appropriate dialogue act is []. Based on
the selected negotiation strategy and dialogue act, the
response is ""
```

Prompts 3: Labeling Reasoning