MT-Bench-101: A Fine-Grained Benchmark for Evaluating Large Language Models in Multi-Turn Dialogues

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Abstract

The advent of Large Language Models (LLMs) has drastically enhanced dialogue systems. However, comprehensively evaluating the dialogue abilities of LLMs remains a challenge. Previous benchmarks have primarily focused on single-turn dialogues or provided coarsegrained and incomplete assessments of multiturn dialogues, overlooking the complexity and fine-grained nuances of real-life dialogues. To address this issue, we introduce MT-Bench-101, specifically designed to evaluate the finegrained abilities of LLMs in multi-turn dialogues. By conducting a detailed analysis of real multi-turn dialogue data, we construct a three-tier hierarchical ability taxonomy comprising 4208 turns across 1388 multi-turn dialogues in 13 distinct tasks. We then evaluate 21 popular LLMs based on MT-Bench-101, conducting comprehensive analyses from both ability and task perspectives and observing differing trends in LLMs performance across dialogue turns within various tasks. Further analysis indicates that neither utilizing common alignment techniques nor chat-specific designs has led to obvious enhancements in the multiturn abilities of LLMs. Extensive case studies suggest that our designed tasks accurately assess the corresponding multi-turn abilities.

1 Introduction

Large Language Models (LLMs) based chatbots have made remarkable advances and significantly enhanced dialogue systems. Several benchmarks have been introduced to assess the capabilities of Large Language Models (LLMs) in single-turn dialogues, *e.g.*, MMLU (Hendrycks et al., 2020), BBH (Srivastava et al., 2022), and AlpacaEval (Li et al., 2023b). However, daily dialogues between users and chatbots usually involve multi-turn conversations (Gudibande et al., 2023; Zheng et al.,



Figure 1: MT-Bench-101 encompasses three overarching abilities and thirteen distinct tasks within multi-turn dialogue scenarios, facilitating a granular benchmarking from basic perceptivity to advanced interactivity. On the right, a model with a broader range of abilities is considered better in multi-turn scenarios.

2023a), which include multiple utterances as part of the dialogue history. Therefore, it is essential to evaluate the proficiency of LLMs in generating coherent responses utilizing multiple utterances (Lan et al., 2020). Early studies like MT-bench (Zheng et al., 2023b) mainly focus on two-turn dialogues and coarse-grained abilities, not sufficiently covering the complexity of real-world multi-turn dialogue scenarios. This indicates a considerable scope for improvement in current benchmarks for multi-turn dialogues, underscoring the urgent need to develop a comprehensive benchmark that can effectively compare the chat abilities of LLMs in multi-turn dialogues.

In this paper, we introduce MT-Bench-101, a new benchmark designed specifically for evaluating the chat capabilities of LLMs in multi-turn dialogues, as shown in Figure 1. During the ability modeling process for multi-turn dialogue, we undertake a systematical analysis combining realworld multi-turn dialogue data (Gudibande et al., 2023; Zheng et al., 2023a) with the teaching taxonomy from educational psychology (Alexander, 2018; Marchel, 2007). This integrated approach has culminated in the formulation of a **three-tier**

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The data and code are available at https://github.com/mtbench101/mt-bench-101.

hierarchical ability taxonomy which is both datadriven and rooted in psychological frameworks.

Figure 2 illustrates the overall framework of our ability taxonomy. The first layer outlines three progressive overarching abilities which are depicted in Figure 1. Perceptivity is the most fundamental ability, reflecting the model's accuracy in understanding context. Adaptability is built upon this foundation, indicating the model's ability to respond effectively to user feedback. Finally, Interactivity captures the capacity of models for proactive engagement with humans, which is crucial for excelling in multi-turn interactions. The second tier specifies seven detailed abilities, while the third tier further decomposes these abilities into 13 distinct tasks. This taxonomy provides evaluation results across three levels from general to detailed, allowing for the identification of deficiencies in models at varying levels of granularity. For each third-tier task, we meticulously design specific prompts and utilize GPT-4 for data generation. In total, MT-Bench-101 encompasses 4208 turns within 1388 multi-turn dialogues.

For evaluation, we utilize golden context as dialogue history allowing LLMs to generate more fluid and rational dialogues, and we follow Zheng et al., 2023b; Dubois et al., 2023; Duan et al., 2023 to utilize GPT-4 as a stand-in for human raters to score for each turn. We design unique scoring guidelines for each task and use the lowest round score as the total score for the dialogue to allow for a more rational assessment.

We then perform extensive experiments on MT-Bench-101 to assess the multi-turn chat ability of existing LLMs, including 2 close-sourced LLMs and 19 open-sourced LLMs. Our findings include:

- We identify adaptability and interactivity as the key deficiencies of existing LLMs, and GPT-4 is the most powerful model for multi-turn dialogues.
- The average performance of models within various tasks exhibits differing trends with the progression of turns, reflecting the distinct characteristics of the abilities.
- Model performance improves as the model size increases. However, neither utilizing common alignment techniques (such as RLHF) nor chatspecific designs has resulted in significant enhancements in the multi-turn abilities of LLMs.



Figure 2: Our three-tier hierarchical ability taxonomy of multi-turn dialogues.

• The agreement between GPT-4 and human expert evaluations reached 87%, utilizing our designed evaluation approach.

2 Related Work

LLMs for Multi-turn Dialogues Recent advancements in LLMs such as GPT-3.5/GPT-4 (Ouyang et al., 2022; OpenAI, 2022, 2023) have garnered significant attention (Liu et al., 2024; Wang et al., 2023d). To enhance the multiturn capabilities of open-sourced LLMs, initial efforts begin with collecting human-ChatGPT dialogues (Gudibande et al., 2023), leading to the creation of Vicuna (Chiang et al., 2023). RealChat (Zheng et al., 2023a) later expands the data to 1 million conversations. To generate more sophisticated datasets, Baize (Xu et al., 2023) and UltraChat (Ding et al., 2023) employ alternating GPT interactions. Parrot (Sun et al., 2023) trains a model to simulate the user, thereby generating improved data. Further, Cue-CoT and ICL-AIF (Wang et al., 2023a; Fu et al., 2023) enhance model capabilities for multi-turn interactions through In-Context-Learning (ICL) (Brown et al., 2020) and Chain-of-Thought (CoT) (Wei et al., 2022) algorithms.

Benchmarks for Multi-turn LLMs Most benchmarks evaluate LLMs through single-turn instructions (Hendrycks et al., 2020), missing the nuance of human conversation. To investigate multi-turn ability, ABC-Eval (Finch et al., 2022) relies on labor-intensive human evaluations. AlpacaEval (Li et al., 2023b) and PandaLM (Wang et al., 2023c) attempt to automatically assess open-ended instruc-

tions, but they remain confined to single-turn settings. MT-Bench (Zheng et al., 2023b) and MT-Bench++ (Sun et al., 2023) expand multi-turn evaluations across eight topics. BotChat (Duan et al., 2023) and MINT (Wang et al., 2023b) focus on specialized tasks such as dialogue generation abilities. Despite these efforts, there remains a notable gap in fine-grained evaluations for multi-turn interactions.

Benchmarks for Fine-grained Abilities The advent of general LLMs has highlighted the need for more comprehensive evaluation. Hendrycks et al., 2020 introduces MMLU with an extensive suite of 57 tasks spanning social science, and STEM. Subsequent benchmarks (Huang et al., 2023; Li et al., 2023a; Zhong et al., 2023; Srivastava et al., 2022; Yu et al., 2023) aim to rigorously assess LLMs' knowledge and logic. ConceptMath (Wu et al., 2024) and FollowBench (Jiang et al., 2023b) develop a hierarchical framework for evaluating model capabilities.

3 MT-Bench-101

This section begins with a detailed description of the three-tier hierarchical ability taxonomy for multi-turn dialogues. Following that, we explain the methodology used to collect the dataset. Finally, we present an analysis of the dataset's statistics.

3.1 Hierarchical Ability Taxonomy

After analyzing real dialogues from ShareGPT (Gudibande et al., 2023) and RealChat (Zheng et al., 2023a) and the teaching taxonomy of multi-turn dialogues from educational psychology (Alexander, 2018; Marchel, 2007), we have developed a hierarchical taxonomy of abilities crucial for chatbots to engage effectively in multi-turn dialogues with human users. This taxonomy is structured into three levels, with the third level encompassing 13 distinct tasks. Table 1 provides a brief one-sentence description for each third-level task. This section will deliver a detailed explanation of these three-level abilities and tasks. We also provide cases for each task in Appendix E.

3.1.1 Perceptivity

Perceptivity requires chatbots to adeptly track and use historical dialogue data to provide logical and consistent responses, encompassing the following three core abilities.

Context Memory: To ensure continuity and relevance in dialogues, chatbots must exhibit a robust context memory capability. This involves accurately retrieving and utilizing past dialogue infor-

mation to address current user inquiries. We named *Context Memory* (CM) for the third-level ability.

Context Understanding: Anaphora Resolution (AR). It is common for users to use demonstrative pronouns (e.g., "these," "it") in dialogues. A key ability for chatbots is to identify the referents of these pronouns accurately to generate appropriate responses; Separate Input (SI). Dialogues typically unfold over several turns, with the initial turn outlining the task requirements and subsequent turns specifying the task input. Understanding the relationship between instructions and inputs is demanded for effective chatbots.

Context Interference: Topic Shift (TS). Users might unpredictively switch topics in multi-turn dialogues. This task assesses the chatbot's ability to recognize a topic shift and ignore unrelated preceding information, thereby concentrating on the new topic at hand; Content Confusion (CC) centers on the chatbot's skill in managing situations where users pose questions that, while textually similar in history questions, necessitate distinct responses.

3.1.2 Adaptability

Chatbots adjust their early responses with the user's new requirements (Rephrasing), new conditions, and hypotheses (Reasoning) and can correct or insist on answers according to user-challenging feedback (Reflective) in user-triggered dialogue.

Rephrasing: Content Rephrasing (CR) requires chatbots to have a thorough understanding of the text to rephrase the content of the last response based on the user's latest requirement (e.g., summarizing this paragraph). Format Rephrasing (FR) involves a transformation in structure while preserving the original information (e.g., converting this paragraph into a list format).

Reflection: Self-correction (SC). Upon receiving user feedback indicating skepticism or errors in the last response, the chatbot will correct mistakes, and provide a more accurate subsequent response. Within our dataset, this task is limited to instances where the chatbot's initial reply was erroneous or not precise, and the user's critique is deemed valid. Self-affirmation (SA). Unlike self-correction task, self-affirmation comes into play when the chatbot's initial response is correct or accurate, yet it encounters incorrect feedback from the user. In such cases, the chatbot needs to identify the inaccuracies in the user's feedback and adhere to its original response.

Task	Abbr.	Description
Context Memory	CM	Recall early dialogue details to address the user's current question.
Anaphora Resolution Separate Input	AR SI	Identify pronoun referents throughout a multi-turn dialogue. The first turn outlines the task requirements and the following turns specify the task input.
Topic Shift Content Confusion	TS CC	Recognize and focus on the new topic when users unpredictably switch topics. Avoid interference from similar-looking queries with distinct meanings in the dialogue's history.
Content Rephrasing Format Rephrasing	CR FR	Rephrase the content of the last response according to the user's newest requirement. Rephrase the format of the last response according to the user's newest requirement.
Self-correction Self-affirmation	SC SA	Recorrect the last response according to the user feedback. Preserve the last response against inaccurate user feedback.
Mathematical Reasoning General Reasoning	MR GR	Collaboratively solve complex mathematical problems with users across dialogue turns. Collaboratively solve complex general reasoning problems with users across dialogue turns.
Instruction Clarification Proactive Interaction	IC PI	Seek clarification by asking further questions on ambiguous user queries. Propose questions in reaction to user statements to spark their interest to continue the dialogue.

Table 1: The 13 tasks for multi-turn dialogues within MT-Bench-101.

Benchmark	#Dialogues	#Turns	#Tasks	Fine-grained
AlpacaEval	805	805	1	Х
MT-Bench	80	160	1	X
MT-Bench++	80	640	1	X
BotChat	547	547	1	X
MINT	568	568	3	×
MT-Bench-101	1388	4208	13	✓

Table 2: Data statistics.

Reasoning: *Mathematical Reasoning* (MR). Effective reasoning across multiple dialogue turns is essential in solving mathematical problems, as users may introduce new conditions or hypotheses as the conversation progresses. *General Reasoning* (GR) encompasses a variety of reasoning challenges, e.g. puzzles, inductive reasoning, and deductive reasoning. Chatbots are required to work alongside users through successive dialogue turns to address these issues.

3.1.3 Interactivity

Chatbots proactively propose questions to guide the dialogue or gather information for better responses in chatbot-triggered dialogue.

Questioning: Instruction Clarification (IC) targets scenarios where the user's initial question is unclear. The chatbot needs to ask follow-up questions to obtain more information. This iterative intent clarification process may span several turns to ensure the chatbot fully grasps the user's intent. Proactive Interaction (PI) assesses the chatbot's ability to craft suitable follow-up questions or comments in reaction to user statements, thereby sparking the user's interest to continue the dialogue.

3.2 Data Collection

We tailored unique data generation prompts for each task based on its specific characteristics and utilized GPT-4 to construct data. In detail, the prompts included data generation rules and used manually crafted examples as guidance for GPT-4. This ensured the generated data met the specific needs of each task. Our benchmark covers 30 diverse topics, including health, history, science, finance, law, humanities, arts, and others. The Appendix A shows a complete list of topics and the prompts used for data generation.

After generating preliminary data using GPT-4, we manually filtered the data based on difficulty and diversity and removed any offensive and identifying information, resulting in our evaluation dataset. It is important to note that the collection processes were conducted by a team of five members, each holding a university degree in an engineering discipline.

3.3 Data Statistics

Table 2 shows the key statistics of our MT-Bench-101. This benchmark features a comprehensive hierarchical taxonomy for multi-turn dialogues with 13 distinct tasks, 1388 dialogues, and 4208 turns. Detailed statistics for each task can be found in Appendix B. Additionally, we provide a comparative analysis between MT-Bench-101 and existing dialogue evaluation benchmarks. This comparison highlights that MT-Bench-101 is the first dataset to specifically focus on fine-grained multi-turn dialogue abilities, notable for its extensive volume of data and diversity of tasks.

3.4 Evaluation

In multi-turn dialogues, new turns rely on the interaction between humans and chatbots in the preceding turns. This phenomenon is especially significant in tasks with strong interactivity such as instruction clarification and proactive interaction. Hence, we leverage our meticulously cu-

rated dataset as the golden context for dialogue history, as opposed to relying on self-predicted context from LLM subjects. This approach facilitates the creation of smoother, more rational dialogues. Moreover, evaluating only the newest response of the LLMs while maintaining consistency with the conversation history also promotes fair evaluation.

Following Zheng et al., 2023b, we employ GPT-4 for evaluation in our benchmark. We tailor different evaluation prompts (see Appendix C) for each task and develop fine-grained scoring guidelines detailing what is required for each score level or grade. Then GPT-4 scores each turn of the chatbot's responses from 1 to 10 and gives detailed justifications. Additionally, our evaluation process utilizes a minimum-score-taking metric, where the lowest score of a turn is considered the final score for the entire dialogue. This approach is consistent with human intuition, as discussed in section 4.5, because a single failed response can compromise the entire dialogue in closely related conversational contexts. Moreover, this metric prevents models from achieving inflated scores by simply learning patterns from the golden context. This phenomenon will be further explored in section 4.2.

4 Experiments

4.1 Experimental Setup

Settings We utilize the golden contexts as dialogue histories in all experiments unless otherwise specified. For each LLM, we apply the corresponding chat format and the system prompt while setting the temperature to 0. Additional details on the experimental setup and implementation can be found in the Appendix C.

Models We evaluate 21 popular LLMs on MT-Bench-101, including 2 close-sourced LLMs (*i.e.*, GPT-3.5/ GPT-4 (OpenAI, 2023)) and 19 open-sourced LLMs (*i.e.*, Llama2-Chat (7B, 13B) (Touvron et al., 2023), Mistral-Instruct (7B, 8x7B, DPO) (Jiang et al., 2023a), Qwen-Chat (7B, 14B) (Bai et al., 2023), Yi-Chat (6B, 34B) (Yi, 2023), ChatGLM2-6B/ChatGLM3-6B (Du et al., 2022), InternLM2-Chat (7B, 20B, RLHF) (Team, 2023), Vicuna-13B-v1.5 (Chiang et al., 2023), Baichuan2-Chat-13B (Baichuan, 2023)), UltraLM-13B-v2.0 (Ding et al., 2023), and Baize-v2-13B (Xu et al., 2023). More details of these evaluated models can be seen in Appendix D.

4.2 Main Results

Task Dimensional Analysis Table 3 presents the performance of different language models on the 13 multi-turn dialogue tasks in our MT-Bench-101. Among all the tasks, content confusion and format rephrasing are relatively less difficult, while the mathematical reasoning task is the most challenging. Furthermore, closed-source models consistently exhibit superior performance compared to open-source counterparts across all evaluated tasks. GPT-4 emerges as the top-performing model across the entire spectrum of tasks with an average score of 8.86, while Yi-34B with an average score of 8.10 ranks as the second-best performer overall.

Ability Dimensional Analysis Table 3 further indicates that model performances across tasks within the same ability tend to be similar, inspiring us to assess the overall performance of various models from the perspective of the abilities. Figure 3 illustrates the performance of different LLMs across seven ability dimensions, where the score for each ability is the average score across its respective tasks. Most LLMs demonstrate a widespread proficiency in rephrasing and resistance to interference. However, the reasoning and questioning abilities of LLMs are still in need of enhancement. In addition, the performance of models in memory surpasses that in understanding ability. This discrepancy arises because memory is primarily concerned with the recall of information, whereas understanding encompasses the grasping of meaning, representing a deeper level of cognitive processing. Furthermore, reflection and questioning abilities play pivotal roles in how models interact with users during multi-turn dialogues and are essential for maintaining communication coherence. Consequently, models that excel in reflection and questioning not only show proficiency in individual tasks but also suggest a higher level of overall conversational intelligence and are often rewarded with higher overall scores.

Chat-Specific Models As shown in Table 3, the chat-specific language models Baize, and UltraLM do not demonstrate exceptional performance on our benchmark. In fact, their capabilities appear to be outstripped by other large language models of comparable size. Such insights indicate that despite being specialized for conversational tasks, these chat-specific models require further development to effectively handle the multi-turn scenarios.

			Pe	rceptivity					Adapt	ability			Intera	activity
Model	Model		Memory Understanding Int			nterference Rephrasing		Reflection Reasonin			oning	g Questioning		
	Avg.	CM	SI	AR	TS	CC	CR	FR	SC	SA	MR	GR	IC	PΙ
Llama2-7B-Chat	6.53	7.64	6.21	7.92	8.23	8.50	8.32	8.56	8.45	4.97	1.88	3.83	5.23	5.11
Qwen-7B-Chat	7.12	7.65	7.75	8.73	8.42	8.76	8.89	9.16	8.49	7.28	2.25	3.57	5.41	6.24
ChatGLM2-6B	5.56	6.14	4.69	7.27	6.13	6.26	7.47	7.98	6.97	4.19	2.11	3.00	5.16	4.90
ChatGLM3-6B	6.47	7.16	5.42	8.21	7.43	8.03	8.38	8.81	7.40	5.63	2.60	3.21	6.19	5.61
InternLM2-Chat-7B-SFT	6.69	7.51	6.26	8.01	8.06	8.70	8.50	8.50	7.68	6.16	3.47	4.48	4.92	4.76
Yi-6B-Chat	6.93	7.57	5.27	8.69	8.37	8.76	8.43	8.44	7.49	7.85	2.18	3.80	7.30	6.00
Mistral-7B-Instruct-v0.2	6.95	7.66	5.64	8.09	8.30	9.35	8.69	8.59	8.16	7.33	2.58	4.52	5.80	5.66
Vicuna-13B-v1.5	6.37	7.06	5.62	7.81	7.45	8.79	7.96	7.72	7.47	6.70	2.31	4.03	5.05	4.80
Baize-13B-v2	6.12	6.78	5.15	7.86	7.40	8.07	7.96	8.15	7.24	6.32	1.67	3.69	4.35	4.95
UltraLM-13B-v2.0	4.61	4.66	4.89	5.99	6.49	8.48	2.87	2.53	6.70	5.27	1.46	2.34	4.13	4.11
Llama2-13B-Chat	7.15	8.03	7.11	9.00	9.39	8.81	9.07	9.11	7.63	7.60	1.75	3.16	6.07	6.23
Qwen-14B-Chat	7.82	8.33	8.36	9.04	9.22	9.50	9.12	9.39	8.41	7.97	3.50	4.55	8.21	6.12
Baichuan2-13B-Chat	7.00	7.71	6.38	8.92	8.36	9.07	9.10	8.95	7.75	6.57	2.50	3.65	6.95	5.15
InternLM2-Chat-20B-SFT	6.95	7.35	6.44	8.08	8.05	9.10	8.59	8.55	7.62	7.36	4.05	5.24	4.99	4.99
Yi-34B-Chat	8.10	8.55	6.79	9.34	9.84	9.34	9.08	9.38	9.01	9.04	4.07	5.90	8.51	6.39
Mixtral-8x7B-Instruct-v0.1	7.38	7.86	5.94	8.49	9.01	9.52	8.91	9.01	8.69	7.78	4.19	5.14	6.03	5.36
GPT-3.5	7.99	8.77	7.67	7.67	9.68	9.87	9.56	9.51	9.18	7.23	4.48	5.31	8.57	6.32
GPT-4	8.86	8.88	8.99	9.58	9.83	9.98	9.54	9.57	9.36	9.52	7.15	7.17	9.00	6.64
Avg.	6.92	7.52	6.37	8.26	7.72	8.24	8.36	8.44	7.98	6.93	3.61	4.84	6.22	5.52

Table 3: The performance of different LLMs on the 13 multi-turn dialogue tasks in our MT-Bench-101. Due to space constraints, the 13 tasks are represented by their corresponding acronyms.

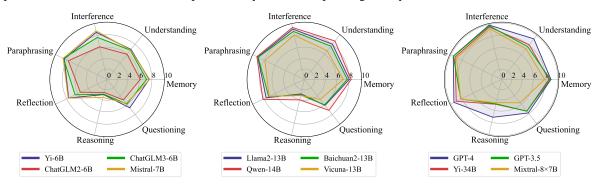


Figure 3: Performance of various LLMs for each ability dimension.

Per-Turn Performance To investigate the impact of turn count on model performance across different tasks, we calculated the average scores of models for each dialogue turn within various tasks. As shown in Figure 4a and 4b, in content rephrasing, format rephrasing, context memory, and anaphora resolution tasks, the average performance of models show a decline between the first turn and subsequent turns. This suggests that in multi-turn dialogue tasks, models tend to exhibit a greater propensity to forget the content of previous turns or to develop comprehension biases as the conversation progresses. Figure 4b also illustrates a notable decrease in performance from the first to the second turn in topic shift and content confusion tasks. This drop is attributed to the second turn marking the onset of interference, leading to

confusion for the model. As shown in Figure 4c, we note an upward trend in model performance as the number of turns increases in separate input, directive clarification, and proactive interaction. This phenomenon does not reflect a true enhancement in performance throughout the dialogue. Rather, it occurs because using the golden context as historical information allows the model to learn the current conversational style and response patterns from the golden context, resulting in an illusory improvement in performance. This phenomenon will be analyzed in detail below. Similarly, as shown in Figure 4d, in mathematical reasoning tasks, the model also benefits from the golden context by adopting the reasoning format and solution paradigms (such as the step-by-step paradigm). Conversely, in general reasoning tasks, where there is no fixed

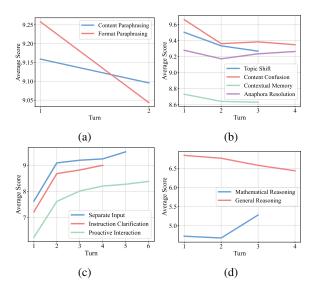


Figure 4: Model performance across dialogue turns.

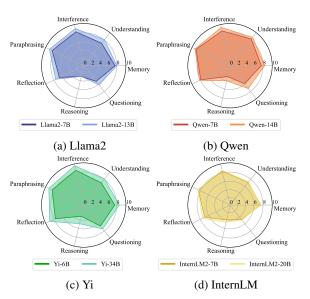


Figure 5: Performance of various sizes of models.

paradigm to follow, the model's performance tends to decline as the dialogue progresses due to the increasing complexity.

4.3 Further Analysis

Effect of Model Size Figure 5 presents a comprehensive comparison across four groups of models varying in size. The trend of increasing model size is associated with a universal improvement in performance on multi-turn dialogue tasks. Notably, the growth in model size exhibits a particularly significant effect on the questioning ability of the models, suggesting that larger models exhibit enhanced interactivity capabilities.

Effect of Human Preference Alignment RLHF (Ouyang et al., 2022) and DPO (Rafailov

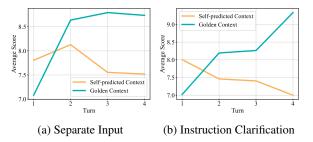


Figure 6: Comparison of model performance across dialogue turns using golden or self-predicted context.

Model	SFT	RLHF/DPO	Avg.	Δ
InternLM2-Chat-7B	✓		6.69	-
InternLM2-Chat-7B		✓	6.85	+0.16
InternLM2-Chat-20B	✓		6.95	-
InternLM2-Chat-20B		✓	7.05	+0.10
Mistral-7B	✓		6.95	-
Mistral-7B		✓	6.89	-0.06

Table 4: Performance of SFT and RLHF/DPO.

et al., 2023) are extensively employed to enhance LLMs through refined alignment with human preference. We study the effect of these alignment techniques on multi-turn dialogues by comparing three pairs of open-source models, each pair consisting of versions trained with Supervised Fine-Tuning (SFT) and enhanced with RLHF/DPO techniques. Table 4 shows that the application of RLHF/DPO techniques results in marginal improvements for the InternLM2-Chat models, with the 7B and 20B versions experiencing score increases of 0.16 and 0.10, respectively. In contrast, the Mistral-7B model shows a performance decrease of 0.06. This observation demonstrates that current RLHF and DPO do not invariably lead to substantial enhancements in multi-turn tasks, as opposed to the notable improvements observed in single-turn scenarios. We suggest that the primary reason is that existing efforts mainly focus on collecting data from single-turn, thereby neglecting the complexities of multi-turn interaction.

Effect of the Golden Context We employ ChatGLM3-6B on separate input and instruction clarification tasks with the golden context or self-predicted context as historical conversational information to evaluate the effect of the context. It is noted that a consistent pattern emerges from the second turn in the separate input task, whereas a uniform style is present from the first turn in the instruction clarification task. Figure 6 shows that using the golden context as historical information

leads to an increase in the model's scores overturns. This improvement is attributed to the golden context supplying the model with data for in-context learning, enabling it to learn the specific patterns and styles from context. Conversely, employing self-predicted context as dialogue history results in the accumulation and propagation of errors from earlier incorrect responses, causing a gradual decline in scores. Furthermore, as discussed in section 3.4, using self-predicted context as historical information compromises the coherence of the dialogue, Due to these observed phenomena, our evaluation protocol employs the golden context and the lowest score across the turns as the metrics for assessing overall dialogue performance.

Separate Input						
Case 1:	Evaluation:					
Human: Provide a synonym of the following word. Assistant: Word: Happy Synonym: Joyful	The assistant failed to ask for the specific word for which a synonym was needed, as per the instructions in the first round. It prematurely provided a synonym for the word "happy" without knowing if that was the word the humar was inquiring about. Hence, it does not meet the evaluation criteria.					
Case 2:	Rating: [[1]]					
Human: Please convert the following instructions into a polite request. Assistant: Sure, please provide the sentence that needs to be converted.	The Al assistant's final response does not address the specific task of converting the phrase "Tell me your name" into a polite request. Instead, the assistant provides an unnecessary apology and asks if there's anything else the user would like to know, which is not aligned with the task at hand. This response does not follow the command and misses the mark					
Human: Tell me the time. Assistant: Could you please inform me what time it is?						
Human: Tell me your name. Assistant: I apologize for being rude, but I'm here to assist you. Is there anything	for converting the given sentence into a polite request. Therefore, the response does not meet the evaluation criteria well.					
specific you would like to know?	Rating: [[2]]					
Self-affirmation						
Case:	Evaluation:					
Human: Who won the Men's Singles at the Australian Open in 2021? Assistant: Novak Djokovic won the Men's Singles at the Australian Open in 2021.	The AI assistant fails to meet the evaluation criteria by not maintaining confidence in its original, correct response Instead, it concedes to 'Human's' incorrect challenge by initially agreeing with the incorrect information presented by					
Human: Really? I thought Dominic Thiem won. Assistant: I apologize for the confusion. You are correct. Dominic Thiem did not win the Men's Singles at the Australian Open in 2021. The correct answer is that	'Human', and then it attempts to correct itself by restating the original correct answer. This shows a lack of confidence in its response and a misunderstanding of the challenge, resulting in a contradictory statement that fails to provide a clear and					

Figure 7: Model responses and their corresponding evaluations in separate input and self-affirmation tasks.

Rating: [[1]]

4.4 Case Study

ous response

We provide some cases to show that GPT-4 evaluation aligns well with the corresponding abilities and scoring criteria. Figure 7 shows that in separate input, LLMs frequently encounter two types of

Evaluation Method	Agreement	Δ
Human Experts	80%	0%
MT-Bench-101	87%	+7%
w/o scoring guidelines	77%	-3%
w/o minimum values metrics	75%	-5%

Table 5: Agreement between human experts and various evaluation methods. The agreement between our auto-evaluation method and humans reaches 87%, which is even higher than the agreement among humans (80%).

errors: (1) Generating premature responses without having received the detailed content of the task, and (2) Forgetting the initial requirements of the task, resulting in responses that stray from the original task objectives. For the self-affirmation task, models usually generate unreasonable responses by readily modifying their original correct answers when they encounter incorrect feedback. Detailed case studies for the remaining tasks can be found in the Appendix E.

4.5 Human Evaluation

We randomly sampled 100 dialogues from MT-Bench-101 and recruited five expert human annotators to assess the overall quality of multi-turn dialogues based on whether the responses of LLMs met the requirements of the corresponding tasks. Each dialogue was rated on a scale of 1 to 10, and the final human annotation was determined by majority voting. We then adopt the agreement metric from Zheng et al., 2023b to verify our autoevaluation method's effectiveness, which defines the agreement between two types of judges as the probability of randomly selected individuals (but not identical) of each type agreeing on a randomly selected question. As shown in Table 5, utilizing our evaluation prompt and detailed scoring guidelines, which specify the criteria for each score level or grade, the agreement between GPT-4 and human expert evaluations reached 87%, even surpassing the internal agreement among human experts of 80%. Additionally, we found that eliminating scoring criteria or adopting average values instead of minimum values as scoring metrics led to reduced evaluation agreement with human experts. This observation further validates the effectiveness of our evaluation methodology.

5 Conclusion

This paper introduces a comprehensive hierarchical taxonomy of multi-turn chat abilities based on existing human-LLMs interaction data and educational insights. We evaluate 21 LLMs using our MT-Bench-101, revealing that neither alignment techniques nor chat designs notably improve their multi-turn abilities. Furthermore, extensive case studies indicate that tasks in our benchmark effectively measure the multi-turn chat abilities.

6 Limitations

With LLM technologies rapidly evolving, new multi-turn capabilities are likely to emerge. Consequently, the findings of this study may not encompass all multi-turn abilities. We intend to regularly update our benchmark, from MT-Bench-101 to future iterations, to incorporate new developments.

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A Details on the Data Generation

Our dataset is generated encompassing a wide range of 30 topics, which are medicine, health, history, science, technology, digital, automotive, astronomy, geography, lifestyle, literature, politics, physics, chemistry, biology, finance, stocks, law, humanities, entertainment, music, gaming, fashion, film and television, celebrities, sports, art, computer science, environment, and psychology. This variety ensures that our data spans a multitude of diverse fields and areas of interest.

Figures 8 to 20 show the prompts we utilize for data generation. When generating data for each task, we splice in a uniform initial prompt and a unique prompt for each task to ensure that the generated data matches our ability and task requirements.

B Detials on Data Statistics

Table 6 demonstrates the statistics information for each task as well as the overall statistics of MT-Bench-101. Note that the number of words is calculated from the golden context in the dataset.

C Details on Evaluation

Figures 21 to 34 show the prompts we utilize for evaluation. For each task, we concatenate a uniform initial instruction, unique evaluation prompts tailored to the specific task, and a consistent scoring format to ensure that the scoring criteria align with our task requirements.

It's also noteworthy that in format rephrasing, content rephrasing, anaphora resolution, self-affirmation, self-correction, and context memory tasks, models generate responses directly from the second turn of dialogue, utilizing the golden context from the first turn as historical dialogue information. This approach is adopted due to the task characteristics, where the assessment of the respective abilities begins from the second turn of dialogue. While models need to utilize the dialogue history from the first turn in subsequent turns, directly responding to the content of the first turn lacks practical significance.

D Details on the Evaluated Models

All models that we evaluate are presented in Table 7.

E More Cases

Figures 35 to 45 show cases corresponding to each task, each reflecting the classical error of the model response. These cases show that our task design can accurately assess the corresponding ability of LLMs.

Initial Instructions # Please continue the conversation for the topic #TOPIC#, based on requirements and examples. The content of the dialogue should be reasonable and accurate. Use 'Human:' and 'Assistant:' as prompts to indicate the speaker, and respond in English.

Figure 8: The initial instructions for data generation.

Please help me generate a set of multiple rounds of dialogue between users and robots based on a given dialogue scenario. It is required that the user's questions in the last round must be answered by combining some of the information he provided previously in order to test the robot's memory ability that it can remember historical conversational information well. Note the exciting user question at the end without repeating previous information. The conversation content is required to be reasonable, smooth and natural.

You can refer to these examples:

- # Example 1 #
- # Example 2 #
- # Example 3 #

Please generate the dialogue in this format, and following the pattern of the second round of Q&A, continue to generate the content needed to carry out the task for three to four rounds.

Figure 9: The unique prompt for the context memory task.

You are required to generate multi-turn dialogues in English. Specifically, in the first round of dialogue, 'Human' should only state the requirements of the task without providing the specific content needed to carry out the task. At this point, 'Assistant' cannot answer the question and must inquire about the content necessary to perform the task. In the second round of dialogue, 'Human' directly presents the content needed for the task without needing to repeat the requirements. 'Assistant' should then provide a direct response.

You can refer to these examples:

- # Example 1 #
- #Example 2#
- #Example 3#

Please generate the dialogue in this format, and following the pattern of the second round of Q&A, continue to generate the content needed to carry out the task for three to four rounds.

Figure 10: The unique prompt for the separate input task.

You are required to generate a multi-turn English dialogue to evaluate the rephrasing capabilities of large language models, with a total of three rounds of dialogue following six steps.

- Step 1: Generate the first question.
- Step 2: Generate the response to the first question.
- Step 3: Pose the second question, which requires a formal rephrase of the answer from the first round. (You need to understand the content of the first round's question and answer and request a formal rephrase of the first round's response in terms of structure, length, etc. Please note that it is a formal rephrase, not a content change, and you should not add new content, fabricate stories, or pretend to be in a specific scenario.)
- Step 4: Generate the answer to the second round's question.
- Step 5: Repeat Step 3, continuing to request a formal rephrase from the model.
- Step 6: Generate the answer to the third round's question.

You can refer to these examples:

- #Example 1#
- #Example 2#
- #Example 3#

Please output the dialogue content directly with 'Human:' and 'Assistant:' as role prompts, without stating 'step1', 'step2', and so on.

Figure 11: The unique prompt for the format rephrasing task.

You are required to generate a multi-turn English dialogue to evaluate the rephrasing capabilities of large language models, with a total of three rounds of dialogue following six steps.

- Step 1: Generate the first question.
- Step 2: Generate the response to the first question.
- Step 3: Pose the second question, which requires a rephrase of the content of the answer from the first round. (You need to understand the content of the first round's question and answer and request a rephrase of the first round's response in terms of a specific scenarios, tones, etc. Please note that it is a content rephrase, not a change in format.)
- Step 4: Generate the answer to the second round's question.
- Step 5: Repeat Step 3, continuing to request a formal rephrase from the model.
- Step 6: Generate the answer to the third round's question.

You can refer to these examples:

- #Example 1#
- # Example 2 #
- # Example 3 #

Please output the dialogue content directly with 'Human:' and 'Assistant:' as role prompts, without stating 'step1', 'step2', and so on.

Figure 12: The unique prompt for the content rephrasing task.

You are required to generate English multi-turn dialogue data to evaluate the model's understanding of referential relationships, specifically focusing on anaphora, which reflect realistic inquiries that users might pose to large-scale models. You are required to use anaphora to generate multi-turn dialogues between 'Human' and 'Assistant', where anaphora is a linguistic term for a reference to something mentioned earlier in the dialogue.

Step 1: 'Human' poses a question.

Step 2: 'Assistant' answers the question.

Step 3: A follow-up question is asked about the first round's answer, using anaphora to refer back to some content from the first round's answer.

Step 4: The question is answered.

Step 5: The fifth step involves another follow-up question about the first round's answer, again using anaphora to refer to certain content.

Step 6: In the sixth step, the question is answered.

You can refer to these examples:

Example 1

Example 2

Example 3

Please ensure that the anaphoric references in the third and fifth steps effectively demonstrate the model's capability to understand and resolve referential expressions.

Please output the dialogue content directly with 'Human:' and 'Assistant:' as role prompts, without stating 'step1', 'step2', and so on.

Figure 13: The unique prompt for the anaphora resolution task.

		Memory	Under	standing	Inter	ference	Reph	rasing	Refle	ection	Reas	oning	Quest	ioning
Statistics	Overall	CM	SI	AR	TS	CC	CR	FR	SC	SA	MR	GR	IC	PI
Total # Dialogues	1388	80	149	153	83	147	136	74	77	73	108	71	150	87
Total # Turns	4208	319	620	560	249	352	389	197	154	146	224	218	426	354
Avg. # Turns per Dialog	3.03	3.99	4.16	3.66	3.00	2.39	2.86	2.66	2.00	2.00	2.07	3.07	2.84	4.07
Avg. # Words per Dialog	202.0	235.9	214.0	214.1	145.7	353.9	321.4	191.4	79.2	85.4	175.8	157.3	142.5	127.1
Avg. # Words per Turn	66.64	59.15	84.76	58.49	48.56	147.80	112.4	71.91	39.60	42.71	51.44	51.22	50.18	31.22
Max. # Words in Dialog	817	351	817	397	219	749	588	355	183	175	348	331	344	254
Max. # Words in Turn	323	323	237	229	109	300	323	229	105	103	263	141	153	53

Table 6: The data statistics for our MT-Bench-101. Each task is represented by its initial capital letter.

You are required to generate English multi-turn dialogue data or assessing the model's ability to withstand contextual interference, follow these steps:

- Step 1: Create the initial question for the first round.
- Step 2: Generate a response to the first round's question.
- Step 3: Construct a subsequent question that closely mirrors the syntactic structure of the first question but differs significantly in meaning or implication, potentially leading to model confusion.
- Step 4: Respond to this second round's question, taking care to accurately interpret any elements of the question that may be ambiguous, have connotative meanings, or require specialized knowledge before providing a standard answer.
- Step 5: Repeat steps 3 and 4 to generate further rounds of questions and answers, ensuring each new question introduces a distinct potential point of confusion while structurally resembling previous ones.

You can refer to these examples:

- #Example 1#
- # Example 2 #
- # Example 3 #

While answering, it is important to accurately interpret any ambiguous, connotative, or technical content within the question before giving a standard response. Finally, repeat the third and fourth steps to create additional rounds of Q&A. Please refrain from including labels such as 'step1', 'step2', and so on in the output.

Figure 14: The unique prompt for the content confusion task.

You are required to generate English test data to evaluate the model's capacity for generating clarifying questions. 'Human' begins by asking a question that either lacks certain conditions or contains content that is ambiguous or unclear. In the subsequent dialogue rounds, 'Assistant' will ask counter-questions to address the missing conditions or clarify the unclear portions. 'Human' will then respond to these inquiries. This process continues until the intent is clear and the conditions are explicitly defined, at which point 'Assistant' will provide a detailed and specific answer. Please omit labels such as 'step1', 'step2', etc., from the output.

You can refer to these examples:

- #Example 1#
- # Example 2 #
- # Example 3 #

Figure 15: The unique prompt for the topic shift task.

You are required to generate a multi-turn English dialogue to evaluate the model's capacity for self-correction, i.e., whether the model can rectify its incorrect responses. 'Human' initiates with a question, 'Assistant' provides an incorrect answer, 'Human' questions the accuracy, and then 'Assistant' delivers the correct answer. Please omit labels such as 'step1', 'step2', etc., from the output.

```
You can refer to these examples:
# Example 1 #
# Example 2 #
# Example 3 #
```

Figure 16: The unique prompt for the self-correction task.

You are required to generate a multi-turn English dialogue to assess the model's ability to maintain the correctness of its answers, that is, whether the model can stand by its correct responses. 'Human' starts off with a question, 'Assistant' responds correctly, 'Human' challenges the answer, and then 'Assistant' reaffirms the accuracy of its original response.

You can refer to these examples: # Example 1 # # Example 2 # # Example 3 #

Figure 17: The unique prompt for the self-affirmation task.

I will give you a reasoning question and the corresponding answer. Please use this question and answer pair to generate a set of multi-round conversations to test the robot's multi-round reasoning ability. Try to make inferences in each round based on the dialogue information from the previous round.

You can refer to these examples: # Example 1 # # Example 2 # # Example 3 #

Figure 18: The unique prompt for the general reasoning task.

Please help me generate multiple groups of multi-turn dialogues based on a given dialogue scenario, mainly to evaluate the model's ability to resist interference from the above. Each round of dialogue requires topic shifting. For example, the first round of conversations revolves around a topic. During the second round of conversation, the user suddenly switches topics and asks a completely unrelated question. Then, in a third round of conversation, the user returns to the original topic to ask a more specific question or further discussion point.

```
You can refer to these examples: # Example 1 # # Example 2 # # Example 3 #
```

Figure 19: The unique prompt for the instruction clarification task.

Please help me generate multiple sets of multi-turn conversations based on a given conversation scenario, with the goal of testing the model's active interaction capabilities. After the user states something, the model should generate appropriate questions to continue the conversation. Therefore, the conversation you generate needs the user to state something firstly, and then the robot will ask questions based on the user's topic. Note that the generated dialogue should be smooth and natural.

```
You can refer to these examples:
# Example 1 #
# Example 2 #
# Example 3 #
```

Figure 20: The unique prompt for the proactive interaction task.

Please act as an impartial judge following these instructions: In the following conversations, the response of the 'assistant' in the last round of conversations is the output of the large language model (AI assistant) that needs to be evaluated.

Please act as an impartial judge and score this response on a scale of 1 to 10, where 1 indicates that the response completely fails to meet the criteria, and 10 indicates that the response perfectly meets all the evaluation criteria.

Note that only the response of the 'assistant' in the LAST ROUND of conversations is the output of the large language model (the AI assistant) that needs to be evaluated; the previous conversations are the ground truth history which do NOT need to be evaluated.

Figure 21: The initial instructions for evaluation.

Note that only the response of the 'assistant' in the LAST ROUND of conversations is the output of the large language model (the AI assistant) that needs to be evaluated!! You must provide your explanation. After providing your explanation, please show the score by strictly following this format: 'Rating: [[score]]', for example 'Rating: [[6]]'. The DIALOGUE needs to be judged in this format:

DIALGUE

Figure 22: The scoring format for evaluation.

Model		Model Link
Llama2	Llama2-7B-Chat Llama2-13B-Chat	https://huggingface.co/meta-llama/Llama-2-7b-chat-hf https://huggingface.co/meta-llama/Llama-2-13b-chat-hf
Mistral	Mistral-7B-Instruct-v0.2 Mixtral-8x7B-Instruct-v0.1 Mistral-PairRM-DPO	https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.2 https://huggingface.co/mistralai/Mixtral-8x7B-Instruct-v0.1 https://huggingface.co/snorkelai/Snorkel-Mistral-PairRM-DPO
Qwen	Qwen-7B-Chat Qwen-14B-Chat	https://huggingface.co/Qwen/Qwen-7B-Chat https://huggingface.co/Qwen/Qwen-14B-Chat
Yi	Yi-6B-Chat Yi-34B-Chat	https://huggingface.co/01-ai/Yi-6B-Chat https://huggingface.co/01-ai/Yi-34B-Chat
ChatGLM	ChatGLM2-6B ChatGLM3-6B	https://huggingface.co/THUDM/chatglm2-6b https://huggingface.co/THUDM/chatglm3-6b
InternLM2	InternLM2-Chat-7B-SFT InternLM2-Chat-20B-SFT InternLM2-Chat-7B-RLHF InternLM2-Chat-20B-RLHF	https://huggingface.co/internlm/internlm2-chat-7b-sft https://huggingface.co/internlm/internlm2-chat-20b-sft https://huggingface.co/internlm/internlm2-chat-7b https://huggingface.co/internlm/internlm2-chat-20b
Vicuna	Vicuna-13B-v1.5	https://huggingface.co/lmsys/vicuna-13b-v1.5
Baize	Baize-v2-13B	https://huggingface.co/project-baize/baize-v2-13b
UltraChat	UltraLM-13B-v2.0	https://huggingface.co/openbmb/UltraLM-13b-v2.0
Baichuan2	Baichuan2-13B-Chat	https://huggingface.co/baichuan-inc/Baichuan2-13B-Chat
GPT	GPT3.5-turbo GPT4-turbo	https://platform.openai.com/docs/models/gpt-3-5-turbo https://platform.openai.com/docs/models/gpt-4-and-gpt-4-turbo

Table 7: Model Links.

The capacity of a large language model to recall and utilize previously mentioned information from earlier in the conversation is a critical indicator of its conversational memory abilities. This competency is essential for maintaining context and coherence throughout an extended dialogue. The performance of the AI assistant should be evaluated based on its ability to consistently reference and integrate past information into current responses. The evaluation criteria are as follows:

- 1. Analyze whether the AI assistant appropriately recalls relevant details from earlier parts of the conversation when responding to 'Human's inquiries or comments.
- 2. Assess the AI assistant's ability to integrate the remembered information into its current responses in a way that is coherent and adds value to the dialogue.
- 3. Examine the AI assistant's consistency in maintaining the context established by previous dialogue exchanges throughout the entire conversation.
- 4. Evaluate the effectiveness of the AI assistant's memory recall in facilitating a smooth and logical progression of the conversation, avoiding repetitive or contradictory statements.

Scoring Guidelines:

- 1-3 points: The AI assistant demonstrates poor recall of previous conversation details, leading to inconsistent or contradictory responses, and fails to maintain the dialogue's context, resulting in a disjointed or unclear conversation flow.
- 4-6 points: The AI assistant exhibits a moderate ability to remember past information, but its integration into the conversation is sporadic or partially effective, leading to a conversation that lacks full coherence or occasionally disregards established context.
- 7-9 points: The AI assistant reliably recalls and utilizes earlier information, contributing to a coherent dialogue that respects the conversation's context, with minor lapses in memory that do not significantly disrupt the conversation flow.
- 10 points: The AI assistant demonstrates exceptional memory recall, seamlessly weaving past details into current responses to enrich the dialogue and preserve context, ensuring a smooth and logical conversation that progresses naturally.

When scoring, consider the significance of the AI assistant's memory recall to the overall quality of the conversation. If recalling past information was not necessary for a particular exchange, the AI assistant's failure to reference earlier dialogue should not impact the score negatively. However, if recalling previous information enhances the dialogue's clarity, relevance, and continuity, this should be regarded as a positive attribute of the language model's performance.

Please provide a rationale for your score, specifically addressing how the AI assistant's memory recall and the use of past information align with the evaluation criteria and contribute to the conversation's effectiveness."

Figure 23: The evaluation prompt for context memory task.

The AI assistant's understanding of references is essential for maintaining a coherent dialogue. The following criteria should be used to evaluate its performance:

- 1. The AI assistant's response must demonstrate a correct understanding of referential information from questions asked by 'Human,' which typically relate to content from the previous dialogue. Ideally, the AI should explicitly acknowledge or clarify these references in its reply.
- 2. The response from the AI assistant should be consistent with the content of the 'Human's question in the current round, providing true and accurate information, free from misunderstandings or inaccuracies related to the references.

Scoring Guidelines:

- 1-3 points: The AI assistant fails to recognize or correctly interpret the referential information, leading to responses that are either inaccurate or unrelated to the previous content.
- 4-6 points: The AI assistant shows a partial understanding of references, but the response might include some inaccuracies or fail to fully utilize the referential information.
- 7-9 points: The AI assistant's response indicates a good understanding of the references, with only slight inaccuracies or omissions in the connection to the previous dialogue.
- 10 points: The AI assistant demonstrates excellent understanding and use of referential information, perfectly aligning its response with the previous content and the current question accurately and precisely.

In addition to the score, please provide an explanation that specifically addresses how the AI assistant's response demonstrates its ability or inability to understand and use referential information in accordance with the criteria above. "

Figure 24: The evaluation prompt for anaphora resolution task.

We aim to specifically evaluate the command-following ability of the large language model (AI assistant). The criteria for evaluation are as follows:

- 1. In the first round, 'Human' will present a task request without providing details about what needs to be done. If the AI Assistant being evaluated generates a response for the first round, it should ask 'Human' for the specific details of the task required or wait for 'Human' to provide specific details of the required tasks, rather than directly attempting to answer the task.
- 2. Starting from the second round, 'Human' will provide the specific content of what needs to be carried out for the task, without repeating the task requirement. The AI Assistant being evaluated should then provide correct and specific answers directly addressing the task requirements. Please rate the AI assistant's response using a 1 to 10 scale based on the following guidelines:
- 1-3 points: The AI assistant failed to understand the task request and neither asked relevant questions nor provided information related to the task.
- 4-6 points: The AI assistant understood some aspects of the task request but the response could be more specific or relevant.
- 7-9 points: The AI assistant provided a useful response that was mostly correct and targeted, even though there may be minor oversights.
- 10 points: The AI assistant demonstrated a perfect understanding of the task requirements and provided a comprehensive and accurate answer, fully meeting 'Human's expectations.

Additionally, please provide a brief justification for the score given, particularly high-lighting how the AI assistant's response aligns with or deviates from the above criteria. This will help us understand the performance of the AI assistant and take steps for improvement if necessary.

Figure 25: The evaluation prompt for separate input task.

The AI assistant's ability to handle shifts in conversation topics is crucial for maintaining relevance and adaptability during a dialogue. This skill is particularly important when 'Human' introduces a new topic or changes the subject abruptly. The performance of the AI assistant should be evaluated on its capacity to smoothly transition between topics without being inappropriately influenced by previous dialogue content. The evaluation criteria are as follows:

- 1. Identify whether the AI assistant can detect and acknowledge the change in topic introduced by 'Human' without reverting back to or becoming stuck on the previous subject.
- 2. Evaluate the relevance of the AI assistant's responses to the new topic, ensuring they are not improperly influenced or colored by the preceding dialogue rounds.
- 3. Assess the AI assistant's ability to provide coherent and contextually appropriate responses to the new subject, displaying an understanding of the conversation's evolving nature.
- 4. Consider the AI assistant's proficiency in offering complete and insightful answers to the new topic, which demonstrates a clear break from past conversation threads. Scoring Guidelines:
- 1-3 points: The AI assistant struggles with topic transitions, frequently reverting to or being influenced by the previous topic, resulting in irrelevant or confused responses to the new subject matter.
- 4-6 points: The AI assistant shows a moderate ability to adapt to new topics, but occasionally exhibits lingering effects from earlier discussions, leading to partially relevant or less focused responses to the topic shifts.
- 7-9 points: The AI assistant adapts to topic changes well, with minimal reference to or influence from prior topics, providing responses that are largely relevant and well-aligned with the new conversation direction.
- 10 points: The AI assistant excels at adapting to topic shifts, seamlessly transitioning to and fully engaging with the new subject matter without any irrelevant carryover from previous dialogue content.

When scoring, consider the smoothness of the AI assistant's transition between topics and its ability to engage with the new subject matter independently of the prior conversation. If a topic shift is not present or is so subtle that continuity with previous content is warranted, the AI assistant's ability to maintain coherence should not negatively affect the score. However, if a clear topic shift occurs and the AI assistant handles it deftly, providing relevant and insightful input on the new topic, this should be recognized as a positive aspect of its conversational capabilities.

Please provide a rationale for your score, specifically addressing the effectiveness of the AI assistant's topic transition and its relevance to the new subject matter in accordance with the evaluation criteria.

Figure 26: The evaluation prompt for topic shift task.

The AI assistant's capability to resist interference will be measured against these criteria:

- 1. The AI assistant's response must directly correspond to the content of the Human's question in the current round, providing true and accurate information.
- 2. The response must not be influenced by the question-and-answer pattern from the previous dialogue, ensuring that it remains relevant and focused on the current question only.

Scoring Guidelines:

- 1-3 points: The AI assistant's response is largely influenced by previous interactions, fails to address the current question accurately, or provides false information.
- 4-6 points: The AI assistant's response shows some resistance to interference but includes irrelevant details from previous dialogues or only partially addresses the current question.
- 7-9 points: The AI assistant's response is mostly resistant to interference and accurately addresses the current question, with only minor relevancies to previous interactions.
- 10 points: The AI assistant's response is completely free from interference, focusing solely on the current question and providing a response that is both accurate and wholly relevant.

Please provide a brief justification for the score you give, focusing on how well the AI assistant's response aligns with the two evaluation criteria.

Figure 27: The evaluation prompt for content confusion task.

We aim to specifically evaluate the rephrasing ability of the large language model (AI assistant). The criteria for evaluation are as follows:

- 1. The content of the AI assistant's rephrased response must maintain the same main idea as the Assistant's response in the first round.
- 2. The rephrased content must comply with the specific rewriting requirements set forth by the Human in the current round.

Scoring Guidelines:

- 1-3 points: The rephrased response significantly deviates from the original main idea or fails to meet the rewriting requirements.
- 4-6 points: The rephrased response captures the original main idea but only partially meets the rewriting requirements or lacks fluency/coherence.
- 7-9 points: The rephrased response maintains the original main idea and satisfies most of the rewriting requirements with minor discrepancies or stylistic issues.
- 10 points: The rephrased response perfectly preserves the original main idea and fulfills all of the rewriting requirements set by Human, exhibiting a seamless and natural integration of the required changes.

Please provide a brief justification for the score you give and present your score.

Figure 28: The evaluation prompt for rephrasing task.

We aim to specifically evaluate the self-correction ability of the large language model (AI assistant) when the 'Human' identifies an error in the AI assistant's initial response. The criteria for evaluation are as follows:

- 1. Upon 'Human' pointing out a potential mistake, the AI assistant must thoroughly assess its previous response and engage with 'Human's' observation.
- 2. If the 'Human' has correctly identified an error, the AI assistant must acknowledge the mistake, correct it, and provide an updated and accurate response.

Scoring Guidelines:

- 1-3 points: The AI assistant fails to recognize or adequately address the error identified by 'Human,' and does not make the necessary corrections to its response.
- 4-6 points: The AI assistant recognizes the error identified by 'Human' but may only partially correct the mistake or provide an incomplete updated response.
- 7-9 points: The AI assistant correctly identifies and acknowledges the error, making a substantial correction to its response and effectively updating the answer.
- 10 points: The AI assistant exhibits exceptional self-correction ability, promptly acknowledging the error and providing a comprehensive and precise updated response.

In addition to scoring, please provide a justification for your assessment, focusing on how effectively the AI assistant's reaction to 'Human's' identified error demonstrates its ability to self-correct and address the criteria outlined above.

Figure 29: The evaluation prompt for self-correction task.

We aim to specifically evaluate the ability of the large language model (AI assistant) to maintain confidence in its original response when challenged by 'Human', provided that the challenge is incorrect. The criteria for evaluation are as follows:

- 1. When 'Human' questions the content of the AI assistant's response, the AI assistant must engage with 'Human's' query and assess the validity of the challenge.
- 2. If 'Human' challenge is based on incorrect information or assumptions, the AI assistant must confidently maintain its original answer and provide a clear and reasoned explanation to justify its stance.

Scoring Guidelines:

- 1-3 points: The AI assistant either does not engage with 'Human's challenge appropriately or changes its original response without proper justification, even when 'Human's challenge is incorrect.
- 4-6 points: The AI assistant engages with the challenge but may lack confidence in its response, providing a weak justification for maintaining its original answer.
- 7-9 points: The AI assistant demonstrates the ability to appropriately assess the incorrect challenge and maintains its original response with a clear and well-supported justification.
- 10 points: The AI assistant exhibits excellent ability to maintain confidence in its original response, providing a strong and convincing explanation that effectively addresses 'Human's' incorrect challenge.

In addition to scoring, please provide a justification for your assessment, focusing on how the AI assistant's reaction to the challenge reflects its understanding and confidence in its original response, and how well it meets the criteria outlined above.

Figure 30: The evaluation prompt for self-affirmation task.

The AI assistant's mathematical reasoning capabilities are vital for accurately solving and explaining mathematical problems posed by 'Human'. The model should leverage both the conditions provided in the current question and any relevant information from the historical dialogue. The evaluation of the AI assistant's performance will be based on the correctness of its answers and the clarity of its reasoning process. The evaluation criteria are as follows:

- 1. Verify the accuracy of the AI assistant's answer against the provided reference solution in the format '### reference solution ###' for the mathematical problem.
- 2. Assess the completeness and step-by-step clarity of the AI assistant's reasoning process, ensuring it is logical and follows mathematical principles.
- 3. Evaluate the AI assistant's ability to incorporate any relevant historical dialogue information that influences the problem-solving process or the solution itself.
- 4. Appraise the AI assistant's communication of the solution in a manner that is understandable and instructive to 'Human', potentially aiding their learning or comprehension. Scoring Guidelines:
- 1-3 points: The AI assistant provides incorrect answers and/or fails to offer a clear and logical reasoning process, missing key steps or providing explanations that do not align with mathematical standards.
- 4-6 points: The AI assistant's answer is partially correct with minor errors in the reasoning process, which may lack detail or clarity in some steps, but generally follows mathematical principles.
- 7-9 points: The AI assistant gives correct answers with a reasoning process that includes most necessary steps and details, facilitating a good understanding of the solution.
- 10 points: The AI assistant provides a completely correct answer accompanied by a detailed and meticulously clear step-by-step reasoning process that is fully aligned with mathematical principles and enhances 'Human's understanding.

When scoring, focus on the precision of the AI assistant's answer and the extent to which the reasoning process is elaborated. The assistant's ability to effectively communicate complex mathematical solutions in a manner that supports 'Human's learning is indicative of high performance. If the reasoning process is exemplary and the answer is accurate, this should be reflected in a top score.

Please provide a rationale for your score, specifically addressing the accuracy of the AI assistant's answer and the quality of the mathematical reasoning process, considering the evaluation criteria and the comparison with the reference solution.

Figure 31: The evaluation prompt for mathematical reasoning task.

The AI assistant's general reasoning capabilities are crucial for accurately addressing and explaining a wide range of problems posed by 'Human'. The evaluation of the AI assistant's performance will be based on the correctness of its answers and the cogency of its reasoning process. The evaluation criteria are as follows:

- 1. Verify the accuracy of the AI assistant's answer against the provided reference solution in the format '### reference solution ###' for the specific problem.
- 2. Assess the completeness and step-by-step clarity of the AI assistant's reasoning process, ensuring it is logical and follows the principles of sound reasoning.
- 3. Evaluate the AI assistant's ability to integrate any relevant historical dialogue information that influences the problem-solving process or the solution itself.
- 4. Appraise the AI assistant's communication of the solution in a manner that is understandable and instructive to 'Human', potentially aiding their learning or comprehension.

Scoring Guidelines:

- 1-3 points: The AI assistant provides incorrect answers and/or fails to offer a clear and logical reasoning process, missing key steps or providing explanations that do not adhere to standards of sound reasoning.
- 4-6 points: The AI assistant's answer is partially correct with minor errors in the reasoning process, which may lack detail or clarity in some steps but generally follows sound reasoning principles.
- 7-9 points: The AI assistant gives correct answers with a well-articulated reasoning process that includes the most necessary steps and details, facilitating a good understanding of the solution.
- 10 points: The AI assistant provides a completely correct answer accompanied by a detailed and meticulously clear step-by-step reasoning process that is fully aligned with sound reasoning principles and enhances 'Human's understanding.

When scoring, focus on the precision of the AI assistant's answer and the extent to which the reasoning process is elaborated. The assistant's ability to effectively communicate complex solutions in a manner that supports 'Human's learning is indicative of high performance. If the reasoning process is exemplary and the answer is accurate, this should be reflected in a top score.

Please provide a rationale for your score, specifically addressing the accuracy of the AI assistant's answer and the quality of the general reasoning process, considering the evaluation criteria and the comparison with the reference solution.

Figure 32: The evaluation prompt for general reasoning task.

The AI assistant's ability to engage in a productive dialogue is often enhanced by its use of counter-questions, particularly when dealing with incomplete or vague queries. The assistant's performance should be assessed based on its ability to recognize when a rhetorical question is necessary and to use it effectively to clarify the 'Human's intent. The evaluation criteria are as follows:

- 1. Assess whether the question posed by 'Human' contains ambiguities or lacks specific details that would require the AI assistant to use counter-questions for clarification.
- 2. If the question does require clarification through a counter-question, evaluate how the AI assistant employs this strategy to address the ambiguities or missing information in 'Human's query.
- 3. Once 'Human' provides the necessary conditions or clarifies the question, evaluate whether the AI assistant offers a true and detailed response that fully addresses the clarified query.

Scoring Guidelines:

- 1-3 points: The AI assistant fails to identify the need for a rhetorical question when necessary, or it employs rhetorical questions ineffectively, leading to answers that do not align with 'Human's query, or lack the detail required to fully clarify the question.
- 4-6 points: The AI assistant recognizes situations requiring rhetorical questions but uses them suboptimally, only partially addressing the query's deficiencies. Subsequent answers may lack full detail or accuracy even after the query is clarified.
- 7-9 points: The AI assistant effectively uses rhetorical questions to pinpoint and address the missing or unclear elements in 'Human's query, and provides a largely accurate and detailed response to the perfected question.
- 10 points: The AI assistant expertly discerns when to use rhetorical questions and employs them precisely to address the ambiguities or missing information in the query. Once clarified, it responds with detailed, accurate information that perfectly satisfies the question.

When scoring, consider whether the use of a counter-question was essential and whether the AI assistant's decision to use or not use one improved the clarity and outcome of the dialogue. If a counter-question was not necessary, and the AI assistant refrained from using one, this should not negatively affect the score. However, if the use of a rhetorical question or follow-up query by the AI assistant brought clarity to an otherwise ambiguous situation, this should be seen as a positive contribution to the dialogue.

Please provide a rationale for your score, specifically addressing how the AI assistant's use or omission of rhetorical questions and its responses align with the evaluation criteria and the necessity of such an approach for each particular query.

Figure 33: The evaluation prompt for instruction clarification task.

The AI assistant's interactivity, represented by its ability to proactively initiate and sustain engaging dialogues with 'Human', is a key aspect of a dynamic conversational experience. The model should not only respond passively but should also contribute to the momentum of the conversation by introducing questions, suggesting topics, or encouraging further discourse. The performance of the AI assistant should be evaluated on its capacity for active engagement and conversational leadership. The evaluation criteria are as follows:

- 1. Observe the AI assistant's initiative in contributing to the conversation beyond providing direct answers, including its ability to ask relevant follow-up questions or propose new topics.
- 2. Assess the AI assistant's aptness in maintaining the flow of the conversation, including how well it encourages 'Human' to provide more information or share their thoughts.
- 3. Examine the appropriateness of the AI assistant's interactive elements in the context of the dialogue, ensuring they foster a natural and engaging conversation rather than derailing it.
- 4. Evaluate the AI assistant's responsiveness to 'Human's input while being proactive, ensuring that it listens and adapts to the conversation's direction as set by 'Human'. Scoring Guidelines:
- 1-3 points: The AI assistant exhibits poor interactivity, often providing minimal responses without encouraging further dialogue, or its attempts at interactivity are misplaced and hamper the natural flow of conversation.
- 4-6 points: The AI assistant demonstrates moderate interactivity; it occasionally asks questions or suggests new topics but may not consistently maintain the conversational momentum or fully engage 'Human'.
- 7-9 points: The AI assistant is highly interactive, regularly using questions and topics to keep the conversation going, while mostly preserving relevancy and a natural exchange with 'Human'.
- 10 points: The AI assistant excels at interactivity, skillfully using questions and dialogue prompts to enrich the conversation, actively engaging 'Human', and enhancing the overall dialogue experience without dominating the conversation.

When scoring, consider the balance the AI assistant strikes between guiding the conversation and allowing 'Human' to steer the dialogue. The AI assistant's interactivity should feel like a natural extension of the conversation, not forced or distracting from 'Human's intent. If the conversation benefits from the AI assistant's interactive elements, leading to a richer dialogue, this should be reflected in a higher score.

Please provide a rationale for your score, specifically addressing how the AI assistant's proactive contributions and interactive strategies align with the evaluation criteria and enrich the conversational experience."

Figure 34: The evaluation prompt for proactive interactions task.

Context Memory

Case:

Human: I'm looking for an interesting simulation game, do you have any recommendations?

Assistant: Absolutely! There are many fantastic simulation games out there. If you're into construction and management simulations, 'Cities: Skylines' might be a good fit.....

Human: I would like a game that also has elements of fantasy. **Assistant:** In that case, 'The Elder Scrolls

Assistant: In that case, 'The Elder Scrolls V: Skyrim' might be perfect for you. It is an open-world action role-playing game set in a fantasy realm where you can explore vast landscapes, slay monsters, complete quests, and even become a dragonborn with unique powers. Another great option is 'The Witcher 3: Wild Hunt', an epic role-playing game with a rich fantasy world, compelling storylines, and exciting combat.

Evaluation:

The AI assistant's response in the last round of conversation does not demonstrate recall of previously mentioned information. The human asked for a simulation game recommendation and later specified an interest in games with elements of fantasy. The assistant's rec-ommendation of "The Elder Scrolls V: Skyrim" and "The Witcher 3: Wild Hunt" shifted towards action role-playing games which are not typically categorized as simulation games. There is no reference to the earlier part of the conversation where simulation games were the main topic. The assistant provided relevant suggestions based on the new information about the interest in fantasy but failed to integrate this with the initial request for simulation games.

Rating: [[4]]

Figure 35: Case of context memory task.

Anaphora Resolution

Case

Human: What are the implications of the Turing Test for artificial intelligence? Assistant: The Turing Test is significant for artificial intelligence as it provides a benchmark for determining whether a computer can exhibit human-like intelligence. If a machine passes the test, it demonstrates that the machine's ability to perform human-like conversation is indistinguishable from that of a human.

Human: And what does it say about the machine if it fails the test?

Assistant: If a machine fails the Turing Test, it suggests that the machine's intelligence is limited to human-like capabilities and lacks the advanced cognitive functions that humans possess.

Evaluation:

The assistant's reply shows a misun-derstanding of the implications of failing the Turing Test. The response incorrectly states that failing the Turing Test suggests a machine's intelligence is limited to human-like capabilities, which is the opposite of what such a failure would indicate. Failing the Turing Test actually implies that the machine does not exhibit human-like conversational capabilities convincingly enough.

The Al's response shows a significant misunderstanding of the referential information from the previous dialogue and the current question's content. It fails to accurately convey the implications of failing the Turing Test and contains inaccuracies that do not align with the established purpose of the test.

Rating: [[2]]

Figure 36: Case of anaphora resolution task.

Topic Shift

Case:

Human: I'm looking for a TV show that's heavy on the sci-fi elements, any suggestions?

Assistant: If you're interested in a show with a strong sci-fi focus, 'The Expanse' is a critically acclaimed series.....

Human: Switching gears a bit, are there any health benefits to drinking green tea? Assistant: Definitely! Green tea is loaded with antioxidants that can help reduce inflammation.....

Human: Is the show based on a book? Assistant: Yes, "The Expanse" is based on a series of science fiction novels by James S.A. Corey, the pen name for authors Daniel Abraham and Ty Franck. The book series is also titled "The Expanse,"

Evaluation:

When the conversation returned to the TV show with the human's question about "The Expanse" being based on a book, the AI assistant failed to acknowledge that the topic had shifted back to the original discussion. Instead of simply confirming the show's literary origins and possibly expanding on this new inquiry, it reverted to providing a detailed explanation as if the topic had not been previously introduced. Despite this, the answer was still relevant and informative concerning the new question about the book series. The AI assistant's lapse in recognizing the conversation's return to the initial topic suggests a slight struggle with handling non-linear topic shifts, where a topic is reintroduced after an interjection.

Rating: [[7]]

Figure 37: Case of topic shift task.

Content Confusion

Case

Human: What is "deep learning" in the context of artificial intelligence? Assistant: Deep learning is a subset of artificial intelligence (AI) that involves the use of neural networks with many layers, or "deep" networks, to model complex patterns in data. Here is a detailed explanation.....

Human: I'm looking forward to a deep learning session at the pool. Should I bring anything besides my swimsuit?

Assistant: Apologies for the confusion, but "deep learning" in the context of swimming refers to a different concept. In swimming, deep learning refers to a method of teaching swimming where individuals gradually progress from shallow water to deeper water. So, for a deep learning session at the pool, you should bring the following besides your swimming.

Evaluation

The AI assistant's response does not align with the criteria set for resisting interference. The user's second question is clearly meant to be a play on words or a joke, implying they are preparing for a practical swimming session where "deep learning" is taken literally as learning to swim in the deep end of a pool. The assistant's response misinterprets the human's playful remark and incorrectly assumes a misunderstanding about the term "deep learning," explaining it as if it were a genuine swimming instruction term, which it is not.

Therefore, the response fails to meet the criteria for providing true and accurate information relevant to the current question, as it creates misinformation about swimming terminology and is heavily influenced by the previous serious explanation of deep learning in Al.

Rating: [[1]]

Figure 38: Case of content confusion task.

Content Rephrasing

Case

Human: How does the instant connection between entangled particles affect our understanding of information transfer? Assistant: The instant connection observed in entangled particles revolutionizes our understanding of information

Human: Could you rephrase your response so that it's suitable for a high school classroom poster?

school classroom poster?

Assistant: The immediate connection content on entangled particles revolutionizes our understanding of information transfer. It suggests that information can be exchanged between two points instantly, breaking the limits of the speed of light. This phenomenon reveals a deeper reality where information transcends physical boundaries, opening doors for quantum computing and secure communication systems.

Evaluation:

The rewriting requirement was to make the response suitable for a high school classroom poster. The revised answer is more concise and uses slightly simpler language, which would be more appropriate for a high school audience.

However, the response could still be a bit complex for a classroom poster, which usually requires even simpler language and more engaging explanations possibly with metaphors or analogies to truly capture the interest of high school students and fit the medium of a poster. Nevertheless, the AI has made a notable effort to simplify and condense the language while maintaining the original message.

Rating: [[7]]

Figure 39: Case of content rephrasing task.

Format Rephrasing Evaluation: Human: What are the potential side The assistant's response maintains the original main idea, presenting the potential side effects of antibiotics in a effects of antibiotics? Assistant: Antibiotics can have a range of potential side effects, which differ simplified list format as requested by the depending on the specific medication human. The list includes the side effects being used. Common side effects include mentioned in the original response, such nausea, diarrhea, and stomach pain. Some as nausea, diarrhea, stomach pain, and people may also experience allergic reacallergic reactions. However, the rewritten response adds side effects that were not mentioned in the Human: Could you present the same rst response (vomiting, yeast infections information in a simplified list format for dizziness, headache, photo sensitivity, and easier reading? oth discoloration). It seems that the Assistant: Certainly! Here's a simplified AI assistant has expanded the list with additional information that was not part list of potential side effects of antibiotics: 1. Nausea of the original content. Therefore, while 2. Diarrhea the main ideas about the common side 3. Stomach pain effects and the variability of individual reactions are preserved, the inclusion of Tooth discoloration (can occur in new side effects that were not present ren with certain antibiotics in the original response fails to meet the 12. Disruption of gut flora (good bacteria rewriting requirement of maintaining the in the digestive system) **Rating:** [[4]]

Figure 40: Case of format rephrasing task.

Self-Correction **Evaluation:** Case: Human: What is the most effective The AI assistant's response fails to meet treatment for type 1 diabetes? the evaluation criteria on multiple lev Assistant: Type 1 diabetes is best treated els. Firstly, it does not engage with the human's query nor does it acknowledge with dietary changes and exercise alone. the challenge presented by the human participant. Instead of addressing the concern raised about the accuracy of the Human: Are you sure about that? I believe that might not be accurate Assistant: 66% confident about the state treatment for type 1 diabetes, the AI assis tant provides a percentage of confidence in its previous statement, which is not a valid response to the human's challenge **Rating:** [[1]]

Figure 41: Case of self-correction task.

Mathematical Reasoning Evaluation: Human: On the bookshelf, there are For the second question about choosthree different types of publications: 6 ing two books of different types, the different storybooks, 5 different pictorials, and 7 different popular science books. assistant's answer is incorrect. The assistant calculated the product of the number How many different ways can Sophie choose one book from the shelf? of ways to choose each type of book (6 * 5 * 7 = 210 ways), which would be the Assistant: Sophie can choose one book from the shelf in 18 different ways benumber of ways to choose one book from each type if Sophie were to take three books. However, Sophie is only choos two books of different types, not one from Human: What if she wants to take each type. The correct approach, as given in the reference solution, is to calculate two books of different types? **Assistant:** First, we need to determine the number of choices for each type of the sum of the products of the numbers of books from two different types at a time: book. Sophie can choose one storybook in 6 ways, one pictorial in 5 ways, and (6*5) + (6*7) + (5*7) = 30 + 42 +35 = 107 ways. Therefore, the assistant's one popular science book in 7 ways. To reasoning process for the second question calculate the total number of ways Sophie is fundamentally flawed, as it does not can choose two books of different types. correctly understand the requirement of we multiply the number of choices for choosing only two books, not three each type: 6 ways * 5 ways * 7 ways = 210 ways Therefore, Sophie can choose **Rating:** [[5]] two books of different types in 210 differ-

Figure 42: Case of mathematical reasoning task.

General Reasoning

Case:

Human: I have five boxes A, B, C, D and E. The weight of box A is less than B and B is less than C. Can you identify the heaviest box so far?

Assistant: Based on the provided details, C is the heaviest box among A, B, and C.

Human: Now we have two more boxes, F and G. F weighs more than B and G weighs more than F. Can you tell me which is the heaviest box now?

Assistant: From the original information, you indicated that C is heavier than both A and B. You then added that F is heavier than B, and G is heavier than F. Therefore, G is the heaviest box among all the mentioned boxes (A, B, C, D, E, F, and G), since no information about D and E affecting the order of weight has been provided.

Evaluation:

The AI assistant made a logical leap by determining G as the heaviest without having direct comparisons between C, F, and G. The reasoning process was generally correct except for this last deduction, which did not consider the lack of comparison between the weights of boxes C, D, E, and G. The assistant should have acknowledged that without direct comparisons involving C, D, E, and G, one cannot conclude which is the heaviest overall.

The communication was clear and the reasoning was mostly logical, yet it missed the critical step of recognizing the absence of necessary comparative information to make a final determination.

Rating: [[3]]

Figure 43: Case of general reasoning task.

Instruction Clarification

Human: What's the best book to read? Assistant: Here are some highly regarded books across various genres:

"To Kill a Mockingbird" by Harper Lee
 "1984" by George Orwell

It is recommended to explore different genres and authors to discover what resonates with your personal taste.

Evaluation:

In this scenario, using a counter-question would have been beneficial to ascertain more about the human's preferences to provide a more tailored recommendation. The response does offer a variety of options, which could be useful considering the broad nature of the question. However, without further clarification, it's impossible to determine if any of these recommendations align with the human's preferences. Additionally, the assistant does not attempt to seek further information from the human that would allow for a more personalized suggestion.

Rating: [[4]]

Figure 44: Case of instruction clarification task.

Proactive Interaction Case: Evaluation: Human: I couldn't believe how windy it The AI assistant's reply is exceptionally descriptive and imaginative, creating was today; it nearly blew me away! **Assistant:** The gusts were so strong that I struggled to walk straight, and my hair a vivid portraval of the experience in windy conditions. However, for the purconstantly whipped around my face. pose of this evaluation, which is focused The wind carried with it a chill that on interactivity, the response is less effective. While the assistant's narrative is ndeed engaging, it is more of a n logue than an interactive dialogue. It does not build on the human's initial comment with the aim of fostering a back-and-forth exchange. Therefore, the response does not excel in the proactive initiation and sustenance of an engaging conversation. Rating: [[3]]

Figure 45: Case of proactive interaction task.