EasyTool: Enhancing LLM-based Agents with Concise Tool Instruction

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Abstract

There has been a rising interest in utilizing tools in applications of autonomous agents based on large language models (LLMs) to address intricate real-world tasks. To develop LLM-based agents, it usually requires LLMs to understand many tool functions from different tool documentations. However, these documentations could be diverse, redundant, or incomplete, which immensely affects the capability of LLMs in using tools. To solve this, we introduce EasyTool, a framework transforming diverse and lengthy tool documentation into a unified and concise tool instruction for easier tool usage. EasyTool purifies essential information from extensive tool documentation of different sources, and elaborates a unified interface (*i.e.*, tool instruction) to offer standardized tool descriptions and functionalities for LLM-based agents. Extensive experiments on multiple different tasks demonstrate that EasyTool can significantly reduce token consumption and improve the performance of LLM-based agents on tool utilization in real-world scenarios. Our code is available at https://github.com/microsoft/JARVIS/tree/main/easytool.

1 Introduction

Large language models (LLMs) OpenAI (2023); Touvron et al. (2023a;b); Team & Google (2023) have recently ignited the spark of LLM-based autonomous agents Shen et al. (2023a); Gravitas (2023), which aim to interact with the real-world scenarios and address complex user requests. A rising trend in enhancing their effectiveness is to endow them with the capability of using external tools Schick et al. (2023); Shen et al. (2023a); Qin et al. (2023). To bridge the gap between LLMs and tool usage, agents usually first analyze a user request, conduct planning or reasoning to decompose it into sub-tasks, and then select the most suitable tools for execution to obtain the final answer. Therefore, improving LLMs' capability to use tools precisely has been critical to developing an autonomous agent.

Previously, some researchers Schick et al. (2023); Qin et al. (2023); Patil et al. (2023); Parisi et al. (2022); Hao et al. (2023) fine-tune open-source LLMs to generate calling functions to use tools. However, these methods usually require additional datasets with tool use for training, cannot be extended to widely deployed black-box LLMs (*e.g.*, ChatGPT OpenAI (2022; 2023) and Gemini Team & Google (2023)), and lack flexibility in integrating external tools in a plug-and-play way. Another line of work Shen et al. (2023a); Song et al. (2023); Lu et al. (2023); Xu et al. (2023) retrieves and calls external tools by providing tool documentation and few-shot demonstrations of tool functionality. However, these methods struggle with limited context length and face difficulties when handling unusual tools, and thus hinder the development of an omnipotent LLM-based agent. Therefore, extensive effort is still required to efficiently and effectively improve the quality of tool utilization.

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For tool utilization, tool documentation plays an indispensable component, which could include multiple meta information like tool descriptions, tool parameters, demonstrations and so on. However, as shown in Figure 1, we summarize the issues from existing documentation that could hinder the tool utilization of LLM-based agents:

- *Inconsistency*: Massive tools from different sources often have inconsistent and diverse documentation formats, posing new challenges for LLMs to understand;
- *Redundancy*: Tool documentation could encompass massive redundant and useless information, making it harder to grasp tool functionality and resulting in excessive token consumption in prompts;
- *Incompleteness*: We expect the tool documentation to provide useful information to describe its functions, parameters and demonstrations for instructions. However, the absence of critical information in some tool documentations impedes effective tool utilization.

Overall, we regard the information provided by tool documentation as a critical element in instructing LLMs to use tools. However, the above issues in tool documentation bring some challenges to LLM-based agents to understand, especially considering the increasing of massive and diverse tools from different domains. Therefore, how to parse the documentation, extract the most essential information and provide a unified format has become a necessary topic to effectively use tools.

In this paper, we introduce EASYTOOL, an easy and effective method to create clear, structured, and unified instructions from tool documentations for improving LLM-based agents in using tools. High-quality tool instructions should follow two criteria: easy to 1) understand its functionality for selection and 2) predict its parameters for usage. To this end, we first collect massive tool documentations from different sources (*e.g.*, RestBench Song et al. (2023) and ToolBench Qin et al. (2023)). Instead of directly using these various tool documentations with different complicated structures, we transform these documentations into a more concise and unified tool instruction, which includes standard *tool descriptions* and guidelines for *tool functionality*. The converted tool descriptions can eliminate irrelevant content and only keep the core functionality of each tool for LLMs to attend to. Moreover, EASYTOOL provides detailed information for tool usage (*e.g.*, its parameters with demonstrations generated by Chat-GPT OpenAI (2022)) in tool functionality guidelines to instruct LLMs with tool usage.

Figure 1: An illustration of the proposed EASY-TOOL, and some issues in tool documentation, *e.g.*, Inconsistency, Redundancy, Incompleteness. The documentations can be polished and refined by EASYTOOL into more concise and effective tool instructions for better tool usage.

Extensive experiments on multiple datasets demonstrate these concise tool instructions generated by EASYTOOL can significantly reduce incorrect tool usage. Furthermore, we also prove that the capability of EASYTOOL can be generalized to open-source LLMs in a plug-and-play way and greatly improve their performance on tool utilization in different real-world scenarios. Our contributions can be summarized as:

- We analyze and explore the limitations of current tool utilization in LLM-based agents and first point out the deficiencies of tool documentation that hinder LLMs in using tools.

- To address these issues, we propose EASYTOOL, which creates high-quality tool instructions from documentation to facilitate tool usage in LLM-based agents.

- Experimental results on three datasets from distinct domains show that our EASYTOOL effectively and efficiently improves the capability of LLMs in tool utilization.
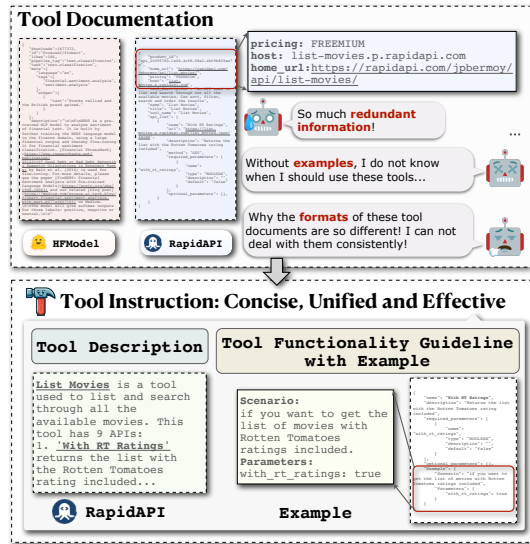
2 RELATED WORK

With the emergence of powerful LLMs OpenAI (2023); Touvron et al. (2023a;b), using tools has been considered a new trend to enhance the capabilities of LLMs A conventional strategy is to build synthetic data Schick et al. (2023); Qin et al. (2023); Li et al. (2023); Patil et al. (2023); Shen et al. (2023b) involved tool use and then fine-tune LLMs to generate text with tool invocation. However, these methods cannot be extended to some powerful closed LLMs, and lack the capability to use new tools. Although some methods Hao et al. (2023) attempted to fine-tune LLMs to obtain tool embeddings for plug-and-play usage, they still require additional data for training to get tool embeddings.

Therefore, there has arisen another branch Shen et al. (2023a); Song et al. (2023); Gravitas (2023) that directly used LLMs as the controller and feed tool descriptions into prompts to instruct LLMs to understand and call tools. These methods do not need extra training and can use external tools in a plug-and-play paradigm, but they are limited to context sizes and the quality of tool documentation. As a result, these methods will lead to some failed or incorrect tool invocation Zhang et al. (2023). Some work Hsieh et al. (2023); Xu et al. (2023) attempts to revise tool documentation to support a zero-shot tool utilization, but some inherent issues of tool documentation in real-world scenarios still hinder the effective and efficient usage of many tools. Besides, different from naive prompt compression Mu et al. (2023); Jiang et al. (2023b), which is only suitable to compress plain prompt, the streamlined information from tool documentation should satisfy specific format and need to confirm the accuracy of tool invocation when processing user requests.
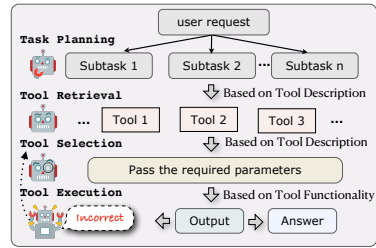

Figure 2: The four-stage framework of LLM-based agents in tool-usage applications.

3 PRELIMINARY

In this section, we first present the formulation to define the tool utilization in LLM-based agents and the limitations.

3.1 TASK FORMULATION

Motivated by previous works (Shen et al., 2023a; Song et al., 2023), just as shown in Figure 2, the pipeline of LLM-based agents for tool utilization can be summarized as a four-stage framework as:

- **Task Planning:** Agents analyze a user request $\mathcal{T}$ and decompose it into subtasks $\mathcal{T} = \{t_1, t_2, ..., t_n\}$ with specific dependencies and execution orders, each optimized for execution with a single tool.

- **Tool Retrieval:** Here, the focus is on matching these subtasks with suitable tools from the tool inventory based on the similarity between the subtasks and tools. The aim is to select the top-K tools $\{a_1, a_2, ..., a_K\}$, that have the highest similarity to each subtask, forming a set of candidate tools for each.

- **Tool Selection:** In this stage, the most appropriate tool for each subtask from the set $\{a_1, a_2, ..., a_K\}$ is chosen based on its description. This stage also includes preparing the parameters for tool execution, as specified in its document.

- **Tool Execution:** After tool selection and parameter setup, the tool is executed. If a tool fails during execution, the process reverts to the tool selection stage for an alternative choice. This retry mechanism continues until successful execution or until the maximum trial $\mathcal{R}$ is reached.

After these stages, agents can orchestrate different tools and use their powers to generate the final answer for each user request.

3.2 ANALYSIS

Previous studies typically adhere to the established paradigm, instructing LLMs with the tool documents to use tools. However, we argue that relying on the tool document can hinder the performance of LLM-based agents due to its inherent limitations.

Inconsistency In the real world, a wide variety of tools from different sources results in substantial diversity in terms of format, style, and guidelines. As a result, this diversity contributes to a mess of tool documentations without a cohesive and standardized structure, posing a significant challenge for LLMs to effectively use these tools.

Redundancy Generally, the tool documents from different communities usually contain redundant information (*e.g.*, URLs, IDs, and etc). In practical application, we just require LLMs to understand the core function of the tool and then decide whether to use and how to use this tool. As shown in Table 1, we analyze multiple tool-based benchmarks that reveal a high proportion of redundant information in many tool documentations. For example, the average length of tool documentations used in Tool-Bench is approximately 2,530 tokens

Table 1: The statistics of tool documentations in tool benchmarks. We report the average length of the tool description with parameters ($\text{Token}_{\texttt{Desc.}}$), the average length of the tool documentations ($\text{Token}_{\texttt{Doc.}}$) and whether the benchmarks have tool usage scenarios and example (**Exp.**).

Dataset	$\text{Token}_{\texttt{Desc.}}$	$\text{Token}_{\texttt{Doc.}}$	Exp.
RestBench (Song et al., 2023)	58	3,881	✗
Gorilla (Patil et al., 2023)	88	284	✗
ToolAlpaca (Tang et al., 2023)	567	7,661	✗
ToolBench (Qin et al., 2023)	744	2,530	✗
HFmodels (Shen et al., 2023a)	777	1,196	✓

in Table 1.[1] This useless information can severely hinder LLMs from retrieving and selecting tools, leading to an incorrect tool invocation. Moreover, LLMs are constrained by a maximum context length, yet tool documentations are typically lengthy. This excessive length can limit the range of tool options available for LLMs to consider, posing a challenge for efficient tool selection.

Incompleteness Previous work has demonstrated that LLMs may pass invalid parameters, leading to tool execution failure (Song et al., 2023; Qin et al., 2023; Zhang et al., 2023; Shen et al., 2023b). As shown in Table 1, unlike human-oriented instruction manuals that provide usage scenarios and examples, existing tool documentations typically lack such context, only offering example codes for tool invocation or results. This leads to LLMs struggling to know when and how to refer to the examples to pass the correct parameters, resulting in invalid parameters.

4 METHOD

As aforementioned, polishing, streamlining, and enhancing the tool documentation is important to improve tool utilization in LLM-based agents. In this paper, we introduce EASYTOOL, a simple method to condense tool documentation into more concise and effective tool instructions. The overall workflow is illustrated in Figure 1. Our framework comprises two stages: the first stage is to re-organize the original tool documentation by eliminating the irrelevant information and only keeping the function description of each tool (§ 4.1). Afterwards, for each tool, we further design a functional-guideline instruction for LLMs and enable LLMs to further refine the tool documentation by providing parameters of each tool and simultaneously the examples to instruct LLMs for usage (§ 4.2).

4.1 TOOL DESCRIPTION GENERATION

As described above, tool documentation usually includes plenty of irrelevant information that makes it difficult to understand practical usage for LLMs. Moreover, some tools that enable multiple built-in functions for different scenarios are not always comprehensively described. For instance, Google Maps offers both distance calculations and coordinate provision, but its description might not cover

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[1]We adopt `cl100k_base` encoding. The code is in `https://github.com/openai/tiktoken`.

I: Tool Description Generation

/ I: Task prompt */*
Your task is to create a concise and effective tool usage description based on the tool documentation. You should ensure the description only contains the purposes of the tool without irrelevant information.
Here is an example:
/ Examples */*
`{Tool Documentation}`
Tool usage description:
`{Tool_name}` is a tool that can `{General_Purposes}`.
This tool has `{Number}` multiple built-in functions:
1. `{Function_1}` is to `{Functionality_of_Function_1}`
2. `{Function_2}` is to ...
/ Auto generation of tool description */*
`{Tool Documentation of 'Aviation Weather Center'}`
Tool usage description:
'Aviation Weather Center' is a tool which can provide official aviation weather data...

II: Tool Function Guidelines Construction

/ Task prompt */*
Your task is to create the scenario that will use the tool. 1. You are given a tool with its purpose and its parameters list. The scenario should adopt the parameters in the list. 2. If the parameters and parameters are both null, you should set: `{"Scenario":XX, "Parameters":{}}`. Here is an example:
/ Examples */*
`{Tool_name}` is a tool that can `{General_Purposes}`.
`{Function_i}` is to `{Functionality_of_Function_i}`
`{Parameter List of Function_i}`
One scenario for `{Function_i}` of `{Tool_name}` is: `{"Scenario":XX, "Parameters":{XX}}`
/ Auto-construction for Tool Function Guidelines */*
'Ebay' can get products from Ebay in a specific country. 'Product Details' in 'Ebay' gets the product details for a given product id and a specific country.
`{Parameter List of 'Product Details'}`
One scenario for 'Product Details' of 'Ebay' is:
{"Scenario": "if you want to know the details of the product with product ID 1954 in Germany from Ebay", "Parameters":{"product_id": 1954, "country": "Germany"}}.

Table 2: Examples of prompt for ChatGPT for tool description generation and tool function guidelines construction. *Green texts* are generated by ChatGPT.

all functionalities. To address this, we expect to use LLMs to polish and streamline these tool documentations and decode them into more concise and effective tool descriptions. Here, just as shown in Table 2 (I), we design an instruction and require LLMs (*i.e.*, ChatGPT) to convert tool documentation to summarize its general purpose by following the designed instruction. We also add extra demonstrations into the instruction to enhance the instruction-following of LLMs in parsing tool documentation.

4.2 TOOL FUNCTIONALITY GUIDELINES CONSTRUCTION

The tool descriptions generated in the previous step aid LLMs in tool retrieval and selection. However, we still need to predict the correct parameters of each tool for a successful execution. Previous work Qin et al. (2023); Zhang et al. (2023); Xu et al. (2023) also confirms that many open-source LLMs are still inadequate in executing tools, resulting in parameter errors. Therefore, we further polish our tool descriptions in the first stage to supplement the parameters in the tool instructions. Here, we design another instruction that requires LLMs to extract parameters from tool documentation and then organize it into a structured output, thus facilitating LLMs to invoke tools. As shown in Table 2 (II), we use ChatGPT to create examples, including scenarios and parameter names with values to demonstrate how to input parameters for different scenarios and enhance LLMs to precisely use tools. To verify the quality of generated examples for the tool functionality guidelines, we input the parameters to execute the tools to confirm the correct input of parameters and the accuracy of results.

Table 3: Results of LLMs on ToolBench. Win rate (denoted as **Win**) is calculated by comparing each model with ChatGPT-ReACT. The win rate higher than 50% means the model performs better than ChatGPT-ReACT. Apart from adopting retriever (*i.e.*, +Re.), all methods use the ground truth toolset to select tools. The best results are **bolded**, and the second best ones are underlined.

Model	Method	I2-Category			I3-Instruction			Average		
		Pass	Win	Success	Pass	Win	Success	Pass	Win	Success
ChatGPT	ReACT	39.0	-	18.0	23.0	-	1.0	31.0	-	9.5
	DFSDT	64.5	63.0	24.0	60.0	70.0	6.0	62.3	66.5	15.0
	+EASYTOOL	74.5	76.5	68.5	65.0	88.0	37.0	69.8	82.3	52.8
	+EASYTOOL +Re.	69.0	71.0	60.5	66.0	89.0	42.0	67.5	80.0	51.3
ToolLLaMA-7B	ReACT	30.0	45.5	9.5	22.0	49.0	3.0	26.0	47.3	6.3
	DFSDT	66.0	55.0	24.0	56.0	56.0	6.0	61.0	55.5	15.0
	DFSDT+Re.	57.0	60.0	11.5	54.0	69.0	2.0	55.5	64.5	6.8
Vicuna-7B	ReACT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	DFSDT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	+EASYTOOL	72.5	77.0	40.5	68.0	81.0	34.0	70.3	79.0	37.3
	+EASYTOOL +Re.	75.0	68.0	46.5	67.0	85.0	36.0	71.0	76.5	41.3
Mistral-7B	ReACT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	DFSDT	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	+EASYTOOL	75.0	76.0	56.0	66.0	87.0	38.0	70.5	81.5	47.0
	+EASYTOOL +Re.	74.5	71.5	54.5	68.0	88.0	38.0	71.3	79.8	46.3
GPT-4	ReACT	67.5	53.5	27.0	40.0	71.0	4.0	53.8	62.3	15.5
	DFSDT	69.5	57.0	42.0	59.0	73.0	50.0	64.3	65.0	46.0
	+EASYTOOL	76.5	78.5	76.0	69.0	89.0	64.0	72.8	83.8	70.0
	+EASYTOOL +Re.	72.5	72.0	73.5	69.0	90.0	53.0	70.8	81.0	63.3

4.3 EVALUATION

To assess the quality of tool descriptions, we select 100 examples from ToolBench and employ three annotators to evaluate their accuracy. The results confirm the high accuracy of all generated tool descriptions. To assess the plausibility of the scenarios, we also sample 100 tool functionality guidelines from ToolBench and employ three annotators to evaluate the plausibility of the scenarios. The results show that all of the scenarios are reasonable. The annotation details for quality evaluation of tool instruction are shown in Appendix A.[2]

5 EXPERIMENT

In this section, we adopt EASYTOOL to three distinct tool-use applications to show that EASYTOOL can help LLM-based agents better utilize tools.

5.1 REAL-WORLD QUESTION ANSWERING

Since LLMs are still limited to their training data, it is essential for LLMs to use external tools to access up-to-date information in response to user requests.

Benchmark We choose ToolBench (Qin et al., 2023), a dataset containing diverse user requests with a massive set of publicly available REST APIs spanning 49 categories from RapidAPI Hub. We use the most difficult subsets of ToolBench to evaluate our method, *i.e.*, I2-Category (200 test data) and I3-Instruction (100 test data), which contain complex user requests that need multiple tools from different categories to solve. On average, an I2-Category request needs 6.76 tools, and an I3-Instruction request needs 8.24 tools. Each data sample of ToolBench consists of a user request

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[2]The evaluation on the robustness of the prompts in Table 2 is shown in Appendix D. We also compare with prompt compression methods in Appendix E.

Table 4: The average number of tokens in each tool documentation ($\text{Token}_{\text{Doc.}}$) and tool instruction generated by EASYTOOL ($\text{Token}_{\text{Ins.}}$). We also report the reduced ratio (*i.e.* **Reduce (%)**) for reference.

Dataset	$\text{Token}_{\text{Doc.}}$	$\text{Token}_{\text{Ins.}}$	Reduce (%)
ToolBench	2,530	748	70.43%
RestBench	3,881	103	97.35%

Table 5: The performance of different retrievers for two subsets in ToolBench. We report **NDCG@1** and **NDCG@5**.

Method	I2-Category		I3-Instruction	
	@1	@5	@1	@5
BERT Retriever	68.2	77.9	**81.7**	87.1
Ada	36.8	30.7	54.6	46.8
+ EASYTOOL	**73.4**	**82.7**	80.1	**88.5**

with a ground truth toolset, and thus models only need to select and execute the tools from the toolset to complete the user request.

For evaluation, ToolBench designs two evaluation metrics based on ChatGPT: (1) **Pass Rate**, calculated by the proportion of instructions successfully completed within a limited budget; (2) **Win Rate**, measured by asking a ChatGPT evaluator to select its preference for two solution paths. Furthermore, we also measure **Success Rate**, which asks GPT-4 to check whether the responses can reasonably and accurately answer the user requests.[3]

Baselines Following Qin et al. (2023), we select ChatGPT (OpenAI, 2022), GPT-4 (OpenAI, 2023), Vicuna-7B (Chiang et al., 2023), and ToolLLaMA-7B as baselines and apply both ReACT (Yao et al., 2023) and DFSDT (Qin et al., 2023) to them. ToolLLaMA-7B is fine-tuned from a 7B LLaMA model (Touvron et al., 2023a) on ToolBench. We do not adopt ToolLLaMA-7B on EASYTOOL due to its poor instruction-following capability. Furthermore, we also adopt Mistral-Instruct-7B (Jiang et al., 2023a) for comparison, which exhibits great instruction-following capability.[4]

Main Result We simplify the tool documentation from ToolBench into concise tool instructions with EASYTOOL.[5] Each tool instruction consists of a tool description and functionality guidelines. As shown in Table 4, with EASYTOOL, replacing tool documentation with our tool instruction can greatly reduce the token cost of each tool. Especially in ToolBench, the token cost was reduced by 70.43%. Furthermore, results in Table 3 show that: *1)* With the EASYTOOL generated tool instructions, LLMs can achieve state-of-the-art performance. Notably, ChatGPT + DFSDT-EASYTOOL even surpasses GPT-4 + DFSDT in success rate, indicating the superiority of tool Instructions over tool documentation in facilitating tool utilization for LLMs; *2)* Vicuna and Mistral-Instruct-7B result in a failure when directly using tools. Based on previous experiences Shen et al. (2023b), we attribute this phenomenon to the lack of training in formatted data (*e.g.*, function call). However, tool instructions generated by EASYTOOL can help these models to better understand the usage of tools, even making them outperform the fine-tuned method, *i.e.*, ToolLLaMA; *3)* Mistral-Instruct-7B outperforms Vicuna-7B with EASYTOOL, indicating that models with better instruction-following capabilities can achieve greater improvements with high-quality tool instructions.

EASYTOOL can help retrieve high-quality tools. In real-world scenarios, asking users to manually recommend tools from a large pool for LLMs to select may not be practical. Therefore, ToolBench also provides a dense retriever based on BERT-base (Devlin et al., 2019) to retrieve relevant tools for solving user requests, and claims that it outperforms `text-embedding-ada-002`, *i.e.* Ada (Ouyang et al., 2022), which retrieves tools based on the cosine embedding similarity between the subtasks decomposed by user requests and original tool descriptions in ToolBench. We argue that the poor performance of Ada may be due to low-quality tool descriptions, which often contain irrelevant details and lack clear functionality guidelines. Thus, we adopt the tool description generated by EASYTOOL to replace the original tool descriptions. Following Qin et al. (2023), we compare the performance of these retrieval methods using NDCG (Järvelin & Kekäläinen, 2002). Results in Table 5 show that providing tool descriptions generated by EASYTOOL can greatly improve the retrieval performance.

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[3]The prompt template for evaluating success rate is shown in Appendix B.1

[4]Detailed information of baselines is shown in Appendix B.2

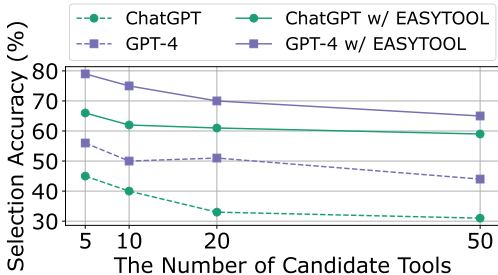[5]The data examples of ToolBench are provided in Appendix F.1.

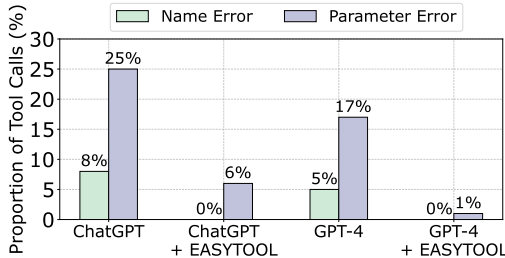Figure 3: The selection accuracy of LLMs on I1-instruciton of ToolBench.

Figure 4: Error rates of tool calls in different LLMs. The results are evaluated by **human annotators**.

EASYTOOL can better help LLMs with tool selection and execution. To answer this question, we utilize the I1-Instruciton of ToolBench, which comprises 100 user requests solvable by a single tool. We first obtain the golden tool from I1-Instruction and then retrieve other different tools based on cosine embedding similarity between the user request and tool descriptions as candidate tools. Then, we evaluate LLMs' tool selection accuracy with varying numbers of candidate tools (5, 10, 20, 50), using either original ToolBench descriptions or those generated by EASYTOOL. Figure 3 illustrates, EASYTOOL-enhanced descriptions enable LLMs to more effectively select the correct tool from a larger pool. For each subtask in I2-Category and I3-Instruction, we retrieve the top 10 most similar tools using our tool descriptions and ask models to select and execute them. As shown in Table 3, using these retrieved tools proves to be comparable, and sometimes even superior, to the ground truth tool set. The rationale is that EASYTOOL-Retriever can retrieve similar tools with better functionalities to replace some tools in the ground truth tool set.

Error Analysis We follow Zhang et al. (2023) and define two types of error, *i.e.*, Tool name error and parameter error. Tool name error means models call non-existent tool functions that are not in the tool inventory, and parameter error means models pass invalid parameters; both errors lead to unsuccessful tool execution. We sample 100 data from I2-Category and I3-Instruction and employ annotators to manually examine the output of ChatGPT and GPT-4 with tool documentation and tool instruction generated by EASYTOOL. We present the error rates of each error type on ToolBench in Figure 4. The results show that LLMs may generate non-existent tool names and pass invalid parameters to the right tool functions. However, our EASYTOOL, with its concise and effective tool instruction, can significantly reduce these incorrect behaviors, leading to successful tool execution.

5.2 REAL-WORLD WEB SERVICES

Real-world web services often need to execute tools following a specific order. For example, a shopping cart Web Service requires the user to add items to the shopping cart before performing the checkout operation. We aim to explore the capability of LLMs to find correct tool solution paths.

Benchmark and Baselines We select RestBench (Song et al., 2023), which consists of tasks in real-world web service scenarios. We evaluate our method on a subset of RestBench, *i.e.*, TMDB. TMDB is a movie information website that offers 55 official RESTful APIs as tools, which cover information on movies, TVs, actors, and images. Following the evaluation metric in RestBench, we use the correct path rate (CP%) to measure accuracy, which is the proportion of the model-generated tool path containing the gold tool path as a subsequence.

We choose RestGPT (Song et al., 2023) as our base model. The RestGPT has two versions, *i.e.*, Vicuna-13B-based RestGPT and ChatGPT-based RestGPT. For Vicuna-13B-based RestGPT, we compare our method with ToolDec. For ChatGPT-based RestGPT, we compare our method with ReAct since ToolDec cannot apply in close-sourced models.

EASYTOOL can help find correct tool solution paths. We simplify the long tool documentation from RestBench into concise tool instructions with EASYTOOL for LLMs to use.[6] For comparison,

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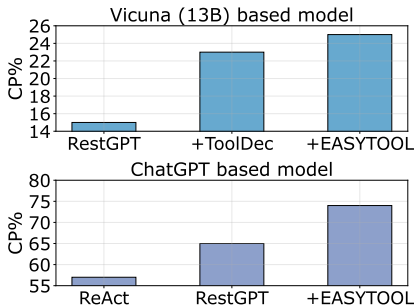[6]The data examples of RestBench are provided in Appendix F.2.

Figure 5: The correct path rate (CP%) on two versions of RestBench with different methods.

Figure 6: The accuracy of Vicuna-30B and ChatGPT on the FuncQA.

Model	One-hop (↑)	Multi-hop (↑)	Error (↓)
Vicuna-30B	15.00	1.00	-
+ CoT	13.33	4.00	-
+ ReAct	45.00	7.35	20.31
+ EASYTOOL	**65.00**	**11.76**	**10.15**
ChatGPT	55.00	9.00	-
+ CoT	48.33	17.64	-
+ ReAct	85.00	41.17	9.38
+ EASYTOOL	**91.66**	**48.53**	**2.34**

we use a prompt from Song et al. (2023) containing original TMDB tool descriptions and four examples. Table 4 demonstrates that EASYTOOL significantly reduces the token cost. Additionally, Figure 5 highlights the considerable improvement in the correct path rate, signifying EASYTOOL's effectiveness in aiding LLMs to find the correct tool solution paths.

5.3 NUMERICAL REASONING

Now, we explore whether EASYTOOL can endow LLMs with better tool-handling capability in complex math problems even without tool documentation.

Benchmark and Baselines We adopt FuncQA (Hao et al., 2023) to evaluate our method, which tests the numerical reasoning ability of LLMs complex math problems, involving 13 arithmetic operations tools (*e.g.*, multiply, power, lcm) We use the two subsets of FuncQA. *i.e.* **one-hop** and **multi-hop** questions, to evaluate our method. The one-hop questions consist of 68 math problems solvable with just one operation. The 60 multi-hop questions require a few reasoning steps, averaging 2.78 tool uses per question. We measure accuracy by calculating the percentage of correctly answered problems, with a 0.1% error tolerance. We also measure tool error rate (*i.e.*, **Error**), the proportion of tasks that have at least one tool-related error. Following Hao et al. (2023), We select Vicuna-30B and ChatGPT as base models and compare our method with 0-shot learning, Chain-of-thought (CoT) prompting and ReAct. For ReAct, We follow the settings in (Hao et al., 2023), which provide four examples including five tool demonstrations for LLMs.

Result Unlike the other datasets, FuncQA only provides the name and calling function of a tool as documentation, without any other tool descriptions for further usage demonstration. Therefore, by only leveraging the provided tool name and calling function, we can also apply EASYTOOL to generate tool descriptions with usage scenarios to construct tool instruction for FuncQA.[7] Results in Table 6 show that: *1)* The tool instructions generated based on our method (+ EASYTOOL) significantly improve the tool utilization ability of LLMs on complex math problems; *2)* Furthermore, a lower tool error rate of models with EASYTOOL indicates that compared to few-shot learning with demonstrations, concise and effective tool instructions can better guide models to select correct tools and pass valid parameters.

6 CONCLUSION

In this paper, we introduce EASYTOOL, an easy but effective method to enhance the tool utilization capabilities of LLM-based agents through the simplification and refinement of tool documentation into a clear, structured and practical tool instruction. Our comprehensive experiments demonstrate that EASYTOOL can effectively enhance performance in different real-world applications. We hope EASYTOOL can be a significant development in the field of LLM-based agents.

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[7]The data examples of FuncQA are provided in Appendix F.3.

ETHICS STATEMENT

We acknowledge that all authors are informed about and adhere to the ICLR Code of Ethics and the Code of Conduct.

Use of Human Annotations Our institution recruited annotators to implement the annotations of tool descriptions and functionality guidelines. We ensure the privacy rights of the annotators are respected during the annotation process. The annotators receive compensation exceeding the local minimum wage and have consented to the use of tool instructions generated by EASYTOOL for research purposes. Appendix A provides further details on the annotations.

Risks The tool benchmarks in our experiment are sourced from publicly available sources. However, we cannot guarantee that they are devoid of socially harmful or toxic language. Furthermore, evaluating the data quality of tool instructions is based on common sense, which can vary among individuals from diverse backgrounds.

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A CROWD-SOURCING DETAILS FOR TOOL INSTRUCTION EVALUATION

We have recruited a team of two undergraduates. We pay each annotator $8/h, exceeding the local minimum wage. The screenshots of the instructions and interface for tool description and functionality guideline annotation are shown in Figure 8 and Figure 9.

B DETAILS OF TOOLBENCH

B.1 SUCCESS RATE EVALUATION

The prompt of the success rate evaluation is given in List 1.

Listing 1: Instruction templates for GPT-4 to evaluate the success rate of the results on ToolBench

```
Please check whether the response can reasonably and accurately answer
the question. If it can, please output 'YES'; If not, please output 'NO'

You need to give reasons first and then decide whether the response can
reasonably and accurately answer the question. You must only output in a
parsible JSON format. Two example outputs look like:

Example 1: {"Reason": "The reason why you think the response can
reasonably and accurately answer the question", "Choice": "Yes"}
"Example 2: {"Reason": "The reason why you think the response cannot
reasonably and accurately answer the question", "Choice": "No"}

This is the user's question: {question}
This is the response: {answer}
Output:
```

B.2 THE DETAILS OF BASELINES ON TOOLBENCH

Vicuna-7B (Chiang et al., 2023) is the LLaMA variant fine-tuned on instructions and user-shared conversations. Mistral-Instruct-7B (Jiang et al., 2023a) is the Mistral-7B variant fine-tuned on instructions, which exhibits great instruction-following and reasoning capability. The ReAct in Qin et al. (2023) first decomposes the use request into subtasks and then plans the tool calls to complete the subtasks. The DFSDT in Qin et al. (2023) adopts a depth-first search-based decision tree to enable LLMs to make deliberate decisions by assessing different reasoning paths.

Following the setting in Qin et al. (2023), for ChatGPT and GPT-4, we directly leverage the function call to use tools [8]. For other models, we synthesize input in function call format to these models.

C TOOL INSTRUCTION GENERATION

The prompt of the tool instruction generation is given in List 2.

Listing 2: Instruction templates for GPT-4 to generate the tool instruction for FuncQA

```
Your task is to generate a tool instruction for the tool given the
function of the tool.
The tool instruction consists of two parts: tool description and tool
function guidelines.

The tool description only contains the purposes of the tool without other
 irrelevant information. Here is an example:
'add_' returns the sum of all the arguments passed to it, normalized to 2
 decimal places.

The tool function guidelines introduce the parameters with examples that
contain the scenario adopting the parameters. Here is an example:
```

---
[8] https://openai.com/blog/function-calling-and-other-api-updates

```
"Usage":
{
    "required_parameters":[
        {
            "name":"input",
            "type":"List"
        }
    ],
        "Example":{
            "Scenario":"if you want to add 2 to 1.",
            "Parameters":{
                "input":[2,1]
            }
        }
    }
}

You should first generate the tool description and then give the tool
function guidelines. You must only output in a parsible JSON format. Two
example outputs look like:
{"tool_description": XX, "Usage": XX}

This is the tool name: {tool_name}
This is the function of tool: {tool_function}
Output:
```

D ROBUSTNESS EVALUATION

In this section, we aim to evaluate the robustness of the task prompts in Table 2. We ask ChatGPT
to rewrite these task prompts three times and the new task prompts are shown in List 3. We sample
100 tool documentations from ToolBench and ask ChatGPT to generate tool descriptions and tool
functionality guidelines based on the new task prompts. Then we ask two annotators to evaluate
the quality of four results (one from our task prompts, and three from ChatGPT generated task
prompts). The results in Figure 7 show that the changes to the task prompt, without altering the actual
meaning, do not affect the quality of the tool description and tool functionality guidelines, thereby
demonstrating the robustness of our prompts.

Listing 3: The ChatGPT generated task prompts for tool description generation and tool function
guidelines construction.

```
Prompt-1:
- Tool Description:
Your assignment involves developing a succinct and practical description
on using a specific tool, as outlined in its documentation. This
description should focus solely on the tool's functions, excluding any
extraneous details.
- Tool Function Guidelines:
Create a scenario that incorporates the use of a specified tool, ensuring
 it utilizes the provided parameters.
Receive a description of a tool, including its purpose and a list of
parameters. Design a scenario that effectively employs these parameters.
If both "required_parameters" and "optional_parameters" are absent,
format your response as:
{"Scenario": XX, "Parameters": {}}.

Prompt-2:
- Tool Description:
Your assignment involves crafting a succinct and practical description of
 a tool, using its documentation as a reference. Focus on outlining the
tool's functions, excluding any extraneous details.
- Tool Function Guidelines:
Your assignment involves developing a scenario that utilizes a specified
tool. Here are the guidelines:
```
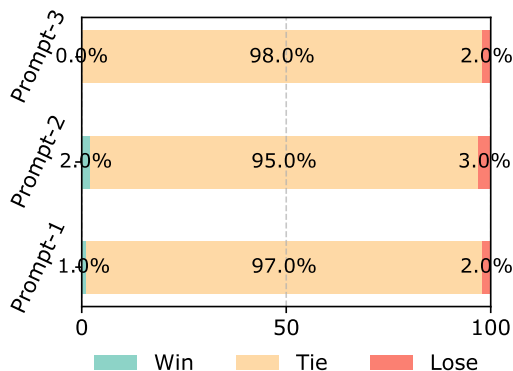
Figure 7: Comparison of our task prompts with ChatGPT generated task prompts. Percentage of wins, ties and losses are calculated.

```
You will receive information about a tool, including its intended use and
 a list of parameters. Your scenario should incorporate these parameters.
In cases where both "required_parameters" and "optional_parameters" are
absent, format your response as follows:
{"Scenario": XX, "Parameters": {}}.

Prompt-3:
- Tool Description:
Your assignment involves writing a succinct and clear description of a
tool's usage, guided by its documentation. This description should
exclusively focus on the tool's functions, omitting any extraneous
details.
- Tool Function Guidelines:
Your assignment involves crafting a scenario that utilizes a specific
tool. Here's how to proceed:
First, familiarize yourself with the tool's intended use and its
available parameters. Then, design a scenario that effectively
incorporates these parameters.
In cases where both "required_parameters" and "optional_parameters" are
absent, format your response as follows:
{"Scenario": XX, "Parameters": {}}.
```

E PROMPT COMPRESSION METHOD

We also adopt LLMLingua Jiang et al. (2023b), a prompt compression method, to identify and remove non-essential tokens in tool documentation. As shown in Table 6, this method can not be applied to our task since it may compress some tokens in parameters and functions, which are essential for successful tool execution.

F EXAMPLES OF TOOL INSTRUCTION

F.1 DATA EXAMPLES OF TOOLBENCH

Table 7 presents some examples of tool instructions generated by EASYTOOL in ToolBench for a better understanding.

F.2 DATA EXAMPLES OF RESTBENCH

Table 8 presents some examples of tool instructions generated by EASYTOOL in RestBench for a better understanding.

Thanks for participating in this HIT! Please spend some time reading this instruction to better understand our HIT! In this hit, you need to first read the tool document and then check whether the tool description for the tool is correct.

Tool documents are mostly sourced from the internet and authored by the service providers. As a result, the original tool descriptions often contain extraneous information such as URLs, product IDs, and recommendation terms, and do not clearly convey the tool's purpose. Moreover, many tools in the inventory have multiple built-in functions that serve various purposes in different scenarios. For example, Google Maps can calculate distances between locations and provide coordinates. However, not all tool functionalities are comprehensively covered in its description. Therefore, we focus on create a concise and effective tool description for the tool based on the tool document, which focuses on the purpose of tools as outlined in the tool documents. Next, you need to manually examine the tool description and check whether the tool description for the tool is correct or not.

Tool Document

Textbox

```json
{
    "product_id": "api_22b7f33d-d1fe-4062-b5bc-69bdd3d4e502",
    "tool_description": "Unleash the Power of Tokopedia: Effortlessly Retrieve Shop and Product
Information with Our API!",
    "home_url": "https://rapidapi.com/dytra/api/tokopedia-super-api/",
    "name": "Tokopedia Super API",
    "title": "Tokopedia Super API",
    "pricing": "FREEMIUM",
    "tool_name": "Tokopedia Super API",
    "host": "tokopedia-super-api.p.rapidapi.com",
    "api_list": [
      {
        "name": "sortProductsMaster",
        "url": "https://tokopedia-super-api.p.rapidapi.com/sortProductsMaster",
        "description": "the list of available sorting methods",
        "method": "GET",
        "required_parameters": [],
        "optional_parameters": [],
        "code": "import requests

url = "https://tokopedia-super-api.p.rapidapi.com/sortProductsMaster"
```

Tool Description

Textbox

'Tokopedia Super API' can effortlessly retrieve shop and product information.
This tool has 1 API:
1. 'sortProductsMaster' can provide the list of available sorting methods.

Please check whether the tool description for the tool is correct or not.

Correct

Incorrect

Figure 8: The screenshots of the instructions and interface for tool description annotation.

F.3   DATA EXAMPLES OF FUNCQA

Table 9 presents some examples of tool instructions generated by EASYTOOL in FuncQA for a better understanding.

Thanks for participating in this HIT! Please spend some time reading this instruction to better understand our HIT! In this hit, you need to first read the tool functionality guidelines and then check whether the scenarios in examples for the tool is reasonable.

The tool functionality guidelines not only contain the required and optional parameters from the tool documents, but also contain examples generated by large language models (LLMs) to demonstrate how to input parameters, including scenarios and parameter names with values. We have already executed the tool to verify that the parameters are correctly input and yield accurate results. Next, you need to manually assess the plausibility of the scenarios generated by LLMs.

The parameters in tool functionality guidelines

Textbox

```
{
    "name": "Product Details",
    "description": "Get the product details for a given product id and a specific country.",
    "required_parameters": [
        {
            "name": "product_id",
            "type": "NUMBER",
            "description": "ID of the product. Can be obtained from the url of the product or by using the
`/search` endpoint.",
            "default": "195499451557"
        }
    ],
    "optional_parameters": [
        {
            "name": "country",
            "type": "STRING",
            "description": "Valid country to return offers for.",
            "default": "germany"
        },
        {
            "name": "country_code",
```

Example

Textbox

```
{
    "Scenario": "if you want to know the details of the product with product ID 195499451557 in
Germany",
    "Parameters": {
        "product_id": 195499451557,
        "country": "germany",
        "country_code": "de"
    }
}
```

Please check whether the scenario in the example is reasonable or not.

Yes

No

Figure 9: The screenshots of the instructions and interface for tool functionality guidelines annotation.

Tool Documentation:
```
{
    "product_id": "api_b04d269d-c7dd-4b84-8e17-6fba24d64d3d",
    "tool_description": "Get Products from Ebay (Unofficial)",
    "home_url": "https://rapidapi.com/felixeschmittfes/api/ebay32/",
    "name": "Ebay",
    "title": "Ebay",
    "pricing": "FREEMIUM",
    "tool_name": "Ebay",
    "host": "ebay32.p.rapidapi.com",
    "api_list": [
        {
            "name": "Product Details",
            "url": "https://ebay32.p.rapidapi.com/product/195499451557",
            "description": "Get the product details for a given product
            id and a specific country.",
            "method": "GET",
            "required_parameters": [
                {
                    "name": "product_id",
                    "type": "NUMBER",
                    "description": "ID of the product. Can be obtained
                    from the url of the product or by using the `/search`
                     endpoint.",
                    "default": "195499451557"
                }
            ],
            "optional_parameters": [
                {
                    "name": "country",
                    "type": "STRING",
                    "description": "Valid country to return offers for.\
                    nValid values are in description of this endpoint.\
                    nDefault: `united states`.",
                    "default": "germany"
                },
                {
                    "name": "country_code",
                    "type": "STRING",
                    "description": "Country code of the valid country to
                    return offers for.\nValid values are in description
                    of this endpoint.\nDefault: `us`.",
                    "default": "de"
                }
            ]
        }
    ]
}
```

Tool Instruction Compressed By LLMLingua:
```
{
  "product "_b04d269d-c7be-fba24d64d",
 "_ "Get fromay (Unofficial "://id./fixeschmittfes/ay/ " " " " " "FREEM " "
  ".p. "_ [   " "Product Details",
            "url": "https://ebay32.p.rapidapi.com/product/195499451557",
            "description": "Get the product details for a given product
            id and a specific country.
Default country is `United States`.
Specify country with country name or country code.
```

Table 6: The original tool documentation and tool instruction compressed by LLMLingua.

```
Tool Description:
/* Example 1 */
'TokopediaApi' can search and retrieve product details from Tokopedia.
This tool has 2 APIs: 1. 'Search Product' can search for products on
Tokopedia based on a query string and action type. 2. 'Get Product Detail
' can retrieve detailed information about a product on Tokopedia based on
 its slug.
/* Example 2 */
'Tokopedia Super API' can effortlessly retrieve shop and product
information. This tool has 1 API: 1. 'sortProductsMaster' can provide the
 list of available sorting methods.

Tool Function Guidelines:
/* Example 1 */
{
    "name": "Search Product",
    "description": "Search The Product",
    "required_parameters": [
        {
            "name": "query",
            "type": "STRING",
            "description": "",
            "default": "Celana Jeans"
        },
        {
            "name": "act",
            "type": "STRING",
            "description": "",
            "default": "search"
        }
    ],
    "optional_parameters": [],
    "Example": {
        "Scenario": "if you want to search for a product with the query '
        Celana Jeans' using the 'search' action",
        "Parameters": {
            "query": "Celana Jeans",
            "act": "search"
        }
    }
}
/* Example 2 */
{
    "name": "sortProductsMaster",
    "description": "the list of available sorting methods",
    "required_parameters": [],
    "optional_parameters": [],
    "Example": {
        "Scenario": "if you want to retrieve the list of available
        sorting methods for products using Tokopedia Super API",
        "Parameters": {}
    }
}
```

Table 7: The tool instruction of ToolBench generated by EASYTOOL.

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```
Tool Description:
/* Example 1 */
'/tv/latest' can get the most newly created TV show.
/* Example 2 */
'/search/collection' can search for collections, which can obtain
collection_id.

Tool Function Guidelines:
/* Example 1 */
{
    "tool_usage": "GET /person/{person_id}/tv_credits",
    "Example": {
        "Scenario": "If you want to get the TV show credits of a person
        with person_id 456.",
        "Parameters": {
            "input": "GET /person/456/tv_credits"
        }
    }
}
/* Example 2 */
{
    "tool_usage": "GET /tv/latest",
    "Example": {
        "Scenario": "If you want to get the most newly created TV show.",
        "Parameters": {
            "input": "GET /tv/latest"
        }
    }
}
```

Table 8: The tool instruction of RestBench generated by EASYTOOL.

```
Tool Description:
/* Example 1 */
'add_' returns the sum of all the arguments passed to it, normalized to 2
 decimal places.
/* Example 2 */
'subtract_' returns the difference of the arguments passed to it,
starting with the first argument and subtracting all subsequent arguments
, normalized to 2 decimal places.

Tool Function Guidelines:
/* Example 1 */
{
    "required_parameters":[
        {
            "name":"input",
            "type":"List"
        }
    ],
    "Example":{
        "Scenario":"if you want to add 2 to 1.",
        "Parameters":{
        "input":[2,1]
        }
    }
}
/* Example 2 */
{
    "required_parameters": [
        {
            "name": "input",
            "type": "List"
        }
    ],
    "Example": {
        "Scenario": "if you want to subtract 2 from 1.",
        "Parameters": {
            "input": [1,2]
        }
    }
}
```

Table 9: The tool instruction of FuncQA generated by EASYTOOL.