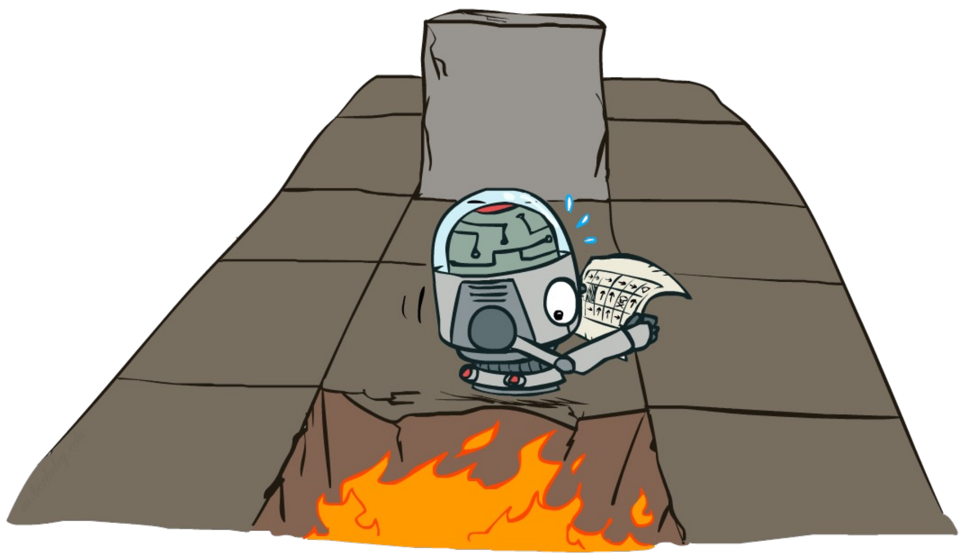
Announcements

Assignments:

- P3: Logic Plan
  - Checkpoint Due Friday 3/3, 10 pm (tomorrow)
  - All Due Friday 3/17, 10pm (after spring break)
- HW6 (online)
  - Due Tues 3/14, 10 pm

AI: Representation and Problem Solving

Markov Decision Processes II

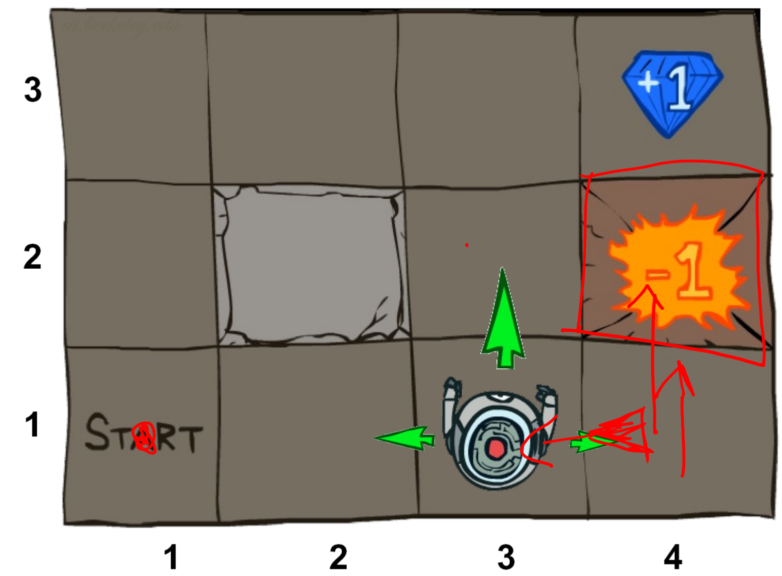


Instructor: Stephanie Rosenthal

Slide credits: CMU AI and http://ai.berkeley.edu

Recap: Grid World

- A maze-like problem
  - The agent lives in a grid
  - Walls block the agent's path
- Noisy movement: actions do not always go as planned
  - 80% of the time, the action North takes the agent North
  - 10% of the time, North takes the agent West; 10% East
  - If there is a wall in the direction the agent would have been taken, the agent stays put
- The agent receives rewards each time step
  - Small "living" reward each step (can be negative)
  - Big rewards come at the end (good or bad)

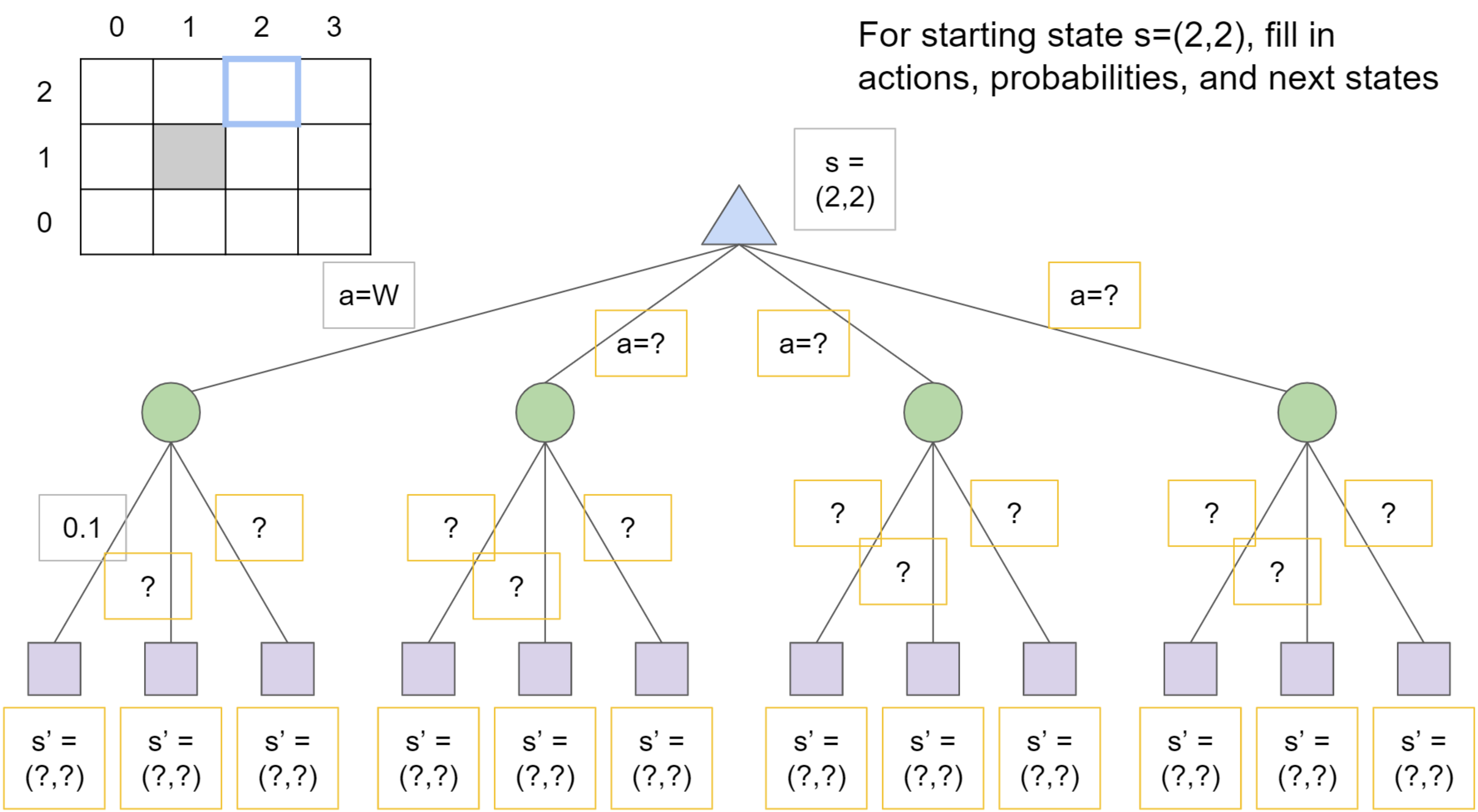


$R(s, a, s')$ $R(s)$

$R(s')$ $R(a)$

Grid World

For starting state s=(2,2), fill in actions, probabilities, and next states



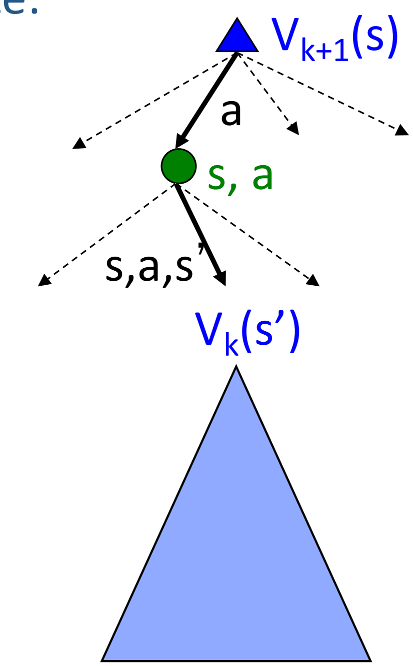
Value Iteration

Start with $V_0(s) = 0$: no time steps left means an expected reward sum of zero

Given vector of $V_k(s)$ values, do one ply of expectimax from each state:

$$V_{k+1}(s) \leftarrow \max_a \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma V_k(s')\right]$$

Repeat until convergence



Theorem: will converge to unique optimal values

- Basic idea: approximations get refined towards optimal values
- Policy may converge long before values do

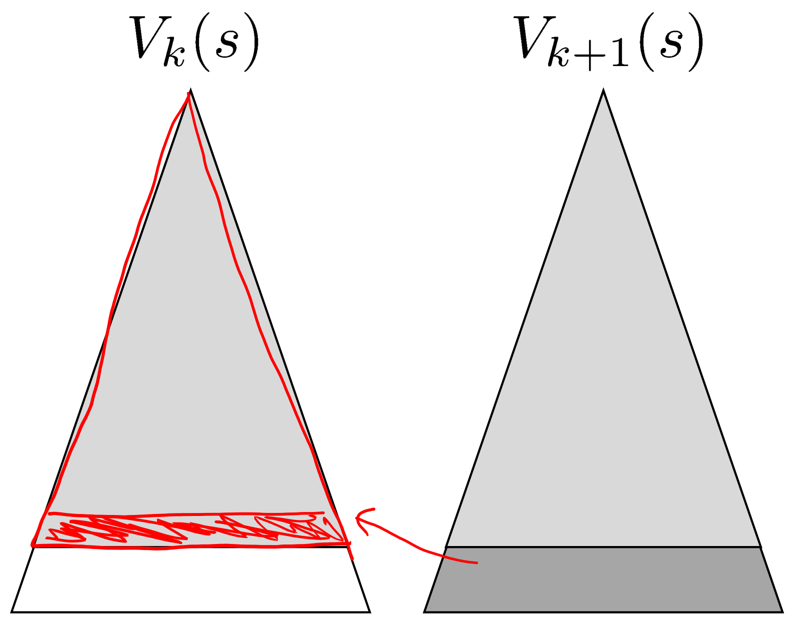
Value Iteration Convergence

How do we know the V_k vectors are going to converge?

Case 1: If the tree has maximum depth M, then V_M holds the actual untruncated values

Case 2: If the discount is less than 1

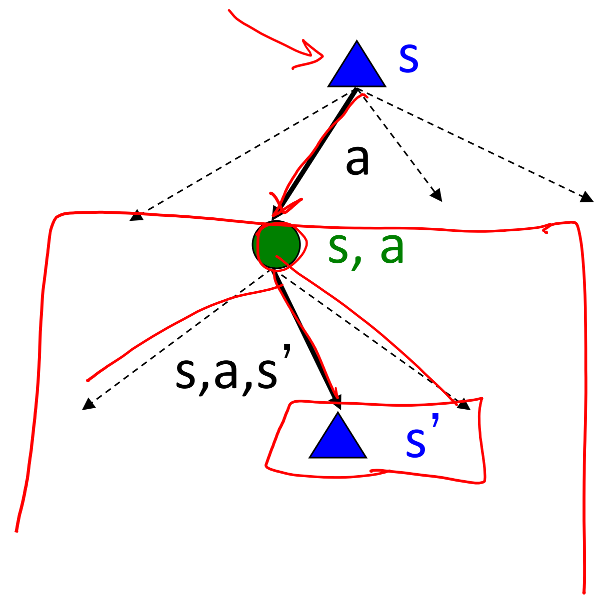
- Sketch: For any state V_k and V_{k+1} can be viewed as depth k+1 expectimax results in nearly identical search trees
- The difference is that on the bottom layer, V_{k+1} has actual rewards while V_k has zeros
- That last layer is at best all R_{MAX}
- It is at worst R_{MIN}
- But everything is discounted by γ^k that far out
- So V_k and V_{k+1} are at most $\gamma^k \max|R|$ different
- So as k increases, the values converge



Values of States

Fundamental operation: compute the (expectimax) value of a state

- Expected utility under optimal action
- Average sum of (discounted) rewards
- This is just what expectimax computed!



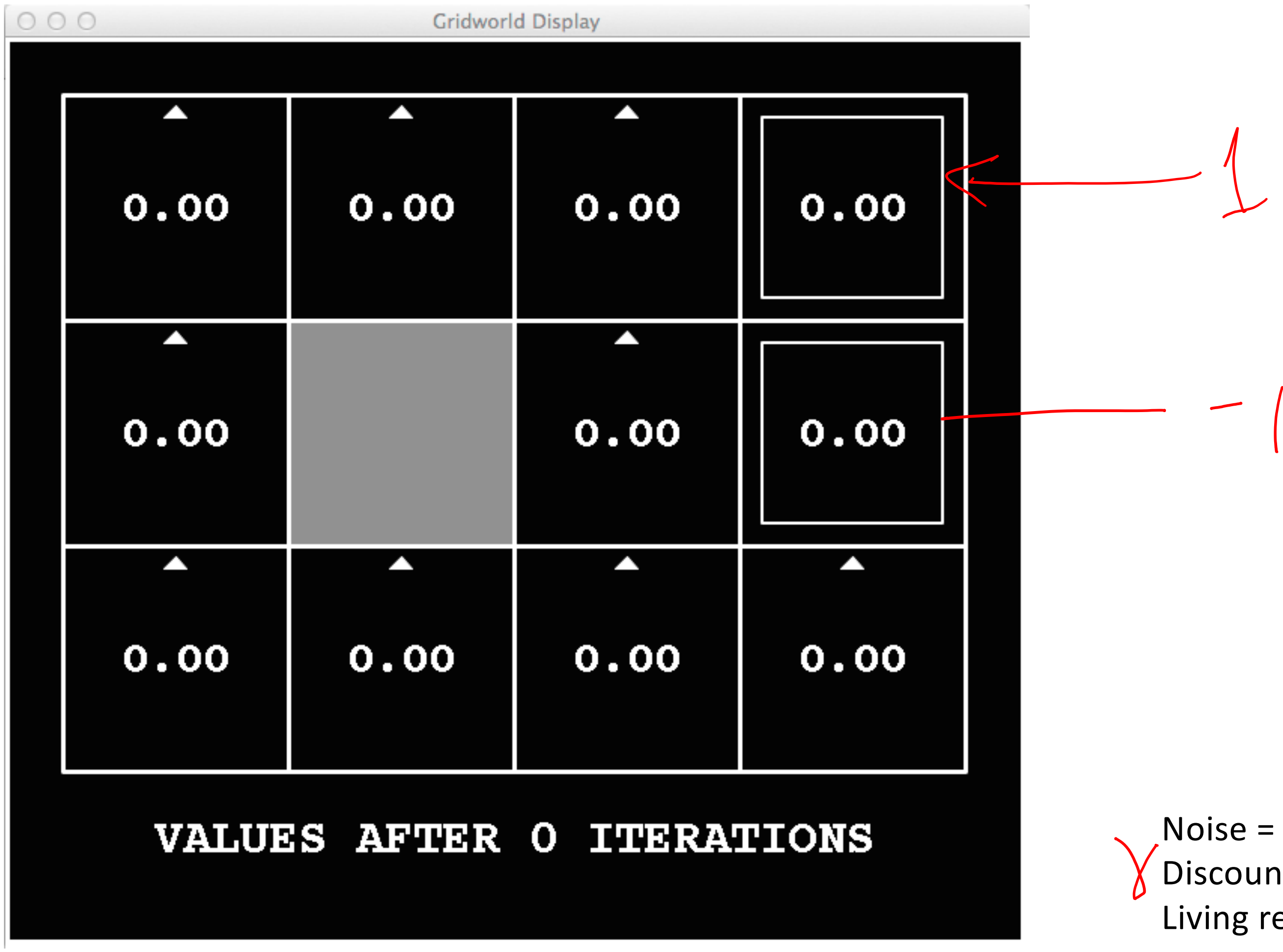
Recursive definition of value:

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

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

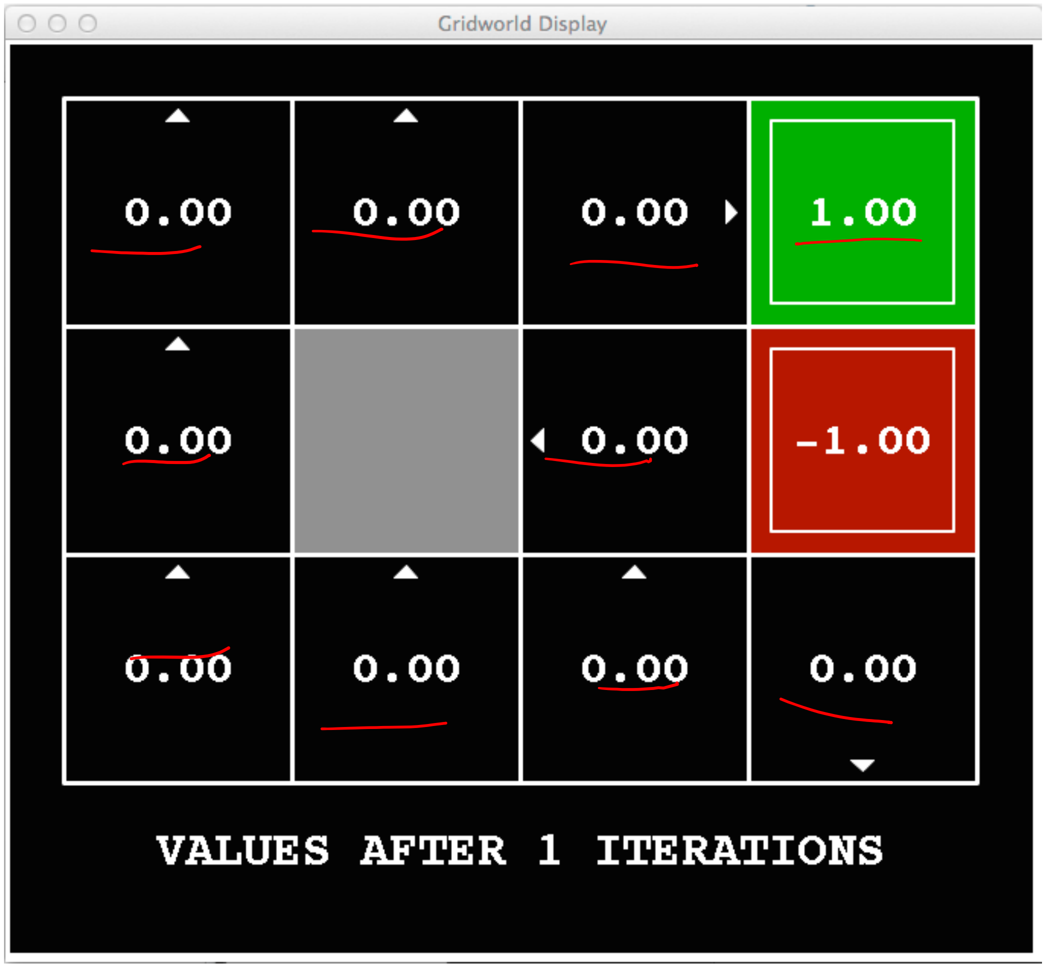
$$V^*(s) = \max_a \sum_{s'} T(s,a,s')\left[R(s,a,s') + \gamma V^*(s')\right]$$

k=0



Noise = 0.2
Discount = 0.9
Living reward = 0

k=1



Noise = 0.2
Discount = 0.9
Living reward = 0

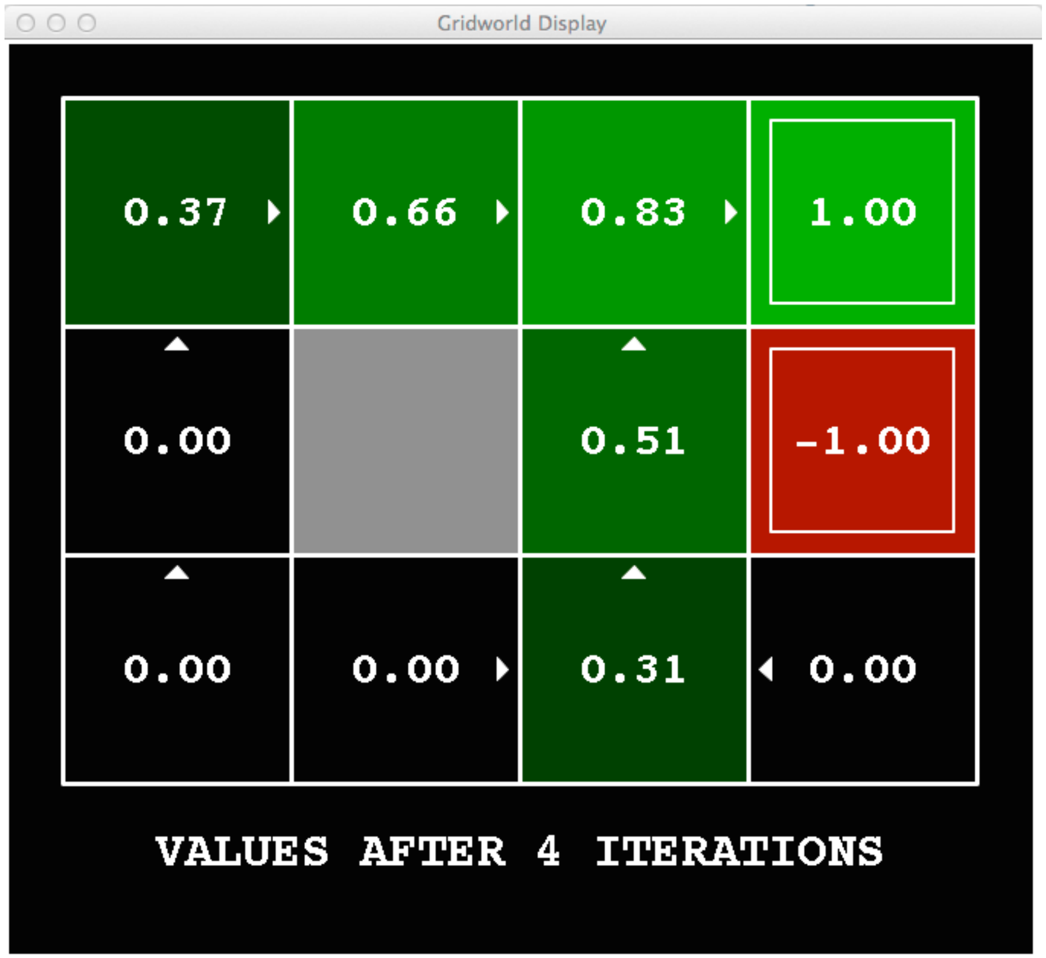
k=2

Noise = 0.2
Discount = 0.9
Living reward = 0

k=3

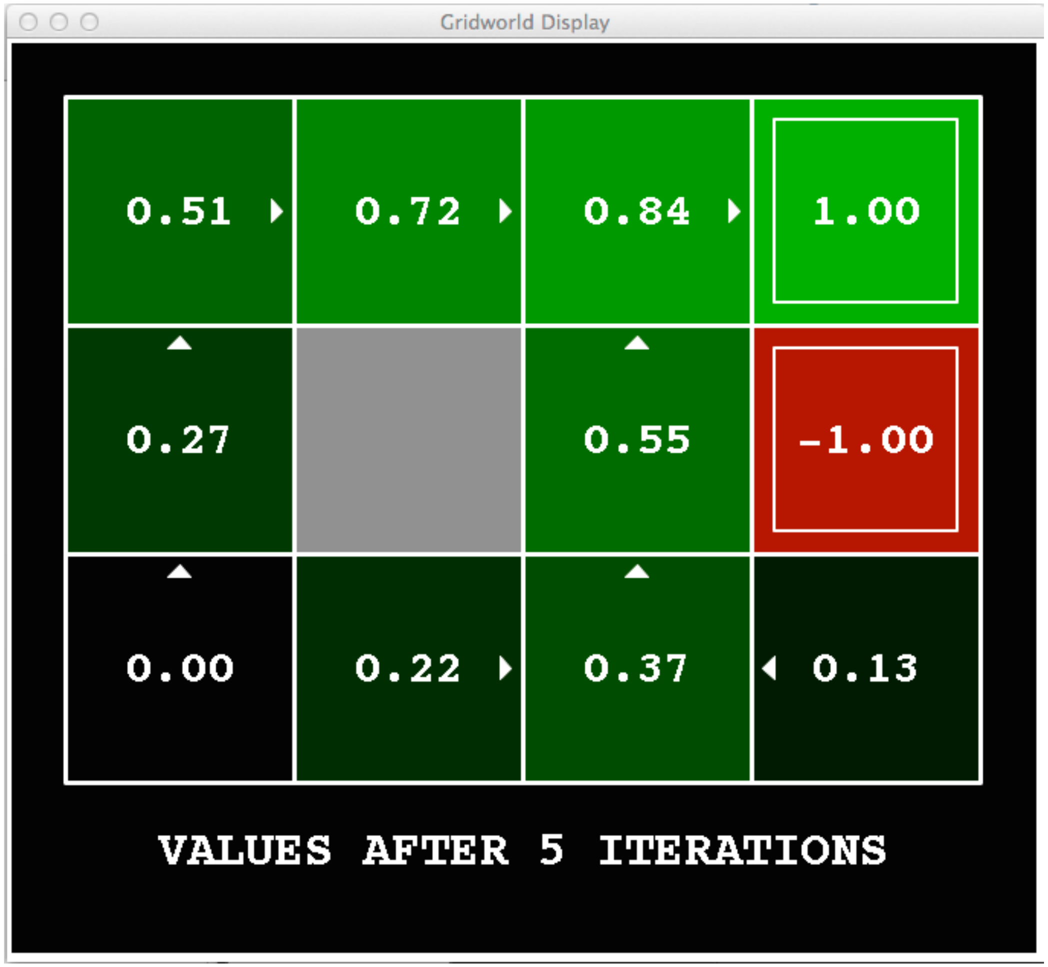
Noise = 0.2
Discount = 0.9
Living reward = 0

k=4



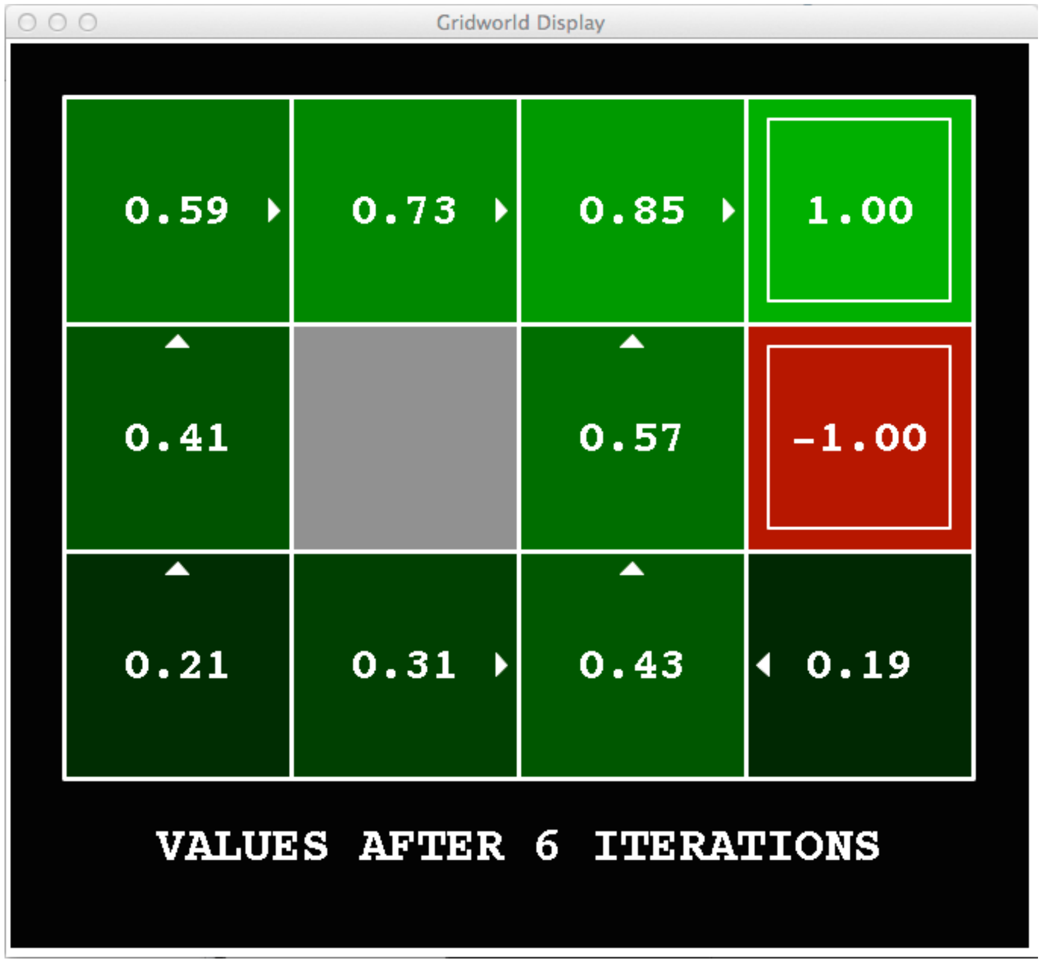
Noise = 0.2
Discount = 0.9
Living reward = 0

k=5



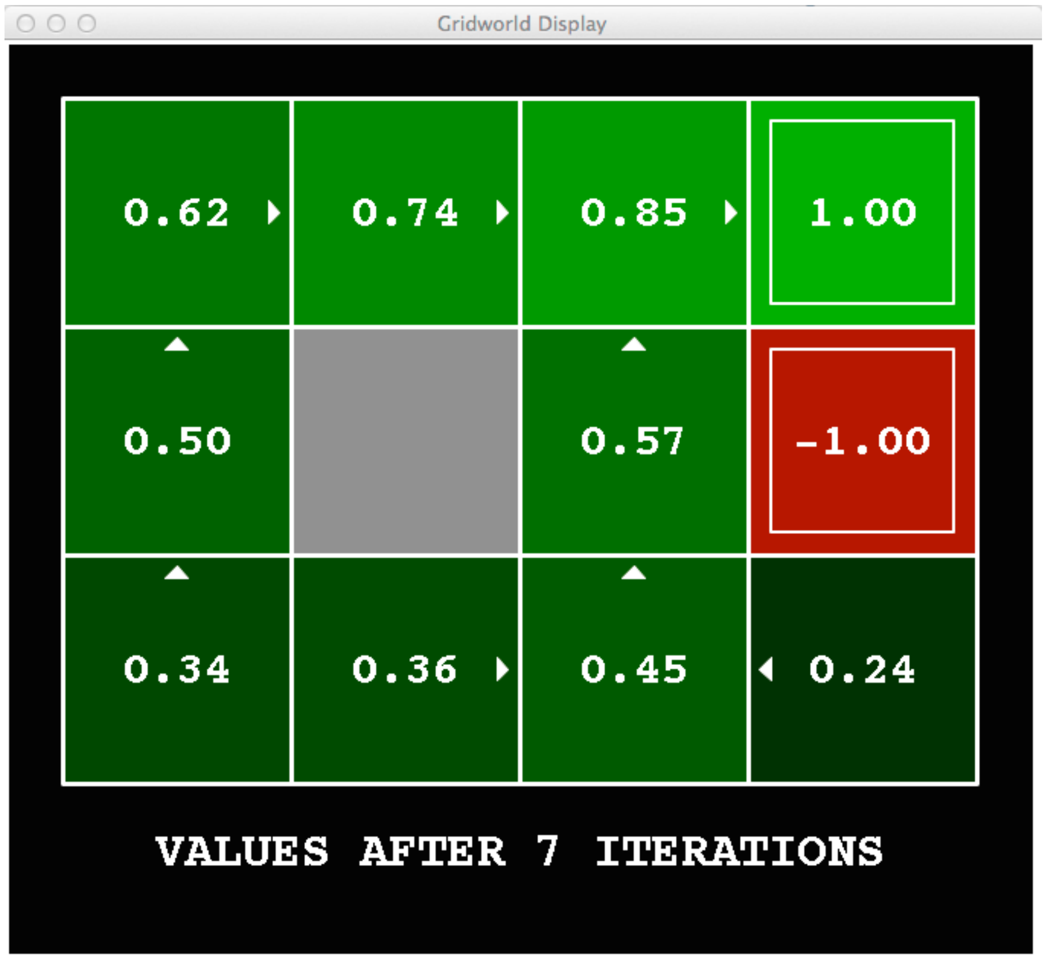
Noise = 0.2
Discount = 0.9
Living reward = 0

k=6



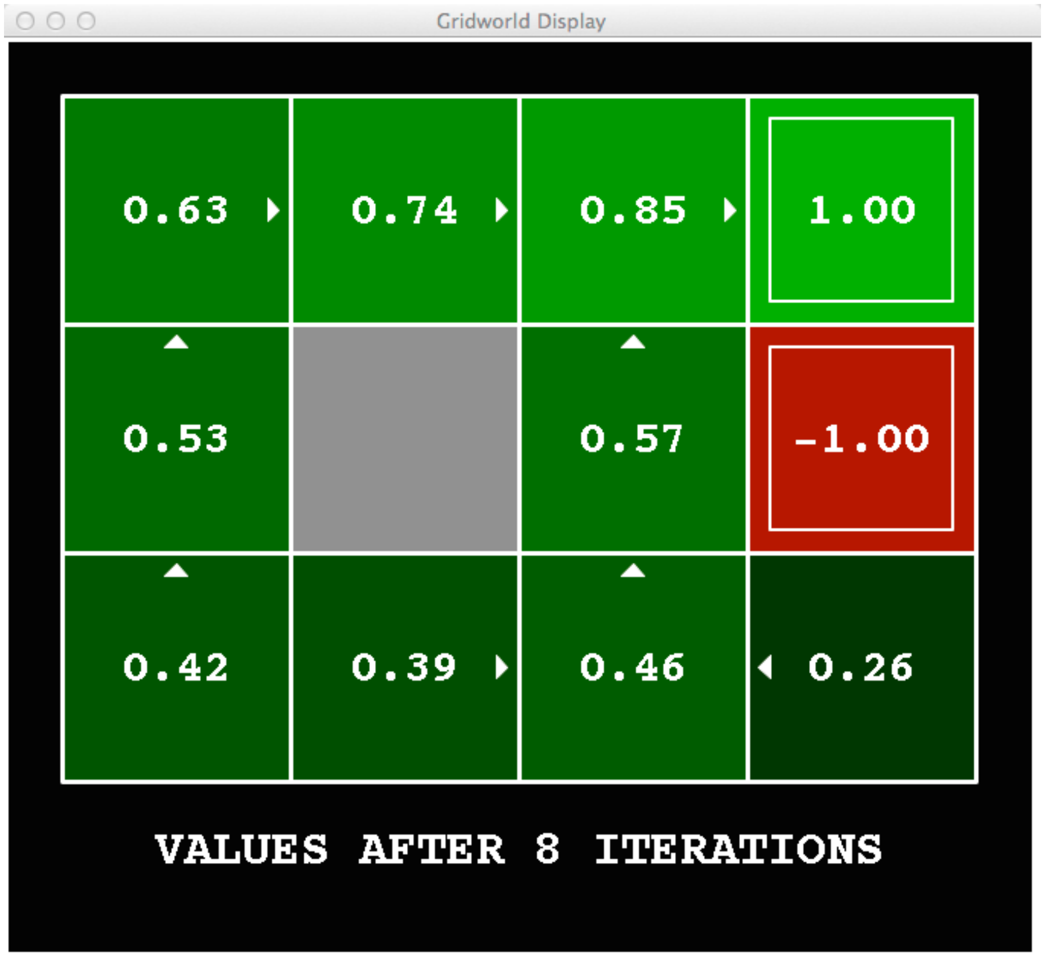
Noise = 0.2
Discount = 0.9
Living reward = 0

k=7



Noise = 0.2
Discount = 0.9
Living reward = 0

k=8

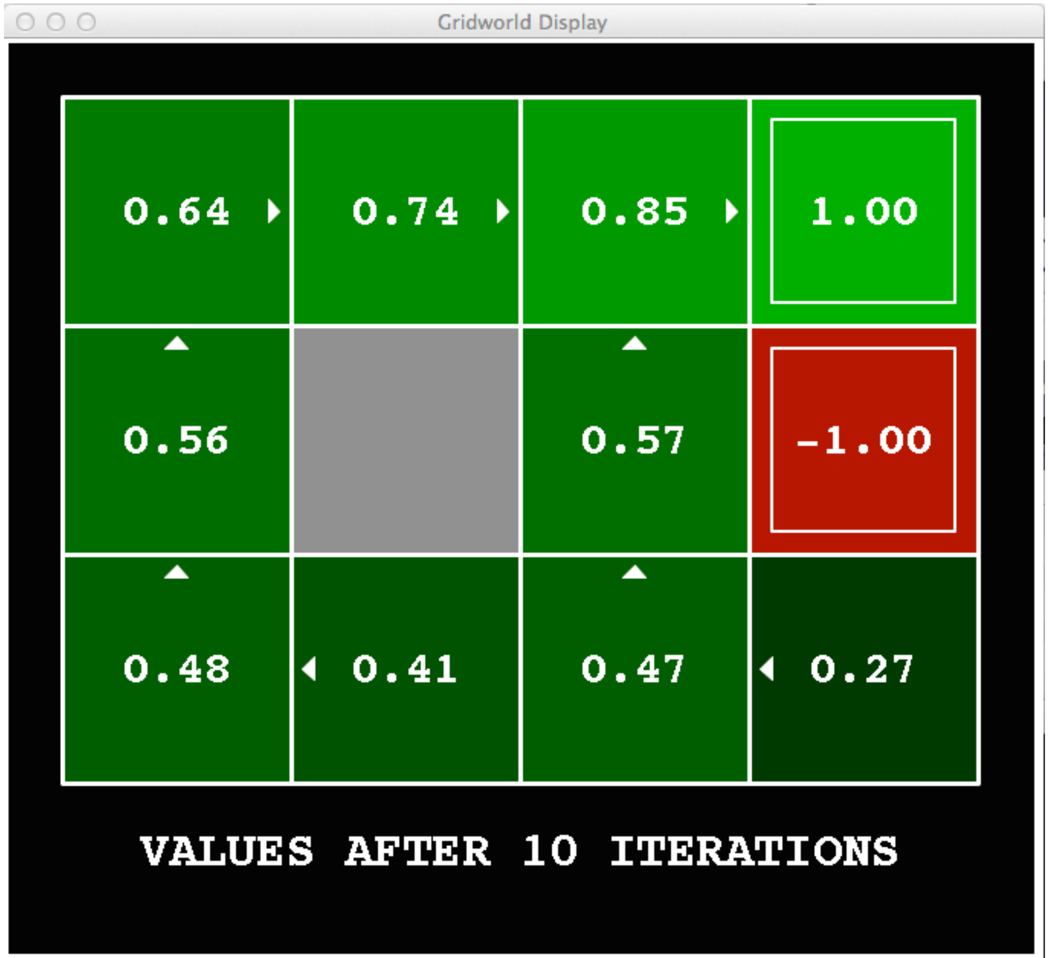


Noise = 0.2
Discount = 0.9
Living reward = 0

k=9

Noise = 0.2
Discount = 0.9
Living reward = 0

k=10

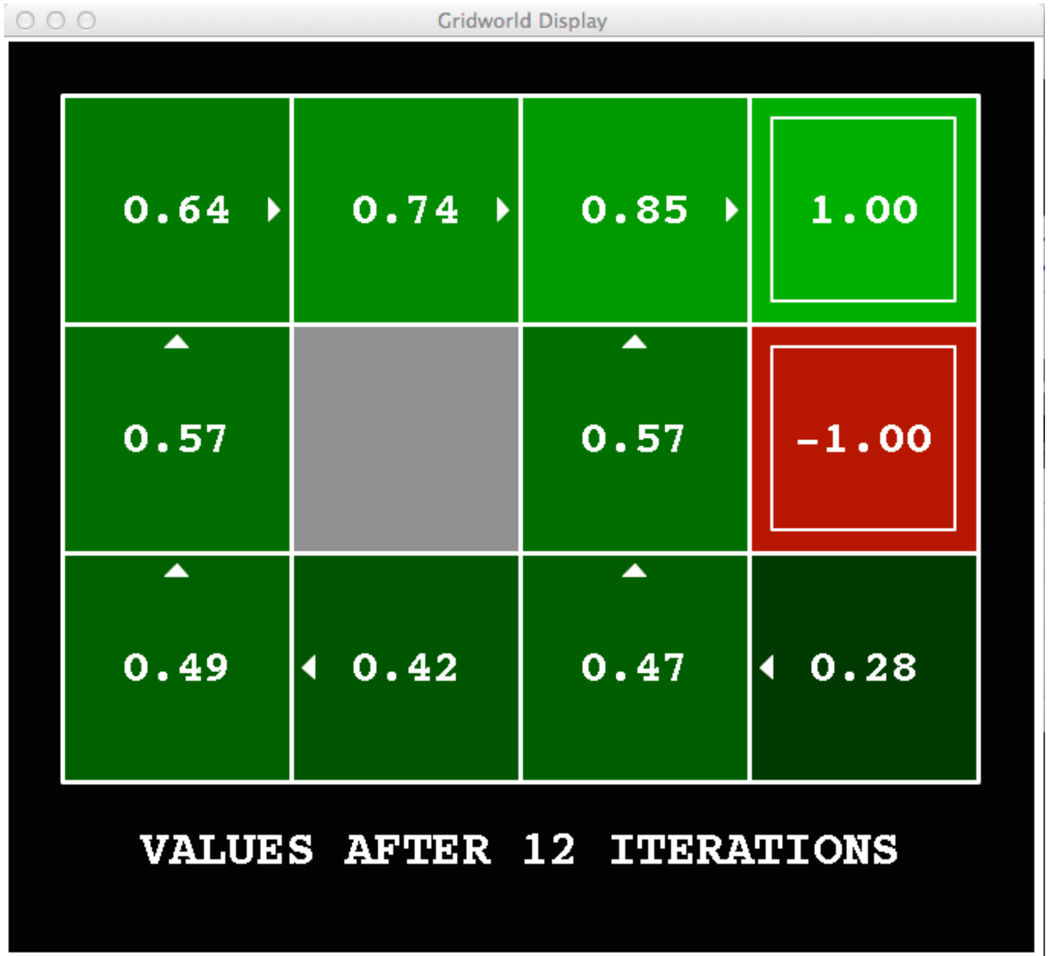


Noise = 0.2
Discount = 0.9
Living reward = 0

k=11

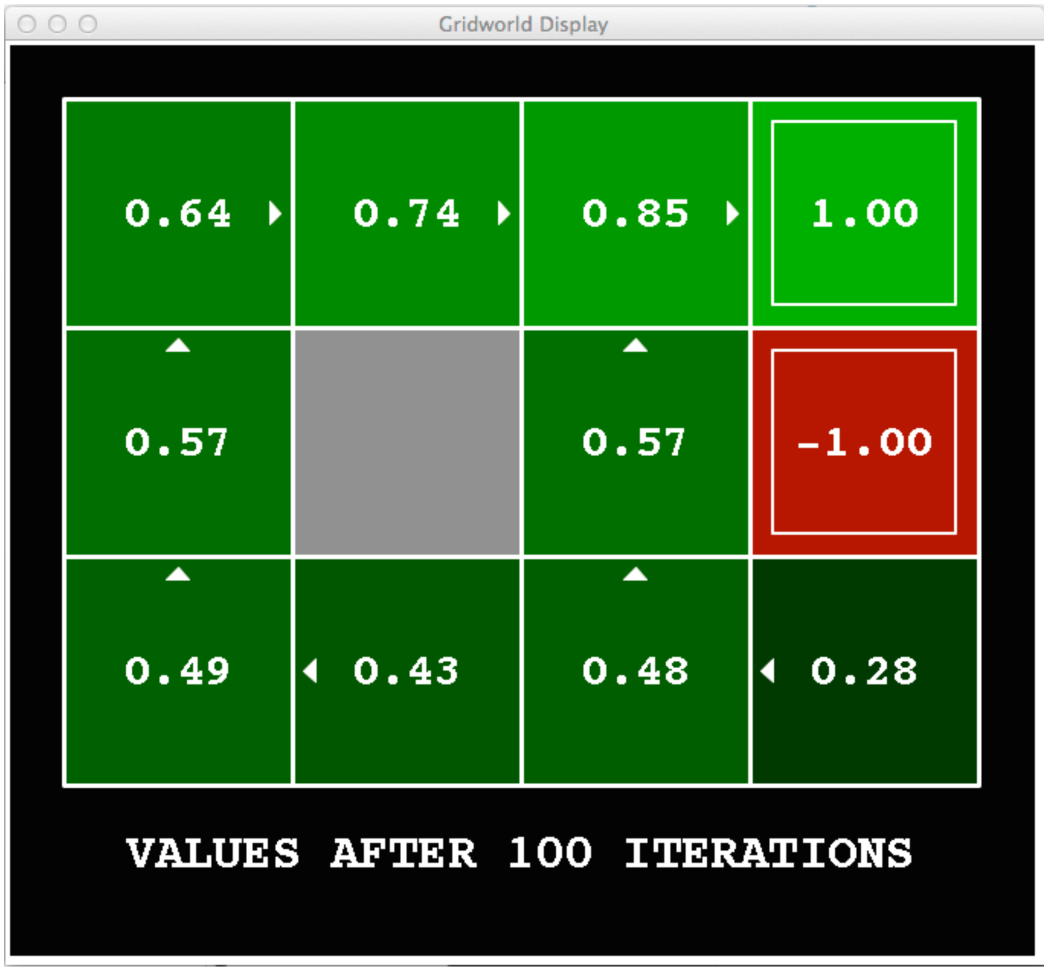
Noise = 0.2
Discount = 0.9
Living reward = 0

k=12



Noise = 0.2
Discount = 0.9
Living reward = 0

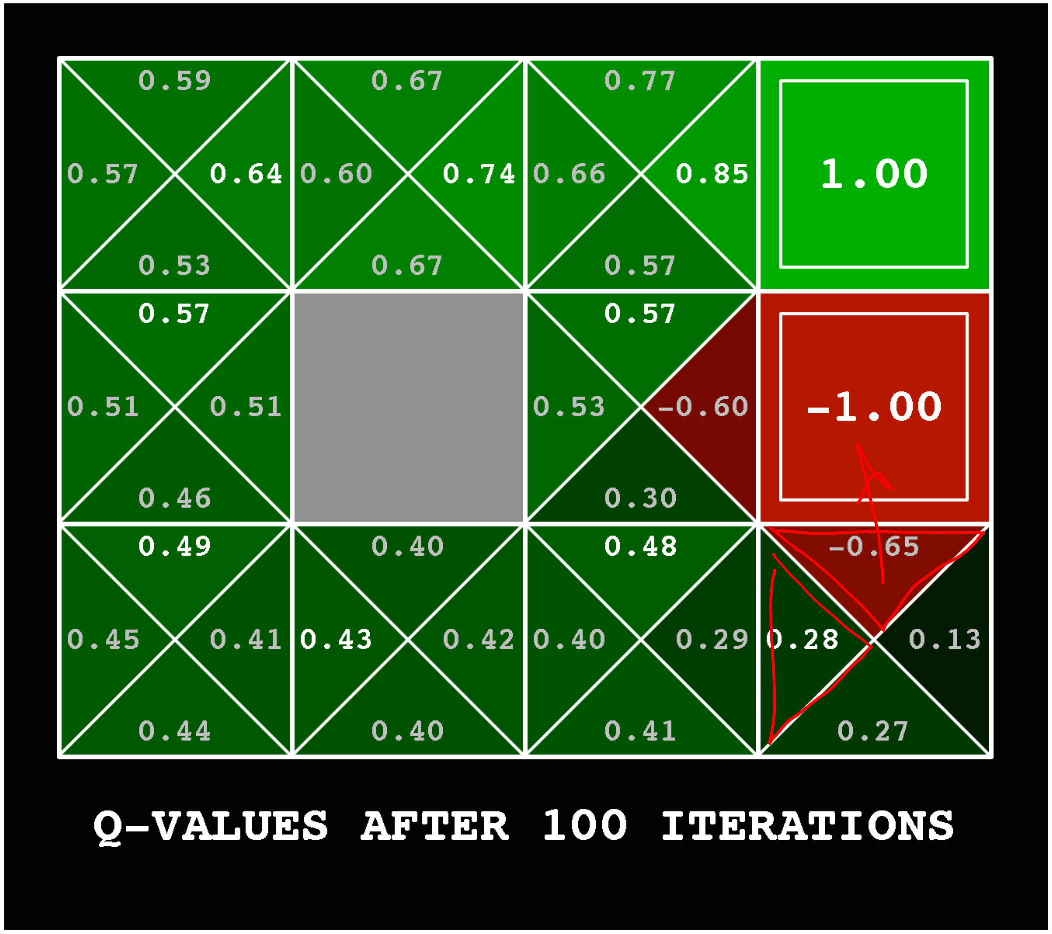
k=100



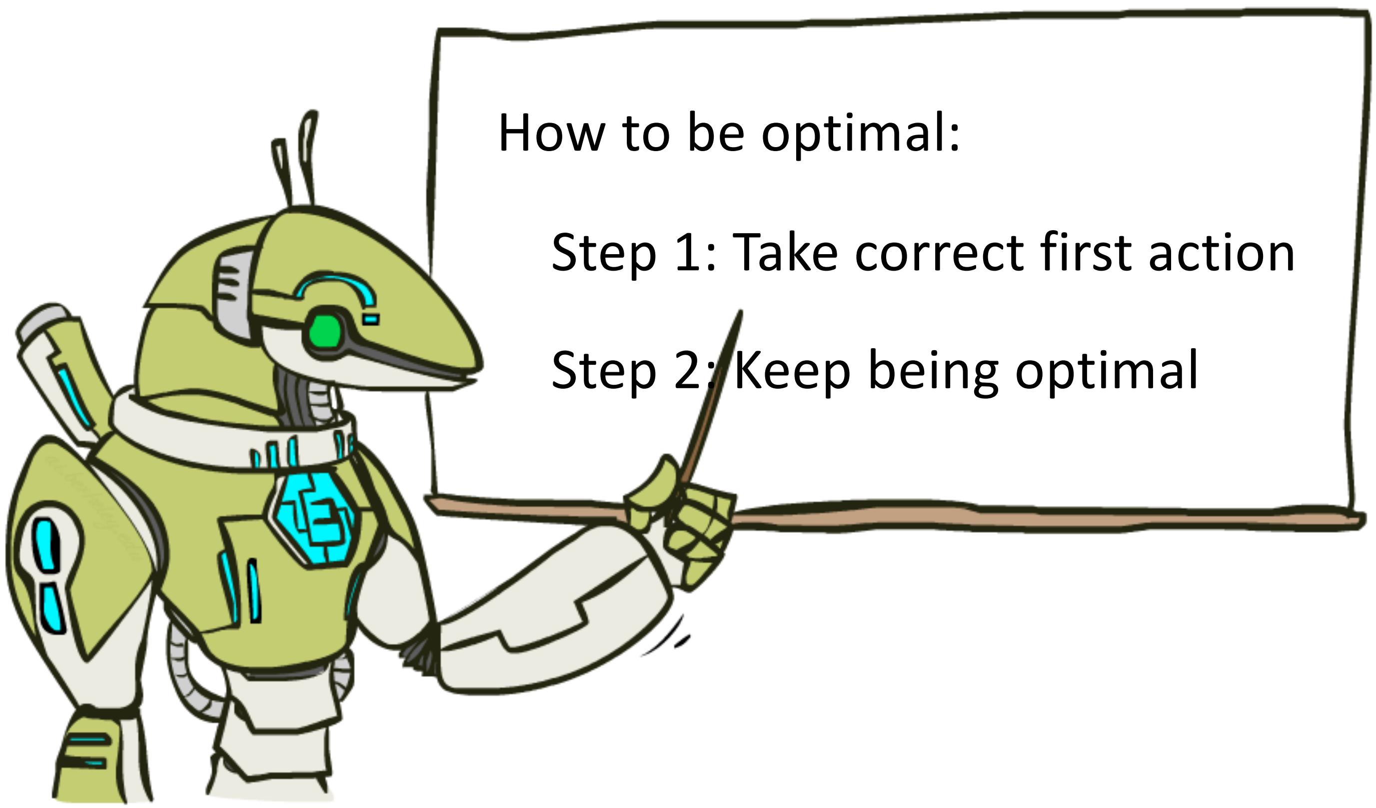
Noise = 0.2
Discount = 0.9
Living reward = 0

Gridworld Values V*

Gridworld: Q*


0.59
0.57
0.64
0.53
0.67
0.60
0.74
0.67
0.77
0.66
0.85
0.57
1.00
0.57
0.51
0.51
0.46
0.57
0.53
-0.60
0.30
-1.00
0.49
0.45
0.41
0.44
0.40
0.43
0.42
0.40
0.48
0.40
0.29
0.41
-0.65
0.28
0.13
0.27
Q-VALUES AFTER 100 ITERATIONS

The Bellman Equations



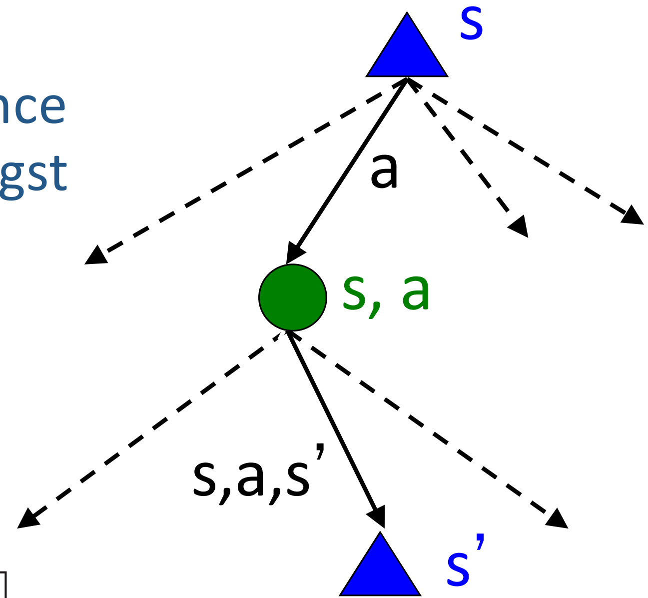
The Bellman Equations

Definition of "optimal utility" via expectimax recurrence gives a simple one-step lookahead relationship amongst optimal utility values

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

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

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

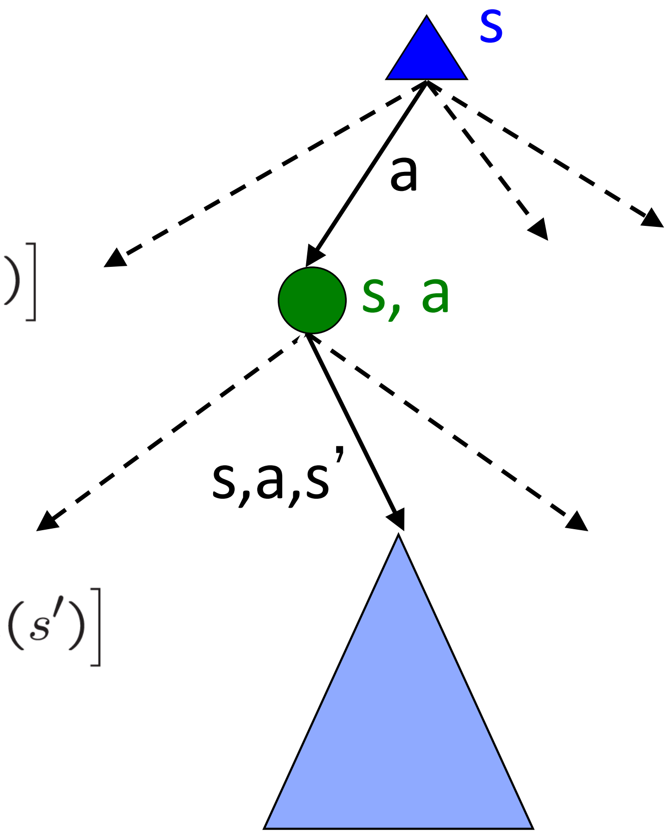


These are the Bellman equations, and they characterize optimal values in a way we'll use over and over

Value Iteration

Bellman equations characterize the optimal values:

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



Value iteration computes them:

$$V_{k+1}(s) \leftarrow \max_a \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma V_k(s')\right]$$

Value iteration is just a fixed point solution method

- … though the V_k vectors are also interpretable as time-limited values

MDP Notation

Standard expectimax: $V(s) = \max_a \sum_{s'} P(s'|s,a) V(s')$

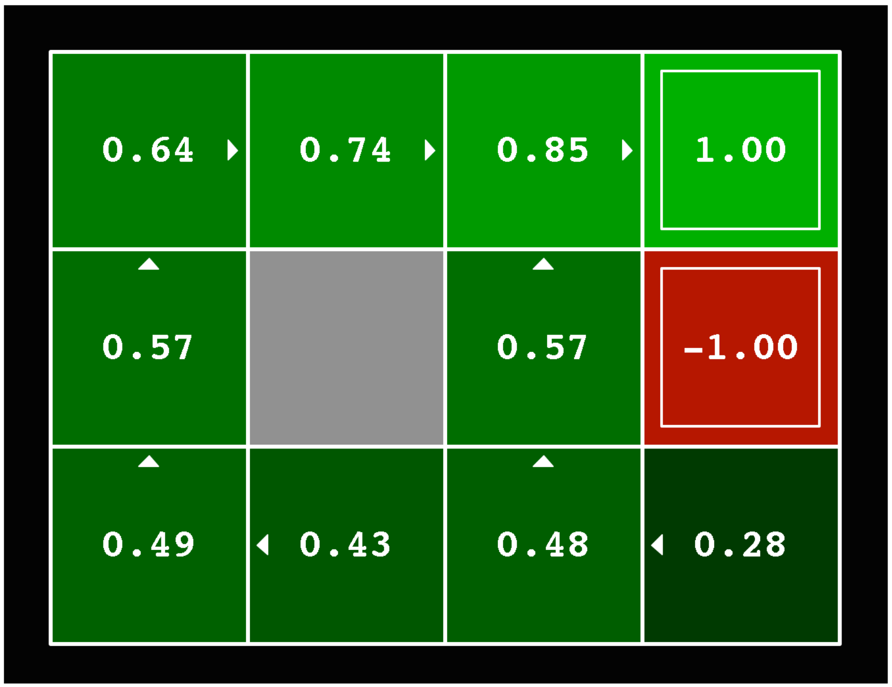
Bellman equations: $V^*(s) = \max_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V^*(s')]$

Value iteration: $V_{k+1}(s) = \max_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V_k(s')], \quad \forall s$

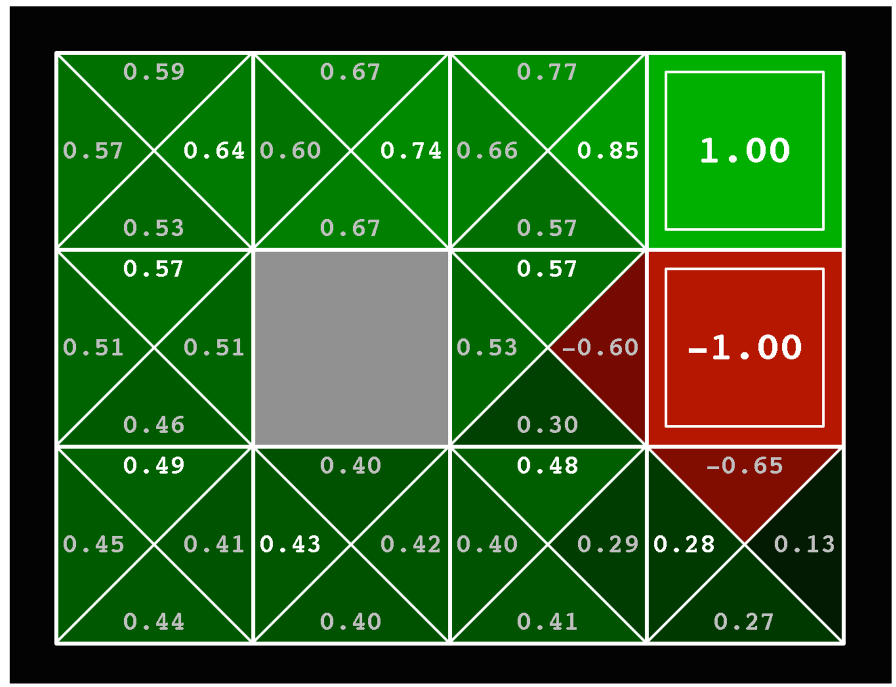
Solved MDP! Now what?

What are we going to do with these values??

$V^*(s)$



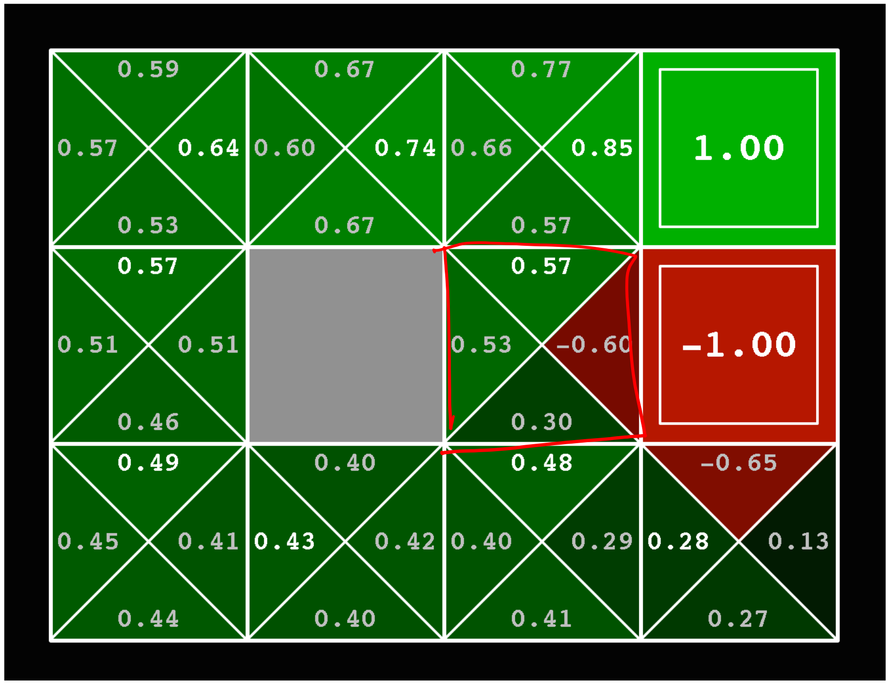
$Q^*(s,a)$



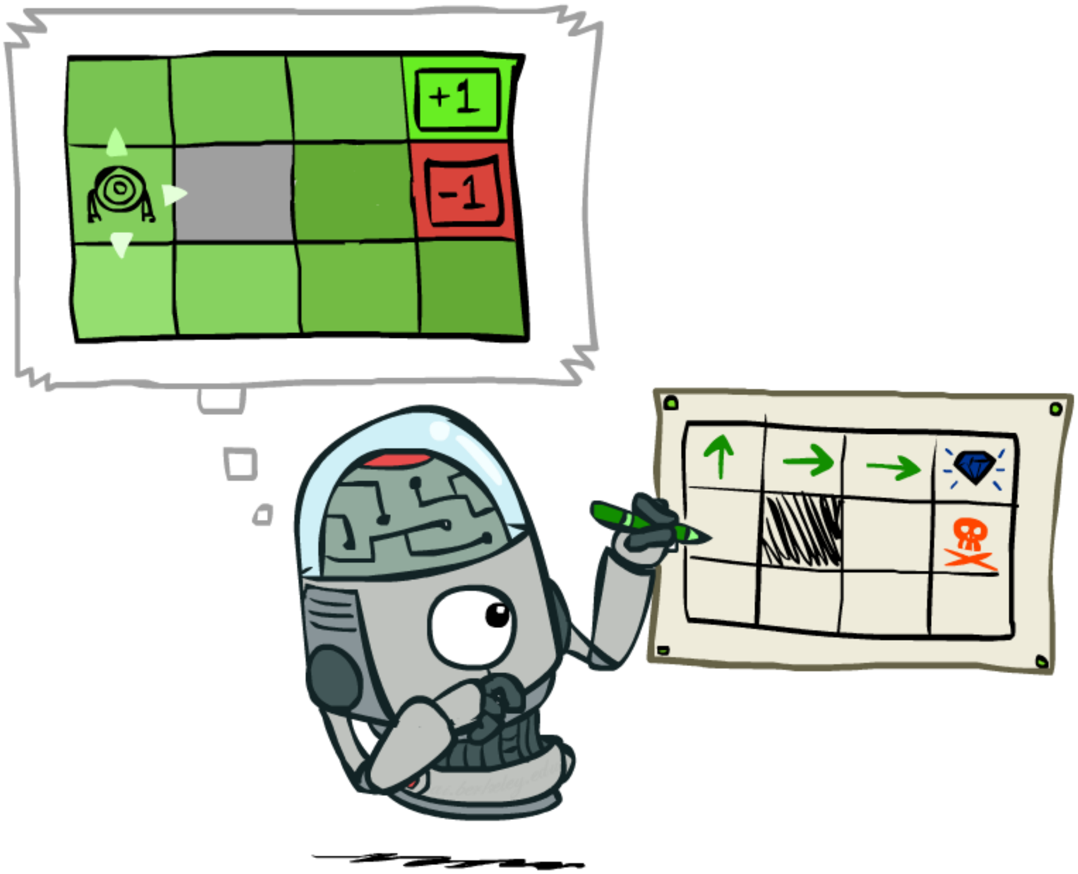
Poll 1

If you need to extract a policy, would you rather have

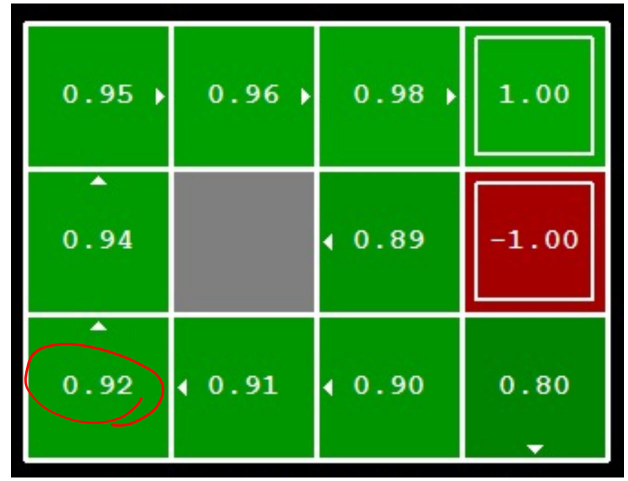
A) Values, B) Q-values?



Policy Extraction



Policy Extraction - Computing Actions from Values



Let’s imagine we have the optimal values V*(s)

How should we act?

- It’s not obvious!

We need to do a mini-expectimax (one step)

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

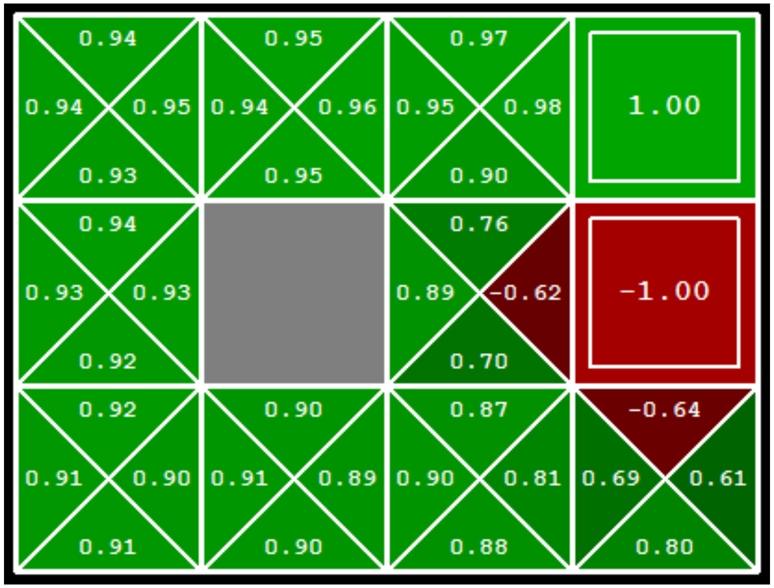
$$\pi^*(s) = \arg\max_a \sum_{s'} T(s,a,s')[R(s,a,s') + \gamma V^*(s')]$$

$O(S^2 A)$

This is called policy extraction, since it gets the policy implied by the values

Computing Actions from Q-Values

Let's imagine we have the optimal q-values:



How should we act?

- Completely trivial to decide!

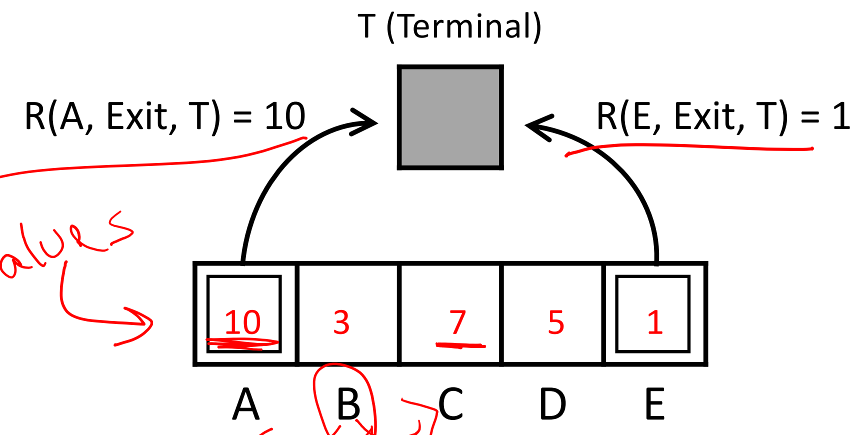
$$\pi^*(s) = \arg\max_a Q^*(s,a)$$

Important lesson: actions are easier to select from q-values than values!

Poll 2

Practice Policy Extraction

$$\pi(s) = argmax_a \, [R(s, a, s') + \gamma V(s')]$$



Deterministic Actions: East and West

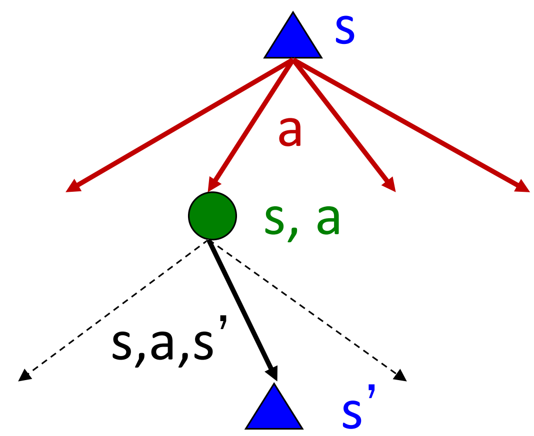
Gamma: 0.5

What is the policy for B?

Value Iteration Notes

Value iteration repeats the Bellman updates:

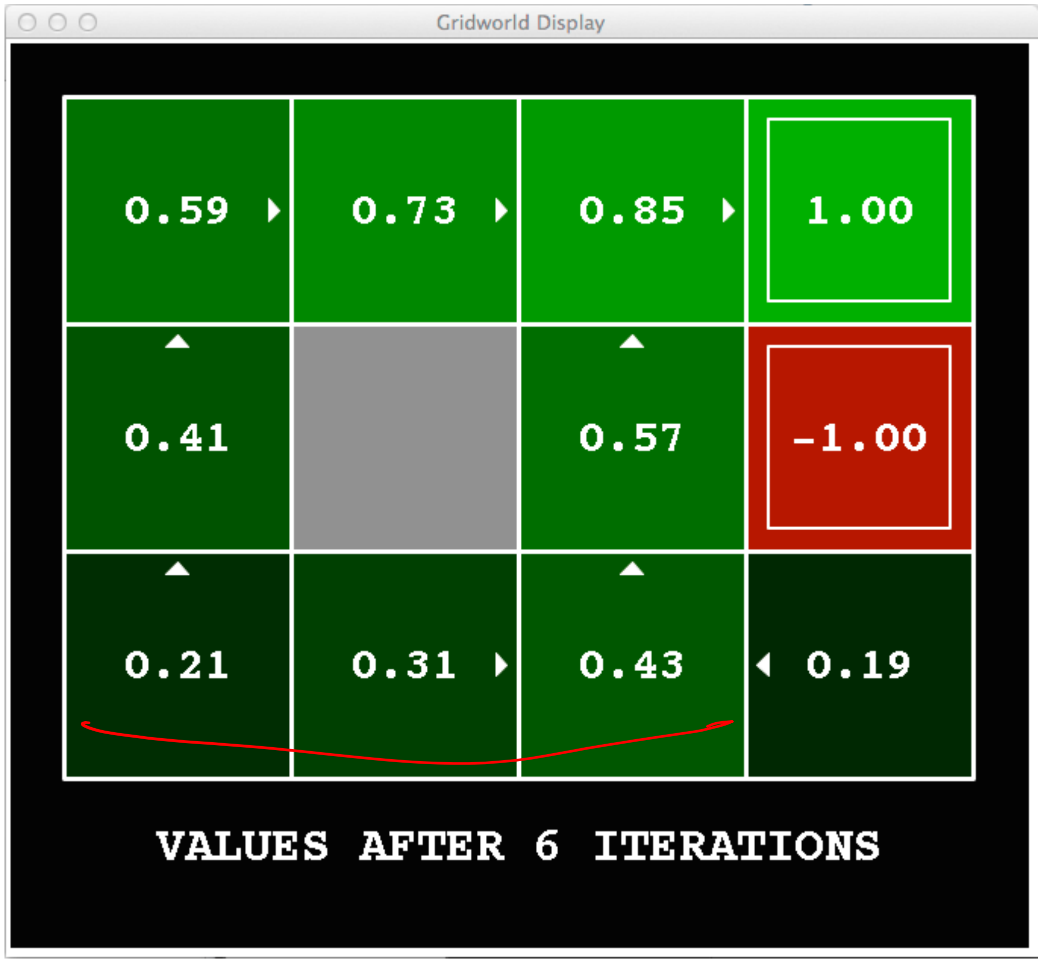
$$V_{k+1}(s) \leftarrow \max_a \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma V_k(s')\right]$$



Things to notice when running value iteration:

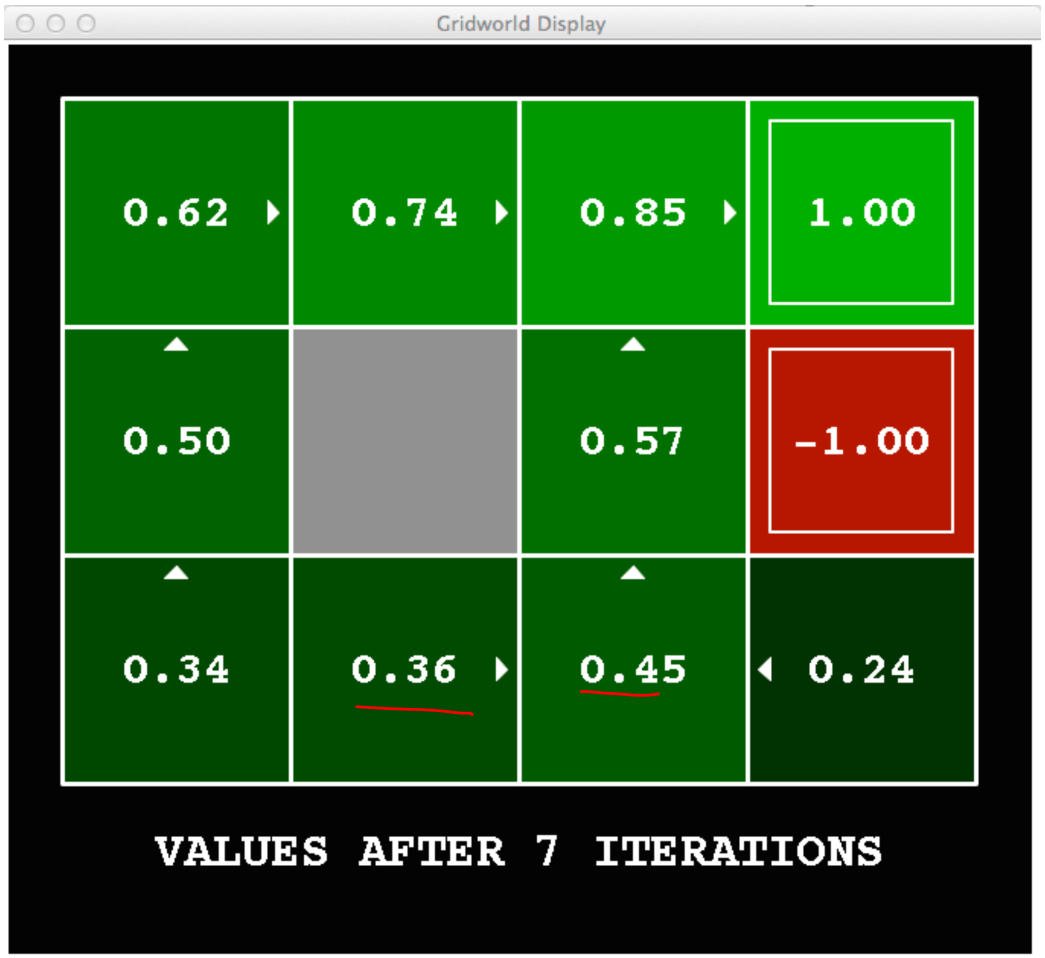
- It's slow – $O(|S|^2|A|)$ per iteration
- The "max" at each state rarely changes
- The optimal policy appears before the values converge (but we don't know that the policy is optimal until the values converge)

k=6



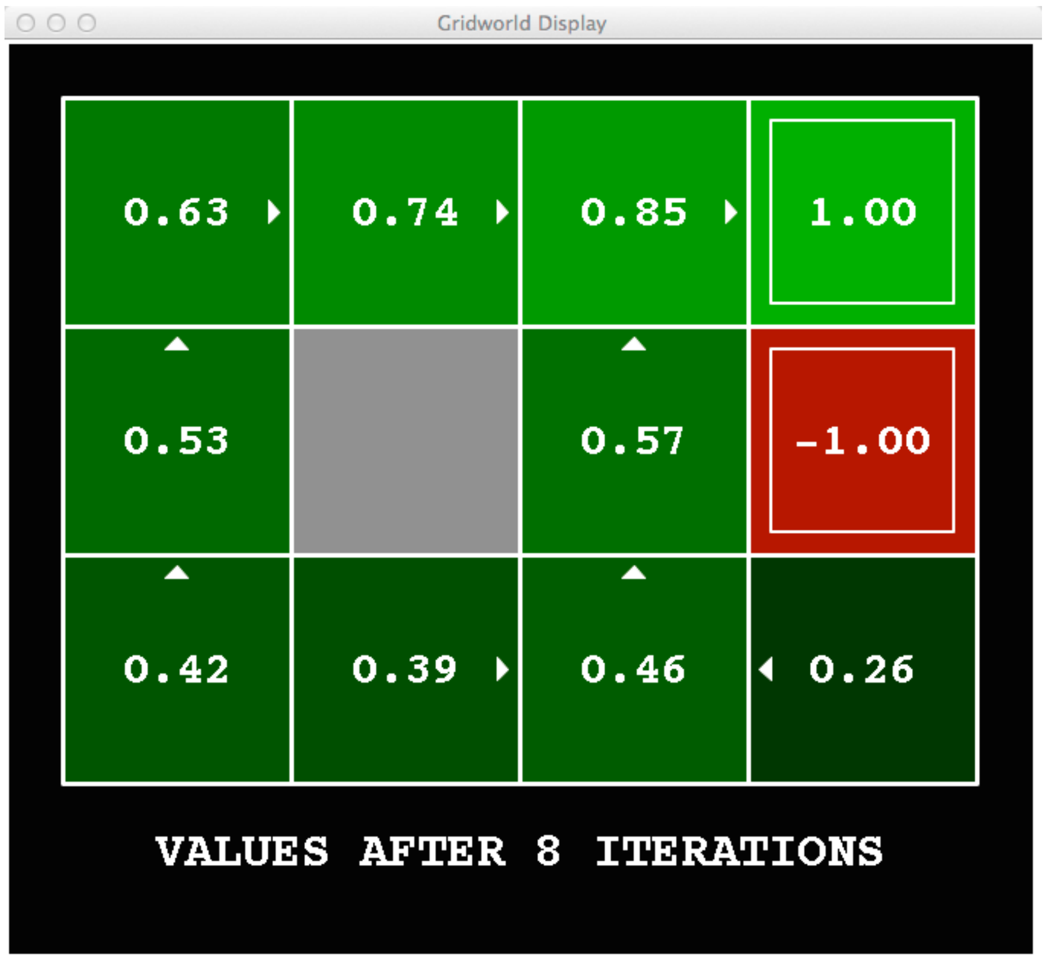
Noise = 0.2
Discount = 0.9
Living reward = 0

k=7



Noise = 0.2
Discount = 0.9
Living reward = 0

k=8



Noise = 0.2
Discount = 0.9
Living reward = 0

k=9

Noise = 0.2
Discount = 0.9
Living reward = 0

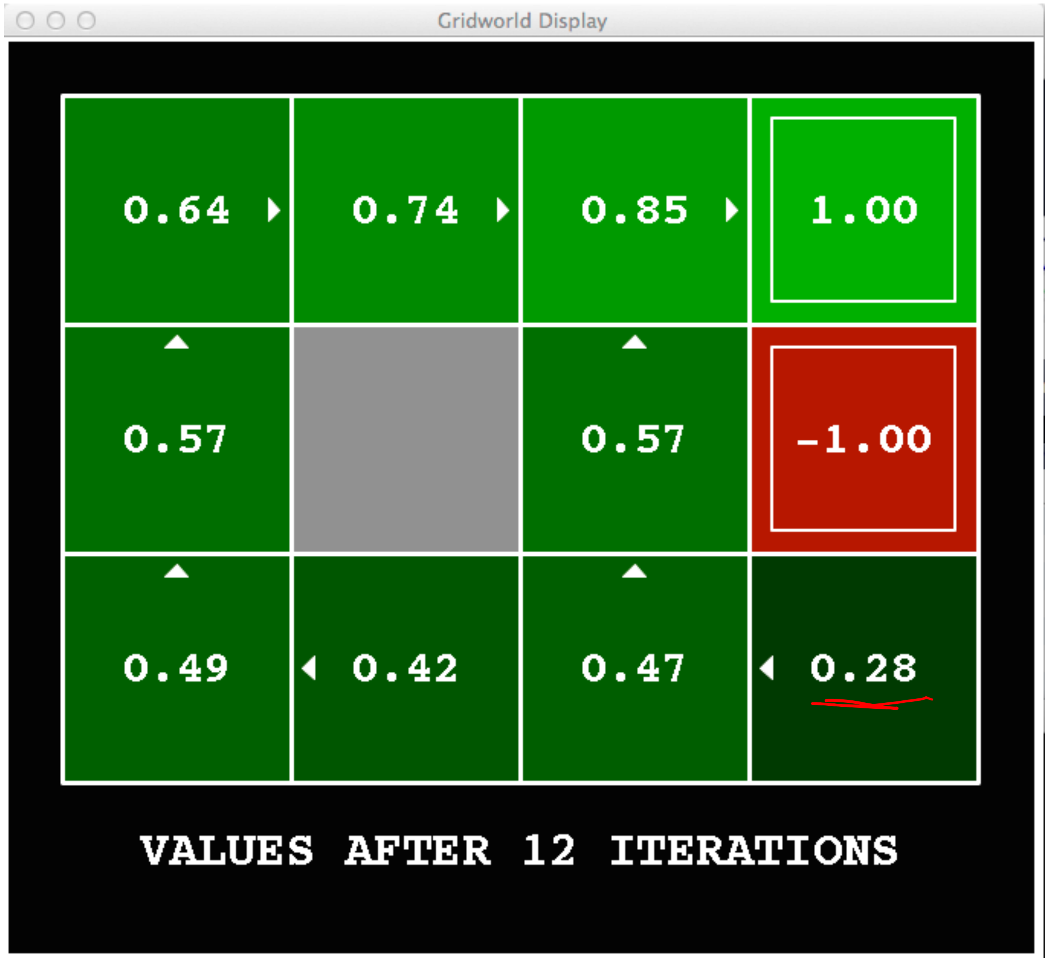
k=10

Noise = 0.2
Discount = 0.9
Living reward = 0

k=11

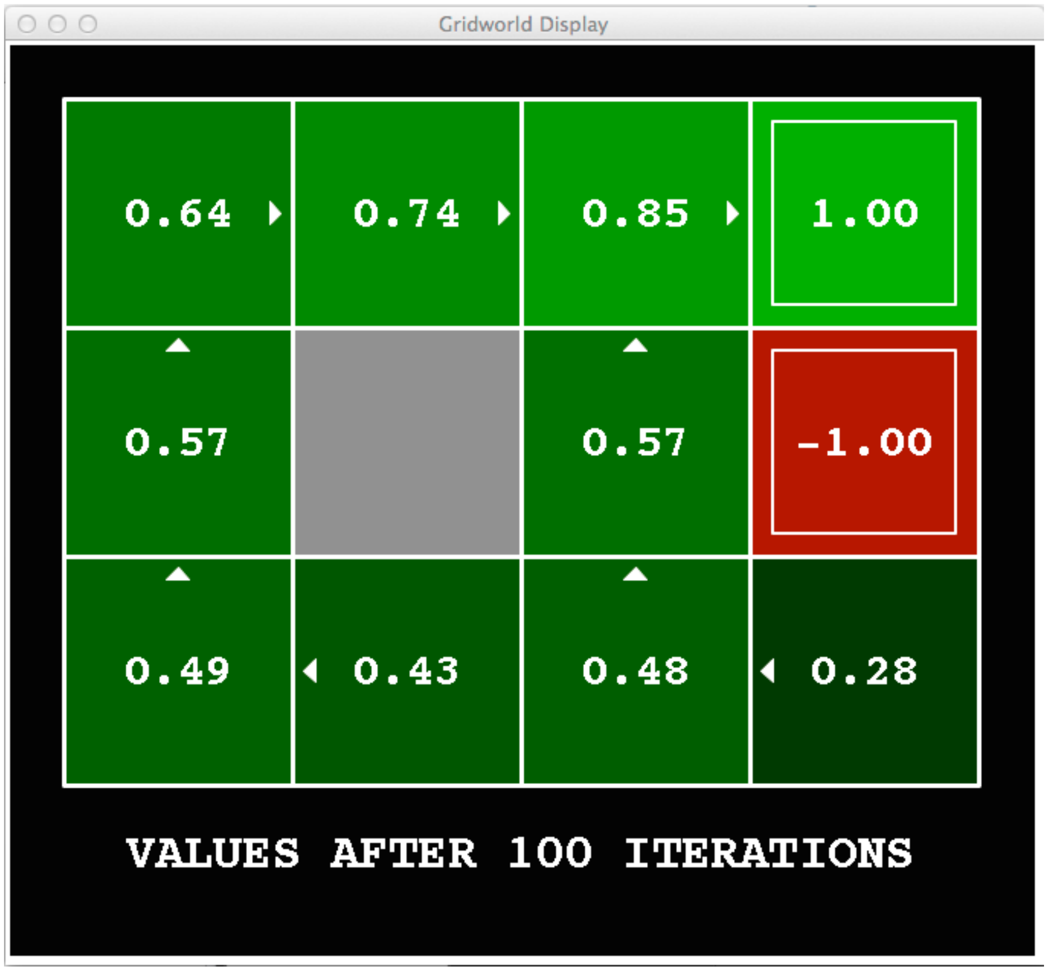
Noise = 0.2
Discount = 0.9
Living reward = 0

k=12



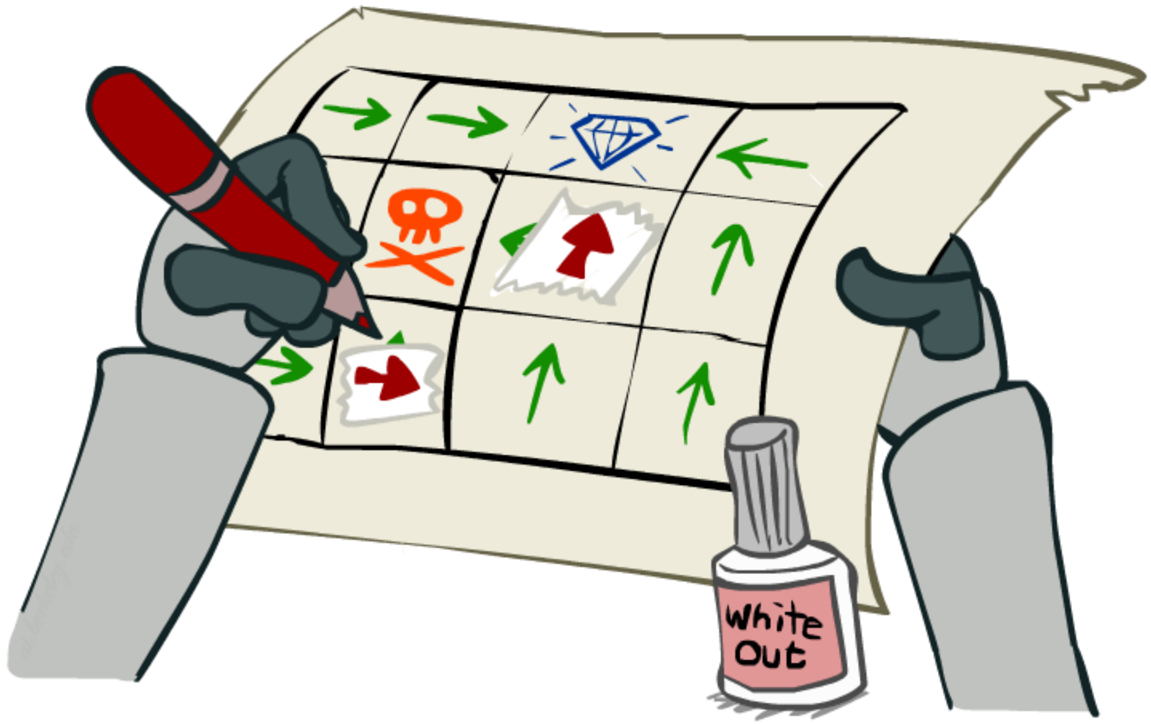
Noise = 0.2
Discount = 0.9
Living reward = 0

k=100



Noise = 0.2
Discount = 0.9
Living reward = 0

Policy Iteration



Two Methods for Solving MDPs

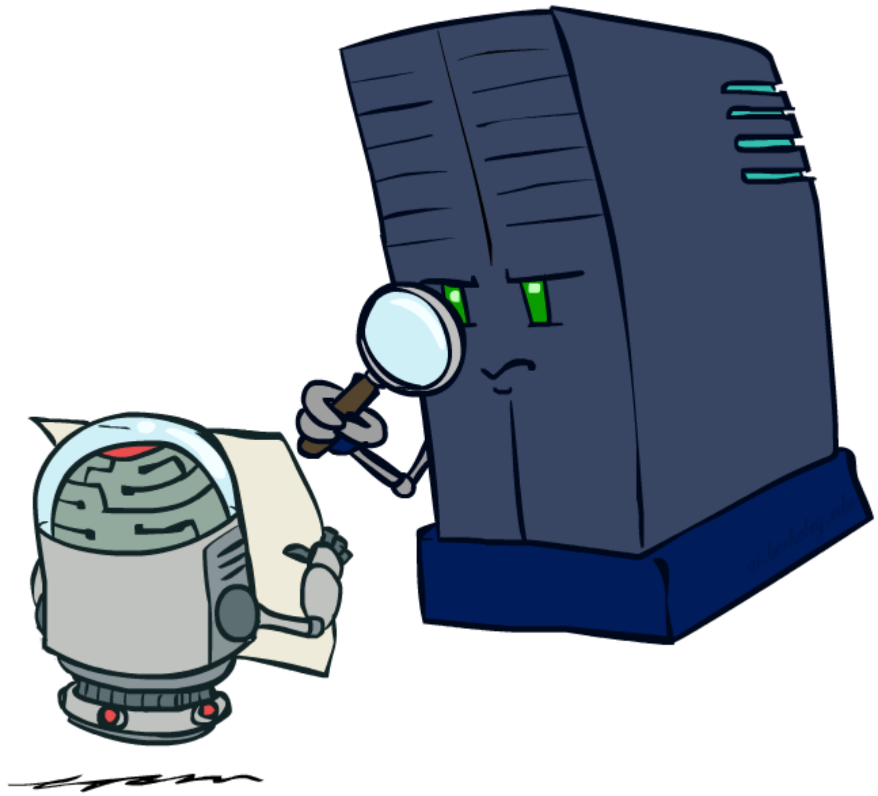
Value iteration + policy extraction

- Step 1: Value iteration: calculate values for all states by running one ply of the Bellman equations using values from previous iteration **until convergence**
- Step 2: Policy extraction: compute policy by running one ply of the Bellman equations using values from value iteration

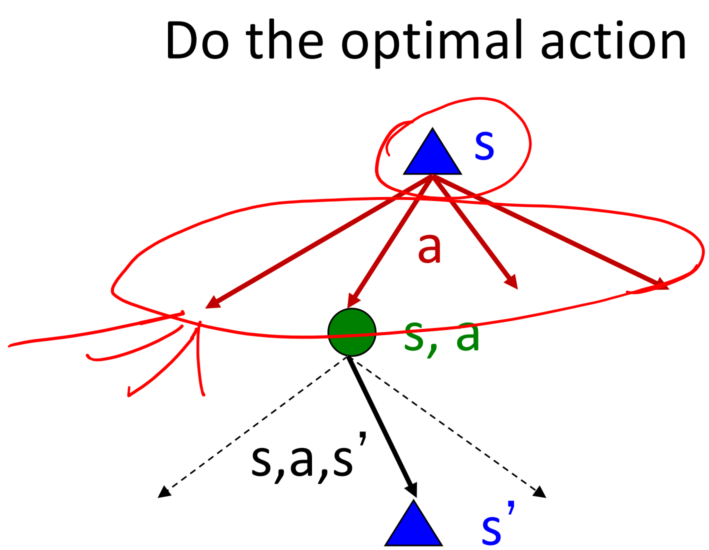
Policy iteration

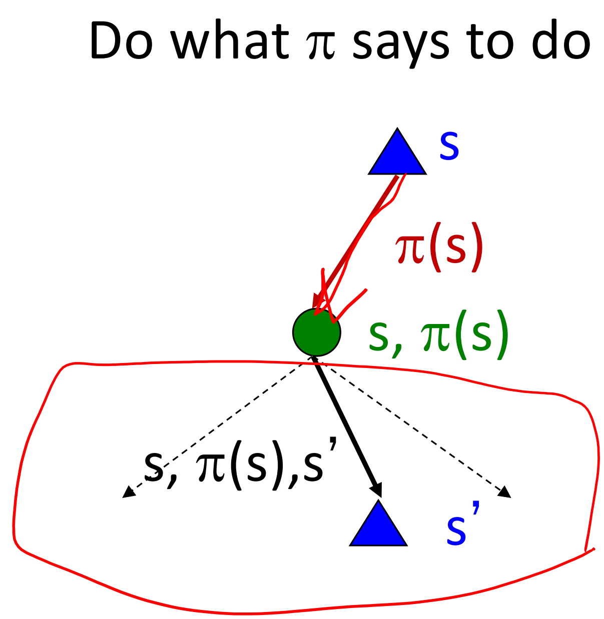
- Step 1: Policy evaluation: calculate values for some fixed policy (not optimal values!) **until convergence**
- Step 2: Policy improvement: update policy by running one ply of the Bellman equations using values from policy evaluation
- Repeat steps until policy converges

Policy Evaluation



Fixed Policies





Expectimax trees max over all actions to compute the optimal values

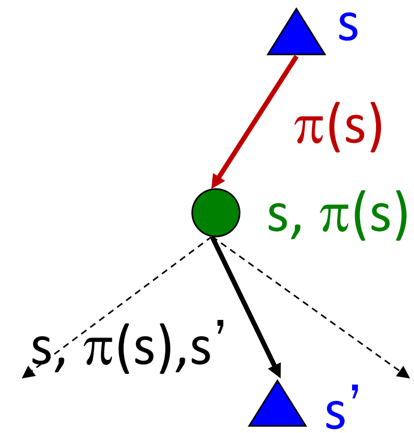
If we fixed some policy $\pi(s)$, then the tree would be simpler
– only one action per state

- … though the tree's value would depend on which policy we fixed

Policy Evaluation - Utilities for a Fixed Policy

Another basic operation: compute the utility of a state s under a fixed (generally non-optimal) policy

$\pi: S \to A$



Define the utility of a state s, under a fixed policy π:

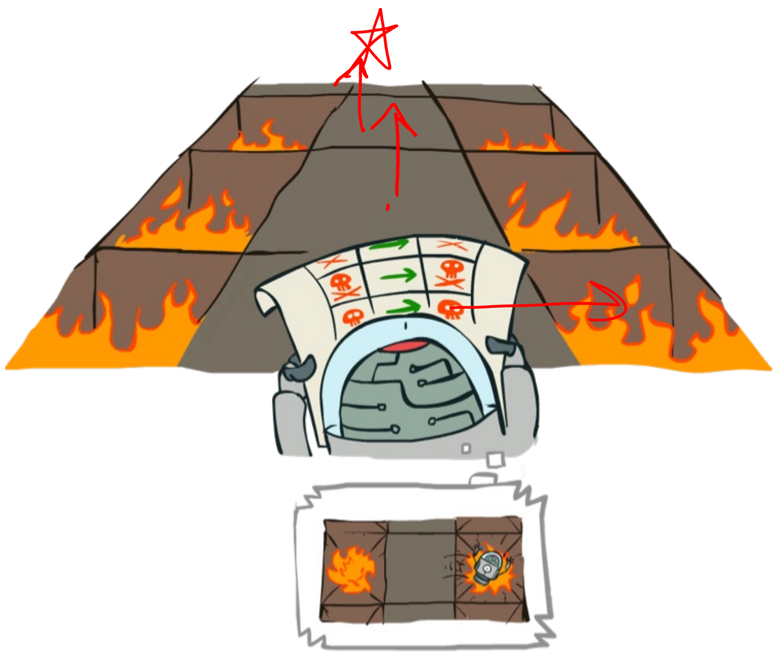
$V^{\pi}(s)$ = expected total discounted rewards starting in s and following π

Recursive relation (one-step look-ahead / Bellman equation):

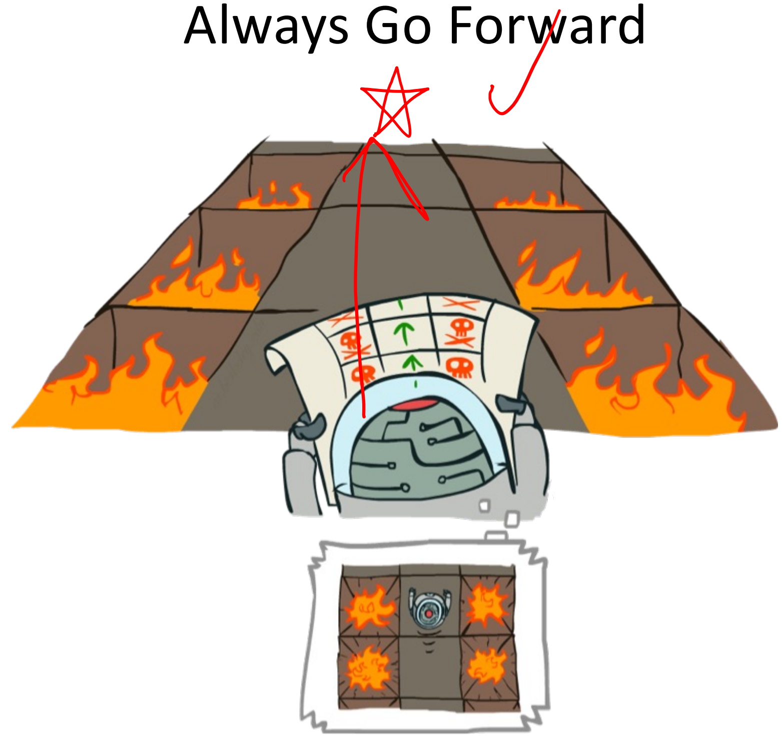
$$V^{\pi}(s) = \sum_{s'} T(s, \pi(s), s')[R(s, \pi(s), s') + \gamma V^{\pi}(s')]$$

Example: Policy Evaluation

Always Go Right



Always Go Forward

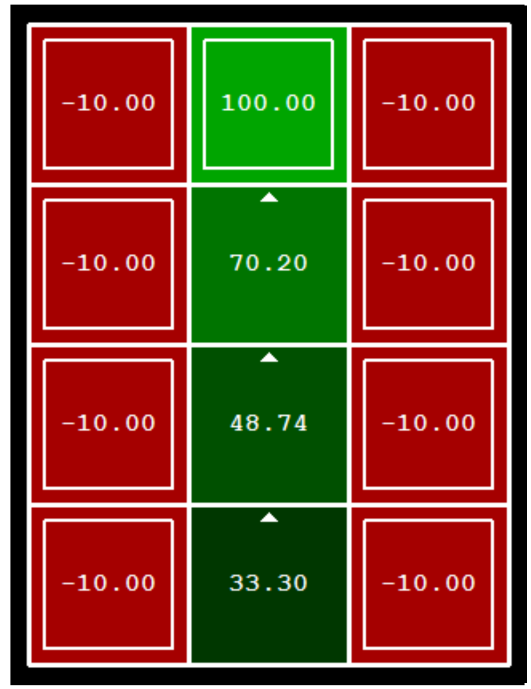


Example: Policy Evaluation

V^{π_0}

Always Go Right

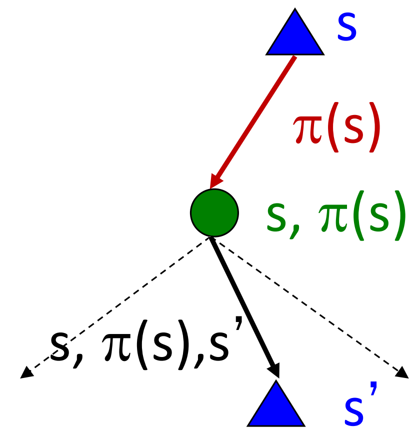
Always Go Forward



Policy Evaluation

How do we calculate the V's for a fixed policy π?

Idea 1: Turn recursive Bellman equations into updates
(like value iteration)



$$V_0^\pi(s) = 0$$

$$V_{k+1}^\pi(s) \leftarrow \sum_{s'} T(s,\pi(s),s')[R(s,\pi(s),s') + \gamma V_k^\pi(s')]$$

Efficiency: $O(|S|^2)$ per iteration

Idea 2: Without the maxes, the Bellman equations are just a linear system

- Solve with your favorite linear system solver

Policy Iteration

Alternative approach for optimal values:

- Step 1: Policy evaluation: calculate values for some fixed policy (not optimal values!) **until convergence**
- Step 2: Policy improvement: update policy by running one ply of the Bellman equations using values from policy evaluation
- Repeat steps until policy converges

This is policy iteration

- It's still optimal!
- Can converge faster under some conditions

Policy Iteration:

Evaluation: For fixed current policy π, find values with policy evaluation:

- Iterate until values converge:

$$V^{\pi_i}_{k+1}(s) \leftarrow \sum_{s'} T(s, \pi_i(s), s') \left[R(s, \pi_i(s), s') + \gamma V^{\pi_i}_k(s')\right]$$

Improvement: For fixed values, get a better policy using **policy extraction**

- One-step look-ahead:

$$\pi_{i+1}(s) = \arg\max_a \sum_{s'} T(s, a, s') \left[R(s, a, s') + \gamma V^{\pi_i}(s')\right]$$

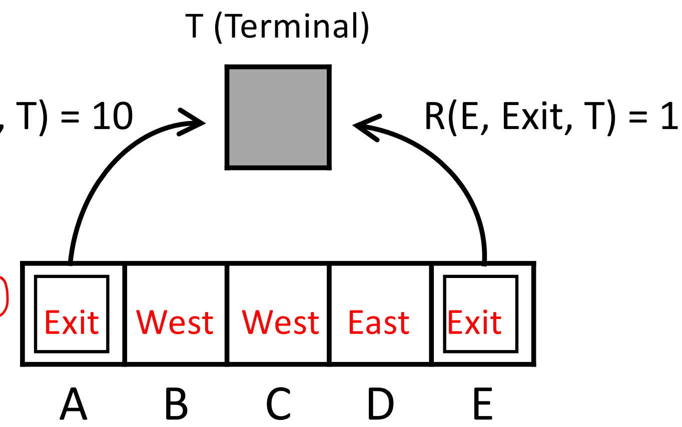
In-Class Activity

Practice Policy Evaluation

$$V_0^{\pi}(s) = 0$$

$$V_{k+1}^{\pi}(s) \leftarrow \sum_{s'} T(s, \pi(s), s')[R(s, \pi(s), s') + \gamma V_k^{\pi}(s')]$$

	A	B	C	D	E	T
k=0	0	0	0	0	0	0
k=1	10				1	0
						0



Deterministic Actions: East and West
Gamma: 0.5

A) What are the converged values $V^{*\pi}$ under π to the right?

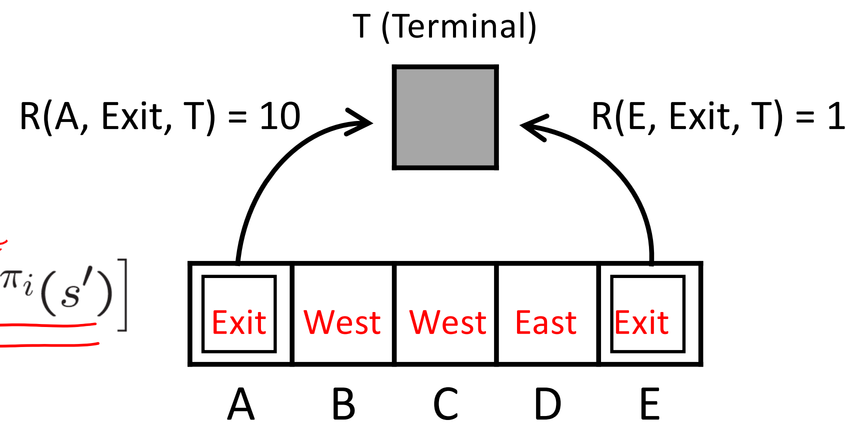
B) What are the converged values $V^{*\pi}$ under π below (same transition rules)?

A	B	C	D	E
Exit	East	West	East	Exit

In-Class Activity 2

Practice Policy Improvement

$$\pi_{i+1}(s) = \arg\max_a \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma V^{\pi_i}(s') \right]$$



Deterministic Actions: East and West
Gamma: 0.5

C) Based on your answer to A, what is the new policy?

D – Poll

D) Based on your answer to B, what is the new policy?

B, C

A	B	C	D	E
Exit	East	West	East	Exit

Two Methods for Solving MDPs

Value iteration + policy extraction

- Step 1: Value iteration:

$V_{k+1}(s) = \max_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V_k(s')]$, $\forall s$ **until convergence**

- Step 2: Policy extraction:

$\pi_V(s) = \underset{a}{\operatorname{argmax}} \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V(s')]$, $\forall s$

Policy iteration

- Step 1: Policy evaluation:

$V_{k+1}^{\pi}(s) = \sum_{s'} P(s'|s,\pi(s))[R(s,\pi(s),s') + \gamma V_k^{\pi}(s')]$, $\forall s$ **until convergence**

- Step 2: Policy improvement:

$\pi_{new}(s) = \underset{a}{\operatorname{argmax}} \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V^{\pi_{old}}(s')]$, $\forall s$

- Repeat steps until policy converges

Comparison

Both value iteration and policy iteration compute the same thing (all optimal values)

In value iteration:

- Every iteration updates both the values and (implicitly) the policy
- We don't track the policy, but taking the max over actions implicitly recomputes it

In policy iteration:

- We do several passes that update values with fixed policy (each pass is fast because we consider only one action, not all of them; however we do many passes)
- After the policy is evaluated, a new policy is chosen (slow like a value iteration pass)
- The new policy will be better (or we're done)

(Both are dynamic programs for solving MDPs)

Summary: MDP Algorithms

So you want to….

- Compute optimal values: use value iteration or policy iteration
- Compute values for a particular policy: use policy evaluation
- Turn your values into a policy: use policy extraction (one-step lookahead)

These all look the same!

- They basically are – they are all variations of Bellman updates
- They all use one-step lookahead expectimax fragments
- They differ only in whether we plug in a fixed policy or max over actions

MDP Notation

Standard expectimax: $V(s) = \max_a \sum_{s'} P(s'|s,a)V(s')$

Bellman equations: $V^*(s) = \max_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V^*(s')]$

Value iteration: $V_{k+1}(s) = \max_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V_k(s')], \quad \forall\, s$

Q-iteration: $Q_{k+1}(s,a) = \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma \max_{a'} Q_k(s',a')], \quad \forall\, s,a$

Policy extraction: $\pi_V(s) = \operatorname{argmax}_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V(s')], \quad \forall\, s$

Policy evaluation: $V_{k+1}^{\pi}(s) = \sum_{s'} P(s'|s,\pi(s))[R(s,\pi(s),s') + \gamma V_k^{\pi}(s')], \quad \forall\, s$

Policy improvement: $\pi_{new}(s) = \operatorname{argmax}_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V^{\pi_{old}}(s')], \quad \forall\, s$

MDP Notation

Standard expectimax: $V(s) = \max_a \sum_{s'} P(s'|s,a)V(s')$

Bellman equations: $V^*(s) = \max_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V^*(s')]$

Value iteration: $V_{k+1}(s) = \max_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V_k(s')], \quad \forall\, s$

Q-iteration: $Q_{k+1}(s,a) = \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma \max_{a'} Q_k(s',a')], \quad \forall\, s,a$

Policy extraction: $\pi_V(s) = \operatorname{argmax}_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V(s')], \quad \forall\, s$

Policy evaluation: $V_{k+1}^{\pi}(s) = \sum_{s'} P(s'|s,\pi(s))[R(s,\pi(s),s') + \gamma V_k^{\pi}(s')], \quad \forall\, s$

Policy improvement: $\pi_{new}(s) = \operatorname{argmax}_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V^{\pi_{old}}(s')], \quad \forall\, s$

MDP Notation

Standard expectimax: $V(s) = \max_a \sum_{s'} P(s'|s,a)V(s')$

Bellman equations: $V^*(s) = \max_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V^*(s')]$

Value iteration: $V_{k+1}(s) = \max_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V_k(s')], \quad \forall\, s$

Q-iteration: $Q_{k+1}(s,a) = \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma \max_{a'} Q_k(s',a')], \quad \forall\, s,a$

Policy extraction: $\pi_V(s) = \operatorname{argmax}_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V(s')], \quad \forall\, s$

Policy evaluation: $V^{\pi}_{k+1}(s) = \sum_{s'} P(s'|s,\pi(s))[R(s,\pi(s),s') + \gamma V^{\pi}_k(s')], \quad \forall\, s$

Policy improvement: $\pi_{new}(s) = \operatorname{argmax}_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V^{\pi_{old}}(s')], \quad \forall\, s$

MDP Notation

Standard expectimax: $V(s) = \max_a \sum_{s'} P(s'|s,a)V(s')$

Bellman equations: $V^*(s) = \max_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V^*(s')]$

Value iteration: $V_{k+1}(s) = \max_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V_k(s')], \quad \forall s$

Q-iteration: $Q_{k+1}(s,a) = \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma \max_{a'} Q_k(s',a')], \quad \forall s,a$

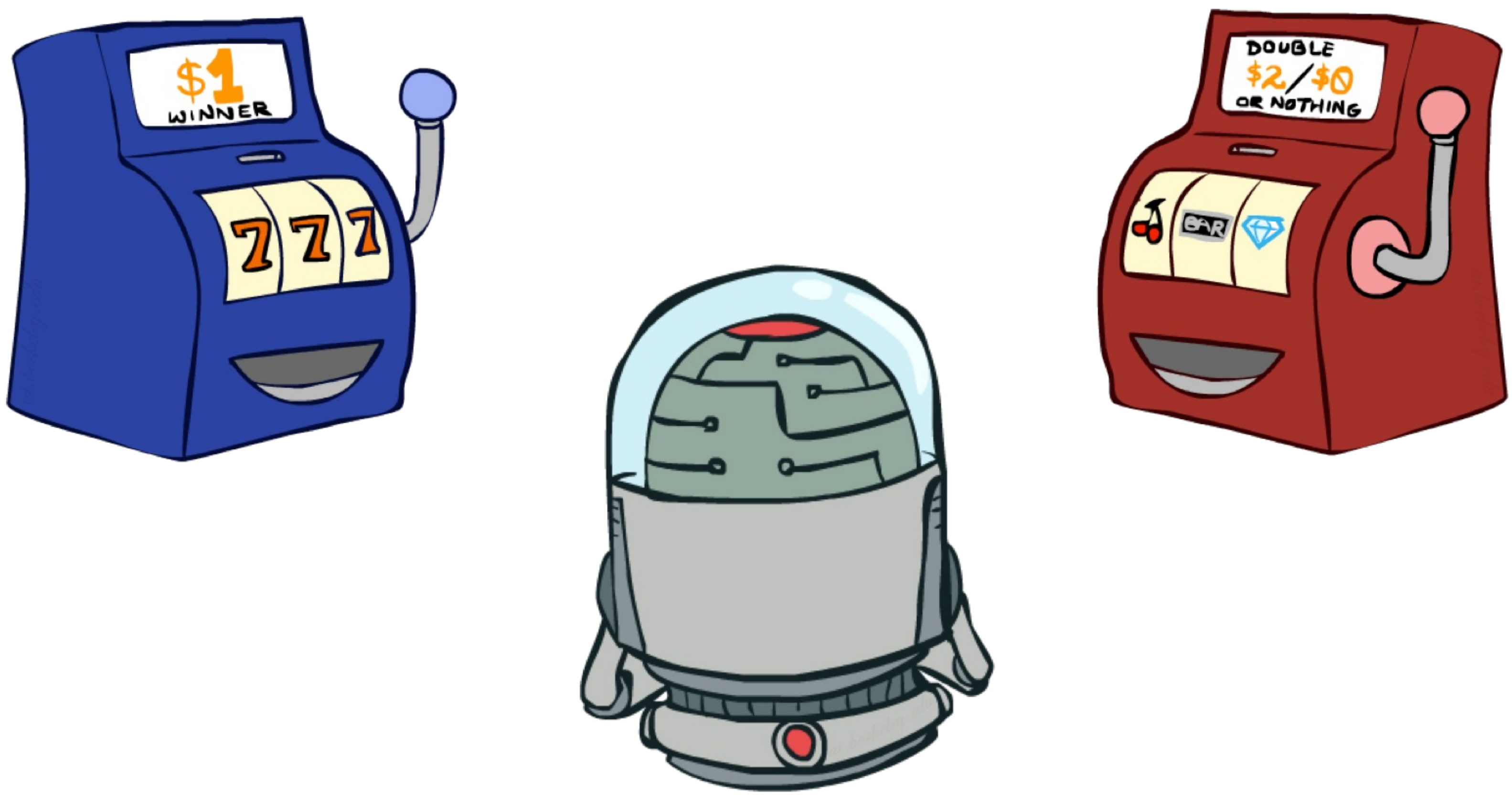
Policy extraction: $\pi_V(s) = \text{argmax}_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V(s')], \quad \forall s$

Policy evaluation: $V_{k+1}^{\pi}(s) = \sum_{s'} P(s'|s,\pi(s))[R(s,\pi(s),s') + \gamma V_k^{\pi}(s')], \quad \forall s$

Policy improvement: $\pi_{new}(s) = \text{argmax}_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V^{\pi_{old}}(s')], \quad \forall s$

Next Time: Reinforcement Learning!

Double Bandits



Slide: ai.berkeley.edu

Double-Bandit MDP

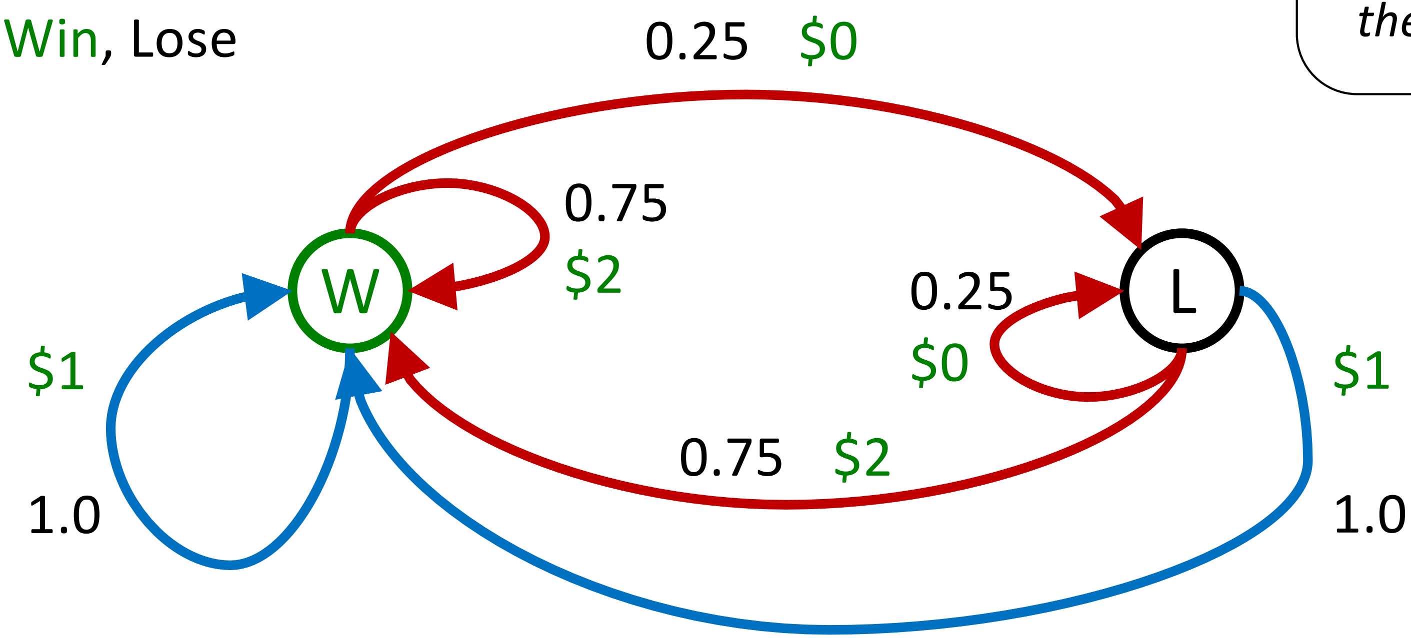
Actions: *Blue*, *Red*

States: Win, Lose

No discount

100 time steps

Both states have the same value



Slide: ai.berkeley.edu

Offline Planning

No discount

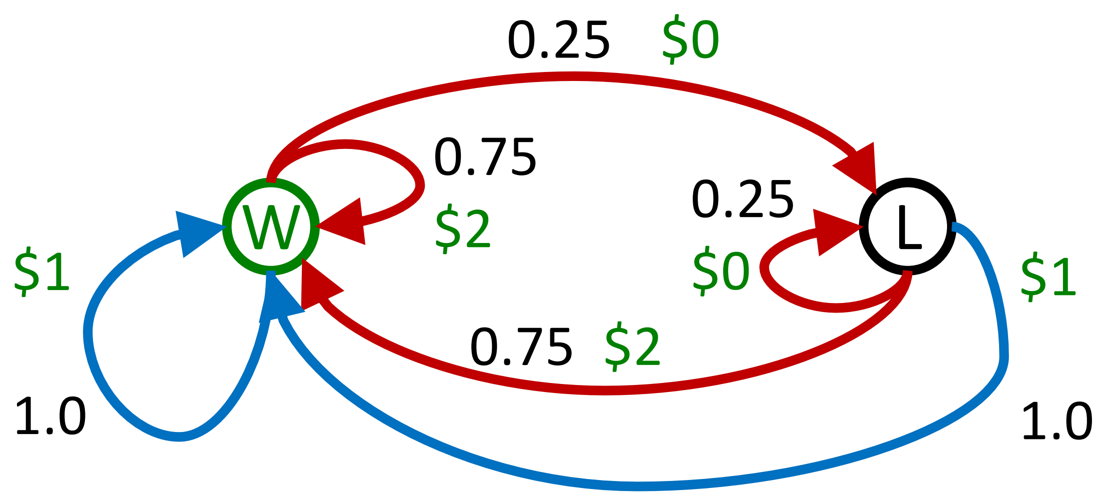
100 time steps

Both states have the same value

Solving MDPs is offline planning

- You determine all quantities through computation
- You need to know the details of the MDP
- You do not actually play the game!

	Value
Play Red	150
Play Blue	100



Slide: ai.berkeley.edu

Let's Play!

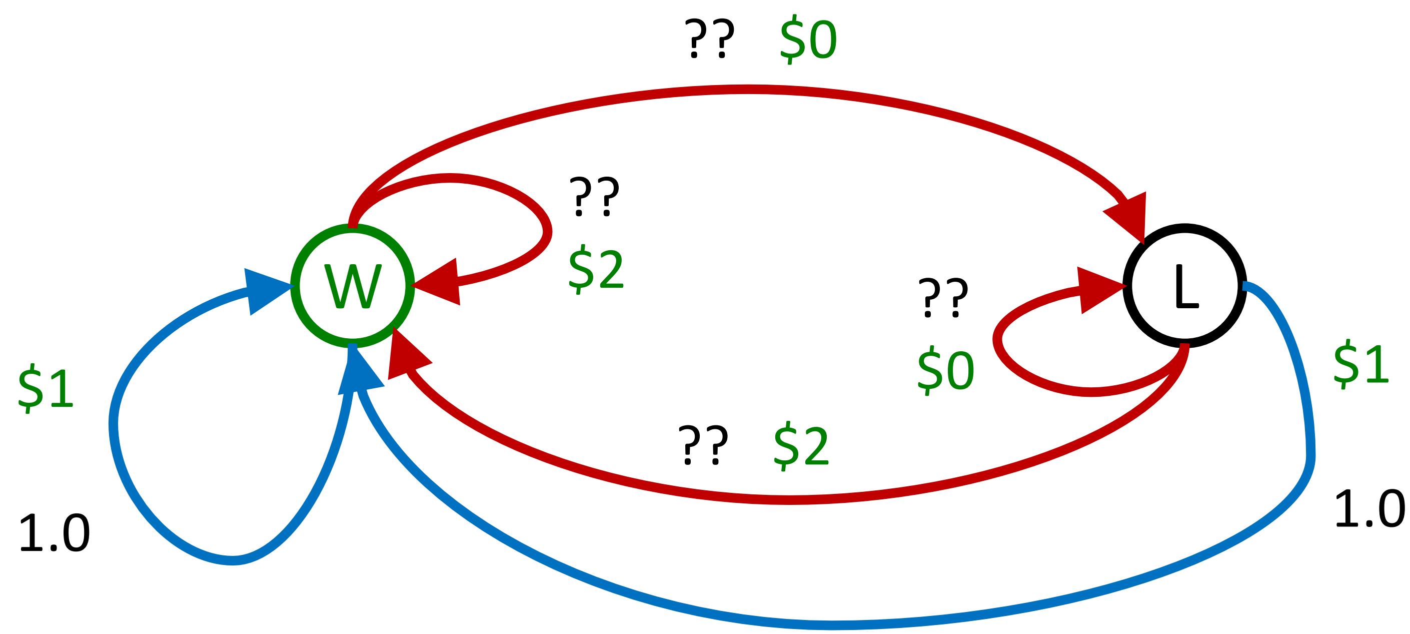
$2 $2 $0 $2 $2

$2 $2 $0 $0 $0

Slide: ai.berkeley.edu

Online Planning

Rules changed! Red's win chance is different.



Slide: ai.berkeley.edu

Let’s Play!

$0 $0 $0 $2 $0

$2 $0 $0 $0 $0

Slide: ai.berkeley.edu

What Just Happened?

That wasn't planning, it was learning!

- Specifically, reinforcement learning
- There was an MDP, but you couldn't solve it with just computation
- You needed to actually act to figure it out

Important ideas in reinforcement learning that came up

- Exploration: you have to try unknown actions to get information
- Exploitation: eventually, you have to use what you know
- Regret: even if you learn intelligently, you make mistakes
- Sampling: because of chance, you have to try things repeatedly
- Difficulty: learning can be much harder than solving a known MDP

Slide: ai.berkeley.edu