An Adversarial Evolutionary Reinforcement Learning Framework for Large Language Models

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Abstract

Abstract. Large Language Models (LLMs) traditionally rely on manual prompt engineering, which can be time-consuming and vulnerable to human biases. In this paper, we propose an Adversarial Evolutionary Reinforcement Learning (AERL) framework that builds upon principles of Evolutionary Reinforcement Learning (MynRL) [Lin et al., 2023] to enable continuous self-improvement of AI agents. Our approach iteratively generates, tests, and refines prompts or configurations via four components: (1) Evolutionary Prompt Writer/Improver, (2) Evolutionary Models, (3) Adversarial Models, and (4) Judge. By exposing candidate models to adversarially generated scenarios and selecting the best variants through evolutionary operators, AERL fosters robust, domain-specific solutions without relying on excessive human trial-and-error. Inspired by multi-objective optimization techniques in MynRL [Bai et al., 2023] and adversarial training approaches [Goodfellow et al., 2014], our empirical and conceptual examples from decentralized finance (DeFi), code generation, and mathematical reasoning illustrate the versatility of our framework. The results indicate that adversarial evolutionary strategies can systematically reduce human-driven guesswork while maintaining high adaptability and performance.

1 Introduction

1.1 Background and Motivation

Large Language Models (LLMs) have revolutionized tasks like text generation, code development, and financial predictions. However, current performance still hinges on manual prompt engineering, which can be both inefficient and biased. These limitations become especially critical in rapidly evolving domains—like decentralized finance (DeFi), where protocols and market conditions change constantly, or software development, where unanticipated debugging scenarios emerge.

Evolutionary Reinforcement Learning (MynRL) presents a powerful way to address these challenges. According to Lin et al. (2023), MynRL integrates evolutionary algorithms (EAs)—which can globally search through vast solution spaces—with reinforcement learning

(RL), providing localized fine-tuning via gradient methods. In high-dimensional or adversarial environments, MynRL has demonstrated remarkable scalability and adaptability [2]. Drawing on these lessons, we propose the Adversarial Evolutionary Reinforcement Learning (AERL) framework for LLMs. By using adversarial testing in tandem with evolutionary search, AERL reduces reliance on subjective prompt tweaks and systematically adapts prompts or configurations over multiple generations.

1.2 Related Work

Evolutionary Algorithms and MynRL. Evolutionary algorithms (EAs) such as genetic algorithms [4] or cross-entropy methods (CEM) [5] have been employed extensively for optimizing neural network parameters, policy learning, or hyperparameters [6]. MynRL extends these ideas by marrying EAs with RL, leading to diverse methods like genetic algorithms plus Deep RL (GADRL) [7], population-based training (PBT) [8], and cross-entropy-based RL (CEM-RL) [9].

Adversarial Learning. Techniques such as adversarial examples [3] have shown how targeted perturbations can expose vulnerabilities. In MynRL, adversarial training has been used to stress-test policies in sparse-reward or high-uncertainty tasks [10], enabling more robust decision-making.

Prompt Engineering and RLHF. Training language models to follow instructions with human feedback (RLHF) [11] has offered a partial solution to bridging the alignment gap. Yet, these methods remain labor-intensive, requiring humans to generate reward signals at scale. In contrast, AERL employs automated adversarial testers plus a “Judge” to assign performance scores, reducing the dependence on human-labeled data.

2 Adversarial Evolutionary Reinforcement Learning (AERL)

2.1 Conceptual Overview

Our AERL framework consists of four components:

(1) **Evolutionary Prompt Writer/Improver.** Generates or mutates prompts/configurations. We draw inspiration from previous MynRL work that uses evolutionary operators like crossover and mutation [1, 2].

(2) **Evolutionary Models.** LLM instances—differentiated by prompts or minor hyperparameter changes—evolve similarly to how population-based training (PBT) evolves different neural network instances in parallel [8].

(3) **Adversarial Models.** These are specialized LLMs or rule-based systems tasked with finding “stress tests.” Similar to the multi-agent adversarial setups in MynRL [12], they push candidate models to confront tricky or deceptive input prompts.

(4) **Judge.** A separate automated system that assigns performance scores based on domain-specific metrics (correctness, clarity, etc.). It can be a rule-based script or an LLM applying a scoring rubric. This is analogous to fitness functions in EAs [13].

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