HighMATH: Evaluating Math Reasoning of Large Language Models in Breadth and Depth

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Abstract

With the rapid development of large language models (LLMs) in math reasoning, the accuracy of models on existing math benchmarks has gradually approached 90% or even higher. More challenging math benchmarks are hence urgently in need to satisfy the increasing evaluation demands. To bridge this gap, we propose HighMATH. Problems in HighMATH are collected according to 3 criteria: problem complexity, knowledge domain diversity and fine-grained annotations. We collect 5,293 problems from Chinese senior high school mathematics exams published in 2024, covering 8 subjects and 7 levels of difficulty, with each problem involving an average of more than 2.4 knowledge points. We conduct a thorough evaluation of latest LLMs on the curated HighMATH, including o1-like models. Evaluation results demonstrate that the accuracy of advanced LLMs on HighMATH is significantly lower than that on previous math reasoning benchmarks. Even with the use of majority voting and a Python executor, the highest accuracy does not exceed 62% on HighMATH. Our results also suggest that properly trained smaller LLMs may have great potential in math reasoning.

1 Introduction

LLMs have achieved significant progress in math reasoning (Li et al., 2024). When the challenging MATH (Hendrycks et al., 2021b) benchmark was initially proposed for evaluation, the accuracy of LLMs did not reach 20%. However, in just three years, LLMs are capable of achieving over 60% accuracy (Yang et al., 2024). Recently, with the emergence and application of techniques such as automatic process supervision (Wang et al., 2024), test-time scaling (Qi et al., 2024; Chen et al., 2024), and reinforcement learning (Rafailov et al., 2023; Ouyang et al., 2022), many models even achieve or exceed 90% accuracy on MATH (DeepSeek-AI et al., 2025). This rapid development of LLMs in math reasoning indicates that existing math benchmarks are no longer sufficient to evaluate and differentiate latest LLMs.

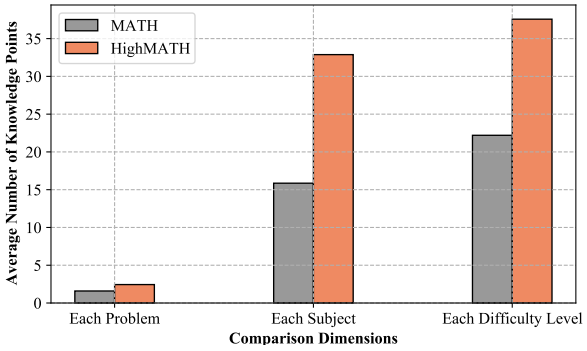

Figure 1: Comparison of HighMATH vs MATH. We count the number of knowledge points in each problem, subject, and difficulty level in the problems sampled from HighMATH and MATH. It can be seen that HighMATH contains a higher average number of knowledge points than MATH.

Particularly, commonly used benchmarks, such as GSM8K (Cobbe et al., 2021), MATH (Hendrycks et al., 2021b), CMATH (Wei et al., 2023), and GAOKAO (Zhang et al., 2023), all suffer from these limitations. GSM8K and CMATH, which originate from elementary school math, present problems that are simple and do not allow for complex reasoning, making it difficult to deeply evaluate advanced LLMs. MATH, sourced from American high school math competitions, is quite challenging but typically presents problems with limited knowledge points, thus lacking the ability to evaluate LLMs in integrating multiple mathematical subjects. GAOKAO, C-EVAL (Huang et al., 2023), M3KE (Liu et al., 2023), and other comprehensive benchmarks (Hendrycks et al., 2021a; Zhong et al., 2024) are designed for multidisciplinary evaluation, where math is only one of these subjects, featuring fewer problems and

Benchmarks	MATH	GAOKAO	C-EVAL	M3KE	Ours
Language	En	Zh	Zh	Zh	Zh
Size	5,000	936	669	796	5,293
Problem Type	MWP	MCQ Fill-in-the-Blank MWP	MCQ	MCQ	MWP
Question Len.	191.13	185.92	76.28	46.24	158.63
Solution Len.	519.96	305.86	-	-	603.16
Subject/Level Label	✔	✗	✗	✗	✔

Table 1: Comparison of our benchmark against previous math benchmarks. MWP: Math Word Problem, MCQ: Multi-choice Questions. Question Len. and Solution Len. are the average character lengths we count.

coarser granularity.

To mitigate these challenges, we propose new Chinese math benchmark HighMATH. Our dataset offers a more comprehensive and challenging assessment of LLMs in math reasoning by meticulously integrating a wide range of mathematical concepts, and knowledge into math problems with multiple reasoning steps. It contains 5,293 math problems, with each problem containing an average of more than 2.4 knowledge points, as shown in Figure 1. It covers all major areas of high school mathematics, including 8 domains, i.e., Function Derivatives, Counting Principles, Trigonometric Functions and Triangle Solutions, Plane Analytic Geometry, Sequences, Solid Geometry, Statistics and Probability, and others (Logic, Sets, Inequalities, Complex Numbers reasoning). In addition to subject annotation, we categorize problems into difficulty levels from 1 to 7. We also collect problems with multiple sub-questions into a subset called HighMATH-HARD. The average number of characters of problems and their solutions in HighMATH-HARD are 249 and 1,201 respectively, posing great challenges to LLMs in math reasoning.

We evaluate 14 LLMs (including both open- and closed-source models) on HighMATH. Compared to MATH, all models exhibit a significant drop in accuracy on HighMath, with even the latest reasoning language model, o1-mini, achieving only 52.53% accuracy. The o1-like model, DeepSeek-R1-distill-Qwen-32B, achieves only 31.22%. We also evaluate LLMs under the majority voting, pass@N settings, and with the assistance of a Python executor. However, these can only improve reasoning performance to a certain extent, indicating the difficulty of our benchmark.

Our contributions are summarized as follows.

- We propose a new challenging bechmark for evaluating LLMs in math reasoning. The dataset covers a wide range of mathematical concepts and typically examines multiple mathematical knowledge points in a single problem. Additionally, it has a sufficient number of problems, requires complex reasoning, and is finely annotated.
- We conduct thorough evaluations of the latest LLMs, including both o1-like models and those specifically trained for mathematical reasoning.
- We carry out an in-depth analysis of the evaluation results. The results show that the potential of small LLMs for mathematical reasoning is enormous. The pass@8 accuracy of the 1.5B model even surpasses that of many 7B models.

2 Related Work

Mathematical Reasoning Benchmarks. Our work is most closely related to MATH. We carefully analyze data in MATH (Hendrycks et al., 2021b) and find that, although it originates from American high school math competitions, it includes simple questions as well, such as those from the AMC10 competition, which contains ninth-grade mathematics. In terms of subject division, algebra content is categorized into prealgebra, intermediate algebra, and algebra, making up three of the seven categories. Additionally, almost all current LLMs use MATH training dataset to train their models. Previous analyses on contaminated samples discover that some existing training datasets, including the MATH training dataset, contain a significant number of problems that are highly similar in concept or structure to those in the test datasets (Yang et al.,

2024). We speculate that these limitations may gradually render the MATH dataset inadequate for meeting the evaluation needs of LLMs. Detailed comparison of our benchmark to MATH is presented in Figure 1 and Table 1.

Datasets for evaluating mathematical reasoning in Chinese context are usually integrated into multidisciplinary or knowledge evaluation benchmarks or suites, such as the GAOKAO benchmark (Zhang et al., 2023). The GAOKAO benchmark collects questions from past college entrance examination papers, gathering 936 questions by the year 2024. The questions are categorized into multiple-choice questions, fill-in-the-blank questions, and math word problems. Other benchmarks, like C-EVAL (Huang et al., 2023), M3KE (Liu et al., 2023), etc., broadly include various levels of math questions, such as elementary and advanced mathematics. These mathematical reasoning evaluation datasets suffer from three issues. First, the scale is relatively small; the number of problems is usually fewer than 1K. Second, the evaluation data are not meticulously categorized and divided, making the evaluation results less useful for understanding different mathematical reasoning abilities and levels. Third, unlike the MATH dataset, where all questions are math word problems, the above datasets mainly consist of single-choice and fill-in-the-blank questions, with a limited number of math word problems. We conduct a statistical analysis on the character length of problems and solutions in the above datasets. Results are shown in Table 1. The datasets that contain only multi-choice questions, such as C-EVAL and M3KE, have the shortest average question length. The average length of solutions in HighMATH is about twice that of GAOKAO, indicating that the problems in our dataset are more complex and require more reasoning steps.

Transformed Datasets. Currently, mathematical reasoning evaluations often use static benchmarks, which are prone to data contamination. To prevent or bypass this issue, efforts have been dedicated into (1) new datasets in different formats, (2) dynamic benchmarks and (3) synthetic datasets. MathVista collects multimodal math problems (Lu et al., 2024). Work (Zhu et al., 2023) attempt to develop dynamic test sets. However, unlike elementary mathematics, more challenging math problems are difficult to implement in dynamic evaluations. Other efforts (Mirzadeh et al., 2024; Gulati et al., 2024; Wei et al., 2023) modify the original information in the questions of the GSM8K or other datasets, such as variable names or numeric values, using templates to generate variants of the original problems for evaluation. Among these methods, adding information unrelated to the questions can cause model performance to drop by as much as 65%. Our dataset shows that even with pure text, without data synthesis, LLMs still face challenges when performing mathematical reasoning.

3 Benchmark Curation

3.1 Motivation

Our work is motivated by the limitations of existing math benchmarks. Therefore, our design aims to create a dataset with appropriate difficulty, broad coverage of mathematical knowledge points, and fine-grained annotations. To this end, we decide to focus on math exams related to the Chinese college entrance, i.e., senior high school math exams.

Compared to elementary and middle school math, senior high school math covers knowledge about different mathematical concepts and presents a certain level of difficulty. We specifically collect questions that test Chinese high school senior students' mastery of comprehensive mathematical knowledge. These questions are often examining a variety of knowledge points within a single problem. Additionally, we choose math word problems as the test format. Although multiple-choice questions are easy to standardize and convenient for evaluation, the probability of selecting the correct answer is relatively high. Evaluation results hence may not accurately reflect the true reasoning capability of models. Therefore, during data collection, besides the original math word problems, we also convert valuable multiple-choice and fill-in-the-blank questions into math word problems for evaluation.

3.2 Data Collection

Subject Division. Based on the 2019 Chinese college entrance examination mathematics syllabus, we organize the collected data into eight subjects, which basically cover all the outlined knowledge points in the syllabus. The specific subjects and their corresponding mathematical contents are presented in Table 2.

Data Sources. HighMATH collects data from various sources, mainly from joint provincial examinations and mock exam papers from educational institutions published between January and May 2024. Both of the selected papers are designed to

Subject Category	Category Content	Size
Counting Principle	Permutations, combinations, binomial theorem, etc.	194
Logic Set Inequality Complex	Includes common operations, basic set operations, inductive proofs, linear programming, and proofs of inequalities, etc.	783
Function Derivative	Includes derivatives of one-variable functions and their applications, basic elementary functions and their properties, etc.	955
Solid Geometry	Relationships of points, lines, and planes in space, volumes of cylinders, spheres, inscribed spheres, circumscribed spheres, sectional problems, etc.	548
Trigonometric Functions and Triangle Solving	Includes trigonometric functions, trigonometric identity transformations, solving triangles, plane vectors, etc.	787
Plane Analytical Geometry	Includes conic sections, lines and circles, plane vectors, etc.	1081
Sequences	Arithmetic sequences, geometric sequences, etc.	609
Statistics Probability	Random variables and their distributions, random events and probabilities, distribution tables and hypergeometric distributions, data statistical analysis, etc.	336

Table 2: A comprehensive overview of mathematical subjects and their specific contents is provided. The number of problems each subject contains is listed in the Size column.

assess the senior high school students' mastery of a variety of mathematical knowledge and reasoning capabilities. The problems in those papers are carefully selected or created by experienced teachers and exam setters to ensure quality. The diverse range of sources not only enhances the representativeness and challenge of the dataset, but also reflects the breadth of the college entrance examination. Moreover, to further reduce the risk of data contamination, we select papers saved in scanned PDF format rather than formats that can be directly crawled or parsed.

Data Processing. After collection, all files undergo automatic recognition followed by a review by a human annotator. Specifically, all the papers are first processed by OCR to recognize the problem and solution text, then math expressions are converted into LaTeX format using Mathpix. After that, the LaTeX expressions are compiled into a human-readable form. They are manually proofread for accuracy before being organized into the final standardized dataset. Annotators are also responsible for assigning difficulty levels ranging from 1 (easiest) to 7 (most difficult). All annotators are college students who have passed the college entrance examination and have rich experience and intuition with these problems. After the initial standardization of the data is completed, the leader of the annotators conducts multiple screenings and corrections to ensure annotation accuracy and consistency, thus ensuring the dataset's quality for efficient and precise use. The annotated information and the final standardized format are illustrated in an example in Table 3.

3.3 Data Statistics

In order to demonstrate that HighMATH covers a rich variety of mathematical concepts and more knowledge points assessed by a single problem, we sample instances and conduct an analysis for comparison with MATH. The MATH dataset contains 7 categories and 5 difficulty levels, from which we randomly sample 70 problems. The HighMATH dataset includes 8 categories and 7 difficulty levels, resulting in 108 sampled problems. Annotators label the core knowledge points assessed by these sampled problems and the number of knowledge points that exist. After labeling, we analyze the results from three perspectives. First, we analyze the average number of knowledge points per problem. The MATH dataset averages 1.59 knowledge points per question, while the HighMATH dataset averages 2.4. Second, we evaluate the average number of knowledge points across subjects and difficulty levels. Results are shown in Figure 1. In both subject categories and difficulty levels, the average number of knowledge points in HighMATH exceeds those in the MATH dataset. Specifically, the average number of knowledge points is 2.07 times that of the MATH dataset for each subject, and the average number of knowledge points is 1.69 times that of the MATH dataset for each difficulty level. Additionally, we conduct a manual evaluation to compare the breadth of knowledge points

Information	Example in Chinese	English Translation
Question:	在 $\left(2x^3-\frac{1}{x}\right)^6$ 的展开式中, x^2 项的系数为?	In the expansion of $\left(2x^3-\frac{1}{x}\right)^6$, what is the coefficient of the x^2 term?
Solution:	【分析】由二项式展开式的通项公式写出其通项公式 $T_{k+1}=(-1)^k\times 2^{6-k}\times C_6^k\times x^{18-4k}$, 令 $18-4k=2$ 确定 k 的值, 然后计算 x^2 项的系数即可.【详解】展开式的通项公式 $T_{k+1}=\mathrm{C}_6^k\left(2x^3\right)^{6-k}\left(-\frac{1}{x}\right)^k=(-1)^k\times 2^{6-k}\times \mathrm{C}_6^k\times x^{18-4k}$,令 $18-4k=2$ 可得, $k=4$,则 x^2 项的系数为 $(-1)^4\times 2^{6-4}\times C_6^4=4\times 15=60$.	【Analysis】Using the general term formula of binomial expansion, write out the general term formula $T_{k+1}=(-1)^k\times 2^{6-k}\times C_6^k\times x^{18-4k}$, Set $18-4k=2$ to determine the value of k, then calculate the coefficient of the x^2 term. 【Detailed Solution】 The general term formula of the expansion is: $T_{k+1}=\mathrm{C}_6^k\left(2x^3\right)^{6-k}\left(-\frac{1}{x}\right)^k=(-1)^k\times 2^{6-k}\times \mathrm{C}_6^k\times x^{18-4k}$ Setting $18-4k=2$, we get $k=4$ Therefore, the coefficient of the x^2 term is: $(-1)^4\times 2^{6-4}\times C_6^4=4\times 15=60$.
Subject:	计数原理	Counting Principle
Level:	2	
Answer:	60	

Table 3: Illustration of annotated math word problems in HighMATH.

covered in HighMATH and MATH. We asked undergraduate students majoring in mathematics to evaluate the two datasets. The evaluation results show that, compared to MATH, HighMATH covers a more comprehensive range of knowledge, essentially encompassing all aspects of high school mathematics. Other evaluation opinions are shown in Appendix A. All manual annotations will be published along with the datasets.

4 Experiments

We conducted extensive experiments on HighMATH to evaluate 14 latest LLMs, including both open- and closed-source models. Among them, o1-like models were also evaluated.

4.1 Models

We evaluate four types of models: the first group of models are closed-source models accessed through APIs (OpenAI o1-mini). The second group of models includes open-source models designed for general purposes (Qwen-2.5-Instruct, Llama-3-Instruct); the third type comprises open-source LLMs that are fine-tuned for math reasoning (Qwen-2.5-Math, Qwen-2.5-Math-Instruct, deepseek-math-instruct, deepseek-math-rl, Mathstral-v0.1); Additionally, we evaluated some recently released o1-like open-source LLMs specifically designed for complex reasoning (QwQ-32B-Preview, Skywork-o1-Open-Llama-3.1, DeepSeek-R1-Distill-Qwen). We evaluated models of different sizes within the same open-source model series whenever possible, with model sizes ranging from 1.5B to 72B parameters.

4.2 Evaluation Strategies

We employed four evaluation settings to provide a comprehensive analysis of model performance on HighMATH.

Zero-shot Evaluation: Zero-shot evaluation refers to the process where the model makes predictions on inputs and directly performs the evaluation task without having seen any specific samples before. During the evaluation, we only give the model a system prompt instructing it to write the final answer in a box, and directly provide the problem in the user prompt. This method is the most direct and widely used evaluation approach.

Majority Vote Mechanism: The majority vote (Wang et al., 2022) mechanism involves selecting the most frequent answer from multiple inference responses (eight in our experiment) as the final decision, which is then compared to the ground truth. This approach helps assess the model's consistency and reliability in providing correct answers over multiple runs.

Pass@N: Pass@N is a metric used to evaluate the model's ability to find at least one correct answer within the top N most likely generated answers (eight in our experiment). It is commonly used to measure the model's recall capability and the diversity of generated responses. As an evaluation standard, Pass@N reveals the model's performance when generating multiple candidate answers, emphasizing its ability to cover a wide range of possibilities.

MODEL	HighMATH	HighMATH-HARD	Major Vote	Pass@8	Python Executor
	Closed-Source LLM				
o1-mini	52.53	-	-	-	-
	General Purpose Open-Source LLMs				
Qwen-2.5-Instruct-7B	21.71	5.87	43.34	57	-
Llama-3-Instruct-8B	6.49	1.34	8.9	20.73	-
	Mathematics Open-Source LLMs				
Qwen-2.5-Math-Instruct-1.5B	16.05	5.2	48.29	58.11	42.11
Qwen-2.5-Math-7B	9.15	0.42	28.83	42.05	-
Qwen-2.5-Math-Instruct-7B	43.71	18.44	51.76	60.44	46.41
Qwen-2.5-Math-Instruct-72B	51.56	24.48	-	-	50.62
deepseek-math-7b-instruct	15.73	3.1	19.22	35.93	-
deepseek-math-7b-rl	8.15	1.93	16.78	24.68	-
Mathstral-7B-v0.1	21.12	5.53	29.73	48.98	-
	o1-like Open-Source LLMs				
QwQ-32B-Preview	45.41	12.57	54.61	59.9	-
Skywork-o1-Open-Llama-3.1-8B	45.8	17.94	51.2	61.49	-
DeepSeek-R1-Distill-Qwen-7B	29.68	5.53	43.44	45.07	-
DeepSeek-R1-Distill-Qwen-32B	31.22	6.87	45.53	47.24	-

Table 4: Main results.

Solving with Python Executor: This evaluation method involves using the Python Executor to enhance the logic and computational accuracy of LLM's responses. During experiments, we evaluated Qwen models, which provide relevant interfaces using this method. Specifically, after generating a response, the model sends the response to a relevant agent, which then regenerates and provides the final response.

5 Main Result

We divided all the problems from HighMATH into two categories for evaluation. The first category consists of problems that contain only one question, totaling 4,100 problems, and the second includes problems with multiple questions, totaling 1,193 problems (labeled "HighMATH-HARD" in Table 4). As shown in the results in Table 4, OpenAI o1-mini performs best in addressing single-question problems, achieving an accuracy rate of 52.53%. Among all 7B models, Qwen-2.5-Math-Instruct performs the best, with an accuracy rate multiple times that of other models. In the o1-like models, Skywork-o1-Open-Llama-3.1 stands out, even surpassing the QWQ model of 32b in accuracy. There is also an interesting phenomenon in the comparison of models within the same series. It can be seen that Qwen-2.5-Instruct, Qwen-2.5-Math, and Qwen-2.5-Math-Instruct, which are based on the same 7B base model, show significant differences. Comparing Qwen-2.5-Instruct and Qwen-2.5-Math, it is evident that even though Qwen-2.5-Math has been trained with a substantial new mathematical corpus, its performance is greatly influenced by whether the model has undergone instruction-following tuning. Qwen-2.5-Math-Instruct, which combines the advantages of the two previous models, achieves the best results, indicating that both factors are important in model training. Additionally, we observed that: for the Qwen-math series models, as model size increases, performance on HighMATH does not improve linearly. Comparing the 7B model with the 72B model, there is only an 8% improvement in single-question problems' evaluation, which does not align with the expected behavior of the scaling law. This also shows that the application of techniques such as test-time scaling, process supervision, and reinforcement learning to small LLMs is reducing the advantages of large LLMs during

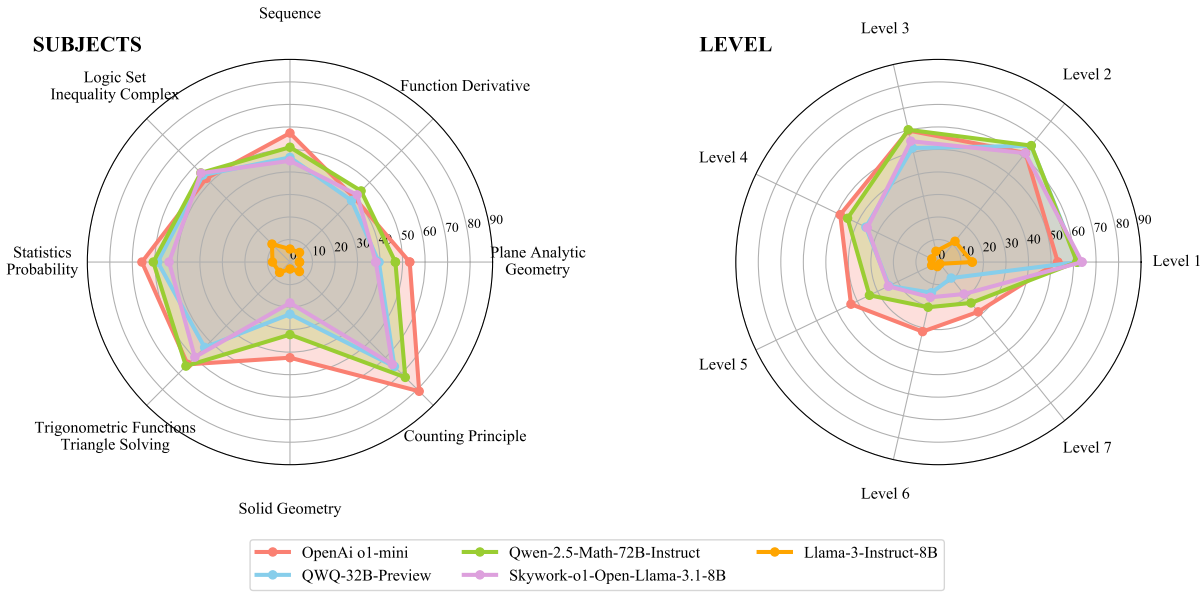

Figure 2: Analysis of question types and difficulty levels.

training.

The accuracy of all models drastically decreases in the evaluation of multi-question problems. The best-performing model, Qwen-2.5-Math-Instruct, has an accuracy in multi-question problems that is less than half of its accuracy in single-question problems. Models that perform poorly on single-question problems tend to perform even worse on multi-question problems. Among the o1-like models, the accuracy of QWQ-32B-Preview on multi-question problems is surprisingly 5.87% lower than that of Qwen-2.5-Math-Instruct 7B. Besides Skywork-o1-Open-Llama-3.1-8B, other o1-like models also fail to meet the expected results, which may indicate that a more complex reasoning process does not necessarily improve accuracy.

The majority vote and pass@8 evaluation settings significantly improve the accuracy of each model in reasoning on single-question problems, although the degree of improvement varies. The most noticeable increases occur in models that originally have lower accuracies. For example, the pass@8 accuracy of the Qwen 1.5B model even surpasses that of many 7B models. These results may indicate that these smaller LLMs already possess strong mathematical reasoning abilities, but the responses they generate in a single pass are very unstable, leading to poor accuracy performance. Using a Python executor can effectively mitigate this issue. However, it is worth noting that there is an upper limit to the accuracy achievable with majority vote, pass@8, or using a Python executor on HighMATH. The highest accuracy is achieved by Skywork-o1-Open-Llama-3.1 under the pass@8 evaluation setting, reaching only 61.49%.

6 Analysis of Problem Subjects and Difficulty Levels

We conducted an analysis of performance across problem subjects and difficulty levels between o1-mini, QWQ-32B-Preview, Qwen-2.5-Math-Instruct-72B, Skywork-o1-Open-Llama-3.1-8B, and the Meta-Llama-3-8B-Instruct model. All comparisons are conducted under the evaluation results of single-question problems.

6.1 Problem Subjects

The left radargrame in Figure 2 shows that the compared models generally perform consistently across different categories of math problems. OpenAI o1-mini not only outperforms other models in overall accuracy on HighMATH but also performs best in five subjects of math problems, though it is slightly inferior in two categories. This indicates that OpenAI o1-mini is still demonstrates competitiveness in the current evaluation tasks. Clearly, compared to the Meta-Llama-3-8B-Instruct model, the Skywork-o1-Open-Llama-3.1-8B model shows significant improvements in accuracy across all categories. This finding again highlights that, with effective training and optimization strategies, even relatively smaller models can exhibit reasoning

Dataset	MATH	MATH500
Qwen-2.5-Math-Instruct-7B	76.6	75

Table 5: Evaluate Qwen-2.5-Math-Instruct-7b on MATH and MATH500.

Dataset	1000-Zh	1000-En
Qwen-2.5-Math-Instruct-7B	40.7	38.6

Table 6: The impact of language on mathematical evaluation.

abilities on par with larger models.

We also observe that the models perform well in subjects such as Counting Principle, Sequences, and Statistics. We speculate that mathematical problems in these fields often exhibit strong structural characteristics, including clear rules and logic. The models can leverage a large number of mathematical formulas, derivation processes, and rules to perform calculations, making accurate reasoning more achievable. Furthermore, the richness of the training data and the standardized nature of the problems make these areas particularly advantageous for complex reasoning models to demonstrate their strengths. However, models perform poorly in subjects such as Solid Geometry and Plane Analytic Geometry. We believe that these subjects require the models to possess strong spatial imagination, complex geometric reasoning abilities, and a deep understanding of geometric transformations and shapes.

6.2 Difficulty Level

The accuracy of all models decreases as the difficulty level increases. OpenAI o1-mini surpasses other models in accuracy for problems at Level 4 and above, demonstrating its advantage in complex mathematical reasoning. Overall, performance differences below Level 3 are not significant. However, for more difficult problems, performance aligns with the scaling law principle. As model size increases (e.g., Qwen QWQ-32B-Preview, Qwen-2.5-Math-72B-Instruct), larger models progressively outperform smaller ones in high-difficulty problems, indicating a positive correlation between model size and performance on challenging tasks.

7 Ablation Study

To demonstrate the effectiveness of our dataset, we conducted identical tests on the Qwen-2.5-Math model using both MATH and MATH-500. As shown in Table 5, both MATH and MATH-500 achieve a 75% accuracy under the zero-shot evaluation setting. Under the same settings, HighMATH achieves an accuracy of 43.71%, showing a significant difference of 31.29 percentage points compared to the other datasets. This difference validate the effectiveness of using HighMATH for evaluation.

To test whether language affects mathematical reasoning, we extracted 1,000 questions proportionally from the eight subjects of HighMATH and translated them into English using GPT-4-0613 for testing the Qwen-2.5-Math-Instruct-7B. Experimental results, shown in Table 6, indicate that the accuracy slightly decreases with the translated questions, but the change is not significant. Therefore, although HighMATH is based on a Chinese context, it remains relevant for testing models trained in other languages.

8 Conclusion

We propose a new mathematical reasoning dataset, HighMATH, for LLM evaluations. HighMATH features a comprehensive inclusion of different subjects of mathematical concepts, with multiple knowledge points integrated into each problem. Additionally, HighMATH includes fine-grained annotations, divided into 8 categories and 7 difficulty levels, totaling 5,293 problems. Based on HighMATH, we have conducted a comprehensive evaluation of the most recent popular LLMs. The evaluation results confirm the effectiveness of our dataset, with the best model achieving an accuracy of 62%.

Limitations

While our benchmark provides a comprehensive evaluation of LLMs' math reasoning abilities at the high school level, it has some limitations. First, it does not cover university-level mathematics or advanced Olympiad problems, focusing instead only on high school content. Additionally, considering the current progress in reasoning capabilities of models like o1 and DeepSeek-R1, we believe that it is equally crucial to evaluate each reasoning step generated by the model, not just focusing on the final answer. This may help to more accurately measure the model's performance in complex logical reasoning processes.

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9 Appendices

A Human Evaluation Opinions on HighMATH and MATH

- Problems in MATH are simpler and more direct, lacking integration of knowledge points, which means they do not combine two or more knowledge points for examination.
- Problems in HighMATH are more obscure, requiring people to engage in logical thinking to understand the meaning of the questions.
- The HighMATH dataset covers a more comprehensive range of knowledge, essentially encompassing all aspects of high school mathematics.