Revisiting Follow-the-Perturbed-Leader with Unbounded Perturbations in Bandit Problems

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Best-of-both-worlds in bandit problems

- A policy that achieves (near) optimal performance in
 - Adversarial bandit: loss is chosen by an adversary.
 - Stochastic bandit: loss is generated from an unknown fixed distribution.
 without knowing the underlying environments.

■ For example, in multi-armed bandits (MAB), goal is to achieve $O(\sqrt{KT})$ adversarial regret $O(\log T)$ stochastic regret

Recent advances in BOBW literature

Follow-the-Regularized-Leader (FTRL)

- Successful framework in BOBW
- Play an arm w.p. $w_t \in \Delta^{K-1}$ $w_t = \operatorname{argmin}_w \{ w^{\mathsf{T}} \hat{L}_t + \Phi(w) / \eta_t \}$
- $\Phi \ge 0$: regularization function
 - Tsallis entropy: BOBW in MAB [Zimmert+2021]
 - Tsallis + Shannon: BOBW in semibandits and graph bandits. [Zimmert+2019, Ito+2022]
- Have to solve optimization problems.

Follow-the-Perturbed-Leader (FTPL)

- Relatively less studied in BOBW
- Play an arm $i_t \in \{1, ..., K\}$ $i_t = \operatorname{argmin}_i \{\hat{L}_{t,i} r_{t,i}/\eta_t\}$
- $r_{t,j} \sim D$: random perturbation
 - Frechet-type: BOBW in MAB
 - Perturbations over $[0, \infty)$. [Honda+2023, Lee+2024]
 - Frechet: BOBW in semi-bandits
 - $O(\log T)$ stochastic regret [Zhan+2025]
- Simple, but limited understanding

Relationship between FTPL and FTRL

- ■When K = 2,* FTRL → FTPL is possible. [Abernethy+2016]
- ■FTRL with Tsallis entropy is successful in BOBW literature.
 - When K = 2, FTRL with Tsallis entropy = FTPL with a Frechet-type perturbation.
 - FTPL with certain Frechet-type can achieve BOBW in MAB.
 - But in general, there may be no FTPL for given FTRL. [Hofbauer+2002]

Can we leverage such relationships to obtain BOBW results of FTPL?

*) Strictly speaking, 1d optimization.

Revisiting perturbations on the real line

Such relationship has been extensively studied for perturbations with support R. [Hofbauer+2002, Feng+2017, Fosgerau+2020]

Hybrid regularizer: sum of Tsallis, Shannon, log-barrier...



- Hybrid perturbations: how to design?
 - Sum of perturbations? Generated from mixed distribution?
 - Need more understanding on FTPL in BOBW literature.

In this paper...

- 1. Extend BOBW to asymmetric Frechet-type perturbations
 - whose support is the real line
 - a bridge between BOBW in bandits and discrete choice theory
 - Include Laplace-Pareto perturbation, a kind of hybrid perturbations.
- 2. If perturbations corresponds to Tsallis entropy exists, it would be <u>symmetric</u> Frechet-type over R! (when K=2)

In this paper...

■Then, can we obtain BOBW result for symmetric Frechet?

3. Partially yes

- $\odot K = 2$: we obtain BOBW results. (as equivalence suggests!)
- $\otimes K \geq 3$: we find a counterexample that current analysis fails.
- Conjecture; there exists an adversary that incurs at least $O(\sqrt{KT \log K})$ regret.

Unbounded, i.i.d. perturbations (online learning literature)

Gumbel

- EXP3
- MNL model
- FTRL with Shannon entropy

- Gaussian
- unbounded hazard
- near-optimal sto. regret(Kim and Tewari, 2019)
- conjectured linear adv. regret(Abernethy et al. 2015)

Bounded hazard function (Abernethy et al., 2015, Kim and Tewari, 2019)

- Gamma, Weibull
- semi-infinite
- near-optimal adv. regret

Fréchet-type perturbation (BOBW literature)

Results in Section 5:

- Symmetric Fréchet-type
- BOBW if K=2
- near-optimal adv. regret (bounded hazard)
- our conjecture for K ≥ 3: cannot be optimal(at most near-optimal)

Our BOBW results (Section 4) - unbounded, asymmetric

- -> connection to discrete choice theory
- Laplace-Pareto
- BOBW
- hybrid-type -> connection to FTRL with hybrid regularizer

Previous BOBW results – semi-infinite

- Fréchet, Pareto
- semi-infinite
- BOBW

(Honda et al. 2023, Lee et al. 2024)