TOOLDIAL: MULTI-TURN DIALOGUE GENERATION METHOD FOR TOOL-AUGMENTED LANGUAGE MODELS

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ABSTRACT

Tool-Augmented Language Models (TALMs) leverage external APIs to answer user queries across various domains. However, existing benchmark datasets for TALM research often feature simplistic dialogues that do not reflect real-world scenarios, such as the need for models to ask clarifying questions or proactively call additional APIs when essential information is missing. To address these limitations, we construct and release ToolDial, a dataset comprising 11,111 multi-turn dialogues, with an average of 8.95 turns per dialogue, based on APIs from RapidAPI. ToolDial has two key characteristics. First, the dialogues incorporate 16 user and system actions (e.g., "request", "clarify", "fail inform") to capture the rich dynamics of real-world interactions. Second, we simulate dialogues where the system requests necessary information from the user based on API documentation and seeks additional APIs if the user fails to provide the required information. To facilitate this process, we introduce a method for generating an API graph that represents input and output compatibility between APIs. Using ToolDial, we evaluate a suite of language models on their ability to predict correct actions and extract input parameter values for API calls from the dialogue history. Modern language models achieve accuracy scores below 70%, indicating substantial room for improvement. We provide a detailed analysis of the areas where these models fall short.[1]

1 INTRODUCTION

A Tool-Augmented Language Model (TALM) is a language model designed to select and call appropriate tools (usually APIs) while interacting with the user to answer the user's query. By leveraging external tools, the TALM can conduct complex tasks beyond its parametric knowledge and adapt its actions based on API results. Recent TALM benchmarks mostly feature single-turn interactions (Qin et al., 2023; Tang et al., 2023) with a primary focus on improving tool selection and reasoning capabilities to address complex user queries within a single turn. However, such interactions do not reflect real-world scenarios where the TALM should request additional information from the user or the user clarifies their intent. Even in studies that involve multi-turn interactions (Li et al., 2023), dialogues tend to be short and limited to scenarios where the TALM asks the user for more details. The lack of richer datasets that reflect complex user-system interactions makes it difficult to accurately assess the ability of modern language models to handle challenging tool use scenarios in the wild, such as when the system identifies and requests information from the user based on available APIs, or when the user cannot provide requested information, requiring the model to call additional APIs to obtain the information.

To address this issue, we present a new dataset named ToolDial, which consists of multi-turn dialogues between the user and TALM based on APIs from RapidAPI[2]. The main focus of our dataset is to simulate dialogues where multiple APIs should be called in sequence (e.g., due to the user failing to provide information that is needed to call the main API) and where the user and the TALM can take diverse actions (16 total), such as clarifying the user's intent or handling the user's failure to provide requested information. To that end, our data generation pipeline consists of four steps, as shown in Figure 1. First, to facilitate selecting two APIs that should be called in sequence, we

[1] We will release all the source code and data upon the publication of the paper.
[2] https://rapidapi.com/hub

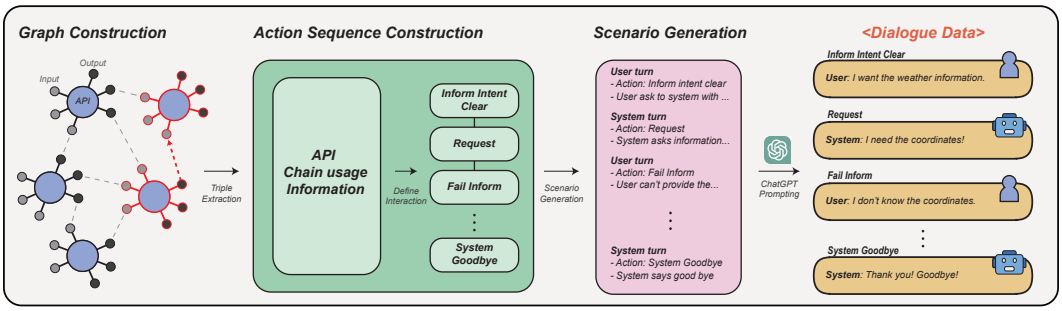

Figure 1: Overall structure of ToolDial. This represents the whole pipeline of our method.

construct an API graph where nodes are APIs and edges between two APIs indicate that one API's output can be used as input for the other API (§3.1). Second, to simulate rich dynamics between the user and TALM, we define 16 types of user and system actions informed by the literature of task-oriented dialogue systems and compile 23 plausible sequences of actions that are likely to occur in dialogues (e.g., Inform Intent Clear → Retriever Call → Request → Fail Inform) (§3.2). Third, to generate each dialogue, we select a pair of APIs from the API graph and choose a sequence of actions that serves as a skeleton. Based on this, we enrich the skeleton by augmenting it with instructions specific to the APIs and the context of each turn (§3.3). Fourth, we convert the sequence of actions and dialogue states into natural utterances to complete a dialogue (§3.4). As a result, ToolDial contains 11,111 dialogues with an average of 8.95 turns per dialogue.

Based on ToolDial, we designed three evaluation tasks to assess a suite of language models in their ability to use tool. Specifically, we evaluated their ability (1) to predict appropriate actions to progress toward answering the user query, (2) to choose the correct API and predict dialogue states (i.e., extracting user-informed values for API inputs), and (3) to generate responses faithful to API outputs. We found that GPT-based models struggle with dialogue state prediction, and their performance declines as the dialogue length increases. Additionally, these models perform poorly at predicting next actions, particularly struggling with requesting input parameters and asking clarifying questions. For smaller Llama models, they generally underperform compared to GPT-based models, but fine-tuning on our dataset significantly improved the overall performance. Notably, it led to substantial improvements in many actions that GPT models struggled with. Our experiments suggest that ToolDial can be a valuable resource for both assessing and improving TALMs in complex multi-turn interactions with users.

The main contributions of our work are summarized as follows:

- We generate and release ToolDial, a dataset consisting of dialogues that reflect real-world interactions between the user and a TALM, encompassing 16 user and system actions.
- We present a framework for creating a large-scale and multi-turn dialogue benchmark using an API graph and GPT with minimal human effort.
- We provide insights into the abilities of various language models to answer user queries while interacting with the user across multiple turns and using external APIs.

2 Related Works

Tool Augmented Language Models Table 1 compares our dataset with existing benchmarks. Recent research on TALM has evolved toward investigating how to effectively select tools and determine which reasoning steps (Yao et al., 2023) are beneficial for solving complex problems (Schick et al., 2023; Shen et al., 2023; Qin et al., 2023; Patil et al., 2023; Tang et al., 2023). Similar to our work, ToolNet (Liu et al., 2024) leverages an API graph, but this graph connects APIs that are called back-to-back in dialogues without considering the compatibility of the input and output of APIs. Most existing datasets contain single-turn dialogues between the user and a TALM. TaskBench (Shen et al., 2024) attempted to construct graphs by matching API inputs and outputs and generating user queries that can be solved using API chains. However, they did not propose

Table 1: Comparison between ToolDial and other TALM datasets. We derived the number of actions based on how many action types occur in each dataset with our action taxonomy as a reference.

Resource	**ToolDial**	**ToolBench**	**API-Bank**	**ToolAlpaca**
Real-world API?	✓	✓	✓	X
Multi-turn Scenario?	✓	X	✓	X
Multi-tool Scenario?	✓	✓	✓	X
Multi-step Reasoning?	✓	✓	✓	X
Situation Complexity?	✓	X	X	X
Number of Actions	**16**	3	7	3
Number of Dialogues	**11,111**	188,304	6,860	4,889
Avg. Turn per Dialogue	**8.95**	2	2.84	2

a method for graph construction, and focused solely on inferring the sequence of APIs required to solve a user query in a single turn rather than through a multi-turn dialogue. Although API-Bank (Li et al., 2023) contains multi-turn interactions, the number of turns in each dialogue is limited (2.84 on average), and the interactions are relatively simplistic. ToolTalk (Farn & Shin, 2023) also reflects some degree of multi-turn interactions (6.44 on average), but it relies on dialogue generation using human annotators, resulting in only a small amount of data (a total of 78 dialogues).

Task-Oriented Dialogue System A Task-Oriented Dialogue System (TOD) is a goal-oriented dialogue system that processes user queries, understands the intent, and provides answers based on database searches or tool calls. Representative datasets for TOD include MultiWOZ (Budzianowski et al., 2020) and Schema-Guided Dialogue (SGD) (Rastogi et al., 2020). MultiWOZ is a multi-turn dialogue dataset generated by human annotators, which reflects the interactions between users and the system. Additionally, the annotations of dialogue states allow for the evaluation of a system's ability to track dialogue states. The Schema-Guided Dialogue (SGD) dataset also consists of multi-turn dialogues. Notably, the way SGD was generated shares similarities with our data generation method, particularly in that an action sequence is chosen first for each dialogue, and then utterances are generated. However, the main difference is that SGD relied on human annotators for action sequence generation, whereas our work does not require additional human annotators for generating action sequences. The literature on TOD offers useful concepts such as dialogue state tracking (Moghe et al., 2024a) and rich taxonomies of user and system actions that occur in interactions with real-world agents. There have also been attempts to transfer TOD datasets into TALM-style data (Moghe et al., 2024b). We designed the ToolDial dataset by referencing the benchmark dataset of TOD (e.g., the format of dialogue states in MultiWOZ and action types in SGD).

3 TOOLDIAL

The dialogues in ToolDial are generated to reflect complex interactions between the user and system in realistic situations involving chained API usage (i.e., the output of one API is used as the input for another API). To achieve this, we follow four steps, as shown in Figure 1. First, we construct an API graph by connecting the input and output entities of APIs (§3.1). This graph plays a critical role in selecting interdependent APIs to be used for each dialogue. Second, we define 16 types of user and system actions to capture the complex dynamics in interactions with tool agents. Based on these actions, we create 23 plausible action sequences that are likely to occur in dialogues (§3.2). Third, to generate a dialogue, we choose a pair of APIs from the API graph, select an action sequence, and augment the action sequence with instructions specific to the APIs and the context of each turn (§3.3). Lastly, we generate utterances that reflect the dialogue states using GPT-4o (§3.4). These processes are carried out with minimal human effort and without the need for additional human annotators.

3.1 GRAPH CONSTRUCTION

Motivation To simulate dialogues where APIs should be called in sequence to fulfill the user's need (e.g. the user fails to provide a necessary argument for an API, and thus the system should

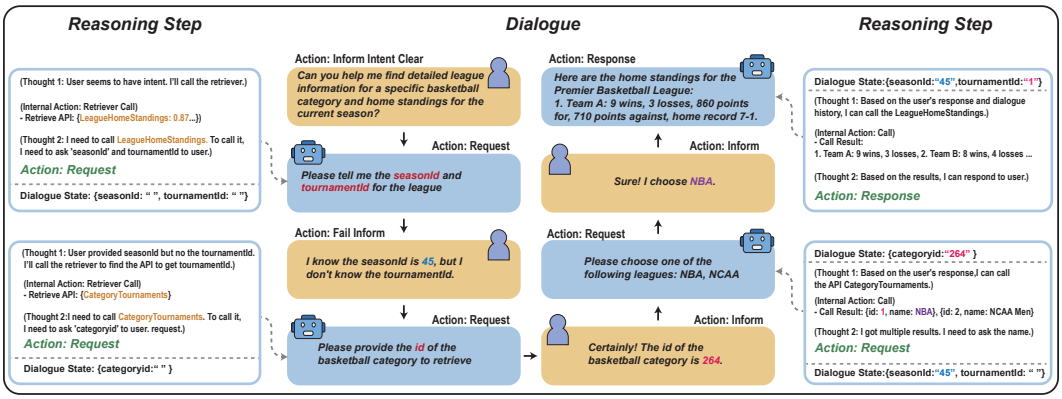

Figure 2: A high-level overview of ToolDial dialogue dataset. This illustrates each turn's user and TALM actions, along with corresponding utterances. It also shows the reasoning steps TALM undergoes, including API calls and retriever calls, before asking or responding to the user.

proactively find and run another API that can provide it), it is necessary to identify which API's output can be used as the input for another API (i.e., API chaining). To facilitate this, we construct an API graph where APIs from Rapid API are represented as nodes, and two APIs are connected by an edge if one API's output can be used as input for the other API. Eventually, this API graph will be used in dialogue generation by allowing us to easily select compatible APIs to be called in sequence.

Settings To determine whether to build an edge between two APIs, we used the names and descriptions of their input and output entities in the API documentation from Rapid API. However, the input and output entities often have generic names (e.g., 'id') and their descriptions do not sufficiently explain their meanings. To address this, we augmented the descriptions using GPT-4o-mini with the API documentation and instructions (A.1). For the name, we summarized the augmented description into a 5- to 7-word sentence to replace the original name. Additionally, we extracted 4 to 5 keywords from the descriptions to represent the API to distinguish APIs from excessively different domains during edge construction (A.2).

Edge Construction Using the API's keyword and the name and description of their input and output entities, we established three criteria to construct edges $Edge$ based on their similarities. This can be formalized as (1).

$$Edge = \begin{cases} 1, & \text{if } emb(d_o, d_i) > t_d \wedge emb(d_o + k_o, d_i + k_i) > t_k \wedge \text{LCS}(n_o, n_i) > t_l \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where i, o represent the input and output entities, $d, k, n, d + k$ denote the description, keywords, name, and the concatenation of keywords and description, respectively. emb is the embedding of the description obtained from the S-Bert model all-mpnet-base-v2 (Reimers & Gurevych, 2019). LCS stands for the longest common subsequence (Hirschberg, 1977). t represents the threshold for each criterion. With embedding similarity of d_i, d_o and longest common subsequence similarity of n_i, n_o, we aimed to match input and output entities that exactly correspond to each other. By using the embedding similarity of $d_i + k_i, d_o + k_o$, we prevented the matching of entities from excessively different domains. As a result, we construct 6,145 edges from 500 million edge candidates (4,474 x 4,474 API pairs, with each pair averaging 25 edge candidates).

Edge Evaluation To verify the edges in the constructed graph, we design an automated evaluation metric to classify whether each edge is valid. Directly calling the API can be the most reliable method for validating edges, but it requires a substantial amount of time and cost and suffers from non-executable APIs in Rapid API. To address this, we utilize StableToolBench (Guo et al., 2024), an API simulator based on large language models. StableToolBench can generate API outputs similar to real API calls, allowing us to validate edges in a similar way to actual API calls. However,

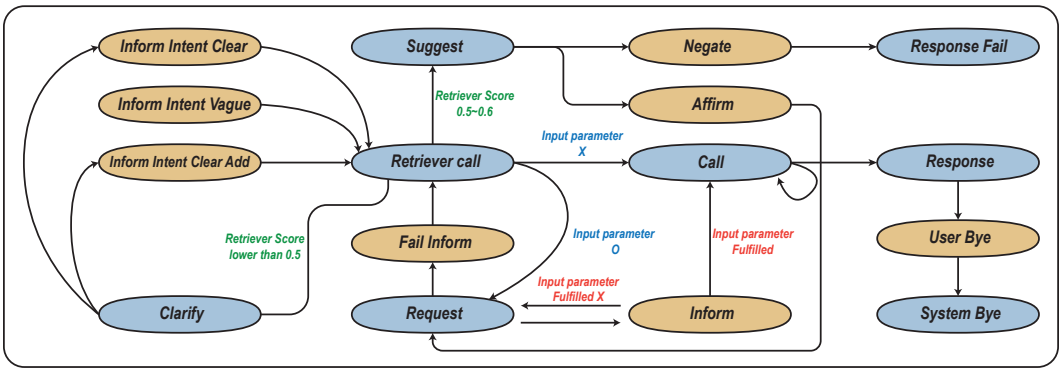

Figure 3: Action graph based on predefined user and system actions. This represents the whole multi turn interaction between user and TALM in our dataset.

StableToolBench has some issues; for example, the same API outputs results in different formats upon multiple calls. We fixed such issues by augmenting StableToolBench with additional information from API documentation (A.11). We sampled 200 edges from our API graph and measured the Matthews Correlation Coefficient (Matthews, 1975) against human evaluations, resulting in a score of 0.868. This score indicates a strong correlation between the evaluation metric and human judgment. For the 6,145 constructed edges, the precision (the proportion of valid edges among constructed edges) was 71%. This indicates that our constructed graph covers most valid edges at the expense of 30% invalid edges. Next, to estimate the amount of missing edges, we measured Negative Predictive Value (the proportion of invalid edges among non-constructed edges). Since the graph has too many unconstructed edges (i.e., no connection between APIs), we sampled 5,501 pairs of input and output entities that are not connected. The NPV score shows 94%, indicating that among the candidates that can be edges, the proportion missing is small. For dialogue generation, we discarded the invalid edges for the subsequent steps.

3.2 Action Sequences

Motivation In dialogue systems, an action refers to a dialogue act representing a specific behavior taken by the user or system during a conversation (e.g., "request information", "deny suggestion", etc.). A taxonomy of user and system actions allows a dialogue system to manage dialogue flow effectively, by focusing on high-level behaviors before generating utterances and providing interpretability. We compile a taxonomy that covers a wide range of actions occurring in user-system interactions so that the generated dialogues and trained systems reflect the complexity of the real world. To generate a dialogue in the next step, we will first choose a plausible sequence of actions (i.e., dialogue flow) as a skeleton before generating utterances (a similar approach was adopted in SGD (Rastogi et al., 2020)).

Definition of Actions We have defined a total of 16 actions that the user and system can take. User actions include three types of informing their intents: "Inform intent clear" (unambiguous queries that can specify the correct API); "Inform intent add" (unambiguous queries along with one additional input entity of the corresponding API); and "Inform intent vague" (ambiguous queries). There are also actions such as "Inform" and "Fail inform", which refer to the success and failure to provide an API's input entities requested by the system. With "Affirm" and "Negate", the user can accept and reject the system's suggestions, respectively.

System actions include "Request", which asks the user for information, and "Response", which provides answers to the user's query. When the user's query is ambiguous, the system may take actions like "Clarify" or "Suggest" to make the user's query more precise. We also define internal system actions such as "Retriever call" and "Call", which occur during the TALM's reasoning steps. The "Retriever call" action retrieves the appropriate API, and "Call" executes the selected API once all input parameters have been obtained from the dialogue history (A.3).

Action Sequences Based on the predefined actions, we defined plausible action sequences. ToolDial is created by combining API pairs from the API graph with action sequences. The types of combinable action sequences depend on whether the APIs in the pair require input parameters, and the form of their outputs (e.g., single value vs. list of values).

For example, in Figure 2, the "CategoryTournaments" API outputs "id", which can serve as the input parameter "tournamentId" for the "LeagueHomeStandings" API. Both APIs need input parameters to call, and "CategoryTournaments" returns a list of "id"s. In this case, the high-level action sequence is as follows:

- (inform intent) → retriever call → request → fail inform → retriever call → request → inform → call → request → inform → call → response.

There are three request actions in this action sequence. The first request is for the input parameters needed to execute "LeagueHomeStandings", the second is to execute "CategoryTournaments", and the third is to select one "id" from the multiple IDs output by "CategoryTournaments". In Figure 2, "CategoryTournaments" is an API that returns multiple "id"s, requiring an additional user prompt to select the correct value (see the 6th turn of Figure 2).

If the APIs in Figure 2 require no input parameters or returned single values instead of lists, the number of "request" actions will be 1 or 2, altering the overall flow. We constructed high-level action flows based on the characteristics of each API pair. We also construct different action sequences depending on whether the inform intent is clear or vague, and if vague, whether it transitions into clarify or suggest actions. Additionally, we designed different action sequences based on the user's fail inform action within the same API pair (see details in A.5). The whole rules about action sequence can be visualized as Figure 3 (see all types of action sequences in A.6).

3.3 Scenario Instruction Generation

Given the API graph and action sequences, we proceed to generate dialogues. For each dialogue to generate, instead of generating utterances directly, however, we first choose APIs to be used in the dialogue and then build a skeleton by choosing an action sequence and augmenting with user query and instruction. This skeleton is called a **scenario instruction** (A.8) and will later be converted to utterances in the next phase of dialogue generation (§3.4).

User Query Generation For each dialogue, we randomly sample one API or two connected APIs from the API graph. We also randomly sample an action sequence to be used in the dialogue. The next key step is to generate a user query that is relevant to the API(s). We prompt GPT-4o with the names and documentation of the API(s) and instruct it to generate a user query that covers all the API(s). For example, given two APIs "search weather station (input: coordinates, output: weather station)" and "nearby weather station coordinate API (input: location name, output: coordinates)", GPT generated the query "I'm going hiking next week, and I'd like to know a nearby weather station". This query becomes the first user utterance, initiating the dialogue.

Instruction Generation During the dialogue scenario generation stage, we plan what information each user and system utterance should include in each turn to perform the corresponding action (e.g., input parameters the system would request, parameter values the user would provide, etc.). For instance, the dialogue in Figure 3 is generated from a instruction like the following:

- Inform intent clear: the user utters a pre-constructed query related with API LeagueHomeStandings and CategoryTournament.
- (Retriever call) → request: the system to ask the user for **seasonId** and **tournamentId**.
- Fail inform: the user responds with seasonId **45** but fails to provide tournamentId.
- (Retriever call) → request: the system prompts the user for **id**.
- Inform: the user responds with the requested information.
- (call) → request: the system asks the user for the **name** variable, to select one **id** from multiple results.
- Inform: Instruction: the user responds with **NBA**

Table 2: Overall statistics of ToolDial.

Metric	Value
Train	8,859
Validation	1,086
Test	1,166
Total	11,111
# of turns	99,476
# of turns per dialogue	8.95

Table 3: Dialogue quality scores.

Criterion	G-Eval	Humans
Naturalness (1–3)	2.28	2.54
Coherence (1–3)	2.58	2.81
Efficiency (1–3)	2.81	2.60
Correctness (0–1)	0.90	0.95

- (call) $\rightarrow$ response: the system responds based on the results of the call.

For parameter values (e.g., 45, 264, NBA), plausible inputs and outputs for the API used in dialogue generation are first generated and then utilized. Scenario prompts are created with predefined templates for each action and filling them with the API's input parameters and values. During this process, the **dialogue state** and **retriever status** (A.4) used in the experiment are also automatically generated for each turn, using the same values and APIs.

3.4 Dialogue Generation

Data Generation We prompted GPT-4o with simple instructions, the scenario instruction, and the relationship between the two APIs in the API pair. Based on this guideline, GPT-4o generates each utterance of user and system that aligns with each turn's dialogue state. We utilize all combinations of valid edges and scenarios (samples in Figure 2).

Data Statistics Our dataset ToolDial contains 11,111 dialogues in English that reflect various scenarios that can happen in the real world. The statistics of ToolDial are shown in Table 2. ToolDial is constructed based on 23 types of action sequences and has an average of 8.95 turns per dialogue.

Data Quality To assess the quality of our dataset, we sampled a total of 100 dialogues from all action sequences and evaluated them using both G-Eval (Liu et al., 2023) and human annotators[3]. The evaluation criteria are as follows:

- Naturalness (1–3): Is the dialogue a natural interaction between the user and TALM?
- Coherence (1–3): Are the user' and the TALM's utterances relevant to and coherent with the dialogue context?
- Efficiency (1–3): Is the system's reasoning and actions to perform the user's request efficient and natural?
- Correctness (True or False): Is the system's response consistent with the output of the API call?

Table 3 presents the scores from G-Eval and human annotators. On average, G-Eval assigned high scores when evaluating the 100 sample dialogues across four criteria. The dialogues received particularly high scores in Efficiency, indicating that the TALM efficiently performed the necessary steps to call APIs and collect information.

Model Biases In ToolDial, we have leveraged several methods to mitigate GPT's biases in dialogue generation. When GPT generates dialogues *without any guidance*, the resulting dialogues tend to be overly repetitive and monotonous. Specifically, certain types of APIs are disproportionately preferred, and the actions performed by both the user and system lack variety, typically following a simple "inform intent - response" pattern. In ToolDial, we address this by creating dialogue data using 473 real-world APIs spanning 23 domains from Rapid API (§3.1) and incorporating 16 actions and 23 action sequences to cover diverse scenarios (§3.2). Furthermore, for certain actions, GPT-generated utterances tend to have overly consistent speaking styles. As a solution, we predefined

[3]Three Master's students majoring in data science volunteered as annotators. The authors are not included.

Table 4: Evaluation scores on three tasks. (**w GT**: ground-truth labels are included in the dialogue history, **w/o GT**: no ground-truth labels are provided)

Model	Dialogue State Tracking		Action Prediction		Faithfulness
	w GT	w/o GT	w GT	w/o GT	w/o GT
GPT-3.5-turbo	38.8	33.1	53.5	54.1	95.4
GPT-4o-mini	58.8	67.7	63.7	60.2	96.6
GPT-4-turbo	77.5	68.6	64.2	61.5	**97.1**
GPT-4o	81.4	67.8	57.6	63.7	96.7
CodeLlama-7b-Instruct-hf	47.2	28.9	35.7	30.0	81.7
Qwen2.5-Coder-7B-Instruct	48.9	34.2	55.8	46.8	93.9
Llama3-8B-Instruct	53.4	24.5	37.7	35.5	91.5
TD-Llama	**92.7**	**72.2**	**77.5**	**91.0**	88.4

speaking styles for specific actions (A.7) and incorporated a mechanism to randomly select from these predefined speaking styles during the scenario instruction generation (§3.3).

4 EXPERIMENTS

In these experiments, we designed evaluation tasks to assess the capabilities that TALM should possess when engaging in multi-turn interactions with users. The input to the model includes

$$\mathcal{H}_n = (u_1, s_1, \ldots, u_n, s_n), \quad \mathcal{R}_n = (r_1, r_2, \ldots, r_n), \quad r_n = \{t_n, \mathcal{A}_n, \mathcal{RS}_n, \mathcal{D}_n, \mathcal{DS}_n\} \tag{2}$$

where $\mathcal{H}_n$ is the dialogue history up to the n-th turn, and u_i and s_i are the utterances of the user and TALM in the i-th turn. $\mathcal{R}_n$ represents the reasoning steps of the TALM up to the n-th turn, where r_i is the reasoning step in turn i. Each reasoning step includes the thought t, action $\mathcal{A}$, retriever status $\mathcal{RS}$, retrieved API documentation $\mathcal{D}$ from the retriever, and dialogue state $\mathcal{DS}$ of the corresponding turn (see the formation of dialogue state and retriever status in A.4). The reasoning step of Figure 2 illustrates each component. We used $\mathcal{H}_n$ and $\mathcal{R}_n$ to predict $\mathcal{DS}$ and $\mathcal{A}$ in each turn to evaluate whether the model accurately captures the dialogue context, extracts the appropriate information, and takes the correct action. Additionally, we evaluated the last utterance s_n where $\mathcal{A}_n$ ="response" in order to assess the consistency between the model's response and the output of the API call.

4.1 EVALUATION TASKS

Dialogue State Tracking Dialogue State Tracking (DST) evaluates the model's ability to determine which API should be called based on the dialogue history, as well as the accuracy of the collected input parameter values. DST can be formalized as

$$\mathcal{DS}_n = \mathcal{M}(\mathcal{H}_{n-1}, \mathcal{R}_{n-1}, u_n) \tag{3}$$

where $\mathcal{DS}_n$ is the dialogue state of turn n, $\mathcal{M}$ is the TALM's output, $\mathcal{H}_{n-1}$ and $\mathcal{R}_{n-1}$ are the dialogue history and the TALM's reasoning steps up to turn $n-1$. We evaluate a total of 6,747 annotated dialogue states within the test set. Each turn's label dialogue state dictionary and predicted dialogue state dictionary are converted to lowercase, and special characters are removed. The evaluation is based on whether the two dialogue states matched completely.

Action Prediction The action prediction task involves selecting the next action to be taken based on the dialogue history and reasoning steps. For this task, the reasoning steps do not include ground-truth thought t, as it offers a direct cue for which action to take. Action prediction is formalized as

$$\mathcal{A}_n = \mathcal{M}(\mathcal{H}_{n-1}, (\mathcal{R}_{n-1} \setminus t), u_n) \tag{4}$$

where $\mathcal{A}_n$ is the system action in turn n. We evaluate a total of 9,200 annotated actions within the test set. Each turn's label action and predicted action are converted to lowercase, and special characters were removed. Evaluation is based on whether they matched exactly.

Table 5: F1 score for each action in the action prediction task. This indicates that fine-tuning with our data supports the system in selecting appropriate actions in multi-turn conversations.

		response	responsefail	request	retrievercall	clarify	systembye	suggest	call
w GT	GPT-3.5-turbo	63.8	0.0	28.4	66.2	1.3	95.5	0.0	53.4
	GPT-4o-mini	78.9	0.0	44.3	67.4	64.5	97.2	0.0	67.0
	GPT-4-turbo	93.6	0.0	18.1	87.5	56.7	97.2	**29.9**	56.4
	GPT-4o	88.3	0.0	13.7	74.9	29.6	97.2	24.6	54.1
	Llama3-8b-Inst	46.4	0.0	8.5	23.7	0.0	99.8	14.0	44.4
	TD-Llama	**100.0**	**77.5**	**44.8**	**97.2**	**77.4**	**99.9**	16.8	**68.6**
w/o GT	GPT-3.5-turbo	70.7	0.0	1.3	77.6	0.0	93.0	0.0	49.7
	GPT-4o-mini	88.5	0.0	36.1	62.6	0.0	97.2	0.0	65.1
	GPT-4-turbo	96.6	0.0	10.8	79.9	40.6	97.2	35.5	57.8
	GPT-4o	95.8	0.0	14.3	81.2	38.6	97.2	46.1	62.0
	Llama3-8b-Inst	30.5	0.0	1.9	27.3	0.0	93.1	9.4	42.0
	TD-Llama	**98.2**	**99.1**	**78.4**	**94.5**	**99.8**	**100.0**	**99.9**	**86.9**

Faithfulness For TALM, generating responses faithful to API call results is critical. We evaluate whether the final response of the TALM is grounded in the API call output. We provide the model with dialogue history that includes the API call results and use G-Eval (Liu et al., 2023) to assess whether the responses reflect the API call output. The evaluation method aligns with the correctness criteria outlined in Dialogue Generation (§3.4). We evaluate a total of 943 system's responses (removing response fail) within the test set. Following the same method as G-Eval, a GPT model with temperature set above 0 evaluates each response for 10 times. The average of the 10 results (all either 0 or 1) is used as the score.

4.2 Experiment Settings

In the real world, the model is not provided with ground-truth actions or dialogue states in the dialogue history. Hence, we evaluate models in two settings: "with GT (ground truth)" and "without GT". The latter is to see the upperbound performance of the models assuming that all prior predictions are correct. "With GT" uses formulation (3) and (4), and "without GT" is formalized as

$$\mathcal{DS}_n^{wogt} = \mathcal{M}(\mathcal{H}_{n-1}, (\mathcal{R}_{n-1} \setminus \mathcal{DS}), u_n), \quad \mathcal{A}_n^{wogt} = \mathcal{M}(\mathcal{H}_{n-1}, (\mathcal{R}_{n-1} \setminus (t \cup \mathcal{A})), u_n) \tag{5}$$

For the faithfulness task, we only conduct the experiment in the "without GT" setting, as the model generates the final turn response and no ground-truth label exists in $\mathcal{H}_{n-1}$ or $\mathcal{R}_{n-1}$ (All instruction prompts used in each task are in A.13).

As baseline models, we choose GPT-3.5-turbo, GPT-4o-mini, GPT-4-turbo, GPT-4o, and CodeLlama-7b-Instruct-hf, Qwen2.5-Coder-7B-Instruct, and LLaMA3-8B-instruct. We also instruction-tuned LLaMA3-8B-instruct with the ToolDial dataset (TD-Llama) and conducted the same experiments.

4.3 Results

The experiment results are summarized in Table 4.

Dialogue State Tracking For the GPT-based models (rows 1–4), we observed that the latest versions outperform their predecessors. Additionally, both closed-source and open-source LLMs scored lower in the "w/o GT" setting compared to the "with GT" setting, as expected. Instruct-tuning the Llama model (TD-Llama) on our dataset (row 7) significantly enhances its performance in both settings, demonstrating the value of our dataset for training TALMs. Furthermore, we observed that accuracy decreases as the number of turns increases (A.10). For TD-Llama, performance remains stable in the "with GT" setting even with longer turns. However, in the "w/o GT" setting, which better reflects real-world scenarios, performance declines as the number of turns increases. This suggests that dialogue state tracking over multiple turns in real-world settings remains a challenging task (Detailed error analysis of DST is provided in A.9).

Action Prediction In the action prediction task, GPT models (rows 1–4) achieved an accuracy of around 60%, which suggests that there is significant room for improvement. On the other hand,

Llama3-8B-Instruct received a much lower accuracy of around 35%, indicating the difficulty in determining appropriate actions based on dialogue history. However, once fine-tuned on our dataset, TD-Llama (row 6) achieved an accuracy of 77.5% and 91.0% on with GT and w/o GT respectively, outperforming GPT models.

To better understand the models' performance across actions, Table 5 shows the F1-score for each action. Here, GPT models show relatively low scores for predicting actions like "Request", "Clarify", and "Suggest". This result is consistent with our observation that ChatGPT often rushes to provide answers without collecting further information or asking clarifying questions. These actions are essential in real-world interactions to serve the user's needs precisely, and TD-Llama demonstrates improved performance on these actions. Another notable result is the low performance of GPT models on the Response Fail" action. When the user refuses to proceed with a suggested API, the models often attempt to clarify the user's intent ('Clarify") rather than acknowledging the failure and terminating the dialogue. While this move could be considered somewhat reasonable, it violates the instruction provided in the prompt and may bother the user.

Faithfulness GPT models achieved over a 90% accuracy in the correctness task. However, the performance of the smaller Llama-based models remains around 88.4%. This demonstrates that small language models are vulnerable to hallucination, and we need better methods for improving the faithfulness of these models.

Overall Performance To solve user's query in real world, generating correct reasoning trace (dialogue state, action) with dialogue history and user's last utterance is crucial for each turn. We evaluate the overall performance of the fine-tuned TD-llama model in this context. We assess whether the model can generates correct dialogue state and action after 5,213 user utterances in the test set. A result is marked as True if both the action and dialogue state are accurately generated for each reasoning step; otherwise, it is marked as False. This evaluation yields a performance score of 76.6%. Additionally, for 1,166 test dialogues, we measure the rate at which the reasoning trace for all turns is accurately generated from the first to the last turn, achieving an accuracy rate of approximately 57.1%. This suggests that there is significant room for improvement on overall performance

5 Conclusion

In this work, we created ToolDial, a multi-turn dialogue dataset that reflects interactions between users and TALM in real-world scenarios. To generate realistic dialogues, we constructed and employed an API graph that represents the interdependency between APIs, aiming to simulate scenarios where the TALM should call multiple APIs to obtain necessary information. In addition, we defined 16 user and system actions to reflect rich the dynamics in tool use conversations. To generate a dialogue, we first sampled APIs and an action sequence as a skeleton. This skeleton was in turn augmented with dialogue states specific to the APIs and finally converted to utterances using GPT. Our evaluation demonstrates that modern language models perform poorly in predicting proper actions and dialogue states in complex multi-turn interactions. We believe ToolDial can serve as a valuable resource for advancing the field of TALM.

References

Paweł Budzianowski, Tsung-Hsien Wen, Bo-Hsiang Tseng, Iñigo Casanueva, Stefan Ultes, Osman Ramadan, and Milica Gašić. Multiwoz – a large-scale multi-domain wizard-of-oz dataset for task-oriented dialogue modelling, 2020. URL https://arxiv.org/abs/1810.00278.

Nicholas Farn and Richard Shin. Tooltalk: Evaluating tool-usage in a conversational setting, 2023. URL https://arxiv.org/abs/2311.10775.

Zhicheng Guo, Sijie Cheng, Hao Wang, Shihao Liang, Yujia Qin, Peng Li, Zhiyuan Liu, Maosong Sun, and Yang Liu. Stabletoolbench: Towards stable large-scale benchmarking on tool learning of large language models, 2024. URL https://arxiv.org/abs/2403.07714.

Daniel S. Hirschberg. Algorithms for the longest common subsequence problem. *J. ACM*, 24 (4):664–675, October 1977. ISSN 0004-5411. doi: 10.1145/322033.322044. URL https://doi.org/10.1145/322033.322044.

Minghao Li, Yingxiu Zhao, Bowen Yu, Feifan Song, Hangyu Li, Haiyang Yu, Zhoujun Li, Fei Huang, and Yongbin Li. Api-bank: A comprehensive benchmark for tool-augmented llms, 2023. URL https://arxiv.org/abs/2304.08244.

Xukun Liu, Zhiyuan Peng, Xiaoyuan Yi, Xing Xie, Lirong Xiang, Yuchen Liu, and Dongkuan Xu. Toolnet: Connecting large language models with massive tools via tool graph, 2024. URL https://arxiv.org/abs/2403.00839.

Yang Liu, Dan Iter, Yichong Xu, Shuohang Wang, Ruochen Xu, and Chenguang Zhu. G-eval: Nlg evaluation using gpt-4 with better human alignment, 2023. URL https://arxiv.org/abs/2303.16634.

Brian W. Matthews. Comparison of the predicted and observed secondary structure of t4 phage lysozyme. *Biochimica et biophysica acta*, 405 2:442–51, 1975. URL https://api.semanticscholar.org/CorpusID:44596673.

Nikita Moghe, Patrick Xia, Jacob Andreas, Jason Eisner, Benjamin Van Durme, and Harsh Jhamtani. Interpreting user requests in the context of natural language standing instructions, 2024a. URL https://arxiv.org/abs/2311.09796.

Nikita Moghe, Patrick Xia, Jacob Andreas, Jason Eisner, Benjamin Van Durme, and Harsh Jhamtani. Interpreting user requests in the context of natural language standing instructions, 2024b. URL https://arxiv.org/abs/2311.09796.

Shishir G. Patil, Tianjun Zhang, Xin Wang, and Joseph E. Gonzalez. Gorilla: Large language model connected with massive apis, 2023. URL https://arxiv.org/abs/2305.15334.

Yujia Qin, Shihao Liang, Yining Ye, Kunlun Zhu, Lan Yan, Yaxi Lu, Yankai Lin, Xin Cong, Xiangru Tang, Bill Qian, Sihan Zhao, Lauren Hong, Runchu Tian, Ruobing Xie, Jie Zhou, Mark Gerstein, Dahai Li, Zhiyuan Liu, and Maosong Sun. Toolllm: Facilitating large language models to master 16000+ real-world apis, 2023. URL https://arxiv.org/abs/2307.16789.

Abhinav Rastogi, Xiaoxue Zang, Srinivas Sunkara, Raghav Gupta, and Pranav Khaitan. Towards scalable multi-domain conversational agents: The schema-guided dialogue dataset, 2020. URL https://arxiv.org/abs/1909.05855.

Nils Reimers and Iryna Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks, 2019. URL https://arxiv.org/abs/1908.10084.

Timo Schick, Jane Dwivedi-Yu, Roberto Dessì, Roberta Raileanu, Maria Lomeli, Luke Zettlemoyer, Nicola Cancedda, and Thomas Scialom. Toolformer: Language models can teach themselves to use tools, 2023. URL https://arxiv.org/abs/2302.04761.

Yongliang Shen, Kaitao Song, Xu Tan, Dongsheng Li, Weiming Lu, and Yueting Zhuang. Hugginggpt: Solving ai tasks with chatgpt and its friends in huggingface. In *Advances in Neural Information Processing Systems*, 2023.

Yongliang Shen, Kaitao Song, Xu Tan, Wenqi Zhang, Kan Ren, Siyu Yuan, Weiming Lu, Dongsheng Li, and Yueting Zhuang. Taskbench: Benchmarking large language models for task automation, 2024. URL https://arxiv.org/abs/2311.18760.

Qiaoyu Tang, Ziliang Deng, Hongyu Lin, Xianpei Han, Qiao Liang, Boxi Cao, and Le Sun. Toolalpaca: Generalized tool learning for language models with 3000 simulated cases, 2023. URL https://arxiv.org/abs/2306.05301.

Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik Narasimhan, and Yuan Cao. React: Synergizing reasoning and acting in language models, 2023. URL https://arxiv.org/abs/2210.03629.

A APPENDIX

A.1 ENTITY DESCRIPTION GENERATION

Table 6: Prompt used to generate input entity

Prompt for generating input entity descriptions
System You are an intelligent annotator. Your mission is to write the description of input parameters more specifically, referring to the given information. Write as specifically as possible, referring to the given information. The new description should be based on the existing description but rewritten to better reflect the content of the API description and API endpoint description than before. Just return the input and its description, not individual words. For example: Category of the API: Data Description of the Category: APIs facilitate the seamless exchange of data between applications and databases, enabling developers to integrate functionalities securely and swiftly. API Name: YouTube Media Downloader API Description: A scraper API for YouTube search and download. Get videos, subtitles, comments without age or region limits (proxy URL supported). API Endpoint Name: Get Channel Details API Endpoint Description: This endpoint fetches details of a YouTube channel. List of input parameters: Input parameter name: channelId Description: Channel ID, custom URL name, or handle. @ is required as a prefix for a channel handle. Input parameter name: lang Description: Language code (ISO-639) for localized results. Defaults to en-US. Unsupported codes will fallback to en-US. For this, you should return: [[“channelId”, “The unique identifier for the YouTube channel, which can be the channel’s ID, a custom URL name, or a channel handle. When using a channel handle, ensure to prefix it with ‘@’ (e.g., ‘@channelname’)”.], [“lang”, “The language code (ISO-639) used to specify the language for the localized results. If not provided, the default is ‘en-US’. In case an unsupported language code is supplied, the results will revert to ‘en-US’”.]] Now, I’ll give you another description. Follow the instructions, referring to the example. Write as specifically as possible, referring to the given information. The new description should be based on the existing description but written in a way that better reflects the content of the API description and API endpoint description than before. Just return the input and its description, not individual words.

Table 7: Prompt used to generate output entity description

Prompt for generating output entity descriptions
System You are an intelligent annotator. Your mission is to write the description of the output components of an API endpoint, referring to the given information below. For example: Category of the API: Data Description of the Category: APIs facilitate the seamless exchange of data between applications and databases, enabling developers to integrate functionalities securely and swiftly. API Name: YouTube Media Downloader API Description: A scraper API for YouTube search and download. Get videos, subtitles, comments without age or region limits (proxy URL supported). API Endpoint Name: Get Channel Details API Endpoint Description: This endpoint fetches details of a YouTube channel. Based on the given description, write the description of the output component of this API endpoint. Write as specifically as possible. Do not generate examples for each component. The description should reflect as closely as possible the description of the API and the API endpoint, so that even someone seeing this API endpoint for the first time can understand exactly what the output component means. (A component separated with — refers to the hierarchy of the schema. For example, avatar—height refers to the height of the avatar.)

Output components: [{ “name”: “status” }, { “name”: “type” }, { “name”: “id” }, { “name”: “name” }, { “name”: “handle” }, { “name”: “description” }, { “name”: “isVerified” }, { “name”: “isVerifiedArtist” }, { “name”: “subscriberCountText” }, { “name”: “videoCountText” }, { “name”: “viewCountText” }, { “name”: “joinedDateText” }, { “name”: “country” }, { “name”: “links—title” }, { “name”: “links—url” }, { “name”: “avatar—url” }, { “name”: “avatar—width” }, { “name”: “avatar—height” }]
For this example, you have to return,
[{ “name”: “status”, “description”: “Indicates whether the API call was successful. True means the call was successful, while False means it failed” }, { “name”: “type”, “description”: “Specifies the type of YouTube channel, such as ’User’ or ’Brand’, indicating the category of the channel”. }, { “name”: “id”, “description”: “The unique identifier assigned to the YouTube channel, which can be used to reference the channel in other API calls or services”. }, { “name”: “name”, “description”: “The official name of the YouTube channel as displayed on the platform, which is set by the channel owner”. }, { “name”: “handle”, “description”: “The unique handle of the YouTube channel, which often appears in the URL of the channel’s page”. }, { “name”: “description”, “description”: “A textual description provided by the channel owner that gives an overview of the channel’s content, themes, and purpose”. }, { “name”: “isVerified”, “description”: “Indicates whether the YouTube channel is verified by YouTube. A verified status signifies authenticity and is usually granted to public figures, brands, and popular content creators”. }, { “name”: “isVerifiedArtist”, “description”: “Specifies if the YouTube channel is recognized as a verified artist’s channel, which is a special status for musicians and bands to highlight their official content”. }, { “name”: “subscriberCountText”, “description”: “A human-readable representation of the number of subscribers the channel has, formatted for display purposes”. }, { “name”: “videoCountText”, “description”: “A human-readable representation of the total number of videos uploaded by the channel, formatted for display purposes”. }, { “name”: “viewCountText”, “description”: “A human-readable representation of the total number of views across all videos on the channel, formatted for display purposes”. }, { “name”: “joinedDateText”, “description”: “A human-readable representation of the date when the YouTube channel was created, formatted for display purposes”. }, { “name”: “country”, “description”: “The country where the YouTube channel is registered or primarily based, providing geographical context”. }, { “name”: “links—title”, “description”: “The title of an external link provided by the channel, which can lead to the channel’s social media profiles, websites, or other related content”. }, { “name”: “links—url”, “description”: “The URL of an external link associated with the channel, which directs users to other online presences of the channel”. }, { “name”: “avatar—url”, “description”: “The URL of the channel’s avatar image, which is the profile picture displayed on the channel’s page”. }, { “name”: “avatar—width”, “description”: “The width of the avatar image in pixels, providing information about the image dimensions”. }, { “name”: “avatar—height”, “description”: “The height of the avatar image in pixels, providing information about the image dimensions”. }]
Now, I’ll give you another API endpoint description. Write the description of the output components and return it in the same format as the example. Just return the result, not individual words. Based on the given description, write the description of the output components of this API endpoint. Write as specifically as possible. Do not generate examples for each component. The description should reflect the API and the API endpoint as closely as possible, so that even someone seeing this API endpoint for the first time can understand exactly what the output component means. (A component separated with — refers to the hierarchy of the schema. For example, avatar—height refers to the height of the avatar.)
Fill the <Your response>.
<Your response>

A.2 KEYWORDS EXTRACTION

Table 8: Prompt used to extract keywords

Prompt for extracting keywords
System Extract the keywords from the given paragraph. Prioritize proper nouns first and nouns second, selecting up to 4 words that best describe the paragraph. Return the keywords in CSV format. Remember, the maximum is 4 words. Paragraph:

A.3 USER AND SYSTEM ACTION LIST

Our work defines eight user actions and eight system actions, which form the basis for conceptualizing interactions. Table 3 and Table 4 provide the names and descriptions of these actions.

Table 9: User action and description

User Action	Description
Inform intent clear	Say what one wants specifically.
Inform intent clear add	Say what one wants specifically with the information of input parameter.
Inform intent vague	Say what one wants vaguely.
Inform	Inform the requested information to system.
Fail inform	Fail to reply to system's request.
Affirm	Agree to the system's proposition.
Negate	Deny the system's proposal.
User bye	Say thank you and goodbye to system.

Table 10: TALM action and description

System Action	Description
Request	Asks some information to user.
Response	Reply to user's request based on the result of API call.
Clarify	If user's query is vague, re-ask user to get intent specifically.
Suggest	Making a suggestion for an unclear user's intent and asking whether it satisfies the user.
Response fail	Notify the user that the system cannot execute the request due to insufficient information.
System bye	System says goodbye to user politely.
Call	Call the API with collected information from user or else and don't reply to user yet.
Retriever call	Call the retriever to find proper API to satisfy user's requests.

A.4 DIALOGUE STATE AND RETRIEVER STATUS ANNOTATION FORMAT

Our data is annotated with "retriever status" each turn. This indicates whether the retriever was called for each turn of the conversation, the APIs retrieved as a result, and their respective retriever scores. The actions that the TALM should take vary depending on the retriever score. If there is an API with a score of 0.6 or higher, the TALM asks the user for input parameters to call it. If the score is between 0.5 and 0.6, the TALM suggests the retrieved API, and if the score is lower, it asks for clarification of the user's query. Format of retriever status can have three types described below.

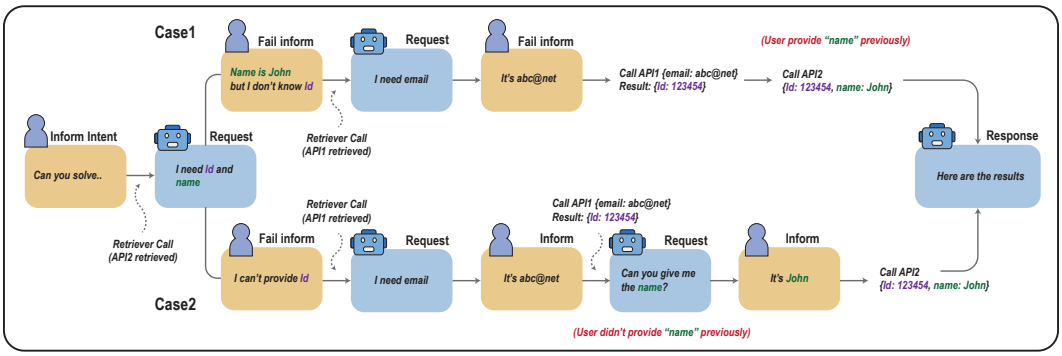

Figure 4: Possible cases of two action sequences according to perform types "Fail inform".

- **When retriever is not called**
  {Retriever status: false, Retrieved API: none}
- **Situation where the TALM needs to find the appropriate API to solve the user's query.**
  {Retriever status: true, Retrieved API: {API 1: 0.65, API2: 0.54, API3: 0.51...}}
- **Situation that TALM needs to obtain an input parameter that the user has not provided.**
  {Retriever status: true, Retrieved API: [Output component of source API to procure target API's input parameter param1 → output1]}

Additionally, our dataset is labeled with the dialogue state for each turn. The dialogue state includes the API that the TALM is currently attempting to execute and the input parameter information collected for that API, based on the dialogue history. The dialogue state has the following format.

- **When there is no confirmed API**
  {API confirmed: false, API status: none}
- **When the API is confirmed**
  {API confirmed: true, API status: {API name: "API1", Required parameters: {param1: " ", param2: " "}, Optional parameters: {param3: " "}}}
- **When the API is confirmed and some input parameter information can be extracted from dialogue history**
  {API confirmed: true, API status: {API name: "API1", Required parameters: {param1: "value1", param2: " "}, Optional parameters: {param3: "value3"}}}

A.5 Variation of Fail inform Action

User can perform "Fail Inform" in two ways: either indicating they don't know one parameter while providing the rest, or simply stating they don't know the missing parameter without further input. Figure 4 shows

A.6 Comprehensive Action Sequences

Assuming that at most two APIs are called in a dialogue, a total of 23 action sequences are derived for data generation. Among these, 15 sequences involve two APIs, 7 involve one API, and 1 involves a failure to call any APIs. The 15 sequences with two APIs are further categorized based on the type of action sequence request: either directly requesting input parameters from the user (request) or making an additional request to select an appropriate value from multiple results (request - multi).

Table 11: Action Sequences with two APIs

No.	Action Sequence
1	'inform_intent_vague', 'retriever_call', 'suggest', 'affirm', 'request', 'fail_inform', 'retriever_call', 'request', 'inform', 'call', 'call', 'response', 'user_bye', 'system_bye'

2	‘inform_intent_vague’, ‘retriever_call’, ‘suggest’, ‘affirm’, ‘request’, ‘fail_inform’, ‘retriever_call’, ‘call’, ‘request’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
3	‘inform_intent_vague’, ‘retriever_call’, ‘clarify’, ‘inform_intent_clear’, ‘retriever_call’, ‘request’, ‘fail_inform’, ‘retriever_call’, ‘call’, ‘request’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
4	‘inform_intent_vague’, ‘retriever_call’, ‘clarify’, ‘inform_intent_clear’, ‘retriever_call’, ‘request’, ‘fail_inform’, ‘retriever_call’, ‘request’, ‘inform’, ‘call’, ‘request-multi’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
5	‘inform_intent_vague’, ‘retriever_call’, ‘clarify’, ‘inform_intent_clear’, ‘retriever_call’, ‘request’, ‘fail_inform’, ‘retriever_call’, ‘request’, ‘inform’, ‘call’, ‘request’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
6	‘inform_intent_clear’, ‘retriever_call’, ‘request’, ‘fail_inform’, ‘retriever_call’, ‘call’, ‘request-multi’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
7	‘inform_intent_clear’, ‘retriever_call’, ‘request’, ‘fail_inform’, ‘retriever_call’, ‘request’, ‘inform’, ‘call’, ‘request’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
8	‘inform_intent_clear’, ‘retriever_call’, ‘request’, ‘fail_inform’, ‘retriever_call’, ‘request’, ‘inform’, ‘call’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
9	‘inform_intent_clear’, ‘retriever_call’, ‘request’, ‘fail_inform’, ‘retriever_call’, ‘call’, ‘request’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
10	‘inform_intent_vague’, ‘retriever_call’, ‘suggest’, ‘affirm’, ‘request’, ‘fail_inform’, ‘retriever_call’, ‘request’, ‘inform’, ‘call’, ‘request-multi’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
11	‘inform_intent_vague’, ‘retriever_call’, ‘clarify’, ‘inform_intent_clear’, ‘retriever_call’, ‘request’, ‘fail_inform’, ‘retriever_call’, ‘request’, ‘inform’, ‘call’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
12	‘inform_intent_vague’, ‘retriever_call’, ‘suggest’, ‘affirm’, ‘request’, ‘fail_inform’, ‘retriever_call’, ‘request’, ‘inform’, ‘call’, ‘request’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
13	‘inform_intent_clear’, ‘retriever_call’, ‘request’, ‘fail_inform’, ‘retriever_call’, ‘request’, ‘inform’, ‘call’, ‘request-multi’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
14	‘inform_intent_vague’, ‘retriever_call’, ‘clarify’, ‘inform_intent_clear’, ‘retriever_call’, ‘request’, ‘fail_inform’, ‘retriever_call’, ‘call’, ‘request-multi’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
15	‘inform_intent_vague’, ‘retriever_call’, ‘suggest’, ‘affirm’, ‘request’, ‘fail_inform’, ‘retriever_call’, ‘call’, ‘request-multi’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’

Table 12: Action Sequences with one API

No.	Action Sequence
1	‘inform_intent_vague’, ‘retriever_call’, ‘clarify’, ‘inform_intent_clear’, ‘retriever_call’, ‘request’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
2	‘inform_intent_vague’, ‘retriever_call’, ‘clarify’, ‘inform_intent_clear_add’, ‘retriever_call’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
3	‘inform_intent_vague’, ‘retriever_call’, ‘suggest’, ‘affirm’, ‘request’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
4	‘inform_intent_vague’, ‘retriever_call’, ‘clarify’, ‘inform_intent_clear_add’, ‘retriever_call’, ‘request’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
5	‘inform_intent_clear_add’, ‘retriever_call’, ‘request’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
6	‘inform_intent_clear_add’, ‘retriever_call’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’
7	‘inform_intent_clear’, ‘retriever_call’, ‘request’, ‘inform’, ‘call’, ‘response’, ‘user_bye’, ‘system_bye’

Table 13: Action Sequence with failure

No.	Action Sequence
1	'inform_intent_vague', 'retriever_call', 'suggest', 'negate', 'response_fail'

A.7 UTTERANCE STYLE

We have defined several utterance styles for some actions to prevent GPT from generating consistent speaking styles.

- User Action
  - Inform
    - Sure! ∼, Ok ∼, Certainly!
  - Affirm
    - Yes, that works., That would be great. Sure, that sounds good., Yes, please proceed.
  - Negate
    - No, that's not what I meant, I'm good. Thank you though, Umm... that's not what I want
- System Action
  - Request
    - To call ∼, I need ∼, May I ask for ∼, Please tell me ∼,
  - Clarify
    - Could you please provide more ∼, I'm not sure I understand. Can you clarify ∼, Could you explain that in more ∼, Can you clarify your ∼

A.8 SCENARIO PROMPT

We use detailed dialogue scenario prompts to ensure that the predefined interactions are accurately reflected in the dialogue data and that the correct entities are included in each utterance. Table 5 show the example of scenario prompt.

Table 14: Prompt used to simulate APIs. Continued on the next page.

Scenario prompt
User turn -user action: inform_intent_vague (Say what one wants vaguely.) -situation: User requests something from the system. User says "Can you provide detailed information about a city I plan to visit, including its geographical context and population data, so I can find some highly-rated local businesses with good reviews and contact details nearby?"
System turn -system action: retriever_call (Call the retriever to find the proper API to satisfy the user's request.) -situation: The system, having received the user's query, calls the retriever to find an appropriate API. In this turn, the system's thought is, "The user seems to have intent. I will call the retriever". Retriever status: retriever_call: 'true', retrieved_api: 'Data—local_business_data—Search Nearby': 0.56445915, 'Data—local_business_data—Search In Area': 0.5539355, 'Mapping—places—Place properties': 0.5367253, 'Location—spott—Search places': 0.53351307, 'Data—serpwow—Google Place and Maps Details': 0.5169816 Dialogue state: api_confirmed: 'false', api_status: 'none'

System turn
-system action: suggest (Make a suggestion for an unclear user intent and ask whether it satisfies the user.)
-situation: Since the user's query is unclear, no API with a retriever score higher than 0.6 has been found. However, several APIs have scores between 0.5 and 0.6. The system asks whether it would be appropriate to run Data—local_business_data—Search Nearby, which has the highest score among them, and retrieve the result. At this time, the system does not mention the name of the API directly.
Retriever status: retriever_call: 'false', retrieved_api: 'none'
Dialogue state: api_confirmed: 'false', api_status: 'none'

User turn
-user action: affirm (Agree to the system's proposition.)
-situation: User agrees with the system's proposition. User's speech should follow this format: "Yes, please proceed".

System turn
-user action: request (Asks some information to user.)
-situation: System asks user to..

A.9 DST Error Analysis

Table 15: DST error analysis for GPT models

	GPT-3.5-turbo		**GPT-4o-mini**		**GPT-4-turbo**		**GPT-4o**	
	W GT	**W/O GT**	**W GT**	**W/O GT**	**W GT**	**W/O GT**	**W GT**	**W/O GT**
# of Error	4128	4512	2781	2177	1515	2117	1257	2169
Generation Err	0	0	0	0	0	0	0	0
API Conf Err (GT = T)	1609	1841	1060	504	211	224	243	1607
API Conf Err (GT = F)	750	410	848	373	692	891	343	133
Format Err	532	502	153	0	0	74	0	531
Slot Err	1139	1674	508	912	430	774	443	221
Value Err	561	630	398	823	498	626	495	221

Table 16: DST error analysis for Llama3-8b-instruct and TD-llama

	Llama3-8b-instruct		**TD-llama**	
	W GT	**W/O GT**	**W GT**	**W/O GT**
# of Err	3138	5090	492	1873
Generation Err	3	0	260	1619
API Conf Err (GT = T)	583	1014	30	1
API Conf Err (GT = F)	723	923	0	0
Format Err	531	319	61	103
Slot Err	1101	2663	6	23
Value Err	846	1423	134	144

Tables 15 and Table 16 present the error analysis results for each model on the dialogue state tracking (DST) task. We categorized the errors in DST as follows.

- **Generation Error:** This occurs when the dialogue state dictionary is not generated at all.

- **API Confirmation Error (GT = True):** This error happens when the API is confirmed (`api_confirmed=true`), but is incorrectly predicted as not confirmed (`api_confirmed=false`).
- **API Confirmation Error (GT = False):** This error occurs when the API is not confirmed (`api_confirmed=false`), but the model incorrectly predicts it as confirmed (`api_confirmed=true`).
- **Format Error:** This occurs when the dialogue state does not fully generate all fields such as `api_confirmed`, `api_status`, required parameters, and optional parameters.
- **Slot Error:** When `api_confirmed` is true, this error involves generating a dialogue state that does not include all required and optional parameter slots as specified in the API documentation.
- **Value Error:** This error involves incorrectly extracting the slot's value from the dialogue history, with the following types:
  - **Extracting Input Value from Multiple Result Error:** This error occurs when an appropriate value cannot be selected from multiple results returned by the API output (as seen in turns 6 and 7 of Figure 2).
  - **Inform Intent Add Error:** This occurs when there is a value within the user query that could be used as an input parameter (`inform intent clear add`), but the model fails to track it.
  - **Other General Input Parameter Extraction Errors:** Errors that occur in typical situations where the input parameter is extracted incorrectly.

The error analysis tables show error counts, where slot and value errors can overlap in a single prediction, causing their sum to exceed the total errors.

A.10 DST ACCURACY BASED ON TURN LENGTH

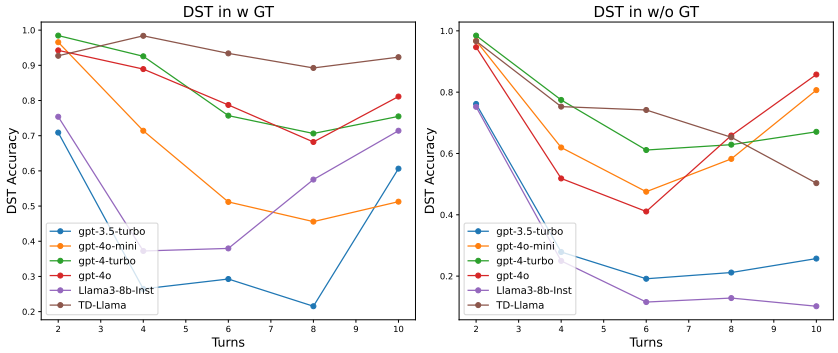

Figure 5: DST Accuracy for each model as the number of dialogue turns increases.

A.11 REMOVING MISMATCH ERRORS

Blow examples shows the mismatch errors that occur during edge construction. There is a domain mismatch and an entity mismatch.

Domain mismatch

API 1

- **Domain and Tools: Sports basketapi**
- API name: LeagueTopPlayersPlayoffs
- Entity name: tournamentId

- Entity Description: The id of the specific basketball tournament for which the top players in the playoffs are being retrieved.

API 2

- **Domain and Tools: Sports baseballapi**
- API name: PlayerRegularSeasonStatistics
- Entity name: tournamentId
- Entity Description: The id of the specific baseball tournament for which the regular season statistics of a player are being requested.

Entity mismatch

API 1

- Domain and Tools: Sports icehockeyapi
- API name: PlayerRegularSeasonStatistics
- **Entity name: playerId**
- Entity Description: The unique identifier for a specific ice hockey player whose regular season statistics are being requested.

API 2

- Domain and Tools: Sports icehockeyapi
- API name: LeaguePlayoffsTopPlayers
- **Entity name: seasonId**
- Entity Description: The id of the specific ice hockey season for which the top players are being retrieved during the playoffs.

A.12 Prompt Format for the Experiment

Table 18 presents the prompt format used in the experiments conducted in our work. Both open-source and closed-source LLMs utilized this format. DST involves predicting all dialogue states present in the format for each dialogue, while action prediction focuses on predicting all actions. In the case of action prediction, all "thought" within the format are removed prior to the task. The W/O GT setting requires predicting the dialogue state and action for each turn using the dialogue history in the format without any dialogue states or actions included in the reasoning steps (for DST and action prediction, respectively).

A.13 Evaluation Prompts

We release all the prompts used in our experiments. Table 17 contains the prompt used for evaluating edges in graph construction (§3.1), Table 19 includes the prompt used for dialogue state tracking evaluation, Table 20 provides the prompt used for action prediction evaluation, and Table 21 presents the prompt used for faithfulness evaluation.

Table 17: Prompt used to evaluate edges.

Edge Evaluaiton Prompt

System

Your task is to determine whether the source attribute in the response from the source API is compatible with the api input of the target API. Then, craft a JSON formatted response that aligns with the expected output of the API, guided by the provided examples. For your judgment, we will provide descriptions of tool description, API Documentation, source attribute and target attribute of both APIs.

The judgment is a two step process. In the first step, determine whether the two attributes are compatible based on a deep understanding of the source attribute and target attribute. Determine whether the source attribute and target attribute are compatible through attribute descriptions. The second step is to determine whether the input of the target API is compatible with the intent of the target API. If both steps are considered compatible, follow the Output format for True to output the result. If not, follow the Output format for False to output the result. Your responses must adhere to a specific JSON structure, which is as follows:

Output format for True:

```
{"error": "","response": "<Your_Response>"}
```

Output format for False:

```
{"error": "Invalid Edge Error","response": "<Your_Response>"}
```

The response field should contain the content you formulate based on the API's functionality and the input provided. Ensure that your responses are meaningful, directly addressing the API's intended functionality. If the provided examples are mostly error messages or lack substantial content, use your judgment to create relevant and accurate responses. The key is to maintain the JSON format's integrity while ensuring that your response is an accurate reflection of the API's intended output within the tool. Please note that your answer should not contain anything other than a json format object, which should be parsable directly to json.

Note that:

- Your response should be around 100 to 200 words, containing rich information given the api input parameters. Keep Your answer short and simple.
- Your response must be effective and have practical content.
- If the api response example if null or ineffective, ignore the example and give your independent response.

User

API Documentation:

source API Documentation JSON file
target API Documentation JSON file
source attribute: description of source attribute
tource attribute: description of target attribute

API Examples:

Example input 1: Example response 1
Example input 2: Example response 2
Example input 3: Example response 3

API Input:

Argument JSON string, e.g:

```
{"category":"Logistics", "tool_name": "SQUAKE",
"api_name": "Checkhealth", "tool_input": "{}",
"strip": "filter"}
```

Table 18: Prompt Format for the Experiment

Prompt for generating input entity descriptions
User: Can you provide insights into which articles on NYTimes.com have been shared the most on social media platforms, particularly Facebook, to understand active engagement trends? **System:** - Thought: The user seems to have intent. I will call the retriever. - Action: retriever call - Retriever status: {retriever_call: true, retrieved_api: {NYTimesAPI: 0.71, . . . }} - API documentation: {api_name: NYTimesAPI, (with required and optional parameter informations)} - Thought: Based on results of the retriever, I need to call NYTimesAPI. To call it, I need to ask "share_type" and "period" to the user. - Action: request - Retriever status: {retriever_call: false, retrieved_api: none} - Message: Could you please provide the type of sharing on Facebook for articles and the time period for retrieving popular articles? - Dialogue State: <Current dialogue state> **User:** Certainly! The share type is Facebook and the period is 7 days. **System:** - Dialogue State: <Current dialogue state> - Thought: Based on the user's response, now I can call the API NYTimesAPI - Action: call . . .

Table 19: Instruction prompt for the Dialogue State Tracking task

Dialogue state tracking task evaluation prompt

System

Instruction: You will be given part of a dialogue between the user and the system. In this dialogue, the user is requesting information from the system, and the system will execute an API call to retrieve the necessary information.

Your task is to output the appropriate dialogue state for the current turn, based on the dialogue provided.

System Rules:

1. The system selects the API with the highest score from among the APIs in the retriever status that have a score of 0.6 or higher and are suitable for processing the user's query.
2. If no API has a score higher than 0.6, the system cannot confirm the API to call.

Dialogue state format:

Case 1. When the API has not been confirmed (if the retrieved API does not have a score of 0.6 or higher):

```
{'api_confirmed': 'false', 'api_status': 'none'}
```

- The API is not confirmed, so api_confirmed is set to false.
- Therefore, api_status is 'none'.
- If api_confirmed is false, api_status must be 'none'.

Case 2. When the API is confirmed (if the retrieved API has a score of 0.6 or higher):

```
{'api_confirmed': 'true', 'api_status': {'api_name': 'API1',
'required_parameters': {'param1': '', 'param2': 'value1'},
'optional_parameters': {'param3': ''}}}
```

- The API is confirmed, so api_confirmed is set to true.
- api_status contains the name of the API and the input parameter list needed for the API call. Any parameter whose value can be extracted from the dialogue history will have its value filled in.
- The 'param1', 'param2', and 'param3' in Case 2 are just example values. Do not use these parameters. Refer to the given API documentation on each turn.
- The input parameters should always be determined by consulting the API documentation. Do not hallucinate them.

Now, part of the dialogue will be given. Just generate the dialogue state in the given format, without adding any extra words.

Dialogue:

```
{dialogue_history}
```

Table 20: Instruction prompt for the Action prediction task

Action prediction task evaluation prompt

System

Instruction: You will be given part of a dialogue between the user and the system. In this dialogue, the user is requesting information from the system, and the system will execute an API call to retrieve the necessary information.

Your task is to predict the action that the system should take after the last utterance of the user. Read the dialogue history and return the one action that is most appropriate for the system to take next. The actions that the system can take are as follows:

- Request: Asks the user for some information.
- Response: Replies to the user's request based on the result of the API call.
- Clarify: If the user's query is vague, re-ask the user to specify their intent. If there is no API in the most recently retrieved results with a score above 0.5, "clarify" is required.
- Suggest: Makes a suggestion for an unclear user's intent and asks whether it satisfies the user. If there is an API in the most recently retrieved results with a score above 0.5 but none exceeding 0.6, a 'suggest' action is required.
- Response fail: Notifies the user that the system cannot execute the request due to insufficient information.
- System bye: Politely says goodbye to the user.
- Call: Calls the API with the collected information from the user or other sources but does not reply to the user yet.
- Retriever call: Calls the retriever to find the proper API to satisfy the user's request. The system should call the retriever in the following two situations:
    1. When the user specifies a requirement, and the system needs to search for an API to fulfill it.
    2. When the user does not provide the input parameters required for an API call, and the system needs to search for another API to obtain those parameters.

Of the eight actions given, return only the one that you think is most appropriate. Do not return any value other than the action provided above. Just return the action, not a single word more.

Dialogue History:

`{dialogue_history}`

Table 21: Instruction prompt for the Faithfulness task

Correctness task evaluation prompt

System

Instruction: You will be given part of a dialogue between the user and the system. In this dialogue, the user is requesting information from the system, and the system will execute an API call to retrieve the necessary information. Your task is to generate a response that satisfies the user's initial query based on the API call results provided in the dialogue history.

Dialogue History:

`{dialogue_history}`