

FASTCURL: Curriculum Reinforcement Learning with Stage-wise Context Scaling for Efficient Training R1-like Reasoning Models

Mingyang Song, Mao Zheng, Zheng Li, Wenjie Yang, Xuan Luo

Tencent Hunyuan

nickmysong@tencent.com

Abstract

Improving training efficiency continues to be one of the primary challenges in large-scale Reinforcement Learning (RL). In this paper, we investigate how *context length* and *the complexity of training data* influence the RL scaling training process of R1-distilled reasoning models, e.g., DeepSeek-R1-Distill-Qwen-1.5B. Our experimental results reveal that: (1) *simply controlling the context length and selecting the training data based on the input prompt length can effectively improve the training efficiency of RL scaling, achieving better performance with more concise CoT*; (2) *properly scaling the context length helps mitigate entropy collapse*; and (3) *carefully choosing the context length facilitates achieving efficient LLM training and reasoning*. Inspired by these insights, we propose **FASTCURL**, a curriculum RL framework with stage-wise context scaling to achieve efficient LLM training and reasoning. Extensive experimental results demonstrate that **FASTCURL-1.5B-V3** significantly outperforms state-of-the-art reasoning models on five competition-level benchmarks and achieves 49.6% accuracy on AIME 2024. Furthermore, **FASTCURL-1.5B-Preview** surpasses DeepScaleR-1.5B-Preview on five benchmarks while only using a single node with 8 GPUs and a total of 50% of training steps, as shown in Figure 1. The code, training data, and models have been publicly released¹.

1 Introduction

Large Language Models (LLMs) have emerged as immensely potent AI instruments, showcasing extraordinary proficiency in comprehending natural language and executing downstream tasks (Zhao et al., 2023; Minaee et al., 2024; Chen et al., 2025). Lately, test-time scaling (Snell et al., 2024; Muenighoff et al., 2025) has demonstrated a robust correlation between extending the generation length of Chain-of-Thought (CoT) (Wei et al., 2023) and improving the reasoning capabilities of LLMs.

¹<https://github.com/nick7nlp/FastCuRL>

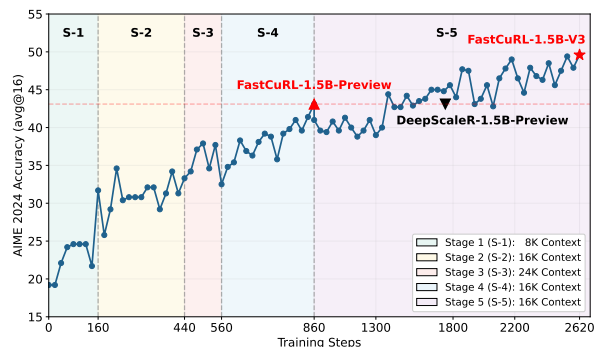


Figure 1: FastCuRL’s accuracy on AIME 2024 as training progresses across five training stages. Specifically, S-5 indicates Stage 5 in the training process.

A primary finding from recent breakthroughs, exemplified by DeepSeek-R1 (DeepSeek-AI, 2025), have revealed a notable scaling phenomenon in the training process of Reinforcement Learning (RL). Inspired by these findings, scaling RL for training LLMs has emerged as a promising paradigm for tackling complex reasoning tasks. This has sparked numerous valuable research efforts aimed at exploring and replicating reasoning models similar to DeepSeek-R1 (Face, 2025; Hu et al., 2025; Zeng et al., 2025; Liu et al., 2025). These initiatives typically begin with R1-distilled or pre-trained models and extend the generation length of CoT reasoning to enhance performance.

However, excessively long CoT responses significantly increase computational overhead during model training and deployment. Moreover, recent studies (Yeo et al., 2025; Wu et al., 2025; Team, 2025a) have identified an inherent overthinking phenomenon in reasoning models, which includes irrelevant details and repetitive thinking patterns. This kind of information leads to inefficient use of computational resources and undermines reasoning accuracy, which causes models to stray from valid logical pathways, resulting in incorrect answers. To this end, recent studies (Team, 2025a; Luo et al.,

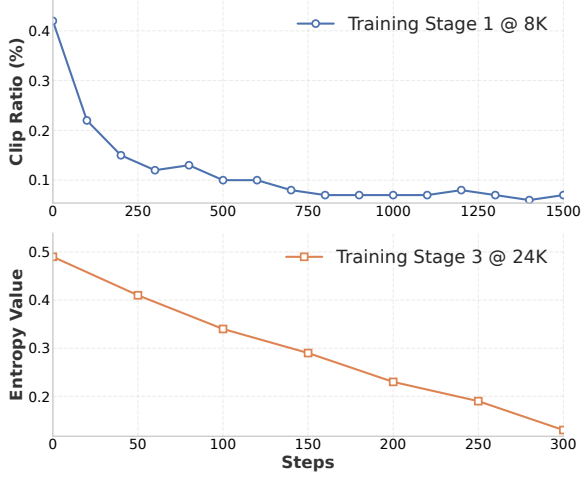


Figure 2: Partial training curves of DeepScaleR. Data points are smoothed using a running average (window size = 10) and plotted at uniform intervals.

2025; Liu et al., 2025; Song and Zheng, 2025) focus on efficient reasoning for optimizing the model to generate more concise CoT outputs. Among them, DeepScaleR (Luo et al., 2025) propose to iteratively increase the context length from 8K to 24K to train the DEEPSEEK-R1-DISTILL-QWEN-1.5B model toward more concise reasoning, outperforming OpenAI’s o1-preview (OpenAI, 2024). By observing the training logs² of DeepScaleR in Figure 2, we find two issues:

- When the context length is 8K, about 42% of the model’s outputs are clipped, which reduces the training efficiency.
- When training in the third stage with a context length of 24K, the model’s entropy collapses³, reducing its exploration capabilities.

The prior work and the aforementioned issues naturally motivate two research questions:

- **Question 1:** Does simultaneously controlling the model’s context length and the complexity of the training dataset help the training process of R1-like reasoning models?
- **Question 2:** What impact does setting different context lengths have on the RL training process of R1-like reasoning models?

²<https://github.com/agentica-project/rllm>

³Entropy reflects the exploration capability of LLMs during RL training. Typically, a rapid decrease in entropy might lead to premature convergence, preventing the model from achieving the expected performance.

To this end, in this paper, we investigate how the model’s context length and the complexity of the training dataset influence the training process of R1-like reasoning models. Motivated by our observations, we propose **FASTCURL**, a *simple yet efficient Curriculum Reinforcement Learning* framework with a stage-wise context scaling strategy to improve the RL training efficiency and achieve concise CoT. Specifically, the proposed method alternates between CoT compression (long-to-short) and extension (short-to-long). We first compress CoT reasoning outputs, then extend them, and repeat this compress–extend cycle. The main goal of our method is to enhance CoT quality progressively. We hypothesize that this dynamic interplay fosters higher-quality reasoning by iteratively refining essential logical dependencies while pruning redundant or spurious steps. Meanwhile, during the iterative process, we control the complexity of the training samples, thereby ensuring training efficiency. Extensive experimental results demonstrate that our model **FASTCURL-1.5B-V3** outperforms recent state-of-the-art reasoning baselines across five competition-level benchmarks, AIME 2024, AMC 2023, MATH 500, Minerva Math, and Olympiad-Bench. Furthermore, our model **FASTCURL-1.5B-Preview** surpasses DeepScaleR-1.5B-Preview on five competition-level benchmarks and only uses 50% training steps on a single node with 8 GPUs. We hope the findings presented in this paper, the models we have released, and the open-sourced code will benefit future research.

2 Methodology

Our method for achieving efficient LLM reasoning integrates three main components: (1) a resource-efficient RL algorithm, (2) a complexity-aware, mathematics-focused dataset, and (3) a stage-wise context scaling approach. This section provides a detailed description of the first two components.

2.1 Reinforcement Learning Algorithm

To train our model efficiently, we adopt the Group Relative Policy Optimization (GRPO) (Shao et al., 2024), which is utilized in DeepSeek-AI (2025). GRPO eliminates the necessity of maintaining a critic model, which is usually comparable in size to the policy model, by estimating baseline scores directly from group-level scores, significantly lowering the computational overhead. For each problem q , GRPO directly samples a group of G responses

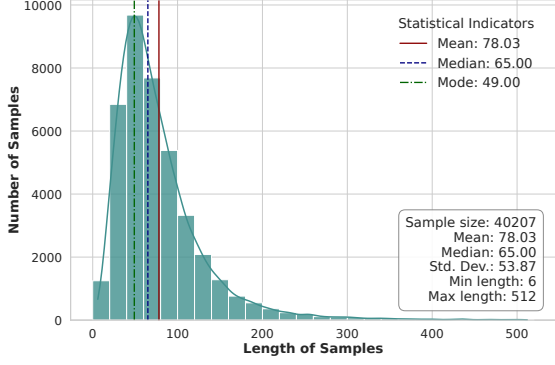


Figure 3: Prompt length distribution. The prompt length is computed based on the number of tokens.

$\{o_1, o_2, \dots, o_G\}$ from the old policy $\pi_{\theta_{\text{old}}}$ and optimizes the trained policy π_{θ} by maximizing the following objective:

$$\begin{aligned} \mathcal{J}_{\text{GRPO}}(\theta) = & \mathbb{E}_{[q \sim P(Q), \{o_i\}_{i=1}^G \sim \pi_{\theta_{\text{old}}}(\cdot|q)]} \\ & \frac{1}{G} \sum_{i=1}^G \left(\min \left(\frac{\pi_{\theta}(o_i|q)}{\pi_{\theta_{\text{old}}}(o_i|q)} A_i, \right. \right. \\ & \left. \left. \text{clip} \left(\frac{\pi_{\theta}(o_i|q)}{\pi_{\theta_{\text{old}}}(o_i|q)}, 1 - \varepsilon, 1 + \varepsilon \right) A_i \right) \right. \\ & \left. - \beta \mathbb{D}_{\text{KL}}[\pi_{\theta} || \pi_{\text{ref}}] \right), \end{aligned} \quad (1)$$

where β denotes the coefficient of the KL penalty and the advantage A_i is computed from a group of rewards $\{r_1, r_2, \dots, r_G\}$:

$$A_i = \frac{r_i - \text{mean}(\{r_1, r_2, \dots, r_G\})}{\text{std}(\{r_1, r_2, \dots, r_G\})}. \quad (2)$$

To enhance the exploration capabilities of the policy model, we introduce an entropy bonus term,

$$\begin{aligned} \mathcal{J}_{\text{GRPO}}^{\dagger}(\theta) = & \mathbb{E}_{[q \sim P(Q), \{o_i\}_{i=1}^G \sim \pi_{\theta_{\text{old}}}(\cdot|q)]} \\ & \frac{1}{G} \sum_{i=1}^G \left(\min \left(\frac{\pi_{\theta}(o_i|q)}{\pi_{\theta_{\text{old}}}(o_i|q)} A_i, \right. \right. \\ & \left. \left. \text{clip} \left(\frac{\pi_{\theta}(o_i|q)}{\pi_{\theta_{\text{old}}}(o_i|q)}, 1 - \varepsilon, 1 + \varepsilon \right) A_i \right) \right. \\ & \left. - \beta \mathbb{D}_{\text{KL}}[\pi_{\theta} || \pi_{\text{ref}}] + \alpha \mathbb{H}(\pi_{\theta}(o_i|q)) \right), \end{aligned} \quad (3)$$

where $\mathbb{H}(\pi_{\theta}(o_i|q))$ indicates the entropy term and α denotes the entropy coefficient.

Similar to the prior work (DeepSeek-AI, 2025; Luo et al., 2025), we leverage a rule-based reward model composed of two distinct criteria designed to balance answer correctness and clarity of structure without relying on an LLM-based reward model. To evaluate correctness objectively, we require the

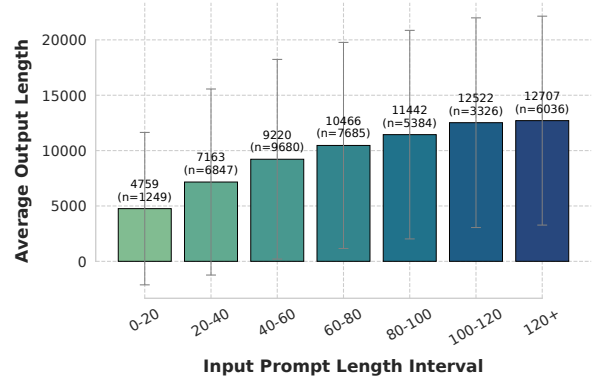


Figure 4: Distribution of output length across different input prompt length intervals in the training dataset. This distribution illustrates the average output length (in tokens) generated by DEEPSEEK-R1-DISTILL-QWEN-1.5B, with error bars indicating standard deviation. Each bar is annotated with the mean output length and sample size (n) for the corresponding input length interval.

Data	Prompt Len.	Output Len.	#Samples
L1	48.26	8805.78	25168
L2	78.03	10063.44	40207
L3	132.22	12168.16	15039

Table 1: Statistics of L1, L2, L3. The prompt and output length is computed based on the number of tokens.

trained model to present its final answer enclosed within a `\boxed{}` format, assigning a binary score of 1 for correct answers and 0 for incorrect ones. To encourage structural clarity, the model must explicitly encapsulate its reasoning within tags, with compliance being rewarded positively.

2.2 Complexity-Aware Data Selection

To ensure a fair comparison, we directly employ the dataset from DeepScaleR as the training data. The DeepScaleR dataset (Luo et al., 2025) consists of 40,315 unique mathematics-specific problem-answer pairs collected from AIME (1984-2023), AMC (prior to 2023), Omni-MATH, and the Still dataset (Balunović et al., 2025; Gao et al., 2024; Min et al., 2024). We perform a simple filtering of the original dataset based on prompt length, resulting in 40,207 data samples. The statistics of the filtered dataset are shown in Figure 3.

As illustrated in Figure 2, during the first training stage, over 42% of training samples are clipped at the beginning of the training steps due to exceeding the maximum response length. By observing and analyzing the clipped responses, we find that

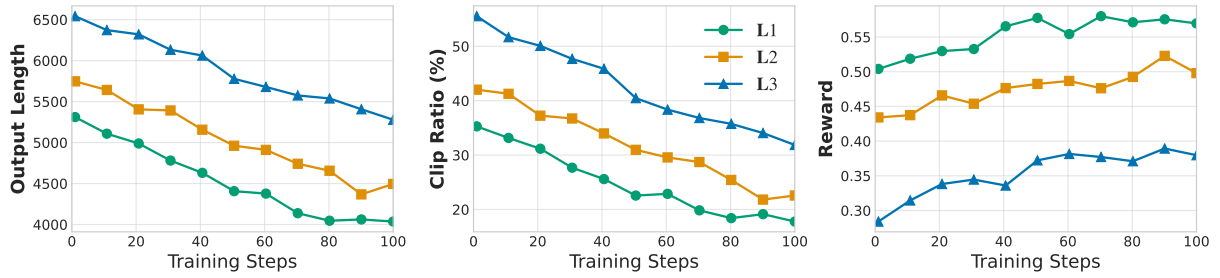


Figure 5: The average clip ratio, output length, and reward in RL training with 8K context length on L1, L2, and L3 datasets. Data points are smoothed using a running average (window size = 10) and plotted at uniform intervals.

they mainly correspond to two types of problems. The first type pertains to challenging problems requiring long CoT responses to solve. The second involves questions laden with numerous conditions, prompting the model to verify each condition repeatedly during problem-solving. This repetitive verification may result in redundant thinking patterns, ultimately causing the reasoning responses to be unduly long. Both situations may impact the model training efficiency during the 8K context.

After observing the above phenomenon, we utilize DEEPSEEK-R1-DISTILL-QWEN-1.5B to infer all the training data of DeepScaleR to obtain responses and analyze the response lengths, as shown in Figure 4. Specifically, the given figure examines the relationship between input length and output length. Interestingly, we find a correlation between the two—that is, the longer the input, the longer the corresponding output. Based on this observation, we assume a hypothesis that for complex reasoning tasks, there exists a relationship between the complexity of the problem prompt and the length of the output response generated by the model when solving it. Generally, the more complex the problem, the longer the output the model needs to produce to arrive at a solution. Based on this hypothesis, we directly divide the original training dataset (referred to as L2) into two training data subsets based on the average input prompt length: one representing a short CoT reasoning dataset (designated as L1) and the other constituting a long CoT reasoning dataset (labeled as L3). Finally, the average input length of each dataset as shown in Table 1.

Next, we conduct experiments and analyses on these three datasets under different context lengths to observe and investigate the two questions raised in the prior section. It is important to note that this paper focuses on low-resource scenarios. Therefore, during training, when using different datasets

at each stage, we train for only one epoch and utilize a single node with 8 GPUs.

3 Experiments

We designed a set of experiments, constrained by available computational resources, to investigate our central research question (Section 1): *how do model context length and training data complexity affect the RL training of R1-like reasoning models?* By analyzing the training behavior of small LLMs, we aim to extract practical insights. The objective is to move beyond simply providing empirical evidence of performance gains and to offer clear, actionable guidance for both academic and industrial implementation.

3.1 Experimental Setup

In this work, we choose a 1.5B parameter model DEEPSEEK-R1-DISTILL-QWEN-1.5B (DeepSeek-AI, 2025) as the base model. We utilize the AdamW optimizer with a constant learning rate of 1×10^{-6} for optimization. For rollout, we set the temperature to 0.6 and sample 16 responses per prompt. We do not utilize a system prompt; instead, we add "Let's think step by step and output the final answer within `\boxed{}`." at the end of each problem. Detailed parameters are shown in Figure 2.

3.2 Baselines

In this paper, we conduct evaluations against 1.5B and 7B parameter language models, which includes DEEPSEEK-R1-DISTILL-QWEN-1.5B (DeepSeek-AI, 2025), QWEN2.5-MATH-7B-Instruct (Yang et al., 2024), DeepScaleR-1.5B-Preview (Luo et al., 2025), QWEN2.5-7B-SimpleRL (Zeng et al., 2025), RSTAR-MATH-7B (Guan et al., 2025), STILL-3-1.5B-Preview (Team, 2025b), and EURUS-2-7B-PRIME (Cui et al., 2025).

EXPERIMENTS (STAGES)	TRAINING STEPS	CONTEXT LENGTH INPUT OUTPUT (K)	TRAINING DATA	BATCH SIZE	ROLLOUT	α (FOR ENTROPY)	β (FOR KL)	AVG.
EXP-1 (3)	3	1K 8, 16, 24	L1, L2, L3	128, 64, 64	8, 8, 8	0.001	0.001	0.550
EXP-2 (3)	3	1K 8, 16, 24	L1, L3, L2	128, 64, 64	8, 8, 8	0.001	0.001	0.540
EXP-3 (3)	3	1K 8, 16, 24	L1, L2, L2	128, 64, 64	8, 8, 8	0.001	0.001	0.552
EXP-4 (4)	4	1K 8, 16, 24, 32	L1, L2, L3, L2	128, 64, 64, 64	8, 8, 8, 16	0.001	0.001	0.566
EXP-5 (4)	4	1K 8, 16, 24, 24	L1, L2, L3, L2	128, 64, 64, 64	8, 8, 8, 16	0.001	0.001	0.565
EXP-6 (4)	4	1K 8, 16, 24, 16	L1, L2, L3, L2	128, 64, 64, 64	8, 8, 8, 16	0.001	0.001	0.575
EXP-7 (5)	5	1K 8, 16, 24, 16, 8	L1, L2, L3, L2, L2	128, 64, 64, 64, 64	8, 8, 8, 16, 16	0.001	0.001	0.535
EXP-8 (5)	5	1K 8, 16, 24, 16, 16	L1, L2, L3, L2, L2	128, 64, 64, 64, 64	8, 8, 8, 16, 16	0.001	0.001	0.567
EXP-9 (5)	5	1K 8, 16, 24, 16, 24	L1, L2, L3, L2, L2	128, 64, 64, 64, 64	8, 8, 8, 16, 16	0.001	0.001	0.556
EXP-10 (5)	5	1K 8, 16, 24, 16, 16	L1, L2, L3, L2, L2	128, 64, 64, 64, 64	8, 8, 8, 16, 16	0.000001	0.000	0.600
EXP-11 (5)	5	1K 8, 16, 24, 16, 16	L1, L2, L3, L2, L2	128, 64, 64, 64, 64	8, 8, 8, 16, 16	0.000	0.000	0.616

Table 2: Experimental setups combining different context lengths and data complexities.

Model	MATH 500	AIME 2024	AMC 2023	Minerva Math	OlympiadBench	Avg. Score
QWEN2.5-MATH-7B-Instruct	79.8	13.3	50.6	34.6	40.7	43.8
RSTAR-MATH-7B	78.4	26.7	47.5	-	47.1	-
EURUS-2-7B-PRIME	79.2	26.7	57.8	38.6	42.1	48.9
QWEN2.5-7B-SimpleRL	82.4	26.7	62.5	39.7	43.3	50.9
DEEPSEEK-R1-DISTILL-QWEN-1.5B	82.8	28.8	62.9	26.5	43.3	48.9
STILL-3-1.5B-Preview	84.4	32.5	66.7	29.0	45.4	51.6
DEEPSALER-1.5B-Preview	87.8	43.1	73.6	30.2	50.0	56.9
FASTCURL-1.5B-Preview	88.0	43.1	74.2	31.6	50.4	57.5
FASTCURL-1.5B-V2	89.3	47.5	77.0	32.8	53.3	60.0
FASTCURL-1.5B-V3	90.5	49.6	78.5	34.7	54.5	61.6

Table 3: PASS@1 performance across competition-level mathematical benchmarks.

3.3 Benchmarks

To comprehensively evaluate the performance, we select five competition-level benchmark datasets: MATH 500 (Hendrycks et al., 2021), AIME 2024⁴, AMC 2023⁵, Minerva Math (Lewkowycz et al., 2022), and OlympiadBench (He et al., 2024).

3.4 Evaluation Metric

Following the prior work (DeepSeek-AI, 2025), we set the maximum context length to 32,768 tokens and use PASS@1 as the evaluation metric. Specifically, we adopt **a sampling temperature of 0.6** and **a top-p value of 1.0** to generate k responses for each question, typically $k = 16$. Specifically, PASS@1 is then calculated as:

$$\text{PASS@1} = \frac{1}{k} \sum_{i=1}^k p_i, \quad (4)$$

where p_i is the correctness of the i -th response.

⁴<https://huggingface.co/datasets/AI-MO/aimo-validation-aimo>

⁵<https://huggingface.co/datasets/AI-MO/aimo-validation-amc>

3.5 Main Processes and Results

In this section, we first validate the effectiveness of the complexity-aware data selection strategy. Then, we design a series of progressive experiments with varying context lengths and data complexities and analyze the experimental results.

3.5.1 Main Results

Table 3 presents a comprehensive comparative analysis of the PASS@1 performance of our models against several state-of-the-art open-source baselines. The results unequivocally demonstrate the superiority of our proposed approach. Specifically, our final model, FASTCURL-1.5B-V3, achieves an average score of 61.6, significantly outperforming all baselines, including those with larger parameters. More specifically, FASTCURL-1.5B-V3 establishes new state-of-the-art results across all five competition-level benchmarks, scoring 90.5 on MATH 500, 49.6 on AIME 2024, 78.5 on AMC 2023, 34.7 on Minerva Math, and 54.5 on OlympiadBench. The consistent performance progression from FASTCURL-1.5B-Preview (57.5) to

Model	Training Steps	Training Stages	Number of GPUs Used in Each Stage
DEEPSCALER-1.5B-Preview	$\sim 1,750$	3	8, 16, 32
FASTCURL-1.5B-Preview (EXP-6)	~ 860	4	8, 8, 8, 8
FASTCURL-1.5B-V2 (EXP-10)	$\sim 1,710$	5	8, 8, 8, 8, 8
FASTCURL-1.5B-V3 (EXP-11)	$\sim 2,620$	5	8, 8, 8, 8, 8

Table 4: Training configurations and computational resources for different model variants. For fair comparison, training steps are normalized such that two steps with batch size 64 are equivalent to one step with batch size 128.



Figure 6: Entropy values of our models across all RL training stages. Here, data points are smoothed using a running average (window size = 10) and plotted at uniform intervals.

V3 (61.6) further validates the effectiveness and scalability of our training method.

In addition to overall performance, our models exhibit enhanced generalization capabilities. The initial FASTCURL-1.5B-Preview model already shows improvement over the DEEPSCALER-1.5B-Preview on the AMC 2023 (74.2 vs. 73.6) and Minerva Math (31.6 vs. 30.2) test sets. This advantage is substantially amplified in our final model, FASTCURL-1.5B-V3, which widens the performance gap with scores of 78.5 and 34.7, respectively. From the perspective of training efficiency, these superior results are achieved with remarkable resource savings. Compared to the training regimen of the DEEPSCALER-1.5B-Preview, our method utilizes only 50% of the training steps. It requires just a single node with 8 GPUs, thereby reducing training costs by more than half, as shown in Table 4. This demonstrates that our approach not only yields a more powerful model but also represents a more computationally efficient for developing advanced reasoning capabilities.

3.5.2 Analyzing Entropy in RL Training

Figure 6 presents the policy entropy and model performance across all training steps, segmented into five distinct stages (S-1 through S-5). The entropy trajectory exhibits three characteristic regimes: (i) gradual increase from 0.17 to 0.28 during initial exploration (S-1 to S-3), (ii) peak exploration at 0.40 during S-4, and (iii) substantial collapse to 0.22 in the final stage (S-5).

A central challenge in RL scaling is managing the exploration-exploitation trade-off, where a standard failure mode is "entropy collapse." This phenomenon occurs when the policy rapidly becomes deterministic, leading to a sharp decrease in entropy and causing the policy to prematurely converge to a sub-optimal local optimum, thereby losing its ability to discover more effective strategies. However, as depicted in Figure 6, our approach deviates significantly from this standard pattern. Instead of a premature collapse, the policy entropy demonstrates a prolonged and even increasing stage of exploration (S-2 to S-4), indicating that the policy actively maintains stochasticity. This sustained exploration is critical for navigating complex solution spaces and avoiding early stagnation.

By adjusting the reasoning context length and training data complexity, we effectively reinvigorate the policy’s exploratory drive at key training intervals. The pronounced entropy peak in S-4 exemplifies this effect, where the agent is stimulated to explore novel behaviors rather than settling for its current policy. Crucially, this period of heightened exploration lays the groundwork for a more effective exploitation stage in S-5. As the policy finally converges and entropy decreases, the model’s performance, measured by AIME 2024 Accuracy, continues to ascend to its peak. This demonstrates that our method successfully mitigates premature entropy collapse, enabling the model to achieve a significantly higher performance ceiling.

Model	# Average Output Length			# Average Frequency of "Wait" and "wait"		
	TOTAL	CORRECT	INCORRECT	TOTAL	CORRECT	INCORRECT
DEEPSEEK-R1-DISTILL-QWEN-1.5B	16390	8126	18775	107	49	129
FASTCURL-1.5B-Preview	8654	7091	12010	80	47	104

Table 5: Statistics of the outputs of DEEPSEEK-R1-DISTILL-QWEN-1.5B and **FASTCURL-1.5B-Preview**.

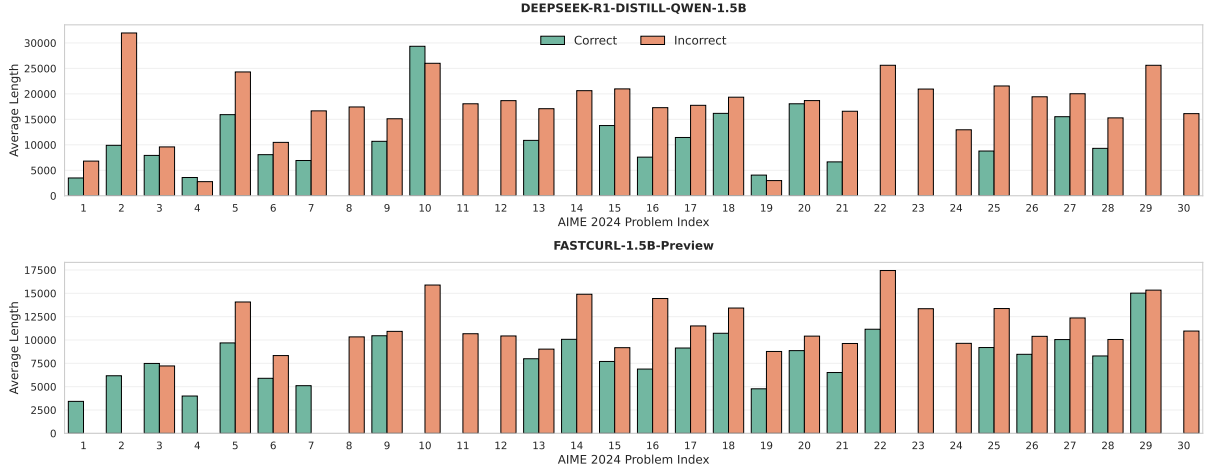


Figure 7: Comparison of average response lengths (in tokens) between correct and incorrect answers for DEEPSEEK-R1-DISTILL-QWEN-1.5B (top) and FASTCURL-1.5B-Preview (bottom) on AIME 2024 problems. Green and orange bars represent correct and incorrect answers, respectively. The x-axis shows problem indices (1-30). The height of each bar reflects the average token count across 16 rollout solutions of each problem. Problems displaying only orange bars indicate cases where all 16 solutions failed to produce a correct answer.

3.5.3 Dataset Complexity Verification

To validate the effectiveness of our dataset selection approach, we train three reasoning models under identical settings on **L1**, **L2**, and **L3** with an 8K context length. As illustrated in Figure 5, the experimental results demonstrate consistent patterns across all three metrics that align with our expectations. The output length progressively increases from **L1** to **L3** throughout the training process, with models trained on more complex datasets generating substantially longer responses, reflecting the additional reasoning steps required for solving complex problems. Correspondingly, the clip ratio exhibits the exact ordering ($L3 > L2 > L1$), indicating that complex problems naturally demand longer solution outputs that more frequently exceed the context length. While the reward scores show an inverse relationship, with **L1** achieving the highest scores due to its simpler problems, this pattern is expected. This observation demonstrates the inherent trade-off between problem complexity and output length, which supports our hypothesis that problem complexity directly correlates with

required output length; more complex problems necessitate longer, more detailed reasoning outputs to arrive at correct solutions, thereby validating the importance of complexity-aware data selection.

3.5.4 Multi-Stage Experimental Results

In our experiments, we conduct three sets of multi-stage experiments, comprising 3, 4, and 5 training stages, respectively. The specific parameter settings are detailed in Table 3, and the corresponding results are presented in Table 2. In the first set of experiments, Exp-3 outperforms Exp-1 but requires additional training steps, as it is trained twice on the **L2** dataset. Considering the trade-off between performance and computational cost, we select Exp-1 as the base model for the second stage. Following the first stage, we observe that the average response length is between 6,000 and 7,000 tokens. This observation motivates our subsequent evaluation of various context lengths. As shown in Table 2, a 16K context length (Exp-6) yields the best performance, surpassing the longer 24K and 32K settings. Consequently, we select Exp-6 as the base model for the third stage.

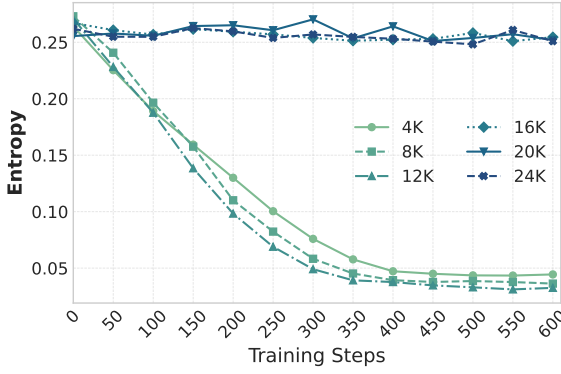


Figure 8: Entropy curves of different context lengths. Here, data points are smoothed using a running average (window size = 10) and plotted at uniform intervals.

Informed by the second set of experiments, we conduct a third set evaluating context lengths of 24K, 16K, and 8K. As shown in Table 2, the 16K context still achieves the best performance, though it shows negligible improvement over the fourth stage. Our analysis of this phenomenon suggests that during compression and extension, the model’s output length is initially constrained by the shorter context of the first stage. This constraint appears to compress the length of the thought process while enhancing its quality.

As the context length extensions in subsequent stages, the model begins to explore problems requiring longer CoT outputs. However, this expansion improves the model’s performance but also introduces repetitive thinking patterns. These patterns may not improve reasoning capabilities; on the contrary, they may diminish the model’s exploratory efficiency, particularly at excessively long context lengths. Therefore, we posit that subsequent context compression, as performed in the fourth stage, is necessary to improve CoT quality and enhance exploratory efficiency.

In the third set of experiments, we observe that neither increasing nor decreasing the context length from 16K yields comparable performance, suggesting that 16K represents an optimal configuration. This finding prompts a critical question: Does an optimal context length, or "sweet spot", exist for R1-like models? Specifically, we investigate whether 16K is the precise optimum for the DEEPSEEK-R1-DISTILL-QWEN-1.5B model or simply the best-performing value among the tested configurations of 8K and 24K.

To investigate this question, we conduct a comprehensive series of experiments examining model

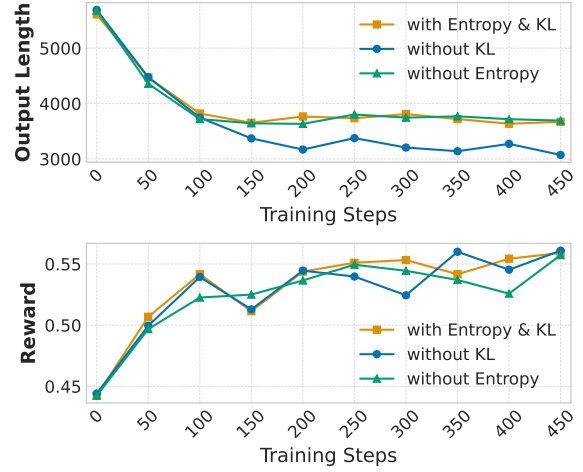


Figure 9: Performance comparison of training with and without Entropy bonus at 8k context length.

behavior across a finer-grained spectrum of context lengths. We train the model with various context length configurations while holding the entropy coefficient constant at 1×10^{-6} to observe entropy dynamics. As illustrated in Figure 8, our findings reveal a notable dichotomy. For context lengths of 4K, 8K, and 12K, the entropy exhibits a rapid decline, indicating a significant degradation in the model’s exploratory capabilities. In contrast, for context lengths of 16K, 20K, and 24K, the entropy demonstrates remarkable stability, converging to and maintaining a consistent value.

Inspired by the above findings, we continue to train **FASTCURL-1.5B-Preview** under a 16K context and adjust the coefficients of KL and Entropy (Table 2). Results in Table 3 show that after being incentivized in the prior stages, the performance of **FASTCURL-1.5B-V3** gradually increases in Stage 5 and achieves an accuracy of 49.6% on AIME 2024, supporting the above raised question.

3.5.5 Analyzing Generated CoT Outputs

Table 5 presents comparative statistics on the response characteristics of DEEPSEEK-R1-DISTILL-QWEN-1.5B and FASTCURL-1.5B-Preview. The results focus on two key metrics: average output length and frequency of the term "wait"/"Wait" in responses. The DEEPSEEK-R1-DISTILL-QWEN-1.5B produces significantly longer responses overall (50.5% longer than FASTCURL-1.5B-Preview). Interestingly, both models show a pattern where incorrect responses tend to be substantially longer than correct ones. The frequency of "wait"/"Wait" terms is indicative of reflection behaviors in the R1-

like reasoning models. DEEPSEEK-R1-DISTILL-QWEN-1.5B uses these terms approximately 36% more frequently than FASTCURL-1.5B-Preview overall. Similarly, both models show significantly higher usage of these terms in incorrect responses compared to correct ones.

Figure 7 compares FASTCURL-1.5B-Preview and DEEPSEEK-R1-DISTILL-QWEN-1.5B on the AIME 2024, measuring the average response length between correct and incorrect answers at the problem level to observe and analyse whether the long incorrect response is related to the difficulty of the problem. Across both models, incorrect answers (red bars) almost universally have greater average response lengths than correct answers (green bars). This suggests that models tend to generate more verbose content when producing incorrect answers, potentially reflecting "over-explanation" or "verbose reasoning" when the model is uncertain.

3.5.6 Ablation Study

Figure 9 presents a comprehensive comparison of model performance under different regularization configurations at an 8k context length. The upper panel demonstrates that models incorporating Entropy regularization (with Entropy & KL) or KL divergence alone (without Entropy) maintain consistently higher output lengths around 3,700-3,900 tokens throughout training, while the model without KL divergence regularization exhibits notably shorter outputs, stabilizing at approximately 3,000-3,500 tokens. This suggests that KL divergence plays a critical role in preventing output length collapse during long-context generation. The lower panel reveals that all three configurations achieve comparable reward scores, converging to approximately 0.55 after initial training steps, indicating that the choice of regularization strategy primarily affects generation length rather than quality. Notably, the combination of entropy bonus and KL divergence (orange line) demonstrates the most stable training dynamics across both metrics, suggesting potential synergistic effects between these two regularization techniques in balancing exploration and exploitation during policy optimization.

4 Related Work

Advancements in RL methodologies have considerably enhanced the reasoning capabilities of LLMs. A pivotal development in this domain is OpenAI’s o1 (OpenAI, 2024), which employs RL training to promote the development of long CoT reasoning in

LLMs. This approach has significantly enhanced performance on complex mathematical and programming benchmarks. Building upon this foundation, DeepSeek-R1 (DeepSeek-AI, 2025) demonstrates that pure RL post-training via Group Reinforcement Policy Optimization (GRPO), without needing supervised pre-training, can directly perform robust CoT reasoning capabilities. Notably, this method not only achieves performance competitive with o1 but also exhibits emergent behaviors such as self-verification and multi-step planning. Building on these advancements, the research community has been collectively working to study and apply the methodology of DeepSeek-R1 to enhance the CoT reasoning capabilities of various sizes of language models, yielding remarkable progress, such as Face (2025); Luo et al. (2025); Zeng et al. (2025); Liu et al. (2025); Yu et al. (2025); Song and Zheng (2025). Different from the existing approaches, we employ an iterative stage-wise scaling method that alternates between CoT compression (long-to-short) and CoT extension (short-to-long) training stages. We initially compress the CoT outputs, subsequently perform extension, followed by re-compression and re-extension in a cyclical manner. Specifically, we hypothesize that this dynamic interplay between compression and extension facilitates the emergence of higher-quality reasoning responses by iteratively refining the essential logical dependencies while eliminating redundant or spurious CoT reasoning outputs.

5 Conclusion

We investigate how the model’s context length and the complexity of the training dataset influence the training process of R1-like reasoning models. Motivated by our findings, we propose **FASTCURL**, a simple yet effective curriculum reinforcement learning framework incorporating a stage-wise context scaling strategy. This method is designed to accelerate the training efficiency and improve the model’s long CoT reasoning capabilities. Experimental results demonstrate that FASTCURL-1.5B-Preview achieves better performance and reduces computational resource consumption by more than 50%, with all training phases efficiently executed using a single node with 8 GPUs.

6 Limitations

In this paper, we verify the proposed methodology exclusively on a 1.5B parameter language model.

Extending the proposed methodology to models of diverse scales represents a critical avenue for future investigation. Moreover, while this work demonstrates the substantial impact of complexity-aware data selection through a relatively straightforward stratification approach, the observed performance gains suggest that more sophisticated data selection methodologies could potentially yield superior outcomes. Meanwhile, this observation motivates several research directions, including the development of adaptive context length and dynamic KL penalty controlling mechanisms, both of which could further optimize the balance between exploration and convergence in preference learning.

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