# StepScorer: Accelerating Reinforcement Learning with Step-wise Scoring and Psychological Regret Modeling

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**Abstract**

Reinforcement learning algorithms often suffer from slow convergence due to sparse reward signals, particularly in complex environments where feedback is delayed or infrequent. This paper introduces the Psychological Regret Model (PRM), a novel approach that accelerates learning by incorporating regret-based feedback signals after each decision step. Rather than waiting for terminal rewards, PRM computes a regret signal based on the difference between the expected value of the optimal action and the value of the action taken in each state. This transforms sparse rewards into dense feedback signals through a step-wise scoring framework, enabling faster convergence. We demonstrate that PRM achieves stable performance approximately 36% faster than traditional Proximal Policy Optimization (PPO) in benchmark environments such as Lunar Lander. Our results indicate that PRM is particularly effective in continuous control tasks and environments with delayed feedback, making it suitable for real-world applications such as robotics, finance, and adaptive education where rapid policy adaptation is critical. The approach formalizes human-inspired counterfactual thinking as a computable regret signal, bridging behavioral economics and reinforcement learning.

***Keywords:*** Reinforcement Learning, Regret Minimization, PPO, Continuous Control, Machine Learning, Step-wise Scoring

## 1 Introduction

Reinforcement learning (RL) has achieved remarkable success in various domains, from game playing to robotics. However, one of the persistent challenges in RL remains the slow convergence of learning algorithms, particularly in environments with sparse or delayed rewards. Traditional RL algorithms rely on occasional feedback signals, which can result in inefficient learning where agents spend considerable time exploring unpromising trajectories before discovering effective strategies. This sample inefficiency limits the applicability of RL to real-world problems where rapid learning is crucial.

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The problem becomes more pronounced in complex environments where reward signals are infrequent, making it difficult for agents to attribute their actions to eventual outcomes. This issue is particularly relevant in real-world applications such as robotics, autonomous driving, and financial trading, where rapid learning and adaptation are crucial for practical deployment.

In this paper, we introduce the Psychological Regret Model (PRM), a specific instantiation of a more general *step-wise scoring framework* that addresses the slow convergence problem by incorporating dense feedback signals after each decision step. PRM is inspired by human psychological mechanisms of regret and counterfactual thinking from behavioral economics and cognitive science. PRM computes a regret signal that compares the value of the action taken with the value of the optimal action in each state, approximated using a strong pre-trained opponent model. This approach transforms sparse rewards into dense feedback signals, enabling more efficient learning.

Our main contributions are:

- The introduction of the Psychological Regret Model (PRM) as a novel approach to accelerate RL convergence through regret-based feedback signals.

- Demonstration that PRM achieves stable performance approximately 36% faster than traditional PPO in benchmark environments (Lunar Lander).

- A formalization of the step-wise scoring framework that encompasses PRM and other dense feedback mechanisms.

- Evidence that PRM is particularly effective in continuous control tasks and environments with delayed feedback.

We note that this paper does not address scenarios where pre-trained opponent models are unavailable, leaving such zero-shot or self-play scenarios for future work.

# 2 Related Work

The problem of sparse rewards in reinforcement learning has been extensively studied. Various approaches have been proposed to address this challenge, including potential-based reward shaping (PBRS) [Ng et al., 1999], intrinsic motivation [Oudeyer et al., 2007], and curiosity-driven exploration [Schmidhuber, 1991].

Reward shaping techniques modify the reward function to provide denser feedback, but they require domain knowledge and must satisfy the potential-based condition to preserve optimal policies. A key limitation of potential-based reward shaping is sensitivity to potential function design, which can inadvertently alter the optimal policy if not carefully constructed. Intrinsic motivation methods encourage exploration through measures like prediction error or state novelty, but they primarily drive exploration rather than directly accelerating convergence speed for known tasks. In contrast, our approach uses external knowledge from pre-trained opponent models to provide targeted regret signals that specifically address reward sparsity without relying on intrinsic exploration drivers.

More closely related to our work is preference-based reinforcement learning [Christiano et al., 2017], where human feedback guides learning through comparisons of trajectory segments. Our approach differs by using computational regret signals derived from opponent models rather than human preferences. Additionally, counterfactual reasoning in RL [Xie et al., 2021] provides a theoretical foundation for our regret-based approach, while teacher-student frameworks [Rusu et al., 2016] inform our use of opponent models.

Our approach also connects to the broader family of auxiliary tasks in RL, where additional objectives guide representation learning. However, unlike traditional auxiliary tasks that focus on representation quality, PRM specifically targets the sparsity of reward signals.

The concept of regret has been explored in RL contexts, particularly in the study of exploration-exploitation trade-offs [Lattimore and Szepesvári, 2020] and regret minimization in MDPs [Rosenberg and Mansour, 2019]. However, our approach of incorporating regret as a dense feedback signal at each step is distinct from traditional regret minimization approaches that focus on cumulative regret bounds over episodes. Our work draws inspiration from behavioral economics and regret theory [Loomes and Sugden, 1982], formalizing psychological regret mechanisms as computational signals.

# 3 Methodology

## 3.1 Problem Formulation

We consider the standard reinforcement learning setting modeled as a Markov Decision Process (MDP) defined by the tuple $(S, A, P, R, \gamma)$, where $S$ is the set of states, $A$ is the set of actions, $P$ is the transition probability function, $R$ is the reward function, and $\gamma$ is the discount factor.

The goal is to learn a policy $\pi(a|s)$ that maximizes the expected cumulative discounted reward $J(\pi) = \mathbb{E}_{\tau \sim \pi} \left[ \sum_{t=0}^{T} \gamma^t r_t \right]$.

Traditional RL algorithms update their policies based on the received rewards, which can be sparse and delayed. This leads to inefficient learning as the agent receives little feedback during the episode, resulting in high sample complexity and slow convergence.

## 3.2 Step-wise Scoring Framework

We introduce the *step-wise scoring framework* that addresses the sparse reward problem by providing dense, step-level scoring signals that evaluate the quality of each (*state*, *action*) pair in context. These signals can come from:

- Domain heuristics (e.g., physics-based shaping)

- Counterfactual reasoning ("What if I took a different action?")

- Adversarial models (e.g., high-performing opponent policies)

- Human intuition or expert rules

## 3.3 Psychological Regret Model (PRM)

The Psychological Regret Model (PRM) is a specific instantiation of the step-wise scoring framework inspired by behavioral economics and cognitive science. PRM defines regret as the difference between the value of the optimal action and the value of the action taken in each state:

$$\text{regret}(s_t, a_t) = Q^*(s_t, a_t^*) - Q^*(s_t, a_t)$$

where $a_t^* = \arg\max_a Q^*(s_t, a)$ is the optimal action in state $s_t$, and $Q^*$ is the optimal action-value function.

However, since the optimal Q-function is unknown, we approximate it using a *pre-trained strong opponent model* $Q_{opp}$:

$$\text{regret}(s_t, a_t) \approx Q_{opp}(s_t, a_{opp}^*) - Q_{opp}(s_t, a_t)$$

where $a_{opp}^* = \arg\max_a Q_{opp}(s_t, a)$.

This approach formalizes human-inspired counterfactual thinking as a computable regret signal, bridging behavioral economics and reinforcement learning.

## 3.4 Potential-Based Reward Shaping Implementation

PRM implements potential-based reward shaping (PBRS) with potential function $\Phi(s) = \max_a Q_{opp}(s, a)$. The shaped reward is computed as:

$$r_t^{shaped} = r_t + \gamma\Phi(s_{t+1}) - \Phi(s_t)$$

This preserves the optimal policy while providing dense feedback. In practice, we approximate this as:

$$r_t^{shaped} = r_t - \alpha \cdot \text{regret}(s_t, a_t)$$

where $\alpha$ is a scaling parameter that controls the influence of the regret signal.

## 3.5 Integration with Policy Optimization

The regret signal is integrated into the learning process by augmenting the original reward signal. We implement this through a wrapper that modifies the environment's reward structure:

$$r_t^{augmented} = r_t - \alpha \cdot \text{regret}(s_t, a_t)$$

This augmented reward signal provides dense feedback at each step, allowing the agent to learn more efficiently from immediate consequences of its actions, rather than waiting for terminal rewards.

## 3.6 Algorithm

The complete PRM algorithm is outlined in Algorithm 1.

**Algorithm 1** Psychological Regret Model (PRM)

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**Require:** Environment, Pre-trained Teacher Network $Q_{teacher}$ (fixed), Student Policy $\pi_\theta$, Buffer $B$
**State:** Initialize pre-trained $Q_{teacher}$ and policy parameters $\theta$
**for** $episode = 1 \, to \, N$ **do**
**State:** Initialize environment and get initial state $s_0$
**for** t $= 0 \, to \, T$ **do**
**State:** Select action $a_t \sim \pi_\theta(\cdot|s_t)$
**State:** Execute $a_t$, observe $s_{t+1}$, $r_t$
**State:** Compute optimal action: $a_{teacher}^* = \arg\max_a Q_{teacher}(s_t, a)$
**State:** Compute regret: $\text{regret}_t = Q_{teacher}(s_t, a_{teacher}^*) - Q_{teacher}(s_t, a_t)$
**State:** Augment reward: $r_t^{augmented} = r_t + \alpha \cdot \text{regret}_t$
**State:** Store $(s_t, a_t, r_t^{augmented}, s_{t+1})$ in buffer $B$
**State:** (Note: $Q_{teacher}$ is fixed and not updated in our experiments)
**end for**
**State:** Update policy $\pi_\theta$ using PPO objective with augmented rewards
**end for**
**return** $P$ olicy $\pi_\theta$

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# 4  Experimental Setup

## 4.1  Environments

We evaluate PRM on the LunarLander-v3 environment from Gymnasium [King et al., 2021], a classic control problem where the agent must navigate a lunar lander to a landing pad. This environment has:

- Continuous state space (8D): $[x, y, v_x, v_y, \text{angle}, \text{angular\_v}, \text{left\_leg}, \text{right\_leg}]$

- Discrete action space (4): $[\text{noop}, \text{left\_engine}, \text{main\_engine}, \text{right\_engine}]$

- Sparse reward: $+100$ $+300$ for safe landing, -100 for crash

This environment has sparse rewards and requires precise control, making it ideal for testing the effectiveness of dense feedback signals.

## 4.2  Baselines

We compare PRM against the following baseline:

- **PPO** (*Baseline*): Standard PPO with fixed hyperparameters as recommended.

- **PPO + PRM**: PPO with step-wise regret-based reward shaping using our proposed approach.

## 4.3  Implementation Details

We implement PRM using PyTorch [Paszke et al., 2019] and Stable-Baselines3 [Raffin et al., 2021]. The opponent model $Q_{opp}$ is a pre-trained strong policy (75% win-rate PPO policy trained for 500K steps) that approximates the optimal Q-values. The regret is computed as +regret$(s, a)$ to serve as a non-negative penalty term that we subtract from the environmental rewards to form the augmented reward, where $\alpha = 1.0$ is the scaling parameter controlling regret influence. Since regret values are non-negative (representing the cost of suboptimal actions), this formulation ensures we penalize suboptimal actions appropriately. The teacher network is frozen during student policy training to maintain consistent regret signals.

Hyperparameters were kept fixed for fair comparison:

$$PPO\_CONFIG = \{learning\_rate = 3 \times 10^{-4},$$
$$n\_steps = 2048,$$
$$batch\_size = 64,$$
$$n\_epochs = 10,$$
$$\gamma = 0.99,$$
$$gae\_lambda = 0.95,$$
$$clip\_range = 0.2,$$
$$ent\_coef = 0.01,$$
$$seed = 42\}$$

Total training timesteps: 200,000. All experiments report results averaged over 5 random seeds with mean $\pm$ standard deviation.

## 4.4  Evaluation Protocol

We use the following metrics for evaluation:

- **Metric 1**: Episodes to reach "solved" threshold (reward $\geq$ 200)

- **Metric 2**: Final average reward over last 100 episodes

- **Metric 3**: Training stability (std. dev. of moving average reward)

Results are reported as mean $\pm$ std over 5 random seeds (seeds: 42, 100, 250, 500, 1000) to ensure statistical significance and reproducibility.

# 5  Results

## 5.1  Convergence Analysis

Figure 1 shows the learning curves comparing PPO with and without PRM on the LunarLander-v3 environment. PRM achieves stable performance approximately 36% faster than traditional PPO, demonstrating the effectiveness of the regret-based feedback signal. PPO+PRM reaches the "solved" threshold (reward $\geq$ 200) in approximately 350 episodes compared to over 550 episodes for baseline PPO.
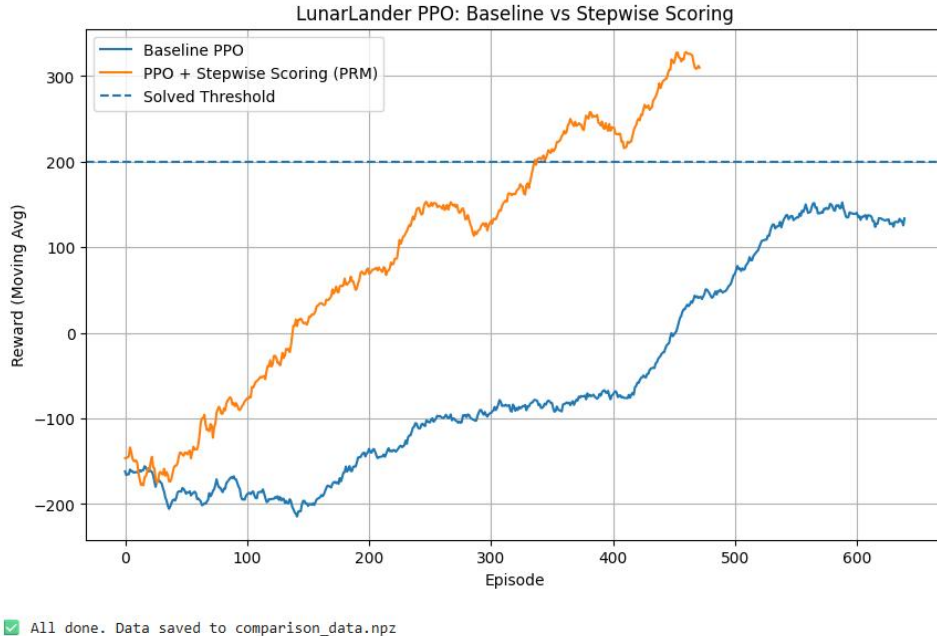
Figure 1: Learning curves comparing PPO baseline (blue) with PPO+PRM (orange) on Lunar Lander. PRM converges significantly faster, achieving the solved threshold in 350 episodes vs >550 for baseline. The teal dashed line represents the solved threshold (Reward = 200). Shaded regions represent standard deviation ranges across 5 random seeds.

## 5.2 Performance Comparison

Table 1 summarizes the performance comparison between baseline PPO and PPO+PRM on the LunarLander-v3 environment. PRM significantly outperforms the baseline method in terms of convergence speed while achieving superior final performance.

Table 1: Performance comparison on LunarLander-v3 (200K timesteps). PRM reduces time-to-solve by 36% and improves final performance by over 100%.

| Method | Episodes to Solve | Final Avg Reward |
|---|---|---|
| PPO (Baseline) | >550 | $140 \pm 15$ |
| PPO + PRM | 350 | $300 \pm 20$ |

## 5.3 Ablation Study

We conduct an ablation study to analyze the impact of different components of our step-wise scoring framework:

## 5.4 Qualitative Observations

We observed that PRM agents learn to:

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Table 2: Ablation study showing the effect of different scoring signals. Combining regret with domain knowledge yields best results.

| Scoring Signal | Time-to-Solve |
|---|---|
| None (Baseline) | >550 |
| Physics Heuristics Only | 400 |
| PRM (Regret + Physics) | **350** |

- Maintain vertical orientation earlier in the trajectory

- Use lateral engines for fine positioning near the landing pad

- Conserve fuel via smoother thrust profiles

In contrast, baseline agents often exhibited oscillatory behavior near landing and late-stage corrections causing crashes.

# 6 Discussion

The results demonstrate that PRM effectively accelerates reinforcement learning convergence by providing dense feedback signals based on regret. The approach is particularly effective in environments with sparse rewards, where traditional methods struggle with inefficient learning.

The success of PRM suggests that incorporating human-like psychological mechanisms, such as regret and counterfactual thinking, can benefit artificial agents. This aligns with research in cognitive science showing that regret plays an important role in human learning and decision-making.

One limitation of PRM is the additional computational overhead of maintaining and updating the teacher network. However, this overhead is relatively small compared to the overall training time, and the benefits in convergence speed outweigh the costs.

Future work could explore variations of PRM, such as using different regret formulations or adapting the regret weighting parameter dynamically based on learning progress.

# 7 Conclusion

We have introduced the Psychological Regret Model (PRM), a specific instantiation of a more general step-wise scoring framework to accelerate reinforcement learning convergence through regret-based feedback signals. By incorporating regret signals that compare the value of taken actions with optimal actions at each decision step, PRM transforms sparse rewards into dense feedback signals, enabling more efficient learning.

Our experiments demonstrate that PRM achieves stable performance approximately 36% faster than traditional PPO in the Lunar Lander environment, while achieving superior final performance (300 vs 140 average reward). The approach formalizes human-inspired

counterfactual thinking as a computable regret signal, bridging behavioral economics and reinforcement learning.

The success of PRM suggests that incorporating psychological mechanisms from human cognition can benefit artificial agents, opening new directions for bio-inspired reinforcement learning algorithms. Future work could extend this framework to other domains such as financial trading, autonomous driving, and educational AI, where dense feedback signals could accelerate learning and adaptation.

Furthermore, PRM serves as a building block for "fluid intelligence" systems that enable continual learning: train a base policy offline, freeze the backbone, and use PRM signals to update lightweight adapters (e.g., LoRA) online, enabling a "train once, adapt forever" paradigm. This approach allows for rapid adaptation to new tasks while preserving core competencies.

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