

# Reinforcement Learning

An Introduction  
second edition

Richard S. Sutton and Andrew G. Barto



# Introduction

- Characteristics: trial-and-error search and delayed reward
- Exploration and exploitation trade-off
- Elements of RL:
  - Policy - mapping from states of the environment to actions (agent's behavior)
  - Reward - feedback signal every time step that defines the goal
  - Value function - indicates the long-term desirability of states
  - Model – used for planning

# Chapter 2 - Multi-armed Bandits

# k-armed Bandit

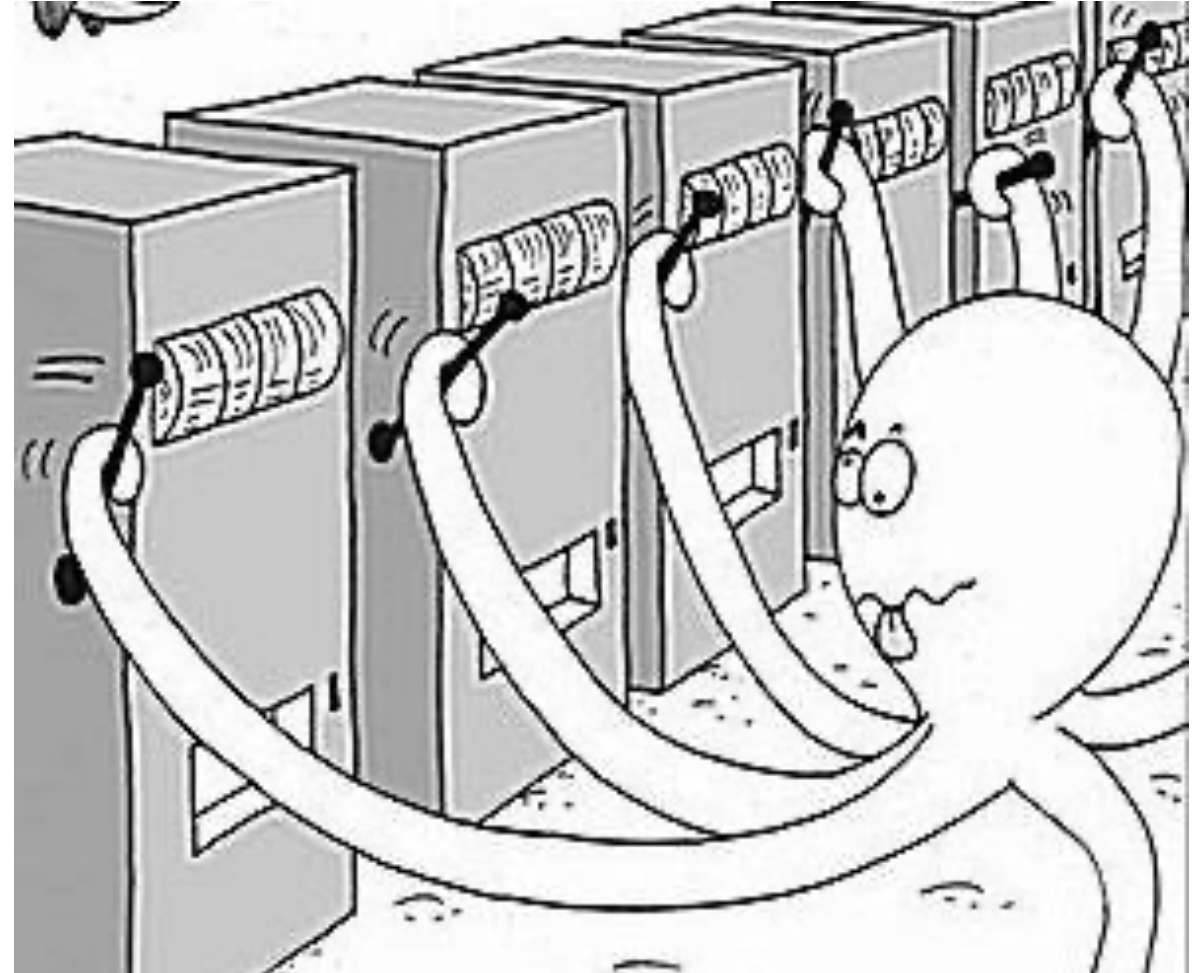
- Value of an action is the expected reward

$$q_*(a) \doteq \mathbb{E}[R_t \mid A_t = a] .$$

- Sample-average estimation
- Greedy actions

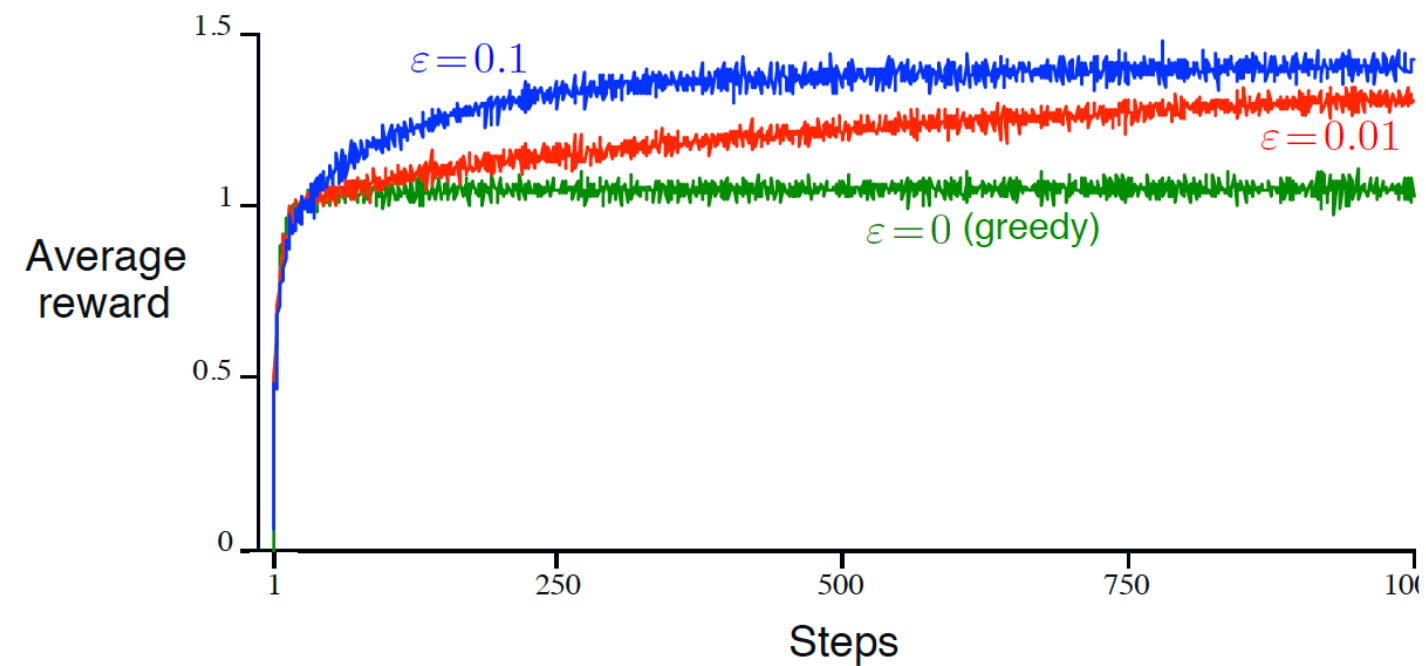
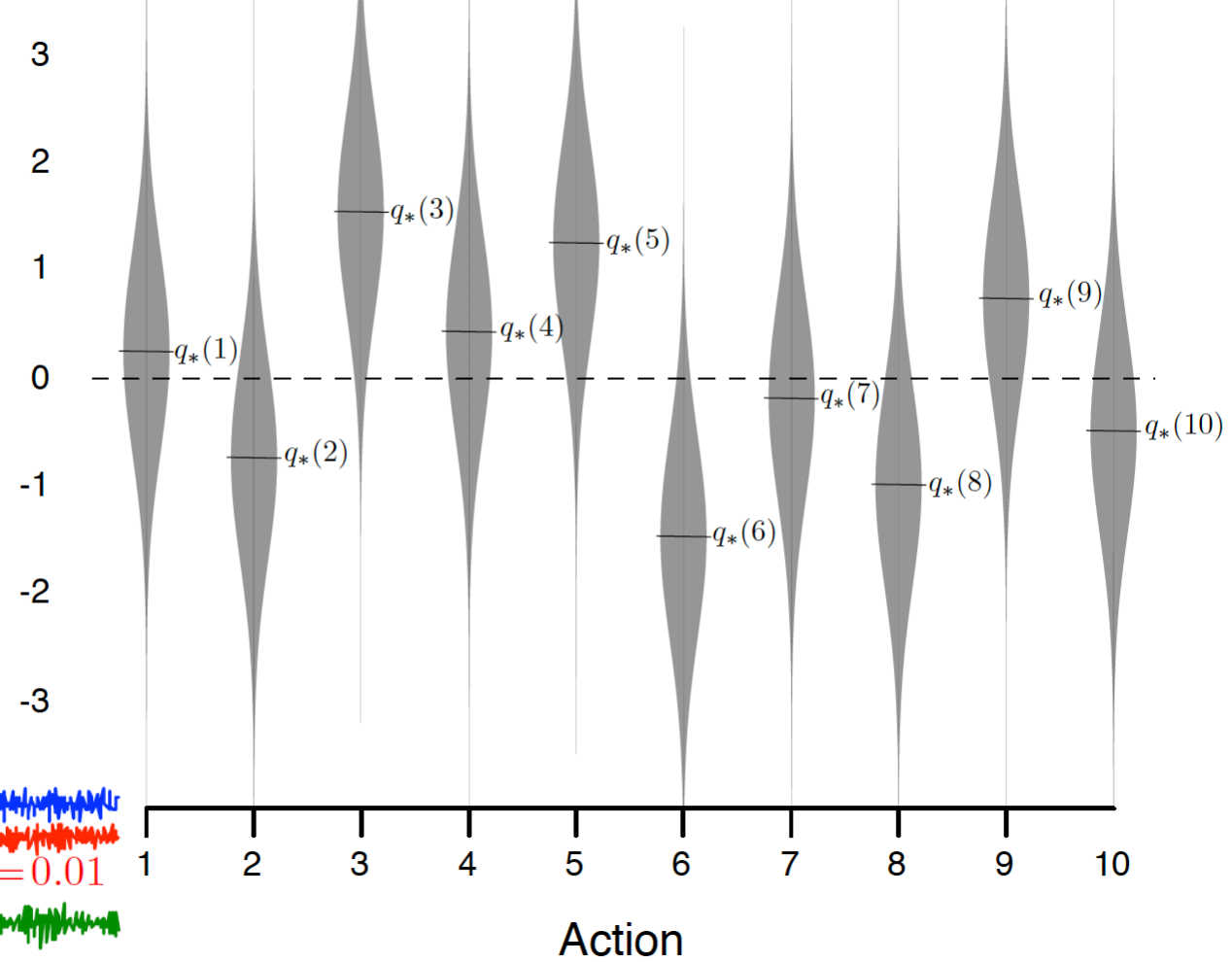
$$A_t \doteq \operatorname{argmax}_a Q_t(a),$$

- Epsilon greedy



# 10-armed Testbed

Reward  
distribution



# Incremental action value

Exponential recency-weighted average for nonstationary problems

$$Q_{n+1} = \frac{1}{n} \sum_{i=1}^n R_i = Q_n + \frac{1}{n} [R_n - Q_n] = Q_n + \alpha [R_n - Q_n]$$

$$\text{NewEstimate} \leftarrow \text{OldEstimate} + \text{StepSize} [\text{Target} - \text{OldEstimate}].$$

## A simple bandit algorithm

Initialize, for  $a = 1$  to  $k$ :

$$Q(a) \leftarrow 0$$

$$N(a) \leftarrow 0$$

Loop forever:

$$A \leftarrow \begin{cases} \operatorname{argmax}_a Q(a) & \text{with probability } 1 - \varepsilon \\ \text{a random action} & \text{with probability } \varepsilon \end{cases} \quad (\text{breaking ties randomly})$$

$$R \leftarrow \text{bandit}(A)$$

$$N(A) \leftarrow N(A) + 1$$

$$Q(A) \leftarrow Q(A) + \frac{1}{N(A)} [R - Q(A)]$$



# Balancing exploration and exploitation

Distribution free:

- Epsilon greedy
- Optimistic initial values
- Upper-confidence-bound (UCB) action selection

Bayesian methods:

- Gittins index
- Posterior sampling or Thompson sampling

