6.825 Techniques in Artificial Intelligence

Reinforcement Learning

- Exploration
- Q learning
- Extensions and examples

Reinforcement Learning

What do you do when you don’t know how the world works?

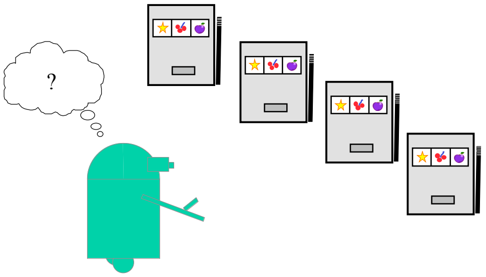
One option:

- estimate R (reward function) and P (transition function) from data
- solve for optimal policy given estimated R and P

Another option:

- estimate a value function directly

Bandit Problems



Bandit Strategies

- switch on a loser
- always choose the apparent best
- choose the apparent best 90% of the time; choose randomly the other 10%
- consider both the amount of experience you’ve had with each arm and the payoff
- etc…

Arms are like actions in a single-state MDP

Imagine what this problem is like in a multi-state MDP!

Q Function

A different way to write down the recursive value function equation.

Q*(s,a) is the expected discounted future reward for starting in state s, taking action a, and continuing optimally thereafter.

$$Q^*(s,a) = R(s) + \gamma \sum_{s'} \Pr(s' \mid s,a) \max_{a'} Q^*(s',a')$$

$$\pi^*(s) = \arg\max_a Q^*(s,a)$$

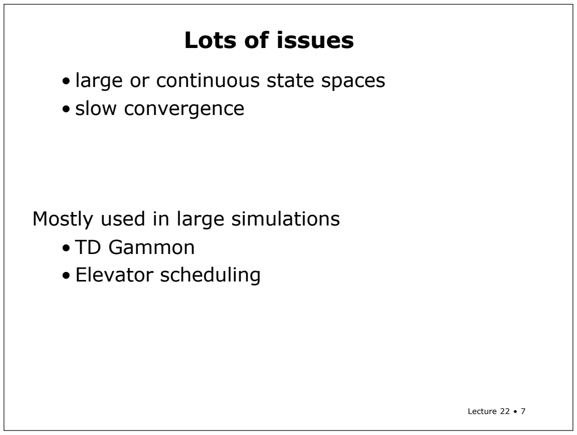
Q Learning

A piece of experience in the world is $\langle s,a,r,s' \rangle$

- Initialize Q(s,a) arbitrarily
- After each experience, update Q:

$$Q(s,a) \leftarrow (1-\alpha)Q(s,a) + \alpha q(r,s')$$
$$q(r,s') = r + \gamma \max_{a'} Q(s',a')$$

Guaranteed to converge to optimal Q if the world is really an MDP



Lots of issues

- large or continuous state spaces
- slow convergence

Mostly used in large simulations

- TD Gammon
- Elevator scheduling