Format-Adapter: Improving Reasoning Capability of LLMs by Adapting Suitable Format

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Abstract

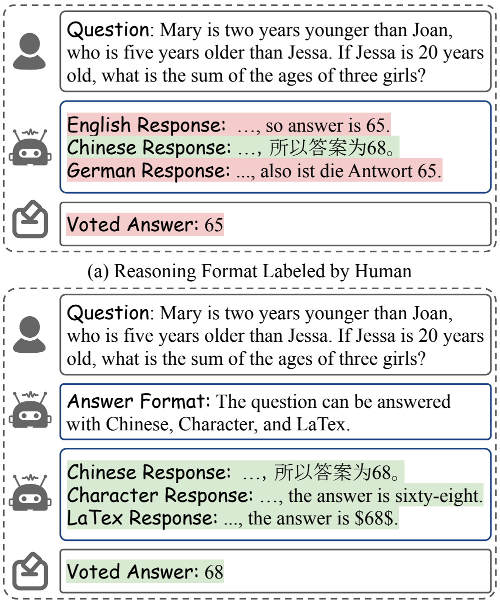
Generating and voting multiple answers is an effective method to mitigate reasoning inconsistencies of large language models (LLMs). Prior works have shown that multiple reasoning formats outperform a single format when generating multiple answers. However, previous works using multiple formats rely on formats labeled by humans, which could be unsuitable for all tasks and have high labeling costs. To address this issue, we adapt suitable formats to the given tasks by generating and selecting formats. We first propose how to measure the reasoning error when generating multiple answers. Then, we introduce FORMAT-ADAPTER, which utilizes LLMs to generate and select suitable reasoning formats by minimizing the error measurement we present. We conduct experiments on math and commonsense reasoning tasks, where FORMAT-ADAPTER achieves a 4.3% performance improvement on average over previous works, demonstrating the effectiveness.

1 Introduction

The prior research has revealed that, due to the inconsistency, one question could yield different responses when suffering minor variations in the input or parameters, resulting in incorrect results (Wang et al., 2022). To address this issue, previous works propose to generate multiple responses to mitigate the impact of model inconsistencies (Wang et al., 2023; Yao et al., 2023; Besta et al., 2024). Specifically, such methods generate multiple answers to a given question by varying parameters and then select the most appropriate response as the final answer by scoring and voting.

However, the above works rely on the fixed *reasoning format*[1], which limits the model performance since different questions could suit different reasoning formats (Cheng et al., 2023; Chen et al., 2023; He et al., 2024), as shown in Figure 1. Therefore, many prior works try to enhance the reasoning performance by employing various reasoning formats (Luo et al., 2024; Zhang et al., 2024b). For example, CLIP (Qin et al., 2023) proposes using varied natural languages to generate different answers in numerical reasoning tasks. Similarly, FlexTaF (Zhang et al., 2024a) addresses table reasoning tasks by generating different answers through diverse table formats.

However, the above methods rely on manually designed reasoning formats, which have the following issues: *(i)* Manually designed formats could **not be suitable for the task**; *(ii)* Manually designing formats for each task **incurs significant overhead**. To address these issues, in this paper: *(i)* We dis-



(b) Reasoning Format Generated by LLM

Figure 1: The comparison between the previous work (a) and FORMAT-ADAPTER (b) instructed to reason with different formats. The red parts denote the incorrect answers and the green parts denote the correct ones. The previous work employs the formats labeled by humans, which could be not suitable for the given question and LLM. FORMAT-ADAPTER generates and selects the suitable formats, achieving better performance.

[1] In this paper, we define the *reasoning format* as LLMs how to present the reasoning process.

cuss ***why adapting multiple formats outperforms using a single format*** during reasoning; *(ii)* We propose ***using LLMs to generate and select suitable formats*** to enhance reasoning performance.

We first propose how to measure the error of the reasoning with multiple responses. Based on the measurement, we discuss that generating with a single format can only enhance reasoning robustness while using multiple formats can further enhance reasoning capabilities. Then, we propose FORMAT-ADAPTER, which utilizes LLMs to generate and select suitable reasoning formats. We use LLMs to derive reasoning formats without human involvement, lowering the overhead of the format design. Besides, we propose to adapt reasoning formats by reducing the error measurement we present, ensuring that the format is suitable for the task.

To evaluate the effectiveness of FORMAT-ADAPTER, we adapt our method to two mainstream reasoning tasks: math reasoning (GSM8K (Cobbe et al., 2021), MATH (Saxton et al., 2019)) and commonsense reasoning (ARC-Challenge (Yadav et al., 2019), GPQA (Yadav et al., 2019)). The experimental results show that, compared with baselines with the single format, FORMAT-ADAPTER brings 4.1% performance improvement on average, proving the effectiveness of FORMAT-ADAPTER. We also compare FORMAT-ADAPTER with baselines using multiple reasoning formats, where our method brings 4.7% improvement on average, showing the necessity of the format selection.

Our contributions are as follows:

- To shed light on further research, we discuss why generating multiple answers with multiple formats outperforms single format;
- To enhance the reasoning ability of LLMs, we present FORMAT-ADAPTER, which generates and selects suitable formats using LLMs;
- Experiments show that our method brings 4.3% improvement on average over all baselines, showing the effectiveness of FORMAT-ADAPTER.

2 Preliminaries

To prove the effectiveness of employing multiple reasoning formats and shed light on future research, in this section, we discuss: *(i)* How to measure the error of reasoning with a single reasoning format of LLMs; *(ii)* How to measure the error of reasoning employing multiple reasoning formats of LLMs and why it outperforms using the single format.

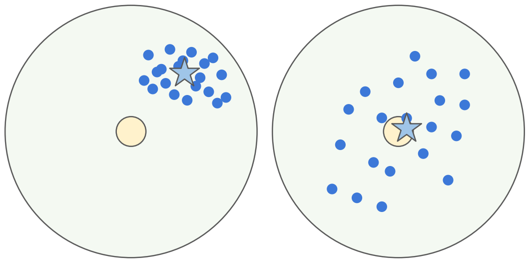


Figure 2: The comparison between using the single format (left) and multiple formats (right) with the same number of geenrated answers. The yellow ◯ denotes the correct answer, the blue • denotes different predictions, and the blue ☆ denotes the average prediction. Compared with the single format, the average prediction of multiple formats is closer to the correct answer, showing better performance.

2.1 Error of Single Reasoning Format

First, we discuss the error of the general ensemble method (Sagi and Rokach, 2018), since generating multiple responses and voting can be regarded as an ensemble method. In this paper, we use the error function $L(x, y)$ as follows:

$$L(x,y) = \begin{cases} 1 & \text{if } x \neq y \\ 0 & \text{if } x = y \end{cases} \tag{1}$$

The function L represents whether the prediction result matches the correct answer exactly. We define $D = \{(x_i, y_i)\}_{|D|}$ as the experimental dataset, $\{\phi_i\}_m$ as the set of m predictors, and $\bar{\phi} = \mathsf{avg}(\phi_{im})$ as the ensemble predictors. Proved by Wood et al. (2024), the error of ensemble learning with m predictors on the dataset D can be expressed as the error over the dataset minus the divergence among the individual predictors, that is:

$$\begin{aligned} \mathbb{E}_D\left[L(\bar{\phi}, y)\right] &= \frac{1}{m}\sum_{i=1}^{m}\mathbb{E}_D\left[L\left(\phi_i, y\right)\right] \\ &\quad - \mathbb{E}_D\left[\frac{1}{m}\sum_{i=1}^{m} L\left(\phi_i, \bar{\phi}\right)\right] \end{aligned} \tag{2}$$

Then we discuss the error of generating multiple responses using LLMs. For a model employing a single reasoning format, we assume the used format is $\mathtt{f}$ and the model is ϕ. Since only parameters (e.g., random seed, temperature) are altered during reasoning, we can regard the predictor as applying a perturbation to the model inherent performance $\phi \circ \mathtt{f}$, expressed as $\phi_i = \phi \circ \mathtt{f} + \delta_i$, where δ_i denotes the perturbation. It can be derived that generating one single answer using ϕ_i can be present as:

$$\mathbb{E}_D\left[L(\phi_i, y)\right] = \mathbb{E}_D\left[L\left(\phi \circ \mathtt{f} + \delta_i, y\right)\right] \quad (3)$$

We assume an ideal scenario where the average of all predictors represents the inherent performance of the model, i.e., $\lim_{m\to\infty} \bar{\phi} = \phi \circ \mathtt{f}$. It can be proven that the error in generating multiple answers using a single reasoning format satisfies:

$$\mathbb{E}_D\left[L(\bar{\phi}, y)\right] = \mathbb{E}_D\left[L\left(\phi \circ \mathtt{f}, y\right)\right] \quad (4)$$

Appendix A.1 presents the prove of Equation 4. It can be seen that, compared with Equation 3, generating multiple answers can eliminate the perturbation δ, enhancing the robustness. However, when using single format f, Equation 4 is determined by ϕ, showing that enhancing performance relies on improving the model capability.

2.2 Error of Multiple Reasoning Format

In the following, we discuss the error of using multiple reasoning formats and why it outperforms the single format. During reasoning, we employ multiple formats $\{f_i\}_m$ with one single model ϕ, so we can assume the predictors to be $\phi_i = \phi \circ \mathtt{f}_i + \delta_i$. It can be proved that the reasoning error follows:

$$\begin{aligned}\mathbb{E}_D\left[L(\bar{\phi}, y)\right] &= \frac{1}{m}\sum_{i=1}^{m}\mathbb{E}_D\left[L(\phi \circ \mathtt{f}_i, y)\right] \\ &- \mathbb{E}_D\left[\frac{1}{m}\sum_{i=1}^{m} L(\phi \circ \mathtt{f}_i, \bar{\phi})\right]\end{aligned} \quad (5)$$

The prove of Equation 5 can be seen in Appendix A.2. In the equation, the first term denotes the average error over all predictions and correct answers, and the second term measures the divergence between different reasoning formats. It can be observed that, even with the same model, we can combine different reasoning formats to minimize error, thereby improving performance, as shown in the right part of Figure 2.

3 Methodology

This section introduces FORMAT-ADAPTER, which leverages LLMs to generate and select the suitable reasoning formats to enhance reasoning performance. An illustration of our method is shown in Figure 3. The prompts we used are provided in Appendix B. We also discuss the efficiency of FORMAT-ADAPTER in Appendix E.

3.1 Format Generation

This step is designed to generate candidate reasoning formats, ensuring both the relevancy and diversity of the generated formats. Relevancy means that the generated reasoning formats are relevant to the given task. Diversity demands that the generated reasoning formats be varied to ensure suitable reasoning formats for various user questions.

To ensure relevancy, several demonstrations and an example of the task are provided during generation to help LLMs learn how to produce task-relevant reasoning formats. To ensure diversity, we design the instruction to ask LLMs to generate reasoning formats across multiple categories, where each category consists of multiple formats. For instance, as shown in Figure 3, *Natural Language* is the reasoning format category, while *English* and *Chinese* are the reasoning formats of this category. In summary, the input includes several demonstrations, the task definition, and an example of the task, while the output consists of multiple reasoning formats. Appendix D discusses the generated formats under each setting.

3.2 Answer Generation

This step generates corresponding answers for each generated reasoning format. First, the instruction is rewritten according to each reasoning format to ensure that the answer generation follows the given reasoning format. We take the original instruction of the task (Appendix B) and the reasoning format as input and ask LLMs to output the rewritten instruction based on the reasoning format. Then, the rewritten instruction is used to generate different reasoning answers for the given user question. Following prior work (Qin et al., 2023), zero-shot learning is applied by inputting the rewritten instruction and the user question to output answers in the specified reasoning format.

3.3 Answer Scoring

After obtaining answers in different reasoning formats, based on Equation 5, we aim to select the suitable reasoning formats that minimize the error. However, in Equation 5, the error between the prediction and the answer $L(\phi \circ f_i, y)$ is difficult to compute, as the correct answer y is unknown. Therefore, we use LLMs to score the answers in each reasoning format to estimate the probability that the predicted answer is correct. Following Zheng et al. (2023), we input the user question and

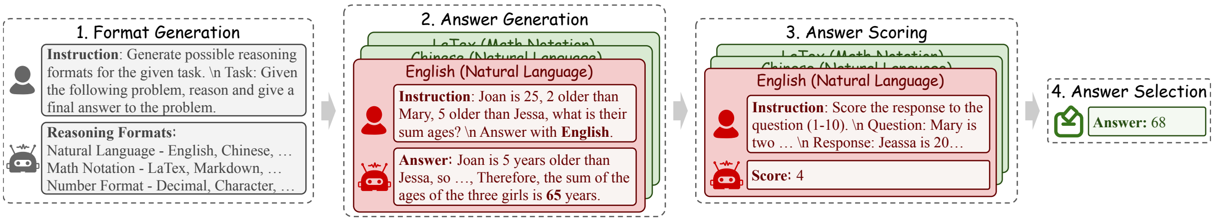


Figure 3: The pipeline of FORMAT-ADAPTER, which consists of: *(i) Format Generation*: Generate possible reasoning formats of the given task; *(ii) Answer Generation*: Generate the answer using each reasoning format; *(iii) Answer Scoring*: Score whether each generated answer is correct using LLMs; *(iv) Answer Selection*: Select the final answer with Equation 5. Red and green represent the reasoning formats of incorrect and correct respectively.

the predicted answer, outputting a score from 1 to 10 to represent the degree to the probability that the answer is correct. To ensure that there is the same scale between the first term and the second term of Equation 5, we divide the rating by 10 to correspond to the interval of $[0, 1]$.

3.4 Answer Selection

Based on the predicted answers and corresponding scores of different reasoning formats, we discuss how to select the final answers based on Equation 5. Specifically, given the dataset D and the model ϕ, we hope to find suitable reasoning formats to minimize the error that satisfies:

$$\{\mathtt{f}_i\}_n = \underset{\{\mathtt{f}_i\}_n \subseteq \{\mathtt{f}_i\}_m}{\arg\min}\ \mathbb{E}_D\left[L(\bar{q}, y)\right] \tag{6}$$

In Equation 5, the first term can be directly calculated by averaging scores obtained in §3.3. The second term requires calculating the average difference between all results and the average result, where we take the average prediction $\bar{\phi}(x)$ as the answer appearing most frequently among all outcomes. Considering computational efficiency, we adopt a greedy algorithm to select formats: we add each format $\mathtt{f}_i$ one by one to the selected results, where if the value of Equation 5 decreases, we retain $\mathtt{f}_i$; otherwise, we remove $\mathtt{f}_i$. Due to the inherent scoring errors of LLMs, we do not directly use the answer with the highest score within the selected set. Instead, we choose the most frequently occurring answer as the final answer.

4 Experiment

4.1 Experimental Setup

4.1.1 Datasets

To validate the effectiveness of our method, following Dubey et al. (2024), we conduct experiments on two mainstream reasoning tasks: commonsense reasoning (ARC-Challenge-Hard (Yadav et al., 2019), GPQA (Rein et al., 2024)) and math reasoning (GSM8K (Cobbe et al., 2021), MATH (Saxton et al., 2019)). Commonsense reasoning requires the model to apply commonsense knowledge to comprehend and answer questions. On the other hand, math reasoning demands the model to solve mathematical problems.

Due to the high cost of generating multiple answers, we employ the subsets of the above benchmarks to reduce computational overhead while maintaining a robust performance evaluation. Specifically, for GSM8K and ARC-Challenge (ARC-C), we sample 256 questions that are not well solved by the current LLMs, referred to as GSM8K-Hard and ARC-C-Hard, respectively. For MATH, we utilize the version of MATH500 (Lightman et al., 2024), which samples 500 questions from the original dataset. For GPQA, we employ the original test set, comprising 448 questions.

4.1.2 Models

We conduct the experiments with the models of Llama3.1-Instruct (Dubey et al., 2024) and GPT-4o (OpenAI et al., 2024). Llama3.1 is one of the most mainstream and high-performing open-source LLMs. GPT-4o, on the other hand, currently represents one of the most powerful LLMs in terms of reasoning capabilities. Our selection ensures coverage of diverse application scenarios.

4.1.3 Baselines

To better reflect the effectiveness of FORMAT-ADAPTER, we compare our method with two types of baselines. The first type uses the single reasoning format, including Single, Self-Consistency (SC) (Wang et al., 2023), Tree-of-Thought (ToT) (Yao et al., 2023), and DTV (Zhou et al., 2024). Another type uses multiple reasoning formats, including CLIP (Qin et al., 2023), MultiPoT (Luo et al., 2024), and FlexTaF (Zhang et al., 2024a). We introduce the above baselines in Appendix C.

4.1.4 Metrics

We use Exact Match (EM) as the evaluation metric for all datasets, which measures whether the predicted result is completely identical to the ground truth. Additionally, we evaluate methods that generate multiple answers under two settings: Vote and Oracle. Vote refers to selecting one answer from all generated answers as the final result, reflecting the actual performance of the method. Oracle, on the other hand, considers a question correct if there exists one of the generated answers matches the ground truth, reflecting the performance upper bound of the method.

4.1.5 Implement Details

Following the previous work (Qin et al., 2023), we evaluate FORMAT-ADAPTER using zero-shot. The numbers and types of reasoning formats of FORMAT-ADAPTER under different settings can be seen in Appendix D.

4.2 Main Experiment

4.2.1 Baselines with Single Format

The experimental results of FORMAT-ADAPTER compared with baselines using the single reasoning format (Appendix C) are shown in Table 1. The table shows that, compared with the best baseline results under each setting, FORMAT-ADAPTER brings 4.1% performance improvement on average, showing the effectiveness of FORMAT-ADAPTER. We also compare the efficiency across different methods in Appendix E.3. Besides, from Table 1, we can also observe that:

Model The improvement brought by FORMAT-ADAPTER on different models depends on the difficulty of the dataset. For relatively simple datasets like GSM8K and ARC-Challenge, our method demonstrates more significant improvements on models with a small scale. Conversely, for more challenging datasets such as MATH and GPQA, our method achieves more notable improvements on larger models. This is because, for complex datasets, smaller models lack the necessary knowledge to solve such problems due to their limited scale, where simply altering the reasoning format cannot introduce new knowledge, leading to negligible performance gains. On the other hand, models with larger scales already exhibit strong performance for simpler datasets, making the improvements brought by our method less pronounced compared to smaller models.

Metric FORMAT-ADAPTER demonstrates performance improvements in both the Vote and Oracle settings, indicating that our method not only enhances actual performance but also effectively encourages the model to utilize diverse reasoning formats to generate correct answers. These results also confirm that the most suitable reasoning format varies across different types of questions. However, there remains a significant performance gap between the Vote and Oracle settings in our method, which can be attributed to the following reasons: *(i)* The scoring quality of LLMs is suboptimal, making it challenging to accurately assess whether a predicted result is correct; *(ii)* Specifically, for datasets such as ARC-Challenge and GPQA, where the answers are choices, LLMs could produce correct results while following incorrect reasoning processes, resulting in lower scores, which can also explain why the performance gap between Vote and Oracle is larger for these datasets compared to math reasoning datasets.

4.2.2 Baselines with Multiple Format

The performance comparison between FORMAT-ADAPTER and baselines employing multiple reasoning formats is presented in Table 2. Following the setup of MultiPoT, we select 263 problems from MATH500 that can be resolved using code-based solutions. About FlexTaF, we conduct experiments on the table QA task with 100 data from WikiTQ (Pasupat and Liang, 2015) sampled by Zhang et al. (2024a). As observed from the table, FORMAT-ADAPTER achieves an average improvement of 4.7% over the best performance of the baselines under each setting, demonstrating the effectiveness of our method.

4.3 Ablation Study

To demonstrate the effectiveness of each step of FORMAT-ADAPTER, we conduct ablation studies. The experimental results are shown in Table 3. From the table, we can observe that removing any individual step results in a performance decline, thereby validating the importance of each step in FORMAT-ADAPTER. Furthermore, the table reveals the following insights: *(i)* Removing the Select step leads to the most significant performance drop, indicating that in many questions, only a few reasoning formats yield correct answers, necessitating the Select step to identify the correct solutions; *(ii)* The performance degradation of the ablation study is more pronounced in smaller-scale models

Model	Method	GSM8K-Hard		MATH500		ARC-C-Hard		GPQA	
		Vote	Oracle	Vote	Oracle	Vote	Oracle	Vote	Oracle
Llama3.1-8b	Single	23.0	–	47.8	–	16.8	–	28.1	–
	SC	36.7	55.1	51.4	63.0	18.4	23.4	30.8	59.2
	ToT	43.0	53.9	52.8	56.8	24.2	33.8	32.8	46.7
	DTV	51.6	56.2	55.4	56.4	39.1	42.6	32.6	50.0
	FORMAT-ADAPTER	**54.7**	**89.8**	**56.8**	**75.0**	**57.4**	**91.4**	**33.9**	**93.8**
Llama3.1-70b	Single	66.0	–	63.4	–	68.0	–	43.1	–
	SC	70.3	77.3	64.4	72.8	69.1	69.9	46.2	66.5
	ToT	71.5	77.6	67.2	75.2	70.7	72.3	48.0	73.2
	DTV	71.7	84.3	65.8	81.8	69.9	73.8	50.2	75.9
	FORMAT-ADAPTER	**76.2**	**94.9**	**70.4**	**85.4**	**71.5**	**88.7**	**51.0**	**96.4**
GPT-4o	Single	73.4	–	71.0	–	77.0	–	48.9	–
	SC	74.1	82.8	71.4	83.2	78.9	83.2	49.1	70.8
	FORMAT-ADAPTER	**78.4**	**95.1**	**76.8**	**86.6**	**80.1**	**96.9**	**51.6**	**96.6**

Table 1: EM of FORMAT-ADAPTER and baselines using the single reasoning format. The best results of each setting are marked in **bold**. Due to the limitations of computing resources, we only compare FORMAT-ADAPTER with Self-Consistency on GPT-4o.

Dataset	Method	8b	70b
MATH263	CLIP	53.0	66.9
	MultiPoT	57.4	72.2
	FORMAT-ADAPTER	**60.1**	**77.2**
WikiTQ100	FlexTaF	38.0	60.0
	FORMAT-ADAPTER	**48.0**	**61.0**

Table 2: EM of FORMAT-ADAPTER and baselines using multiple reasoning formats on Llama3.1. The best results of each setting are marked in **bold**.

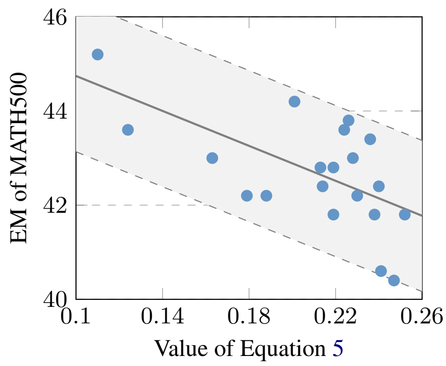


Figure 4: The performance on MATH with different formats using Llama3.1-8b. Different blue • denotes the result using different formats, where the formats used are randomly sampled from that generated by FORMAT-ADAPTER. The correlation coefficient is -0.652.

compared to larger ones, which suggests that models with smaller scales generate fewer reasoning formats capable of producing correct answers, relying more heavily on the Rewrite and Select steps to achieve correct results.

4.4 Analysis

In this section, we adapt analysis experiments to understand better how FORMAT-ADAPTER improves the reasoning performance and to guide the parameter selection. Due to the high reasoning cost, we only employ Llama3.1 as the experimental LLMs. We also adapt the case study to understand better how FORMAT-ADAPTER improves the performance, which is discussed in Appendix G.

4.4.1 Reasoning Error

To demonstrate that Equation 5 effectively reflects the reasoning error, we conduct statistical analysis on MATH to evaluate the model performance corresponding to different values of Equation 5. The experimental results are shown in Figure 4, from which we can observe that: *(i)* As the value of Equation 5 gradually increases, the model performance consistently declines, indicating that the error is indeed progressively growing; *(ii)* The error obtained in Figure 4 is predominantly concentrated around 0.22, suggesting that most reasoning formats yield similar results, while these results are inferior to the best results, indicating that the majority of reasoning formats do not produce the correct answers, showing the necessity to select the most suitable reasoning format for each question.

4.4.2 Reasoning Format Category

To examine the performance of different reasoning formats and inspire future work, we analyze the average performance improvement achieved under various settings with different reasoning format categories. We also list the most suitable reasoning format for each task in Appendix D. The results are shown in Figure 5, from which we can see that: *(i)* For the results using the single reasoning format category, its performance improvement

Model	Method	GSM8K-Hard	MATH500	ARC-C-Hard	GPQA
Llama3.1-8b	FORMAT-ADAPTER	54.7	56.8	57.4	33.5
	- Rewrite	51.6 (−3.1)	53.6 (−3.2)	52.0 (−5.4)	32.4 (−1.1)
	- Select	49.2 (−5.5)	47.8 (−9.0)	54.7 (−2.7)	25.4 (−8.1)
	- Score	53.9 (−0.8)	54.2 (−2.6)	52.7 (−4.7)	30.1 (−3.4)
Llama3.1-70b	FORMAT-ADAPTER	76.2	70.4	71.5	51.0
	- Rewrite	75.4 (−0.8)	69.6 (−0.8)	68.8 (−2.7)	47.1 (−3.9)
	- Select	75.0 (−1.2)	68.6 (−1.8)	66.4 (−5.1)	44.2 (−6.8)
	- Score	73.8 (−2.4)	70.2 (−0.2)	69.9 (−1.6)	47.3 (−3.7)

Table 3: The ablation study results under: *(i)* Rewrite: Generate answers without rewriting instructions; *(ii)* Select: Vote the answer from the responses with the highest score; *(iii)* Score: Set all answers with the same score of 1.0.

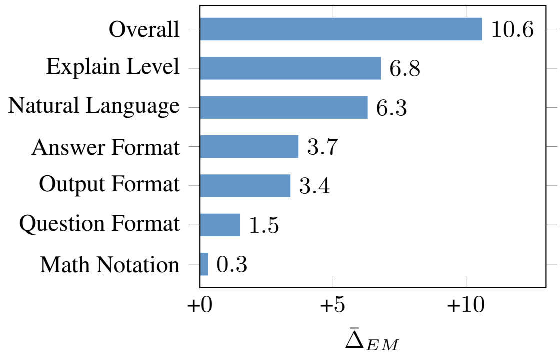


Figure 5: The average performance improvement brought by FORMAT-ADAPTER with different reasoning categories having more than four formats. $\bar{\Delta}_{EM}$ denotes the average EM improvement compared to Self-Consistency. Overall denotes the performance using all reasoning categories generated by FORMAT-ADAPTER.

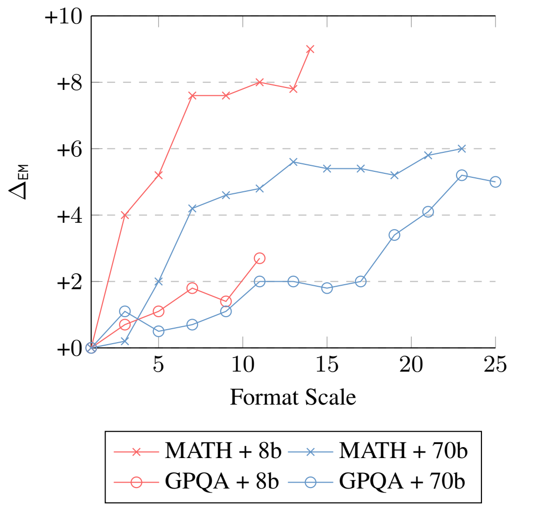


Figure 6: The average performance improvement brought by FORMAT-ADAPTER on MATH and GPQA using Llama3.1. Δ_{EM} denotes the EM improvement compared with the result using the single format.

is determined by the variation in answers generated by the corresponding formats of this category. For the categories with low improvements (e.g., Math Notation), the answers across different formats are largely similar, with performance close to that of Self-Consistency. In contrast, reasoning categories with higher performance improvements (e.g., Explain Level) exhibit greater variability in the answers generated by different formats, making it more likely to include the correct result; *(ii)* Even for the best-performing single category, its performance improvement is still lower than that achieved by using all reasoning categories (Overall), which indicates that the most suitable reasoning formats vary across questions, and combining different reasoning categories and formats during reasoning is necessary to achieve optimal results.

4.4.3 Reasoning Format Scale

Considering the computational resource limitations in practical applications, we evaluate the performance of FORMAT-ADAPTER under different scales of reasoning formats. The experimental results, as shown in Figure 6, reveal that performance consistently improves across different settings as the scale of formats increases, demonstrating the necessity of incorporating more reasoning formats to enhance performance. Besides, when a small number (< 5) of formats are used, FORMAT-ADAPTER also brings a significant improvement, proving the effectiveness of FORMAT-ADAPTER under low computational resources.

Additionally, the performance improvement in each setting follows a trend: it initially increases significantly, then stabilizes, and finally experiences another notable rise. This phenomenon can be explained as follows: *(i)* Initially, the primary performance bottleneck lies in the inconsistency of LLMs, where increasing the number of reasoning formats enhances the robustness of reasoning, thereby improving the performance. *(ii)* Once using a sufficient number of reasoning formats, the performance bottleneck shifts to whether the reasoning formats are suitable for the user question, where adding new formats makes it more likely that the format is suitable for the question, leading to further performance improvements.

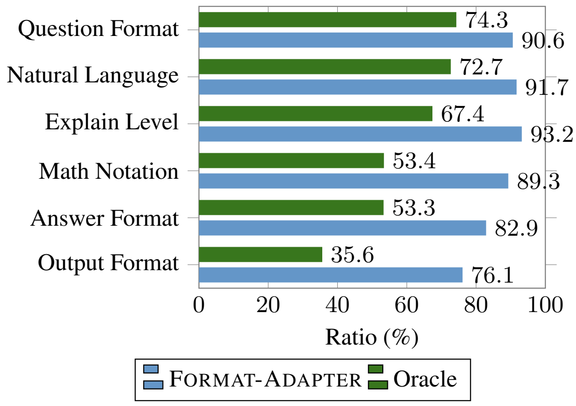


Figure 7: The average ratio over all datasets of each reasoning format category that is selected by FORMAT-ADAPTER (blue) and that contains the format that can solve the question correctly (Oracle, green).

4.4.4 Format Selection Ratio

To better understand the impact of different reasoning formats on reasoning performance, we compute the ratio of formats selected by FORMAT-ADAPTER or containing the correct answer, as shown in Figure 7. From the figure, we can observe the following: *(i)* For different reasoning formats, the ratio selected by FORMAT-ADAPTER follows a trend similar to that of Oracle, indicating that FORMAT-ADAPTER tends to select the appropriate formats, i.e., those that contain the correct answer, thus demonstrating the effectiveness of FORMAT-ADAPTER; *(ii)* Compared to the average performance of Oracle with FORMAT-ADAPTER in Table 1 (89.4%), the best single format still shows a performance gap of 15.1%, indicating that different questions suit different formats, suggesting that multiple formats are necessary during reasoning. *(iii)* FORMAT-ADAPTER selects a relatively high proportion ($> 70\%$) for each category, indicating that LLMs tend to assign higher scores during the Score step, resulting in that FORMAT-ADAPTER selecting many categories that do not contain the correct answer, suggesting the need for further improvement in the scoring method in future work.

5 Related Works

Previous studies have shown that LLMs could exhibit inconsistency during reasoning, producing inconsistent answers when faced with input or parameter perturbations (Adiwardana et al., 2020; Camburu et al., 2020; Elazar et al., 2021). To address this issue, Wang et al. (2023) proposes Self-Consistency, which generates multiple outputs for the same input and selects the final answer through voting, thereby reducing the impact of perturbations. Subsequent works have sought to improve upon Self-Consistency to further enhance the performance (Li et al., 2024; Besta et al., 2024; Wang et al., 2024). For example, Tree-of-Thought (Yao et al., 2023) decomposes the reasoning process and ensures consistency at each reasoning step as a tree, while DTV (Zhou et al., 2024) employs Isabelle formalism to represent answers, improving the accuracy of answer selection. Notably, many studies have demonstrated that employing diverse reasoning formats to generate answers outperforms relying on a single format to produce multiple outputs (Zhang et al., 2024a,b; He et al., 2024). For instance, CLIP (Qin et al., 2023) uses different natural language formulations to generate answers, and MultiPoT (Luo et al., 2024) leverages multiple programming languages for answer generation.

However, the above methods rely on predefined reasoning formats manually annotated by humans, which can be inefficient and suboptimal, as the most suitable reasoning format varies across questions. To address this limitation, we first analyze why utilizing multiple reasoning formats outperforms single-format reasoning and propose an optimization objective based on this insight. Guided by this objective, we leverage LLMs to generate and select the most suitable reasoning format, thereby reducing the cost of human annotations and improving reasoning performance.

6 Conclusion

In this paper, we propose FORMAT-ADAPTER, which generates multiple answers using different reasoning formats, reducing inconsistencies and improving the performance of LLMs. First, we present how to measure reasoning errors when generating multiple answers, showing that multiple reasoning formats outperform a single format. Then, we present FORMAT-ADAPTER, which uses LLMs to generate and select the suitable reasoning formats, improving reasoning performance by reducing the error measurement we present. We conduct experiments on math and commonsense reasoning, where FORMAT-ADAPTER improves performance by an average of 4.3% compared to previous methods, demonstrating its effectiveness. We also analyze the relationship between our error measurement and performance, showing a negative correlation that confirms its accuracy in measuring reasoning errors when generating multiple answers.

Limitations

(i) We have not yet experimented with FORMAT-ADAPTER on more tasks, such as question answering and code generation, where in the future, we will apply FORMAT-ADAPTER to a wider range of tasks to further demonstrate its effectiveness; *(ii)* Generating multiple answers incurs significant computational overhead, where in future work, we will explore ways to reduce the computational cost while maintaining or even improving reasoning performance.

Ethics Statement

All datasets and models used in this paper are publicly available, and our usage follows their licenses and terms.

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A Prove of Equations

Lemma 1. *Let $m, \phi, \bar{\phi}$ follow the definition in §2.1. If $\lim_{m\to\infty} \bar{\phi} = \phi \circ \mathsf{f}$, we can derive that $\lim_{m\to\infty} \delta_m = 0$.*

Proof. Considering that $\bar{\phi} = \mathsf{avg}(\phi_i) = \mathsf{avg}(\phi \circ \mathsf{f} + \delta_i)$, we can derive that

$$\mathsf{avg}(\phi \circ \mathsf{f} + \delta_i) = \phi \circ \mathsf{f}(m \to \infty)$$

Therefore, $\mathsf{avg}(\delta_i) = 0(m \to \infty)$. Assume, for contradiction, that $\lim_{m\to\infty} \delta_m \neq 0$. Then, there exists some $\epsilon > 0$ such that for large enough m, $\delta_m \geq \epsilon$. For large m, the average of the first m terms is

$$\frac{\delta_1 + \delta_2 + \cdots + \delta_m}{m}$$

Since the average tends to 0, for sufficiently large m, we must have

$$\frac{\delta_1 + \delta_2 + \cdots + \delta_m}{m} < \epsilon$$

However, if infinitely many $\delta_m \geq \epsilon$, this contradicts the fact that the average tends to 0. Thus, $\lim_{m\to\infty} \delta_m = 0$. □

Considering Lemma 1, in the following prove, we substitute $m \to \infty$ with $\delta_m \to 0$.

A.1 Prove of Equation 4

Theorem 1. *Let $D, L, m, \phi, \bar{\phi}$ follow the definition in §2.1. We can derive that:*

$$\lim_{\delta_i \to 0} \mathbb{E}_D \left[L(\bar{\phi}, y) \right] = \frac{1}{m} \sum_{i=1}^{m} L\left(\phi \circ \mathsf{f}, y\right)$$

Proof.

$$\frac{1}{m} \sum_{i=1}^{m} \mathbb{E}_D \left[L\left(\phi_i, y\right) \right] \tag{7}$$

$$= \frac{1}{m} \sum_{i=1}^{m} \mathbb{E}_D \left[L\left(\phi \circ \mathsf{f} + \delta_i, y\right) \right] \tag{8}$$

$$= \mathbb{E}_D \left[L\left(\phi \circ \mathsf{f}, y\right) \right] (\delta_i \to 0) \tag{9}$$

Considering that:

$$\bar{\phi} = \frac{1}{m} \sum_{i=1}^{m} \phi_i \tag{10}$$

$$= \frac{1}{m} \sum_{i=1}^{m} \phi \circ \mathsf{f}(\delta_i \to 0) \tag{11}$$

$$= \phi \circ \mathsf{f} \tag{12}$$

We can derive that:

$$\mathbb{E}_D \left[\frac{1}{m} \sum_{i=1}^{m} L\left(\phi_i, \bar{\phi}\right) \right] \tag{13}$$

$$= \mathbb{E}_D \left[\frac{1}{m} \sum_{i=1}^{m} L\left(\phi \circ \mathsf{f} + \delta_i, \bar{\phi}\right) \right] \tag{14}$$

$$= \mathbb{E}_D \left[\frac{1}{m} \sum_{i=1}^{m} L\left(\phi \circ \mathsf{f}, \phi \circ \mathsf{f}\right) \right] (\delta_i \to 0) \tag{15}$$

$$= 0 \tag{16}$$

Based on Equation 2, we can derive that:

$$\mathbb{E}_D \left[L(\bar{\phi}, y) \right] \tag{17}$$

$$= \frac{1}{m} \sum_{i=1}^{m} \mathbb{E}_D \left[L\left(\phi_i, y\right) \right] \tag{18}$$

$$- \mathbb{E}_D \left[\frac{1}{m} \sum_{i=1}^{m} L\left(\phi_i, \bar{\phi}\right) \right] \tag{19}$$

$$= \mathbb{E}_D \left[L\left(\phi \circ \mathsf{f}, y\right) \right] (\delta_i \to 0) \tag{20}$$

□

A.2 Prove of Equation 5

Theorem 2. *Let $D, L, m, \phi, \bar{\phi}$ follow the definition in §2.2. we can derive that:*

$$\lim_{\delta_i \to 0} \mathbb{E}_D \left[L(\bar{\phi}, y) \right] \tag{21}$$

$$= \frac{1}{m} \sum_{i=1}^{m} \mathbb{E}_D \left[L(\phi \circ \mathsf{f}_i, y) \right] \tag{22}$$

$$- \mathbb{E}_D [\frac{1}{m} \sum_{i=1}^{m} L(\phi \circ \mathsf{f}_i, \bar{\phi})] \tag{23}$$

Proof.

$$\frac{1}{m} \sum_{i=1}^{m} \mathbb{E}_D \left[L\left(\phi_i, y\right) \right] \tag{24}$$

$$= \frac{1}{m} \sum_{i=1}^{m} \mathbb{E}_D \left[L\left(\phi \circ \mathsf{f}_i + \delta_i, y\right) \right] \tag{25}$$

$$= \frac{1}{m} \sum_{i=1}^{m} L\left(\phi \circ \mathsf{f}_i, y\right) (\delta_i \to 0) \tag{26}$$

$$\lim_{\delta_i \to 0} \mathbb{E}_D \left[\frac{1}{m} \sum_{i=1}^{m} L\left(\phi_i, \bar{\phi}\right) \right] \tag{27}$$

$$= \mathbb{E}_D \left[\frac{1}{m} \sum_{i=1}^{m} L\left(\phi \circ f_i, \bar{\phi}\right) \right] \tag{28}$$

Based on Equation 2, we can derive that:

$$\mathbb{E}_D\left[L(\bar{\phi}, y)\right] \tag{29}$$

$$= \frac{1}{m}\sum_{i=1}^{m}\mathbb{E}_D\left[L\left(\phi_i, y\right)\right] \tag{30}$$

$$- \mathbb{E}_D\left[\frac{1}{m}\sum_{i=1}^{m}L\left(\phi_i, \bar{\phi}\right)\right] \tag{31}$$

$$= \frac{1}{m}\sum_{i=1}^{m}\mathbb{E}_D\left[L(\phi \circ \mathtt{f}_i, y)\right] \tag{32}$$

$$- \mathbb{E}_D[\frac{1}{m}\sum_{i=1}^{m}L(\phi \circ \mathtt{f}_i, \bar{\phi})](\delta_i \to 0) \tag{33}$$

□

B Prompts of FORMAT-ADAPTER

The prompts of FORMAT-ADAPTER are shown in Table 4. The prompt for the instruction rewriting is provided in the code since this prompt is too long. The prompts of the answer generation of each task follow Dubey et al. (2024), which can be found in https://huggingface.co/datasets/meta-llama/Llama-3.1-8B-Instruct-evals.

C Baselines of Main Experiments

C.1 Single Format

Single is to generate one answer using one format with Chain-of-Thought (Wei et al., 2022). The prompts we used follow Dubey et al. (2024).

Self-Consistency (SC) is similar to Single, while we generate multiple answers for each question. The generation number is the same as the format number of FORMAT-ADAPTER for each task and we set temperature as 0.5, top_p as 0.9. The prompts are the same with Single.

Tree-of-Thought (ToT) is to generate the reasoning process step by step, where it votes the results of each step, which is used as the input for the next step. The parameters and prompts we used are following the default of the paper.

DTV asks models to generate Isabelle formulations (Nipkow et al., 2002) to answer the questions, which can be executed automatically to ensure the logical correctness of the consistent answers. The parameters and prompts we used are following the default of the paper.

C.2 Multiple Format

CLIP asks LLMs to answer the given questions in different natural languages since different questions could suit different languages. The natural languages, parameters, and prompts we used follow the default of the paper.

MultiPoT aims to improve Program-of-Thought (Chen et al., 2023), which asks LLMs to solve problems with different program languages. The program languages, parameters, and prompts we used follow the default of the paper.

FlexTaF is designed to solve the table reasoning task, which demands LLMs to reason with different tabular formats. The table formats, parameters, and prompts we used follow the default of the paper.

D Reasoning Formats of FORMAT-ADAPTER

In this section, we list the reasoning formats generated by different LLMs on various datasets, as shown in Table 5. We rename some reasoning categories in the experiments of §4.4 to ensure that the similar categories can be compared together. From the table, we can observe that: *(i)* Compared to small-scale LLMs, large-scale LLMs are capable of generating a wider variety of reasoning formats, leading to a more significant performance improvement as demonstrated in Table 2; *(ii)* Compared with simple datasets (e.g., GSM8K), a greater number of reasoning formats are generated on more complex datasets (e.g., MATH, GPQA), as more solving approaches are available for complex questions, thus resulting in more diverse reasoning formats.

E Efficiency of FORMAT-ADAPTER

In this section, we discuss the efficiency of FORMAT-ADAPTER. We focus on two main aspects: the efficiency of the format generation, and the efficiency during inference.

E.1 Efficiency during Format Generation

Let the number of generated formats be M, and $t_{\mathcal{M}}$ represents the average time that LLM $\mathcal{M}$ takes to process a single data. Considering that format generation requires both generation and rewriting, the efficiency of format generation is $2Mt_{\mathcal{M}} = O(Mt_{\mathcal{M}})$.

Based on the discussion, we can adjust M to control the efficiency of format generation. Fur-

The prompt of Format Generation

You are requested to generate possible answer formats that can be changed for the given task, where I want to generate different answers in different formats of the given task.
For each task, you MUST generate the possible answer formats quoted with ** of the task, the number of answer formats of each task MUST > 3.
Here are several examples:

—

Task: Code Generation.
In this task, you are given a question, and then you should generate the Python code to answer the question.
Input: Today is the last day of the first quarter of 2008. What is the date one year ago from today?
Output:

```python
from datetime import datetime, timedelta
today = datetime(2008, 3, 31)
one_year_ago = today - timedelta(days=365)
```

The possible answer formats that can be changed are:
1. Natural Language: The natural languages of questions can be changed, like change as **Chinese, French, German, Spanish**.
2. Code Language: The code languages of answers can be changed, like change to **Java, C++, R, JavaScript**.

—

Based on the above examples, generate the possible answer formats to be changed for the following task.

Task: {task_name}
{task_definition}
Output: {answer}

The prompt of Answer Scoring

Please act as an impartial judge and evaluate the quality of the response provided by an AI assistant to the user question displayed below. Your evaluation should consider correctness and helpfulness. You will be given a assistant's answer. Identify and correct any mistakes. Be as objective as possible. After providing your explanation, you must rate the response on a scale of 1 to 10 by strictly following this format: "[rating]", for example: "Rating: [5]".

[Question]
{question}

[The Start of Assistant's Answer]
{answer}
[The End of Assistant's Answer]

Table 4: The prompts of FORMAT-ADAPTER.

thermore, in practical applications, since format generation is performed offline, the cost of this step can be ignored during online inference.

E.2 Efficiency during Reasoning

Let the number of formats selected for each query during inference be denoted as m, the total number of user queries be N, and t_s represents the time to select a single format. Since inference involves format selection, answer generation, and answer scoring, the total inference efficiency is given by $NMt_s + 2mNt_{\mathcal{M}}$. Given that $t_s \ll t_{\mathcal{M}}$ in practice, the overall inference efficiency simplifies to $O(mNt_{\mathcal{M}})$.

It can be observed that the inference efficiency of FORMAT-ADAPTER is comparable to that of Self-Consistency, while FORMAT-ADAPTER offers a significant performance improvement. Considering that prior research indicates that there is a positive correlation between model performance and inference time (Snell et al., 2024; Zhong et al., 2024), it is important to balance efficiency and performance based on the specific application scenario. For example, when computational resources are limited, the number of reasoning formats used can be reduced to enhance inference efficiency.

Model	GSM8K-Hard	MATH500	ARC-C-Hard	GPQA
Llama3.1-8b	**natural language (6)**, code language (2), mathematical notation (2), text format (2), answer style (2), response format (1)	**natural language (6)**, step-by-step format (3), text format (2), explanation level (1), mathematical notation (2)	**natural language (8)**, answer format (2), code language (6), explanation level (4), answer style (2), output format (3)	natural language (5), answer format (5), **explanation level (6)**, code language (5), answer style (4), explanation format (5), step-by-step format (4), explanation style (5), mathematical notation (4)
Llama3.1-70b	mathematical notation (4), natural language (4), problem format (4), answer format (4), **reasoning style (3)**, unit of measurement (3)	mathematical notation (3), problem format (5), **solution approach (3)**, answer format (3), unit system (3), problem complexity (3)	natural language (4), answer format (1), question type (1), answer choice format (4), **context format (3)**, answer justification (1)	natural language (4), answer format (9), explanation format (1), **question type (4)**, candidate answer format (7), explanation style (4), answer choice format (7), mathematical notation (6)
GPT-4o	natural language (4), mathematical expression (4), **explanation style (4)**, number representation (5)	**natural language (6)**, explanation format (2), notation style (2), answer presentation (2), units in solution (2), solution format (3), mathematical representation (3), concluding sentence format (3)	**natural language (5)**, numerical representation (3), answer structure (2), answer explanation (4), response format (3), question format (4), contextual explanation (2), answer representation (8)	natural language (4), numerical representation (3), answer presentation (2), **explanation detail (2)**, answer format (3)

Table 5: The reasoning categories generated by FORMAT-ADAPTER on different models and datasets. The number after each category is the format number corresponding to the category. The category with the best performance under each setting is marked in **bold**.

Method	SC	ToT	DTV	FORMAT-ADAPTER
Tokens	3889.9	24611.4	17816.4	25297.0

Table 6: The average output tokens per question on MATH using Llama3.1-8b.

E.3 Average Output Tokens of Different Method

To compare the efficiency of FORMAT-ADAPTER with other baselines in practical applications, we measure the average number of tokens output per question, as shown in Table 6. Although FORMAT-ADAPTER is less efficient than Self-Consistency, our method is closer to that of Tree-of-Thought. Considering the performance improvements of FORMAT-ADAPTER over both Self-Consistency and Tree-of-Thought, a balance between efficiency and performance must be considered in practical applications.

F Performance Using All Generated Formats

To validate the necessity of the reasoning format selection of FORMAT-ADAPTER, we compare its performance with that of using all formats without selection. The experimental results, as shown in Table 7, indicate that FORMAT-ADAPTER consistently outperforms that directly using all reasoning formats across all settings, which demonstrates the importance of selecting appropriate reasoning formats.

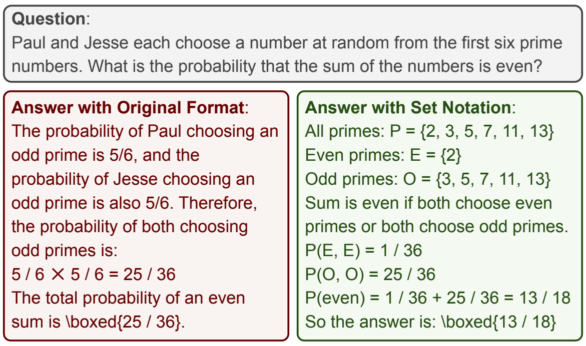

Figure 8: An example sampled from MATH answered using different reasoning formats. The correct part is marked in red, and the incorrect part is marked in green.

G Case Study

To better understand how FORMAT-ADAPTER improves reasoning performance, we present a case study, as shown in Figure 8. From the figure, it can be observed that when using the original reasoning format, the model overlooks that 2 is also an odd number, leading to an incorrect answer. However, when reasoning with the set notation, the model successfully accounts for all odd numbers, resulting in the correct answer. Therefore, utilizing different reasoning formats helps the model approach questions from multiple perspectives and different

Model	Method	GSM8K-Hard	MATH500	ARC-C-Hard	GPQA
Llama3.1-8b	All	53.9	54.0	42.2	33.9
	FORMAT-ADAPTER	**54.7**	**56.8**	**57.4**	**33.9**
Llama3.1-70b	All	73.8	70.2	69.9	47.5
	FORMAT-ADAPTER	**76.2**	**70.4**	**71.5**	**51.0**

Table 7: The performance with all formats or the formats selected by FORMAT-ADAPTER. All denotes using all generated formats. The best performance under each setting is marked in **bold**.

questions require different reasoning formats. As such, it is essential to integrate various reasoning formats to obtain the correct solution.