



Critique-RL: Training Language Models for Critiquing through Two-Stage Reinforcement Learning

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Training critiquing language models ^a to assess and provide feedback on model outputs is a promising way to improve LLMs for complex reasoning tasks. However, existing approaches typically rely on stronger supervisors for annotating critique data. To address this, we propose Critique-RL, an online RL approach for developing critiquing language models without stronger supervision. Our approach operates on a two-player paradigm: the actor generates a response, the critic provides feedback, and the actor refines the response accordingly. We first reveal that relying solely on indirect reward signals from the actor’s outputs for RL optimization often leads to unsatisfactory critics: while their helpfulness (i.e., providing constructive feedback) improves, the discriminability (i.e., determining whether a response is high-quality or not) remains poor, resulting in marginal performance gains. To overcome this, Critique-RL adopts a two-stage optimization strategy. In stage I, it reinforces the discriminability of the critic with direct rule-based reward signals; in stage II, it introduces indirect rewards based on actor refinement to improve the critic’s helpfulness, while maintaining its discriminability via appropriate regularization. Extensive experiments across various tasks and models show that Critique-RL delivers substantial performance improvements. For example, it achieves a 9.02% gain on in-domain tasks and a 5.70% gain on out-of-domain tasks for Qwen2.5-7B, highlighting its potential.

^aIt can also be referred to as a critique model or critic.

1. Introduction

With the development of large language models (Dubey et al., 2024; Jiang et al., 2023; OpenAI, 2023; Ouyang et al., 2022; Touvron et al., 2023), providing reliable supervision for them has become a critical research challenge (Bowman et al., 2022; Saunders et al., 2022), especially for tasks that are difficult even for humans, such as complex reasoning, sequential decision-making, and coding (Kumar et al., 2024; Qu et al., 2024; Shinn et al., 2023; Snell et al., 2024). This problem is often referred to as scalable oversight (Bowman et al., 2022). One effective method for scalable oversight is to train critiquing lan-

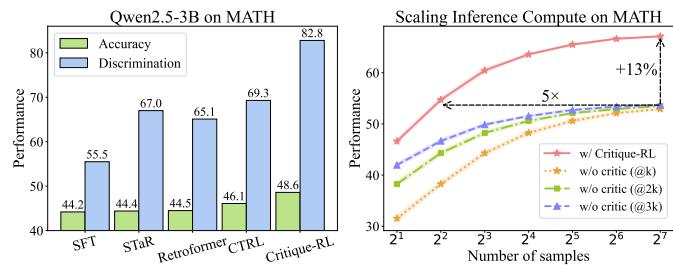


Figure 1 | Left: Critique-RL achieves better performance and discrimination on MATH. **Right:** Inference compute scaling for Critique-RL, with @2k and @3k indicating sampling amounts that are 2 times and 3 times the x-axis value, respectively. Critique-RL improves the performance ceiling and is more compute-efficient.

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¹Our code are available at <https://github.com/WooooDyy/Critique-RL>.

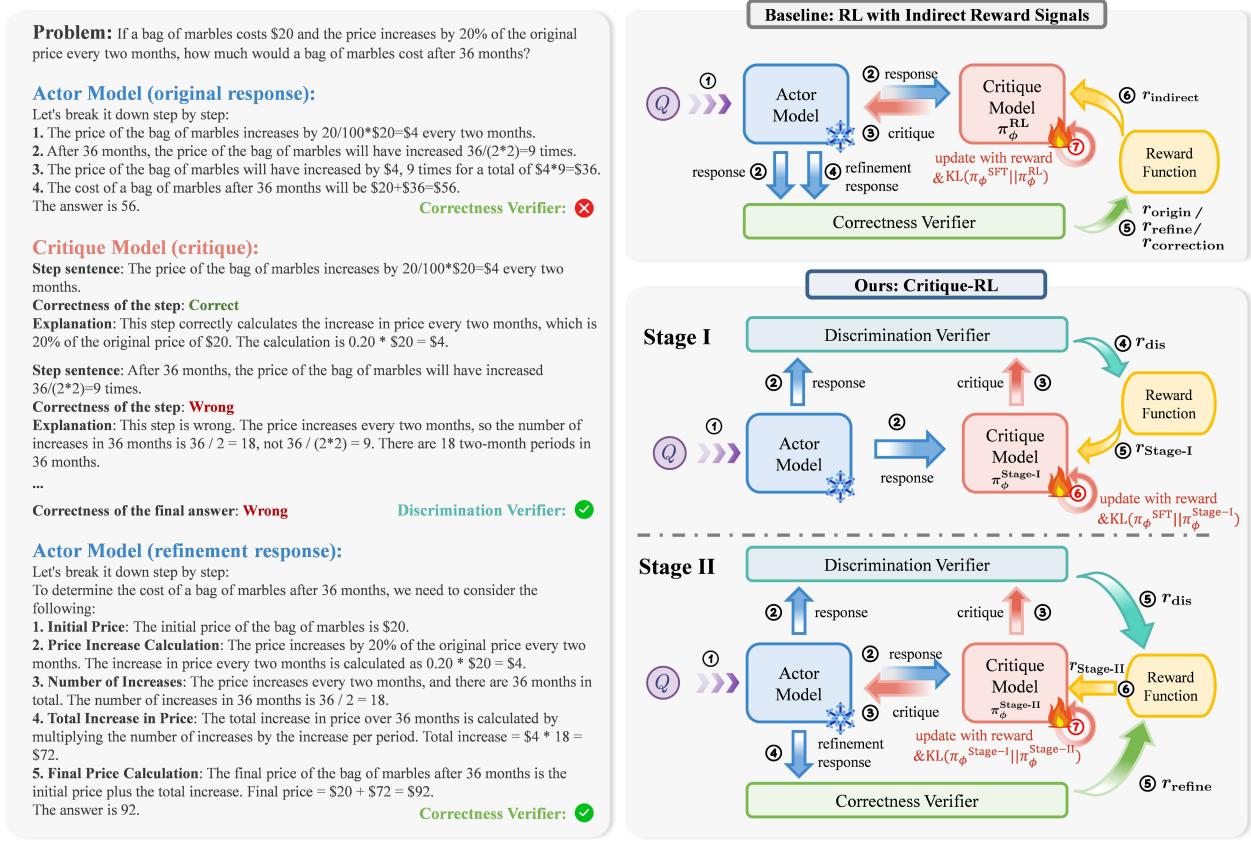


Figure 2 | Left: A case illustrating the two-player actor-critic interaction, including the original response from the actor, the critique from the critic, and the refinement from the Actor. **Right:** Overview of our method and its comparison with baseline RL. The snowflake icon on the Actor indicates that it is fixed, while the fire icon on the Critic indicates that it will be updated. Our method employs a two-stage RL process. It optimizes discriminability of critique models in Stage I, and optimizes helpfulness while maintaining discriminability in Stage II.

guage models to assess and provide feedback to model outputs (Akyürek et al., 2023; Welleck et al., 2023; Xi et al., 2024; Yao et al., 2024). Based on this feedback, actor models can refine and optimize their behavior or outputs.

Existing work in training critique models typically assumes a stronger supervisor to provide labeled critique data, which is often expensive and difficult to scale (Bowman et al., 2022; Saunders et al., 2022; Xi et al., 2024). Moreover, the data labeled by the supervisor often differs significantly from the learner's output distribution (Kumar et al., 2024). Another line of work does not train the model but instead relies on the model's inherent abilities, using prompt engineering to elicit its critiquing abilities (Bai et al., 2022; Dhuliawala et al., 2024; Madaan et al., 2023). However, such methods typically assume an oracle verifier during testing, allowing the critique model to bypass discrimination (i.e., determining whether a response is high-quality) and instead focus only on offering helpful feedback for revision (Gou et al., 2024; Xi et al., 2024). Without the oracle verifier, they often meet performance bottleneck (Huang et al., 2024).

In this work, we aim to develop critiquing language models without relying on stronger supervision or an oracle reward function during testing. To this end, we propose Critique-RL, an online RL approach based on two-player actor-critic interaction (Xi et al., 2024; Yao et al., 2024) for developing critique models. In our approach, there are two main roles: the actor and critic. The critic assesses

(discriminability) and provides natural language feedback (helpfulness) for the actor’s output, and the actor performs refinement accordingly (Saunders et al., 2022).

To build our method, we first use the correctness of the actor’s two attempts to shape the reward signals for the RL optimization of critique models (§4.1), following approaches like Retroformer (Yao et al., 2024) and CTRL (Xie et al., 2025), where such indirect signals are shown to reflect the quality of critiques. However, this approach fails to develop satisfactory critique models, i.e., with low performance. Delving into the optimization process, we reveal that while the helpfulness of the critique models improves, their discriminability is not well optimized, leading to an optimization bottleneck and even a collapse of RL training.

To address the challenges, Critique-RL employs a two-stage RL approach (§4.2). Specifically, as shown in Figure 2, in the first stage, we optimize the discriminability of the critique models using direct rule-based reward signals. In the second stage, we introduce indirect rewards based on the correctness of actor refinement to enhance the helpfulness, while using appropriate regularization to maintain their discriminability. In-depth training dynamics shows that our method addresses the training collapse and stably optimizes both discriminability and helpfulness. Extensive experiments show that our method outperforms baselines across different models and tasks, yielding a 9.02% improvement on in-domain tasks and 5.70% improvement on out-of-domain tasks for Qwen2.5-7B. It is also noteworthy that critique models trained with our method can generalize to unseen tasks, demonstrating its promise for scalable oversight.

In summary, our main contributions are:

1. Delving into the RL optimization process, we reveal that solely depending on indirect reward signals of actor’s output correctness cannot develop effective critique models, which poses conflict and optimization challenges between the discriminative and feedback capabilities of critics.
2. We then propose Critique-RL, a novel two-stage RL approach to develop critique models for providing accurate assessment and helpful feedback for model outputs.
3. We perform in-depth experiments, ablation and analysis to show the effectiveness and stability of our method. We hope our work provides insights for the community.

2. Related Work

Prompt engineering for eliciting critiquing ability from language models. As a key technique for scalable oversight (Bowman et al., 2022), many previous works have explored the use of prompt engineering to elicit the critiquing and reflection abilities of LLMs (Bai et al., 2022; Dhuliawala et al., 2024; Madaan et al., 2023; Ye et al., 2023). These methods typically rely on an oracle verifier including answer matching or external tools at test time for discrimination, allowing the LLM to focus solely on providing natural language feedback (Huang et al., 2024; Xi et al., 2024). However, in the absence of an external verifier, even SOTA models face significant challenges (Huang et al., 2024; Saunders et al., 2022; Welleck et al., 2023; Xu et al., 2024). In this work, we do not assume an oracle verifier; instead, we train critique models through RL to optimize both discriminability and the ability to provide helpful feedback.

Fine-tuning language models for critiquing. Previously, a line of work has explored fine-tuning-based approaches for training critique models (Bowman et al., 2022; Saunders et al., 2022; Xi et al., 2024). However, these methods primarily rely on a stronger supervisor for data annotation, which is costly and difficult to scale (Xi et al., 2024). To address this issue, some researchers have proposed self-improvement-based methods to train models for self-critiquing (Tang et al., 2025; Yuan et al.,

2025; Zheng et al., 2024). Unlike these approaches, we adopt a two-player paradigm and train a separated critique model through RL.

Reinforcement learning for language models. RL has become an essential component of LLM post-training, such as RLHF for alignment (Ouyang et al., 2022; Shao et al., 2024; Wang et al., 2024; Zheng et al., 2023). Additionally, various works have leveraged RL to enhance language models’ performance in reasoning (Kumar et al., 2024; Snell et al., 2024), coding (Kumar et al., 2024), and decision-making tasks (Shinn et al., 2023). Furthermore, some studies explore using RL to improve LM’s ability for self-reflection and self-correction (Kumar et al., 2024; McAleese et al., 2024; Shinn et al., 2023; Welleck et al., 2023; Xu et al., 2024; Ye et al., 2023). Other methods, such as Retroformer (Yao et al., 2024) and CTRL (Xie et al., 2025), leverage indirect reward signals to optimize critique model’s helpfulness, targeting decision-making tasks and coding tasks, respectively. However, their RL phase overlooks the joint optimization of discriminability and helpfulness. Different from them, we propose a two-stage Critique-RL approach to optimize both discriminability and helpfulness, effectively developing critique models.

3. Preliminaries

3.1. The Two-Player Interaction Framework

The multi-agent framework in this work consists of two main roles (Xi et al., 2024; Yao et al., 2024): the actor model and the critique model. It operates through a response-critique-refinement process.

Specifically, given a question x , the actor model is expected to generate an original response $y = \pi_\theta(x)$, which includes both the reasoning trajectory and the final answer. The correctness verifier then provides an oracle reward $r_{\text{oracle}}(x, y)$ to the actor model. Subsequently, the critique model π_ϕ takes the question-response pair (x, y) as input and produces critique $c = \pi_\phi(x, y)$, which should include assessment of the response correctness (discriminability) and offer constructive natural language feedback (helpfulness). Based on this critique, the actor model generates a refinement response $y' = \pi_\theta(x, y, c)$, and subsequently receives an oracle reward $r_{\text{oracle}}(x, y')$. Using these rewards, i.e., $r_{\text{oracle}}(x, y)$ and $r_{\text{oracle}}(x, y')$, we can design different reward functions $r_c(\cdot)$ for critique models, which will be shown in §4.

3.2. Policy Gradient for LLMs

Policy gradient methods (Sutton et al., 1999), e.g., REINFORCE (Ahmadian et al., 2024; Kumar et al., 2024), are common techniques to perform RL on LLMs (Ouyang et al., 2022). For the policy critique model π_ϕ parameterized by ϕ , the objective of policy gradient is to find an optimal policy that maximizes the reward function $r_c(\cdot)$. It is typically expressed as maximizing:

$$\mathbb{E}_{c \sim \pi_\phi(\cdot|x,y), y' \sim \pi_\theta(x,y,c)} [r_c(x, y, c, y')], \quad (1)$$

where $\mathbb{E}_{c \sim \pi_\phi(\cdot|x,y), y' \sim \pi_\theta(x,y,c)}$ denotes the expectation over the critique sampled from the critic π_ϕ and the refinement response sampled from the actor π_θ . This gradient is used to optimize the critique model via gradient ascent. The positive critique is “reinforced” by increasing its probability.

3.3. Evaluation Metrics

To evaluate the performance of the critique model, we consider the following metrics: (1) **Acc@Refine**: the accuracy of the actor model’s refinement response; (2) **Δ** : the improvement in the actor model’s

accuracy between the original and refinement response, which measures the effectiveness of the critique model; (3) $\Delta^{c \rightarrow i}$: the change rate from an originally correct response to an incorrect refinement response. A lower value is better; (4) $\Delta^{i \rightarrow c}$: the change rate from an originally incorrect response to a correct refinement response. A higher value is better; (5) **Acc@Dis**: a direct metric to measure the discriminability of the critique model, which quantifies the accuracy of whether the correctness accessed by the critic aligns with the true correctness of the original response.

4. Methodology

4.1. Motivating Findings: RL with Indirect Reward Signals Is Insufficient for Training Satisfactory Critique Models

In the two-player actor-critic framework (Xi et al., 2024; Yao et al., 2024), a natural and intuitive way to optimize the critiquing language models is to shape the reward signals derived from the actor’s two attempts (original and refinement responses). We explore several reward shaping approaches, demonstrate their failure modes, and investigate why they fail to incentivize satisfactory critiquing ability.

Analysis setups: data, models, and training methods. Our preliminary experiments are on GSM8K (Cobbe et al., 2021), and the backbone model is Qwen2.5-3B (Team, 2024). Following previous work (Xi et al., 2024), we train an actor model capable of generating responses and faithfully refining them according to critiques. To build the SFT dataset for initializing a base critique model, we prompt Qwen2.5-3B-Instruct to obtain critique data $\mathcal{D}_{\text{SFT}} = \{x, y, c\}_{i=1}^{|\mathcal{D}_{\text{SFT}}|}$, rather than using annotations from SOTA commercial models like GPT-4o (OpenAI, 2023). We filter the critique data based on the correctness of refinement to ensure the quality.

Next, we train the critique model π_ϕ using the SFT loss:

$$\mathcal{L}_{\text{SFT}}(\phi) = \mathbb{E}_{(x,y,c) \sim \mathcal{D}_{\text{SFT}}} \left[\log \pi_\phi(c|x, y) \right]. \quad (2)$$

We then employ policy gradient (Sutton et al., 1999) to maximize:

$$\mathbb{E}_{c \sim \pi_\phi^{\text{RL}}(\cdot|x, y), y' \sim \pi_\theta(\cdot|x, y)} \left[r_c(x, y, c, y') - \beta \text{KL}(\pi_\phi^{\text{SFT}}(c|x, y) || \pi_\phi^{\text{RL}}(c|x, y)) \right], \quad (3)$$

where π_θ is the fixed actor model, π_ϕ^{SFT} is the SFT model. Each x is a query sampled from the RL dataset \mathcal{D}_{RL} , y is the original response. $\text{KL}(\cdot || \cdot)$ means the KL-divergence which constrains the distance between the RL model and the SFT model, and β is a scaling factor. $r_c(\cdot)$ is the reward function for critique models. Here, with r_{oracle} being the oracle reward function that verifies the correctness of an actor response, $r_c(\cdot)$ can be r_{refine} which represents the correctness of the refinement:

$$r_{\text{refine}}(x, y, c, y') = r_{\text{oracle}}(x, y'), \quad (4)$$

or it can be r_Δ which represents the difference in correctness between the actor’s two attempts:

$$r_\Delta(x, y, c, y') = r_{\text{oracle}}(x, y') - r_{\text{oracle}}(x, y). \quad (5)$$

Moreover, we also include $r_{\text{correction}}$ as $r_c(\cdot)$ for reinforcing the ability to correct incorrect responses:

$$r_{\text{correction}}(x, y, c, y') = \begin{cases} 1.0, & r_{\text{oracle}}(x, y) = 0 \text{ and } r_{\text{oracle}}(x, y') = 1, \\ 0.2, & r_{\text{oracle}}(x, y) = 1 \text{ and } r_{\text{oracle}}(x, y') = 1, \\ 0.0, & r_{\text{oracle}}(x, y') = 0. \end{cases} \quad (6)$$

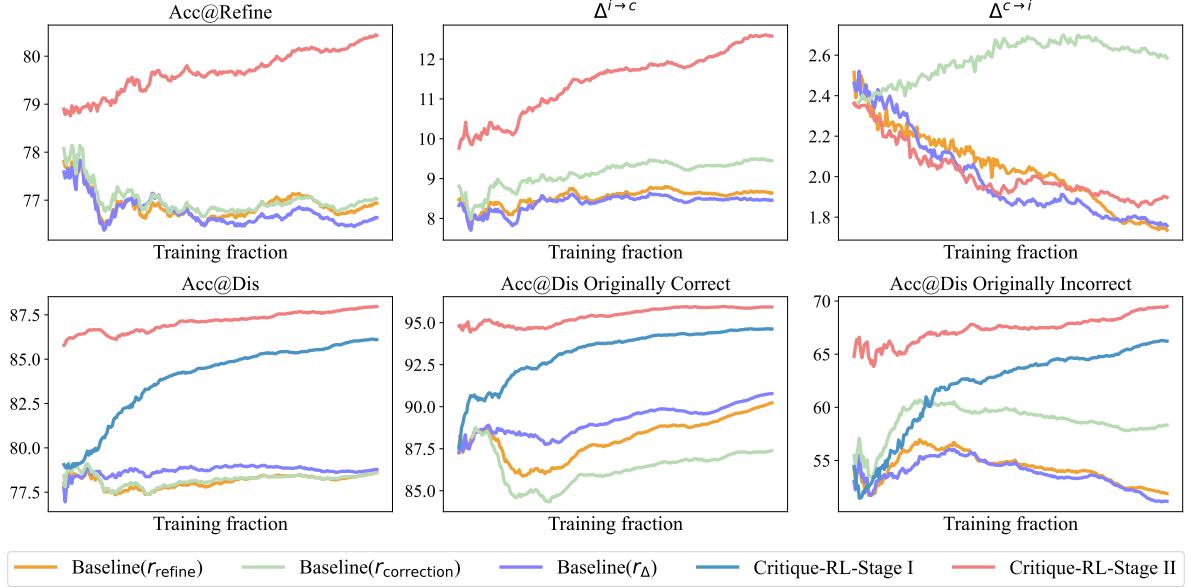


Figure 3 | Training dynamics of preliminary experiments. “Acc@Dis Originally Correct” and “Acc@Dis Originally Incorrect” refer to the discrimination accuracy of originally correct and incorrect responses, respectively. Baselines using indirect reward signals to optimize helpfulness tend to exhibit overly conservative or aggressive behavior as the discriminability is not well optimized. In contrast, our Critique-RL optimizes discriminability in Stage I, and optimizes helpfulness while maintaining discriminability in Stage II, achieving better in Acc@Refine, $\Delta^{c \rightarrow i}$ and $\Delta^{i \rightarrow c}$.

Empirical findings and behavior analysis. We illustrate the training dynamics during RL in Figure 3. Optimizing with r_{refine} and r_{Δ} can reduce $\Delta^{c \rightarrow i}$, preventing originally correct responses from being altered incorrectly, but its $\Delta^{i \rightarrow c}$ is not significantly optimized, meaning its error correction performance is not good enough. This phenomenon reveals that the critique model is overly **conservative**, encouraging the actor to not change its answers. As a result, the final Acc@Refine is not satisfactory.

In contrast, optimizing with $r_{\text{correction}}$ improves $\Delta^{i \rightarrow c}$, but fails to effectively reduce $\Delta^{c \rightarrow i}$. This means it often provides more **aggressive** suggestions, encouraging the actor model to correct incorrect responses, but it also introduces a greater risk of turning originally correct answers into incorrect ones. Similarly, the final Acc@Refine is also not satisfactory.

Analyzing underlying reasons for the failure modes. To reveal the reasons behind the above failure modes, we also visualize the discrimination performance of the critiquing language models during RL in Figure 3. We find that as RL progresses, all three reward functions r_{refine} , r_{Δ} and $r_{\text{correction}}$ fail to optimize discriminability effectively. For originally correct and incorrect responses, they can only optimize the judgment for one, while the ability to judge the other is reduced. This may be because both of the indirect reward functions are based on the actor’s responses, targeting helpfulness and overlooking discriminability. This motivates the proposal of our method.

4.2. Two-Stage Critique-RL

Key challenges. Based on the previous analysis, we have identified two key challenges in RL for critiquing language models: (1) optimizing the discriminability of critique models to improve their accuracy in judging both correct and incorrect original responses; (2) improving the quality of the model’s feedback, i.e., helpfulness, while maintaining its discriminability, to prevent the issues of

being overly aggressive or overly conservative.

Method overview. To address the above challenges, we propose the two-stage Critique-RL. In the first stage, our method explicitly optimizes the discriminability of the critique model using direct reward signals. We then use the resulting model $\pi_\phi^{\text{Stage-I}}$ as the initialization for the second stage. In the second stage, we introduce a reward function based on the actor’s response to optimize the critic’s helpfulness, while also incorporating appropriate regularization to maintain its discriminability. We illustrate our method in Figure 2 and the algorithm is summarized in Algorithm 1.

Algorithm 1: Critique-RL

Input: Actor model π_θ , base critique model π_ϕ , SFT dataset \mathcal{D}_{SFT} , RL dataset \mathcal{D}_{RL} , function that extracts the correctness of a response judged by a critique f , oracle reward function r_{oracle} , discrimination reward function r_{dis} .

1 **Procedure** Supervised Fine-tuning:

2 $\pi_\phi^{\text{SFT}} \leftarrow \pi_\phi$;

3 Update π_ϕ^{SFT} by minimizing $\mathcal{L}_{\text{SFT}}(\phi) = \mathbb{E}_{(x,y,c) \sim \mathcal{D}_{\text{SFT}}} [\log \pi_\phi(c|x, y)]$;

4 **Procedure** Critique-RL Stage I: optimizing discriminability through direct reward signals.

5 $\pi_\phi^{\text{Stage-I}} \leftarrow \pi_\phi^{\text{SFT}}$;

6 **for** batch in \mathcal{D}_{RL} **do**

7 **for** x in batch **do**

8 Generate y and c with π_θ and $\pi_\phi^{\text{Stage-I}}$;

9 Compute discrimination reward with $r_{\text{dis}}(x, y, c) = \mathbb{1}(f(x, y, c) = r_{\text{oracle}}(x, y))$;

10 **end**

11 Update $\pi_\phi^{\text{Stage-I}}$ by maximizing

12 $\mathbb{E}_{c \sim \pi_\phi^{\text{Stage-I}}(\cdot|x, y)} [r_{\text{dis}}(x, y, c) - \beta \text{KL}(\pi_\phi^{\text{SFT}}(c|x, y) || \pi_\phi^{\text{Stage-I}}(c|x, y))]$;

13 **end**

14 **Procedure** Critique-RL Stage II: optimization helpfulness while maintaining discriminability.

15 $\pi_\phi^{\text{Stage-II}} \leftarrow \pi_\phi^{\text{Stage-I}}$;

16 **for** batch in \mathcal{D}_{RL} **do**

17 **for** x in batch **do**

18 Generate y, c and y' with π_θ and $\pi_\phi^{\text{Stage-II}}$;

19 Compute discrimination reward with $r_{\text{dis}}(x, y, c) = \mathbb{1}(f(x, y, c) = r_{\text{oracle}}(x, y))$;

20 Compute refinement reward with $r_{\text{refine}} = r_{\text{oracle}}(x, y')$;

21 **end**

22 Update $\pi_\phi^{\text{Stage-II}}$ by maximizing

23 $\mathbb{E}_{c \sim \pi_\phi^{\text{Stage-II}}(\cdot|x, y), y' \sim \pi_\theta(\cdot|x, y, c)} [r_{\text{refine}} + \beta_1 r_{\text{dis}}(x, y, c) - \beta_2 \text{KL}(\pi_\phi^{\text{Stage-I}}(c|x, y) || \pi_\phi^{\text{Stage-II}}(c|x, y))]$.

24 **end**

Stage I: optimizing discriminability through direct reward signals. We decouple the discriminability and helpfulness of the critique models (Saunders et al., 2022). In Stage I, we shape the reward based solely on the actor’s original response. Given (x, y) , critique models are prompted to give correctness judgments for each step, and also provide a judgment for the final answer. Based

on this, we define the discriminability reward function of the critique models as:

$$r_{\text{dis}}(x, y, c) = \mathbb{1}(f(x, y, c) = r_{\text{oracle}}(x, y)), \quad (7)$$

where $f(x, y, c)$ is the critique model's judgment of the correctness of the original response. $\mathbb{1}(\cdot)$ is indicator function that returns 1 only when the condition inside the parentheses holds, and 0 otherwise. Based on this, our Stage I RL maximizes:

$$\mathbb{E}_{c \sim \pi_{\phi}^{\text{Stage-I}}(\cdot|x, y)} \left[r_{\text{dis}}(x, y, c) - \beta \text{KL}(\pi_{\phi}^{\text{SFT}}(c|x, y) || \pi_{\phi}^{\text{Stage-I}}(c|x, y)) \right], \quad (8)$$

where the KL divergence with the SFT model is still used to stabilize the training. As shown in Figure 3, our Stage I RL can effectively and stably optimize discriminability, regardless of the correctness of the original response.

Stage II: optimizing helpfulness while maintaining discriminability. The goal of the second stage of Critique-RL is to optimize the helpfulness of the critique models without sacrificing their discriminability, thereby avoiding overly conservative or overly aggressive behavior patterns. To achieve this, we introduce a reward function r_{refine} based on actor refinement correctness. Meanwhile, to preserve the model's discriminability, we retain r_{dis} and introduce a regularization term based on the KL divergence with the Stage I model $\pi_{\phi}^{\text{Stage-I}}$. Specifically, we maximize the following objective:

$$\mathbb{E}_{c \sim \pi_{\phi}^{\text{Stage-II}}(\cdot|x, y), y' \sim \pi_{\theta}(\cdot|x, y, c)} \left[r_{\text{refine}} + \beta_1 r_{\text{dis}}(x, y, c) - \beta_2 \text{KL}(\pi_{\phi}^{\text{Stage-I}}(c|x, y) || \pi_{\phi}^{\text{Stage-II}}(c|x, y)) \right], \quad (9)$$

where β_1 and β_2 are scaling factors. As shown in Figure 3, our Stage II effectively optimizes the model's helpfulness, increasing $\Delta^{i \rightarrow c}$ and decreasing $\Delta^{c \rightarrow i}$, ultimately leading to a stable improvement in Acc@Refine and Δ . Our method also performs strongly on the test set (see §5).

5. Experiments

5.1. Experimental Setup

Datasets. Focusing on mathematical reasoning tasks, we select 5 different commonly-used tasks, including free-from and multiple-choice. Following Ding et al. (2025), we construct training set with the train-split of MATH (Hendrycks et al., 2021), GSM8K (Cobbe et al., 2021), AQUA (Ling et al., 2017). The testset of the three tasks are used as in-domain testset, while the test-split of SVAMP (Patel et al., 2021), TheoremQA (Chen et al., 2023), are used as our OOD (out-of-domain) testset.

Models and baselines. Our experiments are mainly conducted on Qwen2.5 series (Team, 2024), i.e., Qwen2.5-3B and Qwen2.5-7B. Besides, we also conduct experiments on other models like Qwen2.5-72B, Llama3.2 (Dubey et al., 2024) and DeepSeek-R1-Distill-Qwen-7B (DeepSeek-AI, 2025) (see Appendix A and Appendix B). We include several baselines: (1) SFT which fine-tunes models with critique data. (2) STar (Zelikman et al., 2022) which iteratively fine-tunes critique models on self-generated data and filtered based on the refinement correctness of the actor. (3) RL baselines that leverages indirect outcome-based reward as baselines, i.e., Retroformer (Yao et al., 2024) which uses PPO and CTRL (Xie et al., 2025) which uses GRPO.

Table 1 | Main results. The best performance is in **bold** and underlined, while the second-best performance is underlined. Our method is marked in blue. No Critic means the actor model performs reasoning only, and we report the reasoning performance. For other methods, we report the Acc@Refine performance for the acc column.

Model	Method	MATH			GSM8K			AQuA		
		Acc	Δ	Acc@Dis	Acc	Δ	Acc@Dis	Acc	Δ	Acc@Dis
Qwen2.5-3B	No Critic	36.90	–	–	66.03	–	–	50.00	–	–
	SFT	44.24	7.34	66.51	69.14	3.11	76.34	46.46	-3.54	61.97
	STaR	44.38	7.48	66.97	<u>71.95</u>	<u>5.91</u>	74.79	50.39	0.39	<u>66.13</u>
	Retroformer	44.54	7.64	65.11	70.51	4.47	<u>77.59</u>	51.18	1.18	58.44
	CTRL	46.14	9.24	69.29	70.58	4.55	76.71	53.54	3.54	62.20
	Critique-RL	48.60	11.70	82.80	75.89	9.86	87.44	56.69	6.69	69.92
Qwen2.5-7B	No Critic	45.74	–	–	75.66	–	–	63.39	–	–
	SFT	51.84	6.10	67.59	78.77	3.11	79.42	59.45	-3.94	68.67
	STaR	<u>54.06</u>	<u>8.32</u>	69.71	80.52	4.85	81.03	57.87	-5.51	<u>72.18</u>
	Retroformer	52.34	6.60	68.03	80.82	5.16	77.05	63.39	0.00	70.56
	CTRL	53.86	8.12	<u>71.42</u>	81.35	<u>5.69</u>	83.44	64.96	1.57	71.66
	Critique-RL	58.40	12.66	85.20	87.72	12.05	90.43	65.75	2.36	78.09

Implementation details. All experiments are conducted on 8 NVIDIA A800 GPUs. To initialize an actor that can reason and refine based on the critiquing feedback, we follow Ding et al. (2025); Xi et al. (2024) to construct a dataset of 21,973 reasoning traces and 12,000 refinement responses. For critique data, we construct a set of 6,000 examples, with 2,000 examples in each training task. For fine-tuning actors, we set epoch to 3 and learning rate to $5e - 6$, and remains fixed during further training phase; for fine-tuning critics, we set epoch to 5 and learning rate to $5e - 6$. We use the same base model for the actor and the critique model. For STaR and RL, we perform SFT to obtain an initialized model. In RL, we set KL coefficient to 0.01. In Critique-RL, we use RLOO as our base algorithm as it performs well and does not require a value model. In Stage II, β_1 is set to 0.2. We train the critique model for 500 steps at each stage and report best results. During evaluation, the temperature is set to 0. For inference-compute scaling and Pass@K, we set temperature to 0.7.

5.2. Main Results

Generally, critique models can significantly improve actor’s reasoning performance. The results in Table 1 demonstrate that when introducing critique models, the actor’s reasoning performance can be boosted by a large margin. For example, in the MATH task, even the SFT Baseline outperforms the model without a critic by 7.34 and 6.10 points on the 3B and 7B models, respectively. This suggests that critique models are an effective scalable oversight method, as discussed in McAleese et al. (2024); Saunders et al. (2022).

RL-based methods outperforms fine-tuning-based ones. Both SFT and STaR methods lead to promising critique models, but in most cases, online RL-based methods perform better, especially our Critique-RL. For instance, on the 3B model, our method surpasses the SFT method by an average of 7.11 points on accuracy across three datasets. It is worth noting that on AQuA, fine-tuning-based SFT and STaR may lead to negative impact on performance, while our method provides significant positive improvements. This reveals that online RL methods have greater potential and adaptability in eliciting the model’s critiquing ability, similar to the findings in McAleese et al. (2024).

Critique-RL consistently outperforms other baselines in discrimination and final accuracy. In terms of discrimination, our method also significantly outperforms other baselines, such as surpassing CTRL by 5.31, 6.36 points for 3B and 7B models on GSM8K, respectively. This reveals that our discrimination-related reward shaping can effectively optimizes discriminability. Thanks to this and the helpfulness reward design in the second stage, our method shows a significant improvement in final performance compared to other baselines. For example, on the 7B model, our method outperforms Retroformer by an average of 5.11 and 12.69 points on accuracy and discriminability, across three datasets.

5.3. Iterative Improvement of Critique-RL

Furthermore, we validate the iterative improvement capability of Critique-RL through two key aspects: (1) Iterative refinement process: During the i -th iteration, the critic generates critique $c_i = \pi_\phi(x, y_0, c_1, \dots, c_{i-1}, y_{i-1})$, while the actor produces the refined response $y_i = \pi_\theta(x, y_0, c_1, \dots, y_{i-1}, c_i)$ accordingly. (2) Iterative training process: We alternately conduct the two-stage training of Critique-RL (Stage I and Stage II) to optimize the critique model. The detailed results are shown in Figure 4 and Table 2, respectively.

First, as demonstrated in Figure 4, through iterative critique and refinement, the model exhibits consistent Acc gains on Qwen2.5-3B, with each iteration achieving measurable improvements. Second, iterative training leads to further performance enhancement, with detailed results using Qwen2.5-3B on MATH dataset shown in Table 2. Specifically, both Stage I and Stage II of Critique-RL demonstrate consistent improvement in Acc and Acc@Dis metrics. Compared to the first iteration, the second iteration improves by 2.40 and 3.68 points on accuracy and discriminability.

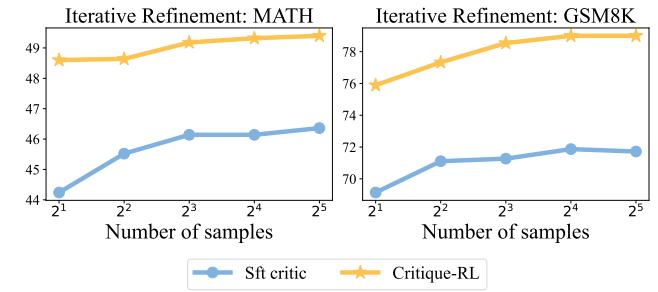


Figure 4 | Results of critique-refinement of Critique-RL using Qwen2.5-3B.

Table 2 | Results of iterative training of Critique-RL using Qwen2.5-3B on MATH.

Method	Acc	Δ	Acc@Dis
No Critic	36.9	—	—
SFT	44.2	7.3	66.5
Critique-RL			
Iteration 1, Stage I	45.9	9.0	78.7
Iteration 1, Stage II	48.6	11.7	82.8
Iteration 2, Stage I	49.5	12.6	85.0
Iteration 2, Stage II	51.0	14.1	86.5

6. Discussion and Analysis

Ablation on different stages. We conduct ablation experiments to validate the importance of different components. The results are shown in Table 3. Both Stage I and Stage II are crucial, and removing either of them leads to a performance drop. This indicates that optimizing both discriminability and helpfulness is essential in developing critique models.

Ablation on reward design for Stage II. Next, we perform a deeper analysis of the reward design in Stage II. First, if we remove the discrimination-related reward term r_{dis} and KL-based regularization $\text{KL}(\pi_\phi^{\text{Stage-I}} || \pi_\phi^{\text{Stage-II}})$, the discriminability and accuracy suffer a significant drop. This further emphasizes that when optimizing for helpfulness, it is crucial to maintain the model’s discrimination ability. Second, when we replace the reward function r_{refine} in Stage II with another reward function, i.e., r_Δ

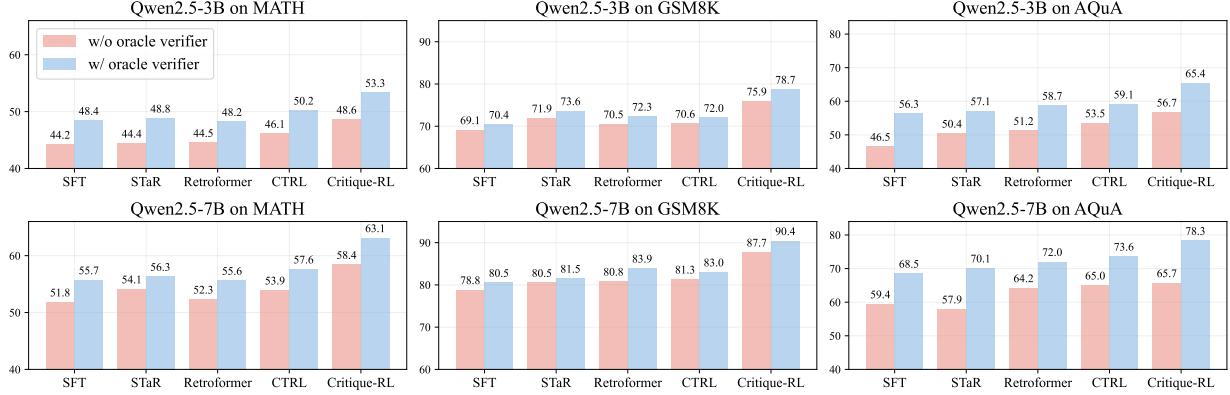


Figure 5 | Performance with and without the oracle verifier. When the oracle verifier is available, the model no longer needs to make discrimination and just needs to provide useful feedback. This allows us to evaluate the model’s helpfulness more accurately.

and $r_{\text{correction}}$, we observe a slight performance drop. This may be because r_{refine} directly optimizes the Acc@Refine metric, which aligns most closely with the test-time scenario.

Analysis of helpfulness when the oracle verifier Is available. Many previous works have relied on an external oracle verifier to assess the actor’s reasoning results (Bai et al., 2022; Dhuliawala et al., 2024; Madaan et al., 2023; Ye et al., 2023). In this scenario, the model’s judgment ability is isolated, allowing us to better evaluate the critique model’s helpfulness. We conduct relevant experiments, and the results are shown in Figure 5. We find that when the oracle verifier is available, all baselines show performance improvements. In this case, our method still outperforms others across different datasets and models, indicating that our approach significantly enhances the model’s helpfulness. Furthermore, comparisons with other RL baselines reveal that the optimization of discriminability in our method also implicitly contributes to the improvement of helpfulness, suggesting that the two abilities are not entirely independent. This further emphasizes the importance of optimizing both abilities jointly in developing critique models.

Evaluation of test-time inference compute scaling for Critique-RL. We investigate whether Critique-RL can be combined with inference-time compute scaling strategy. Following Qu et al. (2024); Snell et al. (2024); Xi et al. (2024), we leverage the commonly used majority vote (MV@K) (Wang et al., 2023) which evaluates whether the most frequent answer among K samples is correct. The results of

Table 3 | Ablation study using Qwen2.5-3B. We report the Acc@Refine. “w/o” means without; “Stage II w/o discrimination” means in Stage II, we remove r_{dis} and $\text{KL}(\pi_{\phi}^{\text{Stage-I}} || \pi_{\phi}^{\text{Stage-II}})$; “Stage II w/ r_{Δ} ” and “Stage II w/ $r_{\text{correction}}$ ” mean replacing the r_{refine} with the corresponding reward function.

Method	MATH		AQuA	
	Acc@Refine	Acc@Dis	Acc@Refine	Acc@Dis
Critique-RL (Ours)	48.6	82.8	56.7	69.9
-w/o Stage I	47.6	79.7	53.9	66.5
-w/o Stage II	45.9	78.7	54.7	68.2
-Stage II w/o discrimination	47.3	77.7	53.5	61.6
-Stage II w/ r_{Δ}	<u>48.2</u>	<u>82.6</u>	53.9	<u>68.4</u>
-Stage II w/ $r_{\text{correction}}$	47.7	82.0	<u>54.7</u>	68.4

MATH are shown in Figure 1 and the results of GSM8K are shown in Figure 6 of Appendix D. Compared to the baseline, Critique-RL significantly increases the performance ceiling and shows a more sustained upward trend as inference compute scales. More importantly, performing $K \times$ response-critique-refinement sampling is more compute-efficient than conducting $3K \times$ parallel sampling responses, suggesting the compute-efficiency of Critique-RL.

Generalization to OOD tasks. We also validate the generalization of the models trained by Critique-RL on OOD tasks. The results in Table 4 show that the models trained still delivers significant performance improvements, further demonstrating the potential of this scalable oversight approach.

More experiments and qualitative analysis. We conduct extensive experiments to show the effectiveness and working mechanism of Critique-RL, with the detailed results presented in the Appendix: (1) In addition to the Qwen2.5 series (Team, 2024), we evaluate our method on additional model types like strong reasoning model and different architectures including Llama3.2 (see Appendix A and Appendix B). (2) We compare Critique-RL with other refinement methods including Self-Refine (Madaan et al., 2023), SuperCorrect (Yang et al., 2024) and Critic-Cot (Zheng et al., 2024), and the results are presented in Appendix C. (3) We also perform test-time scaling analysis of sampling multiple refinement on the same response, with results presented in Appendix D. (4) We conduct experiments on summarization tasks using CNN/DailyMail (Hermann et al., 2015) dataset to investigate our method’s generalization ability on open-ended tasks where rule-based verifier cannot be directly applied, the results are in Appendix E. (5) We perform a qualitative analysis on how Critique-RL works and provide several examples in Appendix H.

7. Conclusion

In this paper, we propose Critique-RL, an RL approach for developing critique models. Through in-depth analysis, we highlight the importance of explicitly optimizing model discriminability and propose a two-stage RL approach that effectively optimizes both discriminability and helpfulness. We validate its stability and superiority through detailed experiments, and further uncover its working mechanism through ablation studies and analyses. We hope that our work can provide insights for the scalable oversight community of language models.

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Table 4 | Out-of-domain evaluation of Critique-RL.

Model	Method	SVAMP		TheoremQA	
		Acc	Pass@10	Acc	Pass@10
Qwen2.5-3B	No Critic	70.7	92.0	15.1	34.8
	SFT	74.7	95.7	15.3	36.1
	Retroformer	75.0	96.0	16.1	37.0
	CTRL	76.0	95.7	15.8	36.5
Qwen2.5-7B	Critique-RL	78.3	96.3	16.8	37.8
	No Critic	80.3	95.7	19.4	39.8
	SFT	83.0	95.7	20.5	41.9
	Retroformer	84.0	96.0	20.0	42.3
	CTRL	85.1	96.7	21.1	42.9
	Critique-RL	89.7	97.0	21.4	43.0

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Appendix

A. Performance on Varying Base Models

To further investigate the Critique-RL in varying base models, we conduct two types of experiments. In the first setting, we use a strong reasoning model DeepSeek-R1-Distill-Qwen-7B ([DeepSeek-AI, 2025](#)) as our actor model while using Qwen2.5-7B as our critic model. This evaluation setting investigates the generalization of Critique-RL to reasoning models. The results in Table 5 reveal that,

Table 5 | Performance on DeepSeek-R1-Distill-Qwen-7B as actor.

Method	In-Domain: MATH-500			OOD: TheoremQA		
	Acc	Δ	Acc@Dis	Acc	Δ	Acc@Dis
No Critic	84.60	-	-	21.63	-	-
SFT	85.60	1.00	83.40	29.75	8.13	24.38
Retroformer	85.80	1.20	84.80	29.38	7.75	22.38
CTRL	85.80	1.20	84.80	29.00	7.38	21.25
Critique-RL	86.60	2.00	93.00	30.38	8.75	51.13

besides non-reasoning models (Qwen2.5-3B, Qwen2.5-7B) with structured CoT, our method is also effective for reasoning models with complex CoT structures on both in-domain and out-of-domain tasks, particularly in terms of the Acc@Dis achieved by the critique models. While DeepSeek-R1-Distill-Qwen-7B already performs strongly on MATH-500, critique models can still offer marginal gains in reasoning accuracy. More impressively, on the TheoremQA dataset which spans diverse domains including Math, EECS, Physics and Finance, critique models substantially boost performance, highlighting the strong generalization ability of our approach. Notably, Critique-RL outperforms SFT, Retroformer, and CTRL by 26.75, 28.75, 29.88 points in Acc@Dis, respectively, on the TheoremQA dataset—doubling the performance of these baselines.

In the second setting, we use Qwen2.5-72B-Instruct as the actor model and Qwen2.5-7B as the critique model to investigate weak-to-strong generalization. The results in Table 6 show that Critique-RL improves actor performance even in large-scale settings, though with less pronounced gains compared to smaller-actor settings. Nonetheless, it still outperforms baselines on both in-domain and out-of-domain tasks. Notably, our method achieves significantly higher discrimination, confirming the effectiveness of our discrimination-based reward shaping.

B. Performance on Varying Model Series

To evaluate the effectiveness and generalization capability of Critique-RL, we conduct experiments using the Llama3.2-3B ([Dubey et al., 2024](#)) model on the GSM8K dataset. As shown in Table 7, Critique-RL proves effective not only on Qwen2.5 models but also on Llama3.2 models, particularly in enhancing the discriminability of the critique models. These results highlight the adaptability and robust performance of Critique-RL across different model architectures.

C. Comparison with Other Important Refinement Methods

To further validate the advantages of Critique-RL over other refinement methods, we conduct evaluations of other refinement methods including Self-Refine ([Madaan et al., 2023](#)), SuperCorrect ([Yang et al., 2024](#)) and Critic-Cot ([Zheng et al., 2024](#)) with Qwen2.5-3B on GSM8K. For a fairer com-

Table 6 | Performance on Qwen2.5-72B-Instruct as actor.

Method	In-Domain: MATH-500			OOD: TheoremQA		
	Acc	Δ	Acc@Dis	Acc	Δ	Acc@Dis
No Critic	79.14	-	-	21.38	-	-
SFT	79.20	0.06	80.20	21.63	0.25	23.00
Retroformer	79.20	0.06	80.60	21.75	0.38	21.38
CTRL	79.40	0.26	79.40	21.50	0.13	21.13
Critique-RL	80.34	1.20	89.20	23.50	2.13	46.63

Table 7 | Performance on Llama3.2-3B with GSM8K.

Method	GSM8K		
	Acc	Δ	Acc@Dis
No Critic	49.28	-	-
SFT	50.80	1.52	68.11
Retroformer	52.08	2.81	63.85
CTRL	52.24	2.96	66.01
Critique-RL	52.99	3.72	75.04

parison, we train the models in Self-Refine and Critic-CoT using the same dataset(sampled from Qwen2.5-3B-Instruct) as Critique-RL. In terms of SuperCorrect, we choose Deepseek-R1 ([DeepSeek-AI, 2025](#)) as the teacher model to create both the Hierarchical Thought Templates and positive critique datasets. The results are presented in Table 8. Critique-RL significantly outperforms all other methods in both Acc and Acc@Dis, surpassing Critic-CoT and SuperCorrect by 5.31 and 3.11 points in terms of Acc, respectively. Moreover, Critique-RL outperforms Self-Refine across refinement iterations, demonstrating its greater effectiveness. Notably, SuperCorrect exhibited poor discriminability, likely because it simply used teacher model data as positive examples and student model data as negative ones for DPO training. Given the GSM8K dataset’s simplicity, the student model’s output is not consistently inferior to teacher model’s, leading to potential impairment to the model’s discriminability.

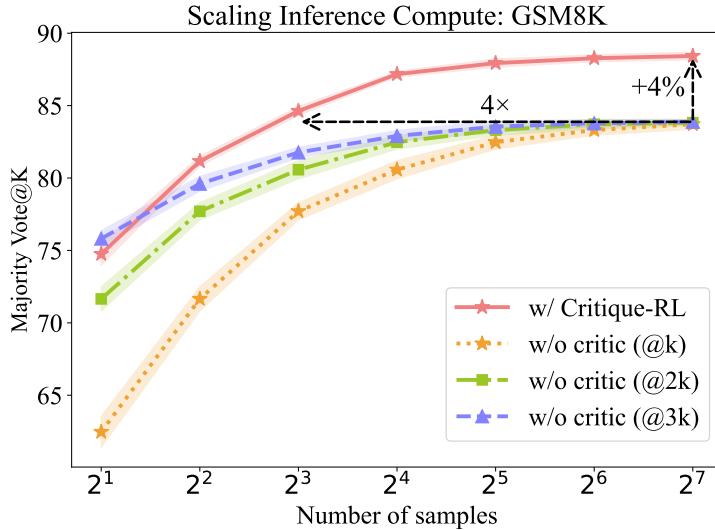
These refinement methods are implemented using SFT (Self-Refine), self-improve (Critic-CoT) or intricate SFT+DPO (SuperCorrect) approaches, wheras Critique-RL employs an online RL methodology, which accounts for its observed performance advantages.

D. More Test-time Scaling Results

The results of inference compute scaling on GSM8K are illustrated in Figure 6. Similar to the findings on MATH, Critique-RL is more compute-efficient and significantly increases the performance ceiling, validating the potential of our approach. In addition, we evaluate the refine compute scaling of SFT and Critique-RL across MATH, GSM8K, and AQUA, as illustrated in Figure 7. Critique-RL consistently achieves approximately twice the sampling efficiency of SFT. Notably, with the 7B model on GSM8K, Critique-RL’s Pass@1 even surpasses the SFT’s Pass@64, demonstrating the effectiveness of our approach.

Table 8 | Comparison with other refinement methods with Qwen2.5-3B on GSM8K.

Method	GSM8K	
	Acc	Acc@Dis
Self-Refine	iteration=1	71.42
	iteration=2	72.71
Critic-CoT	70.58	74.70
SuperCorrect	72.78	62.17
Critique-RL (Ours)	75.89	87.44

**Figure 6** | Inference compute scaling for Critique-RL, with @2k and @3k indicating sampling amounts that are 2 times and 3 times the x-axis value, respectively. Critique-RL improves the performance ceiling and is more compute-efficient.

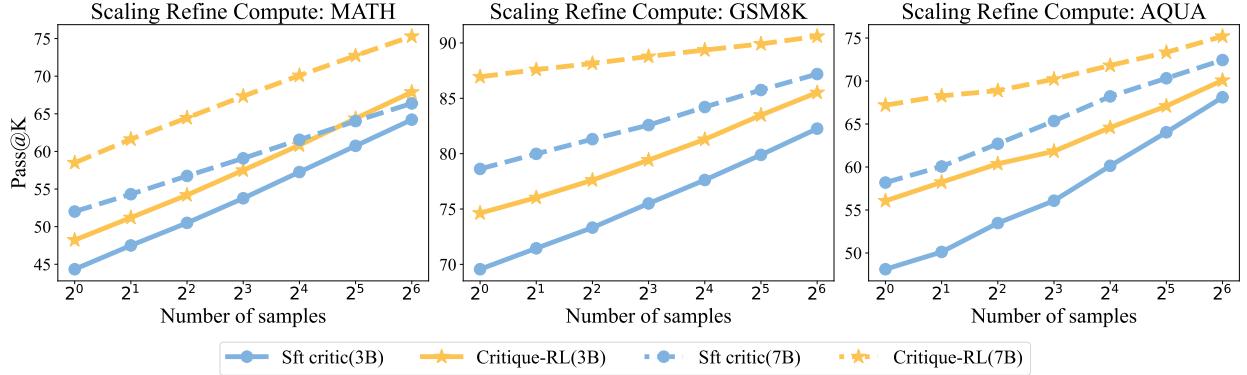
E. Performance on Summarization Task

For open-ended tasks where rule-based verifiers cannot be directly applied, reward signals can be provided through additional reward models or AI feedback (e.g., using GPT-4o (OpenAI, 2023) for judgement).

We conduct experiments of Critique-RL with Qwen2.5-7B-Insturct (Team, 2024) on summarization task using CNN/DailyMail (Hermann et al., 2015) dataset. Specifically, given an article x , the actor model generates an original summary y . The reward model (Skywork-Reward-V2-Llama-3.1-8B (Liu et al., 2025)) then evaluates the summary, with its output linearly scaled to a 1-10 range, i.e., $r_{\text{oracle}}(x, y)$. Subsequently, the critique model produces critique c , which includes comments about the summary across key criteria, a quality score from 1-10, and improvement suggestions. The actor model then generates a revised summary y' accordingly, which is also scored by the reward model to yield a refinement score $r_{\text{refine}} = r_{\text{oracle}}(x, y')$. Based on this, we define the discrimination reward function of the critique model as:

$$r_{\text{dis}}(x, y, c) = \max(0, 1 - \frac{|f(x, y, c) - r_{\text{oracle}}(x, y)|}{\delta})$$

where $f(x, y, c)$ is the quality score of the original summary from critique model. δ is the permissible maximum error range.

**Figure 7** | Refine compute scaling for Critique-RL and SFT critic with Qwen2.5-3B and Qwen2.5-7B.

In stage I, we optimize the discriminability of the critique model using $r_{\text{dis}}(x, y, c)$; In stage II, we optimize the helpfulness while maintaining discriminability using the following reward function:

$$r_{\text{stageII}} = r_{\text{refine}} + \beta_1 r_{\text{dis}}(x, y, c)$$

In our experiments, we select 5000 training and 1000 test queries from CNN/DailyMail 3.0.0’s official splits. The results are presented in the Table 9.

The results reveal that Critique-RL can effectively optimize discriminability, yielding improvement in summary quality. We use MSE and MAE to measure the error between the quality scores produced by the critique model and those from the reward model. Specifically, Critique-RL outperforms baseline by 0.87 points in Score, 7.87 points in MSE@Dis and 1.79 points in MAE@Dis. These improvements demonstrate the strong generalization ability of our approach to open-ended tasks, contributing to scalable oversight.

Table 9 | Performance on summarization task using Qwen2.5-7B-Instruct. We report the original Score by reward model. The MSE@Dis stands for mean square error, and MAE@Dis stands for mean absolute error, where smaller values indicate stronger discrimination abilities.

Method	CNN/MD			
	Score↑	Delta↑	MSE@Dis↓	MAE@Dis↓
No Critic	19.69	-	-	-
7B-Instruct	19.94	0.25	9.46	2.77
Critique-RL (Ours)	20.81	1.12	1.59	0.98

F. Validating the Effectiveness of Critique Model

Introducing a separate critique model leads to increased manual effort and additional complexity. To validate the usage of the critique model, we compare Critique-RL with actor-only RL method to show that training a critique model provides significant benefits over directly optimizing the actor. In particular, for actor-only method, we conduct experiments on directly RL the actor and SCoRe (Kumar et al., 2024); for actor-critic paradigm, we use a SFT-based critique model as well as our Critique-RL. For a fairer comparison, we train the actor model using the same reasoning traces as Critique-RL in direct RL and using the same reasoning, critique and refinement dataset as Critique-RL in SCoRe. All experiments are conducted with Qwen2.5-7B on the Math dataset.

The results in Table 10 show that Critique-RL significantly outperforms Directly RL by 8.62 points in terms of Acc. Also Critique-RL outperforms SCoRe by 12.69 points in terms of Acc@Dis, and 1.88 points in terms of Acc. Note that during the training process of Critique-RL, the actor model remained fixed and is thus inherently weaker in reasoning and refinement than the trained SCoRe actor model. Importantly, the trained critique model can be flexibly applied to other stronger actor

Table 10 | Comparison with actor-only RL method.

Category	Method	MATH	
		Acc	Acc@Dis
Actor-only	Directly RL	49.78	-
	SCoRe	56.52	72.51
Actor-Critique	SFT	51.84	67.59
	Critique-RL	58.40	85.20

models (weak-to-strong) and reasoning models to further improve their performance (see Appendix A). This modularity and transferability are advantages that SCoRe lacks.

Moreover, we conduct the test-time scaling experiment. The majority vote (MV@K) results are as shown in Table 11. The results show that even the actor model has been well-trained, generating parallel responses still underperforms Critique-RL’s response-critique-refinement process. Notably, Critique-RL’s MV@1 even surpasses Directly RL’s MV@12. This highlights the compute-efficiency of Critique-RL.

Table 11 | Performance comparison between Directly RL and Critique-RL under MV@K.

K	Directly RL			Critique-RL MV@K
	MV@K	MV@2K	MV@3K	
1	49.78	50.05	52.39	58.40
2	50.05	53.49	55.04	59.10
4	53.49	55.08	56.75	65.91

G. Sensitivity Analysis

For solidness, we provide details about different values for β , β_1 , β_2 and training steps per stage.

Experiments on different values for β , β_1 , and β_2 . We exemplify our selection of the parameters β , β_1 , and β_2 by presenting the performance of the Qwen2.5-3B model on the GSM8K dataset as an example. The results in Table 12 reveal that these parameters are not sensitive, so we ultimately choose $\beta = 0.01$, $\beta_1 = 0.9$, and $\beta_2 = 0.95$ for our experiments.

Experiments on different training steps per stage. We show the performance of the two stages of Critique-RL at different training steps with Qwen2.5-3B on MATH dataset. The results in Table 13 indicate that within 500 steps of Stage I, the model’s discriminability was substantially enhanced, with Acc@Dis rising from 66.51 to 78.68. During Stage II, the model maintained this discriminability while further improving helpfulness, with Acc increasing from 45.90 to 48.60.

While further refinement of parameters could potentially yield additional performance gains, the current experimental outcomes are already statistically sound and adequately substantiate our core conclusions.

H. Qualitative Analysis

We perform a qualitative investigation into how Critique-RL works and provide several examples in Appendix H. In Figure 8, facing the originally incorrect response, the critique model after SFT is un-

Table 12 | Results of different values for β , β_1 , and β_2 with Qwen2.5-3B on GSM8K.

Parameter	Value	Acc	Delta	Acc@Dis
β	0.008	74.60	8.57	86.24
	0.01	75.89	9.86	87.44
	0.012	74.22	8.19	87.10
β_1	0.88	74.60	8.57	86.18
	0.9	75.89	9.86	87.44
	0.92	74.68	8.65	86.09
β_2	0.93	74.68	8.65	85.99
	0.95	75.89	9.86	87.44
	0.97	74.37	8.34	85.74

Table 13 | Results of different training steps per stage with Qwen2.5-3B on MATH.

Step	Critique-RL Stage I		Critique-RL Stage II	
	Acc	Acc@Dis	Acc	Acc@Dis
0	44.24	66.51	45.90	78.68
100	44.22	68.26	45.88	80.56
200	44.60	71.53	46.82	81.77
300	44.89	75.72	47.02	82.47
400	45.18	78.20	47.90	83.06
500	45.90	78.68	48.60	82.80

able to detect errors, leading the actor’s refinement response to retain the same errors. However, the model trained after Critique-RL identifies the errors in the original response and provides detailed, constructive suggestions for modification, leading to the correct refinement response. In Figure 9, model trained after Critique-RL Stage I is able to detect errors, demonstrating its discriminability. However, the model provides the actor with low-quality suggestion, causing the actor’s refinement response to be incorrect. In contrast, for the same erroneous original response, model trained after Critique-RL Stage II not only detects the error but also offers a constructive suggestion, ultimately leading to the correct refinement response, demonstrating the advantage of two-stage RL process.

To directly assess the quality of critiques generated by Critique-RL, we randomly collect 600 critiques that successfully helped refine incorrect answer into correct ones. We leverage GPT-4o with ground-truth answers and solutions as references to evaluate quality more accurately. The results show that 96.2% of these critiques made correct discriminative judgments, and 93.3% were rated as high-quality, demonstrating that Critique-RL produces reliable and helpful critiques.

<p>Problem: Each person in a certain household consumes 0.2 kg of rice every meal. Supposing 5 members of the household eat rice every lunch and dinner, how many weeks will a 42 kg bag of rice last?</p>	
<p>Ground Truth Answer:</p> <ul style="list-style-type: none"> • Each person eats 0.2 kg/meal \times 2 meals/day = <<0.2*2=0.4>> 0.4 kg of rice per day. • So, the 5 members consume 0.4 kg/day/person \times 5 people = <<0.4*5=2>> 2 kg of rice per day. • In a week, the household consumes 2 kg/day \times 7 days/week = <<2*7=14>> 14 kg of rice. • Thus, 42 kg of rice will last 42 kg / 14 kg/week = <<42/14=3>> 3 weeks. <p>The answer is 3.</p>	<p>Actor Model (original response):</p> <p>Let's break it down step by step:</p> <ol style="list-style-type: none"> 1. The household consumes 0.2 kg of rice per meal * 2 meals per day = 0.4 kg of rice per day. 2. The household consumes 0.4 kg of rice per day * 5 days per week = 2 kg of rice per week. 3. A 42 kg bag of rice will last 42 kg / 2 kg per week = 21 weeks. <p>The answer is 21.</p> <p>Correctness Verifier: </p>
<p>Critique Model after SFT</p> <p>Critique Model (critique):</p> <p>Step sentence: The household consumes 0.2 kg of rice per meal * 2 meals per day = 0.4 kg of rice per day. Correctness of the step: Correct</p> <p>Explanation: This step correctly calculates the daily rice consumption by multiplying the amount consumed per meal (0.2 kg) by the number of meals per day (2).</p> <p>Step sentence: The household consumes 0.4 kg of rice per day * 5 days per week = 2 kg of rice per week. Correctness of the step: Correct</p> <p>Explanation: This step correctly calculates the weekly rice consumption by multiplying the daily consumption (0.4 kg) by the number of days in a week (5).</p> <p>Step sentence: A 42 kg bag of rice will last 42 kg / 2 kg per week = 21 weeks. Correctness of the step: Correct</p> <p>Explanation: This step correctly calculates the number of weeks the 42 kg bag of rice will last by dividing the total amount of rice by the weekly consumption (2 kg per week).</p> <p>Correctness of the final answer: Correct</p> <p>Explanation: The final answer of 21 weeks is correct based on the calculations provided in the solution.</p> <p>Discrimination Verifier: </p>	<p>Critique Model after Critique-RL Training</p> <p>Critique Model (critique):</p> <p>Step sentence: The household consumes 0.2 kg of rice per meal * 2 meals per day = 0.4 kg of rice per day. Correctness of the step: Wrong</p> <p>Explanation: This step is wrong because it incorrectly calculates the daily rice consumption. Since 5 members of the household eat rice every lunch and dinner, and each person consumes 0.2 kg of rice per meal, the daily consumption is: $5 \text{ members} \times 2 \text{ meals/day} \times 0.2 \text{ kg/meal} = 2 \text{ kg/day}$</p> <p>Step sentence: The household consumes 0.4 kg of rice per day * 5 days per week = 2 kg of rice per week. Correctness of the step: Wrong</p> <p>Explanation: This step is wrong because it incorrectly calculates the weekly rice consumption. Given the correct daily consumption is 2 kg/day, the weekly consumption is: $2 \text{ kg/day} \times 7 \text{ days/week} = 14 \text{ kg/week}$</p> <p>Step sentence: A 42 kg bag of rice will last 42 kg / 2 kg per week = 21 weeks. Correctness of the step: Wrong</p> <p>Explanation: This step is wrong because it incorrectly calculates the duration the rice will last. Given the correct weekly consumption is 14 kg/week, the duration the 42 kg bag will last is: $42 \text{ kg} \div 14 \text{ kg/week} = 3 \text{ weeks}$</p> <p>Correctness of the final answer: Wrong</p> <p>Explanation: The final answer of 21 weeks is incorrect. The correct answer is 3 weeks.</p> <p>Discrimination Verifier: </p> <p>Actor Model (refinement response):</p> <p>Let's break it down step by step:</p> <ol style="list-style-type: none"> 1. Calculate the daily rice consumption: The household consumes 0.2 kg of rice per meal. Since there are 2 meals per day, the daily consumption is: $0.2 \text{ kg/meal} \times 2 \text{ meals/day} = 0.4 \text{ kg/day}$ 2. Calculate the weekly rice consumption: The household consumes 0.4 kg of rice per day. Since there are 5 days per week, the weekly consumption is: $0.4 \text{ kg/day} \times 5 \text{ days/week} = 2 \text{ kg/week}$ 3. Calculate how many weeks a 42 kg bag of rice will last: A 42 kg bag of rice will last: $42 \text{ kg} \div 2 \text{ kg/week} = 21 \text{ weeks}$ <p>The answer is 21.</p> <p>Correctness Verifier: </p> <p>Actor Model (refinement response):</p> <p>Let's break it down step by step:</p> <p>To determine how many weeks a 42 kg bag of rice will last for a household, we need to consider the following:</p> <ol style="list-style-type: none"> 1. Daily Rice Consumption Calculation: There are 5 members in the household. Each member consumes 0.2 kg of rice per meal. Each member eats rice at 2 meals per day (lunch and dinner). Therefore, the total daily rice consumption is: $5 \text{ members} \times 2 \text{ meals/day} \times 0.2 \text{ kg/meal} = 2 \text{ kg/day}$ 2. Weekly Rice Consumption Calculation: The daily consumption is 2 kg. There are 7 days in a week. Therefore, the weekly rice consumption is: $2 \text{ kg/day} \times 7 \text{ days/week} = 14 \text{ kg/week}$ 3. Duration of the Rice Will Last: The household has a 42 kg bag of rice. The weekly consumption is 14 kg. Therefore, the number of weeks the rice will last is: $42 \text{ kg} \div 14 \text{ kg/week} = 3 \text{ weeks}$ <p>The answer is 3.</p> <p>Correctness Verifier: </p>

Figure 8 | Example 1 of qualitative analysis. The actor's original response is incorrect. The model after SFT is unable to detect errors in the response, leading the actor's refinement response to retain the same errors. However, the model trained after Critique-RL identifies the errors in the original response and provides detailed, constructive suggestions for modification, leading to the correct refinement response.

<p>Problem: Dennis uses 1 pound of butter for every dozen croissants that he makes. He needs to make 6 dozen croissants. The grocery store currently has a promotion for buy one pound of butter get one half off. If the butter costs \$4.00 a pound, how much will it cost him to purchase 6 pounds of butter?</p>	
<p>Ground Truth Answer:</p> <ul style="list-style-type: none"> 1 pound of butter makes 1 dozen croissants and he needs to make 6 dozen so he needs $1 * 6 = <<1*6-6>>6$ pounds of butter. The butter is \$4.00 a pound and currently on sale for buy one get one half off so every unit of 2 pounds of butter will cost $4 * 1.5 = \\$<<4*1.5-6.00>>6.00$. He needs 6 pounds of butter and the current promotion is for a unit of 2 pounds of butter so he needs to buy $6/2 = <<6/2-3>>3$ units worth of butter. The sale price is \$6.00 per 2 pounds of butter and he needs to buy 3 units of butter so $6 * 3 = \\$<<6*3=18.00>>18.00$ worth of butter. <p>The answer is 18.</p>	<p>Actor Model (original response):</p> <p>Let's break it down step by step:</p> <ol style="list-style-type: none"> He needs to buy 3 pounds of butter because $6 / 2 = 3$. 3 pounds of butter would cost \$12 because $3 * 4 = 12$. He will pay \$6 because $12 / 2 = 6$. <p>The answer is 6.</p> <p>Correctness Verifier: ✗</p>
<p>Critique Model after Critique-RL Stage I Training</p> <p>Critique Model (critique):</p> <p>Step sentence: He needs to buy 3 pounds of butter because $6 / 2 = 3$. Correctness of the step: Wrong Explanation: Dennis needs to make 6 dozen croissants, and he uses 1 pound of butter per dozen. Therefore, he needs 6 pounds of butter. The calculation $6 / 2 = 3$ is incorrect. He needs to buy 6 pounds, not 3.</p> <p>Step sentence: 3 pounds of butter would cost \$12 because $3 * 4 = 12$. Correctness of the step: Wrong Explanation: Although the calculation of the cost is correct (3 pounds at \$4 per pound equals \$12), the premise is wrong. Dennis needs 6 pounds of butter, not 3. The correct calculation should be 6 pounds at \$4 per pound, which equals \$24.</p> <p>Step sentence: He will pay \$6 because $12 / 2 = 6$. Correctness of the step: Wrong Explanation: The calculation $12 / 2 = 6$ is correct based on the promotion (buy one pound get one half off), but it does not apply to the correct amount of butter needed. Dennis needs 6 pounds, not 3. The correct calculation should be based on the full price of 6 pounds, which is \$24.</p> <p>Correctness of the final answer: Wrong Explanation: The final answer of 6 is incorrect. Based on the correct calculations, Dennis needs 6 pounds of butter at \$4 per pound, which totals \$24.</p> <p>Actor Model (refinement response):</p> <p>Let's break it down step by step: To determine how much it will cost Dennis to purchase 6 pounds of butter, we need to consider the following:</p> <ol style="list-style-type: none"> Butter Requirement: Dennis needs to make 6 dozen croissants, and he uses 1 pound of butter per dozen. Therefore, he needs 6 pounds of butter. Promotion Details: The store has a promotion where you buy one pound of butter and get the next pound at half price. Cost Calculation: <ul style="list-style-type: none"> Full Price for 6 Pounds: Since the promotion applies to each pair of pounds, we need to calculate the cost based on the full price for 6 pounds. Cost for 6 Pounds: The cost of 6 pounds of butter at \$4 per pound is \$24. Therefore, the total cost for 6 pounds of butter is \$24. <p>The answer is 24.</p> <p>Correctness Verifier: ✗</p>	<p>Critique Model after Critique-RL Stage II Training</p> <p>Critique Model (critique):</p> <p>Step sentence: He needs to buy 3 pounds of butter because $6 / 2 = 3$. Correctness of the step: Wrong Explanation: Dennis needs to make 6 dozen croissants, and he uses 1 pound of butter per dozen. Therefore, he needs 6 pounds of butter. The promotion does not change the fact that he needs 6 pounds. The calculation $6 / 2 = 3$ is irrelevant to the problem.</p> <p>Step sentence: 3 pounds of butter would cost \$12 because $3 * 4 = 12$. Correctness of the step: Wrong Explanation: Although the promotion is "buy one pound of butter, get one half off," Dennis needs 6 pounds of butter. The promotion applies to each pound he buys, so for every 2 pounds, he pays \$4 + \$2 = \$6. Since he needs 6 pounds, he can take advantage of the promotion 3 times (6 pounds / 2 pounds per promotion). Therefore, the total cost is $3 * \\$6 = \\18.</p> <p>Step sentence: He will pay \$6 because $12 / 2 = 6$. Correctness of the step: Wrong Explanation: The calculation "$12 / 2 = 6$" is incorrect. Based on the previous explanation, the total cost is $3 * \\$6 = \\18. Therefore, he will pay \$18 instead of \$6.</p> <p>Correctness of the final answer: Wrong Explanation: The final answer of 6 is incorrect. Given the promotion, Dennis will pay \$18 for 6 pounds of butter.</p> <p>Discrimination Verifier: ✅</p> <p>Actor Model (refinement response):</p> <p>Let's break it down step by step: To determine how much it will cost Dennis to purchase 6 pounds of butter, we need to consider the following:</p> <ol style="list-style-type: none"> Butter Requirement: Dennis needs to make 6 dozen croissants, and he uses 1 pound of butter per dozen. Therefore, he needs 6 pounds of butter. Promotion Details: The promotion is "buy one pound of butter, get one half off." This means for every 2 pounds of butter purchased, Dennis pays for 1 pound at full price and gets the second pound at half price. Cost Calculation: <ul style="list-style-type: none"> For every 2 pounds of butter, Dennis pays \$4 for the first pound and \$2 for the second pound, totaling \$6 for 2 pounds. Since Dennis needs 6 pounds, he can take advantage of the promotion 3 times (6 pounds / 2 pounds per promotion). Therefore, the total cost is $3 * \\$6 = \\18. <p>The answer is 18.</p> <p>Correctness Verifier: ✅</p>

Figure 9 | Example 2 of qualitative analysis. The actor's original response is incorrect. The model trained after Critique-RL Stage I is able to detect this error, demonstrating its discriminability. However, the model provides the actor with low-quality suggestion, causing the actor's refinement response to be incorrect. In contrast, for the same erroneous original response, model trained after Critique-RL Stage II not only detects the error but also offers a constructive suggestion, ultimately leading to the correct refinement response, demonstrating the advantage of two-stage RL process.