MAGICORE: Multi-Agent, Iterative, Coarse-to-Fine Refinement for Reasoning

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Abstract

Large language model (LLM) reasoning can be improved by scaling test-time compute with 002 aggregation, i.e., generating multiple samples and aggregating over them. While improving performance, this strategy often reaches a saturation point beyond which additional compute provides no return. Refinement offers an al-800 ternative by using model-generated feedback to improve answer quality. However, refinement faces three key challenges: (1) Excessive refinement: Uniformly refining all instances 011 012 can cause over-correction and reduce overall performance. (2) Inability to localize and address errors: LLMs struggle to identify and correct their own mistakes. (3) Insufficient refinement: Stopping refinement too soon could leave errors unaddressed. To tackle these is-017 sues, we propose MAGICORE, a framework for Multi-Agent Iteration for Coarse-to-fine 020 **Refinement.** MAGICORE mitigates excessive 021 refinement by categorizing problems as easy or hard, solving easy problems with coarse-022 grained aggregation, and solving the hard ones with fine-grained multi-agent refinement. To 025 better localize errors, we incorporate external step-wise reward model scores, and to ensure sufficient refinement, we iteratively refine the solutions using a multi-agent setup. We evaluate MAGICORE on Llama-3-8B and GPT-3.5 and show its effectiveness across seven reasoning datasets. One iteration of MAGI-CORE beats Self-Consistency by 3.4%, Bestof-k by 3.2%, and Self-Refine by 4.0% even when these baselines use k = 120, and MAGI-CORE uses less than 50% of the compute. ¹

1 Introduction

Imagine a person taking a math exam with problems of varying difficulty; even before answering any question, an effective exam-taker might first distinguish between easier and more challenging problems, deciding how much effort to budget for each one (Son and Metcalfe, 2000; Dodeen, 2015). To maximize their score, the student would likely spend minimal time on the easy problems and focus more on the harder ones, refining their answers where needed. Misallocating effort could not only waste time but even lower their score, as overthinking simple problems might lead to mistakes; similarly failing to dedicate enough thought to hard problems will lead to poor results. For Large Language Models (LLMs) performing reasoning tasks, several test-time approaches dedicate more computation to improve performance. These approaches sample multiple solutions to the same question and aggregate over the resulting answers (e.g. Self-Consistency (SC; Wang et al., 2022), Best-of-ksampling (Lightman et al., 2023; Sun et al., 2024; Wang et al., 2023)). However, applying aggregation strategies uniformly may waste computation on easier problems where the performance saturates quickly, and has diminishing gains on the harder problems even when more samples are generated. Refinement - where solutions are instead critiqued and improved upon during resampling offers a possible avenue for breaking out of the aggregation rut. This mirrors human reasoning, where incorporating feedback (rather than simply retrying) can improve answers, often in an iterative fashion. For example, a teacher might improve a student's understanding by providing multiple rounds of feedback on a test (Pan and Sana, 2021; Roediger and Karpicke, 2006; Wojcikowski and Kirk, 2013).

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While refinement seems promising, it faces three key challenges that current work has yet to fully address, as outlined in Fig. 1: (1) Excessive refinement: the LLM must know when to refine and when not to. While refinement can help on incorrectly solved problems, uniformly refining all instances can cause over-refinement, where solutions that were already correct before refinement

¹Code is provided with the supplementary materials.



Figure 1: **Top:** Three main issues in refinement: (1) *Excessive refinement;* (2) *Inability to localize and address errors;* (3) *Insufficient refinement.* **Bottom:** Our joint solution to address these issues. MAGICORE adapts resource allocation based on problem difficulty and refines only when encountering hard problems to avoid excessive refinement. For hard cases requiring refinement, we employ a multi-agent setup that iteratively reviews and refines the solutions based on targeted feedback generated with step-wise PRM scores.

are "overthought" and flipped to incorrect, reducing the overall performance (Huang et al., 2024; Shridhar et al., 2024; Stechly et al., 2024). (2) **Inability to localize and address errors**: LLMs struggle to identify their own mistakes (i.e., steps needing refinement) and struggle to correct them without explicit instructions. (3) **Insufficient Refinement**: deciding how much refinement is needed is non-trivial – stopping refinement early could leave errors unaddressed, i.e., hard problems might be "underthought" by a single refinement iteration.

To enable better test-time scaling for aggregation and to address the three issues in refinement, we propose a unified solution, MAGICORE: Multi-Agent Iteration for Coarse-to-fine Refinement. As shown in Fig. 1, our approach leverages external global and local Reward Models (RMs) that enhance both aggregation and refinement processes. To avoid excessive refinement, we perform *selec*tive refinement (see Fig. 1(a)): we start by generating multiple reasoning chains from the LLM and scoring them with the RMs, using the entropy of the final answer distribution to classify examples as easy or hard. Given LLMs' general inability to localize errors (Tyen et al., 2024), we leverage step-by-step scores from a process reward model (PRM) to help the LLM pinpoint low-scoring steps (which are likely to be incorrect); this process is shown in Fig. 1(b). Moreover, to help LLMs refine effectively once the errors have been localized, we propose a *multi-agent system* consisting of three agents: the Solver, the Reviewer, and the Refiner. For each problem, the Solver generates reasoning

chains, the Reviewer gives targeted feedback based on step-by-step RM scores, and the Refiner improves the solutions using this feedback. Finally, to address the issue of insufficient refinement, we *iterate the review-refine process*, using the quality and the entropy of the answers at each iteration as a stopping criterion (cf. Fig. 1(c)). While these three issues – selective refinement, error localization, and iterative refinement – might seem independent, addressing them jointly is more effective. Empirically, MAGICORE consistently outperforms baselines that tackle these issues in isolation, as confirmed by our ablation studies in Table 5.

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We evaluate MAGICORE on seven reasoning datasets (including math, commonsense and logical reasoning) with two LLMs: Llama-3-8B and GPT-3.5. Notably, MAGICORE shows consistent improvements over all aggregation and refinement baselines across datasets and models. Specifically, just one iteration of MAGICORE on Llama-3-8B already outperforms Best-of-k sampling (Lightman et al., 2023) by 3.2% and Self-Consistency (Wang et al., 2022) by 3.4%, while using roughly half of the test-time compute. MAGICORE also outperforms a combination of Self-Refine (Madaan et al., 2023) and Self-Consistency by 4.0% and these trends also hold true for GPT-3.5. Moreover, MAGICORE effectively decides when to use refinement and when *not* to, leading to a 6.4% improvement over the strongest Best-of-k baseline on MATH (Hendrycks et al., 2021b), whereas uniformly applying refinement to all samples can result in a *drop* of 5.2%, highlighting the key role

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148played by selective refinement. MAGICORE also149scales better with more iterations of refinement, and150continues to improve while the baselines stagnate.

2 Methodology

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In MAGICORE, we incorporate three types of models: (1) an LLM interchangeably performing three roles: the Solver, the Reviewer, and the Refiner, (2) an Outcome Reward Model (ORM) for generating global, solution-level correctness score, and (3) a Process Reward Model (PRM) for generating local step-by-step correctness scores. Both the ORM and PRM contribute to (1) assessing problem difficulty and (2) final answer selection via Weighted Self-Consistency (Li et al., 2023) (see Appendix B).

Overview. We present MAGICORE in Fig. 2. 162 The process begins with the Solver generating kreasoning chains for each problem, followed by 164 the ORM and PRM providing solution-level scores. 165 Next, the input problem's difficulty is classified based on two criteria (top-right of Fig. 2): (1) the 167 quality of the majority answer and (2) the RMs' 168 answer confidence. Refinement is initiated only 169 when the problem is deemed difficult, which oc-170 curs when the majority answer receives a low average RM score and the answer distribution is flat -172 indicating no single answer is significantly better 173 than the others (i.e., low confidence). For these 174 hard samples requiring refinement, we employ a 175 multi-agent setup with three agents: the Solver, the 176 Reviewer, and the Refiner (bottom of Fig. 2). The 177 Reviewer uses the step-wise scores from the PRM to generate targeted feedback, and the Refiner then 179 enhances the k solutions based on this feedback. The review-and-refine cycle can iterate multiple 181 times to ensure sufficient and effective refinement.

2.1 Classifying Problem Difficulty

We categorize each problem's difficulty as easy or hard using the following conditions (cf. Fig. 2).

a) Is the Majority Answer of High Quality? The Solver generates k solutions for the input question and we group them by their final answers. From the largest cluster of solutions, we calculate the average RM score and normalize it by the average score across all solutions, denoted as S_{avg} . If $S_{avg} \ge 0$ after normalization, this condition will be *true*, meaning the majority answer is already high-quality (as measured by both ORM and PRM scores, see Appendix C), and hence no refinement is needed. Otherwise, we deem the example to be a possible candidate for refinement and evaluate the second condition below.

b) Is Reward Models' Answer Confidence High? In this condition, we check if the RMs are confident in any single answer; if this is not the case, the problem is a possible candidate for refinement. We measure confidence via the entropy of the distribution over answers, obtained by weighting answer clusters by their average RM scores, in line with Weighted Self-Consistency (Li et al., 2023).

Coarse-to-Fine Decision. If *either* of the conditions is met (the quality of the answer is high *or* the RMs are confident on an answer), an instance is marked as easy and delegated to the coarsegrained method: Weighted Self-Consistency (Li et al., 2023), using the sum of the solution-level scores generated by both ORM and PRM. Conversely, if *both* conditions are not satisfied, the instance is marked as hard and delegated to the fine-grained method (as described in Section 2.2), addressing Issue 1 (excessive refinement) by only refining solutions for the hard problems.

2.2 Fine-Grained Multi-Agent Refinement

For hard instances that fail both conditions, we need to employ refinement to unlock improvements (see the bottom part of Fig. 2). Our refinement setup has three agents: (1) the *Solver*, which generates the initial solution (2) the *Reviewer*, which takes step-wise PRM scores and a reasoning chain as input, and generates targeted feedback that pinpoints the errors within the chain, and (3) the *Refiner*, which takes the feedback generated by the Reviewer to refine the previous chain.

Solver generates k solutions. The Solver is responsible for generating the initial k solutions. Recall that in Section 2.1, we assess problem difficulty using k generated solutions. When a problem is classified as easy, we aggregate the k solution without refinement. When a problem is classified as hard, we can directly re-use the k solutions *already generated* by the Solver.

Reviewer generates targeted feedback. To assist the Reviewer in generating useful feedback to localize errors better ("Issue 2" in Fig. 1), we supply the Reviewer with external step-wise PRM scores for each step of the solution. The goal of the Reviewer is to incorporate these step-wise correctness scores to generate actionable feedback. We append these scores to the end of each step and pass the result to the Reviewer. That is, it takes a chain with the



Figure 2: MAGICORE classify problem difficulty based on two conditions: (1) the quality of the majority answer and (2) the RM's answer confidence. A problem is considered hard when the majority answer receives a low average RM score *and* the answer distribution is flat (i.e., low confidence). For these hard problems, we employ a multi-agent setup – The Solver generates k reasoning chains, passing them to the PRM to pinpoint errors. The Reviewer turns scores into targeted feedback, and the Refiner improves the k solutions using the Reviewer's feedback. This review-refine process repeats until either of the two conditions passes, or a maximum iteration is reached.

PRM scores as input, and is prompted to identify problematic steps that need refinement and possible ways to fix them. The prompt for the Reviewer is shown in Appendix I.

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Refiner improves solutions w/ feedback. Inspired by the finding that LLM can resolve errors when explicitly pointed out (Tyen et al., 2024), the Refiner agent focuses exclusively on *how the step should be modified* so as to resolve the error based on feedback from the Reviewer. That is, the Refiner uses the targeted feedback generated by the Reviewer to refine the reasoning chain that was generated by the Solver. The prompt for the Refiner is shown in Appendix I.

Iterating the refinement process. For some hard instances, one round of refinement may be insufficient, as the Reviewer may have generated some irrelevant feedback or the Refiner may not have fixed the highlighted step adequately ("Issue 3" in Fig. 1). Thus, the Reviewer and the Refiner need 266 to collaborate with each other over the course of 267 multiple refinement iterations. To prevent excessive refinement, we re-evaluate the two conditions described in Section 2.1 in each iteration. The refinement continues until (a) one of the conditions 271 is met, or (b) a predefined maximum number of 272

iterations is reached.

Final answer selection. The refinement process described above operates on all k chains simultaneously, producing k refined chains in each iteration. At the end of each iteration, we use the ORM to assess whether the refined solution has improved based on its global correctness score. In other words, by the end of each iteration, we have 2k reasoning chains – k initial and k refined – but retain only the top k based on their global ORM scores. Here we choose to base the decision on the ORM score because the targeted feedback is generated with PRM's step-wise scores, so selecting the solution via another scoring model avoids overfitting. Finally, the answer is selected using Weighted Self-Consistency over these retained top k chains, at the end of each iteration.

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3 Experimental Setup

Implementation Details. We develop MAGI-CORE with Llama3-8B-Instruct (AI@Meta, 2024) and GPT-3.5-Turbo (OpenAI, 2022) as the base LLMs. Based on their strong performance on standard reward modeling evaluations (Lambert et al., 2024), we choose InternLM-7B (Cai et al., 2024) as the ORM, and Math-Shepherd-7B (Wang

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et al., 2023) as the PRM for computing the RM scores. By default, we sample k = 40 reasoning chains in each iteration for MAGICORE, and the decoding temperature is set to 0.8. The maximum number of iterations is set to 3, with additional analysis in Fig. 3 and Table 12. We compare against different categories of strong baselines as follows, and leave more comparisons against promptingbased baselines to Table 7 in the Appendix.

- Vanilla Prompting. The first baseline we compare to is zero-shot Chain-of-Thought (Wei et al., 2022); note that this only generates one reasoning chain per question without aggregation.
- Iterative Prompting. We also compare MAGI-CORE to an iterative prompting method, Self-Refine (SR) (Madaan et al., 2023), which refines the initial CoT answer via iteratively prompting the LLM to generate feedback and refine the previous output accordingly.
- Aggregation-based Methods. The third category generates multiple samples for each question. Here, we sample k solutions from the same LLM and select the final answer either via k-way Self-Consistency (SC) (Wang et al., 2022) or according to the highest ORM score (**Best-of-***k*) (Lightman et al., 2023; Sun et al., 2024; Wang et al., 2023). Note that we give these baselines more samples than MAGICORE.
- Iterative Baseline with Aggregation. To enable a fair comparison, we also report a stronger version of self-refine by combining Self-Refine and Self-Consistency (SR+SC), i.e., a baseline that is iterative, refines, and aggregates. Specifically, this baseline applies Self-Refine for k samples in parallel, and the final answer is derived by aggregating the k refined solutions.

Datasets. We evaluate MAGICORE mainly on five math reasoning datasets. Later in Section 4.2, we further show MAGICORE's effectiveness on commonsense (ARC-challenge; Clark et al. (2018)) and logical reasoning (Date Understanding; Srivastava et al. (2022)) tasks. The first class of math datasets is math word problems: GSM8K (Cobbe et al., 2021), SVAMP (Patel et al., 2021), and MATH (Hendrycks et al., 2021b). GSM8K and SVAMP consist of grade school-level math problems, with 1,312 and 1,000 test samples. MATH comprises high-school math competitions spanning diverse topics and a total of 5,000 problems. Following previous works (Lightman et al., 2023; Wang et al., 2023), we evaluate MATH performance on a representative subset of 500 samples. We also evaluate on math splits of general benchmarks that test language models' world knowledge and problem-solving abilities over various subjects such as MMLU-Math (Hendrycks et al., 2021a; Yue et al., 2024) and SAT (Zhong et al., 2023) with 974 and 220 test instances respectively.

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4 **Results and Analysis**

4.1 Main Results

MAGICORE outperforms all baselines at the first iteration. We present our main results in Table 1. First, one iteration of MAGICORE already outperforms all baselines. Compared to aggregation-based methods, which generate multiple responses for each problem without refinement, MAGICORE improves over Best-of-120 by 3.2% (absolute) averaged across the five datasets on Llama-3-8B, despite using $2 \times$ fewer samples. Note that our method's first iteration only involves 40 samples for easy problems and 40 refined chains for the *subset* of hard problems, making our k = 55on average. When compared to 120-way SC, our method shows an even greater average improvement of 3.3% on Llama-3-8B and 3.2% on GPT-3.5. Turning to refinement-based methods, we run them with up to 5 iterations and only report the best in Table 1 (denoted as "Best Iter"), leaving a more detailed comparison in Fig. 3 and Table 12. On average, MAGICORE shows 17.1% and 13.5% improvements over SR for Llama-3-8B and GPT-3.5. As SR alone is a weaker baseline without aggregating multiple samples, we also compare to SR + SC, and find that even with its best iteration, MAGI-CORE outperforms SR + SC by 5.4% (Llama-3-8B) and 4.9% (GPT-3.5) on average. This suggests that adaptively addressing challenging instances with targeted refinement improves overall performance, while reducing compute for easy problems.

MAGICORE continues to improve with more iterations. While MAGICORE already beats all baselines after the very first iteration, in Table 1, we also observe a clear upward trend in performance as the number of iterations increases. We illustrate this further in Fig. 3, which presents the accuracy across successive iterations. Our comparison includes Best-of-k and SR + SC with k = 40, with accuracy averaged across five datasets. We find that while SR + SC fluctuates around the same range of 70%, MAGICORE continues to improve and stabilize at the third iteration with 75.6% accuracy (with

	MMLU	MATH	SVAMP	GSM8K	SAT	Avg.	
Llama3-8B-Instruct							
Zero-shot CoT	50.4	24.2	72.4	80.1	58.2	57.1	
Self-Refine (Best Iter)	49.8	24.0	72.6	79.6	59.6	57.1	
Best-of- $k \ (k = 120)$	62.6	41.4	88.7	90.1	72.4	71.0	
k-way SC ($k = 120$)	63.0	40.6	89.8	90.3	70.5	70.8	
Self-Refine + k-way SC (Best Iter)	62.3	41.0	89.2	90.3	68.0	70.2	
MAGICORE (Iter=1)	67.3	46.0	91.4	91.1	75.0	74.2	
MAGICORE (Iter=2)	68.4	47.2	91.1	92.3	76.4	75.1	
MAGICORE (Iter=3)	68.9 (+5.6%)	47.8 (+5.2%)	91.3 (+1.7%)	91.6 (+1.3%)	78.2 (+5.8%)	75.6 (+4.3%)	
		GPT-3.5-Tu	ırbo				
Zero-shot CoT	62.5	37.2	78.1	78.5	76.8	66.6	
Self-Refine (Best Iter)	61.1	37.4	77.9	78.4	77.1	66.4	
Best-of- $k \ (k = 120)$	70.1	50.6	87.7	90.5	87.8	77.3	
k-way SC ($k = 120$)	70.4	51.2	86.9	89.8	87.6	77.1	
Self-Refine + k-way SC (Best Iter)	70.1	49.4	88.1	88.1	84.5	76.0	
MAGICORE (Iter=1)	73.7	57.2	89.4	91.1	90.1	80.3	
MAGICORE (Iter=2)	73.3	57.8	90.1	91.1	90.9	80.6	
MAGICORE (Iter=3)	73.6 (+3.5%)	58.6 (+8.0%)	90.1 (+2.4%)	91.4 (+0.9%)	90.9 (+3.1%)	80.9 (+3.6%)	

Table 1: Performance comparison of methods and models. (+x%) is compared to the strongest baseline (Best-of-k) shown in blue. Across models and datasets, MAGICORE consistently improves. Notably, MAGICORE surpasses all baselines after the *first iteration* of refinement, even when the baselines use a larger sample size (k = 120).



Ours Best-of-k Ours (k=15)k-way SC 50.0 47.5 45.0 Accuracy 42.5 40.0 37.5 35.0 40 100 120 1020 Effective Sample Size (k)

Figure 3: Comparison of our method with baselines across iterations, averaged across five datasets with k = 40. See Table 12 for full results.

Figure 4: Comparison of MAGICORE, k-way SC, and Best-of-k with different k on MATH.

a noticeable 1.4% improvement compared to the first iteration). This highlights the importance of our iterative refinement and the ability to overcome insufficient refinement for hard instances.

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MAGICORE outperforms aggregation-basedmethods despite using less computation. InFig. 4, we further compare the cost and performance of MAGICORE with Best-of-k and SC onMATH and MMLU using Llama-3-8B, studyinghow performance changes as we increase the number of reasoning chains generated per question k.Note that we sample k reasoning chains per question for baselines, whereas, in our method, we addk more samples in each iteration for a subset of

hard problems, and plot the average number of samples in Fig. 4. The trend in Fig. 4 shows that MAGICORE consistently outperforms k-way SC and Best-of-k at any given k. Moreover, while SC saturates and stops improving at around k = 40, MAGICORE continues to improve with increasing k. Notably, MAGICORE with k = 15 already performs better than Best-of-120 and 120-way SC, highlighting the cost-effectiveness of our method. We also show that MAGICORE is also more costefficient in terms of token count in Fig. 5.

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4.2 Additional Analyses of MAGICORE

Selective refinement avoids over-correcting and improves overall performance. In Section 1, we

Method	MMLU	MATH
Aggregation-Only	64.7	44.0
Refinement-Only	60.9	38.8

Table 2: Comparison when uniformly adopting aggregation (i.e., Weighted SC) or refinement to *all instances*.

noted that excessive refinement could potentially 427 hurt performance by flipping correct answers to 428 429 incorrect ones. Here, we provide a quantitative analysis of this claim. Recall that we have two 430 methods: coarse aggregation (Weighted SC) and 431 fine refinement (multi-agent iteration) which we 432 apply selectively depending on predicted problem 433 difficulty (c.f. Section 2.1). In Table 2, we mea-434 sure the performance of each method when applied 435 uniformly to *all* instances, regardless of the prob-436 lem difficulty. We find that uniformly applying 437 refinement actually degrades performance; com-438 paring Weighted SC (the "Aggregation-Only" in 439 440 row 1) to refinement-only (row 2), we see that refining all samples leads to 3.8% and 5.2% drops 441 on MMLU and MATH, respectively, pointing to 442 the over-correction issue. Conversely, one iteration 443 of our selective refinement (row 3) targets only the 444 445 challenging instances where the weighted majority vote is unlikely to succeed, resulting in up to 2.6%446 improvement compared to uniformly applying ag-447 448 gregation (row 1). This demonstrates that our selec-449 tive refinement not only avoids over-correction but also enhances overall performance by effectively 450 allocating more resources to harder problems. 451

PRM-based feedback enables better refinement. 452 453 Having demonstrated that selectively applying refinement in MAGICORE is crucial for achieving 454 improvements, we now compare the refinement 455 process with and without using a PRM. To this end, 456 without using a PRM, we ask the LLM to generate 457 an updated solution based on its own previous rea-458 soning, referring to this as LLM Self-Refinement. 459 Compared to the full MAGICORE in row 4 of Ta-460 ble 3, using LLM's self-refinement (row 1) results 461 in an average drop of 1.5%, indicating that using 462 the LLM for refinement is less effective than us-463 ing a PRM. To further examine how sensitive the 464 refinement process is to the score quality, in row 465 466 2, we replace the actual PRM scores with random scores. The result is worse than row 4, indicating 467 that PRM scores help in localizing errors. Finally, 468 we test whether the global ORM score can offer 469 a similar advantage as using the local PRM score. 470

Refinement Variants	MMLU	MATH
LLM Self-Refinement	65.9	44.4
Random Step Score	66.4	43.8
ORM Score (No Step Score)	66.8	45.2
MAGICORE (PRM Step Score)	67.3	46.0

Table 3: Refinement variants in MAGICORE. Using PRM scores for refinement performs the best.

Criterion for Refinement	MMLU	MATH
Prompt (classification)	65.2	45.0
Prompt (confidence)	64.7	44.4
Condition 1 only	66.4	43.6
Condition 2 only	66.1	44.2
Cond. 1 & Cond. 2	67.3	46.0

Table 4: Different ways of detecting hard problems (i.e. criterion for refinement). Our two conditions, when used together, are the most effective.

In row 3, instead of appending the step-wise score in each step, we place the global ORM score at the end of the response to generate the feedback. Result shows that it performs slightly worse than using the PRM score, suggesting that while global correctness is also a strong signal, local correctness scores help the LLM to identify and correct errors more effectively. 471

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The two conditions for classifying problem difficulty are the most effective when used together. In MAGICORE, we use reward models to classify each instance as easy or hard. Given that the RMs are also fine-tuned LLMs, we investigate whether prompting the LLM to perform this classification directly could replace the external RMs. We compare two settings in the first two rows, where we prompt Llama3-8B-Instruct to evaluate the difficulty of an instance. In the first setting (classification), the LLM generates a binary label. In the second setting (confidence), it produces a confidence score ranging from 0 to 1, indicating whether refinement is required - that is, whether the example is easy or hard. Results in Table 4 show that the LLM is less effective at determining instance difficulty compared to a reward model, as evidenced by a performance drop of 1.6% - 2.6%. In rows 3 and 4, we also examine the performance when only one of the conditions of MAGICORE (c.f. Section 2.1) is used to decide difficulty. Specifically, when only condition 1 is applied, an instance is classified as hard if the majority answer's quality is low. Conversely, when only condition 2 is applied, an instance is classified as hard if the RM's

Method	MMLU	MATH
Only Address Issue 1	64.7	44.0
Only Address Issue 2	65.9	45.4
Only Address Issue 3	60.3	36.4
MAgICoRE (Iter = 3)	68.9	47.8

Table 5: Ablation study on addressing each refinement (c.f. Fig. 1) issue one at a time.

Method	ARC	Date
Zero-shot	66.5	52.5
40-way SC	85.5	72.5
120-way SC	86.0	72.5
MAgICoRE (Iter = 1)	87.5	79.5
MAgICoRE (Iter = 2)	88.0	79.5
MAgICoRE (Iter = 3)	88.5	80.5

Table 6: MAGICORE also generalizes to commonsense reasoning and logical reasoning tasks.

answer confidence is low, regardless of the majority answer's quality. Results indicate that while each condition individually outperforms LLM selfverification, combining both yields the best performance. Indeed, in Appendix E, we find that MAGI-CORE's assessment of problem difficulty shows the highest agreement with human-annotated labels.

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All three issues must be addressed jointly. To investigate the importance of each refinement issue, we conduct an ablation study to address each issue individually in Table 5 under the following settings: (1) Only Address Issue 1 (Excessive Refinement): Here, we apply selective refinement only, without PRM step-wise scores for feedback generation and without iterations. (2) Only Address Issue 2 (Inability to Localize and Address Errors): Here, we use PRM scores for feedback generation and refine all instances uniformly (i.e. no selective refinement) for one iteration. (3) Only Address Issue 3 (Insuf*ficient Refinement*): Here, we iteratively refine all samples without incorporating PRM scores (i.e. no error localization) and without performing selective refinement. The results show that only addressing one single refinement issue at a time leads to a performance drop, highlighting the need for a joint solution as we proposed in MAGICORE. We find that only addressing insufficient refinement (Issue 3) causes the highest drop in performance, as it fails to efficiently localize errors (without the help 533 of PRM) and also performs excessive refinement.

MAGICORE generalizes to other domains.

Table 1 shows the benefits of MAGICORE on math reasoning; however, LLMs have been ap-536

plied to a wide variety of tasks beyond math. Here, we explore expanding MAGICORE to other domains, specifically to a commonsense reasoning task: ARC-Challenge (Clark et al., 2018), and a logical reasoning task: Date Understanding (Srivastava et al., 2022). We sample 200 instances from each dataset and use GPT4o-mini as a PRM for the experiments, as existing standalone PRMs generally only exist for math reasoning. Specifically, we prompt GPT4o-mini to provide step-wise correctness scores without any textual explanations or reasoning, acting the same as a PRM. The prompt is provided in Appendix J. This approach ensures that our agents do not have access to explanations from a stronger model, and we manually verify that explanations are not included with the scores. We conduct this experiment with Llama3-8B-Instruct as the base LLM. Table 6 shows that MAGICORE transfers to commonsense and logical reasoning, outperforming 120-say SC by 2.5% and 8.0%, respectively.

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5 Conclusion

Building on the observation that different problems require varying amounts of computation, we introduced MAGICORE, a method that adaptively allocates more computational resources to more challenging problems and selectively applies refinement where appropriate, i.e., on harder problems. MAGICORE addresses three key issues in refinement: excessive refinement on easy examples, the inability of LLMs to detect and correct errors in their reasoning, and insufficient refinement on hard instances. Our approach tackles these issues by employing both global and local external reward models to decide which samples to refine. We then incorporate local correctness scores to generate targeted feedback and an iterative multi-agent communication framework to refine solutions for hard problems. Our results across five math datasets and two models show that our coarse-to-fine method consistently outperforms both coarse-grained aggregation and fine-grained refinement alone at any given budget and even outperforms baselines using substantially more computation. In our ablations, we demonstrate the importance of selective refinement, showing that performance generally drops when refining all samples uniformly. We also highlight the role of iteration in our framework, showing increased performance across iterations even as baselines stagnate.

Limitations

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Like all test-time scaling, MAGICORE improves performance by adding computation via additional samples, trading some efficiency for better perfor-590 mance. We show that MAGICORE makes better 591 use of additional compute than the baselines by performing targeted refinement and thus better us-593 ing inference-time compute; indeed, while baselines like Best-of-k and Self-Consistency stagnate 595 with additional compute, MAGICORE continues 596 to improve. Nevertheless, our method increases the 597 computational cost of inference, and relies on starting with a base number of samples to establish the 599 difficulty and quality of existing solutions. In addition to requiring multiple solutions, MAGICORE uses feedback from both ORMs and PRMs to improve refinement. These models must be separately trained to provide rewards for a given domain and therefore do not exist for all problem types. However, we also note that MAGICORE is modular, and thus allows for newer and better ORMs and 607 PRMs to be swapped in as they become available. MAGICORE is designed to improve the reasoning of LLMs, and thus has no additional risks beyond 610 those inherent to LLMs generally. 611

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A Related Work

Improving Reasoning by Aggregation. Self-Consistency (SC; Wang et al., 2022) generates kreasoning chains and marginalizes over the chains to obtain answer clusters; the most frequent answer is selected as the final prediction. While simple and effective, it generates k solutions for every sample, as both past work and our work show that SC saturates when k increases (Chen et al., 2024b; Li et al., 2024a). Several studies adaptively determine the number of samples (k) required for each instance to address this (Aggarwal et al., 2023; Li et al., 2024b). However, the performance of such approaches is upper-bounded by SC – they address the cost issue but do not enhance overall performance. To surpass SC, Yin et al. (2024) propose using the LLM to evaluate answer clusters, taking into account both frequency and the LLM-evaluated quality of the answers. Instead, we propose using external RMs to decide between coarse-grained aggregation and fine-grained refinement, identify errors, and aid refinement; this allows us to improve over aggregation or refinement alone.

LLM-based Verification and Refinement. Past 907 work mostly uses RMs for verification purposes (Li et al., 2023; Khalifa et al., 2023; Cobbe et al., 909 2021; Lightman et al., 2023). Havrilla et al. (2024) 910 considers local correctness for refinement in a non-911 adaptive way and requires specific data curation 912 with fine-tuning, while our work is adaptive and 913 uses off-the-shelf global and local models. An-914 other line of work has proposed using the LLM 915 itself as a verifier, in place of an RM (Liu et al., 916 2024; Zhang et al., 2024; Aggarwal et al., 2023; 917 Madaan et al., 2023). However, recent work shows 918 the inability of LLMs to "self-verify" their own 919 reasoning (Huang et al., 2024; Stechly et al., 2023; Kamoi et al., 2024; Tyen et al., 2024; Kamoi et al., 921 2024). Hence, MAGICORE uses external global 922 and local reward models (Wang et al., 2023; Cai 923 et al., 2024) for selective coarse-to-fine refinement. 924 Shridhar et al. (2024) trained specific models to decide when to refine and when to trust refined solutions. This contrasts with our method, where the decision to refine is based on a coarse-to-fine 928 resource allocation method that differentiates easy 930 from hard problems (for which we use global and local reward models), and where refinement is done 931 based on off-the-shelf models. We also iteratively refine guided by global correctness to ensure sufficient refinement, whereas Shridhar et al. (2024) 934

refine only once. Wadhwa et al. (2024) propose a multi-agent detect-critique-refine pipeline for generation tasks. MAGICORE instead focuses on reasoning tasks and uses external RMs for selective coarse-to-fine refinement (whereas Wadhwa et al. (2024)'s detection uses the same metric as their evaluation, which is infeasible in reasoning where the metric – accuracy – requires access to the gold answer).

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Multi-Agent Systems with LLMs. LLMs can be used in multi-agent systems, where the agents interact, collaborate, and compete (Wang et al., 2024; Lu et al., 2024; Feng et al., 2024). Related to our work, one line of multi-agent research focuses on structured debates or discussions between LLM agents, where the interaction helps refine and improve previously generated solutions (Du et al., 2023; Liang et al., 2023; Yin et al., 2023; Chen et al., 2024a). These studies show improvements over single-agent systems, but a major challenge in multi-agent systems is achieving a correct consensus among LLMs; external feedback can help prevent this consensus from aligning with the agents' internal and possibly erroneous outputs. Therefore, MAGICORE's multi-agent refinement incorporates external RMs for more objective scoring, enabling the generation of targeted feedback for better refinement.

B Self-Consistency and Weighted Self-Consistency.

Self-Consistency (Wang et al., 2022) is a popular decoding method that uses majority voting to aggregate predictions from different reasoning chains, thus marginalizing over chains. It generates k solutions per question and selects the most frequent final answer from these samples. While simple and effective, this method assigns uniform weight to each reasoning chain, which fails to account for the quality of each solution. To address this limitation, Li et al. (2023) propose Weighted Self-Consistency, accounting for each solution's quality. Formally, both Self-Consistency and Weighted Self-Consistency choose a final answer via:

$$\hat{y} = \arg\max_{y} \sum_{i=1}^{k} \mathbb{1}_{y_i = y} \mathcal{V}(q; r_i)$$
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where $\mathcal{V}(\cdot)$ is a constant 1 in Self-Consistency979and the quality measurement (e.g., RM score) in980Weighted Self-Consistency. In MAGICORE's final981

answer selection, we use the sum of the solutionlevel scores generated by both ORM and PRM as $\mathcal{V}(\cdot)$. Throughout MAGICORE, in cases where we need solution-level PRM scores (compatible with ORM scores), we accumulate the PRM step scores by taking their product (Sun et al., 2024), so that the aggregated PRM score corresponds to a solution.

C Details of the Conditions

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Condition 1: Is the Majority Answer of High Quality? Given a problem q, to determine the difficulty of the problem at hand, the Solver generates k solutions $R = \{r_1, \ldots, r_k\}$ and final answers $A = \{a_1, \ldots, a_k\}$ per question and cluster the solutions by their final answer. This produces a partition \mathcal{A} with elements \mathcal{A}_i , where $\mathcal{A}_i = \{r_i \in$ $R \mid a_i = a_i$. The majority cluster \mathcal{A}_q has the most "votes", i.e., $\mathcal{A}_g = \operatorname{argmax}_{i \in |\mathcal{A}|} |\mathcal{A}_i|$. We evaluate the majority answer quality by both ORM and PRM separately but with the same procedure, as described below. First, we score every reasoning chain r_i within the majority cluster \mathcal{A}_g . Both ORM and PRM are able to produce a solution-level score, which we denoted as S_i^{RM} . Note that we perform this check using ORM and PRM separately, but for simplicity, we use the same notation for solution-level score, which either comes from the ORM or the PRM. We calculate the average of the solution-level scores from the majority group:

$$\mathcal{S}_{avg}^{ ext{rm}} = rac{1}{|\mathcal{A}_g|} \sum_{i=1}^{|\mathcal{A}_g|} \mathcal{S}_i^{ ext{rm}}$$

This average score informs us of the majority answer's quality. To set a threshold, we normalize S_{avg}^{RM} by using the sample average RM scores (by 1014 computing S_i^{RM} for each sample and then take the 1015 average of these scores). Importantly, this process 1016 does not require any labeled data. After normalization, if the average reward of the majority group 1018 $\mathcal{S}_{avg}^{\text{RM}} \geq 0$, indicating that the quality of the major-1019 ity answer is high, Condition 1 will be true. Oth-1020 erwise, if $S_{avg}^{RM} < 0$, Condition 1 will be *false*, 1021 suggesting that even the most frequent answer is 1022 of poor quality and that the instance might benefit 1023 from refinement. 1024

1025Condition 2: Are Reward Models' Answer Con-1026fidence High? Besides the quality of the major-1027ity answer, we also consider whether the RMs are1028confident enough in any single answer among the

answer clusters. Again we evaluate both ORM and 1029 PRM's answer confidence separately but with the 1030 same procedure, as described below. First, the an-1031 swer distribution is formed by (1) the frequency of 1032 each unique answer and (2) the total RM score of 1033 each answer cluster. We estimate the RM's confi-1034 dence according to this distribution. If the distribu-1035 tion is concentrated, meaning that only one answer 1036 cluster stands out, the RM's answer confidence is 1037 treated as high. Conversely, if the distribution is 1038 diffused and the clusters' scores are more uniform, 1039 then there is no single answer for which the RM 1040 has high confidence, i.e., the RM's confidence is 1041 low. This motivates a targeted step-wise refinement 1042 process to select a more definite answer. Again we 1043 use both ORM and PRM to generate the solution-1044 level score $\mathcal{S}_i^{\text{RM}}$. Given the k reasoning chains 1045 generated along with the solution-level score, we 1046 compute the RM's answer confidence (denoted as 1047 C) using the entropy of the answer cluster weighed 1048 by the RM scores, passing the result through a sig-1049 moid function to normalize it onto [0, 1]. Formally, 1050 the calculation of the entropy can be expressed as: 1051

$$H = -\sum_{i=1}^{n} p(\mathcal{A}_i) \log p(\mathcal{A}_i),$$
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$$p(\mathcal{A}_i) = \frac{\sum_{i=1}^{|\mathcal{A}_i|} \mathcal{S}_i^{\text{RM}}}{\sum\limits_{\mathcal{A}_j \in \mathcal{A}} \sum_{k=1}^{|\mathcal{A}_j|} \mathcal{S}_k^{\text{RM}}}$$
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where n is the number of unique answers among 1055 the k chains, A_i is the *i*-th answer cluster (a set 1056 of reasoning chains leading to the same answer) 1057 and \mathcal{A} is the set of all clusters. Each answer in a 1058 cluster is weighed by its unnormalized solution-1059 level score S_i^{RM} . To normalize entropy onto a 1060 confidence scale, we invert it so that high entropy 1061 corresponds to low confidence. We then apply a 1062 sigmoid function $\sigma(.)$, mapping the values to the 1063 range [0,1]: $C = \sigma(\alpha * (1-H))$. We set α to 1064 2 to let the distribution stretch more evenly between 0 and 1. This transformation establishes 0.5 1066 as a natural threshold for differentiating low and 1067 high confidence, thereby eliminating the need for 1068 any threshold tuning. That is, if an instance has 1069 $C \ge 0.5$, Condition 2 is *true*, meaning that the 1070 RMs are confident on a single answer cluster. Oth-1071 erwise, if C < 0.5, Condition 2 is *false*, suggesting 1072 that the RMs' uncertainty among the k chains is high, necessitating a finer refinement. 1074

Method	MMLU	MATH	SVAMP	GSM8K	SAT	Avg.
120-way SC	63.0	40.6	89.8	90.3	70.5	70.8
120-way SC + PRM (Li et al., 2023)	65.4	44.6	90.8	90.7	72.5	72.8
Self-correct + 120-way SC (Kim et al., 2024)	62.1	38.6	86.2	88.1	65.6	68.1
Least-to-Most + 120-way SC (Zhou et al., 2023)	62.6	40.6	89.0	90.3	68.9	70.3
Multi-Agent Debate + SC (Du et al., 2023)	64.6	41.0	89.6	90.8	72.5	71.7
MAgICoRE (Iter=1)	67.3	46.0	91.4	91.1	75.0	74.2
MAgICoRE (Iter=2)	68.4	47.2	91.1	92.3	76.4	75.1
MAgICoRE (Iter=3)	68.9	47.8	91.3	91.6	78.2	75.6

Table 7: Performance comparison with additional baselines using Llama3-8B-Instruct. Notably, MAGICORE with only one iteration outperforms all baselines despite using fewer samples.

D Additional Experimental Results

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D.1 Comparison with additional baselines.

In addition to Table 1, we also compare with the following baselines: (1) 120-way SC + PRM: The product of step-wise PRM scores is used as the solution-level score. This score is then employed for weighted Self-Consistency, following (Li et al., 2023). (2) Self-correct + 120-way SC: We use the "Self-Correct RCI" prompt from (Kim et al., 2024) to generate 120 solutions per question, which are subsequently aggregated using Self-Consistency. (3) Least-to-Most + 120-way SC: We use the zeroshot Least-to-Most prompt from (Zhou et al., 2023) to generate 120 solutions per question, followed by aggregation via Self-Consistency. (4) Multi-Agent Debate + SC: Following Du et al. (2023), we conduct a three-agent debate over four rounds, repeating this process ten times. The final answers from these ten debates are aggregated using Self-Consistency, yielding 120 generations per question.

We use Llama3-8B-Instruct as the base model. Results show that a single iteration of MAGICORE already outperforms methods that rely on PRM for aggregation (120-way SC + PRM), as well as approaches like Self-Correction, advanced prompting, and multi-agent debate. On average, MAGICORE outperforms 120-way SC + PRM by 2.8% despite using fewer samples, highlighting the limitations of using PRM solely for aggregation. Additionally, MAGICORE exceeds Least-to-Most by 5.3%, showcasing superior adaptability to problem difficulty. Finally, MAGICORE surpasses Multi-agent Debate by 3.9%, indicating that our aggregation and refinement mechanisms scale more effectively at test time.

Aggregation	MMLU	MATH
ORM-Only	66.9	45.4
PRM-Only	66.1	45.0
Both	67.3	46.0

Table 8: Ablation study on the final answer selection,using ORM-only, PRM-only or both.

Method	Accuracy
Zero-shot	72.0
40-way SC	79.2
40-way SC + PRM	79.4
MAgICoRE (Iter = 1)	80.2
MAgICoRE (Iter = 2)	80.4
MAgICoRE (Iter = 3)	80.4

Table 9: MAGICORE can also improve GPT4o-mini on MATH.

D.2 MAGICORE also improves stronger 1110 models like GPT40-mini. 1111

Table 1 shows results with GPT-3.5-Turbo; here, 1112 we show that MAGICORE scales to larger and 1113 stronger models as well. Specifically, we run 1114 MAGICORE using GPT4o-mini on a subset of 1115 MATH data. Due to the high cost of running 1116 GPT4o-mini with k = 120 and the fact that 1117 Fig. 4 shows *decreasing* performance at k = 1201118 for MATH, we only compare to the 40-way SC 1119 with the weighted variation that incorporates PRM 1120 scores for vote weighting (40-way SC + PRM). 1121 Appendix D.1 demonstrates that MAGICORE can 1122 also enhance stronger model's performance, albeit 1123 with a smaller margin of improvement compared 1124 to Llama3-8B and GPT-3.5 shown in Table 1. 1125

	MMLU	MATH
Joint Roles	66.7	44.8
Distinct Agents (Ours)	67.3	46.0

Table 10: MAGICORE's separation of the Reviewer and Refiner roles is more effective than combining them into a single role.

D.3 Separating Reviewer and Refiner roles outperforms combining these roles.

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In Appendix D.2, we examine the effects of com-1128 bining the roles of Reviewer and Refiner by merg-1129 ing their prompts, instructing the model to simul-1130 taneously generate both feedback and a refined so-1131 lution. This method is referred to as "Joint Roles". 1132 In MAGICORE, the Reviewer and Refiner have 1133 distinct, clearly defined roles, which we refer to 1134 as the "Distinct Agents" approach. As before, the 1135 performance comparison is based on the first iter-1136 ation, with all other variables held constant. Our 1137 findings show that maintaining separate roles (as in 1138 our multi-agent setup) leads to better performance, 1139 with the "Joint Roles" configuration resulting in 1140 a 0.6% drop in MMLU and a 1.2% decrease in 1141 MATH. The larger drop in MATH suggests that 1142 its problems are more complex and often require 1143 1144 extended reasoning, making the combined roles less effective, whereas maintaining separate roles 1145 proves to be more beneficial. 1146

D.4 Ablations on reward models for final answer selection.

We report MAGICORE up to three iterations in Table 1 and only report the best-performing iteration of Self-Refine + k-way SC. Here, we provide extended results in table Table 12. We also conducted another ablation study to evaluate the performance when using ORM, PRM, or a the summation of both scores for final answer selection. As shown in Appendix D.1, utilizing ORM's global correctness score yields better results than aggregating PRM's local correctness score. However, the best performance is achieved when both scores are combined for the final answer aggregation.

D.5 Reliable step-wise scores enable LLM refinement.

1163To compare with an oracle PRM, we sample 5001164instances from the Math-Shepherd dataset (Wang1165et al., 2023), which includes gold label correctness1166for each step. Besides the three settings we evalu-

Refinement Variants	Accuracy
No feedback (LLM self-refine)	48.30
Random PRM score	49.60
PRM predicted score	51.20
Oracle PRM score	52.40

Table 11: Comparison of different refinement variants in MAGICORE.

ated in Table 3, we also evaluate the oracle PRM1167score, where feedback uses the gold correctness1168labels. Appendix D.4 shows that the oracle PRM1169score performs the best, followed by the predicted1170PRM score, suggesting that given reliable stepwise1171scores, LLMs can effectively refine their solutions1172and improve.1173

	MMLU	MATH	SVAMP	GSM8K	SAT	Avg.
	Llama3-8	B-Instru	ct			
Zero-shot CoT	50.4	24.2	72.4	80.1	58.2	57.1
Self-Refine (Iter=1)	49.6	24.6	72.0	79.0	57.7	56.3
Self-Refine (Iter=2)	50.2	23.8	72.8	79.6	59.3	57.1
Self-Refine (Iter=3)	49.8	24.0	72.6	79.6	59.6	57.1
Best-of- $k \ (k = 120)$	62.6	41.4	88.7	90.1	72.4	71.0
<i>k</i> -way SC ($k = 120$)	63.0	40.6	89.8	90.3	70.5	70.8
Self-Refine + k-way SC (Iter=0)	62.1	40.4	88.6	90.1	68.2	69.9
Self-Refine + k -way SC (Iter=1)	61.3	40.6	88.9	89.7	67.7	69.6
Self-Refine + k -way SC (Iter=2)	62.7	40.0	88.9	90.1	68.6	70.1
Self-Refine + k -way SC (Iter=3)	62.3	41.0	89.2	90.3	68.0	70.2
Self-Refine + <i>k</i> -way SC (Iter=4)	62.1	41.4	89.2	90.1	67.7	70.1
Self-Refine + <i>k</i> -way SC (Iter=5)	62.7	40.4	88.6	89.7	67.7	69.8
MAGICORE (Iter=1)	67.3	46.0	91.4	91.1	75.0	74.2
MAGICORE (Iter=2)	68.4	47.2	91.1	92.3	76.4	75.1
MAGICORE (Iter=3)	68.9	47.8	91.3	91.6	78.2	75.6
MAGICORE (Iter=4)	68.9	48.0	91.3	91.1	78.2	75.5
MAGICORE (Iter=5)	68.4	48.0	91.1	91.6	78.2	75.5
	GPT-3.	5-Turbo				
Zero-shot CoT	62.5	37.2	78.1	78.5	76.8	66.6
Self-Refine (Iter=1)	62.4	37.4	77.7	77.4	77.3	66.4
Self-Refine (Iter=2)	61.6	37.6	78.6	77.9	76.9	66.5
Self-Refine (Iter=3)	61.1	37.4	77.9	78.4	77.1	66.4
Best-of- k ($k = 120$)	70.1	50.6	87.7	90.5	87.8	77.3
<i>k</i> -way SC ($k = 120$)	70.4	51.2	86.9	89.8	87.6	77.1
Self-Refine + <i>k</i> -way SC (Iter=0)	69.4	49.8	86.9	88.1	85.6	76.0
Self-Refine + k-way SC (Iter=1)	69.8	49.0	87.1	88.3	85.0	75.8
Self-Refine + <i>k</i> -way SC (Iter=2)	70.1	49.4	88.1	88.1	84.5	76.0
Self-Refine + <i>k</i> -way SC (Iter=3)	69.6	48.8	87.3	87.8	85.2	75.7
Self-Refine + <i>k</i> -way SC (Iter=4)	69.8	48.4	87.1	87.1	85.0	75.5
Self-Refine + k-way SC (Iter=5)	69.6	48.6	87.3	87.4	84.5	75.5
MAGICORE (Iter=1)	73.7	57.2	89.4	91.1	90.1	80.3
MAGICORE (Iter=2)	73.3	57.8	90.1	91.1	90.9	80.6
MAGICORE (Iter=3)	73.6	58.6	90.1	91.4	90.9	80.9
MAGICORE (Iter=4)	73.6	58.0	89.9	91.4	90.9	80.8
MAGICORE (Iter=5)	73.4	57.6	89.4	91.1	90.9	80.5

Table 12: Extended version of Table 1. Here we show all more iterations for Self-Refine + k-way SC and MAGICORE. While SR + SC does not show a clear improvement with more iterations, MAGICORE continues to improve, peaking at the third iteration.

	Р	R	F1
Random	68.4	49.6	57.5
Prompt-based (classification)	65.9	10.3	17.8
Prompt-based (confidence)	0.0	0.0	0.0
MAGICORE	86.3	67.6	75.8

Table 13: The Precision (P), Recall (R) and F1 of the model predicted problem difficulty.

E Model-Predicted vs. Human-Annotated Problem Difficulty

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We analyze the model's prediction of problem dif-1176 ficulty. Specifically, we utilize the MATH dataset, 1177 which includes human-annotated difficulty levels 1178 ranging from 1 to 5, with higher levels indicating 1179 increased problem complexity. For our analysis, 1180 we split the problems as follows: (1) Easy: Levels 1181 1 and 2 and (2) Hard: Levels 4 and 5. We exclude 1182 Level 3 problems to create a clearer distinction be-1183 tween easy and hard categories. We compare the 1184 overlap between our model's predictions and these 1185 human-annotated levels. We treat hard as the pos-1186 itive label. The results are presented in Table 13. 1187 To provide a comparative analysis, we include: (1) 1188 a random baseline that assigns easy and hard la-1189 1190 bels at random, (2) a prompt-based baseline that directly prompts the LLM to classify the problem 1191 difficulty, and (3) another prompt-based baseline 1192 that prompts the LLM to generate a confidence 1193 score when answering, where a confidence score of 1194 ≥ 0.5 is classified as "easy". Results show that our 1195 conditions substantially outperform all baselines. 1196 Interestingly, the prompt-based methods perform 1197 worse than the random baseline, particularly the 1198 one relying on confidence scores, which classifies 1199 all problems as easy; this method scores 0 for both 1200 precision and recall since we treat "hard" as the 1201 positive label, so it has 0 true positives. This sug-1202 gests that our framework is highly effective at dis-1203 tinguishing true problem difficulty based on the 1204 conditions outlined in our methodology.

F Dataset Statistics and Licenses.

1207We provide the sample sizes and licenses of the
datasets used in this work in Table 14. All the
datasets are in English and all datasets are used in
a fashion consistent with their intended use.

G Token Count Analysis

In Fig. 4, we are mainly comparing the number of 1212 generations (k) per question with the baselines. To 1213 provide a more granular analysis, we break down 1214 the generations at the token level and compare costs 1215 in terms of token counts. The results are detailed 1216 in Fig. 5. For Self-Consistency, the input tokens 1217 are counted only once per question, as it uses the 1218 same input to generate k responses. In contrast, 1219 the input token count for MAGICORE includes all 1220 prompts across all agents - Solver, Reviewer, and 1221 Refiner. We also include the token count for the 1222 ORM and PRM in MAGICORE. Since the cost 1223 of input tokens is typically $0.25 \times$ that of output 1224 tokens², we present the normalized total token cost 1225 as $0.25 \times \text{input} + 1 \times \text{output}$. Results in Fig. 5 show 1226 that (1) scaling Self-Consistency from k = 40 to 1227 k = 120 largely increases token overhead while 1228 yielding marginal improvements. (2) MAGICORE 1229 exhibits superior scalability, achieving substantially 1230 higher performance gains with increased token us-1231 age. On MMLU, MATH and SAT, we observe a 1232 clear upward trend with an increased token count; 1233 MAGICORE consistently improves with additional 1234 tokens (unlike SC which tends to stagnate). (3) The 1235 first iteration of MAGICORE outperforms 120-way 1236 SC fewer tokens. 1237

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H Discussion of external reward models.

External reward models play an important role MAGICORE and are used in the solutions to all three problems (excessive refinement, inability to localize and address errors, and insufficient refinement). While MAGICORE does utilize external reward models, our framework is modular and can readily incorporate new reward models as they emerge. As the community is actively advancing the performance of reward models evidenced by a benchmark for reward models (Lambert et al., 2024), MAGICORE is thus complementary to and enhanced by progress in reward modeling, rather than constrained by it. While it is possible to train a custom error-identification model, this approach is often data-dependent and prone to obsolescence. In contrast, MAGICORE's modular design overcomes this limitation by enabling the integration of new state-of-the-art models as they become available. Moreover, our experiments in Table 6 indicate

²See https://openai.com/api/pricing, https:// www.anthropic.com/pricing#anthropic-api, and https: //ai.google.dev/pricing#1_5pro

	Sample Size	License
MMLU-Math (Hendrycks et al., 2021a)	974	MIT License
MATH (Hendrycks et al., 2021b)	500	MIT License
SVAMP (Patel et al., 2021)	1,000	MIT License
GSM8K (Cobbe et al., 2021)	1,312	MIT License
SAT (Zhong et al., 2023)	220	MIT License
ARC-Challenge (Clark et al., 2018)	200	CC-by-SA-4.0
Date Understanding (Srivastava et al., 2022)	200	Apache License

Table 14: The statistics and licenses of the datasets used in this study.



Figure 5: Token count comparison with Self-Consistency across different datasets. Scaling Self-Consistency from k = 40 to k = 120 introduces substantial token overhead while providing marginal improvements. In contrast, MAGICORE demonstrates superior scalability, delivering much higher performance gains with an increased token count. Notably, the first iteration of MAGICORE consistently outperforms 120-way SC while using fewer tokens.

that when trained reward models are unavailable, we can use sufficiently strong LLMs in place of trained RMs. For example, we use GPT4o-mini as a reward model for commonsense and logical reasoning.

I Prompt for the Reviewer and the Refiner

Reviewer's Prompt

Your task is to provide step-by-step feedback to the current solution.

You will be given a math problem and a current solution, along with the scores for each step based on its correctness.

- You will find (Score: n/10) at the end of each step.

- The maximum (best) score is 10, which means that this step is 100% correct (and 0% incorrect).

- The minimum (worst) score is 0, which means that this step is 100% incorrect (and 0% correct).

Pay attention to the steps having scores lower than 6, and carefully identify the errors in those steps.Provide your explanation of the error and how it can be fixed. DO NOT propose a new solution, just

the explanation.

Question:

{question} Current Solution:

{solution}

{solution}

Let's review the steps with lower scores and identify the errors.

{feedback}

Refiner's Prompt

Your task is to fix the error in the given solution, based on the teacher's feedback.

- After reviewing the solution and feedback, provide a better solution to fix the mistakes you found. Question:

{question} Current Solution: {solution} Teacher Feedback: {reviewer_feedback}

Revised Solution:

Let's review the solution and the feedback, and then refine the current solution.

After reviewing the solution and feedback, let's solve this math problem again.

{refined_solution}

J Prompt for GPT4o-mini as PRM

GPT4o-mini as PRM Prompt

You will be given a question and its corresponding step-by-step solution.

Your task is to evaluate the correctness of each step in the solution by assigning a score between 1 and 10.

Your response should be formatted as follows:

score: <comma separated scores>

where the length of the list corresponds to the number of steps in the solution.

Each step is clearly separated in the solution by <Step 1:>, <Step 2:> ... <Step k:>, your output score list should be the exact same length as k.

Question: {question}

Solution: {solution}

score:

K Qualitative Examples of Refinement

QUESTION: Josh decides to try flipping a house. He buys a house for \$80,000 and then puts in \$50,000 in repairs. This increased the value of the house by 150%. How much profit did he make? (Gold answer: **70000**)

SOLVER'S OUTPUT (BEFORE REFINEMENT):

Step 1: Calculate the value of the house after repairs. The house is worth 80,000 after repairs. It is 150% higher than before. So the value is (1 + 150/100) * 80,000 * (3/2) is 120,000. So the house is worth 120,000 after repairs. (Score: 2/10)

Step 2: Calculate the cost of repairs. The cost of repairs is 50,000. (Score: 2/10)

Step 3: Calculate the profit. The profit is the difference between the value after repairs and the cost before repairs. 120,000 - 80,000 - 50,000 is 30,000 (incorrect).

REVIEWER'S OUTPUT:

Step 1: The low score of 2 suggests an error in this step. The problem states that the value of the house increased by 150%, not that the value is 150% higher than before.

Step 2: The cost of repairs is indeed \$50,000.

Step 3: The low score of 3 suggests an error in this step. The profit would be: 200,000 (value after repairs) - 80,000 (cost before repairs) - 50,000 (cost of repairs) = 70,000

REFINER'S OUTPUT:

Step 1: Calculate the value of the house after repairs. The house is worth 80,000 after repairs. It is increased by 150%. So the value is $80,000 \ge (1 + 150/100) = 80,000 \ge 2.5 = 200,000$. Step 2: Calculate the cost of repairs. The cost of repairs is 50,000.

Step 3: Calculate the profit. The profit is the difference between the value after repairs and the cost before repairs. 200,000 - 80,000 - 50,000 is 70,000 (correct).

Table 15: A qualitative example of our multi-agent refinement on GSM8K using Llama3-8B-Instruct. The score at the end of each step is provided by the PRM.

QUESTION: The Greek army contained two types of soldiers: the upper class and the lower class soldiers. If there were a total of 5 upper class soldiers, and 10 lower class soldiers in a certain part of Athens, and the battle of Thermopylae demands a force of 4 upper class soldiers and 8 lower class soldiers, how many different battalions can be sent? (Gold answer: **225**)

SOLVER'S OUTPUT (BEFORE REFINEMENT):

Step 1: Find out the number of upper class soldiers left. We have 5 upper class soldiers and we need 4. So we have 5 - 4 = 1 upper class soldiers left. (Score: 9/10)

Step 2: Find out the number of lower class soldiers left. We have 10 lower class soldiers and we need 8. So we have 10 - 8 = 2 lower class soldiers left. (Score: 9/10)

Step 3: Find out the number of different battalions. We have 1 upper class soldier and 2 lower class soldiers. The number of different battalions is the number of ways we can arrange 1 upper class soldier and 2 lower class soldiers. This is 3. (Score: 5/10) (incorrect).

REVIEWER'S OUTPUT:

Step 1 and Step 2: The scores of 9/10 suggest that these steps are mostly correct. However, we should be careful when calculating the number of upper and lower class soldiers left.

Step 3: The low score of 5 suggests an error in this step. The problem asks for the number of different battalions, not the number of ways to arrange the soldiers. The correct solution is to find the number of ways to choose 4 upper class soldiers from the available 5 and 8 lower class soldiers from the available 10.

REFINER'S OUTPUT:

Step 1: Find out the number of upper class soldiers needed. We need 4 upper class soldiers.

Step 2: Find out the number of lower class soldiers needed. We need 8 lower class soldiers.

Step 3: Find out the number of different battalions. We can choose 4 upper class soldiers from the 5 available in 5C4 = 5 ways. We can choose 8 lower class soldiers from the 10 available in 10C8 = 45 ways. The number of different battalions is the number of ways to choose 4 upper class soldiers and 8 lower class soldiers, which is $5 \times 45 = 225$. (correct).

Table 16: A qualitative example of our multi-agent refinement on MATH using Llama3-8B-Instruct. The score at the end of each step is provided by the PRM.

L Qualitative Examples of Over-Correction

QUESTION: A new program had 60 downloads in the first month. The number of downloads in the second month was three times as many as the downloads in the first month, but then reduced by 30% in the third month. How many downloads did the program have total over the three months? (Gold answer: **366**)

SOLVER'S OUTPUT (BEFORE REFINEMENT):

Step 1: Determine the number of downloads for the second month. The number of downloads for the second month was three times as many as the first month, so it was 60 * 3 = 180. (Score: 10/10) Step 2: Determine the number of downloads for the third month. There was a reduction of 30%, so we calculate 180 * (1 - 0.30) = 180 * 0.7 = 126. (Score: 10/10)

Step 3: Determine the total number of downloads for the three months. There were 60 downloads in the first month, and 180 downloads in the second month. So the total number of downloads for the first two months is 60 + 180 = 240. Then, there were 126 downloads in the third month. So the total number of downloads over the three months is 240 + 126 = 366. (Score: 6/10) (correct).

REVIEWER'S OUTPUT:

Step 1-2: The high scores of 10 suggest that these steps are correct.

Step 3: The score of 6 suggests that this step is mostly correct. However, the improvement you could make is to explicitly state the calculation for the total number of downloads, rather than just stating the result.

REFINER'S OUTPUT:

Step 1: Determine the downloads in the second month. Three times 60 is $3 \ge 60 = 180$. Then 30% of 180 is $180 \ge 0.3 = 54$. 180 - 54 is 126. So 126 downloads in the second month.

Step 2: Determine the total downloads over the three months. 60 downloads in the first month, and 126 downloads in the second month, and 126 - 54 = 72 downloads in the third month. 60 + 126 + 72 is 258. The answer is 258. (incorrect).

Table 17: A qualitative example of over-correction on GSM8K using Llama3-8B-Instruct.

QUESTION: If $f(x) = \frac{3x-2}{x-2}$, what is the value of f(-2) + f(-1) + f(0)? Express your answer as a common fraction. (Gold answer: $\frac{14}{3}$)

SOLVER'S OUTPUT (BEFORE REFINEMENT):

Step 1: Determine the values of f(-2), f(-1), and f(0) by plugging the values into the expression for f(x). $f(-2) = \frac{3(-2)-2}{-2-2} = \frac{-6-2}{-4} = \frac{-8}{-4} = 2,$

$$f(-1) = \frac{3(-1)-2}{-1-2} = \frac{-3-2}{-3} = \frac{-5}{-3} = \frac{5}{3},$$

 $\begin{array}{l} f(0) = \frac{3(0)-2}{0-2} = \frac{0-2}{-2} = \frac{-2}{-2} = 1. \text{ (Score: 10/10)} \\ \text{Step 2: Add the values of } f(-2), f(-1), \text{ and } f(0) \text{ to obtain } f(-2) + f(-1) + f(0) = 2 + \frac{5}{3} + 1. \end{array}$

 $\frac{6}{3} + \frac{5}{3} + \frac{3}{3} = \frac{14}{3}.$ Final Answer: The final answer is $\boxed{\frac{14}{3}}$. I hope it is correct. (Score: 7/10) (correct).

REVIEWER'S OUTPUT:

Step 1: The scores of 10/10 suggest that this step is correct.

Step 2: The high score of 7 suggests that this step is mostly correct. However, it might be beneficial to include intermediate steps for clarity.

REFINER'S OUTPUT:

Step 1: We can calculate f(-2), f(-1), and f(0) using the given expression for f(x): $f(-2) = \frac{3(-2)-2}{-2-2} = \frac{-4}{-4} = 1$,

$$f(-1) = \frac{3(-1)-2}{-1-2} = \frac{-3}{-3} = 1,$$

 $f(0) = \frac{3(0)-2}{0-2} = \frac{-2}{-2} = 1.$ Step 2: Now we can add these values together: $f(-2) + f(-1) + f(0) = 1 + 1 + 1 = \frac{3}{1}$ Final Answer: The final answer is $\begin{bmatrix} \frac{3}{1} \end{bmatrix}$. I hope it is correct. (incorrect).

Table 18: A qualitative example of over-correction on MATH using Llama3-8B-Instruct.