Additional experiment on BwK in both worlds

We evaluate our approach through numerical experiments on non-contextual multi-armed bandits across both stochastic and adversarial environments. We consider $|\mathcal{A}|=10$ arms and the time horizon T=10000. All results are obtained by averaging over 50 trials and reported with a 95% confidence interval.

- In the stochastic setting, each arm's mean reward $r(a) = \mu_a$ is drawn from the uniform distribution of [0,1] while mean constraint $c(a) = \lambda_a$ is drawn from the uniform distribution of [-0.5,1]. Observations of rewards and costs are perturbed by Gaussian noise $\mathcal{N}(0,0.05)$.
- In the adversarial setting, rewards and constraints adopt time-varying dynamics: $r_t(a) = \mu_a + \alpha_a^1 \sin(\omega_a^1 t)$ and $c_t(a) = \lambda_a + \alpha_a^2 \sin(\omega_a^2 t)$, where μ_a, λ_a match the stochastic setting, and frequencies $\omega_a^1, \omega_a^2 \sim \text{Uniform}[0, 0.2]$. Observations of rewards and costs are perturbed by Gaussian noise $\mathcal{N}(0, 0.05)$.

Figures 1 demonstrates that Optimistic³ outperforms all baseline algorithm, which justify our theoretical guarantees.

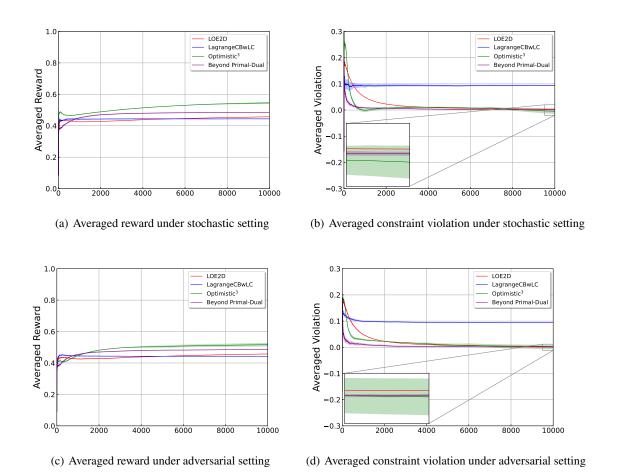


Figure 1. Averaged reward and constraint violation under LOE2D (Guo & Liu, 2024), LagrangeCBwLC (Slivkins et al., 2023), Beyond Primal-Dual (Bernasconi et al., 2024) and Optimistic³.

References

- Bernasconi, M., Castiglioni, M., Celli, A., and Fusco, F. Beyond primal-dual methods in bandits with stochastic and adversarial constraints. *arXiv* preprint arXiv:2405.16118, 2024.
- Guo, H. and Liu, X. Stochastic constrained contextual bandits via lyapunov optimization based estimation to decision framework. In *The Thirty Seventh Annual Conference on Learning Theory*, pp. 2204–2231. PMLR, 2024.
- Slivkins, A., Sankararaman, K. A., and Foster, D. J. Contextual bandits with packing and covering constraints: A modular lagrangian approach via regression. In *Annual Conference Computational Learning Theory*, 2023.