Near Optimal Non-asymptotic Sample Complexity of 1-Identification

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INTRODUCTION

Model Setting and Notations

- K: Number of arms.
- δ: Tolerance level of wrong identification
- $\nu = \{\nu_a\}_{a=1}^K$: Reward distribution of arm a
- μ_a: Mean reward of arm $a \in [K]$
  $\Delta_{i,j} = |\mu_i - \mu_j|$, WLOG, $\mu_1 \geq \mu_2 \geq \cdots \geq \mu_K$
- μ_0: Known threshold for comparison
- $\mathcal{S}^{\text{pos}} = \{\nu : \mu_1 > \mu_0\}$, $\mathcal{S}^{\text{neg}} = \{\nu : \mu_1 < \mu_0\}$, For $\Delta > 0$,
  $\mathcal{S}^{\text{pos}}_{\Delta} = \{\nu : \mu_1 - \mu_0 \geq \Delta\}$, $\mathcal{S}^{\text{neg}}_{\Delta} = \{\nu : \mu_0 - \mu_1 \geq \Delta\}$.
- A_t: Action in round t
- X_t: Observed reward in round t
- $H(t) = \{(A_s, X_s)\}_{s=1}^t$: History collected up to time t.

Known Information

- K, μ_0, δ

Unknown Information

- ν_a, μ_a, for all $a \in [K]$

Dynamics and Model Uncertainty

At each round $t = 1, 2, \cdots$, the Decision Maker

1. Pull an arm $A_t \in [K]$, A_t is $\sigma(H(t-1))$-measurable,
2. Receive the outcome $X_t \sim \nu_{A_t}$,
3. Update the history $H(t) = H(t-1) \cup \{(A_t, X_t)\}$

The agent stops at the end of time step τ,
τ is a stopping time with respect to the filtration $\{\sigma(H(t))\}_{t=1}^{\infty}$
Upon stopping, the agent outputs arm $\hat{a} \in [K] \cup \{\text{None}\}$

Definition of PAC Requirement

$i^*(\nu)$:

- $i^*(\nu) = \{a : \mu_a \geq \mu_0\}$, for $\nu \in \mathcal{S}^{\text{pos}}$
- $i^*(\nu) = \{\text{None}\}$, for $\nu \in \mathcal{S}^{\text{neg}}$

δ-PAC:

- A pulling strategy is δ-PAC, if for any $\delta \in (0,1)$, $\nu \in \mathcal{S}^{\text{pos}} \cup \mathcal{S}^{\text{neg}}$, it satisfies $\Pr_\nu(\tau < +\infty, \hat{a} \in i^*(\nu)) > 1 - \delta$.

(Δ, δ)-PAC:

- A pulling strategy is (Δ, δ)-PAC, if it is δ-PAC, and for any $\Delta, \delta > 0$, we have $\sup_{\nu \in \mathcal{S}^{\text{pos}}_{\Delta} \cup \mathcal{S}^{\text{neg}}_{\Delta}} \mathbb{E}_\nu \tau < +\infty$.

Objective: Minimize $\mathbb{E}\tau$

The agent aims to design a (Δ, δ)-PAC pulling strategy $(\pi, \tau, \hat{a})$ that minimizes the *sampling complexity* $\mathbb{E}[\tau]$.

Lit Review

Algorithm	Bound	Opt in pos	Opt in Neg
S-TaS	$\lim_{\delta \to 0} \frac{\mathbb{E}\tau}{\log \frac{1}{\delta}} = \begin{cases} H & \text{pos} \\ H_1^{\text{neg}} & \text{neg} \end{cases}$	√	√
HDoC	$\mathbb{E}\tau \leq \begin{cases} O(H \log \frac{K}{\delta} + H_1 \log\log \frac{1}{\delta} + \frac{K}{\epsilon^2}) & \text{pos} \\ O(H_1^{\text{neg}} \log \frac{K}{\delta} + \frac{K}{\epsilon^2}) & \text{neg} \end{cases}$	×	×
APGAI	$\mathbb{E}\tau \leq \begin{cases} O(H_0(\log \frac{K}{\delta})) & \text{pos} \\ O(H_1^{\text{neg}}(\log \frac{K}{\delta})) & \text{neg} \end{cases}$	×	√
SEE (*)	$\mathbb{E}\tau \leq \begin{cases} O(H \log \frac{1}{\delta}) + O(H_1^{\text{pos}} \log \frac{K}{\Delta_{0,1}}) & \text{pos} \\ O(H_1^{\text{neg}}(\log \frac{1}{\delta} + \log H_1^{\text{neg}})) & \text{neg} \end{cases}$	√	√
Lower Bound (*)	$\mathbb{E}\tau \geq \begin{cases} \Omega(H \log \frac{1}{\delta} + \frac{1}{m} H_1^{\text{low}} - \frac{1}{\Delta_{1,m+1}^2}) & \text{pos} \\ \Omega(H_1^{\text{neg}} \log \frac{1}{\delta}) & \text{neg} \end{cases}$	NA	NA

(*) denotes the result is from this paper

Extra Comments

- S-TaS(Degenne & Koolen 2019): only achieves asympttotic optimality
- HDoC(Kano et.al 2018), APGAI(Jourdan et.al2023) are not (Δ, δ)-PAC
  - Two-armed instance
  - Arm 1 Gaussian, $\mu_1 > \mu_0$, Arm 2 Constant, $\mu_2 = \mu_0$
  - $\text{UCB}_1 < \mu_0$ holds with non-zero prob, then HDoC and APGAI will never stop
- SEE is nearly optimal
  - $\nu \in \mathcal{S}^{\text{neg}}$, all the arms are below μ_0
  - Only one arm is above μ_0
- For SEE, If $\nu \in \mathcal{S}^{\text{pos}}$, coefficient of $\log \frac{1}{\delta}$ is independent of arm number K

Algorithm

Sequential Exploration Exploitation (Informal)

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procedure SEE(Input: Action set $[K]$, threshold $\mu_0$, tolerance level $\delta$, $C > 1$).
    Tune $\{\delta_k, T_k^{\text{et}}, T_k^{\text{ee}}\}_{k=1}^{+\infty}$.
    for Phase $k = 1, 2, \cdots$ do
        (Exploration) Run algorithm LUCB_G with tolerance level $\delta_k$ and previous exploration history.
        Stops until one of the two conditions holds.
        • Total pulling times in all exploration phases is not greater than $T_k^{\text{ee}}$.
        Take $\hat{a}_k = \text{Not Complete}$.
        • LUCB_G stops and output $\hat{a}_k \in [K] \cup \{\text{None}\}$.
        if $\hat{a}_k \in [K]$ then
            (Exploitation) Keep pulling arm $\hat{a}_k$ with independent samples
            Stops until one of the two conditions holds.
            • Pulling times of $\hat{a}_k$ is not smaller than $T_k^{\text{et}}$.
            • LCB defined by $\delta$ is above $\mu_0$, output $\hat{a}_k$ as a qualified arm
        else if $\hat{a}_k = \text{None}$ and $\delta_k < \frac{\delta}{3}$ then
            Output the instance is negative
        end if
    end for
    return $x$
end procedure
```

Notation on Complexity

$$H_1^{\text{neg}} = \sum_{a=1}^{K} \frac{2}{\Delta_{0,a}^2}, H_1^{\text{low}} = \sum_{a:\mu_a<\mu_0} \frac{2}{\Delta_{1,a}^2},$$

$$H_1^{\text{pos}} = \sum_{a=1}^{K} \frac{2}{\max\{\Delta_{0,a}^2, \Delta_{1,a}^2\}}, H = \frac{2}{\Delta_{0,1}^2}$$

$$H_1 = \sum_{a=2}^{K} \frac{2}{\Delta_{1,a}^2}, H_0 = \sum_{a:\mu_a \geq \mu_0} \frac{2}{\Delta_{0,a}^2},$$

$$H_1^{\text{BAI}} = \frac{2}{\Delta_{0,1}^2} + \sum_{a=2}^{K} \frac{2}{\Delta_{1,a}^2}.$$

Key Ideas Behind the Algorithm

Property of LUCB_G

- LUCB_G is an adapted BAI alg
  - Pull arms with highest UCB
  - Return an arm whose LCB is greater than μ_0
- Take $\delta' \in (0,1)$ as input for LUCB_G.
  Conditioned on event holds with prob $1 - O(\delta')$, LUCB_G
  - return $\mu_{\hat{a}} > \mu_0$ with pulling times $O(H_1^{\text{pos}}(\log \frac{1}{\delta'} + \log H_1^{\text{pos}}))$
  - return None, with pulling times $O(H_1^{\text{neg}}(\log \frac{1}{\delta'} + \log H_1^{\text{neg}})$
- Take $\delta' \in (0,1)$ as input for LUCB.
  If the event doesn't hold, LUCB might never stop

Conduct Exploration

- Call LUCB_G for exploration, decreasing $\{\delta_k\}_{k=1}^{+\infty}$ as tolerance level for each phase
- Since it might get stuck in a non-stopping loop, set up maximum pulling tiems T_k^{ee}

Conduct Exploitation, if $\hat{a}_k \in [K]$

- Keep pulling $\hat{a}_k$ with new samples
- Output $\hat{a}_k$ if its $\text{LCB}(\delta) > \mu_0$

Accept $\hat{a}_k = \text{None}$

- Only when $\delta_k = \Theta(\delta)$
- Inspired by Degenne & Koolen 2019, negative instance is similar to Best Arm Identification

Numeric Settings

Benchmark Algorithms

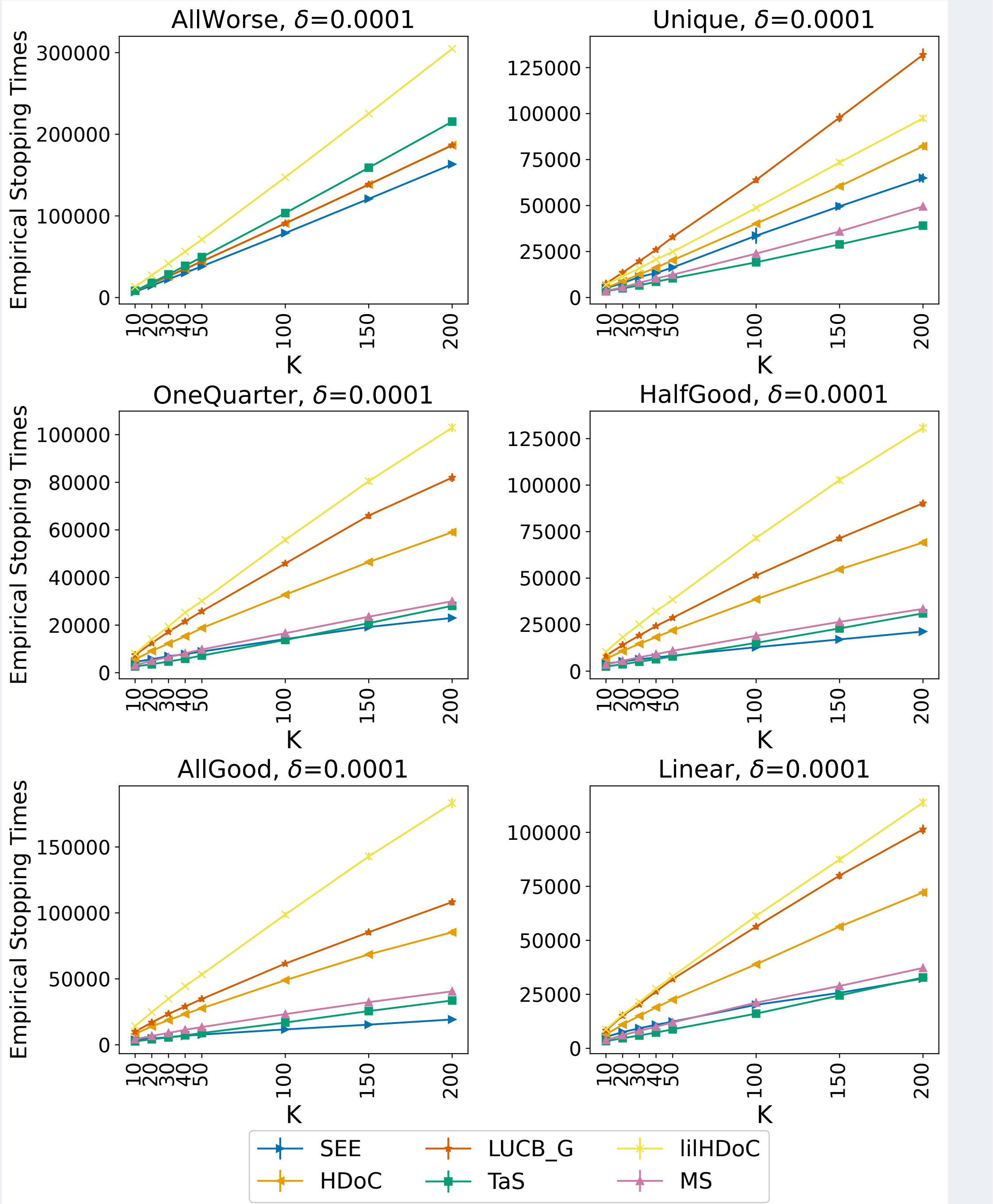
- Adapted Murphy Sampling (Kaufmann et.al 2018)
- Adapted Track and Stop (Garivier & Kaufmann 2016)
- HDoC, LUCB_G (Kano et.al 2018)
- lilHDoC (Tsai et.al 2024)

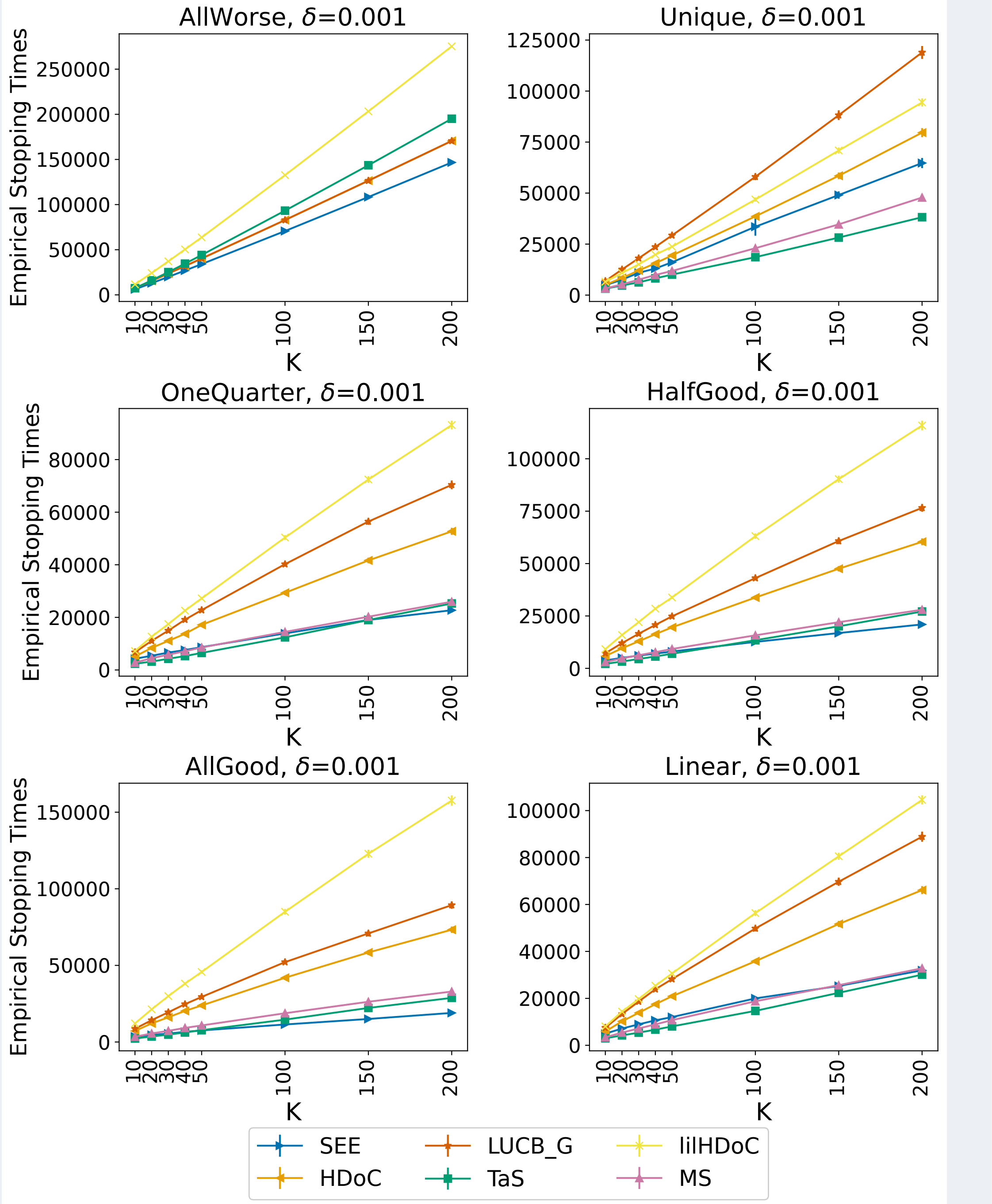
Instance Setting

- All the mean rewards are below μ_0
- Fraction of Qualified Arms (100%, 50%, 25%, Unique)
- Linear reward vector

Numeric Experiments

Numeric Experiments


AllWorse, δ=0.0001
Unique, δ=0.0001
OneQuarter, δ=0.0001
HalfGood, δ=0.0001
AllGood, δ=0.0001
Linear, δ=0.0001
Empirical Stopping Times
K
SEE
HDoC
LUCB_G
TaS
lilHDoC
MS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