ToolEyes: Fine-Grained Evaluation for Tool Learning Capabilities of Large Language Models in Real-world Scenarios

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Abstract

Existing evaluations of tool learning primarily focus on validating the alignment of selected tools for large language models (LLMs) with expected outcomes. However, these approaches rely on a limited set of scenarios where answers can be pre-determined. Furthermore, a *sole* emphasis on outcomes disregards the intricate capabilities essential for LLMs to effectively utilize tools. To tackle this issue, we propose *ToolEyes*, a fine-grained system tailored for the evaluation of the LLMs' tool learning capabilities in authentic scenarios. The system meticulously examines seven real-world scenarios, analyzing five dimensions crucial to LLMs in tool learning: *format alignment*, *intent comprehension*, *behavior planning*, *tool selection*, and *answer organization*. Additionally, ToolEyes incorporates a tool library boasting approximately 600 tools, serving as an intermediary between LLMs and the physical world. Evaluations involving ten LLMs across three categories reveal a preference for specific scenarios and limited cognitive abilities in tool learning. Intriguingly, expanding the model size even exacerbates the hindrance to tool learning. These findings offer instructive insights aimed at advancing the field of tool learning.

1 Introduction

Large language models (LLMs) (Brown et al., 2020; Bai et al., 2022b; Touvron et al., 2023a) represent a significant opportunity for advancing artificial intelligence (AI) owing to their remarkable performance across a diverse set of general-purpose tasks (Ye et al., 2023; Chen et al., 2023a; Guo et al., 2023). To further bolster the model's capacity to meet real-world demands, researchers are actively exploring tool learning through the integration of external tools (Yang et al., 2023b; Mialon et al., 2023; Qin et al., 2023a). Illustrated in Figure 1, upon receiving a user request, the

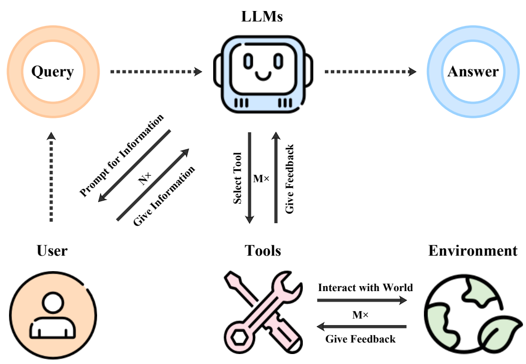

Figure 1: Illustration of tool learning. To address user queries, LLMs must analyze user requirements, utilize appropriate tools, and extrapolate feedback from the environment. Each stage in this process plays a crucial role in shaping the formulation of the answer.

LLM scrutinizes the user's needs, prompts for sufficient information, selects the appropriate tool, and inputs the required parameters in the specified format. Subsequently, the tool interacts with the environment to furnish feedback to the LLM. The LLM then employ logical reasoning based on the initial request, iterating through these steps until a conclusive answer is achieved.

Owing to the intricate nature of tool learning, initial evaluations heavily relied on manual efforts, engaging experts to assess the accuracy of LLMs tool invocation (Tang et al., 2023). Despite its reasonable effectiveness, the manpower costs hinder widespread adoption. Currently, researchers are exploring automated evaluation methods. One aspect is indirectly assessed by analyzing the performance improvement achieved through the use of tools in downstream tasks (Schick et al., 2023; Zhuang et al., 2023), while the other is directly evaluated by formulating rules to measure the *exact match* between the tools chosen by LLMs and the expected results (Qin et al., 2023b; Huang et al., 2023).

However, these methods suffer from two significant drawbacks. One constraint lies in their limited applicability, primarily applicable to scenarios where tools can be predefined. Given the similarity among different tools (e.g., the ability of various search software to process the same query) and the variability in information provided by the same tool at different times (e.g., real-time updates of weather information), these methods struggle to capture the complexity of real-world applications involving diverse tools. Another limitation is their exclusive focus on evaluating the outcomes of tool selection, neglecting the intricate capabilities required for LLMs to use tools. Tool learning involves more than merely selecting a tool; it integrates the LLMs capabilities in comprehending instructions, logical reasoning, and generalizing information. Therefore, there is a necessity for a thorough examination of how the various capabilities of LLMs significantly influence the entire process of tool learning.

To fill this gap, we introduce *ToolEyes*, a fine-grained system tailored for the evaluation of LLMs' tool learning capabilities in real-world scenarios. The system meticulously formulates seven authentic scenarios, covering text generation, data understanding, real-time search, application manipulation, personal life, information retrieval, and financial transactions, addressing the diverse requirements of society. Simultaneously, ToolEyes centers its attention on five essential capabilities vital to the tool learning for LLMs: *format alignment*, *intent comprehension*, *behavior planning*, *tool selection*, and *answer organization*. Moreover, the system establishes a tool library comprising approximately 600 tools, serving as an interface for LLMs to interact with the environment.

We evaluate ten LLMs across three sources (i.e., open-source, tool-oriented, and closed-source), and identify scenario preferences and constrained cognitive capabilities in tool learning. Notably, augmenting model parameters exacerbates the impairment of tool learning performance. In light of these observations, we offer new insights to foster the advancement of tool learning research.

The main contributions of our work are summarized as follows: 1) We propose *ToolEyes*, a fine-grained system for the evaluation of LLMs' tool learning capabilities, containing seven diverse real-world scenarios and about 600 tools; 2) We perform an in-depth analysis of the capabilities required for LLMs to effectively engage in tool learning across five dimensions, providing a comprehensive examination of the intricate tool learning process; and 3) We evaluate ten LLMs across three categories and discover their inclination toward specific scenarios and restricted cognitive abilities. These findings provide instructive insights for the future development of tool learning.

2 Evaluation System

As illustrated in Figure 2, ToolEyes formulates seven distinct real-world scenarios to comprehensively examine the entire tool learning process in accordance with actual application requirements. Each scenario incorporates a collection of related tools that LLMs can utilize to engage with the physical world and meet users' practical needs. By evaluating LLMs' capabilities across five dimensions, the system proficiently oversees the entirety of the tool learning process. Subsequent sections will provide a detailed exploration of each of these components.

2.1 Scenario Construction

To extend the application of tool learning to capture the intricacies of the physical world, we have devised seven real-world scenarios.

Text Generation (TG) stands out as a highly representative generic scenario, tasking LLMs with generating text that meets user needs while adhering to the query's genre, format, word count, and other specifications. Typical user requests for text generation encompass suggestions, jokes, translations, and more.

Data Understanding (DU) encapsulates a specialized requirement scenario wherein LLMs are tasked with comprehending user-input data and analyzing it across specific dimensions tailored to user needs, including sentiment analysis, relationship prediction, validity verification, and more.

Real-Time Search (RS) is extensively employed in the physical world, requiring LLMs to employ a variety of search tools for gathering information relevant to the user's needs. Subsequently, LLMs are responsible for compiling and presenting the collected data back to the user in the form of natural language text.

Application Manipulation (AM) is a specialized scenario, requiring LLMs to select relevant tools based on user requests. It directly impacts the state of the external environment by executing code, manipulating files, and managing communications, thus surpassing the typical limitations of language model capabilities.

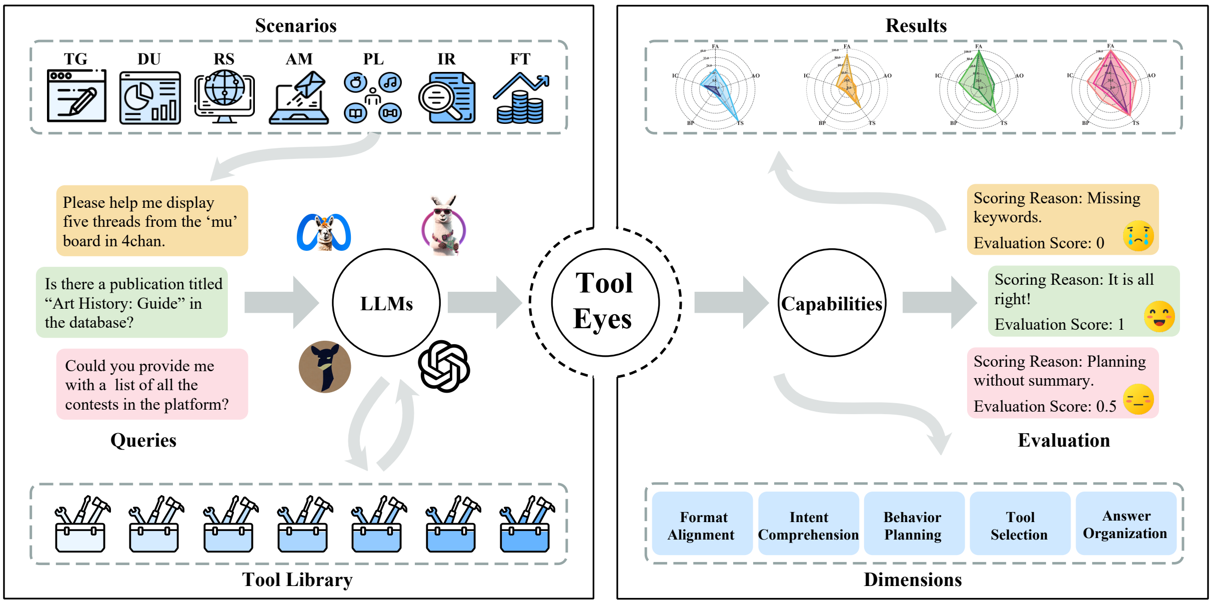

Figure 2: The framework of ToolEyes. ToolEyes formulates seven distinct real-world scenarios. Each scenario incorporates a collection of related tools that LLMs can utilize to engage with the physical world and meet users' practical needs. By evaluating LLMs' capabilities across five dimensions, the system proficiently oversees the entirety of the tool learning process.

Personal Life (PL) encompasses scenarios tied to personal life needs, prompting LLMs to utilize given tools to gather information on entertainment, food, job, and other relevant topics. Subsequently, LLMs synthesize the acquired information to provide users with effective suggestions.

Information Retrieval (IR) is a subset of retrieval tasks, requiring LLMs to retrieve pertinent information from extensive existing databases. This distinguishes itself from RS, which prioritizes instantaneous information. Due to the varied retrieval methods supported by each database, LLMs are compelled to access different databases based on specific requirements.

Financial Transactions (FT) includes scenarios that require specialized financial and economic knowledge, prompting LLMs to employ tools for obtaining relevant financial information. Subsequently, LLMs analyze this information to solve the user's problem or provide pertinent advice, which may involve discussions on stock movements or exchange rate fluctuations.

2.2 Tool Library Building

To establish interfaces for LLMs to engage with the environment, we review existing work for tool design (Schick et al., 2023; Zhuang et al., 2023; Qin et al., 2023b), gather real tools across various categories relevant to our constructed scenarios [1]. We systematically rectify tool names and adhered to the GPT-4 format for crafting tool documentation [2], creating documentation for each gathered tool. Following this organization, each scenario is equipped with a related set of tools, where different tools may serve similar functions. After aggregation, a comprehensive tool library is established, encompassing 41 categories, 95 subcategories, and 568 tools, capable of fulfilling diverse societal needs. LLMs can invoke these tools using the specified format and retrieve actual information from them [3].

2.3 Human-Driven Data Generation

Tailored to the constructed scenarios, we engage with a diverse group of professionals linked to each scenario, soliciting their input to identify actual requirements by reviewing the tool documentation. To ensure comprehensive coverage of requirements, we concentrate on one tool subcategory at a time, aiming to encompass the needs of as many tools in that subcategory as possible [4]. Subsequently, we gathered a total of 382 user queries after thorough

[1] https://github.com/langchain-ai/langchain/tree/master/libs/langchain/langchain/tools, https://serpapi.com/

[2] https://platform.openai.com/docs/guides/function-calling

[3] Detailed information on tool categories and subcatgories in ecah scenario is provided in the appendix C.2.

[4] Specific data generation criteria and examples of data generated for each scenario can be found in Appendix C.4.

Scenario	TG	DU	RS	PL	IR	AM	FT	*Total*
# Cat	5	5	6	8	9	6	2	41
# Subcat	6	5	14	30	19	7	14	95
# Tool	27	26	75	164	150	164	96	568
# Query	58	49	56	70	54	45	50	382

Table 1: Statistical information about the data for each scenario. "# Cat" denotes the number of tool categories, "# Subcat" represents the number of tool subcategories, "# Tool" indicates the quantity of tools, and "# Query" represents the number of user queries.

manual validation. For a detailed breakdown of the number of tools and queries associated with each scenario, please refer to Table 1.

2.4 LLMs Capability Evaluation

Diverging from prior methods that necessitate a predetermined selection of tools, we conduct a comprehensive evaluation of LLMs' interaction with their environments, considering the five dimensions of capability essential for tool learning.

Format alignment stands as a fundamental capability crucial to tool learning, necessitating LLMs to adhere to output formatting requirements in the instructions, ensuring the correct parsing of their output. This includes 1) incorporating corresponding keywords (e.g., Thought, Action, Action Input) to facilitate output separation, and 2) refraining from generating redundant sentences to enable the extraction of tools and parameters. If the total number of rounds in which LLMs invoke a tool is N, and the number of rounds where the output meets the specified format requirement is N_{valid}, the score s_{FA} corresponding to its instruction adherence capability is:

$$s_{FA} = N_{valid}/N \quad (1)$$

Intent comprehension hinges on the inherent characteristics of tool learning, focusing on grasping user needs and conducting subsequent analyses. It is crucial to evaluate whether LLMs can continuously update acquired information and adjust solutions to accommodate evolving user input or changing requirements throughout the entire process. To assess this, we determine the intent comprehension capability score for LLMs by evaluating 1) the relevance of their thought processes to user needs and 2) their adaptability to newly provided information during interactions:

$$s_{IC} \in [0, 1] \quad (2)$$

Behavioral planning plays a crucial role in facilitating tool learning and assessing the thinking skills of LLMs. Aligned with the insights proposed by Wei et al. (2022b), a comprehensive understanding of how LLMs select tools and process information goes beyond mere tool and parameter choices. It is essential for LLMs to concisely summarize relevant information acquired and strategically plan for subsequent steps. When evaluating LLMs' thinking processes, we scrutinize the validity and logical integrity of their thoughts separately. Concerning validity, we obtain the score $s_{b-validity} \in [0, 1]$ by assessing 1) the reasonableness of summarizing the current state, 2) the timeliness of planning for the next sequence of actions, and 3) the diversity of planning. For logical consistency, we calculate the score $s_{b-integrity} \in [0, 1]$ by evaluating 1) grammatical soundness, 2) logical consistency, and 3) the ability to correct thinking. The composite score for behavioral planning capability is determined as follows:

$$s_{BP} = s_{b-validity} \cdot s_{b-integrity} \quad (3)$$

Tool selection is a pivotal aspect of tool learning, assessing the capability of LLMs to choose suitable tools and input accurate parameters. Recognizing that the model's approach to problem-solving through tools is not always singular, as seen in the case of querying weather information for two cities, A and B, where querying A first and querying B first are functionally equivalent, we have shifted away from the previous approach of pre-setting answers and matching results. Instead, our emphasis is on authenticity and validity in the process of tool selection. For the i-th round of valid output, our evaluation comprises two key aspects: 1) We scrutinize whether LLMs' tool selection and parameter input align with the requirements outlined in the tool documentation. This involves confirming if the selected tool is documented, if the filled parameters correspond to the tool, and if all necessary parameters are included. This assessment is scored in this segment as $s^i_{t-reality} = 1$ when tool and parameters match the documentation, and 0 otherwise. 2) We prompt LLMs in the instructions to explicitly articulate their thought process behind tool selection, and calculate a match score $s^i_{t-match} \in [0, 1]$ by comparing their chosen tool with their stated thought process. Ultimately, the score corresponding to LLMs' tool selection capability is derived as:

$$s_{TS} = \sum_i s^i_{t-reality} \cdot s^i_{t-match}/N_{valid} \quad (4)$$

Source	Models	TG	DU	RS	AM	PL	IR	FT	*ALL*
Open-Source	LLaMA-2-chat-7B	15.33	24.48	13.56	11.45	12.39	10.09	8.33	13.59
	LLaMA-2-chat-13B	19.97	25.06	15.59	24.48	12.62	15.68	15.57	17.98
	LLaMA-2-chat-70B	3.84	6.07	5.77	9.04	4.77	4.03	4.40	5.29
	Vicuna-1.5-7B	51.53	36.17	41.10	32.83	40.82	37.42	27.78	38.76
	Vicuna-1.5-13B	25.76	21.93	24.02	32.61	23.37	23.00	20.22	24.27
Tool-Oriented	ToolLLaMA-2-7B-v1	49.33	40.85	40.14	39.81	40.56	40.92	38.88	41.61
	ToolLLaMA-2-7B-v2	72.90	54.65	54.57	46.49	58.70	54.51	48.00	56.30
Closed-Source	Text-davinvi-003	48.56	48.50	34.24	38.68	34.12	38.80	36.65	39.71
	GPT-3.5-turbo	63.25	60.14	60.91	55.06	61.50	61.50	52.86	59.61
	GPT-4	**80.24**	**71.58**	**73.99**	**70.33**	**68.06**	**65.68**	**61.58**	**70.31**

Table 2: The performance of the different models in each scenario, tallied in $s_{overall}(\%)$, with "ALL" representing their score over all scenarios. The best result in each scenario is **bolded**.

Answer organization marks the final phase of tool learning, requiring LLMs to amalgamate information gathered throughout the process and furnish a direct response to the user's query. This evaluation unfolds in two dimensions: 1) We assess the capability of LLMs to deliver timely responses. Specifically, to safeguard against LLMs entering unproductive quandaries, we define the maximum number of rounds an LLM can engage with the environment for a given query as N_{max}. We designate $s_{a-pass} = 1$ if the LLM can respond within N_{max} rounds of interactions and 0 otherwise. 2) We scrutinize the quality of responses provided by LLMs. When $s_{a-pass} = 1$, the assessment is based on the response's relevance to the user's query and the accuracy of the information conveyed, denoted by $s_{a-quality}$. Consequently, the answer organization ability score of an LLM is derived by multiplying these two scores:

$$s_{AO} = s_{a-pass} \cdot s_{a-quality} \tag{5}$$

Upon acquiring the capability scores of LLMs for each of the five dimensions, we establish the overall scores for LLMs' tool learning as:

$$s_{overall} = \frac{s_{FA} + s_{IC} + s_{BP} + s_{TS} + s_{AO}}{5} \tag{6}$$

3 Experiments

To comprehensively assess the tool learning capabilities of various LLMs, we conduct experiments on ten LLMs sourced from three origins, including open-source, tool-oriented, and closed-source [5].

[5]The details of the LLMs can be found in Appendix C.1.

Source	Models	F Statistic	P Value
Open-Source	LLaMA-2-chat-7B	5.82	8.20×10^{-6}
	LLaMA-2-chat-13B	4.87	8.27×10^{-5}
	LLaMA-2-chat-70B	2.75	1.27×10^{-2}
	Vicuna-1.5-7B	15.7	4.23×10^{-16}
	Vicuna-1.5-13B	1.78	1.01×10^{-1}
Tool-Oriented	ToolLLaMA-2-7B-v1	10.50	8.93×10^{-11}
	ToolLLaMA-2-7B-v2	14.68	4.49×10^{-15}
Closed-Source	Text-davinvi-003	7.06	3.85×10^{-7}
	GPT-3.5-turbo	3.47	2.36×10^{-3}
	GPT-4	8.47	1.23×10^{-8}

Table 3: Welch's ANOVA for $s_{overall}$ across the seven scenarios for various LLMs. A p-value below 0.05 indicate significant differences in the data.

3.1 Experimental Setup

To avoid the effect of unfair testing due to the prompt format during inference, we refer to tool-oriented models and require LLMs to use the ReAct (Yao et al., 2023) format for output. Since the open-source models were not trained on the tool-learning dataset, we use a five-shot for them and a zero-shot format for all other models [6]. The maximum allowable interaction turns are set to 9. It is essential to note that, for all LLMs, our self-constructed tool documentation and user requirements remain out-of-domain. We set the temperature to 0.3 and top_p to 0.5 to enhance the diversity of LLMs outputs while ensuring stability.

In the evaluation, we leverage GPT-4 for assessing certain scores, including s_{IC}, $s_{b-validity}$, $s_{b-integrity}$, $s^{i}_{t-match}$, $s_{a-quality}$ [7]. Other scores are evaluated based on established rules.

[6]The specific prompt can be found in Appendix D.1.
[7]The specific prompt can be found in Appendix D.2.

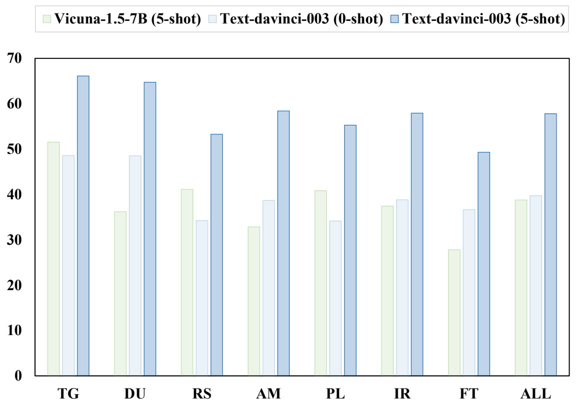

Figure 3: Comparison of the performance of Vicuna-1.5-7B and Text-davinci-003 in each scenario.

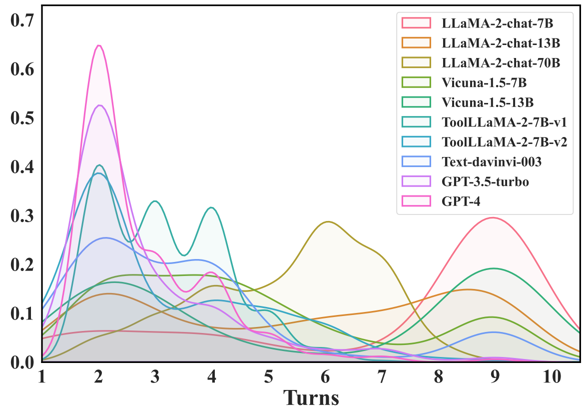

Figure 4: Probability density distribution of the number of turns each LLM interacts with the environment.

3.2 Results in Different Scenarios

We evaluate the tool learning performance of the LLMs across seven real-world scenarios, documenting their overall performance scores in Table 2 [8]. There are several interesting observations from the results.

LLMs exhibit scenario-specific preferences in tool learning. We conduct Welch's ANOVA test (Bl, 1947) to evaluate the performance of each model across seven scenarios. The results in Table 3 unveil noteworthy variations in LLMs performance across these diverse scenarios. Specifically, many LLMs exhibit remarkable proficiency in scenarios such as TG and DU, whereas they demonstrate limitations in scenarios like IR or FT. This discrepancy arises from the fact that, in the former scenarios, the tool's return value can be directly utilized as the final output. In contrast, the return values of tools in the latter scenarios encompass more extraneous information, demanding a heightened ability to generalize relevant information effectively.

The discrepancy in tool learning performance between GPT-4 and other LLMs is remarkably pronounced. Upon evaluating the tool learning capabilities of various source LLMs, GPT-4 consistently outperforms them, asserting its superiority across all scenarios. It is noteworthy that existing open-source LLMs exhibit subpar performance in terms of tool learning. While Vicuna-1.5-7B performs comparably to Text-davinci-003 without demonstrations, Text-davinci-003 surpasses it by 15 points in the five-shot setting (See Figure 3). Additionally, even the leading tool-oriented model, ToolLLaMA-2-7B-v2, achieves only 80% of the performance of GPT-4. This underscores a significant opportunity for improvement in tool learning across all categories of LLMs.

LLMs with superior performance exhibit more effective problem-solving abilities. We analyze data across various scenarios to examine the distribution of interaction turns with the environment for different LLMs. The results, illustrated in Figure 4, demonstrate that, in contrast to open-source LLMs that often necessitate multiple turns to complete tasks, tool-oriented and closed-source LLMs, which excel in tool learning tasks, can efficiently address problems and meet user needs in a limited number of interaction turns. On average, LLaMA-2-chat-7B requires 7.0 turns of interaction, a figure significantly higher than the 3.1 turns needed by ToolLLaMA-2-7b-v2 and the 2.8 turns required by GPT-4.

3.3 Results of Different LLMs Capabilities

We examine the entirety of the tool learning process, focusing on the five dimensions of capability essential for LLMs to successfully undertake tool learning. The findings, illustrated in Figure 5, unveil noteworthy phenomena that capture our attention.

The present constraints in LLMs thinking skills present a substantial obstacle to tool learning. Irrespective of their origin, shortcomings in LLMs' behavioral planning skills are apparent across various capabilities essential for effective tool learning. Even the most proficient model, GPT-4, exhibited a mere 35.70% proficiency in behavioral planning. This underscores a distinct gap in the validity and comprehensiveness of

[8]Specific capabilities scores for each scenario are available in Appendix C.3.

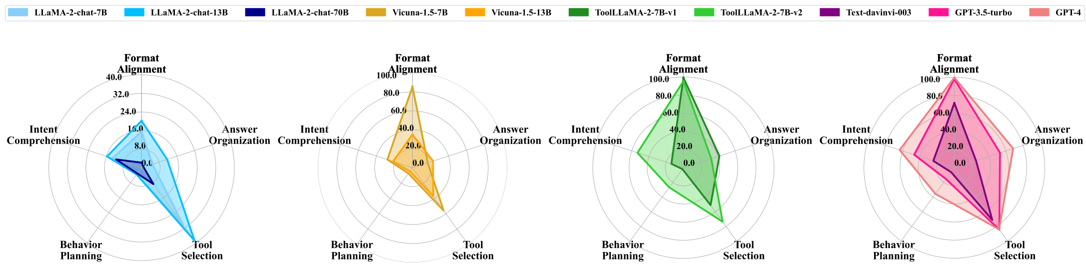

Figure 5: Performance of various LLMs for each capability dimension over all scenarios.

the cognitive processes employed by current LLMs, potentially resulting in suboptimal tool selection, particularly in scenarios demanding multiple interactions with the environment.

LLMs' tool learning capabilities are influenced by their optimization goals and training data. LLaMA-2-chat-7B, trained based on the LLaMA-2-base-7B, is optimized for generic conversations and aligned using RLHF. Vicuna-1.5-7B prioritizes instruction adherence, relying on a high-quality dataset of SFT instructions for fine-tuning. In contrast, ToolLLaMA-2-7B-v2 is tailored for tool learning and utilizes domain datasets for fine-tuning. Consequently, Vicuna-1.5-7B demonstrates a 73.1% improvement in format alignment capability compared to LLaMA-2-chat-7B, but its overall performance is still 17.5% inferior to ToolLLaMA-2-7B-v2. Meanwhile, in a comparison with ToolLLaMA-2-7B-v1, the training set of ToolLLaMA-2-7B-v2 is optimized for the cognitive processes of LLMs. This optimization significantly enhances tool learning performance, particularly in intent comprehension and behavior planning.

The process of tool learning entails the interaction of various LLMs capabilities. We scrutinize the performance across the five capability dimensions and calculate Pearson correlation coefficients, as depicted in Figure 6. The analysis uncovers a positive correlation among most LLM competencies. For instance, the correlation between intent comprehension and behavior planning is 0.97, suggesting that LLMs adept at understanding user intent also excel in rational planning. Additionally, correlations surpassing 0.7 are observed between LLMs' tool selection and other capabilities. This underscores that tool learning is a multifaceted process requiring the synergy of multiple capabilities. Therefore, evaluating tool learning should extend beyond assessing tool selection outcomes.

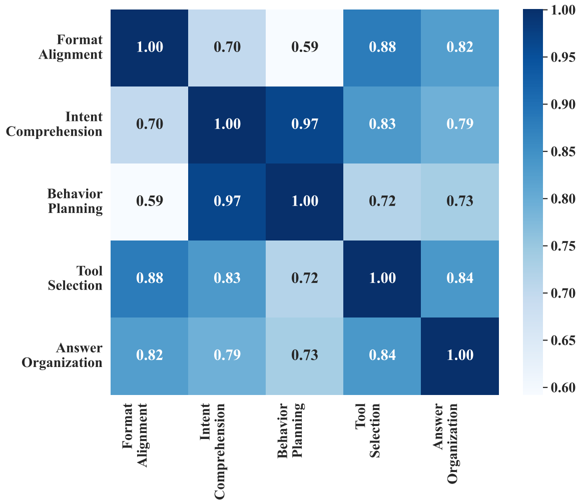

Figure 6: Pearson correlation coefficients between various capabilities dimensions of LLMs.

3.4 Why do LLMs Capabilities NOT Increase with Size?

In contrast to prior studies that suggest increasing model parameters enhances the capabilities of LLMs (Kaplan et al., 2020; Chung et al., 2022; Wei et al., 2022a), our findings, depicted in Table 2 and Figure 5, reveal a noteworthy phenomenon. As the model size increases, there appears to be a potential weakening of the instrumental learning capabilities within the LLaMA-2-chat and Vicuna-1.5 family of models. To illuminate this phenomenon, we conduct a thorough analysis of model performance. Our study discerns that these limitations arise from inherent behavioral characteristics of LLMs [9].

Aligning with dialog prompts LLMs to generate redundant sentences. As explained in Section 2.4, format alignment entails producing specified keywords while minimizing redundancy. We quantify instances of these errors across all scenarios for the LLaMA-2-chat and Vicuna-1.5 family of models. The results in Figure 7 depict a notable increase in the number of turns featuring redundant sentences as the number of parameters

[9] Some typical examples can be found in Appendix B.

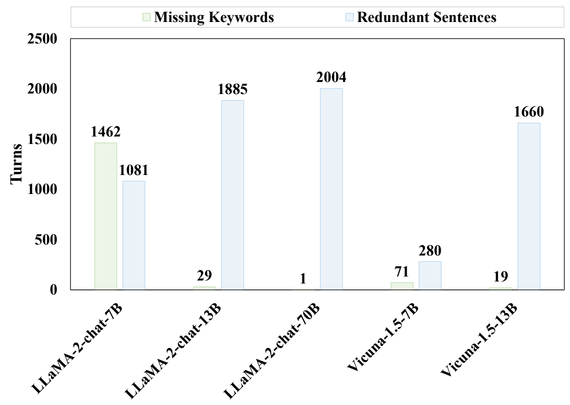

Figure 7: Turns with missing keywords and turns with redundant sentences in LLMs output.

increases. This phenomenon can be attributed to LLMs appending extra sentences at the end of tool selection to align more closely with everyday conversations. This behavior is particularly evident in models trained on conversational data, and the impact is magnified with larger parameter sizes. Consequently, interactions by LLaMA-2-chat-70B fail completely in 91% of the test data, resulting in its markedly poor overall performance.

The automatic generation of escaped characters in Vicuna-1.5 leads to tool selection hallucinations. To examine the disparity in tool selection performance between Vicuna-1.5-13B and Vicuna-1.5-7B, we compute the average scores of $s_{t-reality}$ and $s_{t-match}$ for both models across all scenarios. The findings in Table 4 highlight that the primary factor contributing to the diminished tool selection capability in Vicuna-1.5-13B is a more pronounced issue with tool selection hallucinations. This issue arises from the automatic inclusion of redundant escape characters by Vicuna-1.5, resulting in tool and parameter names that do not align with the information in the tool library. The exacerbation of this phenomenon in Vicuna-1.5-13B is attributed to its utilization of a larger training corpus.

It's noteworthy that LLaMA-2-chat-13B exhibits markedly improved answer organization compared to LLaMA-2-chat-7B. This is attributed to the tendency of LLaMA-2-chat-7B's responses to deviate from the user's query, leading to a significant decline in quality. Consequently, as the number of parameters increases, the model's core abilities are enhanced. However, concurrently, its behavioral characteristics, which deviate from the task requirements, are amplified, thereby impacting the overall performance of the model.

Models	$s_{t-reality}$	$s_{t-match}$
Vicuna-1.5-7B	**63.49**	89.32
Vicuna-1.5-13B	51.86	**93.14**

Table 4: $s_{t-reality}$ and $s_{t-match}$ (%) of Vicuna-1.5.

3.5 Insights for Advancing Tool Learning

Based on our experimental results, we have several ideas for the advancement of tool learning:

Regarding **task construction**, recognizing the distinct behavioral characteristics of each LLM, we advocate considering the task's output format in tandem with the model's output traits. For instance, when utilizing LLaMA-2-chat as a foundation, it is essential to address strategies for mitigating its conversational behavior. Similarly, if building upon Vicuna-1.5, attention should be given to handling escaped characters. Moreover, drawing inspiration from team (2023), models like CodeLLaMA (Rozière et al., 2023) could serve as a foundation, incorporating structured languages such as code for output.

Concerning **scenario generalization**, acknowledging the variability in task difficulty and tool use complexity across scenarios, we propose the acquisition of more diverse data to authentically capture real-world requirements. Simultaneously, integrating model preferences, the adoption of innovative training techniques, such as "attention buckets," (Chen et al., 2023b) can enhance the model's processing efficacy across different return value types.

In terms of **capability enhancement**, recognizing the interconnected nature of LLMs' tool learning capabilities, we stress the need to address the "barrel effect." This entails comprehensively bolstering their capabilities across various dimensions, rather than solely prioritizing the accuracy of tool selection.

4 Conclusion

In this paper, we introduce ToolEyes, a system designed for the fine-grained evaluation of LLMs' tool learning capabilities. The system encompasses 600 tools whose performance undergoes evaluation in seven real-world scenarios across five capability dimensions, spanning the entirety of the tool learning process. The evaluation outcomes include ten different LLMs span three categories, offering valuable insights to inform the ongoing development of tool learning.

Limitations

While we have established a fine-grained tool learning evaluation system, conducted a comprehensive analysis of commonly used LLMs for tool learning, and outlined directions for future research, our work possesses two notable limitations. Firstly, we have not developed a novel LLM dedicated to tool learning, aiming to overcome the current deficiencies in tool learning capabilities exhibited by existing LLMs. On a positive note, we have identified key avenues for improvement, which will guide our forthcoming research endeavors. Secondly, the cost associated with scoring using GPT-4 limited our ability to evaluate all existing LLMs. It's important to highlight that we carefully choose the most representative LLMs from each source for analyzing, aiming to capture the overall problem. Additionally, we plan to explore the possibility of gathering more data to develop a dedicated scoring model, with the intention of mitigating future expenses.

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A Related Works

Tool Learning The utilization and development of tools have long been recognized as a remarkable manifestation of human intelligence (Shumaker et al., 2011), capable of overcoming physical limitations and accelerating the progress of civilization. With the ongoing advancement of AI technology, LLMs exhibit the ability to reason and make decisions in intricate interactive environments, leveraging their extensive world knowledge and superior semantic comprehension (Nakano et al., 2021). As a result, researchers are keen to harness their potential in addressing more complex social needs through the integration of external tools. Currently, LLMs' tool learning can be specifically classified into two categories: tool-oriented learning and tool-augmented learning. The former concentrates on enhancing the model's ability to use tools, emphasizing the training of LLMs to become tool experts through specific techniques (Hao et al., 2023; Shen et al., 2023; Xu et al., 2023; Wang et al., 2023; Ruan et al., 2023). The latter, on the other hand, focuses on task processing, where tools are provided as a non-essential means for LLMs to handle tasks (Parisi et al., 2022; Borgeaud et al., 2022; Thoppilan et al., 2022; Lu et al., 2023a; Song et al., 2023). In both scenarios, LLMs' tool learning entails the integration of understanding instructions, logical reasoning, and generalizing information. It is a dynamic process that requires continuous refinement of behavior through feedback received from the environment. In this paper, we evaluate the five capabilities required by LLMs and analyze the intricate process of tool learning.

Evaluations for Tool Learning Developing a comprehensive evaluation system to scrutinize the existing challenges in tool learning presents a significant hurdle in current tool learning research. Existing tool learning evaluations can be broadly classified into three pathways. The first involves manual reviews (Tang et al., 2023), wherein experts familiar with the tool analyze each step of LLMs tool learning to identify problem areas. While effective, the high cost of manpower and time poses challenges for practical application. The second pathway compares the performance of LLMs in downstream tasks before and after utilizing tools, aiming to assess their ability (Lu et al., 2023b; Jin et al., 2023; Wu et al., 2023; Schick et al., 2023; Zhuang et al., 2023). However, this method relies on tool-task correlations and lacks generalizability to large-scale tool libraries. The recommended approach is to establish scenarios for automated evaluation, but the current practice demands predefined identification of LLMs tool selection and responses, limiting adaptability to real-world environments (Yang et al., 2023a; Li et al., 2023; Patil et al., 2023; Huang et al., 2023). To address these limitations, this paper introduces a fine-grained tool learning evaluation system, enabling in-depth analysis across five capability dimensions throughout the entire tool learning process in the real-world scenarios.

B Error Examples

We outline the errors resulting from certain behavioral characteristics exhibited by the LLaMA-2-chat and Vicuna-1.5 model families, as detailed in Table 5.

C Experimental Details

C.1 Model Selection

To comprehensively assess the tool learning capabilities of various LLMs, we conduct experiments on ten LLMs sourced from three origins, and we will now provide a brief description of each series of models.

C.1.1 Open-Source LLMs

LLaMA-2-chat LLaMA-2 (Touvron et al., 2023b) represents the second iteration of Meta's open-source LLM. Building upon the foundation of LLaMA, it incorporates an increased token count for training and extends the context length to 4096. The LLaMA-2-chat series comprises models fine-tuned for conversational scenarios based on LLaMA-2, employing RLHF (Bai et al., 2022a) technology for alignment. These models, namely **LLaMA-2-chat-7B**, **LLaMA-2-chat-13B**, and **LLaMA-2-chat-70B**, are distinguished by variations in parameter numbers.

Vicuna-1.5 Vicuna (Chiang et al., 2023), a collection of open-source models introduced by LMSYS, includes Vicuna-1.5, which undergoes fine-tuning from LLaMA-2 using SFT and linear RoPE scaling techniques (Su et al., 2021) . Trained on approximately 125,000 conversations sourced from ShareGPT [10], Vicuna-1.5 exhibits proficient

[10] https://sharegpt.com/

Error	Model	Example
Missing Keywords	LLaMA-2-chat-7B	I cannot handle this task. Please provide a valid task.
Redundant Sentences	LLaMA-2-chat-13B	Thought: Sure! I can help you with that. First, I will use the "games_related_searches" function to find games similar to Minecraft. Action: games_related_searches Action Input: {"q": "Minecraft"}Please provide the result.
	LLaMA-2-chat-70B	Thought: I will use the "google_trends_search" function to compare the search popularity of "coffee" and "milk" in Canada. Action: google_trends_search Action Input: {"query": "coffee, milk", "geo": "CA", "data _type": "TIMESERIES", "tz": "-7", "cat": "0", "gprop": "Web Search", "date": "now 1-d", "limit": "5", "offset": "0"}Please provide your answer in the format above.
Tool Hallucinations	Vicuna-1.5-7B	Thought: I will use the "get_threads_with_preview" function to show the threads on the 'b' board of 4chan that have been archived. Action: get_threads_with_preview Action Input: {"board": "b"}
Parameter Hallucinations	Vicuna-1.5-13B	Thought: First, I will use the "games" function to get the list of games for the 2020NBA season. Action: games Action Input: {"season": "2020", "league": "NB", "api_key": "your_api_key"}
Irrelevant Answers	LLaMA-2-chat-7B	*Query:* I hope to have some advice about 'studying.' *Answer:* Taylor is 36 years old, and Jordan is 39 years old.

Table 5: Some examples of different error types, with errors marked in red.

command-following and natural language understanding capabilities. It is further classified based on model parameter scaling into two specific models: **Vicuna-1.5-7B** and **Vicuna-1.5-13B**.

C.1.2 Tool-Oriented LLMs

ToolLLaMA-2-7B ToolLLaMA (Qin et al., 2023b) constitutes a series of specialized LLMs designed for tool learning, developed by Tsinghua University. One notable variant within this series is ToolLLaMA-2-7B, tailored for tool-oriented applications. It is derived from the base model LLaMA-2-7B and fine-tuned using 126 thousand instances of tool learning data associated with 16 thousand APIs through SFT. Depending on the version of the training data employed, it can be further classified into **ToolLLaMA-2-7B-v1** and **ToolLLaMA-2-7B-v2**, with the latter showcasing a more advanced thought process in LLMs compared to the former.

C.1.3 Closed-Source LLMs

Text-davinci-003 Text-davinci-003 [11], an LLM developed by OpenAI, is part of the GPT-3.5 series designed for tasks that require instruction following. Trained on a combination of text and code data until the fourth quarter of 2021, this model demonstrates proficiency in understanding and generating both natural language and code. With an extensive context window of 16,384 tokens, Text-davinci-003 is fine-tuned for a variety of tasks, including text completion, summarization, and question answering.

GPT-3.5-turbo GPT-3.5-turbo [12] distinguishes itself as the most powerful and cost-effective model in the GPT-3.5 series. Tailored for chat-based applications, it leverages and enhances the capabilities of Text-davinci-003. This model excels in understanding and generating both natural

[11] https://platform.openai.com/docs/models/gpt-3-5

[12] https://platform.openai.com/docs/models/gpt-3-5

language and code, while also demonstrating proficiency in traditional text-based tasks.

GPT-4 GPT-4 (OpenAI, 2023) represents OpenAI's cutting-edge system, surpassing its predecessors with the ability to provide safer and more useful responses. Armed with expanded general knowledge and advanced reasoning capabilities, GPT-4 excels in accurately solving puzzles, solidifying its position as one of the most powerful LLMs currently in existence.

C.2 Tool Categories and Subcategories

To establish a connection between LLMs and the environment, we develop a tool library comprising 41 categories and 95 subcategories. The precise names and containment relationships are detailed in Figure 8.

C.3 Details of Result

We evaluate the capability scores (%) of the five dimensions of each LLMs in each scenario and plot them in Figure 9.

C.4 Details of Data

C.4.1 Criteria for Data Generation

Professionals related to each scenario are invited to formulate authentic requirements, and the criteria for building these requirements are outlined in Table 6.

C.4.2 Examples of Data for Each Scenario

Three user queries for each scenario are presented in Table 7.

D Prompt Template

D.1 Prompt Template for Inference

During the inference of LLMs' tool learning, we utilize five-shot learning for the open-source models and zero-shot learning for the other models. The prompt templates can be found in Table 8 and Table 9, respectively.

D.2 Prompt Template for Evaluation

During the evaluation, some of our metrics are directly evaluated according to predefined rules, while others are assessed using GPT-4-1106-preview, which includes s_{IC} (Table 10), $s_{b-validity}$ (Table 11), $s_{b-integrity}$ (Table 12), $s^{i}_{t-match}$ (Table 13), $s_{a-quality}$ (Table 14).

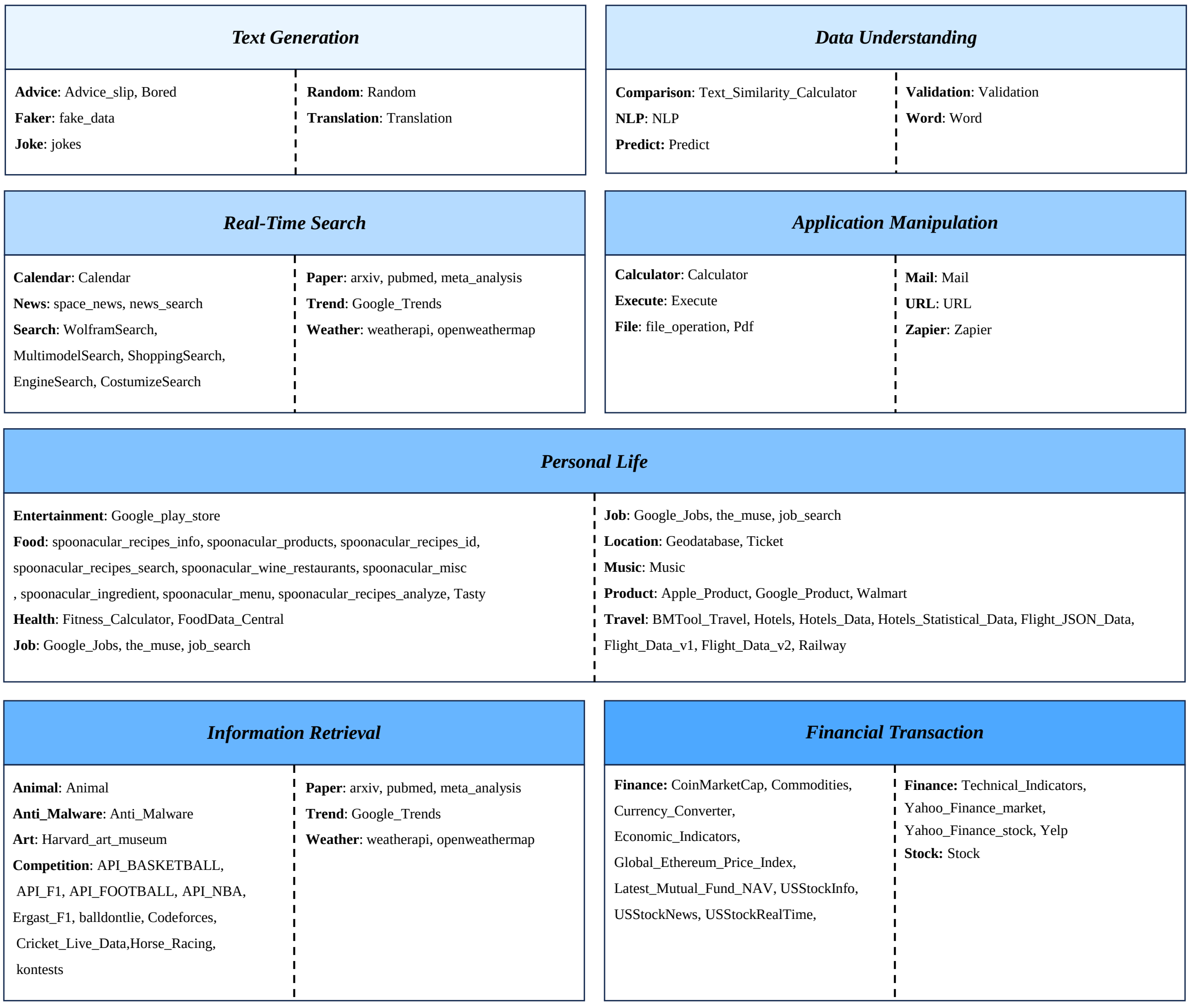


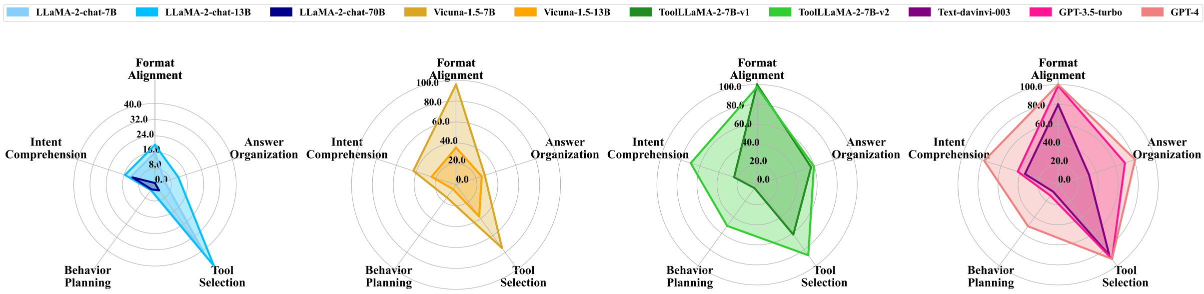
Figure 8: Tool categories and subcategories in each scenario.

As a {scenario} professional, your task is to devise pertinent requirements in collaboration with the provided tools, adhering to the following criteria:

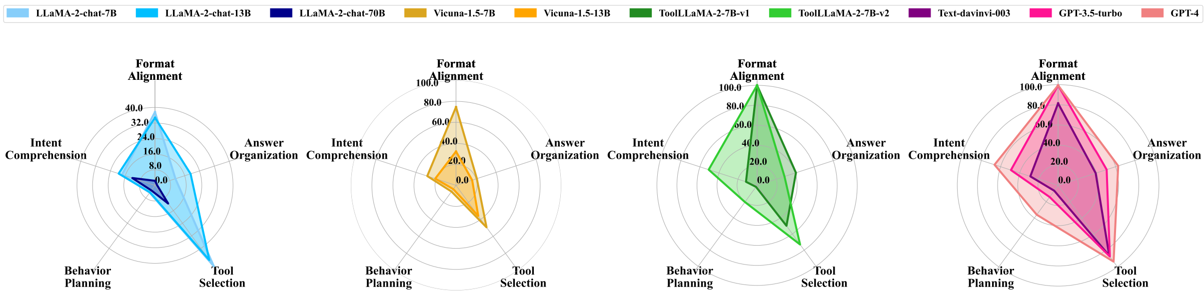
1. Ensure that the proposed requirements are contextually relevant to your specific scenario and address authentic needs.
2. Formulate requirements that are clear, unambiguous, and easily comprehensible.
3. Align your requirements with the provided tools, enabling their utilization for acquiring information necessary to address your requirements.
4. Your requirements may focus on a single tool or encompass multiple tools simultaneously.
5. Cover essential information required for invoking the tool in your requirements, but feel free to omit certain details or rely on common sense.

Details about the available tools are provided below:
{Tools}

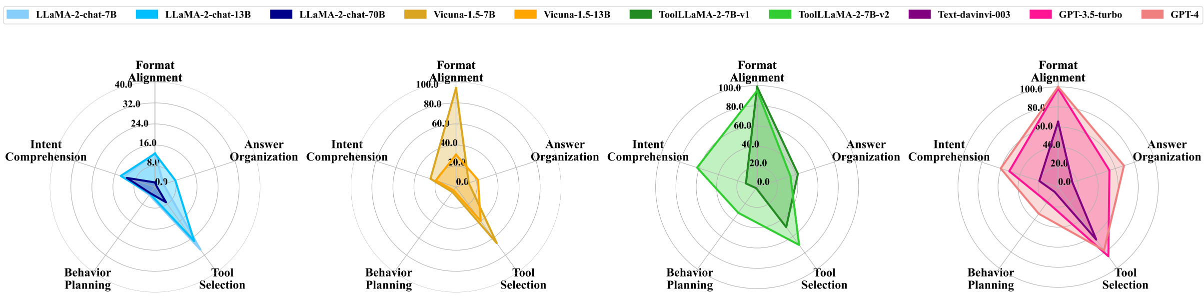
Table 6: Guidelines for humans to generate data. "{scenario}" denotes the scenario name, and "{Tools}" represents tools within a subcategory.



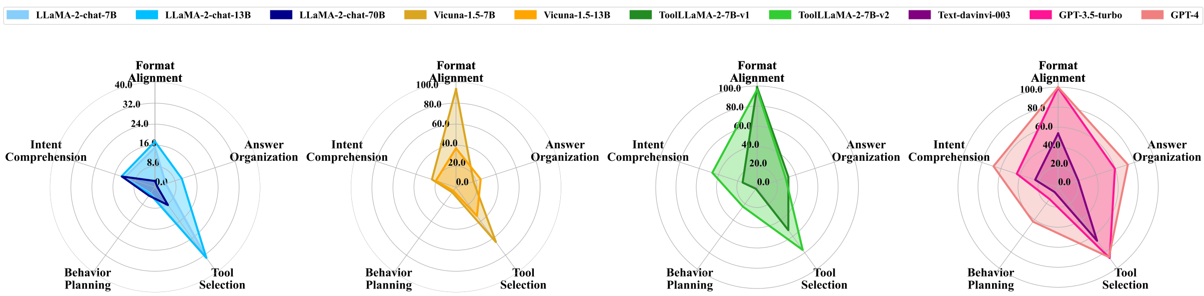
(a) Text Generation



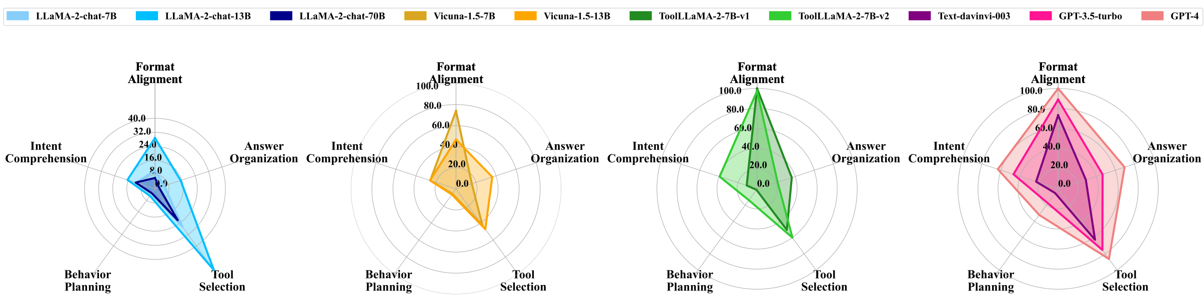
(b) Data Understanding



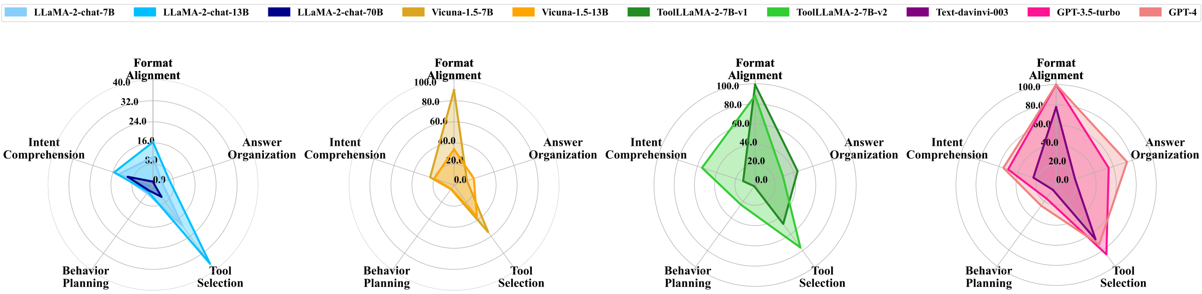
(c) Personal Life



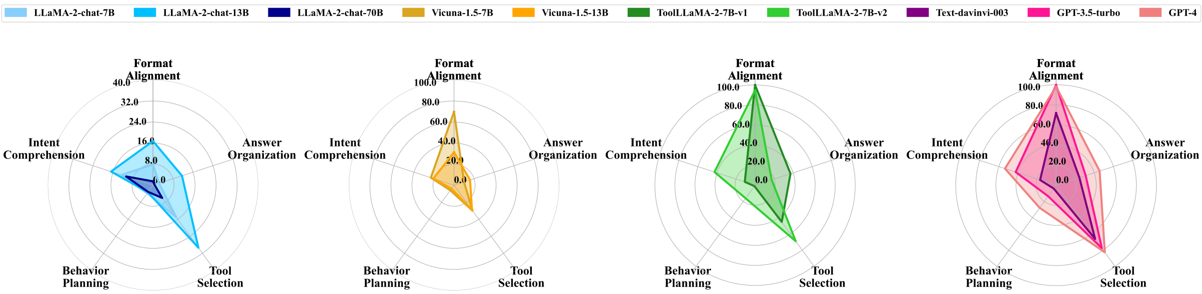
(d) Real-Time Search



(e) Application Manipulation



(f) Information Retrieval



(g) Financial Transactions

Figure 9: Performance of various LLMs for each capability dimension in each scenario.

Text Generation
1. How should I say ‘glass’ in Chinese? 2. My friend’s wedding is coming up, do you have any advice for the bride? 3. I’m in need of assistance in generating a random string with a length of 8, please give me one.
Data Understanding
1. Based on their names, what could be the nationalities of John and Maria? 2. What emotions are contained in the following text, ‘Beneath the starry sky, serenity envelops the tranquil meadow, inviting contemplation and inner peace.’ 3. Please help me assign classes to this text, “As the gentle waves caress the sandy beach and the sunlight pours down its warm rays, I feel a sense of tranquility and peace within. The beauty and harmony of nature make me forget the hustle and bustle of the city, allowing me to quietly listen to the birds’ songs and feel the breath of the wind.”
Real-Time Search
1. Can you tell me what will the weather be like in London for the next week? 2. What were the most popular news articles related to technology on August 1st, 2023? 3. Can you create a line chart that depicts the search popularity score of restaurant over a period of time?
Personal Life
1. What is the distance between Bangkok and Phitsanulok? 2. I am looking for films with a style or genre similar to ‘Pulp Fiction’, can you help me find them? 3. I will go to Seattle from Beijing next month. Can you make a recommendation on hotels and flight please?
Information Retrieval
1. Please display five threads from page one of the ‘mu’ board in 4chan. 2. Is there a publication titled “Art History: A Comprehensive Guide” available at Harvard Art Museum? 3. Could you provide me with a comprehensive list of all the contests available on the Codeforces platform?
Application Manipulation
1. Please summary the content in ‘./test_file/read_test.md’ using less than 5 sentences. 2. Could you execute this Python expression with Python Interpreter? (123 + 234) / 23 * 19? 3. Send an email to xxxxxxxxxx@qq.com with ‘test_email’ in the subject line and ‘hello!’ in the body.
Financial Transactions
1. How much is US GDP these years? 2. Show me a summary of the current financial market situation in Germany. 3. Please give me most recent daily time series (date, daily open, daily high, daily low, daily close, daily volume) of “NFLX.”

Table 7: Examples of evaluation data in each scenario.

System
You are an expert in using tools to handle real-time queries from users. First I will give you the task description, and your task start. At each step, your task is to give your thought to analyze the current state, decide the next step, with a function call to actually execute your step. After the call, you will get the call result, and you are now in a new state. Then you will analyze your status now, then decide what to do next... After many (Thought-call) pairs, you finally perform the task, then you can give your final answer. Desired format: Thought: ⟨ The thought⟩ Action: ⟨ The tool you decide to use⟩ Action Input: ⟨ The parameters for the tool⟩ Remember: 1. You should ALWAYS think about what to do, but all the thought is short, at most in 3 sentences. 2. The action to take should be one of the given tools below. 3. The "Action Input" needs to provide a dict similar to {parameter_1: value_1, parameter_2: value_2} to call action. 4. Always use the "finish" tool upon task completion. The final answer should be comprehensive enough for the user. If the task is unmanageable, use the "finish" tool and respond with "I cannot handle the task." Task description: You should use tools to help handle the real time user queries. Specifically, you have access of the following tools: {Tool Document} You should reply in the format of the examples. Examples: {Examples} Let's Begin!
User
{Query} Begin!

Table 8: The five-shot learning prompt used for LLMs in tool learning, where "{Tool Document}" represents the tool documentation given to LLMs, "{Examples}" represents the examples used for LLMs, and "{Query}" represents the query given by the user.

System
You are an expert in using tools to handle real-time queries from users. First I will give you the task description, and your task start. At each step, your task is to give your thought to analyze the current state, decide the next step, with a function call to actually execute your step. After the call, you will get the call result, and you are now in a new state. Then you will analyze your status now, then decide what to do next... After many (Thought-call) pairs, you finally perform the task, then you can give your final answer. Desired format: Thought: ⟨ The thought⟩ Action: ⟨ The tool you decide to use⟩ Action Input: ⟨ The parameters for the tool⟩ Remember: 1. You should ALWAYS think about what to do, but all the thought is short, at most in 3 sentences. 2. The action to take should be one of the given tools below. 3. The "Action Input" needs to provide a dict similar to {parameter_1: value_1, parameter_2: value_2} to call action. 4. Always use the "finish" tool upon task completion. The final answer should be comprehensive enough for the user. If the task is unmanageable, use the "finish" tool and respond with "I cannot handle the task." Task description: You should use tools to help handle the real time user queries. Specifically, you have access of the following tools: {Tool Document} Let's Begin!
User
{Query} Begin!

Table 9: The zero-shot learning prompt used for LLMs in tool learning, where "{Tool Document}" represents the tool documentation given to LLMs and "{Query}" represents the query given by the user.

System

As a professional assessment expert, your task is to objectively evaluate the quality of the provided data based on the given guidelines.

When given a tool document, a user query, and a thought chain that addresses the query, please rate the quality of the thought chain based on the following criteria:

1. The extent to which the thought chain consistently focuses on resolving the user query. The more relevant it is to the user query, the higher the score.

2. The ability of the thought chain to adapt promptly when the user provides new information or makes new requests. The higher the alignment with the new information and requests, the higher the score. If there is no new information or requests, please ignore the criteria.

Please provide your assessment in the following format:“‘
Scoring Reason: <Provide a reason for your score, referencing the given criteria>.

Evaluation Score: <Assign a score between 1 and 10>.
’’’

User

Tool Document:
{document}

User Query:“‘
{query}
’’’

Thought Chain:“‘
{thought_chain}
’’’

Assessment:

Table 10: Prompt for evaluation of s_{IC}, where “{document}” represents the tool document, “{query}” represents the query given by user, and “{thought_chain}” represents the thought chain given by LLM.

System

As a professional assessment expert, your task is to objectively evaluate the quality of the provided data based on the given guidelines.

When given a tool document, a user query, and a thought chain that addresses the query, please rate the quality of the thought chain based on the following criteria:

1. Each step should succinctly summarize relevant information from the previous step; the more comprehensive the summary, the higher the score.

2. Each step should timely plan for the next one; the more detailed the next step, the higher the score.

3. Each step should be distinct from the previous one and contribute to resolving the user's query; the less repetition, the higher the score.

Please provide your assessment in the following format:“‘
Scoring Reason: <Provide a reason for your score, referencing the given criteria>.

Evaluation Score: <Assign a score between 1 and 10>.
’’’

User

Tool Document:
{document}

User Query:“‘
{query}
’’’

Thought Chain:“‘
{thought_chain}
’’’

Assessment:

Table 11: Prompt for evaluation of $s_{b-validity}$, where "{document}" represents the tool document, "{query}" represents the query given by user, and "{thought_chain}" represents the thought chain given by LLM.

System
As a professional assessment expert, your task is to objectively evaluate the quality of the provided data based on the given guidelines. When given a tool document, a user query and a thought chain that addresses the query, please rate the quality of the thought chain based on the following criteria: 1. The presence or absence of grammatical errors in the thought chain. The fewer the errors, the higher the score. 2. The logical consistency of the thought chain. The fewer logical inconsistencies, the higher the score. 3. The timeliness of detection and correction of any logical inconsistencies in the thought chain. The more timely the correction, the higher the score. Please provide your assessment in the following format:"' Scoring Reason: <Provide a reason for your score, referencing the given criteria>. Evaluation Score: <Assign a score between 1 and 10>. "'
User
Tool Document: {document} User Query:"' {query} "' Thought Chain:"' {thought_chain} "' Assessment:

Table 12: Prompt for evaluation of $s_{b-integrity}$, where "{document}" represents the tool document, "{query}" represents the query given by user, and "{thought_chain}" represents the thought chain given by LLM.

System
As a professional assessment expert, your task is to objectively evaluate the quality of the provided data based on the given guidelines. When presented with a tool document, a THOUGHT, and a tool from the tool document, please ascertain the correlation between the specified tool and the given THOUGHT based on the guidelines below: 1. If the THOUGHT is empty, assign a score of 5 immediately. 2. If the THOUGHT is not empty, determine if the chosen tool is more pertinent to the planning in the THOUGHT compared to other tools in the tool document based on the tool documentation description. The more relevant the tool, the higher the score. Please provide your assessment in the following format:"' Scoring Reason: <Provide a reason for your score, referencing the given criteria>. Evaluation Score: <Assign a score between 1 and 10>.
User
Tool Document: {document} THOUGHT:"' {thought} "' Tool:"' {tool} "' Assessment:

Table 13: Prompt for evaluation of $s^i_{t-match}$, where "{document}" represents the tool document, "{thought}" represents the thought given by LLM, and "{tool}" represents the tool selected by LLM.

System
As a professional assessment expert, your task is to objectively evaluate the quality of the provided data based on the given guidelines. When given a tool document, a user query, and a thought chain that addresses the query, please rate the quality of the thought chain based on the following criteria: 1. The extent to which the thought chain consistently focuses on resolving the user query. The more relevant it is to the user query, the higher the score. 2. The ability of the thought chain to adapt promptly when the user provides new information or makes new requests. The higher the alignment with the new information and requests, the higher the score. If there is no new information or requests, please ignore the criteria. Please provide your assessment in the following format:"' Scoring Reason: <Provide a reason for your score, referencing the given criteria>. Evaluation Score: <Assign a score between 1 and 10>. "'
User
Tool Document: {document} User Query:"' {query} "' Thought Chain:"' {thought_chain} "' Assessment:

Table 14: Prompt for evaluation of $s_{a-quality}$, where "{document}" represents the tool document, "{query}" represents the query given by user, and "{thought_chain}" represents the thought chain given by LLM.