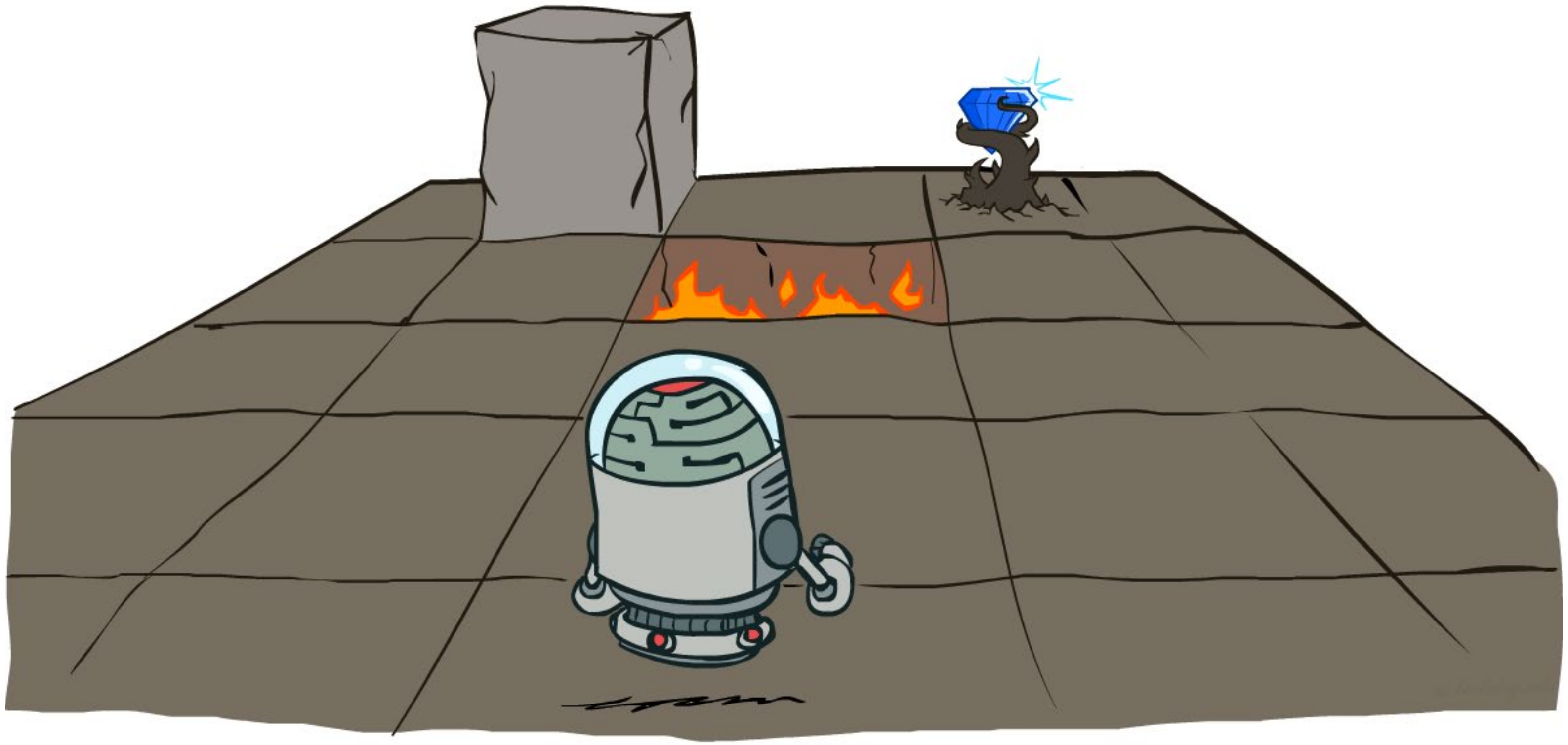
CS 348
Intro to Artificial Intelligence
Day 7

Markov Decision Processes

- Class business
  - Anonymous feedback: https://forms.gle/RJtdYQXCnpru3SeZ7
  - Lab 1 test cases on Piazza, second resubmission (40% penalty) due April 24, 7pm
  - Lab 2 (N queens) due today 7pm
  - Lab 3 (A*) Due April 28
  - Lab 4 (Tic Tac Toe) Due May 5
- MDP’s(17.1-17.3)

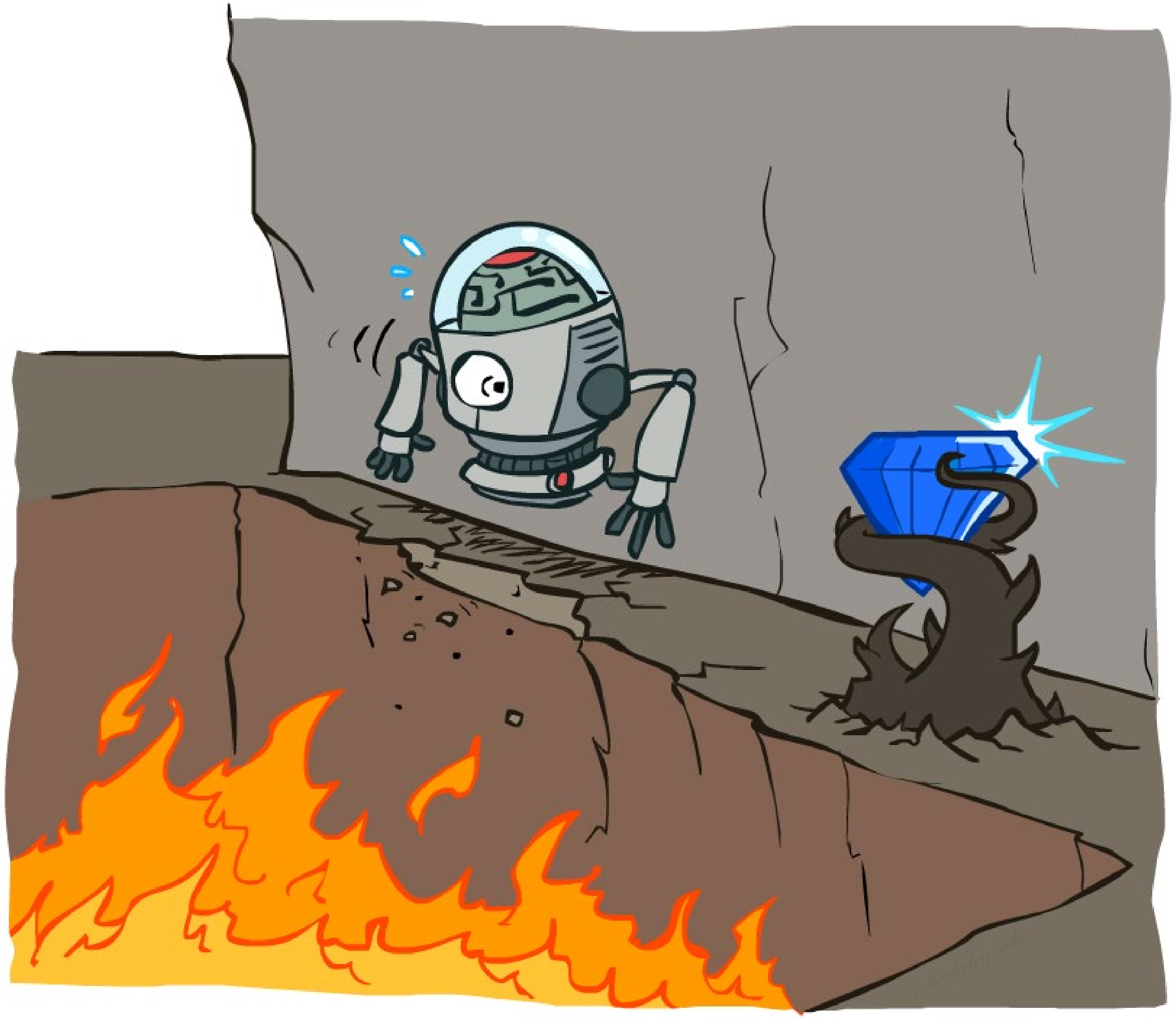
- Introduce Lab 5 (Sudoku solver) Due May 12

Markov Decision Processes



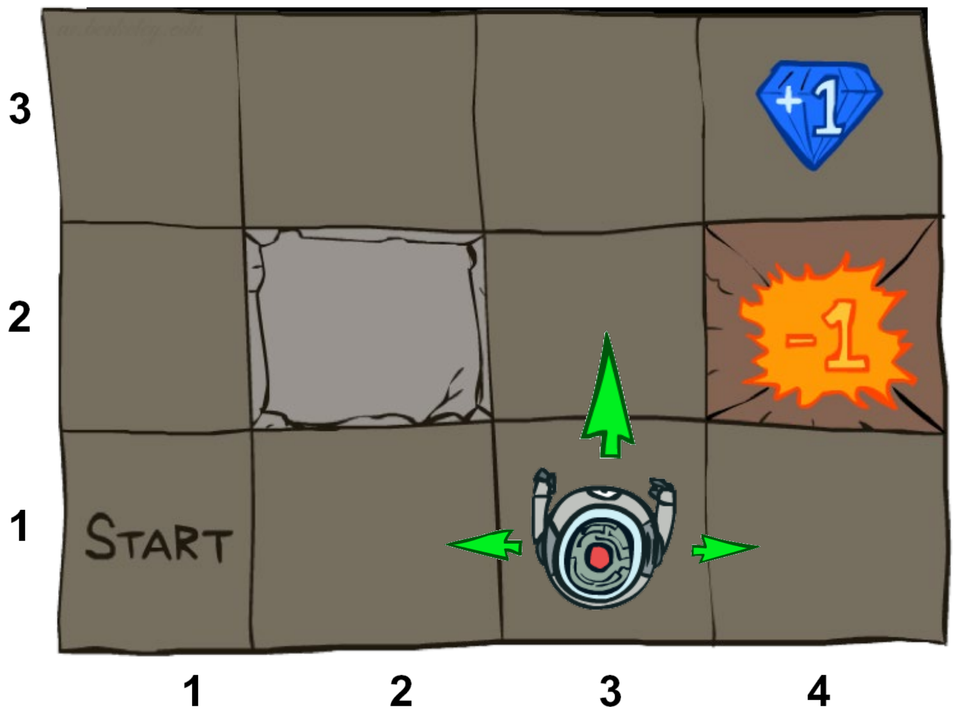
[Based on slides by Dan Klein and Pieter Abbeel]

Non-Deterministic Search



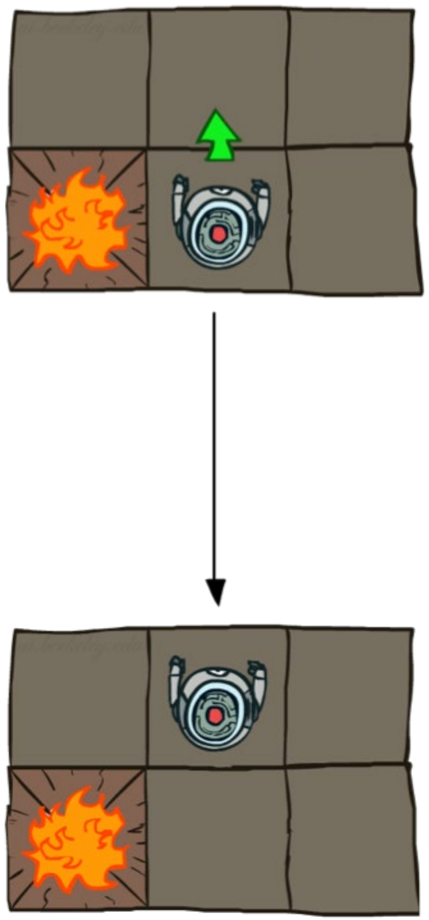
Example: Grid World

- A maze-like problem
  - The agent lives in a grid
  - Walls block the agent's path
  - Special exit actions
- Noisy movement: actions do not always go as planned
  - 80% of the time, the action North takes the agent North (if there is no wall there)
  - 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)
- Goal: maximize sum of rewards

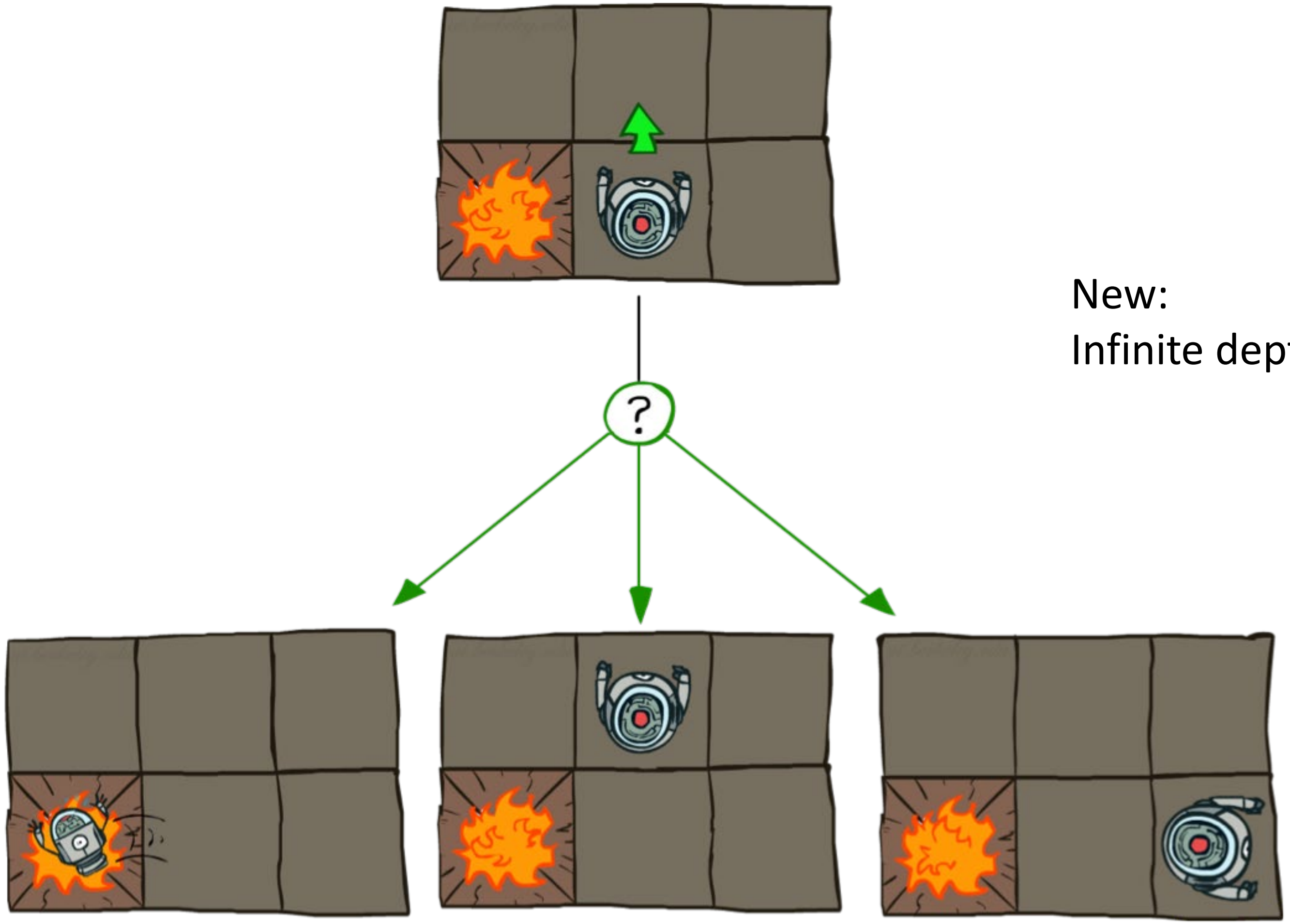


Grid World Actions

Deterministic Grid World



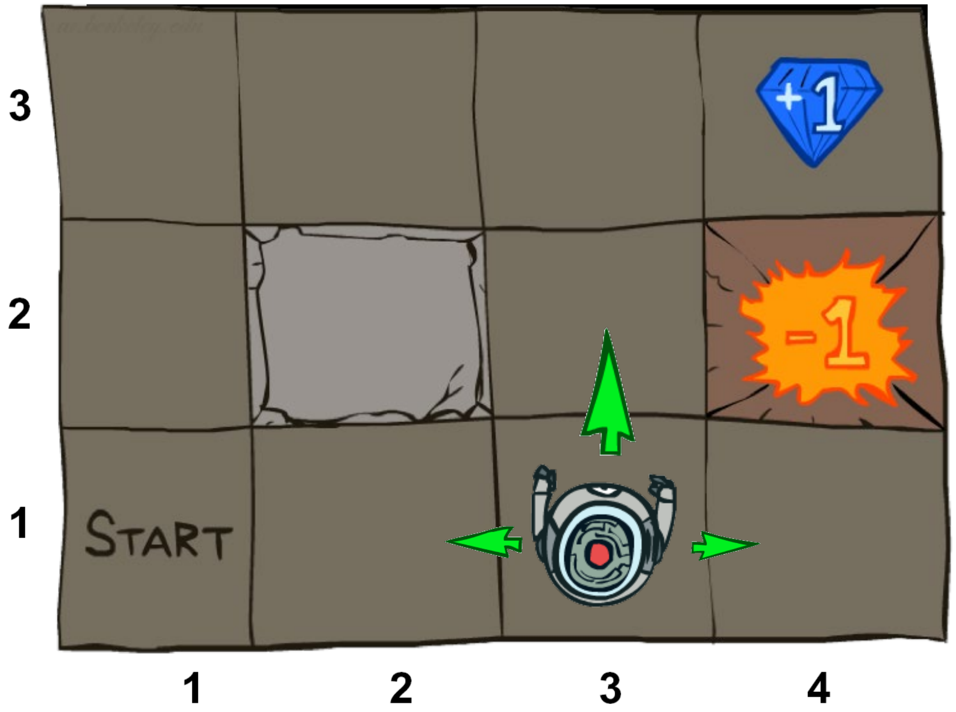
Stochastic Grid World



New:
Infinite depth

Markov Decision Processes

- An MDP is defined by:
  - A set of states $s \in S$
  - A set of actions $a \in A$
  - A transition function T(s, a, s')
    - Probability that a from s leads to s', i.e., P(s'| s, a)
    - Also called the model or the dynamics
  - A reward function R(s, a, s')
  - A start state
  - Maybe a terminal state



- MDPs are non-deterministic search problems
  - One way to solve them is with expectimax search
  - We'll have a new tool soon

What is Markov about MDPs?

- “Markov” generally means that given the present state, the future and the past are independent

- For Markov decision processes, “Markov” means action outcomes depend only on the current state

$$P(S_{t+1} = s' | S_t = s_t, A_t = a_t, S_{t-1} = s_{t-1}, A_{t-1}, \dots S_0 = s_0)$$

$$=$$

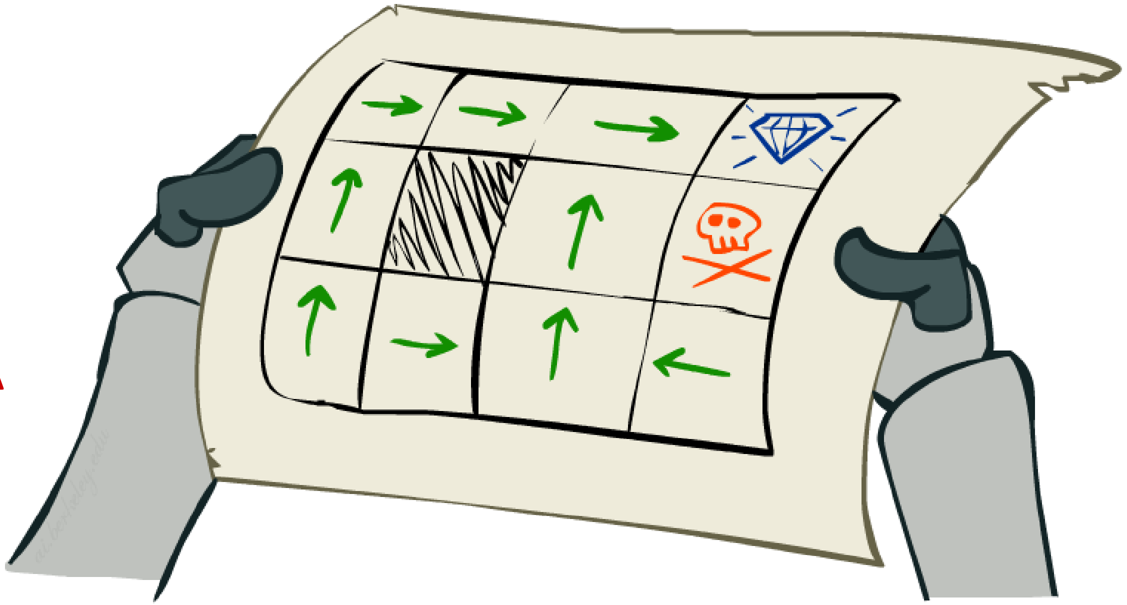
$$P(S_{t+1} = s' | S_t = s_t, A_t = a_t)$$

- This is just like search, where the successor function could only depend on the current state (not the history)

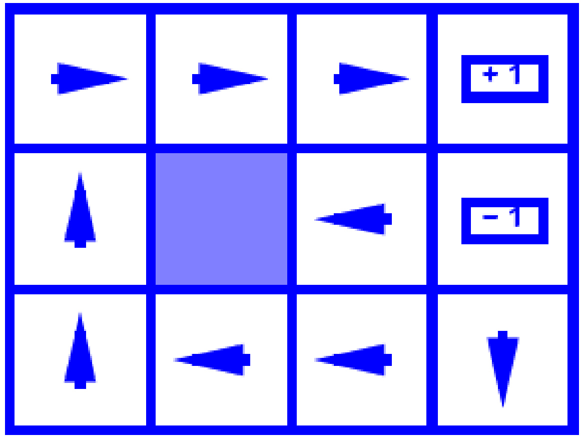
Andrey Markov
(1856-1922)

Goal: Policies

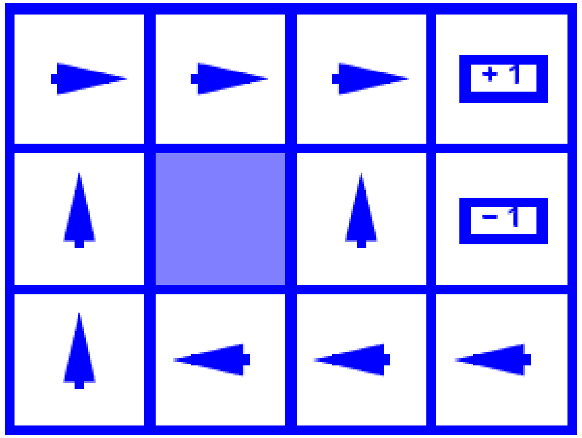
- In deterministic single-agent search problems, we wanted an optimal plan, or sequence of actions, from start to a goal
- For MDPs, we want an optimal policy $\pi^*: S \rightarrow A$
  - A policy π gives an action for each state
  - An optimal policy is one that maximizes expected utility if followed
  - An explicit policy defines a reflex agent
- Expectimax didn't compute entire policies
  - It computed the action for a single state only



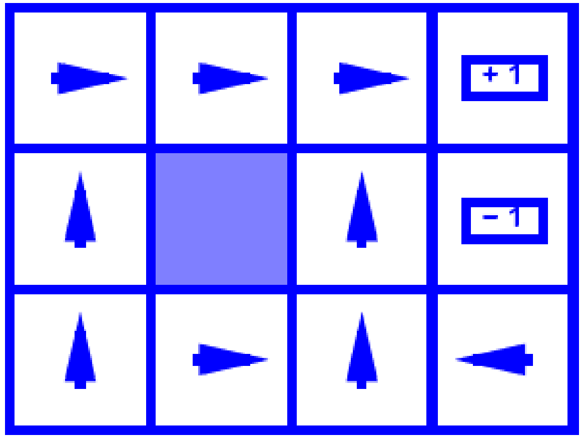
Optimal Policies



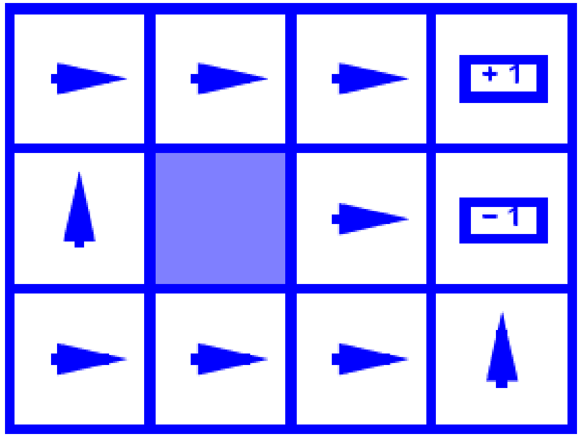
R(s) = -0.01



R(s) = -0.03

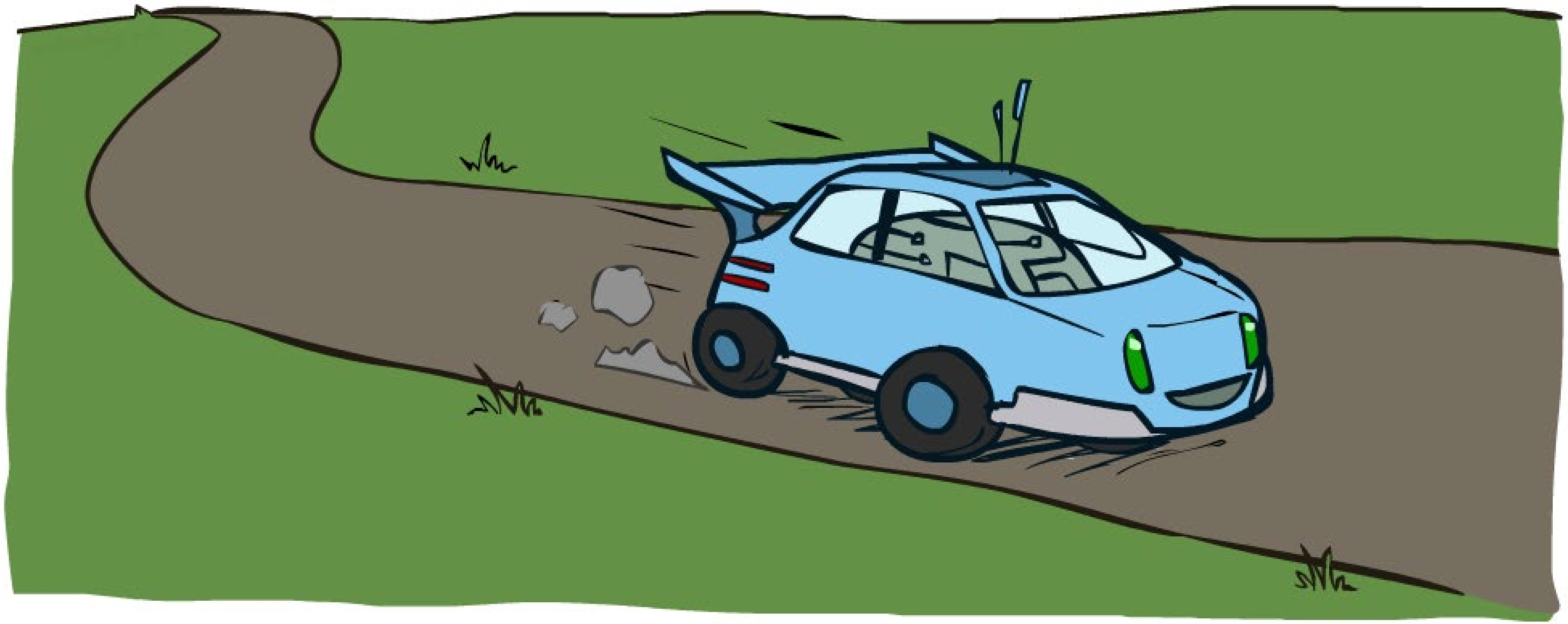


R(s) = -0.4



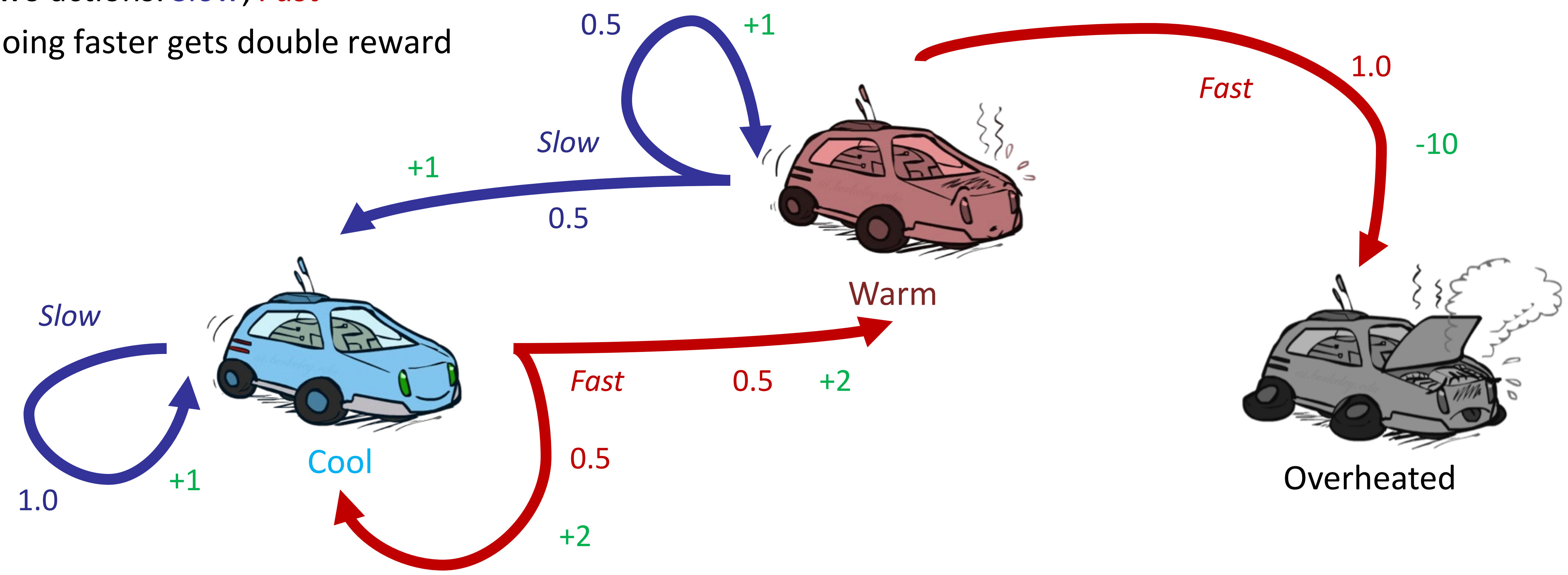
R(s) = -2.0

Example: Racing

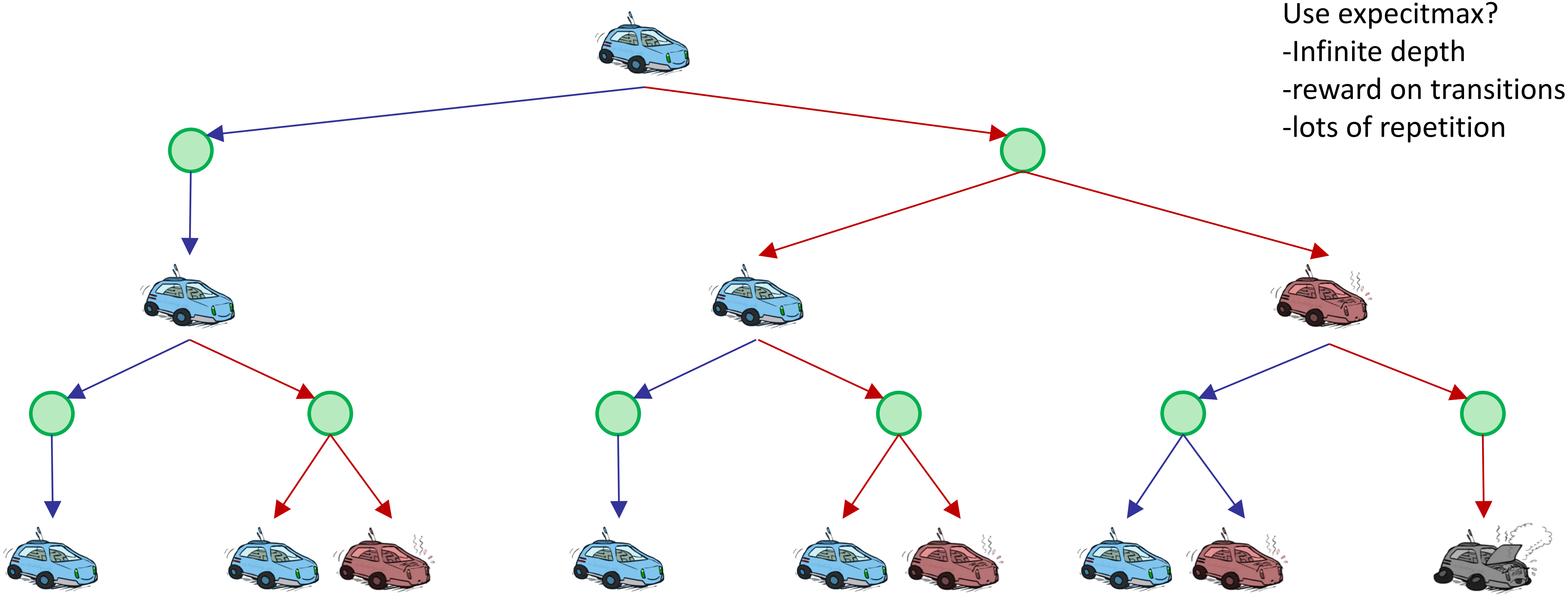


Example: Racing

- A robot car wants to travel far, quickly
- Three states: Cool, Warm, Overheated
- Two actions: *Slow*, *Fast*
- Going faster gets double reward



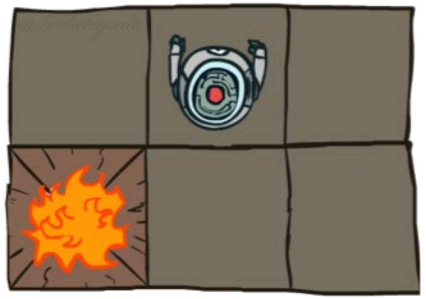
Racing Search Tree

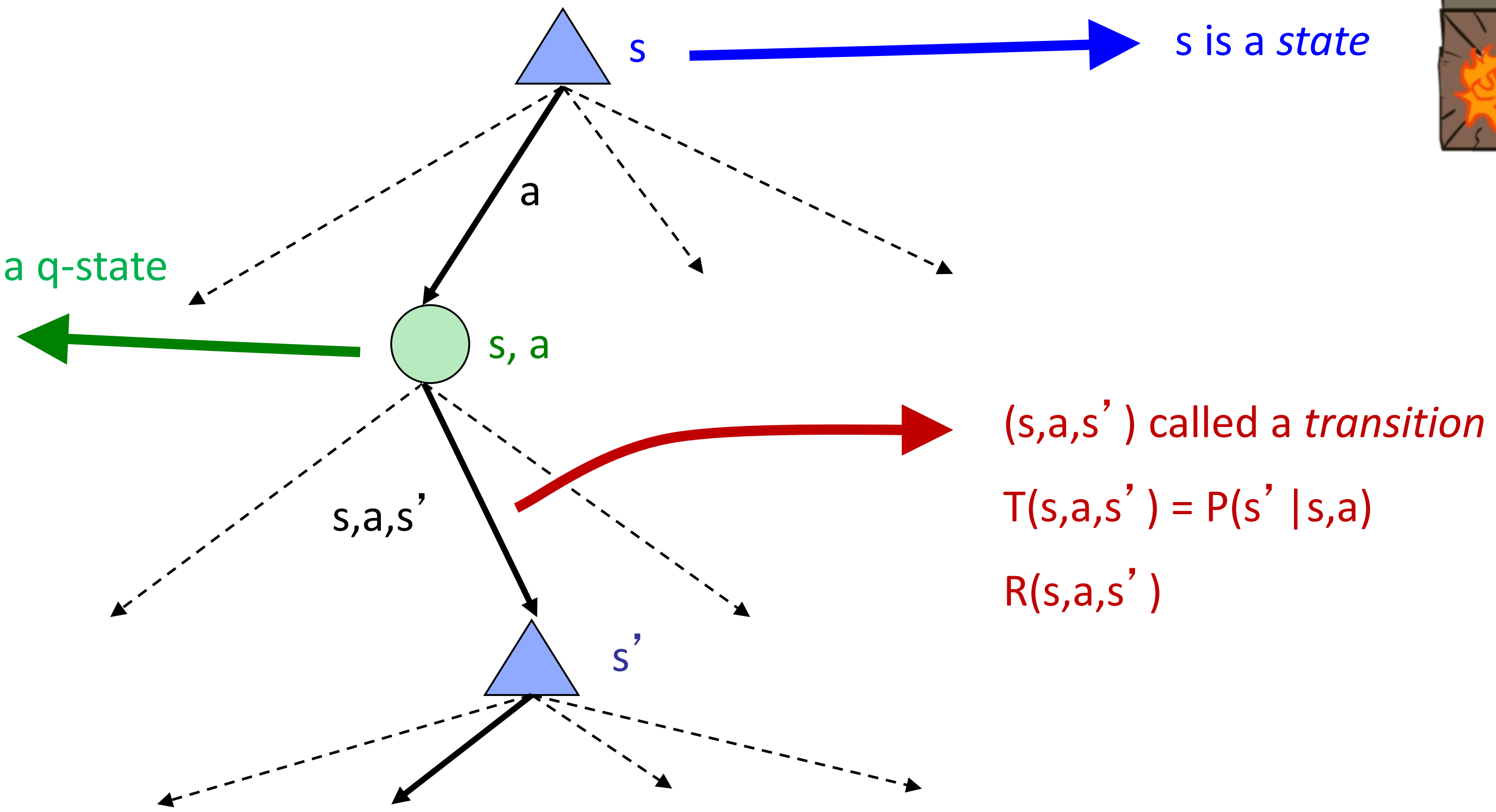


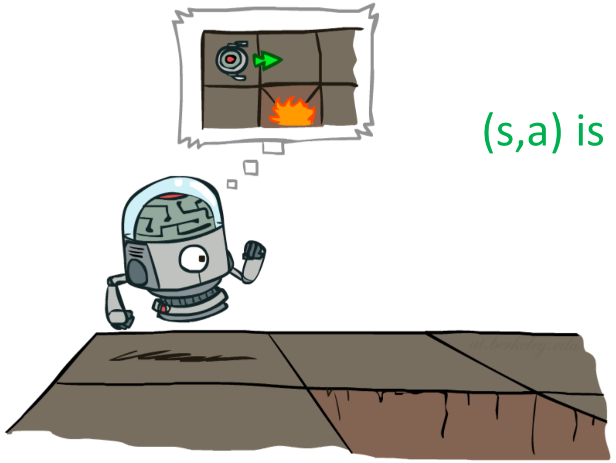
Use expecitmax?
-Infinite depth
-reward on transitions
-lots of repetition

MDP Search Trees

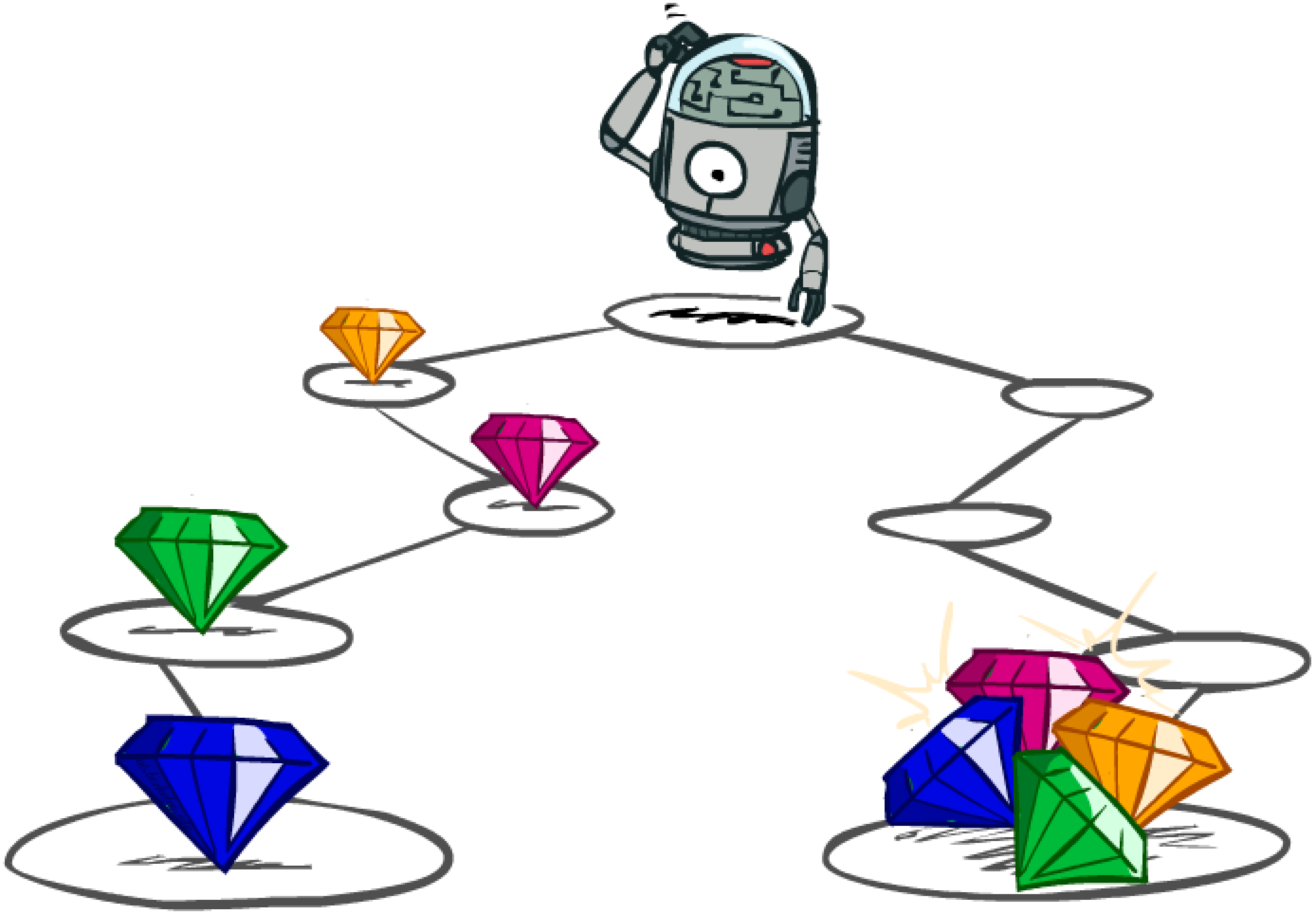
- Each MDP state projects an expectimax-like search tree







Utilities of Sequences

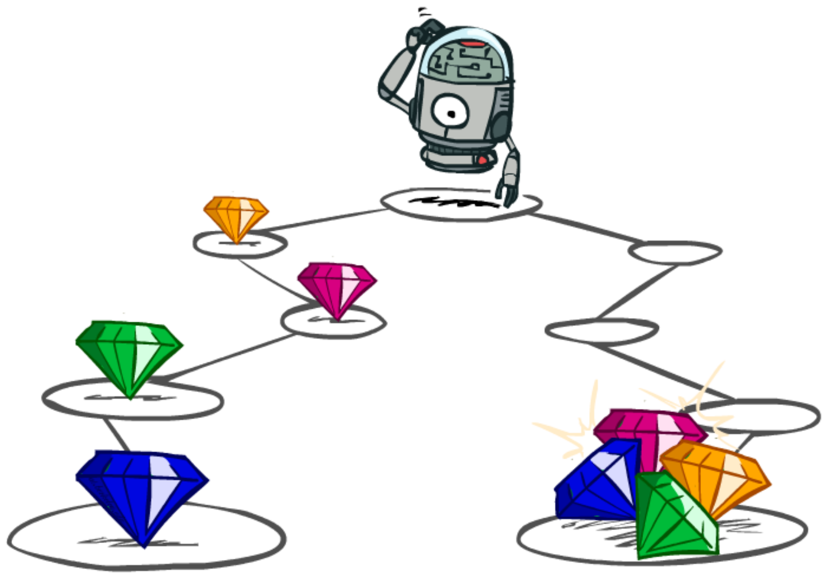


Utilities of Sequences

- What preferences should an agent have over reward sequences?

- More or less? [1, 2, 2] or [2, 3, 4]

- Now or later? [0, 0, 1] or [1, 0, 0]



Discounting

- It's reasonable to maximize the sum of rewards
- It's also reasonable to prefer rewards now to rewards later
- One solution: values of rewards decay exponentially

1

Worth Now

γ

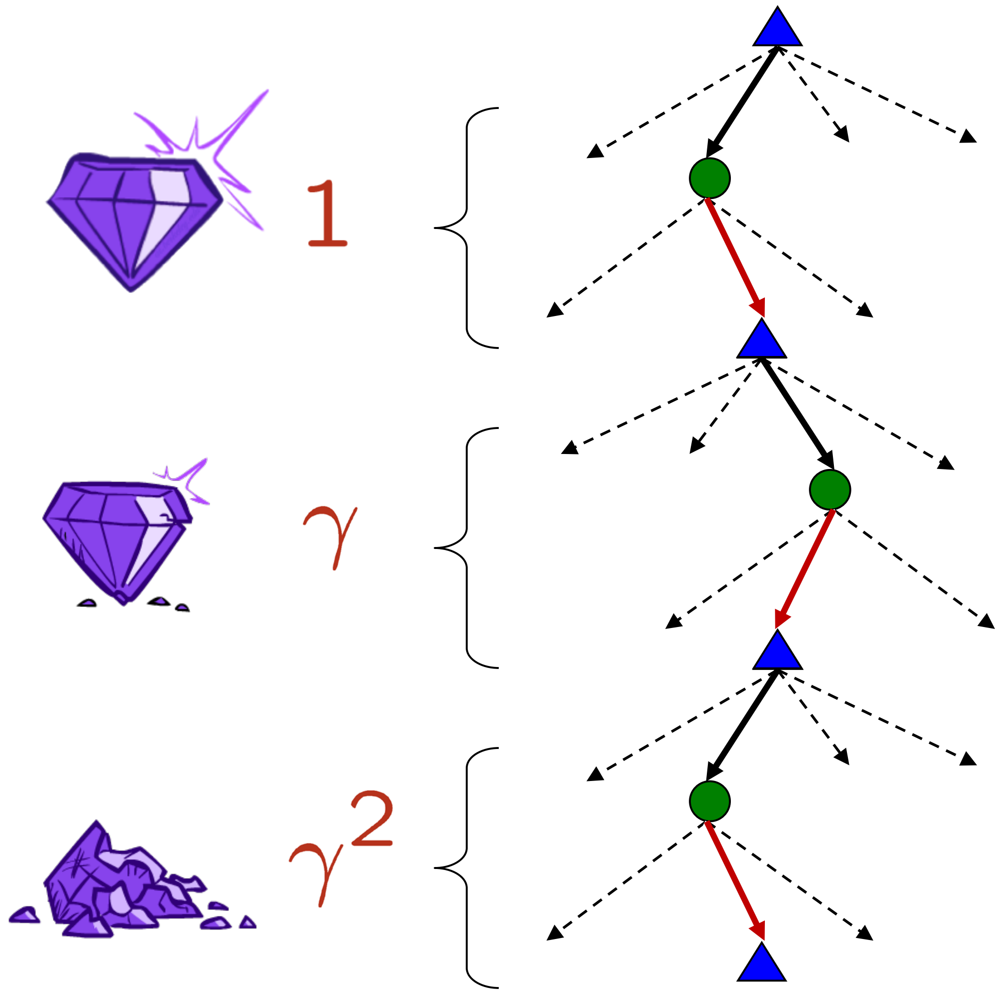
Worth Next Step

γ^2

Worth In Two Steps

Discounting

- How to discount?
  - Each time we descend a level, we multiply in the discount once
- Why discount?
  - Sooner rewards probably do have higher utility than later rewards
  - Also helps our algorithms converge
- Example: discount of 0.5
  - U([1,2,3]) = 1*1 + 0.5*2 + 0.25*3
  - U([1,2,3]) < U([3,2,1])



Discounting

- Given:

10				1
a	b	c	d	e

  - Actions: East, West, and Exit (only available in exit states a, e)
  - Transitions: deterministic

- For $\gamma = 1$, what is the optimal policy?

10				1

- For $\gamma = 0.1$, what is the optimal policy?

10				1

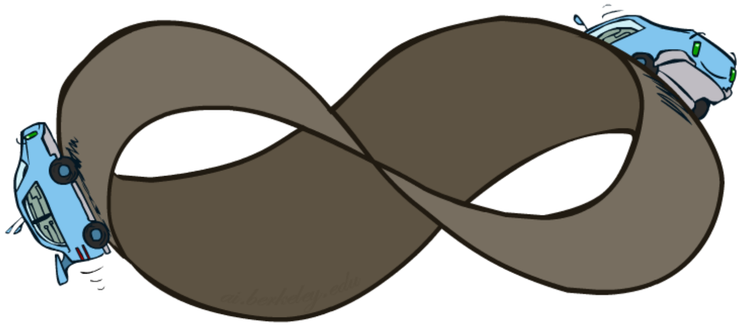
- For which γ are West and East equally good when in state d?

Infinite Utilities?!

- Problem: What if the game lasts forever? Do we get infinite rewards?
- Solutions:
  - Finite horizon: (similar to depth-limited search)
    - Terminate episodes after a fixed T steps (e.g. life)
  - Discounting: use $0 < \gamma < 1$

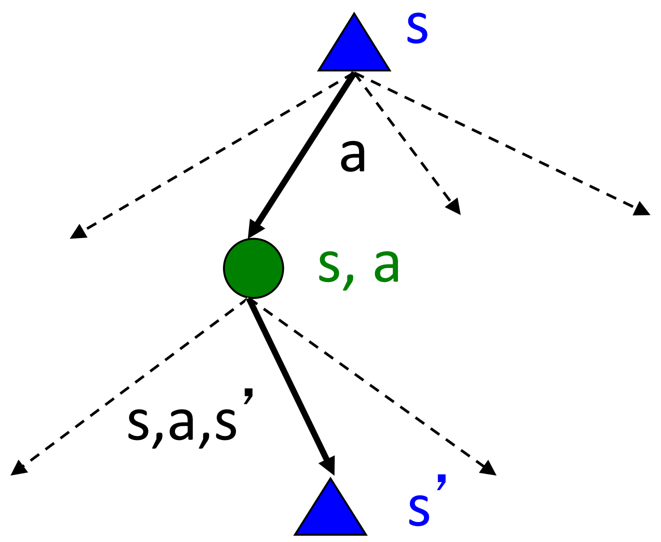
$$U([r_0, \ldots r_\infty]) = \sum_{t=0}^{\infty} \gamma^t r_t \leq R_{\max}/(1 - \gamma)$$

    - Smaller γ means smaller "horizon" – shorter term focus



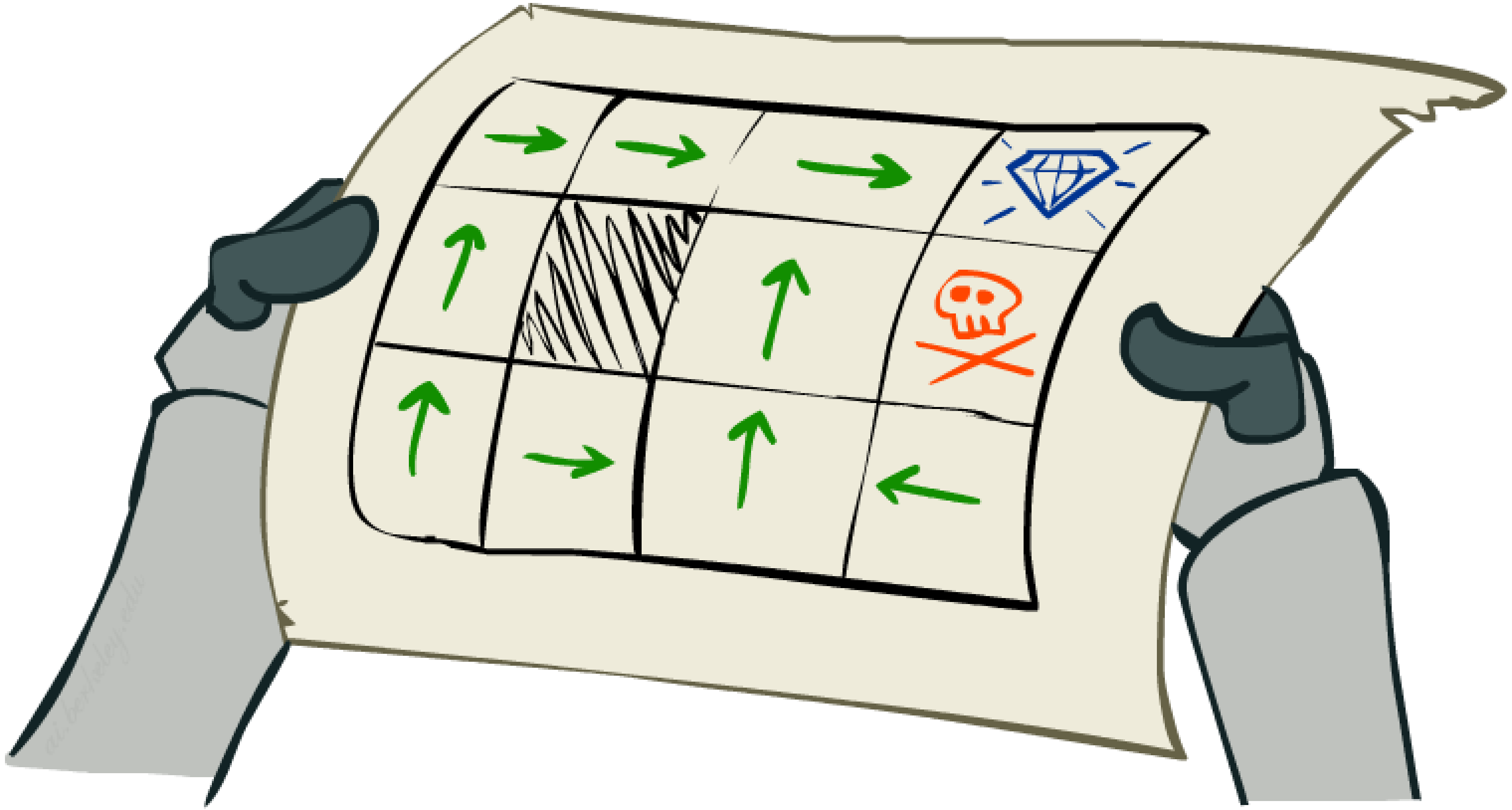
Recap: Defining MDPs

- Markov decision processes:
  - Set of states S
  - Start state s_0
  - Set of actions A
  - Transitions P(s’|s,a) (or T(s,a,s’))
  - Rewards R(s,a,s’) (and discount γ)



- MDP quantities so far:
  - Policy = Choice of action for each state
  - Utility = sum of (discounted) rewards

Solving MDPs



Optimal Quantities

- The value (utility) of a state s:

  $V^*(s)$ = expected utility starting in s and acting optimally

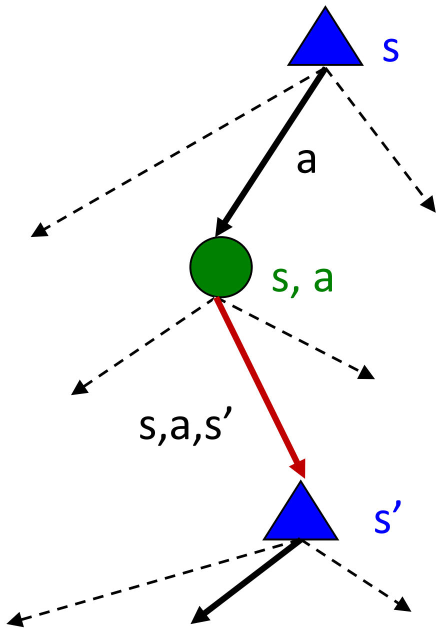
- The value (utility) of a q-state (s,a):

  $Q^*(s,a)$ = expected utility starting out having taken action a from state s and (thereafter) acting optimally

- The optimal policy:

  $\pi^*(s)$ = optimal action from state s

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

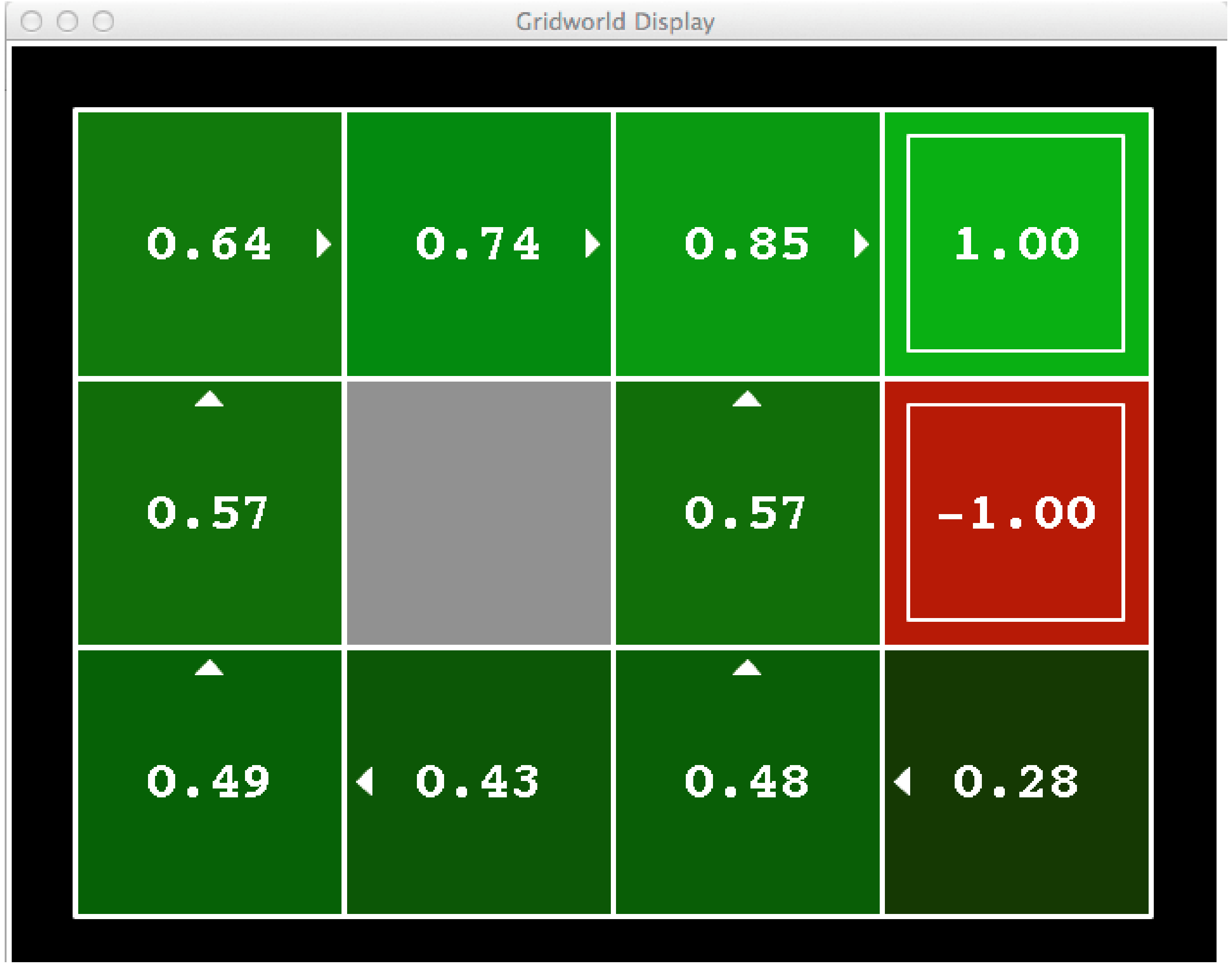


s is a *state*

(s, a) is a *q-state*

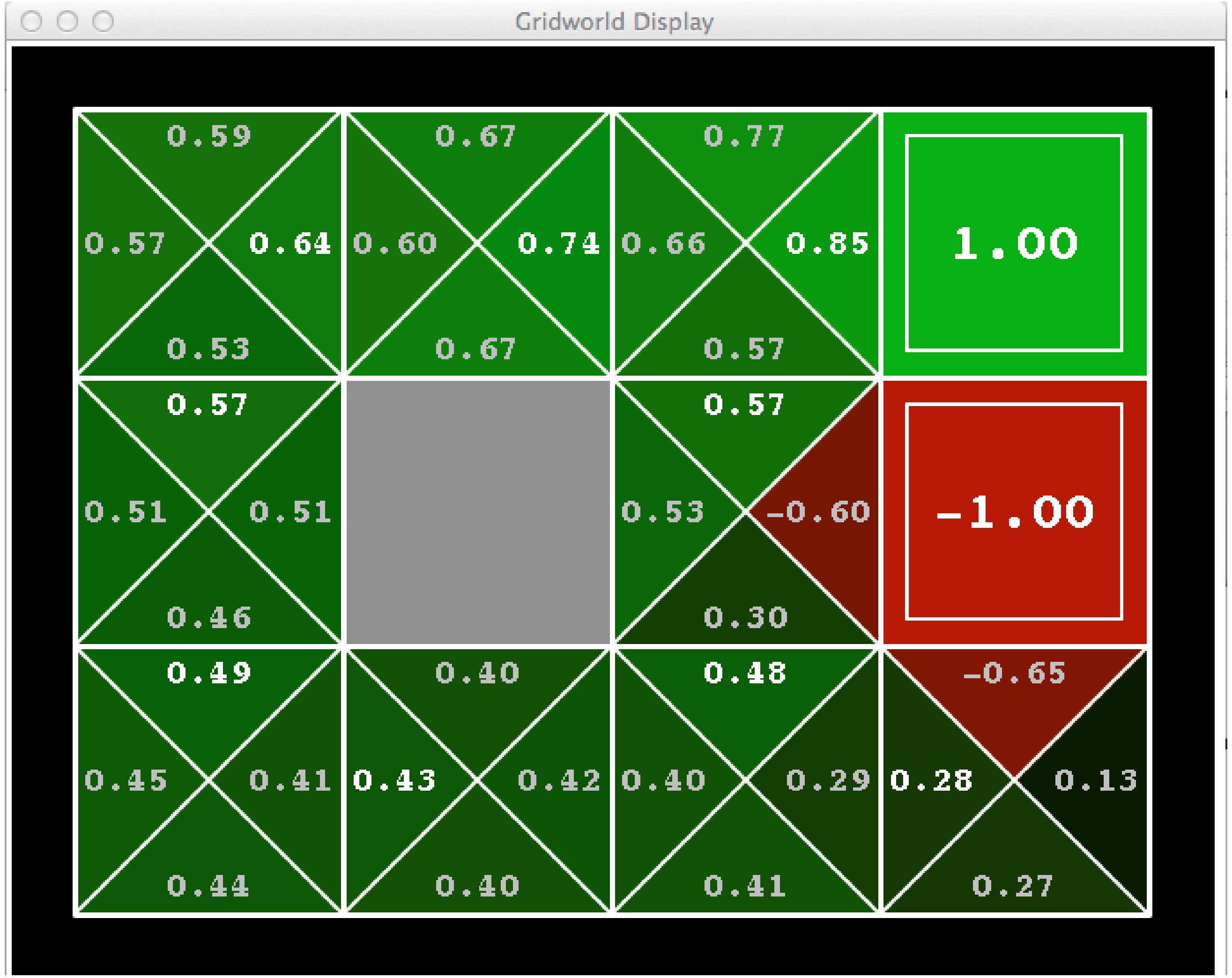
(s,a,s') is a *transition*

Gridworld V Values



Noise = 0.2
Discount = 0.9
Living reward = 0

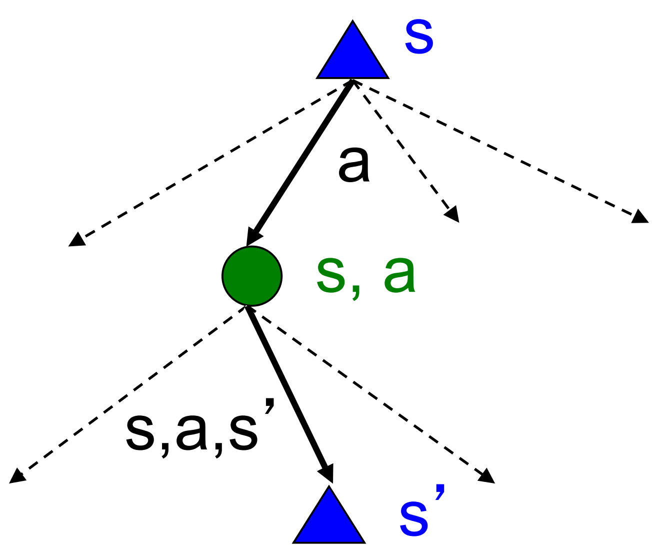
Gridworld Q Values



Noise = 0.2
Discount = 0.9
Living reward = 0

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!



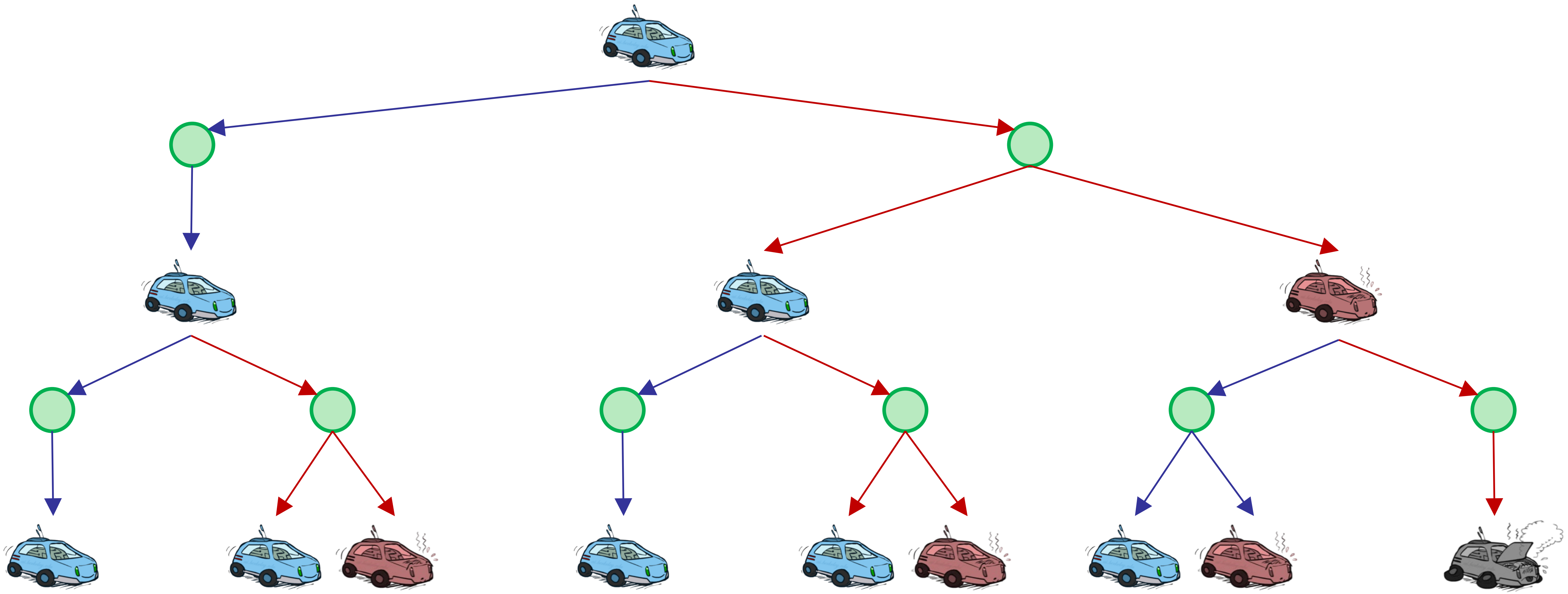
- Recursive definition of value:

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

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

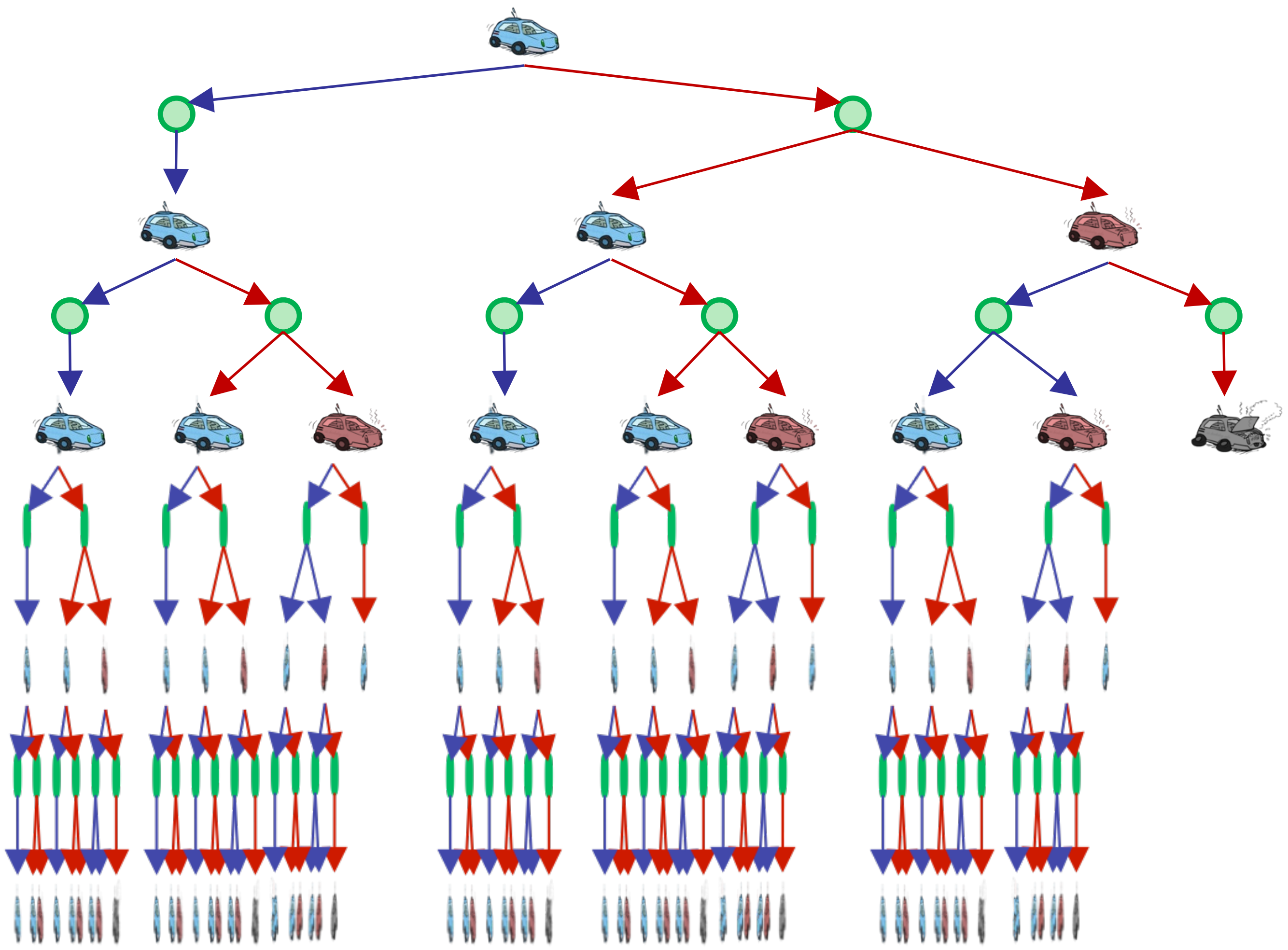
$$V^*(s) = \max_a \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma V^*(s') \right]$$

Racing Search Tree



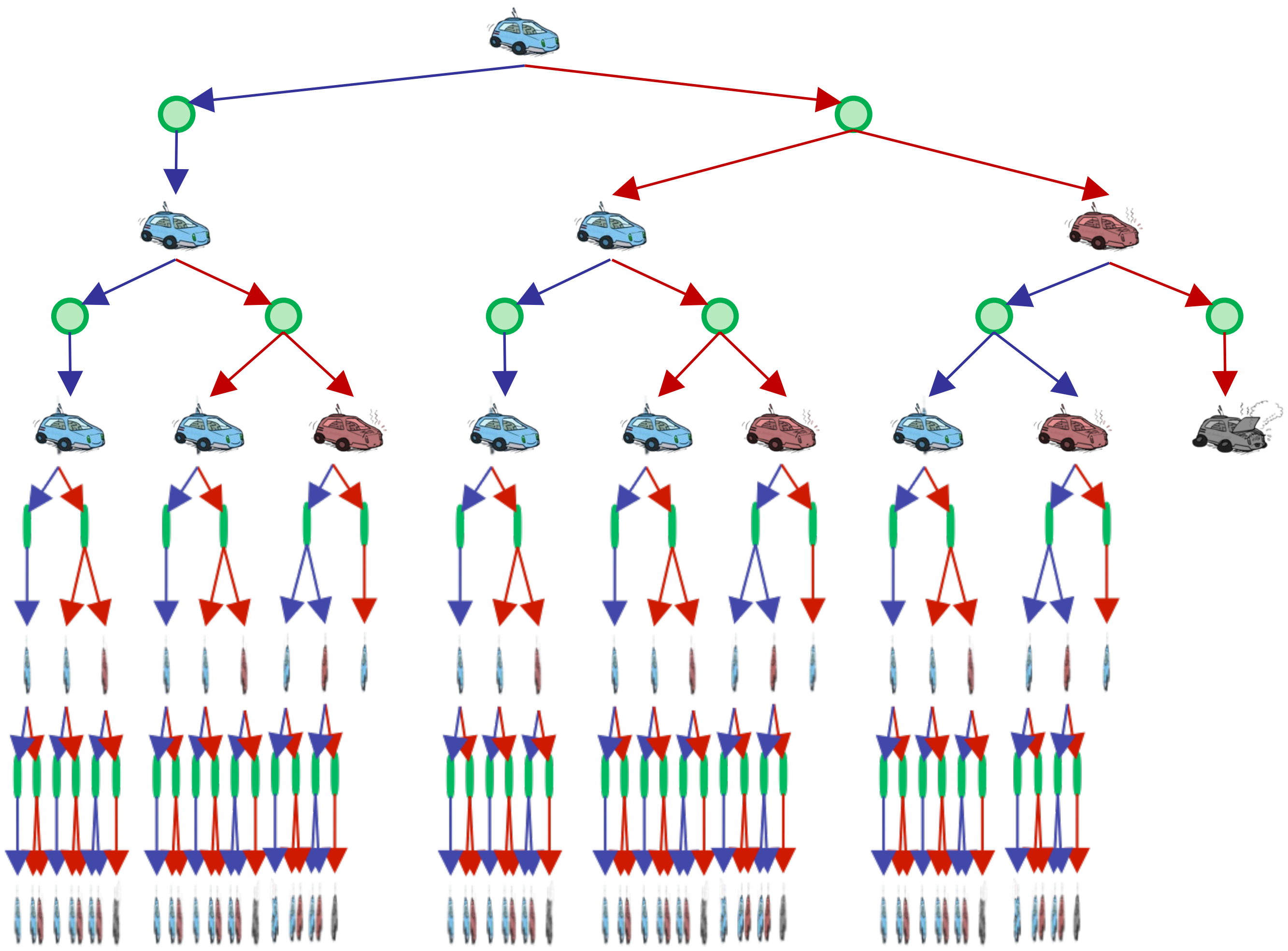
Racing Search Tree

Lots of repetition!



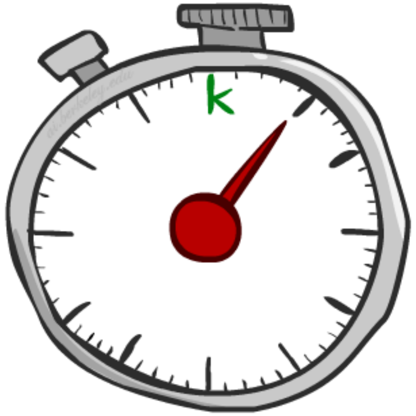
Racing Search Tree

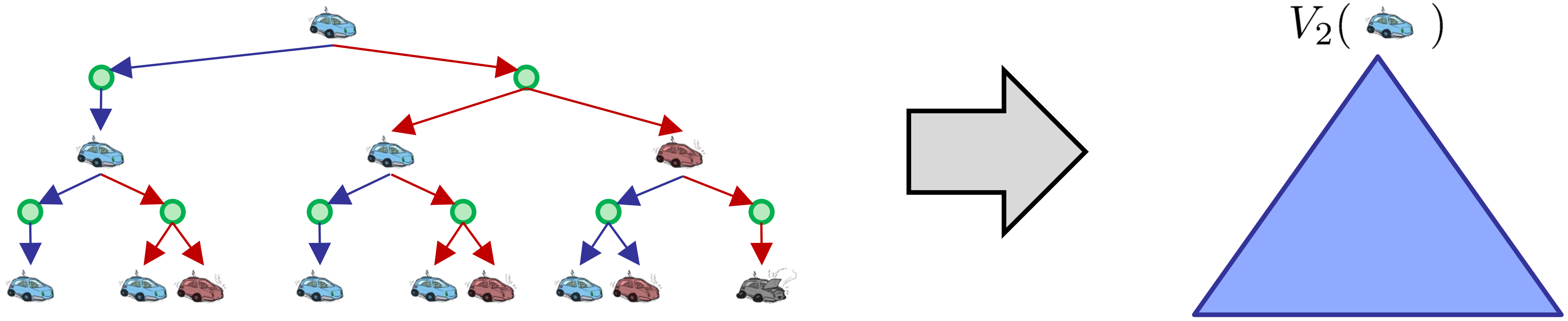
- We're doing way too much work with expectimax!
- Problem: States are repeated
  - Idea: Only compute needed quantities once
- Problem: Tree goes on forever
  - Idea: Do a depth-limited computation, but with increasing depths until change is small
  - Note: deep parts of the tree eventually don't matter if $\gamma < 1$



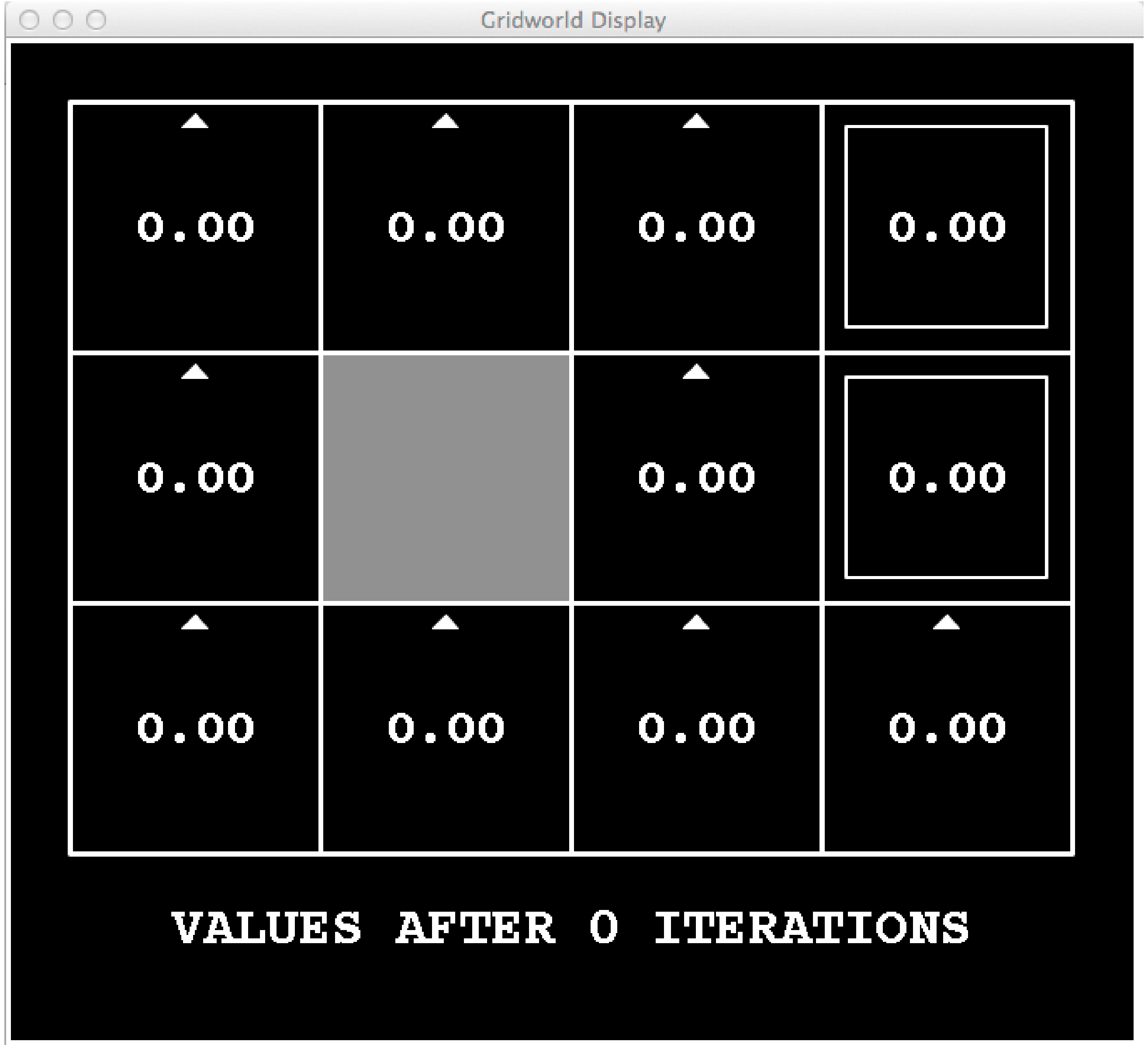
Time-Limited Values

- Key idea: time-limited values
- Define $V_k(s)$ to be the optimal value of s if the game ends in k more time steps
  - Equivalently, it's what a depth-k expectimax would give from s



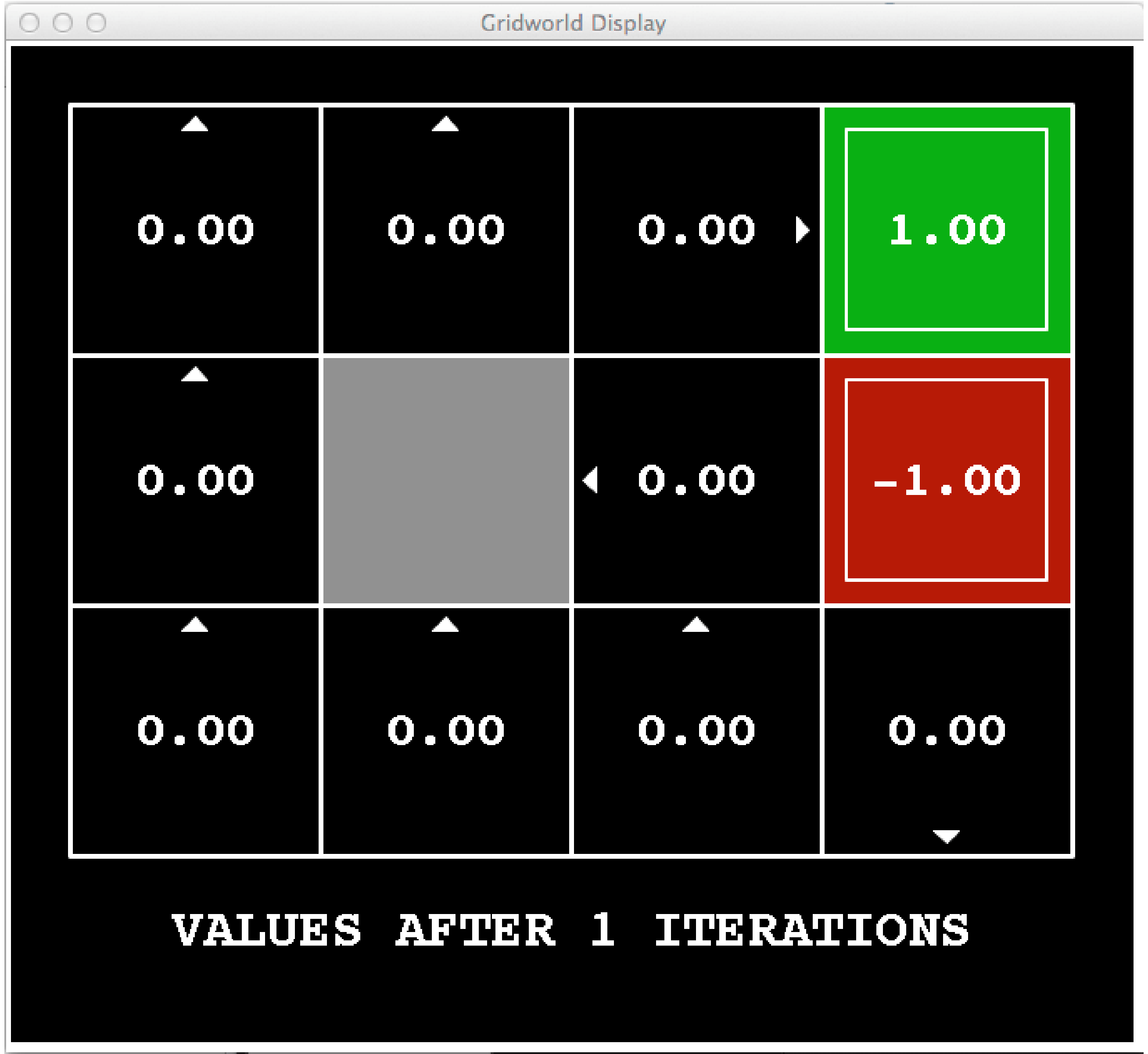


k=0



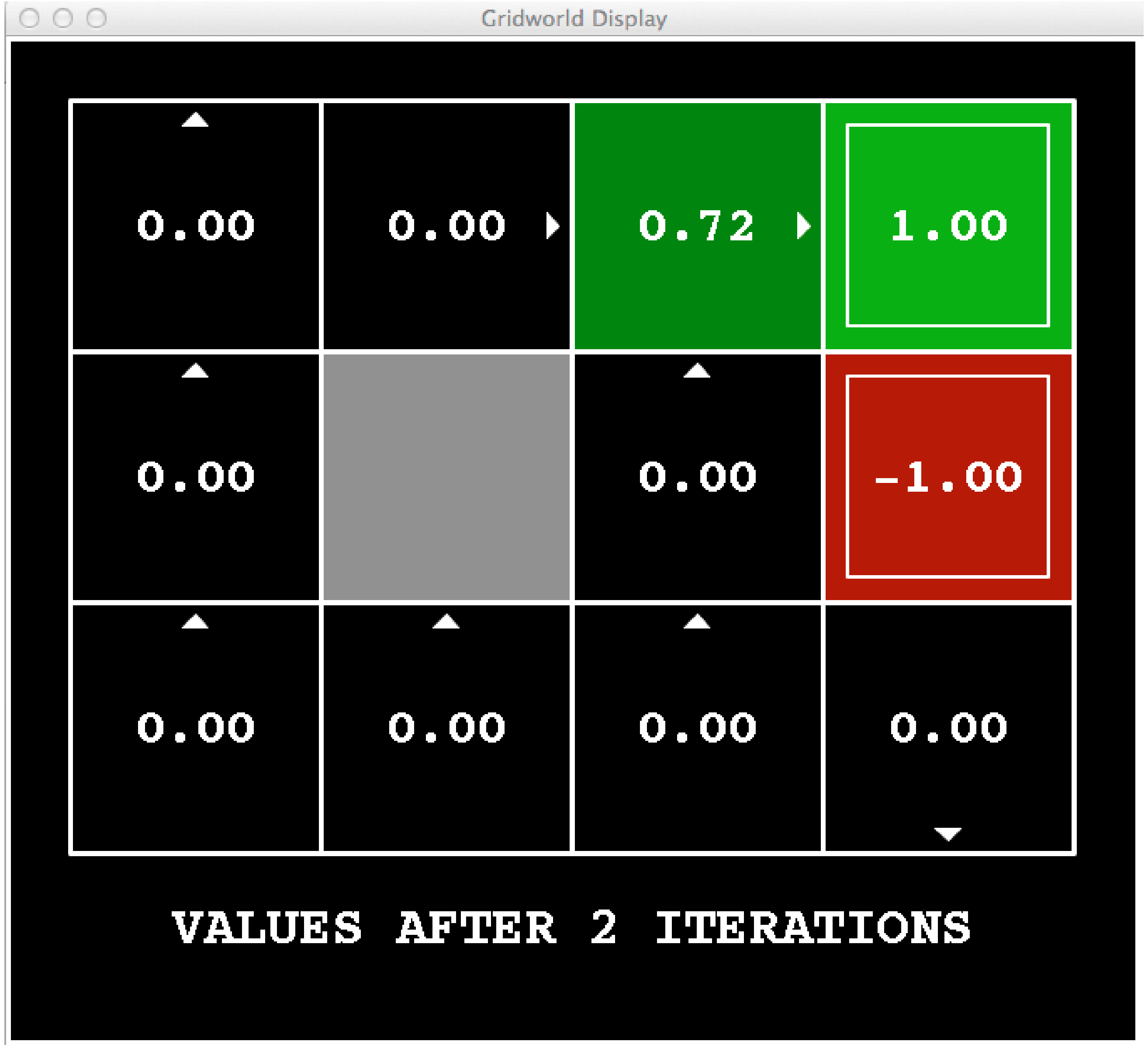
Noise = 0.2
Discount = 0.9
Living reward = 0

k=1



Noise = 0.2
Discount = 0.9
Living reward = 0

k=2

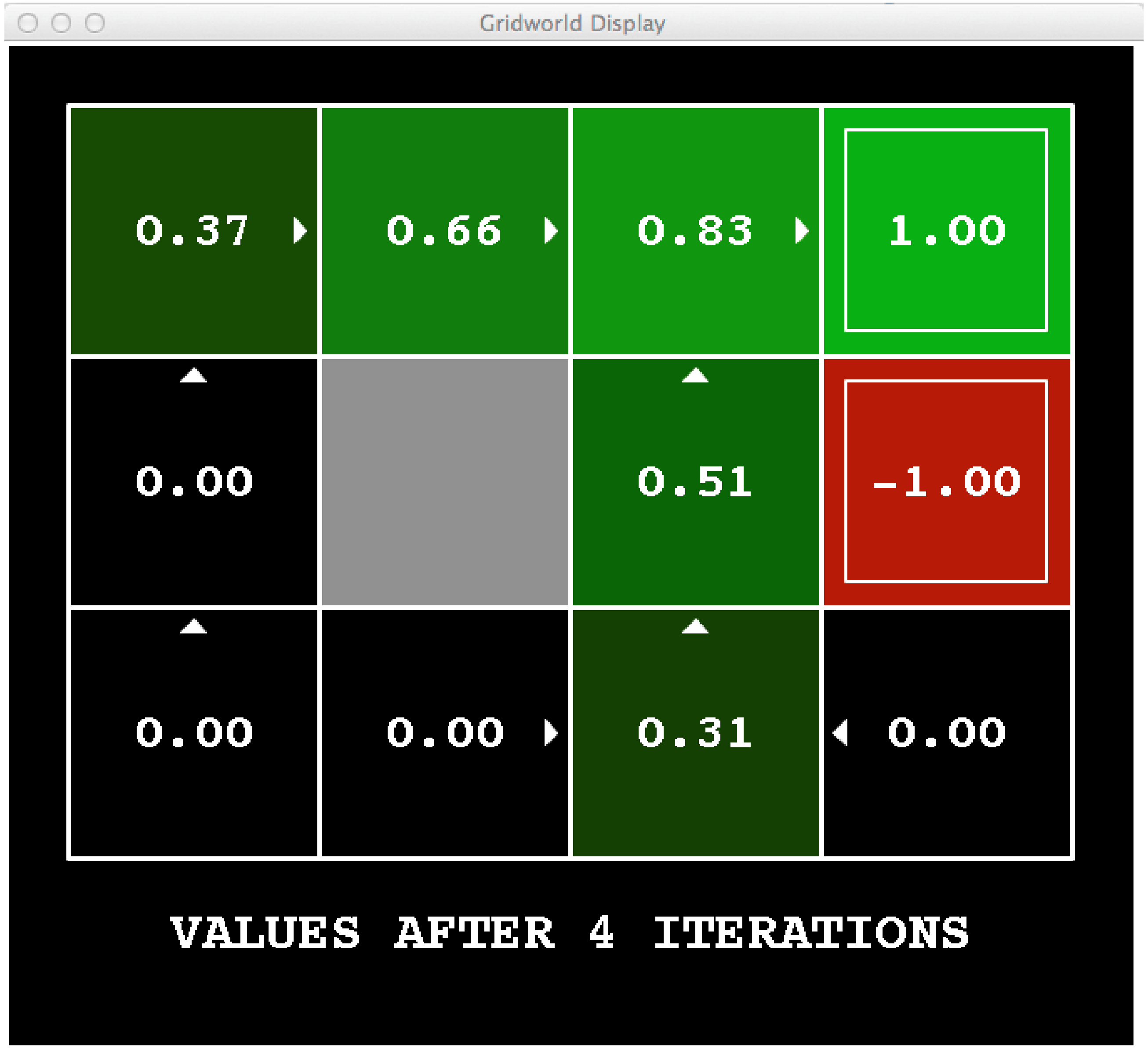


Noise = 0.2
Discount = 0.9
Living reward = 0

k=3

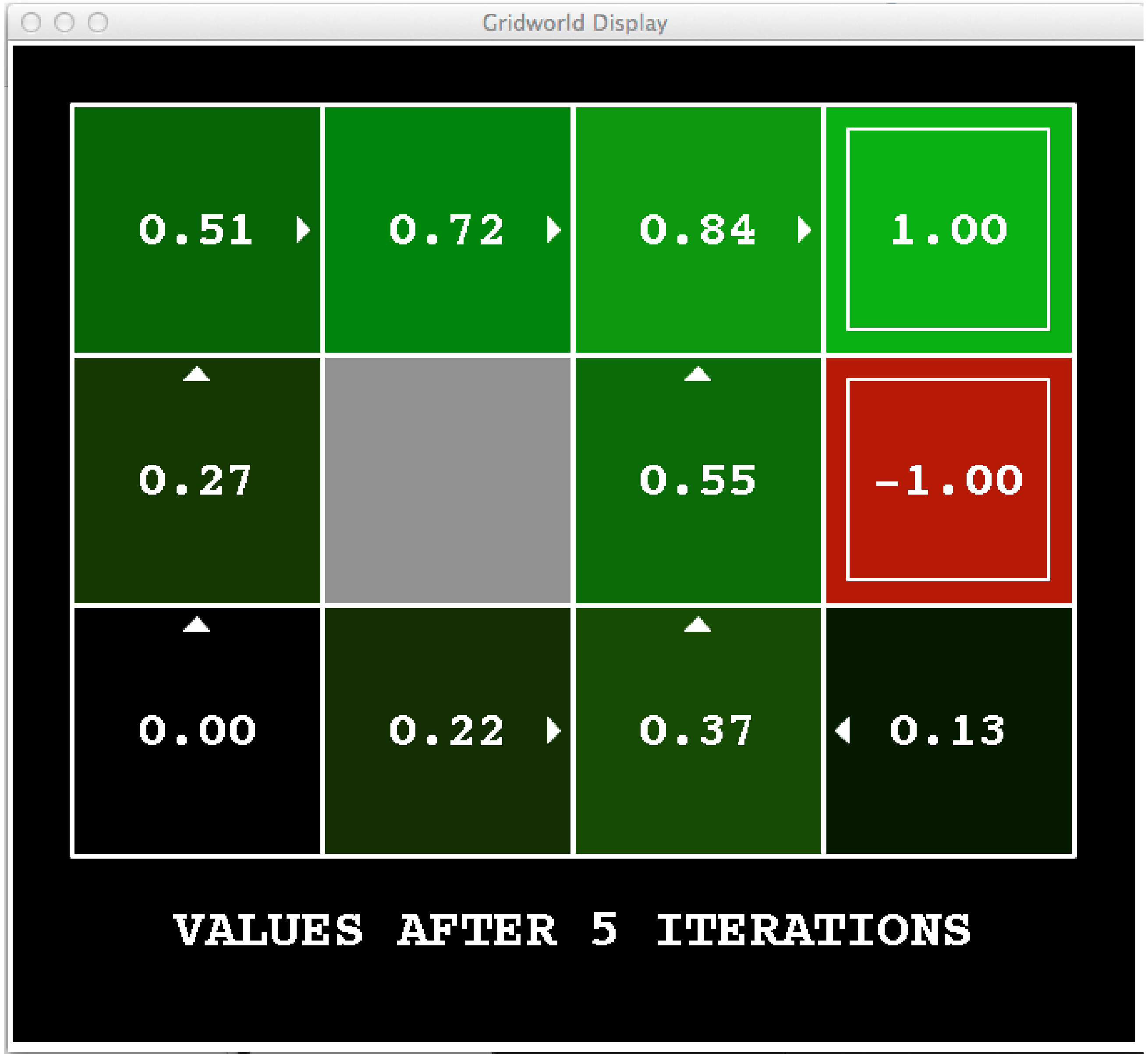
Noise = 0.2
Discount = 0.9
Living reward = 0

k=4



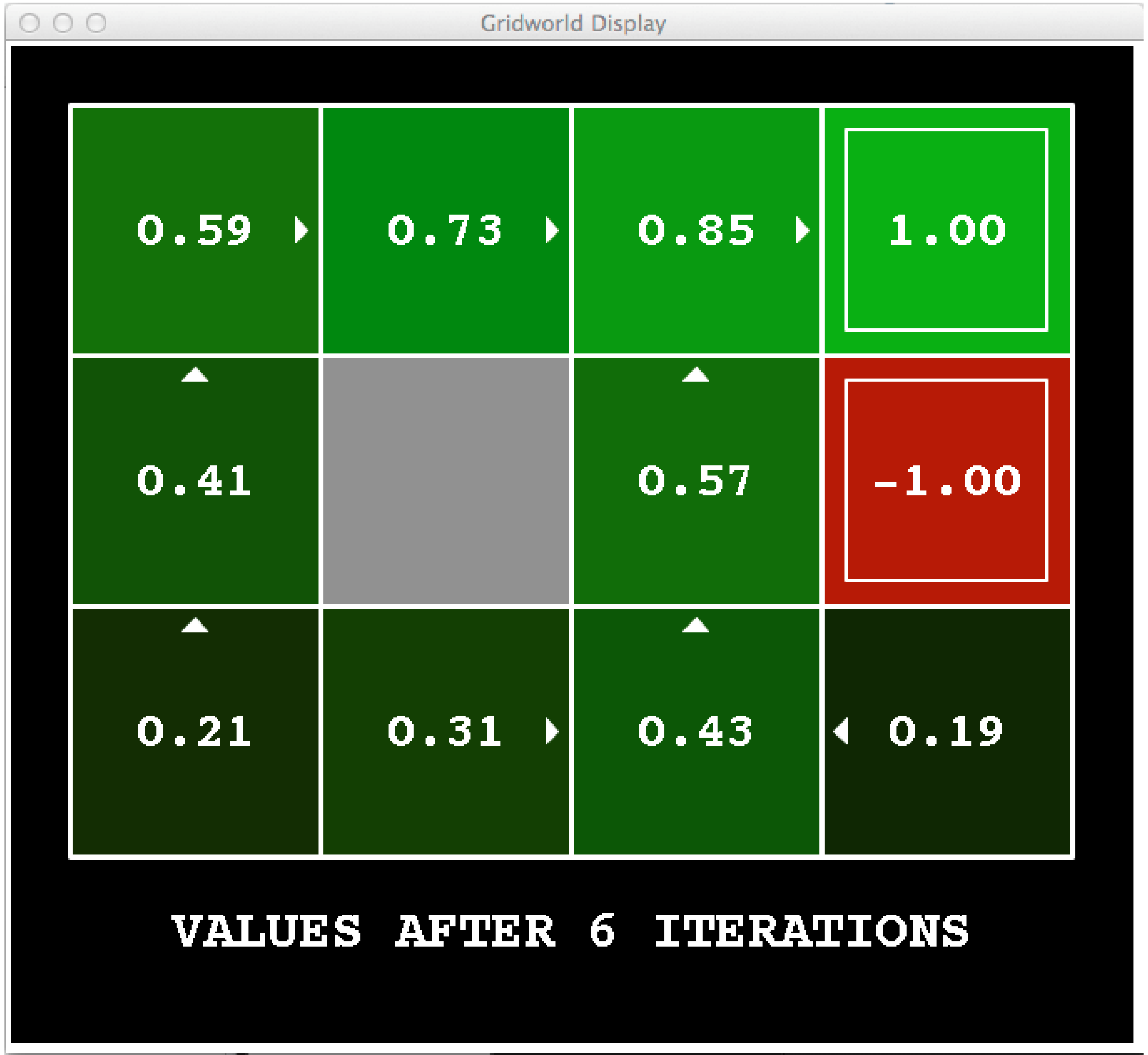
Noise = 0.2
Discount = 0.9
Living reward = 0

k=5



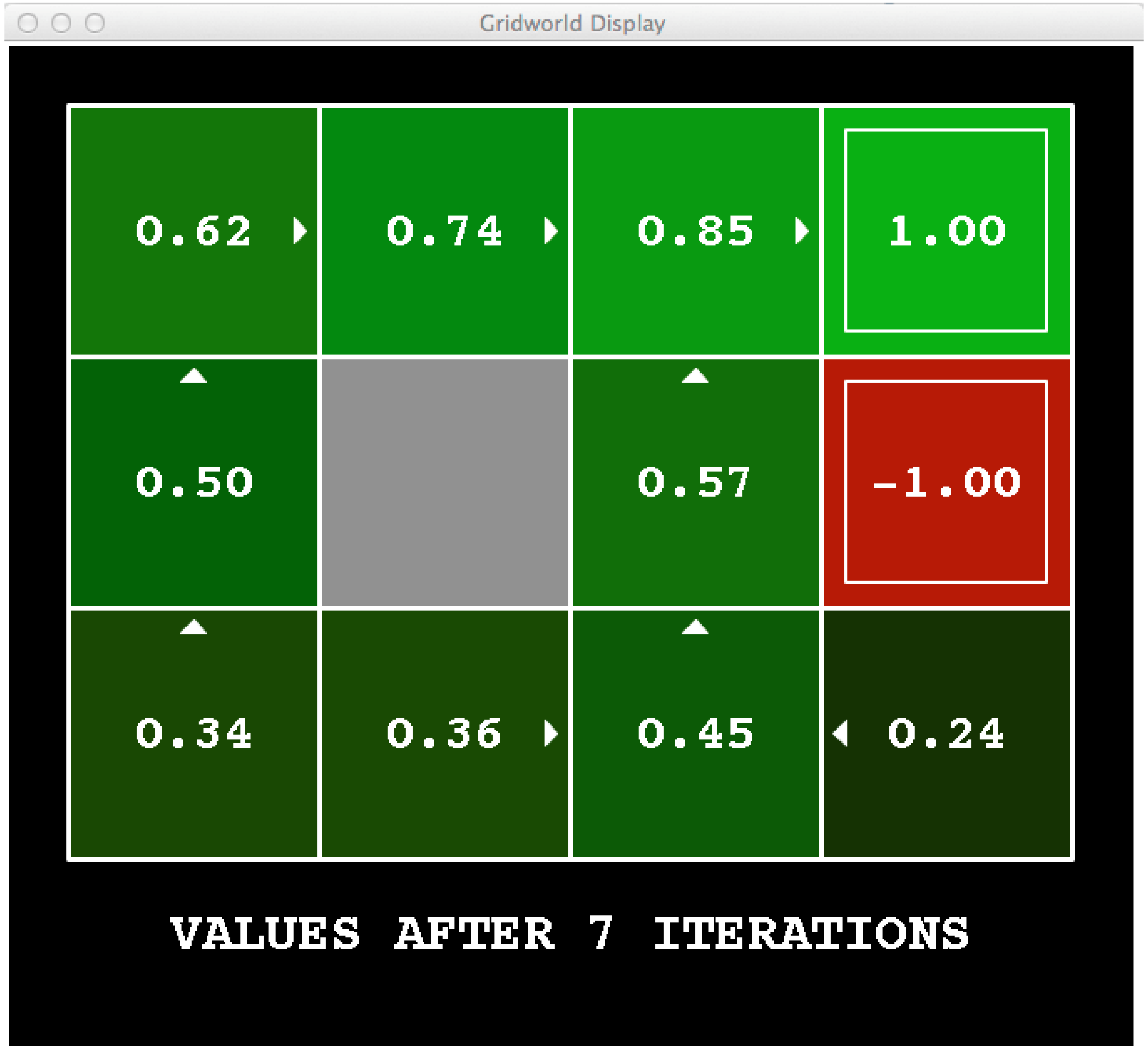
Noise = 0.2
Discount = 0.9
Living reward = 0

k=6



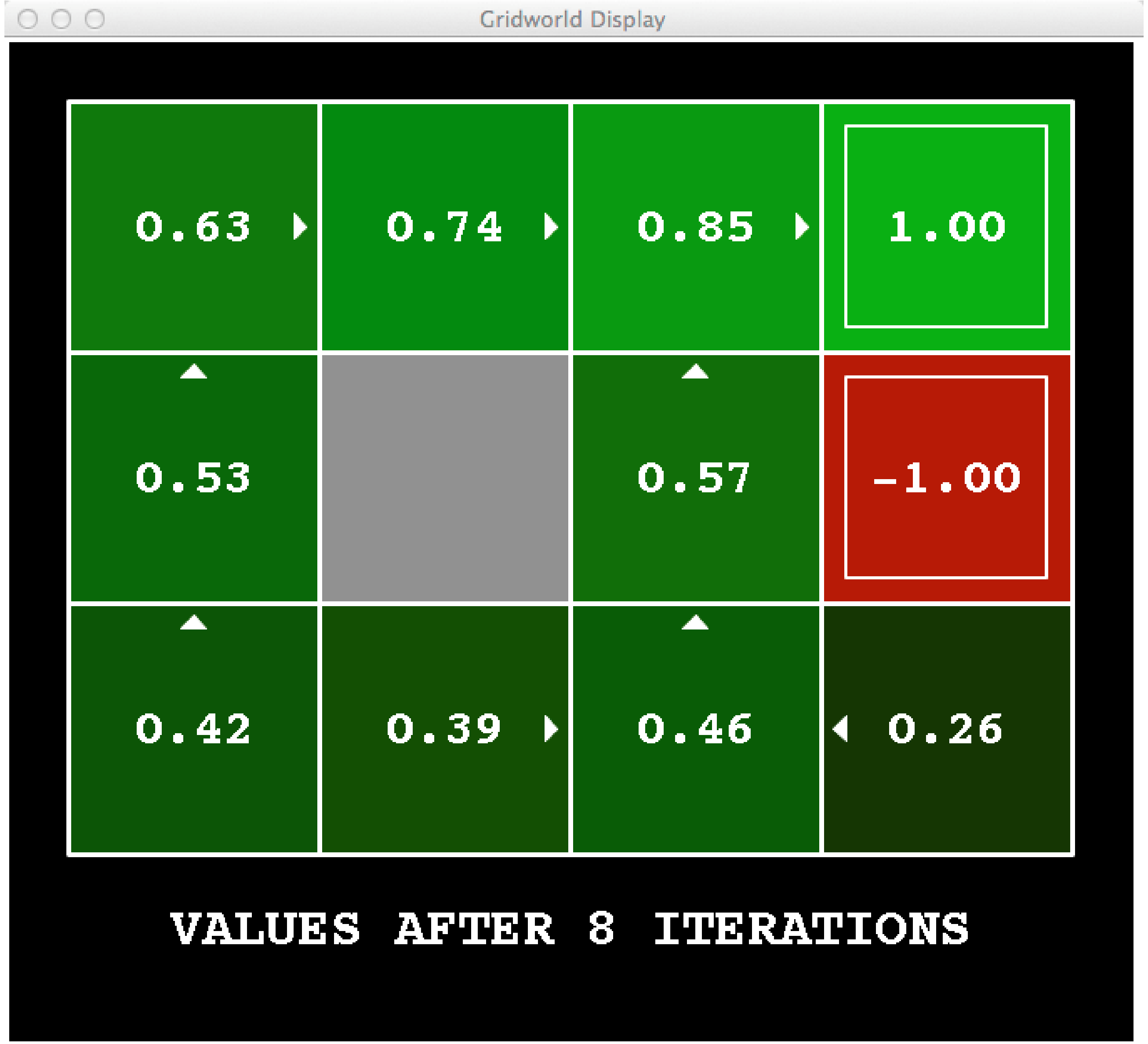
Noise = 0.2
Discount = 0.9
Living reward = 0

k=7



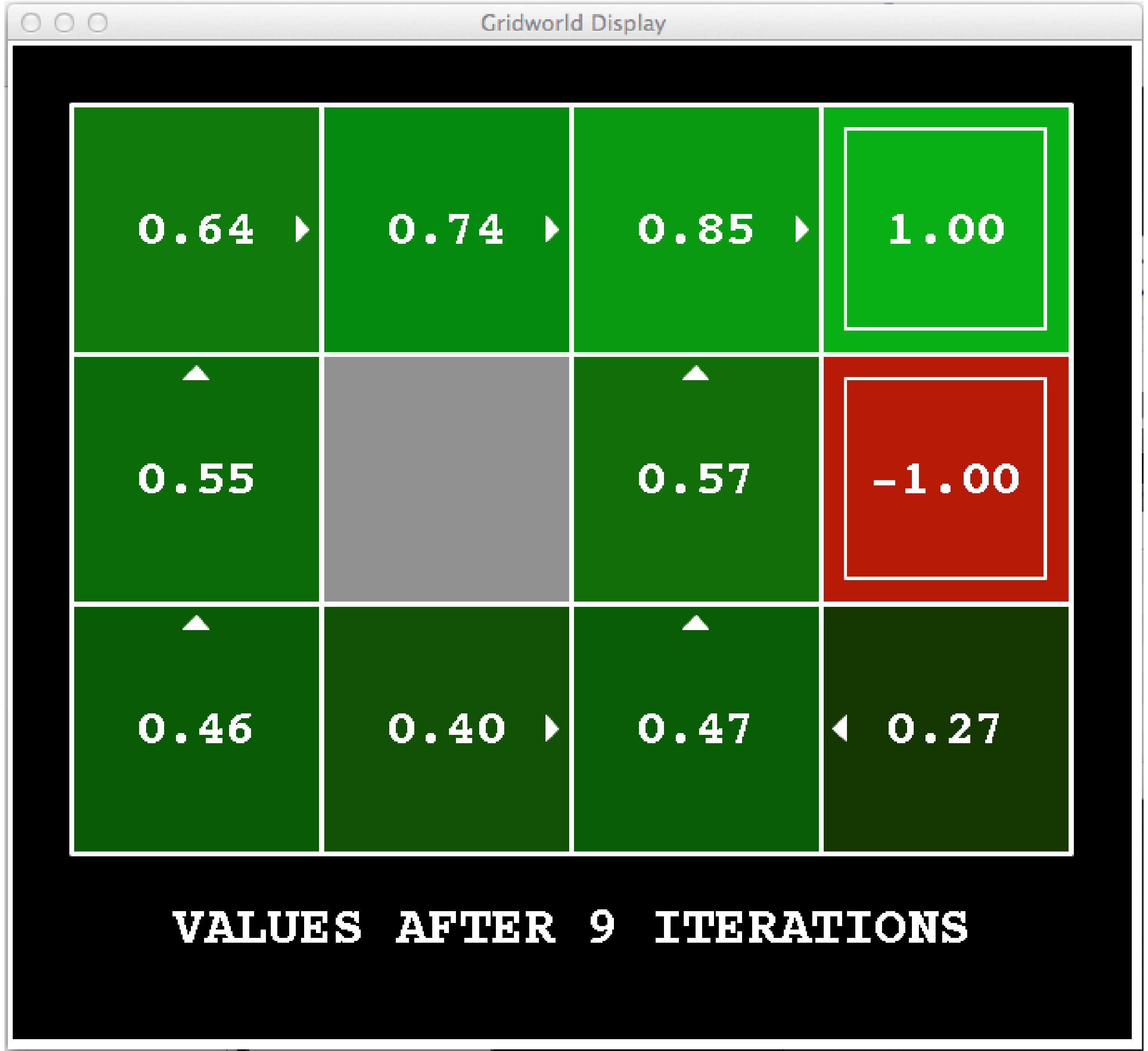
Noise = 0.2
Discount = 0.9
Living reward = 0

k=8



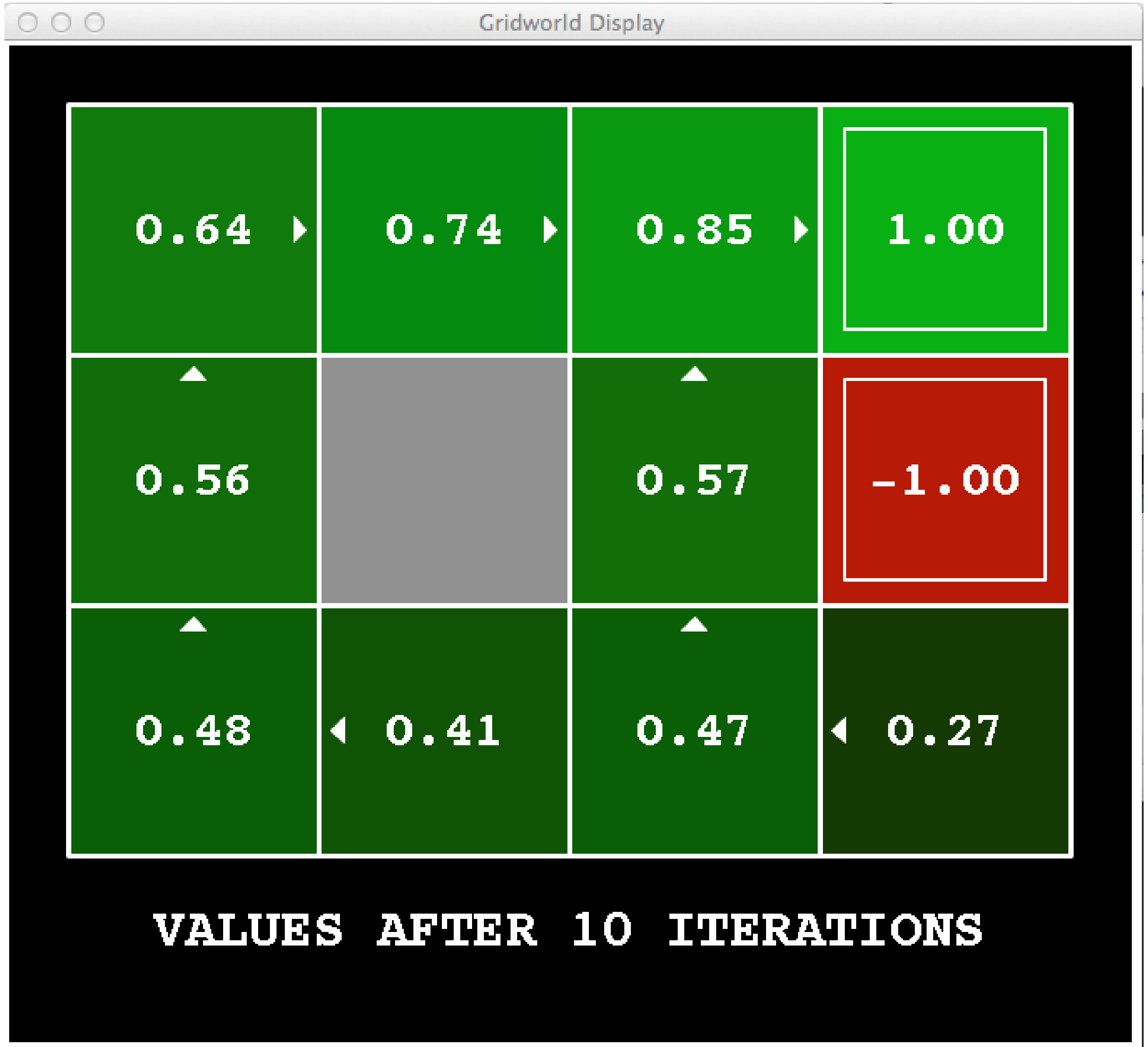
Noise = 0.2
Discount = 0.9
Living reward = 0

k=9



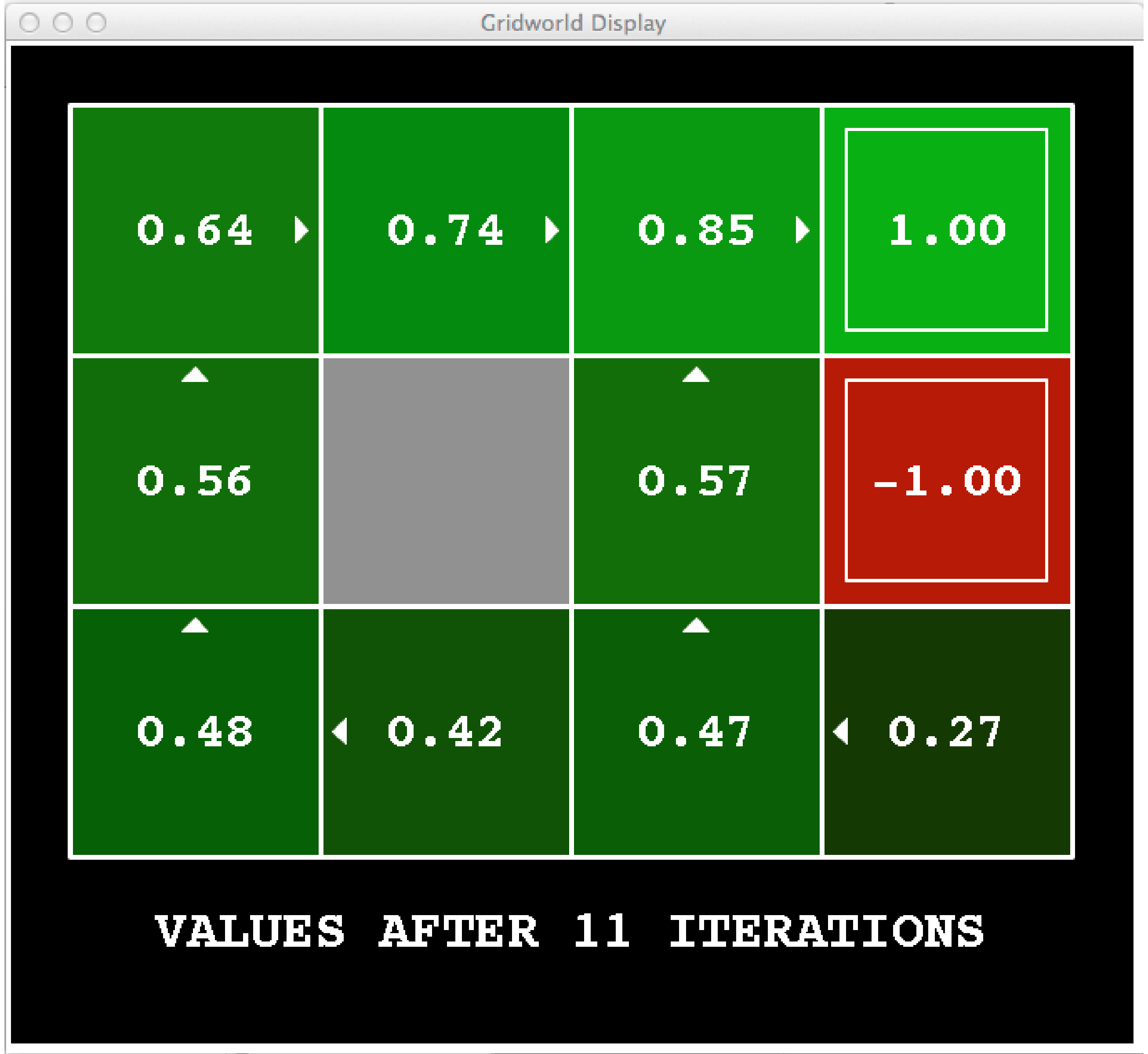
Noise = 0.2
Discount = 0.9
Living reward = 0

k=10



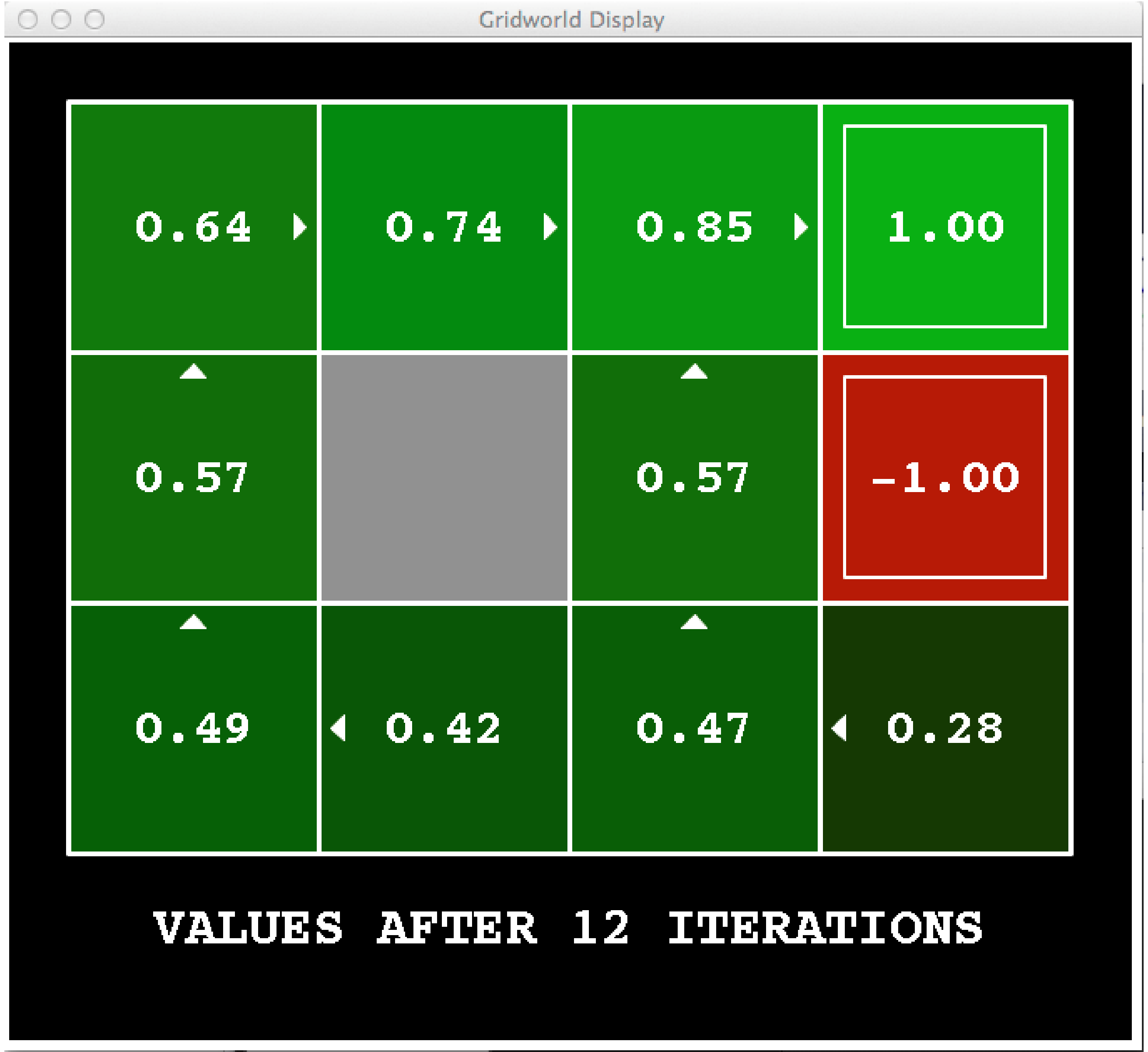
Noise = 0.2
Discount = 0.9
Living reward = 0

k=11



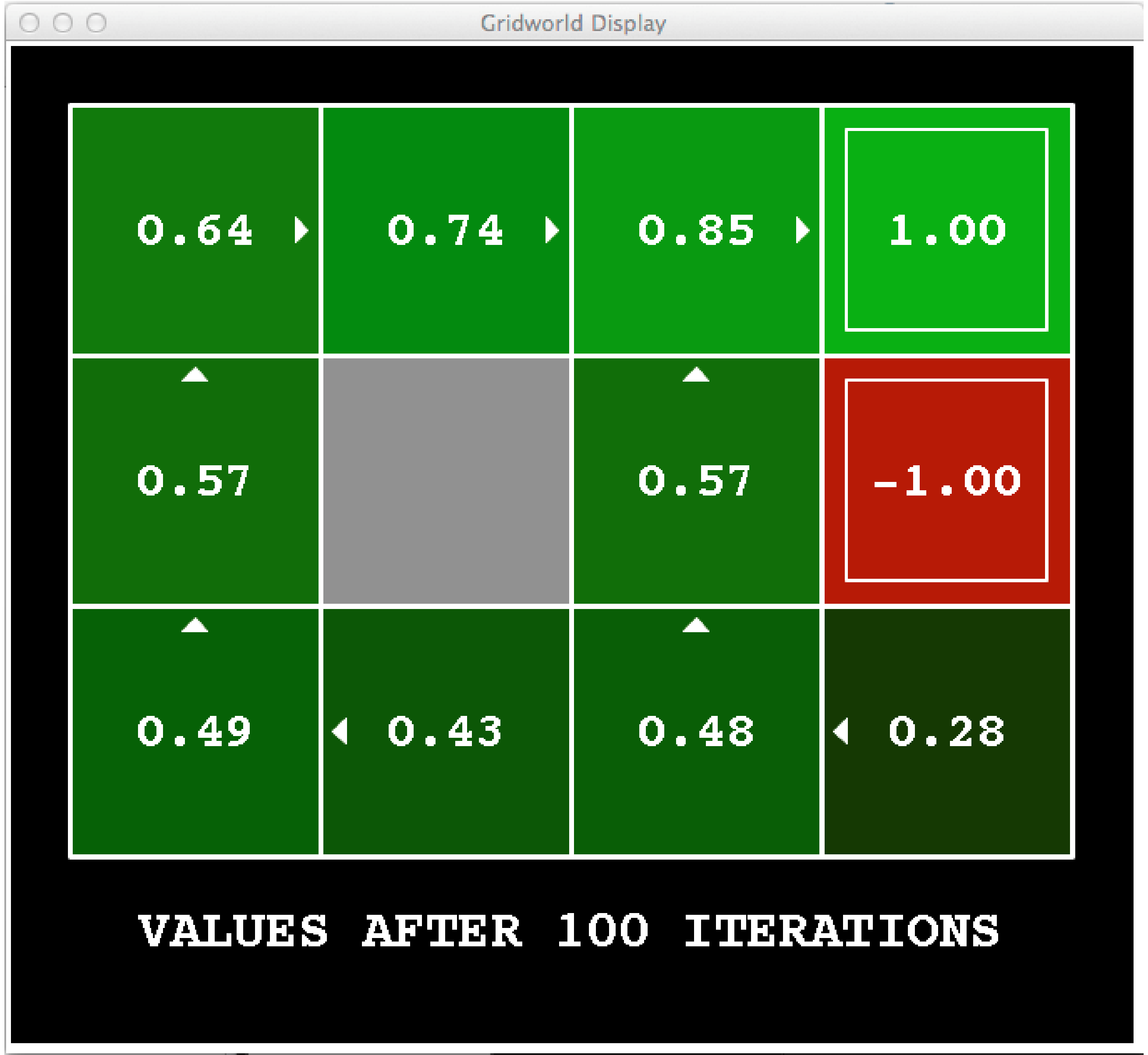
Noise = 0.2
Discount = 0.9
Living reward = 0

k=12



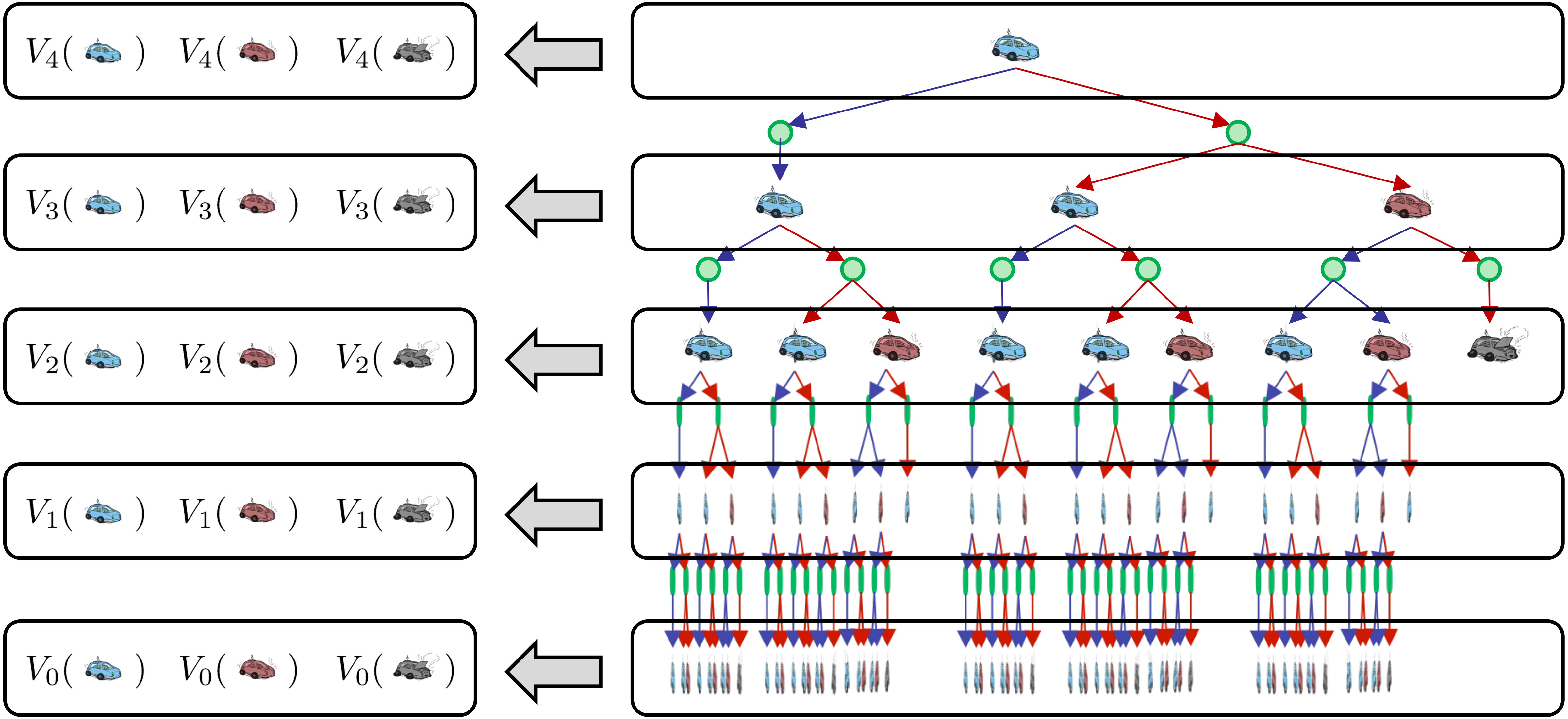
Noise = 0.2
Discount = 0.9
Living reward = 0

k=100

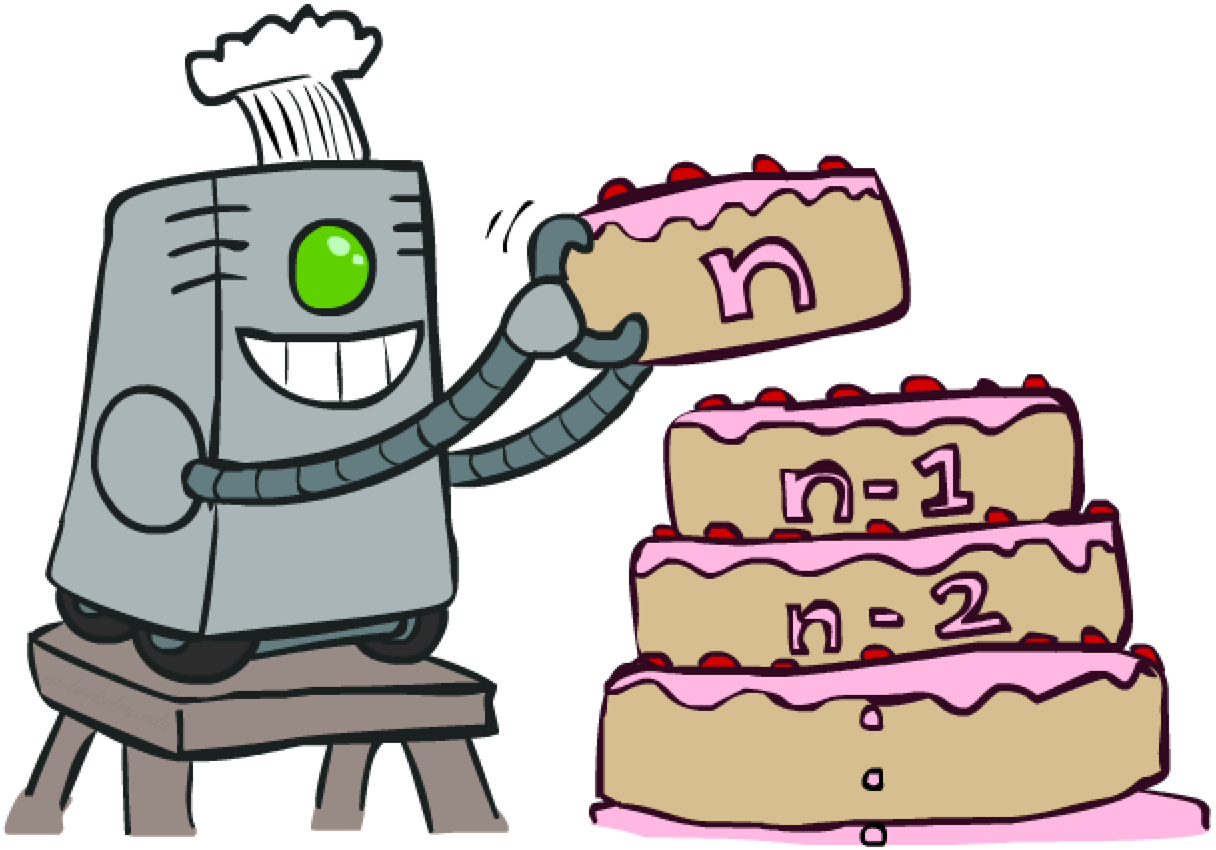


Noise = 0.2
Discount = 0.9
Living reward = 0

Computing Time-Limited Values



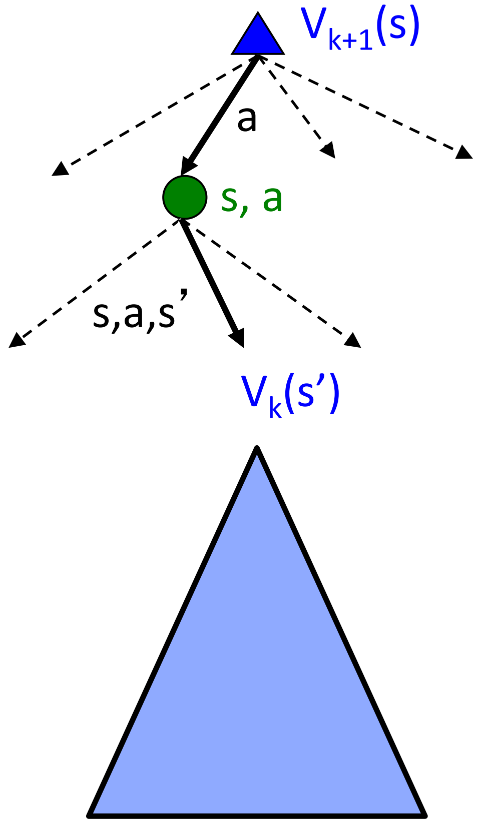
Value Iteration



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:

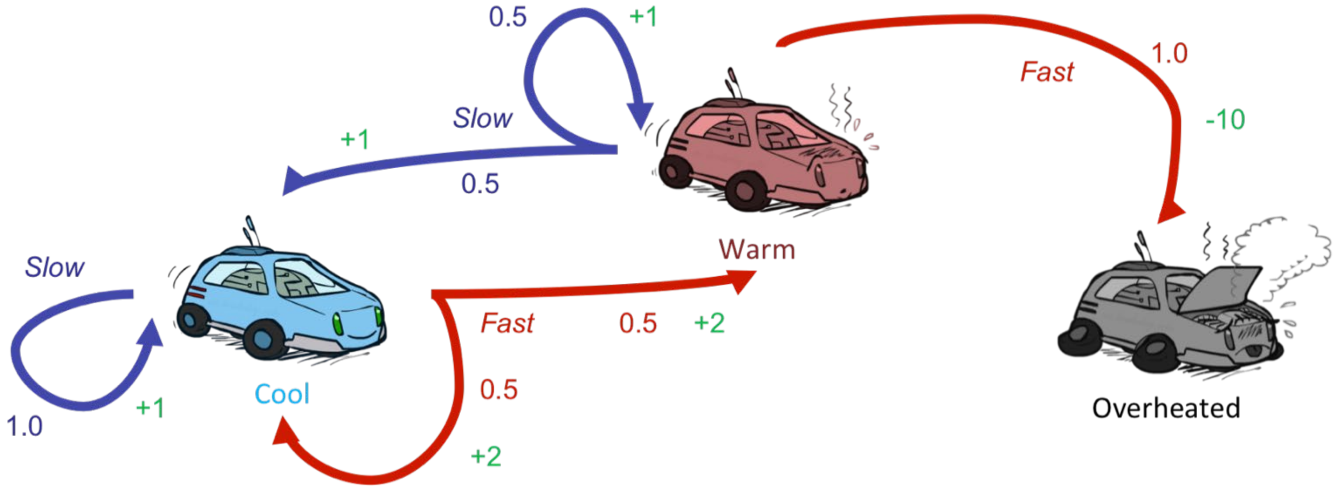
$$V_{k+1}(s) \leftarrow \max_a \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma V_k(s') \right]$$



- 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

Example: Value Iteration

V_2	3.5	2.5	0
V_1	2	1	0
V_0	0	0	0

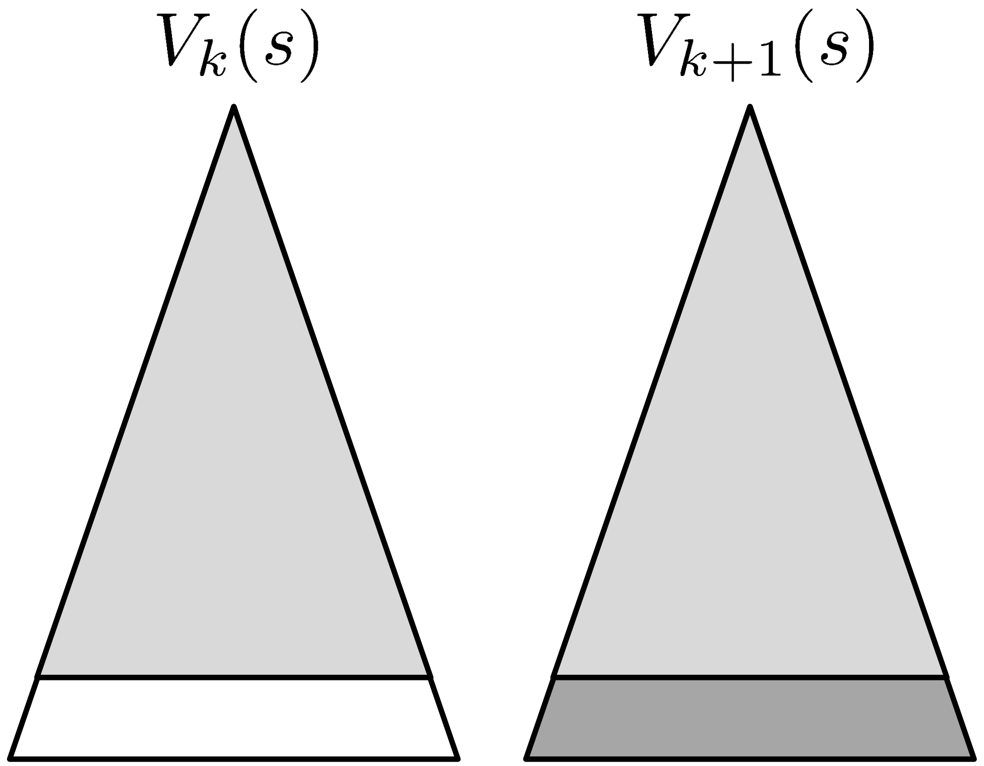


Assume no discount!

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

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



Lab 5 CSP: sudoku Due May 12,7pm

- Build 2 functions
  - Backtracking
  - Forward checking
- Both modify board with solution found and return number of recursive calls.

7	8		4			1	2	
6				7	5			9
			6		1		7	8
		7		4		2	6	
		1		5		9	3	
9		4		6				5
	7		3				1	2
1	2				7	4		
	4	9	2		6			7

Will be represented by:
sudoku[0]=[7,8,0,4,0,0,1,2,0]
sudoku[1]=[6,0,0,0,7,5,0,0,9]
sudoku[2]=[0,0,0,6,0,1,0,7,8]
sudoku[3]=[0,0,7,0,4,0,2,6,0]
sudoku[4]=[0,0,1,0,5,0,9,3,0]
sudoku[5]=[9,0,4,0,6,0,0,0,5]
sudoku[6]=[0,7,0,3,0,0,0,1,2]
sudoku[7]=[1,2,0,0,0,7,4,0,0]
sudoku[8]=[0,4,9,2,0,6,0,0,7]

Lab 5 Sudoku CSP

- For backtracking:
  - Check before recursion for assignment that violates constraints
- For Forward checking:
  - Check for empty domains due to new assignment before recursion.
  - Don’t implement full arc consistency

7	8		4			1	2	
6				7	5			9
			6		1		7	8
		7		4		2	6	
		1		5		9	3	
9		4		6				5
	7		3				1	2
1	2				7	4		
	4	9	2		6			7

Will be represented by:
sudoku[0]=[7,8,0,4,0,0,1,2,0]
sudoku[1]=[6,0,0,0,7,5,0,0,9]
sudoku[2]=[0,0,0,6,0,1,0,7,8]
sudoku[3]=[0,0,7,0,4,0,2,6,0]
sudoku[4]=[0,0,1,0,5,0,9,3,0]
sudoku[5]=[9,0,4,0,6,0,0,0,5]
sudoku[6]=[0,7,0,3,0,0,0,1,2]
sudoku[7]=[1,2,0,0,0,7,4,0,0]
sudoku[8]=[0,4,9,2,0,6,0,0,7]