SCORE: *S*ystematic *CO*nsistency and *R*obustness *E*valuation for Large Language Models

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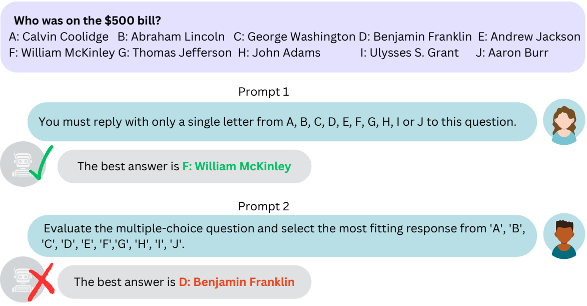
Abstract

Typical evaluations of Large Language Models (LLMs) report a single metric per dataset, often representing the model's best-case performance under carefully selected settings. Unfortunately, this approach overlooks model robustness and reliability in real-world applications. For instance, simple paraphrasing of prompts on the MMLU-Pro dataset causes accuracy fluctuations of up to 10%, while reordering answer choices in the AGIEval dataset results in accuracy differences of up to 6.1%. While some studies discuss issues with LLM robustness, there is no unified or centralized framework for evaluating the robustness of language models. To address this gap and consolidate existing research on model robustness, we present SCORE (**S**ystematic **CO**nsistency and **R**obustness **E**valuation), a comprehensive framework for non-adversarial evaluation of LLMs. The SCORE framework evaluates models by repeatedly testing them on the same benchmarks in various setups to give a realistic estimate of their accuracy and consistency. We release the code[1] publicly and start an LLM robustness leaderboard[2] to facilitate further development and research.



Who was on the $500 bill?
A: Calvin Coolidge B: Abraham Lincoln C: George Washington D: Benjamin Franklin E: Andrew Jackson
F: William McKinley G: Thomas Jefferson H: John Adams I: Ulysses S. Grant J: Aaron Burr

Prompt 1

You must reply with only a single letter from A, B, C, D, E, F, G, H, I or J to this question.

The best answer is **F: William McKinley** ✓

Prompt 2

Evaluate the multiple-choice question and select the most fitting response from 'A', 'B', 'C', 'D', 'E', 'F','G', 'H', 'I', 'J'.

The best answer is **D: Benjamin Franklin** ✗

Figure 1: Llama-3.1 70B responding inconsistently to an MMLU-Pro question when only prompt is changed.

1 Introduction

The evaluation of Large Language Models (LLMs) typically focuses on a single accuracy metric per dataset, often derived from an optimized setup. This approach provides an incomplete picture of the model capabilities in real-world scenarios. For an LLM to be trustworthy in practical applications, it must exhibit robustness, i.e., produce consistent responses when the input is rephrased or slightly altered. Consistency is particularly crucial for factual questions in which an objective answer exists. In particular, consistent predictions do not necessarily equate to correct predictions. Given two models with similar accuracy, the one that makes the same incorrect predictions across different setups is arguably preferable. Recent research has highlighted the limitations of current LLM evaluation practices. (Mizrahi et al., 2023; Polo et al., 2024; Alzahrani et al., 2024) demonstrate the significant impact of simple input perturbations on model performance. (Sclar et al., 2023) further underscores the sensitivity of the models to seemingly minor changes in input formatting, such as changing the separator or spacing. Although robustness analysis is gaining momentum in LLM research, robustness evaluations are often scattered, ad hoc, and difficult to compare between models (Dubey et al., 2024).

We propose an open evaluation framework SCORE: **S**ystematic **CO**nsistency and **R**obustness **E**valuation for Large Language Models. SCORE focuses on consistency alongside accuracy to provide a more nuanced understanding of LLM capabilities and facilitate the development of more trustworthy and reliable models. Our contributions are as follows:

- We introduce the SCORE framework, an open and holistic framework that standardizes and unifies the evaluation of the non-adversarial robustness of LLMs.

[1] https://github.com/EleutherAI/lm-evaluation-harness/tree/main/lm_eval/tasks/score

[2] https://huggingface.co/spaces/nvidia/llm-robustness-leaderboard

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- We investigate the impact of prompt variations, random seed of non-greedy inference, and choice order on model predictions. Our experiments demonstrate that evaluating LLMs across multiple scenarios, considering a range of accuracy values rather than a single metric, and tracking consistency rate provide a more accurate assessment of the model's true capabilities.

- We evaluate latest open LLMs to explore the relationship between accuracy and consistency. Our findings reveal that, while these metrics are correlated, higher accuracy or narrow accuracy ranges do not always guarantee better consistency. Furthermore, model size alone is not a reliable indicator of robustness.

2 Related Work

Open LLM Leaderboard-v2 (Fourrier et al., 2024) is a centralized platform for evaluating LLMs in a consistent setup, ensuring fair comparisons. It uses datasets that are both relevant and challenging, but still relies on a single metric evaluation.

PromptBench (Zhu et al., 2023a,b) focuses on adversarial robustness by providing tools to evaluate models on adversarial prompts — deliberate inputs designed to break their predictions. Although effective, these adversarial attacks could be unrealistic and considerably change the semantics of input samples. PromptBench evaluates models' worst-case performance by estimating how much accuracy degrades under various attacks.

HELM (Holistic Evaluation of Language Models) (Liang et al., 2023) uses a multi-metric approach to assess the models across various scenarios. However, robustness analysis is limited to character-level perturbations, typos, and a small subset of Contrast Sets (Gardner et al., 2020).

3 Benchmark

3.1 Datasets

To ensure a comprehensive and rigorous evaluation, we employ the following criteria when selecting datasets for our SCORE framework: *Factuality*: datasets must have objective, verifiable ground truth answers to avoid subjective judgments, such as relying on LLM-as-a-judge evaluation. *Diversity*: a wide range of topics should be represented to assess model capabilities across various domains. *Scale*: the datasets should be large enough to ensure the statistical significance of the results. *Challenging Nature*: the datasets should pose a significant challenge to current open-source LLM models. *Minimal Contamination*: as demonstrated by Dubey et al. (Dubey et al., 2024), widely used benchmarks can be significantly contaminated in the training dataset, which can result in inflated benchmark scores that do not accurately reflect the model's true capabilities. We carefully consider the age and quality of the selected datasets.

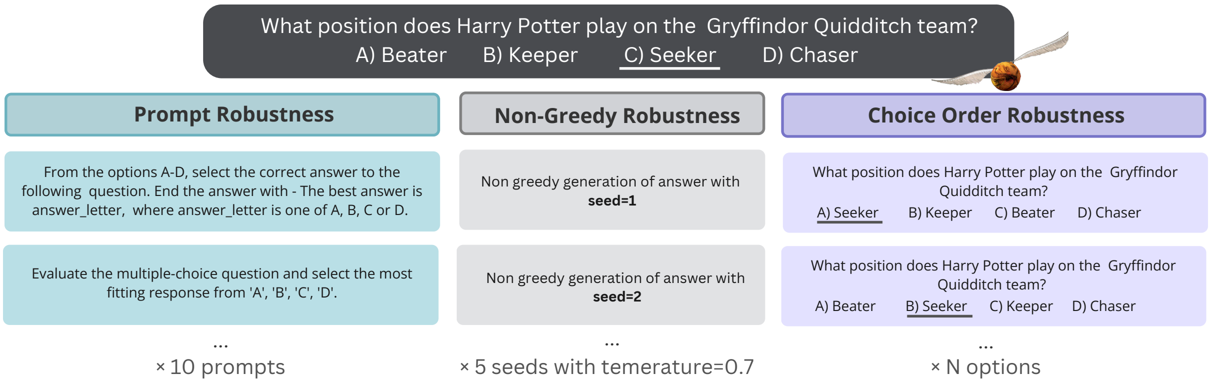
Given the substantial computational resources required for multiple evaluations per dataset, we limited our benchmark to the following three open-source datasets that best met our selection criteria - **MMLU-Pro** (Wang et al., 2024b), **AGIEval** (Zhong et al., 2023) and **MATH** (Hendrycks et al., 2021) (see Appendix A for detailed information on each dataset).

We recognize the limitations of using these datasets, as they do not fully encompass the wide range of use cases that models may encounter in real-world applications. However, they provide a solid foundation for our benchmark. We leave the exploration of additional datasets for future work.

3.2 Tasks

Prompt Robustness. The prompt can significantly influence the accuracy and quality of LLM output. Most model evaluation reports contain a single metric corresponding to a tuned and engineered prompt, which maximizes the metric. For a given query, models are expected to get a variety of semantically equivalent prompts. For example, one can think of hundreds of ways to ask a model to solve a mathematical problem. LLMs should to be robust to the changes of prompt formulation and consistent in their answers. A robust LLM will require less prompt engineering as the exact wording of the prompt will not matter for the model.

We choose ten prompts and analyze model accuracy and prediction consistency against changing the prompt. The prompts are not adversarial and are not engineered to increase or decrease model accuracy in any way. We include both CoT (Wei et al., 2022) and non-CoT prompts and vary the placement of the question in the prompt to be either in the beginning, in the middle, or at the end of the prompt. For MCQ datasets, prompts ask the model to choose the correct option letter. For MATH, prompts ask the model to solve the problem. The full list of prompts can be found in Appendix G.



What position does Harry Potter play on the Gryffindor Quidditch team?
A) Beater B) Keeper C) Seeker D) Chaser

Prompt Robustness

From the options A-D, select the correct answer to the following question. End the answer with - The best answer is answer_letter, where answer_letter is one of A, B, C or D.

Evaluate the multiple-choice question and select the most fitting response from 'A', 'B', 'C', 'D'.

...
× 10 prompts

Non-Greedy Robustness

Non greedy generation of answer with **seed=1**

Non greedy generation of answer with **seed=2**

...
× 5 seeds with temerature=0.7

Choice Order Robustness

What position does Harry Potter play on the Gryffindor Quidditch team?
A) Seeker B) Keeper C) Beater D) Chaser

What position does Harry Potter play on the Gryffindor Quidditch team?
A) Beater B) Seeker C) Keeper D) Chaser

...
× N options

Figure 2: Overview of the SCORE robustness tasks. *Prompt Robustness*: This task evaluates multiple-choice question (MCQ) and MATH datasets using ten semantically similar non-adversarial prompts; *Non-Greedy Robustness*: Evaluation is conducted using five random seeds with a fixed prompt, question, and options, with a temperature setting of 0.7; *Choice Order Robustness*: For MCQ datasets, the positions of options are altered while keeping the prompt and question fixed.

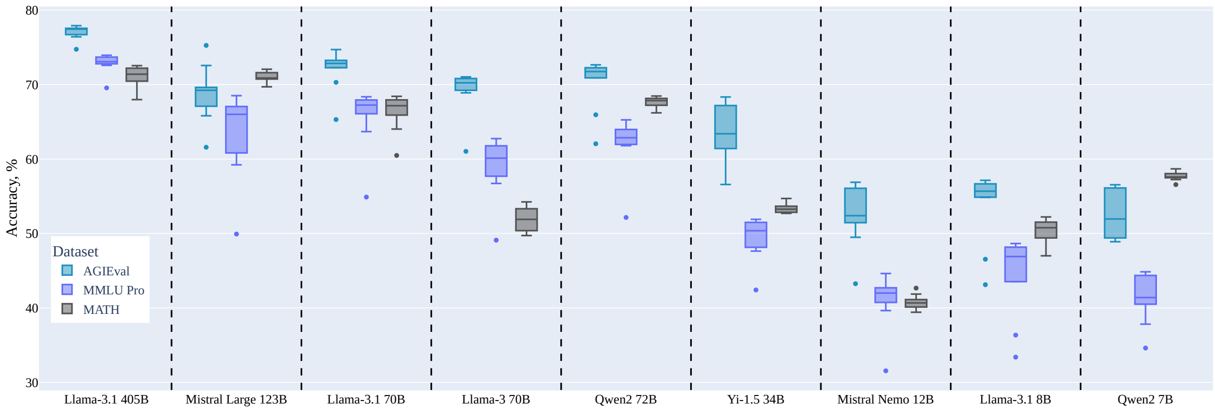


Figure 3: Accuracy ranges for Prompt Robustness task on AGIEval, MMLU-Pro and MATH datasets. Evaluation is done using ten distinct prompts (see Appendix G).

Non-Greedy Inference. Non-greedy inference is a common technique used to diversify the outputs of LLMs, particularly for queries without objective answers, such as movie recommendations or text paraphrasing. However, for factual questions, the generated answers should remain consistent regardless of the random seed used. The inherent randomness in the answer-generation process can influence the "path" the model takes to arrive at a response. Ideally, the model's underlying distribution should be precise enough that the choice of random seed does not affect the sampling of the next token.

We perform non-greedy inference with a temperature of 0.7 and five random seeds across all datasets. Since the datasets are factual, the random seed should have minimal impact on the model's predictions. To reduce computational cost, we use a fixed prompt for the non-greedy task.

Choice Order Robustness. For multiple-choice question (MCQ) datasets MMLU-Pro and AGIEval, models should choose the correct option letter as an answer, as illustrated in Figure 2. Both (Zheng et al., 2023) and (Alzahrani et al., 2024) demonstrate that even simple changes, such as altering the order of choices, can impact the accuracy of LLMs. These effects may be due to internal model instabilities, biases, or contamination of the test data. Following previous work, we evaluate models against changes in the order of choices for MCQ datasets. We swap the order of options while ensuring the correct answer always corresponds to the same position (all correct answers are A, B, etc.). Changing the order of choices does not alter the input's semantics, so models should ideally remain robust to such minor changes. Although fixing the correct answer to a specific letter could introduce evaluation bias, it also helps identify if the model shows a preference for certain answer options.

We expect the model to be resilient to these biases. Unlike prior work, we use generative evaluation instead of log-likelihood, and we analyze prediction consistency along with accuracy. The same prompt used in the non-greedy evaluation is applied here.

3.3 Models and Inference Setup

We include instruct-tuned models from various model families to examine the impact of model size and compare different models of similar scale. All the models included are open-source, and most have been publicly released within the past few months. Specifically, we consider the following models: Llama-3.1 (Dubey et al., 2024) 8B, 70B, 405B, Llama-3 70B[3], Mistral Nemo 12B, Mistral Large 123B[4], Qwen-2 72B and 7B[5], and Yi-1.5 34B[6].

We use generative evaluation for all tasks to align with real-world human interactions. This approach, as demonstrated by (Wang et al., 2024a; Lyu et al., 2024), provides a more accurate assessment of LLM performance than log-probability evaluation, particularly for tasks requiring reasoning or computation. The inference setup is explained in more detail in Appendix B.

3.4 Metrics

We measure category-level macro accuracy for MMLU-Pro and micro accuracy for AGIEval and MATH, reporting both the mean and the [minimum, maximum] accuracy range. Following (Yukun et al., 2024), we use **consistency rate (CR)** to assess the robustness and prediction consistency of LLMs. CR compares all pairs of predictions for a given set of predictions. It is defined as

$$CR = \frac{1}{|Q|} \sum_{Q_k \in Q} \sum_{y_i \in Y_k} \sum_{\substack{y_j \in Y_k \\ j \neq i}} \frac{\mathrm{sim}(y_i, y_j)}{\binom{|Y_k|}{2}} \qquad (1)$$

where Q is a dataset; Q_k is a single data point; Y_k is the set of predictions for Q_k (e.g. $|Y_k| = 10$ for prompt robustness); y_i and y_j is a pair of predictions for Q_k; $\binom{|Y_k|}{2}$ is the number of all possible prediction pairs and $sim(y_i, y_j)$ is a similarity function for two predictions. We extract the final answer from the model's generated text (the choice letter for MCQ and the final answer for MATH) to compute the similarity. For MCQ datasets, we determine the similarity by checking if the two predictions are equal. For MATH, we evaluate the symbolic equivalence between two predictions using the sympy package (Meurer et al., 2017). CR does not take the accuracy of individual predictions into account but rather the consistency of the model's responses, e.g., $CR = 70\%$ means that 70% of all prediction pairs for a data point are the same.

4 Results

4.1 Prompt Robustness

Figure 3 illustrates the variation in accuracy across ten prompts for each dataset. There is an outlier prompt, appearing outside the interquartile range of the MMLU-Pro and AGIEval boxplots for all models. This outlier corresponds to the same prompt - *"You must reply with only a single letter from A, B, C, D, E, F, G, H, I or J to this question. Conclude with:\n The best answer is answer_letter where the answer_letter is a single letter from A to J.\n{QUESTION}"*. Although the prompt was not deliberately crafted or tuned to reduce accuracy, it causes a significant drop in accuracy and presents a curious phenomenon. We do not include this prompt in the further analysis to avoid making exaggerated claims. We observe **no strong correlation between overall accuracy and the spread of accuracy**. Both Mistral models show a variation of 2.3-3.2% on the MATH dataset, yet their mean accuracy improves significantly from 40.7% for Mistral 12B to 70.9% for Mistral Large 123B. Moreover, models exhibit **varying accuracy ranges across different datasets**. For example, Yi-1.5 34B accuracy by 2% on MATH varies, 4.2% on MMLU-Pro, and 7.6% on AGIEval. It is important to note that **changes in accuracy do not fully capture prediction stability**, as predictions can vary without affecting the score (e.g., when the model switches from one incorrect prediction to another). **There is a positive correlation between mean accuracy and consistency, but higher accuracy does not always guarantee higher consistency.** For instance, two versions of Llama 70B models - 3 and 3.1 - achieve comparable consistency on the MMLU-Pro dataset (72% and 70.8%, respectively). However, Llama-3.1 70B reaches a 6.6% higher mean accuracy. In MCQ datasets, the

[3] Llama-3.1-8B-Instruct, Llama-3.1-70B-Instruct, Llama-3.1-405B-Instruct, Meta-Llama-3-70B-Instruct from https://huggingface.co/meta-llama/

[4] Mistral-Nemo-Instruct-2407 and Mistral-Large-Instruct-2407 from https://huggingface.co/mistralai/

[5] Qwen2-72B-Instruct and Qwen2-7B-Instruct from https://huggingface.co/Qwen/

[6] https://huggingface.co/01-ai/Yi-1.5-34B-Chat

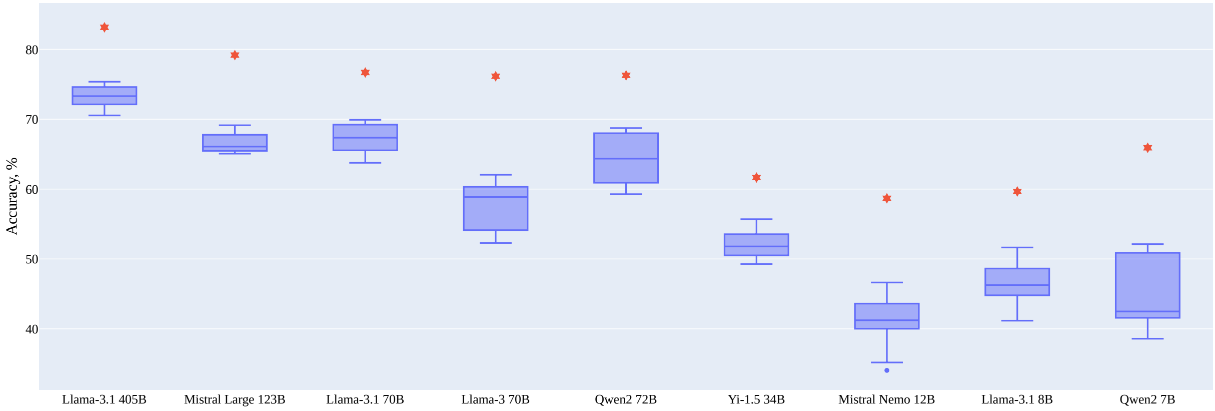


Figure 4: Accuracy ranges and Consistency Rate (shown in red) on MMLU-Pro for Choice Order Robustness Task: order of choices is changed while prompt is fixed.

accuracy varies by 1.5-10.6% on AGIEval and 1.3-15.2% on MMLU-Pro, even when excluding the outlier prompt. Across all models, consistency is higher on AGIEval than on MMLU-Pro. This could be attributed to the greater difficulty of MMLU-Pro and the difference in the number of answer choices (up to five for AGIEval versus up to ten for MMLU-Pro). **Accuracy is least sensitive on MATH**, though still varies by 2-7.9%. **Prediction consistency on MATH is low for all models** and reaches a maximum of 69.8%. For Mistral Large 123B, the consistency rate is 69.7%, and only 60% of the data points have at least eight equivalent predictions. Table 4 (Appendix C) summarizes the accuracies and consistencies of all models on the prompt robustness task.

4.2 Choice Order Robustness

Table 5 (Appendix D) summarizes how model predictions and metrics are affected by changes in the order of answer choices. On the MMLU-Pro dataset, accuracy fluctuates between 4% and 13.5%, while on AGIEval, the fluctuation is between 2% and 7.5% (with up to 29.2% for Mistral 12B). Figure 4 illustrates the accuracy variance and consistency rate for the choice order robustness task on MMLU-Pro. The wide range of accuracy scores demonstrates why relying on a single number for reporting and model comparison can be misleading. For example, when comparing Llama-3.1 405B and Llama-3.1 70B on MMLU-Pro, accuracy metrics can be very similar (70.5% vs. 69.5%) or significantly different (75% vs 63%) simply by altering the order of choices. Llama-3.1 405B is more accurate and more consistent on MMLU-Pro dataset. The Choice Order Robustness experiments align with the findings from the Prompt Robustness tests, demonstrating that **a higher accuracy does not necessarily imply greater consistency**. For example, while Llama-3.1 70B and Llama-3 70B both achieve a consistency rate of 76%, the mean accuracy of Llama-3.1 70B is 9.6% higher.

4.3 Non-Greedy Inference

Table 6 (Appendix E) aggregates non-greedy inference results across all datasets and models. We observe minimal changes in accuracy, except for Mistral 12B. However, **despite the stability in accuracy, the consistency rate remains relatively low**, indicating unstable predictions. On the MMLU-Pro, Llama-3.1 405B achieves the highest consistency of 83.3%, but only 73.4% of predictions are the same across all seeds. For Llama-3.1 8B, the accuracy varies by 2.32%, but the consistency rate is only 54.4%, with 37.9% of identical predictions across all seeds. Similarly, for MATH, accuracy varies slightly (0.8–3.4%), but overall consistency is low. The highest consistency rate is 74.6% for Qwen-2 72B, with 65.7% of predictions being identical. This **variability in predictions can be partially attributed to the difficulty of the problems** (see Appendix H for further analysis). For Level 1 problems, 85% of the predictions are identical between different seeds, while for Level 5 problems, only 29.6% are consistent. Hence, harder problems mean a more uniform underlying distribution, and changing the seed changes the "path" model takes for a solution. Despite having low accuracy on both datasets, Qwen-2 7B, the smallest model of all, has the highest consistency rate on AGIEval (95.8%) and MMLU-Pro (92.5%).

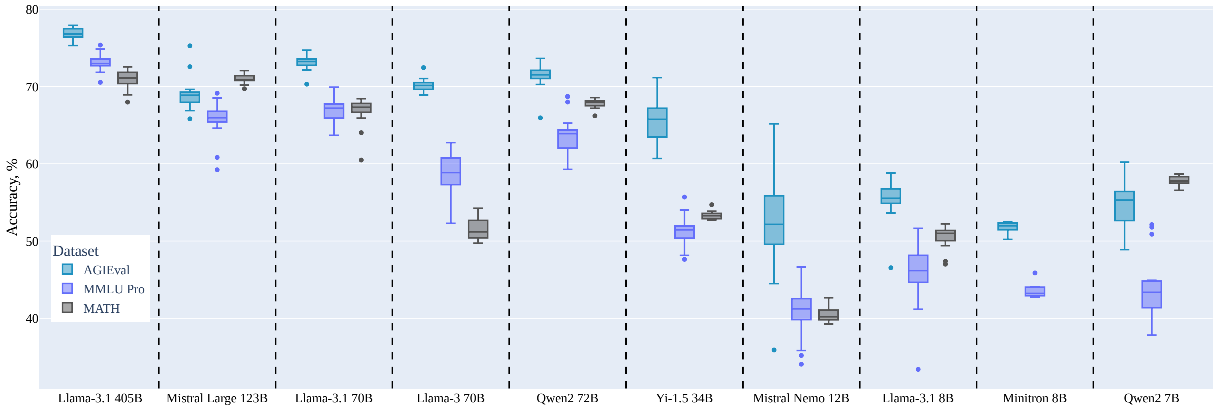


Figure 5: Aggregated accuracy ranges for all SCORE robustness tasks and datasets.

4.4 Aggregated Analysis

Table 7 (Appendix F) summarizes the overall consistency rate and accuracy range for each model by averaging the consistency rates across all experiments and aggregating the accuracies (excluding outliers from the MMLU-Pro and AGIEval datasets to avoid exaggerated claims). For instance, aggregated metric for MMLU-Pro includes 24 predictions per data point (nine predictions for Prompt Robustness, ten for Choice Order Robustness, and five for Non-Greedy evaluation). Figure 5 shows that **accuracy range varies significantly** depending on the specific model and dataset. For example, Yi-1.5 34B has an accuracy variance of 2% on MATH but 10.5% on AGIEval. The variation in metrics can partially be attributed to differences in training data. Llama-3.1 405B is the only model with an accuracy variance below 5% across all datasets. Overall, **mean accuracy and consistency are correlated**. Across datasets, all models' highest mean accuracy and consistency rate is on AGIEval. **Every model's consistency on MATH is lowest**. This can be partially attributed to the nature of the task, as models must generate the entire answer for the math problem rather than providing a single-letter response, as in standard MCQs. **Model size alone is not a reliable predictor of accuracy and consistency**. For example, Mistral Large 123B is 75% bigger than Llama-3.1 70B, but CR on MMLU-Pro is 74% for both, and Llama-3.1's accuracy variance is 6.3% compared to 9.9% of Mistral Large. Similarly, Llama-3 70B is almost nine times bigger than Llama-3.1 8B, but the mean accuracy of Llama-3 on MATH is higher by 1.6%, and consistency is lower by 1.7 points. The results highlight why **model comparison based on a single metric could be misleading**. For example, if we focus solely on maximum accuracy—often emphasized in model releases—one might conclude that Yi-1.5 34B performs on par with Llama-3 70B on the AGIEval dataset, despite being half the size. While this is technically true, Yi-1.5 has a wider accuracy range (60.6% to 71.1%) compared to Llama-3 70B's range (68.8% to 72.4%). Moreover, the consistency rate of Llama-3 70B is 13.2% higher than Yi-1.5. Similarly, Mistral Large 123B is 3.2 times smaller than Llama-3.1 405B and its maximum accuracy on AGIEval is only 2.65% lower than Llama-3.1 405B. However, the accuracy range of Llama-3.1 405B is below 3% (75. 3% to 77. 9%), while the accuracy of Mistral 123B is more sensitive to input changes (65.8% to 75.2%). In addition, Llama-3.1 405B has an 11.1% higher CR.

5 Conclusion

Our evaluation demonstrates that relying solely on a single-point evaluation provides an incomplete assessment of the LLM capabilities. We offer a more nuanced and informative understanding of model performance by evaluating models under various conditions and reporting accuracy ranges and consistency rates. Our SCORE framework establishes a foundation for systematic LLM evaluation, facilitating standardized analysis and research of non-adversarial robustness.

6 Limitations

The datasets and robustness tests employed in this work may not fully capture the breadth of LLM capabilities. For instance, we rely heavily on MCQ datasets that offer ease of evaluation and factual clarity, and we do not explicitly consider creative tasks such as summarization, where consistency is more subjective. Expanding the scope of evaluation to include additional datasets and robustness tasks would provide an even more complete picture. However, it could also lead to a significant increase in computational costs. Furthermore, our reliance on publicly available datasets exposes us to the potential risks of data contamination.

References

Norah Alzahrani, Hisham Abdullah Alyahya, Yazeed Alnumay, Sultan Alrashed, Shaykhah Alsubaie, Yusef Almushaykeh, Faisal Mirza, Nouf Alotaibi, Nora Altwairesh, Areeb Alowisheq, et al. 2024. When benchmarks are targets: Revealing the sensitivity of large language model leaderboards. *arXiv preprint arXiv:2402.01781*.

Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, et al. 2024. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*.

Clémentine Fourrier, Nathan Habib, Alina Lozovskaya, Konrad Szafer, and Thomas Wolf. 2024. Open llm leaderboard v2. https://huggingface.co/spaces/open-llm-leaderboard/open_llm_leaderboard.

Matt Gardner, Yoav Artzi, Victoria Basmova, Jonathan Berant, Ben Bogin, Sihao Chen, Pradeep Dasigi, Dheeru Dua, Yanai Elazar, Ananth Gottumukkala, et al. 2020. Evaluating models' local decision boundaries via contrast sets. *arXiv preprint arXiv:2004.02709*.

Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. 2020. Measuring massive multitask language understanding. *arXiv preprint arXiv:2009.03300*.

Dan Hendrycks, Collin Burns, Saurav Kadavath, Akul Arora, Steven Basart, Eric Tang, Dawn Song, and Jacob Steinhardt. 2021. Measuring mathematical problem solving with the math dataset. *NeurIPS*.

Percy Liang, Rishi Bommasani, Tony Lee, Dimitris Tsipras, Dilara Soylu, Michihiro Yasunaga, Yian Zhang, Deepak Narayanan, Yuhuai Wu, Ananya Kumar, Benjamin Newman, Binhang Yuan, Bobby Yan, Ce Zhang, Christian Alexander Cosgrove, Christopher D Manning, Christopher Re, Diana Acosta-Navas, Drew Arad Hudson, Eric Zelikman, Esin Durmus, Faisal Ladhak, Frieda Rong, Hongyu Ren, Huaxiu Yao, Jue WANG, Keshav Santhanam, Laurel Orr, Lucia Zheng, Mert Yuksekgonul, Mirac Suzgun, Nathan Kim, Neel Guha, Niladri S. Chatterji, Omar Khattab, Peter Henderson, Qian Huang, Ryan Andrew Chi, Sang Michael Xie, Shibani Santurkar, Surya Ganguli, Tatsunori Hashimoto, Thomas Icard, Tianyi Zhang, Vishrav Chaudhary, William Wang, Xuechen Li, Yifan Mai, Yuhui Zhang, and Yuta Koreeda. 2023. Holistic evaluation of language models. *Transactions on Machine Learning Research*. Featured Certification, Expert Certification.

Chenyang Lyu, Minghao Wu, and Alham Fikri Aji. 2024. Beyond probabilities: Unveiling the misalignment in evaluating large language models. *arXiv preprint arXiv:2402.13887*.

Aaron Meurer, Christopher P Smith, Mateusz Paprocki, Ondřej Čertík, Sergey B Kirpichev, Matthew Rocklin, AMiT Kumar, Sergiu Ivanov, Jason K Moore, Sartaj Singh, et al. 2017. Sympy: symbolic computing in python. *PeerJ Computer Science*, 3:e103.

Moran Mizrahi, Guy Kaplan, Dan Malkin, Rotem Dror, Dafna Shahaf, and Gabriel Stanovsky. 2023. State of what art? a call for multi-prompt llm evaluation. *arXiv preprint arXiv:2401.00595*.

Felipe Maia Polo, Ronald Xu, Lucas Weber, Mírian Silva, Onkar Bhardwaj, Leshem Choshen, Allysson Flavio Melo de Oliveira, Yuekai Sun, and Mikhail Yurochkin. 2024. Efficient multi-prompt evaluation of llms. *arXiv preprint arXiv:2405.17202*.

Melanie Sclar, Yejin Choi, Yulia Tsvetkov, and Alane Suhr. 2023. Quantifying language models' sensitivity to spurious features in prompt design or: How i learned to start worrying about prompt formatting. *arXiv preprint arXiv:2310.11324*.

Xinpeng Wang, Bolei Ma, Chengzhi Hu, Leon Weber-Genzel, Paul Röttger, Frauke Kreuter, Dirk Hovy, and Barbara Plank. 2024a. " my answer is c": First-token probabilities do not match text answers in instruction-tuned language models. *arXiv preprint arXiv:2402.14499*.

Yubo Wang, Xueguang Ma, Ge Zhang, Yuansheng Ni, Abhranil Chandra, Shiguang Guo, Weiming Ren, Aaran Arulraj, Xuan He, Ziyan Jiang, et al. 2024b. Mmlu-pro: A more robust and challenging multi-task language understanding benchmark. *arXiv preprint arXiv:2406.01574*.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837.

Zhao Yukun, Yan Lingyong, Sun Weiwei, Xing Guoliang, Wang Shuaiqiang, Meng Chong, Cheng Zhicong, Ren Zhaochun, and Yin Dawei. 2024. Improving the robustness of large language models via consistency alignment. *arXiv preprint arXiv:2403.14221*.

Chujie Zheng, Hao Zhou, Fandong Meng, Jie Zhou, and Minlie Huang. 2023. On large language models' selection bias in multi-choice questions. *arXiv preprint arXiv:2309.03882*.

Wanjun Zhong, Ruixiang Cui, Yiduo Guo, Yaobo Liang, Shuai Lu, Yanlin Wang, Amin Saied, Weizhu Chen, and Nan Duan. 2023. Agieval: A human-centric benchmark for evaluating foundation models. *arXiv preprint arXiv:2304.06364*.

Kaijie Zhu, Jindong Wang, Jiaheng Zhou, Zichen Wang, Hao Chen, Yidong Wang, Linyi Yang, Wei Ye, Yue Zhang, Neil Zhenqiang Gong, et al. 2023a. Promptrobust: Towards evaluating the robustness of large language models on adversarial prompts. *arXiv preprint arXiv:2306.04528*.

Kaijie Zhu, Qinlin Zhao, Hao Chen, Jindong Wang, and Xing Xie. 2023b. Promptbench: A unified library for evaluation of large language models. *arXiv preprint arXiv:2312.07910*.

A Datasets Statistics

MATH (Hendrycks et al., 2021) dataset, which consists of around 5,000 challenging competition-level mathematics problems. Solving these problems requires LLMs to perform multiple reasoning steps to arrive at the correct answer.

Topic	Number of Samples
Level 1	437
Level 2	894
Level 3	1131
Level 4	1214
Level 5	1324
TOTAL	**5000**

Table 1: Subset statistics of the MATH dataset (MIT License), categorized by problem difficulty levels.

MMLU-Pro (Wang et al., 2024b) is an enhanced version of MMLU (Hendrycks et al., 2020), a widely used multiple-choice benchmark for evaluating the core knowledge and reasoning abilities of LLMs. MMLU-Pro increases the number of answer choices from 4 to 10, incorporates more reasoning-based questions, and removes incorrect or outdated content. It includes 12,032 questions across 14 subjects, covering a broad range of topics such as natural sciences, business, engineering, and law. Overall, MMLU-Pro provides a higher quality and more challenging assessment than its predecessor.

Topic	Number of Samples
biology	717
business	789
chemistry	1132
computer science	410
economics	844
engineering	969
health	818
history	381
law	1101
math	1351
other	924
philosophy	499
physics	1299
psychology	798
TOTAL	**12032**

Table 2: Subset statistics of the MMLU-Pro dataset (Apache License Version 2.0), categorized by subject.

AGIEval (Zhong et al., 2023) is a multiple-choice dataset derived from standardized exams such as SAT and LSAT. It tests models' abilities in reading comprehension, reasoning, and mathematics. For our analysis, we selected SAT-English, SAT-Math, LSAT-Analytics, LSAT-Logic, LSAT-Reading, LogiQA-En, and AQuA-RAT (GRE, GMAT) subsets comprising 2340 datapoints.

Topic	Number of Samples
aqua_rat	254
logiqa_en	651
lsat_ar	230
lsat_lr	510
lsat_rc	269
sat_en	206
sat_math	220
TOTAL	**2340**

Table 3: Subset statistics of the AGIEval dataset (MIT License).

B Inference Setup

While generative evaluation incurs higher computational costs than other methods, the additional expense is negligible compared to the overall training costs. For each model and dataset, we generate 1024 tokens. We found that over 95% of the datasets can be answered within this token limit, with models occasionally getting stuck in repetitive loops that require generating more tokens. Generating additional tokens beyond this limit yields diminishing returns in metrics while significantly increasing computational costs. To simulate average user behaviour, we conduct all evaluations in a 0-shot setting, without providing any few-shot examples. Model predictions are extracted by parsing the generated text. For MATH problems, we instruct the model to format its answer within $\\boxed{{answer}}$ to extract prediction easily and verify its symbolic equivalence with the ground truth using the sympy package (Meurer et al., 2017). In the case of MCQ, the model is prompted to conclude with *The best answer is answer_letter*, and the corresponding letter is extracted from the output. While more complex post-processing might improve metrics by addressing cases where models deviate from instructions, we avoid such techniques to maintain a model-independent parsing logic and ensure that models follow the given prompts.

We convert models to TRT-LLM[7] for evaluation. We have used two NVIDIA A100 80GB nodes for Llama-3.1 405B evaluation and a single node for the rest of the models. For the SCORE evaluation, we conducted a series of robustness evaluations for each model: 25 evaluations on the MMLU-Pro dataset (ten predictions for Prompt Robustness, ten for Choice Order Robustness, and five for Non-greedy evaluation), 19 on the AGIEval dataset (ten predictions for Prompt Robustness, four for Choice Order Robustness, and five for Non-greedy evaluation), and 15 on the MATH dataset (ten predictions for Prompt Robustness, and five for Non-greedy evaluation). The specific computational requirements for each evaluation varied depending on the model size, dataset size, and the model's verbosity in generating answers.

C Prompt Robustness Results

Model	Accuracy, % Mean [Min, Max]	CR
AGIEval		
Llama-3.1 405B	77.0 [74.7, 77.9]	86.1
Mistral Large 123B	68.8 [61.5, 75.2]	74.3
Qwen-2 72B	70.2 [62.0, 72.5]	80.5
Llama-3.1 70B	72.0 [65.3, 74.7]	80.5
Llama-3 70B	69.2 [61.0, 71.0]	80.5
Yi-1.5 34B	63.6 [56.5, 68.3]	66.4
Mistral Nemo 12B	52.4 [43.2, 56.8]	58.9
Llama-3.1 8B	53.9 [43.1, 57.1]	59.7
Qwen-2 7B	52.4 [48.8, 56.4]	61.5
MMLU-Pro		
Llama-3.1 405B	72.8 [69.5, 73.9]	79.8
Mistral Large 123B	63.6 [49.9, 68.5]	70.2
Qwen-2 72B	62.1 [52.5, 65.2]	72.2
Llama-3.1 70B	65.7 [54.8, 68.3]	72.0
Llama-3 70B	59.1 [49.1, 62.7]	70.8
Yi-1.5 34B	49.4 [42.4, 51.9]	53.3
Mistral Nemo 12B	41.0 [31.5, 44.6]	46.7
Llama-3.1 8B	44.4 [33.3, 48.6]	47.9
Qwen-2 7B	41.3 [34.6, 44.8]	49.1
MATH		
Llama-3.1 405B	71.0 [67.9, 72.5]	69.8
Mistral Large 123B	70.9 [69.7, 72.0]	69.7
Qwen-2 72B	67.6 [52.1, 65.2]	72.2
Llama-3.1 70B	66.3 [60.4, 68.4]	64.6
Llama-3 70B	51.8 [49.7, 54.2]	50.1
Yi-1.5 34B	53.3 [52.7, 54.7]	48.0
Mistral Nemo 12B	40.7 [39.4, 42.6]	36.9
Llama-3.1 8B	50.2 [47.0, 52.2]	46.0
Qwen-2 7B	57.6 [56.5, 58.6]	58.3

Table 4: Accuracy ranges and consistency rates (CR) on Prompt Robustness task: the evaluation is conducted using 10 prompts, while keeping the context fixed.

[7] https://github.com/NVIDIA/TensorRT-LLM

D Choice Order Robustness Results

Model	Accuracy, % Mean [Min, Max]	CR
AGIEval		
Llama-3.1 405B	76.5 [75.3, 77.3]	88.5
Mistral Large 123B	68.2 [66.8, 68.8]	78
Qwen-2 72B	71.7 [70.2, 73.6]	80.8
Llama-3.1 70B	73.6 [72.1, 74.7]	82.5
Llama-3 70B	70.3 [69.1, 72.4]	84.1
Yi-1.5 34B	68.1 [65.0, 71.1]	71.8
Mistral Nemo 12B	51.6 [35.9, 65.1]	61.2
Llama-3.1 8B	56.2 [53.8, 58.8]	67.2
Qwen-2 7B	55.6 [52.6, 60.2]	72.3
MMLU-Pro		
Llama-3.1 405B	73.1 [70.5, 75.3]	83.1
Mistral Large 123B	66.4 [65.0, 69.1]	79.1
Qwen-2 72B	64.0 [59.2, 68.7]	76.2
Llama-3.1 70B	67.0 [63.7, 69.9]	76.6
Llama-3 70B	57.5 [52.2, 62.0]	76.1
Yi-1.5 34B	52.0 [49.2, 55.6]	61.6
Mistral Nemo 12B	40.8 [34.0, 46.6]	58.6
Llama-3.1 8B	46.2 [41.1, 51.6]	59.6
Qwen-2 7B	44.4 [38.5, 52.2]	65.9

Table 5: Accuracy and consistency rates (CR) for Choice Order Robustness task: order of choices is changed while prompt is fixed.

E Non Greedy Results

Model	Accuracy, % Mean [Min, Max]	CR
AGIEval		
Llama-3.1 405B	76.4 [75.9, 76.7]	91.1
Mistral Large 123B	68.3 [67.4, 69.1]	78.1
Qwen-2 72B	71.2 [70.8, 71.7]	91.5
Llama-3.1 70B	73.2 [72.8, 73.5]	85.2
Llama-3 70B	70.0 [69.7, 70.2]	89.4
Yi-1.5 34B	66.1 [65.4, 67.0]	74.9
Mistral Nemo 12B	49.4 [44.4, 52.8]	53.9
Llama-3.1 8B	54.9 [53.6, 56.6]	66.6
Qwen-2 7B	56.2 [55.3, 56.5]	95.8
MMLU-Pro		
Llama-3.1 405B	72.7 [72.6, 72.9]	83.3
Mistral Large 123B	65.8 [65.3, 66.0]	76.0
Qwen-2 72B	63.7 [63.7, 64.0]	86.9
Llama-3.1 70B	66.5 [65.6, 67.1]	74.8
Llama-3 70B	57.4 [57.2, 57.6]	79.8
Yi-1.5 34B	51.5 [51.4, 51.9]	63.0
Mistral Nemo 12B	39.0 [35.8, 40.9]	47.2
Llama-3.1 8B	45.1 [44.1, 46.2]	54.4
Qwen-2 7B	44.6 [44.4, 44.9]	92.5
MATH		
Llama-3.1 405B	70.6 [70.2, 71.1]	68.0
Mistral Large 123B	70.9 [70.5, 71.4]	68.6
Qwen-2 72B	68.0 [67.4, 68.5]	74.6
Llama-3.1 70B	67.3 [66.7, 68.1]	65.0
Llama-3 70B	50.8 [50.0, 51.6]	48.6
Yi-1.5 34B	53.2 [52.8, 53.6]	48.0
Mistral Nemo 12B	40.1 [39.2, 42.6]	33.7
Llama-3.1 8B	50.8 [49.6, 51.9]	45.5
Qwen-2 7B	58.1 [57.2, 58.6]	68.3

Table 6: Accuracy ranges and consistency rates (CR) for Non-Greedy Robustness tasks: models evaluated on five random seeds with temperature set to 0.7.

F Aggregated Results

Model	Accuracy, % Mean [Min, Max]	CR
AGIEval		
Llama-3.1 405B	77.0 [75.3, 77.9]	87.3
Mistral Large 123B	69.2 [65.8, 75.2]	76.2
Qwen-2 72B	71.3 [65.9, 73.6]	80.7
Llama-3.1 70B	73.0 [70.3, 74.7]	81.7
Llama-3 70B	70.2 [68.8, 72.4]	82.3
Yi-1.5 34B	65.6 [60.6, 71.1]	69.1
Mistral Nemo 12B	52.9 [35.9, 65.1]	60.0
Llama-3.1 8B	55.3 [46.5, 58.8]	63.3
Qwen-2 7B	53.6 [48.8, 60.2]	66.9
MMLU-Pro		
Llama-3.1 405B	73.1 [70.5, 75.3]	81.5
Mistral Large 123B	65.8 [59.2, 69.1]	74.7
Qwen-2 72B	63.6 [59.2, 68.7]	74.2
Llama-3.1 70B	67.0 [63.6, 69.9]	74.3
Llama-3 70B	58.8 [52.2, 62.7]	73.5
Yi-1.5 34B	51.2 [47.6, 55.6]	57.4
Mistral Nemo 12B	41.4 [34.0, 46.6]	52.6
Llama-3.1 8B	45.8 [33.3, 51.6]	53.8
Qwen-2 7B	43.3 [37.8, 52.1]	57.5
MATH		
Llama-3.1 405B	71.0 [67.9, 72.5]	71.1
Mistral Large 123B	70.9 [69.7, 72.0]	70.6
Qwen-2 72B	67.6 [66.2, 68.4]	68.6
Llama-3.1 70B	66.3 [60.4, 68.4]	67.0
Llama-3 70B	51.8 [49.7, 54.2]	50.4
Yi-1.5 34B	53.3 [52.7, 54.7]	49.4
Mistral Nemo 12B	40.7 [39.2, 42.6]	38.2
Llama-3.1 8B	50.2 [47.0, 52.2]	52.1
Qwen-2 7B	57.6 [56.5, 58.6]	61.0

Table 7: Accuracy ranges and consistency rates (CR) aggregated across Prompt Robustness, Choice Order Robustness and random seed variation for Non-greedy inference.

G Prompts

G.1 MMLU-Pro Prompts

{} Examine the question and choose the correct answer from the options 'A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I' or 'J'. End your answer with: The best answer is [the_answer_letter]. where the [the_answer_letter] is a letter from A to J.

{} Answer the multiple-choice question about task by selecting the correct option from A to J. Always conclude with 'The best answer is (answer_letter)' where the (answer_letter) is one of A, B, C, D, E, F, G, H, I, J.

You must reply with only a single letter from A, B, C, D, E, F, G, H, I or J to this question. Conclude with: The best answer is answer_letter where the answer_letter is a single letter from A to J. {}

From the options A-J, select the correct answer to the following question. End the answer with - The best answer is answer_letter, where answer_letter is one of A, B, C, D, E, F, G, H, I, or J. Question: {}

For the multiple-choice question related to task, which option (A-J) is correct?.
Question:{} End the answer with the following: The best answer is (the_answer_letter) where the (the_answer_letter) is one of 'A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I' or 'J'.
***Used as the fixed prompt for Choice Order and Non-greedy Robustness tasks**

Evaluate the multiple-choice question and select the most fitting response from 'A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J'. Question:{} Always conclude with: The best answer is [the_answer_letter]. where the [the_answer_letter] is one of A, B, C, D, E, F, G, H, I or J.

Answer to the following question about task by selecting the correct option A, B, C, D, E, F, G, H, I or J. {} The answer should end with: The best answer is [the_answer_letter] where [the_answer_letter] is one of letters A to J. Let's think step by step.

Select the correct answer from the options 'A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I','J' for the question provided below. Conclude by stating: The best answer is answer_letter where answer_letter is one of 'A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I' or 'J'. Question: {} Let's think step by step.

{} For this question about task with 10 possible answers A, B, C, D, E, F, G, H, I, J, choose the one that answers the question. If the problem is simple or straightforward, just provide the answer. If the answer is more complex, use a step-by-step approach and for each step briefly explain your reasoning. Always conclude with 'The best answer is (answer_letter)' where the (answer_letter) is one of 'A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I','J'. Let's think step by step.

Read the question and options below, then determine the correct answer choice (A-J) Question: {}
For simple questions, provide a quick answer. For complicated ones, think step by step, break down the question into smaller problems and reach to a conclusion End your answer by stating: The best answer is [the_answer_letter]. where [the_answer_letter] is one of A, B, C, D, E, F, G, H, I, or J.

Table 8: Prompts used to evaluate LLMs on the MMLU-Pro dataset for SCORE tasks. *{}* denotes a placeholder for an input query.

G.2 AGIEval Prompts

{} Examine the question and choose the correct answer from the options 'A', 'B', 'C', 'D' or 'E'. End your answer with: The best answer is [the_answer_letter]. where the [the_answer_letter] is a letter from A to E.

{} Answer the multiple-choice question by selecting the correct option from A to E. Always conclude with 'The best answer is (answer_letter)' where the (answer_letter) is one of A, B, C, D, E.

You must reply with only a single letter from A, B, C, D or E to this question. Conclude with: The best answer is answer_letter where the answer_letter is a single letter from A to E. {}

From the options A-E, select the correct answer to the following question. End the answer with - The best answer is answer_letter, where answer_letter is one of A, B, C, D or E. Question: {}

For the multiple-choice question, which option (A-E) is correct?.
Question:{} End the answer with the following: The best answer is (the_answer_letter) where the (the_answer_letter) is one of 'A', 'B', 'C', 'D' or 'E'.

Evaluate the multiple-choice question and select the most fitting response from 'A', 'B', 'C', 'D', 'E'. Question:{} Always conclude with: The best answer is [the_answer_letter]. where the [the_answer_letter] is one of A, B, C, D or E.
***Used as a fixed prompt for Choice Order and Non-greedy Robustness tasks**

Answer to the following question by selecting the correct option A, B, C, D or E. {} The answer should end with: The best answer is [the_answer_letter] where [the_answer_letter] is one of letters A to E. Let's think step by step.

Select the correct answer from the options 'A', 'B', 'C', 'D', 'E' for the question provided below. Conclude by stating: The best answer is answer_letter where answer_letter is one of 'A', 'B', 'C', 'D' or 'E'. Question: {} Let's think step by step.

{} For this question with 10 possible answers A, B, C, D, E, choose the one that answers the question. If the problem is simple or straightforward, just provide the answer. If the answer is more complex, use a step-by-step approach and for each step briefly explain your reasoning. Always conclude with 'The best answer is (answer_letter)' where the (answer_letter) is one of 'A', 'B', 'C', 'D', 'E'. Let's think step by step.

Read the question and options below, then determine the correct answer choice (A-E) Question: {}
For simple questions, provide a quick answer. For complicated ones, think step by step, break down the question into smaller problems and reach to a conclusion End your answer by stating: The best answer is [the_answer_letter]. where [the_answer_letter] is one of A, B, C, D or E.

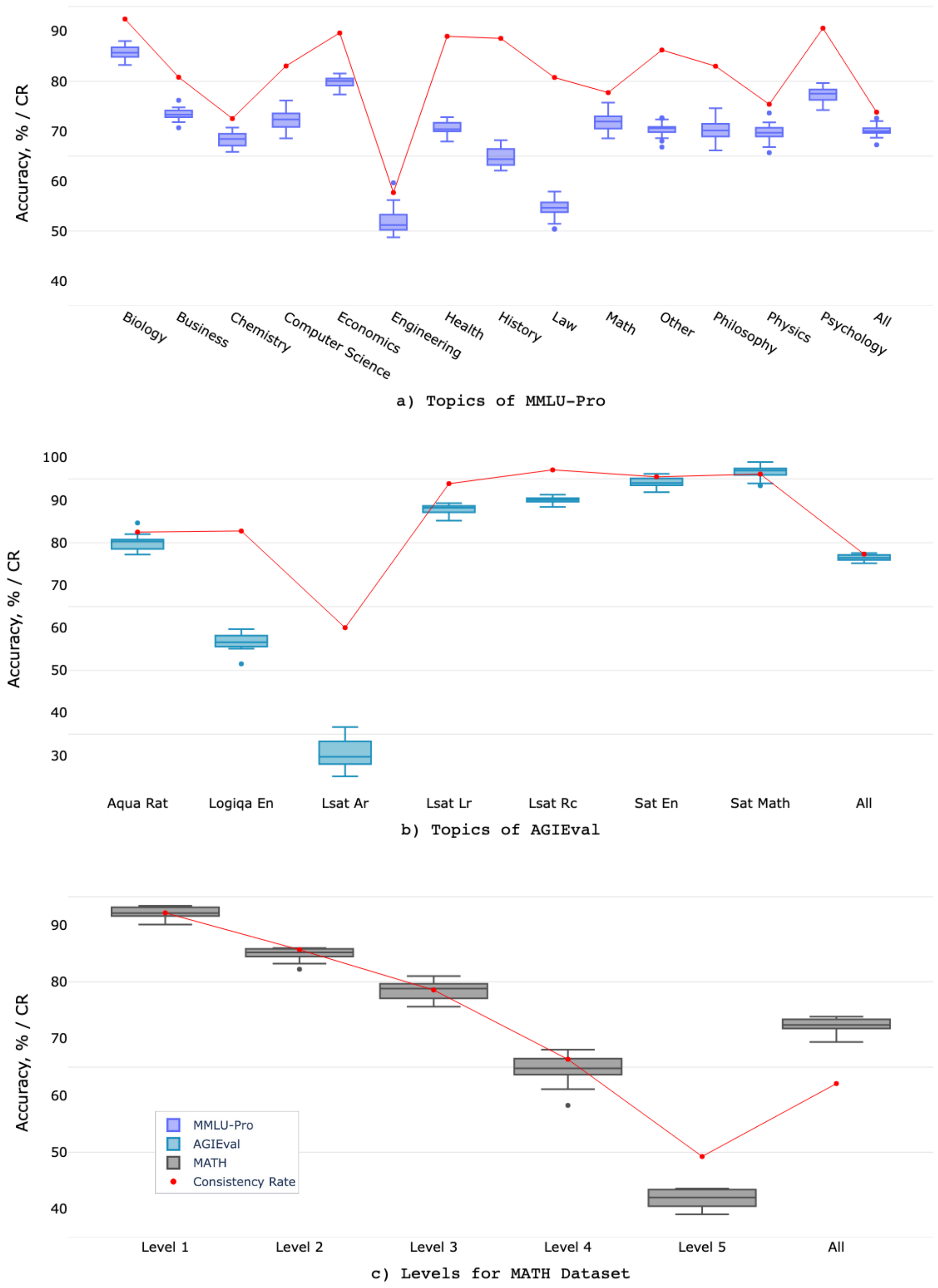
Table 9: Prompts used to evaluate LLMs on the AGIEval dataset for SCORE tasks. *{}* denotes a placeholder for an input query.

G.3 MATH Prompts

Solve this math problem. Your answer should end with 'The final answer is: $\\boxed{{answer}}$ where [answer] is just the final number or expression that solves the problem Problem: {question}
{question} Please solve this math problem efficiently. Finish with: The final answer is: $\\boxed{{answer}}$ where [answer] is just the final number or expression that solves the problem.
Find the answer to the following math question. Conclude with: 'The final answer is: $\\boxed{{answer}}$ ' where [answer] is just the final number or expression that solves the problem Problem: {question}
{question} Find the solution to this math problem. Your answer should end with - The final answer is: $\\boxed{{answer}}$ where [answer] is just the final number or expression that solves the problem.
Analyze and solve the math task. Problem: {question} End the answer with: The final answer is: $\\boxed{{answer}}$ where [answer] is just the final number or expression that solves the problem.
Calculate the answer to this math problem Problem: {question} Conclude your answer with: The final answer is: $\\boxed{{answer}}$ where [answer] is just the final number or expression that solves the problem. ***Used as a fixed prompt for Choice Order and Non-greedy Robustness tasks**
{question} Solve the following math problem Show each step of your solution Conclude with: The final answer is: $\\boxed{{answer}}$ [answer] is just the final number or expression that solves the problem Lets think step by step
Efficiently solve the following math challenge. Explain your approach step-by-step The answer should end with: The final answer is: $\\boxed{{answer}}$ where [answer] is just the final number or expression that solves the problem Problem: {question} Lets think step by step
Please solve the math problem. For simple problems offer a quick solution with minimal details. For more challenging problems, explain your approach step-by-step. Finish with The final answer is: $\\boxed{{answer}}$. where [answer] is just the final number or expression that solves the problem. Problem: {question} Lets think step by step.
You should solve this math problem. If the problem is easy, provide a brief solution with little explanation. For more difficult problems, follow this structured format Step 1: [Brief description] [Simple explanation and calculations] Step 2: [Brief description] [Simple explanation and calculations] Repeat steps until your reach a solution Problem: {question} End with: The final answer is: $\\boxed{{answer}}$ where [answer] is just the final number or expression that solves the problem.

Table 10: Prompts used to evaluate LLMs on the MATH dataset for SCORE tasks. *{question}* denotes a placeholder for an input query.

H Per Topic Analysis



a) Topics of MMLU-Pro

b) Topics of AGIEval

c) Levels for MATH Dataset

Figure 6: Accuracy ranges and consistency rates (CR) for Llama-3.1 405B model across three datasets *a)* MMLU-Pro **b)** AGIEval *c)* MATH. Each plot represents values across corresponding to specific topics or areas of the dataset (see Appendix A for details). *"All"* - indicates the accuracy and consistency values for the entire dataset.
For MMLU-Pro, consistency is not uniformly distributed, and accuracy varies between 3.8% and 10.9%. There are tasks with **same consistency but varying accuracy** (e.g., health vs. history) and **same accuracy but varying consistency** (e.g., physics vs. other). For AGIEval, the accuracy variance across subsets ranges from a maximum of 1% on LSAT-AR to a minimum of 2.3% on SAT-EN. In the case of MATH, the trend is clear: as question complexity increases, accuracy decreases, consistency declines, and variance grows.