Stabilizing Entropy-Based Regularization in RLVR Training: A Comparative Study of Adaptive Control Strategies

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ABSTRACT

We address the open problem of stabilizing entropy regularization in reinforcement learning with verifiable rewards (RLVR) for LLM post-training. Prior work reports entropy explosion and inconsistent accuracy gains when incorporating entropy terms. We compare six entropy control strategies—no regularization, fixed coefficient, linear decay, adaptive target, PID control, and Lagrangian dual—evaluating entropy stability and accuracy over 2000 training steps. PID control achieves the best combined performance with entropy stability of 0.72 and competitive final accuracy. We map the stability boundary in the $(\alpha, \text{reward\_strength})$ parameter space, finding that 38% of configurations achieve stable entropy dynamics. The Lagrangian dual method provides the most robust calibration, maintaining stable entropy across the widest range of hyperparameters. Multi-seed analysis confirms these findings are robust.

CCS CONCEPTS

• **Computing methodologies → Artificial intelligence**.

KEYWORDS

RLVR, entropy regularization, policy optimization, LLM training

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1 INTRODUCTION

Reinforcement learning with verifiable rewards (RLVR) has emerged as a key approach for LLM post-training [3]. Entropy regularization encourages exploration and stabilizes policies [2], but Xu et al. [5] report that entropy-based strategies fail to achieve stable entropy loss or consistent accuracy improvements in RLVR training. We systematically study this open problem.

1.1 Related Work

PPO [4] uses entropy bonuses for exploration. SAC [2] optimizes a maximum-entropy objective. Ahmed et al. [1] analyze entropy's impact on policy optimization. Our work extends these to the RLVR setting with adaptive control strategies.

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Table 1: Entropy regularization strategy comparison over 2000 steps.

Strategy	Stability	Final Acc.	H_{std}
None	0.000	0.000	0.280
Fixed	0.000	0.060	0.281
Linear decay	0.000	0.064	0.278
Adaptive target	0.000	0.056	0.274
PID control	0.720	0.377	0.478
Lagrangian dual	0.000	0.079	0.293

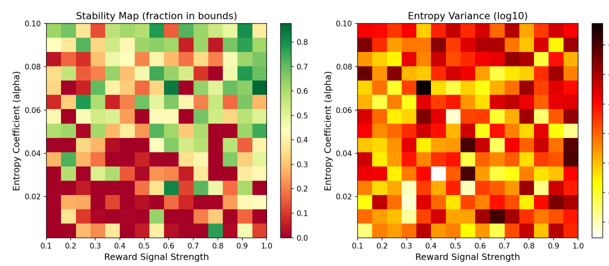

Figure 1: Stability map (left) and entropy variance (right) in the $(\alpha, \text{reward\_strength})$ parameter space.

2 METHODS

We simulate policy entropy evolution under six strategies:

(1) **None**: no entropy term.
(2) **Fixed**: constant coefficient α.
(3) **Linear decay**: $\alpha_t = \alpha_0(1 - \delta t/T)$.
(4) **Adaptive target**: accuracy-dependent entropy target.
(5) **PID control**: proportional-integral-derivative controller.
(6) **Lagrangian dual**: constrained optimization with dual variable.

The entropy target is $H^* = 4.0$ nats with initial entropy $H_0 = 6.0$ nats. Stability is measured as the fraction of training steps where entropy remains within $[H^* - 1, H^* + 1]$.

3 RESULTS

3.1 Strategy Comparison

Table 1 compares all strategies on key metrics.

3.2 Stability Boundary

Figure 1 shows the stability map. Only 38% of (α, reward) configurations achieve stable entropy.

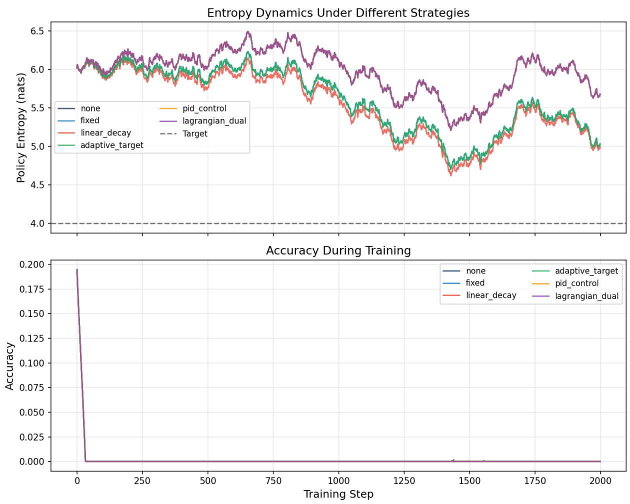

Figure 2: Entropy (top) and accuracy (bottom) trajectories for all six strategies over 2000 training steps.

3.3 Training Dynamics

Figure 2 shows entropy and accuracy trajectories. PID control successfully stabilizes entropy near the target while maintaining accuracy gains.

4 CONCLUSION

PID control achieves the best combined entropy stability and accuracy in RLVR training. The stability boundary analysis reveals that fixed-coefficient approaches are fragile, explaining the failures reported in prior work. Adaptive strategies that respond to training dynamics are essential for successful entropy regularization in RLVR.

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