

Large Language Models as Zero-shot Dialogue State Tracker through Function Calling

Anonymous ACL submission

Abstract

Large language models (LLMs) are increasingly prevalent in conversational systems due to their advanced understanding and generative capabilities in general contexts. However, their effectiveness in task-oriented dialogues (TOD), which requires not only response generation but also effective dialogue state tracking (DST) within specific tasks and domains, remains less satisfying. In this work, we propose a novel approach FNCTOD for solving DST with LLMs through function calling. This method improves zero-shot DST, allowing adaptation to diverse domains without extensive data collection or model tuning. Our experimental results demonstrate that our approach achieves exceptional performance with both modestly sized open-source and also proprietary LLMs: with in-context prompting it enables various 7B or 13B parameter models to surpass the previous state-of-the-art (SOTA) achieved by ChatGPT, and improves ChatGPT’s performance beating the SOTA by 5.6% Avg. JGA. Individual model results for GPT-3.5 and GPT-4 are boosted by 4.8% and 14%, respectively. We also show that by fine-tuning on a small collection of diverse task-oriented dialogues, we can equip modestly sized models, specifically a 13B parameter LLaMA2-Chat model, with function-calling capabilities and DST performance comparable to ChatGPT while maintaining their chat capabilities. Code and model will be released.

1 Introduction

Recent years have seen the rapid development of large language models (LLMs) that have demonstrated exceptional natural language understanding and generation capabilities. The integration of LLMs into industry applications, particularly as conversational assistants, is a notable trend. Fine-tuned with conversations between users and assistants, these models are further aligned with human preferences to enhance their ability to de-

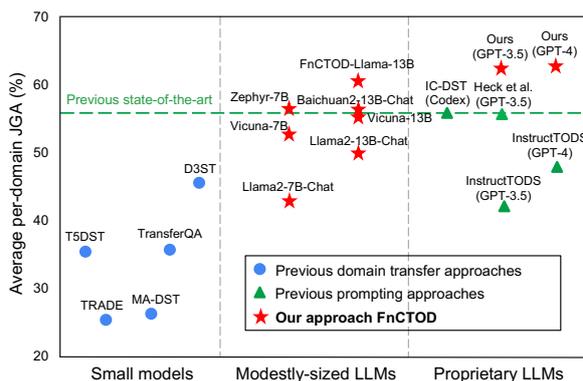


Figure 1: **Zero-shot DST performance comparison** among (1) previous domain transfer approaches using small models; (2) previous prompting approaches exclusively relying on advanced proprietary LLMs; and (3) our approach, compatible with various LLMs, empowers various 7B and 13B models for superior performance and sets new state-of-the-art with GPT-4.

liver fluent, helpful, and polite responses to user inquiries. Notable examples include proprietary systems such as ChatGPT¹ and Claude², as well as open-source models such as LLaMA2-Chat (Touvron et al., 2023), Vicuna (Chiang et al., 2023), Baichuan (Baichuan, 2023).

The primary focus of these chat-tuned LLMs has typically been on responding in general contexts. However, for another important type of conversation, task-oriented dialogues (TOD), the model is required to extract the intentions of users at each turn of the conversation, represented as slot-value pairs of per-domain predefined schemas; a process known as Dialogue State Tracking (DST). The challenge lies in the model’s ability to accurately summarize user needs over multiple turns of conversation and also strictly adhere to a domain-specific ontology. The most direct solutions (Hosseini-Asl et al., 2020; Peng et al., 2020; Su et al., 2021) necessitate training on curated domain-specific annotated

¹<http://chatgpt.openai.com/>

²<https://www.anthropic.com/index/introducing-claude>

Table 1: **Comparison of different zero-shot DST paradigms.** Plug-&Play means the (chat-tuned) LLMs can be equipped with this capability, preserving their conversational capabilities.

Zero-shot DST Paradigms	Base Model	Fine-tuning	Prompting	Plug-&Play
Domain transfer approaches (Lin et al., 2021b,c; Zhao et al., 2022a)	Small LMs	✓	✗	✗
Previous prompting approaches (Heck et al., 2023; Chung et al., 2023)	Advanced proprietary LLMs	✗	✓	✗
FNCTOD (Ours)	Modestly-sized open-source LLMs & Advanced proprietary LLMs	✓	✓	✓

data, a process that is notoriously costly and labor-intensive. Despite efforts in automated dataset creation using GPT-3 (Li et al., 2022), these methods struggle to generalize to unseen domains. To achieve zero-shot DST for unseen domains, prior approaches usually involved domain transfer methods (Campagna et al., 2020; Lin et al., 2021a; Zhao et al., 2022b). However, these still require training on data from similar domains, and their performance has been far from satisfactory.

LLMs exhibit remarkable capabilities for tackling various tasks without the need for task-specific fine-tuning, making them suited for zero-shot DST. However, while there have been initiatives to leverage ChatGPT for zero-shot DST (Hu et al., 2022; Hudeček and Dušek, 2023; Heck et al., 2023; Chung et al., 2023), these methods tend to treat DST as a standalone task rather than chat completion, which the models, especially chat-tuned models, are more proficient in. They usually take the whole conversation as input along with detailed instructions to generate in domain-specific formats. This setup poses challenges due to the long task context and specific output requirements. Consequently, this works exclusively with advanced ChatGPT or Codex models but fails with less powerful LLMs (Hudeček and Dušek, 2023).

In this work, we introduce a novel approach FNCTOD, to address zero-shot DST with LLMs. Our method seamlessly integrates DST as a part of the assistant’s output during chat completion. Specifically, we treat the schema of each task-oriented dialogue domain as a specific function, and DST for this domain as the process of “calling” the corresponding function. We thus instruct LLMs to generate function calls along with the response in the assistant’s output. To achieve this, we convert the domain schema into function specifications, which include the function’s description and required arguments, and incorporate them into the *system prompt* of the LLM. Additionally, we integrate these function calls into the assistant’s output within the *dialogue context*.

As shown in Figure 1, experimental results on

the MultiWOZ benchmark (Budzianowski et al., 2018) represent a significant milestone. Our approach is the first that, without further fine-tuning, enables modestly sized open-source LLMs (7B or 13B parameters) to achieve comparable or superior performance compared to previous state-of-the-art (SOTA) prompting methods that relied exclusively on advanced proprietary LLMs such as ChatGPT and Codex (Hudeček and Dušek, 2023; Heck et al., 2023; Chung et al., 2023). Furthermore, our approach beats the previous zero-shot SOTA by 5.6% Av. JGA, firmly establishing a new standard. It improves ChatGPT performance; beating previous individual best results for GPT-3.5 and GPT-4 by 4.8% and 14%, respectively.

Additionally, we show that by fine-tuning a 13B LLAMA2-CHAT model using a collection of 7,200 task-oriented dialogues — consisting of 200 randomly selected dialogues covering 36 diverse domains, from heterogeneous TOD datasets — we can equip it with function-calling DST abilities comparable to ChatGPT while still maintaining its response generation capabilities.

The comparison with prior studies is summarized in Table 1 and Figure 1. **Our contribution is threefold:** (1) Demonstration that the FnCTOD approach achieves outstanding performance with both open-source and proprietary LLMs through *in-context prompting*: enables open-source 7–13B models to surpass the previous SOTA achieved by ChatGPT, and enhances GPT-4’s performance by 14%, establishing a new SOTA. (2) Bridging the *zero-shot* DST performance gap between open-source models and ChatGPT by fine-tuning on a small collection of diverse dialogues. (3) Showing that function calling DST capabilities can be integrated into existing chat-tuned LLMs while preserving response capabilities.

2 Related Work

2.1 Dialogue State Tracking

DST is an essential, yet challenging task in the construction of TOD systems. Its primary purpose is to

extract and track user goals at each turn throughout the conversation. The tracked dialogue state is usually represented in the slot values of the predefined schema for specific domains. This requires the slot values to adhere closely to the domain-specific schema. Consequently, previous methods have relied on the collection and annotation of domain-specific dialogues for model training (Lee et al., 2019; Wu et al., 2019; Heck et al., 2020; Hosseini-Asl et al., 2020; Peng et al., 2020; Lin et al., 2020). However, obtaining training data is notoriously expensive, even with methods that utilize GPT-3 to automatically simulate such data (Li et al., 2022). Furthermore, these approaches are limited to handling only the domains covered in the training data.

To address zero-shot DST in unseen domains, previous cross-domain transfer strategies based on small models typically leverage extra dialogue corpora in similar domains (Wu et al., 2020; Lin et al., 2021b; Su et al., 2021) or redefining DST in terms of other types of tasks, such as question answering (Lin et al., 2021c) or summarization (Shin et al., 2022) to find appropriate additional training data. Despite these efforts, their overall zero-shot performance remains relatively low.

2.2 Leveraging LLMs for Dialogue Tasks

LLMs (Brown et al., 2020; Chowdhery et al., 2023; OpenAI, 2023) have demonstrated remarkable capabilities in handling various tasks without requiring further fine-tuning. Recent chat/instruction-tuned models further exhibit impressive performance in conversational contexts (Touvron et al., 2023; Chiang et al., 2023; Yang et al., 2023). However, current chat models primarily focus on general conversation, often omitting task-oriented dialogues (TOD). TOD differs from general conversation in that it requires models to not only generate responses but also track dialogue states according to domain-specific schemas. While ChatGPT has shown effectiveness in response generation within TOD (Li et al., 2023c), the performance of zero-shot DST in these models, as explored in recent research on prompting approaches (Hu et al., 2022; Bang et al., 2023; Hudeček and Dušek, 2023; Heck et al., 2023; Zhang et al., 2023; Chung et al., 2023), are still not satisfying, which remains a significant challenge in TOD.

2.3 Tool Usage within LLMs

Early work on tool usage (Parisi et al., 2022; Schick et al., 2023) and the recent launch of GPT-

4 plug-in and function calling features (OpenAI, 2023), have highlighted the importance of function calling for LLMs, encouraging follow-up work (Patil et al., 2023; Shen et al., 2023; Li et al., 2023a). Commonly integrated tools include web browsers, calculators (Cobbe et al., 2021), translation systems, and so on. We are the first to utilize this tool usage/function calling capability to solve the challenging DST task in TOD with LLMs, bridging the gap between general conversation and task-oriented dialogues.

3 Background

3.1 Chat-tuned LLMs

Chat-tuned LLMs are models specifically fine-tuned to interact with users in a conversational manner. This category encompasses proprietary models such as ChatGPT and Claude, as well as open-source models such as Vicuna (Chiang et al., 2023), LLaMA2-Chat (Touvron et al., 2023), and Baichuan (Yang et al., 2023). These chat models typically start as base models that are further fine-tuned with a dialogue format, enabling them to function effectively as conversational agents. As depicted in Figure 2, the dialogue format typically features three distinct roles within two components: (1) the *system* role in the *system prompt* section, which defines the assistant’s roles, responsibilities, and expected behaviors; and (2) the *user* and *assistant* roles in the *dialogue context* section, encompassing their conversation. The model is typically tasked to produce the *assistant*’s responses to the *user*’s input. These chat models are primarily designed to generate helpful, detailed, and friendly responses to general user inquiries, rather than handling task-specific conversations as in TOD.

3.2 DST Task Formulation

In TOD, at each turn of conversation, the task of DST is to summarize the dialogue state S_t given the dialogue context $C_t = \{A_1, U_1, \dots, A_t, U_t\}$, where U_t and A_t represent the user utterance and assistant response at the t -th turn. For simplicity, we will omit the turn index t in subsequent discussions. The dialogue state S is a set of slot-value pairs:

$$S = \{(s_{1,D_1}, v_{1,D_1}), \dots, (s_{i,D_j}, v_{i,D_j})\}, \quad (1)$$

where s_{i,D_j} is the i -th slot in the D_j domain, and v_{i,D_j} is its tracked value. Each domain D_j corresponds to a set of slots for a specific service, API

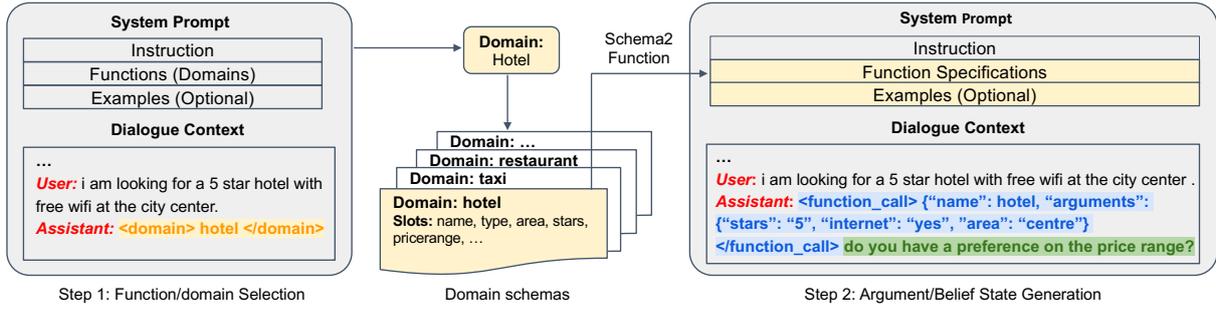


Figure 2: **Overview of our approach that addresses DST via function calling.** The whole prompt includes two sections: *system prompt* and *dialogue context*. The function calling process is executed in two stages. Initially, the model is prompted to determine **the function to be called (function name)**. Following this, the specifications of the predicted function/domain, along with optional demonstration examples, are incorporated into the *system prompt*. This guides the model to generate **function arguments** and subsequently the **response**.

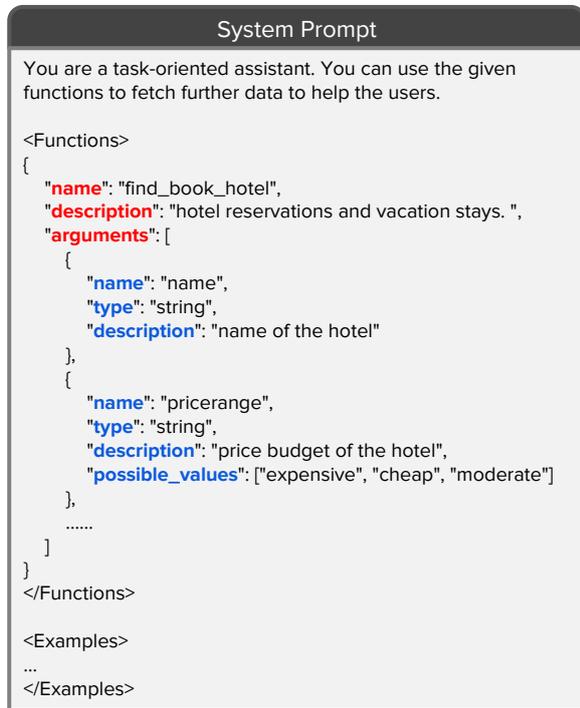


Figure 3: Illustration of the *system prompt* consisting of three components: (1) the overall instruction, (2) function specifications, and (3) optional example conversations. Due to space constraints, only a part of slots/arguments are displayed. The specific example conversations are omitted for brevity.

call, or database query, such as restaurant reservations. In the case of the *restaurant* domain, the slots might include “restaurant-food”, “restaurant-area”, “restaurant-pricerange”, etc. We use S_{D_j} to denote the tracked slots for domain D_j .

4 Approach

Our method redefines DST as function calling, treating each domain as a distinct function, and the slot values within the domain as its arguments.

As shown in Figure 2, this paradigm is represented in chat-tuned models by embedding function specifications within system prompts, as shown in Figure 3. The model is tasked with generating function calls followed by a response, as shown in Figure 4. We provide more details of our approach below.

DST as Function Calling In our formalization, DST is conceptualized as function calling. Each domain D_j is modeled as a unique function F_j , with the associated slot values serving as arguments. Consequently, at each turn of the conversation, the DST task transforms into identifying the correct function F_j and its arguments S_{D_j} :

$$\langle \text{fn_call} \rangle F_j(s_{1,D_1} = v_{1,D_1}, s_{2,D_1} = v_{2,D_1}, \dots, s_{i,D_j} = v_{i,D_j}) \langle / \text{fn_call} \rangle, \quad (2)$$

where “ $\langle \text{fn_call} \rangle$ ” and “ $\langle / \text{fn_call} \rangle$ ” are special tokens. In practice, we use “ $\langle \text{function_call} \rangle$ ” and “ $\langle / \text{function_call} \rangle$ ” to represent them and generate the function call in JSON format. Some examples of function calls generated within a conversation are shown in Figure 4.

Dialogue Prompt Format As shown in Figure 4, we incorporate this function calling as an integral part of the conversation. At each turn of the conversation, given the current conversation context, the chat model is tasked with first generating the function call, followed by the response. To achieve that, we convert the domain schema into function specifications, using JSON, and include them in the *system prompt* within the dialogue prompt, as shown in Figure 3. By doing so, the model can be aware of the supported functions and the correct generation format to call the function.

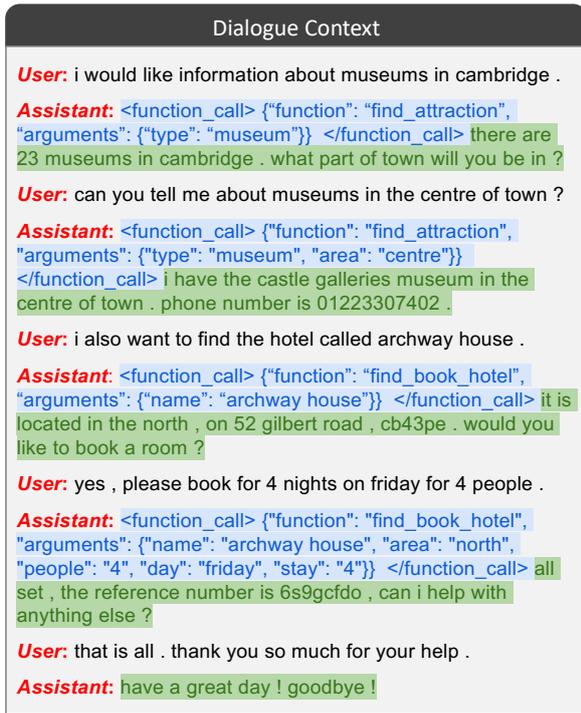


Figure 4: An example of the *dialogue context* including attraction and hotel domains. The assistant output consists of the `function calls` and `response` .

Function Call Decomposition As outlined, the model is required to predict not just which function to call (*i.e.*, function name) but also generate arguments for the predicted functions. To streamline this process and enhance control, we split it into two consecutive steps: **Function Selection** and **Argument Generation**. As shown in Figure 2, for each turn of the conversation, the model first selects a function F_j from the supported functions. In this step, we only include the function descriptions in the *system prompt* and prompt the model to generate only the selected domain/function, surrounded by the special tokens “<domain>” and “</domain>”. Subsequently, we include the full specification of the chosen function F_j in the *system prompt*, prompting the model to generate the corresponding arguments for the function F_j .

In-context Prompting Since the current open-source models are not specifically fine-tuned to generate function calls, there is no guarantee that the model could always generate the correct formats. To address that, we also include in-context example conversations as shown in Figure 4, along with the specification of the predicted function in the *system prompt*. We manually selected a few demonstration examples for each supported domain.

Model Fine-tuning To equip open source models with function calling capabilities without needing demonstration examples, we fine-tune a LLAMA2-13B-CHAT model using a collection of heterogeneous task-oriented dialogue datasets, including WOZ (Mrkšić et al., 2016), CamRest676 (Wen et al., 2016b,a), MSR-E2E (Li et al., 2018), TaskMaster (Byrne et al., 2019) and Schema-Guided Dialogues (SGD) (Rastogi et al., 2020). Note that we deliberately exclude the whole target test dataset. From these datasets, we choose 36 distinct domains/functions with high-quality annotations. Instead of using all the data in those datasets, we randomly sampled 200 dialogues from each domain across the datasets, totaling 7,200 dialogues for training. This sample size has already proved sufficient for effective results.

During training, we incorporate the specifications of all functions invoked in each conversation’s *system prompt*. Our loss calculation focused solely on the function calling aspect of the assistant’s generation. We refrained from fine-tuning the response generation component, in consideration of the LLMs’ existing competence in producing coherent responses and the scarcity of function-calling examples in our dataset. The fine-tuned model is dubbed FNCTOD-LLAMA2-13B.

5 Experiments

5.1 Experimental Setup

Dataset and Metrics We evaluate on the widely-used task-oriented multi-domain dataset **MultiWOZ 2.1** (Budzianowski et al., 2018; Eric et al., 2020). We used the 1,000 dialogues in the test split and measured joint goal accuracy (JGA), which measures the percentage of turns for which all slot values are correctly predicted. This test set spans 5 domains, with each conversation potentially covering multiple domains.

Baselines We compare our approach with two distinct approaches: (1) *Cross-domain transfer approaches*, which involve training on MultiWOZ with one domain excluded and then evaluating on the held-out domain. This category includes methods including TRADE (Wu et al., 2019), MA-DST (Kumar et al., 2020), TransferQA (Lin et al., 2021b), T5DST (Lin et al., 2021c), and D3ST (Zhao et al., 2022a). (2) *Previous prompting approaches* that have only shown efficacy with advanced ChatGPT and Codex. These include IC-DST (Hu et al., 2022) using Codex, (Heck et al.,

Model	Attraction		Hotel		Restaurant		Taxi		Train		JGA	
	JGA	Slot-F1	Average	Overall								
<i>Cross-domain Transfer approaches</i>												
TRADE (Wu et al., 2019)	20.06	–	14.20	–	12.59	–	59.21	–	22.39	–	25.69	–
MA-DST (Kumar et al., 2020)	22.46	–	16.28	–	13.56	–	59.27	–	22.76	–	26.87	–
TransferQA (Lin et al., 2021b)	31.25	–	22.72	–	26.28	–	61.87	–	36.72	–	35.77	–
T5DST (Lin et al., 2021c)	33.09	–	21.21	–	21.65	–	64.62	–	35.43	–	35.20	–
D3ST (Zhao et al., 2022a)	56.40	–	21.80	–	38.20	–	78.40	–	38.70	–	46.70	–
<i>Previous Prompting approaches</i>												
*IC-DST (Codex)	60.00	–	46.70	–	57.30	–	71.40	–	49.40	–	56.96	–
Heck et al. (2023) (GPT-3.5)	52.70	–	42.00	–	55.80	–	70.90	–	60.80	–	56.44	31.50
InstructTODS (GPT-3.5)	30.23	65.38	26.77	76.28	48.28	82.90	56.22	75.33	53.75	83.64	42.02	–
InstructTODS (GPT-4)	39.53	78.99	31.23	84.07	55.86	88.23	63.24	82.71	59.83	89.72	48.16	–
<i>Our approach FNCTOD</i>												
ChatGPT (GPT-3.5)	67.15	87.20	37.56	82.86	60.12	90.21	74.43	86.90	67.29	92.48	61.31	38.56
ChatGPT (GPT-4)	58.77	81.84	45.15	85.07	63.18	91.06	76.39	87.73	69.48	90.16	62.59	38.71
FNCTOD-LLAMA2-13B	62.24	84.99	46.83	85.39	60.27	88.69	67.48	80.39	60.90	89.88	59.54	37.67
ZEPHYR-7B-BETA	56.50	81.97	38.43	79.52	63.18	91.19	74.10	86.56	56.20	90.00	57.68	32.11
VICUNA-7B-V1.5	50.66	74.93	35.00	73.66	52.76	85.25	67.02	80.36	59.66	89.05	53.02	29.45
VICUNA-13B-V1.5	54.25	80.99	38.43	79.96	56.44	87.26	69.11	83.37	58.82	89.26	55.41	31.84
BAICHUAN2-13B-CHAT	53.67	79.57	40.15	81.36	59.02	87.82	69.31	81.95	60.67	89.45	56.56	33.21
LLAMA2-7B-CHAT	42.64	70.18	30.47	69.37	37.60	78.63	63.20	73.80	44.17	82.18	43.44	16.78
LLAMA2-13B-CHAT	49.76	76.80	29.50	67.60	48.87	81.33	64.66	68.97	53.59	85.09	49.28	25.68
LLAMA2-70B-CHAT	50.66	78.26	34.03	76.61	54.48	86.18	66.10	72.60	56.53	87.39	52.36	28.38

Table 2: **Performance comparison on zero-shot DST benchmark.** We compare our approach with cross-domain approaches and prompting approaches relying on ChatGPT (GPT-3.5/4) and Codex. Using our approach, we evaluate [ChatGPT](#), and [our fine-tuned model](#) via zero-shot prompting, and open-source models via few-shot (5-shot) prompting. In addition to per-domain JGA and slot F1 scores, we report the JGA averaged on these five domains (**Average JGA**), and also multi-domain JGA (**Overall JGA**). The baseline results are directly taken from their respective works. The best performances in each column are in **bold**.

2023) and InstructTODS (Chung et al., 2023) using ChatGPT (GPT-3.5/4).

Evaluated Models We evaluate our method on proprietary ChatGPT and various open-source models. For ChatGPT, we evaluated the versions of GPT-3.5-Turbo (gpt-3.5-turbo-1106) and GPT-4 (gpt-4-1106-preview), both of which are already equipped with function calling capabilities. Regarding open-source models, we assessed several widely recognized chat-tuned models of varying sizes, including the 7B parameter model ZEPHYR-7B-BETA (Tunstall et al., 2023), the 7B and 13B versions of VICUNA-V1.5 (Chiang et al., 2023), the 7B, 13B, and 70B versions of LLAMA2-CHAT (Touvron et al., 2023), as well as the 13B parameter model BAICHUAN2-13B-CHAT (Baichuan, 2023). Detailed descriptions and Huggingface model paths of these models can be found in the Appendix.

Additionally, we evaluate our fine-tuned model FNCTOD-LLAMA2-13B. It’s worth noting that unlike these domain transfer baselines, our model is trained exclusively on 7,200 dialogues from datasets other than MultiWOZ, making the setup

*IC-DST requires in-domain data to train the retriever for example selection, making it not strictly zero-shot DST.

more realistic and challenging.

Inference Details For both ChatGPT and our fine-tuned FNCTOD-LLAMA2-13B, which have been equipped with function-calling capabilities, we could perform zero-shot prompting, excluding in-context examples in the system prompt. For the other open-source models, we perform few-shot prompting using five examples (5-shot) by default. It’s worth noting that the shot in zero/few-shot prompting refers to the number of in-context examples used when prompting the models, whereas the shot in zero-shot DST refers to the number of in-domain examples seen in the training data.

5.2 Zero-shot DST Evaluation

Table 2 presents the zero-shot DST performance comparison, with observations summarized below.

Our approach empowers moderately-sized open-source models to surpass previous SOTA results achieved with advanced ChatGPT. Previous prompting approaches showed promising results exclusively with advanced proprietary models but underperformed with less advanced models (Hudeček and Dušek, 2023). Our approach is the first to enable moderately sized open-source models to achieve comparable or superior perfor-

mance compared to previous SOTA results obtained with advanced ChatGPT and Codex. Specifically, the 7B parameter ZEPHYR-7B-BETA and 13B parameter BAICHUAN2-13B-CHAT models outperform the previous SOTA. This significant advancement marks a milestone in the practical application of LLMs for DST and TOD.

Our approach significantly improves ChatGPT’s performance over previous prompting approaches. The efficacy of our approach is demonstrated by improvements of 4.8% (Average JGA) for GPT-3.5, and 14% for GPT-4, compared to previous reported results with each of these models. Our result with GPT-4 beats the previous SOTA prompting approach using Codex by 5.6% Average JGA.

Our fine-tuned 13B parameter model matches the performance of ChatGPT. It is evident that our fine-tuned FNCTOD-LLAMA2-13B significantly improves over its base model LLAMA2-13B-CHAT and achieves a performance comparable to ChatGPT. This demonstrates that we can easily equip moderately sized open-source LLMs with function-calling capabilities and zero-shot DST performance comparable to ChatGPT, marking an exciting advance in bridging the gap between open-source and proprietary models.

5.3 Zero-shot End-to-End TOD Evaluation

In practical settings, a TOD system queries a knowledge base or API using the tracked dialogue states to ground responses. We perform an end-to-end evaluation of both DST and response generation, which is a more realistic and challenging setting. Our FNCTOD approach enables the generation of both dialogue states, *i.e.*, function calls, *and* responses in the assistant’s output. This contrasts with the prompting methods that typically treat DST as a standalone task. Consistent with the previous work on end-to-end zero-shot TOD evaluation (Hudeček and Dušek, 2023), we evaluated using the MultiWOZ 2.2 dataset (Zang et al., 2020) with delexicalized responses. Our evaluation metrics include JGA for DST and *Success* rate for the generated response. Success measures the percentage of dialogues in which the user’s goals were fully met. The results are presented in Table 3.

Compared to previous prompting approaches, by enabling both zero-shot DST and response generation (Hudeček and Dušek, 2023), the superiority of the FnCTOD approach becomes more evident.

Model	JGA	Success
ChatGPT (Hudeček and Dušek, 2023)	21.0	20.0
FNCTOD-LLAMA2-13B	37.9	44.4
ZEPHYR-7B-BETA	32.3	57.5
VICUNA-7B-v1.5	29.4	37.7
VICUNA-13B-v1.5	33.8	23.1
BAICHUAN2-13B-CHAT	33.0	45.7
LLAMA2-7B-CHAT	16.7	24.9
LLAMA2-13B-CHAT	25.8	27.7

Table 3: End-to-end evaluation results on MultiWOZ 2.2, including the evaluation on DST with JGA and also response generation with **Success rate**.

Specifically, all open-source models evaluated using our approach outperform ChatGPT’s results achieved by (Hudeček and Dušek, 2023), except for LLAMA2-7B-CHAT. In addition, the results show that the fine-tuned model FNCTOD-LLAMA2-13B retains its ability to generalize and generate informative responses in a zero-shot TOD setting.

5.4 Ablation Studies

Impact of different numbers of in-context examples Our initial investigation focuses on the influence of varying the number of in-context examples when conducting few-shot prompting with open-source models, which were not originally trained for function call generation. We assessed the performance of various models with different numbers of in-context examples, ranging from 0 to 5. We note that using more than five examples might surpass the context-window capacity (such as 4096 tokens) for some models. The findings are illustrated in Figure 5. The results indicate that the models perform significantly better when in-context examples are utilized compared to zero-shot prompting. Furthermore, there is a consistent performance improvement as the number of examples increases, across most domains and models. This underscores the crucial role of in-context examples when leveraging open-source models for DST through function calling, which is reasonable given that these models were not fine-tuned to equip with the capability to generate function calls in the required format solely according to the function specification within the system prompt.

Impact of function call decomposition In each dialogue turn, the model is required to first identify the appropriate function to call (function selection) and then generate the corresponding arguments for it (argument generation). We compare our two-step

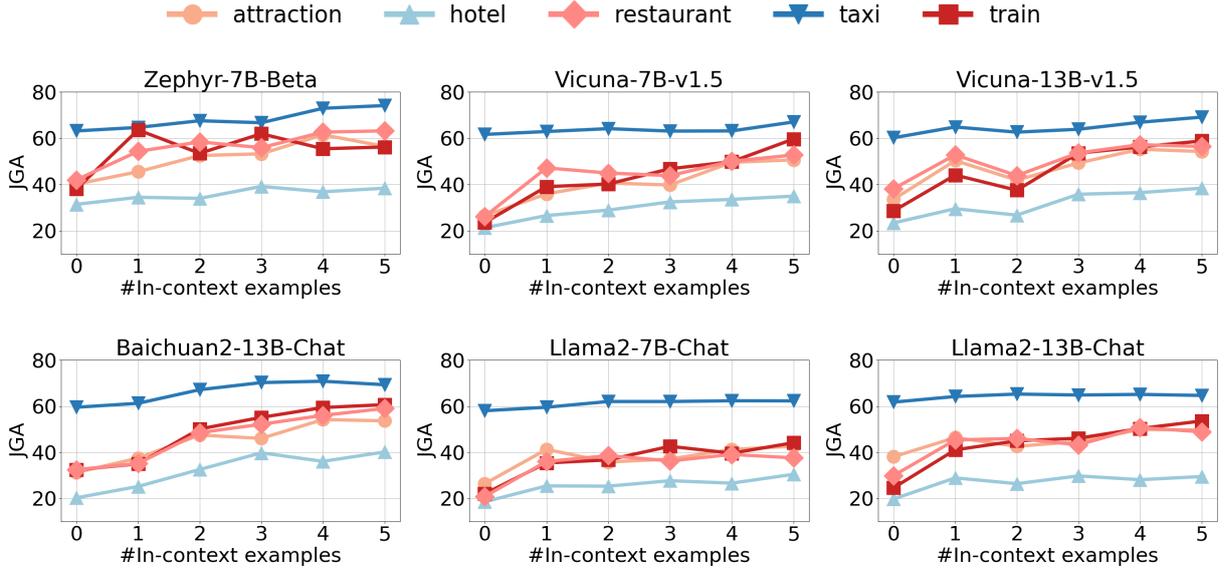


Figure 5: Performance of open-source models with different numbers of in-context examples.

	Attr.	Hotel	Rest.	Taxi	Train
ChatGPT (GPT-3.5)					
w/o decomp.	59.64	32.24	61.39	74.87	49.91
w/ decomp.	67.15	37.56	60.12	74.43	67.29
FNCTOD-LLAMA2-13B					
w/o decomp.	34.77	32.02	56.63	65.40	36.21
w/ decomp.	62.24	46.83	60.27	67.48	60.90

Table 4: Ablation studies on the function call generation decomposition, where decomp. denotes decomposition.

approach with a non-decomposed method, where all supported functions were directly included in the prompt, and the model was tasked with generating the entire function call with both function name and arguments, in one step. This comparison is conducted on ChatGPT and our fine-tuned FNCTOD-LLAMA2-13B, which supports zero-shot prompting. It’s worth noting that the non-decomposed method is the default when using ChatGPT. The results in Table 4 demonstrate that this decomposition consistently leads to performance improvements, highlighting the efficacy of our strategy.

#Data	Attr.	Hotel	Rest.	Taxi	Train	Avg.
100	59.61	44.40	54.33	67.02	54.33	55.94
200	62.24	46.83	60.27	67.48	60.90	59.54
300	69.19	43.68	57.06	64.98	57.60	58.50
400	60.80	43.21	57.39	65.70	53.78	56.18

Table 5: Zero-shot DST performance of FNCTOD-LLAMA2-13B with varying numbers of training data per domain (36 domains in total).

Impact of training data sizes Our results indicate that with as few as 200 samples per domain, totaling 7,200 dialogues across 36 domains, we were able to fine-tune a LLAMA2-13B-CHAT model to match the zero-shot DST performance of ChatGPT. We explored the model’s performance with varying numbers of samples, ranging from 100 to 400 per domain. The results, depicted in Table 5, show that optimal performance is achieved with 200 samples per domain. We speculate that beyond this point, the number of training samples leads to the model over-fitting to domains in the training data and, therefore, less effective at zero-shot generalization.

6 Conclusion

We introduce a new approach to tackle the challenging task of zero-shot DST with LLMs, enabling them to handle both general conversations and task-oriented dialogues in diverse domains without the need for additional data collection. Our experimental results on MultiWOZ demonstrate that our approach not only delivers exceptional performance in advanced ChatGPT models (setting a new benchmark) but also across a range of moderately sized open-source LLMs. Furthermore, we demonstrate that we can fine-tune the open-source model LLAMA-2-13B-CHAT using only 7,200 training samples from 36 diverse domains, resulting in FNCTOD-LLAMA2-13B, which achieves function calling, zero-shot DST performance comparable to ChatGPT.

7 Limitations

In this work, we propose a novel approach to solve zero-shot DST with LLMs. Our approach achieves outstanding performance with various LLMs, both modestly-sized open-source and advanced proprietary LLMs, setting the new state-of-the-art. However, it is important to recognize that the current accuracy may still not yet be high enough for the practical deployment of such zero-shot systems. We anticipate that with further advancements in the NLU and NLG capabilities of base LLMs, our approach could achieve even greater performance levels. In addition, while our approach can handle both the DST and response generation task in TOD, it is worth noting that due to the current lack of a more realistic evaluation setting for response generation in TOD, we used delexicalized responses for evaluation as this is widely used in prior work. This setting and associated metrics have some known shortfalls in terms of being able to game-the-metrics with nonnatural responses as well as presenting a data mismatch with how LLMs are trained. In the era of LLMs, we advocate for the development of more realistic evaluation approaches for full-natural-language-response generation in TOD.

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A Appendix

A.1 Evaluation Details

We evaluated two versions of ChatGPT and six leading chat/instruction-tuned LLMs representing varying sizes and instruction-following and conversational capabilities. The six evaluated open-source models include: ZEPHYR-7B-BETA (Tunstall et al., 2023) is an instruction-tuned version of Mistral-7B (Jiang et al., 2023), which is the leading model among its size on the AlpacaEval leaderboard (Li et al., 2023b). VICUNA-7B-V1.5 and VICUNA-13B-V1.5 (Chiang et al., 2023) are LLAMA-2 models fine-tuned on user conversations with ChatGPT. LLAMA2-7B-CHAT and LLAMA2-13B-CHAT are chat-tuned versions of LLAMA2 models with varying sizes (Touvron et al., 2023). BAICHUAN2-13B-CHAT is also a LLAMA2-13B model further fine-tuned on extensive corpus (Baichuan, 2023). we utilized their checkpoints available on Huggingface³. The specific paths for these models are detailed in Table 8. For inference, the temperature was fixed as 0.3, top_p as 0.2, and max_tokens as 128. For each test case, we conducted a single inference run. All inferences were executed on a cluster equipped with eight 48G NVIDIA RTX A6000 GPUs.

A.2 Training Details

Training Data For constructing our fine-tuning dataset, we selected five high-quality, multi-turn TOD corpora, excluding MultiWOZ, as detailed in Table 9. Each dataset encompasses one or multiple domains. We excluded several domains with low-quality annotations, retaining a total of 36 domains. For our fine-tuning, we exclusively sampled data from the training sets of these datasets to constitute our training data.

Hyperparameters We fine-tuned the LLaMA-2-13b-Chat checkpoint from Huggingface.⁴ We utilize Low Rank Approximation (LoRA) (Hu et al., 2021) and limited our fine-tuning to the parameters in the q_proj and v_proj modules. Further details about the fine-tuning hyperparameters can be found in Table 6. The fine-tuning was conducted on 4 A6000 48GB GPUs.

Hyperparameter	Values
batch size	8
epochs	1
learning rate	0.0003
learning rate scheduler	cosine
weight decay	0.01
cutoff_len	4096
lora_r	16
lora_alpha	16
lora_dropout	0.05
lora_target_modules	q_proj, v_proj

Table 6: Hyperparameters for the model fine-tuning.

Model	Accuracy
ChatGPT (GPT-3.5)	95.54
ChatGPT (GPT-4)	88.62
FNCTOD-LLAMA2-13B	91.68
ZEPHYR-7B-BETA	92.77
VICUNA-7B-v1.5	94.75
VICUNA-13B-v1.5	91.82
BAICHUAN2-13B-CHAT	92.50
LLAMA2-7B-CHAT	91.90
LLAMA2-13B-CHAT	89.34
LLAMA2-70B-CHAT	90.25

Table 7: The function/domain selection accuracy of evaluated models within our approach.

A.3 More Results

A.3.1 Function Selection Accuracy

In our approach, we divide the function call generation process into two steps: (1) Function/domain selection: The model selects a function/domain to call from the list of all supported functions by generating the function name. (2) Argument generation: The model generates the arguments for the selected function. We present the results using the predicted domains instead of oracle domains in Table 2. Additionally, we provide the accuracy of the function/domain prediction in Table 7. It is evident that function/domain selection is a straightforward task for all the evaluated models.

A.3.2 Ablation Studies

We conduct more investigation focused on effective prompt strategies, including the effective dialogue prompt format and methods for describing supported functions.

Impact of the unified dialogue prompt We initiated our analysis into effective prompt strategies

³<https://huggingface.co/models>

⁴<https://huggingface.co/meta-LLaMA/LLaMA-2-13b-chat-hf>

Table 8: Evaluated LLMs in our experiments with their versions or Huggingface model paths.

Model	Model versioning/path
GPT-3.5-Turbo	gpt-3.5-turbo-1106
GPT-4	gpt-4-1106-preview
Zephyr-7B-Beta	https://huggingface.co/HuggingFaceH4/zephyr-7b-beta
Vicuna-7B-v1.5	https://huggingface.co/lmsys/vicuna-7b-v1.5
Vicuna-13B-v1.5	https://huggingface.co/lmsys/vicuna-13b-v1.5
Baichuan2-13B-Chat	https://huggingface.co/baichuan-inc/Baichuan2-13B-Chat
LLaMA2-7B-Chat	https://huggingface.co/meta-llama/Llama-2-7b-chat-hf
LLaMA2-13B-Chat	https://huggingface.co/meta-llama/Llama-2-13b-chat-hf

Dataset	Domains	#Domains
Schema-Guided (Rastogi et al., 2020)	RentalCars_1, RentalCars_2, Buses_1, Buses_2, Events_1, Events_2, Services_1, Services_2, Services_3, Media_1, RideSharing_1, RideSharing_2, Travel_1, Hotels_1, Hotels_2, Hotels_3, Flights_1, Flights_2, Restaurants_1, Calendar_1, Music_1, Music_2, Weather_1, Movies_1, Homes_1, Banks_1	26
CamRest676 (Wen et al., 2016b)	Restaurant	1
MSR-E2E (Li et al., 2018)	Restaurant, Movie, Taxi	3
TaskMaster (Byrne et al., 2019)	pizza_ordering, movie_ticket, auto_repair, uber_lyft, coffee_ordering	5
WOZ (Mrkšić et al., 2016)	Restaurant	1

Table 9: Overview of the multi-turn TOD corpora utilized for fine-tuning, comprising a total of 36 diverse domains. This table details the datasets along with their specific domains and the number of domains included in each dataset.

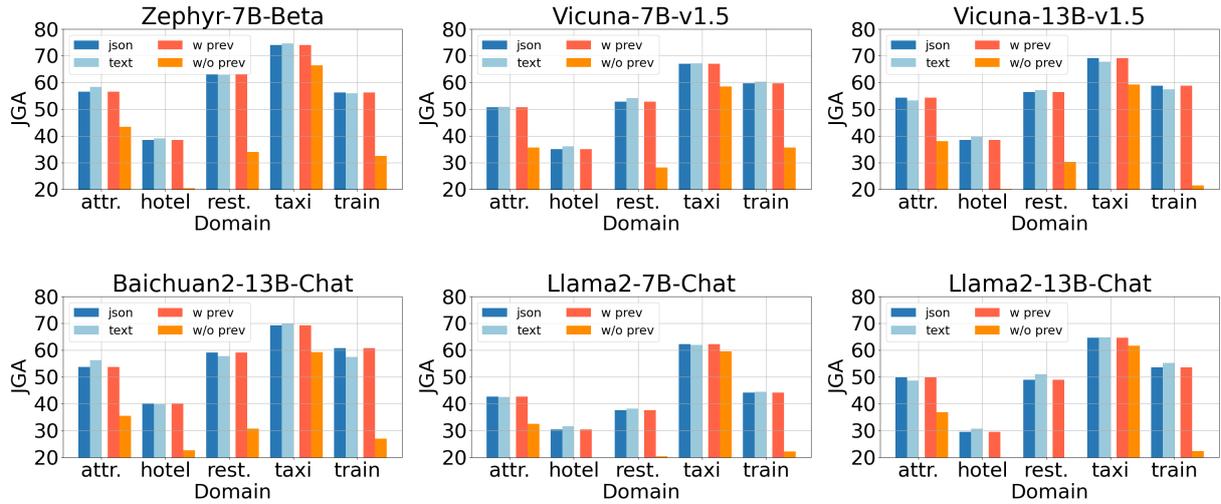


Figure 6: Ablation studies on few-shot prompting with open-source models, regarding different function specification types (json/text) and the unified dialogue format including or not including function calls in previous conversation context (w/ and w/o prev).

888 for in-context prompting using open-source models.
889 In our approach, we seamlessly integrated function
890 calls into the assistant’s output, incorporating them
891 within the conversation context rather than treating
892 them as a separate task. To evaluate its impact,
893 we compared scenarios where function calls were
894 included or omitted from the conversation context.
895 The results, depicted in Figure 6, emphasize the
896 effectiveness of embedding function calls within
897 the conversation context.

Impact of function specification types In addition
898 to directly including function specifications in
899 JSON within the prompt, we experimented with
900 translating the data into more human-readable natural
901 language descriptions. Figure 6 presents a
902 comparison between using the JSON format directly
903 (json) and converting it into natural language
904 descriptions (text). The results indicate that the
905 models perform similarly with both methods of
906 function specification.
907

908 A.4 Prompts

909 **Conversation Context** We adopted the specific
910 chat format for each evaluated LLM used in their
911 fine-tuning, regarding how the conversation is for-
912 matted within the prompt.⁵

913 **System prompt** In our evaluation, we utilized
914 the following system prompt template:

```
915 System prompt
916
917 You are a task-oriented assistant. You can use the
918 given functions to fetch further data to help the users.
919
920 <FUNCTIONS>
921 {Function Specifications}
922 </FUNCTIONS>
923
924 <EXAMPLES>
925 {Example Conversations}
926 </EXAMPLES>
```

915 The parts surrounded in brackets and highlighted
916 in blue serve as placeholders and are replaced with
917 specific function specifications and example con-
918 versations related to that function/domain. The ex-
919 ample part is only employed for few-shot prompt-
920 ing with the models not fine-tuned for function-
921 calling.

923 **Function Specifications** For the function specifi-
924 cation within the system prompt in the prompt, we
925 adhere to ChatGPT’s format. To enhance model
926 comprehension, we also experimented with trans-
927 lating the JSON format into a natural language
928 description to include in the system prompt. An
929 example illustrating both the JSON format and its
930 corresponding natural language description for a
931 specific domain is depicted in Figure 7.

932 **Full Prompt** Combining all components, an ex-
933 ample of the full dialogue prompt is displayed in
934 Figure 8. For clearer illustration, we adopt a more
935 human-readable dialogue format not including the
936 special tokens used in model-specific dialogue for-
937 mats.

⁵<https://github.com/lm-sys/FastChat>

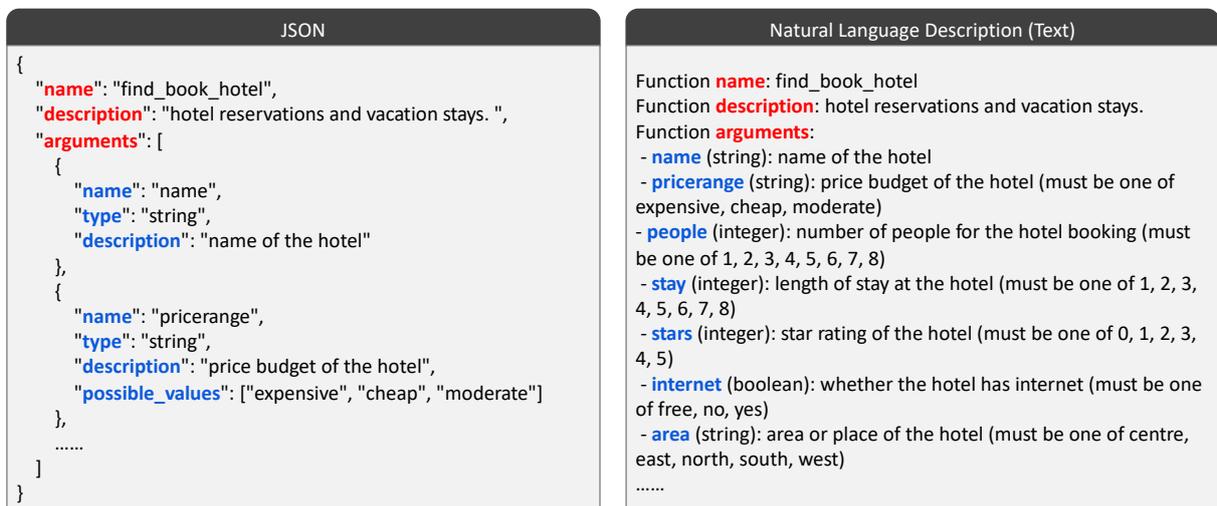


Figure 7: The JSON format (left) and its corresponding natural language description (right) utilized in our evaluation. We take the hotel domain as an example.

The Full Dialogue Prompt

You are a task-oriented assistant. You can use the given functions to fetch further data to help the users.

```
<FUNCTIONS>
<FUNCTION>
{
  "name": "find_attraction",
  "description": "find touristy stuff to do around you.",
  "arguments": [
    {
      "name": "area",
      "type": "string",
      "description": "area to search for attractions",
      "possible_values": ["centre", "east", "north", "south", "west"]
    },
    {
      "name": "name",
      "type": "string",
      "description": "name of the attraction"
    },
    .....
  ]
}
</FUNCTION>
<FUNCTION>
{
  "name": "find_book_hotel",
  "description": "hotel reservations and vacation stays",
  "arguments": [
    {
      "name": "name",
      "type": "string",
      "description": "name of the hotel"
    },
    {
      "name": "pricerange",
      "type": "string",
      "description": "price budget of the hotel",
      "possible_values": ["expensive", "cheap", "moderate"]
    },
    {
      "name": "parking",
      "type": "boolean",
      "description": "whether the hotel has parking",
      "possible_values": ["free", "no", "yes"]
    },
    .....
  ]
}
</FUNCTION>
</FUNCTIONS>
```

To call a function with a JSON object of the following format: {"function": "function_name", "arguments": {"argument1": "argument_value", "argument2": "argument_value"}}

```
User: i would like information about museums in cambridge .
Assistant: <function_call> {"function": "find_attraction", "arguments": {"type": "museum"}} </function_call> there are 23 museums in cambridge . what part of town will you be in ?
User: can you tell me about museums in the centre of town ?
Assistant: <function_call> {"function": "find_attraction", "arguments": {"type": "museum", "area": "centre"}} </function_call> i have the castle galleries museum in the centre of town . phone number is 01223307402 .
User: i also want to find the hotel called archway house .
Assistant: <function_call> {"function": "find_book_hotel", "arguments": {"name": "archway house"}} </function_call> it is located in the north , on 52 gilbert road , cb43pe . would you like to book a room ?
User: yes , please book for 4 nights on friday for 4 people .
Assistant: <function_call> {"function": "find_book_hotel", "arguments": {"name": "archway house", "area": "north", "people": "4", "day": "friday", "stay": "4"}} </function_call> all set , the reference number is 6s9gcfdo , can i help with anything else ?
User: that is all . thank you so much for your help .
Assistant: have a great day ! goodbye !
```

Figure 8: The complete dialogue format employed for model fine-tuning with no demonstration examples. Key components such as the **function specifications** in the system prompt, the **function call**, and the **response** in the assistant's output are highlighted for clarity. It's important to note that for easier comprehension, we've adopted a more human-readable dialogue format, and have simplified some function arguments for clearer visualization. In practice, we use the specific chat format tailored to each evaluated model, and the LLaMA2-Chat format is applied for fine-tuning the LLaMA2-Chat model.