

Single-pass Streaming Lower Bounds for Multi-armed Bandits Exploration with Instance-sensitive Sample Complexity

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Joint work with [Sepehr Assadi](#)



● Motivations and Definitions

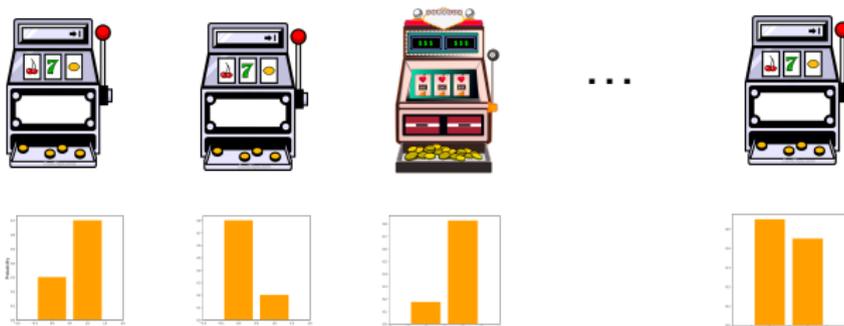
Best Arm Identification Problem

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- Given n arms with unknown rewards.

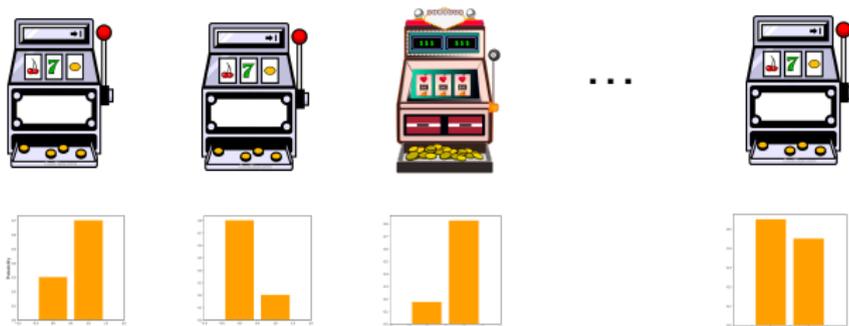
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- Goal: find **arm*** — the **best arm** with highest **mean** of the distribution.

Best Arm Identification Problem

- Given n arms with unknown rewards.
- The rewards follows **Sub-Gaussian distributions**, e.g. **Bernoulli** distribution.
- Parameters $\Delta_{[i]}$: the gap between **the best** and **the i -th best** arms.
- Parameters **may or may not be known**.

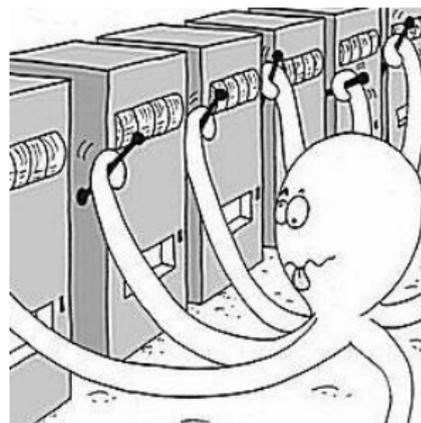
Best Arm Identification Problem

Best Arm Identification Problem

- ❑ Natural Strategy: Pull each arm multiple times and record the empirical rewards.

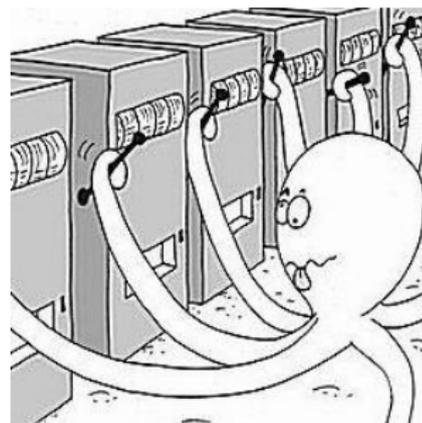
Best Arm Identification Problem

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Best Arm Identification Problem

- ❑ Natural Strategy: Pull each arm multiple times and record the empirical rewards.



- ❑ Goal: Finding the best arm:
 - High enough (constant) probability
 - Minimum number of arm pulls (sample complexity).

Worst-case (w.r.t. $\Delta_{[2]}$):

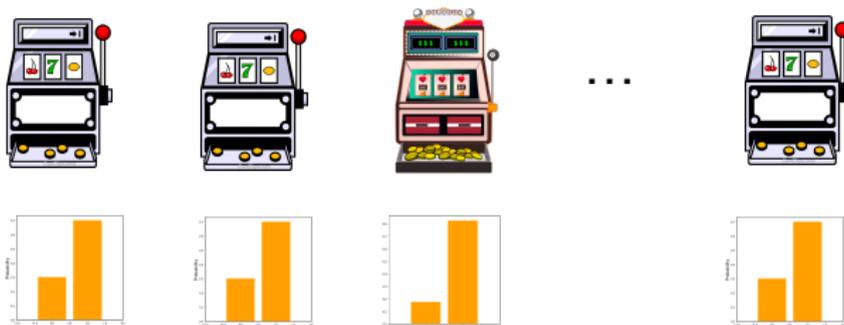
- ❑ $\Theta\left(\frac{n}{\Delta_{[2]}^2}\right)$ sample complexity.
- ❑ Upper bound — Median Elimination (Even-Dar et al., [COLT'02]).
- ❑ Asymptotically matching lower bound (Mannor and Tsitsiklis, [JMLR'04]).

Instance-sensitive (w.r.t. $\{\Delta_{[i]}\}_{i=2}^n$):

- $O(H_2 := \sum_{i=2}^n \frac{1}{\Delta_{[i]}^2} \log \log(\frac{1}{\Delta_i}))$ sample complexity.
- Upper bound algorithms (Karnin et al., [ICML'13]; Jamieson et al., [COLT'14]).

Classical Results

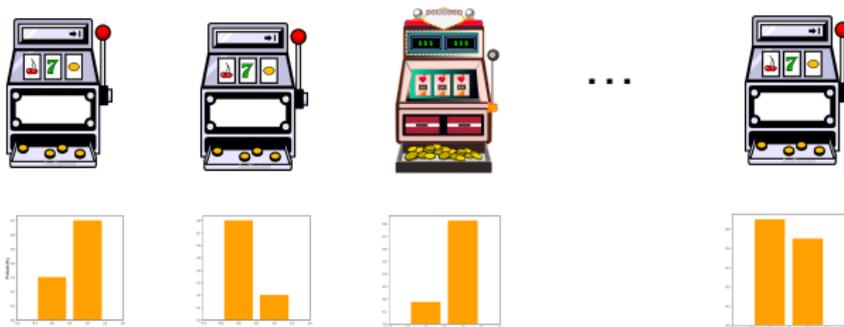
- Another interesting variate: instance-sensitive sample complexity.



$$\Theta\left(\frac{n}{\Delta_{[2]}^2}\right) \approx H_2$$

Classical Results

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$$\Theta\left(\frac{n}{\Delta_{[2]}^2}\right) \gg H_2$$

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A twist on perspective: Memory

- ❑ So far most of the studies focused on smaller number of arm pulls (sample complexity).
- ❑ But is it practical to store all the arms in **massive** datasets?
- ❑ In large-scale applications, **space** becomes important.

Streaming Multi-armed Bandits Problem

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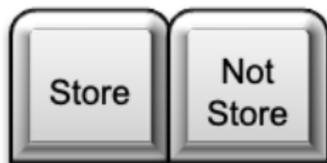
The **Streaming Model** (Assadi and Wang, [STOC'20])

- A stream of arms
 - Algorithm on-the-fly read arms to **memory**
 - Algorithm can **pull** the arriving arm and **store** it
 - Algorithm can **pull a stored arm**
 - Algorithm can **discard a stored arm**
- **Not Stored** or **Discarded** -> cannot be retrieved anymore (lost forever)

Streaming Multi-armed Bandits



$t=1$, read/pull arm 1



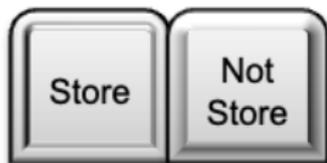
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Streaming Multi-armed Bandits



Store Arm 1



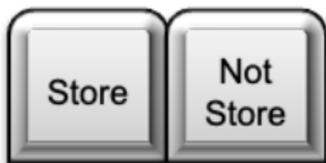
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Streaming Multi-armed Bandits



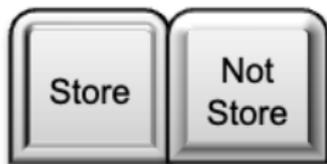
$t=2$, read/pull arm 2



Streaming Multi-armed Bandits



Store Arm 2



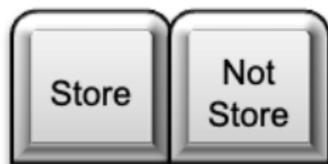
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Streaming Multi-armed Bandits



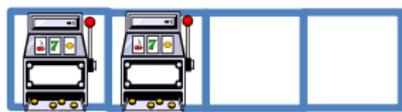
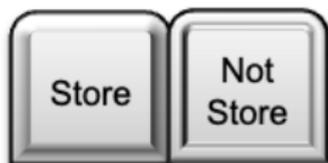
$t=3$, read/pull arm 3



Streaming Multi-armed Bandits



Not Store Arm 3
(lost forever)



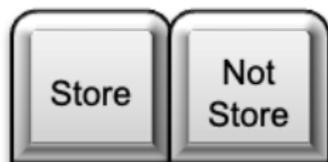
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Streaming Multi-armed Bandits



Continue till the last arm



...



Streaming Multi-armed Bandits

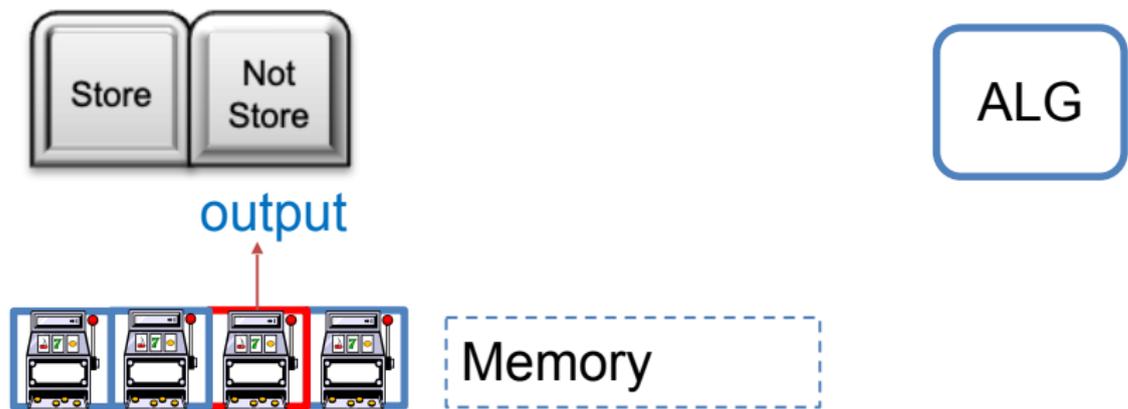
Continue till the last arm



Streaming Multi-armed Bandits

Memory Complexity: the *maximum* number of arms we ever stored.

Continue till the last arm



Streaming MABs Exploration: Worst-case Complexity

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- (Assadi and Wang, [STOC'20]) There exists an algorithm that given parameter $\Delta_{[2]}$, finds the best arm with high constant probability and:
 - $O\left(\frac{n}{\Delta_{[2]}^2}\right)$ Sample Complexity
 - *A Single arm* Space Complexity

Streaming MABs Exploration: Worst-case Complexity

- (Assadi and Wang, [STOC'20]) There exists an algorithm that given parameter $\Delta_{[2]}$, finds the **best arm** with **high constant probability** and:
 - $O\left(\frac{n}{\Delta_{[2]}^2}\right)$ Sample Complexity
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Same memory as we need to *output* the best arm.

Beyond Worst-case Streaming Sample Complexity

- Open questions following Assadi and Wang, [STOC'20]:
 - What if parameter $\Delta_{[2]}$ is not given?
 - What about the instance-sensitive exploration?

$$O(H_2 := \sum_{i=2}^n \frac{1}{\Delta_{[i]}^2} \log \log(\frac{1}{\Delta_i}))$$

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$$O(H_2 := \sum_{i=2}^n \frac{1}{\Delta_{[i]}^2} \log \log(\frac{1}{\Delta_i}))$$

Answers to the above questions in this work.

Main Results: Streaming Lower Bounds

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- ❑ A **very strong lower bound** for streaming MABs algorithms without the knowledge of $\Delta_{[2]}$.
- ❑ If **without** the knowledge of $\Delta_{[2]}$, and no other knowledge, any streaming algorithm to find the best arm:
 - Either has a memory of $\Theta(n)$ arms.
 - Or the sample complexity is $\omega\left(\frac{n}{f(\Delta_{[i]})}\right)$ for every **non-zero** f .

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First Lower Bound — Role of Parameter $\Delta_{[2]}$

- Without the knowledge of $\Delta_{[2]}$, sample complexity is **unbounded** as a function of $\Delta_{[2]}$.
- Sharp contrast to the upper bound by Assadi and Wang, [STOC'20].
- Sharp contrast to the upper bounds in offline algorithms — Karnin et al., [ICML'13]; Jamieson et al., [COLT'14] **do not assume** a known $\Delta_{[2]}$!

- In a single-pass stream, we proved **lower bounds** of $\omega(H_2)$ arm pulls for any streaming algorithm with $o(n)$ arm memory if:
 - Only the parameter $\Delta_{[2]}$ is given.
 - If the parameter $\Delta_{[2]}$ is given, and the arms arrive in a **random order**.
 - If **all** the gap parameters $\{\Delta_{[i]}\}_{i=2}^n$ are given.

A Streaming Algorithm with Strong Assumptions

- ❑ Finally, we devise a single-pass streaming algorithm when **all assumptions hold**.
- ❑ There exists an algorithm that given parameter $\Delta_{[2]}$, a **random order** of the stream, and the **value** of H_2 , finds the **best arm** with **high constant probability** and:
 - $O(H_2 + \text{poly}(\frac{\log(n)}{\Delta_{[2]}}))$ Sample Complexity
 - **A Single arm** Space Complexity

- Our algorithm hinges on new ideas of **budgeting** the stored arm with number of arm pulls.

- The additive $O(\text{poly}(\frac{\log(n)}{\Delta_{[2]}}))$ term is negligible in **large-scale application** context ($n \sim 10^6$ and $\Delta_{[2]} \sim 0.1$ suffice).

- Multi-pass bounds for MABs:
 - What if we are allowed to make **multiple passes** over the arms?
 - Jin et al. [ICML'21]: $O(\log(1/\Delta_{[2]}))$ passes, $O(H_2)$ sample complexity.
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Thank You!