

## Lecture 3 - Jan 20, 2023

### - Mult. Arm Bandits

- Introduction
- Exploration - Exploitation Dilemma
- Epsilon-Greedy Policy
- Optimistic Initial Values
- Upper Confidence Bound Selection Policy
- Gradient-Based Selection Policy
- Thompson Sampling

HW1 → Due Jan 27

Project 1 is Posted → Due Feb 7

TA's first office hour: Friday, Jan 20, 12pm - 1pm

overview:

$$Q^*(a) = E[R | a]$$

$$a^* = \underset{a \in A}{\operatorname{argmax}} Q^*(a)$$

Learning  $\leftarrow$  Distribution are unknown

$\rightarrow$  Policy: a

$\rightarrow$  Estimation  $Q(a)$

$$Q(a) = 0 \text{ for all } a \in A$$

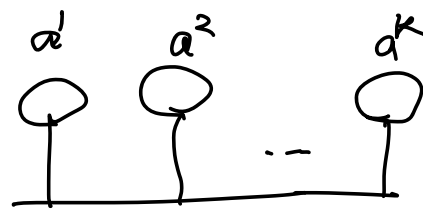
$$Q(a) = Q(a) + \alpha [R - Q(a)]$$

Policy 1:  $\epsilon$ -greedy

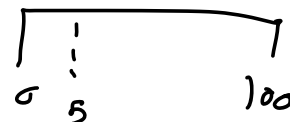
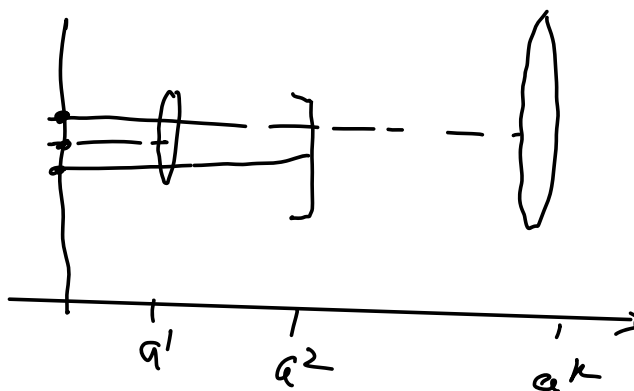
$$a \sim \begin{cases} \underset{a \in A}{\operatorname{argmax}} Q(a) \\ \text{Random}\{a^1, \dots, a^k\} \end{cases}$$

$1-\epsilon \leftarrow$  greedy

$\epsilon \leftarrow$  Random

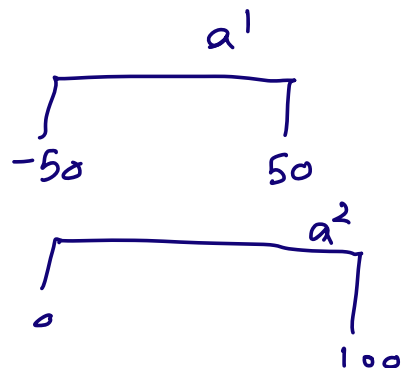


$R|a \leftarrow$  Random Variable



$$a^1 \rightarrow Q(a^1) = 20, Q(a^2) = 0$$

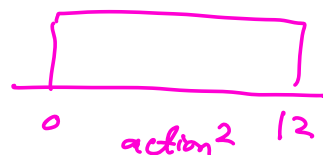
to



$$a^2 \xrightarrow{R=70} Q(a^1) = 20, Q(a^2) = 45$$

Optimistic Initial Value:  $Q^*(a^1) = 5, Q^*(a^2) = 6$

$$Q(a^1) = Q(a^2) = 0$$



Time 1

action  $a^1$

Reward 5

$$Q(a^1) = \frac{Q(a^1)}{5} + \alpha \left[ \frac{R}{5} - \frac{Q(a^1)}{5} \right] = 2.5$$

$$\pi^{\epsilon} \rightarrow \begin{cases} \text{greedy} = a^1 & 1-\epsilon \\ \text{Random} \{a^1, a^2\} & \epsilon \end{cases}$$

$$\epsilon = 0.1 \rightarrow \begin{cases} a^1 \rightarrow 0.95 \\ a^2 \rightarrow 0.05 \end{cases}$$

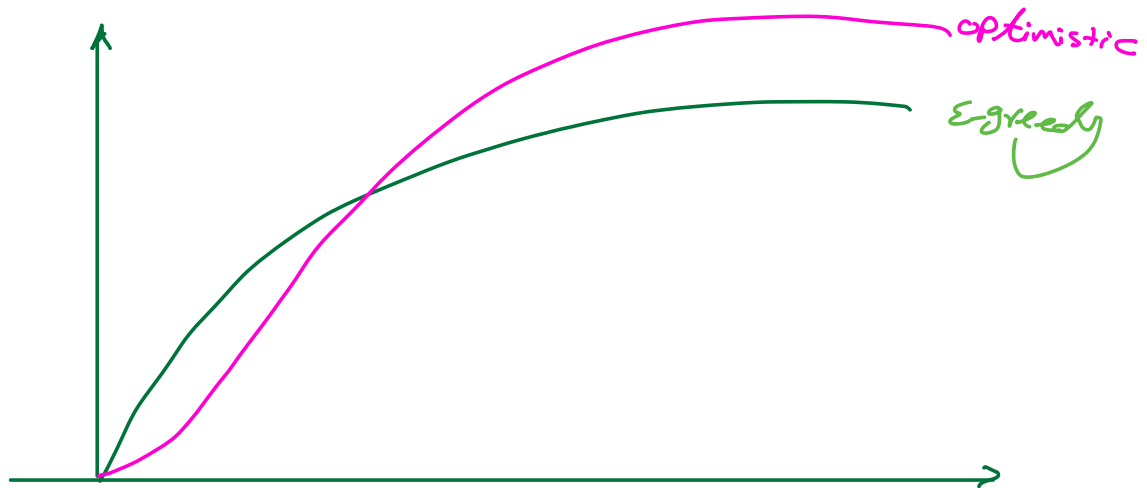
$$\boxed{Q(a^1) = 2.5, Q(a^2) = 0}$$

$$Q(a^1) = Q(a^2) = 15$$

$$Q(a^1) = \frac{Q(a^1)}{15} + \alpha \left[ \frac{R}{5} - \frac{Q(a^1)}{15} \right] = 10$$

$$\pi^{\epsilon} \rightarrow \begin{cases} \text{greedy} = a^2 & 1-\epsilon \\ \text{Random} \{a^1, a^2\} & \epsilon \end{cases} \quad \begin{cases} Q(a^1) = 10 \\ Q(a^2) = 15 \end{cases}$$

$$\epsilon = 0.1 \rightarrow \begin{cases} a^1 \leftarrow 0.05 \\ a^2 \leftarrow 0.95 \end{cases}$$



Upper confidence Bound (UCB)  $\Leftarrow$  Policy

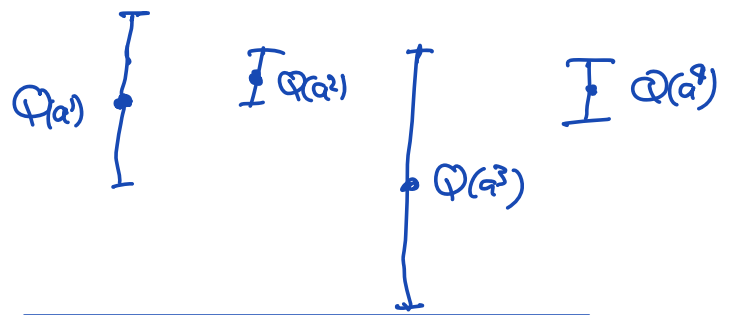
$$a_t = \underset{a \in \{a^1, a^2, \dots, a^k\}}{\operatorname{argmax}} \left[ Q(a) + c \sqrt{\frac{\log t}{N_t(a)}} \right]$$

addition to the current estimate of  $Q(a)$

$t$ : time step

$N_t(a)$ : # that action  $a$  is selected up to time  $t$

$$Q(a) = Q(a) + \alpha [R - Q(a)]$$



$$Q(a^1) = 10$$

$$N(a^1) = 100$$

$$Q(a^2) = 1$$

$$N(a^2) = 1 \leadsto t = 101$$

$$t=102 \rightarrow a_t = \operatorname{argmax} \left[ Q(a) + c \sqrt{\frac{\log t}{N_t(a)}} \right]$$

$$\operatorname{argmax}_{a \in \{a^1, a^2\}} \left\{ \underbrace{10 + c \sqrt{\frac{\log 102}{100}}}_{a^1}, \quad \underbrace{1 + c \sqrt{\frac{\log 102}{1}}}_{a^2} \right\}$$

$$c=1 \leftarrow 10 + 0.213$$

$$1 + 1.52$$

$$c=10 \leftarrow 10 + 2.13$$

$$1 + 15.2$$

$c=0 \Rightarrow$  greedy

$c$  larger  $\rightarrow$  More exploration

Online Learning Algorithms  $\left\{ \begin{array}{l} \text{Exp3} \\ \text{Hedge} \\ \text{Regret Matching} \end{array} \right.$

# Policy: Gradient-Bandit Policy

Directly parametrizing the policy:

$H_t(a)$ : numeric preference for action  $a$

$$P(a_t = a) = \frac{e^{H_t(a)}}{\sum_{i=1}^K e^{H_t(a_i)}} =: \pi_t(a)$$

↑  
Probability of taking  
action  $a$  at time  $t$

Boltzman or Softmax Policy

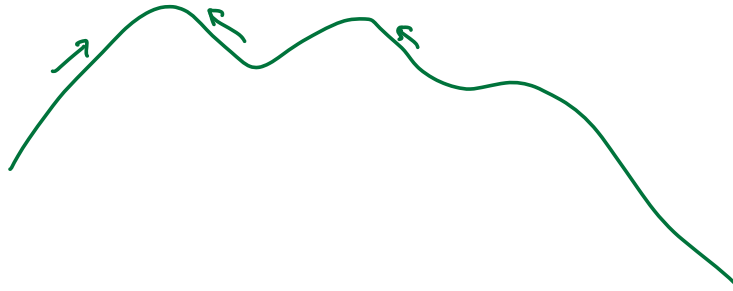
Gibbs distribution

$$\left. \begin{array}{l} H_1(a^1) = 0 \\ H_1(a^2) = 0 \end{array} \right\} \rightarrow \left\{ \begin{array}{l} \pi_1(a^1) = \frac{e^{H_1(a^1)}}{e^{H_1(a^1)} + e^{H_1(a^2)}} = \frac{1}{1+1} = \frac{1}{2} \\ \pi_1(a^2) = \frac{e^0}{e^0 + e^0} = \frac{1}{2} \end{array} \right.$$

$$\left. \begin{array}{l} H_5(a^1) = 8 \\ H_5(a^2) = 0 \end{array} \right\} \rightarrow \left\{ \begin{array}{l} \pi_5(a^1) = \frac{e^8}{e^8 + e^0} = 0.9997 \\ \pi_5(a^2) = \frac{e^0}{e^8 + e^0} = 0.0003 \end{array} \right.$$

$\begin{array}{c} a^2 \\ | \\ a^1 \end{array}$

$$H_{t+1}(a) = H_t(a) + \alpha \frac{\partial E[R_t]}{\partial H_t(a)} \quad \leftarrow \text{Average Reward}$$



$$\begin{cases} H_{t+1}(A_t) = H_t(A_t) + \alpha (R_t - \bar{R}_t) (1 - \pi_t(A_t)) \\ H_{t+1}(a) = H_t(a) - \alpha (R_t - \bar{R}_t) \pi_t(a) \quad \text{for all } a \in A - A_t \end{cases}$$

$A_t$ : action selected at time  $t$

$a$ : all actions except  $A_t$

$\bar{R}_t$ : Average Reward up to current time  $t$  including " $t$ "

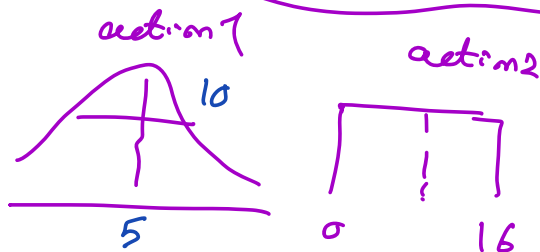
$$\bar{R}_t = 0, \quad R_t = 10, \quad A_t = a^1 \quad A = \{a^1, a^2\}$$

$$\text{Action 1} \rightarrow + \alpha \left( \frac{R_t}{10} - \frac{\bar{R}_t}{0} \right) (1 - \underbrace{\pi_t(A_t)}_{0.6}) \quad \begin{matrix} \pi_t(a^1) = 0.6 \\ \pi_t(a^2) = 0.4 \end{matrix}$$

$$\text{action 2} \rightarrow - \alpha \left( \frac{R_t}{10} - \frac{\bar{R}_t}{0} \right) \underbrace{\pi_t(a)}_{0.4}$$

$$\begin{aligned}
 \text{Action 1} &\rightarrow + \alpha \left( \underbrace{R_t}_{10} - \underbrace{\bar{R}_t}_0 \right) \underbrace{(1 - \pi_t(A_t))}_{0.9999} \frac{e^{H_t(a)}}{\sum_{a'} e^{H_t(a')}} \\
 \text{action 2} &\rightarrow - \alpha \left( \underbrace{R_t}_{10} - \underbrace{\bar{R}_t}_0 \right) \underbrace{\pi_t(a)}_{0.0001}
 \end{aligned}$$

$\begin{cases} \pi_t(a') = 0.9999 \\ \pi_t(a'') = 0.0001 \end{cases}$



$$R^{a'} \sim \mathcal{N}(5, 10)$$

①

$$H_1(a') = H_1(a'') = 0$$

$$\begin{aligned}
 \text{policy} \rightarrow \pi_1(a') &= \frac{e^{H_1(a')}}{e^{H_1(a')} + e^{H_1(a'')}} = \frac{e^0}{e^0 + e^0} = \frac{1}{2} \\
 \pi_1(a'') &= \frac{e^0}{e^0 + e^0} = \frac{1}{2}
 \end{aligned}$$

$$\sim A_1 = a'$$

$$A_1 = a', R_1 = 10 \Rightarrow \bar{R}_1 = \frac{10}{1} = 10$$

preference update

$$\begin{aligned}
 H_2(a') &= \underbrace{H_1(a')}_0 + \underbrace{\alpha}_{0.5} \left[ \underbrace{R_1}_{10} - \underbrace{\bar{R}_1}_{10} \right] \underbrace{(1 - \pi_1(a'))}_{1/2} = 0 \\
 H_2(a'') &= \underbrace{H_1(a'')}_0 - \underbrace{\alpha}_{0.5} \left[ \underbrace{R_1}_{10} - \underbrace{\bar{R}_1}_{10} \right] \underbrace{\pi_1(a'')}_{1/2} = 0
 \end{aligned}$$



②

$$H_2(a^1) = 0, H_2(a^2) = 0$$

$$\begin{aligned} \hookrightarrow \pi_2(a^1) &= \frac{e^0}{e^0 + \bar{e}^0} = \frac{1}{2} \\ \pi_2(a^2) &= \frac{1}{2} \end{aligned} \left. \vphantom{\begin{aligned} \pi_2(a^1) &= \frac{e^0}{e^0 + \bar{e}^0} = \frac{1}{2} \\ \pi_2(a^2) &= \frac{1}{2} \end{aligned}} \right\} \rightarrow A_t = a^2$$

$$A_2 = a^2, R_2 = 2 \Rightarrow \bar{R}_2 = \frac{10 + 2}{2} = 6$$

predecessor update

$$\begin{aligned} \hookrightarrow \begin{cases} H_3(a^2) = \underbrace{H_2(a^2)}_0 + \underbrace{\alpha}_{0.5} \left[ \underbrace{R_2}_2 - \underbrace{\bar{R}_2}_6 \right] \underbrace{(1 - \pi_2(a^2))}_{\frac{1}{2}} = -1 \\ H_3(a^1) = \underbrace{H_2(a^1)}_0 - \underbrace{\alpha}_{0.5} \left[ \underbrace{R_2}_2 - \underbrace{\bar{R}_2}_6 \right] \underbrace{\pi_2(a^1)}_{\frac{1}{2}} = 1 \end{cases} \end{aligned}$$

$$H_3(a^1) = 1, H_3(a^2) = -1$$

$$\begin{aligned} \hookrightarrow \pi_3(a^1) &= \frac{e^1}{e^1 + \bar{e}^1} = 0.88 \\ \pi_3(a^2) &= \frac{\bar{e}^1}{e^1 + \bar{e}^1} = 0.12 \end{aligned} \left. \vphantom{\begin{aligned} \pi_3(a^1) &= \frac{e^1}{e^1 + \bar{e}^1} = 0.88 \\ \pi_3(a^2) &= \frac{\bar{e}^1}{e^1 + \bar{e}^1} = 0.12 \end{aligned}} \right\}$$