Reinforcement Learning I: Temporal Differences

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CS 421: Introduction to Artificial Intelligence

23 Feb 2012

Many slides courtesy of
Dan Klein, Stuart Russell,
or Andrew Moore

Announcements

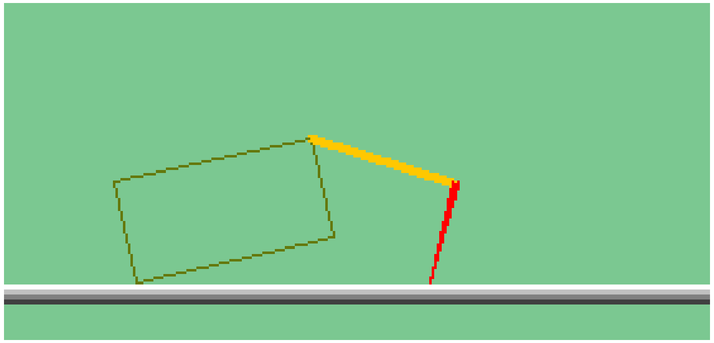
- None...

Survey Results

- Pace:
- Cvg:
- HW:
- P1:
- P2:

Reinforcement Learning

- Reinforcement learning:
  - Still have an MDP:
    - A set of states $s \in S$
    - A set of actions (per state) A
    - A model T(s,a,s')
    - A reward function R(s,a,s')
  - Still looking for a policy $\pi(s)$
  - New twist: don't know T or R
    - I.e. don't know which states are good or what the actions do
    - Must actually try actions and states out to learn



[DEMO]

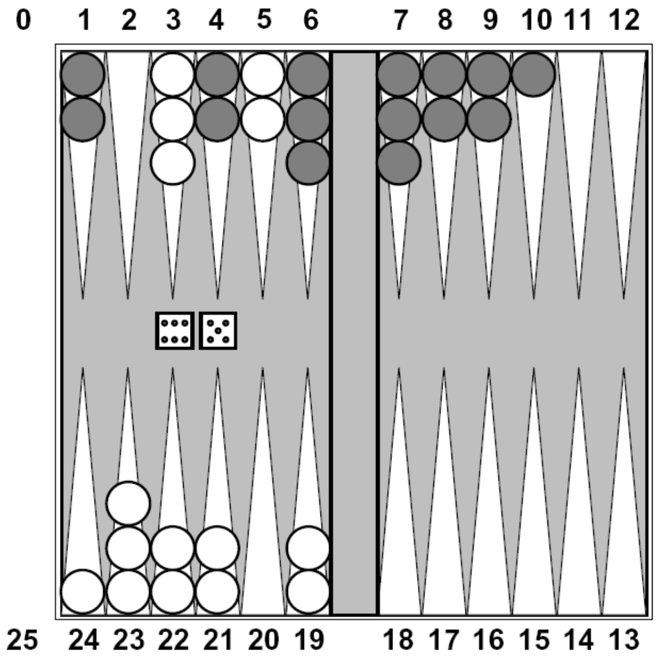
Example: Animal Learning

- RL studied experimentally for more than 60 years in psychology
  - Rewards: food, pain, hunger, drugs, etc.
  - Mechanisms and sophistication debated

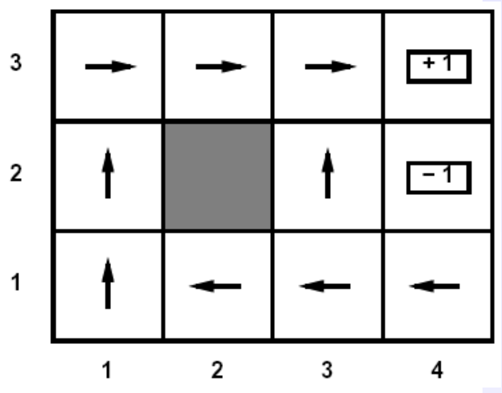
- Example: foraging
  - Bees learn near-optimal foraging plan in field of artificial flowers with controlled nectar supplies
  - Bees have a direct neural connection from nectar intake measurement to motor planning area

Example: Backgammon

- Reward only for win / loss in terminal states, zero otherwise
- TD-Gammon learns a function approximation to V(s) using a neural network
- Combined with depth 3 search, one of the top 3 players in the world
- You could imagine training Pacman this way…
- … but it's tricky!



Passive Learning



- Simplified task
  - You don't know the transitions T(s,a,s')
  - You don't know the rewards R(s,a,s')
  - You are given a policy π(s)
  - Goal: learn the state values (and maybe the model)
- In this case:
  - No choice about what actions to take
  - Just execute the policy and learn from experience
  - We'll get to the general case soon

Example: Direct Estimation

- Episodes:

(1,1) up -1
(1,2) up -1
(1,2) up -1
(1,3) right -1
(2,3) right -1
(3,3) right -1
(3,2) up -1
(3,3) right -1
(4,3) exit +100
(done)

(1,1) up -1
(1,2) up -1
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(3,3) right -1
(3,2) up -1
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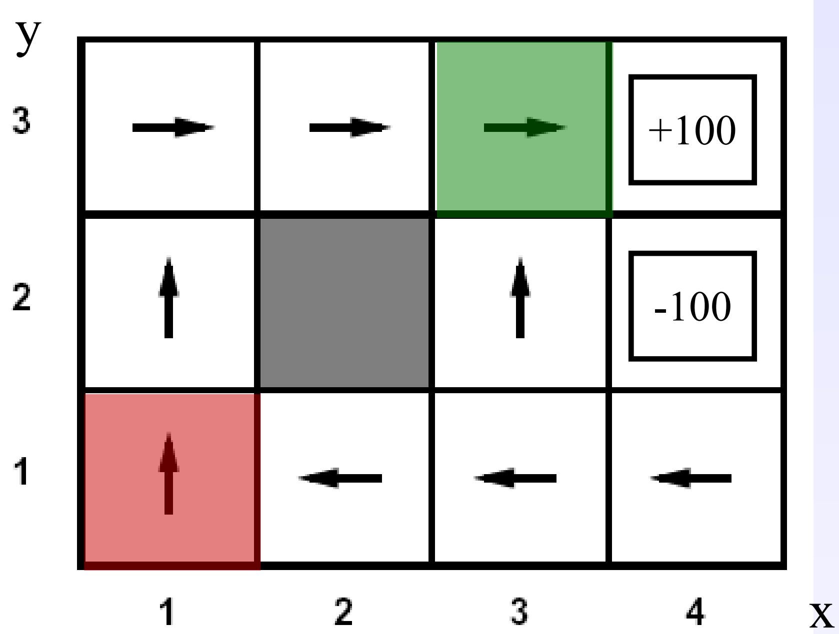
(done)



$\gamma = 1$, R = -1

U(1,1) ~ (92 + -106) / 2 = -7

U(3,3) ~ (99 + 97 + -102) / 3 = 31.3

Model-Based Learning

- In general, want to learn the optimal policy, not evaluate a fixed policy
- Idea: adaptive dynamic programming
  - Learn an initial model of the environment:
  - Solve for the optimal policy for this model (value or policy iteration)
  - Refine model through experience and repeat
  - Crucial: we have to make sure we actually learn about all of the model

Model-Based Learning

- Idea:
  - Learn the model empirically (rather than values)
  - Solve the MDP as if the learned model were correct

- Empirical model learning
  - Simplest case:
    - Count outcomes for each s,a
    - Normalize to give estimate of T(s,a,s')
    - Discover R(s,a,s') the first time we experience (s,a,s')
  - More complex learners are possible (e.g. if we know that all squares have related action outcomes, e.g. "stationary noise")

Example: Model-Based Learning

- Episodes:

(1,1) up -1
(1,2) up -1
(1,2) up -1
(1,3) right -1
(2,3) right -1
(3,3) right -1
(3,2) up -1
(3,3) right -1
(4,3) exit +100
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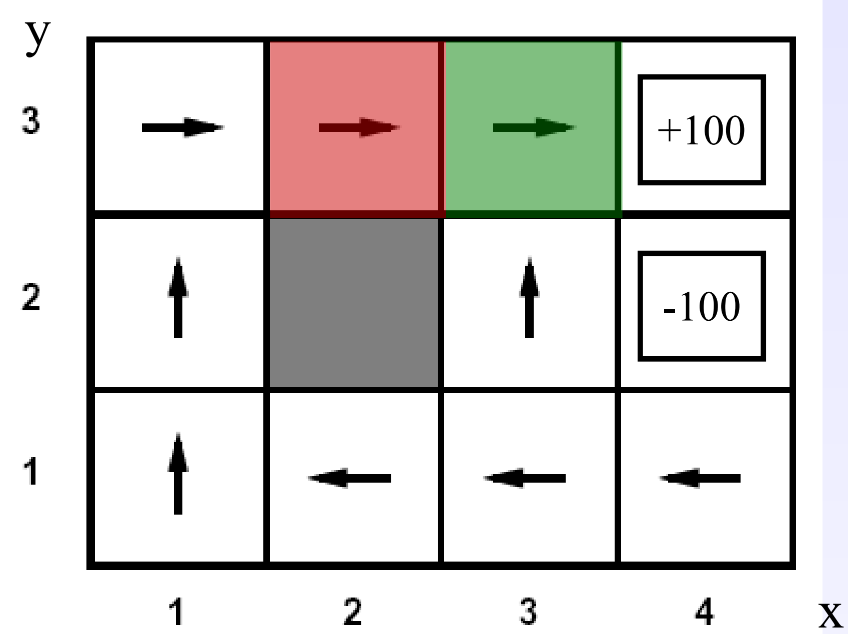


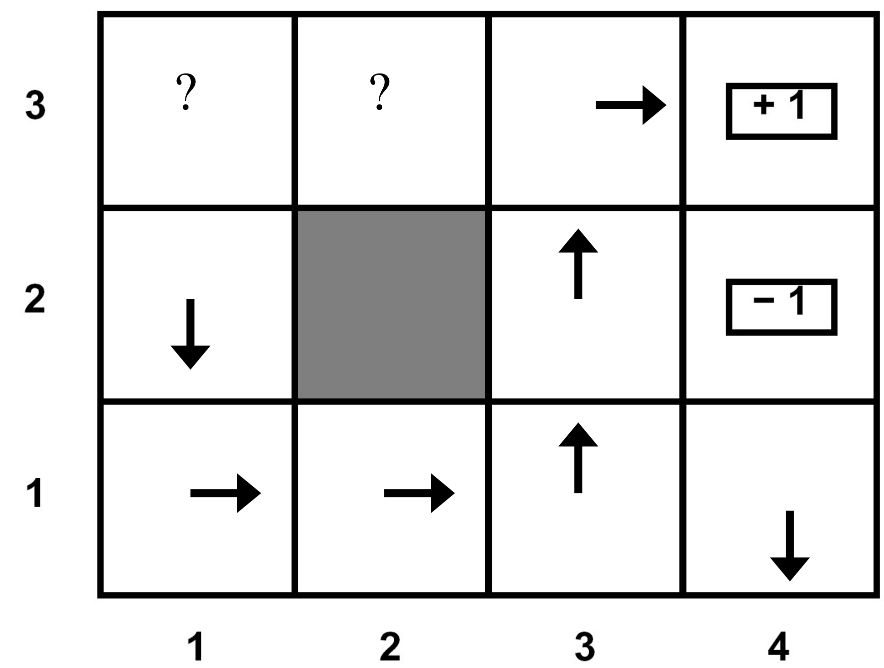
$\gamma = 1$

T(<3,3>, right, <4,3>) = 1 / 3

T(<2,3>, right, <3,3>) = 2 / 2

Example: Greedy ADP

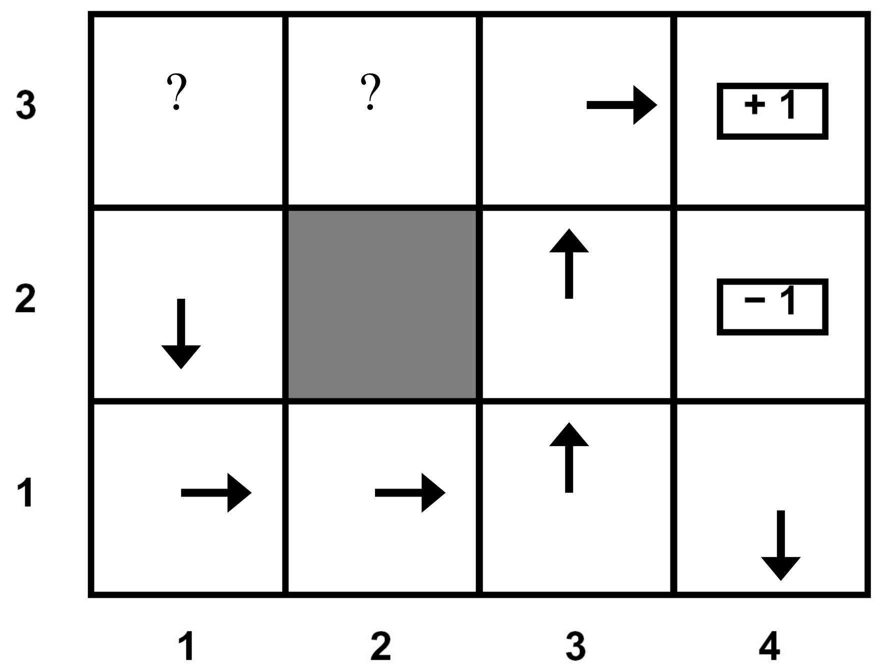
- Imagine we find the lower path to the good exit first
- Some states will never be visited following this policy from (1,1)
- We'll keep re-using this policy because following it never collects the regions of the model we need to learn the optimal policy



What Went Wrong?

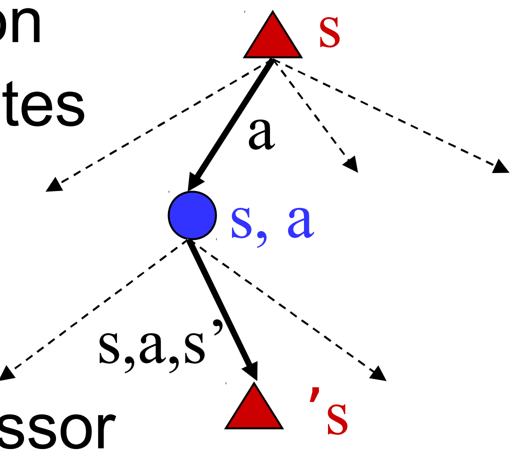
- Problem with following optimal policy for current model:
  - Never learn about better regions of the space if current policy neglects them

- Fundamental tradeoff: exploration vs. exploitation
  - Exploration: must take actions with suboptimal estimates to discover new rewards and increase eventual utility
  - Exploitation: once the true optimal policy is learned, exploration reduces utility
  - Systems must explore in the beginning and exploit in the limit



Model-Free Learning

- Big idea: why bother learning T?
  - Update V each time we experience a transition
  - Frequent outcomes will contribute more updates (over time)
- Temporal difference learning (TD)
  - Policy still fixed!
  - Move values toward value of whatever successor occurs



$$V^{\pi}(s) \leftarrow \sum_{s'} T(s,\pi(s),s')[R(s,a,s') + \gamma V^{\pi}(s')]$$

$$sample = R(s,a,s') + \gamma V^{\pi}(s')$$

$$V^{\pi}(s) \leftarrow V^{\pi}(s) + \alpha(sample - V^{\pi}(s))$$

Example: Passive TD

$$V^{\pi}(s) \leftarrow V^{\pi}(s) + \alpha \left[R(s,a,s') + \gamma V^{\pi}(s') - V^{\pi}(s) \right]$$

(1,1) up -1
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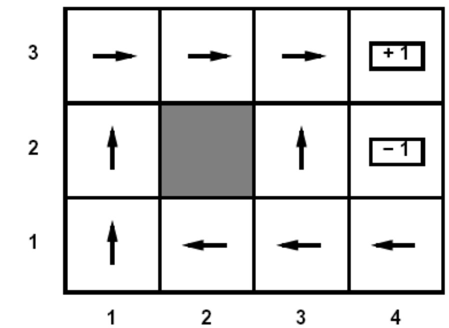
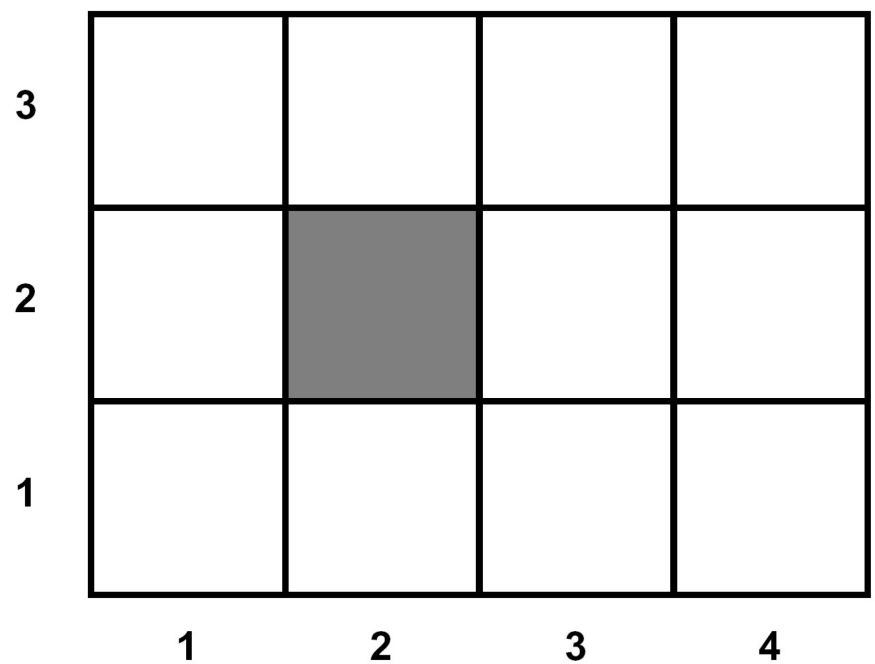
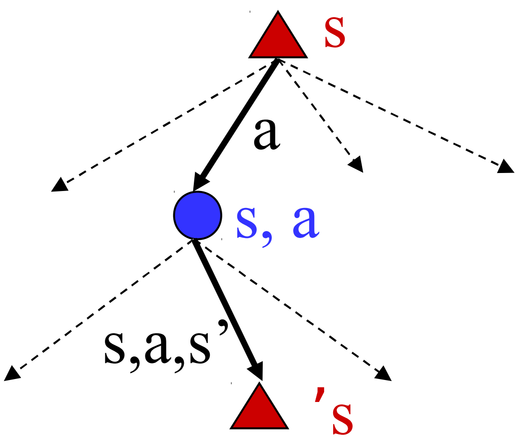




Take $\gamma = 1$, $\alpha = 0.5$

Problems with TD Value Learning

- TD value leaning is model-free for policy evaluation
- However, if we want to turn our value estimates into a policy, we're sunk:



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

$$Q^*(s,a) = \sum_{s'} T(s,a,s')\left[R(s,a,s') + \gamma V^*(s')\right]$$

- Idea: learn Q-values directly
- Makes action selection model-free too!