## Coordination without communication in two players multi-armed bandits

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## Stochastic three-armed bandits

- Let $T \geq 1$ fixed, and let $\mathbf{p}=\left(p_{1}, p_{2}, p_{3}\right) \in[0,1]^{3}$ be unknown from the player.
- Loss functions: let $\left(\ell_{t}(i)\right)_{1 \leq i \leq 3,1 \leq t \leq T}$ be independent variables with

$$
\mathbb{P}\left(\ell_{t}(i)=0\right)=1-p_{i} \quad \text { and } \quad \mathbb{P}\left(\ell_{t}(i)=1\right)=p_{i} .
$$

- At each step $t$, the player chooses an arm $i_{t}$ and receives the loss $\ell_{t}\left(i_{t}\right)$.
- Regret: $R_{T}=\left(\sum_{t=1}^{T} \ell_{t}\left(i_{t}\right)\right)-\mathbf{p}^{*} T$, where $\mathbf{p}^{*}=\min \left(p_{1}, p_{2}, p_{3}\right)$.
- Goal: find a strategy for which $\max _{\mathbf{p}} \mathbb{E}\left[R_{T}\right]$ is small.


## Stochastic three-armed bandits

- Motivations: clinical trials, online advertising...
- Two settings:
- Full information: at time $t$, the player observes $\left(\ell_{t}(1), \ell_{t}(2), \ell_{t}(3)\right)$.
- Bandits: at time $t$, the player only observes $\ell_{t}\left(i_{t}\right)$.
- In both settings, the minimax expected regret is of order $\sqrt{T}$ :
- If $\left|p_{1}-p_{2}\right| \approx \frac{1}{\sqrt{T}}$, difficult to distinguish the best arm with $T$ observations.
- Full information strategy: follow the best arm.
- Bandit strategy: explore everything at the beginning, discard an arm when it is significantly behind others.
- Again: $T \geq 1$, a vector $\mathbf{p}=\left(p_{1}, p_{2}, p_{3}\right)$ and $\ell_{t}(i)$ are independent Bernoulli with parameter $p_{i}$.
- Two players $A$ and $B$. At time $t$, player $A$ (resp. $B$ ) picks arm $i_{t}^{A}$ (resp. $i_{t}^{B}$ ), with no communication between players.
- Collisions are penalized: player $A$ (resp. $B$ ) observes the loss:

$$
\mathbb{1}_{i_{t}^{A}=i_{t}^{B}}+\mathbb{1}_{i_{t}^{A} \neq i_{t}^{B}} \ell_{t}\left(i_{t}^{A}\right) \quad\left(\text { resp. } \ell_{t}\left(i_{t}^{B}\right)\right) .
$$

- Regret:

$$
R_{T}=\sum_{t=1}^{T}\left(2 \cdot \mathbb{1}_{i_{t}^{A}=i_{t}^{B}}+\mathbb{1}_{i_{t}^{A} \neq i_{t}^{B}}\left(\ell_{t}\left(i_{t}^{A}\right)+\ell_{t}\left(i_{t}^{B}\right)\right)\right)-\mathbf{p}^{*} T
$$

$$
\text { where } \mathbf{p}^{*}=\min \left(p_{1}+p_{2}, p_{2}+p_{3}, p_{3}+p_{1}\right)
$$

- Again, we want to minimise $\max _{\mathbf{p}} \mathbb{E}\left[R_{T}\right]$.
- Motivations:
- Situations where gains on an arm have to be "shared" between the players who played this arm.
- Cognitive radios (finding available channels).
- Naive algorithms:
- A plays the best arms and $B$ the second best? But then what if $p_{1}=p_{2} \ll p_{3}$ ?
- A plays preferably arm 1 and $B$ plays preferably arm 3? Then what if $p_{2} \ll p_{1}=p_{3}$ ?


## Bounds on the minimax regret

- Some of the previous works:
- Regret $\widetilde{O}(\sqrt{T})$ for $p_{1}, p_{2}, p_{3}$ bounded away from 1 [Lugosi-Mehrabian 2018] ( $m$ players, $k$ arms, stochastic).
- Regret $\widetilde{O}\left(T^{3 / 4}\right)$ [Bubeck-Li-Peres-Sellke 2019] (2 players, $k$ arms, works for adversarial bandits).
- Both "cheat" by using collisions as an implicit form of communication.


## Theorem (Bubeck-B. 2020)

There is a randomized strategy (using shared randomness) such that

$$
\max _{\mathbf{p}} \mathbb{E}\left[R_{T}\right]=O(\sqrt{T \log T})
$$

and

$$
\mathbb{P}(\text { there is at least one collision })=o(1) .
$$

## A full-information toy model

- To isolate the problem of collisions from the usual exploration vs exploitation trade-off, we look at a full information toy model:
- $\operatorname{Fix} \mathbf{p}=\left(p_{1}, p_{2}, p_{3}\right) \in[0,1]^{3}$.
- $\left(\ell_{t}^{A}(i), \ell_{t}^{B}(i)\right)_{1 \leq i \leq 3,1 \leq t \leq T}$ are independent Bernoulli with parameter $p_{i}$.
- At time $t$, player $A$ picks $i_{t}^{A}$ and observes $\left(\ell_{t}^{A}(1), \ell_{t}^{A}(2), \ell_{t}^{A}(3)\right)$ (even if there is a collision), and similarly for $B$.
- Regret computed as in the 2-player bandit model.
- No way to use collisions to communicate!


## Theorem (Bubeck-B. 2020)

In the full-information toy model, the minimax expected regret is at least $c \sqrt{T \log T}$.

## Why not $\sqrt{T}$ ? A topological obstruction

- We represent the set of possible $\mathbf{p}$ (restricted to the plane $\left.\left\{p_{1}+p_{2}+p_{3}=\frac{3}{2}\right\}\right)$.
$\{1,2\}$ are the best arms

$$
\{2,3\}
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\begin{aligned}
& i^{A}=1 \\
& i^{B}=2
\end{aligned}
$$

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$\{1,2\}$ are the best arms $\quad \begin{aligned} & i^{A}=2 \\ & i^{B}=1\end{aligned}$
$\begin{array}{ll}i^{A}=1 \\ i^{B}=2\end{array}$
$\begin{array}{ll}\left(\frac{1}{2}, \frac{1}{2}, \frac{1}{2}\right) \\ \{2,3\} & i^{A}=3 \\ i^{B}=2\end{array}$


## Why not $\sqrt{T}$ ? A topological obstruction

- Topological obstruction: it is not possible to always play what seems best.
- To fix this:
- either take the risk of a collision in the $\{1,2\}$ region (very costly),
- or do a suboptimal play to pass "smoothly" from $\left\{i^{A}=1, i^{B}=2\right\}$ to $\left\{i^{A}=2, i^{B}=1\right\}$.
- The second option is less costly, provided the location of the suboptimal play is randomized.


## Strategy for the toy model

- Let $\mathbf{q}_{t}^{A}=\left(\frac{1}{t-1} \sum_{s=1}^{t-1} \ell_{s}^{A}(i)\right)_{1 \leq i \leq 3}$ be the estimate of $\mathbf{p}$ at time $t$ according to $A$ (and similarly define $\mathbf{q}_{t}^{B}$ ).
- Then $A$ (resp. $B$ ) plays according to the position of $\mathbf{q}_{t}^{A}$ (resp. $\mathbf{q}_{t}^{B}$ ) in the following diagram (where $w_{t}=100 \sqrt{\frac{\log T}{t}}$ ):



## Sketch of proof for the toy model

- Collisions are not possible between neighbour regions, so to have a collision, a player must make an error of more than $\frac{w_{t}}{2}$.
- So by Hoeffding:

$$
\mathbb{P}(\text { collision }) \leq \mathbb{P}\left(\text { error } \geq \frac{w_{t}}{2}\right) \leq \exp \left(-\frac{t}{2}\left(\frac{w_{t}}{2}\right)^{2}\right) \leq T^{-50}
$$

- The loss caused by a suboptimal play in the interface is $O(d(\mathbf{p}, \mathcal{D}))$.
- The interface is at a random angle, so the probability to be in the interface is $O\left(\frac{w_{t}}{d(\mathbf{p}, \mathcal{D})}\right)$.
- So the total expected loss is $O\left(\sum_{t=1}^{T} w_{t}\right)=O(\sqrt{T \log T})$.
- Similar to the one for the toy model, but each player needs to have some information about every arm.
- Close to a boundary, explore both possibilities. E.g. near the boundary between $\left\{i^{A}=2, i^{B}=1\right\}$ and $\left\{i^{A}=3, i^{B}=1\right\}$, player $A$ alternates between arms 2 and 3 ).
- Players alternate roles regularly so each has a reasonable estimate of each arm.



## More arms, more players

## Theorem (Bubeck-B-Sellke. 2020)

For multiplayers multi-armed bandits with $m$ players and $K \geq m$ arms, there is a randomized strategy with no collision at all with high probability and

$$
\max _{\mathbf{p}} \mathbb{E}\left[R_{T}\right]=O\left(m K^{11 / 2} \sqrt{T \log T}\right) .
$$

- Similar ideas, but the geometric picture is much more complicated:



## THANK You!

