Efficient RL Training for Reasoning Models via Length-Aware Optimization

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Code: https://github.com/lblankl/Short-RL

Abstract

Long reasoning models, such as OpenAI o1 or DeepSeek R1, have demonstrated remarkable performance on reasoning tasks but often incur a long reasoning path with significant memory and time costs. Existing methods primarily aim to shorten reasoning paths by introducing additional training data and stages. In this paper, we propose three critical reward designs integrated directly into the rule-based reinforcement learning process of long reasoning models, which reduce the response length without extra training stages. Experiments on four settings show that our method significantly decreases response length while maintaining or even improving performance. Specifically, in a logic reasoning setting, we achieve a 40% reduction in response length averaged by steps alongside a 14% gain in performance. For math problems, we reduce response length averaged by steps by 33% while preserving performance.

1 Introduction

Recent advancements in long reasoning models (LRMs) have demonstrated exceptional performance across diverse reasoning tasks. Leveraging large-scale, rule-based reinforcement learning (RL), these models have developed advanced cognitive capabilities, including self-reflection, self-critique, and self-correction [1; 2; 3]

However, increased reasoning length introduces significant challenges. During inference, longer responses lead to higher computational costs and heavier KV caches, drastically slowing down the decoding process. During training, the growing response length considerably slows down the training process, and may even make large-scale training on specific tasks impractical [2].

Existing methods for reducing redundant response length in LRMs have primarily relied on supervised fine-tuning or off-policy RL strategies [4; 5; 6; 7; 8; 9; 10; 11; 12]. There is also active research on prompt-guided efficient reasoning, which seeks to reduce response length through prompt engineering [13; 14; 15; 16]. While promising, these methods tend to be task-specific and often degrade overall model performance. Other lines of work investigate shortening reasoning through model merging or collaborative agent frameworks [17; 18]. Additionally, some approaches propose dynamically routing reasoning behavior based on the input question or user intent [19; 20; 21; 22; 23; 24]. However, these approaches are not directly applicable to the on-policy RL frameworks commonly used in LRMs training. One promising approach, the direct length-reward method proposed by Kimi [25],

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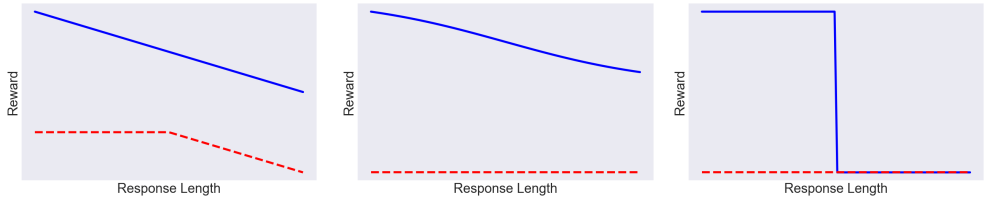
incorporates response length as a factor in the RL reward function. While this method shows potential, our reproduction of Kimi's length reward reveals significant limitations. When applied early in the RL training process, it drastically shortens response length but disrupts the model's exploratory behavior, leading to suboptimal performance. Moreover, other length rewards [26; 27] also show degraded performance. This highlights the need for a effective approach that can be directly applied in the on-policy RL training.

To address this challenge, we propose a novel method, Short-RL, designed to regulate response length during RL training without compromising model performance. Through a detailed analysis of the Kimi length-reward approach, we identify its adverse effects on learning dynamics, particularly its tendency to suppress reasoning diversity in the early stages of training. Motivated by these findings, we introduce three innovative enhancements to the length-reward framework, each aimed at balancing efficiency and reasoning quality:

- **Correctness-Conditioned Length Reward**: reward computation is restricted to correctly answered samples.
- **Neutral Length Zone**: exempts responses within an acceptable length range from length penalties, allowing the model to retain flexibility in exploring responses with appropriate lengths.
- **Accuracy-Aware Length Reward**: automatically disables length rewards when batch accuracy falls below a specified threshold.

Our approach effectively regulates response length during training without compromising—and in some cases enhancing—model performance. Experimental results on logical reasoning tasks show a 40% average reduction in response length during training, alongside a 14% improvement in evaluation scores. In the mathematical reasoning setting, our method achieves a 33% reduction in average response length while maintaining performance comparable to standard RL training.

2 Methodology



(a) Kimi (b) Efficient (c) ThinkPrune

Figure 1: Reward values as a function of response length, where blue lines indicate rewards for correct responses and red lines represent rewards for incorrect responses.

2.1 Length-Aware Optimization

A straightforward approach to reducing reasoning length is to incorporate a length penalty into the original reward function. Generally, the length reward can be incorporated into the rule-based reward as follows:

$$R(x, y) = C(y) + \alpha \cdot S(y) \tag{1}$$

, where $C(y)$ denotes the rule-based reward and $S(y)$ denotes the length reward. α is a coefficient.

A brief visualization of three main length rewards (Kimi [25]; Efficient [26]; ThinkPrune [27], combined with rule-based rewards) is plotted in Figure 1.

In this work, we primarily focus on the Kimi length reward, though the reward design we propose is broadly applicable to other length-based reward functions as well.

2.1.1 Limitations of Length Reward in Early Training

In the original Kimi 1.5 paper [25], the length reward is not applied during the initial stage of reinforcement learning training. Instead, standard policy optimization is performed first, and a

constant length penalty is introduced only in the later training phase. The authors claim that applying the length reward too early negatively affects training performance. Our reproduction results in Appendix 6.1 also verified this.

2.2 Short-RL

In this subsection, we identify two major issues with the direct length reward proposed by Kimi and introduce three key reward design principles that are critical for optimizing model performance.

2.2.1 Problem 1: Length Reward Bias as a Barrier to Exploratory Behavior

The $\ell_{\min}$ and $\ell_{\max}$ values defined by Kimi are computed based on all responses to a given problem x. Furthermore, Kimi applies the length reward function $\text{reward}_{\text{len}} = \min(0, \lambda)$ when the answer is incorrect. This leads to longer incorrect responses being penalized more severely than shorter ones. Additionally, the reward function is formulated as a linear function that favors shorter responses, assigning them higher rewards while penalizing longer ones. This design incentivizes convergence toward the shortest possible outputs, thereby diminishing response diversity.

These two aspects of the reward function suppress model exploration and increase the risk of the model converging to suboptimal local minima. Notably, a similar limitation is observed in the reward formulation proposed by [26].

To address this issue, we propose two reward design modifications that help preserve model diversity:

Reward Design I: Correctness-Conditioned Length Reward

We propose that length-based rewards should be applied only to correct responses. Specifically, the length reward is computed exclusively for correct answers, with $\ell_{\min}$ and $\ell_{\max}$ calculated solely from correct responses to each question. This approach is similar to the reward scaling strategy adopted by [26] and [27], who similarly restrict reward adjustments to correct outputs.

Reward Design II: Neutral Length Zone

To avoid penalizing responses that fall within an acceptable length range, we introduce a hyperparameter τ_ℓ, referred to as the *length tolerance*. For correct responses, the length reward is defined as follows:

- If the response length $\ell(i)$ satisfies $\ell(i) \leq \ell_{\min} + \tau_\ell$, the length reward is set to 0.5, matching the reward for the shortest correct response.
- For responses exceeding this threshold, the length reward is set to the value λ as defined earlier.

2.2.2 Problem 2: Instability Performance due to Length Penalty

In the Kimi setting, the length reward is applied at every training step, regardless of model performance or prediction quality. That is, each gradient update includes a penalty on longer responses. In our experiments, we find that although Design I and Design II help retain response diversity, in some cases, model performance is still degraded.

To address this issue, we propose to stop the application of the length reward until the training process has stabilized—namely, when batch accuracy shows consistent improvement.

Reward Design III: Accuracy-Aware Length Reward

We define a hyperparameter τ_{acc} that controls the accuracy threshold. For each training batch, we compute the batch accuracy acc over all rollout samples, and maintain $\text{acc}_{\max}$, the maximum accuracy achieved up to that point in training. The length reward is applied only when the condition $\text{acc} \geq \text{acc}_{\max} - \tau_{\text{acc}}$ is satisfied.

3 Experiments

3.1 Experimental Settings

We evaluate our method across two distinct domains: logic reasoning and mathematical reasoning. The logic reasoning domain is represented by the Logic-RL project [28], while the mathematical

Table 1: Logic-RL valuation on the final checkpoint.

Method	In Domain								Out of Domain		Average Response Length	
	ppl2	ppl3	ppl4	ppl5	ppl6	ppl7	ppl8	Average	AMC	AIME	Averaged by Steps	Last
Standard	82	87	88	81	76	69	70	79	39.76	7.77	1477	2632
Kimi (post)	84	88	89	84	79	74	76	82	39.89	8.13	1477	763
Efficient	76	81	79	77	62	48	51	68	37.35	7.77	772	843
ThinkPrune	80	84	86	82	70	66	64	76	38.47	7.35	832	793
Short-RL	**97**	**97**	**99**	**95**	**92**	**83**	**87**	**93**	**42.17**	**8.74**	889	535

Table 2: Evaluation of math reasoning.

Model	Math Benchmarks						Average Response Length	
	AIME2024	AMC23	MATH500	Minerva Math	Olympiad Bench	Average	Averaged by Steps	Last
Standard	26.67	59.04	**81.40**	**26.10**	42.65	47.17	2523	3072
Kimi (post)	23.33	**61.45**	81.00	25.37	**42.79**	46.79	2523	1678
Efficient	20.00	49.40	57.8	16.54	33.73	35.49	1517	1537
ThinkPrune	26.67	56.63	78.40	25.74	41.31	45.75	1589	1621
Short-RL	**30.00**	**60.24**	80.60	**26.47**	**42.65**	**47.99**	1692	1700
Open Reasoner Zero								
Standard	16.67	**50.60**	**78.80**	30.88	38.04	43.00	746	840
Kimi (post)	**20.00**	49.40	77.40	**31.25**	**38.63**	**43.34**	746	621
Efficient	13.33	46.99	66.40	26.47	35.96	37.83	578	655
ThinkPrune	13.33	48.19	76.80	27.57	37.15	40.61	677	682
Short-RL	16.67	**50.60**	78.60	30.52	38.19	42.92	660	670
SimpleRL-Reason								
Standard	13.33	48.19	77.00	**32.72**	**39.97**	42.24	703	791
Kimi (post)	16.67	48.19	77.40	31.99	39.67	42.78	703	601
Efficient	6.67	38.55	64.8	22.06	28.68	32.15	492	532
ThinkPrune	10.00	46.99	69.40	31.62	37.30	39.06	613	598
Short-RL	**20.00**	**49.40**	**78.20**	**32.72**	39.23	**43.91**	554	620

reasoning domain includes three settings: DeepScaleR [29], SimpleRL-Reason [30], and Open-Reasoner-Zero [31]. In all experiments, we employ the same model architecture and training framework [32] as used in the original projects. Details can be found in Training Details.

3.1.1 Evaluation Metrics

For Logic-RL, we evaluate the final accuracy on 2- to 8-person tasks using Logic-RL's evaluation script. To assess generalization, we also evaluate out-of-domain performance on the AIME and AMC benchmarks following Logic-RL's protocol. Additionally, we report two token-length metrics: (1) step-wise average response length during training, reflecting training speed, and (2) average response length at the final step, indicating inference speed after training.

For math reasoning, evaluation is carried out across five benchmark datasets: AIME2024[33], AMC23[34], MATH-500[35], Minerva Math[36], and Olympiad Bench[37]. We also report two token-length metrics too.

3.1.2 Baselines

We compare our method with the following baselines:

- **Standard**: Reinforcement learning with standard rule-based rewards.
- **Kimi**: Rule-based rewards augmented with the Kimi length reward ($\alpha = 1$). **Note that the Kimi length reward was originally applied in a post-RL stage after a standard RL stage. Directly applying this reward function may lead to issues and varying the choice of α remains susceptible to reward hacking (discussed in Section 2.1.1)**. Thus we provide a Kimi (post) baseline to show the best performance of Kimi reward function applied after the standard RL. For this two-stage approach, we report the step-wise average response length during the first (standard RL) stage in the tables.

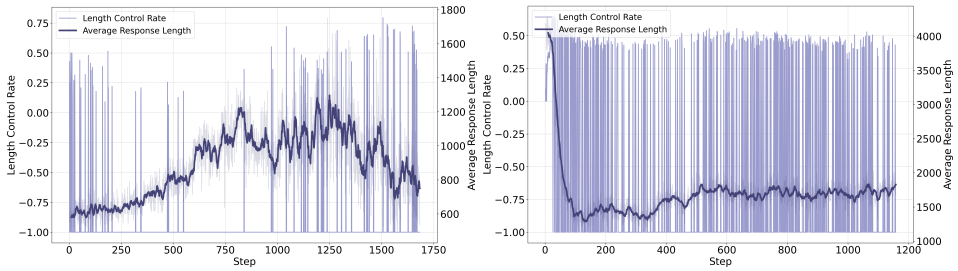
- **Efficient**: A length-aware scaling reward from [26], where we select optimal α values from $0.02, 0.05, 0.08, 0.10$ for each method: Logic-RL ($\alpha = 0.05$), DeepScaleR ($\alpha = 0.10$), and both SimpleRL-Reason and Open-Reasoner-Zero ($\alpha = 0.02$). Note that the α used in Efficient (as a scaling factor) differs from the α used in our method. Additionally, the experimental results in their paper already show an obvious trade-off between accuracy and response length.
- **ThinkPrune**: A length-aware reward proposed by [27]. We select the length limit that yields a comparable average response length to our method: 1700 for Logic-RL, 2500 for DeepScaler, 1500 for OpenReasonerZero and SimpleRL-Reason.

3.2 Main Results

As is shown in Table 1, our proposed Short-RL method effectively regulates response length while consistently outperforming standard RL approaches in terms of accuracy on logic reasoning tasks. Specifically, Short-RL achieves a 40% reduction in step-wise average response length while delivering statistically significant accuracy gains across all evaluated tasks.

Quantitative evaluation on math reasoning tasks in Table 2 reveals that Short-RL achieves 33% , 11% , 21% reduction in step-averaged response length compared to standard RL approaches across the three settings respectively. In contrast, the Kimi, Efficient and ThinkPrune baselines demonstrate poorer performance.

4 Track the Length Reward



(a) Logic-RL (b) DeepScaleR

Figure 2: Tracking the length reward during training

During training, we monitor the application of length rewards. We introduce a batch-wise metric called length control rate (γ_ℓ). For each batch, let N be the number of correct responses. Among these, R denotes the number of responses with $\text{reward}_{\text{len}} < 0.5$. We then define:

$$\gamma_\ell = \begin{cases} \frac{R}{N}, & \text{if } N \neq 0 \text{ and acc} \geq \text{acc}_{\max} - \tau_{\text{acc}} \\ 0, & \text{if } N = 0 \\ -1, & \text{if acc} < \text{acc}_{\max} - \tau_{\text{acc}} \end{cases} \tag{2}$$

, We track the proposed metrics and the average response length during training in two experiments, as shown in Figure 2. We observe that the length reward is distributed throughout the training process. In DeepScaleR, length rewards are applied more frequently.

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Ahmad, Lauren Yang, Leo Liu, Leon Maksin, Leyton Ho, Liam Fedus, Lilian Weng, Linden Li, Lindsay McCallum, Lindsey Held, Lorenz Kuhn, Lukas Kondraciuk, Lukasz Kaiser, Luke Metz, Madelaine Boyd, Maja Trebacz, Manas Joglekar, Mark Chen, Marko Tintor, Mason Meyer, Matt Jones, Matt Kaufer, Max Schwarzer, Meghan Shah, Mehmet Yatbaz, Melody Y. Guan, Mengyuan Xu, Mengyuan Yan, Mia Glaese, Mianna Chen, Michael Lampe, Michael Malek, Michele Wang, Michelle Fradin, Mike McClay, Mikhail Pavlov, Miles Wang, Mingxuan Wang, Mira Murati, Mo Bavarian, Mostafa Rohaninejad, Nat McAleese, Neil Chowdhury, Neil Chowdhury, Nick Ryder, Nikolas Tezak, Noam Brown, Ofir Nachum, Oleg Boiko, Oleg Murk, Olivia Watkins, Patrick Chao, Paul Ashbourne, Pavel Izmailov, Peter Zhokhov, Rachel Dias, Rahul Arora, Randall Lin, Rapha Gontijo Lopes, Raz Gaon, Reah Miyara, Reimar Leike, Renny Hwang, Rhythm Garg, Robin Brown, Roshan James, Rui Shu, Ryan Cheu, Ryan Greene, Saachi Jain, Sam Altman, Sam Toizer, Sam Toyer, Samuel Miserendino, Sandhini Agarwal, Santiago Hernandez, Sasha Baker, Scott McKinney, Scottie Yan, Shengjia Zhao, Shengli Hu, Shibani Santurkar, Shraman Ray Chaudhuri, Shuyuan Zhang, Siyuan Fu, Spencer Papay, Steph Lin, Suchir Balaji, Suvansh Sanjeev, Szymon Sidor, Tal Broda, Aidan Clark, Tao Wang, Taylor Gordon, Ted Sanders, Tejal Patwardhan, Thibault Sottiaux, Thomas Degry, Thomas Dimson, Tianhao Zheng, Timur Garipov, Tom Stasi, Trapit Bansal, Trevor Creech, Troy Peterson, Tyna Eloundou, Valerie Qi, Vineet Kosaraju, Vinnie Monaco, Vitchyr Pong, Vlad Fomenko, Weiyi Zheng, Wenda Zhou, Wes McCabe, Wojciech Zaremba, Yann Dubois, Yinghai Lu, Yining Chen, Young Cha, Yu Bai, Yuchen He, Yuchen Zhang, Yunyun Wang, Zheng Shao, and Zhuohan Li. Openai o1 system card, 2024.

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6 Appendix

6.1 Reproduction of Kimi length reward

We reproduced the experimental setup of Logic-RL [28] and modified it to include the Kimi length reward from the beginning of training. Specifically, we varied the weight coefficient α across the values $[1, 0.5, 0.1, 0.01]$, keeping all other hyperparameters fixed. We then evaluated the resulting models on the `ppl5` dataset (logic puzzles with 5 people) [38], measuring both test accuracy and average response length. All models were trained from scratch for 3 epochs. As shown in Figure 3, directly incorporating the length reward from the start results in a reward hacking phenomenon, with response lengths rapidly collapsing to very short outputs.

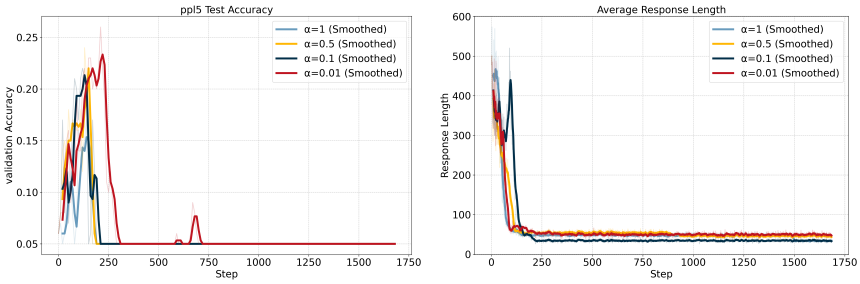


Figure 3: Test accuracy (left) and average response length (right) across different values of α.

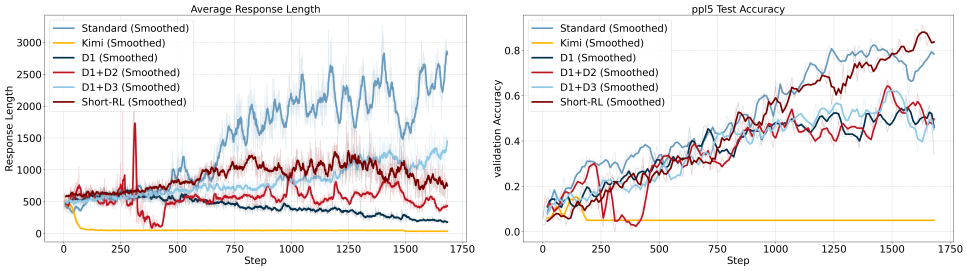
6.2 Ablation Study

6.2.1 Component Ablation

We conduct an ablation study to evaluate the impact of our proposed designs. All experiments are performed on the Logic-RL dataset and use the same length reward weight $\alpha = 1$.

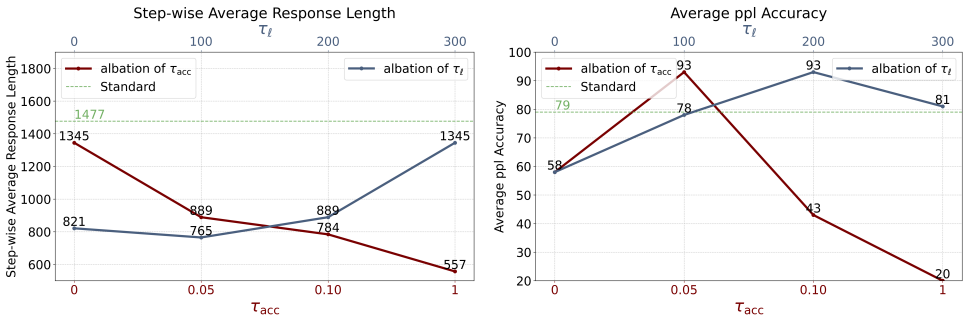
We compare the accuracy and average response length curves across several configurations. D1 applies standard RL using our proposed length reward design I. D1+D2 incorporates both design I and design II, while D1+D3 combines design I and design III. Finally, our proposed method, Short-RL, integrates all three designs: I, II, and III.

As shown in Figure 4, our proposed reward designs significantly improve both response length control and validation accuracy. The subfigure 4a shows that the Standard baseline generates overly long responses, while the Kimi baseline collapses to very short outputs. In contrast, our designs (D1, D1+D2, D1+D3) progressively stabilize length generation, with Short-RL achieving the most balanced outcome. The subfigure 4a illustrates consistent accuracy gains from our designs. Short-RL consistently achieving the highest accuracy. Even partial configurations (D1+D2, D1+D3) outperform Kimi, underscoring the effectiveness and complementarity of each design component. Note that the ppl5 test set here differs from the final evaluation set, following the practice of Logic-RL.



(a) Response Length (b) Accuracy

Figure 4: Ablation study on three reward designs



(a) (b)

Figure 5: Ablation study on the impact of length tolerance and accuracy tolerance, with both factors plotted on a shared y-axis. The upper x-axis represents the length tolerance, while the lower x-axis represents the accuracy tolerance.

6.2.2 Impact of Length and Accuracy Tolerance

We vary the τ_ℓ among 0, 100, 200, and 300, while fixing the τ_{acc} to 0.05. The comparisons of step-wise average response length and average accuracy on ppl tasks are shown in Figure 5. We observe that an overly small length tolerance (e.g., 0) leads to shorter average responses and degraded performance. But the model is not too sensitive to the choice of length tolerance. Varying the choice

Setting	Logic-RL	DeepScaleR	Open Reasoner Zero	SimpleRL-Reason
learning rate	1e-6	1e-6	5e-7	5e-7
batch size	8	128	64	16
ppo_mini_batch_size	32	64	256	64
ppo_micro_batch_size	8	32	64	2
rollout_n	8	8	8	8
temperature	0.7	0.6	1.0	1.0
kl_loss_coef	0.001	0.001	0.001	0.0001
epochs	3	3	1	3
max_response_length	4096	8192	4096	8192
algorithm	reinforce++	grpo	grpo	grpo
τ_ℓ	200	100	100	50
τ_{acc}	0.05	0.05	0.02	0.05
α	1	1	1	1
Model	Qwen2.5-7B	DeepSeek Distill Qwen-1.5B	Qwen2.5-7B	Qwen2.5-7B

Table 3: Training details.

among 100, 200, 300 still achieves good performance. Larger length tolerance may result in longer average response length. For this setting, a length tolerance of around 200 achieves the best balance.

We vary τ_{acc} among 0, 0.05, 0.10, and 1.0, while fixing the τ_ℓ to 200. Figure 5 shows that model performance is sensitive to this parameter. Specifically, higher τ_{acc} (e.g., 1.0) leads to shorter response lengths and degraded performance. A good choice in this setting may be around 0.05.

```
<|im_start|>system\nYou are a helpful assistant. The
assistant first thinks about the reasoning process in
the mind and then provides the user with the answer. The
reasoning process and answer are enclosed within <think>
</think> and<answer> </answer> tags, respectively, i.e.,
<think> reasoning process here </think><answer> answer
here </answer>.  Now the user asks you to solve a
logical reasoning problem. After thinking, when you
finally reach a conclusion, clearly state the identity
of each character within <answer> </answer> tags. i.e.,
<answer> (1) Zoey is a knight\n(2) ...
</answer>.\n<|im_end|>\n<|im_start|>user\n{quiz}\n<|im_e
nd|>\n<|im_start|>assistant\n<think>
```

(a)

```
The user asks a question, and the Assistant solves
it.The assistant first thinks about the reasoning
process in the mind and then provides the user with the
final answer. The reasoning process and answer are
enclosed within <think> </think> and <answer> </answer>
tags, respectively, i.e., <think> reasoning process here
</think><answer> answer here </answer>.
\n\nUser:{question}\nAssistant: <think>
```

(b)

Figure 6: The prompt template for Logic-RL and Math-RL.

6.3 Training Details

Our experiments were conducted using a compute node equipped with 8 NVIDIA H100 GPUs. The CUDA version we use is 12.3.

6.3.1 Logic-RL Training and Evaluation Details

The training and evaluation prompt template (Figure 6a) used in Logic-RL remains the same as in the original GitHub project. The training hyperparameters are listed in Table 3. During evaluation, we directly use the code from Logic-RL, which applies a temperature of 1.0 and top_p=1.0 for logic tasks, and a temperature of 0.8 with top_p= 0.95 for math tasks.

6.3.2 Training and Evaluation Details for Math

The training and evaluation prompt template for three math settings is shown in Figure 6b. The training hyperparameters are listed in Table 3. During evaluation, we directly use the code from DeepScaleR, which employs a temperature of 1.0.

6.3.3 Reward Details

In all the math experiments, the standard reward employs a format and outcome-based reward scheme. That is:

$$\text{reward} = \begin{cases} 3 & \text{, the format is correct and the answer is right} \\ -0.5 & \text{, the format is correct and the answer is wrong} \\ -3 & \text{, the format is wrong} \end{cases} \tag{3}$$

. In Logic-RL experiments, we directly use their original standard reward design.