

# Rotting Infinitely Many-Armed Bandits

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# Motivation

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## Infinitely many-armed bandits with rotting rewards

A variant of multi-armed bandits with **infinitely many actions** where the mean reward for a selected action is **decreasing**.

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- Decreasing medicine efficacy from **drug tolerance** in clinical trials

# Related Work

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In our work, we consider **rotting bandits** with **infinitely many arms**.

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## Regret

$$\mathbb{E}[R(T)] = \mathbb{E} \left[ \sum_{t=1}^T (1 - \mu_t(a_t)) \right].$$

# Contributions

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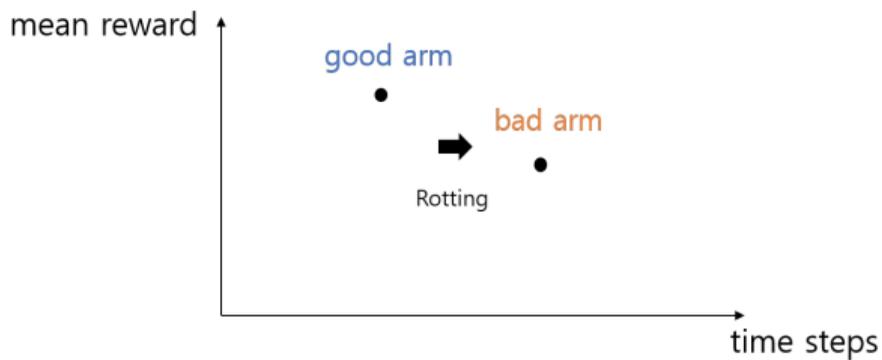
$$\mathbb{E}[R(T)] = \tilde{O}\left(\max\left\{\varrho^{1/3}T, \sqrt{T}\right\}\right).$$

- Without knowing  $\varrho$ , we propose another algorithm achieving

$$\mathbb{E}[R(T)] = \tilde{O}\left(\max\left\{\varrho^{1/3}T, T^{3/4}\right\}\right).$$

# Challenge

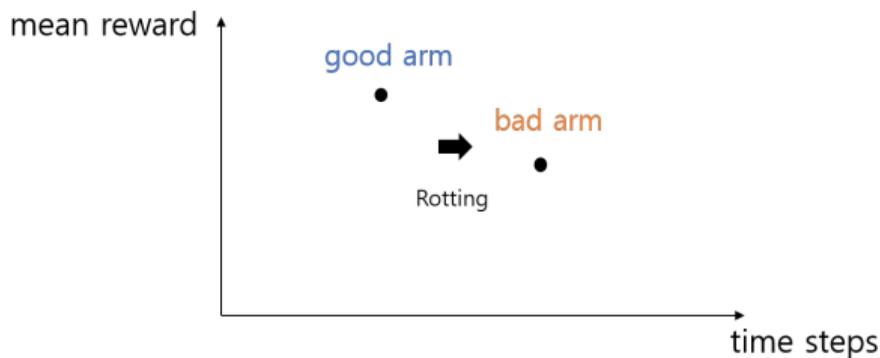
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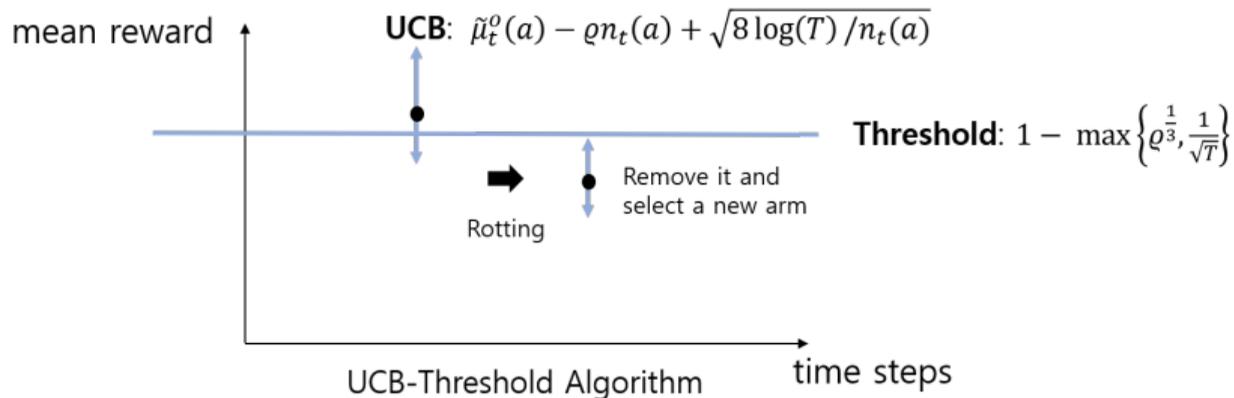
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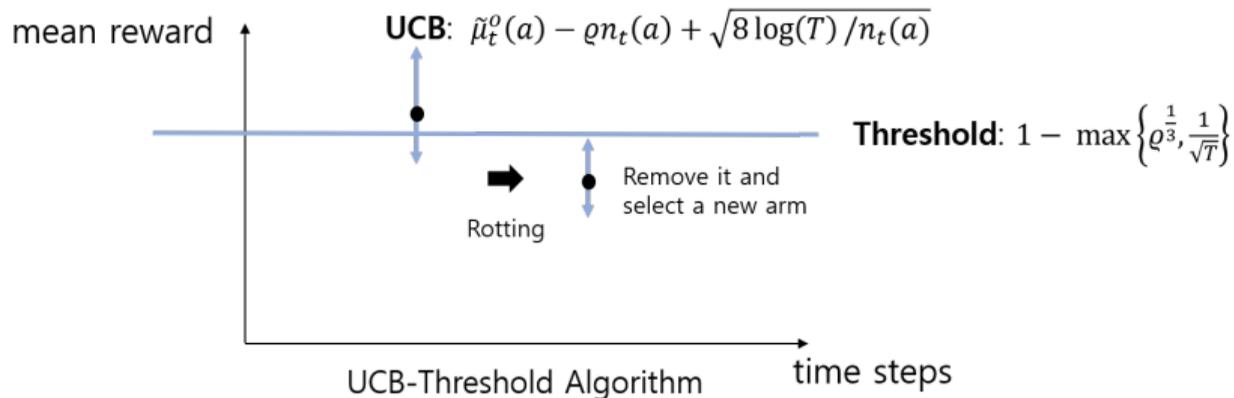
- Due to rotting, an initially good arm can become a bad arm by pulling the arm several times.
- Therefore, even though we found a good arm at some point, it is necessary to continue exploring a new good arm over a time horizon  $T$ .

# Algorithms



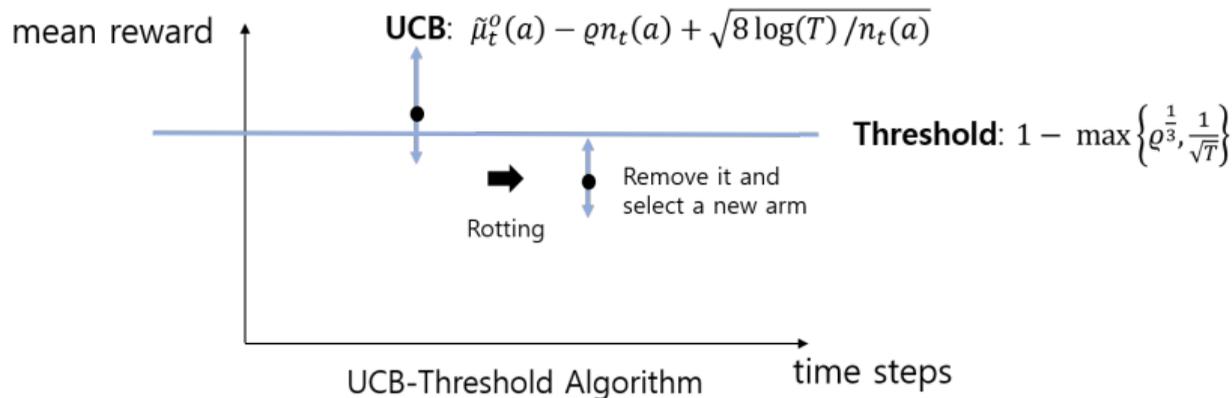
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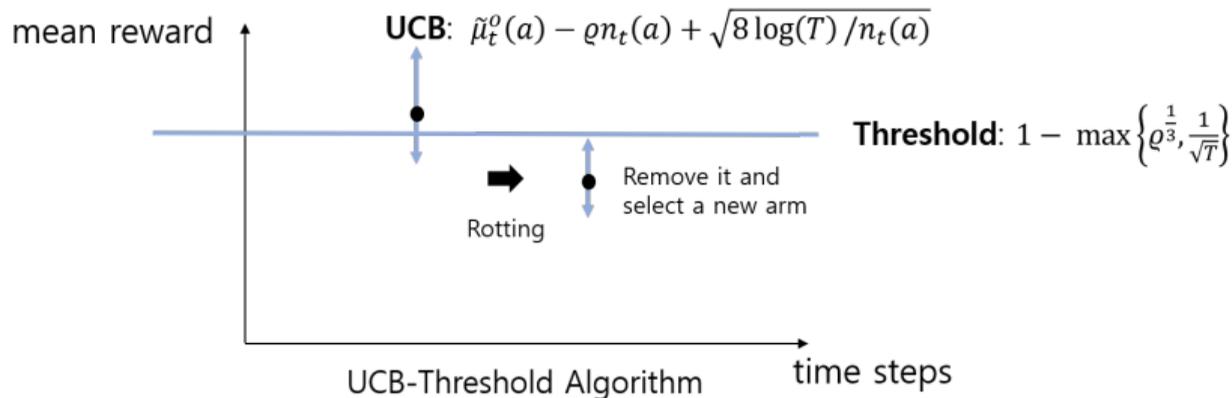
- Our proposed algorithm utilizes **UCB** (upper confidence bound) and **threshold**.
- The algorithm pulls an arm until its UCB value falls below a threshold value, which implies that the arm becomes a bad arm.
- Then, it removes the arm and selects a new arm. Repeat this procedure.

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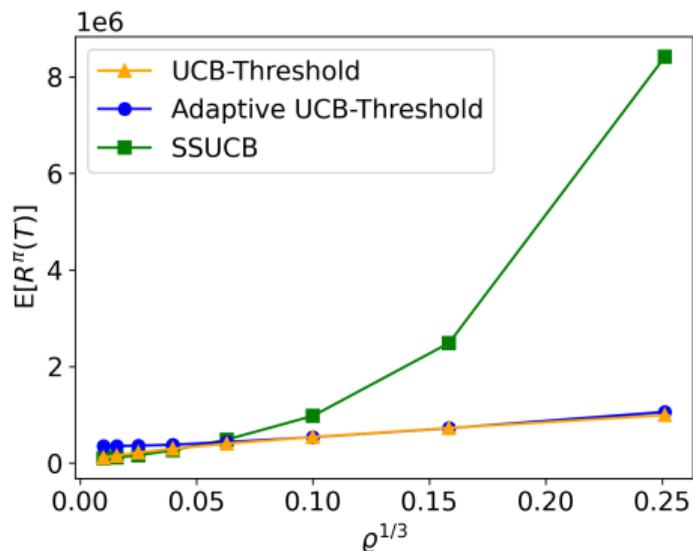
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- Information of  $\varrho$  is used to determine the UCB and threshold.
- Without knowing  $\varrho$ , we propose an adaptive UCB-Threshold algorithm using the Bandit-over-Bandit approach (Cheung et al. 2019).

# Experiment result



- Our algorithms show robust performance by increasing  $\rho$  compared with SSUCB (Bayati et al. 2020), which is known to be near-optimal in a stationary setting.

**Thank you**

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# References

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