

CS 747, Autumn 2022: Lecture 1

Shivaram Kalyanakrishnan

Department of Computer Science and Engineering
Indian Institute of Technology Bombay

Autumn 2022

Multi-armed Bandits

1. The exploration-exploitation dilemma
2. Definitions: Bandit, Algorithm
3. ϵ -greedy algorithms

Multi-armed Bandits

1. The exploration-exploitation dilemma
2. Definitions: Bandit, Algorithm
3. ϵ -greedy algorithms

A Game

Coin 1



$$\mathbb{P}\{\text{heads}\} = p_1$$

Coin 2



$$\mathbb{P}\{\text{heads}\} = p_2$$

Coin 3



$$\mathbb{P}\{\text{heads}\} = p_3$$

- p_1 , p_2 , and p_3 are **unknown**.
- You are given a total of 20 tosses.
- Maximise the total number of heads!

A Game

Coin 1



$$\mathbb{P}\{\text{heads}\} = p_1$$

Coin 2



$$\mathbb{P}\{\text{heads}\} = p_2$$

Coin 3



$$\mathbb{P}\{\text{heads}\} = p_3$$

- p_1 , p_2 , and p_3 are **unknown**.
- You are given a total of 20 tosses.
- Maximise the total number of heads!

Let's play!

A Game

Coin 1



$$\mathbb{P}\{\text{heads}\} = p_1$$

Coin 2



$$\mathbb{P}\{\text{heads}\} = p_2$$

Coin 3



$$\mathbb{P}\{\text{heads}\} = p_3$$

- p_1 , p_2 , and p_3 are **unknown**.
 - You are given a total of 20 tosses.
 - Maximise the total number of heads!
- Let's play!**
- If you knew p_1 , p_2 , p_3 beforehand, how would you have played?

A Game

Coin 1



$$\mathbb{P}\{\text{heads}\} = p_1$$

Coin 2



$$\mathbb{P}\{\text{heads}\} = p_2$$

Coin 3



$$\mathbb{P}\{\text{heads}\} = p_3$$

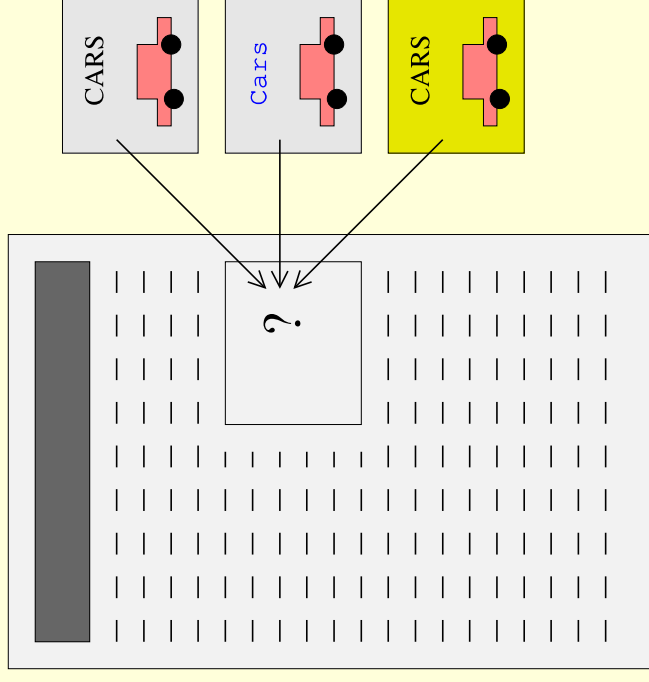
- p_1 , p_2 , and p_3 are **unknown**.
- You are given a total of 20 tosses.
- Maximise the total number of heads!

Let's play!

- If you knew p_1 , p_2 , p_3 beforehand, how would you have played? How many heads would you have got in 20 tosses?

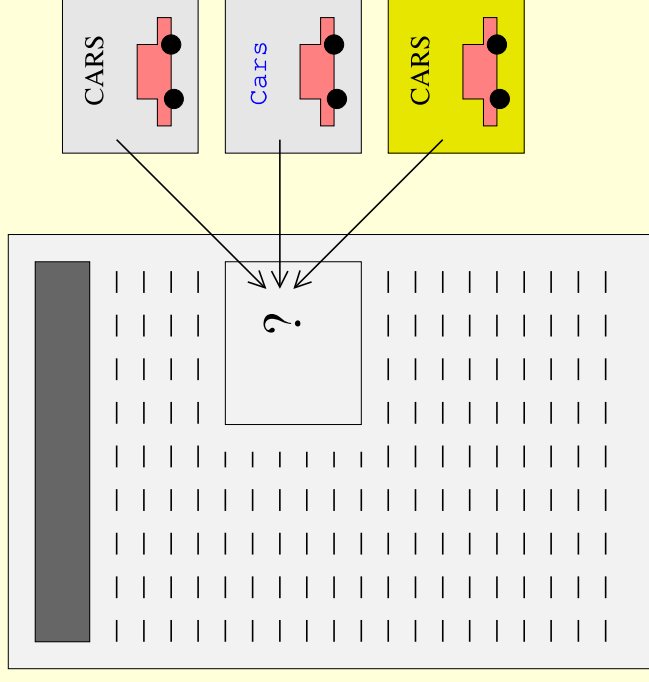
To Explore or to Exploit?

- On-line advertising: Template optimisation



To Explore or to Exploit?

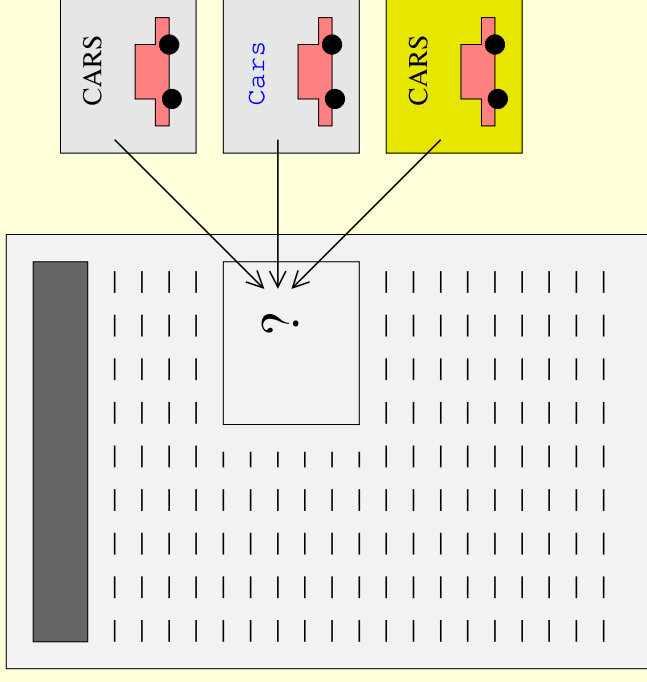
- On-line advertising: Template optimisation



- Clinical trials

To Explore or to Exploit?

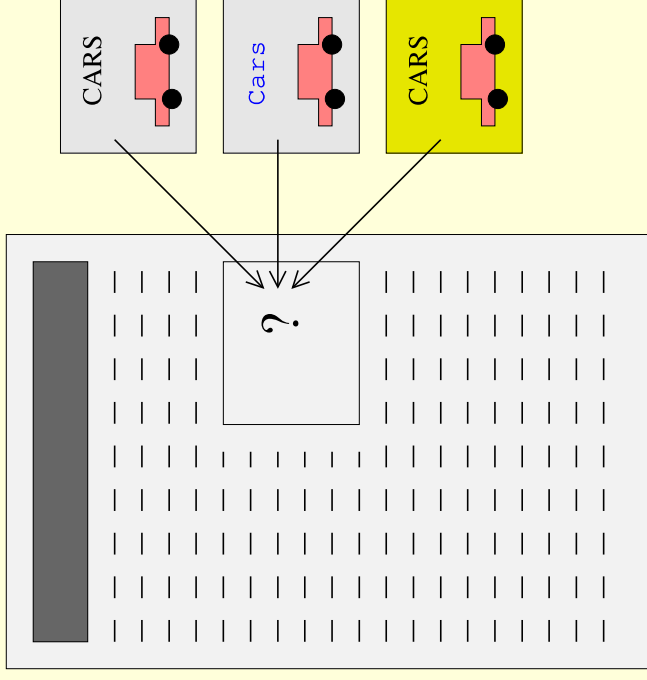
- On-line advertising: Template optimisation



- Clinical trials
- Packet routing in communication networks

To Explore or to Exploit?

- On-line advertising: Template optimisation

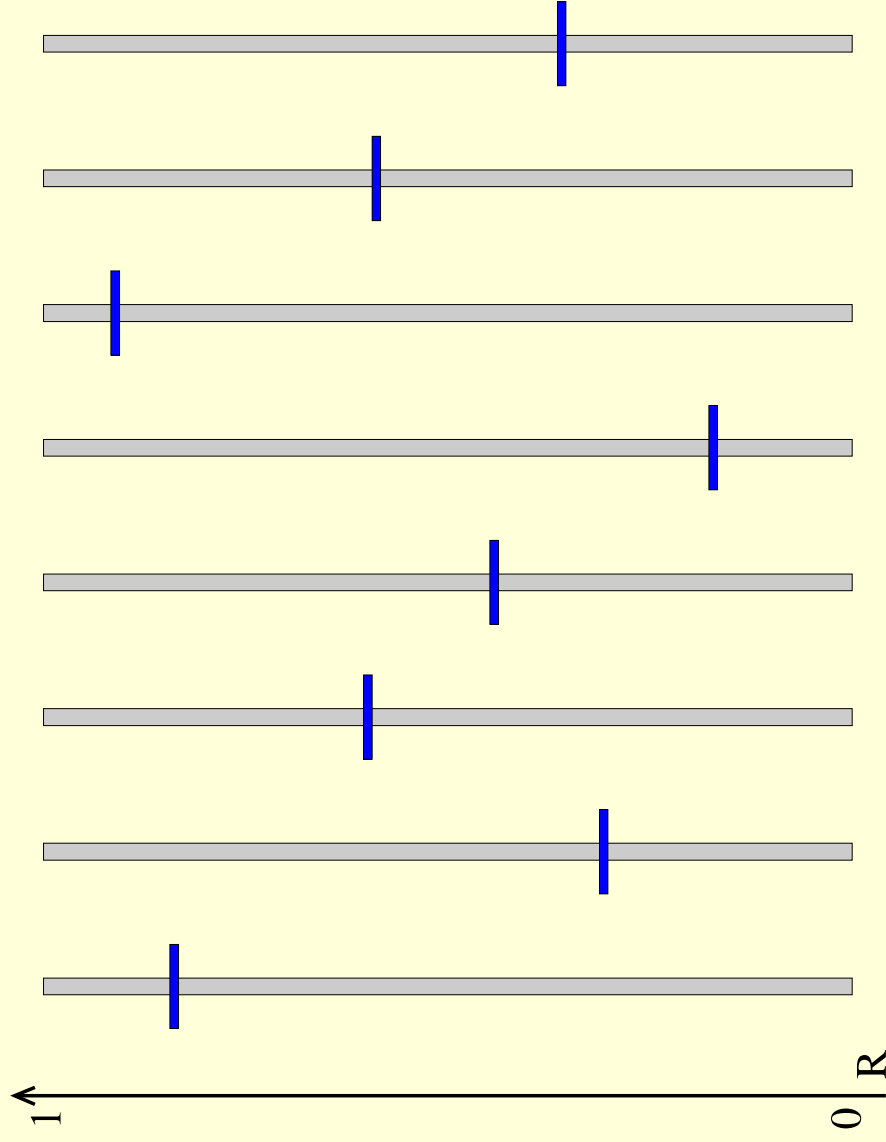


- Clinical trials
- Packet routing in communication networks
- Game playing and reinforcement learning

Multi-armed Bandits

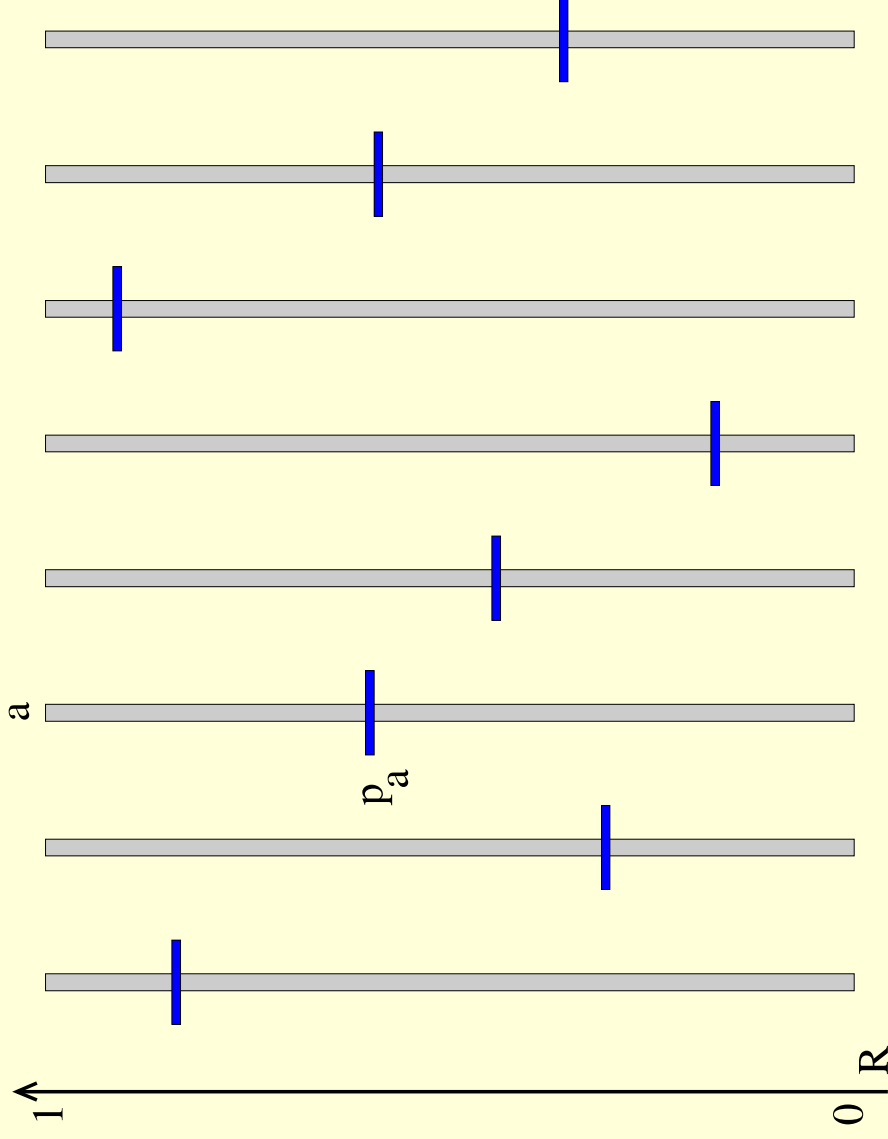
1. The exploration-exploitation dilemma
2. Definitions: Bandit, Algorithm
3. ϵ -greedy algorithms

Stochastic Multi-armed Bandits



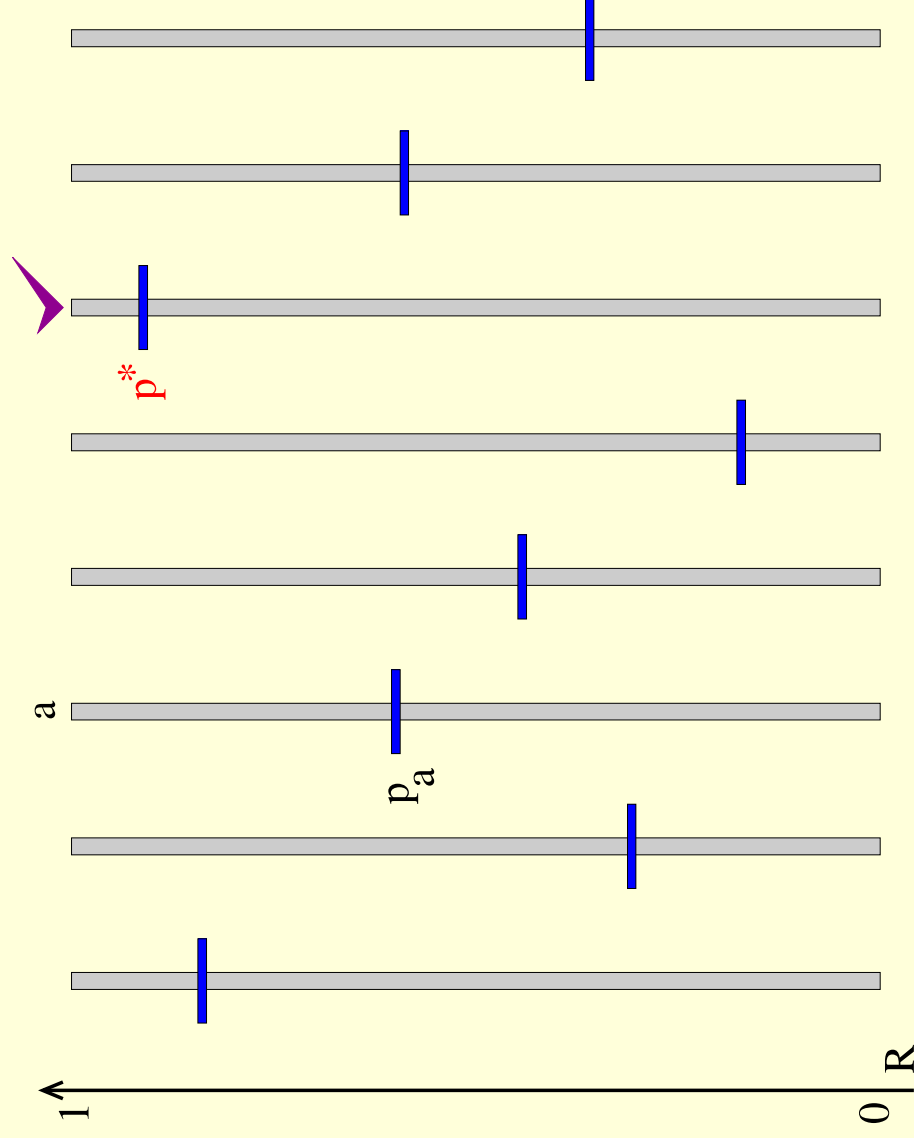
- n arms, each associated with a Bernoulli distribution (rewards are 0 or 1).

Stochastic Multi-armed Bandits



- n arms, each associated with a Bernoulli distribution (rewards are 0 or 1).
- Let A be the set of arms. Arm $a \in A$ has mean reward p_a .

Stochastic Multi-armed Bandits



- n arms, each associated with a Bernoulli distribution (rewards are 0 or 1).
- Let A be the set of arms. Arm $a \in A$ has mean reward p_a .
- Highest mean is p^* .

One-armed Bandits



[1]

1. <https://pxhere.com/en/photo/942387>.

Algorithm

- Here is what an algorithm does—

For $t = 0, 1, 2, \dots, T - 1$:

- Given the history $h^t = (a^0, r^0, a^1, r^1, a^2, r^2, \dots, a^{t-1}, r^{t-1})$,
- Pick an arm a^t to sample (or “pull”), and
- Obtain a reward r^t drawn from the distribution corresponding to arm a^t .

Algorithm

- Here is what an algorithm does—

For $t = 0, 1, 2, \dots, T - 1$:

- Given the history $h^t = (a^0, r^0, a^1, r^1, a^2, r^2, \dots, a^{t-1}, r^{t-1})$,
 - Pick an arm a^t to sample (or “pull”), and
 - Obtain a reward r^t drawn from the distribution corresponding to arm a^t .
- T is the total sampling budget, or the horizon.

Algorithm

- Here is what an algorithm does—

For $t = 0, 1, 2, \dots, T - 1$:

- Given the history $h^t = (a^0, r^0, a^1, r^1, a^2, r^2, \dots, a^{t-1}, r^{t-1})$,
- Pick an arm a^t to sample (or “pull”), and
- Obtain a reward r^t drawn from the distribution corresponding to arm a^t .

- T is the total sampling budget, or the horizon.
- Formally: a **deterministic algorithm** is a mapping from the set of all histories to the set of all arms.

Algorithm

- Here is what an algorithm does—

For $t = 0, 1, 2, \dots, T - 1$:

- Given the history $h^t = (a^0, r^0, a^1, r^1, a^2, r^2, \dots, a^{t-1}, r^{t-1})$,
- Pick an arm a^t to sample (or “pull”), and
- Obtain a reward r^t drawn from the distribution corresponding to arm a^t .

- T is the total sampling budget, or the horizon.
- Formally: a **deterministic algorithm** is a mapping from the set of all histories to the set of all arms.
- Formally: a **randomised algorithm** is a mapping from the set of all histories to the set of all probability distributions over arms.

Algorithm

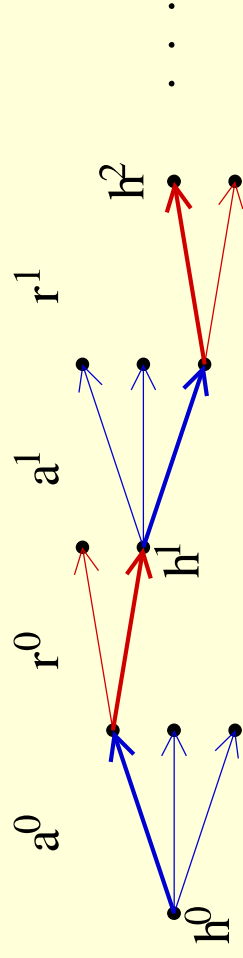
- Here is what an algorithm does—

For $t = 0, 1, 2, \dots, T - 1$:

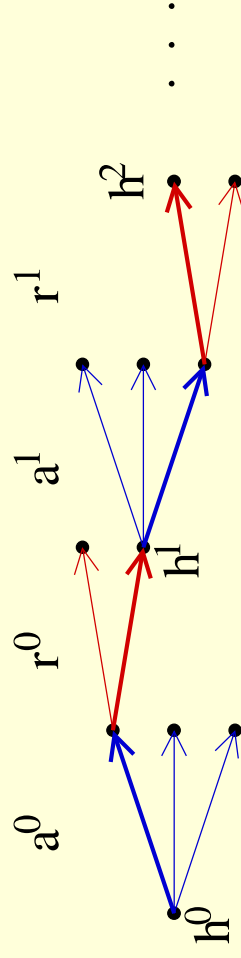
- Given the history $h^t = (a^0, r^0, a^1, r^1, a^2, r^2, \dots, a^{t-1}, r^{t-1})$,
- Pick an arm a^t to sample (or “pull”), and
- Obtain a reward r^t drawn from the distribution corresponding to arm a^t .

- T is the total sampling budget, or the horizon.
- Formally: a **deterministic algorithm** is a mapping from the set of all histories to the set of all arms.
- Formally: a **randomised algorithm** is a mapping from the set of all histories to the set of all probability distributions over arms.
- The algorithm picks the arm to pull; the bandit instance returns the reward.

Illustration

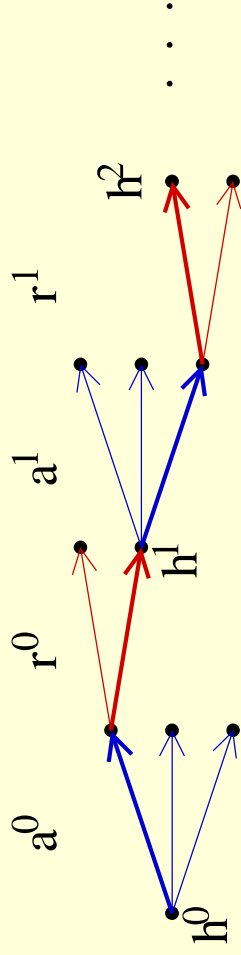


Illustration



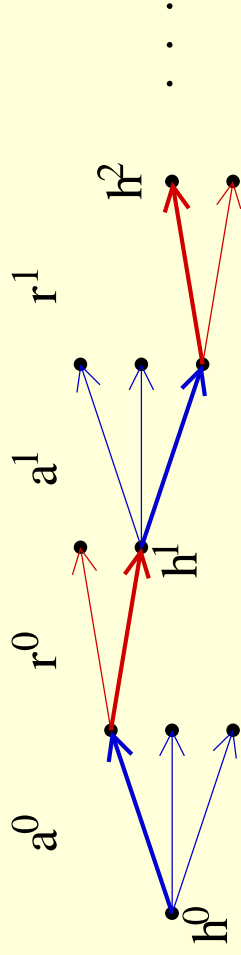
- Consider $h^T = (a^0, r^0, a^1, r^1, \dots, a^{T-1}, r^{T-1})$.

Illustration

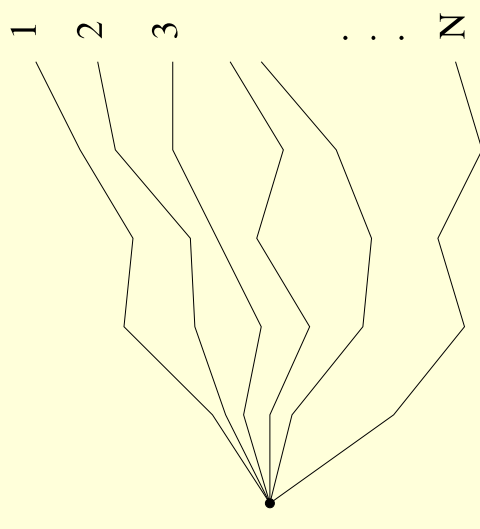


- Consider $h^T = (a^0, r^0, a^1, r^1, \dots, a^{T-1}, r^{T-1})$.
Observe that $\mathbb{P}\{h^T\} = \prod_{t=0}^{T-1} \mathbb{P}\{a^t|h^t\}\mathbb{P}\{r^t|a^t\}$, where $\mathbb{P}\{a^t|h^t\}$ is decided by the algorithm, $\mathbb{P}\{r^t|a^t\}$ comes from the bandit instance.

Illustration

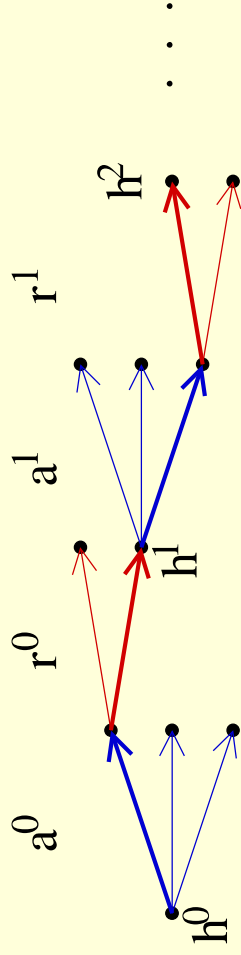


- An algorithm, bandit instance pair can generate many possible T -length histories.



- Consider $h^T = (a^0, r^0, a^1, r^1, \dots, a^{T-1}, r^{T-1})$.
Observe that $\mathbb{P}\{h^T\} = \prod_{t=0}^{T-1} \mathbb{P}\{a^t|h^t\}\mathbb{P}\{r^t|a^t\}$, where $\mathbb{P}\{a^t|h^t\}$ is decided by the algorithm, $\mathbb{P}\{r^t|a^t\}$ comes from the bandit instance.

Illustration



- Consider $h^T = (a^0, r^0, a^1, r^1, \dots, a^{T-1}, r^{T-1})$.

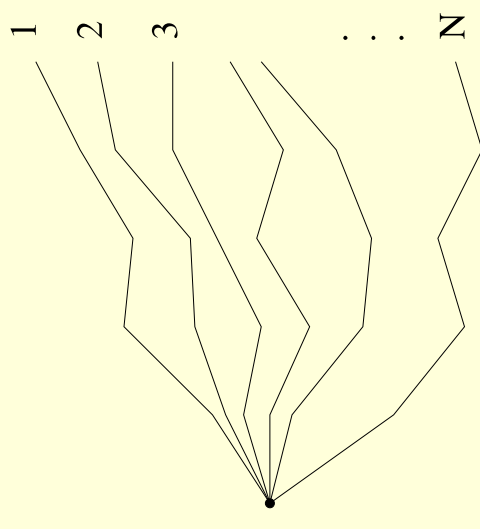
Observe that

$\mathbb{P}\{h^T\} = \prod_{t=0}^{T-1} \mathbb{P}\{a^t|h^t\} \mathbb{P}\{r^t|a^t\}$, where

$\mathbb{P}\{a^t|h^t\}$ is decided by the algorithm,

$\mathbb{P}\{r^t|a^t\}$ comes from the bandit instance.

- An algorithm, bandit instance pair can generate many possible T -length histories.



How many histories possible if the algorithm is deterministic and rewards 0–1?

Multi-armed Bandits

1. The exploration-exploitation dilemma
2. Definitions: Bandit, Algorithm
3. ϵ -greedy algorithms

ϵ -greedy Algorithms

- Parameter $\epsilon \in [0, 1]$ controls the amount of exploration.

ϵ -greedy Algorithms

- Parameter $\epsilon \in [0, 1]$ controls the amount of exploration.
- $\epsilon G1$
 - If $t \leq \epsilon T$, sample an arm uniformly at random.
 - At $t = \lfloor \epsilon T \rfloor$, identify a^{best} , an arm with the highest empirical mean.
 - If $t > \epsilon T$, sample a^{best} .

ϵ -greedy Algorithms

- Parameter $\epsilon \in [0, 1]$ controls the amount of exploration.
- ϵ G1
 - If $t \leq \epsilon T$, sample an arm uniformly at random.
 - At $t = \lfloor \epsilon T \rfloor$, identify a^{best} , an arm with the highest empirical mean.
 - If $t > \epsilon T$, sample a^{best} .
- ϵ G2
 - If $t \leq \epsilon T$, sample an arm uniformly at random.
 - If $t > \epsilon T$, sample an arm with the **highest empirical mean**.

ϵ -greedy Algorithms

- Parameter $\epsilon \in [0, 1]$ controls the amount of exploration.
- ϵ G1
 - If $t \leq \epsilon T$, sample an arm uniformly at random.
 - At $t = \lfloor \epsilon T \rfloor$, identify a^{best} , an arm with the highest empirical mean.
 - If $t > \epsilon T$, sample a^{best} .
- ϵ G2
 - If $t \leq \epsilon T$, sample an arm uniformly at random.
 - If $t > \epsilon T$, sample an arm with the highest empirical mean.
- ϵ G3
 - With probability ϵ , sample an arm uniformly at random; with probability $1 - \epsilon$, sample an arm with the highest empirical mean.

Questions

- Are ϵG_1 , ϵG_2 , ϵG_3 deterministic or randomised algorithms?

Questions

- Are $\epsilon G1$, $\epsilon G2$, $\epsilon G3$ deterministic or randomised algorithms?
- Fix a 4-armed bandit instance with means $p_1 > p_2 > p_3 > p_4$.
 - If $\epsilon = 1$, what is the expected reward of $\epsilon G1$?

Questions

- Are $\epsilon G1$, $\epsilon G2$, $\epsilon G3$ deterministic or randomised algorithms?
- Fix a 4-armed bandit instance with means $p_1 > p_2 > p_3 > p_4$.
 - If $\epsilon = 1$, what is the expected reward of $\epsilon G1$?
 - If $\epsilon = 0.8$ and T is relatively large, what is the expected reward of $\epsilon G1$?

Questions

- Are $\epsilon G1$, $\epsilon G2$, $\epsilon G3$ deterministic or randomised algorithms?
- Fix a 4-armed bandit instance with means $p_1 > p_2 > p_3 > p_4$.
 - If $\epsilon = 1$, what is the expected reward of $\epsilon G1$?
 - If $\epsilon = 0.8$ and T is relatively large, what is the expected reward of $\epsilon G1$?
- Does $\epsilon G1$ perform worse than $\epsilon G2$ on each run?

Multi-armed Bandits

1. The exploration-exploitation dilemma
2. Definitions: Bandit, Algorithm
3. ϵ -greedy algorithms

Multi-armed Bandits

1. The exploration-exploitation dilemma
2. Definitions: Bandit, Algorithm
3. ϵ -greedy algorithms

Next class: What is a “good” algorithm? What is the “best” algorithm?