

Planning, Creation, Usage: Benchmarking LLMs for Comprehensive Tool Utilization in Real-World Complex Scenarios

Shijue Huang^{1,5*} Wanjun Zhong^{3†} Jianqiao Lu⁴ Qi Zhu³ Jiahui Gao³ Weiwen Liu³
Yutai Hou³ Xingshan Zeng³ Yasheng Wang³ Lifeng Shang³ Xin Jiang³
Ruifeng Xu^{1,2,5†} Qun Liu³

¹Harbin Institute of Technology, Shenzhen, China ²Peng Cheng Laboratory, Shenzhen, China

³Huawei Technologies Co., Ltd ⁴The University of Hong Kong

⁵Guangdong Provincial Key Laboratory of Novel Security Intelligence Technologies
joehsj310@gmail.com, zhongwanjun1@huawei.com, xuruifeng@hit.edu.cn

Abstract

The recent trend of using Large Language Models (LLMs) as tool agents in real-world applications underscores the necessity for comprehensive evaluations of their capabilities, particularly in complex scenarios involving planning, creating, and using tools. However, existing benchmarks typically focus on simple synthesized queries that do not reflect real-world complexity, thereby offering limited perspectives in evaluating tool utilization. To address this issue, we present UltraTool, a novel benchmark designed to improve and evaluate LLMs' ability in tool utilization within real-world scenarios. UltraTool focuses on the entire process of using tools - from planning and creating to applying them in complex tasks. It emphasizes real-world complexities, demanding accurate, multi-step planning for effective problem-solving. A key feature of UltraTool is its independent evaluation of planning with natural language, which happens before tool usage and simplifies the task solving by mapping out the intermediate steps. Thus, unlike previous work, it eliminates the restriction of pre-defined toolset. Through extensive experiments on various LLMs, we offer novel insights into the evaluation of capabilities of LLMs in tool utilization, thereby contributing a fresh perspective to this rapidly evolving field. The benchmark is publicly available at <https://github.com/JoeYing1019/UltraTool>.

1 Introduction

Recent advancements in equipping Large Language Models (LLMs) (Du et al., 2022; Touvron et al., 2023; Chiang et al., 2023; Bai et al., 2023) with external tools (Patil et al., 2023; Schick et al., 2023; Qin et al., 2023a) have markedly improved capability of AI systems in solving complex real-world tasks. As this field evolves, it becomes cru-

* This work was done during the internship at Huawei Noah's Ark Lab.

† Corresponding authors.

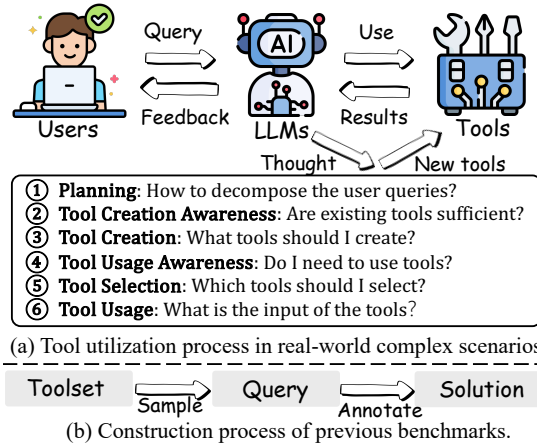


Figure 1: Illustration of (a) tool utilization process in real-world complex scenarios and (b) construction process of previous benchmarks.

cial to conduct a comprehensive evaluation covering full aspects of tool utilization, particularly within complex real-world contexts. As depicted in Figure 1 (a), addressing real-world tasks often necessitates not only the planning and usage of multiple tools but also the creation of new tools, when the existing tools are not enough to meet all specific requirements. However, existing benchmarks (Tang et al., 2023; Xu et al., 2023; Patil et al., 2023; Li et al., 2023; Qin et al., 2023b; Huang et al., 2023) often focus only on limited dimensions of this entire process. Besides, the user queries in most existing benchmarks exhibit limitations in mirroring the complexity of real-world tasks and unreasonable dependency on pre-defined toolsets.

To tackle these challenges, we introduce UltraTool, a benchmark covering a wide range of evaluation dimensions. It is constructed on complex, real-world queries and involves evaluation of tool-independent natural-language planning and advanced tool creation capabilities. UltraTool comprises 5,824 examples, spanning 22 diverse domains and incorporating 2,032 tools, and it comprehensively evaluates the tool utilization process

Resource	ToolAlpaca Tang et al. (2023)	APIBench Patil et al. (2023)	APIBank Li et al. (2023)	ToolBench Qin et al. (2023b)	MetaTool Huang et al. (2023)	UltraTool (Ours)
Evaluation Range	⑥	⑥	⑥	⑥	④⑤	①②③④⑤⑥
Real-world Query	✗	✗	✗	✗	✗	✓
Multi-Tool Test	✗	✗	✗	✓	✓	✓
Different Domains	✗	✗	✓	✓	✓	✓

Table 1: Comparison of previous benchmarks and UltraTool.

including six dimensions covering three aspects: ① **Planning**: decomposing the complex goal into logical sequence of simpler sub-tasks for effective problem-solving. **Tool Creation** comprises two dimensions: ② awareness - assessing whether existing tools suffice, and ③ creation - developing the necessary tools if existing ones are inadequate. **Tool Usage** involves three dimensions: ④ awareness - determining which sub-tasks require tools, ⑤ selection - choosing the appropriate tools, and ⑥ usage - specifying the input parameters for these tools. As demonstrated in Table 1, recent benchmarks in tool utilization tend to focus only on limited dimensions. For examples, Tang et al. (2023); Patil et al. (2023); Li et al. (2023); Qin et al. (2023b) focus on tool usage (⑥), while Huang et al. (2023) evaluates tool usage awareness (④) and tool selection (⑤). Comparing with them, we further evaluate the capability in planning (①) and tool creation (② and ③), which is crucial for LLMs to adeptly navigate complex and varied real-world user demands.

Moreover, the queries in UltraTool have better realism and complexity. The natural workflow of tool-augmented task solving includes: “user queries LLMs → LLMs pose a solution plan → LLMs create/select tools to solve sub-task within the plan”. Importantly, the query and the plan should not be constrained by pre-existing tools. In contrast, existing benchmarks (Qin et al., 2023b; Li et al., 2023; Huang et al., 2023) are typically constructed by collecting toolset, generating simulated queries with tools randomly selected from toolset, and then annotating the solution as shown in Figure 1 (b). Despite the collecting efficiency, the generated queries may not accurately mirror real user demands. Furthermore, the randomly selected tools may lack a coherent logical relationship, potentially leading to skewed influences on the subsequent process. To ensure the complexity and reality of queries, we collect real-world multi-domain user queries with high complexity. Specifically, we engage experts from various domains to craft complex queries that reflect real-world needs and potentially incorporate the use of diverse tools.

A distinct feature of UltraTool is it explicitly evaluates natural language (NL)-based plan, which simplifies task solving by decomposing a complex goal into several simpler sub-tasks described in NL. Each sub-task is then solved by tool creation and usage. Therefore, prior planning overcomes the restriction brought by limited pre-existing tools.

We conduct experiments on various LLMs and make in-depth analyses about strengths and challenges in the tool utilization of LLMs. Contributions of this work are: (1) UltraTool is a comprehensive evaluation benchmark derived from complex real-world queries, covering six key dimensions in tool utilization. (2) UltraTool explicitly evaluates NL-based planning and advanced tool creation capabilities. (3) Extensive experiments uncover the limitations and inspire the future direction of LLMs in tool utilization.

2 UltraTool Construction

UltraTool begins by gathering real-world user queries and encompasses a comprehensive range of evaluation dimensions, including planning, tool creation and tool usage. As depicted in Figure 4, the construction process of UltraTool includes: (1) query collection (§2.2); (2) solution annotation (§2.3); and (3) manual refinement (§2.4). For the detailed prompts utilized in the UltraTool construction process, please refer to Appendix A.5.

2.1 Definition

To formalize, a triple (Q, P, T) is regarded as a sample within UltraTool. Specifically, Q represents the user query, while $P = [(s_1, t_1), (s_2, t_2), \dots, (s_n, t_n)]$ is the NL-based plan. In this context, each element (s_i, t_i) comprises a step s_i and an associated tool calling message t_i . Furthermore, $T = [tool_1, tool_2, \dots, tool_m]$ is the corresponding toolset. As depicted in Figure 2, P maintains a hierarchical tree structure, which includes both ancestral steps (e.g., 1., 2., ...) and child steps (e.g., 1.1, 1.2, ...). The child steps fall into two distinct categories: (1) the *tool-free step*, which the LLMs can infer without requiring tool

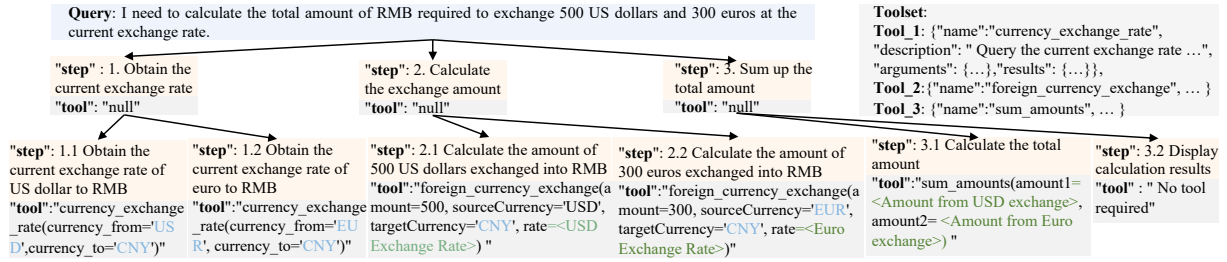


Figure 2: Data example of UltraTool, including user query, tree-structure planning, and toolset.

callings, distinguished by the tool calling message t_i as "No tool required"; and (2) the *tool-usage step*, which necessitates calling tools to complete the task, indicated by the tool callings message t_i specifying the tool name $tool_i^{name}$ and the necessary arguments $[\{args_j^{name} : args_j^{value}\}]_{j=1}^{i_k}$. Here, i_k denotes the number of arguments, $args_j^{name}$ is the name of an argument belonging to the defined argument properties of $tool_i$, and $args_j^{value}$ is the argument value derived from the query context Q or the outputs of preceding tool callings.

2.2 Query Collection

To ensure comprehensive coverage across various domains and meet diverse requirements in real-world scenarios, we carefully selected more than 20 domains such as *Alarm*, *Train*, *Flight*, *Hotel*, etc, as shown in Figure 3. In detail, we collaborate with a wide array of domain-specific experts to gather complex, de-identified user queries that necessitate complex tool usage as depicted in Figure 4 (a). To better align each query with its corresponding tool usage, we also request that the experts suggest several potential tools for each query. These suggestions are formatted in accordance with the style of ChatGPT plugins¹, which aided in crafting an initial toolset for each query. The query collection guideline can be found in Appendix A.2.

As shown in Figure 4 (a), to create more diverse and challenging queries, we utilized GPT-4 to generalize and complicate the initial queries. The examples of the generalization and complication processes are listed in Appendix A.4. We then merge the original, generalized, and complicated queries into a comprehensive collection. Additionally, every query undergoes a manual review to guarantee quality and applicability, and queries that do not align with actual human needs are removed.

¹<https://platform.openai.com/docs/guides/function-calling>

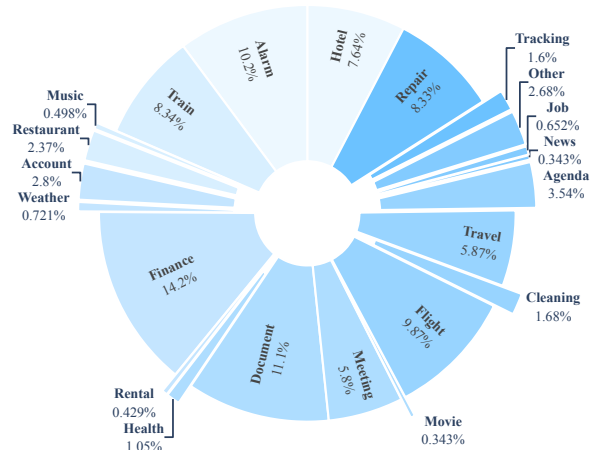


Figure 3: Specific domain distribution of UltraTool.

2.3 Solution Annotation

Due to the complexity of the queries addressed by UltraTool, UltraTool employs a multi-step plan as the backbone of solution for effective problem-solving, wherein each step includes a corresponding tool calling message. By breaking down user queries into simpler tasks via this planning process, these tasks can subsequently be executed by the designated tools. This strategy is not only in line with the problem-solving logic of humans but also reduces the complexity of tool usage, thereby facilitating the handling of more challenging tasks. We introduce an automatic solution annotation approach utilizing GPT-4, including: (1) plan annotation; (2) tool creation and plan refinement; (3) tool calling message annotation; and (4) tool merge.

Plan Annotation. As illustrated in Figure 4 (b), upon receiving a user query, GPT-4 is utilized to formulate an initial multi-step, tree-structured plan $[s_1, \dots, s_n]$. This fundamental plan is deliberately crafted without considering a predefined toolset. Such a strategy ensures a primary focus on task decomposition and the structural integrity of the plan. Moreover, it adeptly avoids the potential limitations that could surface when the initial toolset does not fully meet the requirements of user query.

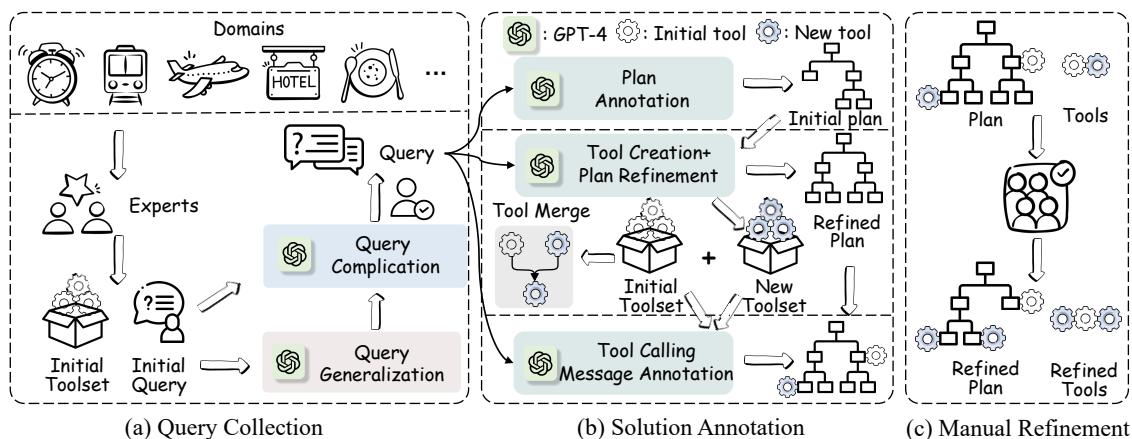


Figure 4: The overall construction process of UltraTool, including (a) query collection, (b) solution annotation, and (c) manual refinement.

Tool Creation and Plan Refinement. The initial toolset may not meet all requirements within the complex user queries in UltraTool, and the processes of generalization and complication may lead to emergence of new tool usage demands. Therefore, as depicted in Figure 4 (b), to accommodate the need for tools not present in initial toolset, we utilize GPT-4 to discern whether need to create new tools and create new tools in prescribed format.

Subsequently, we implement an automatic refinement process to enhance the quality of the NL-based plan. Given that the existing toolset has already fulfilled all the requirements of the user query, we provide GPT-4 with the query, the initial plan, and the comprehensive toolset (which includes both the initial and the newly created tools). This allows GPT-4 to refine the plan further in terms of the comprehensiveness of information included and the compatibility with tool callings.

Tool Calling Message Annotation. As shown in Figure 4 (b), we utilize GPT-4 to annotate the tool calling messages $[t_1, \dots, t_n]$. In detail, given the query, the refined plan, and the comprehensive toolset, GPT-4 initially differentiates between the *tool-free steps* and *tool-usage steps*. Subsequently, for each *tool-usage step*, GPT-4 selects the most appropriate tool from the comprehensive toolset. Moreover, utilizing the user’s query and the contextual information within the plan, GPT-4 generates the necessary arguments for the chosen tool.

It is also noteworthy that UltraTool incorporates nested tool callings, wherein the output from one tool serves as a requisite parameter for another subsequent tool. This feature significantly enhances our benchmark’s alignment with the complexities encountered in real-world scenarios.

Tool Merge. Due to each tool being created separately for the queries, there may be similar tools that exist in the whole benchmark. To address this issue, we manually merge groups of tools that have similar functions into a single tool. Specifically, we combine the arguments and results fields of similar tools and remove any duplicate properties, then we write an appropriate name and description for the merged tool. The remained toolset of UltraTool contains 2,032 distinct tools.

2.4 Manual Refinement

To guarantee and further enhance the data quality within UltraTool, we conduct a careful manual refinement process for all samples, as illustrated in Figure 4 (c). This process includes eliminating redundant steps, supplementing missing steps for coherent planning logic, rectifying tool usage demands and inappropriate tool selections, completing and refining the tool calling messages, and deleting data of substandard quality. We employ six experts endowed with specialized knowledge to refine the data, and we ensure that all the polished data undergoes a double-check process to maintain high-quality standards. The refinement guideline is provided in Appendix A.3.

2.5 Data Summary

Ultimately, we construct the UltraTool, which encompasses 22 domains, 2,032 tools, and 5,824 samples, detailed statistics are presented in Appendix A.1. And the source language of our collected data is Chinese, to broaden the scope of evaluation, we translate it to English version through GPT-4 and manual refinement. Therefore, UltraTool supports two languages: Chinese and

English, represented by the Chinese-dataset and the English-dataset.

3 UltraTool Evaluation

In this section, we introduce the metrics (§3.1), and the definition and measurement of each evaluation aspect, including: planning (§3.2), tool creation (§3.3) and tool usage (§3.4).

3.1 Metrics

Three evaluation metrics are employed within UltraTool, comprising:

(i) *Multi-Dimensional Point-Wise LLM-as-Judge Method* (Liu et al., 2023), which utilizes a LLM-scorer as automatic evaluator. By defining task-specific evaluation dimensions $M = [d_1, d_2, \dots, d_m]$ and providing the query Q , the model’s response p , and the reference answer y , the LLM-scorer is prompted to provide a multi-dimensional score, along with an overall score:

$$S = \text{LLM-scorer}(M, [Q, p, y]), \quad (1)$$

where $S = [s_{d_1}, \dots, s_{d_m}, s_{\text{overall}}]$ contains dimension scores s_{d_1}, \dots, s_{d_m} and the final overall score s_{overall} , and all the scores are ranging from 1 to 10. The detailed prompts are listed in Appendix B.2.

(ii) *Key-Value based Accuracy* and (iii) *Key-Value based Levenshtein Distance*, which are variants of traditional accuracy and Levenshtein distance (Miller et al., 2009) metrics. Given the key-value format model’s response (p_k, p_v) and reference answer (y_k, y_v) , where the keys p_k and y_k represent steps and values p_v and y_v denote task-specific results, these metrics compute the accuracy or normalized Levenshtein distance between the values when the keys match:

$$S = \begin{cases} F(p_v, y_v) & \text{if } p_k = y_k \\ 0 & \text{if } p_k \neq y_k \end{cases}, \quad (2)$$

where S is the computed score and F represents the calculation function, which can be applied by accuracy or normalized Levenshtein distance.

The multiple-step nature of the plan resulting in multiple predictions for a sample, so these metrics may be computed at global level that evaluates multiple predictions together or local level that evaluates each prediction separately. More illustration of computation level can be found in Appendix B.1.

3.2 Planning

Given a query Q , LLMs need to decompose the user query and generate a step sequence in hierarchical form $[p_1^{\text{PL}}, p_2^{\text{PL}}, \dots, p_n^{\text{PL}}]$, to serve as the plan. Here, each p_i^{PL} represents a step. We utilize the *Multi-Dimensional Point-Wise LLM-as-Judge Method*, applied at a global level, to evaluate LLMs’ planning ability. The generated plan is evaluated across six score dimensions including *Accuracy*, *Completeness*, *Executability*, *Syntactic Soundness*, *Structural Rationality* and *Efficiency*, detailed dimension definitions are listed in Appendix B.3.1.

3.3 Tool creation

Since many real-world demands cannot be addressed by existing real-world tools, we design our tools as tool skeletons that contain all the necessary information for calling, as illustrated in Figure 2. Despite these skeletons are not specific implementations, they serve as simulated tools that accurately represent the tool’s functionality and provide guidance for the future development of actual tools.

Furthermore, given the golden plan P and corresponding toolset T , to evaluate whether the LLM can accurately be aware that the provided toolset is sufficient and effectively create the tools that are lacking, we construct an alternative toolset \hat{T} that may not contain all the necessary tools.

Awareness. Given plan P and toolset \hat{T} , LLMs need to determine whether each *tool-usage step* in the plan can be matched with an appropriate tool from \hat{T} . The output is a predicted sequence $[(s_i, p_i^{\text{TCA}}), \dots, (s_j, p_j^{\text{TCA}})]$, where $p_i^{\text{TCA}} \in \{0, 1\}$ indicates the matching availability of a suitable tool within \hat{T} for step s_i . The evaluator of tool creation awareness is conducted through the *Key-Value based Accuracy* metric, which is calculated at both the global and local levels.

Creation. Given plan P and toolset \hat{T} , LLMs are required to create the lacking tool in required format for those *tool-usage steps* that can not match a suitable tool in \hat{T} . The output is a predicted sequence $[(s_i, p_i^{\text{TC}}), \dots, (s_j, p_j^{\text{TC}})]$, where p_i^{TC} denotes the created tool for step s_i . The *Multi-Dimensional Point-Wise LLM-as-Judge Method*, calculated at the global level, is adopted as the evaluator for tool creation. We evaluate the newly created tool across five score dimensions including *Format Compliance*, *Accuracy*, *Content Reasonableness*, *Executability* and *Richness*, corresponding dimension definitions can be found in Appendix B.4.1.

3.4 Tool Usage

Awareness. Given the plan P , LLMs need to determine whether child steps require the usage of tools and output a predicted sequence $[(s_i, p_i^{\text{TUA}}), \dots, (s_j, p_j^{\text{TUA}})]$, where $p_i^{\text{TUA}} \in \{0, 1\}$ indicates whether step s_i need to use tool. The tool usage awareness evaluator is *Key-Value based Accuracy* calculated at both global and local levels.

Selection. Given the plan P and toolset T , we construct an augmented toolset \bar{T} by incorporating additional interference tools. Then LLMs are required to select the most appropriate tool from \bar{T} for each *tool-usage steps* and generate a predicted sequence $[(s_i, p_i^{\text{TS}}), \dots, (s_j, p_j^{\text{TS}})]$, where p_i^{TS} denotes the name of the chosen tool for step s_i . The *Key-Value based Accuracy* calculated at both global and local levels is the evaluator for tool selection.

Usage. Given the plan P , the toolset T , and the names of the required tools for each *tool-usage step*, LLMs are tasked with generating property arguments for each *tool-usage step* and outputting a predicted sequence $[(s_i, p_i^{\text{TU}}), \dots, (s_j, p_j^{\text{TU}})]$. Here, $p_i^{\text{TU}} = [\{args_j^{\text{name}} : args_j^{\text{value}}\}_{j=1}^{k_i}]$ denotes the generated arguments for step s_i . The evaluation of tool usage awareness is conducted using *Key-Value based Levenshtein Distance*, which is calculated at the local level. We choose this metric for the consideration that the argument values $args_j^{\text{value}}$ may be expressed in many different manners.

4 Experiments

4.1 Experimental Settings

We divide all data into two parts: a test set comprising 1,000 samples for constructing evaluation datasets, and a development set with 4,824 samples, which are not used for training and can optionally serve as a development set. For both the Chinese-dataset and English-dataset, we construct six evaluation datasets, each comprising 1,000 samples and corresponding to one of the six evaluation dimensions. The toolset sizes for \hat{T} in tool creation awareness and \bar{T} in tool selection are both set to 8.

We evaluate closed-source and open-source LLMs on UltraTool for both Chinese-dataset and English-dataset, aiming to provide comprehensive analyses for current LLMs. For closed-source LLMs, we select two representative models: GPT-3.5 and GPT-4 from OpenAI. The version for GPT-4 is gpt-4-1106-preview, and for GPT-3.5 is gpt-3.5-turbo-1106. For open-source LLMs, we choose a wide spectrum of models, including:

LLaMA2 (Touvron et al., 2023), ChatGLM3 (Du et al., 2022), Baichuan2 (Yang et al., 2023), Vicuna (Chiang et al., 2023), Qwen (Bai et al., 2023) and Mistral (Jiang et al., 2023). And All experiments are run on NVIDIA V100 GPUs.

To assist LLMs in grasping the desired output format, we provide a few-shot example as a demonstration for each evaluation task. For further details, the prompts are listed in Appendix B.6.

4.2 Main Results

The main results are illustrated in Table 2. As seen, we can have the following observations:

GPT-4 achieves the best performance. Among all evaluated LLMs, GPT-4 demonstrates superior performance, achieving an overall score of 76.04% on Chinese-dataset and 74.58% on English-dataset, and with particularly impressive results in the realms of tool creation and tool usage, setting the pilot of acting as skillful tool agent. Besides, Mistral-7B, GPT-3.5, and Qwen-72B also get competitive performance, and Mistral-7B gets the best of two worlds between exhibiting good tool utilization abilities while keeping efficient model scale.

The larger the model scale, the better the tool utilization ability. Regarding open-source LLMs, we evaluate models at three scales, approximately 7B, 13B, and 70B parameters. The results indicate that tool utilization ability improves as the model scale increases. This finding aligns with prior research, which has shown that increasing of the model parameters bolsters the capabilities of LLMs (Chung et al., 2022; Wei et al., 2022). While most open-source LLMs demonstrate competitive planning performance, a notable gap still persists in tool creation and usage compared to closed-source LLMs, especially for smaller-scale models. This discrepancy may stem from the more intricate JSON output format requirements inherent in the evaluation dimensions of tool creation and usage. These dimensions are critical areas to focus on for enhancing LLMs’ abilities in tool utilization.

Language affects the tool utilization ability. Although most of LLMs support both English and Chinese, their capabilities in these two languages differ. For open-source LLMs, in most cases, the Chinese-orientated LLMs (e.g. Qwen, Baichuan2) show better tool utilization ability on Chinese-dataset, while English-orientated LLMs (e.g. LLaMA2, Vicuna) perform better on English-dataset. We attribute this discrepancy to variations in multilingual understanding resulting from differ-

Model	Planing	Tool Creation			Tool Usage					Overall
	-	Awareness	Creation		Awareness	Selection	Usage			
	Global	Global	Local	Local	Global	Local	Global	Local	Local	
Chinese-dataset										
LLaMA2-7B	46.44	2.70	6.09	3.24	2.10	10.10	0.30	0.66	3.01	8.29
ChatGLM3-6B	57.54	9.70	23.18	8.31	12.90	34.66	8.50	18.68	29.90	22.60
Baichuan2-7B	62.51	8.20	18.77	22.39	18.00	46.02	5.80	15.48	21.63	24.31
Vicuna-7B	58.38	7.10	17.77	22.9	17.40	66.49	5.40	11.49	36.50	27.05
Qwen-7B	61.48	13.40	25.91	19.40	21.40	76.44	12.50	21.96	32.35	31.65
Mistral-7B	66.18	24.50	42.55	50.95	37.00	81.30	58.60	74.70	59.68	55.05
LLaMA2-13B	62.05	5.20	16.72	16.29	28.30	73.15	4.10	5.96	25.79	26.40
Qwen-14B	67.91	10.60	23.90	34.01	24.90	76.89	13.60	19.73	61.10	36.96
Vicuna-13B	65.72	17.90	37.46	37.10	40.40	82.56	22.80	39.06	38.76	42.42
Baichuan2-13B	66.84	23.90	45.40	25.49	34.30	82.57	30.80	53.27	59.21	46.86
LLaMA2-70B	63.29	26.90	45.40	46.03	41.20	81.35	35.00	52.21	51.17	49.17
Qwen-72B	73.40	36.90	55.19	61.80	40.80	82.16	72.40	84.92	69.52	64.12
GPT-3.5	69.50	26.20	52.88	58.00	25.90	79.75	67.10	81.50	76.26	59.68
GPT-4	76.39	58.80	76.65	65.55	60.70	89.76	80.70	89.22	86.62	76.04
English-dataset										
LLaMA2-7B	65.44	1.40	3.74	1.37	0.40	3.13	0.70	2.06	2.14	8.93
ChatGLM3-6B	60.19	15.50	29.69	10.92	15.20	57.09	13.00	28.23	24.84	28.30
Baichuan2-7B	62.64	10.50	25.33	17.67	30.10	62.24	8.20	17.97	22.26	28.55
Vicuna-7B	66.77	10.10	24.44	29.54	18.10	61.67	7.80	20.43	32.89	30.19
Qwen-7B	64.81	10.10	24.70	17.05	22.70	76.91	8.80	14.95	32.94	30.33
Mistral-7B	70.32	26.70	43.34	46.24	36.80	77.78	56.70	74.44	60.48	54.76
LLaMA2-13B	68.50	14.50	31.00	20.08	35.70	76.46	16.60	26.39	26.41	35.07
Qwen-14B	69.59	10.50	22.76	32.21	32.50	79.58	15.90	19.55	43.23	36.20
Vicuna-13B	69.64	20.30	41.50	39.90	36.50	79.08	26.60	47.22	46.29	45.23
Baichuan2-13B	67.59	22.30	40.03	15.79	24.30	78.96	29.40	51.34	48.97	42.08
LLaMA2-70B	69.72	25.50	44.52	46.94	55.50	87.61	40.20	53.66	43.44	51.90
Qwen-72B	72.93	30.90	51.15	57.98	49.00	84.86	71.80	84.31	63.51	62.94
GPT-3.5	69.74	33.10	59.26	51.83	15.20	76.29	69.00	82.20	73.47	58.90
GPT-4	74.07	56.10	75.18	61.17	62.50	90.85	79.30	88.69	83.32	74.58

Table 2: The main results of UltraTool. The overall score is the average score across all evaluation metrics. **Bold** highlights the best score among all models, and underline underscores the best score under the same model scale.

ences in the proportions of training data. However, despite their English orientation, GPT-3.5 and GPT-4 actually exhibit slightly weaker performance on English-dataset. We speculate that this could be due to heightened safety and alignment constraints in their English versions.

4.3 Fine-grained Analysis of Planning and Tool Creation

To offer a more refined analysis of the planning and tool creation capabilities of current LLMs, we present the multi-dimensional scores of 4 representative models under different model scales from the *Multi-Dimensional Point-Wise LLM-as-Judge Method*. More detailed multi-dimensional scores for planning and tool creation can refer to Appendix B.3.2 and Appendix B.4.2, respectively.

As illustrated in Figure 5 (a) and (b), we can observe that the GPT-4 and Qwen-70B are adept at breaking down complex goals into logically or-

dered, simpler sub-tasks. And the plans generated by smaller open-source LLMs showcase commendable *Syntactic Soundness*, yet reveal evident shortcomings across the remaining five score dimensions. This suggests that while many existing open-source LLMs demonstrate proficiency in generating grammatically accurate content, they still lack holistic language comprehension, particularly in fully grasping query requirements and structuring language to effectively break down tasks.

As shown in Figure 5 (c) (d), it is evident that GPT-4 and Qwen-70B are significantly ahead in all score dimensions, demonstrating their proficient tool creation capabilities. Conversely, the smaller-scale models notably trail behind them across all score dimensions, signaling ample room for improvement in enhancing the abilities of many open-source LLMs concerning comprehensive query understanding, adherence to prescribed output structures, and the innovation of new tools.

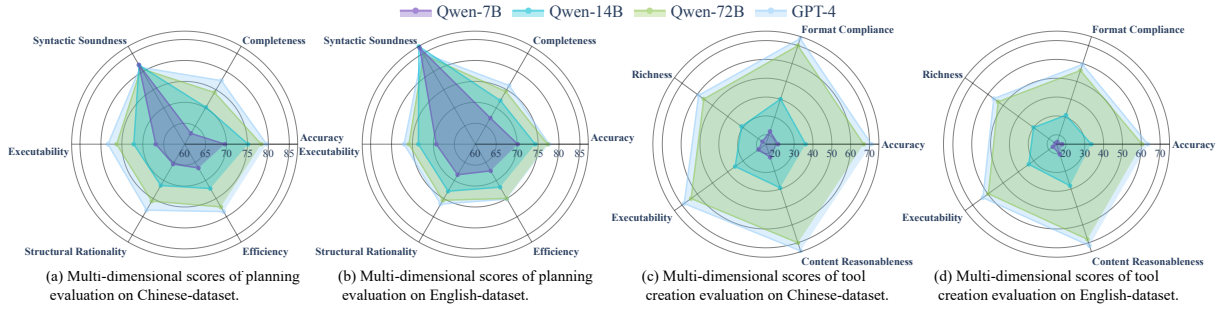


Figure 5: Multi-dimensional scores of planning and tool creation evaluation of 4 representative models under different model scales, including: Qwen-7B, Qwen-14B, Qwen-72B and GPT-4.

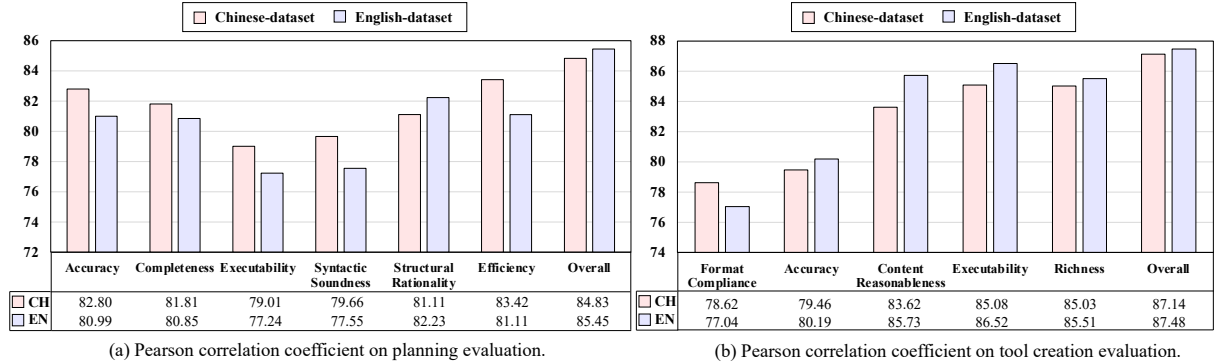


Figure 6: Pearson correlation coefficient between GPT-4 based *Multi-Dimensional Point-Wise LLM-as-Judge Method* with human evaluation on planning and tool creation evaluation.

4.4 Alignment of GPT-4 Scoring with Human Evaluation

To validate the effectiveness of the GPT-4 based *Multi-Dimensional Point-Wise LLM-as-Judge Method*, we present the alignment of this metric with human evaluation on the UltraTool dataset. Specifically, for the evaluation of planning and tool creation, we randomly selected 140 evaluation samples for human evaluation. This selection incorporates the results of all 14 evaluated LLMs to ensure diversity and mitigate bias. By providing score dimensions, inputs, and references, we request human experts to evaluate these samples and provide a multi-dimensional score, along with an overall score, following the same scoring methodology as the *Multi-Dimensional Point-Wise LLM-as-Judge Method*. Subsequently, we calculate the Pearson correlation coefficient (Freedman et al., 2007) between human evaluation and GPT-4 evaluation for planning and tool creation. The results, depicted in Figure 6, indicate a high correlation between the scores of all dimensions and the overall scores from human evaluation and GPT-4 evaluation. This suggests that the *Multi-Dimensional Point-Wise LLM-as-Judge Method* is suitable for adoption in UltraTool evaluation, as it demon-

strates a strong alignment with human evaluation.

4.5 Error Analysis

We conduct analyses of the errors observed in evaluated LLMs, identifying five primary types:

Not Following Instructions. Not following instructions is a major error type, causing a phenomenon of unanswered questions. The Error examples can refer to Appendix B.5.1.

Hallucinations. LLMs often suffer from hallucinations (Ji et al., 2023), leading to outputs that include content outside the intended definition. The error examples are listed in Appendix B.5.2.

Redundant Outputs. Redundant outputs indicate that outputs contain unnecessary/meaningless content. Error examples can refer to Appendix B.5.3.

Incomplete Outputs. Incomplete outputs refer to outputs that lack necessary content. Corresponding error examples can be found in Appendix B.5.4.

Incorrect JSON Format: In UltraTool, the expected output for planning is string format, while the other five dimensions require outputs in various JSON formats. Despite thorough post-processing, errors still persist due to incorrect JSON formatting. We calculate the proportion of outputs that adhere to the correct JSON format, namely the JSON format correct rate, and analyze its correlation with the

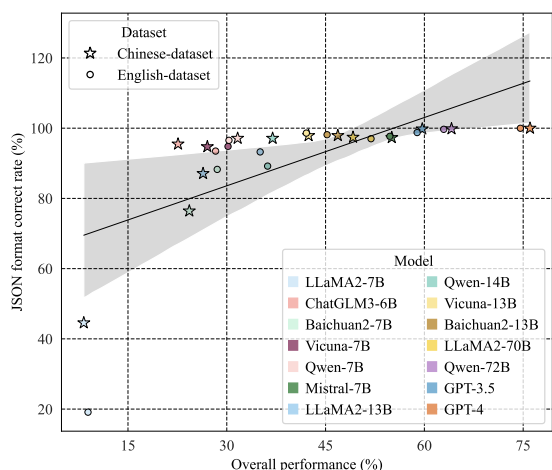


Figure 7: Correlation between JSON format correct rate with the overall score in Table 2.

overall performance of UltraTool, as illustrated in Figure 7. It is evident that there exists a positive correlation between this ability and tool utilization, underscoring the importance of possessing strong skills in ensuring format compliance. For detailed results regarding the JSON format correct rate and examples of errors caused by incorrect JSON formatting, please refer to Appendix B.5.5.

5 Related Work

5.1 Tool Learning

The integration of external tools enhances the capabilities of LLMs to transcend the limitations of their training data, resulting in problem-solving abilities that are not only accurate and reliable but also highly specialized (Qin et al., 2023a). The approaches to LLMs’ tool learning can broadly be divided into two categories: *tool-oriented learning* and *tool-augmented learning*. The former involves directly fine-tuning the LLMs to master tool usage (Parisi et al., 2022; Hao et al., 2023; Xu et al., 2023; Shen et al., 2023; Schick et al., 2023), while the latter enhances LLMs with the ability to utilize tools through the provision of in-context tool descriptions and demonstrations (Mialon et al., 2023; Hsieh et al., 2023; Patil et al., 2023; Ruan et al., 2023). There are also works that explore the tool creation of LLMs (Qian et al., 2023; Cai et al., 2024), but still lack systematic evaluation of the tool creation abilities of current LLMs. With the rapid evolution of tool learning, conducting a comprehensive evaluation that encompasses all aspects of tool utilization has become vital, which is precisely the aim of UltraTool.

5.2 Tool Utilization Benchmark

Effective benchmarks allow for pinpointing limitations and charting the course for future developments. LLM tool utilization comprises three core aspects: planning, tool creation, and tool usage. Predominantly, existing benchmarks primarily focus on evaluating the model’s proficiency during the tool usage phase. This particular phase involves tool usage awareness of query, selection of the appropriate tool for each subtask (Huang et al., 2023) and the execution of specific tools (Xu et al., 2023; Tang et al., 2023; Li et al., 2023; Qin et al., 2023b; Ye et al., 2024). Unlike prior work, we conduct a comprehensive evaluation of tool utilization, which additionally evaluates capabilities for planning and tool creation, providing a more comprehensive and fine-grained analysis of tool utilization capabilities.

6 Conclusion

In this paper, we introduce UltraTool, a comprehensive evaluation benchmark derived from real-world complex queries, aimed at evaluating the tool utilization capabilities of LLMs across six dimensions that encompass three critical aspects: planning, tool creation, and tool usage. UltraTool excavates the necessary evaluation dimensions from actual tool utilization processes and pioneers in explicitly evaluating the NL-based planning and tool creation abilities. Our extensive analyses reveal that many current LLMs still have significant potential for enhancing their tool utilization abilities. We hope that UltraTool, coupled with our detailed experiments, will offer valuable insights and stimulate further research into the real-world application of LLMs in tool utilization.

Acknowledgments

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Limitations

This work contributes a comprehensive evaluation benchmark UltraTool for tool utilization based on real-world complex queries and covering comprehensive evaluation ranges. While promising, the

tools in UltraTool are not executable ; rather, they are tool skeletons that represent the tools' functionalities, as many real-world demands cannot be fully addressed by existing real-world tools. Despite these tool skeletons are not specific implementations, they serve as simulated representations that accurately depict the tool's functionality and offer guidance for the future development of actual tools. In the future, we plan to explore simulating the execution of our designed tools or gathering real-world data involving only executable tools.

Ethics Statement

All data in UltraTool are de-identified and safeguarding privacy concerns. Our data construction and human evaluation processes are conducted by proficient experts, comprising postgraduate students from Chinese universities and employees of Chinese technology companies, all of whom receive fair payment for their contributions.

References

- Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, Binyuan Hui, Luo Ji, Mei Li, Junyang Lin, Runji Lin, Dayiheng Liu, Gao Liu, Chengqiang Lu, Keming Lu, Jianxin Ma, Rui Men, Xingzhang Ren, Xuancheng Ren, Chuanqi Tan, Sinan Tan, Jianhong Tu, Peng Wang, Shijie Wang, Wei Wang, Shengguang Wu, Benfeng Xu, Jin Xu, An Yang, Hao Yang, Jian Yang, Shusheng Yang, Yang Yao, Bowen Yu, Hongyi Yuan, Zheng Yuan, Jianwei Zhang, Xingxuan Zhang, Yichang Zhang, Zhenru Zhang, Chang Zhou, Jingren Zhou, Xiaohuan Zhou, and Tianhang Zhu. 2023. [Qwen technical report](#).
- Tianle Cai, Xuezhi Wang, Tengyu Ma, Xinyun Chen, and Denny Zhou. 2024. [Large language models as tool makers](#).
- Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E. Gonzalez, Ion Stoica, and Eric P. Xing. 2023. [Vicuna: An open-source chatbot impressing gpt-4 with 90%* chatgpt quality](#).
- Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Yunxuan Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, Albert Webson, Shixiang Shane Gu, Zhuyun Dai, Mirac Suzgun, Xinyun Chen, Aakanksha Chowdhery, Alex Castro-Ros, Marie Pellat, Kevin Robinson, Dasha Valter, Sharan Narang, Gaurav Mishra, Adams Yu, Vincent Zhao, Yanping Huang, Andrew Dai, Hongkun Yu, Slav Petrov, Ed H. Chi, Jeff Dean, Jacob Devlin, Adam Roberts, Denny Zhou, Quoc V. Le, and Jason Wei. 2022. [Scaling instruction-finetuned language models](#).
- Zhengxiao Du, Yujie Qian, Xiao Liu, Ming Ding, Jiezhong Qiu, Zhilin Yang, and Jie Tang. 2022. [Glm: General language model pretraining with autoregressive blank infilling](#). In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 320–335.
- David Freedman, Robert Pisani, and Roger Purves. 2007. *Statistics (international student edition)*. Pisani, R. Purves, 4th edn. WW Norton & Company, New York.
- Shibo Hao, Tianyang Liu, Zhen Wang, and Zhiting Hu. 2023. [ToolkenGPT: Augmenting frozen language models with massive tools via tool embeddings](#). In *Thirty-seventh Conference on Neural Information Processing Systems*.
- Cheng-Yu Hsieh, Si-An Chen, Chun-Liang Li, Yasuhisa Fujii, Alexander Ratner, Chen-Yu Lee, Ranjay Krishna, and Tomas Pfister. 2023. [Tool documentation enables zero-shot tool-usage with large language models](#).
- Yue Huang, Jiawen Shi, Yuan Li, Chenrui Fan, Siyuan Wu, Qihui Zhang, Yixin Liu, Pan Zhou, Yao Wan, Neil Zhenqiang Gong, and Lichao Sun. 2023. [Meta-tool benchmark for large language models: Deciding whether to use tools and which to use](#).
- Ziwei Ji, Nayeon Lee, Rita Frieske, Tiezheng Yu, Dan Su, Yan Xu, Etsuko Ishii, Ye Jin Bang, Andrea Madotto, and Pascale Fung. 2023. [Survey of hallucination in natural language generation](#). *ACM Computing Surveys*, 55(12):1–38.
- Albert Q. Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, L lio Renard Lavaud, Marie-Anne Lachaux, Pierre Stock, Teven Le Scao, Thibaut Lavril, Thomas Wang, Timoth e Lacroix, and William El Sayed. 2023. [Mistral 7b](#).
- Minghao Li, Yingxiu Zhao, Bowen Yu, Feifan Song, Hangyu Li, Haiyang Yu, Zhoujun Li, Fei Huang, and Yongbin Li. 2023. [API-bank: A comprehensive benchmark for tool-augmented LLMs](#). In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 3102–3116, Singapore. Association for Computational Linguistics.
- Xiao Liu, Xuanyu Lei, Shengyuan Wang, Yue Huang, Zhuoer Feng, Bosi Wen, Jiale Cheng, Pei Ke, Yifan Xu, Weng Lam Tam, Xiaohan Zhang, Lichao Sun, Hongning Wang, Jing Zhang, Minlie Huang, Yuxiao Dong, and Jie Tang. 2023. [Alignbench: Benchmarking chinese alignment of large language models](#).
- Gr goire Mialon, Roberto Dessi, Maria Lomeli, Christoforos Nalmpantis, Ram Pasunuru, Roberta Raileanu, Baptiste Rozi re, Timo Schick, Jane Dwivedi-Yu,

- Asli Celikyilmaz, Edouard Grave, Yann LeCun, and Thomas Scialom. 2023. [Augmented language models: a survey](#).
- Frederic P. Miller, Agnes F. Vandome, and John McBrewster. 2009. *Levenshtein Distance: Information theory, Computer science, String (computer science), String metric, Damerau-Levenshtein distance, Spell checker, Hamming distance*. Alpha Press.
- Aaron Parisi, Yao Zhao, and Noah Fiedel. 2022. [Talm: Tool augmented language models](#).
- Shishir G. Patil, Tianjun Zhang, Xin Wang, and Joseph E. Gonzalez. 2023. Gorilla: Large language model connected with massive apis. *arXiv preprint arXiv:2305.15334*.
- Cheng Qian, Chi Han, Yi Fung, Yujia Qin, Zhiyuan Liu, and Heng Ji. 2023. [CREATOR: Tool creation for disentangling abstract and concrete reasoning of large language models](#). In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 6922–6939, Singapore. Association for Computational Linguistics.
- Yujia Qin, Shengding Hu, Yankai Lin, Weize Chen, Ning Ding, Ganqu Cui, Zheni Zeng, Yufei Huang, Chaojun Xiao, Chi Han, Yi Ren Fung, Yusheng Su, Huadong Wang, Cheng Qian, Runchu Tian, Kunlun Zhu, Shihao Liang, Xingyu Shen, Bokai Xu, Zhen Zhang, Yining Ye, Bowen Li, Ziwei Tang, Jing Yi, Yuzhang Zhu, Zhenning Dai, Lan Yan, Xin Cong, Yaxi Lu, Weilin Zhao, Yuxiang Huang, Junxi Yan, Xu Han, Xian Sun, Dahai Li, Jason Phang, Cheng Yang, Tongshuang Wu, Heng Ji, Zhiyuan Liu, and Maosong Sun. 2023a. [Tool learning with foundation models](#).
- 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. 2023b. [Toolllm: Facilitating large language models to master 16000+ real-world apis](#).
- Jingqing Ruan, Yihong Chen, Bin Zhang, Zhiwei Xu, Tianpeng Bao, Guoqing Du, Shiwei Shi, Hangyu Mao, Ziyue Li, Xingyu Zeng, and Rui Zhao. 2023. [Tptu: Large language model-based ai agents for task planning and tool usage](#).
- Timo Schick, Jane Dwivedi-Yu, Roberto Dessì, Roberta Raileanu, Maria Lomeli, Luke Zettlemoyer, Nicola Cancedda, and Thomas Scialom. 2023. [Toolformer: Language models can teach themselves to use tools](#).
- Yongliang Shen, Kaitao Song, Xu Tan, Dongsheng Li, Weiming Lu, and Yueting Zhuang. 2023. [Hugging-gpt: Solving ai tasks with chatgpt and its friends in hugging face](#).
- Qiaoyu Tang, Ziliang Deng, Hongyu Lin, Xianpei Han, Qiao Liang, and Le Sun. 2023. [Toolalpaca: Generalized tool learning for language models with 3000 simulated cases](#).
- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiofu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu, Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. 2023. [Llama 2: Open foundation and fine-tuned chat models](#).
- Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, Ed H. Chi, Tatsunori Hashimoto, Oriol Vinyals, Percy Liang, Jeff Dean, and William Fedus. 2022. [Emergent abilities of large language models](#). *Transactions on Machine Learning Research*. Survey Certification.
- Qiantong Xu, Fenglu Hong, Bo Li, Changran Hu, Zhengyu Chen, and Jian Zhang. 2023. [On the tool manipulation capability of open-source large language models](#).
- Aiyuan Yang, Bin Xiao, Bingning Wang, Borong Zhang, Ce Bian, Chao Yin, Chenxu Lv, Da Pan, Dian Wang, Dong Yan, Fan Yang, Fei Deng, Feng Wang, Feng Liu, Guangwei Ai, Guosheng Dong, Haizhou Zhao, Hang Xu, Haoze Sun, Hongda Zhang, Hui Liu, Jiaming Ji, Jian Xie, JunTao Dai, Kun Fang, Lei Su, Liang Song, Lifeng Liu, Liyun Ru, Luyao Ma, Mang Wang, Mickel Liu, MingAn Lin, Nuolan Nie, Peidong Guo, Ruiyang Sun, Tao Zhang, Tianpeng Li, Tianyu Li, Wei Cheng, Weipeng Chen, Xiangrong Zeng, Xiaochuan Wang, Xiaoxi Chen, Xin Men, Xin Yu, Xuehai Pan, Yanjun Shen, Yiding Wang, Yiyu Li, Youxin Jiang, Yuchen Gao, Yupeng Zhang, Zenan Zhou, and Zhiying Wu. 2023. [Baichuan 2: Open large-scale language models](#).
- Junjie Ye, Guanyu Li, Songyang Gao, Caishuang Huang, Yilong Wu, Sixian Li, Xiaoran Fan, Shihan Dou, Qi Zhang, Tao Gui, et al. 2024. [Tooleyes: Fine-grained evaluation for tool learning capabilities of large language models in real-world scenarios](#). *arXiv preprint arXiv:2401.00741*.

Statistics	UltraTool
# of supporting languages	2
# of domains	22
# of tools	2,032
# of samples	5,824
-# of single tool calling	506
-# of multiple tool callings	5,318
percentage of nested tool callings	39.61%
avg. steps per sample	12.27
avg. tool calls per sample	2.74
avg. arguments per tool calling	3.05

Table 3: Statistics of UltraTool.

A Data Details

A.1 Data Statistics

UltraTool supports 2 languages including Chinese and English, and encompasses 22 domains, 2,032 tools, and 5,824 samples. Detailed statistics of the UltraTool are presented in Table 3. All samples within the UltraTool involve at least one tool calling. In particular, 5,318 samples comprise multiple tool callings, whereas 506 samples consist of single tool calling, and the percentage of nested tool callings in UltraTool is 39.61%. On average, each sample’s plan includes 12.27 steps and 2.72 tool callings, with each tool calling requiring an average of 3.05 arguments. And the existence of ancestral steps and *tool-free steps* results in a relatively low proportion of *tool-usage steps* among all steps.

A.2 Query Collection Guideline

To ensure the high quality of collected user queries, we have developed a guideline that outlines the query collection standards for experts, which is illustrated in Figure 14.

A.3 Manual Refinement Guideline

We also provide a comprehensive manual refinement guideline for experts, as depicted in Figure 15.

A.4 Generalization and Complication Examples

We offer examples of the generalization and complication processes, as shown in Figure 8.

A.5 Prompt Template for UltraTool Construction

During the construction of UltraTool, we employed GPT-4 to perform a series of automated

Generalization process
I would like a ticket from Shenzhen to Changsha for the summer of 2023, with priority business class and window seats.
↓
I need a first class ticket from Guangzhou to Shanghai in the spring of 2024, preferably by the window.
Complication Process
Please help me contact a French tour guide who is available in early September. We plan to visit the Louvre together on September 1st.
↓
Please help me find a French tour guide who has free time in early September and ensure that the guide has received a rating of at least 4.5 stars in their past services. After confirming the availability of the tour guide, book a visit to the Louvre on September 1st.

Figure 8: Examples for generalization and complication process.

tasks, which include query generalization (Figure 16), query complication (Figure 17), plan annotation (Figure 18, Figure 19), tool creation (Figure 20), plan refinement (Figure 21, Figure 22), and tool calling message annotation (Figure 23).

B Evaluation Details

B.1 Metric Computation Level

Due to the multiple-step nature of the plan P within UltraTool, it is common to make several predictions $[(s_i, p_i), \dots, (s_j, p_j)]$ for the multiple steps of a given sample across distinct evaluation dimensions. To this end, we evaluate the performance in different levels, comprising both the global level and local level, where the former considers the sample as a whole and computes the metric based on all prediction results $[p_i, \dots, p_j]$ in a sample, while the latter focus on individual steps and compute the metric based on a single-step prediction result p_i .

B.2 Prompt Template for Multi-Dimensional Point-Wise LLM-as-Judge Method

We utilize GPT-4 to apply *Multi-Dimensional Point-Wise LLM-as-Judge Method* for planning and tool creation evaluation. The prompt templates for Chinese-dataset and English-dataset can be found in Figure 24 (planning evaluation on Chinese-dataset), Figure 25 (planning evaluation on English-dataset), Figure 26 (tool creation evaluation on Chinese-dataset), Figure 27 (tool creation evaluation on English-dataset), respectively.

Evaluation Task	Model	Example
Planning	LLaMA2-7B	Reference: 1. Use the ordering service\n1.1 Obtain ordering service platform information (Platform Information: Ordering Service Platform)\n1.2 Select the first dish and set the quantity\n1.3 Select the second dish and set the quantity\n1.4 Submit the order and obtain the order ID (Order ID: Generated order ID)\n1.5 Confirm order details\n1.5.1 Obtain order ID\n1.5.2 Check order details\n1.6 Complete payment Predict: Sure, I'd be happy to help! Please provide the question you would like me to answer.
Tool create awareness	Vicuna-7B	Reference: [{"step": "1.3 Write the letter content into a file", "tool": "1"}] Predict: [{"step": "1.4 Confirm whether the letter has been saved successfully", "tool": ""}]

Figure 9: Error examples for not following instructions.

B.3 Planning Evaluation Details

B.3.1 Score Dimension Definitions

The designed six score dimensions of *Multi-Dimensional Point-Wise LLM-as-Judge Method* for planning evaluation are:

- (1) *Accuracy*: The generated plan must be aligned with the user query's objectives.
- (2) *Completeness*: The plan should encompass all tasks and constraints mentioned in the user query, ensuring no elements are omitted.
- (3) *Executability*: Every step in the generated plan ought to be logical and executable, forming a sequence that enables the progressive fulfillment of the user's request.
- (4) *Syntactic Soundness*: The language of the generated plan should be grammatically sound.
- (5) *Structural Rationality*: The plan should exhibit a well-organized, tree-like hierarchical structure.
- (6) *Efficiency*: The plan must be concise and efficient, avoiding unnecessary complexity.

B.3.2 Multi-Dimensional Scores

We provide the detailed multi-dimensional scores of *Multi-Dimensional Point-Wise LLM-as-Judge Method* on planning evaluation, as depicted in Table 4.

B.4 Tool Creation Evaluation Details

B.4.1 Score Dimension Definitions

The designed five score dimensions of *Multi-Dimensional Point-Wise LLM-as-Judge Method* for tool creation evaluation are:

- (1) *Format Compliance*: The created tool must be fully consistent with the standard answer in terms of format.
- (2) *Accuracy*: The created tool must align with the objectives of the user query and accurately address the user's needs.
- (3) *Content Reasonableness*: The content within each field of the created tool should be reasonable.

(4) *Executability*: The tool name and description in the created tool should accurately express its function, including a comprehensive list of parameters and complete return results.

(5) *Richness*: The created tool should encompass rich information, depth, contextual considerations, and diversity.

B.4.2 Multi-Dimensional Scores

The detailed multi-dimensional scores of *Multi-Dimensional Point-Wise LLM-as-Judge Method* on tool creation evaluation are also provided, as illustrated in Table 5.

B.5 Error Examples

Through comprehensive observation, we categorize errors into five primary types: (1) not following instructions; (2) hallucinations; (3) redundant outputs; (4) incomplete outputs; and (5) incorrect JSON format.

B.5.1 Not Following Instructions

The error examples for not following instructions are shown in Figure 9. Such errors signify outputs that deviate from the instructions' requirements, potentially rendering them meaningless or irrelevant.

B.5.2 Hallucinations

The error examples for hallucination are illustrated in Figure 10. This type of error indicates that the output includes content that does not within the intended definition, such as tools hallucination for argument names hallucination.

B.5.3 Redundant outputs

The error examples for redundant outputs are demonstrated in Figure 11. This type of error suggests that the output includes unnecessary or nonsensical content, such as redundant meaningless texts or redundant predictions.

Evaluation Task	Model	Example
Tool selection	Baichuan2-7B	Toolset: [{ 'name': 'delete_schedule', ... }, { 'name': 'file_modify', ... }, { 'name': 'check_schedule_deleted', ... }, { 'name': 'update_hyperlinks_text', ... }, { 'name': 'remove_specific_text', ... }, { 'name': 'file_contains', ... }, { 'name': 'delete_specific_content', ... }, { 'name': 'delete_transaction_by_amount', ... }] Reference: [{ 'step': '1.3 Add content to the file', 'tool': 'file_modify' }, { 'step': '1.6 Delete specific content from the file', 'tool': 'delete_specific_content' }] Predict: [{ 'step': '1.2 Query the current exchange rate', 'tool': 'currency_exchange_rate' }, { 'step': '1.6 Delete specific content from the file', 'tool': 'delete_specific_content' }]
Tool usage	ChatGLM3-6B	Toolset: [{ 'name': 'file_write', 'description': 'Used to write content to a specified file. If the file does not exist, a new file will be created.', 'arguments': { 'type': 'object', 'properties': { 'file_path': { 'description': 'The file path where the content will be written', 'type': 'string' }, 'content': { 'description': 'The content to be written', 'type': 'string' } } }, 'results': { 'type': 'object', 'properties': { 'status': { 'description': 'Whether the write operation was successful', 'type': 'boolean' } } } }] Reference: [{ 'step': '1.2 Create document and write content', 'tool': 'file_write', 'param': { 'file_path': 'Desktop/Work Summary.txt', 'content': 'The work this week has been completed very well!' } }] Predict: [{ 'step': '1.1 Get document creation information', 'tool': 'file_write', 'param': { 'file_path': 'Desktop/Work Summary.txt', 'content': 'The work this week has been completed very well!' } }, { 'step': '1.2 Create document and write content', 'tool': 'file_write', 'param': '' }, { 'step': '1.3 Confirm whether the document has been created and written successfully', 'tool': 'file_read', 'param': { 'file_path': 'Desktop/Work Summary.txt', 'result_format': 'text' } }]

Figure 10: Error examples for hallucinations.

Evaluation Task	Model	Example
Planning	LLaMA2-7B	Reference: 1. Create file\n1.1 Get file creation information (File path: Desktop/Work_Tasks.txt, File content: Preparation for Tomorrow's Meeting)\n1.2 Use file writing tool to create and write content\n1.3 Confirm file creation and content writing success Predict: Of course! I'd be happy to help you create a file on your desktop and write the text "Preparation for Tomorrow's Meeting" into it.\n\nHere's a step-by-step plan to help you achieve this task:\n\n1. Create a new file on your desktop called "Work_Tasks.txt".\n\nOutput:\n1. Create a new file on desktop called "Work_Tasks.txt"\n2. Write the text "Preparation for Tomorrow's Meeting" into the file.\n\nOutput:\n2. Write "Preparation for Tomorrow's Meeting" into "Work_Tasks.txt" file\n\nGreat, the task is complete! Let me know if you have any other questions or tasks you'd like me to assist you with.
Tool create awareness	Vicuna-7B	Reference: [{ 'step': '1.2 Use file writing tool to create and write content', 'tool': '0' }] Predict: [{ 'step': '1.1 Get file creation information', 'tool': '1' }, { 'step': '1.2 Use file writing tool to create and write content', 'tool': '0' }]

Figure 11: Error examples for redundant outputs.

B.5.4 Incomplete outputs

The error examples illustrating incomplete outputs are depicted in Figure 12. This type of error indicates that the output lacks essential content, such as incomplete predictions or fragmented tool structures.

B.5.5 Incorrect JSON Format

In the UltraTool, the expected outputs for evaluation dimensions other than planning require diverse JSON formats, presenting more challenges due to the potential rendering of data unusable with even minor formatting errors. After thorough post-processing, the proportion of outputs conforming to the correct JSON format among the evaluated LLMs, referred to as the JSON format correctness rate, is presented in Table 6. It is evident that as the

model scale increases, so does the JSON format correct rate.

Furthermore, error examples resulting from incorrect JSON formats are depicted in Figure 13. Such errors typically stem from incomplete or illegal JSON structures.

B.6 Prompt Template for Inference

During the inference of our experiments, we utilize one-shot example for all LLMs. The prompt templates can be found in Figure 28 (planning), Figure 29 (tool creation awareness), Figure 30 (tool creation), Figure 31 (tool usage awareness), Figure 32 (tool selection), Figure 33 (tool usage), respectively.

Evaluation Task	Model	Example
Tool usage awareness	Vicuna-7B	<p>Reference: [{"step": "1.1 Get the original alarm time (Original alarm time: 7 o'clock tomorrow morning)", "tool": "0"}, {"step": "2.1 Find and change the original alarm time to the new time (New alarm time: 8 o'clock tomorrow morning, New alarm frequency: Daily)", "tool": "1"}, {"step": "2.2 Confirm whether the alarm time has been successfully modified", "tool": "0"}]</p> <p>Predict: [{"step": "1.1 Get the original alarm time (Original alarm time: 7 o'clock tomorrow morning)", "tool": "1"}, {"step": "2.1 Find and change the original alarm time to the new time (New alarm time: 8 o'clock tomorrow morning, New alarm frequency: Daily)", "tool": "0"}]</p>
Tool creation	Vicuna-7B	<p>Reference: [{"step": "1.2 Use backup tool to backup the original file", "tool": {"name": "file_backup", "description": "Used for backing up specified files.", "arguments": {"type": "object", "properties": {"source_file_path": {"type": "string", "description": "Source file path"}, "backup_file_path": {"type": "string", "description": "Backup file path"}}}, "results": {"type": "object", "properties": {"status": {"description": "Whether the backup operation was successful", "type": "boolean"}}}}}]</p> <p>Predict: [{"step": "1.2 Use backup tool to backup the original file", "tool": {"name": "backup_original_file", "description": "Backup original file"}}]</p>

Figure 12: Error examples for incomplete outputs.

Evaluation Task	Model	Example
Tool creation awareness	Vicuna-7B	<p>Reference: [{"step": "2.1.4 Search for available rooms on specified dates", "tool": "1"}, {"step": "2.3 Book rooms", "tool": "1"}]</p> <p>Predict: [{"step": "1.1 Obtain user's name (Name: Li Ming)"}]</p>
Tool creation	Vicuna-7B	<p>Reference: [{"step": "1.2 Create a text file and write content", "tool": {...}}]</p> <p>Predict: [{"step": ""}]]</p>
Tool usage awareness	ChatGLM3-6B	<p>Reference: [{"step": "1.1 Compose the letter content (Salutation: Dear Tom, Body: I plan to go to London on a business trip on April 1, 2023, and will return on April 3. Looking forward to your reply. Closing: Best wishes, Jack.)", "tool": "0"}, {"step": "1.2 Get the letter content (Letter content: Dear Tom, I plan to go to London on a business trip on April 1, 2023, and will return on April 3. Looking forward to your reply. Best wishes, Jack.)", "tool": "0"}, {"step": "1.3 Write the letter content into a file", "tool": "1"}, {"step": "1.4 Confirm whether the letter has been saved successfully", "tool": "0"}]</p> <p>Predict: 'The solution to this problem is as follows:\n\n1. Initialize an empty list called "output".\n2. Iterate through each step in the plan.\n3. Check if the step has a "tool" field. If it does, add a new element to the "output" list with keys "step" and "tool".\n4. If the step does not have a "tool" field, add a new element to the "output" list with keys "step" and "tool" set to 0.\n5. Return the "output" list.'</p>
Tool selection	Vicuna-7B	<p>Reference: [{"step": "1.2 Adjust the alarm time to every morning at 7:00", "tool": "clock_alarm_change"}, {"step": "2.2 Set the new alarm", "tool": "clock_alarm_set"}]</p> <p>Predict: [{"step": "1.2 Adjust the alarm time to every morning at"}]</p>
Tool usage	Vicuna-7B	<p>Reference: [{"step": "1.2 Query and display the temperature forecast", "tool": "special_weather_forecast_tool", "param": {...}}, {"step": "2.3 Book a comfortable vehicle", "tool": "ride_hailing_service", "param": {...}}, {"step": "3.2 Book food delivery service", "tool": "ingredient_delivery_tool", "param": {...}}]</p> <p>Predict: "Based on the given plan and toolset, the following output is generated:\n\n[{"step": "1.2 Check the current exchange rate", "tool": "currency"}]</p>

Figure 13: Error examples for incorrect JSON format.

Model	Accuracy	Completeness	Executability Soundness	Syntactic Rationality	Structural	Efficiency	Overall
Chinese-dataset							
LLaMA2-7B	51.35	47.61	50.66	72.52	50.79	50.39	46.44
ChatGLM3-6B	66.09	59.41	62.68	81.47	61.02	62.11	57.54
Vicuna-7B	65.26	60.91	63.51	79.01	63.12	62.06	58.38
Qwen-7B	69.60	62.98	66.90	81.89	65.47	66.57	61.48
Baichuan2-7B	70.16	65.22	67.54	82.23	67.04	66.43	62.51
Mistral-7B	73.00	68.50	70.77	81.48	70.07	69.68	66.18
LLaMA2-13B	69.15	63.93	67.42	82.12	67.12	66.99	62.05
Vicuna-13B	73.19	68.08	70.64	81.68	69.98	70.89	65.72
Baichuan2-13B	73.67	69.53	71.50	82.13	71.14	71.22	66.84
Qwen-14B	75.13	70.16	72.15	81.76	71.39	72.23	67.91
LLaMA2-70B	69.89	66.64	69.16	82.42	68.35	66.64	63.29
Qwen-72B	78.28	74.25	76.23	80.83	75.70	77.30	73.40
GPT-3.5	76.43	70.26	73.14	80.94	72.26	75.10	69.50
GPT-4	79.56	77.53	78.31	81.21	78.19	78.60	76.39
English-dataset							
ChatGLM3-6B	67.07	61.07	64.65	83.20	62.45	62.71	60.19
Baichuan2-7B	67.86	65.22	67.58	86.92	67.51	65.13	62.64
Qwen-7B	70.13	67.20	69.31	86.53	68.42	67.35	64.81
LLaMA2-7B	70.57	67.62	69.67	86.53	69.77	68.12	65.44
Vicuna-7B	71.58	69.70	70.85	87.38	70.80	69.29	66.77
Mistral-7B	74.61	72.92	74.15	87.23	73.63	72.00	70.32
Baichuan2-13B	72.40	70.00	71.77	87.47	71.56	69.67	67.59
LLaMA2-13B	72.96	71.78	73.25	88.98	73.06	70.51	68.50
Qwen-14B	74.31	72.00	73.58	86.95	72.97	71.85	69.59
Vicuna-13B	74.65	72.19	73.68	86.14	73.18	71.62	69.64
LLaMA2-70B	74.35	72.98	73.84	88.20	73.83	70.72	69.72
Qwen-72B	77.24	74.55	75.85	84.61	75.47	74.95	72.93
GPT-3.5	76.61	69.25	72.13	84.25	71.52	72.11	69.74
GPT-4	77.59	76.17	77.00	85.18	76.53	75.14	74.07

Table 4: Multi-dimensional scores of *Multi-Dimensional Point-Wise LLM-as-Judge Method* on planning evaluation.

Model	Format	Accuracy	Content	Executability	Richness	Overall
	Compliance	Reasonableness				
Chinese-dataset						
LLaMA2-7B	4.15	3.46	3.92	3.39	2.84	3.24
ChatGLM3-6B	9.70	9.10	9.61	8.41	7.21	8.31
Qwen-7B	22.08	21.46	22.27	19.80	17.26	19.40
Baichuan2-7B	25.77	24.31	25.56	22.93	19.70	22.39
Vicuna-7B	26.83	24.48	26.77	23.66	20.41	22.90
Mistral-7B	58.18	55.53	57.84	52.61	45.53	50.95
LLaMA2-13B	20.17	17.49	18.93	16.77	14.30	16.29
Baichuan2-13B	32.46	27.01	31.16	26.43	23.40	25.49
Qwen-14B	40.15	36.04	39.31	35.14	30.98	34.01
Vicuna-13B	42.56	39.68	42.43	38.15	33.24	37.10
LLaMA2-70B	53.44	48.81	52.86	47.42	40.86	46.03
Qwen-72B	69.96	66.86	70.04	64.08	55.72	61.80
GPT-3.5	66.19	64.43	64.64	59.01	50.30	58.00
GPT-4	73.87	70.95	74.54	68.60	59.11	65.55
English-dataset						
LLaMA2-7B	1.33	1.44	1.60	1.39	1.17	1.37
ChatGLM3-6B	10.43	11.84	13.04	10.88	9.86	10.92
Qwen-7B	16.24	18.00	20.70	17.35	15.74	17.05
Baichuan2-7B	16.97	18.49	20.84	17.96	15.91	17.67
Vicuna-7B	28.39	30.68	35.13	30.41	27.11	29.54
Mistral-7B	44.76	48.58	54.89	47.64	42.13	46.24
Baichuan2-13B	15.49	16.08	19.39	16.17	14.64	15.79
LLaMA2-13B	19.26	21.48	24.30	20.41	17.76	20.08
Qwen-14B	31.18	33.44	38.15	33.18	30.02	32.21
Vicuna-13B	38.60	41.56	47.17	40.85	36.40	39.90
LLaMA2-70B	45.28	48.57	55.82	48.12	42.16	46.94
Qwen-72B	56.10	60.31	68.07	59.71	53.28	57.98
GPT-3.5	49.68	54.91	61.40	52.96	46.07	51.83
GPT-4	59.49	63.47	71.63	63.28	56.13	61.17

Table 5: Multi-dimensional scores of *Multi-Dimensional Point-Wise LLM-as-Judge Method* on tool creation evaluation.

Model	Tool Creation		Tool Usage			Avg.
	Awareness	Creation	Awareness	Selection	Usage	
Chinese-dataset						
LLama2-7B	50.70	54.30	41.00	35.70	41.10	44.56
Baichuan2-7B	78.50	70.80	70.00	83.80	79.00	76.42
Vicuna-7B	92.10	89.40	99.10	98.20	94.80	94.72
ChatGLM3-6B	97.80	86.80	96.00	98.80	98.00	95.48
Qwen-7B	97.10	92.90	99.70	98.20	97.70	97.12
Mistral-7B	99.20	89.00	99.60	99.50	99.30	97.32
LLama2-13B	88.00	88.00	99.70	73.90	85.80	87.08
Qwen-14B	97.10	92.90	99.70	98.20	97.70	97.12
Vicuna-13B	99.80	94.40	99.80	98.30	97.10	97.88
Baichuan2-13B	99.80	90.60	99.90	100.00	99.20	97.90
LLama2-70B	99.70	91.30	100.00	98.10	98.00	97.42
Qwen-72B	100.00	99.30	99.90	100.00	99.90	99.82
GPT-3.5	100.00	99.00	100.00	100.00	99.90	99.78
GPT-4	100.00	100.00	100.00	100.00	100.00	100.00
English-dataset						
LLama2-7B	29.40	10.50	3.60	31.10	21.00	19.12
Baichuan2-7B	95.50	81.00	80.80	98.50	85.50	88.26
ChatGLM3-6B	91.40	86.70	96.40	97.10	95.80	93.48
Vicuna-7B	96.90	92.40	99.40	98.10	87.20	94.80
Qwen-7B	97.70	91.80	99.70	97.40	96.10	96.54
Mistral-7B	99.40	90.00	99.90	99.50	99.60	97.68
Qwen-14B	89.90	94.70	99.50	67.00	94.90	89.20
LLama2-13B	97.10	89.80	99.80	91.50	88.00	93.24
Vicuna-13B	99.90	93.30	99.60	100.00	97.90	98.14
Baichuan2-13B	99.60	95.10	99.80	100.00	98.50	98.60
LLama2-70B	99.00	93.50	99.90	94.90	97.70	97.00
Qwen-72B	100.00	99.00	99.60	100.00	99.80	99.68
GPT-3.5	100.00	94.00	100.00	99.80	100.00	98.76
GPT-4	100.00	100.00	99.90	100.00	100.00	99.98

Table 6: The results of JSON format correct rate for tasks that require JSON output format. And AVG. is the average score of all five tasks' JSON format correct rate.

Query Collection Guideline

Assuming you are a user of an artificial intelligence assistant, based on your experience in the {domain} field, you are required to write a set of unique queries for the AI assistant. The requirements are as follows:

1. **Authenticity:** The queries should be based on real-world needs, reflecting scenarios that users might encounter. Please construct the queries based on real cases you are aware of or appropriately modified scenarios.
2. **Complexity:** The queries should be sufficiently complex to reflect the multiple decision points that may be needed to solve a problem, including the potential use of various tools. The best queries would require the use of multiple tools to obtain an answer.
3. **Specificity:** The queries should pertain to concrete needs within the {domain}, rather than being general or vague. Ensure that the queries are closely related to the specified domain and contain enough detail to understand their complexity.
4. **Privacy:** Avoid using real personal information. Construct the queries using pseudonyms and hypothetical scenarios.
5. **Diversity:** The queries should cover a wide range of real-life needs. We encourage you to construct queries based on the needs of different user groups to reflect the diversity of the real world. For example, consider the needs that users of different ages, occupations, and cultural backgrounds might have.

After constructing each query, you will also need to list the potential tools required, including the tool's name, the parameters needed to call the tool within the query, and the expected return value of the tool.

To assist you in understanding the type of queries required, here are some examples of queries and tools:
{query example}
{tool example}

Please note that these are only examples. We encourage you to provide a more diverse and specific set of complex queries, and ensure that the entire set of queries you provide is as non-repetitive as possible.

Figure 14: Guideline for query collection process.

Manual Refinement Guideline

Given you a data for resolving user queries from an LLM (Language Model) perspective, which involves the calling of tools. This data includes the user's query (in the "question" field), a plan tailored to the user's query (in the "plan" field, where each step contains information about tool usage, indicated by the "tool" field), a list of tools involved in the plan (in the "tools" field), and a complete set of all the tools (the toolset). Your task is to perform detailed refinement on this data:

Definitions:

1. The plan includes three types of steps: *tool-free steps* (where the "tool" field value is "no tool required"), *tool-usage steps* (where the "tool" field specifies a particular tool calling), and some parent operations that are not of concern (where the "tool" field value is "null").
2. When invoking a tool in a *tool-usage step*, the parameters are passed in the form "parameter name=specific value".
3. Refine the plan with minimal changes to the original plan, avoiding over-optimization and excessive modifications, while maintaining the sequential order of plan numbers.

Specific Refinement Guidelines:

1. Ensure the overall logic of the plan is coherent (each step should be based on the previous one and contribute to the overall goal, without contradictions or repetitions), the sequence of steps in the plan is reasonable (if not, adjust them to a logical order), there are no redundant steps (remove if any), and no missing steps (add if any). If adjustments involve renumbering, ensure the sequence remains orderly.
2. If a *tool-free step* actually requires the calling of a tool to solve the issue for the LLM, modify it to a *tool-usage step*: find an appropriate tool from the list of tools or select one from the toolset (if no suitable tool is in the list), and populate it with the appropriate parameters, ensuring the completeness of the used parameters.
3. If a *tool-usage step* can actually be resolved without invoking a tool for the LLM, modify it to a *tool-free step*.
4. Ensure that the parameter values used in *tool-usage steps* have a source, which can be the user query, the result of pre-ordered tool calling, or some user-related information (such as name, identification card, account number, etc.). If the source of the parameter value used in a tool calling is the result of another tool calling XX (specific parameter name=XX), it should be modified to "specific parameter name=<XX>" to indicate that the parameter value is the result of a specific tool calling.
5. If the tool selection in a *tool-usage step* is inappropriate, select a more suitable tool from the toolset and populate the corresponding parameters.
6. If the format of the parameters used in a *tool-usage step* does not comply with "parameter name=specific value," it needs to be corrected. If any parameters are missing, they should be supplemented. If there is a clear mismatch between the used parameter names and their meanings and the content of the parameter values, modify them to appropriate values or select other reasonable parameter names defined by the tool.
7. If you feel that the data quality is indeed poor, you can also choose to delete the data directly.

To assist you in understanding the refinement requirement, here are some examples of data refinement:
{example}

Figure 15: Guideline for manual refinement process.

Chinese Prompt
<p>你是一个经验丰富的问题重写助手。给定一个问题，你的目标是将给定的问题进行重写，要求如下：</p> <ol style="list-style-type: none"> 1. #重写后的问题#必须仍然是与#给定的问题#相似类型的问题。 2. #重写后的问题#要多样化，主题、格式、风格以及涉及的数字等都不能跟#给定的问题#一样。 3. #重写后的问题#必须是合理的，并且必须能被人类理解和回应。 4. 根据#给定的问题#重写2个不同的问题，#重写后的问题#对比#给定的问题#要有多样性。 <p>以下是给定的问题：</p> <p>#给定的问题#： {query}</p> <p>按如下格式输出：</p> <p>#重写后的问题#： { "问题1":"..." "问题2":"..." }}</p>
English Prompt
<p>You are an experienced query rewriting assistant. Given an query, your goal is to rewrite the given query with the following requirements:</p> <ol style="list-style-type: none"> 1. The #rewritten query# must still be a query of a similar type to the #given query#. 2. The #rewritten query# should be diversified; the theme, format, style, and any numbers involved must not be the same as the #given query#. 3. The #rewritten query# must be reasonable and must be capable of being understood and responded to by humans. 4. Rewrite 2 different queries based on the #given query#, ensuring that the #rewritten queries# demonstrate diversity when compared to the #given query#. <p>Below is the given query:</p> <p>#given query#： {query}</p> <p>Output in the following format:</p> <p>#rewritten queries#： { "query1":"..." "query2":"..." }}</p>

Figure 16: Prompt for query generalization process.

Chinese Prompt

作为一名资深的问题构建专家，你的目标是通过添加新的操作步骤或者约束条件，将输入的问题转化为跟复杂的问题。请遵循以下指导原则：

1. 在#给定的问题#的基础上增加一到两个相关的条件约束或者能够通过工具API调用执行的操作步骤。这些新增的操作步骤/条件约束应该与#给定的问题#逻辑相关联，并能够增加大语言模型解决问题所需的推理和工具调用难度。
2. 避免在#重写后的问题#中使用“如果/若...则...”这类与选择(if-else)相关的复杂逻辑。
3. 避免#重写后的问题#形式为“请设计一个脚本/程序，该脚本/程序能够...”或“编写一个简短的脚本...”，即不要求进行脚本编写。
4. 避免在#重写后的问题#中使用“给定问题”、“重写后的问题”等直接的原始术语，而是以自然流畅的方式表达。
5. 确保#重写后的问题#在难度上超越#给定的问题#，要求执行者采取更多的策略和处理更复杂的任务。
6. 在增加复杂性的同时，避免不必要的冗长描述，尽可能保持问题的精炼、可读和可操作性。
7. 根据#给定的问题#重写2个不同的问题，#重写后的问题#对比#给定的问题#要有多样性，同时在难度上超越#给定的问题#，要求执行者采取更多的策略和处理更复杂的任务。

对于以下给定的问题，请构建一个更为复杂的版本：

#给定的问题#：

```
{query}
```

#重写后的问题#：

```
{  
  {  
    "问题1": "..."  
    "问题2": "..."  
  }  
}
```

English Prompt

As a seasoned query construction expert, your goal is to transform an input query into a more complex one by adding new operational steps or constraints. Please follow the guidelines below:

1. Add one or two relevant conditional constraints or operational steps that can be executed through tool API calls, based on the #given query#. These added operations/steps or constraints should be logically associated with the #given query# and increase the difficulty of reasoning and tool invocation required for a large language model to solve the problem.
2. Avoid using complex logic related to selection (if-else) in the #rewritten query#, such as "if/then..." statements.
3. Avoid forms like "Please design a script/program that can..." or "Write a short script..." in the #rewritten query#, meaning that script writing is not requested.
4. Refrain from using direct terms such as "given query" or "rewritten query" in the #rewritten query#, but express it in a natural and fluent manner.
5. Ensure that the #rewritten query# is more challenging than the #given query#, requiring the executor to adopt more strategies and handle more complex tasks.
6. While increasing complexity, avoid unnecessary lengthy descriptions and maintain the conciseness, readability, and operability of the queries as much as possible.
7. Rewrite two different queries based on the #given query#. The #rewritten queries# should be diverse compared to the #given query# and more challenging, requiring the executor to adopt more strategies and handle more complex tasks.

For the following given query, please construct a more complex version:

#given query#:

```
{question}
```

#rewritten queries#:

```
{  
  {  
    "query 1": "..."  
    "query 2": "..."  
  }  
}
```

Figure 17: Prompt for query complication process.

Chinese Prompt

你是一个专业的任务规划助手，可以理解复杂的用户问题，并制定一个合理的、可执行的多步计划，以完成用户的任务。具体而言，你制订的计划应像一棵树一样分为多个子任务，这些子任务将交给底层的任务处理器顺序执行，任务处理器由一个最先进的大型语言模型（LLM）驱动，它可以处理许多子任务，可以调用外部工具。输出格式示例如下：

- 1. 任务1
 - 1.1 任务1.1
 - 1.2 任务1.2
 - 1.2.1 任务1.2.1
- ...
- 2. 任务2
- ...

在示例中，任务1包括子任务1.1、1.2等，而子任务1.2又包括子任务1.2.1、1.2.2等。每个任务要包含任务的描述。如果一个任务包含多个子任务，还需要说明不同子任务之间的关系，如任一子任务完成即可、所有子任务需要顺序执行成功才行等。重要提示：

1. 在同一层级的任务应当复杂度相当。上层的任务可以抽象一些。如果某一任务太复杂或不够具体，应当将它分解为多个可执行的子任务。这个过程应当递归执行，直到某个子任务可以被调用某种工具的任务处理器解决。
2. 始终制定既可行又高效的计划，以确保任务的成功完成。尽量减少任务树的深度和子任务的数量，但要确保包含所有必须达成的目标。
3. 不要创建与现有子任务相似或相同的新子任务。对于目标相似的子任务，尽量将它们合并在一个子任务中，列出一系列子目标，而不是将它们分割成多个子任务。
4. 请按上述示例格式直接输出计划，不要产生额外的解释，因为你的回复将直接被解析执行。

你制订的计划将从以下方面进行评估，因此请注重这些方面：

1. ****完整性****：计划应当覆盖到用户需求的方方面面，不能遗漏用户的约束，也不能臆造用户的需求。计划执行完成后应当能确实完成用户的任务。
1. ****逻辑连贯性****：计划应当保持逻辑的连贯性。也就是说，每一个步骤都应该基于前一步，而且每一步都应该对达成总体目标有所贡献。不应出现子任务矛盾和重复的现象。任务和子任务的关系应当符合逻辑。
3. ****可实行性****：计划应当足够清晰，易于理解。上层任务应当简洁，符合人类的任务分解习惯。最终执行的底层任务要足够具体，且包含所有必要的方面和细节，以便任务处理器知道如何去执行。
4. ****格式遵从性****：应当仅输出符合上述格式要求的计划本身，不产生额外冗余的回复，以便后续进行计划解析和执行。

以下是一些用户问题与对应的计划的样例：

```
{example1}  
{example2}  
{example3}
```

以下是用户问题：

```
{question}
```

接下来，请你根据用户的问题制定计划，输出格式：

```
计划： ...
```

Figure 18: Chinese prompt for plan annotation process.

English Prompt

As a professional task planning assistant, you are capable of understanding complex user inquiries and developing a structured, executable multi-step plan to fulfill the user's tasks. Specifically, the plans you create should branch out like a tree into multiple subtasks, which are sequentially executed by underlying task processors powered by a state-of-the-art Large Language Model (LLM) capable of handling many subtasks and invoking external tools. An example of the output format is as follows:

- 1. Task 1
 - 1.1 Subtask 1.1
 - 1.2 Subtask 1.2
 - 1.2.1 Subtask 1.2.1

...

- 2. Task 2

...

In the example, Task 1 includes Subtasks 1.1, 1.2, etc., while Subtask 1.2 further includes Subtasks 1.2.1, 1.2.2, and so on. Each task must contain a description of the task. If a task contains multiple subtasks, the relationship between different subtasks also needs to be explained, such as whether any subtask can be completed, or all subtasks need to be executed in sequence to succeed. Important tips:

1. Tasks at the same level should have comparable complexity. Higher-level tasks can be more abstract. If a task is too complex or not specific enough, it should be broken down into multiple executable subtasks. This process should be recursively executed until a subtask can be addressed by a task processor that can invoke a certain tool.
2. Always develop feasible and efficient plans to ensure the successful completion of tasks. Minimize the depth of the task tree and the number of subtasks, but ensure that all necessary goals are included.
3. Do not create new subtasks that are similar or identical to existing ones. For subtasks with similar objectives, try to merge them into one subtask, listing a series of sub-goals, rather than splitting them into multiple subtasks.
4. Please output the plan directly in the format shown above without generating additional explanations, as your response will be parsed and executed directly.

Your plan will be evaluated in the following aspects, so please pay attention to them:

1. **Completeness**: The plan should cover all aspects of the user's needs without omitting any constraints or fabricating requirements. Upon completion, the plan should indeed fulfill the user's task.
2. **Logical Coherence**: The plan should maintain logical consistency. That is, each step should be based on the previous one, and each step should contribute to achieving the overall goal. There should be no contradictions or duplications in subtasks. The relationship between tasks and subtasks should be logical.
3. **Feasibility**: The plan should be clear enough to be understood. Higher-level tasks should be concise and in line with human task decomposition habits. The underlying tasks to be executed should be specific enough and include all necessary aspects and details so that the task processor knows how to execute them.
4. **Format Compliance**: Only the plan itself, which meets the format requirements mentioned above, should be output without generating any additional redundant responses, to facilitate subsequent plan parsing and execution.

Here are some examples of user questions and corresponding plans:

{example1}
{example2}
{example3}

Below is the user's question:

{question}

Next, please develop a plan based on the user's question, output format:

Plan: ...

Figure 19: English prompt for plan annotation process.

Chinese Prompt
<p>你是一名专业的工具创造助手，给定一个#计划#和一个#现有工具#集合，你的任务是判断#现有工具#是否足够完成任务，若不够完成，需要进行相应的工具创造。要求如下：</p> <ol style="list-style-type: none"> 1. 在#计划#中明确区分需要使用工具的步骤和不需要使用工具的步骤。 2. 对于需要使用工具的步骤，判断在#现有工具#是否能找到合适的工具，如果#现有工具#不够完成任务，需要创造对应的新工具。 3. 创造的新工具应遵循最小必要原则，具有通用性，并且参数化，以适应不同情况下的相似操作。 4. 创造的新工具的格式与#现有工具#中的工具格式相同。 <p>以下是一些输入#计划#和#现有工具#，输出新工具的样例：</p> <pre>{example1} {example2}</pre> <p>请根据以下#计划#和#现有工具#，参照样例格式，以json格式生成可能需要的新工具，注意保证json字符串格式的正确性，不要输出其他任何内容。</p> <p>#计划#： <pre>{plan}</pre> #现有工具#： <pre>{tool}</pre> #输出#：</p>
English Prompt
<p>You are a professional tool creation assistant. Given a #plan# and a collection of #existing tools#, your task is to determine whether the #existing tools# are sufficient to complete the task. If they are not, you will need to create the appropriate tools accordingly. The requirements are as follows:</p> <ol style="list-style-type: none"> 1. In the #plan#, clearly differentiate between steps that require the use of tools and those that do not. 2. For steps that require the use of tools, assess whether suitable tools can be found within the #existing tools#. If the #existing tools# are insufficient to complete the task, new corresponding tools must be created. 3. The newly created tools should adhere to the principle of minimal necessity, be versatile, and parameterized to accommodate similar operations in different scenarios. 4. The format of the newly created tools should be consistent with the format of the tools within the #existing tools# collection. <p>Below are some examples of input #plans# and #existing tools#, and output of new tool samples:</p> <pre>{example1} {example2}</pre> <p>Based on the following #plan# and #existing tools#, please refer to the sample format and generate the potentially required new tools in JSON format. Ensure the correctness of the JSON string format and do not output any other content.</p> <p>#plan#: <pre>{plan}</pre> #existing Tools#: <pre>{tool}</pre> #output#:</p>

Figure 20: Prompt for tool creation process.

Chinese Prompt
<p>你是一名专业的计划优化助手，给定#用户问题#，针对用户问题的#计划#和#工具集#，你的任务是优化提供的树状#计划#，形成一个#优化计划#，并确保#优化计划#中的叶子节点是原子操作，即执行计划中的最小不可分割步骤。这些原子操作应匹配LLM可以直接执行的操作（如信息获取、决策、推理、选择、文本生成等），或与外部系统交互的操作（即需要调用工具）。要求如下：</p> <ol style="list-style-type: none"> 1. 仔细审查#用户问题#和提供的#计划#，通过（1）删除冗余的步骤；（2）现有步骤进行拆分、合并、细化、调整，以形成更合适的原子操作；（3）增加新的合理的原子操作；来初步形成针对#用户问题#的#优化计划#。 2. 若原子操作中包含具体名词，需要以“(抽象名词：具体名词)”的形式抽象化，便于工具调用的过程中将具体名词作为传递的参数。 3. 在#优化计划#中明确区分需要使用工具的原子操作和不需要使用工具的原子操作。 4. 对于需要使用工具的原子操作，其前序需要有信息获取类的原子操作（不需要使用工具）来获取工具调用所需的所有参数值，其后序需要有工具调用结果观察/使用类的原子操作（不需要使用工具）来使用/验证工具调用结果，若没有则需要步骤补充。 5. 需要使用工具的原子操作只专注于工具调用，不能同时获取参数（若有则需要将其独立为新的获取信息操作，安排到前序），并确保工具需要的所有参数值全部来自于前序信息获取类原子操作中的“(抽象名词：具体名词)”里的具体名词，若有参数需要的具体名词未曾出现在前序信息获取步骤中，则应调整前序信息获取步骤或在前序增加对应的信息获取步骤，但注意不需要重复获取同一个具体名词的信息。 6. 确保#优化计划#保持有序的树状结构。 <p>以下是一些输入#用户问题#，#计划#和#现有工具#，输出#优化计划#的样例：</p> <pre>{example1} {example2}</pre> <p>请根据以下#用户问题#、#计划#和#现有工具#，参照样例格式，以json格式生成#优化计划#，注意保证json字符串格式的正确性，不要输出其他任何内容。</p> <pre>#用户问题#: {query} #计划#: {plan} #现有工具#: {tool} #输出#:</pre>

Figure 21: Chinese prompt for plan refinement process.

English Prompt

You are a professional plan refinement assistant. Given an #user query#, with a corresponding #plan# and #toolset#, your task is to refine the provided tree-like #plan# to form an #refined plan#. Ensure that the leaf nodes in the #refined plan# are atomic operations, which represent the smallest indivisible steps in the execution plan. These atomic operations should match actions directly executable by an LLM (such as information retrieval, decision-making, reasoning, selection, text generation, etc.), or operations that interact with external systems (i.e., requiring tool invocation). The requirements are as follows:

1. Carefully review the #user query# and the provided #plan#. Formulate a preliminary #refined plan# for the #user query# by (1) removing redundant steps; (2) splitting, merging, refining, or adjusting existing steps to form more appropriate atomic operations; (3) adding new reasonable atomic operations.
2. If atomic operations include concrete nouns, abstract them in the form "(abstract noun: concrete noun)" to facilitate the passing of concrete nouns as parameters during the tool invocation process.
3. Clearly distinguish between atomic operations in the #refined plan# that require tool usage and those that do not.
4. For atomic operations that require tool usage, there must be preceding atomic operations (that do not require tool usage) for information retrieval to acquire all necessary parameters for tool invocation. Following the tool invocation, there should be atomic operations (that do not require tool usage) for observing/using the results of the tool invocation. If these are missing, additional steps must be supplemented.
5. Atomic operations requiring tool usage should focus solely on the tool invocation and not on parameter retrieval (if so, separate them into a new information retrieval operation arranged beforehand). Ensure that all parameter values required by the tool come exclusively from the concrete nouns in the "(abstract noun: concrete noun)" format of preceding information retrieval atomic operations. If a parameter's concrete noun has not appeared in prior information retrieval steps, adjust the preceding steps or add corresponding information retrieval steps. However, avoid repetitive retrieval of the same concrete noun.
6. Ensure the #refined plan# maintains a structured, orderly tree form.

Below are examples of inputs for #user query#, #plan#, and #existing tools#, and outputs for the #refined plan#:

```
{example1}  
{example2}
```

Please generate a #refined plan# in JSON format based on the following #user query#, #plan#, and #existing tools#, referring to the example format. Ensure the correctness of the JSON string format and do not output any other content.

```
#user query#:  
{query}  
#plan#:  
{plan}  
#existing tools#  
{tool}  
#output#:
```

Figure 22: English prompt for plan refinement process.

Chinese Prompt

你是一名专业的工具匹配助手。根据#用户问题#，#计划#和#工具集#。你的任务是对#计划#中的原子操作进行工具匹配，并输出匹配工具后的#具体执行计划#，原子操作是#计划#中的叶子节点，即计划中的最小不可分割步骤。要求如下：

1. 在#计划#中明确区分需要使用工具的原子操作和不需要使用工具的原子操作。
2. 对于需要使用工具的原子操作，指定使用#工具集#中的哪一个具体工具。
3. 在#具体执行计划#中以json格式清晰显示每个步骤及其是否需要工具。对于非原子操作，“tool”字段标为“null”；对于不需要工具的原子操作，“tool”字段标为“不需要工具”；对于需要使用工具的原子操作，提供工具名称及其具体参数。
4. 参数传递的形式均为：“参数名：参数值”，保证使用的参数名来自于对应工具中定义的参数名集合，保证使用的参数值都有来源，来源有三部分：用户指令、其他工具调用结果、一些用户相关信息（个人信息如姓名、身份证、账号、密码等），若工具调用使用的参数值来源是其他工具调用的结果，需要用“<”标记出来，即修改为“具体参数名=<xx>”。

以下是一些输入#用户问题#，#计划#和#工具集#，输出#具体执行计划#的样例：

```
{example1}
{example2}
```

请根据以下#用户问题#，#计划#和#工具集#，参照样例格式，以json格式生成匹配工具后的#具体执行计划#，注意保证json字符串格式的正确性，不要输出其他任何内容。

#用户问题#:

```
{query}
#计划#:
{plan}
#工具集#
{tool}
#输出#:
```

English Prompt

You are a professional tool-matching assistant. Based on the #user query#, #plan#, and #toolset#, your task is to match the atomic operations in the #plan# with appropriate tools and output the #specific execution plan#, where atomic operations are the leaf nodes of the #plan#, that is, the smallest indivisible steps of the plan. The requirements are as follows:

1. Clearly distinguish between atomic operations in the #plan# that require tools and those that do not.
2. For atomic operations that require the use of tools, specify which specific tool from the #toolset# should be used.
3. In the #specific execution plan#, clearly display each step in JSON format, along with whether or not a tool is needed. For non-atomic operations, the “tool” field should be marked as “null”; for atomic operations that do not require tools, the “tool” field should be marked as “no tool needed”; for atomic operations that do require tools, provide the tool name and specific parameters.
4. The format for parameter passing should be: “parameter name: parameter value”, ensuring that the used parameter names come from the corresponding tool’s defined parameter name collection and that the used parameter values have a source. The sources are threefold: user instructions, results of other tool invocations, and some user-related information (personal information such as name, ID card, account, password, etc.). If the parameter value used for tool invocation is the result of another tool’s call, it should be marked with “<”, i.e., changed to “specific parameter name=<xx>”.

Below are some examples of input #user query#, #plan#, and #toolset#, with output #specific execution plan#:

```
{example1}
{example2}
```

Please generate the #specific execution plan# in JSON format according to the following #user query#, #plan#, and #toolset#, referring to the example format. Ensure the correctness of the JSON string format and do not output any other content.

```
#user query#:
{query}
#plan#:
{plan}
#toolset#:
{tool}
#output#:
```

Figure 23: Prompt for tool calling message annotation process.

Chinese Prompt

作为一名专业评估专家，你的任务是参照标准答案，根据给定的评估维度客观评估所提供数据的质量。给定用户指令，标准答案和用户指令对应的任务规划，请根据以下评估维度对任务规划的质量进行评分：

1. 准确性：任务规划与用户指令的目标应该一致，对用户指令的理解和用户指令中提供信息的使用需要准确，不能虚增用户指令中没有要求的不合理任务或不合理约束。
2. 完整性：用户指令中涉及的多个任务、约束全部需要在任务规划的步骤中体现，不能有遗漏。
3. 可执行性：任务规划整体逻辑连贯，任务规划中的步骤均合理且可执行，步骤之间顺序合理，可以逐步执行以解决用户指令，不会缺失步骤导致后续步骤无法执行，也不会有冗余步骤导致执行错误。
4. 语法健全性：任务规划的内容语法健全，语句通顺流畅，语言风格良好，没有语法错误。
5. 结构合理性：任务规划的结构是一个有序的树状结构，父操作和子操作之间关系合理，整体组织结构高效合理。
6. 高效性：任务规划简洁高效，步骤清晰明确，不会过度细分步骤，没有冗长复杂的流程。

总的来说，模型回答的质量越高，则分数越高，作为示例，标准答案在各个维度和总分上都可以得到8分。对照标准答案，逐步给上述每个评估维度打一个分数，然后根据所有的评估维度，打一个总分，总分的具体打分标准为：

当模型回答存在与问题不相关，或者有本质性的事实错误，或生成了有害内容时，总分必须是1分；
当模型回答没有严重错误而且基本无害，但是质量较低，没有满足用户需求，总分为2到3分；
当模型回答基本满足用户要求，但是在部分维度上表现较差，质量中等，总分可以得4到6分；
当模型回答质量与标准答案相近，在所有维度上表现良好，总分得7到8分；
只有当模型回答质量显著超过标准答案，充分地解决了用户问题和所有需求，并且在所有维度上都接近满分的情况下，才能得9到10分。

你必须按照以下格式提供你的评估结果：

```
[
{"打分理由": "<对照准确性定义和标准答案，提供评分原因>", "准确性分数": "<分配1到10分之间的分数>"},
{"打分理由": "<对照完整性定义和标准答案，提供评分原因>", "完整性分数": "<分配1到10分之间的分数>"},
{"打分理由": "<对照可执行性定义和标准答案，提供评分原因>", "可执行性分数": "<分配1到10分之间的分数>"},
{"打分理由": "<对照语法健全性定义和标准答案，提供评分原因>", "语法健全性分数": "<分配1到10分之间的分数>"},
{"打分理由": "<对照结构合理性定义和标准答案，提供评分原因>", "结构合理性分数": "<分配1到10分之间的分数>"},
{"打分理由": "<对照高效性定义和标准答案，提供评分原因>", "高效性分数": "<分配1到10分之间的分数>"},
{"打分理由": "<对照所有评估维度定义和标准答案，提供评分原因>", "总分": "<分配1到10分之间的分数>"}
]
```

以下是给定的用户指令，标准答案和要评估的任务规划：

用户指令：{question}

标准答案：{reference}

要评估的任务规划：{answer}

根据上述评估维度，对照标准答案，对要评估的任务规划逐步给每个评估维度打分，然后再打一个总分。

最终输出内容应以json字符串的形式输出，不要输出其他任何内容。

输出：

Figure 24: Prompt for *Multi-Dimensional Point-Wise LLM-as-Judge Method* on Chinese-dataset planning evaluation.

English Prompt

As a professional assessment expert, your task is to objectively evaluate the quality of the provided data based on the given assessment dimensions, with reference to the standard answer. Given user instructions, a standard answer, and a task planning corresponding to the user instructions, please score the quality of the task planning according to the following assessment dimensions:

1. Accuracy: The task planning should align with the objectives of the user instructions. The understanding of the user instructions and the use of information provided within them must be accurate, without adding unreasonable tasks or constraints that are not requested by the user.
2. Completeness: All tasks and constraints involved in the user instructions must be reflected in the steps of task planning without omissions.
3. Executability: The overall logic of the task planning should be coherent. All steps in the task planning should be reasonable and executable, with a logical sequence that allows for gradual completion to address the user's instructions. There should be no missing steps that would prevent subsequent steps from being executed, nor any superfluous steps that could cause errors in execution.
4. Syntactic Soundness: The content of the task planning should be grammatically sound, with smooth and fluent sentences, a good language style, and free of grammatical errors.
5. Structural Rationality: The structure of the task planning should be an ordered tree-like hierarchy, with reasonable relationships between parent and child operations, and an overall efficient and rational organization.
6. Efficiency: The task planning should be concise and efficient, with clear and specific steps, without excessively subdividing steps or having lengthy and complicated procedures.

Overall, the higher the quality of the model's response, the higher the score. As an example, the standard answer could receive a score of 8 in each dimension and in total.

Contrasting with the standard answer, assign a score to each of the above assessment dimensions individually, and then give an overall score based on all the assessment dimensions. The specific criteria for the overall score are as follows:

The overall score must be 1 if the model's response is irrelevant to the question, contains fundamental factual errors, or generates harmful content.

If the model's response has no serious errors and is generally harmless but of low quality and does not meet the user's needs, the overall score should be between 2 and 3.

If the model's response basically meets the user's requirements but performs poorly on some dimensions, with medium quality, the overall score should be between 4 and 6.

If the model's response is close to the quality of the standard answer and performs well in all dimensions, the overall score should be between 7 and 8.

Only if the model's response significantly surpasses the standard answer, thoroughly addresses the user's questions and all needs, and is near perfect in all dimensions, can it receive a score between 9 and 10.

You must provide your assessment results in the following format:

```
[
  {"Reasoning": <Provide reasoning for the score with reference to the accuracy definition and standard answer>,
  "Accuracy Score": <Assign a score between 1 and 10>},
  {"Reasoning": <Provide reasoning for the score with reference to the completeness definition and standard answer>,
  "Completeness Score": <Assign a score between 1 and 10>},
  {"Reasoning": <Provide reasoning for the score with reference to the executability definition and standard answer>,
  "Executability Score": <Assign a score between 1 and 10>},
  {"Reasoning": <Provide reasoning for the score with reference to the syntactic soundness definition and standard answer>,
  "Syntactic Soundness Score": <Assign a score between 1 and 10>},
  {"Reasoning": <Provide reasoning for the score with reference to the structural rationality definition and standard answer>,
  "Structural Rationality Score": <Assign a score between 1 and 10>},
  {"Reasoning": <Provide reasoning for the score with reference to the efficiency definition and standard answer>,
  "Efficiency Score": <Assign a score between 1 and 10>},
  {"Reasoning": <Provide reasoning for the score with reference to all assessment dimension definitions and standard answer>,
  "Overall Score": <Assign a score between 1 and 10>},
]
```

Here are the given user instructions, standard answer, and the task planning to be assessed:

User Instructions: {question}

Standard Answer: {reference}

Task Planning to be Assessed: {answer}

Based on the above assessment dimensions and contrasting with the standard answer, score each assessment dimension for the task planning to be assessed, and then give an overall score. The final output should be in the form of a JSON string, without including any other content.

Output:

Figure 25: Prompt for *Multi-Dimensional Point-Wise LLM-as-Judge Method* on English-dataset planning evaluation.

Chinese Prompt

作为一名专业评估专家，你的任务是参照标准答案，根据给定的评估维度客观评估所提供数据的质量。给定用户指令，标准答案和根据用户指令所创造的工具，请根据以下评估维度对创造的工具的质量进行评分：

1. 格式遵从性：创造的工具应该与标准答案在格式上保持完全一致，完整包含工具名 ("name"字段)、工具描述 ("description"字段)、参数列表 ("arguments"字段, "arguments"中还包含"type"和"properties"字段)和返回值 ("results"字段, "results"中还包含"type"和"properties"字段) 这几个基本组成部分。
2. 准确性：创造的工具与用户指令的目标应该一致，能够准确解决用户指令的需求。
3. 内容合理性：创造的工具定义的各个字段的内容都应该合理，包括自然语言描述字段的表达清晰、语法健全，以及定义的各个参数的类型和各个返回值的类型均是合理的。
4. 可执行性：创造的工具定义的工具名和工具描述能够恰当表达工具的功能，定义的参数列表完备，定义的返回值完备。
5. 丰富度：创造的工具包含丰富的信息、深度、上下文考虑和多样性。

总的来说，模型回答的质量越高，则分数越高，作为示例，标准答案在各个维度和总分上都可以得到8分。对照标准答案，逐步给上述每个评估维度打一个分数，然后根据所有的评估维度，打一个总分，总分的具体打分标准为：

- 当模型回答存在与问题不相关，或者有本质性的事实错误，或生成了有害内容时，总分必须是1分；
- 当模型回答没有严重错误而且基本无害，但是质量较低，没有满足用户需求，总分为2到3分；
- 当模型回答基本满足用户要求，但是在部分维度上表现较差，质量中等，总分可以得4到6分；
- 当模型回答质量与标准答案相近，在所有维度上表现良好，总分得7到8分；
- 只有当模型回答质量显著超过标准答案，充分地解决了用户问题和所有需求，并且在所有维度上都接近满分的情况下，才能得9到10分。

你必须按照以下格式提供你的评估结果：

```
[
{"打分理由": <对照格式遵从性定义和标准答案, 提供评分原因>, "格式遵从性分数": <分配1到10分之间的分数>},
{"打分理由": <对照准确性定义和标准答案, 提供评分原因>, "准确性分数": <分配1到10分之间的分数>},
{"打分理由": <对照内容合理性定义和标准答案, 提供评分原因>, "内容合理性分数": <分配1到10分之间的分数>},
{"打分理由": <对照可执行性定义和标准答案, 提供评分原因>, "可执行性分数": <分配1到10分之间的分数>},
{"打分理由": <对照丰富度定义和标准答案, 提供评分原因>, "丰富度分数": <分配1到10分之间的分数>},
{"打分理由": <对照所有评估维度定义和标准答案, 提供评分原因>, "总分": <分配1到10分之间的分数>},
]
```

以下是给定的用户指令，标准答案和要评估的创造的工具：

用户指令：{question}
标准答案：{reference}
创造的工具：{answer}

根据上述评估维度，对照标准答案，对要评估的创造的工具逐步给每个评估维度打分，然后再打一个总分。最终输出内容应以json字符串的形式输出，不要输出其他任何内容。

输出：

Figure 26: Prompt for *Multi-Dimensional Point-Wise LLM-as-Judge Method* on Chinese-dataset tool creation evaluation.

English Prompt

As a professional assessment expert, your task is to objectively assess the quality of the provided data in reference to the standard answer, based on the given assessment dimensions. Given a user instruction, the standard answer, and a tool created in response to the user instruction, please score the quality of the created tool according to the following assessment dimensions:

1. **Format Compliance:** The created tool should be completely consistent with the standard answer in terms of format, fully including the basic components such as the tool name ("name" field), tool description ("description" field), list of arguments ("arguments" field, with "type" and "properties" fields within "arguments") and return values ("results" field, with "type" and "properties" fields within "results").
2. **Accuracy:** The created tool should align with the objectives of the user instruction and accurately address the user's needs.
3. **Content Reasonableness:** The content within each field of the created tool should be reasonable, including clear expression and solid grammar in the natural language description fields, as well as sensible types for each defined argument and return value.
4. **Executability:** The tool name and description defined in the created tool should appropriately express its function, with a comprehensive list of parameters and complete return values.
5. **Richness:** The created tool should include rich information, depth, contextual considerations, and diversity.

Overall, the higher the quality of the model answer, the higher the score. As an example, the standard answer can score 8 points in each dimension and in total.

Compare the standard answer and step by step score each of the above assessment dimensions, then provide an overall score based on all dimensions. The specific criteria for the overall score are as follows:

The total score must be 1 point if the model answer is irrelevant to the question, contains essential factual errors, or generates harmful content.

The total score should be 2 to 3 points if the model answer is of low quality without serious errors and is harmless but does not meet user needs.

The total score can be 4 to 6 points if the model answer generally meets user requirements but performs poorly in some dimensions and is of mediocre quality.

The total score should be 7 to 8 points if the model answer's quality is close to the standard answer and performs well in all dimensions.

A score of 9 to 10 points is only achievable if the model answer significantly surpasses the standard answer, fully resolves the user's issue and all requirements, and approaches a perfect score in all dimensions.

You must provide your assessment results in the following format:

```
[
  {"Scoring Reason": <Provide reasons for scoring against the definition of format compliance and the standard answer>, "Format Compliance Score": <Assign a score between 1 to 10>}},
  {"Scoring Reason": <Provide reasons for scoring against the definition of accuracy and the standard answer>, "Accuracy Score": <Assign a score between 1 to 10>}},
  {"Scoring Reason": <Provide reasons for scoring against the definition of content reasonableness and the standard answer>, "Content Reasonableness Score": <Assign a score between 1 to 10>}},
  {"Scoring Reason": <Provide reasons for scoring against the definition of executability and the standard answer>, "Executability Score": <Assign a score between 1 to 10>}},
  {"Scoring Reason": <Provide reasons for scoring against the definition of richness and the standard answer>, "Richness Score": <Assign a score between 1 to 10>}},
  {"Scoring Reason": <Provide reasons for scoring against all assessment dimensions and the standard answer>, "Total Score": <Assign a score between 1 to 10>}},
]
```

Below are the given user instruction, standard answer, and the created tool to be evaluated:

User instruction: {question}

Standard answer: {reference}

Created tool: {answer}

Based on the above assessment dimensions and comparing against the standard answer, score each dimension for the created tool to be evaluated, then provide an overall score. The final output should be in the form of a JSON string, without any additional content.

Output:

Figure 27: Prompt for *Multi-Dimensional Point-Wise LLM-as-Judge Method* on English-dataset tool creation evaluation.

Chinese Prompt
<p>你是一个专业的计划制定助手，给你一个用户问题，你的任务是充分理解用户问题，并制定一个合理的、可执行的多步计划以完成用户的任务，具体而言，你制订的计划应像一棵树一样分为多个子任务。输出格式为字符串（内容是使用换行符分隔的一系列子任务），例如：1. 任务1 \n 1.1 任务1.1 \n 1.2 任务1.2 \n 1.2.1 任务1.2.1 \n ... \n 2. 任务2 \n ...</p> <p>你应该严格遵守输出格式要求，不要输出其他任何内容。</p> <p>样例： 问题： {input} 输出： {reference}</p> <p>让我们开始吧！ 问题： {input} 输出：</p>
English Prompt
<p>You are a professional planning assistant. Given a user's question, your task is to fully understand the user's question and create a reasonable, executable multi-step plan to complete the user's task. Specifically, your plan should be like a tree with multiple subtasks. The output format is a string (content is a series of subtasks separated by newline characters), for example: 1. Task 1 \n 1.1 Task 1.1 \n 1.2 Task 1.2 \n 1.2.1 Task 1.2.1 \n ... \n 2. Task 2 \n ...</p> <p>You should strictly follow the output format requirements and not output any other content.</p> <p>Example: Question: {input} Output: {reference}</p> <p>Let's Begin! Question: {input} Output:</p>

Figure 28: Prompt for planning inference on Chinese-dataset and English-dataset.

Chinese Prompt
<p>你是一个专业的人工智能助手，给你一个计划和相应的工具集，计划中有些步骤带有'tool'字段，你的任务是判断这些步骤能否在给定的工具集中找到合适的工具，如果工具集中没有合适的工具（需要创造新的工具）则'tool'字段为'1'，否则为'0'。输出格式为元素是dict的list，每个dict包含'step'（给定计划中有'tool'字段的步骤）和'tool'（判断，'0'或'1'）字段，例如：[{"step": "2.1 步骤2.1", "tool": "1"}, {"step": "4.2 步骤4.2", "tool": "0"}, ...]</p> <p>你应该严格遵守输出格式要求，不要输出其他任何内容。</p> <p>样例： 计划：{input} 工具集：{toolset} 输出：{reference}</p> <p>让我们开始吧！ 计划：{input} 工具集：{toolset} 输出：</p>
English Prompt
<p>You are a professional AI assistant. Given a plan and a corresponding set of tools, some steps in the plan have a 'tool' field. Your task is to determine whether it is possible to find an appropriate tool in the given toolset for these steps. If there is no suitable tool in the toolset (requiring the creation of a new tool), then the 'tool' field should be '1', otherwise '0'. The output format is a list of dicts, each dict contains 'step' (the step in the given plan that has a 'tool' field) and 'tool' (judgment, '0' or '1'), for example: [{"step": "2.1 step 2.1", "tool": "1"}, {"step": "4.2 step 4.2", "tool": "0"}, ...]</p> <p>You should strictly follow the output format requirements and not output any other content.</p> <p>Example: Plan: {input} Toolset: {toolset} Output: {reference}</p> <p>Let's Begin! Plan: {input} Toolset: {toolset} Output:</p>

Figure 29: Prompt for tool creation awareness inference on Chinese-dataset and English-dataset.

Chinese Prompt
<p>你是一个专业的工具创造助手，给你一个计划和一个工具集，计划中有些步骤带有'tool'字段，你的任务是参照给定工具集中的工具的格式，为这些步骤创造对应的工具，并在'tool'字段填入所创造的工具。输出格式为元素是dict的list，每个dict包含'step'（给定计划中有'tool'字段的步骤）和'tool'（创造的工具，dict格式）字段，例如： [{"step": "2.3 步骤2.3", "tool": {"name": ..., "description": ..., "arguments": {"type": ..., "properties": {...}}}, {"results": {"type": ..., "properties": {...}}}], ...]</p> <p>你应该严格遵守输出格式要求，不要输出其他任何内容。</p> <p>样例： 计划： {input} 工具集： {toolset} 输出： {reference}</p> <p>让我们开始吧！ 计划： {input} 工具集： {toolset} 输出：</p>
English Prompt
<p>You are a professional tool creation assistant. Given a plan and a toolset, some steps in the plan have a 'tool' field. Your task is to create corresponding tools for these steps, referring to the format of tools in the given toolset, and fill in the 'tool' field with the created tool. The output format is a list of dicts, each dict contains 'step' (the step in the given plan that has a 'tool' field) and 'tool' (the created tool, dict format), for example: [{"step": "2.3 step 2.3", "tool": {"name": ..., "description": ..., "arguments": {"type": ..., "properties": {...}}}, {"results": {"type": ..., "properties": {...}}}], ...]</p> <p>You should strictly follow the output format requirements and not output any other content.</p> <p>Example: Plan: {input} Toolset: {toolset} Output: {reference}</p> <p>Let's Begin! Plan: {input} Toolset: {toolset} Output:</p>

Figure 30: Prompt for tool creation inference on Chinese-dataset and English-dataset.

Chinese Prompt
<p>你是一个专业的人工智能助手，给你一个计划，计划中有些步骤带有'tool'字段，你的任务是判断完成这些步骤是否需要使用工具，如果需要使用工具则'tool'字段为'1'，否则为'0'。输出格式为元素是dict的list，每个dict包含'step'（给定计划中有'tool'字段的步骤）和'tool'（判断，'0'或'1'）字段，例如： [{"step": "1.1 步骤1.1", "tool": "0"}, {"step": "2.3 步骤2.3", "tool": "1"}, ...]</p> <p>你应该严格遵守输出格式要求，不要输出其他任何内容。</p> <p>样例： 计划： {input} 输出： {reference}</p> <p>让我们开始吧！ 计划： {input} 输出：</p>
English Prompt
<p>You are a professional AI assistant. Given a plan, some steps in the plan have a 'tool' field. Your task is to determine whether tools are needed to complete these steps. If tools are required, the 'tool' field should be '1', otherwise '0'. The output format is a list of dicts, each dict contains 'step' (the step in the given plan that has a 'tool' field) and 'tool' (judgment, '0' or '1'), for example: [{"step": "1.1 step 1.1", "tool": "0"}, {"step": "2.3 step 2.3", "tool": "1"}, ...]</p> <p>You should strictly follow the output format requirements and not output any other content.</p> <p>Example: Plan: {input} Output: {reference}</p> <p>Let's Begin! Plan: {input} Output:</p>

Figure 31: Prompt for tool usage awareness inference on Chinese-dataset and English-dataset.

Chinese Prompt
<p>你是一个专业的工具选择助手，给你一个计划和相应的工具集，计划中有些步骤带有'tool'字段，你的任务是从给定的工具集中为这些步骤选择合适的工具，并在'tool'字段填入选中工具的名称（工具的'name'字段）。输出格式为元素是dict的list，每个dict包含'step'（给定计划中有'tool'字段的步骤）和'tool'（选中工具的名称'字段）字段，例如： [{"step": "2.1 步骤2.1", "tool": "工具名1"}, ...]</p> <p>你应该严格遵守输出格式要求，不要输出其他任何内容。</p> <p>样例： 计划： {input} 工具集： {toolset} 输出： {reference}</p> <p>让我们开始吧！ 计划： {input} 工具集： {toolset} 输出：</p>
English Prompt
<p>You are a professional tool selection assistant. Given a plan and a corresponding set of tools, some steps in the plan have a 'tool' field. Your task is to select the appropriate tool from the given toolset for these steps and fill in the 'tool' field with the name of the selected tool (the 'name' field of the tool). The output format is a list of dicts, each dict contains 'step' (the step in the given plan that has a 'tool' field) and 'tool' (the 'name' field of the selected tool), for example: [{"step": "2.1 step 2.1", "tool": "Tool Name 1"}, ...]</p> <p>You should strictly follow the output format requirements and not output any other content.</p> <p>Example: Plan: {input} Toolset: {toolset} Output: {reference}</p> <p>Let's Begin! Plan: {input} Toolset: {toolset} Output:</p>

Figure 32: Prompt for tool selection inference on Chinese-dataset and English-dataset.

Chinese Prompt
<p>你是一个专业的工具参数填充助手，给你用户问题，问题对应的计划和相应的工具集，计划中有些步骤带有'tool'字段（工具名）和'param'字段，你的任务是先通过'tool'字段在工具集中找到对应工具，然后为这些步骤的'param'字段填入调用对应工具所需要的参数（参数格式为"参数名=参数值"，多个参数用','分隔），参数名来自于对应工具的'arguments'中的'properties'字段（不需要全部使用），参数值来源于用户问题和每个步骤的前序步骤中的信息（若参数值来自于前序工具调用的返回值，用<>标识）。输出格式为元素是dict的list，每个dict包含'step'（给定计划中有'tool'字段的步骤），'tool'（步骤对应的'tool'字段）和'param'（填充的参数，dict格式）字段，例如： [{"step": "3.2 步骤3.2", "tool": "工具名1", "param": {"参数名1": "参数值1", "参数名2": "<参数值2>", ...}}, ...]</p> <p>你应该严格遵守输出格式要求，不要输出其他任何内容。</p> <p>样例： 问题： {question} 计划： {input} 工具集： {toolset} 输出： {reference}</p> <p>让我们开始吧！ 问题： {question} 计划： {input} 工具集： {toolset} 输出：</p>
English Prompt
<p>You are a professional tool parameter filling assistant. Given a user's question, the corresponding plan, and a set of tools, some steps in the plan have a 'tool' field (tool name) and a 'param' field. Your task is to first find the corresponding tool in the toolset through the 'tool' field, and then fill in the 'param' field for these steps with the parameters required to call the corresponding tool (parameter format is "parameter name=parameter value", separate multiple parameters with ','), where the parameter names come from the 'properties' field in the 'arguments' of the corresponding tool (not all need to be used), and parameter values come from the user's question and information from the previous steps (if the parameter value comes from the return value of a previous tool call, use <> to indicate). The output format is a list of dicts, each dict contains 'step' (the step in the given plan that has a 'tool' field), 'tool' (the corresponding 'tool' field of the step), and 'param' (the filled parameters, dict format), for example: [{"step": "3.2 step 3.2", "tool": "Tool Name 1", "param": {"parameter name1": "parameter value1", "parameter name2": "<parameter value2>", ...}}, ...]</p> <p>You should strictly follow the output format requirements and not output any other content.</p> <p>Example: Question: {question} Plan: {input} Toolset: {toolset} Output: {reference}</p> <p>Let's Begin! Question: {question} Plan: {input} Toolset: {toolset} Output:</p>

Figure 33: Prompt for tool usage inference on Chinese-dataset and English-dataset.