

My Solutions for Exercises of Sutton and Barto 2nd Edition

Andres Espinosa

May 3, 2024

Contents

1	Introduction	2
1.1	Exercise 1.1	2
1.2	Exercise 1.2	2
1.3	Exercise 1.3	2
1.4	Exercise 1.4	2
1.5	Exercise 1.5	2
2	Multi-armed Bandits	3
2.1	Exercise 2.1	3
2.2	Exercise 2.2	3
2.3	Exercise 2.3	3
2.4	Exercise 2.4	3
2.5	Exercise 2.5	4
2.6	Exercise 2.6	4
2.7	Exercise 2.7	4

1 Introduction

1.1 Exercise 1.1

The games would eventually result in a tie for every game. Since the model learns the optimal decision, and tic-tac-toe is a game where it is possible to always end in a tie in the case of optimal playing, the models would converge to always ending in a tie.

1.2 Exercise 1.2

We could model the value function in a way where symmetrical states have the same value function. This would benefit exploration because the agent would be able to learn the value function for a state that it has never truly reached. If the opponent did not take advantage of symmetries but the agent does, the opponent would have to experience a state before getting an approximation of the value function. The agent does not need to reach a state because it can use a symmetrical state as an accurate approximation of the value function for the other symmetrical states.

1.3 Exercise 1.3

Not necessarily, greedy actions can cause agents to get stuck in local minima. An agent could perform better if the greedy actions happen to be the best ones, but there could be a better set of actions that are in states the agent has never seen, and since it hasn't seen the state it may never due to its greedy actions.

1.4 Exercise 1.4

If an agent decides to learn from exploration, then it will learn the policy that it is using; a policy that combines optimal and suboptimal actions. If an agent explores but only learns from the greedy actions, then the value function it learns would be the value function that represents the optimal policy, not the policy it is actually executing (a mix of optimal and explorative).

1.5 Exercise 1.5

The tic-tac-toe is a rather simple problem but an agent could learn faster if it learned the value function of the opponent as well as itself. It could maybe use the opponent's value function to inform it's own since the environment is symmetrical to both of them.

2 Multi-armed Bandits

2.1 Exercise 2.1

Define a_1, a_2 as the two actions that can be taken, ε as the probability of selecting a random action, and r as a randomly generated number $\in [0, 1]$.

$$\text{action} = \begin{cases} \text{random choice of } a_1 \text{ or } a_2 & \text{if } r < \varepsilon \\ \text{greedy choice} & \text{if } r \geq \varepsilon \end{cases} \quad (1)$$

if ε is 0.5, there is a 0.5 probability of taking the greedy choice and 0.5 probability of picking the random choice. The random choice has two actions, therefore there is a choice of picking a_1 or a_2 with 0.25 prob each. $0.25 + 0.50 = 0.75$, therefore the probability of the greedy action getting selected is 0.75

2.2 Exercise 2.2

k -armed bandits with $k = 4$. ε -greedy algorithm setting $Q_1(a) = 0 \forall a$. Sample a trajectory (a_1, r_1, a_2, \dots) as $(1, -1, 2, 1, 2, -2, 2, 2, 3, 0)$

- $A_1 = 1$, Greedy (tie broken) or random
- $A_2 = 2$, Greedy (tie broken) or random
- $A_3 = 2$, Greedy or random
- $A_4 = 2$, Must have been random because average reward of a_2 is now $-1/2$
- $A_5 = 3$, Greedy (tie broken) or random

2.3 Exercise 2.3

In the long run, the $\varepsilon = 0.01$ will perform the best. On average, it will pick the optimal action more frequently while still sampling each action an infinite number of times. In the long run, as $Q(a) \approx q_*(a)$, $\varepsilon = 0.01$ will sample the optimal action 99.1% of the time, whereas $\varepsilon = 0.1$ will sample the optimal action 91% of the time, resulting in a smaller frequency of the optimal action being picked and a smaller total reward over the long run.

2.4 Exercise 2.4

Deriving the weighting on prior reward for general case $\alpha_n \neq \alpha$

$$Q_{n+1} = Q_n + \alpha_n[R_n - Q_n] \quad (2)$$

$$Q_{n+1} = \alpha_n R_n + (1 - \alpha_n) Q_n \quad (3)$$

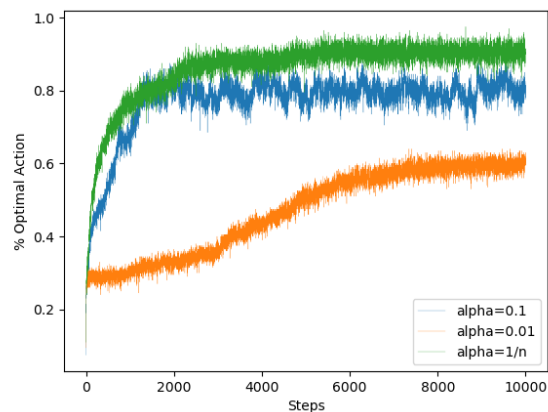
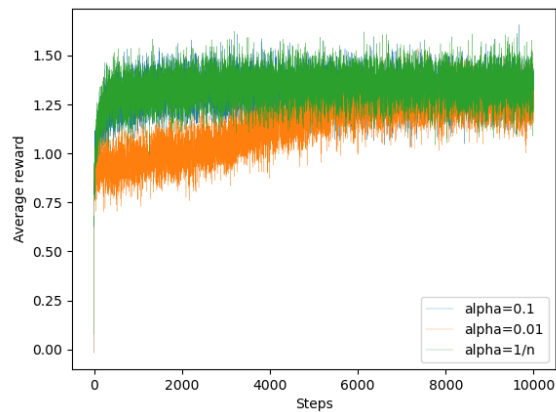
$$Q_{n+1} = \alpha_n R_n + (1 - \alpha_n)[\alpha_{n-1} R_{n-1} + (1 - \alpha_{n-1}) Q_{n-1}] \quad (4)$$

$$Q_{n+1} = \alpha_n R_n + (1 - \alpha_n)\alpha_{n-1} R_{n-1} + (1 - \alpha_n)(1 - \alpha_{n-1}) Q_{n-1} \quad (5)$$

$$Q_{n+1} = Q_1 \prod_{i=1}^n (1 - \alpha_i) + \sum_{i=1}^n R_i \alpha_i \prod_{j=i+1}^n (1 - \alpha_j) \quad (6)$$

2.5 Exercise 2.5

Completed in code



2.6 Exercise 2.6

Optimism will cause every option to look appealing until the option has been sampled enough times. If the option that is appealing happens to be an optimal choice, the decay of the Q value will be slower than that of the other choices.

2.7 Exercise 2.7

$\bar{o}_0 = 0$, therefore $\bar{o}_1 = 0 + \alpha(1 - 0) = \alpha$. $\beta_1 = \alpha/\alpha = 1$. Using the equation derived at the end of exercise 2.4, $Q_1 \prod_{i=1}^n (1 - \alpha_i)$ is 0 since α_1 is 0. Q_n does not include Q_1 so it is without initial bias.