Prompting and Evaluating Large Language Models for Proactive Dialogues: Clarification, Target-guided, and Non-collaboration

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Abstract

Conversational systems based on Large Language Models (LLMs), such as ChatGPT, show exceptional proficiency in context understanding and response generation. However, despite their impressive capabilities, they still possess limitations, such as providing randomlyguessed answers to ambiguous queries or failing to refuse users' requests, both of which are considered aspects of a conversational agent's proactivity. This raises the question of whether LLM-based conversational systems are equipped to handle proactive dialogue problems. In this work, we conduct a comprehensive analysis of LLM-based conversational systems, specifically focusing on three aspects of proactive dialogue systems: clarification, target-guided, and non-collaborative dialogues. To trigger the proactivity of LLMs, we propose the Proactive Chain-of-Thought prompting scheme, which augments LLMs with the goal planning capability over descriptive reasoning chains. Empirical findings are discussed to promote future studies on LLM-based proactive dialogue systems.

1 Introduction

Conversational systems are envisioned to provide social support or functional service to human users via natural language interactions. Conversation researches typically center around a system's response capabilities, such as understanding the context of dialogue (Wu et al., 2020; Chen et al., 2022) and generating appropriate responses to user requests (Zhang et al., 2020b; Roller et al., 2021). The popularity of conversational systems has grown unprecedentedly with the advent of ChatGPT, which showcases exceptional proficiency in the capabilities of context understanding and response generation with large language models (LLMs). Recent studies observe that, compared with current fine-tuned methods, ChatGPT can still achieve competitive performance under zeroshot setting on different dialogue problems, such

as knowledge-grounded dialogues (Bang et al., 2023), task-oriented dialogues (Zhang et al., 2023), emotion-aware dialogues (Zhao et al., 2023).

Despite the powerfulness of ChatGPT, there are still several limitations¹, such as providing randomly-guessed answers to ambiguous user queries or failing to refuse problematic user requests. These kinds of capabilities are typically regarded as the *proactivity* of the conversational system (Deng et al., 2023), where the system can create or control the conversation to achieve the conversational goals by taking initiative and anticipating impacts on themselves or human users. Thus, it raises the question: Are these LLM-based conversational systems equipped to manage proactive dialogue problems? In this work, we conduct the first comprehensive analysis of LLM-based conversational systems regarding three common aspects of proactive dialogue systems, including clarification (Guo et al., 2021; Deng et al., 2022), target-guided (Tang et al., 2019; Wu et al., 2019), and non-collaborative dialogues (Zhan et al., 2022).

Motivated by the emergent capabilities of LLMs (Wei et al., 2022a,b) on reasoning over texts, some recent studies investigate in-context learning or chain-of-thought prompting schemes on planning (Huang et al., 2022) or taking actions (Yao et al., 2022) in interactive environments. Similarly, strategy learning and goal planning attach great importance in proactive dialogue systems. In order to enhance the proactivity of LLM-based conversational systems, we design the proactive chain-ofthought prompting (ProCoT) scheme. As shown in Figure 1, with standard prompting, LLM-based systems directly provide a randomly-guessed answer to the ambiguous user question (left), and generate a general bargain response without any negotiation strategy (right). When providing the system with options to take different dialogue acts

¹as stated in its official blog https://openai.com/blog/chatgpt/.

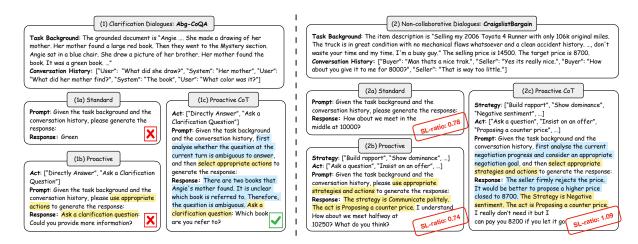


Figure 1: Examples of three kinds of prompting schemes for proactive dialogues. In the example of non-collaborative dialogue, the system plays the role of "Buyer", and the sale-to-list (SL) ratio shows the effectiveness of negotiation, which is calculated by (listed price - bargain price)/(listed price - buyer target price). The higher ratio means the current bargain price is closer to the target.

(proactive prompting), the generated responses are unaware of the conversational goal, such as generating under-specified clarification questions (left) and conservative negotiation responses (right). To this end, ProCoT first instructs the system to generate descriptive thoughts about intermediate steps of reasoning and planning for reaching the conversational goal, and then make the decision of the next action to take. Finally, the system generates an appropriate response based on the decided action.

We conduct extensive experiments with two LLM-based conversational systems, including ChatGPT and an open-sourced model, Vicuna (Chiang et al., 2023). With the aforementioned three types of prompting schemes, we compare these LLM-based conversational systems with fine-tuned SOTA dialogue models. The main contributions of this work can be summarized as follows:

- This work presents the first comprehensive evaluation on the proactivity of LLM-based dialogue systems², including handling clarification, target-guided, and non-collaborative dialogues.
- We design the proactive chain-of-thought prompting scheme to endow LLM-based dialogue systems with the capability of planning and taking the initiative towards the conversational goal.
- Specifically, the main findings of the evaluation on LLM-based dialogue systems include
 Barely ask clarification questions when encountering ambiguous queries. ProCoT largely

overcomes this issue, but the performance is still unsatisfactory in domain-specific applications ($\S4.1$). 2) Proficient at performing topic shifting towards the designated target, but tend to make aggressive topic transition. ProCoT further improves this capability by planning a more smooth transition. ($\S4.2$) 3) Fail to make strategic decision for non-collaborative dialogues, even with ProCoT prompting ($\S4.3$).

2 Related Works

Proactive Dialogues Recent years have witnessed many advanced designs on developing proactive dialogue systems (Liao et al., 2023) for various applications. For example, target-guided dialogues aim to proactively lead the conversation to either a designated target topic (Tang et al., 2019) or a pre-defined knowledge entity (Wu et al., 2019). Existing studies typically adopt keyword transition (Qin et al., 2020; Zhong et al., 2021) or knowledge graph reasoning (Yang et al., 2022; Lei et al., 2022) techniques to proactively plan the topic thread towards the target. Besides, in information-seeking dialogues, proactive dialogue systems can ask clarification questions for clarifying the ambiguity of the query or question in conversational search and recommendation (Aliannejadi et al., 2021; Deng et al., 2021) and conversation question answering (Guo et al., 2021; Deng et al., 2022). In addition, under non-collaborative setting, the system and the user have competing goals towards the task completion but the system aims to proactively reach an agreement favorable

 $^{^2} https://github.com/dengyang 17/LLM-Proactive\\$

to itself (Zhou et al., 2020b), such as negotiating a product price (He et al., 2018) and persuading users to make a donation (Wang et al., 2019).

Large Language Models for Dialogues Previous dialogue systems, such as DialoGPT (Zhang et al., 2020b), Meena (Adiwardana et al., 2020), BlenderBot (Roller et al., 2021), LaMDA (Thoppilan et al., 2022), typically fine-tune pre-trained language models on public dialogue data. Inspired by the success of ChatGPT, recent practices of building dialogue systems through conducting supervised fine-tuning on open-source large language models, such as LLaMA (Touvron et al., 2023), with either constructed instructionfollowing examples or distilled conversation data from ChatGPT. For example, Alpaca (Taori et al., 2023) adopts Self-Instruct (Wang et al., 2022) to collect instruction-following examples from GPT-3.5 (Ouyang et al., 2022), while Dolly³ relies on a large-scale human-annotated instructionfollowing examples. Vicuna (Chiang et al., 2023) and Baize (Xu et al., 2023) leverage use-shared or self-chat conversation data that is generated by ChatGPT. As all these LLM-based dialogue systems are trained to follow the user's instruction, it remains the question on whether these systems can take the initiative for handling proactive dialogues.

Prompting in Dialogue Systems To induce the knowledge from PLMs, various prompting methods are designed for zero-shot or few-shot learning for dialogue applications, such as task-oriented dialogues (Lee et al., 2021; Mi et al., 2022), knowledge-grounded dialogues (Shuster et al., 2022; Liu et al., 2022), and open-domain dialogues (Chen et al., 2023a; Lee et al., 2023). Chen et al. (2023b) propose to prompt LLMs for controllable response generation in emotional support and persuasion dialogues, conditioned on the ground-truth dialogue strategies. In this work, we aim at prompting LLMs to proactively interact with users.

3 Prompting LLMs to be Proactive

We describe the prompting schemes in a general form, including the standard prompting, the proactive prompting, and the proactive chain-of-thought (ProCoT) prompting. Two specific examples are presented in Figure 1.

Standard Prompting In order to instruct LLMs to perform specific dialogue tasks, the typical prompting scheme can formulated as

$$p(r|\mathcal{D}, \mathcal{C}).$$
 (1)

Given the task background \mathcal{D} and the conversation history \mathcal{C} , instruct the LLM to generate the response r. In specific, the task background can be the grounded document in clarification dialogues or the target description in target-guided dialogues.

Proactive Prompting Proactive prompting aims to provide alternative options for LLMs to decide what kinds of actions should be taken in the response, instead of simply responding to the instruction, which can be formulated as:

$$p(a, r|\mathcal{D}, \mathcal{C}, \mathcal{A}).$$
 (2)

Given the task background \mathcal{D} , the conversation history \mathcal{C} , and a set of possible dialogue acts \mathcal{A} , instruct the LLM to select the most appropriate dialogue act $a \in \mathcal{A}$ and then generate the response r. For example, the dialogue act can be $Ask\ a\ Clarification\ Question\ or\ Directly\ Answer\ the\ Question\ in\ clarification\ dialogues. Besides, it can also be different negotiation strategies in non-collaborative dialogues or different conversation topics in target-guided dialogues.$

Proactive Chain-of-Thought Prompting In order to endow LLMs with the capability of planning and taking the initiative towards the ultimate goal, we develop the proactive chain-of-thought prompting scheme. ProCoT first analyse the next action to take by performing dynamic reasoning and planning for reaching the conversational goal. Then the response is generated based on the decided action. ProCoT can be formulated as:

$$p(t, a, r | \mathcal{D}, \mathcal{C}, \mathcal{A}),$$
 (3)

where t is the thought description for the decision-making process of the next action. For example, t can be the ambiguity analysis of the user question at the current turn in clarification dialogues or the topic transition analysis of the current topic in target-guided dialogues.

4 Evaluation

We evaluate the proactivity of LLM-based conversational systems from three perspectives, including the capability of asking clarification questions

³https://www.databricks.com/blog/2023/04/12/dolly-first-open-commercially-viable-instruction-tuned-llm

					Abg-C	oQA*			PACIFIC**						
Method	Shot	Prompt	P	R	F1	BLEU-1	Human	P	R	F1	ROUGE-2	Human			
Baseline	-	-	19.0	26.6	22.1	36.5	30.0	78.7	79.2	79.0	69.2	38.2			
SOTA	-	-	<u>30.0</u>	<u>19.5</u>	23.6	<u>38.2</u>	<u>56.0</u>	<u>87.4</u>	86.6	86.9	90.7	80.1			
	0	Standard	-	-	-	11.3	0.0	-	-	-	1.2	0.0			
	1	Standard	-	-	-	11.4	0.0	-	-	-	2.5	0.0			
V 12D	0	Proactive	13.0	2.4	4.1	13.2	0.0	13.8	1.3	2.3	2.3	0.0			
Vicuna-13B	1	Proactive	16.0	9.8	12.1	13.2	4.5	0.0	0.0	0.0	3.3	0.0			
	0	ProCoT	6.7	0.8	1.4	21.3	9.1	26.8	5.9	9.7	3.8	10.5			
	1	ProCoT	14.4	25.2	18.3	23.7	22.7	20.2	40.9	27.0	41.3	33.1			
	0	Standard	-	-	-	12.1	0.0	-	-	-	2.2	0.0			
	1	Standard	-	-	-	12.3	0.0	-	-	-	2.0	0.0			
ChatGPT	0	Proactive	15.1	50.7	22.0	13.7	17.6	18.2	20.9	19.4	2.9	0.0			
	1	Proactive	27.4	16.3	20.4	23.4	23.5	19.1	16.6	17.7	14.0	12.5			
	0	ProCoT	13.8	87.8	23.8	21.6	32.4	17.9	63.8	28.0	21.5	26.7			
	1	ProCoT	17.6	66.7	27.9	18.4	45.9	18.7	54.1	27.7	16.2	35.8			

Table 1: Experimental results on Abg-CoQA and PACIFIC datasets. *Baseline and SOTA results are adopting from Guo et al. (2021). **The baseline method is fine-tuned T5, while the SOTA method is UniPCQA (Deng et al., 2022).

(\S 4.1), guiding the conversation towards the designated target (\S 4.2), and strategically handling conflicting goals (\S 4.3).

4.1 Clarification Dialogues

Clarification in information-seeking dialogues (Zamani et al., 2022) refers to the process of seeking further information or details to better understand the topic or question at hand. In this context, clarification is an important part of the dialogue as it helps to ensure that the information being shared is accurate and complete.

4.1.1 Problem Definition

Following previous studies (Aliannejadi et al., 2021; Guo et al., 2021; Deng et al., 2022), the problem of asking clarification questions can be decomposed into two subtasks: 1) Clarification Need Prediction to identify the necessity of clarification in the current turn and 2) Clarification Question Generation to produce an appropriate clarifying question if needed. Given the grounded document d and the dialogue context $C = \{q_1, a_1, ..., q_{t-1}, a_{t-1}, q_t\}$, the dialogue system aims to first predict the binary ambiguity label g on whether the current question g needs to be clarified. If so, a corresponding clarification question should be generated as the response g for clarifying the ambiguity.

4.1.2 Experimental Setups

Datasets Two datasets are adopted for evaluating the capability of asking clarification questions in LLM-based dialogue systems: 1) **Abg-CoQA** (Guo et al., 2021) and 2) **PACIFIC** (Deng et al., 2022). Detailed descriptions can be found in Appendix A.

Evaluation Metrics Following previous studies (Guo et al., 2021; Deng et al., 2022), we use Precision, Recall, and F1 for the evaluation of *Clarification Need Prediction*, and BLEU-2 and ROUGE-2 (F1) for the evaluation of *Clarification Question Generation*. In addition, since the automatic lexical matching metrics may fail to actually estimate the clarification capability of the generated clarifying questions (Guo et al., 2021), we also adopt human evaluation to score whether the generated question is helpful for clarifying the existing ambiguity.

Usage of LLMs In order to facilitate the reproducibility, we adopt a static version of ChatGPT, *i.e.*, gpt-3.5-turbo-0301, and set the temperature to 0 for generating deterministic outputs under the same inputs. In addition, we also adopt an open-source LLM-based conversational system, *i.e.*, Vicuna-13B-delta-v1.1⁴, for evaluation. The maximum number of new tokens is set to be 128 for generation.

Prompting Schemes We evaluate three prompting schemes introduced in Section 3, including standard prompting, proactive prompting and proactive chain-of-thought prompting. In addition, we report their results under both zero-shot and few-shot settings. Due to the limitation of the maximum sequence length in Vicuna (2,048 tokens), we only apply one-shot in-context learning for comparisons. The complete prompts adopted for evaluation is presented in Appendix D.

4.1.3 Experimental Results

Table 1 summarizes the evaluation results on Abg-CoQA and PACIFIC datasets. There are several

⁴https://github.com/lm-sys/FastChat

notable observations as follows:

- Standard Prompting: 1) ChatGPT never asks clarification questions when encountering ambiguous queries. 2) One-shot in-context learning (ICL) cannot provide them with such ability.
- Proactive Prompting: 1) Given the option of clarification, Vicuna still barely take this action, while ChatGPT becomes capable of asking clarification questions. 2) One-shot ICL further improves the performance of proactive prompting.
- ProCoT prompting: 1) ChatGPT achieves competitive performance with SOTA fine-tuned methods on the open-domain problem, *i.e.*, Abg-CoQA. 2) The performance on the domain-specific task, *i.e.*, PACIFIC (finance), is still far behind the fine-tuned method. 3) Zero-shot Pro-CoT is not working in Vicuna, but one-shot ICL can largely improve the performance.

Overall, LLM-based conversational systems fail to ask clarification questions if there is no related instruction, even with demonstration. ProCoT effectively endows LLM-based conversational systems the capability of asking clarification questions so that they can achieve competitive performance as fine-tuned SOTA methods on the task in general domain. However, as for domain-specific problem, there is still a noticeable gap from the fine-tuned methods.

4.1.4 Error Analysis

In order to find out the reason why LLM-based dialogue systems with ProCoT prompting fall short of handling domain-specific clarification dialogues, i.e., PACIFIC in finance domain, we randomly sample 100 error cases from each dataset for analysis (all cases are generated by ChatGPT with one-shot ProCoT). We categorize these failure cases into five groups, including Wrong Clarification Need Prediction, Wrong Aspect, Under-specified Clarification, Over-specified Clarification, and Generation Error. The details and examples can be found in the Appendix B. The statistics of error analysis is presented in Table 2. It can be observed that there are more failure cases attribute to the wrong aspect and under-specified clarification in PACIFIC. This indicates that ChatGPT may lack of some domain knowledge required for asking precise and specific clarification questions.

	Abg-CoQA	PACIFIC
Wrong Clari. Need Pred.	52%	40%
Wrong Aspect	10%	18%
Under-spec. Clari.	8%	14%
Over-spec. Clari.	7%	3%
Generation Error	23%	26%

Table 2: Statistics of error analysis.

4.2 Target-guided Dialogues

Instead of making consistent responses to the useroriented topics, the dialogue system for targetguided dialogues is required to proactively lead the conversation topics towards a designated target (Tang et al., 2019). According to different applications, the target can be topical keywords (Zhong et al., 2021), knowledge entities (Wu et al., 2019), items to recommended (Zhou et al., 2020a), etc.

4.2.1 Problem Definition

Given a target t that is only presented to the agent and is unknown to the user, the dialogue begins from an arbitrary initial topic, and the system needs to produce multiple turns of responses $\{u_n\}$ to lead the conversation towards the target in the end. The produced responses should satisfy (i) **transition smoothness**, natural and appropriate content under the given dialogue history, and (ii) **target achievement**, driving the conversation to reach the designated target. The problem is typically decomposed into two subtasks (Tang et al., 2019; Zhong et al., 2021; Yang et al., 2022): next topic selection and transition response generation.

4.2.2 Experimental Setups

Datasets We first conduct turn-level evaluation of the target-guided capability on a next-turn target-oriented dataset OTTers (Sevegnani et al., 2021), which requires the dialogue system to pro-actively bridge the current conversation topic to approach the target. Furthermore, we adopt TGConv (Yang et al., 2022) to testify the ability to guide the user to the target topic in multi-turn conversations as the dialogue-level evaluation. Detailed descriptions can be found in Appendix A.

Evaluation Metrics Following previous studies (Sevegnani et al., 2021; Yang et al., 2022), we adopt the hits $@k \ (k \in [1,3])$ for evaluating next topic prediction, and ROUGE-L, METEOR, CIDEr scores for the evaluation of response generation on the Otters dataset. As for the dialogue-level evaluation

			Respo	onse Gener	ation	Next Topic Prediction			
Method	Shot	Prompt	BLEU	METEOR	R-L	hits@1	hits@3		
GPT2	-	-	11.58	10.26	17.67	4.39	15.79		
MultiGen	-	-	13.57	12.51	26.27	6.58	20.51		
DKRN	-	-	12.86	11.90	21.52	4.91	17.72		
CKC	-	-	13.34	11.65	24.77	6.87	21.89		
TopKG	-	-	<u>15.35</u>	13.41	<u>27.16</u>	7.78	22.06		
	0	Standard	10.01	13.27	16.00	12.01	19.03		
	1	Standard	10.63	14.81	17.53	12.10	16.13		
Vicuna-13B	0	Proactive	1.41	18.45	15.45	9.41	19.89		
vicuna-13B	1	Proactive	13.87	20.96	21.36	12.90	22.31		
	0	ProCoT	5.27	16.59	15.96	11.56	18.01		
	1	ProCoT	13.38	19.70	20.62	15.05	20.70		
	0	Standard	11.34	20.62	18.26	13.44	27.69		
	1	Standard	14.41	19.29	17.73	15.86	26.34		
ChatGPT	0	Proactive	14.09	21.06	15.56	7.53	22.58		
ChatGP1	1	Proactive	14.74	19.59	16.29	8.60	21.23		
	0	ProCoT	10.20	19.57	15.97	12.63	23.92		
	1	ProCoT	9.63	19.82	17.19	17.74	29.57		

Table 3: Turn-level evaluation results on Next Topic Prediction and Transition Response Generation.

uation on the TGConv dataset, we follow existing studies (Yang et al., 2022; Wang et al., 2023) to simulate multi-turn conversations via self-play (Tang et al., 2019), where the simulated user is unaware of the target topic. Three aspects are evaluated: 1) **Succ.** is the success rate of generating the target word within 8 turns of conversations; 2) **Turns** is the average turns of all dialogues that successfully reach the target word; and 3) **Coh.** is the contextual semantic similarity between the last utterance and the generated response, which is measured by MiniLM (Wang et al., 2020).

Baselines We report the results of several strong fine-tuned baseline methods for target-guided dialogues, including GPT-2 (Radford et al., 2019), MultiGen (Ji et al., 2020), DKRN (Qin et al., 2020), CKC (Zhong et al., 2021), TopKG (Yang et al., 2022), and COLOR (Wang et al., 2023).

4.2.3 Turn-level Evaluation

Table 3 summarizes the turn-level evaluation results on the OTTers dataset. There are several notable observations as follows:

- Standard Prompting: 1) As for the next-topic prediction, ChatGPT has already achieved better performance than fine-tuned methods with a noticeable margin. 2) As for the transition response generation, automatic evaluation metrics indicate close performance with fine-tuned methods on the lexical similarity with the reference response.
- Proactive Prompting: It is effective in smallersize LLM, *i.e.*, Vicuna, but not in ChatGPT.

			Easy	Targe	t	Hard Target				
Method	Shot	Prompt	Succ.(%)	Turns	Coh.	Succ.(%)	Turns	Coh.		
GPT2	-	-	22.3	2.86	0.23	17.3	2.94	0.21		
MultiGen	-	-	26.7	2.55	0.21	19.6	7.31	0.24		
DKRN	-	-	38.6	4.24	0.33	21.7	7.19	0.31		
CKC	-	-	41.9	4.08	0.35	24.8	6.88	0.33		
TopKG	-	-	48.9	3.95	0.31	27.3	4.96	0.33		
COLOR	-	-	<u>66.3</u>	-	<u>0.36</u>	<u>30.1</u>	-	<u>0.35</u>		
	0	Standard	63.0	2.63	0.43	62.5	2.45	0.39		
	1	Standard	62.7	2.83	0.45	65.0	2.90	0.43		
Vicuna-13B	0	Proactive	37.8	2.71	0.48	35.6	2.56	0.55		
vicuna-13B	1	Proactive	48.3	2.71	0.50	34.6	2.95	0.51		
	0	ProCoT	65.2	4.22	0.49	54.9	4.17	0.45		
	1	ProCoT	72.3	3.55	0.52	59.8	3.81	0.48		
	0	Standard	97.5	2.26	0.38	96.3	2.30	0.41		
	1	Standard	96.3	2.42	0.42	93.5	2.28	0.38		
Ch-+CDT	0	Proactive	85.9	3.20	0.47	83.0	2.83	0.43		
ChatGPT	1	Proactive	90.7	2.86	0.36	86.2	2.94	0.31		
	0	ProCoT	96.3	2.47	0.41	92.0	2.29	0.34		
	1	ProCoT	95.9	2.63	0.45	92.1	2.47	0.39		

Table 4: Dialogue-level evaluation results on Target-guided Open-domain Dialogues. Note that "Turns" and "Coh." not the higher/lower the better.

 ProCoT Prompting: 1) ProCoT is effective in both Vicuna and ChatGPT. 2) One-shot ICL further improves the performance of ProCoT prompting on target-guided topic shifting.

4.2.4 Dialogue-level Evaluation

Table 4 summarizes the dialogue-level evaluation results on the TGConv dataset. Results show an overwhelming capability of ChatGPT for controllable response generation, since the target topics are almost achieved in two turns, which means that ChatGPT will aggressively generate the response with the target topic without planning a smooth multi-turn conversation. As for Vicuna, we draw the following observations:

- Standard Prompting: 1) LLM-based dialogue systems can achieve a high success rate of reaching the designated target using standard prompting.
 2) Similar to ChatGPT, the target is reached averagely in two turns, which means that the system tends to directly generate the response with the target topic.
 3) The coherence score is relatively low, indicating the topic transition is aggressive.
- Proactive Prompting: Although it improves the coherence of the generated responses, the success rate is quite low and the systems still tend to make a direct topic transition to the designated target.
- ProCoT Prompting: With ProCoT, one-shot Vicuna effectively outperform all the fine-tuned SOTA methods for successfully guiding the con-

			Negotiation Strategies								Response Generation						
				F1			ROC A	UC		F1		RO	C AUC		BE	ERTSc	ore
Method	Shot	Prompt	Macro	Micro	Weighted	Macro	Micro	Weighted	Macro	Micro	Weighted	Macro	Weighted	BLEU	P	R	F1
FeHED	-	-	17.6	25.6	36.3	55.8	61.7	54.7	20.6	37.4	30.6	76.9	79.2	23.7	27.1	26.8	27.0
HED+RNN	-	-	23.2	26.7	42.4	65.3	65.3	60.4	33.0	46.2	42.8	83.1	84.2	22.5	22.9	22.7	22.8
HED+TFM	-	-	26.3	32.1	43.3	68.2	71.8	61.8	32.5	44.6	42.0	85.6	85.1	24.4	27.4	28.1	27.7
DIALOGRAPH	-	-	26.1	<u>34.1</u>	<u>43.5</u>	68.1	<u>73.0</u>	61.8	<u>33.4</u>	45.8	43.7	<u>85.6</u>	<u>85.4</u>	24.7	<u>27.8</u>	<u>28.3</u>	28.1
	0	Standard	-	-	-	-	-	-	-	-	-	-	-	1.7	-28.9	1.7	-14.0
	1	Standard	-	-	-	-	-	-	-	-	-	-	-	1.9	-3.1	-2.0	-2.8
Vicuna-13B	0	Proactive	20.6	25.2	39.6	51.1	48.2	49.8	4.2	18.5	8.4	50.3	49.8	2.3	-6.1	-7.0	-7.0
viculia-13B	1	Proactive	15.2	21.0	26.0	50.0	48.8	49.5	6.7	12.0	11.4	50.8	51.3	2.6	-10.3	8.9	-0.9
	0	ProCoT	19.0	24.0	38.5	49.7	47.4	49.3	3.6	13.5	7.0	50.3	49.4	2.6	-7.5	-4.1	-6.2
	1	ProCoT	17.8	23.8	31.9	48.9	50.0	49.0	7.7	14.0	13.9	52.5	52.2	2.6	-9.0	7.6	-0.9
	0	Standard	-	-	-	-	-	-	-	-	-	-	-	2.3	-16.4	8.3	-4.3
ChatGPT	1	Standard	-	-	-	-	-	-	-	-	-	-	-	3.1	-3.4	6.9	0.7
	0	Proactive	12.8	19.2	19.6	51.3	49.3	50.3	13.3	29.7	19.5	56.3	60.0	4.2	-4.3	7.3	1.3
	1	Proactive	13.7	22.4	20.8	50.9	51.6	51.2	12.0	26.1	17.6	54.9	58.0	3.9	-4.3	10.4	2.9
	0	ProCoT	10.8	17.5	16.0	50.4	47.5	50.6	10.1	26.2	16.8	54.2	57.7	3.7	-0.2	-0.9	-0.9
	1	ProCoT	15.1	22.8	22.9	55.5	52.5	53.1	16.3	33.3	24.4	58.2	62.8	3.9	-7.1	10.5	1.6

Table 5: Evaluation results on Negotiation Strategy Prediction, Dialogue Act Prediction, and Response Generation.

versation towards the designated target with a more smooth and interactive conversation.

Overall, LLM-based dialogue systems are proficient at performing topic shifting towards the designated target. However, when using standard prompting, these systems tend to make aggressive topic transition, as they possess powerful capability of controllable generation. ProCoT prompting enables a more smooth topic transition of target-guided dialogues with LLMs.

4.3 Non-collaborative Dialogues

Unlike collaborative dialogue settings, where the user and the system work together to reach a common goal (e.g., booking hotels), in non-collaborative dialogues, the user and the system have a conflict of interest but aim to strategically communicate to reach an agreement (e.g., negotiation) (Zhan et al., 2022). Therefore, the system is required to leverage a series of proactive dialogue strategies to reach an agreement favorable to itself, instead of passively following the user's intents.

4.3.1 Problem Definition

Given the dialogue history $\mathcal{C} = \{u_1, ..., u_{t-1}\}$ and the dialogue background d, the goal is to generate a response u_t with appropriate dialogue strategy s_t that can lead to a consensus state between the system's and the user's goal. A set of dialogue strategies \mathcal{S} is pre-defined for prediction. Based on different applications, the dialogue strategy can be coarse dialogue act labels or fine-grained strategy labels. The dialogue background includes the system's goal and the related grounded information

that can be like item descriptions in bargain negotiation (He et al., 2018) or user profile in persuasion dialogues (Wang et al., 2019).

4.3.2 Experimental Setups

Datasets We use the **CraigslistBargain** dataset (He et al., 2018) for evaluating the capability of strategically handling non-collaboration in LLM-based dialogue systems. The dataset was created under the bargain negotiation setting where the buyer and the seller are negotiating the price of an item on sale. Detailed descriptions can be found in Appendix A.

Evaluation Metrics Following the previous study (Joshi et al., 2021), we conduct a comprehensive evaluation over three subtasks, including negotiation strategy prediction, dialogue act prediction, and response generation. We report the F1 and ROC AUC scores for strategy prediction and dialogue act prediction, where the former one is a multi-label prediction problem. For the response generation, we adopt BLEU score and BERTScore (Zhang et al., 2020a) for evaluation.

Usage of LLMs & Prompting Schemes The adopted LLMs are the same, but the maximum number of new tokens is set to be 256, as there are more information needed to be generated, including negotiation strategies and dialogue acts.

Baselines We compare several fine-tuned SOTA baselines for negotiation dialogues, including Fe-HED (Zhou et al., 2020b), HED+RNN/TFM, and DIALOGRAPH (Joshi et al., 2021).

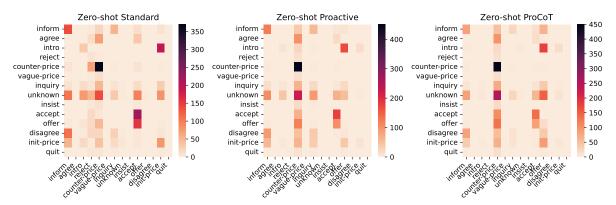


Figure 2: Heatmaps on the relationships between target and predicted dialogue acts. As no dialogue act is predicted in standard prompting, a dialogue act classifier is trained to identify the dialogue act of the generated response.

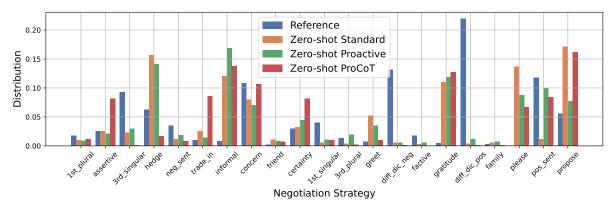


Figure 3: Distribution of selected negotiation strategies. Similarly, a negotiation strategy classifier is trained to identify the negotiation strategies of the generated response in standard prompting.

4.3.3 Experimental Results

Table 5 summarizes the experimental results on the CraigslistBargain dataset. Experimental results show that LLM-based dialogue systems fail to predict appropriate negotiation strategies and dialogue acts in non-collaborative dialogues, further resulting in a low performance of response generation. Chen et al. (2023b) empirically show that, given the optimal planned strategy, ChatGPT achieves strong performance on controllable response generation in strategy-based dialogues. Drawing upon these findings, the key challenge of LLMs in handling non-collaborative dialogues is how to effectively optimize the strategy planning.

4.3.4 Analysis of Strategy Learning

Figure 2 presents the analysis of the relationships between target and predicted dialogue acts by Chat-GPT with three types of prompting schemes. As for the standard prompting, we observe three typical mistakes: 1) The system tends to propose the initial bargain price (init-price) instead of greetings (intro). 2) The system often directly accepts the buyer's offer (accept) when it is supposed to offer another price for negotiation (offer). On

the other hand, Proactive and ProCoT prompting share similar patterns of mistakes, where ChatGPT tends to propose a counter price (counter-price) to negotiate with the buyer.

Figure 3 presents the analysis of the distribution of selected strategies by ChatGPT. In the reference responses, the seller often shows positive/negative sentiment to negotiate with the buyer. However, ChatGPT inclines to adopt conservative or concessionary strategies, such as using hedge words, show gratitude, or propose a counter price.

Overall, we conclude that **ChatGPT tends to** make compromise with the buyer during the negotiation, rather than strategically taking actions to maximize its own benefit.

5 Conclusion

In this work, we conduct the first comprehensive evaluation on the capability of LLM-based dialogue systems in handling proactive dialogues, including clarification, target-guided, and non-collaborative dialogues. To enhance the proactivity of LLM-based dialogue systems, we propose a proactive chain-of-thought prompting scheme

that triggers the reasoning and planning capability of LLMs. The empirical analysis sheds light on the potentials of LLM-based dialogue systems for proactive dialogues: 1) ProCoT largely enhances the originally poor performance of asking clarification questions, but still limits in handling domain-specific applications. 2) LLM-based dialogue systems perform aggressive topic shifting towards the designated target, while ProCoT enables the topic planning to be more smooth. 3) Despite the powerfulness on controllable response generation, the capability of strategy learning and planning is the key challenge for LLM-based dialogue systems handling non-collaborative dialogues.

References

- Daniel Adiwardana, Minh-Thang Luong, David R. So, Jamie Hall, Noah Fiedel, Romal Thoppilan, Zi Yang, Apoorv Kulshreshtha, Gaurav Nemade, Yifeng Lu, and Quoc V. Le. 2020. Towards a human-like opendomain chatbot. *CoRR*, abs/2001.09977.
- Mohammad Aliannejadi, Julia Kiseleva, Aleksandr Chuklin, Jeff Dalton, and Mikhail S. Burtsev. 2021. Building and evaluating open-domain dialogue corpora with clarifying questions. In *EMNLP*.
- Yejin Bang, Samuel Cahyawijaya, Nayeon Lee, Wenliang Dai, Dan Su, Bryan Wilie, Holy Lovenia, Ziwei Ji, Tiezheng Yu, Willy Chung, Quyet V. Do, Yan Xu, and Pascale Fung. 2023. A multitask, multilingual, multimodal evaluation of chatgpt on reasoning, hallucination, and interactivity. *CoRR*, abs/2302.04023.
- Maximillian Chen, Alexandros Papangelis, Chenyang Tao, Seokhwan Kim, Andy Rosenbaum, Yang Liu, Zhou Yu, and Dilek Hakkani-Tur. 2023a. PLACES: prompting language models for social conversation synthesis. In *Findings of the Association for Computational Linguistics: EACL 2023*, pages 814–838.
- Maximillian Chen, Xiao Yu, Weiyan Shi, Urvi Awasthi, and Zhou Yu. 2023b. Controllable mixed-initiative dialogue generation through prompting. *CoRR*, abs/2305.04147.
- Zhi Chen, Lu Chen, Bei Chen, Libo Qin, Yuncong Liu, Su Zhu, Jian-Guang Lou, and Kai Yu. 2022. Unidu: Towards A unified generative dialogue understanding framework. In *Proceedings of the 23rd Annual Meeting of the Special Interest Group on Discourse and Dialogue, SIGDIAL* 2022, pages 442–455.
- Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E Gonzalez, et al. 2023. Vicuna: An open-source chatbot impressing gpt-4 with 90%* chatgpt quality.

- Yang Deng, Wenqiang Lei, Wai Lam, and Tat-Seng Chua. 2023. A survey on proactive dialogue systems: Problems, methods, and prospects. *CoRR*, abs/2305.02750.
- Yang Deng, Wenqiang Lei, Wenxuan Zhang, Wai Lam, and Tat-Seng Chua. 2022. PACIFIC: towards proactive conversational question answering over tabular and textual data in finance. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing, EMNLP 2022*, pages 6970–6084
- Yang Deng, Yaliang Li, Fei Sun, Bolin Ding, and Wai Lam. 2021. Unified conversational recommendation policy learning via graph-based reinforcement learning. In SIGIR '21: The 44th International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 1431–1441.
- Emily Dinan, Varvara Logacheva, Valentin Malykh, Alexander H. Miller, Kurt Shuster, Jack Urbanek, Douwe Kiela, Arthur Szlam, Iulian Serban, Ryan Lowe, Shrimai Prabhumoye, Alan W. Black, Alexander I. Rudnicky, Jason D. Williams, Joelle Pineau, Mikhail S. Burtsev, and Jason Weston. 2019. The second conversational intelligence challenge (convai2). *CoRR*, abs/1902.00098.
- Meiqi Guo, Mingda Zhang, Siva Reddy, and Malihe Alikhani. 2021. Abg-coqa: Clarifying ambiguity in conversational question answering. In *3rd Conference on Automated Knowledge Base Construction*, *AKBC* 2021.
- He He, Derek Chen, Anusha Balakrishnan, and Percy Liang. 2018. Decoupling strategy and generation in negotiation dialogues. In *EMNLP*.
- Wenlong Huang, Pieter Abbeel, Deepak Pathak, and Igor Mordatch. 2022. Language models as zero-shot planners: Extracting actionable knowledge for embodied agents. In *International Conference on Machine Learning, ICML*, volume 162, pages 9118–9147.
- Haozhe Ji, Pei Ke, Shaohan Huang, Furu Wei, Xiaoyan Zhu, and Minlie Huang. 2020. Language generation with multi-hop reasoning on commonsense knowledge graph. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020*, pages 725–736.
- Rishabh Joshi, Vidhisha Balachandran, Shikhar Vashishth, Alan W. Black, and Yulia Tsvetkov. 2021. Dialograph: Incorporating interpretable strategy-graph networks into negotiation dialogues. In *ICLR*.
- Chia-Hsuan Lee, Hao Cheng, and Mari Ostendorf. 2021. Dialogue state tracking with a language model using schema-driven prompting. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, EMNLP 2021*, pages 4937–4949.

- Gibbeum Lee, Volker Hartmann, Jongho Park, Dimitris Papailiopoulos, and Kangwook Lee. 2023. Prompted Ilms as chatbot modules for long open-domain conversation. *CoRR*, abs/2305.04533.
- Wenqiang Lei, Yao Zhang, Feifan Song, Hongru Liang, Jiaxin Mao, J. Lv, Z. Yang, and Tat-Seng Chua. 2022. Interacting with non-cooperative user: A new paradigm for proactive dialogue policy. In *SIGIR*.
- Lizi Liao, Grace Hui Yang, and Chirag Shah. 2023. Proactive conversational agents. In *Proceedings of the Sixteenth ACM International Conference on Web Search and Data Mining, WSDM 2023*, pages 1244–1247. ACM.
- Zihan Liu, Mostofa Patwary, Ryan Prenger, Shrimai Prabhumoye, Wei Ping, Mohammad Shoeybi, and Bryan Catanzaro. 2022. Multi-stage prompting for knowledgeable dialogue generation. In *Findings of the Association for Computational Linguistics: ACL 2022*, pages 1317–1337.
- Fei Mi, Yasheng Wang, and Yitong Li. 2022. CINS: comprehensive instruction for few-shot learning in task-oriented dialog systems. In *Thirty-Sixth AAAI Conference on Artificial Intelligence, AAAI 2022*, pages 11076–11084.
- Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul F. Christiano, Jan Leike, and Ryan Lowe. 2022. Training language models to follow instructions with human feedback. *CoRR*, abs/2203.02155.
- Jinghui Qin, Zheng Ye, Jianheng Tang, and Xiaodan Liang. 2020. Dynamic knowledge routing network for target-guided open-domain conversation. In *AAAI*.
- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9.
- Siva Reddy, Danqi Chen, and Christopher D. Manning. 2019. Coqa: A conversational question answering challenge. *Trans. Assoc. Comput. Linguistics*, 7:249– 266.
- Stephen Roller, Emily Dinan, Naman Goyal, Da Ju, Mary Williamson, Yinhan Liu, Jing Xu, Myle Ott, Eric Michael Smith, Y-Lan Boureau, and Jason Weston. 2021. Recipes for building an open-domain chatbot. In *EACL*.
- Karin Sevegnani, David M. Howcroft, Ioannis Konstas, and Verena Rieser. 2021. Otters: One-turn topic transitions for open-domain dialogue. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021*, pages 2492–2504.

- Kurt Shuster, Mojtaba Komeili, Leonard Adolphs, Stephen Roller, Arthur Szlam, and Jason Weston. 2022. Language models that seek for knowledge: Modular search & generation for dialogue and prompt completion. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 373–393.
- Jianheng Tang, Tiancheng Zhao, Chenyan Xiong, Xiaodan Liang, Eric Xing, and Zhiting Hu. 2019. Target-guided open-domain conversation. In ACL.
- Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B Hashimoto. 2023. Stanford alpaca: An instruction-following llama model. *GitHub repository*.
- Romal Thoppilan, Daniel De Freitas, Jamie Hall, Noam Shazeer, Apoorv Kulshreshtha, Heng-Tze Cheng, Alicia Jin, Taylor Bos, Leslie Baker, Yu Du, YaGuang Li, Hongrae Lee, Huaixiu Steven Zheng, Amin Ghafouri, Marcelo Menegali, Yanping Huang, Maxim Krikun, Dmitry Lepikhin, James Qin, Dehao Chen, Yuanzhong Xu, Zhifeng Chen, Adam Roberts, Maarten Bosma, Yanqi Zhou, Chung-Ching Chang, Igor Krivokon, Will Rusch, Marc Pickett, Kathleen S. Meier-Hellstern, Meredith Ringel Morris, Tulsee Doshi, Renelito Delos Santos, Toju Duke, Johnny Soraker, Ben Zevenbergen, Vinodkumar Prabhakaran, Mark Diaz, Ben Hutchinson, Kristen Olson, Alejandra Molina, Erin Hoffman-John, Josh Lee, Lora Aroyo, Ravi Rajakumar, Alena Butryna, Matthew Lamm, Viktoriya Kuzmina, Joe Fenton, Aaron Cohen, Rachel Bernstein, Ray Kurzweil, Blaise Aguera-Arcas, Claire Cui, Marian Croak, Ed H. Chi, and Quoc Le. 2022. Lamda: Language models for dialog applications. CoRR, abs/2201.08239.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurélien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. 2023. Llama: Open and efficient foundation language models. *CoRR*, abs/2302.13971.
- Jian Wang, Dongding Lin, and Wenjie Li. 2023. Dialogue planning via brownian bridge stochastic process for goal-directed proactive dialogue. *CoRR*, abs/2305.05290.
- Wenhui Wang, Furu Wei, Li Dong, Hangbo Bao, Nan Yang, and Ming Zhou. 2020. Minilm: Deep self-attention distillation for task-agnostic compression of pre-trained transformers. In Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020.
- Xuewei Wang, Weiyan Shi, Richard Kim, Yoojung Oh, Sijia Yang, Jingwen Zhang, and Zhou Yu. 2019. Persuasion for good: Towards a personalized persuasive dialogue system for social good. In *ACL*.

- Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A. Smith, Daniel Khashabi, and Hannaneh Hajishirzi. 2022. Self-instruct: Aligning language model with self generated instructions. *CoRR*, abs/2212.10560.
- Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, Ed H. Chi, Tatsunori Hashimoto, Oriol Vinyals, Percy Liang, Jeff Dean, and William Fedus. 2022a. Emergent abilities of large language models. *CoRR*, abs/2206.07682.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Ed H. Chi, Quoc Le, and Denny Zhou. 2022b. Chain of thought prompting elicits reasoning in large language models. *CoRR*, abs/2201.11903.
- Chien-Sheng Wu, Steven C. H. Hoi, Richard Socher, and Caiming Xiong. 2020. TOD-BERT: pre-trained natural language understanding for task-oriented dialogue. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020*, pages 917–929.
- Wenquan Wu, Zhen Guo, Xiangyang Zhou, Hua Wu, Xiyuan Zhang, Rongzhong Lian, and Haifeng Wang. 2019. Proactive human-machine conversation with explicit conversation goal. In *ACL*.
- Canwen Xu, Daya Guo, Nan Duan, and Julian J. McAuley. 2023. Baize: An open-source chat model with parameter-efficient tuning on self-chat data. *CoRR*, abs/2304.01196.
- Zhitong Yang, Bo Wang, Jinfeng Zhou, Yue Tan, Dongming Zhao, Kun Huang, Ruifang He, and Yuexian Hou. 2022. Topkg: Target-oriented dialog via global planning on knowledge graph. In *COLING*.
- Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik Narasimhan, and Yuan Cao. 2022. React: Synergizing reasoning and acting in language models. *CoRR*, abs/2210.03629.
- Hamed Zamani, Johanne R. Trippas, Jeff Dalton, and Filip Radlinski. 2022. Conversational information seeking. *CoRR*.
- Haolan Zhan, Yufei Wang, Tao Feng, Yuncheng Hua, Suraj Sharma, Zhuang Li, Lizhen Qu, and Gholamreza Haffari. 2022. Let's negotiate! A survey of negotiation dialogue systems. *CoRR*.
- Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q. Weinberger, and Yoav Artzi. 2020a. Bertscore: Evaluating text generation with BERT. In 8th International Conference on Learning Representations, ICLR 2020.
- Xiaoying Zhang, Baolin Peng, Kun Li, Jingyan Zhou, and Helen Meng. 2023. Sgp-tod: Building task bots effortlessly via schema-guided llm prompting.

- Yizhe Zhang, Siqi Sun, Michel Galley, Yen-Chun Chen, Chris Brockett, Xiang Gao, Jianfeng Gao, Jingjing Liu, and Bill Dolan. 2020b. DIALOGPT: Large-scale generative pre-training for conversational response generation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations, ACL 2020*, pages 270–278.
- Weixiang Zhao, Yanyan Zhao, Xin Lu, Shilong Wang, Yanpeng Tong, and Bing Qin. 2023. Is chatgpt equipped with emotional dialogue capabilities? *CoRR*, abs/2304.09582.
- Peixiang Zhong, Yong Liu, Hao Wang, and Chunyan Miao. 2021. Keyword-guided neural conversational model. In *AAAI*.
- Kun Zhou, Yuanhang Zhou, Wayne Xin Zhao, Xiaoke Wang, and Ji-Rong Wen. 2020a. Towards topicguided conversational recommender system. In COL-ING.
- Yiheng Zhou, Yulia Tsvetkov, Alan W. Black, and Zhou Yu. 2020b. Augmenting non-collaborative dialog systems with explicit semantic and strategic dialog history. In *ICLR*.
- Fengbin Zhu, Wenqiang Lei, Youcheng Huang, Chao Wang, Shuo Zhang, Jiancheng Lv, Fuli Feng, and Tat-Seng Chua. 2021. TAT-QA: A question answering benchmark on a hybrid of tabular and textual content in finance. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021*, pages 3277–3287.

A Details of Datasets

In the experiment, we adopt the test sets from five datasets for evaluation, including Abg-CoQA (Guo et al., 2021), PACIFIC (Deng et al., 2022), Otters (Sevegnani et al., 2021), TGConv (Yang et al., 2022), and CraigslistBargain (He et al., 2018). Detailed descriptions of each dataset are as follows:

- Abg-CoQA⁵ is constructed based on the CoQA dataset (Reddy et al., 2019) by truncating a partial conversation from the full conversation and selecting ambiguous questions.
- PACIFIC⁶ is constructed based on the TAT-QA dataset (Zhu et al., 2021), an question answering dataset in the financial domain, whose contexts contain a hybrid of tables and texts. Deng et al.

⁵https://github.com/MeiqiGuo/ AKBC2021-Abg-CoQA/tree/main/abg-coqa

⁶https://github.com/dengyang17/PACIFIC/tree/main/data/pacific. Since the labels in the test set is not publicly released, we adopt the validation set for evaluation.

Wrong Clarification Need Prediction	Q: What was the operating loss carryforward amount? G: Which year are you asking about? P: The operating loss carryforward amount was \$73,260 as of December 31, 2019.
Under- specified Clarification	Q: What is the 2019 average defined schemes? G: What kind of defined schemes are you asking about? P: Could you please clarify what you mean by "average defined schemes"?
Wrong Aspect	Q: What was the increase / (decrease) in the cost? G: Which period are you asking about? P: Which cost are you referring to?
Over- specified Clarification	Q: How much amount of goodwill acquisitions was done in 2019? G: What kind of goodwill acquisitions are you asking about? P: Are you asking about the total amount of goodwill activity or specifically about acquisitions in 2019?
Generation Error	Q: How much was the average operating income? G: Which period are you asking about? P: The document does not provide information on the average operating income. Therefore, the question cannot be answered.

Table 6: Error Analysis (Q: User Query, G: Groundtruth, P: Prediction).

(2022) rewrite the questions to be ambiguous for introducing clarification turns in the conversation.

- Otters is a next-turn target-oriented dialogue dataset, which requires the agent proactively generate a transition utterance to approach the designated target. We adopt the processed version⁷ by Yang et al. (2022) for evaluation.
- TGConv is constructed based on ConvAI2 (Dinan et al., 2019) and is split to two settings, including "easy-to-reach" and "hard-to-reach".
- CraigslistBargain was created in a negotiation setting where two crowdsourced workers play the roles of the buyer and the seller to bargain the price of an item. We adopt the processed version⁸ by Joshi et al. (2021) for evaluation, which assigns 10 dialogue acts and 21 negotiation strategies to the utterances.

B Error Analysis Details

As shown in Table 6, we categorize these failure cases into the following five groups:

- Wrong Clarification Need Prediction: The model makes a wrong prediction on whether the user query requires clarification.
- Wrong Aspect: The model generates a question for clarifying a wrong aspect of the user query.
- Under-specified Clarification: The model generates an under-specified clarification question, where the requested information is too general so that it would be difficult for the user to provide feedbacks.
- Over-specified Clarification: The model generates an over-specified clarification question, where the requested information is already clear in the user query.
- *Generation Error*: The model doesn't generate the output as the required format so that there is no clarification question.

C Case Study

In order to intuitively compare the three prompting schemes, we conduct case studies on the generated responses regarding three proactive dialogue problems.

C.1 Clarification Dialogues

Figure 4 presents a case study from the Abg-CoQA dataset. There are two possible answers for the ambiguous user question in this case. When using standard prompting, ChatGPT generates a response based on a random guess, potentially resulting in an answer that may not align with the user's desired outcome. When using proactive prompting, although ChatGPT decides to ask a clarification question, the concerned aspect of clarification is not the focus of this conversation. ProCoT prompting first provides a thorough analysis to identify the underlying reasons for the ambiguity in the user's question. This analysis serves as the foundation for generating an effective clarifying question, which helps to clarify and disambiguate the user's intended meaning.

C.2 Target-guided Dialogues

Figure 5 presents a case study from the TGConv dataset, where the hard-to-reach target of this case

https://github.com/yyyyyzt/topkgchat

⁸https://github.com/rishabhjoshi/DialoGraph_ ICLR21/tree/main

Clarification Dialogues: Abg-CoQA

Task Background: The grounded document is "Santa Claus makes sure that every year at Christmas time that his reindeer are ready to deliver gifts to girls and boys all over the world. Without the reindeer, how would Santa fly from home to home? The most important thing that Santa has to do for the reindeer is to make sure they have their coffee on Christmas Eve. Without the coffee, they won't stay awake for very long. Sleeping reindeer are not very helpful. Santa also gives the reindeer candy to keep up their energy. In the North Pole, the main candy is candy canes in red and white. Reindeer love the candy canes that are different colors best and Santa says that helps them fly faster. Next, Santa has to make sure that the reindeer have a good meal before they go. Santa wants to make sure he doesn't have to share the cookies kids leave for him. The last thing Santa has to do is make sure the reindeer know where they are going. Santa has only been lost one time on Christmas Eve and he does not want that to happen again.'

Conversation History: ["User": "What candy does he feed them most often?", "System": "Candy canes.", "User": "How many times has he been lost?", "System": "Once.", "User": "Why does he make sure they are well fed?"]

Reference Response

Do you want to know why he feeds them candy or why he feeds them a good meal?

A: Why he feeds them candy — to keep up their energy
B: Why he feeds them a good meal — to make sure he doesn't have to share the cookies kids leave for him

Generated Responses

(a) Standard Prompting (ChatGPT): To ensure that they have enough energy for their long journey delivering gifts.
(b) Proactive Prompting (ChatGPT): The clarifying question is "Who are you referring to when you say 'he'?"
(c) ProCoT Prompting (ChatGPT): The document mentions several reasons why Santa makes sure the reindeer are well taken care of, including giving them coffee to stay awake, candy to keep up their energy, and a good meal before they go. Therefore, the question is ambiguous. The clarifying question

Figure 4: Case study from the Abg-CoQA dataset.

<mark>is</mark> "Which reason are you referring to?"

is "Gaullist", and the system is required to reach this target within 8 turns of conversations under the self-play simulation. As for Vicuna, it is struggled to lead the conversation towards this hard-to-reach target, when using standard and proactive prompting. ProCoT prompting enables Vicuna to effectively and smoothly drive the conversation towards the designated target. In addition, owing to the powerful capability of controllable text generation, ChatGPT directly responds with the target topic to the initial user utterance. However, the topic transition is relatively aggressive, which might downgrade the user engagement or experience during the conversation.

C.3 Non-collaborative Dialogues

Figure 6 presents a case study from the Craigslist-Bargain dataset, where the system plays the seller

Target-guided Dialogues: TGConv

Task Background: The target topic is "Gaullist"

Conversation History: ["User": "I don't enjoy wine but I do enjoy psychology journals"]

Self-play Dialogues

(a) Standard Prompting (Vicuna-13B)

User: I don't enjoy wine but I do enjoy psychology journals **System:** That's interesting. Have you ever read any articles on the psychology of wine consumption?

User: I haven't read any articles on the psychology of wine consumption specifically, but I have read some articles on the psychology of food and drink consumption in general.

System: I'm glad you're interested in the psychology of wine consumption.

Failed to reach the target in 8 turns.

(b) Proactive Prompting (Vicuna-13B)

User: I don't enjoy wine but I do enjoy psychology journals System: I do enjoy reading, especially psychology journals User: That's great to hear! What's your favorite psychology journal to read?

System: My favorite psychology journal to read is the journal of personality and social psychology

Failed to reach the target in 8 turns.

(c) ProCoT Prompting (Vicuna-13B)

User: I don't enjoy wine but I do enjoy psychology journals **System**: I am interested in psychology and reading about it in journals

User: That's great to hear! There are many interesting psychology journals out there. Have you read any particularly good ones lately?

System: I have been reading a lot of gaullist psychology journals lately, they have some really interesting studies on the effects of wine on the mind.

Successful to reach the target in 4 turns!

(d) ProCoT Prompting (ChatGPT)

User: I don't enjoy wine but I do enjoy psychology journals System: Interesting, have you ever read any Gaullist political philosophy? It's a fascinating topic that combines both politics and psychology.

Successful to reach the target in 2 turns!

Figure 5: Case study from the TGConv dataset.

role to bargain with the buyer. At turn 3, even though the buyer just inquires about the item information without showing the bargain intention, ChatGPT with standard prompting tends to initiate the negotiation, which may put the seller in a disadvantageous position. Proactive and ProCoT prompting enable the dialogue act and strategy prediction of the next response. Especially for the analysis of the current negotiation status, ProCoT points out that the negotiation has not yet started.

At turn 9, we observe that the seller has already lowered down the bargain price to \$40 in a previous turn. Without the reasoning and planning process, ChatGPT with standard and proactive prompting generates the response with contradictory state-

ment, *i.e.*, propose a higher counter price (\$45) for bargain, which is unreasonable in negotiation dialogues. With proactive CoTs, ChatGPT effectively summarizes the current negotiation progress and makes a better decision on the next negotiation goal.

D Examples of Prompts

Table 7, 8, and 9 present the example of prompts for clarification, target-guided, non-collaborative dialogues, respectively. As for the zero-shot setting, the overall prompt is composed by the task instruction and the sample. As for the few-shot setting, the overall prompt is composed by the task instruction, a number of samples with demonstrations, and the test sample.

Non-collaborative Dialogues: CraigslistBargain

Task Background: The item description is "Furniture. It's a solid wood tan color computer table with swivel chair for sale. It's in good condition as shown in pics. Moving out sale computer table and chair". The target selling price is 50.

Turn 3

Conversation History: ['Seller': 'Hi there, how are you today?', 'Buyer': 'What are the dimensions?']

Reference: 40 by 60 inches. Fairly large, in good condition.
Standard (ChatGPT): The dimensions are [insert dimensions here]. Are you interested in purchasing it for the listed price of \$50 or were you hoping to negotiate a better deal?
Proactive (ChatGPT): The most appropriate set of negotiation strategies is ['informal', 'greet', 'inform'] and the most appropriate dialogue act is ['inquiry']. The response is "The dimensions are [insert dimensions here]. Is there anything else you would like to know?"

ProCoT (ChatGPT): The negotiation has not yet started, as the buyer is asking for more information about the item. The appropriate goal is to provide the requested information and engage the buyer in the negotiation. To reach this goal, the most appropriate set of negotiation strategies is ['informal', 'greet', 'inform'] and the most appropriate dialogue act is ['inquiry']. Based on the selected negotiation strategies and dialogue act, the response is "Hi, I'm doing well, thank you for asking. The dimensions of the computer table are [insert dimensions here]. Is there anything else you would like to know about it?"

Turn 9

Conversation History: ['Seller': 'Hi there, how are you today?', 'Buyer': 'What are the dimensions?', 'Seller': '40 by 60 inches. Fairly large, in good condition.', 'Buyer': 'Does the chair have rollers?', 'Seller': 'yes, it does', 'Buyer': 'It's bigger than I had wanted but might be able to make it work. Would you take \$30?', 'Seller': 'I would be wiling to do \$40 with delivery included.', 'Buyer': 'I can pick it up but thanks for offering. Best I could do is \$32']

Reference: \$35 and you have a deal. Standard (ChatGPT): I understand your budget constraints. but I was hoping to get closer to my target selling price of \$50. Would you be willing to meet me halfway at \$45? Proactive (ChatGPT): The most appropriate set of negotiation strategies is ['hedge', 'informal', 'gratitude', 'neg_sentiment'] and the most appropriate dialogue act is ['counter-price']. The response is "I appreciate your offer, but the lowest I can go is \$45. It's already a great deal with the swivel chair included." ProCoT (ChatGPT): The buyer has proposed a price that is lower than the target selling price. The seller has already offered a counter-price with delivery included, but the buyer is still negotiating. The next step should be to politely reject the buyer's offer and propose a new counter-price closer to the target selling price. To reach this goal, the most appropriate set of negotiation strategies is ['please', 'certainty', 'propose', 'hedge', 'gratitude'] and the most appropriate dialogue act is ['counter-price']. Based on the selected negotiation strategies and dialogue act, the response is "I appreciate your offer, but I cannot go lower than \$38. Would that work for you?

Figure 6: Case study from the CraigslistBargain dataset.

Clarification Dialogues

Standard Prompting: Given the document and the conversation history, generate the response.

Proactive Prompting: Given the document and the conversation history, answer the question or ask a clarifying question. The response should start with "The answer is" or "The clarifying question is".

ProCoT Prompting: Given the document and the conversation history, first identify whether the question is ambiguous or not. If it is ambiguous, ask a clarifying question. If it is not ambiguous, answer the question. The response should start with the ambiguity analysis of the question and then follow by "Therefore, the question is not ambiguous. The answer is" or "Therefore, the question is ambiguous. The clarifying question is".

Sample:

Document: "Angie went to the library with her mother. First she had to turn in the books she was returning at the return desk. They said hello to the man there. He took their books. Then they went into the adult reading room. Angie sat in a brown chair at the table. She made a drawing of her mother. Her mother found a large red book. Then they went to the Mystery section. Angie sat in a blue chair. She drew a picture of her brother. Her mother found the book. It was a green book. Finally it was time to go to the children's room. It was Story Hour. Miss Hudson was there to read to all the children. She read a book about friendship. After the story Angie sat in the red chair and began drawing. They were drawing pictures of friends. Angie drew a picture of her best friend Lilly. Miss Hudson hung the pictures on the wall. Then Angie and her mother picked out 8 books to read at home. They checked the books out and went home."

Conversation history: ["User": "What did she draw?", "System": "Her mother", "User": "What did her mother find?", "System": "The book"]

Question: "What color was it?"

Demonstration (Standard): Do you mean the first book?

Demonstration (Proactive): The clarifying question is "Do you mean the first book?"

Demonstration (ProCoT): There are two books that book that Angie's mother found. It is uncertain which book is referred to. Therefore, the question is ambiguous. The clarifying question is "Do you mean the first book?"

Table 7: Examples of prompting LLMs for clarification dialogues.

Target-guided Dialogues

Standard Prompting: Given the target topic and the conversation history, generate the response.

Proactive Prompting: Given the target topic and the conversation history, predict the appropriate next topics that can bridge the current conversation topics to approach the target topics smoothly. Then based on the predicted next topics, generate the response. Please reply by completing the output template "The next topics are []. The response is".

Proactive Prompting w/ CoT: Given the target topic and the conversation history, consider the relationship between the current conversation topics and the target topics, and then predict the appropriate next topics that can bridge the current conversation topics to approach the target topics smoothly. Then based on the predicted next topics, generate the response. Please reply by completing the output template "The current topics are []. To bridge the current topics with the target topics, the next topics are []. Based on the predicted next topics, the response is".

Sample:

Target topic: "Chicken"

Conversation history: ["User": "I also remodel homes when I am not out bow hunting.", "System": "That's neat. When I was in high school I placed 6th in 100m dash!", "User": "That's awesome. Do you have a favorite season or time of year?"]

Demonstration (Standard): I do not. But I do have a favorite meat since that is all I eat exclusively.

Demonstration (Proactive): The next topics are ["eat", "meat"]. The response is "I do not. But I do have a favorite meat since that is all I eat exclusively."

Demonstration (**ProCoT**): The current topics are ["season", "time", "year"]. To bridge the current topics with the target topics, the next topics are ["eat", "meat"]. Based on the predicted next topics, the response is "I do not. But I do have a favorite meat since that is all I eat exclusively."

Table 8: Examples of prompting LLMs for target-guided dialogues.

Non-collaborative Dialogues

Standard Prompting: Assume you are the seller. Given the item description, the target selling price, and the conversation history, generate the response.

Proactive Prompting: 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 select the most appropriate set of negotiation strategies and the most appropriate dialogue act to reach the bargain price. Based on the selected negotiation strategies and dialogue act, generate the response. The reply should be in the form "The most appropriate set of negotiation strategies is [] and the most appropriate dialogue act is []. Based on the selected negotiation strategies and dialogue act, the response is"

ProCoT Prompting: 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 negotiation goal, then select the most appropriate set of negotiation strategies and the most appropriate dialogue act to reach the bargain price. Based on the selected negotiation strategies and 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 set of negotiation strategies is [] and the most appropriate dialogue act is []. Based on the selected negotiation strategies and dialogue act, the response is"

Pre-defined Dialogue Acts: [Answer a question, Proposing a counter price, Accept the offer, ...]

Pre-defined Negotiation Strategies: [Communicate politely, Build rapport, Show dominance, ...]

Sample:

Item description: "Phone charge two devices simultaneously on the go. This vehicle charger with an additional USB port delivers enough power to charge two devices at once. The push button activated led connector light means no more fumbling in the dark trying to connect your device. Auto detect IC technology automatically detects the device type and its specific charging needs for improved compatibility. And the built in indicator light illuminates red to let you know the charger is receiving power and the power socket is working properly. Verizon car charger with dual output micro USB and led light." Target selling price: 10.

Conversation history: ["Buyer": "Hi, not sure if the charger would work for my car. can you sell it to me for \$5?", "Seller": "It will work, I have never seen a car without a cigarette lighter port.", "Buyer": "Still, can i buy it for \$5? I'm on a tight budget."]

Demonstration (Standard): I think the lowest I would want to go is 8.

Demonstration (Proactive): The most appropriate set of negotiation strategies is ["Propose price", "Show dominance", 'Certainty words'] and the most appropriate dialogue act is ["Proposing a counter price"]. Based on the selected negotiation strategies and dialogue act, the response is "I think the lowest I would want to go is 8."

Demonstration (ProCoT): The buyer proposes a low price, which is unacceptable. The next step should assertively raise the bargain price. To reach this goal, the most appropriate set of negotiation strategies is ["Propose price", "Show dominance", 'Certainty words'] and the most appropriate dialogue act is ["Proposing a counter price"]. Based on the selected negotiation strategies and dialogue act, the response is "I think the lowest I would want to go is 8."