Competing Bandits in Non-Stationary Matching Markets

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Joint work with

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Outline

- Matching Markets—a Multi Agent Multi-Armed Bandit formulation

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- Competition—Collision—Resolution of conflicts

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- Matching Markets—a Multi Agent Multi-Armed Bandit formulation
- Competition—Collision—Resolution of conflicts
- Dynamic (Non-Stationary) Markets
  - Algorithm for Non-Stationary Matching Markets
  - Insights for 2 agents
  - Analysis: Theoretical and Empirical

Matching Markets

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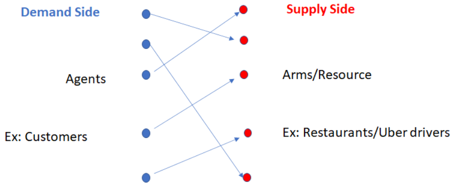
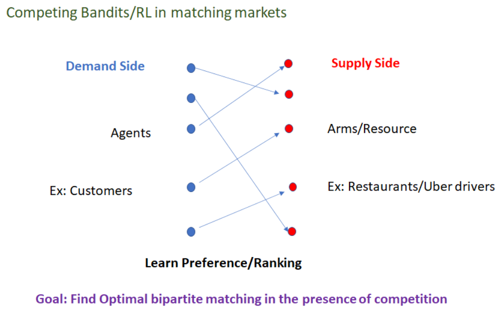
Competing Bandits/RL in matching markets



Learn Preference/Ranking

Goal: Find Optimal bipartite matching in the presence of competition

Matching Markets



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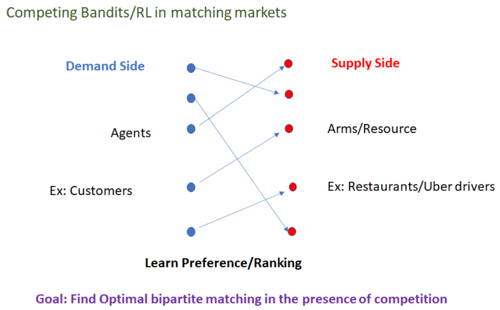

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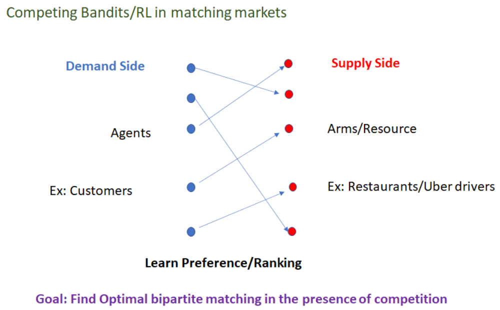
- Motivated by applications in Labor Market (ex. TaskRabbit, Upwork)
- College Admissions (classical motivation, Gale and Shapley, 1962)
- Matching medical interns/residents Dai and Jordan, 2021
- Objective: Match Demand to the Supply side

Matching Markets contd.



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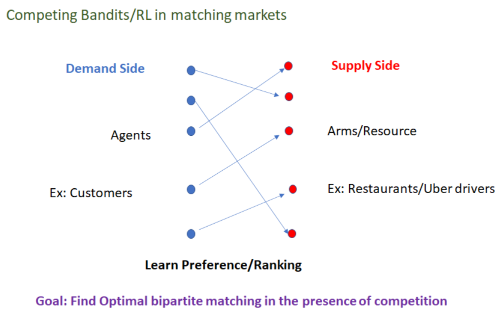

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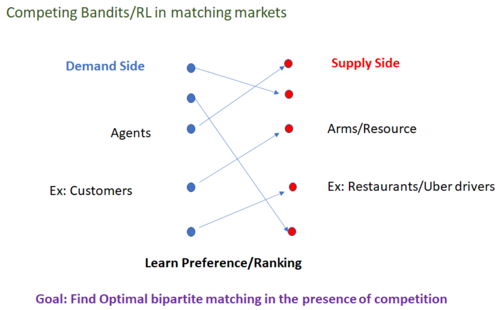

- ♣ Each Agent has a preference over Arms
- ♣ Each Arm has preference over Agents
- ♣ If these preferences were known, a simple solution is Gale Shapley stable matching algorithm.
- ♣ However, we don't know these preferences—learn them via successive interactions between Agents and Arms

Model via Bandits framework

Model via Bandits framework

- Preference modeling via Bandits framework
- We consider N agents and K arms
  - When Agent i pulls arm j–receives a random reward with mean $\mu_{i,j}$
  - Agent i's preference—ordering of the arm means $\{\mu_{i,1}, \mu_{i,2}, \ldots, \mu_{i,k}\}$
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♣ Solving multi-agent multi armed Bandit problem is equivalent to learning preferences

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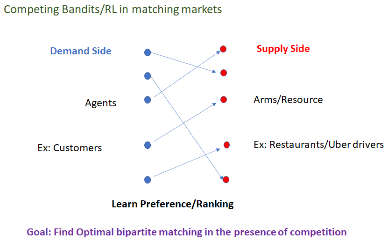
♣ Caveat: There is competition in the system—2 or more agents may go for one arm—need to resolve collision/conflicts

One sided Learning and Conflict Resolution



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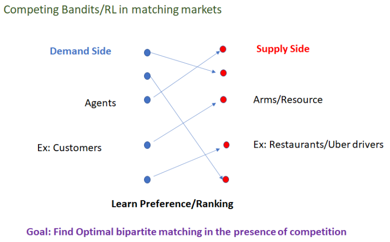

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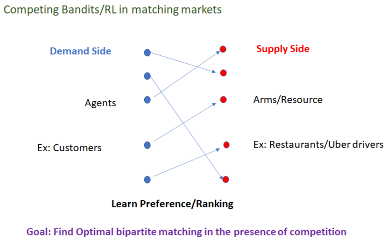

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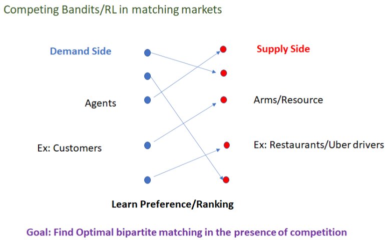

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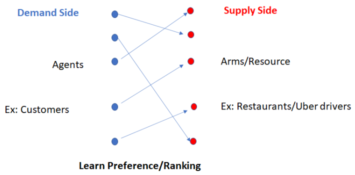
♣ Collision/Competition More than one agents pull same arm–Collision

♣ Reward is given to the Agent with highest rank among the competitors

♣ All other Agents receive 0 reward

Even Simpler model–Serial Dictatorship

Competing Bandits/RL in matching markets



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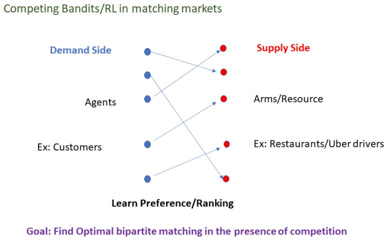

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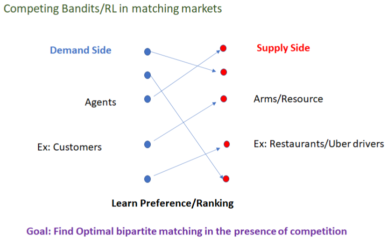

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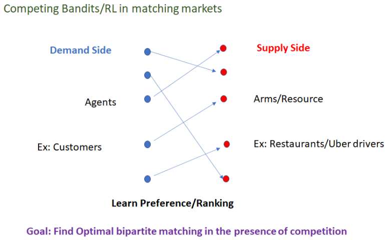

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♣ Under Serial Dictatorship, the matching between Agents and Arms is unique—provides a reference point to characterize Regret

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- Let $L^{(j)}$ be the arm played by an algorithm $\mathbb{A}$.
- Regret of agent j playing $\mathbb{A}$ is

$$R_j = \sum_{t=1}^{T} \mathbb{E}\left[\mu_{j,\ell_*^{(j)}} - \mu_{j,L^{(j)}} (\mathbf{1}_{L^{(j)} \text{matched player } j})\right]$$

UCB based algorithms

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- ♣ With this, regret of $\mathcal{O}(jK \log T)$ is obtained for j-th ranked agent

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- ♣ Assume one sided learning
- ♠ ETGS (Explore-then-Gale-Shapley) by Kong et. al, SODA 23
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♣ We take a step towards bridging the two aforementioned lines of work

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♣ We use smooth varying framework of Wei and Srivastaba '18, Krishnamurthy and Gopalan '21)

- ♣ $|\mu_{.,.,t+1} - \mu_{.,.,t}| \leqslant \delta$ for all agent arm pairs

♣ Maximum drift is δ

♣ Useful in cloud computing, financial applications–decisions in seconds, distribution changes slowly

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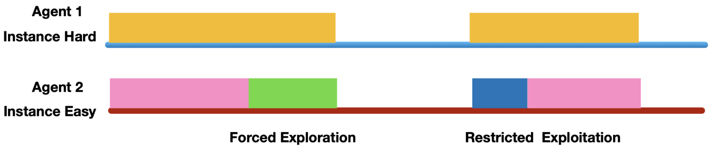

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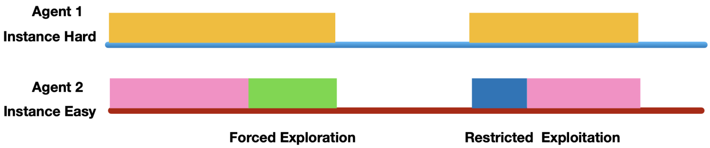

◀ Agent 2 will face additional regret. We characterize this regret.

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♠ Let us now look at the simplest non-trivial problem with $N=2$ agents

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- ♣ Agent 1–highest ranked, faces no collision
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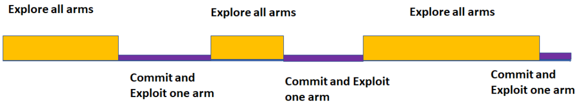

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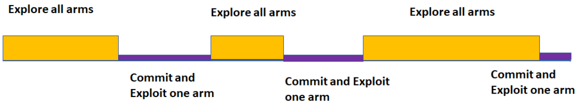

♣ Since arm means are changing, best arm is changing, so Agent 1 Explore and Commits successively over time.

◀ No market aspect, no competition

NSCB for Agent 1 contd.

- Epoch based–$s_1, s_2, ..$ denote starting of epoch
- In 1 epoch: Round robbin to find an *optimal* arm followed by exploiting that arm
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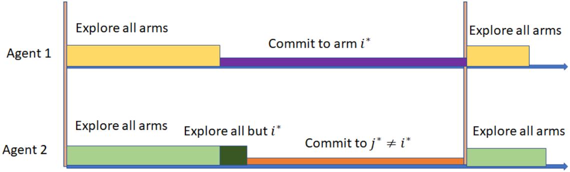

Scenario 1

Scenario 2

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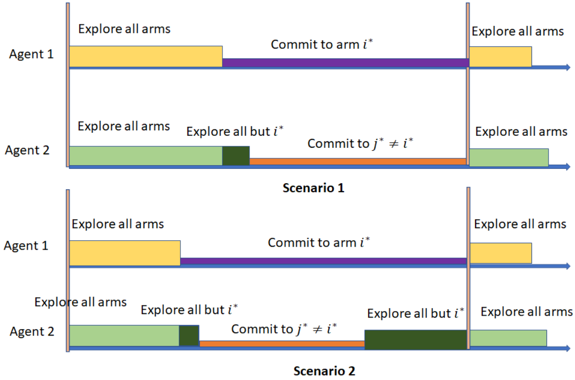

- (Domination 1) Restricted Exploration
- (Domination 2) Commitment to a dominated set of arms

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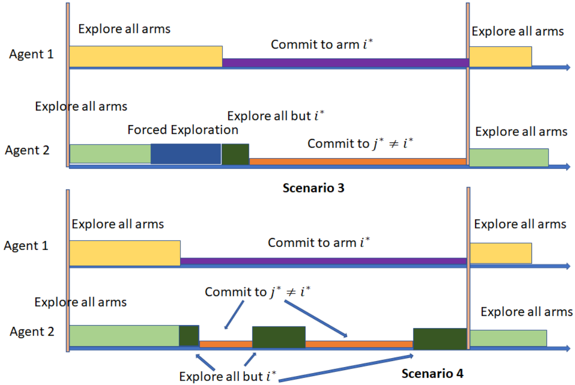

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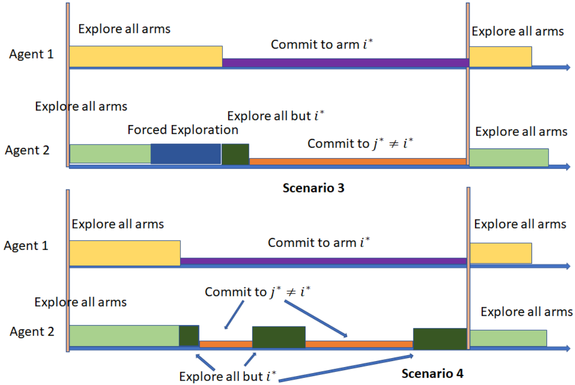

- (Domination 3) Forced Exploration
- (Domination 4) Restricted Exploitation

NSCB for Agent 2 contd.

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Algorithm 2 NSCB with $N = 2$; for Agent 2

Initialize set of tuples $S_2^{(j)} = \phi, \forall\, j \in [k]$, episode index $i_2 \leftarrow 1$
for $t = 1, 2, \ldots, T$ **do**
  Pull-Arm by Agent 2:
  if Agent 1 is not committed **then**
    Play round robbin on $[k]$ (pull arm $t + 1 \,\%\, k$), set $z_t(2) \leftarrow$Explore ALL
  else if Agent 1 is committed to arm j and $S_2^{(j)} = \phi$ **then**
    Play round robbin on $[k] \setminus \{j\}$ (i.e., pull arm index $t\%(k-1)$-th smallest arm id in $[k] \setminus \{j\}$)
    $z_t(2) \leftarrow$Explore-j
  else if Agent 1 is committed to arm j, and $\exists (x, s) \in S_2^{(j)}$ s.t. $s > t$ **then**
    Play arm x; set $z_t(2) \leftarrow$Exploit
  end if
  if $\{z_t(1) \neq z_{t-1}(1)\}$ OR $\{z_t(2) \neq z_{t-1}(2)\}$ **then**
    $i_2 \leftarrow i_2 + 1$, $t_{i_2} \leftarrow t$
  end if
  Test by Agent 2:
  for $j \in [k]$ s.t. $z_t(2) \in$ {Explore-j, Explore ALL} **do**
    if Arm a = Lambda-Opt $(\tilde{\lambda}, [k] \setminus \{j\})$ **then**
      $\tau_{i_2}^{(j)} \leftarrow t - t_{i_2}$, $\text{buffer}_2 = \max\left(\frac{8}{\delta}\sqrt{(k-1)\log T/\tau_{i_2}^{(j)}} - 2(k-2), 0\right)$
      if $\text{buffer}_2 > \tau_{i_2}^{(j)}$ **then**
        $S_2^{(j)} \leftarrow S_2^{(j)} \cup \{(a, \min\{t_{i_2} + \text{buffer}_2, s_{i_1+1})\}$
      end if
    end if
end for

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- Average gap between the pairwise arm-means over a window

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For $\mathcal{C} \subseteq [k]$, the dynamic gap of Agent r on a dominated set $\mathcal{C}$ as,

$$\lambda_t^{\mathcal{C}}[r] = \max_{\lambda \in [0,1]} \left\{ \min_{\substack{a,b \in [k] \setminus \mathcal{C} \\ a \neq b}} \frac{1}{w(\lambda)} \left| \sum_{t'=s}^{t} \mu_{r,a,t'} - \mu_{r,b,t'} \right| \geqslant \lambda \right\},$$

and if such a λ does not exist, we set $\lambda_t^{\mathcal{C}}[r] = c_1 \sqrt{\frac{\log T}{t}}$. Here, $s = t - w(\lambda) + 1$, and $w(\lambda) = \frac{c_0 (k - |\mathcal{C}|) \log T}{\lambda^2}$.

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- No superscript when $\mathcal{C} = \phi$
- When $\delta = 0$, reduced to the usual gap in MAB
- Generalization of the standard gap

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Theorem: Suppose we run `NSCB` with 2 Agents upto horizon T. Then the expected regret for Agent 1 is

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and for Agent 2 is

$$R_2 \lesssim \sum_{l=1}^{m} \left[\left(\frac{1}{\lambda_{\min,l}[2]} + \frac{1}{(\lambda_{\min,l}[1])^2} + \frac{1}{\min_a \lambda_{\min,l}^{\{a\}}[2]} \right) k \log T \right]$$

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- T is divided into m blocks with length $\delta^{-2/3} k^{1/3} \log^{1/3} T$
- $\lambda_{\min,l}[r] = \min_{t \in l\text{-th block}} \lambda_t[r]$, $\lambda^{\{a\}}_{\min,l}[r] = \min_{t \in l\text{-th block}} \lambda^{\{a\}}_t[r]$

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- Regret matches that of UCB-D3 in stationary setup by putting $\delta = 0$. We get a regret of $\mathcal{O}(\frac{1}{\mathsf{Gap}^2} k \log T)$

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♣ When Agent r commits to an arm, it updates the blackboard by the arm index and the committed period

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Algorithm 3 NSCB for r-th Agent

Input: Horizon T, drift limit δ

Initialize $S_r^{(\Omega)} = \phi$ for all $\Omega \subseteq [k]$, and $|\Omega| \leq r-1$, Initialize $i_r \leftarrow 1$, $\mathcal{C}_1(r) = \phi$

RANK ESTIMATION()

for $t = 1, 2, \ldots, T$ **do**

Update State $z_t(r)$**:**

if $|\mathcal{C}_t(r)| < r-1$ **then**

$z_t(r) \leftarrow \texttt{Explore} - \mathcal{C}_t(r)$

else if $\exists (x, s) \in S_r^{(\mathcal{C}_t(r))}$ s.t. $s > t$, **then**

$z_t(r) \leftarrow \texttt{Exploit}(x)$

else

$z_t(r) \leftarrow \texttt{Explore} - \mathcal{C}_t(r)$

end if

if $z_t(r) \neq z_{t-1}(r)$ **then**

$i_r \leftarrow i_r + 1, \;\; t_{i_r} \leftarrow t$

end if

Pull-Arm by Agent r:

if $z_t = \texttt{Explore} - \mathcal{C}_t(r)$ **then**

Play round robbin with $[k] \setminus \mathcal{C}_t(r)$ (i.e., pull $t + (r - |\mathcal{C}_t(r)| - 1)\%(k - |\mathcal{C}_t(r)|)$ smallest arm in $[k] \setminus \mathcal{C}_t(r)$)

else if $z_t = \texttt{Exploit}(x)$ **then**

Play arm x

end if

Test by Agent r**:**

for $\Omega \subseteq [k]$ s.t. $|\Omega| = r-1$ and $z_t(r) = \texttt{Explore-}\mathcal{C}_t(r)$ **do**

if Arm a = Lambda-Opt $(\tilde{\lambda}, [k] \setminus \Omega)$ **then**

$\tau_{i_r}^{(\Omega)} \leftarrow t - t_{i_r}$, $\text{buffer}_r = \max\left(\frac{8}{\delta}\sqrt{(k - |\mathcal{C}_t(r)|)\frac{\log T}{\tau_{i_r}^{(\Omega)}}} - 2(k-r), 0\right)$,

define $\bar{t}_{i_r} = \min\{t_{i_r} + \text{buffer}_{i_r}, t_{i_{r-1}+1}\}$

if $\text{buffer}_{i_r} > \tau_{i_r}$, **then** $S_r^{\Omega} \leftarrow S_r^{\Omega} \cup \{(a, \bar{t}_{i_r})\}$,

else $i_{i_r} \leftarrow i_r + 1, t_{i_r} \leftarrow t$

end if

end if

end for

Updates Black Board:

if $\exists (x, s)$ s.t. $s \geq t+1$, **then** write $(x, \bar{t}_{i_r}, r)$ on the black board **end if**

Updates Dominated set $\mathcal{C}_{t+1}(r)$**:**

Updates $\mathcal{C}_{t+1}(r) = \{x \in [k] : \exists s > t+1$, and $\exists j \leq r-1$ *s.t.* (x, s, j) exists on board$\}$

end if

end for

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♣ Agent r is dominated by Agents $1, \ldots, r-1$–captured in gap def.

♣ Regret of Agent r depends on all the agents $1, \ldots, r-1$

♣ Similar to the 2 Agent case, the first term comes from Exploring all arms, and the second term comes from forced exploration and restricted exploitation.

Learning without Blackboard; $N = 2$

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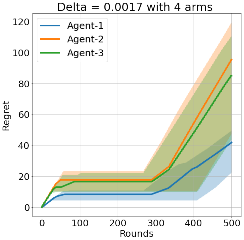
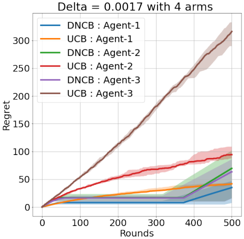
♣ Same idea can be extended to the N Agent setup

Simulations

♣ Consider 3 Agents $N = 3$, 4 Arms $K = 4$



♣ Compare with Dominated UCB of Sankararaman et. al'21



♣ Dominated UCB is for static market–hence large regret

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♣ All works in this framework consider one sided learning to resolve conflict—the two sided learning problem in decentralized framework is still open

♣ Recent Work: Two-Sided Bandit Learning in Fully-Decentralized Matching Markets; Tejas Pagare, Avishek Ghosh, 2023 (short version ICML 2023 Workshop on Preference Learning, Full version under review)

♣ Spurious Markets: Handling adversaries amidst competition?

♣ Structured Markets: Linear/Contextual Bandits?

Reference

♣ Two-Sided Bandit Learning in Fully-Decentralized Matching Markets; Tejas Pagare and Avishek Ghosh – International Conference on Machine Learning (ICML) Workshop on Many Facets of Preference-Based Learning, Hawaii, 2023

♣ Decentralized Competing Bandits In Non-Stationary Matching Markets – Avishek Ghosh, Abishek Sankararaman, Kannan Ramchandran, Tara Javidi and Arya Mazumdar– IEEE Transactions on Information Theory, 2023

Reference contd.

♣ Two-Sided Bandit Learning in Fully-Decentralized Matching Markets; Tejas Pagare and Avishek Ghosh – available at https://tejassp2002.github.io/assets/pdf/MFPL_Workshop_ICML_Tejas_Avishek.pdf

♣ Decentralized Competing Bandits In Non-Stationary Matching Markets – Avishek Ghosh, Abishek Sankararaman, Kannan Ramchandran, Tara Javidi and Arya Mazumdar– available at https://arxiv.org/pdf/2206.00120.pdf

Thank You