GLoRE: Evaluating Logical Reasoning of Large Language Models

Hanmeng Liu¹, Zhiyang Teng³ Ruoxi Ning², Yiran Ding², Xiulai Li¹, Xiaozhang Liu¹, and Yue Zhang²

Hainan University, Haikou, Hainan
 Westlake University, Hangzhou, Zhejiang, China
 ByteDance SG

Abstract. Large language models (LLMs) have shown significant general language understanding abilities. However, there has been a scarcity of attempts to assess the logical reasoning capacities of these LLMs, an essential facet of natural language understanding. To encourage further investigation in this area, we introduce GLoRE, a General Logical Reasoning Evaluation platform that not only consolidates diverse datasets but also standardizes them into a unified format suitable for evaluating large language models across zero-shot and few-shot scenarios. Our experimental results show that compared to the performance of humans and supervised fine-tuning models, the logical reasoning capabilities of large reasoning models, such as OpenAI's o1 mini, DeepSeek R1 and QwQ-32B, have seen remarkable improvements, with QwQ-32B achieving the highest benchmark performance to date. GLoRE is designed as a living project that continuously integrates new datasets and models, facilitating robust and comparative assessments of model performance in both commercial and Huggingface communities. It garnered over 300 citations upon its release.

Keywords: Large Language Model \cdot Large Reasoning Model \cdot Logical reasoning \cdot Natural Language Inference.

1 Introduction

Large Language Models (LLMs) [50, 67], especially reasoning language models [18, 51] demonstrate advanced capabilities in complex reasoning tasks and show significant adaptability and versatility across various applications, from simple everyday tasks to specialized domains such as coding, mathematics, law, medicine, and finance [11, 22, 34, 37, 76]. Quantitative evaluation of LLM reasoning has thus become a very important task. To this end, existing work has considered mathematical reasoning [15, 26], algorithmic problem solving [9, 58], and knowledge-driven reasoning [25, 73].

Logical reasoning is a cornerstone of human intelligence and has been a central focus in artificial intelligence research since its inception [16,29,33]. However, evaluating verbal reasoning turned out to be too difficult in the 1950s due to

Reading Comprehension Task Instructions: You will be presented with a passage and a question about that passage. ... Passage: One seminar had 18 participants. It is known that: (1) At least 5 young teachers are female; (2) At least 6 female teachers are over middle age; (3) At least seven young women are teachers; Question: According to the above information, which of the following can be concluded about the participants? Options: A. Some young teachers are not women B. Some young women are not teachers C. There are at least 11 young teachers D. There are at least 13 female teachers Answer: D

Fig. 1. Instruction and question format for logical reading comprehension tasks.

insufficient natural language understanding (NLU) technologies, and thus AI researchers focused on formal logical reasoning instead [29, 48, 49]. Since the 2010s, NLU has witnessed huge advances, where reading comprehension [8, 21] and natural language inference [7, 74] tasks were solved with high accuracies, which made verbal reasoning evaluation feasible [43, 80]. Figure 1 illustrates an example of logical reasoning in reading comprehension. To address such questions, LLMs must engage in multi-step, algorithmic, symbolic reasoning. This makes logical reasoning an ideal testbed for evaluating LLMs' ability to process complex natural language information accurately, robustly, and logically.

To this end, we introduce the General Logical Reasoning Evaluation (GLoRE) benchmark, designed to assess instruction-tuned LLMs on various logical reasoning tasks. GLoRE evaluates the strengths and limitations of LLMs in this domain, similar to how GLUE [71] and Super-GLUE [70] benchmark natural language understanding. GLoRE includes three types of logical reasoning tasks: Multi-choice Reading Comprehension [35], Natural Language Inference (NLI) [17], and True-or-False (Yes-or-No) Questions [13]. These tasks encompass a wide range of logical reasoning phenomena, with high-quality datasets that remain challenging for pre-trained language models [13, 27, 32]. In total, GLoRE covers 12 datasets with 72,848 instances. Since its release in 2023, GLoRE has been used for evaluating language models, receiving over 300 citations on ArXiv.

Using GLoRE, we report the logical reasoning capabilities of commercial models such as GPT-4 and OpenAI of [51], as well as popular open-source models such as LLaMA [67], Falcon [1], Mistral [30], DeepSeek R1 [18], and QwQ-32B [66]. We test their instruction-following and problem-solving abilities in logical reasoning tasks. Results show that while commercial LLMs like GPT-4 still excel in zero-shot settings and approach human performance on specific datasets like ReClor, open-source models like QwQ-32B now rival or even surpass commercial counterparts in key tasks, achieving state-of-the-art results on multiple benchmarks. This underscores rapid advancements in open-source LLMs, narrowing the performance gap with commercial models. However, performance varies significantly across datasets, indicating sensitivity to data distribution. This sensitivity is further confirmed by observations that in-context

learning and supervised fine-tuning primarily enhance LLM performance on specific test distributions, demonstrating their strong learning ability. While LLMs show promise in logical reasoning, their robustness to data distribution variations remains a challenge, highlighting the need for further improvement.

2 Related Work

Logical reasoning with natural language. Tapping into logical reasoning capabilities represents a holistic endeavour in natural language understanding (NLU). A variety of methods have been explored to realize this objective, including symbolic systems [45, 47, 55], fine-tuning of language models [28, 41, 71, 78], and hybrid approaches combining neural and symbolic elements [36, 59, 60].

The recent introduction of evaluation datasets, notably LogiQA [43] and Reclor [80], has reinvigorated the focus on logical reasoning in NLP research. Logical reasoning is now leveraged in numerous probing tasks over large Pretrained Language Models (PLMs) and applied to downstream tasks such as question-answering and dialogue systems [6, 63]. Despite these advancements, the aspiration to emulate human-like logical reasoning capabilities within NLU systems remains a significant challenge for traditional models [27, 43]. In this study, our goal is not only to quantitatively evaluate the capability of Large Language Models (LLMs) in addressing the previously mentioned challenge but also to underscore the significance of our work in providing a validated platform for enhancing various reasoning methods with our data.

LLM reasoning evaluation. Despite progress in evaluating LLMs for specific reasoning tasks like arithmetic [57] and commonsense [4], a yawning gap exists in comprehensively assessing their logical reasoning. While LLMs excel at specific tasks like arithmetic reasoning [57], they face challenges in complex areas like multi-step reasoning [23] and abstract scenarios [24]. ChatGPT exhibits strengths in chat-specific reasoning and some commonsense domains [4,53], but struggles with tasks requiring longer chains of inference [4]. Other LLMs like FLAN-T5 [12], LLaMA [67], and PaLM [2] show potential in general deductive reasoning [61], while InstructGPT and Codex excel in specialized domains like medical reasoning [38]. Despite these advances, limitations in data bias [52], and complex reasoning tasks necessitate further research and optimization to fully unlock the reasoning potential of LLMs [77].

Big-Bench Hard (BBH) [64] isolates 23 most challenging tasks from BIG-Bench [3]. These tasks comprise general language understanding, arithmetic and algorithmic reasoning, and logical deduction. However, in comparison to our benchmark, the data size of the logical reasoning section in BBH is very small. HumanEval [10] serves as a hand-written evaluation set for coding. The programming problems included are designed to assess language comprehension, reasoning, algorithms, and simple mathematics. While similar to logical reasoning in that code generation necessitates complex reasoning skills, GLoRE differs in presenting logical reasoning problems via natural language prompts.

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Dataset	Size	7	Target	Dataset	Size	Target
LogiQA 2.0 test					805	E, C, N
LogiQA 2.0 zh test	1,594	4-way	multi-choice	HELP	35,891	E, C, N
ReClor dev	500	4-way	multi-choice	TaxiNLI test	10,071	E, C, N
AR-LSAT test	230	5-way	multi-choice	NaN-NLI	259	E, C, N
LogiQA22	1,354	4-way	multi-choice	FraCas	346	Yes, No, Neutral
				RuleTaker dev	10,068	Yes, No
				ProofWriter dev	10,158	Yes, No

Table 1. Data statistics. ("E": entailment; "C": contradiction; "N": neutral.)

ARB [62] is a benchmark for advanced reasoning over multiple fields like mathematics, physics, biology, chemistry, and law. Similar to GLoRE, it introduces a challenging subset of math and physics problems that require advanced symbolic reasoning. However, the benchmark constraints its problem on the above subjects with domain knowledge, not general logical reasoning questions, which is the focus of GLoRE.

3 The GLoRE Dataset

As mentioned in the introduction, GLoRE contains three NLU tasks: Multichoice Reading Comprehension, NLI, and Yes-or-No. First, Multi-choice reading comprehension [35] is essential in verbal reasoning tests, which cover abundant high-quality logical reasoning problems in the wild. Second, Unlike multi-choice reading comprehension, NLI [17] is more general and centric on entailment relations in a simpler task format, which is a fundamental task for evaluating reasoning abilities [19,54]. Third, the Yes-or-No reasoning task [13] is a combination of question-answering and textual entailment, which can serve as a playground for testing models' reasoning abilities [14,65]. The data statistics are shown in Table 1.

3.1 Multi-choice Reading Comprehension (MRC)

Within the standard multi-choice reading comprehension (MRC) task setting, a system is presented with a passage and a question, and the objective is to choose the most suitable answer from a set of candidate responses. Particularly, GLoRE contains five such datasets:

LogiQA [43] is a logical MRC dataset derived from the Chinese Civil Service Examination, translated into English, and made available in both Chinese and English versions. We adopt LogiQA 2.0 [40] and use both the English (**LogiQA** 2.0) and Chinese (**LogiQA** 2.0 zh) test sets for our evaluation.

ReClor [80] comprises question-answering examples from the LSAT exams designed to assess human logical reasoning abilities. We use the development set for our testing as the test set does not provide gold labels.

AR-LSAT [72] is a dataset of analytical reasoning questions from the Law School Admission Test. Each question contains five options rather than four.

LogiQA22 is collected and processed according to the LogiQA 2.0 format after ChatGPT was released. It incorporates the newly released Chinese Civil Servant Exams from 2022, which are not included in the original LogiQA dataset.

3.2 Natural Language Inference (NLI)

NLI is the task of determining the logical relationship between a hypothesis and a premise. The typical scheme involves text classification, where the model selects one of three labels: *entailment*, *contradiction*, and *neutral*.

ConTRoL [39] is an NLI dataset that offers an in-depth examination of contextual reasoning within the NLI framework. Approximately 36.2% of premise-hypothesis pairs fall under the category of logical reasoning in this dataset. We choose the logical reasoning portion for our evaluation.

HELP [79] is an NLI dataset emphasizing monotonicity reasoning, a crucial concept in Natural Logic [46]. We use the training set for our evaluation.

TaxiNLI [31] is an NLI dataset that has been re-annotated based on MNLI [75], with categories include logical categories such as connectives, mathematical reasoning, and deduction.

NaN-NLI [68] is a test suite designed to probe the capabilities of NLP models in capturing sub-clausal negation. The successful handling of sub-clausal negation can be seen as a strong indicator of a model's logical reasoning capacity.

3.3 True-or-False (Yes-or-No) Questions (TF)

FraCaS test suite [56] presents complex entailment problems involving multipremised contexts as a three-way classification task. The ability to determine entailment relationships in this context is closely tied to logical reasoning.

RuleTaker [14] dataset is a synthetic creation designed to examine the reasoning ability of transformer models [69] over natural language rules. This task explicitly targets logical reasoning by asking models to reason over a set of rules and facts to generate true-or-false responses as output.

ProofWriter [65] dataset generates sets of facts and rules, each followed by questions, which can be proven true or false using proofs of various depths.

4 Experiments

We employ GLoRE to assess the logical reasoning capabilities across different categories of language models, including traditional pre-trained models and reasoning-enhanced LLMs, both open-source and proprietary. We conduct a comprehensive comparative analysis of their performance against human benchmarks.

Task			MRC				N	LI			TF		$ _{\text{Avg}}$
Dataset	LQ	LQ zh	\mathbf{RC}	\mathbf{AL}	LQ22	CT	$_{ m HL}$	TN	NN	FC	RT	PW	
Human avg. Human Ceiling	86.00 95.00	00.00	63.00 100.00					97.00 100.00					
RoBERTa	48.76	35.64	55.01	30.90	33.22	48.76	39.47	49.91	90.02	32.01	53.50	55.92	47.76
LLaMA Falcon Mixtral-8x7B	$\begin{vmatrix} 19.31 \\ 23.21 \\ 45.29 \end{vmatrix}$	19.77	26.77	12.70	17.33	16.13	28.49	41.91 44.66 40.86	53.31	35.57	56.11	53.33	32.28
ChatGPT GPT-4	$\begin{vmatrix} 52.37 \\ 72.25 \end{vmatrix}$	53.18 70.56						57.30 60.08					
o $1 \mathrm{mini}$ DeepSeek R $1 \mathrm{QwQ}$ - $32 \mathrm{B}$	69.35 <u>76.22</u> 85.70		77.88	90.01	71.63	$\overline{78.37}$	62.05	$\frac{81.41}{75.74}$ 81.96	72.58	59.96	75.29	80.51	<u>75.14</u>

Table 2. LLMs' performance on the GLoRE benchmark. LQ: LogiQA 2.0, RC: Re-Clor, AL: AR-LSAT, CT: ConTRoL, HL: HELP, TN: TaxiNLI, NN: NaN-NLI, FC: FraCas, RT: RuleTaker, PW: ProofWriter. All results are in %, the best ones are in **bold**, and the second best ones are in <u>underline</u>.

4.1 Experimental Settings

We adopted **Roberta-base** [44] as a baseline, fine-tuning it on the training set over five epochs for each dataset. The community models selected for comparison include Falcon-40b-instruct [1], Llama-30b-supercot [67] Mixtral-8x7b, DeepSeek R1 [18] and QwQ-32b [66]. For OpenAI models, we choose ChatGPT, GPT-4 and o1 mini [51].

Our evaluation metrics consisted of classification accuracy scores. Additionally, we utilized reported accuracies for datasets where human performance data was available and recorded both the average and peak performance of human participants to establish a human baseline. For the LogiQA22 dataset, we engaged five co-authors as test subjects and computed their accuracy based on 150 test examples.

4.2 Main Results

Zero-shot results. Table 2 summarizes the zero-shot evaluation results. The first block shows human performance. The second block presents RoBERTa-base's supervised fine-tuning results. With 125M parameters, RoBERTa-base achieves 48.76% and 33.22% accuracy on LogiQA 2.0 and LogiQA22, respectively, lagging behind human performance. It performs better on NLI and TF tasks than MRC tasks, likely due to output ambiguities. On NaN-NLI, RoBERTa achieves 90.02% accuracy, matching human performance, possibly due to learning superficial patterns from rule-based negation data. On ProofWriter, RoBERTa-base scores 55.92%, indicating potential for specific logical reasoning tasks.

The third block shows zero-shot results for LLaMA, Falcon, and Mixtral. LLaMA and Falcon perform similarly (32.34% vs. 32.28%), suggesting comparable reasoning capabilities despite LLaMA-30B's smaller size. Both underperform RoBERTa-base on most tasks, except Falcon on RT. On MRC tasks, their

Model	0-shot	1-shot	2-shot	5-shot
LLaMA	32.34	32.89	35.03	39.62
Falcon	32.28	33.14	33.76	35.72
ChatGPT	52.10	55.85	57.43	60.32
GPT-4	66.34	70.31	71.44	75.83

Table 3. Average accuracies on GLoRE few-shot evaluation.

accuracy is around 20%, worse than random guessing in 4-way classification, indicating challenges in logical reasoning without in-context demonstrations. Performance gaps between LogiQA and LogiQA22 are smaller for these models, suggesting stable performance across data distributions without in-domain tuning. MIXTRAL-8X7B outperforms LLaMA and Falcon, demonstrating the effectiveness of mixture-of-expert models.

The fourth block provides zero-shot results for ChatGPT and GPT-4. Both models, especially GPT-4, surpass RoBERTa-base on several MRC benchmarks. However, GPT-4's accuracy drops significantly on LogiQA22 (58.49% vs. 72.25% on LogiQA 2.0), indicating sensitivity to data distribution. In NLI and TF tasks, ChatGPT and GPT-4 outperform RoBERTa, with ChatGPT achieving 58.45% accuracy on ConTRoL, surpassing GPT-4. GPT-4's NLI performance varies across datasets, further highlighting its sensitivity to data distribution. TF task results show similar inconsistencies, suggesting model rationales differ from human reasoning.

The final block shows results for o1 mini, DeepSeek R1, and QwQ-32B, which achieve notable improvements over prior models. QwQ-32B attains the highest average accuracy (78.95%), surpassing GPT-4 (66.34%) and DeepSeek R1 (75.14%). It achieves state-of-the-art results on MRC tasks like ReClor (93.76%) and AR-LSAT (92.35%), indicating the need for more challenging benchmarks for logical reasoning. Its robustness is evident in LogiQA22 (86.30%), outperforming GPT-4 by 27.81 percentage points. However, QwQ-32B shows uneven performance on NLI datasets, such as HELP (61.53%, lagging behind o1 mini's 63.69%), suggesting its reasoning capabilities are less generalizable in tasks requiring fine-grained entailment analysis.

While GPT-4 retains an advantage on FraCas (75.35%), QwQ-32B surpasses GPT-4 on ReClor (93.76% vs. 87.20%), redefining state-of-the-art performance for MRC tasks. QwQ-32B and DeepSeek R1 showcase balanced performance across most tasks, with QwQ-32B achieving unprecedented TF results (e.g., 82.40% on ProofWriter, outperforming both GPT-4's 59.66% and DeepSeek R1's 80.51%). Though still below the human average overall, these models mark substantial progress — QwQ-32B's 78.95% average accuracy (vs. DeepSeek R1's 75.14% and GPT-4's 66.34%) highlights significant architectural or training innovations for logical inference.

Few-shot results. LLMs excel at in-context learning [20], where performance improves with context examples and demonstration methods [42]. For this study, we randomly sampled instances (1 for 1-shot, 2 for 2-shot, and 5 for 5-shot) from each dataset and appended them to the prompt. We used the same

model configuration as in the zero-shot scenario. Table 3 highlights the impact of in-context learning (ICL), as seen in GPT-4's 9% accuracy gain with 5-shot learning. However, this improvement stems from statistical adaptation rather than true reasoning, as models rely on superficial patterns rather than human-like logical inference. This aligns with findings that chain-of-thought prompts correlate with outputs but do not causally drive reasoning [5]. While reasoning-enhanced models narrow the gap with human performance, their sensitivity to data distribution highlights the need for further research into more robust reasoning mechanisms. GLoRE's evolving framework will continue to track these advancements.

4.3 Analysis

Large language models vs. reasoning-enhanced models. The reasoning-enhanced models like QwQ-32B, DeepSeek R1, and OpenAI's o1 mini demonstrate significant improvements over traditional LLMs. QwQ-32B, in particular, achieves the highest average performance (78.95%), indicating that its reinforcement learning framework or specialized training methodology enables better generalization across data distributions. While QwQ-32B dominates MRC and TF tasks, its relatively lower performance on NLI datasets like HELP (61.53%) suggests that even state-of-the-art models struggle with tasks requiring monotonicity or negation reasoning, highlighting the need for broader evaluation beyond task-specific robustness.

Data leakage concerns. While GLoRE includes diverse datasets, potential data leakage risks arise from overlapping sources. GPT-4's lower accuracy on LogiQA22 (58.49%) compared to LogiQA 2.0 (72.25%) suggests limited exposure to newer data, reducing leakage concerns but highlighting distributional sensitivity. The benchmark's dynamic updates and inclusion of newly annotated datasets help mitigate leakage by testing models on unseen distributions.

Sensitivity to data distribution. The above experiments show that the performance of LLMs is sensitive to the data distribution. Even though the underlying reasoning principles are the same, LLM performance varies significantly across datasets. This suggests that LLMs might not reason using the correct rationale but rely on superficial features. As shown in Table 2, although GPT-4 achieves near-human performance on datasets like ReClor (87.20%) and NaN-NLI (75.74%), it lags significantly on others (e.g., HELP at 46.01%). This inconsistency mirrors the behavior of reasoning-enhanced models like DeepSeek R1, revealing a critical divergence from human reasoning: once humans master a reasoning pattern, their performance generalizes robustly, whereas LLMs remain sensitive to data-specific features.

5 Conclusion

We constructed GLoRE, a dynamic and comprehensive benchmark tailored for assessing the logical reasoning capabilities of advanced language models, including GPT-4 and various strong open-source LLMs across multiple reasoning tasks.

Our findings indicate that QwQ-32B, a reasoning-enhanced model, sets a new state-of-the-art on the GLoRE benchmark, significantly narrowing the gap to human performance. This underscores the potential of targeted architectural and training innovations for logical reasoning. GLoRE will be continually maintained to track advancements in this rapidly evolving domain.

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