REINFORCEMENT LEARNING FROM DYNAMIC CRITIC FEEDBACK FOR FREE-FORM GENERATIONS

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ABSTRACT

Open-ended generation tasks require outputs to satisfy diverse and often implicit task-specific evaluation rubrics. The sheer number of relevant rubrics leads to prohibitively high verification costs and incomplete assessments of a response, making reinforcement learning (RL) post-training with rubric-based rewards difficult to scale. This problem is exacerbated by the fact that often the best way to combine these rubrics into one single reward is also highly prompt-specific. We propose Reinforcement Learning from Dynamic Critic Feedback (RLDCF), a post-training approach that addresses these challenges via dynamic rubric verification. Our approach employs a large language model (LLM) as a critic that dynamically identifies only the most likely failure modes (e.g., a factual error or unhandled edge case), which are then verified by an external validator to optimize both generator and critic jointly. By training both the generator and the critic, this game enhances the critic's error detection and the generator's output quality while reducing required verifications. Our experiments demonstrate that RLDCF improves factual accuracy in text generation and correctness in code generation, while also outperforming exhaustive verification and reward model methods. We show that dynamic critics are more effective than fixed critics, showcasing the potential of RLDCF for scaling RL post-training to free-form generation tasks.

1 Introduction

Post-training methods for large language models (LLMs) have progressed dramatically over the past few years, from largely manual supervised fine-tuning (SFT) techniques that rely on a combination of manual data curation (Radford et al., 2018; Brown et al., 2020; Shengyu et al., 2023) to reinforcement learning (RL) methods that perform general preference-based optimization (Christiano et al., 2017; Ouyang et al., 2022) or optimize task-specific notions of correctness (Zha et al., 2025). Despite these remarkable results, RL post-training is limited to tasks with clear-cut success criteria (i.e., correctness of an answer or preference of a human user), and it remains unclear how to post-train LLMs with RL on tasks that require producing open-ended or free-form outputs that are hard to verify perfectly.

Perhaps the biggest challenge in building RL post-training methods for free-form generation tasks is the lack of a solid reward function: outputs are typically expected to satisfy several task-specific rubrics. In principle, a task designer could construct a reward by combining these rubrics, but both enumerating and verifying them pose major scalability challenges (Min et al., 2023). For instance, complex code generation requires testing countless edge cases (e.g., empty inputs or specific numbers). Even if such criteria could be enumerated, knowing how to combine them remains difficult (e.g., should correctly handling even numbers outweigh handling primes?). While RLHF-trained reward models or LLM-as-judge approaches (Christiano et al., 2017; Zheng et al., 2023) outsource the job of merging rubrics to a learned or prompted reward model, this often leads to reward hacking (Ziegler et al., 2019; Gao et al., 2023; Skalse et al., 2022; Eisenstein et al., 2023), since the best combination is highly dependent on the prompt and the model being optimized. How can we then train LLMs on free-form generation tasks with several (maybe uncountably many) rubrics?

We introduce Reinforcement Learning from Dynamic Critic Feedback (RLDCF), which formulates the problem into as an adversarial game between a generator and a *critic*. The critic is a model that identifies a single rubric (e.g., one test case) on which the generator's output is likely to fail. Both models are trained jointly: the critic is rewarded when it correctly pinpoints a rubric that the generator fails (verified by an external validator), while the generator is rewarded when the critic is

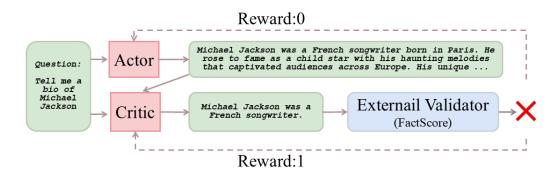


Figure 1: Overview of the RLDCF framework

unable to do so. This formulation eliminates the need to enumerate or verify all rubrics, significantly improving training scalability. At the same time, it ensures that rewards are based on rubrics that are prompt-specific, adversarially chosen, and always on-policy.

We evaluate Reinforcement Learning from Dynamic Critic Feedback on factual text generation and code generation, representing enumerable and non-enumerable verification scenarios respectively. On 8-sentence biography generation, Reinforcement Learning from Dynamic Critic Feedback achieves a FactScore of 0.889, surpassing FactTune-FS's (Tian et al., 2024) 0.867, while reducing verification calls by 5.7×. This efficiency gain scales with task complexity, from 4.4× for 4-sentence to 5.7× for 8-sentence generation. In code generation, despite using only 9% of the training data, Reinforcement Learning from Dynamic Critic Feedback achieves the highest average scores on both base models: 53.2 on Qwen2.5-Coder-7B-Base and 56.6 on Qwen2.5-Coder-7B-Instruct, outperforming AceCoder variants (Zeng et al., 2025).

Our primary contribution is RLDCF, a paradigm for training LLMs on free-form generation tasks. It enhances factuality and code correctness while preventing reward hacking and reducing verification costs, enabling robust optimization for diverse free-form generation tasks.

2 Preliminaries

Our goal is to train a generator that produces a free-form output meeting task requirements, without manually enumerating every rubric. In this section, we formalize this problem, introduce notation, and briefly discuss related concepts of reward models () and enumerative verification (). We then present our approach in the next section.

Problem setup. We consider free-form generation tasks where outputs must satisfy many task-specific requirements, which we call rubrics. For instance, a biography generation task may require that each factual claim is correct, while a code generation task may require the program to handle all edge cases correctly. Formally, let $\mathcal S$ be a distribution over prompts or instructions that may be presented to an LLM. Given $s \in \mathcal S$, a generator LLM $\pi^g(a \mid s)$ is tasked with producing a textual output $a \in \mathcal A$. We choose to use standard notation typically used in RL ($\mathcal S$ denoting the state space and $\mathcal A$ denoting the action space) as we later present an RL training objective. Each instruction s is inherently associated with a set of rubrics (denoted as $\mathcal C(s)$), where each rubric $c \in \mathcal C(s)$ represents a verifiable property the output should satisfy, such as "the claim about Newton's birth year is correct" for biography generation or "the code handles null inputs" for code generation.

We assume access to a binary verification function R(s,a,c) that returns 1 if a generated output $a \sim \pi^g(\cdot|s)$ satisfies the rubric c on instruction s, and attains 0 otherwise. An output a is considered correct only when all rubrics $\mathcal{C}(s)$ associated with instruction s are satisfied. Our goal is to train $\pi^g(\cdot|s)$ to maximize the probability of producing fully correct outputs:

$$\pi_g^* := \arg \max_{\pi} \mathbb{E}_{s \sim \mathcal{S}} \left[\mathbb{E}_{a \sim \pi(\cdot|s)} \left[\prod_{c \in \mathcal{C}(s)} R(s, a, c) \right] \right]. \tag{1}$$

In constrained domains with a single, well-defined rubric (e.g., matching a reference solution in math reasoning), the optimization of object simplifies, allowing standard RL algorithms like PPO (Schulman et al., 2017) or GRPO (Shao et al., 2024) to optimize the policy. However, such

cases are rare in open-ended tasks with diverse rubrics. In these settings, C(s) can be extremely large or even unbounded, making Eq. 1 computationally intractable since every output must be checked against every rubric.

Reward models and enumerative verification. Most approaches to optimizing free-form generation tackle the challenge of diverse rubrics through two paradigms. RLHF (Christiano et al., 2017) trains a single proxy reward model from offline human preference data. While efficient, this optimization is hard because the learned proxy is only as good as its coverage of the preference dataset. When the generator explores beyond this support, the proxy can misalign (Gao et al., 2023), often necessitating additional constraints like KL regularization to avoid collapse. These constraints stabilize training but also limit exploration, making it difficult to scale to highly open-ended tasks (Dong et al., 2024).

Another approach is to enumerate the evaluation criteria and optimize their aggregate, either through prompting (Min et al., 2023; Saha et al., 2025) or via preferences implicitly elicited from humans (Wang et al., 2024b; Mahan et al., 2024). While more faithful to the underlying rubrics (Trivedi et al., 2024), this strategy is fundamentally limited: it assumes the evaluation set $\mathcal{C}(s)$ can be exhaustively listed, which is unrealistic for complex tasks (e.g., all test cases for a nontrivial program). Even when such enumeration is feasible, iterating over the entire set is computationally prohibitive, turning optimization into an intractable verification bottleneck.

3 Reinforcement Learning from Dynamic Critic Feedback

We now introduce our RL post-training approach, called Reinforcement Learning from Dynamic Critic Feedback (RLDCF) for training LLM generators on free-form tasks. Our goal is to provide rewards while avoiding the scalability limits of enumerative verification and the misalignment of static reward models. The core idea is to recast verification as a dynamic process guided by a learned critic. Concretely, we frame training as a two-player game: given an output from the generator, the critic proposes a rubric the output is likely to violate, while the generator aims to satisfy all such rubrics. An external validator then adjudicates whether the output meets the proposed rubric, and this supervision updates both generator and critic. In this way, verification becomes adaptive and adversarial, tailored to the generator's current weaknesses. We now formally derive this approach.

3.1 PROBLEM REFORMULATION

To derive our approach formally, our starting point is the objective of Equation 1, which requires a generation to satisfy all rubrics in the set C(s): Since R(s, a, c) is an indicator function for each c, we can rewrite the requirement that all rubrics are satisfied as a minimum over all rubrics as follows:

$$\mathbb{1}\{R(s, a, c) = 1, \forall c \in \mathcal{C}(s)\} = \min_{c \in \mathcal{C}(s)} \mathbb{1}\{R(s, a, c) = 1\}.$$
 (2)

Intuitively, the minimum selects the worst-case criterion, i.e., the first failure mode encountered by the current model π . Substituting Equation 2 into Equation 1 gives:

$$\pi_g^* = \arg\max_{\pi} \mathbb{E}_{s \sim \mathcal{S}} \left[\mathbb{E}_{a \sim \pi(\cdot|s)} \left[\min_{c \in \mathcal{C}(s)} R(s, a, c) \right] \right]. \tag{3}$$

However, this reformulation by itself does not make the optimization problem simpler: searching over $\mathcal{C}(s)$ is infeasible when $\mathcal{C}(s)$ is large or infinite (e.g., all possible test cases). To address this, we introduce a critic π^c , modeled as a stochastic policy that generates the worst criterion c given the instruction s and action s over rubrics conditioned on s. Then we can rewrite Equation s into the equivalent min-max form:

$$\pi^g \leftarrow \arg\max_{\pi} \min_{\pi^c} \mathbb{E}_{s \sim \mathcal{S}} \left[\mathbb{E}_{a \sim \pi(\cdot|s)} \mathbb{E}_{c \sim \pi^c(\cdot|s,a)} \left[R(s,a,c) \right] \right]. \tag{4}$$

It can be shown that the solution π^g from Equation 4 is the same as that from Eq. (1), but now we bypass the need to enumerate all criteria over C(s) (Madry et al., 2018).

Pretty much like other mini-max optimization problems, we can solve the above optimization problem by iteratively updating π^g and π^c against each other. The optimization goal is to achieve a robust generator π^g that does well even according to the most adversarial critic, upon convergence. More details with respect to the practical optimization algorithm will be provided in Section 3.2.

3.2 PRACTICAL INSTANTIATION OF RLDCF

We now instantiate the two-player adversarial game from the previous section into a practical approach that we can use to train LLMs. As shown in Figure 1, we parameterize three task-agnostic components that interact with each other during RL training. Each component is instantiated differently based on the domain (as detailed in Section 4).

Generator. The generator π^g , is an LLM that is fine-tuned to produce an output $a \in \mathcal{A}$ for an instruction $s \in \mathcal{S}$. RLDCF samples multiple response generations from π^g for each instruction s. We train π^g to maximize the probability of producing outputs that satisfy all task-specific rubrics, as detailed in Section 4. The prompt for the generator is included in the Appendix.

Critic. Our critic π^c is a pre-trained LLM π^c that RLDCF fine-tunes. Specifically, for each instruction s and a query generation output a, the critic is prompted to generate a natural language output representing a rubric c through auto-regressive decoding. The rubric c along with the instruction s and the generation a are then sent to the external validator to obtain a reward signal $R(s,a,c) \in \{0,1\}$. The prompt for the adversarial critic is included in the Appendix.

Validator. The validator is an external tool or process that can verify whether a generated response satisfies a rubric provided as input to it. The validator can be implemented in various ways depending on the domain, such as rule-based checkers or a software tool that evaluates a proposed code on a proposed test-case. Implementation details for specific tasks are discussed in the Appendix.

Updating the generator and critic. At each training step, we sample instructions $s \in \mathcal{S}$ and have the generator π^g produce K candidate outputs a_1, \ldots, a_K . For each (s, a_i) , the adversarial critic π^c proposes a criterion c_i , which is then checked by the validator to yield a binary reward $r_i \in \{0,1\}$. This online feedback provides signals for both policies. Outputs with $r_i = 1$ are treated as positives (a^+) and those with $r_i = 0$ as negatives (a^-) , and the generator is updated using the DPO loss (Rafailov et al., 2023) with respect to the reference generator $\pi^g_{\rm ref}$:

$$\mathcal{L}(\pi^g; \pi_{\text{ref}}^g) = -\mathbb{E}_s \mathbb{E}_{(a^+, a^-)} \left[\log \sigma \left(\beta \log \frac{\pi^g(a^+|s)}{\pi_{\text{ref}}^g(a^+|s)} - \beta \log \frac{\pi^g(a^-|s)}{\pi_{\text{ref}}^g(a^-|s)} \right) \right]. \tag{5}$$

Similarly, for each (s, a) pair, we sample N criteria from π^c . Criteria rejected by the validator (invalid or satisfied by the generator) are treated as negatives (c^-) , while valid, unsatisfied ones are positives (c^+) . The critic is then updated with the same DPO objective relative to its reference policy π^c_{ref} :

$$\mathcal{L}(\pi^{c}; \pi_{\text{ref}}^{c}) = -\mathbb{E}_{s,a} \mathbb{E}_{(c^{+}, c^{-})} \left[\log \sigma \left(\beta \log \frac{\pi^{c}(c^{+}|s, a)}{\pi_{\text{ref}}^{c}(c^{+}|s, a)} - \beta \log \frac{\pi^{c}(c^{-}|s, a)}{\pi_{\text{ref}}^{c}(c^{-}|s, a)} \right) \right].$$
 (6)

In this way, evaluation and improvement are unified: the critic adaptively identifies failure modes, the validator provides ground-truth feedback, and both generator and critic are jointly updated to improve over time. Note that we chose the DPO loss for its simplicity, though any online or offline RL approach could be used for policy optimization.

Algorithm summary. Algorithm 1 summarizes the practical implementation of RLDCF. At a high level, the algorithm follows a standard online RL loop that alternates between policy evaluation and improvement. In each evaluation step, we sample generations from the current generator π^g , have the critic propose a criterion c, and obtain verification to assign rewards. These rewards are then used to update the generator with the DPO objective (Equation 5). Optionally, we also collect evaluation data for the critic by sampling multiple criteria per instruction—generation pair. The critic is then updated with its own DPO objective (Equation 6), allowing it to adaptively identify weaknesses in the generator and provide more effective learning signals.

4 EXPERIMENTS

We now evaluate our approach on two free-form generation tasks: factual text generation (§4.1) and code generation (§4.2). Factual text generation illustrates the enumerable-but-expensive regime, where all claims can in principle be verified but at a cost that scales with text length. This tests RLDCF's ability to maintain verification quality while reducing calls. Code generation, by contrast, represents the non-enumerable regime, where exhaustive verification is impossible due to infinite corner cases and intractable formal checks (Church, 1936). Here, the goal is to expose critical failures through targeted critic proposals. Together, these tasks span the spectrum from costly-but-possible to fundamentally intractable verification, highlighting the broad applicability of RLDCF.

Algorithm 1 RLDCF

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              1: Initialize parameters \pi^g, \pi^c, \pi_{\text{ref}}^g, \pi_{\text{ref}}^c
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              2: for each iteration do
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              3:
                       ## Policy Evaluation for Generator \pi^g.
220
                       for each instruction s do
              4:
221
              5:
                             Generate K generations a_1, ..., a_K \sim \pi^g(\cdot|s)
222
                             Sample a criterion from the adversarial critic for each generation c_i \sim \pi^c(\cdot|s, a_i).
              6:
                             Construct a generator dataset \mathcal{D}_s^g = \{(s, a_i, R(s, a_i, c_i))\}_{i=1}^K
              7:
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                       ## Policy Evaluation for Critic \pi^c.
              8:
                                                                                                                                          ▷ Optional
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              9:
                       for each instruction s, output a do
            10:
                             Generate N criteria c_1, ..., c_N \sim \pi^c(\cdot|s, a)
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                             Construct a critic dataset \mathcal{D}^c_{(s,a)} = \{(s,a,R(s,a,c_j))\}_{j=1}^N
            11:
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                       ## Policy Improvement for Generator \pi^g.
            12:
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                       \pi_{\text{new}}^g \leftarrow \pi^g
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                       14:
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            15:
                                                                                                                                      ▶ Equation 5
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            16:
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                       ## Policy Improvement for Critic \pi^c.
            17:
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            18:
                       \pi^c_{\text{new}} \leftarrow \pi^c
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            19:
                       \begin{array}{c} \underset{\text{ref}}{\overset{\text{--p-sinc}}{\vdash}} \sec p \ \textbf{uo} \\ \bot \ \pi_{\text{new}}^c \leftarrow \pi_{\text{new}}^c - \nabla \mathcal{L}(\pi_{\text{new}}^c, \pi_{\text{ref}}^c) \end{array}
                       for each update step do
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            20:
                                                                                                                                      ⊳ Equation 6
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            21:
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4.1 FACTUAL TEXT GENERATION

4.1.1 SETTINGS

Evaluation data & metrics. We follow (Min et al., 2023; Tian et al., 2024) in adapting a factual text generation task in which the model should produce concise biographies for a given individual. We use 170 topics from the Wikipedia Biography Dataset (Lebret et al., 2016), split into 120 for training and 50 for testing. We use factual precision of the output (as defined by FactScore (Min et al., 2023)) as the primary metric, and also report the counts of correct and incorrect facts. To control for length, the model is instructed to generate either four or eight sentences (see Appendix ??). Since frequent calls to the external validator are costly, we additionally track the number of validator calls.

Base models & baselines. Our base generators are Qwen3-4B and Qwen3-8B. We compare against three baselines: (1) the original base models without task-specific training; (2) FactTune-FS (Tian et al., 2024), a widely used method for factual text generation to represent exhaustive verification using an external validator, FactScore, for all atomic facts; and (3) ArmoRM (Wang et al., 2024a), which represents the reward model based method that produces one reward score for the generated output. Both the generator and critic are initialized from the same backbone models (Qwen3-4B and Qwen3-8B) to ensure fairness. We use FactScore as an external validator, i.e., FactScore checks whether a critic-proposed fact appears in the biography and is correct according to Wikipedia. All methods are trained with multiple rounds of DPO updates, where the generator produces 10 outputs per prompt and the critic proposes 4 rubrics per output.

4.1.2 RESULTS

Table 1 shows that RLDCF achieves the highest factuality scores across model sizes and output lengths, while using significantly fewer verification calls. For instance, on Qwen3-8B with eight-sentence generation, it reaches a FactScore of 0.889, outperforming FactTune-FS (0.867) and ArmoRM (0.723), but with only 77k verification calls compared to 439k for FactTune-FS. This efficiency gap grows with output length: FactTune-FS requires $4.4\times$ more verification calls in the four-sentence setting (169k vs. 39k) and $5.7\times$ more in the eight-sentence setting (439k vs. 77k). This shows that RLDCF scales more efficiently as the generation complexity increases.

Table 1: Performance comparison on factual text generation. RLDCF achieves the highest FactScore across all settings while using fewer verification calls than FactTune-FS.

Method		4-sentence G	eneration		8-sentence Generation				
	# Corr↑	# Incorr↓	FS↑	Calls↓	# Corr↑	# Incorr↓	FS↑	Calls↓	
Qwen3-4B									
Baseline	10.07	6.43	0.610	_	19.62	12.08	0.619	-	
FactTune-FS	10.66	3.48	0.754	214,911	20.65	5.99	0.775	341,657	
ArmoRM	14.54	8.69	0.626	_	21.02	10.02	0.677	-	
RLDCF (Ours)	10.54	3.04	0.776	57,600	21.58	4.84	0.817	48,000	
Qwen3-8B									
Baseline	12.65	5.53	0.696	_	22.51	11.97	0.653	-	
FactTune-FS	13.31	3.63	0.786	168,735	25.10	3.84	0.867	438,949	
ArmoRM	12.96	6.86	0.654	_	23.31	8.92	0.723	_	
RLDCF (Ours)	13.14	3.37	0.796	38,400	24.33	3.03	0.889	76,800	

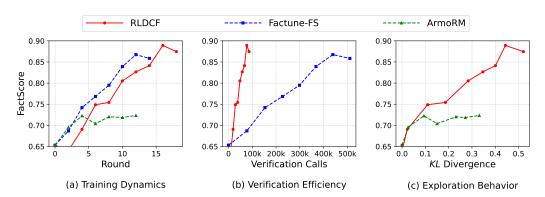


Figure 2: Comparison of training dynamics, verification efficiency, and exploration behavior for RLDCF, FactTune-FS, and ArmoRM on the Qwen3-8B model with 8-sentence generation.

RLDCF's improvements throughout training. Figure 2 shows how the generator's accuracy evolves over training, measured along three axes: training epoch, number of verification calls, and KL divergence from the base model. In Figure 2(a), RLDCF shows a slight initial drop in FactScore (from 0.653 to 0.641). At this early stage, the critic has not yet learned to identify the most obvious errors, so the "mistakes" it proposes are often minor or even incorrect. As a result, the generator receives weak targeted training signals, and factuality temporarily degrades. After several rounds, the critic improves at detecting mistakes, which in turn accelerates generator learning. Once this dynamic stabilizes, the generator's factuality gradually, ultimately reaching 0.889, outperforming FactTune-FS (0.867). This two-phase process illustrates how RLDCF evolves from weak initial supervision to highly efficient, targeted verification.

Figure 2(b) shows that RLDCF achieves the same level of factuality as FacTune-FS with far fewer verification calls (e.g., 67K vs. 368K to achieve 84%). This highlights the inefficiency of FactTune-FS, which repeatedly validates already correct facts, whereas RLDCF dynamically targets high-risk errors, yielding greater verification efficiency and scalability.

Figure 2(c) measures exploration by tracking the KL divergence from the base model. Such deviation can usually be caused by either (1) improvements from the base model through effective exploration, or (2) reward hacking, in which the model overfits to the reward model and drafts without real quality gains. For RLDCF, KL increases alongside monotonic FactScore gains ($0.653 \rightarrow 0.889$), indicating productive exploration. In contrast, RL with a fixed offline reward model (ArmoRM) shows a rise in KL without the corresponding factuality gains, evidence of reward hacking. These dynamics complement Table 1: while both RLDCF and FactTune-FS improve factuality, RLDCF achieves comparable or higher FactScore with far fewer verification calls, whereas ArmoRM inflates output length without consistent accuracy due to its static reward.

Table 2: Generator's test accuracy across critic types.

Method	# Corr	# Incorr	FS	
Base	19.62	12.08	0.619	
Noisy Validator	19.84	12.83	0.607	
Static Critic	17.77	3.77	0.825	
Adversarial Critic	21.58	4.84	0.817	

Adversarial Critic

Epoch

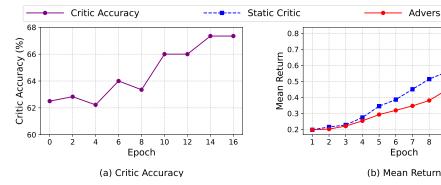


Figure 3: Critic Accuracy Evolution (**Left**) and Mean Return during training (**Right**).

Ablation Study. We compare RLDCF with two ablated variants to isolate the factors driving its effectiveness. In the first, we replace the external validator's outputs with random correctness labels to assess the role of validator reliability. In the second, we freeze the critic model, referred to as a static critic rather than training it adversarially with the generator, to evaluate the importance of adversarial joint training.

As shown in Table 2, noisy validation destabilizes training and reduces performance below the base model, highlighting the importance of reliable validation. The static critic achieves a superficially high FactScore by generating fewer facts, reducing both correct and incorrect facts, unlike the adversarially trained critic that increases correct facts while reducing errors. This indicates that the static critic inflates precision rather than genuine factual improvement. In general, these results highlight that both reliable external verification and a dynamically adapting critic are crucial: Without either, the generator fails to achieve meaningful gains in factual accuracy, validating the core design of RLDCF.

CODE GENERATION

4.2.1 SETTINGS

Evaluation data & metrics. We evaluate code generation performance using widely studied benchmarks: HumanEval (Base and Plus) (Chen et al., 2021; Liu et al., 2023), MBPP (Base and Plus) (Austin et al., 2021; Liu et al., 2023), BigCodeBench (Zhuo et al., 2024), and LiveCodeBench (V4) (Jain et al., 2025). We use Pass1 as a primary metric. For efficiency analysis, we also report the number of test cases executed per successful solution.

Base models & baselines. For training data, we use the AceCode-87K-hard subset (Zeng et al., 2025), consisting of approximately 22K problems. Our base generators include Qwen2.5-Coder-7B-Base and Qwen2.5-Coder-7B-Instruct. We compare against three baselines: (1) the original base models without training; (2) AceCoder-Rule, which employs RL with rule-based binary rewards from test execution; and (3) AceCoder-RM, which uses RL with AceCodeRM-7B trained on approximately 300K preference pairs constructed from AceCode-87K dataset. Our RLDCF approach samples 2k questions from the AceCode-87K-hard subset for training, generates k=8 outputs per prompt (which is consistent with the Acecoder setting) with n=2 critic proposals per generation.

Table 3: Results for HumanEval, MBPP, BigCodeBench Complete and Instruct (BCB-C, BCB-I), and LiveCodeBench, using two different base models. RLDCF achieves the highest average score across benchmarks.

Method	HumanEval		MBPP		BCB-C		BCB-I		LCB	Average
	Base	Plus	Base	Plus	Full	Hard	Full	Hard		
Base: Qwen2.5-Coder-7B-Base										
Baseline	83.5	79.3	80.4	69.3	45.8	16.2	40.2	14.2	28.7	50.8
AceCoder-RM	83.5	75.6	80.2	67.2	41.9	14.9	36.8	16.2	25.7	49.1
AceCoder-Rule	84.1	78.0	82.3	69.3	48.6	18.2	43.2	18.2	28.5	52.3
RLDCF (Ours)	85.7	80.6	82.4	71.6	50.3	20.9	42.1	16.9	28.7	53.2
Base: Qwen2.5-Coder-7B-Instruct										
Baseline	91.5	84.8	82.8	71.4	49.5	19.6	41.8	20.3	34.2	55.2
AceCoder-RM	89.0	84.1	86.0	72.8	50.4	18.9	42.0	19.6	35.0	55.3
AceCoder-Rule	90.9	84.8	84.1	71.7	50.9	23.0	43.3	19.6	34.9	55.9
RLDCF (Ours)	93.3	86.0	83.9	73.0	52.2	24.3	42.3	19.6	35.2	56.6

4.2.2 MAIN RESULTS

Table 3 summarizes results across five widely-used code generation benchmarks. Despite training on only 2,000 problems (9% of the dataset used for AceCoder-RM and AceCoder-Rule), RLDCF achieves the highest average scores: 53.2 using Qwen2.5-Coder-7B-Base and 56.6 using Qwen2.5-Coder-7B-Instruct, consistently outperforming both enumerative method (AceCoder-Rule) and static reward model method (AceCoder-RM) across the majority of benchmarks. We observe from Table 4 that AceCoder-RM not only fails to improve performance but can even degrade it under noisy validation. For example, on HumanEval, performance drops from 91.5 to 89.0 despite using the competetive reward model Acecoder-RM-7B, indicating reward hacking.

This fragility arises from the reward model trained on preference pairs from the AceCoder dataset, which itself contains noisy and incomplete test cases (Zeng et al., 2025). During RL training, as the generator's outputs drift away from the RM's fixed training distribution, these noisy supervision signals are further amplified. The static RM cannot adapt, causing it to favor spurious correlations rather than true correctness, leading the generator to exploit flaws in the reward signal.

RLDCF also suffers from the noisy dataset since we use a simulated solution as validator mentioned in settings. Although the critic is also affected by noise, its continuous adaptation allows it to stay aligned with the generator's changing behavior, preserving meaningful supervision. As a result, RLDCF consistently improves performance across all benchmarks, even in noisy and imperfect validation environments, showing robustness to noisy validation.

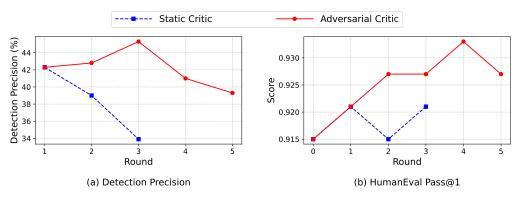


Figure 4: **Ablations on the static critic vs. adversarial critic.** Static critic's detection accuracy degrades from 42.3% to 33.9% as the generator exploits its patterns, yielding minimal performance gains (92.1%) compared to the adversarial critic's continued improvement (93.3%).

4.2.3 ABLATION STUDY

We compare RLDCF with a variant that replaces the adversarially trained critic with a static critic to evaluate the necessity of dynamic adaptation. As shown in Figure 4, the static critic's detection rate, defined by the fraction of test cases generated that correctly expose real errors, drops dramatically from 42.3% to 33.9% over three rounds, as the generator gradually learns to exploit its fixed detection patterns. In contrast, the adversarial critic maintains a stable detection rate greater than 39% by continuously adapting to the evolving behavior of the generator.

This degradation directly impacts performance: with the static critic, the generator plateaus at 92.1% Pass@1, while RLDCF reaches 93.3%. Further analysis shows that 73% of the static critic's test cases in round 3 are minor variations of earlier ones, allowing the generator to avoid detection by simplifying or reducing outputs rather than truly fixing bugs. These results highlight that dynamic adaptation is essential for preventing reward hacking and driving real improvements in code correctness.

5 RELATED WORKS

Reward models. One possibility for evaluating free-form and open-ended generations is to encode all criteria into a single scalar through a learnt reward model. This is usually achieved through learning from an offline dataset of human preferences (Christiano et al., 2017; Ziegler et al., 2019; Yi et al., 2019; Böhm et al., 2019; Rafailov et al., 2023) or absolute ratings (Cui et al., 2024; Wang et al., 2024c). Multi-objective reward models (Wang et al., 2024a; Dong et al., 2024; Ji et al., 2023) with a small pre-defined set of criteria such as truthfulness and honesty have also been introduced to improve robustness and interpretability. In comparison, our work considers a dynamic set of generation-dependent criteria to perform more precise and reliable evaluations for each individual generation.

Enumerative verifications for free-form generations. To obtain a comprehensive and reliable evaluation of free-form generations, the standard practice is to enumerate a set of fine-grained criteria (Zhuge et al., 2024; Min et al., 2023; Saad-Falcon et al., 2024; Chang et al., 2024). While they can be automatically deposed by LLMs for easier domains (Min et al., 2023; Jing et al., 2024), extensive manual annotations are typically required for more complex domains such as travel planning (Xie et al., 2024), codebase generation (Zhao et al., 2025), and research reproduction (Starace et al., 2025). Dedicated computation and actions such as information retrieval (Min et al., 2023) and code execution (Zhuge et al., 2024; Starace et al., 2025) are often needed to validate each individual criterion, causing the cost of checklist-style verification to grow rapidly as task complexity increases. In addition, such methods risk not covering certain types of errors and limit the potential for genuine quality improvement. In contrast, RLDCF adaptively identifies the most informative and critical verifiable failure modes for each instance, providing targeted feedback that covers essential errors without relying on exhaustive or rigidly predefined checks, while also keeping verification cost manageable.

6 Conclusion

We presented Reinforcement Learning from Dynamic Critic Feedback (RLDCF), a new post-training approach for open-ended tasks requiring diverse, task-specific rubrics, where exhaustive enumeration is infeasible and optiomal reward design is unknown. RLDCF formulates training as an adversarial min-max game between a generator and a *critic*, a model that dynamically identifies the worst-case rubric for each output and verifies it externally. By jointly training both models, our approach bypasses the need for exhaustive verification or manual reward design while providing adaptive learning signals that prevent reward hacking. On the factual text generation task and code generation task, RLDCF outperforms competitive baselines with significantly lower verification cost. Ablation studies further confirm the critical role of components such as adversarial critic training.

While we evaluate RLDCF on two domains, we expect it to generalize broadly to other open-ended generation tasks where multiple evaluation criteria make exhaustive or rubric-by-rubric verification infeasible, such as story or scientific text generation. By adaptively selecting the most critical rubric at each step, RLDCF makes RL training practical for complex generation tasks that were previously intractable due to the combinatorial explosion of rubrics or the lack of universal reward functions.

7 REPRODUCABILITY AND ETHICS STATEMENTS

To facilitate reproducibility of our work, we have included core implementation code in the supplementary materials. For the FactScore and code generation benchmarks, we use the default settings from their respective official implementations. All experiments employ DPO (Direct Preference Optimization) training with consistent configurations across tasks. The datasets used in our experiments are publicly available: WikiBiography can be obtained from its official website, and the Acecoder dataset is accessible through its official repository. We plan to release our complete code implementation publicly upon acceptance to further support reproducibility efforts.

The primary goal of our method, Reinforcement Learning from Dynamic Critic Feedback (RLDCF), is to enhance the quality of open-ended generations, such as to improve the factual accuracy of text generation and the correctness of code generation. We believe this is a positive contribution toward developing more reliable and trustworthy AI systems. However, we acknowledge the dual-use potential inherent in any powerful generative technology. While our aim is to reduce errors, an improved generator could still be misused to create convincing but harmful or misleading content if directed by malicious prompts. Similarly, the adversarial critic, designed to find flaws, could potentially be repurposed for malicious critique.

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A VALIDATOR IMPLEMENTATION DETAILS

A.1 FACTSCORE

We follow a strict validation process to ensure both authenticity and factual accuracy. In the first stage, the critic outputs both a suspected erroneous fact and the sentence number containing it. To prevent exploitation through information injection, we use textual entailment checking to verify that the proposed fact genuinely appears in the specified sentence. In the second stage, for proposals passing authenticity checks, we reuse FactScore's atomic fact verification component, which queries Wikipedia knowledge base to provide binary verification of individual factual claims, returning true or false based on external verification.

A.2 ACECODER

Since the AceCoder dataset lacks reference solutions to prevent data contamination, we construct reliable verification anchors by using Qwen2.5-Coder-7B-Instruct to generate solutions for 2000 problems. We filter these solutions using original test cases, retaining only those highly accurate answers (achieving 99.7% accuracy) to serve as simulated ground truth for test case validation. Our validation protocol follows a systematic approach where the critic identifies potential errors by proposing specific test cases that expose code failures. We first execute the critic's test case on the reference solution to obtain the expected output, then execute the same test case on the generated code to obtain the actual output. Finally, we compare these outputs and return R(s,a,c) = 1 if outputs match and 0 if they differ, with execution failures also indicating detected errors. The AceCoder dataset contains noise in GPT-40 generated test cases, which introduces some bias in our reference-based validator but reflects realistic imperfections in verification tools.

B ACTOR PROMPT

B.1 FACTSCORE (FACTUAL TEXT GENERATION)

System message:

You are an AI assistant that provides accurate and concise biographies of individual. Each biography should be exactly four sentences long, highlighting key aspects of the person's life, achievements, and significance.

User message:
Write a biography of {topic}.

B.2 CODE GENERATION

The actor input exactly matches the problem statement provided in TIGER-Lab/AceCode-87K-hard without modification.

User message:

{problem_statement_from_AceCode-87K-hard}

C CRITIC PROMPT

C.1 FACTSCORE (FACTUAL TEXT CRITIC)

```
System message:
```

```
You are a factual checker. Based on your existing knowledge, identify exactly one sentence that contains the most clearly verifiable factual error in the paragraph.

Return your answer in **exactly three lines**:
reason: < briefly explaining what is wrong >
sentence: No sentenc
```

User message:

Here is an example to show the task. Find the sentence that contains the most clearly verifiable factual error in the paragraph about Albert Einstein.

Example paragraph:

- [1] Albert Einstein was awarded the Nobel Prize in Physics in 1921 for his discovery [2] He was born in New York City, United States, and later moved to Europe where he
- [3] Einstein developed the theory of relativity, revolutionizing our understanding of
- [4] His famous equation describes the equivalence of mass and energy.

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811
      Expected answer:
812
      reason: Einstein was actually born in Ulm, Germany, not New York City.
813
      sentence: 2
814
      error_fact: Albert Einstein was born in New York City.
815
      Now apply the same procedure to the paragraph below about {topic}.
816
817
      Paragraph:
818
      {numbered_paragraph}
819
820
      Answer:
821
822
823
824
      C.2 CODE GENERATION CRITIC
825
826
      System message:
827
      You are a code critic. Analyze code for bugs and generate failing test cases.
828
      Strictly follow the format with <think> and <testcase> tags.
829
830
      User message:
831
      Analyze the given problem and generated code to find a test case
832
      that would cause the code to fail.
833
      Problem: {question}
834
835
      Generated code:
836
      '''python
837
      {code}
838
839
      First, think through potential bugs and edge cases in <think> </think> tags.
840
      Then output exactly ONE failing test case inside <testcase> tags using this format:
841
842
      Option A (CALL format)
843
      <testcase> CALL: func_name(arg1, arg2, kw=val) </testcase>
844
      Option B (STDIN format)
      <testcase> STDIN: <raw input here> </testcase>
845
846
      Do NOT include expected outputs or explanations.
847
      {optional_examples_block}
848
```

D RELATED WORK

LLM-as-a-Judge. Because of the common-sense and reasoning capabilities of pre-trained LLMs, they can directly be prompted to serve as a judge to evaluate free-form generations (Zheng et al., 2023; Yuan et al., 2025; Zhu et al., 2025). Their capabilities in evaluations can be further improved through explicit fine-tuning (Wang et al., 2024b; Yuan et al., 2025). They can also be more interpretable and robust by introducing a long Chain-of-Thought (CoT) reasoning to explicitly verify fine-grained criteria (Saha et al., 2025; Wang et al., 2024b; Trivedi et al., 2024). Beyond rubric-only judging, generative verifiers treat verification itself as next-token generation: they first produce verification rationales or counterevidence, and then scoreor select candidates (Zhang et al., 2025; Singhi et al., 2025; Setlur et al., 2025). RLDCF further strengthens the verification of individual criteria by allocating computational resources to perform explicit actions, such as information gathering and code execution, enabling more powerful verification capabilities.

E LM USAGE STATEMENT

During the preparation of this submission, the authors utilized large language models (LLMs) to assist with editing, including improving grammar, phrasing, and clarity. LLMs were also used to help summarize and structure paragraphs based on the authors' own notes and drafts. The authors meticulously reviewed, revised, and take full responsibility for all content, ensuring its scientific accuracy and originality.