Evaluating Language Models as Synthetic Data Generators

Anonymous ACL submission

Abstract

Given the increasing use of synthetic data in language model (LM) post-training, an LM's ability to generate high-quality data has become nearly as crucial as its ability to solve problems directly. While prior works have focused on developing effective data generation methods, they lack systematic comparison of different *LMs as data generators* in a unified setting. To address this gap, we propose AGORABENCH, a benchmark that provides standardized settings and metrics to evaluate LMs' data generation abilities. Through synthesizing 1.26 million training instances using 6 LMs and training 99 student models, we uncover key insights about LMs' data generation capabilities. First, we observe that LMs exhibit distinct strengths. For instance, GPT-4o excels at generating new problems, while Claude-3.5-Sonnet performs better at enhancing existing ones. Furthermore, our analysis reveals that an LM's data generation ability doesn't necessarily correlate with its problem-solving ability. Instead, multiple intrinsic features of data quality—including response quality, perplexity, and instruction difficulty—collectively serve as better indicators. Finally, we demonstrate that strategic choices in output format and cost-conscious model selection significantly impact data generation effectiveness. Our code, checkpoints, and data are all publicly available at this anonymous github link.

1 Introduction

Post-training language models (LMs) on synthetic data is a promising approach for improving their ability to solve a wide range of tasks (Wang et al., 2023; Honovich et al., 2023; Taori et al., 2023; Liu et al., 2024b). While acquiring data through manual annotation continues to play an important role, synthetic data generation offers a scalable complement to human labeling (Viswanathan et al., 2023; Kim et al., 2023b). Hence, numerous works have proposed novel methods to effectively generate high-quality synthetic data (Xu et al., 2024a; Gunasekar et al., 2023; Yue et al., 2023, 2024).

As multiple proprietary LMs with comparable performance emerge and open-source LMs steadily catch up (Hurst et al., 2024; Anthropic, 2024; MetaAI, 2024; Team, 2024), measuring each LM's data generation capabilities has become as crucial as developing new data generation methods. Moreover, companies providing proprietary LMs have begun promoting the use of their latest models for generating synthetic data (Nvidia, 2024). Carefully comparing data generation ability across LMs helps validate these claims and allows practitioners to wisely choose models for data synthesis.

To systematically compare LMs' capabilities as data generators, a *unified experimental setting* is needed, where only the data generator varies, while other components remain fixed. However, as shown in Figure 1, prior works have focused more on demonstrating the effectiveness of their data generation method, leading to various experimental settings that make such comparison challenging. For instance, Self-Instruct (Wang et al., 2023), Alpaca (Taori et al., 2023), WizardLM (Xu et al., 2024a) and Orca (Mukherjee et al., 2023) varied in their choice of LMs for data generation, quantity of synthetic training data, base models used for training, and benchmarks for evaluating the model trained on the synthetic dataset. These heterogeneous settings make it difficult to isolate and measure LMs' data generation capabilities, highlighting the need for controlled settings.

To this end, we propose **AGORABENCH**, a benchmark for evaluating LMs' data generation capabilities across nine settings, combining three domains (math, instruction-following, code) with three data generation methods (instance generation, response generation, quality enhancement). Within each setting, all variables except the data generator are controlled: the same meta-prompt and seed dataset are used, with each LM generating

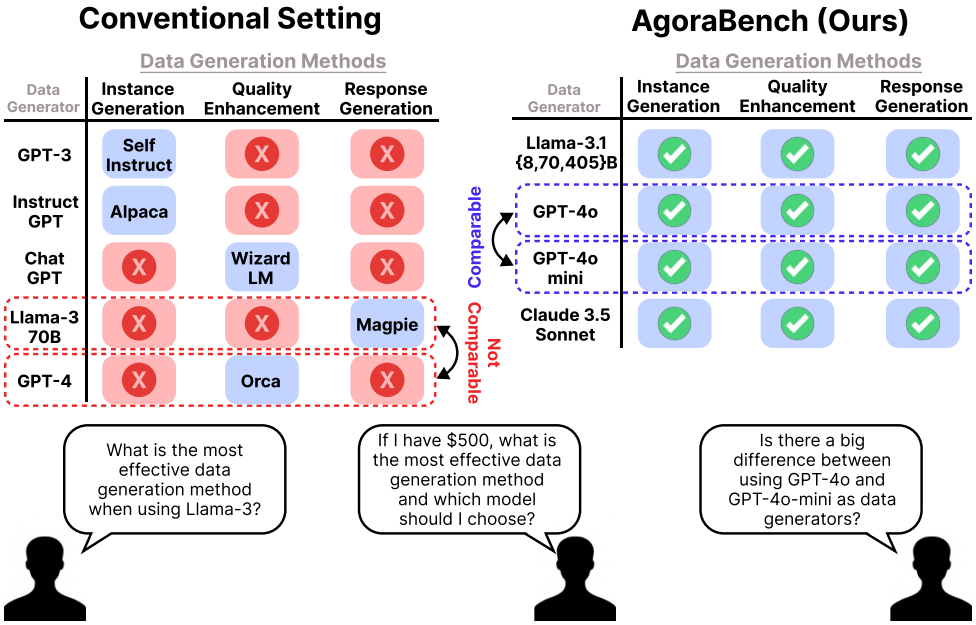


Figure 1: **Illustration of the motivation of AGORABENCH:** Prior works focused on developing new methods to generate synthetic data. In contrast, our work focuses on systematically comparing different LMs as data generators based on existing data generation methods. Further explanation of data generation methods are covered in Section 2.

an identical number of training instances. Llama-3.1-8B is trained on each synthetic dataset and evaluated on a fixed set of benchmarks spanning different capabilities: mathematics, coding, and general instruction-following. To evaluate the quality of synthetic data, we define a metric called **Performance Gap Recovered** (PGR), which measures the relative improvement of the model trained on the data (denoted as 'student model') over its base model. Based on this setting, we assess six LMs as data generators: GPT-4o, GPT-4o-mini, Claude-3.5-Sonnet, and Llama-3.1-Instruct (8, 70, 405B).[1]

Our analysis reveals distinct strengths among different LMs in various kinds of data generation methods. For example, GPT-4o demonstrates superior performance in generating new instances (+ 46.75%), outperforming both Claude-3.5-Sonnet (+ 24.14%) and Llama-3.1-405B-Instruct (+ 10.10%). On the other hand, Claude-3.5-Sonnet excels at refining existing instances (+ 17.89%), surpassing both GPT-4o (+ 6.69%) and GPT-4o-mini (+ 5.49%). These findings demonstrate how AGORABENCH can guide practitioners in selecting appropriate LMs for their specific needs.

Unexpectedly, we also find that LMs with weaker problem-solving ability sometimes outperform stronger ones in data generation—for example, Claude-3.5-Sonnet (+ 23.43%) is less effective than Llama-3.1-8B-Instruct (+ 55.69%) at generating new instances in the code domain. Based on these findings, we investigate whether an LM's data generation ability can be predicted by its problem-solving ability alone. Our analysis reveals no strong correlation between the two capabilities. Instead, multiple intrinsic features of data quality—including instruction difficulty, response quality, and response perplexity—collectively influence the student model's improvement. Furthermore, we demonstrate that the top-5 principal components extracted from intrinsic measurements can explain 93.4% of the variance in the PGR values.

2 Preliminaries: Measuring Data Generation Capabilities of LMs

Notations. Given seed data D_{seed} and a prompt describing the kind of data generation to perform (referred to as a 'meta-prompt') M, a data generator G generates

$$D_G = G(D_{seed}, M), \tag{1}$$

where D_{seed} and D_G can both be expressed as $\{(I_i, R_i) \mid i = 1, \ldots, n\}$ with I denoting an instruction, R denoting a corresponding response, and n denoting the size of the data.

[1] Xu et al. (2024c), a contemporaneous work with ours, also measured various LMs' data generation capabilities. In contrast to our work, they only examine the "response generation" setting, whereas we measure three data generation settings and also do a number of additional analyses on the relationship between the intrinsic quality of data and PGR.

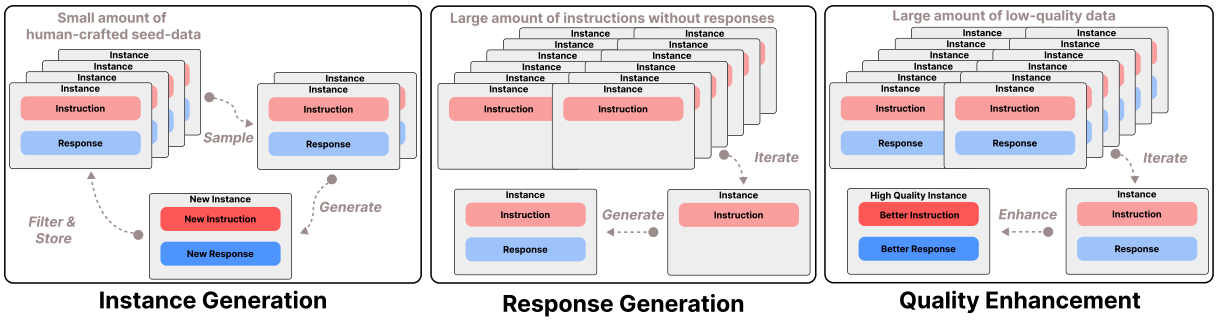


Figure 2: **AGORABENCH tests three data generation methods**: generating new instruction and response pairs (left), generating responses (middle), and enhancing the quality of the instruction and/or the response (right).

Data Generation Methods. As shown in Figure 2, among the various methods for generating data, most can be grouped into three categories: instance generation, response generation, and quality enhancement. These methods work as follows:

- **Instance Generation**: Given a small seed dataset $D_{seed} = \{(I_i, R_i) \mid i = 1, \ldots, m\}$, a few instances are randomly sampled from D_{seed} and used as in-context demonstrations, resulting in the generation of new instances (Honovich et al., 2023; Wang et al., 2023). This process is performed iteratively until $D_G = \{(I_i, R_i) \mid i = 1, \ldots, n\}$ is constructed where $m << n$. Note that the generated instances could also optionally be used as demonstrations as well.
- **Response Generation**: A large set of instructions $D_I = \{(I_i) \mid i = 1, \ldots, n\}$ is given, and G iterates through each instruction I_i to generate a corresponding response R_i (Xu et al., 2024b).
- **Quality Enhancement**: A large set of instructions and responses $D' = \{(I'_i, R'_i) \mid i = 1, \ldots, n\}$ is given. G iterates through each instance to refine I'_i and/or R'_i, such as by explicitly prompting G to "make either/both I'_i, R'_i of higher quality" (*e.g.,* making the instruction more difficult or of higher educational value) (Xu et al., 2024a; Yue et al., 2024).

Metric. An LM's data generation ability can be measured by evaluating the performance improvement of a student model trained on the teacher-generated data. Specifically, we propose a metric, **Performance Gap Recovered (PGR)**, that measures the improvement on a benchmark B relative to a reference model,

$$PGR(G, B) = \frac{\text{score}_B(S_{D_G}) - \text{score}_B(S_\emptyset)}{\text{score}_B(S_{ref}) - \text{score}_B(S_\emptyset)} \times 100 \quad (2)$$

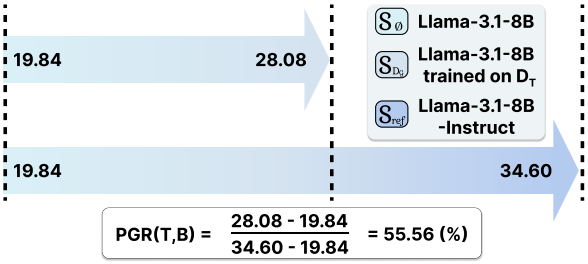


Figure 3: **Illustration of Performance Gap Recovered metric:** The performance gap recovered metric captures the relative improvement of S_{D_G} with respect to S_{ref} where S_{D_G} and S_{ref} is both trained from $S_\emptyset$.

where $S_\emptyset$ denotes a pre-trained LM, S_{D_G} denotes $S_\emptyset$ trained on D_G, S_{ref} denotes a reference model that shares the same pre-trained model $S_\emptyset$ as a base model, and $\text{score}_B(\cdot)$ denotes the score on benchmark B. In our experiments, we use Llama-3.1-8B as $S_\emptyset$ and Llama-3.1-8B-Instruct as S_{ref}.[2]

Intuitively, as illustrated in Figure 3, by using Llama-3.1-8B as $S_\emptyset$ and Llama-3.1-8B-Instruct as S_{ref}, the PGR value represents how much performance was recovered compared to the post-training process for Llama-3.1-8B-Instruct, which was reportedly extensive, training on 10M+ examples of human-curated data (MetaAI, 2024). For example, a PGR value of 50% indicates that S_{D_G} has recovered 50% of the improvement achieved by S_{ref} relative to $S_\emptyset$. A value above 100% indicates S_{D_G} outperforms S_{ref}, while a negative value indicates that training on D_G degraded performance on B compared to few-shot prompting $S_\emptyset$.

Training Student Models. When training the student model ($S_\emptyset$), we employ supervised fine-tuning (SFT), computing the loss only on response

[2]Note that when measuring $\text{score}_B(S_\emptyset)$, $S_\emptyset$ can not solve tasks with zero-shot prompting, so we evaluate their performance with few-shot prompting. In contrast, S_{D_G} and S_{ref} are evaluated with zero-shot prompting.

Domain	Data Generation Method	Seed Data	Seed Data Size	Benchmark
Math	**Instance Generation**	GSM8K, MATH (train set)	14,856	GSM8K, MATH (test set)
	Response Generation	Magpie-Reasoning (math)	10,000	GSM8K, MATH (test set)
	Quality Enhancement	WebInstruct (math)	10,000	GSM8K, MATH (test set)
Code	**Instance Generation**	MBPP (train set), xP3x	874	MBPP, HumanEval (test set)
	Response Generation	Magpie-Reasoning (code)	10,000	MBPP, HumanEval (test set)
	Quality Enhancement	CoNaLa	10,000	MBPP, HumanEval (test set)
Inst. Follow	**Instance Generation**	LIMA	503	AlpacaEval 2.0, Arena-Hard
	Response Generation	Magpie-Pro	10,000	AlpacaEval 2.0, Arena-Hard
	Quality Enhancement	WebInstruct (code)	10,000	AlpacaEval 2.0, Arena-Hard

Table 1: **AGORABENCH Settings:** For each of the nine settings, an LM being evaluated generates 10K instances with the same meta-prompt and seed data. Note that the seed dataset is also used for training in instance generation.

tokens. We directly use the generated data D_G without filtering and do not consider other post-training methods, as our goal is to evaluate the raw data generation capabilities of an LM (G) in the most straightforward setting, not to maximize S_{D_G}'s benchmark performance. The hyper-parameters for training are detailed in Appendix E.

3 Experimental Setting of AGORABENCH

Among various choices, AgoraBench focuses on three core capabilities that are considered crucial for LMs: instruction following, mathematical reasoning, and coding (Chang et al., 2024; Guo et al., 2023; Hurst et al., 2024; Anthropic, 2024). The overall experimental setting of AGORABENCH including the domains, seed datasets, and benchmarks for each setting is listed in Table 1.

Domains. AGORABENCH encompasses three domains: math, code, and instruction following. Evaluating three data generation methods across each domain results in nine distinct settings, each with a dedicated seed dataset (D_{seed}) and benchmark (B). For each setting, the LM employed as the data generator produces 10K training instances.

Then, the student model is trained using data from a single domain to isolate the effect of generated data quality, as cross-domain training could introduce confounding factors through positive or negative transfer (*e.g.*, training on code data improve math (Dong et al., 2023; Zhang et al., 2024)).

Seed Datasets. For each setting, we select seed datasets (D_{seed}) based on different assumptions:

- For **instance generation**, since we expand a small amount of high-quality data into a larger volume, our approach is premised on using high-quality, human-crafted data as seed data. Hence, we use the train subsets of GSM8K (Cobbe et al., 2021) and MATH (Hendrycks et al., 2021) for math, MBPP (Austin et al., 2021) and xP3x (Muennighoff et al., 2023b) for code, and LIMA (Zhou et al., 2024) for instruction following. We exclude instances that exceed 4,096 tokens based on the Llama-3 tokenizer, resulting in 14,856, 874, and 503 seed instances for each of the math, code, and instruction following domains, respectively.

- For **response generation**, we simulate how different data generators can attach responses to a fixed set of instructions to ultimately create better quality data. While we could take arbitrary data and discard their responses for experiments, we utilize the Magpie dataset because Xu et al. (2024b)'s setting closely matches our setting - they first extract instructions by prompting LMs with empty chat templates and then generate responses using two different types of LMs (Llama-3-70B-Instruct and Qwen-2-72B-Instruct). In our experiments, we sample 10K instances from the Magpie dataset (Xu et al., 2024b) for the instruction following domain and also 10K instances from the Magpie-Reasoning dataset for both math and code domains.

- For **quality enhancement**, we test scenarios where complete instances of instructions and responses already exist, but their quality needs improvement before being used for post-training - either because the instructions are too simple or the responses are not sufficiently detailed. We sample 10K instances from WebInstruct (Q-A pairs from the web requiring refinement; see Yue et al. (2024)) for instruction following and math domains. Note that WebInstruct does not contain

Data Generator	Instance Generation				Response Generation				Quality Enhancement			
	Math	Code	Inst.	Avg	Math	Code	Inst.	Avg	Math	Code	Inst.	Avg
GPT-4o	**20.6**	**73.6**	**46.1**	**46.8**	46.7	28.5	**30.3**	**35.2**	**21.9**	-8.8	7.1	6.7
GPT-4o-mini	16.1	41.9	18.0	25.3	**48.1**	18.9	13.7	26.9	17.8	-11.2	9.9	5.5
Claude-3.5-Sonnet	8.9	23.4	40.1	24.1	29.0	**44.5**	12.7	28.8	15.7	**16.1**	**21.8**	**17.9**
Llama-3.1-405B	10.4	12.6	7.4	10.1	31.7	35.4	4.9	24.0	-11.8	7.5	3.6	-0.2
Llama-3.1-70B	9.6	58.7	6.5	24.9	23.0	37.1	4.5	21.5	-21.8	6.9	2.7	-4.1
Llama-3.1-8B	6.5	55.7	6.2	22.8	27.6	25.8	5.0	19.4	-1.7	15.4	3.0	5.6

Table 2: **AGORABENCH RESULTS: How much performance could you recover by generating 10K instances with your LLM, compared to Meta's post-training process for training Llama-3.1-8B-Instruct from Llama-3.1-8B?** The best comparable performances (%) are **bolded**, and the second-best performances (%) are underlined. Note that the Llama models are instruction-tuned versions and that 'Inst.' denotes instruction-following.

domain labels, hence we prompt GPT-4o-mini-2024-07-18 to prepare a separate D_{seed} (further details are in Appendix C). For the code domain, we use CoNaLa, which contains simple instructions paired with 1-3 line code snippets from StackOverflow (Yin et al., 2018).

Benchmarks. We evaluate a student model (S_{D_G})'s performance using two representative benchmarks for each domain. For math, we use the test subsets of GSM8K (Cobbe et al., 2021) and MATH (Hendrycks et al., 2021). For code, we use the test set of MBPP (Austin et al., 2021) and HumanEval (Chen et al., 2021). For instruction following, we evaluate on AlpacaEval-2.0 (Dubois et al., 2024) and Arena-Hard (Li et al., 2024).

4 Experimental Results of AGORABENCH

We compare 6 LMs as data generators (G), namely GPT-4o-2024-08-06 (Hurst et al., 2024), GPT-4o-mini-2024-07-18, Claude-3.5-Sonnet-2024-06-20 (Anthropic, 2024), Llama-3.1-405B-Instruct, Llama-3.1-70B-Instruct, and Llama-3.1-8B-Instruct (Dubey et al., 2024). Also, we use Llama-3.1-8B as the student model ($S_{\emptyset}$). The AGORABENCH results are listed in Table 2.

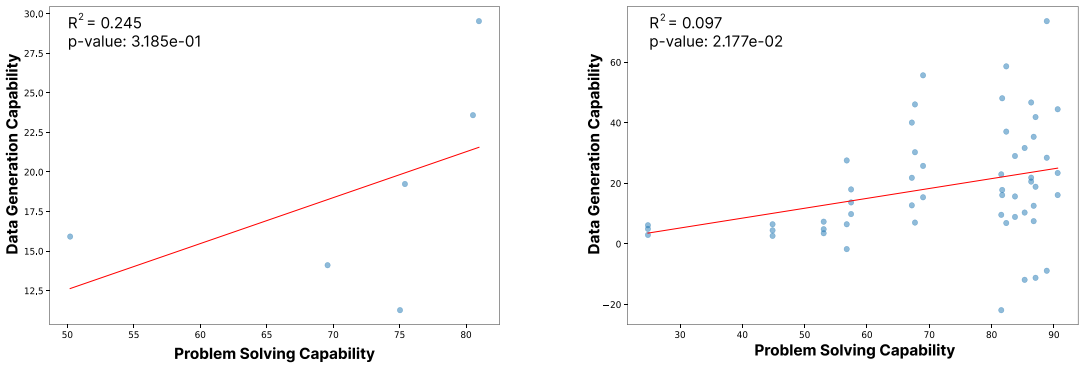
GPT-4o is the overall most performant data generator: Out of the nine experimental settings, GPT-4o achieves the highest PGR scores in five settings. Its performance is particularly notable in instance generation, where it outperforms other LMs as a data generator across all three domains (math at 20.6%, code at 73.6%, instruction following at 46.1%, and total average at 46.8%), while also achieving the highest average PGR score in response generation (35.2%).

Data Generator	API Cost		Prob. Solv.	Data Gen.
	Input	Output	Avg	Agora Bench
GPT-4o	\$2.50	\$10.00	80.9	29.5%
GPT-4o-mini	\$0.15	\$0.60	75.4	19.2%
Claude-3.5-Sonnet	\$3.00	\$15.00	80.5	23.6%
Llama-3.1-405B	\$1.79	\$1.79	75.0	11.3%
Llama-3.1-70B	\$0.35	\$0.40	69.6	14.1%
Llama-3.1-8B	\$0.055	\$0.055	50.2	15.9%

Table 3: **Comparison of API costs, problem-solving ability, and data generation ability:** Our findings reveal that neither the strength nor the cost of an LM guarantees its effectiveness as a data generator. Note that the Llama models are instruction-tuned versions, the specific results of the LMs on each benchmark (averaged as 'Problem Solving average') is in Appendix D, and the AgoraBench results are averaged from Table 2.

Claude-3.5-Sonnet proves particularly effective for quality enhancement: Claude-3.5-Sonnet particularly demonstrates strong performance in quality enhancement, achieving the highest PGR scores in two out of three domains (code at 21.8%, instruction following at 17.9%, and total average at 17.9%). Additionally, it obtains the best PGR score at response generation in the code domain (44.5%), bringing its total number of top performances to three out of nine settings.

Weaker LMs can outperform Stronger LMs: We observe cases where LMs with weaker problem-solving abilities achieve higher Performance Gap Recovered (PGR) scores than their stronger counterparts. In the code domain of instance generation, both Claude-3.5-Sonnet (23.4%) and Llama-3.1-405B-Instruct (12.6%) are outperformed by Llama-3.1-70B-Instruct (58.7%) and Llama-3.1-



Coarse-grained Analysis: Average Scores across all Settings (n=6)

Fine-grained Analysis: Individual Scores per Domain and Generation Setting (n=54)

Figure 4: **Problem-solving and data generation capabilities do not strongly correlate:** Linear regression between problem-solving ability and data generation ability scores at multiple granularity levels yields either low R^2 values ($R^2 < 0.1$) or non-significant relationships ($p > 0.05$), which indicates that it is hard to predict data generation capabilities only using problem-solving capabilities.

8B-Instruct (55.7%). Similarly, in the code domain's quality enhancement setting, GPT-4o (-8.8%) and GPT-4o-mini (-11.2%) show poorer performance compared to other LMs.

Interestingly, as shown in Table 3, the LMs that performed worse for these cases actually score higher on code benchmarks (MBPP and HumanEval), indicating that they possess stronger problem-solving capabilities. This contradiction suggests that a stronger LM does not necessarily generate better training data. We discuss this phenomenon further in Section 5.

GPT-4o, GPT-4o-mini, and Llama-3.1-8B-Instruct are effective data generators that balance both cost and performance: Cost is another crucial factor alongside performance when generating large amounts of synthetic data. Table 3 shows the API costs[3] benchmark scores (*i.e.,* problem-solving ability) and average performance on AGORABENCH (*i.e.,* data generation ability) are listed in Table 3. and average performance on AGORABENCH for all six LMs. Llama-3.1-8B-Instruct outperforms both Llama-3.1-70B-Instruct and Llama-3.1-405B-Instruct while being 6 to 32.5 times less expensive. Similarly, GPT-4o achieves better performance than Claude-3.5-Sonnet at 1.2 to 1.5 times lower cost. These findings suggest that using more expensive LMs does not necessarily guarantee better data generation, highlighting the importance of careful model selection based on specific tasks or domains of interest.

[3]Pricing is based on https://openrouter.ai/.

5 What makes an effective data generator?

In the previous section, we observed an unexpected finding: LMs with weaker problem-solving ability sometimes outperform stronger LMs when generating the same amount of synthetic data under identical conditions. For a better understanding, we examine whether there exists a strong correlation between problem-solving ability and data generation ability (Section 5.1). Then we investigate whether we can predict the degree of improvement in the performance of the student model by analyzing the data generated by each LM (Section 5.2).

5.1 Is the best solver necessarily the best generator?

To examine the relationship between data generation and problem-solving capabilities, we performed linear regression analyses comparing two metrics: average performance on multiple benchmarks (GSM8K, MATH, MBPP, HumanEval, AlpacaEval-2.0, Arena-Hard) and scores from AGORABENCH. We conduct this analysis at two levels of granularity. The first analysis (coarse-grained) uses the overall average AGORABENCH score across all domains and data generation settings. The second analysis (fine-grained) examines individual scores from different domains and data generation settings in AGORABENCH separately.

The results shown in Figure 4 reveal no strong linear correlation between problem-solving capabilities (benchmark scores) and data generation

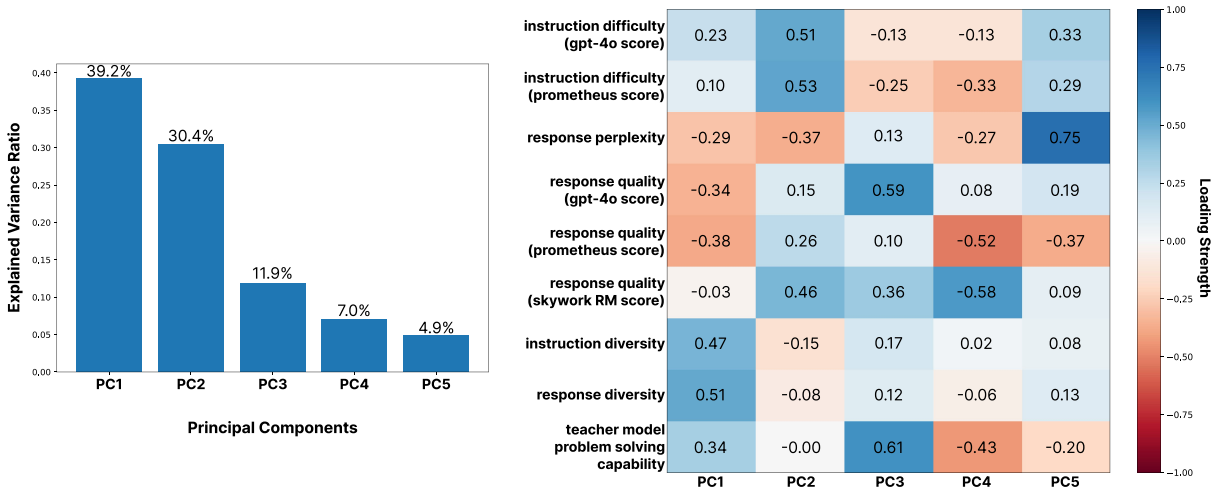


Figure 5: Through a PCA analysis on multiple intrinsic evaluation metrics, we find that there exists **interpretable** low-dimension principal components that **explain** the variance of data generation capabilities up to 93.4%.

capabilities (AGORABENCH PGR scores) at either granularity level. This finding suggests that an LM's performance on traditional benchmarks may not predict its effectiveness as a data generator.

5.2 Can we predict the student model's improvement by looking into the data?

Given that problem-solving ability does not directly predict data generation ability, we explore what other characteristics might define effective data generators. We hypothesize that good data capable of substantially improving student models share extractable features that can be identified by analyzing their intrinsic properties. This understanding is crucial as it informs us of what properties the data from a good data generator might possess. Inspired by Liu et al. (2023b), we conduct an intrinsic evaluation by analyzing various properties of the generated data D_G.

Intrinsic Evaluation Metrics We evaluate (1) the complexity of the instruction I_i (2) the quality of response R_i, (3) the perplexity of R_i using the student model $S_\emptyset$, (4) the diversity of both instructions and responses separately:

- **Response Quality** : We measure the quality of R_i given I_i. First, we use **LLM-as-a-Judge** where we prompt an LM to return a discrete score between 1 and 5 that represents the quality of R_i. We employ two LM judges: (1) Prometheus-2-8x7B (Kim et al., 2024), an open-source LM specialized on assessing LM output and (2) GPT-4o, a proprietary LM widely used as a judge. We use different score rubrics for each domain, listed in Appendix H. Next, we use **Reward Models** that predicts a scalar value score that represents the quality of R_i. We use Skywork-Reward-Llama-3.1-8B (Liu et al., 2024a), one of the top performing reward models on Reward Bench (Lambert et al., 2024).

- **Instruction Complexity (LLM-as-a-Judge Score)**: We measure the difficulty of I_i by prompting an LM to return a discrete score between 1 and 5 that represents the complexity of I_i. Similarly to evaluating response quality, we use Prometheus-2-8x7B and GPT-4o as a judge. The score rubric differs compared to that for evaluating response quality and we use a different score rubrics for each domain, listed in Appendix H.

- **Perplexity of Response**: We measure the **perplexity** of R_i conditioned on I_i using the base model $S_\emptyset$ (Llama-3.1-8B).

- **Instance Diversity**: We separately measure the average **cosine similarity** of instructions within $D_I = \{(I_i) \mid i = 1, \ldots, n\}$ and responses within $D_R = \{(R_i) \mid i = 1, \ldots, n\}$. This represents the extent to which each instruction or response is widely distributed (*i.e.*, diverse) (Ni et al., 2024). We use `dunzhang/stella_en_400M_v5`, a model that is both high-performing on the MTEB benchmark (Muennighoff et al., 2023a) and efficient.

Due to page limits, the full results of the intrinsic evaluation are further detailed in Appendix F.

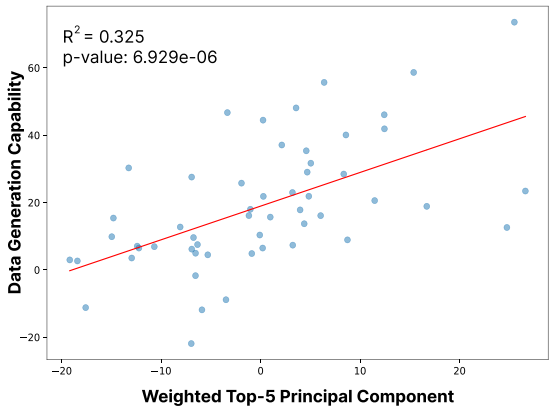


Figure 6: **Principal Components from Intrinsic Metrics Show Stronger Correlation with Data Generation ability:** Linear regression using the weighted top-5 principal components yields a higher explained variance (R^2 = 0.325) and statistical significance ($p < 0.001$) compared to using problem-solving ability scores alone ($R^2 < 0.1$ or $p > 0.05$; see Figure 4).

Intrinsic Metric	Loading Strength	Contribution
Prometheus Score (R.Q.)	0.256	12.18%
Response Perplexity	0.252	12.00%
GPT-4o Score (R.Q.)	0.246	11.71%
Problem-solving Ability	0.240	11.42%
Skywork-RM Score (R.Q.)	0.239	11.38%
Prometheus Score (I.D.)	0.230	10.95%
Diversity (I.D.)	0.226	10.76%
GPT-4o Score (I.D.)	0.223	10.61%
Diversity (R.Q.)	0.189	9.00%

Table 4: **Mean Contributions of Intrinsic Metrics to Principal Components:** Each **loading strength** represents the average magnitude of a feature's loadings across all principal components and the **contribution** are normalized values to represent the relative percentage of each feature's loading strength in the overall component structure. 'I.D.' refers to instruction difficulty metrics and 'R.Q.' refers to response quality metrics.

Experiments Inspired by the experiments from Ruan et al. (2024), we conduct a Principal Component Analysis (PCA) to investigate whether intrinsic evaluation metrics can explain the variability in AGORABENCH results. We opt for PCA rather than multivariate linear regression due to the interdependence among our intrinsic evaluation metrics.

The results, shown in Figure 5, reveal that the top five principal components explain approximately 93.4% of the variance in AGORABENCH results (39.2%, 30.4%, 11.9%, 7.0%, and 4.9% respectively). Moreover, we find that analysis of the component weights reveals interpretable patterns. The first principal component (PC-1) is strongly influenced by instruction difficulty and diversity-related metrics. The second component (PC-2) is affected by response quality and instruction difficulty, while the third component (PC-3) combines diversity-related metrics, response quality, and the LM's problem-solving ability.

Additionally, as shown in Table 4, when we analyze the average loading strengths of each intrinsic evaluation metric (average magnitude of a feature's loadings across all principal components, indicating how strongly each metric influences the overall variance in the data), we observe that the contributions range from 0.189 to 0.256, indicating that all the intrinsic evaluation metrics contribute similarly to the PGR results. Also, we find that response quality-related metrics shows slightly stronger contributions than diversity-related metrics or instruction difficulty-related metrics to the PGR results.

Lastly, we predict data generation capabilities by performing linear regression on the top-5 principal components, weighting each component by its corresponding regression coefficient, as shown in Figure 6. Compared to using problem-solving scores alone (Figure 4), this approach yields a statistically significant relationship ($p < 0.001$) with improved explanatory power ($R^2 = 0.325$). However, the moderate R^2 value suggests that additional intrinsic metrics beyond our current set might be needed to better predict data generation capabilities.

6 Conclusion

In this paper, we introduce AGORABENCH, a benchmark that systematically evaluates LMs' data generation capabilities through standardized settings and metrics. Looking ahead, we envision AGORABENCH enabling two key advances in the field. First, since our findings suggest that problem-solving ability is not the primary determinant of data generation quality, researchers can use our benchmark to identify the core capabilities that make an effective data generator and potentially develop specialized LMs specialized in data generation. Second, AGORABENCH can serve as a practical evaluation framework for practitioners to assess and improve their data generation pipelines - they can use their custom data generation methods, seed datasets, or meta-prompts and compare against our baseline settings. Through these complementary research and applied directions, AGORABENCH aims to accelerate both our theoretical understanding of language models as data generators and their practical deployment in real-world applications.

Limitations & Potential Risks

Due to compute constraints and expensive API costs, the experimental setting of AGORABENCH does not cover the scenarios where (1) different base models beyond Llama-3.1-8B are used and (2) whether our findings will hold when generating more than 10K instances.

Regarding the first limitation, while Llama-3.1-8B is widely adopted as a base model in the community, making our findings particularly relevant for researchers working with similar architectures, investigating the generalizability of our results across different base models remains an important direction for future research. Of particular interest is the variation in response perplexity—one of our intrinsic evaluation metric—across different model architectures, as this metric's behavior is inherently dependent on the base model.

For the second limitation, we conducted preliminary scaling experiments with more cost-effective language models (GPT-4-mini, Llama-3.1-70B-Instruct, and Llama-3.1-8B-Instruct) generating up to 50K instances, as detailed in Appendix B. Future work could explore whether the relative effectiveness rankings among different data generators remain consistent at larger scales, and investigate potential scaling laws in relation to our proposed Performance Gap Recovered metric. Such analysis could provide valuable insights into the optimal volume of synthetic data required for specific applications and model architectures.

Synthetic data holds significant potential in aligning LMs towards human preferences and controlling their behavior. While our study primarily focuses on improvements in mathematical reasoning, coding capabilities, and instruction following abilities, the broader implications for model alignment and control warrant careful consideration. Future work could explore these aspects more explicitly, particularly investigating how synthetic data generation techniques might influence model behavior beyond task performance, including potential biases, safety considerations, and the robustness of aligned behaviors across different contexts and applications. Lastly, we note that the synthetic data generated in our paper is dependent on the terms of use from LM providers: OpenAI, Anthropic, and Meta and that we used Claude-3.5-Sonnet to improve the fluency and grammar of our paper.

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A Related Work

Conventionally, training LMs on human-crafted data was considered the de facto standard for improving an LM's performance on downstream tasks (Mishra et al., 2022; Wei et al., 2021; Wang et al., 2022; Longpre et al., 2023). Yet, based on the in-context learning abilities of LMs (Brown et al., 2020), a series of works demonstrated that LMs could generate novel instances that could be used as post-training data (Wang et al., 2023; Honovich et al., 2022; Kim et al., 2023a).

Since then, different works have proposed various data generation methods and prompts to acquire high-quality data, using stronger LMs as data generators. For instance, Taori et al. (2023) used the same data generation method as Wang et al. (2023), but employed InstructGPT instead of GPT-3-Davinci and trained Llama-1 instead of T5. Xu et al. (2024a) used ChatGPT as their data generator and proposed a method called Evol-Instruct that prompts the data generator to make an existing problem more complex than the original. Mukherjee et al. (2023) used GPT-4 to generate data and improved the original response by adding a chain-of-thought explanation of how the answer was derived. Xu et al. (2024b) proposed Magpie, a data generation method that first prompts an LM with an empty chat template to extract instructions, then iteratively prompts it to generate corresponding responses.

While developing new data generation methods is important, choosing which LM to use as a data generator is an equally crucial problem for both researchers and practitioners. To the best of our knowledge, Xu et al. (2024c), a contemporary work with our work, was the first attempt to measure various LMs' data generation capabilities using existing data generation methods. Yet, their settings were confined to our 'response generation' method, whereas we also tested instance generation and quality enhancement methods.

B Further Analysis Experiments

In this section, we further examine, two critical questions regarding data generation: (1) Should we prioritize quantity using cheaper LMs, or quality using more expensive ones? (Section B.1) And (2) What is the impact of meta-prompt design, particularly when comparing structured JSON format generation against traditional free-form approaches? (Section B.2).

B.1 Quantity or quality?

In Section 4, we demonstrated that in some cases, cheaper LMs can be more effective data generators than their expensive counterparts when producing a fixed number of instances, though expensive models generally perform better. This raises a practical question: Is it more effective to generate a larger quantity of instances using cheaper models rather than fewer instances with more expensive ones?

We scale up our experiment to generate up to 50K instances using GPT-4o-mini, Llama-3.1-70B-Instruct, and Llama-3.1-8B-Instruct across three domains in the instance generation scenario. As shown in Figure 7, generating 50K instances with GPT-4o-mini resulted in better performance than generating 10K instances with GPT-4o at instruction following and math domains and Llama-3.1-8B-Instruct showed similar patterns in code domain. Given that these LMs are at least five times more cost-effective than GPT-4o, our findings suggest that generating larger volumes of synthetic data with more affordable LMs may be more advantageous than generating smaller datasets with expensive ones. Furthermore, this suggests that instruction diversity or response diversity could affect the PGR results when comparing two settings with different number of training instances.

B.2 Effect of Meta-prompts

Recently, Tam et al. (2024) has shown that LMs' problem-solving abilities decrease when generating responses in structured formats (e.g., JSON). Given practitioners' preference for structured outputs when using LMs (Shorten et al., 2024; Liang et al., 2024) it's important to investigate whether this format affects data generation performance. Additionally, we examine the impact of meta-prompt design on generation quality.

To investigate these questions, we create four additional meta-prompts for comparison. For each setting (instance generation and quality enhancement), we had two co-authors create meta-prompts: one developed an unoptimized version (spending less than 10 minutes)[4], while the other created a JSON-format version.

Table 5 presents our findings. Compared to the other meta-prompts, the AGORABENCH meta-prompt achieves the highest scores in five out of six

[4]This contrasts with the main experiments' meta-prompts, which were developed over 2+ hours through iterative trial-and-error during the initial experimental phase.

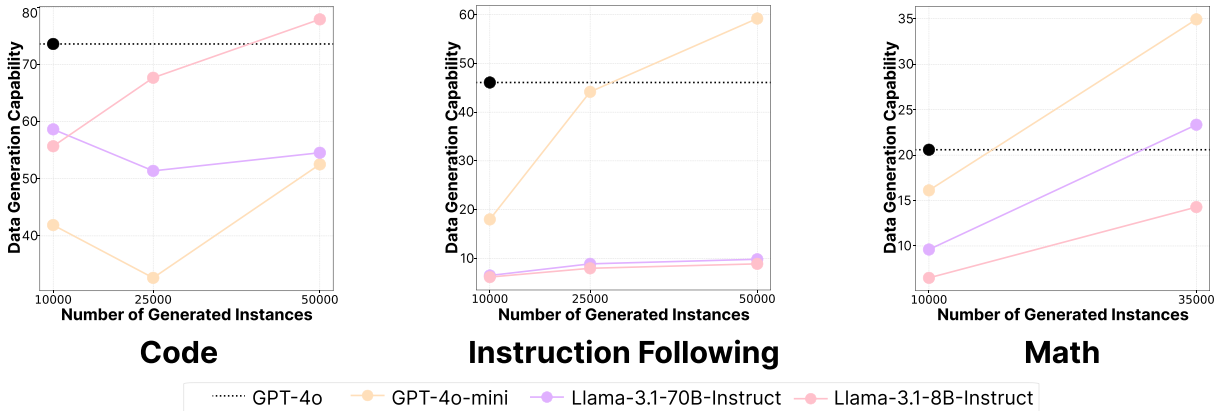

Figure 7: **With a fixed budget, generating large amounts of data with weaker LMs could sometimes be more effective and cheaper than generating a few instances with stronger LMs:** Since GPT-4o-mini is 17 times cheaper than GPT-4o, generating 50K instances is 3.4 times cheaper than generating 10K instances with GPT-4o. Yet, generating 50K instances with GPT-4o-mini achieves higher PGR in instruction following and math domains compared to generating 10K instances with GPT-4o.

Data Generator	AGORABENCH Meta-prompt				Unoptimized Meta-prompt				JSON-format Meta-prompt			
	Math	Code	Inst.	Avg	Math	Code	Inst.	Avg	Math	Code	Inst.	Avg
Instance Generation												
GPT-4o-mini	16.1	41.9	18.0	25.3	12.4	36.8	17.6	22.3	13.8	20.5	19.5	17.9
Llama-3.1-70B	9.6	58.7	6.5	24.9	7.0	46.8	5.8	19.9	8.7	33.5	6.1	16.1
Llama-3.1-8B	6.5	55.7	6.2	22.8	0.7	43.6	4.5	16.3	6.7	31.4	4.4	14.2
Quality Enhancement												
GPT-4o-mini	17.8	-11.2	9.9	5.5	13.0	-6.3	9.4	5.4	15.4	-13.0	9.2	3.8
Llama-3.1-70B	-21.8	6.9	2.7	-4.1	-20.5	-5.5	2.3	-7.9	-18.3	6.5	2.4	-3.1
Llama-3.1-8B	-1.7	15.4	3.0	5.6	-6.6	3.7	3.5	0.2	-2.7	12.0	3.9	4.4

Table 5: **Performance Gap Recovered (%) results with different meta-prompts on instance generation and quality enhancement**. Llama models are instruction-tuned versions and that 'Inst.' denotes instruction-following.

settings, demonstrating the robustness of the setting in AGORABENCH. Comparing the AGORABENCH meta-prompts with unoptimized versions reveals a 3.97% performance gap on average, highlighting the importance of meta-prompt optimization. Furthermore, AGORABENCH meta-prompts using free-form generation achieve 4.45% higher performance compared to JSON-format prompts. This aligns with recent findings that structured format requirements may compromise LM output quality (Tam et al., 2024).

C Response Generation Seed Dataset Construction

In AGORABENCH, we prepare seed datasets for each domain (instruction-following, math, code) separately in order to prevent positive or negative transfer that occurs during training, which could make it difficult to ground the PGR results to the quality of the synthetic data and LMs' data generation capabilities.

We use the WebInstruct data (Yue et al., 2024) for math and instruction-following domains in quality enhancement settings. However, the WebInstruct data does not provide labels of whether the given instance is a math problem or not. Hence, we prompted GPT-4o-mini-2024-07-18 to classify it using the following prompt:

Inference Hyper-parameter	
Temperature	0.2 (math) & 0.0 (other domains)
Top_p	0.95
Max New Tokens	1024
Repetition Penalty	1.03
Training Hyper-parameter	
Base Model	meta-llama/Llama-3.1-8B
Torch dtype	bfloat16
Epoch	5
Max Seq Length	4096
Learning Rate	1e-5
Train Batch Size	4
Gradient Accumulation	8
GPU	H100 (80GB) x 4
Random Seed	42
Training Method	Supervised Fine-tuning

Table 6: Hyper-parameters used for inference.

Domain classification for seed data construction

Classify whether the following ”Instance“ consisted of an ”Instruction“ and ”Response“ is either related to:
1. Math-related task such as requiring an answer to a problem, proving a theorem or explaining about a mathematical concept.
2. Other tasks

Provide your answer in only either ”1“ or ”2“, without any greeting message or comment.

Instance:
Instruction: <input>
Response: <output>

Decision:

D Problem Solving Abilities of LMs evaluated as Data Generators

The evaluation results of GPT-4o-2024-08-06, GPT-4o-mini-2024-07-18, Claude-3.5-Sonnet-2024-06-20, Llama-3.1-405B-Instruct, Llama-3.1-70B-Instruct, and Llama-3.1-8B-Instruct are listed in Table 7. We use the settings listed in Appendix E.

E Details for Training and Evaluating Student Models

The hyper-parameters used for training student models and hyper-parameters used for evaluating both student models and LMs employed as the data generator are listed in Table 6.

For evaluation on MBPP and HumanEval, we use the Evalplus library (Liu et al., 2023a). For evaluation on AlpacaEval and ArenaHard, we use the official library, respectively (Dubois et al., 2024; Li et al., 2024). For GSM8K and MATH, we use the datasets provided in huggingface and use our manual script. All the evaluation scripts are publicly available at our repository.

F Intrinsic Evaluation of AgoraBench

The intrinsic evaluation results are listed in Table 8.

G AgoraBench Meta-prompts

Due to space limits, we present the meta-prompts in our repository and the following link.

H Prompt for Intrinsic Evaluation

In the following pages, we list the prompt used for assessing response quality and instruction difficulty with GPT-4o and Prometheus-2-8x7B as well as the score rubrics for used for each domain (instruction-following, math, code).

Evaluation Prompt for Response Quality and Instruction Difficulty

###Task Description:
An instruction (might include an Input inside it), a response to evaluate, and a score rubric representing a evaluation criteria are given.
1. Write a detailed feedback that assess the quality of the response strictly based on the given score rubric, not evaluating in general.
2. After writing a feedback, write a score that is an integer between 1 and 5. You should refer to the score rubric.
3. The output format should look as follows: "Feedback: (write a feedback for criteria) [RESULT] (an integer number between 1 and 5)"
4. Please do not generate any other opening, closing, and explanations.
###The instruction to evaluate:
{instruction}
###Response to evaluate:
{response}
###Score Rubric: {score_rubric}
###Feedback:

Math Response Quality Score Rubirc

Does the solution demonstrate mathematical correctness, reasoning, clarity, and precision?
Score 1 Description: The solution is incorrect or mathematically flawed, with major errors in reasoning, calculations, or logic, making the answer unusable.
Score 2 Description: The solution contains relevant or partially correct information, but has significant errors in calculations or reasoning that substantially affect the result.
Score 3 Description: The solution is mostly correct but may contain minor mistakes or gaps in reasoning. The overall structure and approach are sound, but some calculations or logic may need refinement.
Score 4 Description: The solution is correct, well-reasoned, and clear, though there may be slight room for improvement or minor refinements to become a perfect solution to the problem.
Score 5 Description: The solution is excellent, fully correct, and demonstrates a high level of mathematical precision, clarity, and creativity, with well-articulated reasoning and no errors.

Instruction-following Response Quality Score Rubric

Does the response consider a wide range of factors such as the helpfulness, relevance, accuracy, depth, creativity, and level of detail?

Score 1 Description: The response is not helpful at all or seems helpful on the surface but is actually incorrect such as including incorrect information, naive miscalculations, or unexecutable code.
Score 2 Description: The response contains some relevant or helpful information, but also has major flaws interms of factuality, accuracy, and relevance.
Score 3 Description: The response is mostly correct but minor flaws regarding factuality, accuracy, and relevance still exists, while it is overall an okay response.
Score 4 Description: The response is accurate, relevant, and helpful, although there are some slight improvements that could be made when an expert evaluates the response.
Score 5 Description: The response is excellent. It is completely factual, accurate, relevant, and helpful, demonstrating a high degree of depth and creativity.

Code Response Quality Score Rubric

How effective, efficient, and logically sound is the code solution, focusing on performance, executability, and correctness?

Score 1 Description: The code contains fundamental logic or syntax errors, making it incorrect or unexecutable. It fails to complete the intended task or produces entirely incorrect outputs.
Score 2 Description: The code is partially functional but contains major logic errors or inefficiencies that significantly impact performance or correctness. It may run but produces incorrect or incomplete results.
Score 3 Description: The code is mostly correct and executable, though there may be minor logic issues, inefficiencies, or suboptimal use of data structures or algorithms. The solution functions as intended, but improvements could make it more efficient or robust.
Score 4 Description: The code is fully correct, functional, and reasonably efficient. It completes the task as intended, balancing performance with logical soundness. Minor optimizations could still enhance performance.
Score 5 Description: The code is fully correct, optimally efficient, and logically robust, providing the best possible performance for the task. It executes flawlessly without errors or any significant room for improvement.

Instruction-following Instruction Difficulty Score Rubric

How complex and challenging is the given instruction to answer perfectly?

Score 1 Description: The instruction requires only factual knowledge, without any need for reasoning or critical thinking. A straightforward, single-step response suffices.
Score 2 Description: The instruction requires some reasoning, such as explaining a concept involving multiple simple ideas, solving a straightforward problem, or providing a response that involves a few logical steps, though still simple in nature.
Score 3 Description: The instruction requires a substantial amount of reasoning and the integration of multiple related concepts. Answering it accurately involves a multi-step process and may require intermediate-level knowledge or analytical thinking.
Score 4 Description: The instruction requires advanced reasoning, demanding deep understanding of complex concepts or substantial problem-solving. Answering it requires carefully navigating multiple interrelated ideas or steps, often involving specialized knowledge or sophisticated analytical skills.
Score 5 Description: The instruction is exceptionally challenging and requires high-level reasoning or novel problem-solving. It involves extensive conceptual understanding, abstraction, and potentially innovative thinking, with substantial effort required to arrive at an accurate and complete answer.

Math Instruction Difficulty Score Rubric

How complex and challenging is the math problem to solve?

Score 1 Description: The problem requires only simple operations or direct application of a single, basic concept. Minimal reasoning is needed, and the solution follows immediately from applying a known rule or formula.
Score 2 Description: The problem requires basic reasoning and involves applying a familiar formula or concept with slight variation. It may involve a straightforward multi-step process, but each step is clear and relies on commonly used methods.
Score 3 Description: The problem requires moderate reasoning, combining multiple concepts that interact in a meaningful way. Solving it involves several steps and may require logical sequencing or some abstraction, but the approach is approachable with a solid foundational understanding.
Score 4 Description: The problem demands advanced reasoning, involving multiple interdependent concepts that require careful coordination. Solution steps are less obvious, requiring critical thinking and possibly choosing between multiple solution paths. Solving the problem involves more abstract reasoning or creative application of concepts.
Score 5 Description: The problem is extremely complex and demands sophisticated reasoning and problem-solving skills. It may involve novel combinations of concepts, intricate logical chains, or innovative approaches to solve. This level typically requires significant abstraction, exploration of unconventional methods, and flexibility in adapting mathematical tools.

Code Instruction Difficulty Score Rubric

How complex and challenging is the coding problem to solve?

Score 1 Description: The problem involves implementing simple functionality or a direct operation. It requires minimal logic, with a straightforward approach and no complex decision-making.
Score 2 Description: The problem requires basic control flow, such as using loops or conditional statements. The logic is clear and sequential, with minimal interaction between different parts of the code.
Score 3 Description: The problem involves intermediate logic, combining multiple programming constructs and requiring a coherent structure. Solving it requires handling a sequence of steps with basic data manipulation, but follows a familiar, manageable approach.
Score 4 Description: The problem demands advanced reasoning and use of complex data structures or algorithms. It involves non-trivial interactions, such as managing multiple components and optimizing for efficiency. The solution requires significant algorithmic thinking and structured problem decomposition.
Score 5 Description: The problem is extremely complex, requiring sophisticated algorithm design, efficient data handling, and advanced techniques. It demands innovative approaches, with intricate component interactions and constraints that need careful optimization. Solving it typically requires deep problem-solving skills and adaptability across programming paradigms.

Data Generator	Problem-solving ability						
	GSM8K	MATH	MBPP	Human Eval	Alpaca Eval 2.0	Arena Hard	Average
GPT-4o	96.1	76.6	86.2	91.5	57.5	77.9	80.9
GPT-4o-mini	93.2	70.2	85.7	88.4	50.7	64.2	75.4
Claude-3.5-Sonnet	96.4	71.1	89.2	92.0	52.4	82.0	80.5
Llama-3.1-405B	96.8	73.8	84.5	89.0	39.3	66.8	75.0
Llama-3.1-70B	95.1	68.0	84.2	80.5	38.1	51.6	69.6
Llama-3.1-8B	78.9	34.6	68.5	69.5	24.2	25.5	50.2

Table 7: Problem-solving abilities of LMs measured by benchmark scores.

Data Generator	Instance Generation				Response Generation				Quality Enhancement			
	Math	Code	Inst. Follow	Avg	Math	Code	Inst. Follow	Avg	Math	Code	Inst. Follow	Avg
Instruction Difficulty (LLM-as-a-Judge; GPT-4o Score)												
GPT-4o (2024-08-06)	2.92	3.48	3.06	3.16	2.27	2.21	1.41	1.97	2.44	1.51	1.79	1.91
GPT-4o-mini (2024-07-18)	2.38	3.42	2.89	2.90	2.27	2.21	1.41	1.97	2.47	1.38	1.81	1.89
Claude-3.5-Sonnet (2024-06-20)	3.24	4.03	3.54	3.60	2.27	2.21	1.41	1.97	2.47	1.52	1.83	1.94
Llama-3.1-405B-Instruct	2.74	3.50	2.87	3.04	2.27	2.21	1.41	1.97	2.45	1.47	1.85	1.92
Llama-3.1-70B-Instruct	2.87	3.45	2.96	3.09	2.27	2.21	1.41	1.97	2.48	1.49	1.87	1.95
Llama-3.1-8B-Instruct	3.00	3.52	3.08	3.20	2.27	2.21	1.41	1.97	2.43	1.49	1.83	1.92
Instruction Difficulty (LLM-as-a-Judge; Prometheus-2-8x7B Score)												
GPT-4o (2024-08-06)	3.73	3.57	3.95	3.75	3.00	2.76	2.24	2.67	3.37	2.14	2.50	2.67
GPT-4o-mini (2024-07-18)	3.44	3.38	3.94	3.59	3.00	2.76	2.24	2.67	3.36	1.98	2.53	2.63
Claude-3.5-Sonnet (2024-06-20)	4.11	4.51	4.45	4.36	3.00	2.76	2.24	2.67	3.38	2.24	2.61	2.74
Llama-3.1-405B-Instruct	3.63	3.27	3.84	3.58	3.00	2.76	2.24	2.67	3.35	2.11	2.64	2.70
Llama-3.1-70B-Instruct	3.72	3.43	3.94	3.69	3.00	2.76	2.24	2.67	3.32	2.21	2.76	2.76
Llama-3.1-8B-Instruct	3.86	3.48	3.99	3.78	3.00	2.76	2.24	2.67	3.30	2.09	2.67	2.68
Instruction Difficulty (Perplexity)												
GPT-4o (2024-08-06)	2.13	1.28	3.44	2.28	2.26	4.23	3.41	3.30	2.03	3.60	3.83	3.15
GPT-4o-mini (2024-07-18)	2.05	1.31	3.32	2.23	2.28	2.12	3.20	2.53	2.08	5.50	3.97	3.85
Claude-3.5-Sonnet (2024-06-20)	2.04	1.34	3.18	2.19	2.16	3.48	3.63	3.09	1.99	2.46	3.04	2.50
Llama-3.1-405B-Instruct	1.96	1.29	2.19	1.81	1.90	1.91	2.42	2.08	2.10	3.10	3.90	3.03
Llama-3.1-70B-Instruct	1.78	1.27	2.19	1.74	1.86	1.72	2.52	2.03	2.12	2.84	3.98	2.98
Llama-3.1-8B-Instruct	1.83	1.33	2.08	1.74	1.98	1.81	2.48	2.09	2.06	3.17	3.98	3.07
Response Quality (LLM-as-a-Judge; GPT-4o Score)												
GPT-4o (2024-08-06)	3.72	3.95	4.42	4.03	3.99	3.79	4.44	4.07	3.62	3.66	3.99	3.76
GPT-4o-mini (2024-07-18)	3.96	3.96	4.35	4.09	3.85	3.76	4.41	4.01	3.57	3.22	3.96	3.58
Claude-3.5-Sonnet (2024-06-20)	3.39	4.03	4.34	3.92	3.80	3.75	4.24	3.93	3.64	3.77	4.29	3.90
Llama-3.1-405B-Instruct	3.20	3.74	4.13	3.69	3.51	3.76	4.29	3.85	3.36	3.37	3.80	3.51
Llama-3.1-70B-Instruct	2.97	3.59	4.12	3.56	3.31	3.65	4.22	3.72	3.23	3.22	3.80	3.42
Llama-3.1-8B-Instruct	1.99	2.51	3.82	2.77	2.90	3.26	4.17	3.44	3.05	2.76	3.52	3.11
Response Quality (LLM-as-a-Judge; Prometheus-2-8x7B Score)												
GPT-4o (2024-08-06)	3.93	3.49	4.07	3.83	4.02	3.28	3.97	3.76	3.98	3.28	3.69	3.65
GPT-4o-mini (2024-07-18)	4.05	3.46	4.04	3.85	3.96	3.39	3.93	3.76	3.92	3.04	3.73	3.57
Claude-3.5-Sonnet (2024-06-20)	3.95	3.37	4.04	3.78	3.94	3.29	3.83	3.69	4.00	3.48	4.03	3.84
Llama-3.1-405B-Instruct	3.76	3.24	3.92	3.64	3.81	3.42	3.91	3.71	3.78	3.23	3.66	3.56
Llama-3.1-70B-Instruct	3.68	3.36	3.91	3.65	3.73	3.37	3.86	3.65	3.73	3.20	3.62	3.52
Llama-3.1-8B-Instruct	3.22	3.06	3.81	3.36	3.62	3.24	3.88	3.58	3.68	3.08	3.49	3.42
Response Quality (Reward Model; Skywork-RM-8B Score)												
GPT-4o (2024-08-06)	13.90	23.20	27.79	21.63	8.82	-0.10	8.60	5.77	4.86	-7.48	-4.73	-2.45
GPT-4o-mini (2024-07-18)	5.74	-1.18	7.80	4.12	13.71	23.74	20.71	19.39	3.42	-12.93	-5.16	-4.89
Claude-3.5-Sonnet (2024-06-20)	10.67	20.22	18.20	16.36	5.56	1.67	0.17	2.46	6.29	-5.31	10.76	3.92
Llama-3.1-405B-Instruct	-0.50	19.54	13.63	10.89	-1.23	2.68	10.65	4.03	-1.89	-10.43	-7.35	-6.56
Llama-3.1-70B-Instruct	-2.17	20.42	11.22	9.83	-3.26	2.17	5.85	1.59	-3.04	-11.54	-8.60	-7.72
Llama-3.1-8B-Instruct	-7.71	7.16	3.45	0.97	-3.89	-1.53	8.72	1.10	-3.68	-12.61	-10.15	-8.81
Instruction Diversity (c-dist)												
GPT-4o (2024-08-06)	0.4170	0.4640	0.3047	0.3952	0.3737	0.3958	0.3386	0.3694	0.4263	0.4870	0.2943	0.4025
GPT-4o-mini (2024-07-18)	0.4091	0.5127	0.3013	0.4077	0.3737	0.3958	0.3386	0.3694	0.4270	0.4670	0.2956	0.3965
Claude-3.5-Sonnet (2024-06-20)	0.4124	0.4872	0.2940	0.3979	0.3737	0.3958	0.3386	0.3694	0.4307	0.4903	0.2921	0.4044
Llama-3.1-405B-Instruct	0.3996	0.5411	0.2789	0.4065	0.3737	0.3958	0.3386	0.3694	0.4344	0.4796	0.3033	0.4058
Llama-3.1-70B-Instruct	0.4003	0.5015	0.2682	0.3900	0.3737	0.3958	0.3386	0.3694	0.4232	0.4756	0.3018	0.4022
Llama-3.1-8B-Instruct	0.4201	0.4785	0.2956	0.3981	0.3737	0.3958	0.3386	0.3694	0.4302	0.4619	0.2984	0.3968
Response Diversity (c-dist)												
GPT-4o (2024-08-06)	0.4564	0.5347	0.2918	0.4276	0.4126	0.4719	0.2714	0.3853	0.4455	0.5065	0.2271	0.3930
GPT-4o-mini (2024-07-18)	0.4558	0.5719	0.2814	0.4364	0.4095	0.4726	0.2811	0.3877	0.4577	0.5184	0.2257	0.4006
Claude-3.5-Sonnet (2024-06-20)	0.4719	0.5648	0.3220	0.4529	0.4156	0.4647	0.2788	0.3864	0.4610	0.5141	0.2325	0.4025
Llama-3.1-405B-Instruct	0.4490	0.6122	0.2523	0.4378	0.4037	0.4737	0.2551	0.3775	0.4633	0.5155	0.2239	0.4009
Llama-3.1-70B-Instruct	0.4520	0.5771	0.2596	0.4296	0.4012	0.4784	0.2530	0.3775	0.4571	0.5134	0.2233	0.3979
Llama-3.1-8B-Instruct	0.4768	0.5651	0.2660	0.4360	0.4077	0.4778	0.2530	0.3795	0.4738	0.5143	0.2254	0.4045

Table 8: Intrinsic evaluation results of AGORABENCH.