

# API-Bank: A Benchmark for Tool-Augmented LLMs

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## Abstract

Recent research has shown that Large Language Models (LLMs) can utilize external tools to improve their contextual processing abilities, moving away from the pure language modeling paradigm and paving the way for Artificial General Intelligence. Despite this, there has been a lack of systematic evaluation to demonstrate the efficacy of LLMs using tools to respond to human instructions. This paper presents API-Bank, the first benchmark tailored for Tool-Augmented LLMs. API-Bank includes 53 commonly used API tools, a complete Tool-Augmented LLM workflow, and 264 annotated dialogues that encompass a total of 568 API calls. These resources have been designed to thoroughly evaluate LLMs' ability to plan step-by-step API calls, retrieve relevant APIs, and correctly execute API calls to meet human needs. The experimental results show that GPT-3.5 emerges the ability to use the tools relative to GPT-3, while GPT-4 has stronger planning performance. Nevertheless, there remains considerable scope for further improvement when compared to human performance. Additionally, detailed error analysis and case studies demonstrate the feasibility of Tool-Augmented LLMs for daily use, as well as the primary challenges that future research needs to address.

## 1 Introduction

Over the past several years, significant progress has been made in the development of large language models (LLMs), including GPT-3 (Brown et al., 2020), Codex (Chen et al., 2021), ChatGPT, and impressive GPT-4 (Bubeck et al., 2023). These models exhibit increasingly human-like capabilities, such as powerful conversation, in-context learning, and code generation across a wide range of open-domain tasks. Some researchers even be-

lieve that LLMs could provide a gateway to Artificial General Intelligence (Bubeck et al., 2023).

Despite their usefulness, however, LLMs are still limited as they can only learn from their training data (Brown et al., 2020). This information can become outdated and may not be suitable for all applications (Trivedi et al., 2022; Mialon et al., 2023). Consequently, there has been a surge in research aimed at augmenting LLMs with the ability to use external tools to access up-to-date information (Izacard et al., 2022), perform computations (Schick et al., 2023), and interact with third-party services (Liang et al., 2023) in response to user requests. Tool use has traditionally been viewed as uniquely human behavior, and the emergence of tool use has been considered a significant milestone in primate evolution, even serving to demarcate the appearance of the genus Homo (Ambrose, 2001). Analogous to the timeline of human evolution, we believe that at this current juncture, we must address two key questions: (1) How effective are current LLMs in using tools? (2) What are the remaining obstacles for LLMs to use tools?

In this paper, we introduce API-Bank, the first systematic benchmark for evaluating Tool-Augmented LLMs' ability to use tools. We imagine a vision where, with access to a global repository of tools, LLMs can aid humans in **planning** a requirement by outlining all the steps necessary to achieve it. Subsequently, it will **retrieve** the tool pool for the needed tools and, through possibly multiple rounds of API calls, fulfill the human requirement, thus becoming truly helpful and all-knowing. To achieve this goal, we first simulate the real-world scenario by creating 53 commonly used tools, such as SearchEngine, PlayMusic, BookHotel, ImageCaption, and organize them in an API Pool for LLMs to call. We then propose a complete workflow for LLMs to use these tools, which includes determining whether to call an API, which API to call, generating an API call, and self-assessing the

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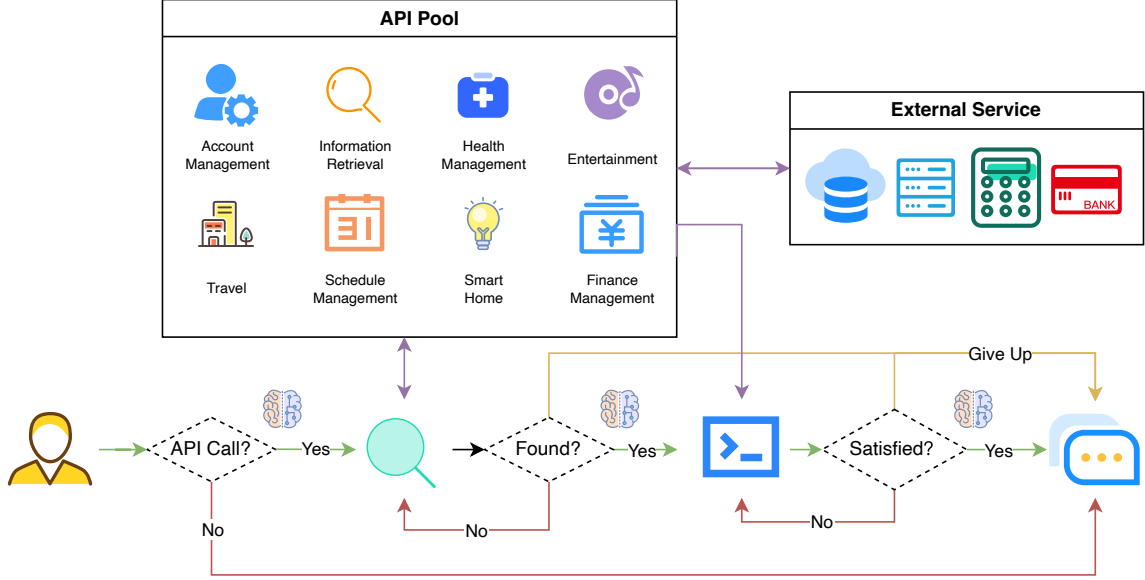


Figure 1: The proposed Tool-Augmented LLMs paradigm.

correctness of the API call. We further manually review 264 dialogues that contain 568 API calls, along with an automated scoring script to fairly evaluate each LLM’s performance in using tools. Similar to our vision, we divide all dialogues into three levels. Level-1 evaluates the LLM’s ability to call the API. Given an API’s description, the model needs to determine whether to **call** the API, call it correctly, and respond appropriately to its return. Level-2 further assesses the LLM’s ability to **retrieve** the API. LLMs must search for possible APIs that may solve the user’s requirement and learn how to use the API. Level-3 examines the LLM’s ability to **plan** API beyond retrieve and call. In this level, the user’s requirement may be unclear and require multiple API steps to solve. For example, "I want to travel from Shanghai to Beijing for a week starting tomorrow. Help me plan the travel route and book flights, tickets, and hotels." LLMs must infer a reasonable travel plan and call flight, hotel, and ticket booking APIs based on the plan, taking into account compatibility issues with time.

On our constructed API-Bank benchmark, we conduct experimental analysis for the first time on the effectiveness of popular LLMs in utilizing API tools. Our findings suggest that calling API is an emergent ability that shares similarities with math word problems (Wei et al., 2022). Specifically, we observe that GPT-3-Davinci struggles to call APIs in the simplest level-1 correctly. However,

with GPT-3.5-Turbo, the correctness of API calls dramatically improves, with around 50% success rate. Moving to level-2, which involves API retrieval, GPT-3.5-Turbo achieves a 40% success rate. However, when it comes to level-3, which requires API planning, GPT-3.5-Turbo encounters numerous errors, necessitating an average of 9.9 rounds of dialogue to complete user requests. This is approximately 38% more than what is required by GPT-4. Meanwhile, it should be noted that GPT-4 remains imperfections, as it utilizes approximately 35% more conversation rounds in API planning when compared to humans. We also provide a detailed error analysis to summarize the obstacles faced by LLMs when using tools. These include refusing to make API calls despite explicit instructions in the prompt and generating non-existent API calls. Overall, our study sheds light on the potential of LLMs to utilize API tools and highlights the challenges that need to be addressed in future research.

	level-1	level-2	level-3
Num of Dialogues	214	50	8
Num of API calls	399	135	34

Table 1: The statistics of API-Bank.

## 2 Tool-Augmented LLMs Paradigm

The existing works on Tool-Augmented LLMs usually teach the language model to use tools in two different ways: In-context learning and Fine-tuning. The former is to show the model the instructions and the examples of all the candidate tools, which can extend the general model directly but is limited by the context length. In comparison, the latter is fine-tuning the language model by annotated data, which has no length problem but will damage the robustness of the model. In this work, we mainly focus on in-context learning and solve its shortage of limited context length.

To address this issue, we design a new paradigm that may be the only solution to use a large number of tools under the context length limit. Figure 1 shows the flowchart of the proposed paradigm. This is an example process for a chatbot, and the paradigm can be generalized to any generative model application.

In the proposed paradigm, there is an API Pool containing various APIs focusing on different aspects of life, as well as a keyword-based API search engine to help the language model find API. Before starting, the model will be given a prompt to explain the whole process and its task, as well as how to use the API search engine.

In the longest path of the whole flowchart, the model needs to make several judgments (the diamonds in the Figure 1) as follows:

**API Call** After each user statement, the model needs to determine if an API call is required to access the external service, which requires the ability to know the boundaries of its knowledge or the need for outside action. This judgment leads to two different options: regular reply or starting the API call process. During the regular reply, the model could chat with people or try to figure out the needs of the user and plan the process of completing them. If the model already understands the user’s needs and decides to start the API call process, it will continue with subsequent steps.

**Find the Right API** To address the input limitations of the model, the model is given only the instructions of the API search engine at the beginning without any specific API introduction. An API search is required before every specific API call. When performing an API search, the model should summarize the demand of the user to a few keywords. The API search engine will look up the API pool, find the best match and return the related

documentation to help the model understand how to use it. The retrieved API may not be what the model needs, so the model has to decide whether to modify the keywords and search them again, or give up the API call and reply.

**Reply after API Call** After completing the API call and obtaining the returned results, the model needs to take action based on the results. If the returned results are expected, the model can reply to the user based on the results. If there is an exception in the API call or the model is not satisfied with the results, the model can choose to refine and call again based on the returned information, or give up the API call and reply.

The pseudo-code description of the complete API call procedure is as follows:

---

### Algorithm 1 API call process

---

```
1: Input:  $us \leftarrow UserStatement$ 
2: if API Call is needed then
3:   while API not found do
4:      $keywords \leftarrow summarize(us)$ 
5:      $api \leftarrow search(keywords)$ 
6:     if Give Up then
7:       break
8:     end if
9:   end while
10:  if API found then
11:     $api\_doc \leftarrow api.documentation$ 
12:    while Response not satisfied do
13:       $api\_call \leftarrow gen\_api\_call(api\_doc, us)$ 
14:       $api\_re \leftarrow execute\_api\_call(api\_call)$ 
15:      if Give Up then
16:        break
17:      end if
18:    end while
19:  end if
20: end if
21: if response then
22:    $re \leftarrow generate\_response(api\_re)$ 
23: else
24:    $re \leftarrow generate\_response()$ 
25: end if
26: Output:  $ResponseToUser$ 
```

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## 3 Benchmark Construction

### 3.1 System Design

The evaluation system mainly contains 53 APIs, supporting databases, and a ToolManager. The complete list of APIs is attached in Appendix A. The built system includes the most common needs of life and work. The other types of AI models are also abstracted in the form of APIs that can be used by the LLMs, which will extend the capabilities of specific aspects of the model. In addition, some operating system interfaces are included to allow models to control external applications.

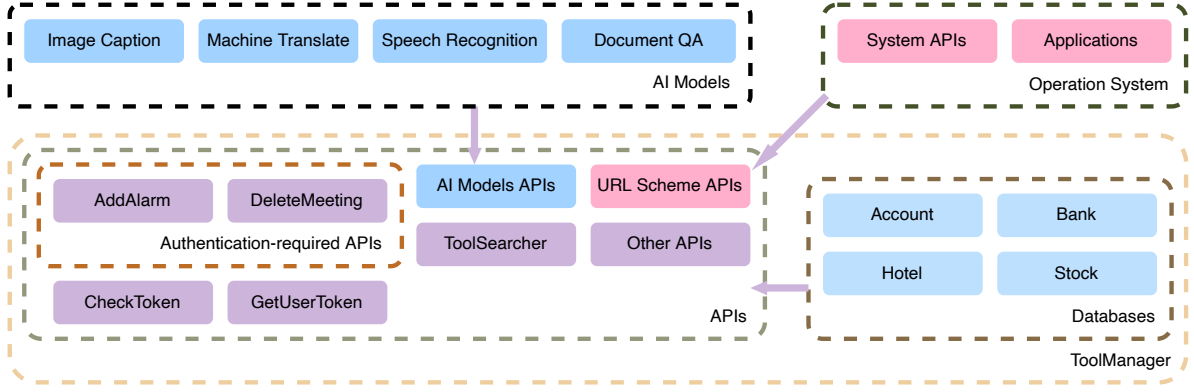


Figure 2: The diagram of the evaluation system.

### 3.1.1 Initial Database

There are several APIs that implement their functions by adding, deleting, modifying, and querying the database. The database increment type API does not require an initial database, while the other three APIs all require the database containing initial elements to implement their functionality. So we prepare initial databases for all the database-related APIs, while each database contains 10 items.

### 3.1.2 Tool Manager

We design a tool manager to ensure that the initial state of the test environment is consistent each time and that database changes are preserved during a round of conversations. During the evaluation, every dialogue requires creating a tool manager to ensure a consistent initial environment. If there are several API calls in the same dialogue, such as a sequence of AddReminder, ModifyReminder, and QueryReminder, the last QueryReminder could see the changes made by the ModifyReminder.

## 3.2 API Implementation

We have constructed around 53 APIs, such as search engines, calendar queries, smart home control, hotel reservations, etc. Each API comprises three categories of API description information: function description, input parameters, and output parameters. For the database-related API, they have a parameter that can be used to specify the database to be used.

As for the implementation details, all APIs need to implement the API interface, which requires them to implement two functions: “call” and “check\_api\_call\_correctness”. The former function is a wrapper for the real functional function, used for recording the input/output parameters and catch-

ing the exception for it, and should output all the information of this API call in the following format:

```
{
  'api_name': self.__class__.__name__,
  'input': input_parameters,
  'output': output_parameters,
  'exception': exception,
}
```

The above format is also the required input format of the “check\_api\_call\_correctness” function, a correctness verification function to compare the ground-truth and the predicted API call made by the model. By comparing the corresponding method name, input parameters, output parameters, and exceptions using the prescribed logic, the function determines whether the two API calls are equivalent. Since different APIs have different judgment logic for correctness, the correctness verification function for each API needs to be implemented independently. For example, ToolSearcher only needs to ensure that the output is consistent with ground-truth to be judged as correct, and does not need to impose restrictions on the keywords entered by the model. On the other hand, AddAlarm needs to check whether the input parameter (Time of the alarm clock) is exactly the same.

**Permission Identification** Some APIs involve manipulating the user’s personal database, such as AddAlarm, DeleteMeeting, etc. Due to security concerns, these APIs must authenticate the identification first. We simulate this process by requiring a token when calling these APIs. The token is a random alphanumeric combination of 18 digits unique to each user. The token and account information (username, password, email) are recorded in the “Account” database. For the evaluated model, if the

user wants to use these APIs, the model must ask the user for their account information, get the user token by calling “GetUserToken” API, and then pass the token as an input parameter to it.

**AI Models** As we said before, other AI models are also involved in the system, such as ImageCaption, SpeechRecognition, Translate, and DocumentQA. Regarding them as API interfaces, LLM does not need to know their model detail or end-to-end joint training. They only need to know their purpose and input/output formats, then can use these AI models to enhance specific aspects of capabilities.

**Operation System URL Scheme** in MacOS/iOS is a way to launch applications or perform specific actions within an application by clicking on a special link or URL. This functionality is similar to what is commonly known as deep links on Android. In this way, the LLMs can manipulate external applications. For now, we implement an API called “PlayMusic”, which will convert the input music name into an URL Scheme string and return it for evaluation, while the corresponding URL is executed directly in the real-world scenario.

### 3.3 Database Initialization

Database-related APIs include operations for querying, deleting, and modifying items in a database. As mentioned earlier, these operations require some initial elements to be included in the database to achieve functionality. We use ChatGPT for data augmentation to synthesize the initial data of the database by guiding it to generate valid API calls for adding items to the database. After that, we execute these calls in our system and record the added item as the initial data.

### 3.4 Dialogue Generation

Our dialogue generation process follows a model-generation-human-modification approach. First, one or multiple APIs of the same type are selected, along with their corresponding API descriptions, which are then used together with a carefully designed prompt to guide ChatGPT in generating a dialogue between users and AI. It is important to note that, aside from the information contained in the API descriptions (e.g., name, functionality, input, and output parameter descriptions), the model is not aware of the implementation logic and content of the database associated with the API. So it needs to make up the inputs to the API and speculate on the corresponding outputs.

However, in order to generate a correct CRUD (create, read, update, delete) type of API call without exception, it is necessary to provide the ChatGPT with at least one item in the database as a reference. Otherwise, the randomly generated API calls are likely to result in errors due to the inability to locate the corresponding item in the database. Therefore, for these types of API calls that require access to a database, we randomly append an item from the database in the prompt for use in the dialogue as needed.

All synthesized dialogues are manually checked for the format, logical consistency, and whether the API calls are reasonable. For example, the generated API calls containing information that is not mentioned at all in the dialog will be dropped. Roughly 50% of the data is dropped during data synthesis.

Since ChatGPT can only speculate on the return value of the API based on the API description provided, there are bound to be differences with the return value of the real call. We must actually run the generated API calls in the system to get the real call results as ground-truth. Any dialogue with incorrectly formatted API calls will be discarded, while those API calls raising exceptions during the execution will be stored for future work.

## 4 Evaluation

In level-1 and level-2, we have a fixed conversation history in our dataset. In this work, we do not focus on ordinary conversation evaluation, but only on the correctness of the API call and the first AI response after the API call.

In level-3, we provide only scenarios and several ground-truth API calls to finish the demands of the user. This test is conducted by human testers and is designed to test the planning ability.

### 4.1 API Call

When evaluating API calls, we give the history of all conversations up to the API call and a prompt with explicit hints to guide the model to make the API call in the prescribed format.

In this process, we evaluate the model’s proficiency in two aspects: (1) determining whether to call the API, and (2) calling the API correctly. To evaluate the model’s ability to determine when to call the API, we provide an explicit hint prompt and check if the model can successfully complete the API call. If the model fails to do so, we con-



sider it lacks the ability to determine when to call the API. To assess the model's ability to call the API correctly, we will detect and parse the API call in the response of the model. After successfully parsing, the predicting API call will be launched in our system and record the corresponding output. The API prediction will be verified by the check function of the corresponding API.

In level-1, the documentation of used APIs in the dialogue will be given in the prompt. In level-2, only that of the ToolSearcher will be given. The ToolSearcher also implements the API interface and will be involved in the evaluation. The prompt for API call evaluation is shown in Figure 3.

*Based on the given API description and the existing conversation history 1..t, please generate the API request that the AI should call in step t+1 and output it in the format of [ApiName(key1='value1', key2='value2', ...)], replace the ApiName with the actual API name, and replace the key and value with the actual parameters.*  
*Your output should start with a square bracket "[" and end with a square bracket "]". Do not output any other explanation or prompt or the result of the API call in your output.*  
*This year is 2023.*

**Input:**  
 User: [User's utterance]  
 AI: [AI's utterance]

**Expected output:**  
 [ApiName(key1='value1', key2='value2', ...)]

**API descriptions:**

Figure 3: The level-1 prompt.

## 4.2 Response After API

The model's responses after receiving the returned results from the API are very crucial since they can reflect if the model can understand the API output. We use the first AI reply after the API call in the generated conversation as the ground-truth. However, the ground-truth can only respond to one form of the correct response, and reasonable responses may not be limited to this one. We are still exploring more reasonable methods of evaluation. For the time being, we evaluate it by measuring the similarity between the generated responses and the ground-truth responses. The prompt for response evaluation is shown in Figure 4.

*Based on the given API description and the existing conversation history 1..t, please generate the next dialog that the AI should response after the API call t.*

*This year is 2023.*

**Input:**

User: [User's utterance]

AI: [AI's utterance]

[ApiName(key1='value1', key2='value2', ...)]

**Expected output:**

AI: [AI's utterance]

**API descriptions:**

Figure 4: The level-2 prompt.

## 4.3 Planning

The Figure 5 shows a level-3 example. This is an instruction prepared for the human testers, whose responsibility is to play the virtual role in the instruction, answer the questions from the model, and ultimately guide the model to complete all the ground-truth API calls. All conversations played out randomly during the evaluation. We evaluate the model's ability to plan by comparing the total amount of dialogue turns for completing all the API calls. To determine the upper limit of this evaluation, we measure human performance for reference purposes. The human and the model are guaranteed to have the same prior knowledge. The testers are given the same prompts as the evaluated models and are guaranteed to be unaware of the other details of the test.

## 4.4 Metrics

For the API call evaluation, we use the Accuracy metric. The Accuracy metric is defined as the number of correct predictions divided by the total number of predictions.

For the response after API evaluation, we use the Rouge metric. The ROUGE-L is a metric used to evaluate the quality of text based on the concept of Longest Common Subsequence (LCS).

The evaluation goal for planning is leading the model to complete the demand of the user as soon as possible. The sign of completion is that the model successfully finished the ground-truth API calls with exactly the same parameters. Therefore, the metric of level-3 is set to the minimal number of turns between the user and the model.

**Scenario:** Meeting schedule

**First Utterance:** Can you please do a meeting booking for me?

**Key Info:**

- Name: John Doe
- Password: pass123
- Email: johndoe@example.com
- Meeting Topic: Quarterly Sales Review
- Start Time: 2023-04-15 09:00
- End Time: 2023-04-15 11:00
- Location: Conference Room 2
- Attendees: ["JohnDoe", "AliceSmith", "BobJohnson"]

**GT API Calls:**

1. [GetUserToken(username="JohnDoe", password="pass123")]
2. [AddMeeting(token="a9s8d7f6g5h4j3k2l1", meeting\_topic="Quarterly Sales Review", start\_time="2023-04-15 09:00:00", end\_time="2023-04-15 11:00:00", location="Conference Room 2", attendees=["JohnDoe", "AliceSmith", "BobJohnson"])]
3. [QueryMeeting(token="a9s8d7f6g5h4j3k2l1", meeting\_topic="Quarterly Sales Review", start\_time="2023-04-15 09:00:00", end\_time="2023-04-15 11:00:00", location="Conference Room 2", attendees=["JohnDoe", "AliceSmith", "BobJohnson"])]

Figure 5: Example of the level-3.

## 4.5 Frontend and Backend Issues

The evaluation in level-3 can be nearly regarded as a simulation of the realistic application. The current ChatGPT-like interaction model essentially has only two sides, which we will call “INPUT” and “OUTPUT” for now. But in practical applications, we need an intermediary, or a wrapper, to pass the chat between the model and the user (Frontend), as well as help the model to interact with the API (Backend). In fact, the “INPUT” should forward the user utterance and the API response to the model. And the “OUTPUT” should forward the bot utterance to the user and pass the API call to the service provider. To address this issue, we explain the whole system in the prompt and require both parties need to indicate the role of the current message in their reply. The prompt of level-3 is shown in Figure 6.

## 5 Experiments

### 5.1 Baselines

GPT-4, GPT-3.5-Turbo, and GPT-3 Davinci are the most advanced natural language processing models developed by OpenAI, a leading research organization in the field of AI. These models are based on the GPT architecture, which is known for its large size and impressive language generation capabilities.

GPT-3 Davinci is the largest and most powerful variant of the GPT-3 family of models. It has been trained on a massive amount of text data and is capable of generating coherent and contextually

relevant responses to a wide range of prompts.

GPT-3.5 models can understand and generate natural language or code. The GPT-3.5-Turbo is the most capable and cost-effective model in the GPT-3.5 family, which has been optimized for chat but works well for traditional completion tasks as well.

GPT-4 is OpenAI’s latest and most advanced language model, which is also a large multimodal model that can accept both image and text inputs and generate text outputs.

### 5.2 Results

We conducted experiments on the Davinci and GPT-3.5-Turbo models. The GPT-4 series was absent from the level-1 & level-2 evaluation since we did not have access to the API of GPT-4 to perform efficient batch testing. The experimental results of level-1 & level-2 are shown in Table 3. For API correctness, the model GPT-3.5-Turbo performs significantly better than the Davinci model, while the latter shows nearly no understanding of how to give API calls. For the dialogue generation after the API call, the GPT-3.5-Turbo model still outperforms the Davinci model, but the margin in level-1 is not as much as that in comparison to API correctness. It shows that the Davinci can read API calls and the results returned, but no ability to create an API call.

The GPT-3.5-Turbo shows relatively good performance on API-Bank, but there is still a lot of room for improvement. We conduct some detailed statistical analysis on the failure of the GPT-3.5-

You will be given a API box, including a set of APIs, such as Calculator, Translator, WikiSearch, etc. When you want to use a API, you must search it by keywords in a API search engine. Try to describ it by these keywords. Then the tool search engine will return you the most related tool information (api name, description, input/output parameters). You need use the tool following the returned information.

I am a client to help you communicate with the user (front stage), as well as help you communicate with the API (back stage). I will forward your response to the right receiver, it requires you to declare the recipient of your reply (User or API) before each reply.

During the dialogue with the user, you can always use the tool search engine (format: **[ToolSearcher(keywords='keyword1 keyword2 ...')]**) to search the tool you need. This searching process is invisible to the user. If the information is beyond your knowledge, call the API for queries if possible.

Here is an example for API search, ChatGPT represent you, and Client represent me.

#### Example:

Client: (User) Can you help me calculate (5+3)\*6?

ChatGPT: (API) [ToolSearcher(keywords='calculator')] (wait for the result)

Client: (API) {"name": "Calculator", "description": "This API provides basic arithmetic operations: addition, subtraction, multiplication, and division.", "input\_parameters": {"formula": {"type": "str", "description": "The formula that needs to be calculated. Only integers are supported. Valid operators are +, -, \*, /, and (, ). For example, '(1 + 2) \* 3'."}}, "output\_parameters": {"result": {"type": "float", "description": "The result of the formula."}}}

ChatGPT: (API) [Calculator(formula='(5+3)\*6')] (wait for the result)

Client: (API) {'result': 48}

ChatGPT: (User) The result of (5+3)\*6 is 48.

**Now, we start. The following is the first utterance of Client:**

Figure 6: The level-3 prompt.

API	GetUserToken	EmergencyKnowledge	DeleteAccount	AddAgenda	QueryBalance	Total
Count	33	12	11	11	11	181

API	ToolSearcher	GetUserToken	SymptomSearch	DeleteAccount	AddAgenda	Total
Count	34	12	8	3	2	80

Table 2: Top 5 error rate APIs in level-1 & level-2.

Model	level-1	level-2
GPT-3.5		
- API correctness	54.64%	40.74%
- dialog after API	0.4622	0.3445
Davinci		
- API correctness	0.50%	1.48%
- dialog after API	0.1035	0.091

Table 3: The result of several baselines on API-Bank. (The metric for API correctness is Accuracy and that for dialog after API is Rouge-L)

	GPT-3.5	GPT-4	Human
Shopping	10	10	7
Reminder	13	5	4
Personal Assistant	16	7	5
Meeting Schedule	7	5	4
Hospital	8	11	6
Health Management	10	7	6
Financial Management	8	5	4
Hotel Booking	7	8	7

Table 4: The results of GPT-3.5, GPT-4, and humans on the level-3.

Turbo model. According to Table 2, the APIs with the highest error rate in level-1 and level-2 are GerUserToken and ToolSearcher, both of which require the model the ability of multiple rounds of calls. This suggests that GPT-3.5 may have difficulty handling inter-dependencies between APIs.

Table 4 presents the results obtained by GPT-3.5-Turbo, GPT-4, and humans on level-3, which

represents the minimum number of turns required to complete all ground-truth API calls. In most scenarios, GPT-4 outperforms GPT-3.5-Turbo and can more efficiently plan and fulfill user needs. While GPT-4 achieves impressive results compared to human performance, it still requires approximately 35% more dialogue turns to accomplish the task. Due to the introduction of uncertainties by testers in this experiment, the results should be considered



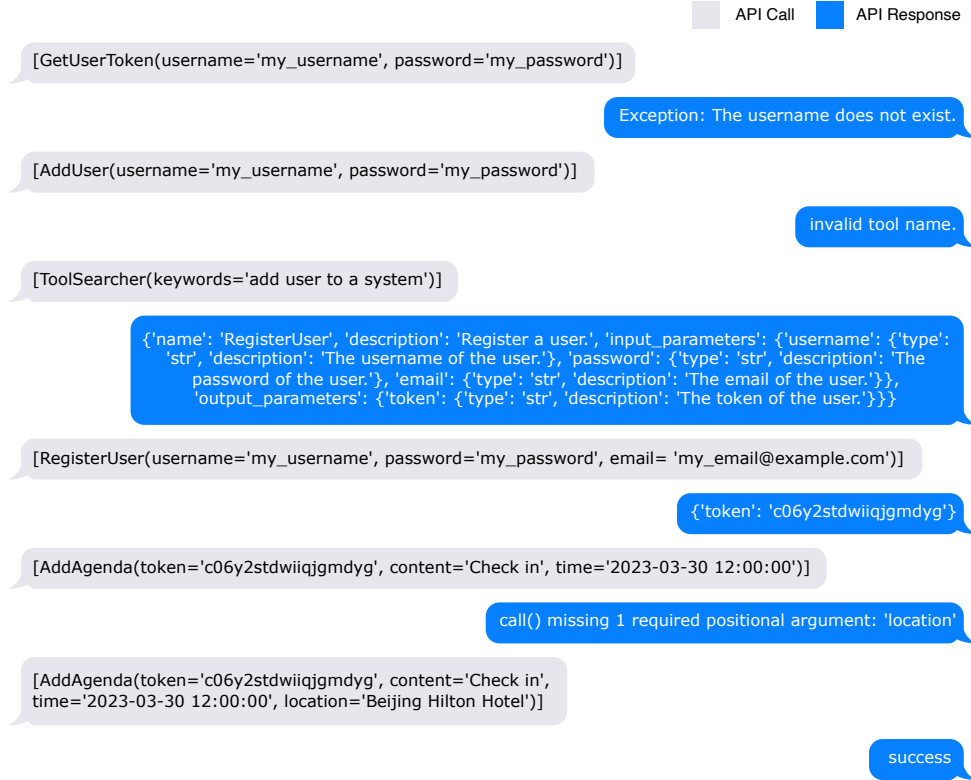


Figure 7: Sample case of the GPT-3.5 model on level-3.

for reference purposes only, and we are exploring more reasonable metrics. In this study, we also conducted a case-by-case analysis, which is presented in the following section.

### 5.3 Case Study

Mistake Type	level-1	level-2
No API Call	127	36
Input Value Mismatch	26	10
API Mismatch	17	30
Input Key Error	11	4
Total	181	80

Table 5: Error cause statistics of GPT-3.5 at level-1 & level-2.

We manually go through and count all the mistakes the GPT-3.5-Turbo model made on level-1 and level-2, and the result shows in Table 5. The most common mistake is that no API call is found in the model response. The model may respond in the following ways: answer directly based on their knowledge, confirm with the user again, explain to the user that an API call is about to be made,

ask the user directly for information that should be queried through the API, etc. Some responses may be reasonable in the normal dialogue between the user and assistant, but we still regard them as false predictions since quite clear instructions have been given in the prompt to make an API call.

The second most popular mistake is the API mismatch, particularly in level-2. The reason for most of these errors is that instead of using ToolSearcher for API search, the model makes up an API name. Or the authentication-required API was used directly without using GetUserToken to authenticate at first.

We also go through the chat history of all the level-3 tests. GPT-3.5-Turbo shows some advantages in talking to users, making API calls, and fulfilling user requirements. First, GPT-3.5-Turbo can refine the ToolSearch query when the returned API candidate is far from what is actually needed. Second, if the required information for an API call has already appeared in the chat history, GPT-3.5-Turbo will call the API directly instead of asking the user again. Third, the model is good at converting the information obtained into the required format.

The GPT-3.5-Turbo also manifests some very serious problems. First, after retrieving the API document, the model sometimes tends to make up the missing input parameters for calling the API directly instead of asking the user. Second, the model is not good at summarizing the user needs as keywords, which leads to bad performance in ToolSearcher. Third, the model still has difficulty understanding the fact that it can make API calls. Instead, it asks the user to call the API. Fourth, the model has serious logic errors and is limited to solving the current issues while ignoring the overall goal. During the level-3 evaluation, the model will be given the response from the API call, even when an exception is raised. The model will use some unexpected ways to solve the exception.

Figure 7 shows a sample case of the GPT-3.5-Turbo model, which is an intercepted part that the model tries to help the user to add an agenda from a complete conversation. The left side comes from the model, and the right side represents the responses from APIs. The model has been given only the documentation of the “GetUserToken”, “AddAgenda” APIs in the chat history without knowing the account information of the user. At the beginning of this part, the model makes up a pair of username and password, and try to get their token. This attempt fails because there is no information about this account in our initial database. After that, the model creatively try to add this made-up account instead of asking the user for real account information. Coincidentally, it searched through the search tool and found an API we provide for adding accounts, which is unexpected by us. Finally, it registered the made-up account and added this calendar for this account, not the user’s account.

From this example, we can conclude that GPT-3.5-Turbo has the ability to iteratively improve its API calls based on the results of the calls evenly to resolve some exceptions. However, it also reflects the stereotyped logic of the model. The ability is limited to solving current problems without judging whether the way of solving them makes sense for the ultimate goal.

## 6 Related Work

Recent research in language modeling has explored the use of external tools to supplement the knowledge stored in the model’s weights. This approach allows for tasks such as exact computation or in-

formation retrieval to be offloaded to external modules such as a Python interpreter or a search engine, which are queried by the model (Mialon et al., 2023). These tools can include other neural networks or even the language model itself. Socratic Models, introduced by Zeng et al.2022, is a modular framework that allows for the composition of different pre-trained models on various modalities. Alternatively, natural language knowledge can be retrieved from external sources, as demonstrated by WebGPT (Nakano et al., 2021) and ReAct (Yao et al., 2022) through the use of search APIs. Other approaches, such as Toolformer (Schick et al., 2023) and ART (Paranjape et al., 2023), leverage a combination of search APIs, question-answering APIs, machine translation APIs, calculators, and other tools to solve various NLP tasks. ChatGPT Plugins<sup>1</sup> and TaskMatrix.AI (Liang et al., 2023) further demonstrate the potential for language models to integrate with thousands to millions of APIs. Despite the promising demonstrations of these approaches, there is currently no benchmark to systematically evaluate the ability of language models to use API tools. While we know that language models have this capability, there is a lack of quantitative metrics to assess it. In this paper, we propose API-Bank to address this challenge and answer two important questions through experimental analysis: (1) How effective are current language models in using tools? (2) What are the remaining obstacles for language models to use tools?

## 7 Conclusion

This paper introduces API-Bank, the first benchmark specifically designed for Tool-Augmented LLMs. It includes a comprehensive Tool-Augmented LLM workflow, 53 commonly used API tools, and 264 annotated dialogues, comprising a total of 568 API calls. Through experimental results, this study quantitatively evaluates the performance of popular LLMs, such as GPT-3, GPT-3.5, and GPT-4, when using tools to fulfill human needs. The results demonstrate the practicality of augmenting LLMs with tools for everyday use and summarize the primary challenges that current LLMs face when utilizing such tools. Overall, the API-Bank benchmark provides a valuable resource for evaluating and advancing the state-of-the-art in Tool-Augmented LLMs. We believe that this research will inspire future studies in this field and

<sup>1</sup><https://openai.com/blog/chatgpt-plugins>

pave the way for the development of more sophisticated AI systems that can intelligently incorporate external resources to meet human requirements.

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## A Appendix

The APIs implemented in API-Bank are listed in the following:

- **Tool Search**
  - ToolSearcher
- **Account Management**
  - RegisterUser
  - DeleteAccount
  - ModifyPassword
  - ForgotPassword
  - CheckToken
  - GetUserToken
- **Information Query and Processing**
  - QueryHistoryToday
  - SearchEngine
  - Wiki
  - Dictionary
  - ImageCaption
  - SpeechRecognition
  - Translate
  - DocumentQA
  - SendEmail
  - Calculator

- **Health Management**

- QueryHealthData
- SymptomSearch
- EmergencyKnowledge
- AppointmentRegistration
- CancelRegistration
- ModifyRegistration
- QueryRegistration
- RecordHealthData

- **Entertainment**

- PlayMusic

- **Travel**

- BookHotel

- **Schedule Management**

- AddReminder
- DeleteReminder
- ModifyReminder
- QueryReminder
- AddMeeting
- DeleteMeeting
- ModifyMeeting
- QueryMeeting
- AddAgenda
- DeleteAgenda
- ModifyAgenda
- QueryAgenda
- AddAlarm
- DeleteAlarm
- ModifyAlarm
- QueryAlarm
- GetToday

- **Smart Home**

- AddScene
- DeleteScene
- ModifyScene
- QueryScene
- TimedSwitch
- CancelTimedSwitch

- **Finance Management**

- OpenBankAccount
- QueryStock
- QueryBalance