RLAC: Reinforcement Learning with Adversarial Critic for Free-Form Generation Tasks

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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 with Adversarial Critic (RLAC), 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 RLAC 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 RLAC 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 (Ziegler et al., 2019a; Stiennon et al., 2020). 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., 2019b; 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 multiple (even uncountable) rubrics?
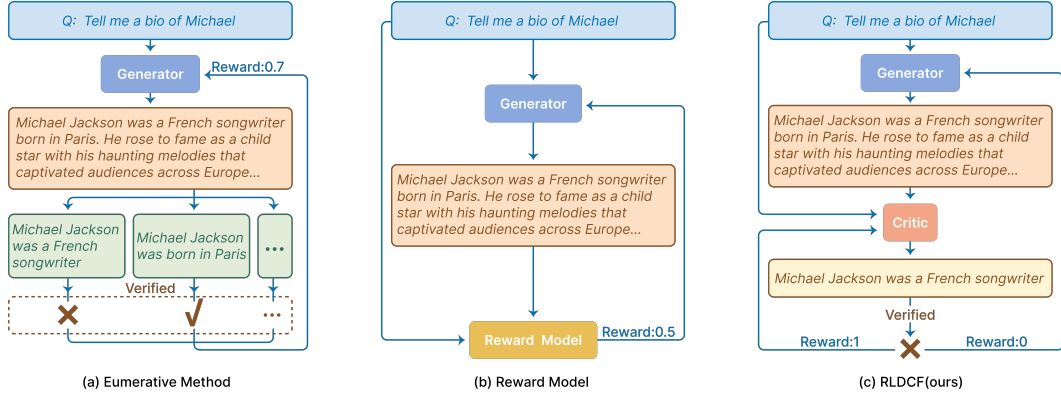
Figure 1: Comparison of three post-training paradigms on a biography example ("Michael Jackson"). **(a) Enumerative verification** explicitly extracts and checks every atomic fact before aggregating a scalar reward, which is accurate but expensive. **(b) Reward-model methods** skip verification and directly predict a scalar reward from a learned judge, which is efficient but prone to reward hacking. In contrast, **(c) RLAC** trains a learned critic to propose one likely-wrong fact (*rubric*) and verifies it via an external validator. If the fact indeed fails, the critic receives reward 1 and the generator 0; otherwise the generator receives 1 and the critic 0. This dynamic, adversarial feedback yields prompt-specific, verifiable, and scalable supervision for free-form generation tasks.

We introduce Reinforcement Learning with Adversarial Critic (RLAC), which formulates the problem as an adversarial game between a generator and a *critic*. The critic is a learned model that proposes a rubric (e.g., one test case) where the generator's output is likely to fail, and an external validator verifies this. 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 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. Figure 1 illustrates how RLAC achieves verification efficiency while maintaining accuracy through adversarial critic-generator dynamics on a biography generation example.

We evaluate Reinforcement Learning with Adversarial Critic on factual text generation and code generation, representing enumerable and non-enumerable verification scenarios, respectively. On 8-sentence biography generation with Qwen3-8B, Reinforcement Learning with Adversarial Critic achieves a FactScore of 0.889, surpassing FactTune-FS's (Tian et al., 2024) 0.867, while reducing verification calls by $5.7\times$. 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 with Adversarial Critic 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 prior methods AceCoder-RM and AceCoder-Rule (Zeng et al., 2025).

Our primary contribution is Reinforcement Learning with Adversarial Critic (RLAC), a novel post-training paradigm that frames free-form LLM optimization as an adversarial game between a generator and a learned critic, with an external validator providing ground-truth feedback. This design avoids exhaustive rubric enumeration and mitigates reward hacking by producing task-specific and on-policy training signals. In experiments, Reinforcement Learning with Adversarial Critic consistently improves factual accuracy while reducing verification costs, and surpasses prior methods on code generation—demonstrating scalable gains across both enumerable and non-enumerable verification tasks.

2 PRELIMINARIES

Our goal is to train an LLM generator that produces a free-form output satisfying requirements of the underlying task, without manually enumerating every rubric for evaluation and grading. In this section, we formalize this problem, introduce notation, and briefly discuss related concepts of reward models (Christiano et al., 2017; Ziegler et al., 2019b; Rafailov et al., 2023) and enumerative verification (Min et al., 2023; Trivedi et al., 2024; Saha et al., 2025; Wang et al., 2024b; Xie et al., 2025). We illustrate these in Figure 1. 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 refer to as 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. A math proof may require proving a certain set of intermediate results. To captures these ideas abstractly, 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 or reward 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 returns 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:

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

In constrained domains with a single, well-defined rubric (e.g., matching a reference final answer in math reasoning), we can solve this opimization problem via standard RL algorithms like PPO (Schulman et al., 2017) or GRPO (Shao et al., 2024). Note that these RL algorithms require evaluating these rubrics on every sample drawn from the policy. However, such cases are rare in open-ended tasks with diverse rubrics. In these settings, $\mathcal{C}(s)$ 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 free-formed generation 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 WITH ADVERSARIAL CRITIC

We now introduce our RL post-training approach, called Reinforcement Learning with Adversarial Critic (RLAC) 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 of a generator response 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 $\mathcal{C}(s)$: 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:

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

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 takes an instruction–generation pair (s,a) as input and outputs a rubric c $\in \mathcal{C}(s)$ in natural language, representing a verifiable property that may fail. An external validator then checks the proposed rubric. Then we can rewrite Equation 3 into the equivalent min-max form:

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

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 $\mathcal{C}(s)$ (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 RLAC

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 $s \in \mathcal{S}$. RLAC 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. The prompt for the generator is included in the Appendix A.1.

Critic. Our critic π^c is a pre-trained LLM that RLAC 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 A.2.

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 B.

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 the generator and the critic. 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 objective (Rafailov et al., 2023) with respect to the reference generator π_{ref}^g:

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

We adopt DPO primarily for its simplicity and stability, it allows direct policy optimization from binary preference signals without requiring explicit reward scaling or KL-penalty tuning. Importantly, RLAC is agnostic to the choice of policy optimization algorithm: Any online or offline RL objective

4

Algorithm 1 RLAC

1: Initialize parameters $\pi^g, \pi^c, \pi^g_{\text{ref}}, \pi^c_{\text{ref}}$
2: **for** each iteration **do**
3:　　## Policy Evaluation for Generator π^g.
4:　　**for** each instruction s **do**
5:　　　　Generate K generations $a_1, ..., a_K \sim \pi^g(\cdot|s)$
6:　　　　Sample a criterion from the adversarial critic for each generation $c_i \sim \pi^c(\cdot|s, a_i)$.
7:　　　　Construct a generator dataset $\mathcal{D}^g_s = \{(s, a_i, R(s, a_i, c_i))\}^K_{i=1}$
8:　　## Policy Evaluation for Critic π^c. 　　　　　　　　　　　　　　　　　　▷ Optional
9:　　**for** each instruction s, output a **do**
10:　　　　Generate N criteria $c_1, ..., c_N \sim \pi^c(\cdot|s, a)$
11:　　　　Construct a critic dataset $\mathcal{D}^c_{(s,a)} = \{(s, a, R(s, a, c_j))\}^N_{j=1}$
12:　　## Policy Improvement for Generator π^g.
13:　　$\pi^g_{\text{new}} \leftarrow \pi^g$
14:　　**for** each update step **do**
15:　　　　$\pi^g_{\text{new}} \leftarrow \pi^g_{\text{new}} - \nabla\mathcal{L}(\pi^g_{\text{new}}, \pi^g_{\text{ref}})$ 　　　　　　　　　▷ Equation 5
16:　　$\pi^g_{\text{ref}} \leftarrow \pi^g$
17:　　## Policy Improvement for Critic π^c. 　　　　　　　　　　　　　　　　　　▷ Optional
18:　　$\pi^c_{\text{new}} \leftarrow \pi^c$
19:　　**for** each update step **do**
20:　　　　$\pi^c_{\text{new}} \leftarrow \pi^c_{\text{new}} - \nabla\mathcal{L}(\pi^c_{\text{new}}, \pi^c_{\text{ref}})$ 　　　　　　　　　▷ Equation 6
21:　　$\pi^c_{\text{ref}} \leftarrow \pi^c$

(e.g. PPO (Schulman et al., 2017), GRPO (Shao et al., 2024)) can be substituted here without affecting the overall framework, since the critic–validator loop provides compatible supervision in all cases.

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}:

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

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.

Algorithm summary. Algorithm 1 summarizes the practical implementation of RLAC. 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 presents the enumerable-but-expensive regime, where all claims can, in principle, be verified but at a cost that scales with length of the text. This tests RLAC'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 RLAC.

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

Method	4-sentence Generation				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	-
RLAC (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	-
RLAC (Ours)	13.14	**3.37**	**0.796**	**38,400**	24.33	**3.03**	**0.889**	**76,800**

4.1 FACTUAL TEXT GENERATION

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. Since frequent calls to the external validator are costly, we additionally track the number of validator calls.

Base models & baselines. We compare RLAC against two dominant paradigms of post-training: (1) enumerative verification, which relies on explicit checking of all atomic facts, and (2) reward-model optimization, which replaces external verification with a learned scalar judge. To represent these paradigms, we evaluate the following baselines and prior approaches: (1) the Qwen3-4B and Qwen3-8B base models as starting generators for our study; (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. These values follow common configurations in preference-based optimization (Rafailov et al., 2023; Tian et al., 2024) and provide a balanced trade-off between exploration diversity and verification cost, ensuring fair comparison across methods.

Results. Table 1 shows that RLAC 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× more verification calls in the four-sentence setting (169k vs. 39k) and 5.7× more in the eight-sentence setting (439k vs. 77k). This shows that RLAC scales more efficiently as the generation complexity increases.

RLAC'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), RLAC 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

(a) Training Dynamics   (b) Verification Efficiency   (c) Exploration Behavior
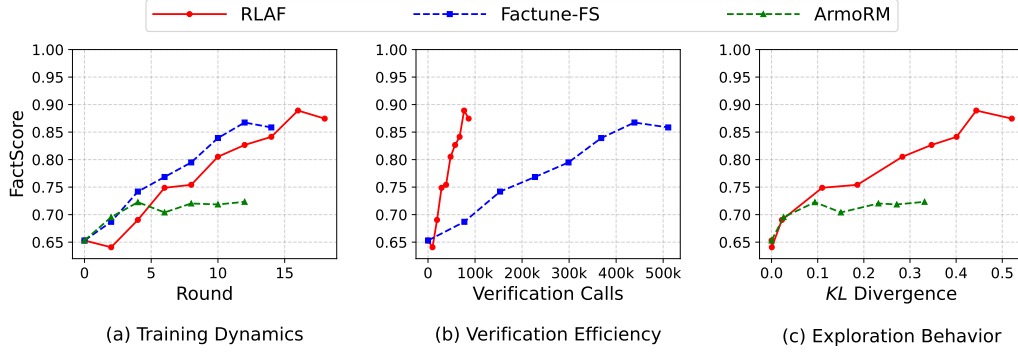
Figure 2: Comparison of training dynamics, verification efficiency, and exploration behavior for RLAC, FactTune-FS, and ArmoRM on the Qwen3-8B model with 8-sentence generation.

stabilizes, the generator's factuality gradually, ultimately reaching 0.889, outperforming FactTune-FS (0.867). This two-phase process illustrates how RLAC evolves from weak initial supervision to highly efficient, targeted verification.

Figure 2(b) shows that RLAC 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 RLAC 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 RLAC, 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 RLAC and FactTune-FS improve factuality, RLAC 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.

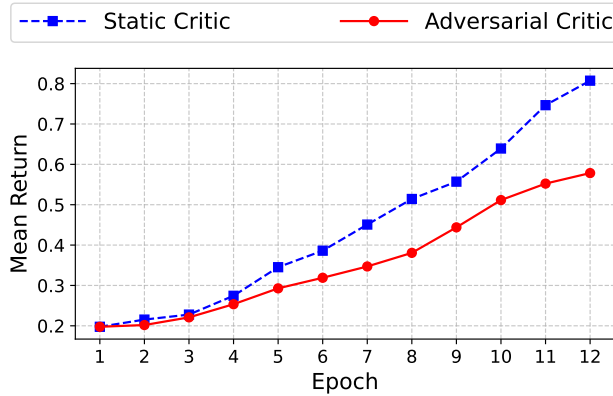| Method	# Corr	# Incorr	FS
Base	19.62	12.08	0.619
Noisy Validator	19.84	12.83	0.607
Static Critic	17.77	**3.77**	**0.825**
Adversarial Critic	**21.58**	4.84	0.817

Figure 3: Average validator outcomes on suspicious facts proposed by the critic during factual biography generation. Higher values indicate that the critic more often misjudges correct facts (i.e., weaker supervision).

Ablation study. We compare RLAC 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. Figure 3 further illustrates these dynamics. The static critic's validator outcomes quickly rise to about 0.81, showing that the generator quickly learns to evade its fixed patterns. In contrast, the adversarial critic's outcomes grow much more slowly and reach a lower level of about 0.6 by round 16, indicating that it continues to surface genuine errors and sustain learning pressure. 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 RLAC.

4.2 CODE GENERATION

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 total number of test cases executed during RL training as the number of validator calls.

Base models & baselines. For training data, we use the AceCode-87K-hard subset (Zeng et al., 2025), consisting of approximately 22K problems. We compare against the following baseline and prior methods: (1) the base model Qwen2.5-Coder-7B-Base and Qwen2.5-Coder-7B-Instruct without training; (2) an enumerative RL method AceCoder-Rule, which employs RL with rule-based binary rewards from test execution; and (3) a reward model method 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.

For all methods, we follow the AceCoder experimental setup using the AceCode-87K-hard subset (Zeng et al., 2025), which contains about 22K problems and generates $k = 8$ outputs per prompt. For training efficiency, our method samples 2k problems randomly from this subset and uses $n = 2$ 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. RLAC 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
RLAC (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	55.1
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
RLAC (Ours)	**93.3**	**86.0**	83.9	**73.0**	**52.2**	**24.3**	42.3	19.6	**35.2**	**56.6**

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), RLAC 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. Similarly, while AceCoder-Rule executed approximately 7.86 million test cases during training, RLAC required 192 thousand to reach higher final performance, reducing verification cost by 97.5% and indicating markedly higher verification efficiency compared with enumerative methods.

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.

RLAC 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, RLAC consistently improves performance across all benchmarks, even in noisy and imperfect validation environments, showing robustness to noisy validation.
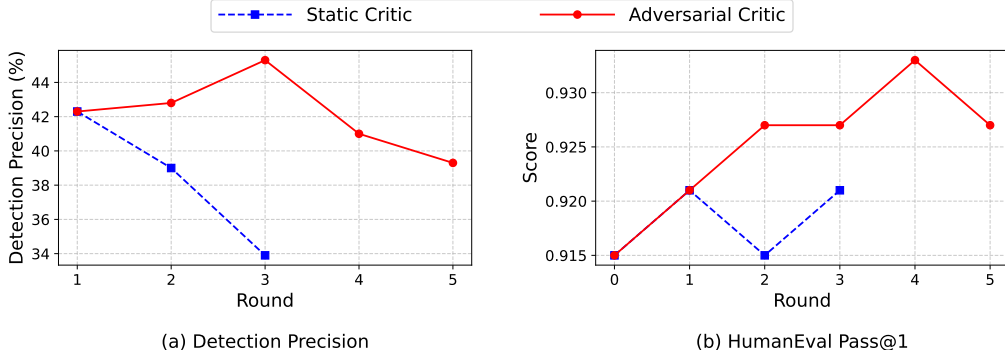

(a) Detection Precision   (b) HumanEval Pass@1

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 (+0.6%) compared to the adversarial critic's continued improvement (+1.8%).

Ablation study. We compare RLAC 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 RLAC reaches 93.3%. Further analysis shows that static critic's test cases critic's output degenerated to 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., 2019b; 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) expose several fixed dimensions (e.g., truthfulness, honesty), improving interpretability but still relying on static, globally defined criteria. Our approach differs conceptually: instead of collapsing all rubrics into a single scalar or a fixed multi-objective vector, we learn a critic that dynamically proposes a verifiable rubric for each instance and grounds its supervision through an external validator. This yields a reward signal that is still scalar for RL optimization, but derived from an objectively checkable criterion rather than a static, unverified proxy, offering better alignment and reliability in open-ended tasks.

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; Xie et al., 2025). 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) require manual rubric design or domain-specific validators (e.g., retrieval and code execution). Because all rubrics must be checked for each output, verification cost scales roughly linearly with the number of possible rubrics and may still miss unlisted error types. In contrast, RLAC replaces exhaustive enumeration with a learned critic that dynamically selects the most informative, verifiable failure mode for each instance. By verifying only this targeted rubric via an external validator, the method retains rubric-level faithfulness while substantially reducing evaluation cost and exposing diverse, on-policy errors that static checklists often overlook.

Outcome-reward RL for reasoning. RL for LLM has been shown to significantly boost model performance in domains where the success of the final answer can be easily checked (OpenAI et al., 2024; Liang et al., 2025; Team et al., 2025; Lambert et al., 2025). This mostly includes the domains of math (Cobbe et al., 2021; Cui et al., 2025; Luo et al., 2025b; Yu et al., 2025), coding (Jimenez et al., 2024; Pan et al., 2024a; Wei et al., 2025; Luo et al., 2025a) , but can be tricky for other domains like agent decision-making (Pan et al., 2024b; Zhai et al., 2024; Bai et al., 2024) and free-form generations (Min et al., 2023; Zhuge et al., 2024). However, RLAC is designed to relax this requirement so that we can apply RL to more general domains where success cannot be easily verified, such as free-form generations.

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 score or select candidates (Zhang et al., 2025; Singhi et al., 2025; Setlur et al., 2025). These approaches, however, use the judge or verifier only as a static evaluator. They produce fixed judgments or explanations but do not learn adaptively from the generator's evolving behaviors. In contrast, RLAC treats the verifier as a learned critic policy within an adversarial training loop: the critic dynamically proposes which rubric to verify for each instance, receives direct feedback from an external validator, and updates jointly with the generator. This design transforms LLM-as-a-judge from a static scoring module into an active, on-policy agent that allocates verification effort where it is most informative.

6 CONCLUSION

We presented Reinforcement Learning with Adversarial Critic (RLAC), a new post-training approach for open-ended tasks requiring diverse, task-specific rubrics, where exhaustive enumeration is infeasible and optimal reward design is unknown. RLAC 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, RLAC 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 RLAC 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, RLAC 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.

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Appendices

A PROMPTS

This section lists the exact prompts used for the **generator model** and **critic model** during data creation and training. They correspond to the input format described in Section 3.2 of the main paper.

A.1 GENERATOR PROMPT

Factual Text Generation

```
System message:
You are an AI assistant that provides accurate and concise biographies
of individuals. 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}.
```

Code Generation

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

User message:
{problem_statement_from_AceCode-87K-hard}
```

A.2 CRITIC PROMPT

Factual Text Generation

```
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: N        N is the number of the most incorrect sentence
(positive integer)
error_fact: F      a brief clause (no more than 8 words) capturing the
wrong claim from that sentence

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 of the photoelectric effect.
[2] He was born in New York City, United States, and later moved to
    Europe where he continued his studies.
[3] Einstein developed the theory of relativity, revolutionizing our
    understanding of space, time, and gravity.
[4] His famous equation describes the equivalence of mass and energy.

Expected answer:
reason: Einstein was actually born in Ulm, Germany, not New York City.
sentence: 2
error_fact: Albert Einstein was born in New York City.
```

```
Now apply the same procedure to the paragraph below about {topic}.

Paragraph:
{numbered_paragraph}

Answer:
```

Code Generation

```
System message:
You are a code critic. Analyze code for bugs and generate failing test
cases.
Strictly follow the format with <think> and <testcase> tags.

User message:
Analyze the given problem and the generated code to find a test case that
would cause the code to fail.

Problem: {question}

Generated code:
```python
{code}
```
First, think through potential bugs and edge cases in <think> </think>
tags.
Then output exactly ONE failing test case inside <testcase> tags using
this format:

Option A (CALL format)
<testcase> CALL: func_name(arg1, arg2, kw=val) </testcase>
Option B (STDIN format)
<testcase> STDIN: <raw input here> </testcase>

Do NOT include expected outputs or explanations.
{optional_examples_block}
```

B   VALIDATOR IMPLEMENTATION DETAILS

This section provides the detailed design of the validator used in our training pipeline, corresponding to Section 3.2 of the main paper.

B.1   FACTUAL TEXT GENERATION

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.

B.2   CODE GENERATION

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. 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 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-4o generated test cases, which introduces some bias in our reference-based validator but reflects realistic imperfections in verification tools.