

Self-Explanation Prompting Improves Dialogue Understanding in Large Language Models

**Haoyu Gao^{123†}, Ting-En Lin², Hangyu Li², Min Yang^{3*},
Yuchuan Wu², Wentao Ma², Fei Huang², Yongbin Li^{2*}**

¹ University of Science and Technology of China ² Alibaba Group

³ Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences

{hy.gao, min.yang}@siat.ac.cn

shuide.lyb@alibaba-inc.com

1. Introduction

Context: James decides to run 3 sprints 3 times a week.
He runs 60 meters each sprint.

Question: How many total meters does he run a week? **Reasoning task**

Context: **Task-oriented Dialogue task**

USER:I'd like to know what's available as cheap Asian Oriental food.
SYSTEM:You must try dojo noodle bar in the centre of town!
USER:I need to get the address please.
...
SYSTEM:The TR1992 leaves at 21:35. would that work for you?
USER:Yes, please book 5 seats for me.

Question:

When does the user need train to arrive?
How many train tickets needed by the user for the train?
What the cuisine that the user explicitly requested of the restaurant?
What the name that the user explicitly requested of the restaurant?
Which day that the user explicitly requested of the restaurant booking?

Figure 1: The input examples for the reasoning task and the task-oriented dialogue are structured into two components: Context and Question.

Task	Dataset	Avg. #Tokens	Context	Answer Search Space	Prompting Method	Focus on
Reasoning	MultiArith GSM8K	16.6 33.6	Short	Internal	Chain-of-Thought Plan-and-Solve	Reasoning Step
Dialog Understanding	SGD MultiWOZ	940.9 1229.7	Long	External	Self-Explanation	Context

Table 1: Comparative analysis of reasoning and dialogue understanding tasks, highlighting the distinctive application of the proposed Self-Explanation method.

2. Method

Here is a dialogue between an user and a system:

USER:Hello, I am looking to book a train that will be departing Cambridge after 13:15.

SYSTEM:The first train leaves at 15:00 and they run every 51 minutes.

USER:I'd like to go to Birmingham New Street on Thursday and **leave after 13:45**. Do you have anything that would work for me?

Please output the **dialogue state** of above dialogue between an user and a system

Large Language Models

Based on the above dialogue, here is the dialogue state:

{"train-departure": "Cambridge", "train-leaveat": "after 13:15", "train-destination": "Birmingham New Street", "train-day": "Thursday", "train-arriveby": "after 13:45"}



Here is a dialogue between an user and a system

USER:Hello, I am looking to book a train that will be departing Cambridge after 13:15.

SYSTEM:The first train leaves at 15:00 and they run every 51 minutes.

USER:I'd like to go to Birmingham New Street on Thursday and **leave after 13:45**. Do you have anything that would work for me?

Please output the **dialogue state** of above dialogue between an user and a system

Let's first analysis the conversation utterance by utterance, **give every utterance an explanation**. Then output the dialogue state of above dialogue based on your explanation to every utterance.

Large Language Models

Explanation of the utterances:

1.The user initiates the conversation and expresses their intention to book a train departing from Cambridge after 13:15

2.In the system's response, it provides information about the train schedule but doesn't make any explicit requests or provide any new information about the user's preferences.

3.In the user's next utterance, they specify that they want to go to Birmingham New Street on Thursday and that they want to leave after 13:45. This is an update to their previous request, where they had only specified that they wanted to depart from Cambridge after 13:15.

Based on the above explanation, here is the dialogue state:

{"train-departure": "Cambridge", "train-day": "Thursday", "train-leaveat": "after 13:45", "train-destination": "Birmingham New Street"}



2. Method

\mathcal{C} : Here is a dialogue between an user and a system
USER: Hello, I am looking to book a train that will be departing
Cambridge after 13:15.
...

\mathcal{Q} : Please output the **dialogue state** of above dialogue between an
user and a system.

\mathcal{I} : Let's first analysis the conversation utterance by utterance, give
every utterance an explanation. Then output the dialogue state of
above dialogue based on your explanation to every utterance.
Explanation of the utterances:
1.The user initiates the conversation and expresses their intention
to book a train departing from Cambridge after 13:15
...

\mathcal{A} : Based on the above explanation, here is the dialogue state:
{ "train-departure": "Cambridge", "train-leaveat" : "after 13:45",
"train-destination": "Birmingham New Street", "train-day":
"Thursday" }

Generate answer based on context and question:

$$\mathcal{A} \sim P(a|\mathcal{Q}, \mathcal{C}) \quad (1)$$

Generate intermediate steps based on context and
question before answering:

$$\mathcal{I} \sim P(i|\mathcal{Q}, \mathcal{C}) \quad (2)$$

Answer according to context and question and
intermediate steps :

$$\mathcal{A} \sim P(a|\mathcal{I}, \mathcal{Q}, \mathcal{C}) \quad (3)$$

3. Experiments

Model	Method	TOD				ERC	RS
		MultiWOZ2.1	STARv2	SGD	SpokenWOZ	MELD	MuTual
Llama2-7B -Chat	Vanilla	1.15	29.51	1.01	1.15	45.9	24.04
	Zero-shot CoT	1.87	26.4	1.09	0.71	46.4	25.66
	Plan-and-Solve	1.66	33.5	4.03	2.57	46.1	26.64
	Self-Explanation	2.7	48.26	5.62	4.82	46.74	31.55
Llama2-70B -Chat	Vanilla	11.28	51.24	8.76	3.68	58.83	56.09
	Zero-shot CoT	8.93	45.09	7.69	6.75	59.92	55.19
	Plan-and-Solve	10.19	50.6	8.06	7.13	59.33	54.74
	Self-Explanation	12.1	56.35	11.18	6.67	60.98	45.26
ChatGPT	Vanilla	35.93	51.88	18.96	13.75	59.14	68.97
	Zero-shot CoT	27.45	51.85	19.69	13.26	61.48	70.61
	Plan-and-Solve	38.33	56.74	21.11	14.5	58.38	69.77
	Self-Explanation	44.44	63.66	21.81	14.89	61.71	71.58
GPT4	Self-Explanation	50.97	70.27	25.75	25.94	63.51	91.87

Table 2: Comparing the performance of Vanilla, zero-shot CoT, Plan-and-Solve, and Self-Explanation prompting methods on six dialogue datasets using different models. For STARv2 and the rest of TOD datasets, we use the weighted F1 score and Joint Goal Accuracy(JGA), respectively. As for MELD and MuTual, the accuracy metric is applied.

3. Experiments

Method	Model	MultiWOZ2.1	TOD		SpokenWOZ	ERC	RS
			STARv2	SGD		MELD	MuTual
Few-shot (Vanilla+4shots)	Llama2-7B-Chat	16.99	31.59	5.95	4.81	45.7	32
	Llama2-70B-Chat	29.1	50.4	5.81	7.7	58.23	56.21
	ChatGPT	40.38	52.39	17.34	14.13	55.09	72.51
Zero-shot (Self-Explanation)	ChatGPT	44.44	63.66	21.81	14.89	61.71	71.58

Table 3: Comparing the performance of Vanilla+4shots and Self-Explanation prompting methods on six dialogue datasets using different models.

3. Experiments

Method	Prompt	MultiWOZ 2.1 (JGA)
Vanilla	Answer the questions based on the above dialogue	35.93
Understand	Before you answer, first understand the dialogue , then answer the questions based on your understanding and original dialogue	36.52
Summary	Before you answer, first summarize the dialogue , then answer the questions based on your summary and original dialogue	40.98
Self-Explanation	Before you answer, first analyze the dialogue utterance by utterance, give every utterance an explanation . Then answer the questions based on your explanation	44.44

Method	Prompt	MultiWOZ2.1 (JGA)
Commentary	Deconstruct the dialogue, giving an interpretative commentary on each sentence.	36.23
Interpret	Review the dialogue carefully and interpret each sentence within the conversation.	38.46
Insights	Go over the conversational sentences one by one, offering insights into their meanings.	39.17
Elucidation	Break down the conversation and furnish an elucidation for every individual sentence.	40.41
Self-Explanation	Analyze the dialogue utterance by utterance, give every utterance an explanation	44.44

Thanks