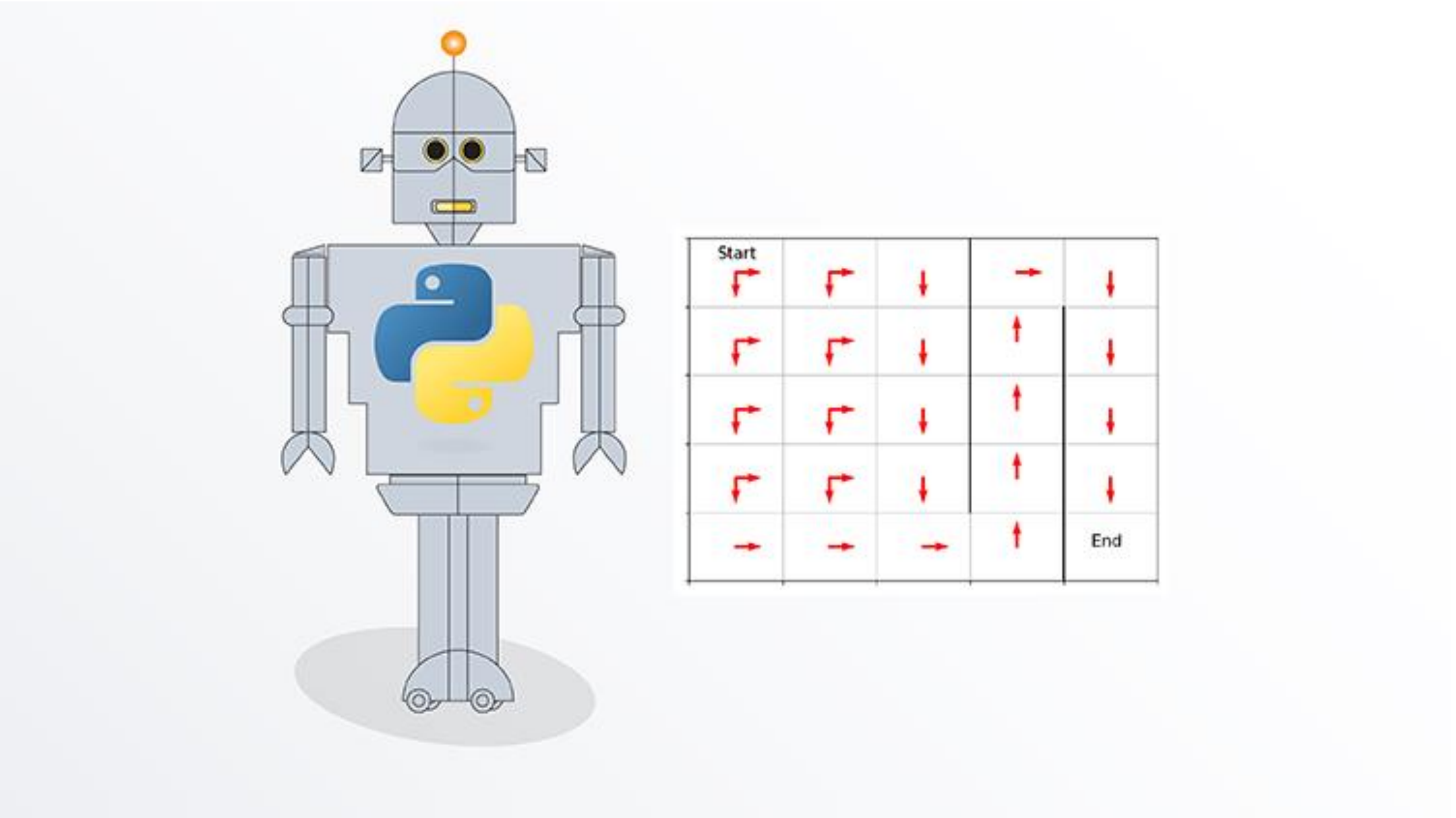
What is Machine Learning?

Chapter 4: Reinforcement Learning



Reinforcement Learning

Definition (see Wikipedia page on Reinforcement Learning)

- Area of machine learning concerned with how software agents should take actions in an environment to maximize the cumulative reward

Informal Definition:

- Learn strategy to maximize the cumulative reward

K Bandit Problem

- One-armed bandit is a nickname for a slot machine
- K Bandit problem:
  - K slot machines n=1,2,…,K each with own mean M_n and payoffs drawn from a normal distribution
  - If means are not known, what strategy to follow to maximize cumulative payoff after many pulls?

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K Bandit Problem

Optimal strategy to get greatest cumulative reward: pull lever for machine with largest mean reward

Agent does not know which machine has largest mean reward -> needs to learn

Greedy Strategy:

- Track sample mean reward for each slot machine
- Pull lever for slot machine with largest current sample mean

Consider example with 2 slot machines

- Machine 1 has actual mean reward = 1
- Machine 2 has actual mean reward = 2

Action	Reward	Cumulative Reward	Machine 1 # Pulls	Machine 1 Total Reward	Machine 1 Sample Mean	Machine 2 # Pulls	Machine 2 Total Reward	Machine 2 Sample Mean
Initial	0	0	0	0	0	0	0	0
Random: Pull M1	1	1	1	1	1	0	0	0
Greedy: Pull M1	-2	-1	2	-1	-0.5	0	0	0
Greedy: Pull M2	1	0	2	-1	-0.5	1	1	1
Greedy: Pull M2	3	3	2	-1	-0.5	2	4	2

Exploit versus Explore in Reinforcement Learning

Issue with Greedy Approach:

- May get stuck pulling lever of machine with lower mean
- Leads to Exploit versus Explore dilemma

Exploit:

- At current position, take action to maximize immediate reward

Explore:

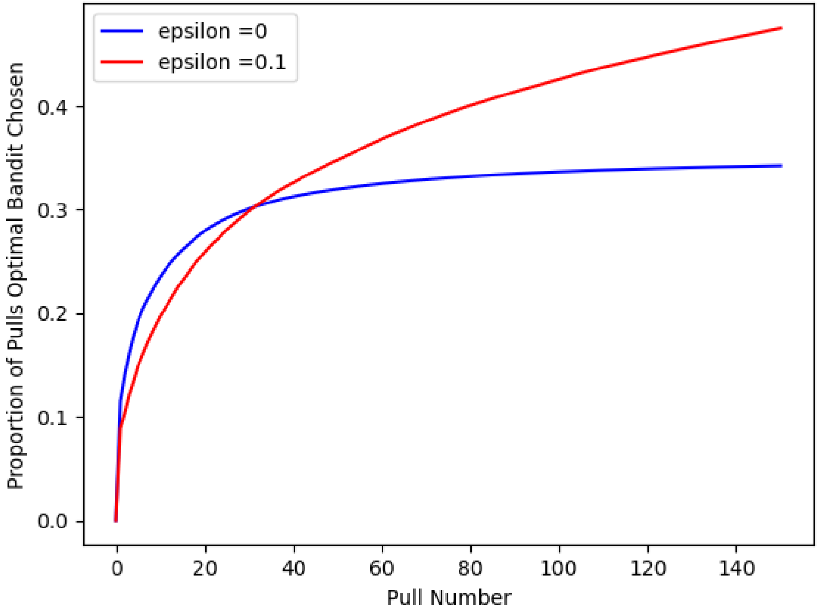
- At current position, take action to learn about environment
- Information acquired in exploration to be used later to hopefully increase cumulative reward

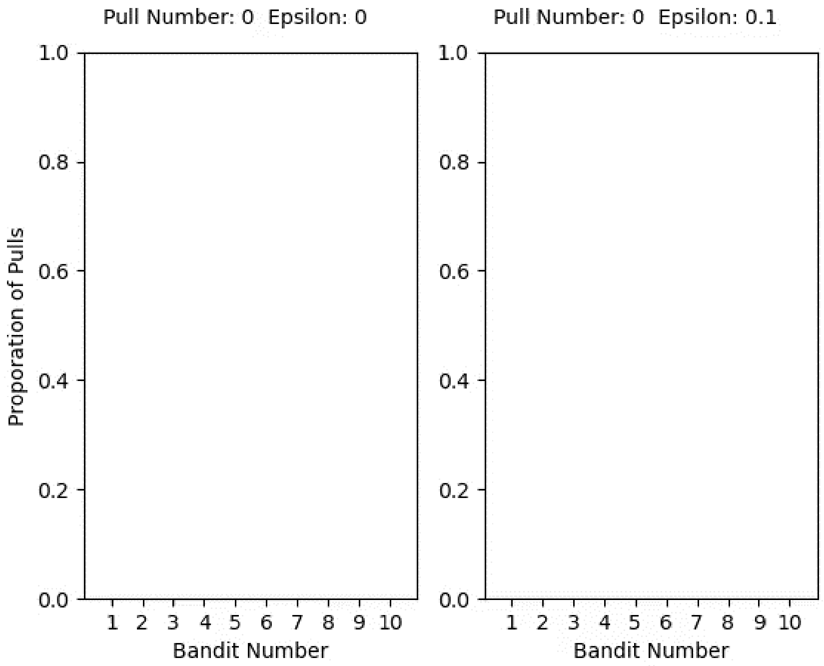
Epsilon Greedy Strategy:

- For ϵ proportion of time pull lever of slot machine at random
- For 1 - ϵ proportion of time pull lever of machine with largest current sample mean

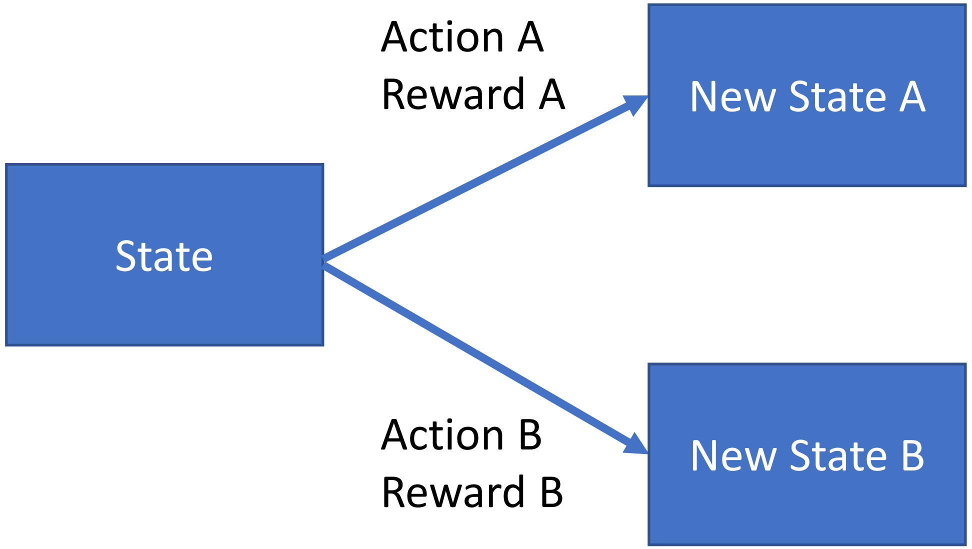
K Bandit Problem - Simulation

- 10 slot machines
- Means drawn from standard normal distribution
- Results averaged over 1000 simulations
- Compare Greedy and Epsilon Greedy Approach with $\epsilon = 0.1$





General Formulation for Reinforcement Learning

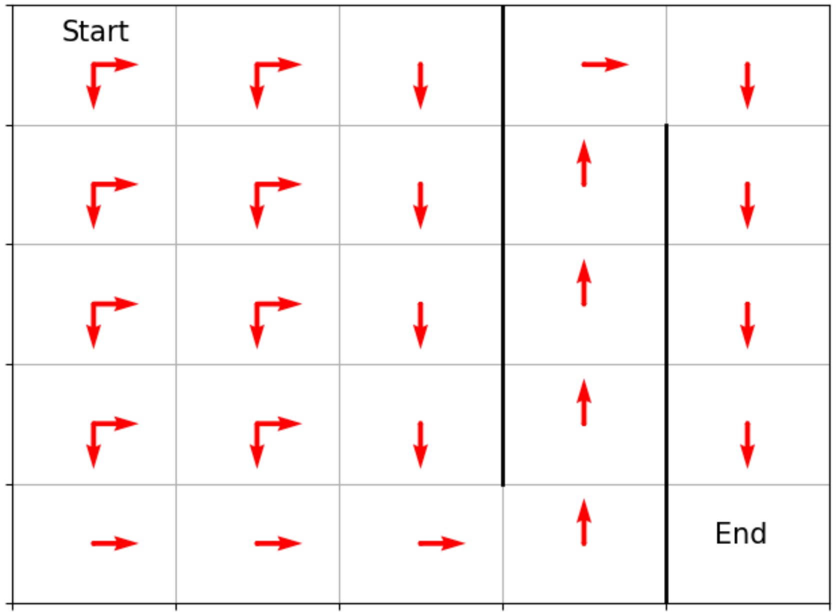


Starting at State

- Agent is allowed to take a number of possible actions, each with a specified reward and leading to a new state, where process is repeated
- Process continues forever or until reaching a terminal state
- Goal: find optimal strategy (action at each state) to maximize total cumulative reward (which may involve discounting)

Maze Problem

- State is location in maze
- Actions: up, down, left or right (stay in same place if action means hitting a wall)
- Reward is -1 for each step (including if hit wall)
- Cumulative reward is (-1) * number of step to go to End
- Goal: find strategy that maximizes cumulative reward from Start to End (equivalent to minimizing number of steps)



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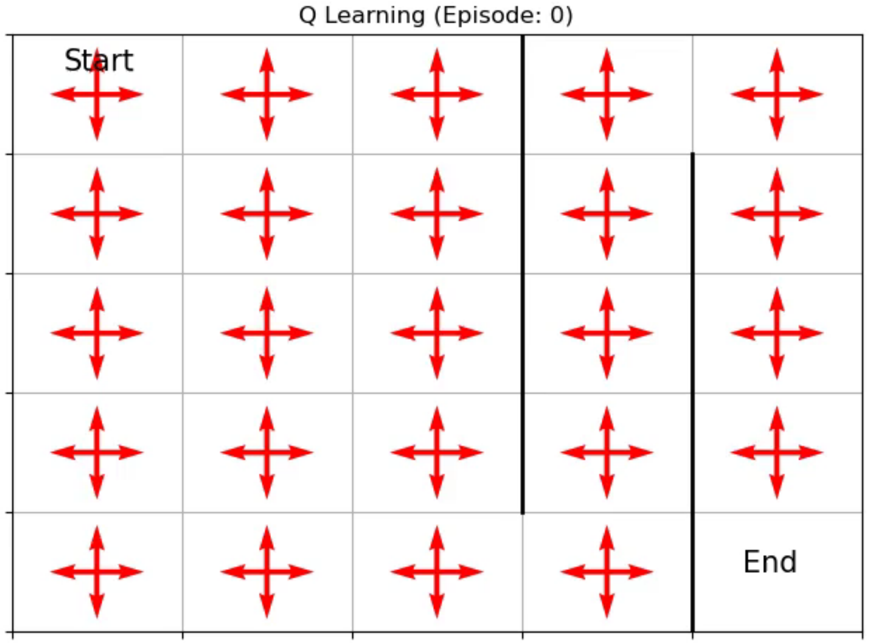
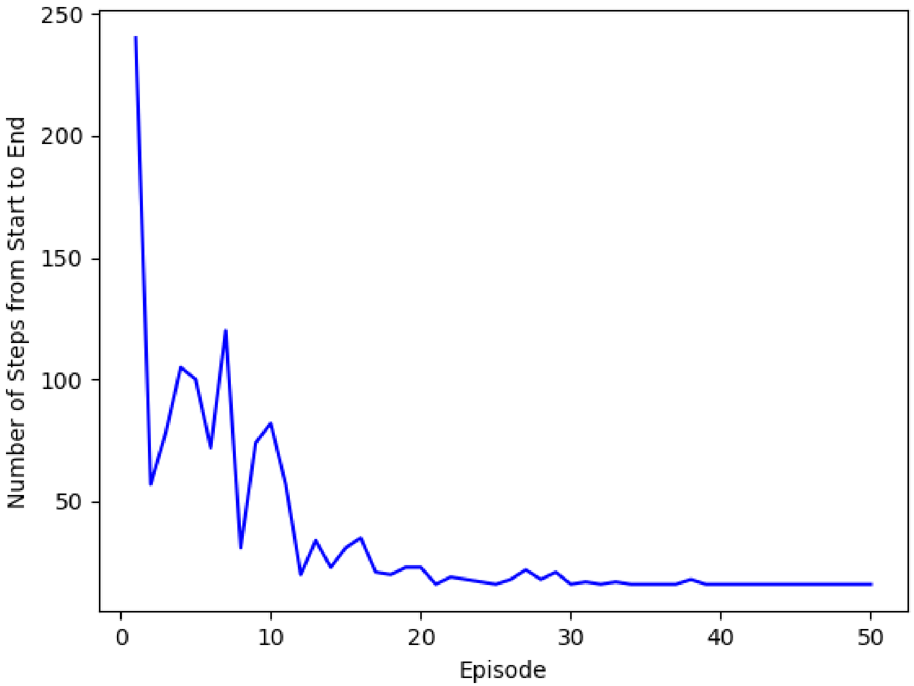
Q Learning Approach to Finding Path

- Use “Q Learning” approach
  - Simulate “episode” (sequence state/action/state/action… to go from Start to Finish)
  - Start with equal probability for up, down, left, or right actions at each state
  - Update “action-value” function Q(s,a) which tracks cumulative reward for each state/action pair
  - Follow greedy strategy -> take action that maximizes cumulative reward
  - Repeat for many episodes
  - This process yields optimal strategy, obtained as maximum of action-value function over all possible actions at each state

Maze: Results from Q Learning

- Animation shows how strategy evolves from initial equally likely actions to optimal actions (actions updated after each episode)
- Plot shows Number of Moves from Start to End as a function of episode
  - Settles down at 16 steps = minimum number of steps from Start to End





Reinforcement Learning: Applications

Application	Notes
Industrial Control	States: location on factory floor, battery status Actions: perform tasks or return to home base for charging Rewards: positive rewards for performing task, negative reward for running out of power in middle of factory floor
Game Playing	States: configuration of pieces on the game board Actions: allowable moves Rewards: typically positive reward for winning game (may be additional intermediate rewards for other accomplishments during play)

Reinforcement Learning: Notes

Component	Notes:
Q Learning and related algorithms	• Suitable if reasonable number of states and actions: • Maze problem has 24 states/4 actions per state -> 96 action values to learn
Dyna Q	• Can reduce number of episodes to learn optimal strategy by incorporating planning as in Dyna Q algorithm
	Must use alternative approaches if there are many states/actions • Chess has astronomical number of configurations of pieces on the board • Use approximation methods to estimate action values for state/action pairs (can use ideas from Supervised Learning)
AlphaZero	Effort to create artificial intelligence program to play chess, shogi and go (see AlphaZero Wikipedia page and see AlphaGo movie on Youtube) • Trained using self play only • Beat other state of the art programs in chess, go, shogi