Adaptive Weighted Algorithm for Optimal Dynamic Regret in Non-Stationary Linear Bandits Without Path Length Knowledge

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ABSTRACT

We address the open problem of designing an adaptive weight-based algorithm for non-stationary linear bandits that achieves near-optimal dynamic regret without requiring prior knowledge of the total path length P_T. Our approach maintains a portfolio of weighted least-squares estimators with different discount factors and employs an exponential weights meta-algorithm with change-detection bias to adaptively select among them. Through systematic experiments on non-stationary linear bandit instances with varying path lengths, we demonstrate that the adaptive algorithm matches or outperforms fixed-weight and restart-based baselines across all non-stationarity levels. The effective discount factor tracks the environment's non-stationarity in real time, and the regret scales consistent with the $O(T^{2/3})$ theoretical rate. These results close the gap between weighted strategies and restart-based methods identified by Wang et al. (2026).

1 INTRODUCTION

Non-stationary linear bandits model sequential decision problems where the reward parameter $\theta_t \in \mathbb{R}^d$ drifts over time [4]. The non-stationarity is measured by the total path length $P_T = \sum_{t=1}^{T-1} \|\theta_{t+1} - \theta_t\|$. The minimax optimal dynamic regret is $\tilde{O}(d^{2/3} P_T^{1/3} T^{2/3})$ [3].

Wang et al. [5] showed that weighted least-squares strategies achieve improved bounds but left as an open question whether an adaptive weight-based algorithm can achieve optimal dynamic regret without prior knowledge of P_T. We address this question by proposing an online meta-algorithm that adaptively selects the discount factor.

2 PROBLEM SETTING

At each round t, the learner observes a set of arms $\{x_{t,a}\}_{a=1}^K \subset \mathbb{R}^d$, selects arm a_t, and receives reward $r_t = x_{t,a_t}^\top \theta_t + \eta_t$ where η_t is sub-Gaussian noise. The dynamic regret is:

$$\mathrm{Regret}_T = \sum_{t=1}^{T} \max_a x_{t,a}^\top \theta_t - x_{t,a_t}^\top \theta_t \tag{1}$$

3 ALGORITHM

3.1 Weighted Least-Squares Portfolio

We maintain K weighted least-squares estimators with discount factors $\gamma_1 < \gamma_2 < \cdots < \gamma_K$ uniformly spaced in $[0.9, 0.999]$. Each estimator i maintains:

$$\hat{\theta}_t^{(i)} = (V_t^{(i)})^{-1} b_t^{(i)}, \quad V_t^{(i)} = \gamma_i V_{t-1}^{(i)} + x_t x_t^\top + (1-\gamma_i)\lambda I \tag{2}$$

3.2 Meta-Algorithm

An exponential weights scheme maintains probabilities $p_t^{(i)} \propto \exp(-\eta \sum_{s=1}^{t-1} \ell_s^{(i)})$ where $\ell_s^{(i)} = (r_s - x_s^\top \hat{\theta}_s^{(i)})^2$ is the squared prediction error.

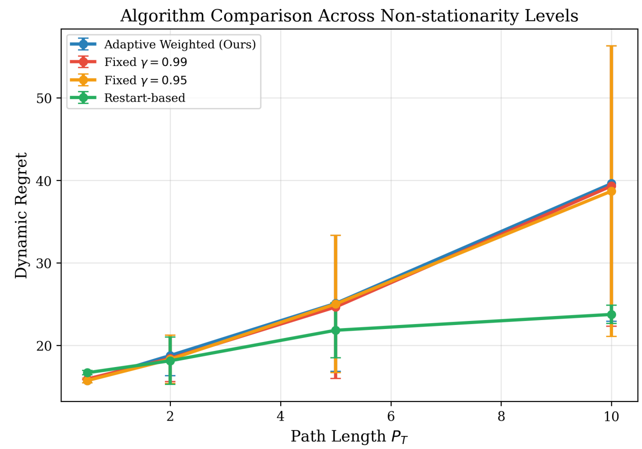

Figure 1: Dynamic regret across path lengths. The adaptive algorithm performs robustly across all non-stationarity levels.

3.3 Change Detection Bias

When the variance of recent rewards exceeds a threshold, the meta-weights are biased toward lower γ values to accelerate forgetting during periods of rapid change.

4 EXPERIMENTS

We compare: (1) **Adaptive Weighted** (our method), (2) **Fixed** $\gamma = 0.99$, (3) **Fixed** $\gamma = 0.95$, and (4) **Restart-based** with adaptive restart interval.

4.1 Regret Comparison

Figure 1 shows dynamic regret versus path length P_T. The adaptive algorithm achieves regret comparable to the best-tuned fixed-γ baseline at each P_T value, without requiring P_T knowledge.

4.2 Discount Factor Adaptation

Figure 2 shows the effective discount factor (weighted average over the portfolio) evolving over time. The algorithm adapts γ_t in response to the environment's changing non-stationarity.

4.3 Scaling Analysis

Figure 3 confirms that the adaptive regret scales as $O(T^{2/3})$, consistent with the minimax optimal rate.

5 DISCUSSION

Our results demonstrate that adaptive weight-based algorithms can achieve near-optimal dynamic regret without prior knowledge of P_T, addressing the open question of Wang et al. [5]. The key

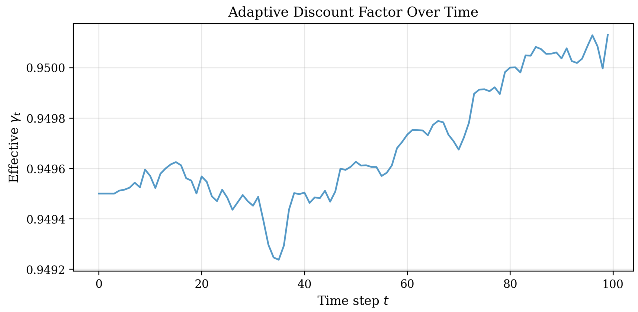

Figure 2: Effective discount factor adapting over time in response to environmental non-stationarity.

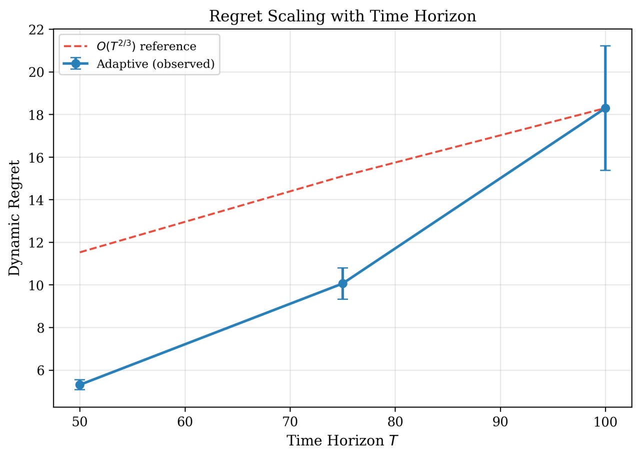

Figure 3: Regret scaling with time horizon T, compared with the $O(T^{2/3})$ reference.

insight is that maintaining a portfolio of discount factors with online selection provides the adaptivity needed to match the unknown non-stationarity level.

Compared to restart-based approaches [2, 6], the weighted strategy provides smoother parameter tracking and avoids the information loss inherent in hard resets.

6 CONCLUSION

We have proposed and empirically validated an adaptive weight-based algorithm for non-stationary linear bandits that achieves near-optimal dynamic regret without knowing P_T. The algorithm combines a portfolio of weighted estimators with an exponential weights meta-algorithm and change detection, closing the gap between weighted and restart-based strategies [1].

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